Recommendation of activity sequences during distributed events

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DOCTORAL THESIS

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Recommendation of Activity Sequences During Distributed Events

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Recommendation of Activity Sequences During Distributed Events

Abstract

Multi-day events such as conventions, festivals, cruise trips, to which we refer to as *distributed events*, have become very popular in recent years, attracting hundreds or thousands of participants. Their programs are usually very dense, making it challenging for the attendees to make a decision which events to join. Recommender systems appear as a common solution in such an environment. While many existing solutions deal with personalised recommendation of single items, recent research focuses on the recommendation of consecutive items that exploits user's behavioural patterns and relations between entities, and handles geographical and temporal constraints.

In this thesis, we first **formulate the problem of recommendation of activity sequences**, classify and discuss the types of influence that have an impact on the estimation of the user's interest in items.

Second, we propose an approach (ANASTASIA) to solve this problem, which aims at **providing an integrated support for users to create a personalised itinerary of activities**. ANASTASIA brings together three components, namely: (1) estimation of the user's interest in sin-

gle items, (2) use of sequential influence on activity performance, and (3) building of an itinerary that takes into account spatio-temporal constraints. Thus, the proposed solution makes use of the methods based on sequence learning and discrete optimisation.

Moreover, stating the lack of publicly available datasets that could be used for the evaluation of event and itinerary recommendation algorithms, we have created two datasets, namely: (1) **event attendance on board of a cruise (Fantasy_db)** based on a conducted user study, and (2) **event attendance at a major comic book convention (DEvIR)**. This allows to perform evaluation of recommendation methods, and contributes to the reproducibility of results.

Recommandation de Séquences d'Activités lors d'Évènements Distribués

Résumé

Les événements distribués, se déroulant sur plusieurs jours et/ou sur plusieurs lieux, tels que les conventions, festivals ou croisières, sont de plus en plus populaires ces dernières années et attirant des milliers de participants. Les programmes de ces événements sont généralement très denses, avec un grand nombre d'activités se déroulant en parallèle. Ainsi, choisir les activités à entreprendre est devenu un véritable défi pour les participants. Les systèmes de recommandation peuvent constituer une solution privilégiée dans ce genre d'environnement. De nombreux travaux en recommandation se sont concentrés sur la recommandation personnalisée d'objets spatiaux (points d'intérêts immuables dans le temps ou événements éphémères) indépendants les uns des autres. Récemment, la communauté scientifique s'est intéressée à la recommandation de séquences de points d'intérêts, exploitant des motifs comportementaux des utilisateurs et incorporant des contraintes spatio-temporelles pour recommander un itinéraire de points d'intérêts. Néanmoins, très peu de travaux se sont intéressés à la problématique de la recommandation de séquence d'activités, problème plus difficile du fait du caractère

éphémère des objets à recommander.

Dans cette thèse, nous proposons tout d'abord une **formalisation du problème de la recommandation de séquences d'activités**. Dans ce cadre, nous proposons et discutons une classification des types d'influences pouvant avoir un impact sur l'estimation de l'intérêt des utilisateurs dans les activités.

Ensuite, nous proposons **ANASTASIA**, une approche de recommandation personnalisée de séquences d'activités lors des événements distribués. Notre approche est basée sur trois composants clés : (1) l'estimation de l'intérêt d'un utilisateur pour une activité, prenant en compte différentes influences, (2) l'intégration de motifs comportementaux d'utilisateurs basés sur leurs historiques d'activités et (3) la construction d'un planning ou séquence d'activités prenant en compte les contraintes spatio-temporelles de l'utilisateur et des activités. Nous explorons ainsi des méthodes issues de l'apprentissage de séquences et de l'optimisation discrète pour résoudre le problème.

Enfin, nous démontrons le manque de jeu de données librement accessibles pour l'évaluation des algorithmes de recommandation d'événements et de séquences d'événements. Nous pallions à ce problème en proposant deux jeux de données, librement accessibles, que nous avons construits au cours de la thèse: **Fantasy_db** et **DEvIR**. Fantasy_db comporte des données de participation à des événements lors d'une croisière, recueillies lors d'une étude utilisateur, tandis que DEvIR réunit des données de participation au Comic Con de San Diego, convention majeure dans le domaine.

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For my loving Mom.

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[1]Office of Nice People (fr.)

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1
Introduction

Leisure activities constitute an important part of our life. Nowadays, the offer of activities to undertake is constantly growing. This can be easily seen not only by the increasing number of social events created and promoted on social networks such as Facebook, Couchsurfing, etc., but also by the appearance of specialised online services and event-based social networks (EBSNs), such as Meetup, Eventbrite, etc. that aim at organising and promoting social events. Moreover, multi-day events (*e.g.* conventions, festivals, cruise trips, exhibitions), united around a certain theme and distributed geographically and temporally (usually, over a couple of days) attract hundreds and sometimes thousands of participants. We refer to that kind of big events as *distributed events* [102].

The variety of options offered on such kind of events is their biggest selling point, and at the same time it makes the decision making process on which activities to undertake and in which order more complex. The participants may then feel overwhelmed by the amount of options and information. In this Thesis, we aim at assisting the users during distributed events. In the following, we describe our motivational scenarios and research objectives.

1.1 Recommendation of Sequences of Activities: Motivational Examples

The problem faced by the attendees consists in the selection of the 'best' items, *i.e.* the 'best' activities to perform. Let us consider two motivational examples in order to illustrate this user's dilemma.

1.1.1 Motivational Example 1: Selection of Activities

Didi is planning her weekend of 2-4 December 2016 (see Fig. 1.1.1). She has preselected 8 activities that she fancies to do but she struggles with the selection. When considered and rated individually, all these activities represent high interest to her (see the five-star rating given next to activity names on Fig. 1.1.1). The five-star rating given next to activity names reflects interest score of a corresponding activity when judged independently (see Fig. 1.1.1).

Suppose, Didi's final choice is to go to Forró Wochenende 2016, hold in Freiburg, Germany. The independent interest judgement of this selection is $\hat{s}(a_1) = 5$. An alternative option could be to chain other activities, *e.g.* $\xi = a_3 \rightarrow a_6 \rightarrow a_7 \rightarrow a_8$. If we consider that the total interest score of such a chaining equals the sum of its parts, then $\hat{s}(\xi) = 20$. Even though $\hat{s}(\xi) > \hat{s}(a_1)$, the final selection is made in favour to a_1, which indicates that not only independent judgements are considered. One can also note that the activities are overlapping in terms of time (*e.g.* $< a_3$ *vs.* $a_4 >$, or $< a_1$ *vs. others* $>$). This implies that they cannot be performed all, even if the user would like to, and this amplifies the need for selection. Thus, while recommending an activity, and especially a sequence of activities, their time availability should be considered.

1.1.2 Motivational Example 2: Creation of Personalised Itineraries

Didi is going to Comic-Con International: San Diego. It is one of the biggest multi-day conventions primarily focused on comic books and related culture. Each year, it offers about 1,900 events, distributed over 4-5 days.

Let us have a look at the program of proposed events at the Convention. Its density is very high. Thus, in order to estimate it (see Fig. 1.1.2), we divide a day into 15-minute timeslots and calculate the number of events occurring at each of them. We can see that the number of competitive events is 37 in average, with the maximum of 112. Such dense variety makes it hard for attendees to select events and organise their time, so that it would be possible to perform the maximum of the activities they would enjoy.

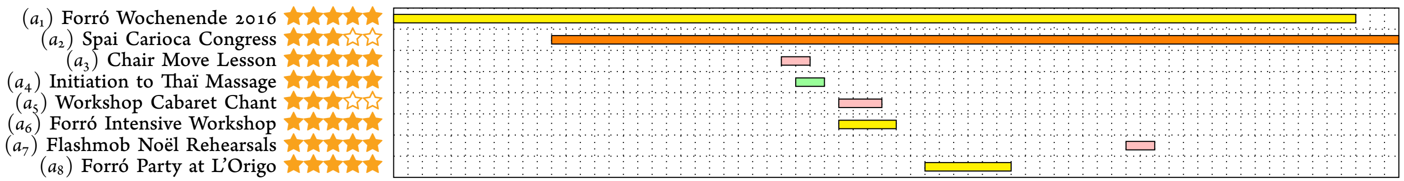


Figure 1.1.1: A choice of activities for a weekend during the time frame 1 December 21:00 - 5 December 01:00 (time windows of their availability). The bar colours indicate categories of activities: yellow - <Dance →Forró>, orange - <Dance →Samba de Gafieira>, pink - <Dance →Chair Dance>, green - <Well Being →Massage →Thaï>.

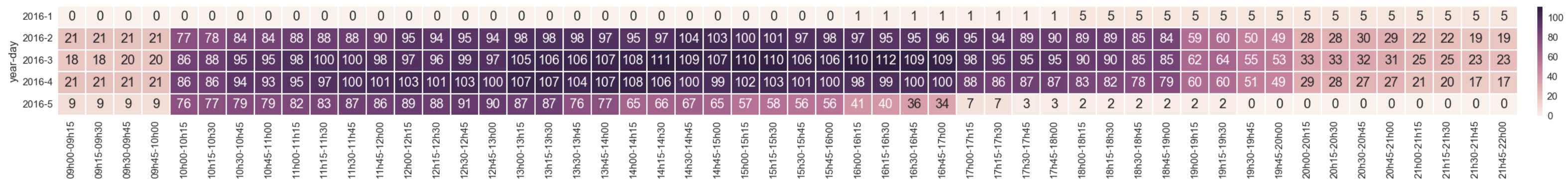


Figure 1.1.2: Heatmap of the overlapping events at Comic-Con 2016 with respect to 15 min long timeslots from 6am to 10pm.

When it comes to the problem of information filtering in order to assist users in the relevant data access by means of suggesting the most appealing items, recommender systems appear as a solution. They are powerful assistance tools in such a decision-making process.

1.2 Dealing with Recommendation of Activity Sequences

A desired assistance in the above scenarios would constitute of a suggestion of a personalised itinerary that may help a user by providing orientations during a distributed event (Scenario 2) or proposing an activity program during a limited time, *e.g.* over a weekend (Scenario 1). By an itinerary, we then understand a sequence of activities that a user can perform, given the limited time of activities, travelling time between their locations, etc.[1] Thus, the problem consists in finding an activity sequence (or itinerary) that maximises the user's satisfaction with attended events while taking into account the spatio-temporal constraints that guarantee the feasibility of the undertaken sequence (*e.g.* limited availability of events, simultaneous events, travelling time, etc.).

This problematic is of interest of Recommender Systems, and has attracted vivid attention from the research community. Recent works have thus focused on proposing novel approaches for event [67, 72], POI [140–142] and trip recommendation [139]. However, to the best of our knowledge, very few effort has been done for recommendation during distributed events [100], and especially itinerary recommendation.

Creating a personalised itinerary (sequence of activities) is a challeng-

[1] In the following, we use the notions *itinerary* and *activity sequence* interchangeably.

ing task in a number of ways. First, it has to be noted that the problem of the recommendation of personalised itineraries has lots in common with the problem of the Event recommendation that aims at providing a user with a list of events he/she is more likely to be interested in. Event recommendation is usually considered as a more complex problem than item recommendation (such as book or movie) [67]. Indeed, as events have a short lifetime and must be recommended to users before they actually occur, no explicit relevance judgements are available, contrary to item or Point-of-interest (POI) for which one may have ratings of users that have already buy the item or visit the POI. To handle this issue, in Event Based Social Networks, researchers have proposed to consider RSVP as binary indicators of interest. RSVP is the French acronym for "Répondez s'il vous plaît", meaning "Please, answer". On EBSN, RSVP are used by user to indicate their intent to attend an event. In the literature, event recommendation is usually considered as a top-k recommendation problem. It can be formulated as a list-wise [67, 89] or pair-wise [72] ranking problem.

It is to note that the Event recommendation problem is known to be intrinsically cold-start as it deals with events happening in the future, implying that no or little user-activity interactions are given [67]. In case of unique activities, the problem of the recommendation of personalised sequences of activities (itineraries) faces the same challenge. Second, aiming at building a feasible sequence of items, various constraints should be satisfied, including the limited availability of an activity, the time and cost of a travel, etc., which bring the task close to the Trip recommendation that seeks to build a feasible path over points of

interest in a given area for a given user. This also amplifies a higher desirability of a sequence of activities compared to a list of top-k [60]. In the context of a distributed event, the process to decide which sub-events or activities to undertake becomes more constrained than in the case of a traditional event recommendation. Indeed, the amount of activities may be higher than usual, while activities occur in parallel. Moreover, the sub-events are unique, short-lived and gathered under the umbrella of a general theme of the event. Itinerary recommendation thus differs from single event recommendation [67, 72].
Third, due to the limited availability of activities and their occurrence at the same time, the act of joining an activity by a user is subject to attendance bias, *i.e.* joining an activity does not necessarily mean being interested in it and vice versa. Thus, a user may miss a desirable activity because of its timing and its competitive activities and in contrast, may join an activity to fill in the gaps between other activities of his/her interest, as we have shown in [82].

1.3 Research Challenges and Questions

In this Thesis, we address the problem of recommendation of activity sequences during distributed events. We summarise the Main Research Goal of this Thesis as follows.

> Provide an integrated support (assistance) for users to create a personalised itinerary of activities and select events to join, in order to facilitate their decision making process.

We approach the Main Research Goal by following two directions, namely

Conceptual and ***Practical***, which we further decompose into research challenges.

We define the Conceptual research challenge as follows:

> Analyse the field of recommendation of sequences of spatial items for a better *understanding, conceptual definition* and *modelling* of the field.

In order to provide an insight into the field of recommendation of sequences of spatial items, and define the problem of recommendation of sequences of spatial items (RSSI), we identify the following research questions:

RC1: How to define the problem of recommendation of sequences of spatial items?

RC2: How is it related to the recommendation of Points-of-Interest and Event Recommendation?

We define the Practical research challenge as follows:

> Provide *an integrated framework* to address the defined problem.

In order to address the Practical research challenge, we define the following research questions:

RC3: What constitute an integrated model for recommendation of sequences of spatial items during distributed events?

- How to provide a user with the best support during a distributed event via personalised recommendation?

- How to bridge the users sequential behaviour in their performance of activities during distributed events and a set of spatio-temporal constraints imposed by the temporary nature of the activities?

RC4: What datasets can be used for evaluation of solution for recommendation of spatio-temporal activity sequences during distributed events?

- What are the requirements for a dataset for recommendation of activity sequences during distributed events?
- How to create test collections for recommendation of spatio-temporal activity sequences during distributed events?

1.4 Contributions & Thesis Outline

On our way to achieve this Main Research Goal, and answer the research questions, the following **contributions** have been made.

C1 Proposal of a generalised definition of the problem of recommendation of sequences of spatial items **RSSI**, overview of related recommendation problems and their solutions, classification of types of influence used for estimation of user's interest scores.

C2 Design and implementation of **a n**ew **a**pproach for **s**hort-**t**erm **a**ctivity **s**equence and **i**tinerary recommend**a**tion during distributed events, **ANASTASIA** [81]. It integrates discrete optimisation methods with sequence learning methods in order to take into account sequential nature of human behaviour and a set of spatio-temporal

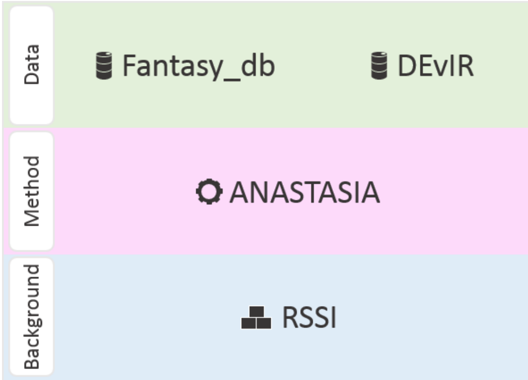


Figure 1.4.1: General overview of contributions.

constraints that originate from temporary natures of activities during distributed events.

C3 Design and building of **test collections** that allow us to perform **evaluation** of our proposed solution:

C3-1 **Fantasy_db**: a dataset for itinerary recommendation on board of a cruise [82]

C3-2 **DEvIR**: a dataset for **ev**ent and **i**tinerary **r**ecommendation during distributed events, namely at Comic-Con International: San Diego [84]

A general overview of the contributions is depicted in Fig. 1.4.1. Thus, the building of the conceptual background (RSSI) has allowed us to propose ANASTASIA, an integrated approach for solving RSSI, and to determine the requirements for the datasets for RSSI that we aimed at satisfying while creating Fanatsy_db and DEvIR, given the lack of available datasets.

Thesis Roadmap. The Thesis consists of four main parts and is organised as follows.

Part I presents the *conceptual direction* of our work. After presenting an introduction to Recommender systems in Chapter 2, we overview the existing approaches for the recommendation of spatial items, namely Point of Interest (POI), Event, and Trip recommendation in Chapter 3. We then introduce the problem of recommendation of sequences of spatial items (**RSSI**) and provide a generalised formalisation for it. In Chapter 4, we review the methodology used for approaching RSSI, and we discuss the types of influence on the user's interest in items (*e.g.* geographical, temporal, textual, etc.) that are used to improve the quality of recommender systems and propose a classification. Finally in Chapter 5, we survey the available datasets that are used for the recommendation of spatial items and related fields, and discuss their applicability to RSSI.

The *practical direction* of the Thesis is presented in **Parts II-IV**. Thus, in **Part II**, we describe our proposed solution for RSSI, that we call ANASTASIA. We present the datasets created for evaluation of approaches to solving RSSI, namely Fantasy_db and DEvIR, in **Part III**. Next, **Part IV** provides experimental results of evaluation of ANASTASIA on the created datasets, and the discussions.

We summarise the conclusions and describe the perspectives and the directions of future work in Chapter 12.

1.5 Publications

The contributions made during the work on this Thesis have resulted in several publications presented at international and national conferences and workshops. We provide a detailed list of the publications together with the table that summarises them. In the list below, we use the tags next to a publication that indicate one of the described above contributions.

1. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. Recommendation of short-term activity sequences during distributed events. Procedia Computer Science, 108 (Supplement C):2069 – 2078, 2017. ISSN 1877-0509. doi: 10.1016/j.procs.2017.05.154. URL `https://doi.org/10.1016/j.procs.2017.05.154`. International Conference on Computational Science, ICCS 2017, 12-14 June 2017, Zurich, Switzerland. **C2**

2. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. DEvIR: Data collection and analysis for the recommendation of events and itineraries (in press). In 52nd Hawaii International Conference on System Sciences, HICSS 2019, Grand Wailea, Maui, Hawaii, USA, January 8-11, 2019, 2019. (in press) **C3-2**

3. **Diana Nurbakova**. Recommendation of activity sequences during distributed events. In Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization, UMAP 2018, Singapore, July 08-11, 2018, pages 261–264, 2018. doi: 10.1145/3209219.3213592. URL `http://doi.acm.org/10.1145/3209219.3213592`.

4. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. Itinerary recommendation for cruises: User study. In Proceedings of

the Workshop on Recommenders in Tourism colocated with 11th ACM Conference on Recommender Systems (RecSys 2017), Como, Italy, August 27, 2017., 2017. **C3-1**

5. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. Recommandation de séquences d'activités lors d'évènements distribués. In CORIA 2018 - 15th French Information Retrieval Conference., 2018. **C2**

6. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. ANASTASIA : recommandation de séquences d'activités spatiotemporelles. In CORIA 2016 - 13th French Information Retrieval Conference., pages 325–334, 2016. **C2**

7. **Diana Nurbakova**, Léa Laporte, Sylvie Calabretto, and Jérôme Gensel. Users psychological profiles for leisure activity recommendation: user study. In Proceedings of International Workshop on Citizens for Recommender Systems, CitRec@RecSys 2017, 31 August 2017, Como, Italy, pages 3:1–3:4, 2017. doi: 10.1145/3127325.3127328. URL http://doi.acm.org/10.1145/3127325.3127328.

8. Jie Yang, Iván Cantador, **Diana Nurbakova**, María E. Cortés-Cediel, and Alessandro Bozzon. Recommender systems for citizens: the CitRec'17 workshop manifesto. In Proceedings of International Workshop on Citizens for Recommender Systems, CitRec@RecSys 2017, 31 August 2017, Como, Italy, pages 1:1–1:4, 2017. doi: 10.1145/3127325.3177871. URL http://doi.acm.org/10.1145/3127325.3177871.

The summary of the publications is given in Tab. 1.5.1.

Table 1.5.1: Publications made during the Thesis.

Contribution	Ref.	Contr. type	Source name	Source type	Rank
ANASTASIA	[81]	Tech.	ICCS-2017	Conf	A
DEvIR	[84]	Data	HICSS-2019	Conf	A
Thesis Wrap-Up	[78]	Proposal	UMAP-2018	DC	(B)
Fantasy_db	[82]	Data	RecTour-2017 @RecSys-2017	WorkS	(B)
ANASTASIA	[83]	Tech.	CORIA-2018	Conf	
ANASTASIA	[79]	Proposal	CORIA-RJC-2016	DC	
DesIR_db	[80]	Data	CitRec-2017 @RecSys-2017	WorkS	(B)
CitRec Manifesto	[129]	Other	CitRec-2017 @RecSys-2017	WorkS	(B)

Contr. type: In this column, the type of a contribution is given. The following abbreviations are used: SoA - state-of-the-art and problem formalisation, Data - dataset, Tech. - solution approach for solving a problem, Proposal - project proposal, Other - other.
Source name: In this column, the names of the conferences, journals, workshops are given.
Source type: In this column, the following abbreviations are used: Conf - Conference, Journ - Journal, WorkS - Workshop, DC - Doctoral Consortium.
Rank: If the Type of a publication is WorkS or DC, in the column Rank we provide the rank of a conference which has hosted the Workshop or Doctoral Consortium in brackets. In case of a national conference, the country flag is given in column Rank.
The **row colour** is used to indicate publications related to the future work (see Chapter 12).

Part I

Recommendation of Sequences of Spatial Items: Problem Definition and State-of-the-Art

2

Recommender Systems at a Glance

Contents

Recommender systems are software tools and techniques that aim at

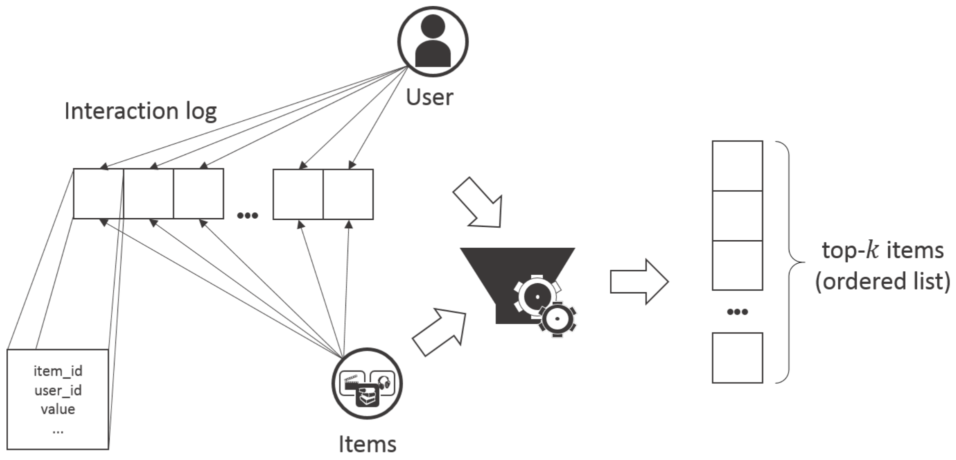


Figure 2.1.1: General overview of recommender systems.

predicting the user's preferences or ratings for unknown items in order to make useful suggestions for users [95]. In this Chapter, we present a brief overview of recommender systems which serves as an introduction to recommendation of sequences of spatial items that is the focus of this Thesis and which we describe in details in the following chapters.

2.1 Recommender Systems: Overview

In this Section, we describe the general overview of recommender systems and provide a definition of recommendation problem.

2.1.1 General overview of recommender systems

We represent the general overview of recommender systems in Fig. 2.1.1. The **input** of a recommender system usually consists of user-item interactions. A recommender system returns a list of top-k unknown items for a given user as the output. The **output** items are ordered with respect to the predicted value of utility of items for a given user (or the user's interest in an item, the user's satisfaction with respect to the item, etc.).

The following notions are used in the schema presented in Fig. 2.1.1.

Items. Items are the objects related to a certain domain (*e.g.* books, music tracks, movies, etc.). Each item may be defined with a set of characteristics.

Users. Individuals that are using a recommender systems, who may have diverse characteristics and goals.

Interactions. Interactions are recorded human-system actions, mainly related to items. Interaction log may contain an explicit feedback the user has provided for items (*e.g.* rating). Ratings are the most popular and the most exploited form of user-item interactions in recommender systems [1, 95]. Though the interactions may come in various forms (*i.e.* numerical, ordinal or binary ratings, unary ratings and implicit feedback), usually, a recommender systems uses only one type of interactions in order to make its prediction.

2.1.2 Recommendation Problem

As we have state above, the goal of a recommender system is to predict the matching between a user and the items, unknown for this user. In the context of recommender systems, by '*unknown*' we understand items that the user has not interacted with yet, so there is no record on this user-item interactions in the interaction log of the system.

The rating prediction problem can be seen as a matrix completion problem. We illustrate it in Fig. 2.1.2. Suppose there is a set of users and a set of items, in our case, pets (*e.g.* cat, dog, bird, fish, etc.). The user-item interactions can then be represented as a user-item matrix, where the

Figure 2.1.2: Illustration of recommender systems as a matrix completion task.

rows denote users, and the columns denote items, and each cell of the matrix corresponds to the user's interaction with the item (in our case, expressed by *like* or *dislike*). Some interactions may be unknown. They are represented as missing values of the matrix. The goal of a recommender systems is then to fill in the missing values by predicting them. The latter will allow to answer a question such as 'Would the last user like a bird as a pet?' (a cell with the question mark in Fig. 2.1.2).
More formally, the rating prediction problem can be formulated as follows [1]: given the set of users *Users* and the set of items *Items*, find a function R, such that for each (u, i) pair it measures the usefulness of the $i \in Items$ for the $u \in Users$, expressed in the form of *Rating*, *i.e.*:

$$R : Users \times Items \rightarrow Rating, \tag{2.1}$$

where *Rating* is "a totally ordered set (*e.g.* non-negative integers or real numbers within a certain range)". Usually, the higher the value of *Rating*, the stronger the user's preference of the item is.

Once the function R is found, a recommender system may return to a user a list of items with the highest scores estimated by R. More formally, for each user $u \in Users$, a recommender system should return such item $i'_u \in Items$ that maximises the user's interest, *i.e.*:

$$\forall u \in Users, i'_u = \arg\max_{i \in Items} R(u, i). \tag{2.2}$$

The systems and techniques will mainly differ in the way they estimate the function R.

2.2 Recommendation Techniques

Recommender systems are usually classified according to their method of estimating the user's interest score in items (function R) into the following categories [1]: (1) content-based recommendation, (2) collaborative filtering based recommendation, and (3) hybrid approaches. We discuss them in the following.

2.2.1 Content-based recommendation

Content-based recommendation is based on the principle that a user is more likely to be interested in the items that are similar to the ones he/she liked in the past. Therefore, the user profiling is needed in order to determine the user's tastes and preferences. A user profile may be provided explicitly through explicit statements from the users, *e.g.* via questionnaires or initial preferences. Thus, some of the websites require the initial specification of the user's preferences while creating an account. As examples, we can cite Meetup, a popular Event-Based Social Network (EBSN), that requires its users to specify the categories of social events a user is interested in, or Deezer, a music streaming service, which asks its users to provide a list of music genres they like.

More formally, let $Content(i) = \vec{w_i}$ be an item profile, representing a set of features of item i as a m-dimensional vector. Let $CBProfile(u) = \vec{w_u}$ be a user profile that is also represented in a m-dimensional vector space, where it is defined as a vector of weights $CBProfile(u) = (w_{u1}, w_{u2}, ..., w_{um})$. In this representation, each weight w_{ul} denotes the importance of the element l for user u. The function R is then defined as a matching function between these two profiles, *i.e.* [1]:

$$R(u, i) = match(ContentBasedProfile(u), Content(i)).$$

Various measure can be used in order to estimate the matching. One of the most commonly used measures is the cosine similarity (*e.g.* [1, 67]), where:

$$cos(\vec{w_u}, \vec{w_i}) = \frac{\vec{w_u} \cdot \vec{w_i}}{||\vec{w_u}||_2 \times ||\vec{w_i}||_2}.$$

These methods are called memory-based, as the estimation is performed based on the entire collection pf previous user-item interactions.

Other types of techniques used in order to estimate the function R are based on models, and therefore are called model-based. The prediction function is often learned from the user's past experience with the system using machine learning techniques. In this case, the assignment of an interest score can be interpreted as a classification problem.

Content-based methods may give the results with high precision [67, 102], are rather easy to implement and interpret, and moreover, are efficient in the situation where there is lack of collaborative information, so that a recommender algorithm may not rely on other users' judgements. It should to be noted that content-based methods are efficient in order to alleviate the new item cold start problem. Though for a new added item, there is no interaction information yet, it is possible to make predictions, if we can represent this item with a vector of features. However, this group of methods have certain limitations.

One of the limitations lies in the 'obvious' recommendations and an excessive overspecialisation of recommendation. Thus, given that the highest scores are acquired by the items that are similar to the ones previously liked by the user, a system will recommend only similar items, even if a user may be interested in different types of items. This limits the diversity of recommendation.

Another issue that arises is related to the new user cold start problem. The latter consists in the lack of defined user profile for a new user (unless it is not specified explicitly by the user), as he/she has not had interactions with items so far. Therefore, a prediction made for this user will not be precise.

Finally, it is to keep in mind that content-based based require sufficient space of features, otherwise it may result in poor user and item profiles, which may make items indistinguishable. In order to overcome this limitations, different dimensions may be considered, *e.g.* textual description based profile, temporal profile, category profile, etc.

For more details about content-based approaches refer to [66].

2.2.2 Collaborative filtering based recommendation

Another group of methods is based on collaborative filtering. The main idea of the latter may be expressed as follows: the interest of a given user in an item is likely to be similar to the interest to this item expressed by similar users [1]. The similar users are the users who have shown a similar rating behaviour to the one of a given user. In other words, collaborative filtering techniques are based on the rating/usage patterns extracted from user-item interactions [56].

Similarly to content-based methods, collaborative filtering algorithms can be sub-divided into two classes: memory-based and model-based.

In memory-based collaborative filtering methods, the predicted value $R(u, i)$ can be defined as the aggregation over the interest scores (ratings) of similar users, *i.e.*:

$$R(u, i) = aggr_{u' \in \hat{U}} R(u', i),$$

where $\hat{U}$ denotes the set of the most similar users to the user u. The approaches differ in the way they define aggregation function and the neighbourhood.

A comprehensive survey on collaborative filtering methods that are based on nearest-neighbours can be found in [28, 75].

Model-based approaches use the previous interactions in order to build a model that is then used for predictions [45, 98, 144]. The models are built over latent factor space. Thus, the recent works have focused mainly on matrix factorisation based collaborative filtering [52, 59, 102, 139].

The basic idea of matrix factorisation lies in the mapping of users and items into a joint latent factor space. The user-item interaction are then represented as inner products in that space [75]. More formally, let U be the set of users and I be the set of items. Each $i \in I$ is associated with a f-dimensional latent vector $q_i \in \mathbb{R}^f$, and each $u \in U$ is associated with f-dimensional latent vector $p_u \in \mathbb{R}^f$. Each element of a user-item interaction matrix r_{ui} can then be defined as the dot product of the corresponding user and item latent vectors, *i.e.*:

$$r_{ui} = q_i^T p_u.$$

The parameter learning is performed by minimising the regularized squared error typically using stochastic gradient descent or least squares method. Collaborative filtering approaches have high prediction accuracy and may integrate temporal dynamics, and implicit feedback. The main challenges arise from data sparsity and cold-start problem.

2.3 Context-Aware Recommender Systems

Recently, the notions of context-aware recommender systems (CARS) [2] and time-aware recommender systems (TARS) [18] have attracted attention of the research community.

Contextual information has been shown to play an important role in recommendation process, allowing to make personalised suggestions for a user 'under certain circumstances' [2]. Thus, it has been reported that incorporating the contextual information into recommendation model improves the prediction accuracy of recommendation models [4, 29, 99, 130, 131] and helps to alleviate the cold-start problem [67, 125]. The most typical examples of context exploited in recommender systems are location and time.

Assuming that the contextual information (denoted *Context*) is known and is defined by a set of contextual attributes of various nature, Formula 2.1 of the rating function sought by a recommender system can then be modified as follows [2]:

$$R : User \times Item \times Context \rightarrow Rating, \tag{2.3}$$

where *User* denotes the domain of users, *Item* denotes the domain of items, and *Rating* is the domain of rating.

Time-aware recommender systems can be understood as a special case of context-aware recommender systems, where context is given by temporal dimension [18]. Thus, the predicted function can be defined as follows:

$$R : User \times Item \times Time \rightarrow Rating, \tag{2.4}$$

where *Time* corresponds to temporal dimension.

Various approaches to model contextual information have been proposed by academic researchers. In this Thesis, we consider context to influence the user's interest in items. In Chapter 4, we discuss different types of influences in details. Here, we limit the description with the review of the generalised definitions of ratings functions sought by CARS and TARS. For more details about context and time-aware recommender systems refer to comprehensive surveys [2, 18].

2.4 Summary

In this Chapter, we have presented a brief introduction to recommender systems. We have presented the general recommendation problem formulation and the state-of-the-art categorisation of techniques, namely:

content-based recommendation and collaborative filtering based recommendation. We have also provided some pointers for more detailed reading. In the following chapters, we will focus on recommendation of sequences of spatial items.

Alice: Would you tell me, please, which way I ought to go from here?
The Cheshire Cat: That depends a good deal on where you want to get to.
Alice: I don't much care where.
The Cheshire Cat: Then it doesn't much matter which way you go.
Alice: ...So long as I get somewhere.
The Cheshire Cat: Oh, you're sure to do that, if only you walk long enough.

Lewis Carroll, Alice in Wonderland

3

Recommendation of Sequences of Spatial Items: Problem Definition

Contents

Table 3.0.1: Statistics on literature related to Recommendation of sequences of spatial items.

Source type	<2009	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Conferences (**68**)	2	3	2	1	3	7	15	13	5	12	4
Journals (**26**)	5	1	1	0	1	2	3	4	5	4	0
Surveys (**19**)	2	1	1	2	0	2	5	3	2	0	1

With the ubiquitous use of mobile devices and the development of location-based systems, personalised recommendation of spatial items has become a crucial direction of recommendation. A *spatial item* is an item associated with a geographical location [122, 123].

In recent years, various research and industry efforts have been undertaken to deal with the problems of recommendation of spatial items, resulting in a great variety of notations and problem definitions, lacking unification. Moreover, a rising interest in sequence recommendations can find its reflections in the field of recommendation of spatial items. However, the problem of recommendation of sequences of spatial items has not been clearly defined yet. To fill in this gap, we propose a formulation of this problem as a special case of sequence-aware recommender systems [90].

In the following sections, we overview the state-of-the-art related to recommendation of sequences of spatial items. We propose the definitions of the concepts of an activity, and activity sequence. Our original definitions and formalisations are given in the purple frames. Thus, in this Part of the Thesis, we are addressing the Main Research Goal from the Conceptual perspective, constituting our Contribution 1 **C1**.

Table 3.0.2: Number of works by source: top-10 conference and journals.

Conferences											Journals										
ACM CIKM	ACM SIGKDD	ACM WSDM	AAAI	ACM SIGIR	ACM UMAP	IJCAI	WebConf	ACM RecSys	ACM UbiComp	Others	ACM TIST	Multimed Tools Appl	UMUAI	ACM Trans. Inf. Syst.	APWeb-WAIM	Commun. ACM	Comput. Oper. Res.	Comput. Intell.&Neurosc.	EJOR	IEEE Data Engin. Bull.	Others
9	5	5	3	3	3	3	3	2	2	30	4	2	2	1	1	1	1	1	1	1	11

The work presented in this Chapter, together with Chapters 4-5, is based upon our review of 94 research articles published mainly in the last six years in the major selective conferences, journals and workshops, including ACM SIGIR, ACM SIGKDD, ACM WSDM, The Web Conference[1], UMUAI, ACM Computing Surveys, ACM TIST, etc. (for more details, see Tab. 3.0.2). The statistics of the reviewed research papers with respect to the publication year is given in Tab. 3.0.1. Moreover, throughout the Part I, we refer to several surveys in order to give more pointers for a reader.

Roadmap. In this Chapter, we first review the concepts of spatial items (see Section 3.1). More precisely, we focus on (1) *single spatial items,* namely Point-of-Interest (POI), Event and Activity, and (2) *sequential items,* such as Trip and Sequence. Next, we overview the recommendation problems of single spatial items and sequential spatial items (see Sections 3.2-3.3). Based on the explored definitions, in Section 3.3, we

[1]Former WWW Conference

Figure 3.1.1: Word cloud of reviewed research papers drawn based on titles and keywords using `word_cloud`[3]generator in Python.

define a generalised problem of Recommendation of Sequences of Spatial Items (RSSI) as a special case of sequence-aware recommender systems [90].

3.1 Spatial Items: Concepts and Definitions

Numerous research efforts in the field of recommender systems have been focusing on personalised recommendation of spatial items. This interest can be visualised in the form of a word cloud depicted in Fig. 3.1.1 which is drawn based on the titles and keywords of the reviewed research papers[2]. Thus, we can see that 'user', 'location', 'travel', 'sequential', 'point of interest', 'event' are in the centre of today's research in the field of recommender systems.

While investigating the concepts of spatial items within the state-of-the-art, we came across three distinct yet related notions, namely *Point*

[2]We excluded the words "recommendation" and "recommender system".

[3]`word_cloud` is a word cloud generator in Python available under MIT license.

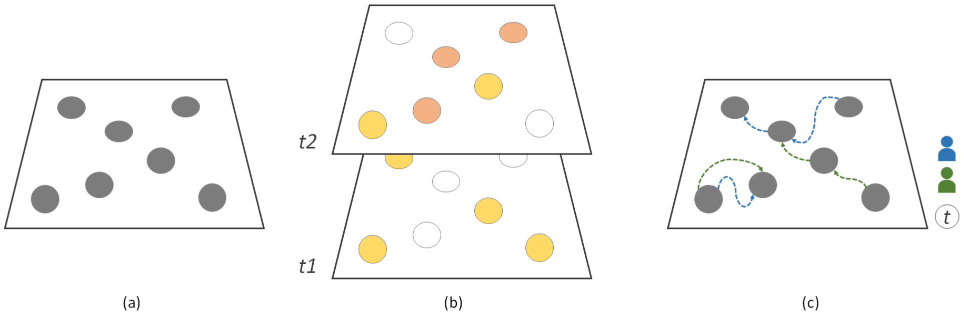


Figure 3.1.2: Visualisation of (a) POIs, (b) events and (c) trajectories with respect to the same geolocations.

of Interest (POI), *Event*, and *Trip*, that are all linked to the notion of location.

Merriam-Webster defines *location* as "a position or site occupied or available for occupancy or marked by some distinguishing feature". In the context of recommender systems, a location can be understood as a geospatial point defined by its coordinates, mainly longitude and latitude. Defining Location-Based Social Networks (LBSN), Zheng *et al.* [145] give the following definition of a location in LBSN: "an instant location of an individual at a given timestamp, or a location history that an individual has accumulated in a certain period"[4]. Mind that the latter definition bridges the spatial and temporal dimensions. Based on the relation to a location (*i.e.* instant location or location history), we distinguish between *single spatial items* (POI and Event), and *sequential spatial items* (Trip).

In order to illustrate the difference between three types of spatial items, we give a schematic representation of POIs (a), events (b), and trajectories (c) on Figure 3.1.2. Let us suppose, there is a space where we

[4]For more discussions about Location-Based Social Networks (LBSNs) and recommendation in LBSNs refer to [5, 145].

define seven locations represented as spots on Fig. 3.1.2. For the sake of simplicity, we consider that a POI can be identified by its location which we assume to be constant. We represent POIs as spots filled in with grey on Fig. 3.1.2 (a). The main question one would ask about a POI is *Where?*.

Figure 3.1.2 (b) depicts a number of events. The snapshots for two time points are given, t_1 and t_2. We use different colours of filling in order to differentiate between items still available from the previous point in time (yellow), and items appeared at a given time point (orange). Locations that do not host any event at a given time are filled in with blank. It can be noted that depending on time, a set of possible options will be different. The questions asked about an event are *Where?* and *When?*.

When it comes to trajectories (see Fig. 3.1.2 (c)), at least two components are considered. The time dimension is taken into consideration, allowing to establish a relation of chronological ordering. Moreover, trajectories are usually user-related. Thus, in the state-of-the-art, trajectories are usually mined from the users traces [146]. The questions asked about a trajectory are *From where To where?*, *When?*, and often *Who?*.

In the following, we provide more details about each concept, their definitions and representation in the state of the art.

3.1.1 Single Spatial Items

Point of Interest (POI)

Probably, the most frequently used term in the recommendation of spatial items is a *Point of Interest* (or *POI*). The definitions differ in their detail and generalisation level, as well as in the list of the attributes used to characterised spatial items. Thus, according to [132], a *POI* is a uniquely identified specific site, while in [15] it is considered being a subjectively interesting attraction that is identified by its "geographic coordinates, name, radius specifying its spatial extent, and a relevance vector" of normalised scores of POI attribution to a set of categories. A check-in based definition is given by [135], according to which, a POI is a location where people have checked in, or according to [20], it is a geo-location with keywords information. In [91] a POI is defined as "a focused geographic entity" that can be permanent (*e.g.* buildings), semi-permanent (*e.g.* restaurants), temporal or periodic (*e.g.* locations of an annual festival). The most generic definition is given by the W3C POI Working Group, where a POI is seen as "a human construct, describing what can be found at a location", a place that has an exceptional meaning for people regarding an activity on that place[5]. An example of a POI issued from Foursquare[6] is given in Tab. 3.1.1. To sum up, we propose the following definition of a POI:

Definition 1 *A **Point of Interest (POI)** denoted* $\mathtt{POI}$ *is a uniquely identified geographic entity that represents certain meaning for people regarding an action one can perform on that place and is generally characterised by its identifier* $\mathtt{id}$*, name* $\mathtt{n}$*, and location* $\mathtt{l}$*, i.e.* $\mathtt{POI} = (\mathtt{id}, \mathtt{n}, \mathtt{l})$*, and may have several additional attributes, e.g. categories, keywords, description, opening time, etc.*

[5]http://www.w3.org/2010/POI/wiki/Main_Page
[6]https://foursquare.com/v/mini-world-lyon/578dcb4e498e9417e4d94a93

Table 3.1.1: Example of POI.

Example 1: Mini World Lyon, Lyon	
Identifier, `id`	578dcb4e498e9417e4d94a93
Name, `n`	**Mini World Lyon**
Location, `l`	(45.764594, 4.925186)
Description, `d`	General Entertainment in Vaulx-en-Velin, Rhône-Alpes
Categories, `c`	venue
Keywords, `kw`	Mini World Lyon, 3 Avenue de Bohlen, Vaulx-en-Velin, Rhône-Alpes, mini world lyon, Entertainment

Event

The second concept considered in recent works is an *event* [53, 67, 72, 125]. Although it has been extensively used in the context of spatial items recommendation, surprisingly, most of work do not provide any definition of the concept of event at all. In practice, we do not have found many definitions in the literature. In [72] an *event* is understood as an information item that is valid for a short period of time, while in [54] it is a phenomenon (that happens over a limited extent in time), process, state, or transition between situations. Finally, [22] defines it as a socio-cultural event organised by cultural institutions (*e.g.* theatre performances, concerts, festivals, exhibitions, workshops, etc.). As it can be seen, the main difference with POI lies in the fact that an event has a temporal nature, more precisely, a short-term life. It is worth noting that the definitions we mentioned previously mostly provide only examples, without determining the attributes that characterise an event. An example of an event taken from Meetup.com[7] is given in Tab. 3.1.2. We suggest the following definition:

[7] https://www.meetup.com/Rocking-Nights-Out-London-Gigs-Drinks/events/252975167/

Table 3.1.2: Example of an Event.

Example 1: Punk Rock Night @177 Bar LONDON Shoreditch	
Identifier, id	252975167
Name, n	**Punk Rock Night @177 Bar LONDON Shoreditch**
Location, l	(51.531463623046875, -0.08042600005865097)
Start Time, t_s	2018-07-26 T19:30+01:00
End Time, t_e	2018-07-27 T21:00+01:00
Description, d	Punk Rock Night @177 Bar LONDON Shoreditch ••What we'll do We're meeting for the 'Out of Line' Punk Rock Night at 'The 177 Bar' in Shoreditch. If you have never been or are new to London, 'The 177 Bar' is a great Alternate Rock Bar hosting live bands - Good beer and cocktails https://www.facebook.com/Number177barkitchen/ - Live at Number 177 bar Entry: £5 https://www.fac
Categories, c	Event
Organiser, h	"type":"Organization", "name":"Rocking Nights Out - London Gigs & Drinks", "url":"https://www.meetup.com/Rocking-Nights-Out-London-Gigs-Drinks/"

Definition 2 *An **Event** denoted* $\mathtt{e}$ *is a planned occasion that is valid for a generally fixed short period of time and takes place in a specific location. Therefore, an event* $\mathtt{e} = (\mathtt{id}, \mathtt{n}, \mathtt{d}, \mathtt{l}, \mathtt{t_s}, \mathtt{t_e}, \mathtt{h})$ *is characterised by its identifier* $\mathtt{id}$*, name* $\mathtt{n}$*, description* $\mathtt{d}$*, location* $\mathtt{l}$*, start time* $\mathtt{t_s}$ *and end time* $\mathtt{t_e}$*, an organiser/host/author* $\mathtt{h}$*, indicating a user or a group who has created or hosts the event*[8]*. It may also have additional attributes, such as categories, periodicity, etc.*

Activity as a new type of spatial items

The interest of an individual in spatial items is less derived from the locations holding them, rather than an action that this individual can perform at this location. However, we can state that the notions of POI

[8]In particular, in the case of an Event-Based Social Network.

and Event described above are very location oriented. Thus in order to switch the focus from the location to the user's experience at this location, in this Thesis, we propose a notion of an *activity*, which is a human-centred concept, despite its closeness to the definition of an event. Moreover, when it comes to human behaviour, the temporality of an activity is an important attribute, which can be understand as the duration of an activity. This notion becomes extremely crucial when considering the time constraints and chaining activities, as in the context of a distributed event. However, the attribute of duration is lacking in the definitions of POI and Event.

We propose the following definition of an activity.

Activity

An **activity** $\mathtt{a}$ represents an action that a user $\mathtt{u}$ can perform at some geographically located point during a particular time window. An activity is, therefore, characterised by its name, location, the time window of its availability (start and end time), its duration, a vector of categories associated with the activity, and its description. It can be then represented as a tuple $\mathtt{a} = (\mathtt{id}, \mathtt{n}, \mathtt{l}, \mathtt{t_s}, \mathtt{t_e}, \delta, \mathtt{c}, \mathtt{d})$, where $\mathtt{id}$ is the identifier of the activity $\mathtt{a}$, $\mathtt{n}$ is its name, $\mathtt{l}$ is the location where it takes place, $\mathtt{t_s}$ and $\mathtt{t_e}$ are the start and the end time (time window) of its availability respectively, δ is the duration of the activity, $\mathtt{c} = (\mathtt{c_1}, \ldots, \mathtt{c_m})$ is a vector of categories associated with the activity, and $\mathtt{d}$ denotes its description.

Some examples of activities are: a conference session, a concert during a festival, an entertainment during the holidays, a theatre performance, etc. More detailed examples of activities are given in Tab. 3.1.3. The first example is issued from the program of on board activities of a cruise[9], and the second one is taken from the program of Comic-Con International: San Diego.

It has to be noted that the duration of an activity may be different from the activity's life time (*i.e.* the time interval limited by start and end time): $\delta \leq \mathtt{t_e} - \mathtt{t_s}$.

Aside from these features of an activity that we consider as primary (*i.e.* being characteristic to an activity), we distinguish between few secondary features that have more constraint-like nature. It should be kept in mind that some of these features may not always be available, depending on an activity itself or its category (*e.g.* age restriction may be more common for leisure activity). We consider the following secondary features:

- *Uniqueness*, `unique`: the quality of an activity reflecting its frequency, that may have the following values:
  - *unique*: an activity happens only once during its limited life time (time window);
  - *periodic*: an activity occurs after a fixed period of time, *e.g.* weekly, monthly, etc.;
  - *repetitive*: an activity occurs multiple times but there is no period of time specified.

[9] http://disneycruiselineblog.com/2015/07/personal-navigators-7-night-eastern-caribbean-cruise-on-disney-fantasy-itinerary-a-june-20-2015/

In the last two cases, an activity will be characterised with multiple time windows and may have multiple locations, *e.g.* movie releases in the same or different cinemas.

- *Admission Fee*, `price`: the price an attendee has to pay for admission.
- *Maximum Number of Attendees*, `max_num`: the maximum number of participants due to the limited availability.
- *Age Restriction*, `age`: minimum and/or maximum age of an attendee to be allowed for admission (*e.g.* 18+/21+ for bars and night clubs).
- *Gender Restriction*, `sex`: an activity reserved for women or men only.

Let $\mathtt{A} = \{\mathtt{a}_1, \mathtt{a}_2, \ldots, \mathtt{a}_\mathtt{N}\}$ be **the set of all available activities**, where $\mathtt{N}$ is the total number of activities.

3.1.2 Sequential Spatial Items

Recently, the attention of the research community has been attracted to sequential items, *i.e. an ordered sequence of items.*

Trip and Trajectory

Various names are used in the literature to refer to sequential spatial items, including *package, trajectory, story, travel route, trip, tour, visiting sequence,* even though their definitions are quite similar. In [135] a *package* is defined as a set of multiple POIs with different types, ordered by the time of visit. A *trajectory* is "a sequence of POIs" [20] or,

Table 3.1.3: Examples of activities.

Example 1: Disney's Fantasy cruise	
Identifier, id	0001
Name, n	**Sailing Away**
Location, l	Deck Stage
Start Time, t_s	20.06.2015, 16h30
End Time, t_e	20.06.2015, 17h15
Duration, δ	45 min
Categories, c	*Characters, Fun For All Ages*
Description, d	It's time to go Sailing Away! Join Mickey and Minnie along with Tinker Bell and the rest of the gang as they welcome you aboard the Disney Fantasy.
Example 2: Comic-Con International: San Diego[10]	
Identifier, id	1fb411d60ea1e81d1c74e5239e6ffbee
Name, n	**Jaws Will Drop, Sides Will Ache... Super Weird Heroes!**
Location, l	Room 28DE
Start Time, t_s	20.07.2017, 10h00
End Time, t_e	20.07.2017, 11h00
Duration, δ	60 min
Categories, c	*1: Programs, Art and Illustration, Books, Comics, Costuming, Humor & Satire*
Description, d	A way-fun, LOL, multimedia show of the kookiest, kraziest, most bizarro leotard-clad bad-guy-bashers of the Golden Age of comic books! See the Hand, a giant hand! See Madam Fatale, the first cross-dressing superhero! See Kangaroo Man (Batman was taken)! See tons more nutty-cool heroes held up to reverence and ridicule! Based on the bestselling book Super Weird Heroes (and its upcoming sequel), this stand-up comedy presentation is by the former creative director of the Muppets, now the Eisner-winning editor of IDW and Yoe Books Craig Yoe. Twenty laugh-riot cosplay changes in all!

more precisely, any subsequence of the "temporally ordered sequence of POIs" visited by the user within a given time interval [15]. Zheng *et al.*[146] define *a spatial trajectory* as a trace of an object moving within geographical spaces, represented by "a series of chronologically ordered points" consisting of geospatial coordinates and a time stamp. It can also be understood as "the motion history of moving objects", a sequence of points associated with temporal and geographical features in a two or three dimensional space [63]. Yu *et al.* [135] use the notion of a *travel route* that stands for a visiting sequence of the recommended POIs, while Zhang *et al.* [139] constrain this concept in space and time, defining a *trip* as an ordered sequence of POIs that starts at a given source location at a given starting time and ends at a given destination location. A similar definition of a *tour* is given by [42], as a sequence of venues with a particular order of visit that includes a starting point and ending point specified by a user. From a graph-based perspective, a *trip* is defined as an acyclic path on an undirected complete weighted graph which has its origin and destination [124]. To wrap up these definitions, we suggest to use the term *Trip* and to define it as follows:

Definition 3 *A **Trip** is a chronologically ordered series of spatial items.*

Activity Sequence as a new type of spatial items

In this Thesis, we propose a generalised definition of an activity sequence or itinerary that brings together the sequential aspect of activity execution and the feasibility of this sequence.

Table 3.1.4: Spatial and temporal constraints.

Constraint	Description	Formulation
Activity availability constraint	An activity can be joined only during its time window, *i.e.* the time when a user starts an activity $\mathtt{a}_{(\mathtt{i})}$, $\mathtt{start}(\mathtt{a}_{(\mathtt{i})})$, should be within a time interval of activity availability.	$\mathtt{t}_{\mathtt{s}}(\mathtt{a}_{(\mathtt{i})}) \leq \mathtt{start}(\mathtt{a}_{(\mathtt{i})}) \leq \mathtt{t}_{\mathtt{e}}(\mathtt{a}_{(\mathtt{i})})$
Activity completion constraint	Given the activity duration $\delta(\mathtt{a}_{(\mathtt{i})})$, a user should be able to accomplish it within its time window. Otherwise, a user is not able to accomplish the activity.	$\mathtt{start}(\mathtt{a}_{(\mathtt{i})}) + \delta(\mathtt{a}_{(\mathtt{i})}) \leq \mathtt{t}_{\mathtt{e}}(\mathtt{a}_{(\mathtt{i})})$
Time budget constraint	The time needed to follow all the activities within an itinerary, including activities duration and travelling time, shall fit the given time budget $\mathtt{T}_{\mathtt{max}}$. It may be defined by a user or set with a fixed value (*e.g.* day time).	$\sum_{a_{(i)} \in \xi(u)} (\mathtt{time}(\mathtt{a}_{(\mathtt{i-1})}, \mathtt{a}_{(\mathtt{i})}) + \delta(\mathtt{a}_{(\mathtt{i})})) \leq \mathtt{T}_{\mathtt{max}}$
Financial budget constraint	The total amount of money needed to attend all activities within an itinerary should be lower than a given financial budget. It may be defined by a user or may be considered as an objective function to minimise. $\mathtt{Price}_{\mathtt{max}}$	$\sum_{\mathtt{a}_{\mathtt{i}} \in (\mathtt{u})} \mathtt{price}(\mathtt{a}_{\mathtt{i}}) \leq \mathtt{Price}_{\mathtt{max}}$
Start and/or Destination constraint	An indication of a starting $\mathtt{a}_{(\mathtt{o})}$ and/or destination $\mathtt{a}_{(\mathtt{s+k})}$ location/activity of an itinerary. It may be defined by a user or a "fake" location/activity may be selected.	

Activity Sequence (Itinerary)

Let $\mathtt{A}$ be the set of all available activities, $\mathtt{N}$ be the total number of activities, $\mathtt{U}$ be the set of users. An **Activity Sequence** (or **Itinerary**) $\xi(u)$ is a feasible chronologically ordered series of activities for a given user $\mathtt{u} \in \mathtt{U}$ accounting for the set of constraints, *i.e.* $\xi(u) = (\mathtt{a}_{(1)} \rightarrow \ldots \rightarrow \mathtt{a}_{(\mathtt{s})} \rightarrow \ldots \rightarrow \mathtt{a}_{(\mathtt{s}+\mathtt{k})})$, $a_{(j)} \in A$, where the numbers in brackets in subscripts $(1), \ldots, (\mathtt{s}), \ldots, (\mathtt{s}+\mathtt{k})$ denote the order of an activity within a sequence, and $1 \leq \mathtt{s} \leq \mathtt{s}+\mathtt{k} \leq \mathtt{N}$.

As we mentioned in the general overview of the problem of recommendation of sequences of spatial items, constraints play an important role. In the following, we propose formulations of certain constraints. Mind, that such formulations bring the recommendation problem close to the problem formulations issued from the field of Operational Research.

Let $\mathtt{start}(\mathtt{a}_{(\mathtt{i})})$ be the time when a user starts an activity $\mathtt{a}_{(\mathtt{i})}$. And let $\mathtt{time}(\mathtt{a}_{(\mathtt{i}-1)}, \mathtt{a}_{(\mathtt{i})})$ be the travelling time needed to go from the location of the activity $\mathtt{a}_{(\mathtt{i}-1)}$ to the one of $\mathtt{a}_{(\mathtt{i})}$. As he/she may join an activity $\mathtt{a}_{(\mathtt{i})}$ only when it becomes available and once he/she has finished to perform the previous activity and moved to the location of the current one, we state:

$\mathtt{start}(\mathtt{a}_{(\mathtt{i})}) = \max\{\mathtt{start}(\mathtt{a}_{(\mathtt{i}-1)}) + (\mathtt{a}_{(\mathtt{i}-1)}) + \mathtt{time}(\mathtt{a}_{(\mathtt{i}-1)}, \mathtt{a}_{(\mathtt{i})}), \mathtt{t}_{\mathtt{s}}(\mathtt{a}_{(\mathtt{i})})\}$.

We define **a set of constraints** that consists of the spatial and temporal constraints, as well as the financial budget conditions. We summarise them in Tab. 3.1.4. All these conditions should be satisfied in order to make a sequence feasible.

Other types of constraints may also be defined depending on the aims of recommendation, *e.g. diversity coverage* (*i.e.* an itinerary should cover the maximum number of activity categories, or geographical areas).

3.2 Recommendation of Single Spatial Items

In the previous Section, we have discussed the definitions of spatial items, namely POI, Event, Trip. Let us now give an overview of the corresponding recommendation problems proposed to deal with various kinds of spatial items.
Similarly to more 'traditional' recommendation domains (*e.g.* movies, books, etc.), recommendation of single spatial items aims at estimating unknown (missing) values of user-item interaction [1] (see Definition 4).

Definition 4 *Let* $\mathtt{U}$ *be a set of users and* $\mathtt{A}$ *be a set of available items. A recommender system aims at finding a* ***satisfaction function*** $\rho(\mathtt{u}, \mathtt{a_i})$*:*

$$\rho : \mathtt{U} \times \mathtt{A} \rightarrow \Re \tag{3.1}$$

which characterises the matching between the item $\mathtt{a_i} \in \mathtt{A}$ *and the interest of the user* $\mathtt{u} \in \mathtt{U}$*. The value assigned by the item satisfaction function to a given item for a given user is referred to as the user's satisfaction score regarding this item. A recommender system then returns the highest-rated items*[11] *for a given user.*

Recommender systems differ in the way they estimate the user's satis-

[11] State-of-the-art recommender systems often return a single item or a list of top-*n* items. However, without loss of generality, it can be said that the output of a recommender system consists of the highest-rated items for a given user.

faction score regarding the items. It should be noted that contrary to 'traditional' recommendation scenarios (*e.g.* recommendation of books, music tracks, movies, etc.), in case of spatial items the user-item interaction is more implicit. Mind that this definition may be extended with context $\mathcal{X}$, *i.e.* $: \mathtt{U} \times \mathtt{A} \times \mathcal{X} \rightarrow \Re$ [2].

3.2.1 POI Recommendation

Probably, the most popular and addressed recommendation problem among problems of recommendation of spatial items is the *POI Recommendation problem*. By combining several problem statements from the literature, it can be defined as follows.

Definition 5 *Let U be the set of users, and P be the set of POIs. Given a check-in activity dataset D and a user u* $\in$ *U with his/her current location l and time t, return a list of POIs that he/she would be interested in [132] at a specific target time [138], but that he/she has not visited yet [65].*

Thus, the POI Recommendation problem is usually considered as a top-*k* recommendation problem.
The POI Recommendation problem should be distinguished from the *POI Prediction problem* that aims at finding a POI a user would visit next, including already visited places, given a check-in activity dataset, the user's current location and time [21, 50, 63].

3.2.2 Event Recommendation

The *Event Recommendation problem* aims at providing a user with a list of events he/she may be interested in. It is generally formulated as a listwise [67, 89] or a pairwise [72] ranking problem and is often solved using a learning-to-rank approach. Thus, Macedo *et al.* define it as follows [67]: given a user and some contextual information (users' temporal and geographical preferences, set of groups to join, event content), find top-*n* events by maximising the user's preference score for a set of candidate events, while minimising a ranking loss function of dissimilarity between the actual and generated lists of events. Moreover, if pairwise preferences are given, the problem can be formulated as follows: given a set of users and the users' feedback on past events available in the form of pairwise preferences within a given time frame, rank a set of future events w.r.t. users' preferences [72].

3.3 Recommendation of Sequences of Spatial Items

In this Thesis, we are interested in recommendation of sequences of spatial items. In the context of the recommendation of a sequence of spatial items, several problems have been defined in the literature. The most commonly used names for identifying a spatial sequence recommendation problem is are: *Trip Recommendation*, *Travel Package Recommendation*, and *Trajectory Scheduling*. These problems have been proposed for different application scenarios mainly in Tourism and are quite close to each other. They are often formulated as optimisation problems but mostly distinguished in their objective function.

Thus, according to [139], the *Trip Recommendation problem* consists in finding an optimal trip route, limited by a time budget, that maximises the user's happiness and satisfies POI availability constraints, given a user, his/her starting and ending points, a starting time, and a time budget.

A similar but demanding more user's efforts formulation is given in [135], where the *Travel Package Recommendation problem* is defined as follows: given check-in records, some travel demands formulated by users, and the physical constraints for the travel activities, find the appropriate sequence of locations that satisfies the physical constraints and requirements of users.

Such formulations can often be reduced to one optimisation problem, generally to an extension of the Travelling Salesman problem. In contrast, Brilhante *et al.* [15] formulate the twofold *Trajectory Scheduling problem*: given a user, a set of POIs, a time budget, a set of trajectories, a user-POI interest function, a cost function, and a travel time of each trajectory, (1) find a subset of all the trajectories limited by the time budget and maximising a user-POI interest function, and then (2) find the tour that joints the subset of found trajectories while minimising the time spent to move from one trajectory to another.

The problem of recommendation of sequences of spatial items may be considered as a special case of *sequence-aware recommender systems* (SARS). A recent comprehensive survey on the latter can be found in [90].

3.3.1 General Overview of the Problem

M. Quadrana *et al.* [90] suggest the high-level overview of SARS presented in Fig. 3.3.1. Given an ordered and usually timestamped log of the user's actions which may not necessarily be related to an item (like in case of the users web search), a sequence-aware recommender system returns an order list of items, where the whole list is considered as a whole, and not as a set of alternatives like in traditional top-k rec-

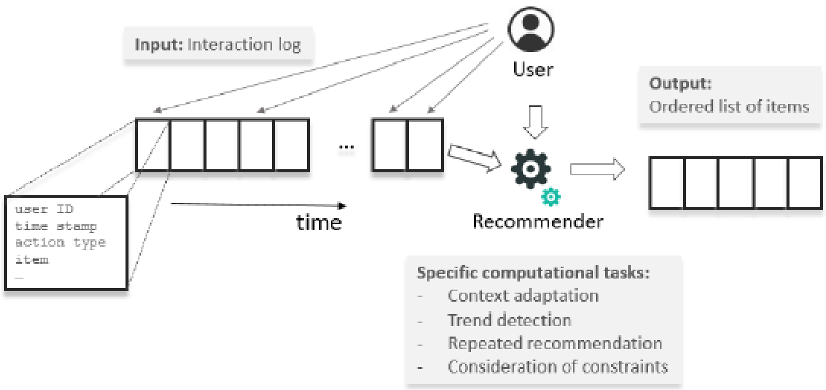


Figure 3.3.1: High-level overview of Sequence-Aware Recommendation Problems [90].

ommendation. The order of the items within the returned list may be relevant.

We modify the high-level overview of SARS for the case of sequences of spatial items (see 3.3.2) by specifying the importance of three components, namely:

1. Time dimension, namely consideration of the *target time* for the output list(s) of items, which is depicted in Fig. 3.3.2 as different output lists with respect to the target time. This is important in the case of spatial items, as they usually have limited availability and might be unique. Therefore, given the same historical data, the output will be different, as the candidate set may vary according to the target time of recommendation.

2. *Constraints*, mainly related but not limited to spatial and time dimension, that influence the output. We precise this aspect, as recommendation of spatial items is usually very conditioned by the accessibility and availability of items

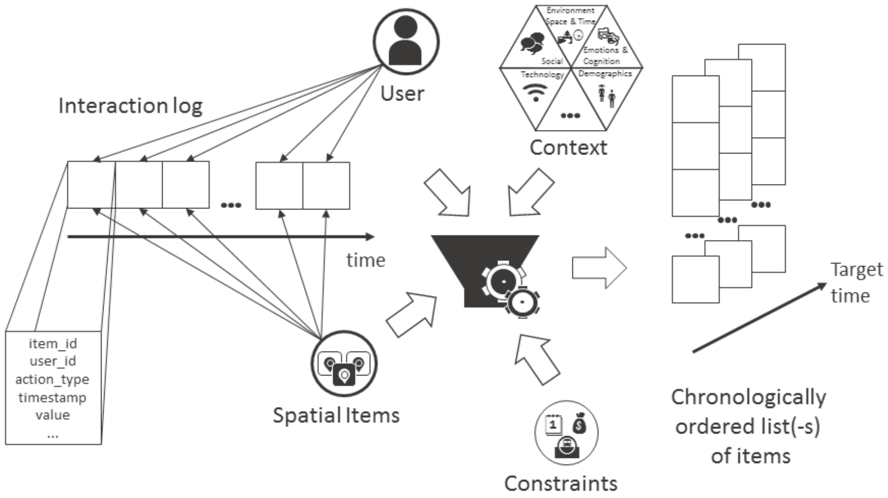


Figure 3.3.2: High-level overview of problems of recommendation of sequences of spatial items.

3. *Context* which is crucial for alleviating the cold-start problem.

Input. Similar to [90], we consider that the input of a recommender system consists of information about user-item interactions, where each entry represents a user-item pair of a specific interaction type (*e.g.* user's rating of an item, RSVP[12], check-in, review, etc.) and a corresponding value. Other information may also be provided, *e.g.* contextual information. Though we consider that a timestamp of an action is an important characteristic of input data, in the case of recommendation of sequences of spatial items it may not be provided. In the case of timestamped check-in data or GPS-tracking data, the items may not be given explicitly, but usually can be assigned. The order of the input data may also be relevant.

[12]RSVP is an acronym for the French phrase "répondez s'il vous plaît" meaning "please respond" that is used to express the user's intent to participate in an activity. In Event-Based Social Networks rsvp is usually assigned one of the following values "yes", "no", "maybe".

Resulting sequence. Generally speaking, a system recommending sequences of spatial items returns chronologically ordered list(-s) of spatial items. From this result perspective, the following components are considered.

- *Multiple outputs*. For the sake of generality, we do not constraint the output of a recommender system to one sequence. Here, two cases are considered:
  - *list of alternatives*: a system returns a list of alternative sequences. For instance, the method proposed in [98] for the POI sequence recommendation problem and denoted HCS provides a user with a list of alternatives on two levels, namely: categories and POIs. In this case, all the alternatives are generated for the same input and the same target time.
  - *variations depending on the target time*: generation of multiple sequences depending on the target time of recommendation or other criteria. A typical example of a scenario can be found in tourism domain when creating recommendations for multi-day trips. Recently, the problem of recommendation for multi-day trips with optimisation of the satisfaction score of 'the worst tour' has been addressed in [40].
- *Ordering*. In case of recommendation of sequences of spatial items, the order of items within a sequence is often relevant, mainly due to the time-related constraints and considerations, *e.g.* limited availability of items, consideration of travelling time between item locations, etc. Thus, the order of items in a resulting sequence

may be determined by the feasibility condition of the sequences.

Constraints. In the case of recommendation of spatial items, the feasibility of a returned sequence of spatial items is often subject to various constraints, that are mainly related to the limited availability of items, their accessibility, their location areas, the cost budget (usually in terms of time), etc. We will provide more discussion later in the paper.

3.3.2 Problem Formulation

We propose to precise the formulation of sequence-aware recommendation problem for the case of sequences of spatial items, as follows:

Recommendation of Sequences of Spatial Items (RSSI)

Let $\mathtt{U}$ be a set of users and $\mathtt{A}$ be a set of spatial items. Let $\mathtt{t}$ be the point in time for which the recommendation is sought. We denote as $\mathtt{A_t} \subset A$ a set of candidate spatial items that are available at time $\mathtt{t}$. Let $\mathcal{P}(\mathtt{A_t})$ be the powerset of $\mathtt{A_t}$, and $\mathtt{N}$ be its power. A candidate sequence $\xi = (\mathtt{a}_{(1)} \to \ldots \to \mathtt{a}_{(s)} \to \ldots \to \mathtt{a}_{(k)})$, where $\mathtt{a}_{(j)} \in \mathtt{A_t}$ and $1 \leq \mathtt{s} \leq \mathtt{k} \leq \mathtt{N}$ is then an element of the set of all permutations of the length $(\mathtt{k})$ of $\mathcal{P}(\mathtt{A_t})$, i.e. $\xi \in \mathtt{S_k}(\mathcal{P}(\mathtt{A_t}))$. We denote the latter set as $\Xi = \mathtt{S_k}(\mathcal{P}(\mathtt{A_t}))$.

The **problem of recommendation of sequences of spatial items (RSSI)** consists in finding the sequence $\xi^* \in \Xi$ for the target user $(u \in U)$ at target time t, s.t.

$$\xi^*(u,t) = \arg\max_{\xi \in \Xi} \sigma(u,\xi), \forall \mathtt{u} \in \mathtt{U}, \tag{3.2}$$

where $\sigma(u, \xi)$, $\sigma : U \times \Xi \rightarrow \Re$ is the **satisfaction function** that returns a satisfaction score for a user $\mathtt{u} \in \mathtt{U}$ w.r.t. a sequence .

The main problem is then to define the satisfaction function $\sigma(u, \xi)$. To do so different factors are considered within existing algorithms on both levels, *i.e.* the level of individual items and a sequence. We discuss them later in the Chapter 4. It is to note that the feasibility of a resulting sequence of spatial items is subject to the set of constraints considered by an instance of the problem. The considerations constraints is of a special importance for the case of recommendation od activity sequences.

For the sake of generality, we can consider the satisfaction regarding a sequence of spatial items being a function of satisfactions regarding individual items, *i.e.* $\sigma(u, \xi) = \mathtt{f}(\rho(u, a_i))$, for $\mathtt{a_i} \in \xi(u)$. The relation (function) $\mathtt{f}$ depends on the computation strategy and factors considered. In the most simplistic case, it can be defined as the sum of the user's individual satisfaction scores regarding all the items within the sequence, *i.e.* $\sigma(u, \xi) = \sum_{a_i \in \xi(u)} \rho(u, a_i)$. Such approach is widely used in the solutions for the Trip recommendation problem (*e.g.* [96, 139]). However, more sophisticated approaches that consider the order and the transitions between items within the sequence could be suggested. As suggested by Masthoff and Gatt [69], various aggregation functions can be used to model a satisfaction function of a sequence of items, which can be considered as a linear combination of satisfactions with previously experienced items and the impact of a new item.

3.4 Summary

In the Chapter, we have explored and discussed the concepts related to recommendation of spatial items, both single and sequential, namely Point of Interest (POI), Event, and Trip (Trajectory). We have overviewed the problems of recommendation of single spatial items and sequential items. We have proposed the notions of Activity and Activity Sequence as new types of spatial items, which are more human-centred and reflect the temporary and sequential nature of human actions.
Based on our analysis of the state-of-the-art, we have suggested a generalised definition of the problem of Recommendation of sequences of spatial items, denoted RSSI, as a special case of sequence-aware recommender systems. This problem is the one we address in the Thesis.

Le véritable voyage, ce n'est pas de parcourir le désert ou de franchir de grandes distances sous-marines, c'est de parvenir en un point exceptionnel où la saveur de l'instant baigne tous les contours de la vie intérieure.

Antoine de Saint-Exupéry,"Le Petit Prince"

4

Recommendation of Sequences of Spatial Items: Methodology and Types of Influence on User's Satisfaction with Items

Contents

In the previous Chapter 3, we have defined the problem of recommendation of sequences of spatial items. In this Chapter, we are reviewing the methodological approaches that can be used in order to address it. These approaches have been mainly proposed in the state-of-the-art for solving the Trip recommendation problem.

Estimation of the user's satisfaction with items play a central part in recommendation algorithms. Therefore, in the second part of this Chapter, we are focusing on the types of influence on the user's satisfaction with items that have been exploited in the state-of-the-art. We propose their classification and review the modelling approaches.

4.1 RSSI: Methodology

The state-of-the-art approaches to solve the problem of recommendation of sequences of spatial items can be grouped into two main categories:

1. *Two-step methods*: The main principle of two-step methods consists in subdividing the initial problem (*i.e.* the RSSI problem) into two sub-problems, namely: (1) the estimation of personalised scores of single items, and (2) the construction of a resulting sequence as a solution for path finding problem, given the

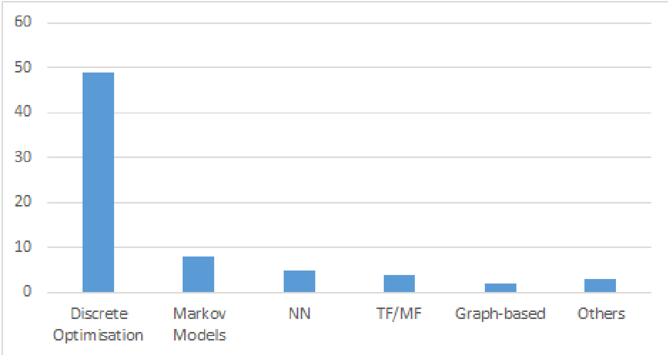


Figure 4.1.1: Methods used for recommendation of sequences of spatial items.

scores of each candidate item and the set of constraints to be satisfied. Thus, the sequence building is often performed based on discrete optimisation methods. The majority of the reviewed approaches for RSSI follows this methodology [41, 116].

2. *Sequence learning techniques*: This group of techniques is based on the extraction of sequential patterns of user behaviour, and/or the modelling of the impact of past user-item interactions on the future ones by estimating the transition probabilities between items.

It is to note, that a majority of the state-of-the-art algorithms for solving the problem of recommendation of sequences of spatial items exploit two-step methods that build sequences using discrete optimisation approaches (see Fig. 4.1.1).

4.1.1 Two-Step Method: Single Item Personalised Scores and Discrete Optimisation

This group of methods consists in the decomposition of the problem of sequence recommendation into two sub-problems: the estimation of single item scores and the sequence construction (*e.g.* [15, 40, 92,

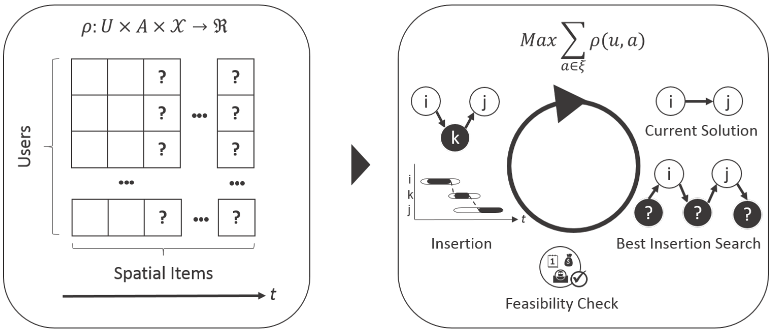


Figure 4.1.2: General overview of a two-step method: (I) estimation of personalised scores, and (II) schedule construction.

93, 111, 119, 124]). A general overview of the two-step is depicted in Fig. 4.1.2.

Thus, based on the past user-item interactions and available contextual information, the approaches first estimate the user's interest scores in unseen items. These scores, together with the users and the items attributes (*e.g.* location, duration, time windows of item availability, etc.) are then given as input for a discrete optimisation algorithm that constructs a feasible sequence that maximises the overall score of a sequence.

Estimation of personalised scores of single items. The first step of this class of methods is dedicated to the search for the user's satisfaction function with single items (Eq. 3.1) and the estimation of personalised scores of single items. The state-of-the-art solutions differ in a way to define this function and types of influences used for estimation. We give an overview of types of influences further in the paper (see Section 4.2). The method used on this step are similar to the ones used in traditional recommendation domains and can be classified to memory-based and model-based. It is to note that in the case of event recommendation and activity sequence recommendation, due to the temporary nature of the items which have limited availability, and are unique (occur only once), there is lack of collaborative information. Thus, content-based and model-based algorithms are mainly used.

Schedule Construction. When it comes to the schedule construction problem, multiple variants that consider different constraints and therefore, various algorithmic approaches to solve them have been proposed and explored in Operational Research (*e.g.* [44, 116]). A typical combinatorial problem that have attracted interest of researchers and practitioners in the context of generating tourist itineraries is called Orienteering Problem (OP). The main goal is to maximise the score collected by visiting nodes in a graph, given starting and ending node, subject to a cost budget [118]. Mind that contrarily to the recommendation settings, the definition of the scores of the nodes, the cost model (*i.e.* duration of visits) is out of the scope of the schedule generation problems treated in Operational Research.
However, it is to note that the advances in the field of Operational Research are commonly used in the purpose of recommendation of sequences of spatial items. Thus, in the domain of trip recommendation, the problem of recommendation of sequences of Points-of-Interest (POI) is usually referred to as Tourist Trip Design Problems [41, 116]. A common approach to solve it undergoes two main phases, namely: (1) assigning interest scores to each item (POI); (2) resolving an instance of optimisation problem, such as OP [40, 139], Vehicle Routing Problem (VRP), or Travelling Salesman Problem (TSP) [15, 135]. Extensive surveys on OP and VRP can be found in [17, 44]. The type of an optimisation problem depends on the objective functions and the types of

constraints that are taken into account.
The main advantage of this group of methods is their accounting for a set of constraints that defines the feasibility of a recommended sequence, in particular time-related constraints, such as time availability, time budget, activity completion etc.
The drawbacks of two step methods are related first, to the computational complexity of the discrete optimisation algorithms resulting in heuristic or greedy search which is time consuming. Second, one of the assumptions of these methods is that the user's interest scores with the items are independent, and that the objective function to maximise is an aggregation of item scores forming a sequence (often a sum) which may result in schedule overload with the number of items.

4.1.2 Sequence Learning Techniques

Another group of methods relies on sequence learning techniques. Their applicability can be explained by sequential nature of human behaviour. However, it is to note that contrarily to the algorithms used for sequence-aware recommendation in other domains (*e.g.* music, e-commerce, web usage, etc.) these methods are exploited less often for the recommendation of sequences of spatial items. One of the possible explanations is that these methods do not take into account temporal and spatial constraints proper to the spatial sequence recommendation.
Advances in sequential data mining are applied to recommendation of sequences of spatial items, mainly in order to predict the next location of a user or the next POI he/she will visit. Thus, based on the users past interactions with items, the state-of-the-art sequence learning methods aim at identify the sequences occurred in the corpus and their frequen-

cies [143]. Based on the obtained transitions, the transition probabilities between items or their categories are estimated. For more details about sequential pattern mining refer to [73].

The most frequently used sequence learning methods use *Markov Models* in order to estimate conditional probabilities of transitions between items [19, 37, 47, 48, 58, 92, 141, 143]. These models are based on Markov property and exploit the user's previous states (*e.g.* the user's visits of locations/POIs) in order to establish the dependencies with the next one. Most of the state-of-the-art algorithms use 1st order Markov Chains which suffer from fixed and limited transition order. In contrast to that, [141] propose to use *n*-th order additive Markov chains which allows to estimate the impact of *n* previous states.

Recent works have been exploiting *Neural Networks* [6, 46, 74, 77, 110] for sequence learning and prediction based on non-linear transitions. This direction is in active research.

It is to note that sequence learning methods are mainly used in the state-of-the-art on recommendation of sequences of spatial items for solving the problem of prediction of the next location or next POI. They are able to capture the dependencies between items, and extract user's behavioural patterns. However, their main limitation for recommendation of spatial items, in particular recommendation of activity sequences during distributed events which is very constrained, lies in the fact that they do not take into account temporal and spatial constraints proper to the spatial sequence recommendation.

4.2 Taxonomy of Types of Influence on User's Interest and Their Implication in Recommendation

Previously, we have described the methodology used for solving the problem of recommendation of sequences of spatial items. A we have stated, the vast majority of existing approaches follows the two-step method, where first the estimation of the user's interest scores in items is performed, followed by the construction of a sequence as the solution of discrete optimisation problem. In this Section, we are investigating the types of influences on the user's interest in spatial items that are exploited in the state-of-the-art.

The interest of an individual in a phenomenon and the satisfaction he/she gets from it are very complex constructs. They are subject to various factors or influences. In this Chapter, we survey the types of influence on user's interest in a spatial item focusing on sequences of items and propose a categorisation of types of influence used in recommendation and discuss their use. First, we present the general overview of our taxonomy and we provide more details about the types of influence in the upcoming Subsections.

4.2.1 General Overview

We propose a tree-like taxonomy of the types of influence on user's interest in a spatial item (see Fig. 4.2.1). We distinguish between 19 types of influence that we group into five main categories according to the entity they are related to, *i.e.* item-specific, user-specific, user-user, item-item, and user-item.

The *Item-specific* influence is derived from the characteristics of an item

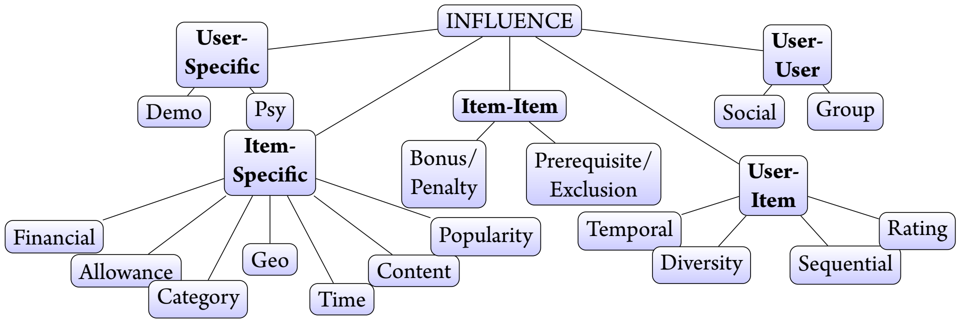


Figure 4.2.1: Diagram of types of influence

itself. It may include its membership to categories (*Category*), geo-location (*Geographic*), time availability (*Time*), description (*Content*), and *Popularity*. Lastly, it may also include limited *Allowance* (due to the number of people, age, etc.) and *Financial* aspect (an item providing a higher gain/reward or being cheaper is more likely to attract a user).

The *User-specific* influence is derived from the user's characteristics and may consist of his/her demographic (*Demo*) and psychological profile (*Psy*).

The *User-User* influence results from the relationship between users and may include *Social* aspect (*e.g.* "friends", connections, or similar users, user's group membership) and *Group* of users (*e.g.* group of people a user is travelling with).

The *Item-Item* influence reflects the relations between items. The items may be considered independent (*i.e.* joining one activity does not have direct influence on any other), or in contrast, there may exist interdependence between items. Here, we consider two types of relation: *Prerequisite/ Exclusion* and *Bonus/Penalty*. The first introduces two relations, namely:

- *prerequisite*: implication of predecessor-follower relation when one item requires the achievement of another one;

- *exclusion*: one item makes impossible to get another one, *e.g.* no chaining two and more similar items (eating at the restaurant after eating at the restaurant) or no sport immediately after having a meal.

The second implies that chaining items may increase/decrease the satisfaction regarding the last activity when compared to the satisfaction level of an activity taken *as is*. For instance, let us consider two activities 'Infra-red sauna' and 'Balinese massage'. The latter has more relaxing effect and therefore, gives more pleasure when preceded by the former. Those two relations are not exploited in the state-of-the-art, leaving room for future research.
Finally, the *User-Item* influence covers the interactions between users and items. It gathers properties related to:

1. the user's rating behaviour if exists (*Rating*) that may include features derived from the explicit feedback, such as the average rating provided by a user, the number of his/her ratings, the comments and reviews left by the user, etc.;

2. sequential patterns (*Sequential*) revealing the user's most typical transitions between items/categories;

3. diversification of interest (*Diversity*);

4. temporal patterns (*Temporal*) reflecting the user's preferences for items w.r.t. the hour of a day, day of the week, etc.

In addition, some *External* factors may also be considered, such as *Weather* and *Transport* (transportation mode).

Table 4.2.1: The use of types of influence for recommendation.

Algorithm	Psychological	Demo	Geographic	Time	Categorical	Content	Popularity	Financial	Social	Group	Sequential	Temporal	Diversity	Weather	Transport
Tourism															
Yu *et al.* [135]			✓		✓		✓					✓	✓		
Zhang *et al.* [139]			✓	✓		✓									
Sang *at al.* [98]		✓	✓		✓						✓	✓			
Brilhante *et al.* [15]			✓		✓		✓				✓				
Chow *et al.* [141]			✓	✓			✓		✓						
Lim *et al.* [61]			✓	✓	✓		✓			✓					
Bohnert&Zukerman [7]			✓			✓						✓			
Elahi *et al.* [32]	✓						✓								
Braunhofer *et al.* [11, 12]	✓	✓													
STS, Braunhofer *et al.* [9, 10, 13]	✓	✓	✓	✓				✓				✓		✓	✓
Biancalana *et al.* [6]			✓	✓	✓							✓		✓	✓
Rakesh *et al.* [92]					✓		✓		✓		✓				
Wang *et al.* [122]			✓			✓	✓				✓				
Sadri *et al.* [97]											✓	✓			
Liu *et al.* [62]			✓			✓									

Table 4.2.1 – *Continued from previous page*

Algorithm	Psychological	Demo	Geographic	Time	Categorical	Content	Popularity	Financial	Social	Group	Sequential	Temporal	Diversity	Weather	Transport
Tang & Wang [110]											✓				
Niu & Zhang [77]											✓				
Hashemi *et al.* [46]		✓	✓			✓					✓				
Bujari *et al.* [16]			✓		✓		✓								✓
He *et al.* [47]											✓				
Chen *et al.* [19]			✓		✓					✓	✓				
He, Li & Liao [48]			✓		✓						✓				
Li *et al.* [58]			✓		✓						✓	✓			
Leckie *et al.* [124]							✓					✓			
Taylor *et al.* [111]							✓					✓			
Leisure															
Macedo *et al.* [67]			✓			✓			✓			✓			
Schaller *et al.* [102]			✓	✓											
Varakantham *et al.* [119]			✓												
Zhang & Wang [144]			✓			✓			✓						
Crowdsourcing															
Fonteles *et al.* [38, 39]			✓	✓		✓	✓								
Others															
Masthoff and Gatt [69]	✓									✓	✓	✓			

Table 4.2.1 – *Continued from previous page*

Algorithm	Psychological	Demo	Geographic	Time	Categorical	Content	Popularity	Financial	Social	Group	Sequential	Temporal	Diversity	Weather	Transport
Figueiredo *et al.* [37]											✓				
Mottini & Acuna-Agost [74]				✓				✓			✓				

What kind of influence is exploited in the algorithms of the state of the art? In order to answer this question, we suggest to explore the solutions through the lens of aforementioned types of influence. In this Chapter, we focus on the recommendation of sequences and thus leave most of the solutions of POI recommendation problem out of the scope of this Thesis. Table 4.2.1 presents a comparative study of the type of influence. The columns identify the types of influence utilised in the state-of-the-art. We have excluded from the table the types of influence that were not used in the referenced works.

It can be seen that the geographical influence headlines the types of influence regarding the usage frequency in the existing algorithms. Another widely used factor is time availability. In contrast, the temporal behaviour patterns are less exploited. A number of works make use of the content information. Another finding is that most of the algorithms use explicit feedback (*e.g.* users' ratings), that is rarely present in the domain of mobile crowdsourcing, or leisure activity.

Our comparative study testifies that many types of influence are barely incorporated into the recommendation process, leaving room for un-

derstanding human behaviour and for some improvement in recommendation. Thus, one promising avenue, in our opinion, is the exploitation of psychological aspects into recommendation of spatial items. Some of the recent works ([36, 115, 126]) have made use of the user's personality in movies and books recommendation. However, to the best of our knowledge, no work has been done in investigating the correlation between the user's personality and the selection of spatial items. Besides, we did not find any work exploiting the item-item relations, and dealing with limited allowance. These research tracks may be investigated as future research directions.
In the following subsections we review the techniques for treating different types of influence used in the state-of-the-art recommendation algorithms.

4.2.2 Item-Specific

As we mentioned before, item-specific influence rises from the features of items themselves and embraces several types of influence, namely Geographical, Content, Popularity, Category, Time Availability, and Financial. In the following, we discuss each of these influences from the implementation point of view, *i.e.* how each influence is reflected in the state-of-the-art algorithms.

Geographical Influence

The idea of geographical proximity is widely exploited by various researchers for recommendation of spatial items. The intuition behind is that geographical influence is related to geographical clustering phenomenon in users' check-in behaviour [134]. It consists of two presuppositions: (1) nearby spatial items (POIs) seem to users more appealing than distant ones; (2) spatial items (POIs) that are geographically closer to the location the user likes are more likely to be visited.

Two common approaches for estimating user's preference towards a spatial item based on its geographical location can be distinguished. The first consists in identifying the areas of user's interest, usually, circular areas centered in the spatial items already visited by the user (*e.g.* [38, 135]). And the second approach is based on the estimation of the distribution of user's mobility patterns (*e.g.* [67, 98, 141]).

Geographical influence or spatial dependence of users' preferences towards POIs (in notations of Yu *et al.* [135]) can be understood as geographical proximity of a POI to the starting position of a user. More precisely, Yu *et al.* consider a circular area centered at the user's starting position as an area of candidate POIs.

Macedo *et al.* [67] explore the distributions of geographic distances between the events attended by the user in the past to model his/her mobility patterns using a kernel density function (namely, bivariate Gaussian kernel).

A similar approach is used by Sang *et al.* [98]. They calculate location similarity as being proportional to the distances between them using Gaussian distribution.

According to the model proposed by Zhang *et al.* [141], the attractive force of a location decreases with spatial distance between an already visited location and a candidate location. More precisely, the authors compute the haversine distance between location coordinates. Then, assuming that the spatial distance between two consecutive check-ins follows a power-law distribution, the authors define the normalised impact of the spatial distance as the complementary cumulative distribution of spatial distance.

In order to match workers and tasks on mobile crowdsourcing platforms, Fonteles *et al.* [38] introduce a spatio-temporal utility function that consists of three elements: spatial relevance, temporal relevance and distance between a location and a user. Note that both spatial relevance and distance represent geographic influence. First, the authors suggest to divide a geographical space into regions and then identify user's areas of interest, *i.e.* areas where the user has accomplished tasks in the past. Density-clustering algorithms can be used for this purpose. The relevance of an area is therefore, the number of tasks accomplished by the user inside this area. Second, Fonteles *et al.* suggest to use the distance between a task location and the user's current position as a penalty to the spatio-temporal utility score.

All the algorithms mentioned above deal with outdoor environments. However, spatial items can also be found in indoor environment. Thus, Bohnert and Zukerman [7] have proposed models of personalised recommendation of exhibits in museums. They considered three types of distances between exhibit areas, namely collaborative item-to-item distance, semantic distance and physical walking distance. They propose a spatial process model that uses all three measures for calculating the correlation between exhibit areas [8]. Therefore, in terms of geographical influence, Bohnert and Zukerman [7] first estimate the physical walking distance between exhibit areas that is calculated as a normalised length of the shortest path between a pair of spatial items using

Dijkstra's algorithm. Second, they model the user's spatial behaviour using spatial processes.

Content Influence

Content-based filtering that makes use of the textual description of an item is a widely used approach in recommendation that also appears as promising in the event recommendation [67]. It allows to retrieve the items with the descriptions similar to the ones the user has previously interacted with. This may be a crucial factor in the context of the event/activity recommendation, recurrent events. However, it is less used in the context of POI recommendation.

A commonly used approach to treat the textual description is a classic bag-of-words model using TF-IDF representation. Thus, Macedo *et al.* [67] use TF-IDF vectors of events and build a user's profile over TF-IDF representations of user's past events weighted by a temporal decay function, reflecting the temporal distance of events to the time of recommendation. Cosine similarity is used as a relevance score.

Fonteles *et al.* [38] define a description similarity utility function for task recommendation for workers on mobile crowdsourcing platforms. They suggest to combine vector space model for a spatial representation of task descriptions and the TF-IDF technique for defining the weights of each term in a description. A similarity measure between a vector of tasks previously accomplished by a user and a candidate task is then calculated.

Apart the description, the text of user's review/comments can also be used. Thus, Zhang *et al.* [139] define a POI content as the union of all the bag-of-words representation of comments of all the users who

have visited this POI. This representations are further used as features to perform collaborative filtering and predict ratings on features.
A semantics oriented approach has been proposed by Bohnert and Zukerman [7] for the recommendation of exhibit areas in museums. In contrast with the above mentioned approaches, this model uses item representation that is not based on item description but annotations performed by experts. The collected annotations were represented as bag of words and populated using WordNet topics and synonyms [34]. The further treatment is similar to other approaches. Thus, the authors use TF-IDF vector representation and calculate semantic similarity using the cosine similarity measure. The semantic similarity is further incorporated into the spatial process framework.

Popularity Influence

The popularity of an item, *i.e.* how many people like/dislike it, is usually considered to have a direct impact on its attraction level. Many researchers exploit this influence in their recommendation approaches. A common approach to estimate item popularity is by counting distinct user-item interactions.
Brilhante *et al.* [15] compute POI popularity as the number of distinct Flickr users with at least one photo taken in the circular region of the POI.
In their hierarchical and sequential model, Sang *et al.* [98] consider POI popularity within a category, *i.e.* the probability of choosing a POI given its category. Sang *et al.* assume it to be proportional to the check-in frequencies under similar user and sensor context (location and time). Yu *et al.* [135] develop more the idea of frequency-based popularity

and consider location popularity being time-dependent. Thus, the authors suggest to estimate location popularity for each month as a weighted combination of the number of visits of the location in a given month over the total number of visits and a normalised average rating score. Moreover, Yu *et al.* [135] consider the popularity of a travel route in order to obtain the best route. Thus, the popularity of a travel route is defined as the average popularity of all POIs within the route.

A more sophisticated approach is proposed by Zhang *et al.* [141]. In order to estimate the attractiveness of a candidate POI, Zhang *et al.* [141] suggest to combine its popularity measure and the check-in frequency from user's friends. The popularity of a POI is defined as the total number of check-ins at this POI. The authors then consider the power-law distribution of popularity.

Categorical Influence

Usually, items can be attributed to a category(-ies), a set or class of items having particular shared properties. This allows to manipulate concepts on a higher level of abstraction. Categorical influence implies that a user who likes items of a particular category is more likely to like other items of the same category. The more often the items of a particular category appear in the user's past interactions with items, the more attractive items of this category are for the user. This idea is widely exploited in recommendation algorithms. Categorical influence is often estimated as a relative frequency of occurrence of items of a particular category in a user's historical data.

Yu *et al.* [135] consider two levels of categorisation of locations (POIs): categories and three types (namely, Food, Venue, Entertainment). Category-wise user's preferences is then estimated as a weighted frequency of user's visits of locations of a given category over his/her visited locations of a given type. It has to be noted, that the category-wise user's preferences are estimated for different time periods.

In TripBuilder [15], categorical preference is considered for each user. Thus, the preference vector is built as a normalised sum of category relevance vectors of all the POIs visited by a user in the past.

Sang *et al.* [98] propose a hierarchical POI sequence recommendation model that has two levels, namely: category sequence and POI sequence. The model is based on the transition probability between POIs and POI categories. The transition probability between POI categories is computed as frequencies of corresponding check-ins under similar user and sensor context (location and time).

Time Availability Influence

Another Item-specific type of influence is related to the time availability of an item. This influence addresses the issue that an activity or another spatial item is limited in time, and therefore, should not be recommended outside its time window, as otherwise, it cannot be accessed. This influence is mostly understood as a constrain. As we pointed out in Section 4.1, the problem of recommendation of a sequence of items (activities, POIs) may be divided into two steps: estimation of user's preference scores regarding individual items and then itinerary construction step. The time availability influence is usually taken into account on the itinerary construction step [39, 102, 139], which allows to exclude the items that cannot be accessed in a specific time.

Financial Influence

Financial influence implies that the cost of an item (*e.g.* admission price, discounts, etc.), including extra expenses associated with it (*e.g.* travel expenses, lodging cost, etc.), has an impact on the attractive force of the item to a user. Generally speaking, the higher the cost (price) is, the less attractive is an item. Or the higher the monetary reward is, the more incentivising an item is. In particular, the latter can be seen in the domain of crowdsourcing.

Financial influence is not widely exploited in the recommendation. A possible reason for that is the lack of information about the cost and user's expenses in available datasets. However, some efforts of incorporating financial influence can be found in the state-of-the-art. Thus, Fonteles *et al.* [38] have introduced reward utility score to incorporate the impact of the reward for a task in a mobile crowdsourcing environment. The authors propose to use directly the total amount of the monetary reward for a task.

4.2.3 User-Specific

User-Specific influence rises from the characteristics of a user. Here, we consider demographic influence and psychological influence. It has to be noted that these kinds of influence are not widely used, due to the lack of such information.

Demographic Influence

Demographic characteristics of users may also be used in order to enhance recommendation [9–13, 46]. The intuition behind is that de-

pending on gender, age group, education, marital status, socio-professional group the preferences of users may differ. It is to note that usually the demographic information is considered to be explicitly provided by a user.
Sang *et al.* [98] consider users' profile information and suggest to use two characteristics of a user: gender and residence[1]. They further calculate the user prior correlation by assigning heuristic scores based on the combination of correspondence of users' gender and residence.

Psychological Influence

It has been shown that the affective state or mood of individuals has an impact on their evaluative judgements [69, 71, 85]. However, as we mentioned above, to the best of our knowledge, no research has been reported on the use of psychological aspect in the recommendation of spatial items. However, it has been shown that users' psychological profiles have an impact on their preferences and item selection in other recommendation domains, such as books, films, music [36, 115, 126]. In their model of satisfaction regarding a sequence of items, Masthoff and Gatt [69] consider an individual's satisfaction regarding an item and a sequence of items to be their affective state. The researchers note that the intensity of satisfaction does change over time and they introduce the decay parameter in their model. The authors state that this decay parameter is likely to depend on user's personality and item duration, however, the further modelling of the relation was out of the scope of their work and, therefore, has not been described.

[1]Though user's residence is not a demographic feature, but we mention it in this section as this information is available in user's profile, is static and is used by Sang *at al.* together with user's gender.

Another consideration made by Masthoff and Gatt [69] relates to the user's satisfaction within a group of users, and more precisely, to the notion of conformity (*i.e.* the influence of judgements by others on those of an individual). Following psychological research, two components of conformity have been observed, namely informational influence and normative influence. The models of the impact of a new item on the user's satisfaction that reflect the informational and normative influences have been proposed. Those models use influence factors that can be learnt explicitly (*i.e.* from a questionnaire). However, the process of implicit acquisition of the degrees of informational and normative influences of the judgements of other group members on the user's emotions and their relation with individual's personality have not been explored yet. Moreover, Masthoff and Gatt [69] have suggested to incorporate into the model the self-reported initial mood of users and the parameter of the degree to which the user's mood influences his/her judgements. Such setting works in the experiment, however, more studies are needed to be able to implicitly acquire the individuals' mood in order to enhance the recommendation. We consider the exploration of psychological influence for recommendation of spatial items to be a prominent direction of future research efforts.

4.2.4 User-User

User-User influence reflects users' social interactions and their impact on the item selection. Here, we consider user's circle of 'friends' and group membership (Social influence), as well as recommendation for groups of users (Group influence).

In some online services (*e.g.* Meetup.com, Foursquare, Facebook), users may interact with each other not only by creating 'friendship' relationship with other users but also by means of group membership. Social interactions may have a strong influence on users' selection of activities [67, 134, 141]. The intuition behind is that 'friends' are assumed to share some interests and many activities of human life are social.

Zhang *et al.* [141] estimate a candidate POI attractiveness for a given user as a combination of its popularity and the check-in frequency at this POI from the user's friends. The social check-in frequency is assumed to follow a power-law distribution. The social influence is then defined as the cumulative distribution of the probability density of social check-in frequency.

In the case of EBSNs, such as Meetup.com, events are organised by groups. A. Macedo *et al.* [67] consider two models of social awareness in the event recommendation, namely *group frequency model* and *multi-relational model*. Group frequency model consists of the calculation of the event relevance score as the frequency of events organised by the same group and attended by the target user over his/her all attended events. In order to take into account more interactions (namely users-groups and groups-events), the authors further suggest to use Multi-Relational Factorization with Bayesian Personalized Ranking (MRBPR) to reconstruct the user-event relation by considering the user-group and group-event relations.

Group Influence

People tend to visit several places (*e.g.* cinema, restaurants, etc.) and activities with a group of friends. When it comes to the recommendation for a group of users, the following issues should be considered: aggregation strategy that allows to find consensus between members of a group regarding an item selection, relationship between users within the group, influence of other group members on the preferences of an individual, privacy of an individual's attitudes and judgements. Nowadays, there has been a bunch of work done in the field of tourism in order to provide high quality POI recommendation for a group of users (*e.g.* [43, 94, 133]). However, this direction has not been widely explored for the recommendation of sequences of spatial items [49] and the recommendation of events.

An interesting approach has been suggested by Masthoff and Gatt [69] who have explored the psychological phenomena of emotional contagion and conformity of an individual's preferences while in a group. The researchers propose a model of group influence on an individual's satisfaction regarding a sequence of items (TV programs) by introducing the notions of emotional contagion and conformity. Thus, *emotional contagion* is understood as the trigger of emotions of others in the group by an individual's emotions, while *conformity* is the act of adjustment of one's judgements with respect to those of others in the group. The emotional contagion has then been assumed to be proportional to the difference between an individual's satisfaction and those of another user in the group weighted by the function of the degree of user's susceptibility and their relationship with each other user. The influence of

conformity has been introduced via two forms, namely *informational influence* (*i.e.* trusting in other people's judgements and adjusting one's behaviour accordingly) and *normative influence* (*i.e.* adjusting one's behaviour to be liked or accepted by the members of the group).
An interesting finding is that when it comes to the recommendation for groups, the research works (*e.g.* [27, 49, 69]) usually suggest to consider users' psychological profiles such as personality traits, emotional contagion, Thomas-Kilmann conflict resolution styles, etc.

4.2.5 Item-Item

For the sake of simplicity, the recommendation items are usually considered being independent. Satisfaction regarding a sequence of items is then often modelled based on the summation of satisfaction with individual items. As it was pointed out in [69], a limitation of a linear approach to satisfaction regarding a sequence of items lies in the fact that satisfaction is increasing/decreasing with sequence length, and is "independent of item order". However, several works from psychology, economy and decision making domains have shown that the item order affects the satisfaction individuals get with items. The dependence of the satisfaction with the current item on the previously experienced items (sequence of items) represents a difficulty for acquisition and evaluation, and is a reason why such relations between items have not been investigated in the recommendation domain. In order to overcome this limitation, Gionis *et al.* [42] suggest to ask a user to explicitly indicate the desired order of the items.

4.2.6 User-Item

User-Item influence rises from user-item interactions within a system. We divide this influence into temporal, sequential, diversity, and rating behaviour.

Temporal Influence

Time information is considered as an important dimension for user modelling and recommendation [18]. It is a widely used contextual information which allows to identify periodicity in user preferences. However, various works interpret and incorporate the concept of time in different ways. Discretisation of time dimension finds it reflection in time splitting based methods.

Time splitting. The intuition behind the time splitting for recommendation purpose is that users tend to perform certain activities and visit certain places depending on the time. Thus, temporal patterns of human behaviour can be extracted. A common idea in existing methods consists in splitting the time axis in order to estimate user's preference regarding particular time slot. The difference then lies in the granularity level of these splits, *e.g.* month [135], day of a week [98], part of a day [135], shorter periods [38, 135]. We assume that the granularity level depends on the type of spatial items (*e.g.* POI, event, activity) and on the duration of an activity/visit.
User preferences towards locations (POIs) are considered to be time - dependent [135]. Yu *et al.* suggest to divide a day into six timeslots and build the user preference profiles for location types w.r.t. each timeslot.

The assumption is that people are more likely "to visit the same type of location in the same time period".

A similar idea of user's temporal preferences w.r.t. event attendance in a certain day of the week and a certain hour of the day is used by Macedo *et al* [67]. Temporal partition is also used by Sang *et al.* [98] in the context of POI recommendation. Based on the relation of adjacence or correspondence of time intervals, the heuristic scores are assigned to the time prior correlation. Fonteles *et al.* [38] suggest to estimate the temporal relevance of a spatial region (Area of Interest) as the number of tasks that can be accomplished at the same hour than the task previously accomplished by the user in this region.

Temporal decay The concept of temporal decay of user's interest can reflect (1) the importance of the user's past interactions for estimation of his/her satisfaction with the next items, or (2) the periodicity in users behaviour. Thus, the check-in data analysis conducted by Sang *et al.* [98] has shown that the repetition level in users' check-in behaviour is considerably high. In order to take into account the possibility of repetitions, the authors introduce the memory retention function that handles the freshness of a check-in at a particular POI, that decays immediately after the visit and then recovers.

The idea of the decay of the user's satisfaction over time has been suggested by Masthoff and Gatt [69] under the concept of emotion wear off over time. Thus, the researchers incorporate a decay parameter into the estimation of an individual's satisfaction with a sequence of items.

Temporal difference. Another approach to deal with temporal influence consists in estimating the temporal difference between items. This strategy is exploited by Zhang *et al.* [141]. The authors estimate the attractive force between locations being inversely proportional to the temporal difference and spatial distance between the two locations, more precisely to their distributions. The temporal difference between of consecutive check-ins has been shown to approximately follow a power-low distribution.

A different understanding of temporal difference between items can be found in the work by Bohnert and Zukerman [7]. The proposed model predicts user's viewing time at exhibits. The authors suggest to use item-based collaborative filtering to estimate item-to-item similarity between exhibit areas using Pearson's correlation coefficient. This collaborative distance is further used in addition to semantic distance and physical walking distance in the spatial process framework [8].

Sequential Influence

Sequential influence seeks to reveal the behavioural patterns of human actions, regarding the chaining of activities/visiting places. Thus, the check-in analysis performed by Sang *et al.* [98] has demonstrated that there exist significant category transition pattens in users' check-in behaviour. When dealing with a sequential influence, a common approach is to retrieve item pairs and estimate transition probabilities between items and/or group of items.

Sang *et al.* [98] consider hierarchical structure of recommendation, *i.e.* first, on category level and then, on POI level. Condition probability based approach has been proposed.

In order to take into account the correlation among certain locations, Yu *et al.* [135] extract the frequent location sequences that consist of a location pair that appear a certain number of times in user's historical records. For each pair of POIs an indicator of being a frequent sequence is then defined.

In order to model the spatio-temporal sequential influence, Zhang *et al.* [141] suggest to compute the transition probabilities between locations in the user's check-in history based on the frequency of past visits. Furthermore, assuming that a new location may depend on all the previously visited POIs in a sequence, the authors consider a *n*th-order additive Markov chain to estimate the sequential probability by summing up the corresponding transition probabilities. The authors then extend their previous work [143] by weighting the transition probabilities with the attractive force between locations.

Sequential influence may also be understood as the impact of the item order within a sequence. As it was mentioned in [49], the order of spatial items within a sequence in the context of the Trip recommendation problem should not be neglected due to the set of constraints, such as the avoidance of detours, limited availability, financial budget, etc.

The conception of order has also been explored by Masthoff and Gatt [69] for recommendation of sequences of items (*e.g.* news stories, video clips, etc.) for a group of users. Thus, the researchers model an individual's satisfaction with a sequence of items by combining the weighted satisfaction with previously experienced items and the impact of the new item containing the assimilation parameter that reflects the degree to which the user's mood influences his/her judgement. This allows to partially take into account the order of items, though more studies are needed for implicitly mining the assimilation parameter from the user's data.

Rating Behaviour Influence

The explicit feedback provided by a user may be used for extracting additional features characterising his/her behaviour. Examples of such features are the average rating provided by a user, the number of his/her ratings, the comments and reviews left by the user, etc. This influence is not exploited in the context of the recommendation of sequences of spatial items. However, it is used in traditional recommendation scenarios, such as movie recommendation [126].

Diversity Influence

Another type of influence that we consider to be promising to explore is the diversity of the user's tastes regarding different attributes of an item. It can be derived from the explicit feedback provided by a user (if exists). An example of such a feature can be found in [126]. This type of influence has not been widely used for the recommendation of sequences of spatial items.

4.3 Summary

In this Chapter, we have presented the methodological approaches used in the state-of-the-art in order to address the problem of recommendation of sequences of spatial items. They can be grouped into two classes, namely (1) two-step methods that sub-divide the problem into two main steps: estimation of personalised scores of items, followed by the itinerary construction step; and (2) method based on sequence learning that estimate the transition probabilities between items. The main limitations of the sequence learning based methods lies in the fact that they do not take into account temporal and spatial constraints proper to the spatial sequence recommendation. In contrast, the two-steps methods account for a number of constraints. However, they do not consider the sequential relationships between items. Thus, a possible improvement is to build an integrated approach that exploits the sequential influence, while accounting for spatio-temporal constraints. We explore this direction in our proposed approach for solving RSSI, that we describe later in the Thesis.

We have also reviewed the types of influence exploited for estimation of the user's satisfaction with items, and have proposed their classification.

5

Recommendation of Sequences of Spatial Items. Evaluation

Contents

In the previous chapters, we have discussed the problem of the recommendation of sequences of spatial items and the related concepts.

We have described different types of influence on user's interest in spatial items. In this chapter, we are focusing on a more practical side of the problem regarding the evaluation process of recommendation algorithms. By *evaluation*, we mean the assessment of the degree to which a recommendation algorithm achieves its goals and objectives.

In this Chapter, we concentrate on the evaluation of approaches to solve RSSI. The evaluation of recommender systems in academic research is often performed *offline* [90, 113]. In offline setting, the evaluation is performed without involving actual users. Thus, an assessment procedure is usually conducted on a static dataset (*e.g.* a snapshot of users interaction with a deployed system, generated datasets, etc.). An offline evaluation usually consists in splitting the data into training and test sets, where the training split is used for learning a model, while the test data is used for prediction and model assessment using evaluation metrics. The effectiveness of an algorithm is then evaluated by measuring the accuracy of the returned results with respect to a ground-truth. The offline evaluation is a predominantly used evaluation methodology for academic research in the field of recommender systems due to its accessibility, low cost and reproducibility of results, when the test collections are publicly available. However, offline evaluations ignore human factor and therefore, 'good' results obtained by a recommender system may differ from real users experience.

Other evaluation methodology include *online* evaluation and *user studies* [106]. Contrarily to offline setting, they imply real-world observations. Thus, online evaluation is conducted by employing an online testing system that is used by real users performing real tasks and that allows to compare multiple algorithms. The users interactions with the system are kept and then analysed. This type of evaluation is mainly used for measuring the impact of a recommender system on users behaviour, which is impossible in offline setting. The employment of such testing system is rather costly and is time consuming. Moreover, it might be reputation-wise risky for a real world company to launch such an evaluation directly, as the users may get dissatisfied, resulting in the loss of attractiveness. For these reasons, online evaluation is usually performed after offline evaluation and user studies.

Like online evaluation, *user studies* inquiry the participation of the real-world users, who measure their satisfaction with a system, usually explicitly [113]. The participants are typically asked to rate their experience on the returned recommendations, and more rarely particular aspects of a recommender system. Such evaluation may be performed in lab environment, where the participants are aware of the experiment contrarily to real-world environment, where the users provide their feedback as part of their use of a system. Importantly, this is the only type of evaluation that may provide qualitative data [106]. Recently, crowdsourcing platforms have become a popular tool for conducting such studies. It is to note, that though this type of evaluation allows to test the behaviour of users, it is rather costly and time consuming. Moreover, the results might be biased, if the the participants do not represent properly the true population of users.

In the following, we overview in more details some aspects of offline evaluation, namely dataset that can be used for quality assessment of a recommendation algorithm for RSSI, and evaluation metrics.

Roadmap. In this Chapter, we first present an overview of existing datasets that could be used for evaluation of solutions of the problem of recommendation of spatial sequences. We discuss their applicability and limitations. Next, we overview the evaluation metrics used in the state-of-the-art in order to assess the quality of approaches for RSSI.

5.1 Datasets for RSSI

Offline evaluation depends a lot on the used data. Recently, some of the datasets used in the state-of-the-art have become available for academic research. In the following, we describe the existing datasets, publicly available for use for evaluation of existing recommendation algorithms. In this section, we present these datasets and discuss their usability for assessing algorithms of recommendation of sequences of spatial items. We categorise the existing datasets into 3 groups w.r.t. the recommendation target, *i.e.*: datasets for single item recommendation; datasets for schedule construction[1]; datasets for sequence recommendation.

5.1.1 Datasets for Single Item Recommendation

Datasets for single item recommendation could be used for assessment of prediction quality of a recommendation algorithm with respect to a single item[2]. Moreover, a sequence may be constructed without consideration of time-related constraints. There is a bunch of datasets available for download that could be used for single item recommendation.

[1]Here, by schedule construction we refer to the optimisation problems issued from Operational Research.

[2]Another reason why we refer to these dataset as 'for single item recommendation' lies in the fact that in the state-of-the-art these datasets have been often used for single item recommendation.

These datasets are created for *evaluation campaigns*, such as TREC Contextual Suggestion track (TREC CS) [24–26]; or are issued from the *logs of location-based social network (LBSN) and event-based social-network (EBSN) systems, e.g.* Yelp, Twitter, Foursquare, Meetup, and Flickr.

TREC Contextual Suggestion Track (TREC CS) task is to provide a ranked list of 50 attractions (venues) given a set of users' profiles and a set of contexts [24, 25]. The track was run as part of TREC 2012-2016. The participants of the campaigns of 2012-2014 could choose as their data source either the open web or the ClueWeb12 dataset. In contrast, TREC 2015 Contextual Suggestion Track provided the participants with the collection of attractions where each entry consists of an attraction ID, a context ID (city), a URL and a title [76]. Users' profiles represent users' past experience of visiting places in a form of 5-point ratings scaled from *strongly uninterested* to *strongly interested*. They can also include some additional information about the user such as user's gender and age, as well as left tags. Contexts is the list of cities that represent user's locations on the city-granularity level. Each context consists of an ID, a city name, a state and a pair of coordinates. Moreover, some optional data about the trip may be provided (i.e. a trip type, a trip duration, the season of the trip, the type of group the person is travelling with).

Few datasets collected from popular LBSNs and EBSNs systems could be accessed, *e.g. i.e.*, Yelp Challenge Dataset [3], Foursquare crawls [127, 128], Twitter crawl [31] and Flickr [112], Meetup [64, 67]. Apart from official APIs provided by the platforms that can be used to query the

[3] http://www.yelp.com/dataset_challenge

data, few data collections used in the recent research works are described and the links to access the datasets are provided. In the following, we discuss some of these instances.

For general statistics of the datasets issued from LBSNxs/EBSNs, see Tab. 5.1.1. The main limitation of these datasets for spatial sequence recommendation is the lack of temporal data. Thus, TREC CS data lack timestamped user-item interactions, TREC CS, Twitter, Flickr, Meetup datasets do not contain temporal information about the items (time availability and service time) nor tour information. As for the Yelp dataset, only aggregated check-in data is provided, making it difficult to retrieve the user's sequences.

5.1.2 Datasets for Schedule Construction

Previously in Chapter 4, we have discussed that a common methodology for modelling and solving the problem of RSSI is a two-step method. It consists in dividing the problem into two phases. On the first phase, one estimates the personalised scores to each candidate item for a given user. On the second one, an itinerary is constructed as a solution for an optimisation problem, such as Travelling Salesman Problem (TSP), Orienteering Problem (OP), etc.

Therefore, when a recommendation approach uses that methodology, its second part can be evaluated on the benchmark instances of the corresponding optimisation (path-finding) problem. We refer to that sort of instances as *Datasets for Schedule Construction*. In the context of recommendation of sequences of spatial items, three big families of optimisation problems should be mentioned, namely Travelling Salesman Problem (TSP), Orienteering Problem (OP) or Vehicle Routing Prob-

Table 5.1.1: General statistics of the LBSN/EBSN datasets for single item recommendation.

Dataset	Items	Users	User-Item	User-User	Format
Yelp Challenge Dataset	61,000	366,000	*reviews*: 1.6 mln *tips*: 500,000	2.9 mln	`json`
Foursquare_1 [127, 128]	3.6 mln	266,000	*check-in*: 33 mln	–	`tsv`
Foursquare_2	1.1 mln	2.2 mln	*ratings*: 2.8 mln *check-in*: 1 mln	27 mln	`dat`
Twitter [31]	–	9,475	*messages*: 377,000	–	`dat`
Yahoo Flickr Creative Commons 100M [112]	249	10,000	*photos*: 49 mln *videos*: 103,506 *user tags*: 68 mln (photos) + 0.4 mln (videos)	–	`s3`
Meetup_1 [64]	1.8 mln	4.1 mln	*rsvp*: 21 mln	–	`csv`
Meetup_2 [67]	617,241	567,250	*rsvp*: 4.2 mln	–	`csv`

Yelp Challenge Dataset: `http://www.yelp.com/dataset_challenge`
Foursquare_1: `https://drive.google.com/file/d/0BwrgZ-IdrTotZ0UoZER2ejI3VVk/view`.
Foursquare_2: `https://github.com/jalbertbowden/foursquare-user-dataset`.
Twitter: `http://www.ark.cs.cmu.edu/GeoText/`.
Yahoo Flickr Creative Commons 100M: The dataset under the Creative Commons copyright license [112]: `http://webscope.sandbox.yahoo.com/catalog.php?datatype=i`. A free Amazon Web Services login is required for access [105].

lem (VRP) [17].

The most used family of such optimisation problems referred to in the recommender system literature is OP (*e.g.* [39, 40, 102, 119, 139]). OP aims at determining a Hamiltonian path limited by the time budget that maximises the collected score by visiting vertices. Nowadays, a great variety of extensions of the OP and VRP has been proposed that take into account various constraints, such as multiple paths and time windows [109]. OP-based solutions differ from personalised sequence recommendation in ignoring the way the scores of vertices have been calculated. These scores are considered to be known. Recently, the work of [121] was the first to address the stochastic time-dependent orienteering problem with time windows.

The test instances of OP and its extensions [118] are available online[4]. This online source consolidates in one place and makes available the benchmark test instances for a bunch of problems starting with Orienteering Problem itself, that is further extended with (multiple) time windows (*e.g.* MCTOPMTW - Multi-Constraint Team Orienteering Problem with Multiple Time Windows [109]), time dependent [120] and stochastic variants [121], as well as cyclic inventory routing problem. The best new solutions for Team Orienteering Problem with Time Windows (TOP-TW) can be found on the web[5]. Most of the OP-based instances represent adaptations of initial instances developed by [23] and [107].

Similarly to OP-based datasets, the testing of routing algorithm can be

[4] `http://www.mech.kuleuven.be/en/cib/op#`

[5] `http://centres.smu.edu.sg/larc/orienteering-problem-library/`

performed on the VRP-based datasets that are available online[6]. This source contains the datasets of VRP and its variants with time windows, multiple depots, split delivery, periodic variants.

The main limitation of these instances is that they can be used only for validating one part of a two-step approach, namely schedule construction, and do not allow to evaluate an approach as the whole. These instances lack users and items information, as in the setting of the optimisation path-finding problems, the item scores are supposed to be known already.

5.1.3 Datasets for Sequence Recommendation

Datasets for Sequence Recommendation consist mainly of timestamped geo-located data allowing to extract sequences of users behaviour. These datasets originate from the interaction logs with the systems (not necessarily recommender systems) [14, 57] or user studies [7, 101–103, 136, 137, 147]. Thus, GeoLife project [136, 137, 147] provides data about users trajectories collected through GPS tracking. TripBuilder knowledge base [14] uses data from LBSNs, enriched with the information from external resources (*i.e.* Wikipedia). Moreover, there are the wprls reporting their results based on the transaction logs of a web/-mobile application designed for a particular event such as Long Night of Museum and Long Night of Music in Munich [101–103]. Moreover, Bohnert *et al.* [7] report their results based on a created application for museum visit in Melbourne.

Table 5.1.2 provides general statistics of these datasets. These datasets usually contain timestamped information about user-item interaction

[6] http://www.bernabe.dorronsoro.es/vrp/

Table 5.1.2: General statistics of the datasets for sequence recommendation.

Source	Dataset	Items	Users	User-Item	User-User	Format
Flickr, Wikipedia, Google Maps	TripBuilder [14]	1,493	22,646	*photos*: 355,674 *trajectories*: 55,474	–	txt
GPS traces	GeoLife [136, 137, 147]	–	182	*trajectories*: 18,670	–	plt
User study	LNMusic & LNMuseum [101–103]	378	1,907	*ratings*: 15,965	–	
	Melbourne Museum dataset [7]	126	14	*pathways*: 158 *viewing durations*: 8,327	–	

TripBuilder: available for download at: https://github.com/igobrilhante/TripBuilder.
GeoLife: available for download at: https://www.microsoft.com/en-us/download/details.aspx?id=52367.

which makes them quite relevant for sequence recommendation. However, they lack data about the availability time windows of the items ([14, 147]), or are rather small [7]. Moreover, some datasets are not available for third parties [57] or there is no information about their availability [7, 101–103].

5.1.4 Summary of Datasets for RSSI

We summarise the overviewed datasets in Tab. 5.1.3. Based on the data available they contain, we indicate the Pros and Cons of their use for assessment of the algorithms of recommendation of sequences of spatial items.

Table 5.1.3: Summary of available datasets, their use for recommendation of sequences of spatial items, Pros and Cons.

Target	Class	Sub-class	Pros	Cons	References
Estimation of person-alised scores	Single Item	POI	+real-world users behaviour +explicit feedback	-no time-related information about the items -no timestamped data	[24–26, 31, 112, 128]
		Event	+real-world users behaviour	-no timestamped data -implicit feedback (no data about actual event attendance) -no time-related information about the items	[64, 67]
Schedule construc-tion	Schedule	OP-based VRP-based	+benchmark instances available +best solutions available +time-related information about the items provided	-synthetic datasets -small size	[30, 109, 118]
Sequence recom-menda-tion	Sequence	Trajectory/ Trip	+real-world users behaviour +timestamped data	-no details about the items (only coordinates) -no time-related information about the items	[14, 147]

Note: OP-based: Orientation Problem and its extensions, VRP-based: Vehicle Routing Problem and its extensions.

5.2 Evaluation Metrics

The output of an approach for RSSI is a list of items over their set. In the offline evaluation setting, the assessment of a recommendation approach is usually performed with accuracy metrics, measuring the degree of matching between a resulting sequence and the ground truth. If the ordering in the resulting sequence is not important, the standard accuracy metrics are usually used, similarly to top-k recommendation. Among the most commonly used accuracy metrics, there are Recall [15, 102, 141], Precision [141], Mean Absolute Error (MAE) [139], Root Mean Square Error (RMSE) [139] . Sang et al. [98] have suggested ordered Accuracy and MAE metrics, applied for evaluating the recommendation of two successive items (POI).
Moreover beyond-accuracy metrics are sometimes used, such as Diversity [135], Popularity [15].
Another group of efficiency metric used for assessment can be applied, when two-step methods are used. In this case, a recommendation algorithm is evaluated with respect to the execution time [15, 139] and overall collected score [15, 40, 139].

5.3 Summary

In this Chapter, we have described evaluation methodology used for assessing approaches for RSSI. We have presented an overview of the datasets that could be used for evaluation of approaches for recommendation of sequences of spatial items, identifying their Pros and Cons. We have also reviewed the evaluation metrics.

Part II

ANASTASIA: A Novel Approach for Short-Term Activity Sequence recommendAtion

Many activities to do nearby
Too many to join them without a plan
Too many to organise all, don't deny
Therefore, the need for RecSys to put the spotlight
In the space of features where uncertainties lie.

To find the way to mine them all
To find the way to match them
To find the way to rate them all
And in the sequence bind them
In the space of features where uncertainties lie.

D.Nurbakova, with the special participation of V. Barellon,
November 2015

6 ANASTASIA: Motivation & Background

Contents

A DISTRIBUTED EVENT is a social event that unites under one umbrella hundreds or thousands of sub-events distributed in space and time [102], providing venues for like-minded people to get absorbed in the universe of the ideas, concepts, and artforms to the promotion of which such events are dedicated. Thus, distributed events include multi-day conventions, festivals, congresses, conventions, etc. Typical examples of them are comic book conventions like Comic-Con International: San Diego, Nights of Museums, such as La Nuit des Musées in France or Lange Nacht der Museen in Berlin or MuseumNacht in Amsterdam, music festivals like Coachella Valley Music and Art Festival or Pinkpop, conferences like The Web Conference[1] or ACM SIGIR Conference, cruise programs, etc.

Roadmap. In this Chapter, we first present the motivation behind the creation of a new approach for recommendation of activity sequences in Section 6.1. Next, in Section 6.2, we provide the problem statement of the problem of recommendation of activity sequences during distributed events, which is based on the general problem definition of RSSI that we have defined in Chapter 3. Moreover, we describe the assumptions and preliminaries for our proposed solution. We then present the closest works that have motivated and inspired us in Section 6.3.

6.1 Motivation

The programs of distributed events are usually very dense and consist of multiple short-lived events happening in parallel. In the context of a distributed event, the process to decide which sub-events or activities

[1]A former WWW Conference.

to undertake becomes more constrained than in the case of a traditional event recommendation. Indeed, the amount of activities may be higher than usual, as activities occur in parallel. Moreover, the sub-events are unique, short-lived and gathered under the umbrella of a general theme of the event. Itinerary recommendation thus differs from single event recommendation [67, 72]. Let us consider two scenarios of organising time during a distributed event, namely (1) on board of a cruise, and (2) at a comic book convention.

Scenario 1. Activities on board of a Cruise. Scoby is enjoying his holidays on board of a 7-night Caribbean cruise ship. Every day, he has to make up his mind which activities to choose among a hundred offered with the average duration of 45 min. And at every given time, there are about 5 activities going on. Then, what is the best way to plan the day in order to get as much fun as Scoby can?

Scenario 2. Events @Comic-Con. Didi is going to Comic-Con International: San Diego. It is one of the biggest multi-day conventions primarily focused on comic books and related culture. Each year, it offers about 1,900 events of the average duration of 53 minutes, distributed over 4-5 days. The density of the program (*i.e.* the number of simultaneously scheduled events with respect to 15-minute ling timeslots) is 37, reaching its peak of 112 parallel events. This makes it hard for attendees to select events and organise their time to be sure, so that it would be possible to perform the maximum of the activities they would enjoy.

Examples of activities of each of the scenarios are given in Tab. 6.1.1.

Table 6.1.1: Example of activities: a cruise on-board activity and an event at a comic book convention.

Example 1. Activity on board of a cruise: *The Comedy & Hypnosis of Ricky Kalmon* [82]
Location: Walt Disney Theatre, $l = (0, 880, 0)$; **Time window**: Day 3, 23:00-23:45, $t = (1435014000, 1435016700)$; **Duration**: $\delta = 2700$; **Categories**: Adults, Variety Show **Description**: Featuring the Comedy & Hypnosis of Ricky Kalmon, as he entertains you in this adult exclusive show.
Example 2. Event @ComicCon: *Jaws Will Drop, Sides Will Ache... Super Weird Heroes!* [78]
Identifier: 1fb411d60ea1e81d1c74e5239e6ffbee **Location**: Room 28DE **Start Time**: 20.07.2017, 10h00 **End Time**: 20.07.2017, 11h00 **Duration**: 60 min **Categories**: *1: Programs, Art and Illustration, Books, Comics, Costuming, Humor & Satire* **Description**: A way-fun, LOL, multimedia show of the kookiest, kraziest, most bizarro leotard-clad bad-guy-bashers of the Golden Age of comic books! See the Hand, a giant hand! See Madam Fatale, the first cross-dressing superhero! See Kangaroo Man (Batman was taken)! See tons more nutty-cool heroes held up to reverence and ridicule! Based on the bestselling book Super Weird Heroes (and its upcoming sequel), this stand-up comedy presentation is by the former creative director of the Muppets, now the Eisner-winning editor of IDW and Yoe Books Craig Yoe. Twenty laugh-riot cosplay changes in all!

The variety of options offered on such kind of events is their biggest selling point, and at the same time it makes more complex the choice on which activities to undertake and in which order. Recommender systems are powerful assistance tools in such a decision-making problems. Recommendation of sequences of activities is a challenging task. The main challenges of the recommendation of activity sequences rely in the fact that activities are unique, happening in future and short-term. Thus, every time a user wants to choose an activity to perform, he/she has to detect an activity he/she may prefer among all the alternatives happening during the same timeslot, taking into account that he/she may not be able to join another activity of interest due to the time availability constraints. Therefore, the objective is not only to define users' interest in upcoming events, but to provide per day personal program (itinerary) of activities. It implies the necessity to recommend activities with no explicit feedback and any external information (*e.g.* reviews) dealing with highly uncertain users' preferences, and to ensure that a user will be able to attend all the selected activities on time. We assume that we have only access to users' past visited locations and the timestamps. This setting is close to the real-world scenario, as the participants of the distributed event usually do not provide explicit ratings to all the activities, they have performed. Moreover, the decision making process that is associated with the selection of activities to perform, especially in the context of a distributed event (such as a cruise journey or a participation in a huge convention) is not simple.

6.2 Problem Statement

The decision-making problem on recommendation of activity sequences during distributed events can be formulated as the problem of recommendation of sequences of spatial items (RSSI problem) (see Chapter 3), where items are represented by activities.

Let $\mathtt{U}$ be a set of users and $\mathtt{A}$ be a set of activities (see Section 3.1.1). Let $\mathtt{t}$ be the point in time for which the recommendation is sought. We denote as $\mathtt{A_t} \subset A$ a set of candidate activities that are available at time $\mathtt{t}$, *i.e.* $t_a(a) \leq \mathtt{t} \leq t_e(a), \forall a \in \mathtt{A_t}$, where $t_s(a)$ and $t_e(a)$ define the time window of availability of the activity a.

Let $\mathcal{P}(\mathtt{A_t})$ be the powerset of $\mathtt{A_t}$, and $\mathtt{N}$ be its power. A candidate sequence $\xi = (\mathtt{a}_{(1)} \rightarrow \ldots \rightarrow \mathtt{a}_{(\mathtt{s})} \rightarrow \ldots \rightarrow \mathtt{a}_{(\mathtt{k})})$, where $\mathtt{a}_{(\mathtt{j})} \in \mathtt{A_t}$ and $1 \leq \mathtt{s} \leq \mathtt{k} \leq \mathtt{N}$ is then an element of the set of all permutations of the length $(\mathtt{k})$ of $\mathcal{P}(\mathtt{A_t})$, i.e. $\xi \in \mathtt{S_k}(\mathcal{P}(\mathtt{A_t}))$. We denote the latter set as $\Xi = \mathtt{S_k}(\mathcal{P}(\mathtt{A_t}))$.

The **problem of recommendation of activity sequences during distributed events** consists in finding the sequence $\xi^* \in \Xi$ for the target user $(u \in U)$ at target time t, s.t.

$$\xi^*(u, t) = \arg\max_{\xi \in \Xi} \sigma(u, \xi), \forall \mathrm{u} \in \mathtt{U},$$

where $\sigma(u, \xi)$, $\sigma : U \times \Xi \rightarrow \Re$ is the satisfaction function that returns a satisfaction score for a user $\mathtt{u} \in \mathtt{U}$ w.r.t. a sequence .

A sequence $\xi^*(u, t)$ should satisfy the following feasibility conditions: (1) activity availability constraint, (2) activity completion constraint, (3) time budget constraint, (4) start and/or destination constraint. We have provided their definitions in Section 3.1.2 of Chapter 3.

We make the following **assumptions**.

1. *Unique activities and visits*: Each activity is unique and short-term, *i.e.*, for each activity there exists only one time window defining its life time. We do not consider periodic activities, as they are rarely present during distributed events.

2. *Satisfaction with a sequence as sum of its components*: The user's satisfaction with an entire sequence of activities can be calculated as the sum of the user's individual satisfaction scores regarding all the items within the sequence, i.e.: $\sigma(u, \xi) = \sum_{a_i \in \xi(u)} \rho(u, a_i)$.

3. *Traceability of users*: the log of users' past experience that consists of geospatial coordinate sets and timestamps is available. A binary user-item matrix, reflecting the users' RSVPs with respect to the available activities can be also considered as a user-item interaction log. We denote by $A_u \subset A$ a set of past activities of the user u. This assumption is also due to the information that is contained in the datasets that we possess.

4. *Attend = Like*: In compliance of the *Traceability of users* assumption, we assume to have an access to a user-activity binary matrix. Such user-item interaction may be considered as the users' implicit feedback to the activities, because we do not have the explicit ratings of events provided by the users. Thus, we assume a user '*to like*' an activity, if there exists a trace (positive value of attendance) in a user-activity matrix. An assumption commonly made in the field of event recommendation is that the users' RSVP

indicating the intentions in joining events may be considered as a proxy value of attendance [67, 72].

5. *Non-stop fun*: in the context of users' attendance of a distributed event, their goal is to get the maximum satisfaction from overall experience [102]. Thus, we assume a user to look for an itinerary filled with activities the entire day.

6. *Moving around in space*: the travelling time of the users between locations is a function of distance. We assume that all the users move with the same constant pace. The distance between locations can be calculated based on the coordinates set that is known.

6.3 Background & Related work

In this Section we present the closest works, that are [102], [143], and [117]. They correspond to three axes, namely: recommender systems for distributed events [102], recommendation using sequential influence [143], and itinerary construction [117].

6.3.1 Recommender Systems for Distributed Events

A note on collaborative filtering and content-based approaches

In more traditional recommendation scenarios (*e.g.* books, movies, music), the prediction of the user's interest in an item can be build upon the interactions of other users, who have similar user-item interaction behaviour to the target user. We illustrate the collaborative filtering approach in Fig. 6.3.1. Suppose, we aim at finding if the target user (golden user in the last row of user-item interaction matrix) will like

Figure 6.3.1: Example of estimation of the user's interest in an item (pets) using collaborative filtering. The prediction is built upon the existing interactions of other users, who have similar interaction behaviour to the target user (coloured with light green).

a bird as a pet or not. Based on her rating behaviour and the rating behaviour of other users, an approach defines similar users (blue and red in the figure). as both of these similar users do not like birds, then the prediction for the target user will be also 'not like'.

When it comes to the events or activities that are scheduled for some moment in future, the user-item interactions have not happened yet at the time of recommendation (see Fig. 6.3.2). In the figure, we indicate the unknown future interactions with interrogation mark. Therefore, one of the possible solution approaches is to build user and item profiles upon a set of features (the second step in the figure), where user profile is build upon his/her past interactions (the third and fourth steps). The matching of user and new item profiles is them performed (the fifth step). based on this matching, the prediction is made. This is a content-based filtering approach.

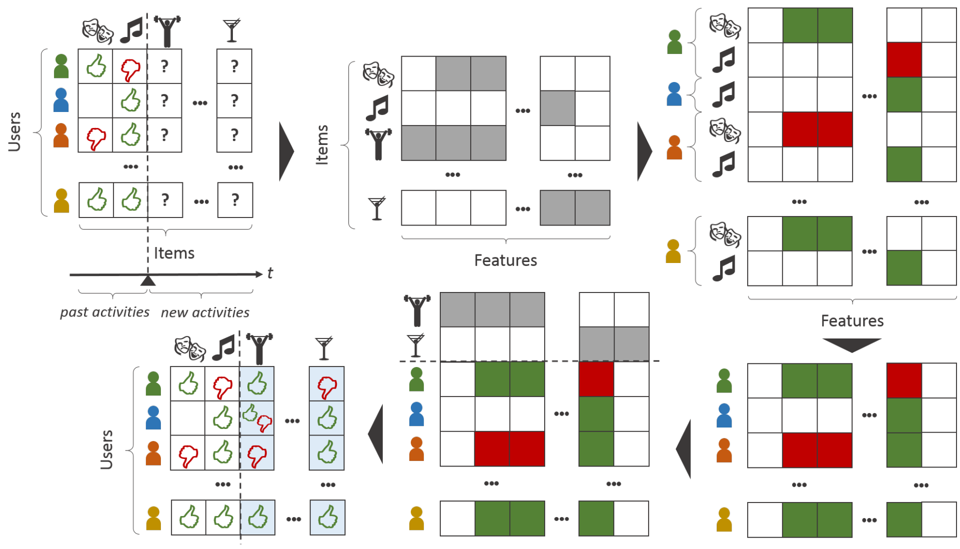


Figure 6.3.2: Estimation of user's interest scores in activities based on user and item profiles.

Recommender system for event recommendation during distributed events

In [102], Schaller *et al.* propose a hybrid recommender systems for events during large festivals organised in Munich, namely Long Night of Music 2012 and Long Night of Munich Museums 2012. They combine three elements:

1. A *Content-based recommender* which uses the similarity between user and event profiles, built over the categories (genres/topics), where user's preferences are defined by the user.

2. A *Collaborative filtering recommender* based on two state-of-the-art algorithms, namely BLITR [45] and SVD-based [86], which both use user ratings for events.

3. A *Temporal contiguity recommender* which exploits the metric pro-

posed in [101] in order to return "the events that form a compact route".

Contrarily to this work, in our approach we do not use collaborative filtering techniques, as we consider that there are no ratings of future events, having access to only binary user-item interactions (see assumption *Traceability of users*). Moreover, this approach returns a list of top-k events, and not an itinerary.

6.3.2 Sequential Influence

Zhang *et al.* [143] have proposed to exploit sequential influence for next-POI recommendation based on a n-th order additive Markov chain. The sequential probability of visiting a new POI (location) is defined as a weighted sum of transition probabilities between locations. This latter is estimated based on a location-location transition graph (L^2TG). Given a set of locations L, timestamped location sequences of user u $S_u = \langle l_1, l_2, ..., l_n \rangle$, a location-location transition graph $G = (L, E)$, consists of locations L and edges $E \subseteq L \times L$, so that: each location l_i is associated with the value $OCount(l_i)$ denoting the number of locations for which the current node l_i is a predecessor within the user's sequences; and each edge $(l_i, l_j) \in E$ corresponds to a transition $l_i \rightarrow l_j$ within the user's sequences and is associated with the value $TCount(l_i, l_j)$ denoting the frequency of this transition.
The transition probability between two locations, denoted $TP(l_i \rightarrow l_j)$

is then defined as follows:

$$TP(l_i \to l_j) = \begin{cases} \frac{TCount(l_i \to l_j)}{OCount(l_j)}, & \text{if } OCount(l_j) \neq 0 \\ 0, & \text{if } InCount(l_j) = 0 \; and \; l_i \neq l_j \\ 1, & \text{if } InCount(l_j) = 0 \; and \; l_i = l_j \end{cases}.$$

Getting inspired by this work, we have used a similar idea for the estimation of transition probabilities between activities, modifying it for the case of unique activities (*i.e.* unique nodes and visits). Note that this method does not take into account any feasibility constraint.

6.3.3 Itinerary construction

In Section 6.2, we have identified the set of assumptions and feasibility constraints. The consideration of such constraints can be modelled as the schedule construction problem. Among various possibilities of defining and approaching the schedule construction problem, we have chosen Orienteering Problem with Time Windows (OPTW) [118]. Given a set of nodes with assigned scores, OPTW aims at finding a path that maximises the total collected score over visited nodes. The sought path is constrained by the total time budget, while satisfying the time availability constraint (*i.e.* limited time windows of nodes).
Iterated Local Search (ILS) [117] is a state-of-the-art algorithm for solving Team Orienteering Problem with Time Windows (TOPTW). The TOPTW is an extension of OPTW, that searches for solution for multiple tours, each limited by the time budget. Therefore, OPTW may be considered a TOPTW where the number of tours equals one. In our problem formulation, we are searching for only one itinerary for a given target time of recommendation. That is why, among OPTW and

Insert

```
For each non included visit:
|       Determine the best possible insert position and Shift;
|       Calculate Ratio;
Insert visit with highest ratio (j);
Visit j: calculate Arrive, Start, Wait;
For each visit after j (until Shift == 0):
|       Update Arrive, Start, Wait, MaxShift, Shift;
Visit j: update MaxShift;
For each visit before j:
|       Update MaxShift;
```

(a)

Shake

```
For each tour:
|       Delete the set of visits (i => j);
|       Calculate Shift;
|       For each visit after j (until Shift == 0):
|       |       Shift visit towards the beginning of the tour;
|       |       Update Arrive, Start, Wait, MaxShift, Shift;
|       For each visit before i:
|       |       Update MaxShift;
```

(b)

ILS

```
S ← 1;
R ← 1;
NumberOfTimesNoImprovement ← 0;
while NumberOfTimesNoImprovement < 150 do
|       while not local optimum do
|       |       Insert;
|       If Solution better than BestFound then
|       |       BestFound ← Solution;
|       |       R ← 1;
|       |       NumberOfTimesNoImprovement ← 0;
|       Else
|       |       NumberOfTimesNoImprovement
|       |               ← NumberOfTimesNoImprovement+1;
|       Shake Solution (R, S);
|       S ← S + R;
|       R ← R+1;
|       If S>=Size of smallest Tour then
|       |       S ← S - Size of smallest Tour;
|       If R==n/(3*m) then
|       |       R ← 1;
Return BestFound;
```

(c)

Figure 6.3.3: Pseudocode of ILS algorithm [117]: (a) ILS insert step, (b) ILS remove step, (c) ILS pseudocode.

TOPTW formulations, we have selected OPTW.

ILS is a heuristic algorithm that iteratively searches for a node to be included in the current path that will maximise the total score of the itinerary. It consists of two main steps: insertion and shake. During the insertion step, the algorithm iteratively inserts a node into the current solution, until the best solution is found (see Fig. 6.3.3 (a)). The shake step is then applied in order to escape the local optima (see Fig. 6.3.3 (b)). The combination of these two steps is executed, until no more improvement in terms of score is achieved (see Fig. 6.3.3 (c)). We present the algorithm in more details as it is the basis of the itinerary construction step of our proposed solution, described later in this Chapter.

ILS: Insert step.

For candidate nodes, a feasibility check is performed to ensure that the insertion of a new node would not make any already included visit violate its time window constraint. In order to do so, for each vertex already included in a solution, two values are recorded, called *Wait* and *Shift*. Let a_i be the arrival time at node i. Due to the time availability constraint, the service at the node (*i.e.* execution of an activity at the node) may start only when its time window opens, $i.e.$ the soonest at its start time t_s. Thus, the time needed for starting the service at node i after the arrival is denoted by $Wait_i$. It is defined as follows:

$$Wait_i = max[0, t_s(i) - a_i]. \tag{6.1}$$

For each candidate node j, the total time cost needed for it insertion between nodes i and k is calculated. It is denoted $Shift_j$ and is defined as follows:

$$Shift_j = t(i,j) + Wait_j + \delta_j + t(j,k) - t(i,k). \tag{6.2}$$

Another measure, calculated for each node is $MaxShift_i$. It is defined as the maximum delay of the service at node i by user (or the maximum time shift), without making any other visit infeasible, *i.e.*:

$$MaxShift_i = min[t_e(i) - start(i), Wait_{i+1} + MaxShift_{i+1}] \tag{6.3}$$

Based on that parameters, the feasibility check of an insertion is defined as follows:

$$Shift_j = t(i,j) + Wait_j + \delta_j + t(j,k) - t(i,k) \leq Wait_k + MaxShift_k. \tag{6.4}$$

Moreover, the performance of an activity at node j should fit the time window of j.

For each candidate node, the best possible insert position is determined by selecting the an insert position providing the lowest *Shift*.

The decision on which feasible node to insert is the made in favour of a node providing the highest ratio:

$$Ratio_i = \frac{\hat{r}_i^2}{Shift_i}, \tag{6.5}$$

where $\hat{r}_i$ is the score of the node i.

In the above formula, the square of the score is used in order to emphasise the higher relevance of the node score over the time cost (*Shift*) in the selection process.

After each insertion, all other nodes within the current solution should be update. Table 6.3.1 provides formulas that are used to update the parameters of nodes after the insertion of a new node k in the path between nodes i and j.

	Node k	Succeeding nodes	Preceding node	Comment
Arrival time	$arrive_k = s_i + \delta_i + t_{ik}$	$arrive_{j^*} = a_j + Shift_{j-1}$		time of arrival at node
Start of the visit	$s_k = a_k + Wait_k$	$s_{j^*} = s_j + Shift_j$		time of start (beginning) of service at node, *i.e.* start of performing an activity
Waiting time	$Wait_k = \max\left[\,0, t_s(k) - a_k\right]$	$Wait_{j^*} = \max\left[0, Wait_j - Shift_{j-1}\right]$		time of waiting the opening of the node, if arrived in advance
Maximum time shift		$MaxShift_{j^*} = MaxShift_j - Shift_j$	$MaxShift_i = \min\left[t_e(i) - s_i, Wait_{i+1} + MaxShift_{i+1}\right]$	maximum time that the start of activity execution may delayed
Time shift (time cost)		$Shift_j = \max\left[0, Shift_{j-1} - Wait_j\right]$		time cost of the isertion of node

Table 6.3.1: Formulae of parameter updates after the insertion of a new node k in the path between nodes i and j.

Figure 6.3.4: Illustration of parameters used in ILS. The following notations are used: a - arrival time, s - service start time, t_s - opening of the time window, t_e - closing of the time window,

Figures 6.3.4-6.3.5 provide illustrations of parameters used in ILS. In Fig. 6.3.4, node i is represented with respect to the time window of its availability (t_s, t_e) as a white oval. The arrival time at node i is symbolised with the a green cross and denoted a. As the arrival time is within the time window, the visit of the node may start immediately after arrival. Thus, the start time denoted s is equal to a. The visit of the node or in other words service at the node i is represented as a black oval. Its length corresponds to the duration (service time) of i, denoted δ.

Now, let suppose that the node i is followed by node j (see Fig. 6.3.5). After performing an activity at node i (black oval in i row), the user travels to node j (blue dot line). The travel takes time $t(i, j)$. The user arrives before the opening of node j (green cross before the white oval in j row), a_j. Therefore, he/she has to wait till the node becomes available (yellow dot line) during time $Wait_j$. Once the node is available $t_s(j)$, the user can start performing activity at that node at start time s_j. The start of the visit may be shifted (delayed) for the time $MaxShift(j)$ (grey oval with dotted line), in this case corresponding to the total availability time of node j, i.e. $MaxShift(j) = t_e(j) - s_j$.

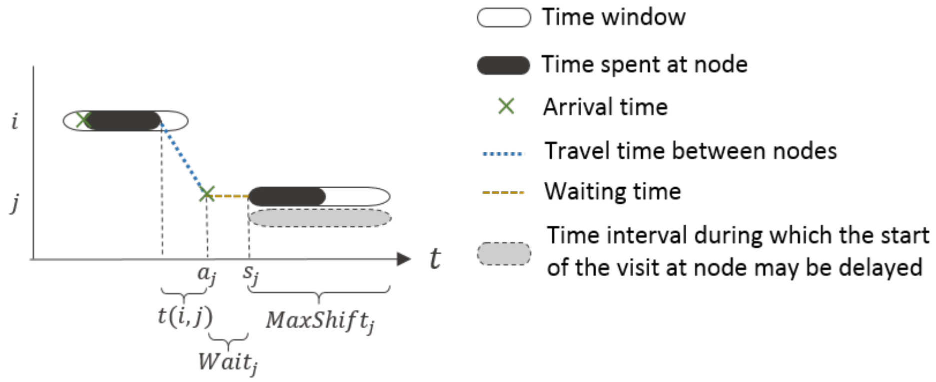


Figure 6.3.5: Illustration of parameters used in ILS. The following notations are used: a - arrival time, s - service start time, t_s - opening of the time window, t_e - closing of the time window, *Wait* - waiting time, *MaxShift* - maximum time shift, $t(i, j)$ - travel time between nodes i and j, δ - activity duration/service time.

ILS: Shake step.

The shake step consists in perturbation of the solution obtained as the result of the Insert step. It is used in order to escape the local optima. The main idea is to remove one or more nodes from the solution, defined by two parameters, namely: R_d denoting the number of consecutive visits to remove, and S_d denoting the node within the solution to start the removal. For the removal, the path is considered to be cyclic. Thus, if while removing the nodes, the last node of the solution is reached, then the removal process continues from the beginning of the solution path.

After the removal, all the nodes succeeding the removed ones get shifted towards the beginning of the path for avoiding the increase of waiting time at nodes. If the shift is not possible due to the time window of a node, then its visit remains unchanged, as well as the succeeding nodes. For the nodes succeeding the removed ones, the update procedure is performed, similarly to the Insert step. For the preceding nodes, only *MaxShift* gets updates.

Our proposed approach ANASTASIA at its final step of itinerary construction is based on the original ILS algorithm. We suggest a modification of the ILS by introducing a weight of node scores to be included in the path.

6.4 Summary

In this Chapter, we have presented the motivation behind the design of a new approach for recommendation of activity sequences during distributed events. We have presented the problem statement, precising the set of assumptions and feasibility constraints for a returned sequence. We have described the background of our proposed solution. In the following Chapter, we describe our approach for recommendation of activity sequences during distributed events, ANASTASIA.

Many activities to do nearby
Too many to join them without a plan
Too many to organise all, don't deny
Therefore, the need for RecSys to put the spotlight
In the space of features where uncertainties lie.

To find the way to mine them all
To find the way to match them
To find the way to rate them all
And in the sequence bind them
In the space of features where uncertainties lie.

November 2015

7 ANASTASIA: Approach Description

Contents

This Chapter provides a description of **ANASTASIA**: **A N**ovel **A**pproach for **S**hort-**T**erm **A**ctivity **S**equences and **I**tinerary recommend**A**tion. We have precised the addressed problem, providing a set of assumptions and sequence feasibility constraints that we take into account, in Section 6.2 of the previous Chapter.

ANASTASIA is a hybrid approach as on the one hand, it follows a two-step methodology for solving the problem of recommendation of activity sequences during distributed events, and the other hand, it makes use of ideas of the transition probabilities between activities issued from the sequence learning methods (see Section 4.1 of Chapter 4). Thus, we treat separately the estimation of personalised scores of activities, measuring the user's interest (or satisfaction) in activities, and the itinerary construction. At the same time, based on the user's past interactions with activities, we estimate the transition probabilities between future activities. In the following, we will present these three parts of ANASTASIA.

Roadmap. In this Chapter, we first give a general overview of ANASTASIA. Then, we present its three parts. Thus, in Section 7.2 describe the computation of personalised scores of activities with respect to three dimensions (influences), namely: categorical, textual and tem-

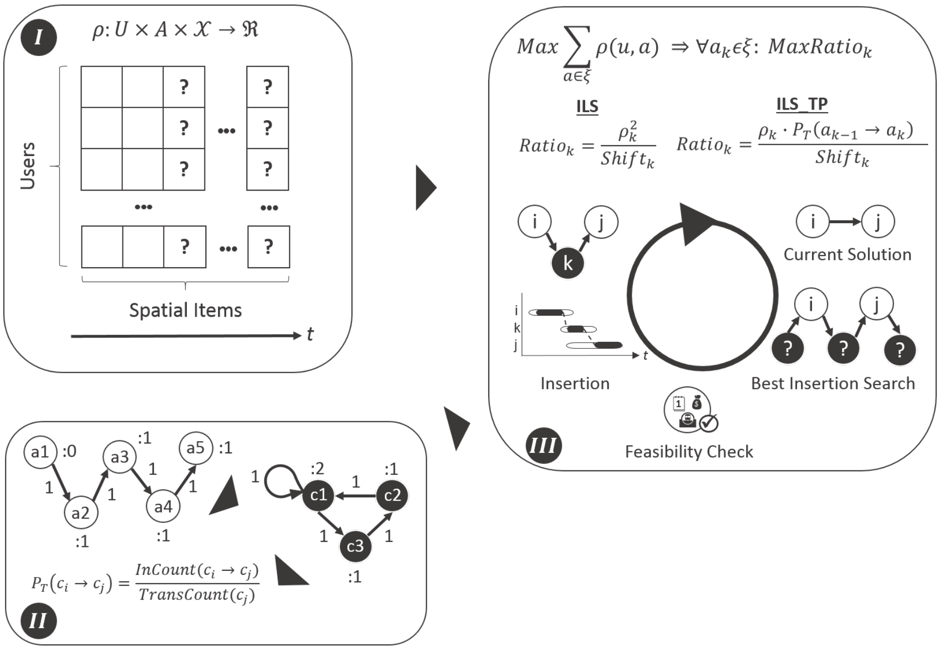


Figure 7.1.1: ANASTASIA: General overview. Part I: Computation of personalised scores of activities. Part II: Extraction of user's behavioural sequences. Part III: Itinerary construction.

poral. Their description is followed by the presentation of two computational strategies. Next, in Section 7.3, we present the estimation of sequential influence for the construction of a personalised itinerary, which consists in estimation of transition probabilities between activities. We then describe an iterative algorithm to construct an itinerary which uses personalised scores of activities and the transition probabilities (Section 7.4). A summary on the proposed approach concludes the Chapter.

7.1 General Overview

We propose an integrated solution for the problem of recommendation of activity sequences, called **ANASTASIA**. It exploits the users' interests, sequential influence, spatial and temporal constraints. It consists of three main parts: I. Computation of personalised scores for each activity. II. Extraction of user's behavioural sequences. 3. Itinerary construction using data provided by the previous steps. A general overview of ANASTASIA is presented in Fig. 7.1.1.

In the first part, based on the user's interactions with past activities, ANASTASIA estimates the user's interest scores with future activities. The estimation is performed with respect to three dimensions exploring three types of influence, namely: categorical, textual, and temporal.

In Part II of ANASTASIA, we estimate the transition probabilities between future activities, based on the user's historical data.

In the third part, given the estimated scores and transition probabilities, we iteratively construct an itinerary (activity sequence) that satisfies the set of constraints.

In the following, we describe each of these parts.

7.2 Part I. Computation of Personalised Scores

One of the key characteristics of activity/event recommendation is the lack of collaborative data. This lack originates from temporary nature of activities. Therefore, we consider content-based methods to be more adapted for recommendation of activity sequences during distributed events.

In the following, we present a user-specific model of the calculation of three scores, namely categorical, textual and temporal that are further used as components for the prediction of the final score. We focus on these three dimensions of the score, as they constitute the main attributed of an activity (see Section 3.1.1).

7.2.1 Categorical Influence

Belonging to a category or a list of categories is one of the main characteristics of an activity. Keeping in mind the uniqueness of activities, we consider the categorical influence to be the most discriminating factor in selection of activities by an individual.

The basic idea in using categorical influence is that the more activities of a certain category a user performs, the more likely this user will continue to join the activities of this category. Thus, we seek to construct a categorical score that would represent the user's interest with the activity categories.

More formally, let $\mathcal{C}|$ be the set of activity categories. We then represent each activity with respect to its category belonging as a $1 \times |\mathcal{C}|$-dimension vector that we denote $\vec{a_{cat}}$. This vector is built so that the i^{th} component of the vector is assigned the value $\frac{1}{|\mathcal{C}(a)|}$, if the activity belongs to the category C_i, and zero, otherwise, *i.e.*:

$$\vec{a_{cat}}(i) = \begin{cases} \frac{1}{|\mathcal{C}(a)|}, & \text{if } a \in C_i, \\ 0, & \text{otherwise} \end{cases},$$

where $|\mathcal{C}_a|$ denotes the number of categories that the activity a is assigned to.

In the case where the categories form a hierarchy, we modify the aforementioned representation as follows. We decompose the set of activity categories $\mathcal{C}$ into two groups, namely: '*main*' categories and '*other*' categories' categories. *Main* categories unite activities into the groups of high-level abstraction, or in the case of categories with hierarchical structure, those which are on the top of the hierarchy. We denote this subset of categories as $\mathcal{C}_{main}$. We denote *other* categories by $\mathcal{C}_{others}$.
We represent each activity as a $1 \times |\mathcal{C}|$-dimension vector $\vec{a_{cat}}$, where a value 1 is assigned to the i^{th} component of the vector, if an activity belongs to a main category C_i, $\frac{1}{|\mathcal{C}_{others}(a)|}$, if an activity belongs to another category, and 0 otherwise, *i.e.*:

$$\vec{a_{cat}}(i) = \begin{cases} 1, & \text{if } a \in C_i \text{ and } C_i \in \mathcal{C}_{main}, \\ \frac{1}{|\mathcal{C}_{others}(a)|}, & \text{if } a \in C_i \text{ and } C_i \in \mathcal{C}_{others},, \\ 0, & \text{otherwise} \end{cases}$$

where $|\mathcal{C}_{others}(a)|$ denotes the number of *other* categories that the activity a is assigned to.
We then model a category-based user profile as follows:

$$\vec{u_{cat}} := agg_{a \in A_u}\Big(\frac{1}{(1+\alpha)^{\tau(a)}} \times \vec{a_{cat}}\Big),$$

where *agg* denotes an aggregation operator (we used the mean in our experiments), $\vec{a_{cat}}$ is a category vector of an activity a, α is a time decay factor (we set $\alpha = 0.01$ similar to [67]), and $\tau(a)$ returns the number of years between the current activity and the user's past activities, if exists. Generally speaking, such representation of the user's profile reflects the weighted frequency of the categories of the activities performed by the user in the past, while taking into account the different impact of the user's past experience with respect to the time. The weighting wr.t. the time is used for differentiating the influence of the past interactions according to their oldness-freshness.

Categorical score based on frequency. Given a user u and an activity a, we then estimate a categorical score of an activity as the sum of the components of the user categorical profile corresponding to the categories of the activity a, *i.e.*

$$\hat{r}_{cat}(a, u) = \vec{u_{cat}} \cdot \mathcal{I}\{a \in \mathcal{C}\}, \tag{7.1}$$

where $\mathcal{I}\{a \in \mathcal{C}\}$ is a vector, each component of which is a binary indicator that an activity a belongs to the i^{th} category.

Categorical score based on similarity. Another possibility is to calculate the category-based score as a similarity measure between a category vector of an upcoming activity a and the user category profile, *i.e.*:

$$\hat{r}_{cat}(u, a) = cos(\vec{u_{cat}}, \vec{a_{cat}}), \tag{7.2}$$

where $cos(\cdot\,,\cdot\,)$ denotes the cosine similarity between vectors that we use as a similarity measure.

7.2.2 Textual Influence

Each activity is characterised by its title and may have a textual description. Based on that textual information, we represent each activity using

TF-IDF (term-frequency inverse document frequency). TF-IDF function is defined as follows [104]:

$$tfidf(w_k, d_j) = tf(w_k, d_j) \times log \frac{n}{df(w_k)},$$

where $tf(w_k, d_j)$ denotes the frequency that the term w_k occurs in d_j, $df(w_k)$ denotes the number of documents in the corpus in which the term w_k occurs (also known as *document frequency*), and n is the total number of documents. In our case, a 'document' consists of activity's title and description, and the total number of documents correspond to the total number of activities, *i.e.* $n = N$. Thus, for each activity we obtain a vector that we denote $\vec{a}$.

We then build the *positive and negative user profiles*. The intuition behind the construction of the positive user profile, built over the past activities performed by the user, lies in the assumption that a user is more likely to be interested in activities that are similar to those he/she has performed in the past.

In contrast, the intuition behind the construction of the negative user profile, which is built over the past activities not performed by the user, is that the activities forming it are of less interest for the user. Therefore, the new activities which are similar to those will also represent less interest for a user. Consequently, the similarity measure between an upcoming activity a and the negative user profile U_{neg}, denoted $cos(U_{neg}, \vec{e})$ can be used as a penalty function in the textual score. Note that the construction of a negative profile is possible in the case of a distributed event, where the number of available option is rather limited. In the context of LBSN, the calculations might be very heavy, as the number of alternatives (*e.g.* all alternative POIs in a city not visited by a user) may be too large.

The positive user profile U_{pos} consists of summarised TF-IDF vectors of activities performed by the user in the past, *i.e.*:

$$U_{pos} = agg_{a \in A_u} \{ \frac{1}{(1+\alpha)^{\tau(a)}} \times \vec{a} \},$$

where agg is an aggregation operator, A_u denotes the set of activities performed by the user u in the past, α is a time decay factor (we set $\alpha = 0.01$ similar to [67]), and $\tau(a)$ returns the number of years between the current activity and the user's past activities, if exists. For the experiments, we use a sum as an aggregation operator.

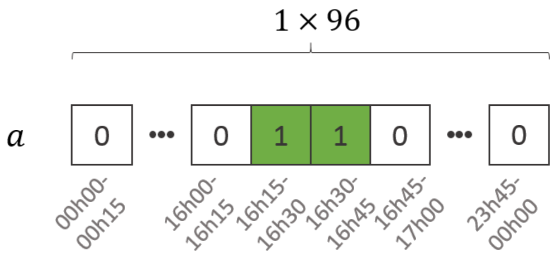
The negative user profiles U_{neg} consists of aggregated TF-IDF vectors of past activities not performed by the user, *i.e.*:

$$U_{neg} = agg_{a \notin A_u} \{ \frac{1}{(1+\alpha)^{\tau(a)}} \times \vec{a} \}.$$

The textual score of an upcoming activity a for a user u is then computed as a linear combination of cosine similarity measures between a TF-IDF vector $\vec{a}$ of an activity a and positive and negative user profiles, as follows:

$$\hat{r}_{cb}(a,u) = \alpha_u \cdot cos(U_{pos}, \vec{a}) - \beta_u \cdot cos(U_{neg}, \vec{a}). \qquad (7.3)$$

The parameters α_u and β_u are defined for a given user as optimisation parameters of the loss function with regularisation over the 10-fold cross-validation sets.



$$t_s(a) = 16h20;\, t_e(a) = 16h40$$

Figure 7.2.1: Representation of an activity as a binary time vector. The activity starts at 16h20 anf ends at 16h40.

7.2.3 Temporal Influence

Another factor that might have an impact on users' decision on joining an activity is the temporal aspect, *i.e.* when an activity takes place. The intuition behind is that there are several parts of a day when a person is more active.

To formalise this intuition, we split a day into 15 minutes long timeslots[1].

We then represent each activity as a binary 1×96-dimensional vector t_a with a vector component set to 1 if the availability time window of an activity includes that timeslot. Example of an activity decomposition into a binary vector with respect to the time slots is given in Fig. 7.2.1.

A user is then represented as the binary vector built over the union of the timeslots of his/her past activities t_u. Figure 7.2.2) illustrates the construction of a user's temporal profile. Thus, if a user has taken part in three activities a_1, a_2, and a_3, his/her time profile will consists in a union of corresponding activity vectors.

[1]Here, we do not take into account a day of the week, as the overall length of a cruise journey or a festival is rather limited.

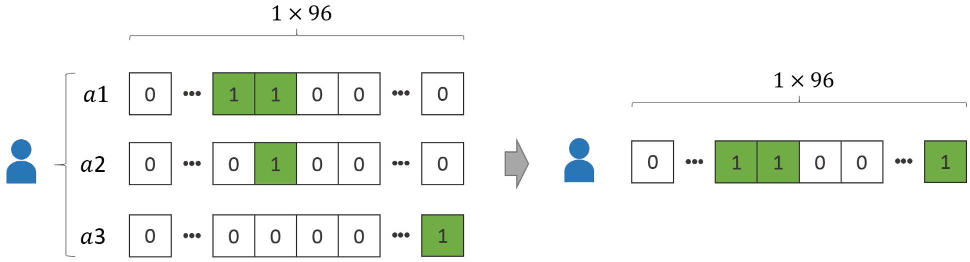


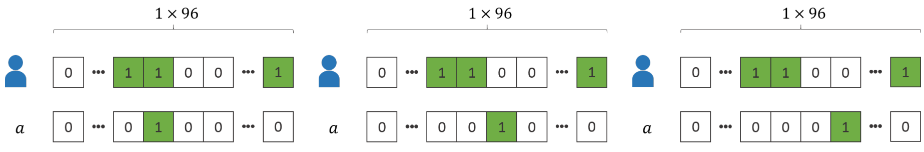
Figure 7.2.2: User's temporal profile.

The temporal score is defined based on the temporal relations between a timeslot vector of an upcoming activity and a user's temporal profile, as:

$$\hat{r}_{time}(a,u) = \begin{cases} 1, & \text{if } t_a \cap t_u \neq \emptyset \\ 0.5, & \text{if } t_a \cap \{t_u - 1 \cup t_u + 1\} \neq \emptyset \\ 0.1, & \text{otherwise} \end{cases}.$$

We adapt the scores proposed in [98] to estimate the time prior correlations between locations. The granularity of the time discretisation we use is different from [98] (7 timeslots per day and 2 types of days: weekday and weekend), we do not assign zero value, but rather 0.1. Moreover, due to our more fine-grained discretisation, instead of assigning one in the case where the timeslots are absolutely identical, we use the intersection.

Figure 7.2.3 provides an illustration of the three cases and corresponding values of the temporal score: (a) an activity a occurs in a time slot in which a user u has already performed activities in the past; (b) an activity a occurs in a time slot following a time slot in which a user u has already performed activities in the past; (c) an activity a occurs in a



$\hat{r}_{time}(a, u) = 1$ (a) $\hat{r}_{time}(a, u) = 0.5$ (b) $\hat{r}_{time}(a, u) = 0.1$ (c)

Figure 7.2.3: Illustration of estimation of temporal score based on a decomposition of an activity and user profile w.r.t. 96 timeslots.

time slot in which a user u has never performed activities in the past.

7.2.4 Combining Influences

Each of the influences described above correspond to different dimensions of the user's preference towards an activity. Therefore, for further improvement of the effectiveness of recommendation, we propose to combine them, making use of the three aforementioned influences. There are various combination techniques, among which we have chosen the following two ways.

First, we propose to define *Hybrid Score* $\hat{r}_{hyb}(u, a)$ as a following combination of the categorical $\hat{r}_{cat}(a, u)$, textual $\hat{r}_{cb}(u, a)$ and temporal $\hat{r}_{time}(a, u)$ scores:

$$\hat{r}_{hyb}(u, a) = (\gamma_u \cdot \hat{r}_{cb}(u, a) + \delta_u \cdot \hat{r}_{cat}(a, u)) \cdot \hat{r}_{time}(a, u), \qquad (7.4)$$

where γ_u and δ_u are defined for a given user as optimisation parameters learned on the past user-item interactions.

Second, we suggest to fit the *logistic regression classifier* with categorical, textual and temporal scores as parameters, and consider the probability of assigning an activity to the class 1 as *Logistic Regression Score* (LogR), *i.e.*:

$$\hat{r}_{log}(u,a) = \frac{1}{1 + e^{-(\eta_0 + \eta_1 \mathbf{x})}}, \tag{7.5}$$

where $\mathbf{x} = (\hat{r}_{cat}, \hat{r}_{cb}, \hat{r}_{time})$, and η_0 and η_1 are the parameters of the logistic regression.

7.2.5 Computational Strategies

We suggest to organise scores estimation process under two strategies that we call *Strategy 1* ('All-at-Once') and *Strategy 2* ('Day-after-Day') strategies. They differ in the way to treat the users' historical data, used in order to build the user profiles.

Figure 7.2.4 illustrates the computational strategies. The set of activities is divided into *past activities* and *new activities* with respect to the time of their availability and the time of recommendation. The users' interactions with the past activities form the users' historical data (dark green cells in Fig. 7.2.4). Let us first consider Strategy 1 (see Fig.7.2.4 (a)). When estimating the user's interest in the new activities, the user's profile is constructed based on the user's historical data.

In case of Strategy 2 (see Fig.7.2.4 (b)), the set of the new activities is sub-divided with respect to the time of their availability into bunches. For the sake of simplicity, we suggest to use a day as time granularity for this division. The main idea of this strategy lies in an iterative enrichment of the users' historical data. Thus, the estimation of the users' interest scores is performed for bunches of activities. Let us consider the activities happening during the time $T_{(k+1)}$. The historical data will then constitute of the users' interactions with the past activities (dark green cells in Fig. 7.2.4 (b)) and the estimations made for the time period T_k (light green cells).

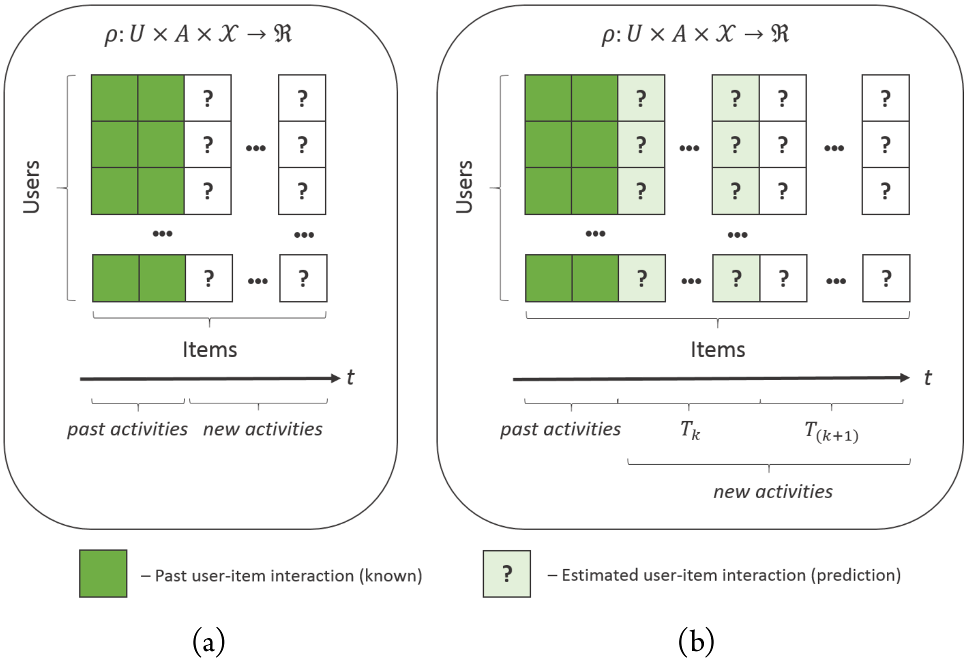


Figure 7.2.4: Computational strategies: (a) Strategy 1 - All-at-once, (b) Strategy 2 - Day-after-Day.

The pseudocodes of the strategies are given in Tab. 7.2.1.

7.3 Part II. Estimation of Transition Probabilities between Activities

Our goal is to retrieve the most typical transitions between consecutive activities, *i.e.* users' activities sub-sequences or behavioural patterns. Two activities are considered to form a sequence if the time interval between the end of the first and the start of the second one is within a fixed threshold [143].

In Section 6.3.2 of the previous Chapter, we have described an approach

Table 7.2.1: Strategy 1 and 2 to estimate the interest scores of activities

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Algorithm 1 Strategy 1: All-at-Once

Require: User's Attendance Matrix $\mathcal{M}$, New activities *NewEvent*
Ensure: Activities scores $\mathcal{R}$
Calculate $\mathcal{R}(NewEvents, \mathcal{M})$
return $\mathcal{R}$

Algorithm 2 Strategy 2: Day-after-Day

Require: User's Attendance Matrix $\mathcal{M}$, New activities *NewEvent*, Number of past days *PastDays*, Total number of days *DayNum*
Ensure: Activity scores $\mathcal{R}$
$\mathcal{M}^{(0)} \leftarrow \mathcal{M}$
for $i \leftarrow PastDays$ **to** $DayNum$ **do**
  Calculate $\mathcal{R}^{(i)}(NewEvent^{(i)}, \mathcal{M}^{(i)})$
  $\mathcal{M}^{(i)} \leftarrow \mathcal{M}^{(i)} \cup \mathcal{R}^{(i)}$
  $\mathcal{R} \leftarrow \mathcal{R} \cup \mathcal{R}^{(i)}$
  $i \leftarrow i + 1$
end for
return $\mathcal{R}$

---

to model the sequences of locations (POIs) visited by a user, proposed in [143]. It consists in the construction of the location-location transition graph. Using this work as the basic idea, we propose to construct an *activity-activity transition graph* (A^2TG) and a *category-category transition graph* (C^2TG) by extending the concept of location-location transition graph used to model the transitions between POIs [143].

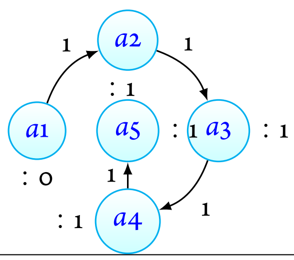
Activity-Activity Transition Graph, A^2TG. The activity-activity transition graph denoted $A^2TG = (V, E)$, models the transitions between activities determined by their time and location. It is constructed for each user based on the user's historical traces and the program of a distributed event. For each user, we retrieve users activity sequences and construct the A^2TG. It is a weighted directed graph. Its nodes, $V = \{a_1, ..., a_N\}$, correspond to the activities undertaken by the user,

and the edges E stand for transitions from one activity to another. Contrarily to [143], where the nodes of location-location transition graph are assigned the number of outcoming edges, each node of A^2TG is assigned the number of incoming edges $InCount(a_i)$. The motivation behind this modification lies in the intuition that the user's satisfaction depends more on the previous experience rather than on the future one. Therefore, the selection of the current activity will rely more on 'what the user did before'. The weight of an edge reflects the number of transitions in the user's historical data, $TransCount(a_i \rightarrow a_j)$.
According to the assumptions described above (see Section 6.2), the activities are unique. Due to this uniqueness, the maximum value of $TransCount(a_i \rightarrow a_j)$ and $InCount(a_i)$ is 1. Moreover, when considered an upcoming activity, the values associated with it will be equal to zero, diminishing the use of A^2TG for further recommendation process. a higher level of abstraction is needed. Therefore, we propose to pass to the level of categories under the assumption that the categories of an activity are known.

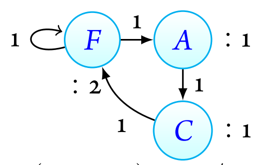
Table 7.3.1: Example of A^2TG, C^2TG and P_T. Node labels stand for $InCount$.

Activity sequence: {*Crafts: Door Hangers* → *Pictionary Challenge* → *Singles' Lunch* → *Goofy* → *The Comedy and Hypnosis of Ricky Kalmon*}
Categories sequence: {*Fun for All Ages* (F) → *Fun for All Ages* (F) → *Adults* (A) → *Characters* (C) → *Fun for All Ages* (F)}

A^2TG:



C^2TG:



$P_T(F \rightarrow A) = 1;$

$P_T(F \rightarrow F) = 1/2$; $P_T(A \rightarrow C) = 1$;
$P_T(C \rightarrow F) = 1/2$

Category-Category Transition Graph, C^2TG. The category-category transition graph, denoted C^2TG, is constructed in a way similar to A^2TG. It is constructed for each user. Its nodes represent categories c_i associated with activities undertaken by the user and are characterised by the number of incoming edges, $InCount(c_i)$, calculated as follows:

$$InCount(c_i) = \sum_{a_j \in c_i} InCount(a_j).$$

The edges stand for transitions between categories and are associated with the number of transitions, $TransCount(c_i \rightarrow c_j)$, which is calculated using the $TransCount$ of corresponding activities as follows:

$$TransCount(c_i \rightarrow c_j) = \sum_{\substack{a_k \in c_j, \\ a_g \in c_i}} TransCount(a_k \rightarrow a_g).$$

Transition probabilities. Given C^2TG, we can define the probability of transition from category c_i to category c_j, denoted $P_T(c_i \rightarrow c_j)$, as follows:

$$P_T(c_i \rightarrow c_j) = \begin{cases} \frac{TransCount(c_i \rightarrow c_j)}{InCount(c_j)}, & \text{if } InCount(c_j) \neq 0 \\ 0, & \text{if } InCount(c_j) = 0 \text{ and } c_i \neq c_j \\ 1, & \text{if } InCount(c_j) = 0 \text{ and } c_i = c_j \end{cases} \tag{7.6}$$

An example of A^2TG, C^2TG and transition probabilities P_T is shown in Tab. 7.3.1.

In order to estimate the transition probability between two activities, their categories should be known. Thus, the transition probability between two activities a_k and a_m can be estimated as the maximum value of the transition probabilities between the corresponding categories, $\mathcal{C}_{a_k}$ and $\mathcal{C}_{a_m}$ respectively, *i.e.*:

$$P_T(a_k \rightarrow a_m) = max_{c_k \in \mathcal{C}_{a_k}, c_m \in \mathcal{C}_{a_m}} \{P_T(c_k \rightarrow c_m)\}. \tag{7.7}$$

7.4 Part III. Itinerary Construction

Given a user, a set of activities A defined by their locations given by coordinates, the time windows of their availability, the duration, personalised interest scores, the travel time between a pair of locations, the fixed starting and ending point, we want to find a sequence of activities that maximises the overall collected score, *i.e.* user's satisfaction from undertaken activities. Therefore, the itinerary construction problem can be formulated as the Orienteering Problem with Time Windows (OPTW) [117].

Orienteering Problem with Time Windows. Orienteering Problem with Time Windows (OPTW) [118] is an optimisation problem, an instance of Orienteering Problem family. The main goal is to maximise the score collected by visiting nodes in a graph, given starting and ending node, subject to a cost budget, while satisfying limited availability constraint, *i.e.* start of visit should occur within the time window of a node. OPTW can be formalised as follows [118]:

Objective function	$Max \sum_{i=2}^{N-1} \sum_{j=2}^{N} r_i x_{ij}$
Starting and Ending point constraint	$\sum_{j=2}^{N} x_{1j} = \sum_{i=1}^{N-1} x_{iN} = 1$
Unique passage of a node/arc constraint	$\sum_{i=1}^{N-1} x_{ik} = \sum_{j=2}^{N} x_{kj} \leq 1; \forall k = 2, \ldots, N-1$
Knapsack constraint (including Time budget constraint)	$\sum_{i=1}^{N-1} \sum_{j=2}^{N} t_{ij} x_{ij} \leq T_{max}$
Timeline of the path constraint	$start(i) + t_{ij} - start(j) \leq M(1 - x_{ij}); \forall i, j = 1, \ldots, N$
Start of visit within time window constraint	$t_s(i) \leq start(i) \leq t_e(i); \forall i = 1, \ldots, N$
Decision variables	$x_{ij} \in \{0, 1\}; \forall i, j = 1, \ldots, N$
Path decision variable	$x_{ij} = \begin{cases} 1, & \text{if } j \text{ is visited after } i \\ 0, & \text{otherwise} \end{cases}$
Position of node i in the path	u_i
Number of nodes	N
Score associated with node i	r_i
Time budget	T_{max}
Travel time needed to pass from node i to j	t_{ij}
Time window assigned to node i	$[t_s(i), t_e(i)]$

Large constant	$M = const$

In the previous Chapter (see Section 6.2), we have identified the set of feasibility constraints, among which *Activity completion constraint*. We add it to our formalisation of OPTW, as follows:

Activity completion constraint	$start(i) + \delta_i \leq t_e(i); \forall i = 1, \ldots, N$

In the above formulation, $start(i)$ denotes the time of start of performing activity at node i, δ_i denotes the duration of activity at node i, and $t_e(i)$ denotes the closing time of node i (activity end time).
In order to solve the aforementioned problem, we propose to modify ILS algorithm [117], described in Section 6.3.3 of the previous Chapter, in order to take into account the activity completion constraint and incorporate the sequential influence on the user's satisfaction score with items. We denote our modified version by **ILS_TP**. We describe it in the following.

ILS_TP. ILS_TP is based on ILS algorithm proposed in [117]. In order to satisfy all the spatio-temporal constraints and make use of sequential influence on the user's preference towards the activities to undertake, we propose an adaptation of the this algorithm.
First, in order to take into account the activity completion constraint, we modify the formula 6.3 of *MaxShift* by including the activity dura-

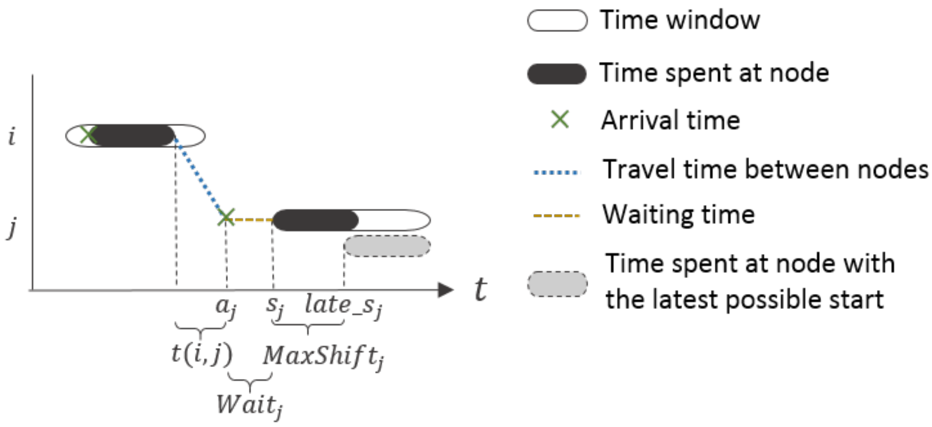


Figure 7.4.1: Illustration of parameters used in ILS. The following notations are used: a - arrival time, s - service start time, t_s - opening of the time window, t_e - closing of the time window, *Wait* - waiting time, *MaxShift* - maximum time shift, $t(i,j)$ - travel time between nodes i and j, δ - activity duration/service time, $late\_s_j$ - the latest time a user may start performing and activity at node j.

tion δ, as follows:

$$MaxShift_i = min[t_e(i) - \delta_i - start(i), Wait_{i+1} + MaxShift_{i+1}] \tag{7.8}$$

We illustrate the modified *MaxShift* in Fig. 7.4.1. Thus, the latest possible time of start of performing an activity at node j is defined by its closing time and activity duration $latest\_start = t_e(i) - \delta_i$. We symbolyse with a grey oval in the figure the time spent by a user at node j, in the case she/he starts performing the activity at the latest time *latest_start*. In this case, $MaxShift_j$ denotes the maximum number of time units, the start of performing an activity at node j may be delayed, so that a user is able to finish it before the end time (closing time) of the node, and without violating the feasibility of the following nodes.

Our second modification consists in incorporating the transitional probabilities between items in ILS. The intuition behind is that incorporating the sequential characteristics, retrieved from already undertaken activities, could enhance the prediction power of itinerary recommendation model.

Thus, we suggest to introduce the transition probabilities between activities to the calculation of the value to be maximised. In other words, we propose to adjust the value of $Ratio_k$ that is maximised at each iteration of ILS, with the transition probability from the previous activity a_{k-1} to the current one a_k, as follows:

$$Ratio_k = \frac{\hat{r}_k * P_T(a_{k-1} \rightarrow a_k)}{Shift_k}, \tag{7.9}$$

where $\hat{r}_k$ is the score of the activity a_k, $P_T(a_{k-1} \rightarrow a_k)$ is the transition probability from the activity a_{k-1} to a_k. We denote our transition probability enhanced ILS as ILS_TP.

7.5 Discussions

In previous sections, we have described our proposed approach, ANASTASIA. In this Section, we provide the discussions about it.

7.5.1 Dealing with User Cold-Start

The estimations of personalised scores described above (see Section 7.2) require the existence of the user's historical data. In order to alleviate the user cold start problem, we suggest to use non-personalised recommendation method for the first day of recommendation. Our intuition is that a primary choice will be made based on activity categories.

This intuition is also reinforced by the fact that when a user registers to a EBSN such as Meetup, or a music website such as Deezer, he/she is usually asked his/her preferences with respect to a category or a genre of items.

Thus, we propose to assign the same scores to the activities of the same categories. We assume that a distributed event has a *'main track'* category, which unites general admission activities. Examples of such main track category will be main track(-s) at a conference, general program events at conventions, etc. For the activities of the 'main track' category, the score to assign is 1. For other activities, we assign 0.5.

This is one of the possibilities. A common approach to deal with the user cold-start problem consists in using the user's additional attributes, such a demographic information (*e.g.* gender, age, occupation, etc.). Recent works have shown that the use of the user's personality may help to cope with cold-start problem [12, 35, 114]. A comparative study of methods for alleviating the user cold-start problem in recommender systems can be found in [108].

Though these methods have shown rather well results, we may not apply them as is, as they require additional data about the users, that we do not possess. Moreover, it can not be easily learnt from external resources, as for the best of our knowledge, there has been no studies done to model the relationships between the user's characteristics and events/activities for recommendation purpose.

7.5.2 Use of Collaborative Filtering

In Section 6.3.1 of the previous Chapter, we have discussed that for the purpose of our recommendation scenario of the users attendance of distributed events, content-based methods are more adopted. Among the reasons, the lack of collaborative data due to the temporary nature of activities, and the new item cold-start problem from which suffer collaborative methods.

However, with the growth of the data, *i.e.* after collecting the data about the users' attendance of several editions of distributed events, the other users' past interactions may be used for predictions. This is a direction for further research.

7.5.3 Incorporation of constraints into sequence learning based methods

As we have shown before, ANASTASIA is a hybrid methods, where we incorporate rather basic sequence learning techniques into a general two-step method. The motivation behind that incorporation direction was the constrained nature of recommendation of activity sequences during distributed events. One could try to find how to effectively deal with constraints in the sequence learning environment.

7.6 Summary

In this Chapter, we have described an approach for solving the problem of recommendation of activity sequences during distributed events, called ANASTASIA. The core of this approach has been presented at the International Conference on Computational Science 2017 [81].

ANASTASIA is a hybrid approach that enriches sequence recommendation methods based on discrete optimisation with sequence learning techniques. Thus, ANASTASIA consists of three parts. On the first step, ANASTASIA exploits categorical, textual and temporal influences to estimate users' interest scores in activities. Next, it makes use of sequential influence in order to estimate the transition probabilities between activities. Two strategies of computation of activity scores have been also suggested. On the last step, once the scores are obtained, the construction of the itinerary is modelled as an instance of the OPTW and an iterative solution has been proposed that incorporates the transition probabilities between activities into the estimation of the best insertion at each step.

The evaluation of this approach is provided in Chapter 11. It is performed on the datasets described in Chapters 9-10.

Part III

Datasets for Recommendation of Activity Sequences during Distributed Events

8

Datasets for Recommendation of Activity Sequence: Requirements

Contents

Data is a important element of recommendation as it comes as the input of a recommender system which generates new data, a recommendation. One can learn from data and evaluate a proposed approach on it. Data used for recommendation of sequences of spatial items may vary according to its origin, purpose, collection way, etc.
In this Thesis, we address the problem of recommendation of sequences of spatial items, and more precisely recommendation of activity sequences during distributed events. In this Chapter, we determine the requirements that consist of desirable characteristics or features a dataset should possess for reflecting a realistic scenario. The latter is important for both, modelling and evaluation of a recommendation approach.

Roadmap. In this Chapter, we identify a number of requirements (desirable features) for a dataset that can be used for recommendation of activity sequences during distributed events. We analyse the compliance of the existing datasets with these requirements.

8.1 Dataset Requirements

In Chapter 5, we have discussed the existing datasets that could be used for recommendation of sequences of spatial items. We characterise the dataset discussed above with respect to the information they provide. Thus, we distinguish several characteristics that could also be considered as requirements for a dataset needed or desired for better modelling of recommendation algorithms and their evaluation. They are determined based on the characteristics contained in the datasets and the definitions of spatial items and the problem of recommendation of spatial items.

We group these characteristics into five types according to the entity they describe, *i.e.* item (unit under consideration), sequence (ordered sequence of items), user (information about users), user-item (relations between users and items), and user-user (relations between users).

8.1.1 Requirements related to items

The first group of requirements is related to the items and their attributes. Thus, as we deal with spatial items, their locations should be provided. The most common form of representing a location is *coordinates*. When defining spatial items, an activity in particular (see Section 3.1.1 of Chapter 3), and the problem of RSSI (see Section 3.3 of Chapter 3), we have accentuated the importance of time dimension, which is mainly due to temporal nature of spatial items (particularly, events and activities). Therefore, the *time windows* of the item availability and the*service time (or duration)* should be provided in the dataset. The *categorisation* of item is also an important characteristic, especially in the case where items are unique (which is usually the case of events in EBSN and activities during distributed events). *Description* is a desirable feature, as it helps to understand what the item is about. However, it may not be provided. Other attributes like *price* or any other *additional attribute* may not be necessarily present.

8.1.2 Requirements related to sequences

The second group of requirements is related to a sequence. This group of characteristics may include various constraints related to a sequence, such as *time budget* which defines the maximum length (duration) of a resulting sequence, its *starting/ending point* or any other attribute. These attributes are desirable but not mandatory.

8.1.3 Requirements related to users

The third group of requirements is related to users and contains *user's personal data, e.g.* demographic information, psychological profile, explicit preferences, etc. These attributes are desirable but not mandatory.

8.1.4 Requirements related to user-item interactions

The fourth group of requirements is related to user-item interactions. Thus, it is mandatory to have *historical data* on user-item interactions. This data serves as the input for a recommender system (see Section 3.3 of Chapter 3). It is to note that the historical data may contain explicit or implicit information about user-item interactions of different types, *e.g.* ratings, rsvps, checkin, etc. Preferably, this data should be timestamped. To underline the explicit scores that a user gave to an item, we can indicate *Score* as an attribute. The latter will also be true for the datasets issued from Operational Research, where the scores are predefined.

8.1.5 Requirements related to user-user relation

The last group of requirements is related to user-user relation. It contains the data about social links between users. It may also contain information about group of users. This data is desirable but not mandatory.

8.1.6 Compliance of the existing dataset with the requirements

We compare the existing datasets discussed in Chapter 5 with respect to the identified requirements in Table 8.1.1. As it can be seen from the table, all the datasets contain geo-localised data, but none of them covers all the aspects that we consider as mandatory for recommendation of sequences of spatial items (given in italics in the table), *i.e.* time windows, coordinates, service time, categories, users historical data. Though we have mentioned only five essential elements, all other characteristics listed in the table are desirable for modelling a recommendation algorithm and its evaluation as their handling shall enhance the quality of recommendation.

Table 8.1.1: Comparison of the available datasets.

		Single Item										Schedule			Sequence	
Entity	Characteristic	TREC CS'13 [24]	TREC CS'14 [25]	TREC CS'15 [26]	Yelp Challenge	Foursquare_1 [128]	Foursquare_2	Flickr [112]	Twitter [31]	Meetup_1 [64]	Meetup_2 [67]	MCTOPMTW [109]	Other OP-TW [118]	Other OP-based [118]	TripBuilder [14]	GeoLife [147]
Item	*Time windows*				✓						✓	✓	✓			
	Coordinates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
	Service Time											✓	✓	✓		
	Categories									✓	✓	✓			✓	
	Price					✓						✓			✓	
	Item Additional Attributes				✓		✓	✓		✓						
	Description							✓	✓		✓					
Sequence	Time budget											✓	✓	✓		
	Starting/Ending Point											✓	✓	✓		✓
	Tour Additional Attributes			✓												✓
User	User's personal data			✓						✓	✓					
User-Item	*Historical Data*	✓	✓	✓		✓	✓	✓	✓	✓	✓				✓	✓
	Score	✓	✓	✓		✓	✓					✓	✓	✓		
User-User	Social links				✓	✓	✓			✓	✓					

Note: *MCTOPMTW*: benchmark instances of the Multi-Constraint Team Orienteering Problem with Multiple Time Windows (MCTOPMTW) [109, 118]. *Other OP-TW*: benchmark instances of OP-based problems with time windows [118], excluding MCTOPMTW *Other OP-based*: benchmark instances of OP-based problems without time windows [118]

To fill in this gap in the existing datasets, during this Thesis, we have created two datasets in compliance with the determined requirements, that can be used for recommendation of activity sequences. Both of the datasets reflect a scenario of users attendance of a big distributed event. To the best of our knowledge, these are the only publicly available datasets for such a scenario.

The first dataset, that we call **Fantasy_db**, reflects an application scenario of cruise attendance and activity performance on board of a cruise. It has been created based on a conducted user study, where we asked the participants to rate the activities and provide their daily plannings. Though this dataset is very rich in data and satisfies the underlined requirements, it is small in size. Thus, in order to overcome this limitation and conduct a better evaluation of our proposed approach, we have created another dataset.

The second dataset, called **DEvIR**, reflects a scenario of users attendance of one of the biggest comic book conventions. We have created this dataset mainly based on a web crawl of the official website of the convention. It contains mainly the rsvp data provided by the attendees using the convention official scheduling application.

We describe these datasets in the following chapters.

8.2 Summary

In this Chapter, we have presented an overview of the datasets that could be used for evaluation of approaches for recommendation of sequences of spatial items. We have identified a list of desirable features of a dataset (requirements) for a better solution modelling and evaluation. Moreover, we have investigated the compliance of the existing datasets to these requirements. Our analysis has shown that there is room and need for datasets for sequence recommendation, in particular during distributed events, as the users behaviour is different when planning several day activities. Therefore, during this Thesis, we have created two datasets in compliance with these requirements, that can be used for recommendation of activity sequences, namely (1) Fantasy_db: a dataset of cruise attendance and activity performance on board of a cruise, and (2) DEvIR: a dataset for event and itinerary recommendation at the biggest comic book convention. We describe these datasets in details in the following Chapters.

9

Fantasy_db: Datasets for Recommendation of Activity Sequence

Contents

Nowadays, the field of leisure activities experiences a substantial growth. In this context, a rising phenomenon is distributed events that gather various activities under one umbrella. They attract more and more attendees. Examples of such events are cruises, festivals, big conferences, conventions, etc.

We consider the case of a cruise, where on each day of the cruise the travellers are proposed a program of on-board activities. In the programs, the availability hours (time windows) of the activities are given, as well as their categories. The activities may overlap in terms of their availability. The travellers then have to decide which activities to undertake in order to spent a better time.

The motivation behind the selection of such scenario lies in rising popularity of cruising, on the one hand. Thus, according to Florida-Caribbean Cruise Association (F-CCA) [33], about 25.3M passengers are expected to cruise globally in 2017, showing a 7% average annual passenger growth rate over the last 30 years. Cruising has become a preferred vacation choice for families, especially with kids, making cruisers population younger and more diverse than non-cruisers. F-CCA reports [33] that cruising is the favourite choice of Millennials and Generation X. Cruisers appreciate the opportunity to relax and get away from it all, see and do new things. Cruise lines offer a vast variety of on-board activities, as well as in ports of call.

On the other hand, providing multi-day holiday on board of a ship, the cruise companies organise multiple activities for the travellers. Therefore, a cruise journey may be considered as a distributed event.

Roadmap. In this Chapter, we present a new dataset for recommendation of activity sequences during distributed events, called Fantasy_db.

We describe it according to the following aspects: (1) objectives and motivation for its creation; (2) data collection process; (3) data structure; (4) compliance with the requirements described in Chapter 8; (5) data analysis and description.

9.1 Objectives and Motivation

We aim at creating a dataset with compliance with the requirements that will reflect a real-world scenario of users attendance of a distributed event. Though many event organisers offer to their participants an application to use, the collected data is usually not publicly available. Therefore, in order to create a dataset, we simulate users attendance of a distributed event by a user study.
Our **objectives** are as follows:

- *To create a dataset of attendance of a distributed event.* To do so, we conduct a user study, asking the respondents to provide their preferences of activities and intentions to attend them during a cruise. Note that being interested in an activity does not necessarily result in undertaken this activity and vice versa. For that reason, we have asked the respondents to provide both, their preferences of activities and binary attendance.

- *To better understand the selection problem faced by the participants by analysing multiple user-activity interactions.* Recommender systems often deal with only one type of user-item interactions, *e.g.* ratings, reviews, check-in, etc. In our user study, the respondents were asked to rate all the activities in terms of the interest in them (*i.e.* provide ratings), and then to create personal schedule for each of the days of a cruise (*i.e.* binary attendance, or rsvp).

9.2 Data Collection

In Chapter 8, we have set the requirements for a RSSI dataset. In order to collect the required data that would reflect a scenario of users attendance of a distributed event, we have conducted a user study. The study was performed via an online survey using Google Forms platform.

Questionnaire. The questionnaire consisted of 4 parts. In the first part *User Profile*, the participants were asked 10 questions about their demographic information and cruising experience.

In the second part of the questionnaire *User Preferences*, we asked the respondents to provide their preferences towards the activities proposed on board of a cruise on 5-point scale, ranging from '*Never*' to '*Won't miss*'. The list of activities used in the survey was taken from the daily programs of Disney's Fantasy 7-nights Eastern Caribbean cruise organised by Disney Cruise Line company (DCL). Activities dedicated exclusively for kids have been excluded from the current list of activities. The original daily programs, referred to as personal navigators in DCL terminology, can be found online[1]. Thus, the participants rated 311 activities. The activities were displayed by their categories.

The third part of the questionnaire *Itinerary Planner* was dedicated to

[1] http://disneycruiselineblog.com/2015/07/personal-navigators-7-night-eastern-caribbean-cruise-on-disney-fantasy-itinerary-a-june-20-2015/

personal itinerary planners. Thus, for each day of the cruise, we asked the participants to indicate the activities they would perform, taking into account the time windows of their availability. The activities were chronologically ordered and displayed by day. The attendance indicator was binary, *i.e.* going or not going. By default, 'not going' value was selected.

The fourth part *Aterwards* consisted of conclusion questions about the participants planning behaviour, such as their way of managing their planning, consideration of venues, etc.

We also provided the participants with the deck plan of the ship that can be found on the web[2] in order to make them familiar with locations of activities. We provide several screenshots of the questionnaire in Fig. 9.2.1. The overview of the questionnaire with examples of questions is given in Tab. 9.3.1. The full questionnaire is given in Appendix A. The estimated duration of completion of the questionnaire was 1 hour.

Participants. The participants were recruited via a link to the online questionnaire sent by email to several research and university mailing lists. Thus, 23 contributions were collected. Statistics concerning the participants are provided in Tab. 9.2.1. The participants were mainly men in age range of 21-30. Only one respondent has experienced DCL cruises before, while 4 respondents reported to had experienced cruises before. Only a third (8) of respondents reported to consider the distance between the venues of activities while selecting them. As for the way of managing the activities to perform, the respondents have got dis-

[2]http://disneycruiselineblog.com/ships/deck-plans-disney-dream-disney-fantasy/

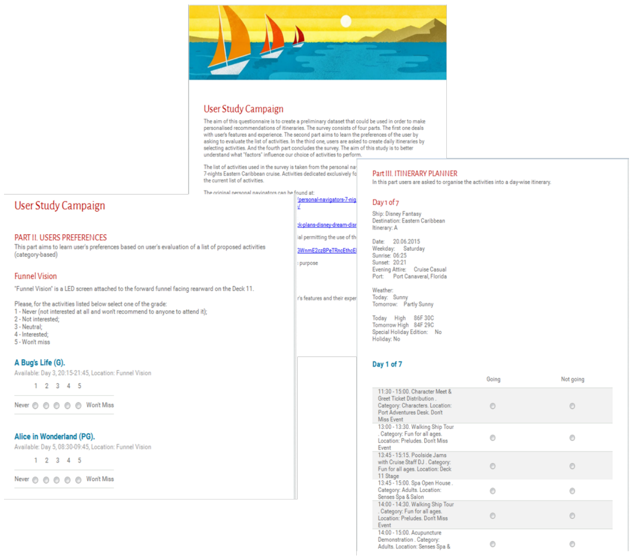


Figure 9.2.1: Screenshots of the questionnaire.

Table 9.2.1: Participants Statistics

Statistic	Value
# Female users	7
# Users already experienced DCL	1
# Users already experienced any cruise	4
# Users considering the distance between venues	8
Managing Activities. Not-to-miss List : Daily planning : No planning	14 : 4 : 5
Age group: 21-30 : $>$ 30	16 : 7

tributed among three groups as follows: the majority of respondents (14) determine a list of not-to-miss activities, when others do not pre-select anything (5) or in contrast, create daily plannings to follow (4).

General statistics of Fantasy_db. Based on the results of the questionnaire described above, we have created a dataset that we call **Fantasy_db**. The general statistics of the obtained dataset are given in Tab. 9.2.2. In the table, we provide statistics concerning two types of categories: original *DCL categories* that are given in activity programs,

Table 9.2.2: Dataset Statistics

# Activities	# Days	# Users	# Locations	# Categories
593	7	23	47	52 = 10 (DCL) + 42 (Other)

and *Other categories* that are a list of more fine-grained categories of activities. The average duration of an activity is 45 minutes. The average number of ongoing simultaneous activities is 5.

9.3 Data Structure

The dataset consists of the following entities:

- *activity*: an entity, containing a list of events from the cruise programs.
- *user*: an entity, containing a list of users who took part in the study.
- *location*: a list of venues where the activities take place.
- *category*: a list of event categories.
- *rsvp*: users RSVPs, indicating users' intentions to take part in an activity, expressed by a binary attribute `value`, attendance imitation.
- *rating*: users rating of activities in terms of their interest on 5-point scale.
- *activity-category*: a list of activity-category pairs.
- *location-location*: distance matrix between locations, reflecting travelling (walking) time between the activity venues.

Table 9.3.1: Description of the parts of the survey. Qnt denotes the number of questions in a section.

Section	Qnt	Description	Question Examples
User Profile	10	Questions on basic user's features and their cruising experience	Your gender: ☐Female ☑Male Have you already experienced DCL (Disney Cruise Line)? Are you aiming to attend the maximum amount of activities mentioned in your Personal Navigator or just a few must-see?
Users Preferences	311	User's evaluation of a list of proposed activities by selecting one of the grades for the listed activities: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2- Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss	**Sailing Away. Don't Miss Event.** *Description:* It's time to go Sailing Away! Join Mickey and Minnie along with Tinker Bell and the rest of the gang as they welcome you abroad the Disney Fantasy. *Available:* Day 1, 16:30-17:15, *Location*: Deck Stage *Never* ○○○○● *Won't miss*
Itinerary Planner	593	Organisation of the activities into a day-wise itinerary. Given an ordered list of activities with their availability hours, the respondents were asked to indicate their intention to join the activity or not by clicking on "Going" or "Not going".	Event | Going | Not going 11:30 - 15:00. Character Meet & Greet Ticket Distribution. Category: Characters. Location: Port Adventures Desk. Don't Miss Event | ☑ | ☐
Afterwards	5	Conclusion questions	When you were having a choice among different activities of your interest, did you consider the distance to the venue while making your choice? How do you usually manage the list of activities to perform during your vacations?

Table 9.3.2: Dataset description.

entity	attributes	attribute description	example
activity	activity_id	identifier	2300575
	name	name	The Comedy & Hypnosis of Ricky Kalmon
	description	textual description	Featuring the Comedy & Hypnosis of Ricky Kalmon, as he entertains you in this adult exclusive show.
	location_id	identifier of the activity venue	200046
	location_name	event venue	Walt Disney Theatre
	start_time	start time	2015-06-22 23:00:00
	end_time	end time	2015-06-22 23:45:00
	duration	activity duration, min	45
	day	day of the event	3
	fee_price	additional fee (if required)	0
	event_of_the_day	binary feature indicating if the activity is classified as '*event of the day*' in the program	0
	not_miss	binary feature indicating if the activity is classified as '*not miss event*' in the program	1
location	location_id	identifier	200046
	location_name	activity venue	Walt Disney Theatre
	is_indoor	binary indicator if the venue is an indoor location	1
	x_coordinate	x_coordinate	0
	y_coordinate	y_coordinate	880
	z_coordinate	z_coordinate	0
	description	description	Deck 3, Forward

Table 9.3.3: Dataset description. – *Continued from previous page*

entity	attributes	attribute description	example
user	user_id	identifier	10001
	gender	binary gender indicator: 1 - female, 0 - male	1
	DCL_experience	binary indicator if a user has experienced a DCL cruise: 1 - yes, 0 - no	1
	cruise_experience	binary indicator if a user has experienced any other cruise: 1 - yes, 0 - no	1
	travel_group	indicator of a group a user is travelling with: 1 - alone, 2 - with your significant other, 3 - with a group of friends, 4 - with family, 5 - with other group	3
	split_behaviour	indicator of user's splitting behaviour when travelling with group: 1 - always together, 2 - split exceptionally, 3 - split often	1
	event_management	binary indicator if a user tries to manage their event list: 0 - no, 1 - yes	1
	max_or_few	binary indicator if a user aims to attend the maximum amount of event or just a few: 0 - just a few, 1 - maximum	1
	event_list_manage	type of user's event management strategy: 1 - daily planning, 2 - list of not-to-miss events, 3 - no planning	2
rating	user_id	user identifier	10001
	activity_id	activity identifier	2300575
	value	user's rating of an event on 5-point scale	5

Table 9.3.4: Dataset description. – *Continued from previous page*

entity	attributes	attribute description	example
rsvp	user_id	user identifier	10001
	activity_id	event identifier	2300575
	value	user's rsvp on activity attendance	1
category	category_id	identifier	50001
	category_name	name	Adults
	short_name	category short name	Adults
	is_main	binary indicator if a category is a DCL category	1
event-category	event_id	event identifier	2300575
	category_id	category identifier	50001
	value	binary indicator of activity-category association	1
location-location	location_1	location 1 identifier	200002
	location_2	location 2 identifier	200016
	value	walking travelling time between locations, sec	420

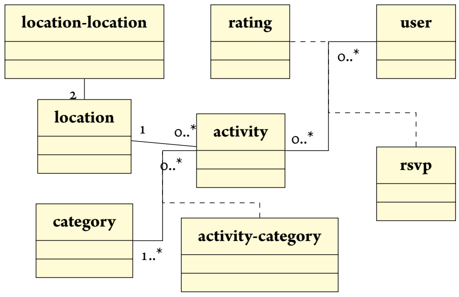


Figure 9.3.1: Conceptual diagram of Fantasy_db.

Figure 9.3.1 depicts a conceptual data diagram of dataset entities. Table 9.3.2 provides a detailed description of attributes of the entities with examples.

9.4 Dataset Compliance with the Requirements

Previously in Chapter 8, we have identified a number of requirements or desirable features of a dataset for recommendation of sequences of spatial items. In this Section, we check the compliance of Fantasy_db with dataset requirements, and summarise it in Tab. 9.4.1.
It can be seen that Fantasy_db meets most of the requirements. As for touring information, such as *Time budget* and *Starting/Ending point*, when solving RSSI, one can consider that *Time budget* is limited by a day time, as the event program of onboard activities is given on daily basis. As for the *starting/ending point*, user's stateroom may be selected if known or a zero point of the coordinate system.

9.5 Data Analysis

Fantasy_db gives a more practical insight into personalised itinerary recommendation and the activity selection process. In the following,

Table 9.4.1: Compliance of Fantasy_db with dataset requirements.

Requirement	Status	Requirement	Status
Time windows	✓	Time budget	×
Coordinates	✓	Starting/Ending point	×
Service Time	✓	Tour additional attributes	×
Categories	✓	User's Historical data	✓
Price	×	Scores	✓
Item Additional Attributes	✓	User's Social links	×
Description	✓	User's personal data	✓

we are analysing the collected data from two perspective, namely:

1. *user's interest vs. attendance*: what is the relationship between the user's interest in activities and and actual participation in this activity?

2. *top-k recommendation vs. itinerary recommendation*: what list of activities better corresponds for a user: top-k recommendation or itinerary recommendation?

This work was presented at the ACM RecSys Workshop on Recommenders in Tourism, RecTour'2017 [82].
Before answering the aforementioned questions, it is to note that recommendation of sequence of spatial items deals mainly with *implicit feedback*. Given that activities are happening in future as in the case of event recommendation [67], there is very little information to handle and there is much less user-item interactions than in traditional recommendation scenarios. We deal with implicit feedback, implying that the degree to which a user likes or not an item is not known. The use of multiple contexts may increase the recommendation performance of

the algorithms.

User's interest vs. Attendance. First, we explore the relationship between the user's interest in activities and and actual participation in this activity, if they always correspond to each other. Our intuition is that due to the limited availability and multiple parallel activities, we may deal with a situation, where a user may miss an activity of his/her interest or in contrast, may join an activity that does not represent a particular interest to him/her. In order to test this intuition, we undertake the following analysis.

We base our investigation on a rare property of Fantasy_db, which is multiple types on user-item interactions, namely user's preferences of activities expressed as a 5-point scale rating and binary indicator of attendance. Thus, for each user we four measures: *Interested & Going*, *Interested & Not Going*, *Not Interested & Going*, and *Not Interested & Not Going*.

Interested & Going measures the number of activities a user was interested in ($rating \geq 4$ or $rating = 3$ if the highest rating given by the user to any activity is equal to 3) and joined (*Interested & Going*).

Interested & Not Going measures the number of activities a user was interested in but did not join (*Interested & Not Going*).

Not Interested & Going measures the number of activities a user was not interested in but joined (*Not Interested & Going*).

Not Interested & Not Going measures the number of activities a user was not interested in and did not join (*Not Interested & Not Going*).

Figure 9.5.1 depicts the distribution of this four measures for each user. The chart shows evidence that individuals miss many activities that rep-

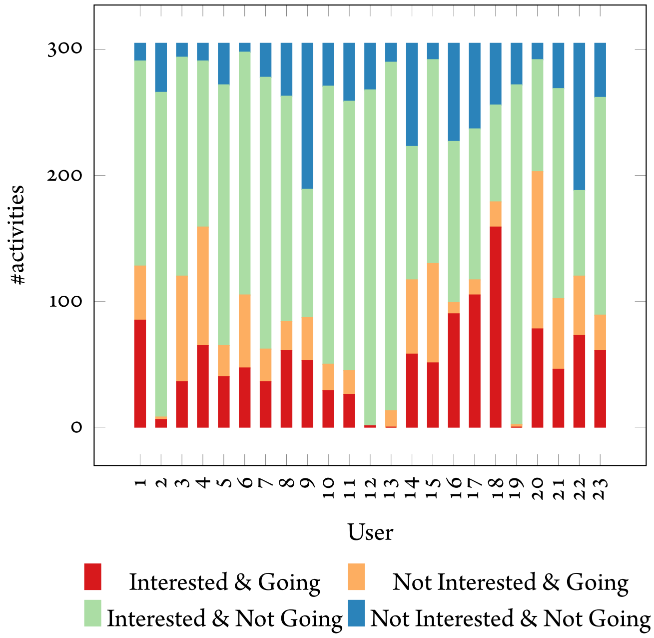


Figure 9.5.1: Distribution of interest in activities and attendance per user.

resent interest to them. Thus, the number of *Interested & Not Going* activities is almost twice higher (1.7621) than *Interested & Going*. It is also surprising that *Not Interested & Going* activities constitute about 43% of all joined activities. A possible reason for the latter is that a user may undertake some activities he/she is not interested in, as intermediate pastime between activities that represent interest to him/her.

TOP-*k* LIST VS. ITINERARY. Second, we wonder if an itinerary recommendation returns more accurate results compare to top-*k* recommendation. Our intuition is that given that activities are competitive and short-lived, which results in the user's preference for one activity over the others in a given time slot, an itinerary (a feasible sequence of activities) may be more desirable than a list of interesting activities. To illustrate this, let us consider the following settings. We compare three top-k item recommendation algorithms against itinerary recommendation from the literature. As history data we consider a binary attendance matrix. We have varied the number of history days from 1to 6. We consider the following algorithms:

Category-based (Cat): This algorithm ranks the candidate activities based on their weighted frequency of corresponding categories.

Content-based (CB): The candidate activities are ranked in descendant order of their textual similarity with the user's past activities. An activity is represented as a TF-IDF vector. The user's profile is built over TF-IDF vectors of activities joined by the user in the past.

Logistic Regression (LogR): We fed a vector of aforementioned scores into a logistic regression model.

ILS + Scores: We used our proposed approach ANASTASIA for itinerary construction.

The algorithms were evaluated in terms of their precision. We returned top-20 activities for each day[3] using top-k recommendation algorithms. Figure 9.5.2 displays the recommendation power of each algorithm with varying number of history days (from 1 to 6). Itinerary recommendation algorithm shows higher precision, proving that an itinerary satisfies better the user's needs.

9.6 Summary

In this Chapter, we have presented Fantasy_db, a dataset for recommendation of activity sequences that satisfies the requirements defined in the previous Chapter (see Chapter 8). Its application scenario is

[3]The average number of joined activities per day is 18.

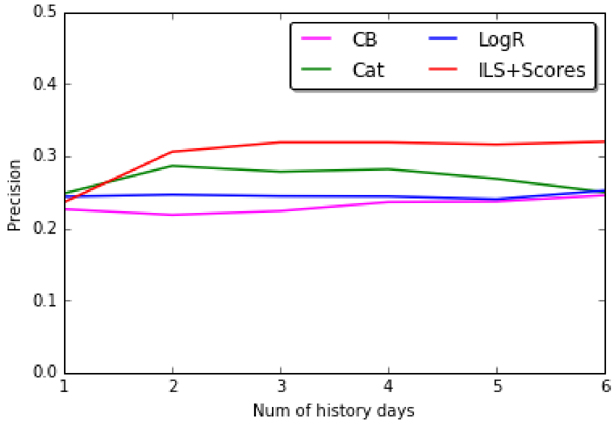


Figure 9.5.2: Precision w.r.t. the number of history days.

users participation in a 7-night cruise. We created Fantasy_db based on a user study. We have conducted this study in order to get a better understanding of human behaviour in terms of leisure activities and planning during distributed events. Here, we have described the undertaken study, resulting dataset and its characteristics. Though this dataset satisfies the requirements, it is rather small in size. Therefore, a larger dataset is needed to insure a better evaluation of the proposed approach.

10

DEvIR: Dataset for Event and Itinerary Recommendation

Contents

In the previous Chapter, we have described Fantasy_db, a dataset for recommendation of activity sequences during distributed events. Though this dataset satisfies the requirements for a RSSI dataset that we have discussed in Chapter 8, Fantasy_db is of small size. In this Chapter, we present DEvIR, a dataset for event and itinerary recommendation, that we created for filling the gap in the existing datasets, and overcomes the limitation of Fantasy_db related to its size. This dataset will allow us to perform a better evaluation of our proposed solution. Moreover, it is a publicly available dataset.

For DEvIR, we consider the case of a comic-book convention, Comic-Con International: San Diego, further referred to as the Convention. It is a comic book convention taking place every year since 1970 in San Diego, California. The program of the Convention is usually dispersed over 5 days, proposing about 390 events per day. Every year, the Convention attracts thousands of attendees. Moreover, the event programs of the Convention since 2013 are available online and the website provides an agenda application, allowing their users to manage their agenda and to indicate on the website if they plan to attend an activity. All these facts make the Convention a perfect distributed event for recommendation of itineraries.

Roadmap. In this Chapter, we present DEvIR, a dataset for event and itinerary recommendation. We describe it according to the following aspects: (1) objectives and motivation for its creation; (2) data collection process; (3) data structure; (4) compliance with the requirements described in Chapter 8; (5) data analysis and description.

10.1 Objectives and Motivation

We aim at creating a dataset that would serve a basis for a more realistic evaluation of event and itinerary recommendation during distributed events. This dataset should satisfy the requirements we identified in Chapter 8 and be large scale. Therefore, we propose to construct a dataset based on a well-known large distributed event, namely the comic book convention (Comic-Con International: San Diego). This work will be presented at the 52nd Hawaii International Conference on System Sciences (HICSS), HICSS-52 [84].

10.2 Data Collection

In this Section, we describe the data collection process we have undertaken in order to acquire **DEvIR**: a new **d**ataset for **ev**ent and **i**tinerary **r**ecommendation.

We have constructed the dataset mainly based on the information available on the official website of the Convention[1]. We have conducted the following process.

In August 2017, we crawled the official website of the convention in order to retrieve the 2013-2017 programs of events and available data about event attendance, namely the lists of events pre-selected by users. By 'users' we denote the users of the scheduling application *Sched* used

[1]Mind, that the website content can be used only in non-commercial purpose, as the copyright is hold by the Convention. Here, we are presenting the data collection process that can be undertaken in order to obtain the data.

by the Convention organisers. In order to mark the events the users would like to attend, they are invited to create their Sched accounts or use their Facebook account to sign up. The users may restrict the access to their profile making it '*private*' in order to hide their identity. The users that have marked an event in their custom schedule appear in the '*Attendees*' section of the corresponding event page. Private users are displayed with 'Private' icon with no further information provided. It should be noted that the users do not rate the events, but save them in their custom agendas.

Algorithm 3 Get Data

```
Require: yearList
Events, Users, User_Event, Locations ← {}
Categories, Tags ← {}
for year in yearList do
    main_domain_sched ← 'https://comiccon'+ TO_STR(year)+'.sched.com/'
    section_url ← main_domain_sched + '/list/descriptions/'
    events ← GetEvents(section_url)
    users ← GetUsers(main_domain_sched)
    user_event ← GetUserEvent(main_domain_sched)
    locations ← GetLocations(events)
    categories ← GetCategories(events)
    tags ← GetTags(events)
    {// Append to the existing sets}
    Events ← Events ∪ {events}
    Users ← Events ∪ {users}
    User_Event ← Events ∪ {user_event}
    Locations ← Locations ∪ {locations}
    Categories ← Categories ∪ {categories}
    Tags ← Tags ∪ {tags}
end for
return Events, Users, User_Event, Locations, Categories, Tags
```

The Convention website gives access to all programs of the past and

Algorithm 4 GetEvents

Require: *section_url*

$events \leftarrow \{\}$
$page \leftarrow ParsePage(section\_url)$ {e.g. using BeautifulSoup in Python}
$ev \leftarrow FindAll('div', \{'class' :' sched - container'\})$
for *ev* in *event_div* **do**
  $id \leftarrow Get(``id)$
  $name \leftarrow Get(text)$
  $link \leftarrow Get(``href)$
  $descr \leftarrow GetDiv(ev, \{'class' : ``tip - description\})$
  $loc, time_s, time_e \leftarrow GetDiv(ev, \{'class' : ``sched - event - details - timeandplace\})$
  $cat \leftarrow GetDiv(ev, \{'class' : ``sched - event - type\})$
  $tag \leftarrow GetDiv(ev, \{'class' : ``tip - custom - fields\})$
  $e \leftarrow < id, name, link, descr, loc, time_s, time_e, cat, tag >$
  $events \leftarrow events \cup \{e\}$
end for
return *events*

ongoing events starting from 2013. We iteratively crawled the program pages for editions 2013-2017, as well as all the corresponding event and user pages (see Algorithm 3). We give an example of parsing procedure for events in Algorithm 4.

10.3 Data Structure

Following the described procedure, we could create a dataset that consists of the following entities[2]:

- *event*: a core entity, containing a list of events from the Convention programs.
- *user*: a core entity, containing a list of users registered at Sched who expressed their intentions to attend events. Please, note that

[2] The dataset is available at: https://github.com/ecafidid/DEvIR

for privacy concerns, we anonymised user names and ids in the dataset.

- *location*: a list of venues where the events take place. We enrich the crawled data with *X* and *Y* coordinates, and the address of the corresponding buildings queried from Google Maps.
- *category*: a hierarchical list of event types (categories). The categories are organised into a two-level structure, where the parent elements represent the main categories (tracks) of the convention or the service categories (*e.g.* 1: Programs, 2: Anime, or U: Updated).
- *tag*: a list of event custom-based tags.
- *event-user*: users RSVPs, indicating users' intentions to attend the events, expressed by a binary attribute `value`.
- *user-user*: a list of user-user pairs who appear on the user's pages in the friends list, where `value` is a binary relation value.
- *event-category*: a list of event-category pairs.
- *event-tag*: a list of event-tag pairs.
- *location-location*: distance matrix between locations, reflecting travelling (walking) time between the buildings of the corresponding buildings queried using Google Maps API.

Figure 10.3.1 depicts a conceptual diagram of dataset entities. Table 10.3.2 provides a detailed description of attributes of the entities with examples. We did not include `event-category`, to Table 10.3.2, as

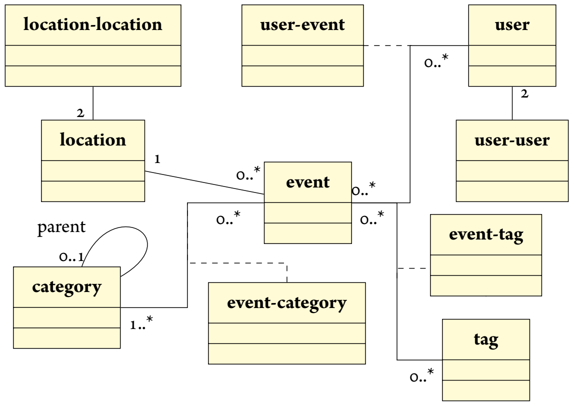


Figure 10.3.1: Conceptual diagram of DEvIR.

these entities can be considered secondary, being derivatives from the lists of categories and tags of events. We mention them separately in order to provide a better representation of relations between entities. Similarly, `location-location` entity can be considered secondary, as it is not issued from the original crawl of the website.

Note on event duration. In Chapter 8, we have stated that *duration* (also referred to as *service time*) is an attribute required for an accurate itinerary recommendation. Note that the actual event duration is often empirical and may vary. Event organisers may provide approximate event duration, or only indicate the time window of event availability. The Convention program does not explicitly indicate event duration, except for a few events. Therefore, when not explicitly indicated in the event description, the duration has been assigned as follows:

- *External source based*: For the events with known or approximately known duration (*e.g.* film, series, board games, etc.), we have queried external sources to obtain the time length, *e.g.* IMDB, YouTube, MyAnimeList, BoardGameGeek, etc.

Table 10.3.1: General statistics of the DEvIR dataset.

	2013	2014	2015	2016	2017
# events	1,760	1,880	2,038	2,184	1,909
# locations	38	38	47	45	47
# categories	115	179	210	213	179
# tags	50	164	191	197	235
# users	11,147	10,945	9,033	10,697	9,001
# user-user	7,818	6,710	4,119	5,220	4,388
# user-event	249,439	247,003	220,565	250,396	202,244
# events per user, mean (std)	22.379 (24.11)	22.57 (24.81)	24.42 (26.15)	23.41 (25.66)	22.472 (24.19)
event avg. duration, min	53.81	52.87	55.88	50.4	51.26

Some events were cancelled. However, we count them in the total number of events as there still exist data of users' interest in them.

- *Default value*: We have assumed the default value to be equal to the time difference between `end_time` and `start_time`. This value has been assigned to the panel sessions, and most of the events of the type '1: Program'.

- *Approximation*: We have assigned approximate value based on the main type of the event: '3: Autograph' - 60, '8: Retailers' - 30, '7: Portfolio Review' - 20. The value selection was performed so that it fits the minimum time window of a given event type and was motivated by attendance rules and procedures described on the website and attendees reports[3].

The general statistics of DEvIR are given in Table 10.3.1. While calculating the number of users and event-user pairs, we removed 'private' users, as we cannot distinguish between them.

[3] https://www.wired.com/2015/07/nerdist-comic-con-guide/

Table 10.3.2: DEvIR description.

entity	attributes	attribute description	example
event	`year`	year of occurrence of the event	2017
	`day`	day of the event	3
	`id`	identifier	550b10edc277c7477eef06d4a6c76c5f
	`name`	name	Fata Morgana
	`link`	link of the event	/event/BSRu/fata-morgana
	`description`	textual description	Held in AA26: Fata Morgana Steven Boyett and Ken Mitchroney
	`time`	scheduling time of the event (string)	Friday July 21, 2017 10:00am - 2:30pm
	`start_time`	start time	2017-07-21 10:00:00
	`end_time`	end time	2017-07-21 14:30:00
	`location`	venue of the event	Sails Pavilion - Autographs
	`location_link`	link to the venue	/venue/Sails+Pavilion+-+Autographs
	`event_type`	list of categories associated with the event	[['3: Autographs', '/type/3%3A+autographs'], ['Group Signing', '/type/3%3A+autographs/group+signing']]
	`event_tag`	list of event tags	[['Held in: AA26', '/tag/Held+in%3A+AA26']]
user	`year`	list of participation years	[2013, 2017]
	`id`	identifier	8
	`user_name`	user name (anonymised)	user000008
	`user_link`	link to the user page	/user000008
	`page_name`	name of user page	user000008
	`about`	personal description	

Table 10.3.3: DEvIR description. – *Continued from previous page.*

entity	attributes	attribute description	example
location	`year`	list of years the venue was used	[2013, 2014]
	`location`	venue name	Marriott Hall 6, Marriott Marquis & Marina
	`location_link`	link to the venue	/venue/Marriott+Hall+6%2C+Marriott+Marquis+%26+Marina
	`address`	address	333 W Harbor Dr, San Diego, CA 92101, USA
	`x_coordinate`	x-coordinate (latitude)	32.7084733
	`y_coordinate`	y-coordinate (longitude)	-117.16742250000001
	`duration`	service time in min	60
category	`year`	list of years the category was used	[2013, 2014, 2015, 2016, 2017]
	`category_name`	category name	Action Figures - Toys - Collectibles
	`category_link`	link to the category	/type/1%3A+programs/action+figures+-+toys+-+ collectibles
	`parent_link`	link to the parent category	/type/1%3A+programs/
tag	`year`	list of years the tag was used	[2014.0, 2015.0, 2017.0]
	`tag_name`	tag name	Ticketed Events
	`tag_link`	link of the tag	/tag/Ticketed+Events
event-user	`year`	year of relation	2017
	`event_id`	`id` of the event	550b10edc277c7477eef06d4a6c76c5f
	`user_id`	`user_link` of the user	/user000008
	`user_name`	`user_name` of the user	user000008
	`value`	binary RSVP value	1
user-user	`year`	year of relation	2017
	`user_1`	`user_link` of the 1st user	/user000008
	`user_2`	`user_link` of the 2nd user	/user000268
	`value`	binary relation value	1

Table 10.4.1: Compliance of DEvIR with dataset requirements.

Requirement	Status	Requirement	Status
Time windows	✓	Time budget	×
Coordinates	✓	Starting/Ending point	×
Service Time	✓	Tour additional attributes	×
Categories	✓	User's Historical data	✓
Price	×	Scores	×
Item Additional Attributes	✓	User's Social links	✓
Description	✓	User's personal data	×

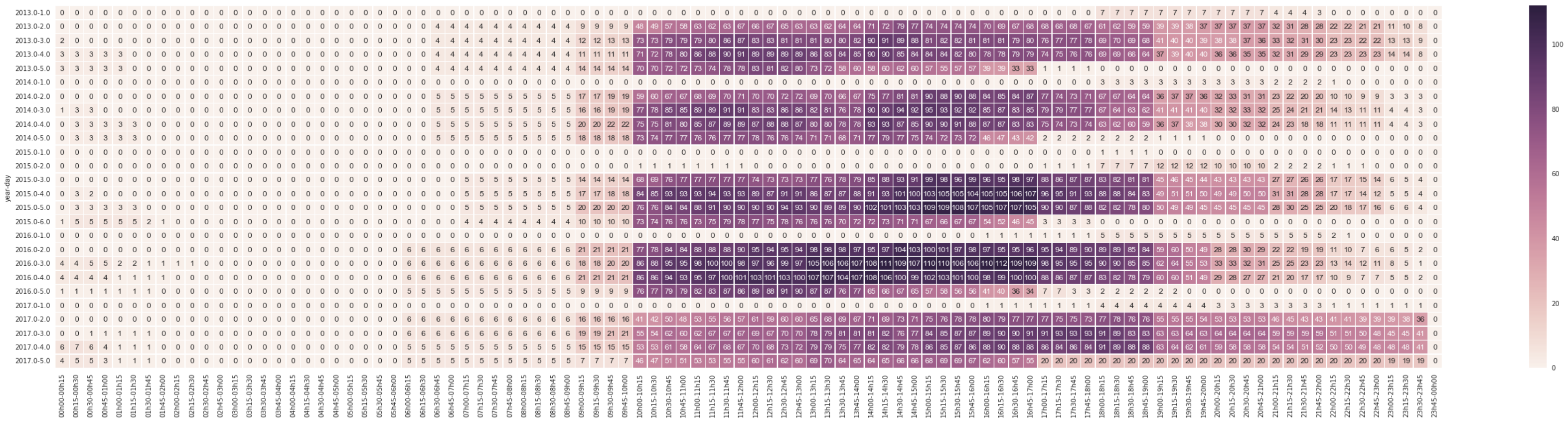
10.4 Dataset Compliance with the Requirements

Previously in Chapter 8, we have identified a number of requirements or desirable features of a dataset for recommendation of sequences of spatial items. In this Section, we check the compliance of DEvIR with dataset requirements, and summarise it in Tab. 10.4.1.

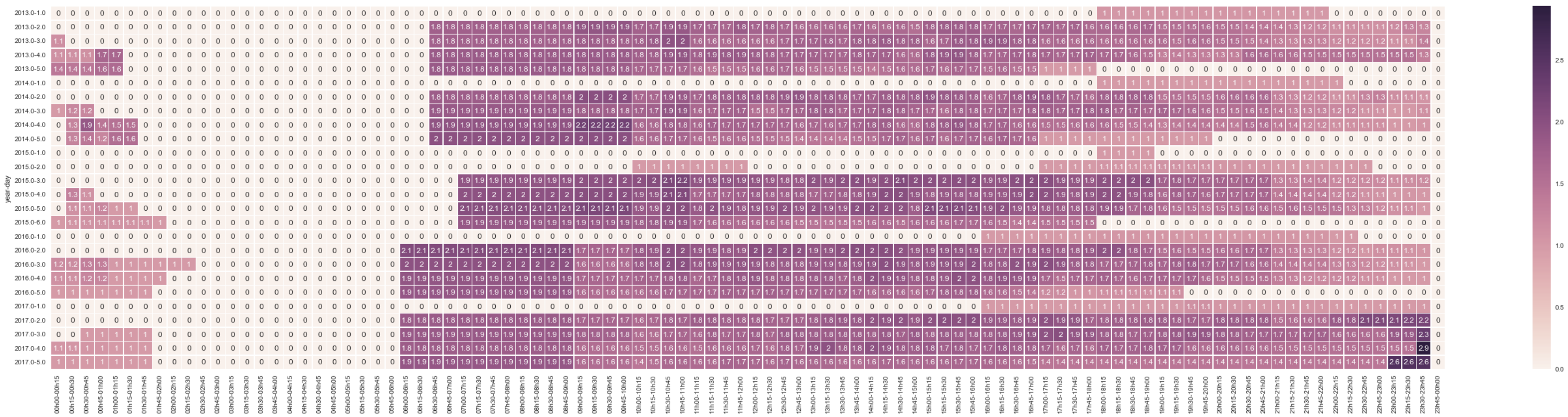
It can be seen that DEvIR meets most of the requirements. Note that *User's Historical data* consists in the user's intentions (rsvp) to attend the events. Apart event *categories*, the tags are also provided in DEvIR. As for touring information, such as *Time budget* and *Starting/Ending point*, one can consider that *Time budget* is limited by a day time, as the convention lasts during several days and its program is given on daily basis.

10.5 Data Analysis

In this Section, we first characterise the data providing general statistics about event attendance. Then, we give examples of DEvIR use for recommendation.



(a)



(b)

Figure 10.5.1: Heatmap of (a) the overlapping events and (b) the overlapping event attendance with respect to 15min timeslots.

Table 10.5.1: Number of events per day.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
2013	15	465	505	500	275	–
2014	10	507	542	531	290	–
2015	1	24	555	588	574	296
2016	16	602	640	624	302	–
2017	16	513	567	533	280	–

10.5.1 General Statistics

In the following we investigate some of the characteristics of the data.

Events and Users Statistics

First, we view the events and users statistics.

Distribution of events by day. We start by depicting the number of proposed events per day (see Tab. 10.5.1). It can be seen, that the maximum number of events (640) was achieved on the 3rd day of 2016 edition. Such an amount of options makes it very hard for attendees to select events of their interest and attend them.

Overlapping Events. As the programs of the Convention is very dense, we would like to estimate the number of overlapping events within a program of the convention. By the overlapping events we understand the simultaneously happening events. In order to estimate this measure, we divide a day into 15-minute timeslots. An event is considered to occur within a timeslot, if the time window of its availability is partially or fully covered by the timeslot. For each timeslot, we calculate the number of events occurring at it. We illustrate the number of over-

Table 10.5.2: Number of editions the users have taken part in.

# editions	1	2	3	4	5
# users	27,451	5,007	1,923	1,001	714

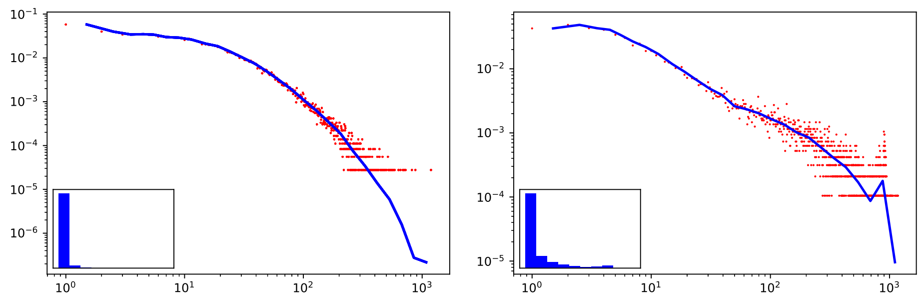
lapping events in a form of a heatmap in Fig. 10.5.1 (a). We exclude from the analysis the timeslots with no scheduled events. The average number of parallel activities is 37. The maximum number of parallel events is 112 and was attained on the 3rd day of 2016 edition during the timeslot 16h15-16h30.

Users History. All recommendation algorithms use users historical data for making predictions about the users preferences in future. Thus, it is interesting to see, if the users in DEvIR have multi-year data. Due to the high popularity of the Convention, many attendees return to the next editions of the convention. Table 10.5.2 summarises the number of users participation in different editions of the Convention. It can be noted that more than 700 users have taken part in all the editions of the Convention, according to the collected data .

User's attendance of events

To get an idea about the user's selection of events, we focus on user-item interactions, which in our case is user's attendance of events. As it could be seen in Tab. 10.3.1, the Convention program is very rich in events. However, one can note that among all the possible options, the users select 23 events in average for the whole duration of the Convention (see Tab. 10.3.1). The attendance of events is not uniform over different events. The variations of the number of RSVPs provided by users for

Figure 10.5.2: Number of RSVPs per event per year.



(a) (b)

Figure 10.5.3: (a) Distribution of the number of events per user. (b) Distribution of the number of attendees per event.

events are depicted in Fig. 10.5.2.

The number of events per user follows the power-law distribution with $\alpha = 3.841$ (see Fig. 10.5.3 (a))[4]. And the number of attendees per event follows the power-law distribution with $\alpha = 2.253$ (see Fig. 10.5.3 (b)). In addition, Table 10.5.3 shows the average number of events selected by users per day. It can be noted, that the distribution of the event selection by users is not uniform over the days. Thus, the average attendance of the events reaches its peak on the third day, while the events of the

[4]For fitting, we used `powerlaw` Python package [3]

Table 10.5.3: Mean and standard deviation of the number of events per user per day.

	1	2	3	4	5	6
2013	1.07 (0.43)	7.94 (7.99)	8.25 (8.19)	8.1 (7.89)	4.55 (4.51)	–
2014	1.05 (0.44)	9.01 (9.25)	8.82 (8.67)	8.22 (7.93)	4.52 (4.54)	–
2015	1.0 (0.0)	1.19 (0.7)	9.6 (9.66)	9.51 (9.02)	9.16 (8.8)	4.46 (4.3)
2016	1.14 (0.71)	9.12 (9.12)	9.34 (9.17)	9.12 (9.05)	4.6 (4.77)	–
2017	1.23 (0.65)	9.19 (9.06)	9.49 (9.16)	8.32 (8.07)	4.41 (4.29)	–

first day lack participants. This is due to the fact that the first day is not a full day of the convention hosting only few events (see Tab. 10.5.1).

User's attendance of overlapping events. In Section 10.5.1 we have estimated the number of overlapping events. The question that rises is if the users attend overlapping events. In order to estimate the number of overlapping events, a user selects, we undertake a similar procedure than for overlapping events. Thus, for each timeslot we calculate the number of simultaneous events the users intent to take part in. The results are presented in a form of a heatmap in Fig. 10.5.1 (b). The average number of activities selected by a user in a given timeslot is 1.5. This characteristic together with the number of overlapping events emphasise the selection problem faced by the users, since they tend to select events that have a high probability to occur simultaneously. It is to mind that we do not possess data about the users actual attendance of events, knowing only their RSVP, so that the explicit preference of

Table 10.5.4: Ratio of the user's events shared with friends to the total amount of the user's events.

2013	2014	2015	2016	2017
0.161	0.140	0.159	0.145	0.126

one event over another for a given user is unknown.

Event attendance with friends. DEvIR possess data about social links between the users, as the users may indicate their '*friends*'. In DEvIR, 5,150 users out of 36,100 have listed at least one friend (referred to as 'users with friends'). The maximum number of friends is 108, while the average number of friends per user is 3.54 (among users with friends). For the users with friends, we have estimated the ratio of events shared with their friends to the total amount of the user's events (Tab 10.5.4). Note that only 15% of the users events get RSVP from the user's friends.

10.5.2 Use for Recommendation

In the previous section, we have given several characteristics of the data in DEvIR. In this Section, we focus on the use of DEvIR for event recommendation. We mirror a realistic recommendation scenario where for each user we generate an ordered list of events. Recommendations are calculated on a daily basis, *i.e.* for each day of a convention edition. In the experiments, we divide the data into train and test sets by adapting the evaluation protocol suggested in [72] as follows. The train set includes the 4 editions of 2013-2016 available in DEvIR. The test set includes the data of 2017. As the recommendations are calculated on

the daily basis, we gradually extend the training set with the data from previous days, *i.e.* for the recommendation for the n^{th} day, the users profiles are modelled based on the users past events from the train set and the days ranging in $(1, n-1)$. It has to be noted that 3,785 out of 9,000 users who expressed their interest in taking part in 2017 edition have taken part in at least one previous edition of the convention. For the users who have previously attended the Convention, there exists historical data, *i.e.* the past user-event interactions, that can be used to create their profiles on the train set. We focus on these users.
In our experiments we use one non-personalised (Popularity-based) and two personalised (Content-based and Category-based) recommendation algorithms, that we describe in the following.

POPULARITY-BASED (POP). Similar to [67], we rank the candidate events in the descending order of their popularity, *i.e.* the number of users who expressed their intention to join the event. It is a non-personalised method.

CONTENT-BASED (CB). We represent each event using the bag-of-words TF-IDF of their description, then we compute the cosine similarity to estimate the similarity between upcoming events and a user's profile. We model a user's profile $\vec{u}$ similar to [67], *i.e.*:

$$\vec{u} := \sum_{e \in E_u} \frac{1}{(1+\alpha)^{\tau(e)}} \times \vec{e},$$

where E_u is the set of the user's past events, e is an event representation using TF-IDF, α is a time decay factor (we set $\alpha = 0.01$ similar to [67]), and $\tau(e)$ returns the number of years between the current events and the user's past events. The content-based score is therefore calculated based on the cosine similarity between the current event and the user's profile, *i.e.*:

$$\hat{s}_{cb}(u, e) = cos(\vec{u}, \vec{e}).$$

Category-based (Cat). Each event is associated with a list of categories. The categories are organised into a 2-level hierarchy. Thus, we distinguish between 12 *main categories* (*i.e.* the categories that are on the top of the hierarchy, the attribute `parent_link` is null) that we denote $\mathcal{C}_{main}$ and 453 *child categories*, denoted $\mathcal{C}_{child}$. We represent each event as a 1×465-dimension binary vector of categories $cat(e)$. We model a category-based user's profile as follows:

$$\vec{u} := agg_{e \in E_u}\Big(\frac{1}{(1+\alpha)^{\tau(e)}} \times cat(e)\Big),$$

where E_u is the set of the user's past events, agg denotes an aggregation function (we used the mean in our experiments), $cat(e)$ is a vector composed of (1) $cat_{main}(e)$, *i.e.* the elements of the main-category vector of the event e, and (2) $\frac{cat_{child}(e)}{|\mathcal{C}_{child}(e)|}$, where $cat_{child}(e)$ denotes the elements of the child-category vector of the event e, $|\mathcal{C}_{child}(e)|$ denotes the number of child categories that the event e is assigned to, α is a time decay factor (we set $\alpha = 0.01$ similar to [67]), and $\tau(e)$ returns the number of years between the current events and the user's past events.. Generally speaking, such representation of the user's profile reflects the weighted frequency of the categories of the events attended by the user in the past. The category-based score is then calculated based on the cosine

Table 10.5.5: Results of the three considered recommendation techniques in terms of Precision@10.

	Day 1	Day 2	Day 3	Day 4	Day 5
Pop	0.0118	0.0568	0.0767	0.0756	0.0428
Cat	0.0138	0.0376	0.0551	0.0531	0.0489
CB	0.0095	0.0312	0.0557	0.0543	0.0495

similarity between the current event and the user's profile, *i.e.*:

$$\hat{s}_{cat}(u, e) = cos(\vec{u}, \vec{e}).$$

We use the *Precision at rank k* (P@k) as the evaluation metric.

Table 10.5.5 presents the precision P@10 of the recommendation algorithms on the DEvIR dataset. As it can be seen, the precision is rather low, but there exists a positive trend with the increase of the number of historical days. This can be explained by the sparsity of data. Moreover, the low precision of the Day 1 can be explained by a low number of events and weak attendance on the first day, which is coherent with the statistics given in Table 10.5.1-10.5.3. In contrast, the highest precision is reached on Day 3. It can be explained by the highest number of the events available on this day, and the highest attendance of the events (see Table 10.5.1-10.5.3). Another surprising finding is the importance of the popularity factor, as popularity-based method outperforms the others for Days 2-4.

However, the top-k results retrieved by the algorithms mentioned above do not take into account the time availability constraint, *i.e.* they do not deal with conflicts when two or more recommended events are happening simultaneously. In the context of a distributed event, time constraints and limited availability of events become crucial. Therefore, it is relevant to construct personalised itineraries of events.

10.6 Summary

In this Part, we have presented an overview of the datasets that could be used for evaluation of approaches for recommendation of sequences of spatial items. We have identified a list of desirable features of a dataset (requirements) for a better solution modelling and evaluation. Moreover, we have investigated the compliance of the existing datasets to these requirements. Our analysis has shown that there is room and need for datasets for sequence recommendation, in particular during distributed events, as the users behaviour is different when planning several day activities.

Therefore, we have created two datasets for recommendation of activity sequences, namely Fantasy_db and DEvIR, that satisfy the requirements. Both of these datasets reflect an actual scenario of users attendance of a distributed event.

We have constructed `Fantasy_db` based on a user study. Its application scenario is users participation in a 7-night cruise. Our analysis of the data has shown that there is

Though this dataset satisfies the requirements and can be used for evaluation of our approach for recommendation of activity sequence, it is rather small in size. Therefore, a larger dataset is needed to insure a better evaluation of the proposed approach.

Therefore, we have created a dataset called `DEvIR` based on a crawl of the website of a big distributed event, namely Comic-Con International

San Diego, one of the largest comic book conventions. DEvIR overcomes the size limitation of Fantasy_db, while satisfying the requirements. We have presented its collection process and have discussed its use for recommendation. The main limitation of DEvIR lies in the fact that user-item interaction are given in form of RSVP, and we do not possess the data about the users actual attendance of the events.

We have performed the evaluation of our proposed approach ANASTASIA on both datasets, Fantasy_db and DEvIR. We describe it in Chapter 11.

Part IV

Evaluation: ANASTASIA on Fantasy_db and DEvIR

C'est une folie de haïr toutes les roses parce que une épine vous a piqué, d'abandonner tous les rêves parce que l'un d'entre eux ne s'est pas réalisé, de renoncer à toutes les tentatives parce qu'on a échoué... Il y aura toujours une autre occasion, un autre ami, un autre amour, une force nouvelle. Pour chaque fin il y a toujours un nouveau départ.

Antoine de Saint-Exupéry,"Le Petit Prince"

11

Evaluation

Contents

We have evaluated the quality of our proposed approach ANASTASIA (see Part II of the Thesis) for recommendation of personalised itineraries (sequences of activities) during distributed events. Given past user-items interactions (binary indications of the user's participation in activities), we measure how well our algorithm predicts user's future participation in activities based on the itineraries constructed for each day of a distributed event. In this Chapter, we describe the evaluation protocol that we have set up for the evaluation of ANASTASIA. We report the experimental results of ANASTASIA when applied to Fantasy_db and propose an evaluation protocol and preliminary results for DEvIR. These two datasets have been described in Part III of the Thesis.

Roadmap. This Chapter is organised in the following way. We start with describing a general evaluation protocol for assessing the quality of a solution for the problem of recommendation of activity sequences during distributed events (see Section 11.1). Next, in Section 11.2, we determine a particular settings used for the evaluation of our proposed approach ANASTASIA on Fantasy_db. Section 11.3 provides the experimental results. In Section 11.4, we propose the settings for evaluation of ANASTASIA on DEvIR, we describe the preliminary observations and results, together with the faced difficulties.

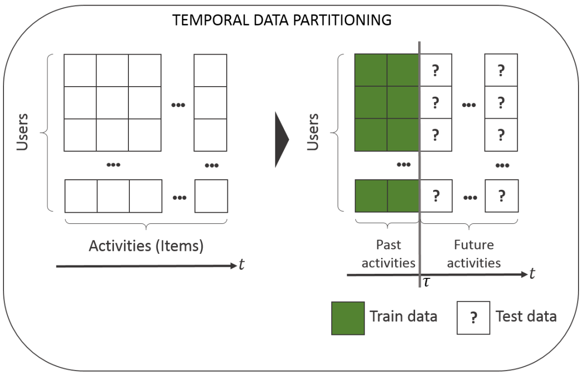


Figure 11.1.1: Data partitioning.

11.1 Evaluation Protocol

We perform offline evaluation of ANASTASIA, our solution approach for recommendation of short-term activity sequences during distributed events. We aim at reflecting the real application scenario of a user's attendance of a distributed event which is organised in some place during several days. Therefore, we suggest to follow the procedure described below.

11.1.1 Data Partitioning

We start with data partitioning (see Fig. 11.1.1). The splitting to train and test sets is performed based on temporal criterion, as follows. The user-item interactions are ordered according to the their timestamps, or if the timestamps are not available, according to the time windows of availability of the items. We then select a temporal threshold τ, that determines the partitioning.

Thus, the interactions with activities that happened before τ are considered past (historical) data, and the corresponding activities are considered as *past activities*. These users interactions constitute then the train set. Similarly, the activities that take place after τ are considered *future activities*, and the corresponding interactions are considered unknown. The latter form the train set. By varying the parameter τ, we simulate the actual time flow.

11.1.2 Model Learning and Assessment

Once the splitting is performed, the models can be learnt on the past interactions (see Fig. 11.1.2). For each splitting defined by the parameter τ, we construct the users profiles and estimate the transition probabilities between items for each target user, based on the users past interactions.

Estimation of the personalised scores

The estimation of the personalised scores is performed for each type of scores using two strategies, as described in Section 7.2 of Chapter 7.
We evaluate the accuracy of predictions delivered using the scores, and its combinations for each remaining days of the distributed event in test set, depending on the parameter τ.
We evaluate the approach in terms of the accuracy of the estimated scores of activities using four standard accuracy metrics, namely: Mean Average Error (MAE), Root Mean Square Error (RMSE), Precision at rank k [106] and Area under the ROC-curve (AUC). The rank k of Precision was defined for each user and set to the average number of daily activities performed by a given user in the past days. The motivation behind such a setting lies in the fact that different users have different density of activities. The lower values of MAE, RMSE and the higher values of Precision and AUC are the better.

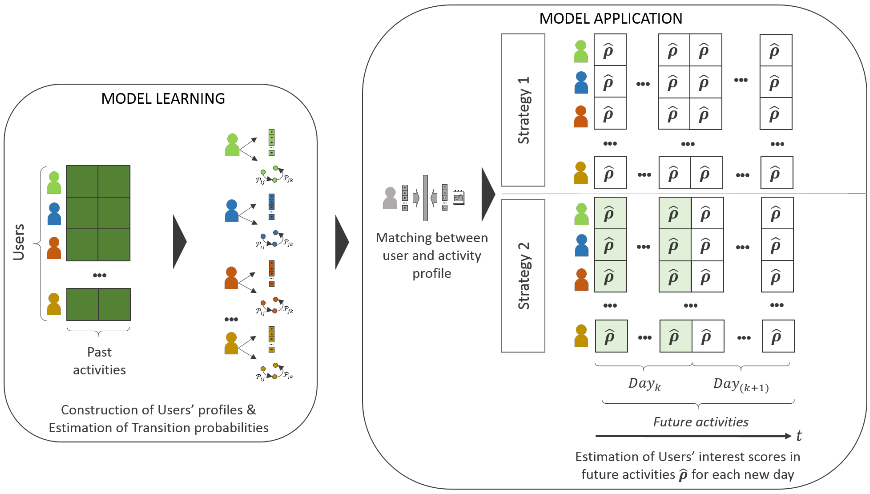


Figure 11.1.2: Model learning on the '*past activities*' for estimation of personalised scores of activities and transition probabilities between activities. Learnt models for estimation of personalised scores of activities are then applied to the '*future activities*'.

Itinerary construction

After estimating the personalised scores of future activities and the transition probabilities between them, we construct resulting sequences/ itineraries using ANASTASIA. The itinerary construction is performed for each day of the distributed event, one itinerary per day. We compare the itinerary construction part of ANASTASIA, that we denote ILS_TP (see Section 7.4), against ILS, a state-of-the-art algorithm for solving TOPTW (see Section 6.3.3). We assess the precision of the returned sequences of activities with respect to the ground truth values of user-item interactions.

11.2 Experimental Set-Up

In this Section, we describe concrete set-ups that we have made for evaluation of ANASTASIA on Fantasy_db.

11.2.1 Temporal splitting: selection of τ

Fantasy_db contains data about cruise activities for 7 days. In our evaluation procedure, we vary the parameter τ of the temporal splitting from 1 to 6. In this case, it reflects the number of history days. Thus, if $\tau = 1$, we construct the itineraries for the remaining 6 days.

11.2.2 Generation of check-in data

First, we identify some of the settings for the estimation of transition probabilities between activities. As we have described in Section 7.3, the first step in estimation of the transition probabilities consists in identifying the user's sequences. Our datasets do not provide timestamped data. Therefore, we have generated 'check-in' time of a user at an activity as a random variable in the range of $[t_s, t_e - \delta]$, in accordance with '*Activity completion constraint*'. We need this data, as the time windows of many activities in the datasets allow to perform it at different time.

In order to identify, the consecutive activities of a user, we have selected the time threshold of 15 minutes. We have set up such value, as it covers the travelling time between most of the locations of activities and is superior than a duration of the shortest activity (10 minutes).

11.2.3 Distance and travel time between locations

In order to construct an itinerary, we need the data about the travel time between the locations of activities. As we have described in Chapter 9, the activities in Fantasy_db may take place in locations of two types: indoor (on-board) and outdoor (*i.e.*, Castaway Cay). For the outdoor environment, we have queried Google Maps to get geographical coordinates. As for the indoor environment, the 3D coordinate system has been applied. In order to calculate the distance and the travel time from an outdoor point to an indoor point or vice versa, the following distances has been considered: the distance from an indoor point to the gangway, and the distance from a ship arrival outdoor point to an outdoor point. The distance has been measured in meters.

The constant pace is considered, giving that an average pace of walking is $54.6m/min$ (or $179.1ft/min$). And in the used coordinate system 1 unit is equal to $0.1132m$ (or $0.372ft$). We use the following formula in order to calculate the distance between two locations:

$$dist(l_i, l_j) = \sqrt{x_i^2 + y_i^2} + 2\sqrt{2}|z_i - z_j|/30 + \sqrt{x_j^2 + y_j^2},$$

where (x, y, z) are the coordinates of locations. $\sqrt{2}$ is used due to the assumption that the angle of the stairs is equal to 45. $|z_i - z_j|/30$ determines the number of levels between the locations in accordance with the assumption '*Moving around in space*' described in Section 6.2).

11.3 Results

We have implemented ANASTASIA using Python 3. In this section, we report the obtained experimental results. In accordance with the defined evaluation protocol, we first assess the prediction of personalised scores of activities and then, the prediction of itineraries.

11.3.1 Evaluation of Prediction of Personalised Scores

Firstly, we evaluated the accuracy of obtained activities scores (see Fig. 11.3.1). It can be seen that the exploitation of multiple factors increases

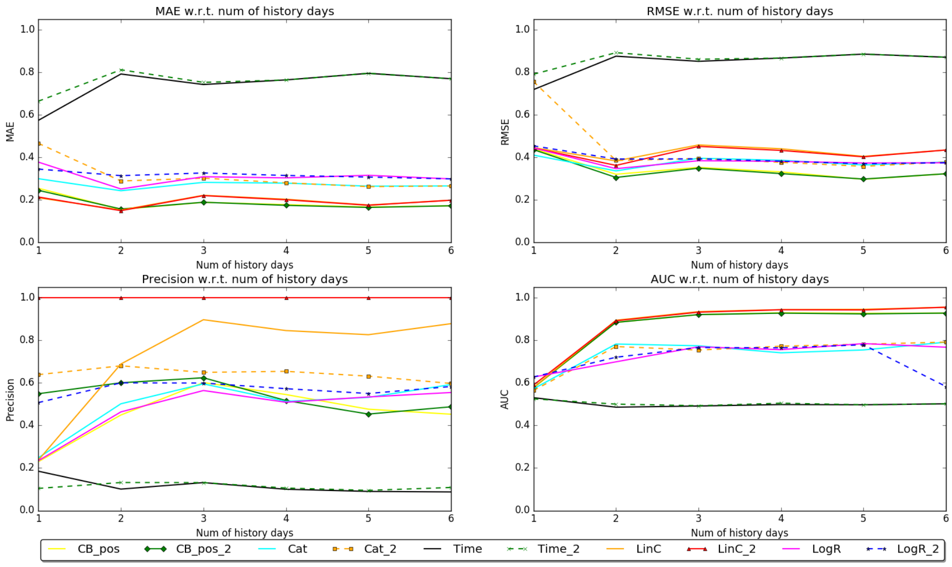


Figure 11.3.1: Values of evaluation metrics of the quality of activities score estimation by ANASTASIA on Fantasy_db.

the predictive power of the model. Thus, the Hybrid scores outperform the others in terms of precision and AUC, while having the second result in terms of MAE. It can be noticed that the performance is enhanced when using the Strategy 2 (the dash lines in the plots). These results were expected since Strategy 2 applies the enrichment of historical data. We can see that considering 2 history days and more dos not affect much the performance of the algorithms.

We find that the results reflect well the users' intentions, in particular the Hybrid score-Strategy 2.

Thus, we selected Hybrid scores under Strategy 1 and 2 for the next evaluation step. We used them as input data for ILS and ILS_TP algorithms. We varied the number of history days from 1 to 6.

Table 11.3.1: Improvement of ILS_TP over ILS in terms of precision, %

History Days	1	2	3	4	5	6	Average
Strategy 1	6.1	3.4	6.5	6.2	9.9	11.3	7.4
Strategy 2	25.0	10.3	4.4	13.5	14.3	11.3	13.5

11.3.2 Evaluation of Recommendation of Itineraries

The obtained results show that incorporating the transition probability into the itinerary construction improves the performance. Thus, the average improvement of ILS_TP over ILS is 7.3% for Hybrid score-Strategy 1 and 14.1% for Hybrid score-Strategy 2 (see Tab. 11.3.1). The variations of performance w.r.t. the number of history days could be explained by the introduction of transition probabilities that are computed over the users' past experience. Table 11.3.2 provides an example of a recommended itinerary.

11.4 Proposal of an Evaluation Protocol for DEvIR

The general evaluation framework for DEvIR remains the same than the one we have described in Section 11.1. In this Section, we propose the settings for the evaluation on DEvIR.
In accordance with the protocol described above, in order to identify the sequences in the users historical data, we suggest to generate the check-in data as described in Section 11.2.2.

11.4.1 Temporal splitting: selection of τ

DEvIR contains data about events at five editions of Comic-Con International: San Diego 2013-2017. In our evaluation procedure, we suggest to select the year 2017 to be the test year, and we further vary the

Table 11.3.2: An example of itinerary. The first column corresponds to the availability time window of an activity, the second one shows the activities list, and in the last one the duration of an activity is given. Italics indicates a match with the Ground Truth.

Time window	Activity	Duration, min
7:00 - 7:30	Yoga	30
8:30 - 9:00	Jake & The Neverland Pirates	30
9:15 - 9:30	*Minnie. Princess*	10
10:00 - 10:30	*Magic Workshop*	30
11:00 - 11-15	Bingo Pre-Sales. $10,000 Mega Jackpot	10
11:00 - 11:30	*Captain's Signing*	10
11:30 - 12:00	1820 Society: Brunch	30
12:45 - 13:15	*Character Dance Party*	30
13:15 - 13:45	Chinese Herbs	30
14:00 - 14:30	*Towel Folding*	30
15:45 - 16:15	Bingo Pre-Sales. Final Jackpot	10
16:15 - 17:00	Bingo: Final Jackpot	45
17:00 - 18:00	*Professional Portraits*	10
17:00 - 18:00	Talent Show Rehearsals	45
18:15 - 19:00	*Disney's Believe*	45
19:15 - 20:30	*Professional Portraits*	10
19:30 - 20:00	Mirror Mirror	25
21:30 - 22:30	*Professional Portraits*	10
21:45 - 22:15	Mirror Mirror	25
22:15 - 22:45	*Club New Year's Eve*	20
23:00 - 23:30	*The Comedy & Magic of David Williamson*	30
23:30 - 00:00	FireLites LIVE	30

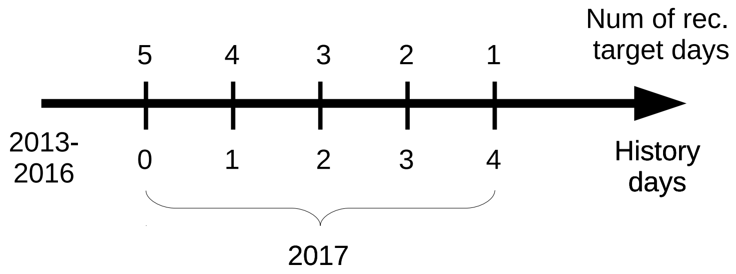


Figure 11.4.1: Illustration of temporal splitting for DEvIR.

parameter τ from 0 to 4, as the number of days of the Convention in 2017 is 5 (see Fig. 11.4.1). The number of target days for recommendation will vary from 5 to 1 accordingly.

11.4.2 Subsetting user-item data with respect to τ

For the evaluation purpose, we propose to select a subset of data from DEvIR with respect to τ, as follows. We select user-item interactions of the users, for whom there exist user-event pairs in 2017, and who have historical data. Thus, the number of users we consider is 2218.

11.4.3 DEvIR: observations

When the score calculation is applied to DEvIR dataset, the results with respect to the accuracy metrics are rather low (see Tab. 11.4.1). One of the possible reasons behind such accuracy lies in the fact that DEvIR dataset contains data about the users attendance of events with 6.25 events per user day in the average (see Tab. 9.2.2). However, when

Table 11.4.1: Prediction accuracy results of ANASTASIA on DEvIR, $P@10$ and AUC.

Method	Strategy	History days, τ 0	1	History days, τ 0	1
		$P@10$		AUC	
Cat_freq	I	0.064	0.076	0.602	0.59
Cat_freq	II	0.032	0.065	0.763	0.581
Cat_sim	I	0.052	0.058	0.571	0.549
Cat_sim	II	0.003	0.027	0.78	0.494
Cb_pos	I	0.014	0.01	0.519	0.486
Cb_pos	II	0.01	0.015	0.501	0.515
Cb	I	0.013	0.011	0.495	0.46
Cb	II	0.01	0.013	0.472	0.5
Time	I	0.02	0.021	0.499	0.5
Time	II	0.019	0.02	0.499	0.5
Hybrid	I	0.025	0.022	0.533	0.502
Hybrid	II	0.03	0.038	0.299	0.526
LogReg	I	0.053	0.06	0.567	0.548
LogReg	II	0.005	0.035	0.648	0.534

evaluating the recommendation of activities, more activities per user are considered. We may also state that the traditional accuracy metrics may be not the best suited for this kind of recommendation task.

We can also note, that Strategy II improves a bit the results for content-based methods (Cb_pos, Cb) and Hybrid method starting from one history day, while decreasing the accuracy for category-based method, both in terms of precision and AUC. However, on Fantasy_db it has gave a significant improvement. This may be due to the fact that in the case of the category-based methods, Strategy II reinforces te selection on the first step which may be not very accurate as described above. It is also to note that Strategy II makes the estimation of the scores slower, due to the user's profile enrichment procedure.

The difference in the results in terms of accuracy on two datasets are due to the data they contain. Thus, Fantasy_db contains data about custom itineraries of the users, while DEvIR contains the data on the users RSVPs.

More investigations are needed. The present work serves the starting point for a new and ongoing research project running in the team.

11.5 Summary

In this Chapter, we have presented the evaluation of our proposed approach ANASTASIA for recommendation of activity sequences during distributed events. We have performed the offline evaluation on a dataset of attendance of distributed events, Fantasy_db and have proposed an evaluation procedure for DEvIR dataset. Thus, this Chapter unites three contributions of this Thesis. **C2** **C3-1** **C3-2**

The obtained experimental results have shown that our proposed solution overperforms the state-of-the-art optimisation algorithm.

Part V

Conclusions and Perspectives

12

Conclusions and Perspectives

12.1 Summary and Contributions

In this Thesis, we have conducted a study on recommendation of sequences of spatial items. First, we have surveyed the state-of-the-art on recommendation of spatial items with a special focus on recommendation of spatial sequences. This study has allowed us to identify the characteristics of the problem in order to well define it, providing a conceptual basis for the work. Moreover, we determined the research directions to investigate.

Our main interest concerns the recommendation of sequences of activities during distributed events (*e.g.* festivals, conventions, cruise trips, etc.). From the perspective of leisure activities, the undertaken conceptual direction of the Thesis helps in *better understanding* and *providing more insight* into the process of selection of leisure activities by individuals. We have investigated different types of influence from the state-of-the-art solutions that may impact the user's interest in an item, and proposed their classification. Moreover, we have provided an overview of available datasets and have discussed their use for recommendation of sequences of activities. The conceptual direction of the Thesis has been extensively described in Part I.

We then focused on practical axis of the work. We have proposed and developed a novel approach for recommendation of personalised itineraries during distributed events, that we call ANASTASIA, presented in Part II of the Thesis. ANASTASIA makes use of users behavioural patterns to construct the planning of events that best suit users constraints and preferences. It is a hybrid approach that integrates categorical, temporal and textual scores of user's interest in an activity. Based on the estimated scores of activities and the extracted behavioural patterns a personalised itinerary is constructed. This approach follows the two-step set-up, used in recommendation of sequences of spatial items, treating the initial problem on two stages, namely: the estimation of personalised score of activities and the construction of the itineraries. The main novelty of the proposed approach lies in the integration of the sequential influence on this general two-step methodology. The sequential influence is modelled as the transition probabilities between activities, estimated based on the extracted behavioural patterns. These transition probabilities are incorporated on the itinerary construction step, while the algorithm is iteratively seeking for the best insertion to make.

Another branch of the practical direction of this Thesis concerns the construction of the test collections that are well-suited for the recommendation of activity sequences during distributed events, reflecting the real application scenarios (see Part III). We have identified the characteristics of the data exploited by activity sequence recommendation. Among the list of 14 characteristics, we distinguish 5 core ones: (1) time windows (start and end time of activity), (2) coordinates (geographical location of an activity), (3) service time (duration of an activity), (4) categories, and (5) users historical data. We used these characteristics as the basis in the process of dataset creation.

We first conducted a user study on the user' participation in the activities on-board of a cruise. The main aim of the study was to simulate cruise attendance and create a dataset that could be used for personalised itinerary construction. Participants were recruited via a link to the online questionnaire sent by email to several research mailing lists. This user study has resulted in a test collection that we call Fantasy_db, which is described in Chapter 9. This dataset has provided some insights into the activity selection problem, and was used for the validation of ANASTASIA. However, the main limitation of Fantasy_db is its rather small size. In order to overcome this limitation, we have constructed another dataset, to which we refer to as DEvIR.

To obtain the DEvIR dataset that can be used as is, we have crawled the website of the comic book convention. DEvIR contains the event programs 2013-2017 and the pre-selection of the program events made by participants, more precisely the following entities: events, locations, categories, tags, event-user, user-user, event-categories, event-tags. We have present the characteristics of the collected data and discussed its usability for evaluating recommendation algorithms in Chapter 10. We have used Fantasy_db for validation and evaluation of ANASTASIA. We have also proposed an evaluation protocol for DEvIR, and have discussed some of the observations that we have made after applying ANASTASIA on it.

12.2 Perspectives

This Thesis presents novel aspects of recommendation of sequences of spatial items, with the special focus on recommendation of activity sequences during distributed events. There are several open research directions that we could not cover in the Thesis but that seem promising. We highlight them here.

12.2.1 Cold Start and User's psychological profiles

Recommendation of sequences of spatial items is rather closed to the event recommendation. Both these recommendation problems suffer from the cold-start problem. Recently, the research community in the field of recommender system has gotten interested in psychological aspects of recommendation and how user's psychological profiles can be used in order to alleviate the cold-start problem [51], improve the recommendation accuracy [55] and helps to eliminate the cold-start problem . Thus, personality-based method have been successfully applied to the movie [55] and music [51] recommendation domains. However, no work has been done in the domain of leisure activities/event recommendation and activity sequence recommendation.

Thus, investigating the impact of psychological profiles of individuals on the selection of leisure activities is an interesting research direction. We foresee three parts of such work, namely: (1) implicit acquisition of users' psychological profiles from their selection of leisure activities, (2) estimation of user's interest scores based on his/her psychological profile, (3) incorporation of these scores into a hybrid event recommendation model.

During this Thesis, we have performed a user study aiming at investigate the correlations between the psychological profiles of individuals and their selection of leisure activities. Thus, we suggested to extend the considered psychological profiles of users (that often consist of the user's personality in literature) by focusing on the following dimensions: (1) Orientations to Happiness (OTH) [87]; (2) Big5 Personality traits (Big5) [70]; and (3) Fear of Missing Out (FoMO) [88]. We have reported some of the results of the conducted study in [80]. The full questionnaire used within the study is given in Appendix B. The main objective of the further work would be study the use of psychological profiles in order to alleviate the cold-start problem and improve the recommendation quality in terms of precision and beyond-precision metrics (*i.e.* serendipity and diversity).

Another step would be to investigate the impact of psychological profiles on activity sequences.

12.2.2 Satisfaction with respect to a sequence of activities

State-of-the-art algorithms for recommendation of sequences of spatial items usually assume that the satisfaction a user gets from experiencing items is independent, without considering previous or alter experience.

Moreover, when it comes to the estimation of overall satisfaction with a sequence, for the sake of simplicity, it is often considered that the overall satisfaction may be calculated as a sum of satisfaction with each of the items forming this sequence. Thus, an interesting direction of future work consists in exploring the interdependence of activities within a sequence in terms of satisfaction a user gets (*e.g.* [69]).

12.2.3 Multiple interaction types

Most of the recommendation methods consider a single type of user-item interactions, *e.g.* graded rating, binary visit, rsvp, etc. However, in real scenarios the individuals may express their intent in joining an event by providing the corresponding rsvp on event-based social network, but finally not go. The contrary is also possible. Though, some of the methods may take into account multiple signals, this problem has not received much attention yet. This may be partially due to the lack of publicly available data. One may also explore how to better combine multiple interactions types using aggregation operators [68].

A

Appendix. Questionnaire for Fantasy_db

USER STUDY CAMPAIGN[1]

The aim of this questionnaire is to create a preliminary dataset that could be used in order to make personalised recommendations of itineraries. The survey consists of four parts. The first one deals with user's features and experience. The second part aims to learn the preferences of the user by asking to evaluate the list of activities. In the third one, users are asked to create daily itineraries by selecting activities. And the fourth part concludes the survey. The aim of this study is to better understand what "factors" influence our choice of activities to perform.

The list of activities used in the survey is taken from the personal navigators of Disney's Fantasy 7-nights Eastern Caribbean cruise. Activities dedicated exclusively for kids have been excluded from the current list of activities.

The original personal navigators can be found at:
https://bit.ly/2xArmVa

The deck plan of the ship can be found at:
https://bit.ly/2xJ3G11

[1]https://goo.gl/forms/dC3Ne8qmBrxdzVAU2

The screenshot of Disney Cruise Line official permitting the use of the personal navigators can be found at:
DCL email
PS: the data will be used only in academic purpose

Part I. User Profile

This part contains questions on basic user's features and their experience.

Your gender:
Please, choose your gender.

○ Female

○ Male

Have you already experienced DCL (Disney Cruise Line)?

○ Yes

○ No

Have you tried any other cruise?

○ Yes

○ No

The type of group you were/are travelling with
Please, choose, the option that best describes you.

○ Travelling alone

○ Travelling with your significant other

○ Travelling with a group of friends

○ Travelling with family (i.e. different generations)

○ Travelling with other group

If you were travelling with a group, have you split to attend different activities or you mostly preferred to stay together?

◯ Always together

◯ Split exceptionally

◯ Split often

Dining Time
Please, select your dining time. PS: Details of your dining rotation and timing are given on your dining tickets. Dining Rooms open at designated seating times and your table is reserved each night of your cruise.

◯ First seating: 17:45

◯ Second seating: 20:15

Optional Questions

Please answer the following questions if you already have experienced a Disney Cruise Line. If you didn't, click on the button at the bottom of this page and go to the next page.
Have you tried to manage the list of your onboard activities?
Taking into account the great variety of parallel activities and other onboard fun (e.g. pool, sunbathing, digital detective quests, sports, etc.), have you tried to plan your daily itinerary?

◯ Yes

◯ No

Were/Are you aiming to attend the maximum amount of activities mentioned in your Personal Navigator or just a few must-see?

◯ Maximum

○ Just a few

What "guidance" have you followed while choosing the onboard activities?

Please, select the options that best describe you. Multiple choice is possible

☐ Cruise Director's recommendations

☐ Personal Navigator - Don't Miss

☐ Your past experience

☐ Recommendations from your dining table-mates

☐ Recommendations from cruise staff

☐ Whatever seems interesting for you

Taking into account the great variety of parallel activities and other onboard fun (e.g. pool, sunbathing, digital detective quests, sports, etc.), have you experienced any trouble of choice?

○ Yes

○ No

PART II. USERS PREFERENCES

This part aims to learn user's preferences based on user's evaluation of a list of proposed activities (category-based)

Funnel Vision

"Funnel Vision" is a LED screen attached to the forward funnel facing rearward on the Deck 11.

Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

A Bug's Life (G). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 20:15-21:45, *Location*: Funnel Vision
Alice in Wonderland (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 5, 08:30-09:45, *Location*: Funnel Vision
Brave (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 15:30-17:00, *Location*: Funnel Vision
Available: Day 7, 14:00-15:30, *Location*: Funnel Vision
Brother Bear (G). | *Never* ○○○○○ *Won't miss*
Available: Day 1, 20:00-21:15, *Location*: Funnel Vision
Buccaneer Blast & Club Pirate. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Fireworks
Available: Day 4, 22:30-23:30, *Location*: Funnel Vision
Cinderella (Classic) (G). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 16:30-17:45, *Location*: Funnel Vision
Disney Channel on Deck (G). | *Never* ○○○○○ *Won't miss*
Description: Don't change that channel! It's time for a Disney Channel afternoon poolside! Your Cruise Staff will host and exciting day of games and contests in between your favourite Disney Channel shows! So sit back, relax, and enjoy the sun!
Available: Day 5, 16:15-16:45, *Location*: Funnel Vision
Disneynature Oceans (G). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 22:00-23:30, *Location*: Funnel Vision
Dumbo (G). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 21:00-22:00, *Location*: Funnel Vision
Enchanted (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 22:30-00:00, *Location*: Funnel Vision
Fantasia (G). | *Never* ○○○○○ *Won't miss*
Available: Day 7, 22:00-00:00, *Location*: Funnel Vision

Finding Nemo (G). | *Never* ○○○○○*Won't miss*
Available: Day 2, 08:30-10:15, *Location*: Funnel Vision
Available: Day 5, 20:15-22:00, *Location*: Funnel Vision
Frozen (PG). | *Never* ○○○○○*Won't miss*
Available: Day 6, 22:00-23:30, *Location*: Funnel Vision
Available: Day 7, 10:00-11:45, *Location*: Funnel Vision
Hercules (G). | *Never* ○○○○○*Won't miss*
Available: Day 5, 11:45-13:15, *Location*: Funnel Vision
Lady and the Tramp (G). | *Never* ○○○○○*Won't miss*
Available: Day 7, 12:15-13:30, *Location*: Funnel Vision
Lilo & Stitch (PG). | *Never* ○○○○○*Won't miss*
Available: Day 7, 08:30-10:00, *Location*: Funnel Vision
Mickey's PiTC (G). | *Never* ○○○○○*Won't miss*
Available: Day 4, 19:45-20:15, *Location*: Funnel Vision
Monsters, Inc. (G). | *Never* ○○○○○*Won't miss*
Available: Day 3, 10:15-11:45, *Location*: Funnel Vision
Movie Challenge Poolside. | *Never* ○○○○○*Won't miss*
Description: So you like movies? And you like bingo? This deck party has them both! Come on out to catch all your favorite movie clips and just maybe your team will win the opportunity to choose the movie played by the pool today!
Available: Day 2, 12:30-13:30, *Location*: Funnel Vision
Movie Prem Ear: Teen Beach Movie 2 (TV-G). | *Never* ○○○○○*Won't miss*
Available: Day 7, 20:00-21:15, *Location*: Funnel Vision
Mulan (G). | *Never* ○○○○○*Won't miss*
Available: Day 5, 10:00-11:30, *Location*: Funnel Vision
Muppet Treasure Island (G). | *Never* ○○○○○*Won't miss*
Available: Day 4, 20:30-22:15, *Location*: Funnel Vision
Peter Pan (G). | *Never* ○○○○○*Won't miss*
Available: Day 4, 16:00-17:15, *Location*: Funnel Vision
Pirates of the Caribbean I (PG-13). | *Never* ○○○○○*Won't miss*
Available: Day 4, 23:30-00:15, *Location*: Funnel Vision

Pixar Short Films (G). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 19:30-20:45, *Location*: Funnel Vision
Ratatouille (G). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 17:15-19:00, *Location*: Funnel Vision
Robin Hood (G). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 18:00-19:00, *Location*: Funnel Vision
Snow White and the Seven Dwarfs (G). | *Never* ○○○○○ *Won't miss*
Available: Day 5, 13:45-15:15, *Location*: Funnel Vision
Star Wars Rebels: Disney Channel XD (G). | *Never* ○○○○○ *Won't miss*
Available: Day 5, 15:15-16:00, *Location*: Funnel Vision
Available: Day 6, 14:15-15:00, *Location*: Funnel Vision
Tangled (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 12:45-13:45, *Location*: Funnel Vision
Tarzan (G). | *Never* ○○○○○ *Won't miss*
Available: Day 1, 17:45-19:00, *Location*: Funnel Vision
The Aristocats (G). | *Never* ○○○○○ *Won't miss*
Available: Day 5, 18:30-20:00, *Location*: Funnel Vision
The Emperor's New Groove (G). | *Never* ○○○○○ *Won't miss*
Available: Day 7, 18:00-19:00, *Location*: Funnel Vision
The Incredibles (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 4, 14:00-16:00, *Location*: Funnel Vision
The Jungle Book (G). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 08:30-09:30, *Location*: Funnel Vision
The Lion King (G). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 15:15-16:45, *Location*: Funnel Vision
The Little Mermaid (G). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 12:15-13:45, *Location*: Funnel Vision
The Muppets (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 17:15-19:00, *Location*: Funnel Vision
The Princess and the Frog (G). | *Never* ○○○○○ *Won't miss*
Available: Day 1, 22:00-23:45, *Location*: Funnel Vision

Tinker Bell (G). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 08:30-10:00, *Location*: Funnel Vision
Toy story (G). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 10:15-11:30, *Location*: Funnel Vision
Toy Story 2 (G). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 10:15-11:45, *Location*: Funnel Vision
Toy Story 3 (G). | *Never* ○○○○○ *Won't miss*
Available: Day 7, 16:00-17:45, *Location*: Funnel Vision
Up (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 5, 22:00-23:30, *Location*: Funnel Vision
WALL-E (G). | *Never* ○○○○○ *Won't miss*
Available: Day 6, 20:00-21:45, *Location*: Funnel Vision
Wreck-It Ralph (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 14:45-16:30, *Location*: Funnel Vision

Buena Vista Theatre

"Buena Vista Theatre" is a grand movie theatre that boasts Art Deco splendor, inspired by the golden age of cinema. Disney Cruise Line was first to introduce 3D movies aboard its ships, adding a whole new dimension in entertainment. Show times occur throughout the day, making it possible to plan a full day of activities and still catch a movie or two. From blockbusters to Disney classics, see a movie in state-of-the-art comfort—and style. (https://disneycruise.disney.go.com/onboard-activities/buena-vista-theater/)
Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

Avengers: Age of Ultron (PG-13). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 17:00-19:22, *Location*: Buena Vista Theatre
Available: Day 2, 20:00-22:22, *Location*: Buena Vista Theatre
Available: Day 5, 15:00-17:22, *Location*: Buena Vista Theatre

Available: Day 5, 22:30-00:52, *Location*: Buena Vista Theatre
Available: Day 6, 10:45-13:07, *Location*: Buena Vista Theatre
Big Hero 6 (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 08:30-10:18, *Location*: Buena Vista Theatre
Available: Day 5, 10:30-12:18, *Location*: Buena Vista Theatre
Cinderella (2015) (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 22:30-00:22, *Location*: Buena Vista Theatre
Available: Day 4, 14:30-16:22, *Location*: Buena Vista Theatre
Available: Day 6, 17:30-19:22, *Location*: Buena Vista Theatre
Available: Day 6, 20:15-22:07, *Location*: Buena Vista Theatre
Disney's Behind the Scenes: Frank Paris. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Come learn about Walt Disney Imagineering - how Imagineers create magical places and experiences for their Guests. The presentation will also give insight as to what Walt Disney Imagineers are currently working on.
Available: Day 3, 14:00-15:00, *Location*: Buena Vista Theatre
Disney's Behind the Scenes: Frank Paris. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Disney Springs is the newest one-of-a-kind shopping, dining and entertainment experience at Walt Disney World. Frank will share some of the wonderful and exciting experiences that will await you in the years to come.
Available: Day 6, 14:00-15:00, *Location*: Buena Vista Theatre
Family Movie Fun Time: Inside Out (PG). | *Never* ○○○○○ *Won't miss*
Description: Come join us for a special opportunity to enjoy Inside Out in the Buena Vista Theatre. We will leave some lights on and turn the volume down as audience members are welcome to talk, leave their seats, move about and (most importantly) have fun!
Available: Day 6, 08:30-10:12, *Location*: Buena Vista Theatre
Inside Out (PG). Event of the Day. | *Never* ○○○○○ *Won't miss*
Description: Meet the little voices inside your head. Movie Special.

Available: Day 3, 14:00-15:42, *Location*: Walt Disney Theatre
Available: Day 4, 17:30-19:12, *Location*: Walt Disney Theatre
Available: Day 4, 20:15-21:57, *Location*: Walt Disney Theatre
Available: Day 4, 23:00-00:42, *Location*: Buena Vista Theatre
Available: Day 5, 12:45-14:27, *Location*: Buena Vista Theatre
Available: Day 6, 14:00-15:42, *Location*: Walt Disney Theatre
Available: Day 7, 13:45-15:27, *Location*: Buena Vista Theatre
Available: Day 7, 17:45-19:27, *Location*: Buena Vista Theatre
Available: Day 7, 20:15-21:57, *Location*: Buena Vista Theatre
Available: Day 7, 22:45-00:27, *Location*: Buena Vista Theatre
McFarland, USA (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 3, 17:15-19:24, *Location*: Buena Vista Theatre
Available: Day 3, 20:00-22:09, *Location*: Buena Vista Theatre
Monkey Kingdom (G). | *Never* ○○○○○ *Won't miss*
Available: Day 1, 22:15-23:36, *Location*: Buena Vista Theatre
Available: Day 2, 15:15-16:36, *Location*: Buena Vista Theatre
Available: Day 3, 08:30-09:51, *Location*: Buena Vista Theatre
Available: Day 5, 18:15-19:36, *Location*: Buena Vista Theatre
Available: Day 5, 20:30-21:51, *Location*: Buena Vista Theatre
Available: Day 7, 16:00-17:21, *Location*: Buena Vista Theatre
Port & Shopping Talk. | *Never* ○○○○○ *Won't miss*
Description: Join your Port and Shopping Guides to learn about the incredible tax & duty free shopping ashore this cruise! Free charm bracelet for all in attendance and a raffle to win over $1000 in prizes and giveaways!
Available: Day 2, 13:45-14:30, *Location*: Buena Vista Theatre
Port & Shopping Talk. | *Never* ○○○○○ *Won't miss*
Description: Join your Port and Shopping Guides to learn about the incredible tax & duty free shopping ashore this cruise! Free charm bracelet for all in attendance and a raffle to win over $1000 in prizes and giveaways!
Available: Day 2, 13:45-14:30, *Location*: Buena Vista Theatre
Port Adventures. | *Never* ○○○○○ *Won't miss*

Available: Day 4, 08:30-13:45, *Location*: Buena Vista Theatre
Strange Magic (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 1, 17:45-19:24, *Location*: Buena Vista Theatre
Available: Day 1, 20:00-21:39, *Location*: Buena Vista Theatre
Tomorrowland (PG). | *Never* ○○○○○ *Won't miss*
Available: Day 2, 10:45-12:55, *Location*: Buena Vista Theatre
Available: Day 2, 22:45-00:55, *Location*: Buena Vista Theatre
Available: Day 4, 17:00-19:10, *Location*: Buena Vista Theatre
Available: Day 4, 20:00-22:10, *Location*: Buena Vista Theatre
Available: Day 6, 22:30-00:40, *Location*: Buena Vista Theatre
Available: Day 7, 09:30-11:12, *Location*: Buena Vista Theatre

Characters

Meet some of Disney's most beloved Characters aboard all Disney Cruise Line ships. Kids and kids-at-heart can meet some of their favorite Disney Characters and capture the moments with photos. You might see them around, but there are the designated locations for Disney Character appearances (https://disneycruise.disney.go.com/onboard-activities/character-greetings/).
Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

Ariel. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 19:45-20:00, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 21:15-21:45, *Location*: Lobby Atrium, Vestibule.
Belle. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 17:15-17:45, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 17:00-17:30, *Location*: Lobby Atrium, Port Side.
Captain Hook & Mr Smee. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 17:30-17:45, *Location*: Deck 4, Balcony.
Available: Day 4, 22:00-22:15, *Location*: Deck 4, Balcony.

Character Meet & Greet Ticket Distribution. Don't Miss Event. | *Never* ○○○○○*Won't miss*
Description: Pick up your tickets today to meet some of your favourite Disney friends. Princess Gathering. Princess Anna & Queen Elsa. Disney Junior Character Breakfast. Tickets are required for each of these meet and greets. Space is limited.
Available: Day 1, 11:30-15:00, *Location*: Port Adventures Desk
Chip & Dale. | *Never* ○○○○○*Won't miss*
Available: Day 3, 21:30-21:45, *Location*: Preludes
Available: Day 5, 16:15-16:30, *Location*: Preludes
Available: Day 6, 17:00-17:15, *Location*: Preludes
Available: Day 7, 09:15-09:30, *Location*: Deck 4, Balcony
Chip & Dale. Beach. | *Never* ○○○○○*Won't miss*
Available: Day 7, 11:45-12:00, *Location*: Post Office
Chip & Dale. Formal. | *Never* ○○○○○*Won't miss*
Available: Day 2, 18:00-18:15, *Location*: Deck 4, Balcony.
Chip & Dale. Pirate. | *Never* ○○○○○*Won't miss*
Available: Day 4, 16:30-16:45, *Location*: Deck 4, Balcony
Available: Day 4, 21:45-22:00, *Location*: Lobby Atrium, Vestibule
Cinderella. | *Never* ○○○○○*Won't miss*
Available: Day 1, 20:00-20:15, *Location*: Deck 4, Balcony
Available: Day 1, 21:30-21:45, *Location*: Deck 4, Balcony
Available: Day 3, 21:45-22:00, *Location*: Lobby Atrium, Vestibule
Available: Day 5, 19:30-20:00, *Location*: Lobby Atrium, Port Side
Daisy. | *Never* ○○○○○*Won't miss*
Available: Day 2, 16:30-16:45, *Location*: Deck 4, Balcony
Available:Day 3, 09:00-09:15, *Location*: Deck 4, Balcony
Available: Day 5, 19:15-19:30, *Location*: Lobby Atrium, Hallway
Daisy. Beach. | *Never* ○○○○○*Won't miss*
Available: Day 7, 12:00-12:15, *Location*: Gangway
Available: Day 7, 16:00-17:00, *Location*: Gangway
Daisy. Formal. | *Never* ○○○○○*Won't miss*
Available: Day 2, 19:30-19:45, *Location*: Preludes

Daisy. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 21:30-21:45, *Location*: Lobby Atrium, Starboard Side
Doc McStuffins. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 13:00-13:15, *Location*: Deck 4, Balcony
Available: Day 6, 09:00-09:15, *Location*: Lobby Atrium, Vestibule
Available: Day 6, 10:00-10:15, *Location*: Lobby Atrium, Vestibule
Donald. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 16:45-17:00, *Location*: Preludes
Available: Day 5, 16:45-17:00, *Location*: Preludes
Available: Day 5, 19:45-20:00, *Location*: Lobby Atrium, Hallway
Available: Day 6, 17:30-17:45, *Location*: Preludes
Available: Day 6, 22:00-22:15, *Location*: Preludes
Available: Day 7, 08:45-09:00, *Location*: Deck 4, Balcony
Available: Day 7, 17:30-17:45, *Location*: Deck 4, Balcony
Donald. Beach. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 12:15-12:30, *Location*: Post Office
Donald. Formal. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 22:00-22:15, *Location*: Preludes
Donald. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 16:15-16:30, *Location*: Lobby Atrium, Starboard Side
Available: Day 4, 21:30-21:45, *Location*: Lobby Atrium, Port Side
Dopey. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 21:30-21:45, *Location*: Deck 4, Balcony
Available: Day 6, 15:00-15:15, *Location*: Deck 4, Balcony
Goofy. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 21:30-21:45, *Location*: Lobby Atrium, Hallway.
Available: Day 2, 13:30-13:45, *Location*: Deck 4, Balcony.
Available: Day 3, 17:30-17:45, *Location*: Deck 4, Balcony.
Available: Day 5, 17:30-17:45, *Location*: Lobby Atrium, Hallway.
Available: Day 6, 19:45-20:00, *Location*: Preludes
Available: Day 6, 21:30-21:45, *Location*: Preludes
Goofy. Beach. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 12:30-12:45, *Location*: Rustmore

Goofy. Formal. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 20:00-20:15, *Location*: Preludes
Goofy. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 17:00-17:15, *Location*: Deck 4, Balcony.
Available: Day 4, 21:30-21:45, *Location*: Deck 4, Balcony
Jack Sparrow. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 17:00-17:15, *Location*: Preludes
Available: Day 4, 20:30-20:45, *Location*: Preludes
Available: Day 7, 13:15-13:30, *Location*: Marge's Barges
Jake. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 16:30-16:45, *Location*: Deck 4, Balcony.
Day 6, 09:30-09:45, *Location*: Lobby Atrium, Vestibule.
Jake
The Neverland Pirates. | *Never* ○○○○○ *Won't miss*
Description: A'Hoy there mates, join us for an adventure in D Lounge with Jake and the Netherland Pirates.
Available: Day 6, 08:30-09:00, *Location*: D Lounge
Jessie. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 09:15-09:30, *Location*: Lobby Atrium, Vestibule.
Available: Day 3, 09:00-09:15, *Location*: Lobby Atrium, Vestibule.
Mickey. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 17:15-17:30, *Location*: Lobby Atrium, Hallway.
Available: Day 1, 19:15-19:30, *Location*: Lobby Atrium, Hallway.
Available: Day 1, 22:00-22:15, *Location*: Lobby Atrium, Hallway.
Available: Day 3, 14:15-14:30, *Location*: Preludes
Available: Day 5, 17:15-17:30, *Location*: Preludes
Available: Day 5, 19:30-19:45, *Location*: Deck 4, Balcony.
Mickey. Beach. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 09:00-09:15, *Location*: Lobby Atrium, Port Side.
Available: Day 7, 12:00-12:15, *Location*: Rustmore
Mickey. Formal. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 19:45-20:00, *Location*: Deck 4, Balcony.
Available: Day 2, 21:45-22:00, *Location*: Deck 4, Balcony.

Available: Day 2, 17:30-17:45, *Location*: Deck 4, Balcony.
Mickey. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 19:00-19:15, *Location*: Lobby Atrium, Port Side.
Available: Day 4, 22:00-22:15, *Location*: Lobby Atrium, Port Side.
Available: Day 4, 17:15-17:45, *Location*: Lobby Atrium, Port Side.
Minnie. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 17:45-18:00, *Location*: Lobby Atrium, Hallway.
Available: Day 1, 19:45-20:00, *Location*: Lobby Atrium, Hallway.
Available: Day 2, 09:00-09:15, *Location*: Deck 4, Balcony.
Available: Day 2, 16:15-16:30, *Location*: Preludes
Available: Day 3, 14:00-14:15, *Location*: Deck 4, Balcony.
Available: Day 3, 14:45-15:00, *Location*: Preludes
Minnie. Formal. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 19:15-19:30, *Location*: Deck 4, Balcony.
Available: Day 2, 21:30-21:45, *Location*: Preludes
Available: Day 2, 22:15-22:30, *Location*: Deck 4, Balcony.
Available: Day 2, 17:45-18:00, *Location*: Preludes
Available: Day 2, 17:00-17:15, *Location*: Deck 4, Balcony.
Minnie. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 22:00-22:15, *Location*: Lobby Atrium, Starboard Side.
Day 4, 16:45-17:15, *Location*: Lobby Atrium, Starboard Side.
Minnie. Princess. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 09:15-09:30, *Location*: Deck 4, Balcony.
Available: Day 6, 10:15-10:30, *Location*: Deck 4, Balcony.
Peter Pan. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 16:30-17:00, *Location*: Lobby Atrium, Port Side.
Available: Day 5, 17:00-17:15, *Location*: Deck 4, Balcony.
Pluto. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 09:30-09:45, *Location*: Deck 4, Balcony.
Available: Day 2, 17:15-17:30, *Location*: Preludes
Available: Day 3, 09:30-09:45, *Location*: Deck 4, Balcony.
Available: Day 3, 16:30-16:45, *Location*: Preludes
Available: Day 3, 22:00-22:15, *Location*: Deck 4, Balcony.

Available: Day 5, 17:00-17:15, *Location*: Lobby Atrium, Hallway.
Port Adventures. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 08:30-13:45
Sea Ya' Real Soon!. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Mickey and Minnie along with the rest of the Walt Disney Characters invite you to join them in the ship's atrium for Sea Ya Real Soon. You won't ant to miss this very special farewell presentation.
Available: Day 7, 16:30-17:00, *Location*: Lobby Atrium
Available: Day 7, 22:15-22:45, *Location*: Lobby Atrium
Sofia. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 14:30-14:45, *Location*: Deck 4, Balcony.
Available: Day 3, 13:30-13:45, *Location*: Deck 4, Balcony.
Available: Day 6, 09:45-10:00, *Location*: Deck 4, Balcony.
Stitch. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 17:00-17:15, *Location*: Preludes
Available: Day 3, 22:00-22:15, *Location*: Preludes
Available: Day 5, 21:30-21:45, *Location*: Preludes
Available: Day 6, 15:30-15:45, *Location*: Deck 4, Balcony.
Stitch. Pirate. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 16:00-16:15, *Location*: Lobby Atrium, Port Side.
Available: Day 4, 19:00-19:15, *Location*: Deck 4, Balcony.
Tiana. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 19:30-19:45, *Location*: Deck 4, Balcony.
Available: Day 3, 19:15-19:30, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 22:00-22:15, *Location*: Lobby Atrium, Port Side.
Tinker Bell. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 17:15-17:30, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 16:45-17:00, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 19:30-19:45, *Location*: Lobby Atrium, Vestibule.
Available: Day 5, 21:45-22:00, *Location*: Lobby Atrium, Vestibule.
Wake Up with Disney Junior. | *Never* ○○○○○ *Won't miss*
Description: What happens when you experience unlimited fun with

your favorite Disney Junior shows? You get an exciting dance party designed especially for preschoolers ages seven and under.
Available: Day 2, 08:30-09:00, *Location*: D Lounge, Deck 4, Midship.
Woody. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 09:45-10:00, *Location*: Lobby Atrium, Vestibule.
Available: Day 3, 09:30-09:45, *Location*: Lobby Atrium, Vestibule.

Fun for All Ages

Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

A Fantasy Come True. Event of the Day. | *Never* ○○○○○ *Won't miss*
Description: Join us tonight in the beautiful Walt Disney Theatre for a magical, musical journey through the wonderland of the Disney Fantasy featuring the Walt Disney Theatre Cast; World Famous Disney Characters and the Comedy and Ventriloquism of David Crone.
Available: Day 1, 18:15-19:00, *Location*: Walt Disney Theatre
Available: Day 1, 20:30-21:30, *Location*: Walt Disney Theatre
A Pirate's Life For Me. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Calling all Pirates, we be! If ye have an adventurous spirit or pirate savvy, come spin the "Wheel of Destiny" fer a treasure trove of fun be ripe for the takin' in this action packed pirate game show.
Available: Day 4, 18:30-19:00, *Location*: D Lounge
Available: Day 4, 21:30-22:00, *Location*: D Lounge
Andrea & Rafaela LIVE. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 22:30-23:00, *Location*: Lobby Atrium
Anyone Can Cook - Apple Shtrudel. | *Never* ○○○○○ *Won't miss*
Description: From our gallery to yours. Join our chefs as they show you how to prepare delicious dishes. Today's Menu - Apple Shtrudel.

Available: Day 6, 14:15-15:00, *Location*: D Lounge
Basketball Free Throw. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff in this fun tournament and see how many you can sink in 30 seconds!
Available: Day 7, 12:30-13:00, *Location*: In Da Shade Game Pavilion
Bingo Pre Sales. Diamond Jackpot Bingo. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 11:00-11:15, *Location*: D Lounge
Bingo: Diamond Jackpot Bingo. | *Never* ○○○○○ *Won't miss*
Description: Join us for 4 cash prize games and your chance to win diamond pendant! Everyone attending will also receive free cruise ship charm! Pre-Sales start 15 minutes prior the game.
Available: Day 2, 11:15-12:00, *Location*: D Lounge
Bingo Pre Sales. $5,000 Mega Jackpot Bingo. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 16:00-16:15, *Location*: D Lounge
Bingo: $5,000 Mega Jackpot Bingo. | *Never* ○○○○○ *Won't miss*
Description: Don't miss your chance to take home big money! 4 CASH prize games and great raffle prizes to be won! Complete the fourth game in 46 numbers or less and win the $5,000 Mega Jackpot! Pre-Sales start 15 minutes prior to game.
Available: Day 2, 16:15-17:00, *Location*: D Lounge
Bingo Pre Sales. DCL Gift Pack Jackpot. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 11:00-11:15, *Location*: D Lounge
Bingo: DCL Gift Pack Jackpot with Sophia Fiori. | *Never* ○○○○○ *Won't miss*
Description: Four CASH prizes games and four Disney Cruise Line gift packs to be won. The jackpot continues to grow and could go at any time! Also you'll have the chance to win Sophia Fiori jewellery pieces in prizes! Pre-Sales start 15 minutes prior to the game.
Available: Day 3, 11:15-12:00, *Location*: D Lounge
Bingo Pre Sales. $7000 Mega Jackpot Bingo. | *Never* ○○○○○ *Won't*

miss
Available: Day 3, 15:45-16:15, *Location*: Buena Vista Theatre
Bingo: $7000 Mega Jackpot Bingo. | *Never* ○○○○○ *Won't miss*
Description: Don't miss your chance to take home big money. 4 CASH prize games and great raffle prizes to be won! Complete the fourth game in 46 numbers or less and win $7,000 Mega Jackpot! Pre-Sales start 30 minutes prior to game.
Available: Day 3, 16:15-17:00, *Location*: Buena Vista Theatre
Bingo Pre-Sales. Double Up Jackpot. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 19:15-19:30, *Location*: D Lounge
Bingo: Double Up Jackpot. | *Never* ○○○○○ *Won't miss*
Description: Special double up session: All electronic cards purchased will be doubled! The snowball jackpot continues to grow and could be won today! Pre-Sales start 15 minutes prior to the game.
Available: Day 5, 19:30-20:15, *Location*: D Lounge
Bingo Pre Sales. $10,000 Mega Jackpot. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 11:00-11:15, *Location*: D Lounge
Bingo: $10,000 Mega Jackpot. | *Never* ○○○○○ *Won't miss*
Description: It's Big, it's Massive, it's Supersized! It's $10,000 MEGA Jackpot Bingo! Take home $10,000 if you can cover your card in 46 numbers or less. If not, we carry on to play for the biggest cash prize of the session. Pre-Dales start 15 minutes prior to game.
Available: Day 6, 11:15-12:00, *Location*: D Lounge
Bingo Pre-Sales. Final Jackpot. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 15:45-16:15, *Location*: Buena Vista Theatre
Bingo: Final Jackpot. | *Never* ○○○○○ *Won't miss*
Description: The snowball jackpot MUST BE WON at this final session! Beat the line and get your cards early. Who will be the lucky winner? It could be you! Pre-Sales start 30 minutes prior to game.
Available: Day 6, 16:15-17:00, *Location*: Buena Vista Theatre
Board Games available in O'Gills Pub. | *Never* ○○○○○ *Won't*

miss
Available: Day 4, 08:30-11:30, *Location*: O'Gills Pub
Buccaneer Blast
Club Pirate. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Fireworks
Available: Day 4, 22:30-23:30, *Location*: Deck Stage
Captain's Signing. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Meet the Master of the Disney Fantasy and have your cruise memories signed.
Available: Day 6, 11:00-11:30, *Location*: White Caps
Captain's Welcome Reception. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Enjoy live music and a cocktail while meeting some of the ship's officers. Lobby Atrium, Deck 3, Midship, 5:00 & 7:30 pm. Enjoy an exclusive photo opportunity with Captain Marco at 5:15 & 7:30 pm, Lobby Atrium.
Available: Day 2, 17:00-18:00, *Location*: Lobby Atrium
Available: Day 2, 19:30-20:30, *Location*: Lobby Atrium
Character Dance Party. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 10:30-11:00, *Location*: Lobby Atrium
Chip It Golf. | *Never* ○○○○○ *Won't miss*
Description: It's par for the course for our Guests 12 and older to compete on our special "greens" in this fun tournament.
Available: Day 3, 15:00-15:30, *Location*: Lobby Atrium
Club D Dance Party. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 19:30-20:15, *Location*: D Lounge
Available: Day 2, 21:45-22:30, *Location*: D Lounge
Club New Year's Eve. | *Never* ○○○○○ *Won't miss*
Description: Club New Year's Eve, you won't want to miss this journey of musical genres in history and performances by some of your favorite Cruise Staff. Bring your family and help us count down to a brand new year!

Available: Day 6, 22:15-22:45, *Location*: D Lounge

Crab Races. | *Never* ○○○○○ *Won't miss*

Description: Watch some local sea creatures make a break for the finish line.

Available: Day 7, 12:30-13:00, *Location*: Island Gazebo 1

Available: Day 7, 13:15-13:45, *Location*: Island Gazebo 2

Crafts: 3D Crafts. | *Never* ○○○○○ *Won't miss*

Available: Day 6, 13:00-13:30, *Location*: La Piazza

Crafts: Door Hangers. | *Never* ○○○○○ *Won't miss*

Available: Day 2, 11:15-12:00, *Location*: La Piazza

Available: Day 4, 11:30-12:15, *Location*: La Piazza

Crafts: Memory Pages. | *Never* ○○○○○ *Won't miss*

Available: Day 3, 11:45-12:30, *Location*: O'Gills Pub

Available: Day 6, 16:00-16:45, *Location*: D Lounge

Crafts: Origami Favorites. | *Never* ○○○○○ *Won't miss*

Available: Day 6, 10:30-11:00, *Location*: La Piazza

Crafts: Origami Flowers. | *Never* ○○○○○ *Won't miss*

Available: Day 2, 16:15-17:00, *Location*: La Piazza

Crafts: Origami Frogs. | *Never* ○○○○○ *Won't miss*

Available: Day 3, 13:45-14:15, *Location*: La Piazza

Available: Day 3, 13:15-13:45, *Location*: La Piazza

Available: Day 6, 09:00-09:30, *Location*: La Piazza

Crafts: Paper Plane Making. | *Never* ○○○○○ *Won't miss*

Available: Day 3, 14:15-15:00, *Location*: La Piazza

Cruisin' for Trivia. | *Never* ○○○○○ *Won't miss*

Description: Navigate your way through a round of questions testing your general knowledge.

Available: Day 4, 14:45-15:15, *Location*: La Piazza

Diamond and Gemstone Seminar. | *Never* ○○○○○ *Won't miss*

Description: Join your Port and Shopping Guides, and become an educated shopper. They will teach you about the exotic gemstones found in the Caribbeans. FREE Tanzanite earrings for all who attend and a raffle to win a gemstone pendant!

Available: Day 3, 15:00-15:45, *Location*: The Tube

Disney Animation: Cartoon Physics. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Go behind the scenes at Walt Disney Animation Studio and see how flat drawings and pencil lines can come to life through basic techniques such as "Stretch and Squash", and create your own "bouncing ball" animation exercise in this entertaining and fun enrichment program.

Available: Day 3, 09:45-10:30, *Location*: D Lounge

Disney Animation: Creating a Character. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Go behind the scenes at Walt Disney Animation Studios as Walt Disney himself talks about his most famous characters, then learn the basic techniques of drawing Mickey and Donald in this fun and interesting enrichment program.

Available: Day 2, 09:45-10:30, *Location*: D Lounge

Disney Animation: Staging a Scene. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Go behind the scenes at Walt Disney Animation Studios and learn how basis poses, silhouette, and placement (long shot, medium shot, close-up) enhance animation storytelling. Then, participate in a drawing exercise where you make the choice to communicate a story in this fun and fascinating enrichment program.

Available: Day 5, 16:00-16:45, *Location*: D Lounge

Disney Castaway Cay 5k. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Your run will now take place on Deck 4 around the Disney Fantasy. We will be straggering the start times every half hour between 8:00 a.m. and 9:30 a.m. Feel free to meet in The Tube, Deck 4 Aft at any one of the following times to begin your run: 8:00, 8:30, 9:00, or 9:30 a.m.

Available: Day 7, 08:00-09:30, *Location*: The Tube

Disney Cruise Line: An Unforgettable Journey. Event of the Day.

| *Never* ○○○○○ *Won't miss*

Description: Join us tonight as we celebrate our magical voyage, inspired by the words and wisdom of the man himself, Walt Disney; featuring the Walt Disney Theatre cast, World Famous Disney Characters and the Comedy

Magic of Magic Dave.

Available: Day 7, 18:15-19:00, *Location*: Walt Disney Theatre

Available: Day 7, 20:30-21:30, *Location*: Walt Disney Theatre

Disney Junior Pirate

Princess Dance Party. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Calling all Pirates and Princesses! Come join us for a family dance party featuring music and fun activities from Jake & the Neverland Pirates and Sofia the First. Whether you favor tiaras or treasure chests, there's something for you at our Disney Junior Pirate & Princess Dance Party. Sofia and Jake will be there - come join them for the fun!

Available: Day 4, 17:00-17:30, *Location*: D Lounge

Disney Trivia. | *Never* ○○○○○ *Won't miss*

Available: Day 2, 10:30-11:00, *Location*: La Piazza

Available: Day 2, 13:15-13:45, *Location*: La Piazza

Available: Day 3, 09:30-10:00, *Location*: La Piazza

Available: Day 3, 16:30-17:00, *Location*: O'Gills Pub

Available: Day 6, 12:00-12:30, *Location*: La Piazza

Available: Day 7, 09:45-10:15, *Location*: D Lounge

Disney Tunes Trivia. | *Never* ○○○○○ *Won't miss*

Available: Day 2, 15:00-15:45, *Location*: La Piazza

Available: Day 6, 15:00-15:30, *Location*: La Piazza

Disney Vacation Club: Group Preview. | *Never* ○○○○○ *Won't miss*

Description: Want to learn more about taking magical vacations year after year? Please see a Disney Vacation Club representative on Deck 4, Midship, or call 7-2805 from your stateroom phone for more information about our interactive group presentation.

Available: Day 2, 12:30-13:15, *Location*: D Lounge
Available: Day 3, 12:30-13:15, *Location*: D Lounge
Available: Day 6, 12:30-13:15, *Location*: D Lounge
Disney Vacation Club: Members Celebration. | *Never* ○○○○○ *Won't miss*
Description: Calling all Disney Vacation Club Members to our exclusive gathering.
Available: Day 1, 14:30-15:15, *Location*: D Lounge
Disney Wishes. Event of the Day. | *Never* ○○○○○ *Won't miss*
Description: On the eve of their graduation, three best friends go on a magical journey down the wishing well. A host of Disney characters help them discover the connection between children who are becoming adults, and adults who stay in touch with being a kid at heart.
Available: Day 3, 20:30-21:30, *Location*: Walt Disney Theatre
Available: Day 3, 18:15-19:15, *Location*: Walt Disney Theatre
Disney's Aladdin: Musical Spectacular. Event of the Day. | *Never* ○○○○○ *Won't miss*
Description: A fast-paced, musical comedy based on the beloved animated film. Aladdin, the "street rat" of Agrabah, meets a wise-cracking Genie, battles the evil Jafar, and falls in love with the beautiful and spirited Princess Jasmine. Disney storytelling at its best.
Available: Day 2, 20:30-21:30, *Location*: Walt Disney Theatre
Available: Day 2, 18:15-19:00, *Location*: Walt Disney Theatre
Disney's Believe. Event of the Day. | *Never* ○○○○○ *Won't miss*
Description: Genie from Aladdin and many of Disney's most beloved magic makers take a father on a magical journey to show him that anything is possible if you just believe.
Available: Day 6, 18:15-19:00, *Location*: Walt Disney Theatre
Available: Day 6, 20:30-21:30, *Location*: Walt Disney Theatre
Disney's Family Fusion. | *Never* ○○○○○ *Won't miss*
Description: Bring the entire family and test your Disney knowledge in the high-tech interactive game-show, Family Fusion.
Available: Day 3, 19:30-20:00, *Location*: D Lounge

Available: Day 3, 22:15-22:45, *Location*: D Lounge
Family Crafts. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 16:15-19:00, *Location*: D Lounge
Available: Day 5, 20:30-21:15, *Location*: D Lounge
Available: Day 6, 09:45-10:30, *Location*: La Piazza
Available: Day 7, 15:30-16:15, *Location*: La Piazza
Family Dance Party. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 19:15-20:15, *Location*: The Tube
Available: Day 2, 19:00-19:30, *Location*: The Tube
Available: Day 3, 19:15-20:15, *Location*: The Tube
Available: Day 5, 19:00-19:30, *Location*: The Tube
Available: Day 7, 19:00-20:15, *Location*: The Tube
Available: Day 7, 21:45-22:30, *Location*: D Lounge
Family Karaoke. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff in D Lounge tonight and sing along to your favourite song - fun for everyone.
Available: Day 1, 22:30-23:30, *Location*: D Lounge
Available: Day 2, 22:30-23:30, *Location*: D Lounge
Available: Day 3, 21:30-22:15, *Location*: D Lounge
Available: Day 3, 22:45-23:30, *Location*: D Lounge
Available: Day 5, 21:30-22:15, *Location*: D Lounge
Available: Day 5, 22:45-23:45, *Location*: D Lounge
Family Superstar Karaoke. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff in D Lounge tonight and sing along to your favourite song - fun for everyone.
Available: Day 7, 22:30-23:45, *Location*: D Lounge
Family Talent Show. | *Never* ○○○○○ *Won't miss*
Description: Our families have been rehearsing and are now ready to show-case their talents. Help them make their performing dreams come true by becoming a part of our live studio audience at the Family Talent Show!
Available: Day 7, 19:30-20:15, *Location*: D Lounge
Family Whale Dig. | *Never* ○○○○○ *Won't miss*

Description: Our island palaeontologist leads us in the excavation of a giant whale skeleton and other fossilized treasures! Make no bones about it, this is an adventure every beachcomber is sure to dig!
Available: Day 7, 13:00-13:45, *Location*: Monstro Point
Father's Day Crafts. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff to make some fun Father's Day crafts for that special male in your life.
Available: Day 2, 09:45-10:30, *Location*: La Piazza
FireLites Live. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 22:30-23:00, *Location*: Lobby Atrium
Available: Day 3, 22:30-23:00, *Location*: Lobby Atrium
Available: Day 5, 22:30-23:00, *Location*: Lobby Atrium
Formal Portraits tonight!. | *Never* ○○○○○ *Won't miss*
Description: Now that the family is dressed up and ready to enjoy the evening, capture the memories in your formal attire by visiting our professional portrait studios located in the Lobby Atrium, Deck 3, Midship.
Available: Day 2, 17:00-18:00, *Location*: Lobby Atrium
Available: Day 2, 19:15-20:30, *Location*: Lobby Atrium
Available: Day 2, 21:30-22:30, *Location*: Lobby Atrium
Inside Out (PG). Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Meet the little voices inside your head.
Available: Day 3, 14:00-15:42, *Location*: Walt Disney Theatre
Available: Day 4, 17:30-19:12, *Location*: Walt Disney Theatre
Available: Day 4, 20:15-21:57, *Location*: Walt Disney Theatre
Available: Day 6, 14:00-15:42, *Location*: Walt Disney Theatre
Available: Day 7, 10:00-11:42, *Location*: Walt Disney Theatre
Interdenominational Service. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 09:30-10:00, *Location*: Outlook
Jack-Jack's Diaper Dash. Reservation required. | *Never* ○○○○○ *Won't miss*
Description: Calling all baby cruisers! It's time to take to the mat to see who's the fastest crawler of the seven seas! Register your baby 15

minutes prior to the big race
Available: Day 6, 11:30-12:00, *Location*: Lobby Atrium
Jake & The Neverland Pirates. | *Never* ○○○○○ *Won't miss*
Description: A'Hoy there mates, join us for an adventure in D Lounge with Jake and the Netherland Pirates.
Available: Day 6, 08:30-09:00, *Location*: D Lounge
Available: Day 7, 09:00-09:30, *Location*: D Lounge
Jewish Sabbath. | *Never* ○○○○○ *Won't miss*
Description: A quiet space is reserved for those wishing to conduct their own service.
Available: Day 7, 17:15-17:45, *Location*: Outlook
Live Guitar with Carrie Stone. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 15:00-15:45, *Location*: Deck 12, Stage.
Available: Day 5, 15:00-15:45, *Location*: Deck 12, Stage.
Available: Day 6, 15:00-15:45, *Location*: Deck 12, Stage.
Available: Day 7, 12:45-13:30, *Location*: Island Gazebo 1
Available: Day 7, 13:45-14:30, *Location*: Island Gazebo 1
Live Music with Andrea Rafaela. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 17:00-18:00, *Location*: Lobby Atrium
Available: Day 2, 21:30-22:15, *Location*: Lobby Atrium
Available: Day 6, 17:15-18:00, *Location*: Lobby Atrium
Available: Day 6, 21:30-22:15, *Location*: Lobby Atrium
Live Music with FireLites. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 21:30-22:15, *Location*: Lobby Atrium
Available: Day 3, 21:30-22:15, *Location*: Lobby Atrium
Available: Day 3, 17:15-18:00, *Location*: Lobby Atrium
Available: Day 5, 17:15-18:00, *Location*: Lobby Atrium
Available: Day 5, 21:30-22:15, *Location*: Lobby Atrium
Available: Day 7, 17:15-18:00, *Location*: Lobby Atrium
Live Music with Rob Sanders. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 17:15-18:00, *Location*: La Piazza
Magic PlayFloor. | *Never* ○○○○○ *Won't miss*

Available: Day 5, 11:15-11:45, *Location*: Oceaneer Club
Magic Workshop. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Magic Dave teaches you the basics of magic in this fun family event.
Available: Day 6, 10:00-10:30, *Location*: D Lounge
Available: Day 7, 10:30-11:00, *Location*: D Lounge
Mandatory Life Boat Drill. | *Never* ○○○○○ *Won't miss*
Description: (All Guests must attend) You will not need to wear your life jacket, however it is critical that your bring your Key To The World card to your Assembly Station. All ship services will be suspended between 3:45 and 4:30 pm. Your Assembly Station is indicated on your Key To The World card
Available: Day 1, 16:00-16:30, *Location*: Assembly Station
Mickey 200. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Don't eat your vegetables... race them in this wild and wacky charge to the finish line. May the best veggie win! (Limited Availability)
Available: Day 2, 14:15-15:00, *Location*: The Tube
Mickey's Pirates in the Caribbean. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: It's a Pirate Celebration, me hearties! Come experience all the pirate fun alongside Captain Mickey Mouse and his famous pirate crew. Play, dance and acquire all the pirate skills needed to become an official member of Mickey's Pirate Crew! (Weather Permitting)
Available: Day 4, 19:45-20:15, *Location*: Deck Stage
Mirror Mirror. | *Never* ○○○○○ *Won't miss*
Description: Head to D Lounge for the fairest game show of them all, Mirror Mirror. Featuring the Magic Mirror and everyone's favorite dwarf, Dopey.
Available: Day 6, 19:30-20:00, *Location*: D Lounge
Available: Day 6, 21:45-22:15, *Location*: D Lounge
Officer Pin Trading. Don't Miss Event. | *Never* ○○○○○ *Won't miss*

Description: Come trade pins with the Officers of the Disney Fantasy.
Available: Day 5, 19:15-20:00, *Location*: Preludes
Open House Toddler Time. | *Never* ○○○○○ *Won't miss*
Description: Your chance to see our toddler space, it's a small nursery
Available: Day 2, 08:00-09:00, *Location*: Open House
Available: Day 3, 08:00-09:00, *Location*: It's a small world nursery
Available: Day 6, 08:00-09:00, *Location*: It's a small world nursery
Pictionary Challenge. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 12:15-12:45, *Location*: La Piazza
Available: Day 4, 14:00-14:30, *Location*: La Piazza
Pirate Crafts. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 15:30-16:30, *Location*: D Lounge
Pirate Games. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Arrgh ye up to the challenge some crazy pirate themed games?
Available: Day 4, 19:30-19:45, *Location*: Deck Stage
Pirate Trivia. | *Never* ○○○○○ *Won't miss*
Description: Test the depths of your pirate knowledge with your Cruise Staff at this swashbuckling trivia event.
Available: Day 4, 16:15-16:45, *Location*: D Lounge
Available: Day 4, 20:30-21:00, *Location*: Preludes
Poolside Jams with Cruise Staff DJ. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 13:45-15:15, *Location*: Deck 11 Stage
Professional Portraits. | *Never* ○○○○○ *Won't miss*
Description: Tonight is your last chance for professional portraits! Capture the magic of your vacation at one of our portrait studios and let the memories live. Visit our professional portrait studios located in the Lobby Atrium, Deck 3, Midship
Available: Day 6, 17:00-18:00, *Location*: Lobby Atrium
Available: Day 6, 19:15-20:30, *Location*: Lobby Atrium
Available: Day 6, 21:30-22:30, *Location*: Lobby Atrium
Rob Sanders LIVE. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 22:30-23:00, *Location*: Lobby Atrium

Available: Day 4, 19:00-19:30, *Location*: Lobby Atrium
Available: Day 6, 17:30-18:00, *Location*: La Piazza
Available: Day 7, 22:45-23:15, *Location*: Lobby Atrium
Sailing Away. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: It's time to go Sailing Away! Join Mickey and Minnie along with Tinker Bell and the rest of the gang as they welcome you abroad the Disney Fantasy.
Available: Day 1, 16:30-17:15, *Location*: Deck Stage
Saludos Amigos Fiesta. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Come see what Donald and his friends are up to this time. Bring the family out to this interactive dance party featuring fun Latin music! Your family will learn to salsa, merengue and just have a Latin good time!
Available: Day 5, 22:15-22:45, *Location*: D Lounge
Sea Ya' Real Soon!. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Mickey and Minnie along with the rest of the Walt Disney Characters invite you to join them in the ship's atrium for Sea Ya Real Soon. You won't ant to miss this very special farewell presentation.
Available: Day 7, 16:30-17:00, *Location*: Lobby Atrium
Available: Day 7, 22:15-22:45, *Location*: Lobby Atrium
So You Think You Know Your Family?. | *Never* ○○○○○ *Won't miss*
Description: This fun-filled family game show is always full of surprises. Find out how well you know, or don't know your family!
Available: Day 1, 19:30-20:15, *Location*: D Lounge
Available: Day 1, 21:45-22:30, *Location*: D Lounge
Talent Show Rehearsals. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 17:00-18:00, *Location*: D Lounge
The Comedy & Hypnosis of Ricky Kalmon. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Enjoy the Comedy and Hypnosis of Ricky Kalmon in this

fun-filled show for the entire family.
Available: Day 2, 14:00-14:45, *Location*: Walt Disney Theatre
The Disney Fantasy's Whistle. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: The Disney Fantasy's whistle, a prominent element of the "Sailing Away" deck party at the start of the cruise, is quite the musical talent. It's able to perform not just the fast musical line of "When You Wish Upon a Star" but also the second line of the song ("makes no difference who you are") plus several measures of "Yo Ho (A Pirate's Life for Me)", "It's a Small World", "Be Our Guest", "Hi Diddle Dee Dee (An Actor's Life for Me)" and "A Dream is a Wish".
Available: Day 7, 17:30-17:45, *Location*: Deck 12
The Magic Dave Show. Event of the Day. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 18:15-19:00, *Location*: Walt Disney Theatre
Available: Day 5, 20:30-21:15, *Location*: Walt Disney Theatre
The Muppets. | *Never* ○○○○○ *Won't miss*
Description: There's Muppet mystery onboard, and Kermit and Pepe need YOU to solve it! Search the ship for clues and use our special detective "badge" to catch the culprit!
Available: Day 7, 09:00-22:00, *Location*: Deck 2
The Quest. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Enjoy the wildes and wackiest scavenger team event on the seven seas!
Available: Day 5, 19:30-20:00, *Location*: The Tube
Toddler Time. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 15:00-16:45, *Location*: Outlook
Available: Day 6, 10:00-11:00, *Location*: Outlook
Available: Day 6, 14:00-15:00, *Location*: Outlook
Towel Folding. | *Never* ○○○○○ *Won't miss*
Description: Learn to create those amazing towel creatures you've seen your stateroom all cruise long.
Available: Day 6, 14:00-14:30, *Location*: The Tube

Variety: David Crone. | *Never* ○○○○○ *Won't miss*
Description: Featuring the Comedy
Ventriloquism of David Crone for Families and Adults
Available: Day 2, 19:30-20:00, *Location*: The Tube
Variety: Michael Dubois. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 19:30-20:00, *Location*: The Tube
Wake Up with Disney Junior. | *Never* ○○○○○ *Won't miss*
Description: What happens when you experience unlimited fun with your favorite Disney Junior shows? You get an exciting dance party designed especially for preschoolers ages seven and under.
Available: Day 2, 08:30-09:00, *Location*: D Lounge
Available: Day 3, 09:00-09:30, *Location*: D Lounge
Available: Day 7, 08:30-09:00, *Location*: D Lounge
Walking Ship Tour. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Enjoy the beauty of the Disney Fantasy with your Cruise Staff in the guided tour.
Available: Day 1, 13:00-13:30, *Location*: Preludes
Available: Day 1, 14:00-14:30, *Location*: Preludes
Available: Day 2, 09:00-09:30, *Location*: Preludes
Xbox Challenge. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 09:00-09:30, *Location*: O'Gills Pub
Xbox Kinect Just Dance Challenge. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 14:00-14:45, *Location*: O'Gills Pub
Youth Activities Open House. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 09:00-10:00, *Location*: Edge
Available: Day 4, 10:00-13:45, *Location*: Oceaneer Club
Available: Day 5, 09:00-11:00, *Location*: Edge
Available: Day 4, 11:00-12:00, *Location*: Vibe
Available: Day 7, 13:45-16:00, *Location*: Oceaneer Club

Scuttle's Cove

Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

Lunch at Pop's Props. | *Never* ○○○○○ *Won't miss*
Available: Day7, 12:00-12:30, *Location*: Scuttle's Cove
Island Crafts. | *Never* ○○○○○ *Won't miss*
Available: Day7, 12:45-13:30, *Location*: Scuttle's Cove
Caribbean Beach Party. | *Never* ○○○○○ *Won't miss*
Available: Day7, 13:45-14:45, *Location*: Scuttle's Cove
Water Games. | *Never* ○○○○○ *Won't miss*
Available: Day7, 15:00-15:30, *Location*: Scuttle's Cove
Whale Dig. | *Never* ○○○○○ *Won't miss*
Available: Day7, 15:45-16:45, *Location*: Scuttle's Cove

Adults

Please, for the activities listed below select one of the grade: 1 - Never (not interested at all and won't recommend to anyone to attend it); 2 - Not interested; 3 - Neutral; 4 - Interested; 5 - Won't miss

1820 Society: Brunch. | *Never* ○○○○○ *Won't miss*
Description: Get to know your fellow 1820 Society members during brunch.
Available: Day 6, 11:30-12:00, *Location*: Cabanas
1820 Society: Farewell. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff and your new friends in this last gathering for some fun.
Available: Day 7, 22:00-22:30, *Location*: The Tube
1820 Society: Game Challenge. | *Never* ○○○○○ *Won't miss*
Description: Join us and play some of your favorite board games.
Available: Day 2, 21:45-22:15, *Location*: O'Gills Pub
Available: Day 3, 17:00-17:45, *Location*: O'Gills Pub

Available: Day 3, 21:45-22:15, *Location*: O'Gills Pub
Available: Day 6, 21:45-22:15, *Location*: O'Gills Pub
1820 Society: Giant Jenga. | *Never* ○○○○○ *Won't miss*
Description: Have some fun with this classic game
Available: Day 5, 16:15-16:45, *Location*: O'Gills Pub
1820 Society: Ice Cream Social. | *Never* ○○○○○ *Won't miss*
Description: Join your fellow Society members for some ice cream and conversation.
Available: Day 4, 16:00-16:30, *Location*: Cove Café
1820 Society: Island Bike Ride. | *Never* ○○○○○ *Won't miss*
Description: Join your Cruise Staff team as they take you on a bike riding adventure around the island. Meet at the Bike Rentals where the fun will begin!
Available: Day 7, 13:00-13:45, *Location*: Bike Rentals
1820 Society: Lunch. | *Never* ○○○○○ *Won't miss*
Description: Get to know your fellow Society members over a spot of lunch.
Available: Day 2, 12:15-12:45, *Location*: Royal Court
Available: Day 3, 12:15-12:45, *Location*: Royal Court
1820 Society: Mini Golf. | *Never* ○○○○○ *Won't miss*
Description: Can you get a hole in one? Give it a try with some mini golf.
Available: Day 2, 15:15-15:45, *Location*: Goofy Golf
1820 Society: Stir it. Blend it. Taste it.. | *Never* ○○○○○ *Won't miss*
Description: Join us for complimentary tasting event including coffee, chai latte and smoothies in Cove Café exclusively for our 18-20 year olds. You can learn how to create your own special coffees as well as plan the activities for the rest of your sailing.
Available: Day 1, 20:00-22:30, *Location*: Cove Café
50's and 60's Music Trivia. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 10:45-11:15, *Location*: O'Gills Pub
70's Music Trivia. | *Never* ○○○○○ *Won't miss*

Description: Let's step back in time and visit Studio 54 as we test your 70's music knowledge.
Available: Day 3, 13:45-14:15, *Location*: O'Gills Pub
70's Remix. | *Never* ○○○○○ *Won't miss*
Description: Join Club DJ Mike Sincere, as he takes you back and remixes 70's hits to keep you dancing.
Available: Day 3, 23:45-00:15, *Location*: The Tube
80's 90's Remix with Club DJ Mike Sincere. | *Never* ○○○○○ *Won't miss*
Description: Join Club DJ Mike Sincere, as he spins the tunes and remix the 80's & 90's!
Available: Day 2, 23:15-00:15, *Location*: The Tube
80's Music Challenge. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: "Moon Walk" back to the 80's as we put your musical knowledge of the decade to the test.
Available: Day 5, 22:30-23:00, *Location*: The Tube
90's Music Trivia. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 14:00-14:30, *Location*: O'Gills Pub
Acupuncture Clinic. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 13:15-13:45, *Location*: Senses Spa & Salon
Acupuncture Demonstration . | *Never* ○○○○○ *Won't miss*
Available: Day 1, 14:00-15:00, *Location*: Senses Spa & Salon
Acupuncture Seminar. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 10:15-10:45, *Location*: Senses Spa & Salon
Acupuncture Seminar Asthma & Allergy Management. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 09:15-09:45, *Location*: Senses Spa & Salon
Acupuncture Seminar: Artritis Solutions. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 09:15-10:00, *Location*: Senses Fitness Center
Acupuncture Stress, Insomnia and Depression. | *Never* ○○○○○ *Won't miss*

Available: Day 3, 15:15-16:00, *Location*: Senses Spa & Salon
Acupuncture: Artbritis and Back Pain Solutions. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 15:15-15:45, *Location*: Senses Spa & Salon
Adult Trivia. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 20:45-21:15, *Location*: O'Gills Pub
Available: Day 5, 13:15-13:45, *Location*: O'Gills Pub
Andrea & Rafaela LIVE. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 23:30-00:00, *Location*: La Piazza
Available: Day 5, 21:30-22:00, *Location*: La Piazza
Available: Day 5, 23:30-00:00, *Location*: La Piazza
Anyone Can Cook: Lobster Ravioli. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: From our galley to yours. Join our chefs as they show you how to prepare delicious dishes. Today's Menu - Lobster Ravioli
Available: Day 2, 14:15-15:00, *Location*: D Lounge
Anyone Can Cook: Sea Bass. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 14:15-15:00, *Location*: D Lounge
Art of The Theme Show Tour. | *Never* ○○○○○ *Won't miss*
Description: Join us for a guided tour highlighting the design, Imagineering and artistry of the Disney Fantasy. This tour is reserved for Guests 18 and over.
Available: Day 2, 09:15-10:15, *Location*: Meridian
Available: Day 3, 09:15-10:15, *Location*: Meridian
Available: Day 5, 14:30-15:30, *Location*: Meridian
Available: Day 6, 09:15-10:15, *Location*: Meridian
Beer Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 16:30-17:30, *Location*: O'Gills Pub
Body's Sculpt Boot Camp. Nominal fee. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 09:00-09:30, *Location*: Senses Fitness Center
Available: Day 3, 09:00-09:45, *Location*: Senses Fitness Center

Available: Day 6, 09:00-09:30, *Location*: Senses Fitness Center
Available: Day 7, 07:30-08:00, *Location*: Senses Fitness Center
Books and Magazines available in Cove Café. | *Never* ○○○○○ *Won't miss*
Available: Day 7, 09:00-11:00, *Location*: Cove Café
Burn Fat Faster. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 16:00-16:30, *Location*: Senses Spa & Salon
Carrie Stone Live. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 18:45-19:00, *Location*: Deck 12, Stage.
Available: Day 4, 19:00-19:30, *Location*: Deck 12, Stage.
Champagne Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 12:15-13:00, *Location*: Ooh La La
Available: Day 6, 13:45-14:15, *Location*: Ooh La La
Chinese Herbs. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 13:15-13:45, *Location*: Senses Spa & Salon
Chocolate & Liquor Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 12:15-13:30, *Location*: Ooh La La
Available: Day 6, 12:15-12:45, *Location*: Ooh La La
Club DJ Mike Sincere. | *Never* ○○○○○ *Won't miss*
Description: DJ Mike Sincere, a Los Angeles native, has been DJing professionally for audiences all over the world. He's spun for companies such as Nike, H&Mm Forever 21, Adidas, G by Guess, Microsoft and the Espy's. Mike has played for celebrities such as Russell Simmons, Missy Elliot, DMC of Run DMC, Estelle and UFC Heavy weight Champion Kane Velasquez. Outside of the Corporate World he is a regular on the Nightclub circuit in Hollywood, Orange Country, Las Vegas and even Hawaii. Mike Sincere's favorite ride at Disneyland is Space Mountain and his favorite Disney character is Mickey Mouse.
Available: Day 1, 21:30-22:00, *Location*: The Tube
Available: Day 1, 23:15-00:15, *Location*: The Tube
Available: Day 2, 21:30-22:15, *Location*: The Tube

Available: Day 3, 21:30-22:15, *Location*: The Tube
Available: Day 6, 21:30-22:15, *Location*: The Tube
Available: Day 6, 23:30-00:15, *Location*: The Tube
Cognac Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 22:00-23:00, *Location*: Cove Café
Available: Day 3, 22:30-23:15, *Location*: Meridian
Complimentary Footprint Analysis. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 17:00-17:45, *Location*: Senses Spa & Salon
Crafts: Origami Creations. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 11:15-11:45, *Location*: O'Gills Pub
Crafts: Tile Coasters. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 09:45-10:15, *Location*: O'Gills Pub
Cruise Staff DJ. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 23:30-00:15, *Location*: The Tube
Detox for Health & Weight Loss. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 11:00-11:30, *Location*: Senses Spa & Salon
Available: Day 6, 14:00-14:30, *Location*: Senses Spa & Salon
Digestive Management Seminar. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 16:30-17:00, *Location*: Senses Fitness Center
Available: Day 7, 16:15-17:00, *Location*: Senses Spa & Salon
Disney Vacation Club: Group Preview. | *Never* ○○○○○ *Won't miss*
Description: Want to learn more about taking magical vacations year after year? Please see a Disney Vacation Club representative on Deck 4, Midship, or call 7-2805 from your stateroom phone for more information about our interactive group presentation.
Available: Day 3, 16:15-17:00, *Location*: D Lounge
Disney's Behind the Scenes: Frank Paris. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Disney Springs is the newest one-of-a-kind shopping, dining and entertainment experience at Walt Disney World. Frank will share some of the wonderful and exciting experiences that will await

you in the years to come.
Available: Day 6, 14:00-15:00, *Location*: Buena Vista Theatre
DJ Requests. | *Never* ○○○○○ *Won't miss*
Available: Day 5, 21:30-22:00, *Location*: The Tube
Available: Day 7, 21:30-22:15, *Location*: The Tube
Eat More to Weigh Less. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 14:00-14:45, *Location*: Senses Spa & Salon
ESPN Dream Team Draft Day - Baseball. | *Never* ○○○○○ *Won't miss*
Description: Play ball! Join the "Commissioner" and engage in this interactive fantasy baseball unlike anything you've ever seen! Can YOU draft the greatest baseball team of all time?
Available: Day 6, 09:45-10:30, *Location*: O'Gills Pub
ESPN Dream Team Draft Day - Basketball. | *Never* ○○○○○ *Won't miss*
Description: Join the "Commissioner" and engage in this interactive fantasy basketball draft unlike anything you've ever seen! Can YOU draft the greatest basketball team of all-time?
Available: Day 5, 17:30-18:15, *Location*: O'Gills Pub
ESPN Dream Team Draft Day - Football. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 11:30-12:15, *Location*: O'Gills Pub
Fab Abs. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 07:45-08:15, *Location*: Senses Fitness Center
Available: Day 3, 07:45-08:30, *Location*: Senses Fitness Center
Available: Day 4, 08:30-09:00, *Location*: Senses Spa & Salon
Available: Day 5, 08:30-09:00, *Location*: Senses Fitness Center
Available: Day 6, 07:45-08:15, *Location*: Senses Fitness Center
Available: Day 7, 08:30-09:00, *Location*: Senses Fitness Center
FireLites LIVE. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 23:30-00:00, *Location*: La Piazza
Footprint Analysis. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 17:15-17:45, *Location*: Senses Spa & Salon

Available: Day 2, 17:00-17:30, *Location*: Senses Spa & Salon
Available: Day 4, 16:00-16:30, *Location*: Senses Spa & Salon
Available: Day 6, 08:30-09:00, *Location*: Senses Spa & Salon
Available: Day 6, 17:00-17:30, *Location*: Senses Spa & Salon
Available: Day 7, 17:00-17:30, *Location*: Senses Spa & Salon
Friends of Bill W.. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 08:30-09:00, *Location*: Outlook
Available: Day 3, 08:30-09:00, *Location*: Outlook
Available: Day 4, 08:30-09:00, *Location*: Outlook
Available: Day 5, 08:30-09:00, *Location*: Outlook
Available: Day 6, 08:30-09:00, *Location*: Outlook
Available: Day 7, 08:30-09:00, *Location*: Outlook
Good Feet Seminar: Walking In Comfort. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 14:00-14:30, *Location*: Senses Fitness Center
Group Cycling. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 16:00-16:30, *Location*: Senses Fitness Center
Available: Day 3, 16:00-16:45, *Location*: Senses Fitness Center
Available: Day 6, 16:00-16:30, *Location*: Senses Fitness Center
How to Increase Your Metabolism. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 11:00-11:45, *Location*: Senses Spa & Salon
Hypnosis Seminar with Ricky Kalmon. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Hypnotist Ricky Kalmon will reveal the secrets of losing weight and reducing stress with the use of self-hypnosis.
Available: Day 3, 11:00-12:00, *Location*: Buena Vista Theatre
Ice Breakers. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 22:15-22:45, *Location*: The Tube
Available: Day 7, 22:15-22:45, *Location*: The Tube
Introduction to Acupuncture. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 10:15-10:45, *Location*: Senses Spa & Salon
Italian Cocktails Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*

Available: Day 3, 16:15-17:00, *Location*: La Piazza
Available: Day 6, 16:15-16:45, *Location*: La Piazza
Know It All Trivia. | *Never* ○○○○○ *Won't miss*
Description: Do you think you know it all? Put yourself to the test as your Club Host, pushes the limits of your knowledge at Know It All Trivia.
Available: Day 3, 12:30-13:00, *Location*: O'Gills Pub
Available: Day 3, 20:30-21:00, *Location*: O'Gills Pub
Available: Day 3, 18:30-19:00, *Location*: O'Gills Pub
Krazy Karaoke followed Club DJ Mike Sincere. | *Never* ○○○○○ *Won't miss*
Description: Take to the stage, grab a microphone and sing your favorite tunes with your Club Host and Cruise Staff DJ.
Available: Day 4, 23:00-00:15, *Location*: The Tube
Live Guitar with Carrie Stone. | *Never* ○○○○○ *Won't miss*
Description: Join Carrie Stone as she plays live guitar for your listening pleasure.
Available: Day 4, 21:30-22:15, *Location*: Deck 12, Stage.
Available: Day 5, 19:30-20:15, *Location*: O'Gills Pub
Live Music with Andrea & Rafaela. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 19:30-20:15, *Location*: La Piazza
Available: Day 1, 21:30-22:15, *Location*: La Piazza
Available: Day 3, 19:30-20:15, *Location*: La Piazza
Available: Day 5, 19:30-20:15, *Location*: La Piazza
Available: Day 7, 19:30-20:15, *Location*: La Piazza
Live Music with FireLites. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 19:30-20:15, *Location*: La Piazza
Available: Day 6, 19:30-20:15, *Location*: La Piazza
Available: Day 7, 11:00-11:45, *Location*: Deck 12
Live Music with Rob Sanders. | *Never* ○○○○○ *Won't miss*
Description: Join Rob Sanders as he plays live for your listening pleasure.
Available: Day 4, 21:30-22:15, *Location*: La Piazza

Available: Day 7, 20:30-21:15, *Location*: La Piazza

London Rocks!. | *Never* ○○○○○*Won't miss*

Description: Hop onboard and hit the dance floor as we take you on a ride through the charts, partying it up to some of the hottest British hits!

Available: Day 5, 23:00-23:30, *Location*: The Tube

Majority Rules. | *Never* ○○○○○*Won't miss*

Description: Join your Club Host, to find out who really rules!

Available: Day 6, 22:15-22:45, *Location*: The Tube

Margarita Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○*Won't miss*

Available: Day 6, 16:30-17:00, *Location*: Ooh La La

Martini Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○*Won't miss*

Available: Day 2, 13:00-13:45, *Location*: Meridian

Available: Day 3, 13:00-13:45, *Location*: Meridian

Available: Day 6, 15:00-16:00, *Location*: Meridian

Match Your Mate. | *Never* ○○○○○*Won't miss Description*: It's time to play everyone's favourite couples game show, Match Your Mate!

Available: Day 1, 22:30-23:15, *Location*: The Tube

Mixology (21+). Nominal fee. Reservation required. | *Never* ○○○○○*Won't miss*

Available: Day 2, 15:00-16:00, *Location*: Meridian

Available: Day 2, 16:00-17:00, *Location*: Skyline

Available: Day 3, 16:00-16:45, *Location*: Skyline

Available: Day 6, 14:00-14:30, *Location*: Skyline

Available: Day 6, 16:00-16:30, *Location*: Skyline

Movie Quotes Trivia. | *Never* ○○○○○*Won't miss*

Available: Day 3, 10:30-11:15, *Location*: O'Gills Pub

Available: Day 6, 10:45-11:30, *Location*: O'Gills Pub

Pop!. | *Never* ○○○○○*Won't miss*

Description: Have you ever been told you are full of useless information about pop culture? If the answer is "Yes", then you have what it takes to

play the high energy game show all about the world of Pop!
Available: Day 5, 22:00-22:30, *Location*: The Tube
Pure Form Pilates. | *Never* ○○○○○ *Won't miss*
Available: Day 4, 17:00-17:30, *Location*: Senses Fitness Center
Available: Day 5, 17:00-17:30, *Location*: Senses Fitness Center
Rum Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 15:00-15:45, *Location*: Meridian
Available: Day 6, 13:00-13:30, *Location*: Meridian
Secrets to a Flatter Stomach. | *Never* ○○○○○ *Won't miss*
Available: Day 6, 11:00-11:30, *Location*: Senses Spa & Salon
Singles' Lunch. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 12:45-13:15, *Location*: Royal Court
Available: Day 3, 12:45-13:15, *Location*: Royal Court
Available: Day 6, 12:15-12:45, *Location*: Royal Court
Sophia Fiori Seminar. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 09:00-09:45, *Location*: The Tube
Spa Open House. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 13:45-15:00, *Location*: Senses Spa & Salon
Spa Raffle. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 15:00-15:30, *Location*: Senses Spa & Salon
Stem to Stern Wine Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 13:45-14:45, *Location*: Ooh La La
Available: Day 3, 13:45-14:30, *Location*: Ooh La La
Sunrise Stretch. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 07:00-07:30, *Location*: Donald's Pool
Available: Day 4, 07:00-07:30, *Location*: Senses Fitness Center
Available: Day 5, 07:00-07:30, *Location*: Senses Fitness Center
Available: Day 7, 07:00-07:30, *Location*: Donald's Pool
Team Trivia. | *Never* ○○○○○ *Won't miss*
Available: Day 3, 19:30-20:00, *Location*: O'Gills Pub
Available: Day 4, 19:45-20:15, *Location*: O'Gills Pub

Available: Day 6, 15:15-15:45, *Location*: O'Gills Pub
Available: Day 6, 18:30-19:00, *Location*: O'Gills Pub
Available: Day 6, 20:45-21:15, *Location*: O'Gills Pub
Tequila & Margarita Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 16:30-17:30, *Location*: Ooh La La
Available: Day 3, 16:30-17:15, *Location*: Ooh La La
The Comedy & Hypnosis of Ricky Kalmon. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Featuring the Comedy & Hypnosis of Ricky Kalmon, as he entertains you in this adult exclusive show.
Available: Day 3, 23:00-23:45, *Location*: Walt Disney Theatre
The Comedy & Jugging of Michael Dubois. | *Never* ○○○○○ *Won't miss*
Description: Featuring the Comedy & Juggling of Michael Dubois, as he entertains you in this adult exclusive show.
Available: Day 7, 22:45-23:15, *Location*: The Tube
The Comedy & Magic of David Williamson. Don't Miss Event. | *Never* ○○○○○ *Won't miss*
Description: Featuring the Comedy and Magic of David Williamson, as he entertains you in this adult exclusive show.
Available: Day 6, 23:00-23:30, *Location*: Walt Disney Theatre
The Comedy & Ventriloquism of David Crone. | *Never* ○○○○○ *Won't miss*
Description: Featuring the Comedy & Ventriloquism of David Crone for Families and Adults
Available: Day 2, 22:45-23:15, *Location*: The Tube
The Quest. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 22:15-22:45, *Location*: The Tube
Tongue & Pulse Analysis. | *Never* ○○○○○ *Won't miss*
Available: Day 1, 16:30-17:00, *Location*: Senses Spa & Salon
TV Tunes Trivia. | *Never* ○○○○○ *Won't miss*
Available: Day 2, 16:15-16:45, *Location*: O'Gills Pub

Available: Day 3, 15:45-16:15, *Location*: O'Gills Pub
Ultimate Disney Trivia. | *Never* ○○○○○*Won't miss*
Available: Day 6, 13:00-13:30, *Location*: O'Gills Pub
Walk in Acupuncture Digestive Management Seminar. | *Never* ○○○○○*Won't miss*
Available: Day 2, 09:00-09:30, *Location*: Senses Spa & Salon
Watch Seminar. | *Never* ○○○○○*Won't miss*
Available: Day 3, 11:45-12:15, *Location*: La Piazza
Whiskey Tasting (21+). Nominal fee. Reservation required. | *Never* ○○○○○*Won't miss*
Available: Day 2, 22:30-23:30, *Location*: Meridian
Available: Day 3, 22:00-22:45, *Location*: Cove Café
Yoga. | *Never* ○○○○○*Won't miss*
Available: Day 3, 07:00-07:45, *Location*: Donald's Pool
Available: Day 6, 07:00-07:30, *Location*: Donald's Pool
Yoga on the Beach. | *Never* ○○○○○*Won't miss*
Available: Day 7, 12:00-12:30, *Location*: Serenity Bay

Part III. ITINERARY PLANNER

In this part users are asked to organise the activities into a day-wise itinerary.

Day 1 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 20.06.2015
Weekday: Saturday
Sunrise: 06:25
Sunset: 20:21
Evening Attire: Cruise Casual
Port: Port Canaveral, Florida

Weather:
Today: Sunny
Tomorrow: Partly Sunny
Today High 86F 30C
Tomorrow High 84F 29C
Special Holiday Edition: No
Holiday: No

Event	Going	Not going
11:30 - 15:00. Character Meet & Greet Ticket Distribution . *Category*: Characters. *Location*: Port Adventures Desk. Don't Miss Event	☐	☐
13:00 - 13:30. Walking Ship Tour . *Category*: Fun for all ages. *Location*: Preludes. Don't Miss Event	☐	☐
13:45 - 15:15. Poolside Jams with Cruise Staff DJ . *Category*: Fun for all ages. *Location*: Deck 11 Stage	☐	☐
13:45 - 15:00. Spa Open House . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
14:00 - 14:30. Walking Ship Tour . *Category*: Fun for all ages. *Location*: Preludes. Don't Miss Event	☐	☐
14:00 - 15:00. Acupuncture Demonstration . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
14:30 - 15:15. Disney Vacation Club: Members Celebration . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
15:00 - 15:30. Spa Raffle . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
16:00 - 16:30. Mandatory Life Boat Drill . *Category*: Fun for all ages. *Location*: Assembly Station	☐	☐
16:30 - 17:15. Sailing Away . *Category*: Fun for all ages. *Location*: Deck Stage. Don't Miss Event	☐	☐
16:30 - 17:00. Tongue & Pulse Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
17:15 - 17:30. Mickey . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐

Event	Going	Not going
17:15 - 17:45. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
17:45 - 19:00. Tarzan. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
17:45 - 19:24. Strange Magic. *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
17:45 - 18:00. Minnie . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
18:15 - 19:00. A Fantasy Come True . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
19:15 - 19:30. Mickey . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
19:15 - 20:15. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:30 - 19:45. Tiana . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:30 - 20:15. So You Think You Know Your Family? . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:30 - 20:15. Live Music with Andrea & Rafaela . *Category*: Adults. *Location*: La Piazza	☐	☐
19:45 - 20:00. Minnie . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
20:00 - 21:15. Brother Bear. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:00 - 21:39. Strange Magic. *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:00 - 20:15. Cinderella . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐

Event	**Going**	**Not going**
20:00 - 22:30. 1820 Society: Stir it. Blend it. Taste it. . *Category*: Adults. *Location*: Cove Café	☐	☐
20:30 - 21:30. A Fantasy Come True . *Category*: Fun for all ages. *Location*: Walt Disney Theatre	☐	☐
21:30 - 21:45. Goofy . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
21:30 - 21:45. Cinderella . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
21:30 - 22:15. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:00. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
21:30 - 22:15. Live Music with Andrea & Rafaela . *Category*: Adults. *Location*: La Piazza	☐	☐
21:45 - 22:30. So You Think You Know Your Family? . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
22:00 - 23:45. The Princess and the Frog. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:00 - 22:15. Mickey . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
22:15 - 23:36. Monkey Kingdom. *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:30 - 23:30. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
22:30 - 23:00. FireLites Live . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:30 - 23:15. Match Your Mate . *Category*: Adults. *Location*: The Tube	☐	☐

Event	**Going**	**Not going**
23:15 - 00:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
23:30 - 00:00. Andrea & Rafaela LIVE . *Category*: Adults. *Location*: La Piazza	☐	☐

Day 2 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 21.06.2015
Weekday: Sunday
Sunrise: 06:14
Sunset: 19:44
Evening Attire: Formal
Port: At Sea

Weather:
Today: Partly Sunny
Tomorrow: Partly Sunny
Today High 84F 29C
Tomorrow High 82F 28C
Special Holiday Edition: No
Holiday: No

Event	**Going**	**Not going**
07:00 - 07:30. Sunrise Stretch . *Category*: Adults. *Location*: Donald's Pool	☐	☐
07:45 - 08:15. Fab Abs . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
08:00 - 09:00. Open House Toddler Time . *Category*: Fun for all ages. *Location*: Open House	☐	☐
08:30 - 10:15. Finding Nemo (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
08:30 - 10:18. Big Hero 6 (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐

Event	Going	Not going
08:30 - 09:00. Wake Up with Disney Junior . *Category*: Characters. *Location*: D Lounge	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
09:00 - 09:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:00 - 09:30. Walking Ship Tour . *Category*: Fun for all ages. *Location*: Preludes	☐	☐
09:00 - 09:30. Boot Camp . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
09:00 - 09:30. Walk in Acupuncture Digestive Management Seminar . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
09:15 - 09:30. Jessie . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:15 - 10:15. Art of The Theme Show Tour . *Category*: Adults. *Location*: Meridian	☐	☐
09:30 - 09:45. Pluto . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:30 - 10:00. Interdenominational Service . *Category*: Fun for all ages. *Location*: Outlook	☐	☐
09:45 - 10:00. Woody . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:45 - 10:30. Disney Animation: Creating a Character . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
09:45 - 10:30. Father's Day Crafts . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
10:15 - 11:30. Toy story (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐

Event	**Going**	**Not going**
10:15 - 10:45. Introduction to Acupuncture . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
10:30 - 11:00. Disney Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
10:45 - 12:55. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
10:45 - 11:15. 50's and 60's Music Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
11:00 - 11:15. Bingo Pre Sales . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:00 - 11:30. Detox for Health & Weight Loss . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
11:15 - 12:00. Bingo - Diamond Jackpot Bingo . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:15 - 12:00. Crafts: Door Hangers . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
11:30 - 12:15. ESPN Dream Team Draft Day - Football . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
12:15 - 12:45. Pictionary Challenge . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
12:15 - 12:45. 1820 Society: Lunch . *Category*: Adults. *Location*: Royal Court	☐	☐
12:15 - 13:00. Champagne Tasting (21+). *Category*: Adults. *Location*: Ooh La La	☐	☐
12:30 - 13:30. Movie Challenge Poolside. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
12:30 - 13:15. Disney Vacation Club - Group Preview . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐

Event	Going	Not going
12:45 - 13:15. Singles' Lunch . *Category*: Adults. *Location*: Royal Court	☐	☐
13:00 - 13:45. Martini Tasting (21+). *Category*: Adults. *Location*: Meridian	☐	☐
13:15 - 13:45. Disney Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
13:15 - 13:45. Acupuncture Clinic . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
13:30 - 13:45. Goofy . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
13:45 - 14:30. Port & Shopping Talk . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
13:45 - 14:45. Stem to Stern Wine Tasting (21+). *Category*: Adults. *Location*: Ooh La La	☐	☐
14:00 - 14:45. The Comedy & Hypnosis of Ricky Kalmon . *Category*: Fun for all ages. *Location*: Walt Disney Theatre	☐	☐
14:00 - 14:30. Good Feet Seminar: Walking In Comfort . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
14:15 - 15:00. Mickey 200 . *Category*: Fun for all ages. *Location*: The Tube. Don't Miss Event	☐	☐
14:15 - 15:00. Anyone Can Cook: Lobster Ravioli . *Category*: Adults. *Location*: D Lounge. Don't Miss Event	☐	☐
15:00 - 15:45. Disney Tunes Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
15:00 - 15:45. Live Guitar with Carrie Stone . *Category*: Fun for all ages. *Location*: Deck 12, Stage	☐	☐

Event	**Going**	**Not going**
15:00 - 16:00. Mixology (21+). *Category*: Adults. *Location*: Meridian	☐	☐
15:15 - 16:36. Monkey Kingdom (G). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
15:15 - 15:45. 1820 Society: Mini Golf . *Category*: Adults. *Location*: Goofy Golf	☐	☐
15:15 - 15:45. Acupuncture: Artbritis and Back Pain Solutions . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
15:30 - 17:00. Brave (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
16:00 - 16:15. Bingo Pre Sales . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:00 - 17:00. Mixology (21+). *Category*: Adults. *Location*: Skyline	☐	☐
16:00 - 16:30. Group Cycling . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
16:15 - 16:30. Minnie . *Category*: Characters. *Location*: Preludes	☐	☐
16:15 - 17:00. Bingo - $5,000 Mega Jackpot Bingo . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:15 - 17:00. Crafts: Origami Flowers . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
16:15 - 16:45. TV Tunes Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
16:30 - 16:45. Daisy . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
16:30 - 17:30. Tequila & Margarita Tasting (21+). *Category*: Adults. *Location*: Ooh La La	☐	☐

Event	**Going**	**Not going**
16:45 - 17:00. Donald . *Category*: Characters. *Location*: Preludes	☐	☐
17:00 - 19:22. Avengers: Age of Ultron (PG-13). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
17:00 - 17:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:00 - 18:00. Captain's Welcome Reception . *Category*: Fun for all ages. *Location*: Lobby Atrium. Don't Miss Event	☐	☐
17:00 - 18:00. Live Music with Andrea & Rafaela . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:00 - 17:30. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
17:00 - 18:00. Formal Portraits tonight! . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:15 - 19:00. Ratatouille (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
17:15 - 17:30. Pluto . *Category*: Characters. *Location*: Preludes	☐	☐
17:30 - 17:45. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:45 - 18:00. Minnie . *Category*: Characters. *Location*: Preludes	☐	☐
18:00 - 18:15. Chip & Dale . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
18:15 - 19:00. Disney's Aladdin: Musical Spectacular . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐

Event	Going	Not going
19:00 - 19:30. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:15 - 19:30. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:15 - 20:30. Formal Portraits tonight! . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
19:30 - 20:45. Pixar Short Films (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
19:30 - 19:45. Daisy . *Category*: Characters. *Location*: Preludes	☐	☐
19:30 - 20:00. Variety: David Crone . *Category*: Fun for all ages. *Location*: The Tube. Don't Miss Event	☐	☐
19:30 - 20:30. Captain's Welcome Reception . *Category*: Fun for all ages. *Location*: Lobby Atrium. Don't Miss Event	☐	☐
19:30 - 20:15. Club D Dance Party . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:30 - 20:15. Live Music with FireLites . *Category*: Adults. *Location*: La Piazza	☐	☐
19:45 - 20:00. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
20:00 - 22:22. Avengers: Age of Ultron (PG-13). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:00 - 20:15. Goofy . *Category*: Characters. *Location*: Preludes	☐	☐
20:30 - 21:30. Disney's Aladdin: Musical Spectacular . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐

Event	**Going**	**Not going**
20:45 - 21:15. Adult Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
21:00 - 22:00. Dumbo (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
21:30 - 21:45. Minnie . *Category*: Characters. *Location*: Preludes	☐	☐
21:30 - 22:15. Live Music with Andrea & Rafaela . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
21:30 - 22:30. Formal Portraits tonight! . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:45 - 22:00. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
21:45 - 22:30. Club D Dance Party . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
21:45 - 22:15. 1820 Society: Game Challenge . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
22:00 - 22:15. Donald . *Category*: Characters. *Location*: Preludes	☐	☐
22:00 - 23:00. Cognac Tasting (21+). *Category*: Adults. *Location*: Cove Café	☐	☐
22:15 - 22:30. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
22:15 - 22:45. The Quest . *Category*: Adults. *Location*: The Tube	☐	☐
22:30 - 00:00. Enchanted (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:30 - 23:30. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐

Event	Going	Not going
22:30 - 23:00. Rob Sanders LIVE . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:30 - 23:30. Whiskey Tasting (21+). *Category*: Adults. *Location*: Meridian	☐	☐
22:45 - 00:55. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:45 - 23:15. The Comedy & Ventriloquism of David Crone . *Category*: Adults. *Location*: The Tube	☐	☐
23:15 - 00:15. 80's 90's Remix with Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐

Day 3 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 22.06.2015
Weekday: Monday
Sunrise: 05:57
Sunset: 19:08
Evening Attire: Cruise Casual
Port: At Sea

Weather:
Today: Sunny
Tomorrow: Sunny
Today High 82F 28C
Tomorrow High 80F 27C
Special Holiday Edition: No
Holiday: No

Event	Going	Not going
07:00 - 07:45. Yoga . *Category*: Adults. *Location*: Donald's Pool	☐	☐
07:45 - 08:30. Fab Abs . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐

Event	**Going**	**Not going**
08:30 - 09:30. The Jungle Book (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
08:30 - 09:51. Monkey Kingdom (G). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
09:00 - 09:15. Jessie . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:00 - 09:15. Daisy . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:00 - 09:30. Wake Up with Disney Junior . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
09:00 - 09:30. Xbox Challenge . *Category*: Fun for all ages. *Location*: O'Gills Pub	☐	☐
09:00 - 09:45. Sophia Fiori Seminar . *Category*: Adults. *Location*: The Tube	☐	☐
09:00 - 09:45. Body Sculpt Boot Camp . *Category*: Adults. *Location*: Senses Fitness Center. Nominal fee	☐	☐
09:15 - 10:15. Art of The Theme Show Tour . *Category*: Adults. *Location*: Meridian	☐	☐
09:15 - 10:00. Acupuncture Seminar: Artritis Solutions . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
09:30 - 09:45. Woody . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:30 - 09:45. Pluto . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:30 - 10:00. Disney Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐

Event	**Going**	**Not going**
09:45 - 10:30. Disney Animation: Cartoon Physics . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
09:45 - 10:15. Crafts: Tile Coasters . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
10:15 - 11:45. Monsters, Inc. (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
10:30 - 11:15. Movie Quotes Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
11:00 - 12:00. Hypnosis Seminar with Ricky Kalmon . *Category*: Buena Vista Theatre. *Location*: . Don't Miss Event	☐	☐
11:00 - 11:15. Bingo Pre Sales . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:00 - 11:45. How to Increase Your Metabolism . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
11:15 - 12:00. Bingo: DCL Gift Pack Jackpot with Sophia Fiori . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:15 - 11:45. Crafts: Origami Creations . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
11:45 - 12:30. Crafts: Memory Pages . *Category*: Fun for all ages. *Location*: O'Gills Pub	☐	☐
11:45 - 12:15. Watch Seminar . *Category*: Adults. *Location*: La Piazza	☐	☐
12:15 - 12:45. 1820 Society: Lunch . *Category*: Adults. *Location*: Royal Court	☐	☐
12:15 - 13:30. Chocolate & Liquor Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐

Event	**Going**	**Not going**
12:30 - 13:15. Disney Vacation Club: Group Preview . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
12:30 - 13:00. Know It All Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
13:45 - 14:15. Crafts: Origami Frogs . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
13:45 - 14:15. 70's Music Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
13:45 - 14:30. Stem to Stern Wine Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐
14:00 - 15:00. Disney's Behind the Scenes: Frank Paris . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre. Don't Miss Event	☐	☐
14:00 - 14:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
14:00 - 15:42. Inside Out (PG). *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Don't Miss Event	☐	☐
14:00 - 14:45. Eat More to Weigh Less . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
14:15 - 14:30. Mickey . *Category*: Characters. *Location*: Preludes	☐	☐
14:15 - 15:00. Crafts: Paper Plane Making . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
14:15 - 15:00. Anyone Can Cook: Sea Bass . *Category*: Adults. *Location*: D Lounge	☐	☐
14:30 - 14:45. Sofia . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐

Event	Going	Not going
14:45 - 16:30. Wreck-It Ralph (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
14:45 - 15:00. Minnie . *Category*: Characters. *Location*: Preludes	☐	☐
15:00 - 15:30. Chip It Golf . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
15:00 - 15:45. Diamond and Gemstone Seminar . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
15:00 - 15:45. Rum Tasting (21+). *Category*: Adults. *Location*: Meridian. Nominal fee. Reservation required	☐	☐
15:15 - 16:00. Acupuncture Stress, Insomnia and Depression . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
15:45 - 16:15. Bingo Pre Sales . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
15:45 - 16:15. TV Tunes Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
16:00 - 16:45. Mixology (21+). *Category*: Adults. *Location*: Skyline. Nominal fee. Reservation required	☐	☐
16:00 - 16:45. Group Cycling . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
16:15 - 17:00. Bingo: $7000 Mega Jackpot Bingo . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
16:15 - 17:00. Disney Vacation Club: Group Preview . *Category*: Adults. *Location*: D Lounge	☐	☐
16:15 - 17:00. Italian Cocktail Tasting (21+). *Category*: Adults. *Location*: La Piazza. Nominal fee. Reservation required	☐	☐

Event	Going	Not going
16:30 - 17:45. Cinderella (Classic) (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
16:30 - 16:45. Pluto . *Category*: Characters. *Location*: Preludes	☐	☐
16:30 - 17:00. Disney Trivia . *Category*: Fun for all ages. *Location*: O'Gills Pub	☐	☐
16:30 - 17:15. Tequila & Margarita Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐
17:00 - 17:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:00 - 17:15. Stitch . *Category*: Characters. *Location*: Preludes	☐	☐
17:00 - 17:45. 1820 Society: Game Challenge . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
19:15 - 19:30. Tiana . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
19:15 - 20:15. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:30 - 20:00. Mickey Mouse . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:30 - 20:00. Disney's Family Fusion . *Category*: Fun for all ages. *Location*: D Lounge, Deck 4, Midship	☐	☐
19:30 - 20:00. Team Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
19:30 - 20:15. Live Music with Andrea & Rafaela . *Category*: Adults. *Location*: La Piazza	☐	☐
19:45 - 20:00. Ariel . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐

Event	**Going**	**Not going**
20:00 - 22:09. McFarland, USA (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:15 - 21:45. A Bug's Life (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:30 - 21:30. Disney Wishes . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
20:30 - 21:00. Know It All Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
21:30 - 21:45. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
21:30 - 21:45. Chip & Dale . *Category*: Characters. *Location*: Preludes	☐	☐
21:30 - 22:15. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
21:30 - 22:15. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
21:45 - 22:00. Cinderella . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
21:45 - 22:15. 1820 Society: Game Challenge . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
22:00 - 23:30. Disneynature Oceans (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:00 - 22:15. Pluto . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
22:00 - 22:15. Stitch . *Category*: Characters. *Location*: Preludes	☐	☐

Event	**Going**	**Not going**
22:00 - 22:45. Whiskey Tasting (21+). *Category*: Adults. *Location*: Cove Café . Nominal fee. Reservation required	☐	☐
22:15 - 22:45. Disney's Family Fusion . *Category*: Fun for all ages. *Location*: D Lounge, Deck 4, Midship	☐	☐
22:15 - 22:45. Ice Breakers . *Category*: Adults. *Location*: The Tube	☐	☐
22:30 - 00:22. Cinderella (2015) (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:30 - 23:00. FireLites Live . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:30 - 23:15. Cognac Tasting (21+). *Category*: Adults. *Location*: Meridian. Nominal fee. Reservation required	☐	☐
22:45 - 23:30. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
12:45 - 13:45. Tangled (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
17:00 - 17:45. Complimentary Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
17:15 - 19:24. McFarland, USA (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
17:15 - 17:45. Belle . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
17:15 - 18:00. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐

Event	**Going**	**Not going**
23:00 - 23:45. The Comedy & Hypnosis of Ricky Kalmon . *Category*: Adults. *Location*: Walt Disney Theatre, Deck 3& 4, Forward. Don't Miss Event	☐	☐
23:45 - 00:15. 70's Remix . *Category*: Adults. *Location*: The Tube	☐	☐
12:45 - 13:15. Singles' Lunch . *Category*: Adults. *Location*: Royal Court	☐	☐
13:00 - 13:15. Doc McStuffins . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
13:00 - 13:45. Martini Tasting (21+). *Category*: Adults. *Location*: Meridian. Nominal fee. Reservation required	☐	☐
13:15 - 13:45. Crafts: Origami Frogs . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
13:30 - 13:45. Sofia . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:30 - 17:45. Goofy . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
18:00 - 19:00. Robin Hood (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
18:15 - 19:15. Disney Wishes . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
18:30 - 19:00. Know It All Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐

Day 4 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 23.06.2015
Weekday: Tuesday
Sunrise: 05:38
Sunset: 18:51
Evening Attire: Pirate or Cruise Casual
All Ashore: 08:00
All Abroad: 18:45
Port: St. Maarten

Weather:
Today: Partly Cloudy
Tomorrow: Sunny
Today High 80F 27C
Tomorrow High 80F 27C
Special Holiday Edition: No
Holiday: No

Event	**Going**	**Not going**
07:00 - 07:30. Sunrise Stretch . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
08:30 - 13:45. Port Adventures . *Category*: Buena Vista Theatre. *Location*:	☐	☐
08:30 - 13:45. Port Adventures . *Category*: Characters. *Location*:	☐	☐
08:30 - 11:30. Board Games available in O'Gills Pub . *Category*: Fun for all ages. *Location*: O'Gills Pub	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
08:30 - 09:00. Fab Abs . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
11:30 - 12:15. Crafts: Door Hangers . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
14:00 - 16:00. The Incredibles (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
14:00 - 14:30. Pictionary Challenge . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐

Event	**Going**	**Not going**
14:30 - 16:22. Cinderella (2015) (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
14:45 - 15:15. Cruisin' for Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
15:30 - 16:30. Pirate Crafts . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:00 - 17:15. Peter Pan (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
16:00 - 16:15. Pirate Stitch . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
16:00 - 16:30. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
16:15 - 16:30. Pirate Donald . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
16:15 - 16:45. Pirate Trivia . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:30 - 17:00. Peter Pan . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
16:30 - 16:45. Pirate Chip & Dale . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
16:45 - 17:15. Pirate Minnie Mouse . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
17:00 - 19:10. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
17:00 - 17:15. Jack Sparrow . *Category*: Characters. *Location*: Preludes	☐	☐

Event	**Going**	**Not going**
17:00 - 17:30. Disney Junior Pirate & Princess Dance Party . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
17:00 - 17:30. Pure Form Pilates . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
17:00 - 17:15. Goofy . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:15 - 17:30. Tinker Bell . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
17:15 - 17:45. Pirate Mickey Mouse . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
17:30 - 19:12. Inside Out (PG). *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
17:30 - 17:45. Captain Hook & Mr Smee . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
18:30 - 19:00. A Pirate's Life For Me . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
18:45 - 19:00. Carrie Stone Live . *Category*: Adults. *Location*: Deck 12, Stage	☐	☐
19:00 - 19:15. Pirate Stitch . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:00 - 19:15. Pirate Mickey . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
19:00 - 19:30. Rob Sanders Live . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
19:00 - 19:30. Carrie Stone Live . *Category*: Adults. *Location*: Deck 12, Stage	☐	☐
19:30 - 19:45. Pirate Games . *Category*: Fun for all ages. *Location*: Deck Stage. Don't Miss Event	☐	☐

Event	Going	Not going
19:45 - 20:15. Mickey's PiTC. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
19:45 - 20:15. Mickey's Pirates in the Caribbean . *Category*: Fun for all ages. *Location*: Deck Stage. Don't Miss Event	☐	☐
19:45 - 20:15. Team Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
20:00 - 22:10. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:15 - 21:57. Inside Out (PG). *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
20:30 - 22:15. Muppet Treasure Island (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:30 - 20:45. Jack Sparrow . *Category*: Characters. *Location*: Preludes	☐	☐
20:30 - 21:00. Pirate Trivia . *Category*: Fun for all ages. *Location*: Preludes	☐	☐
21:30 - 21:45. Pirate Donald . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
21:30 - 21:45. Pirate Daisy . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
21:30 - 22:00. A Pirate's Life For Me . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
21:30 - 22:15. Live Music with Rob Sanders . *Category*: Adults. *Location*: La Piazza	☐	☐
21:30 - 22:15. Live Guitar with Carrie Stone . *Category*: Adults. *Location*: Deck 12, Stage	☐	☐

Event	Going	Not going
21:45 - 22:00. Pirate Chip & Dale . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
22:00 - 22:15. Pirate Mickey . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
22:00 - 22:15. Pirate Minnie . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
22:00 - 22:15. Captain Hook & Mr Smee . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
22:30 - 23:30. Buccaneer Blast & Club Pirate . *Category*: Funnel Vision. *Location*: Deck Stage. Don't Miss Event	☐	☐
23:00 - 00:42. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
23:00 - 00:15. Krazy Karaoke followed Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
23:30 - 00:15. Pirates of the Caribbean I (PG-13). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐

Day 5 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 24.06.2015
Weekday: Wednesday
Sunrise: 05:46
Sunset: 19:00
Evening Attire: Cruise Casual
All Ashore: 07:45
All Abroad: 16:00
Port: St. Thomas & St. John, U.S. Virgin Islands

Weather:
Today: Sunny
Tomorrow: Partly Sunny
Today High 80F 27C
Tomorrow High 82F 28C
Special Holiday Edition: No
Holiday: No

Event	**Going**	**Not going**
07:00 - 07:30. Sunrise Stretch . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
08:30 - 09:45. Alice in Wonderland (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
08:30 - 09:00. Fab Abs . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
10:00 - 11:30. Mulan (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
10:30 - 12:18. Big Hero 6 (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
11:45 - 13:15. Hercules (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
12:45 - 14:27. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
13:15 - 13:45. Adult Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐

Event	**Going**	**Not going**
13:45 - 15:15. Snow White and the Seven Dwarfs (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
14:00 - 14:45. Xbox Kinect Just Dance Challenge . *Category*: Fun for all ages. *Location*: O'Gills Pub	☐	☐
14:30 - 15:30. Art of The Theme Show Tour . *Category*: Adults. *Location*: Meridian	☐	☐
15:00 - 17:22. Avengers: Age of Ultron (PG-13). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
15:00 - 15:45. Live Guitar with Carrie Stone . *Category*: Fun for all ages. *Location*: Deck 12, Stage	☐	☐
15:00 - 16:45. Toddler Time . *Category*: Fun for all ages. *Location*: Outlook	☐	☐
15:15 - 16:00. Star Wars Rebels: Disney Channel XD (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
15:30 - 15:45. Hook & Smee . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
16:00 - 16:45. Disney Animation: Staging a Scene . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
16:00 - 16:30. Burn Fat Faster . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
16:15 - 16:45. Disney Channel on Deck . *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
16:15 - 16:30. Chip & Dale . *Category*: Characters. *Location*: Preludes	☐	☐

Event	**Going**	**Not going**
16:15 - 19:00. Family Crafts . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:15 - 16:45. 1820 Society: Giant Jenga . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
16:30 - 16:45. Minnie . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
16:30 - 16:45. Jake . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
16:30 - 17:00. Digestive Management Seminar . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
16:45 - 17:00. Donald . *Category*: Characters. *Location*: Preludes	☐	☐
16:45 - 17:00. Tinker Bell . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
17:00 - 17:30. Belle . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
17:00 - 17:15. Pluto . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
17:00 - 17:30. Pure Form Pilates . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
17:00 - 17:15. Peter Pan . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:15 - 17:30. Mickey . *Category*: Characters. *Location*: Preludes	☐	☐
17:15 - 18:00. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:30 - 17:45. Goofy . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐

Event	Going	Not going
17:30 - 18:15. ESPN Dream Team Draft Day - Basketball . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
18:15 - 19:36. Monkey Kingdom (G). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
18:15 - 19:00. The Magic Dave Show . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
18:30 - 20:00. The Aristocats (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
19:00 - 19:30. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:15 - 19:30. Daisy . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
19:15 - 19:30. Bingo Pre-Sale . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:15 - 20:00. Officer Pin Trading . *Category*: Fun for all ages. *Location*: Preludes. Don't Miss Event	☐	☐
19:30 - 20:00. Cinderella . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
19:30 - 19:45. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:30 - 20:15. Double Up Jackpot Bingo . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:30 - 20:00. The Quest . *Category*: Fun for all ages. *Location*: The Tube. Don't Miss Event	☐	☐
19:30 - 20:15. Live Guitar with Carrie Stone . *Category*: Adults. *Location*: O'Gills Pub	☐	☐

Event	Going	Not going
19:30 - 20:15. Live Music with Andrea & Rafaela . *Category*: Adults. *Location*: La Piazza	☐	☐
19:30 - 19:45. Tinker Bell . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
19:45 - 20:00. Donald . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
20:00 - 20:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
20:15 - 22:00. Finding Nemo (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:30 - 21:51. Monkey Kingdom (G). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:30 - 21:15. The Magic Dave Show . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
20:30 - 21:15. Family Crafts . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
21:15 - 21:45. Ariel . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
21:30 - 21:45. Stitch . *Category*: Characters. *Location*: Preludes	☐	☐
21:30 - 22:15. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
21:30 - 22:15. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:00. DJ Requests . *Category*: Adults. *Location*: The Tube	☐	☐
21:30 - 22:00. Andrea & Rafaela LIVE . *Category*: Adults. *Location*: La Piazza	☐	☐

Event	**Going**	**Not going**
21:30 - 21:45. Dopey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
21:45 - 22:00. Tinker Bell . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
21:45 - 22:00. Minnie . *Category*: Characters. *Location*: Lobby Atrium, Hallway	☐	☐
22:00 - 23:30. Up (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:00 - 22:15. Hook & Smee . *Category*: Characters. *Location*: Preludes	☐	☐
22:00 - 22:15. Tiara . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
22:00 - 22:30. Pop! . *Category*: Adults. *Location*: The Tube	☐	☐
22:00 - 22:15. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
22:15 - 22:45. Saludos Amigos Fiesta . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
22:30 - 00:52. Avengers: Age of Ultron (PG-13). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:30 - 23:00. FireLites Live . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:30 - 23:00. 80's Music Challenge . *Category*: Adults. *Location*: The Tube. Don't Miss Event	☐	☐
22:45 - 23:45. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
23:00 - 23:30. London Rocks! . *Category*: Adults. *Location*: The Tube	☐	☐

Event	Going	Not going
23:30 - 00:15. Cruise Staff DJ . *Category*: Adults. *Location*: The Tube	☐	☐
23:30 - 00:00. Andrea & Rafaela LIVE . *Category*: Adults. *Location*: La Piazza	☐	☐

Day 6 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 25.06.2015
Weekday: Thursday
Sunrise: 05:56
Sunset: 19:45
Evening Attire: Semi Formal
Port: Day At Sea

Weather:
Today: Partly Sunny
Tomorrow: Partly Sunny
Today High 82F 28C
Tomorrow High 82F 28C
Special Holiday Edition: No
Holiday: No

Event	Going	Not going
07:00 - 07:30. Yoga . *Category*: Adults. *Location*: Donald's Pool	☐	☐
07:45 - 08:15. Fab Abs . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
08:00 - 09:00. Open House Toddler Time . *Category*: Fun for all ages. *Location*: It's a small world nursery	☐	☐
08:30 - 10:00. Tinker Bell (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
08:30 - 10:12. Family Movie Fun Time: Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐

Event	**Going**	**Not going**
08:30 - 09:00. Jake & The Neverland Pirates . *Category*: Characters. *Location*: D Lounge	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
08:30 - 09:00. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
09:00 - 09:15. Doc McStuffins . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:00 - 09:30. Crafts: Origami Frogs . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
09:00 - 09:30. Boot Camp . *Category*: Adults. *Location*: Senses Fitness Center. Nominal fee	☐	☐
09:15 - 09:30. Princess Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:15 - 10:15. Art of The Theme Show Tour . *Category*: Adults. *Location*: Meridian	☐	☐
09:15 - 09:45. Acupuncture Seminar Asthma & Allergy Management . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
09:30 - 09:45. Jake . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐
09:45 - 10:00. Sofia . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:45 - 10:30. Family Crafts . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
09:45 - 10:30. ESPN Dream Team Draft Day - Baseball . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
10:00 - 10:15. Doc McStuffins . *Category*: Characters. *Location*: Lobby Atrium, Vestibule	☐	☐

Event	**Going**	**Not going**
10:00 - 10:30. Magic Workshop . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐
10:00 - 11:00. Toddler Time . *Category*: Fun for all ages. *Location*: Outlook	☐	☐
10:15 - 11:45. Toy Story 2. *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
10:15 - 10:30. Princess Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
10:15 - 10:45. Acupuncture Seminar . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
10:30 - 11:00. Crafts: Origami Favorites . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
10:45 - 13:07. Avengers: Age of Ultron (PG-13). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
10:45 - 11:30. Movie Quotes Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
11:00 - 11:30. Captain's Signing . *Category*: Fun for all ages. *Location*: White Caps. Don't Miss Event	☐	☐
11:00 - 11:15. Bingo Pre Sales . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:00 - 11:30. Secrets to a Flatter Stomach . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
11:15 - 12:00. Bingo: $10,000 Mega Jackpot . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
11:30 - 12:00. Jack-Jack's Diaper Dash . *Category*: Fun for all ages. *Location*: Lobby Atrium. Reservation required	☐	☐

Event	**Going**	**Not going**
11:30 - 12:00. 1820 Society: Brunch . *Category*: Adults. *Location*: Cabanas	☐	☐
12:00 - 12:30. Disney Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
12:15 - 13:45. The Little Mermaid (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
12:15 - 12:45. Singles' Lunch . *Category*: Adults. *Location*: Royal Court	☐	☐
12:15 - 12:45. Chocolate & Liquor Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐
12:30 - 13:15. Disney Vacation Club: Group Preview . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
12:45 - 13:15. Character Dance Party . *Category*: Characters. *Location*: Lobby Atrium	☐	☐
13:00 - 13:30. Crafts: 3D Crafts . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
13:00 - 13:30. Ultimate Disney Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
13:00 - 13:30. Rum Tasting (21+). *Category*: Adults. *Location*: Meridian. Nominal fee. Reservation required	☐	☐
13:15 - 13:45. Chinese Herbs . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
13:45 - 14:15. Champagne Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐
14:00 - 15:00. Disney's Behind the Scenes: Frank Paris . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre. Don't Miss Event	☐	☐

Event	**Going**	**Not going**
14:00 - 15:42. Inside Out (PG). *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Don't Miss Event	☐	☐
14:00 - 14:30. Towel Folding . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
14:00 - 14:30. 90's Music Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
14:00 - 14:30. Detox for Health & Weight Loss . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
14:00 - 14:30. Mixology (21+). *Category*: Adults. *Location*: Skyline. Nominal fee. Reservation required	☐	☐
14:00 - 15:00. Toddler Time . *Category*: Fun for all ages. *Location*: Outlook	☐	☐
14:15 - 15:00. Star Wars Rebels: Disney Channel XD (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
14:15 - 15:00. Anyone Can Cook - Apple Shtrudel . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
15:00 - 15:15. Dopey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
15:00 - 15:30. Disney Tunes Trivia . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
15:00 - 15:45. Live Guitar with Carrie Stone . *Category*: Fun for all ages. *Location*: Deck 12, Stage	☐	☐
15:00 - 16:00. Martini Tasting (21+). *Category*: Adults. *Location*: Meridian. Nominal fee. Reservation required	☐	☐

Event	Going	Not going
15:15 - 16:45. The Lion King (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
15:15 - 15:45. Team Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
15:30 - 15:45. Stitch . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
15:45 - 16:15. Bingo Pre-Sales . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
16:00 - 16:45. Crafts: Memory Pages . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
16:00 - 16:30. Mixology (21+). *Category*: Adults. *Location*: Skyline. Nominal fee. Reservation required	☐	☐
16:00 - 16:30. Group Cycling . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
16:15 - 17:00. Final Jackpot Bingo . *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
16:15 - 16:45. Italian Cocktails Tasting (21+). *Category*: Adults. *Location*: La Piazza. Nominal fee. Reservation required	☐	☐
16:30 - 17:00. Margarita Tasting (21+). *Category*: Adults. *Location*: Ooh La La. Nominal fee. Reservation required	☐	☐
17:00 - 17:15. Chip & Dale . *Category*: Characters. *Location*: Preludes	☐	☐
17:00 - 18:00. Talent Show Rehearsals . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
17:00 - 17:30. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐

Event	Going	Not going
17:00 - 18:00. Professional Portraits . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:15 - 19:00. The Muppets (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
17:15 - 17:30. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:15 - 18:00. Live Music with Andrea & Rafaela . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:30 - 19:22. Cinderella (2015) (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
17:30 - 17:45. Donald . *Category*: Characters. *Location*: Preludes	☐	☐
17:30 - 18:00. Rob Sanders LIVE . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
17:45 - 18:00. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
18:15 - 19:00. Disney's Believe . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
18:30 - 19:00. Team Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
19:00 - 19:30. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:15 - 19:30. Pluto . *Category*: Characters. *Location*: Preludes	☐	☐
19:15 - 20:30. Professional Portraits . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
19:30 - 19:45. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐

Event	**Going**	**Not going**
19:30 - 20:00. Mirror Mirror . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:30 - 20:00. Variety: Michael Dubois . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:30 - 20:15. Live Music with FireLites . *Category*: Adults. *Location*: La Piazza	☐	☐
19:45 - 20:00. Goofy . *Category*: Characters. *Location*: Preludes	☐	☐
20:00 - 21:45. WALL-E (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:00 - 20:15. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
20:15 - 22:07. Cinderella (2015) (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:30 - 21:30. Disney's Believe . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
20:45 - 21:15. Team Trivia . *Category*: Adults. *Location*: O'Gills Pub	☐	☐
21:30 - 21:45. Goofy . *Category*: Characters. *Location*: Preludes	☐	☐
21:30 - 21:45. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
21:30 - 22:15. Live Music with Andrea & Rafaela . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
21:30 - 22:30. Professional Portraits . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐

Event	Going	Not going
21:45 - 22:15. Mirror Mirror . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
21:45 - 22:15. 1820 Society: Game Challenge . *Category*: Adults. *Location*:	☐	☐
22:00 - 23:30. Frozen (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:00 - 22:15. Donald . *Category*: Characters. *Location*: Preludes	☐	☐
22:00 - 22:15. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
22:15 - 22:45. Club New Year's Eve . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
22:15 - 22:45. Majority Rules . *Category*: Adults. *Location*: The Tube	☐	☐
22:30 - 00:40. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:30 - 23:00. Andrea & Rafaela LIVE . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:45 - 23:30. Family Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
23:00 - 23:30. The Comedy & Magic of David Williamson . *Category*: Adults. *Location*: Walt Disney Theatre. Don't Miss Event	☐	☐
23:30 - 00:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐
23:30 - 00:00. FireLites LIVE . *Category*: Adults. *Location*: La Piazza	☐	☐

Day 7 of 7

Ship: Disney Fantasy
Destination: Eastern Caribbean
Itinerary: A
Date: 26.06.2015
Weekday: Friday
Sunrise: 06:20
Sunset: 20:08
Evening Attire: Cruise Casual
All Ashore: 11:30
All Abroad: 17:30
Port: Disney's Castaway Cay

Weather:
Today: Partly Cloudy
Tomorrow: Partly Sunny
Today High 82F 28C
Tomorrow High 84F 29C
Special Holiday Edition: No
Holiday: No

Event	**Going**	**Not going**
07:00 - 07:30. Sunrise Stretch . *Category*: Adults. *Location*: Donald's Pool	☐	☐
07:30 - 08:00. Body's Sculpt Boot Camp . *Category*: Adults. *Location*: Senses Fitness Center. Nominal fee	☐	☐
08:00 - 09:30. Disney Castaway Cay 5k . *Category*: Fun for all ages. *Location*: The Tube. Don't Miss Event	☐	☐
08:30 - 10:00. Lilo & Stitch (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
08:30 - 09:00. Wake Up with Disney Junior . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
08:30 - 09:00. Friends of Bill W. . *Category*: Adults. *Location*: Outlook	☐	☐
08:30 - 09:00. Fab Abs . *Category*: Adults. *Location*: Senses Fitness Center	☐	☐
08:45 - 09:00. Donald . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐

Event	**Going**	**Not going**
09:00 - 09:15. Pluto . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
09:00 - 09:15. Mickey . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
09:00 - 09:30. Jake & The Neverland Pirates . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
09:00 - 11:00. Books and Magazines available in Cove Café . *Category*: Adults. *Location*: Cove Café	☐	☐
09:00 - 22:00. The Muppets . *Category*: Fun for all ages. *Location*: Deck 2 & 5, Midship	☐	☐
09:15 - 09:30. Chip & Dale . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
09:30 - 11:12. Tomorrowland (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
09:30 - 09:45. Minnie . *Category*: Characters. *Location*: Lobby Atrium, Port Side	☐	☐
09:30 - 09:45. Goofy . *Category*: Characters. *Location*: Lobby Atrium, Starboard Side	☐	☐
09:45 - 10:15. Disney Trivia . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
10:00 - 11:45. Frozen (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
10:00 - 11:42. Inside Out (PG). *Category*: Fun for all ages. *Location*: Walt Disney Theatre	☐	☐
10:30 - 11:00. Character Dance Party . *Category*: Characters. *Location*: Lobby Atrium	☐	☐
10:30 - 11:00. Magic Workshop (6+) . *Category*: Fun for all ages. *Location*: D Lounge. Don't Miss Event	☐	☐

Event	**Going**	**Not going**
11:00 - 11:45. Live Music with FireLites . *Category*: Adults. *Location*: Deck 12, Stage	☐	☐
11:45 - 12:00. Chip & Dale . *Category*: Characters. *Location*: Post Office	☐	☐
12:00 - 12:15. Daisy . *Category*: Characters. *Location*: Gangway	☐	☐
12:00 - 12:15. Mickey . *Category*: Characters. *Location*: Rustmore	☐	☐
12:00 - 12:30. Yoga on the Beach . *Category*: Adults. *Location*: Serenity Bay	☐	☐
12:15 - 13:30. Lady and the Tramp (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
12:15 - 12:30. Donald . *Category*: Characters. *Location*: Post Office	☐	☐
12:30 - 12:45. Minnie . *Category*: Characters. *Location*: Scuttle's Cove	☐	☐
12:30 - 12:45. Goofy . *Category*: Characters. *Location*: Rustmore	☐	☐
12:30 - 13:00. Crab Races . *Category*: Fun for all ages. *Location*: Island Gazebo 1	☐	☐
12:30 - 13:00. Basketball Free Throw . *Category*: Fun for all ages. *Location*: In Da Shade Game Pavilion	☐	☐
12:45 - 13:30. Live Guitar with Carrie Stone . *Category*: Fun for all ages. *Location*: Island Gazebo 1	☐	☐
13:00 - 13:45. Family Whale Dig . *Category*: Fun for all ages. *Location*: Monstro Point	☐	☐
13:00 - 13:45. 1820 Society: Island Bike Ride . *Category*: Adults. *Location*: Bike Rentals	☐	☐

Event	**Going**	**Not going**
13:15 - 13:30. Jack Sparrow . *Category*: Characters. *Location*: Marge's Barges	☐	☐
13:15 - 13:45. Crab Races . *Category*: Fun for all ages. *Location*: Island Gazebo 2	☐	☐
13:45 - 15:27. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
13:45 - 14:30. Live Guitar with Carrie Stone . *Category*: Fun for all ages. *Location*: Island Gazebo 1	☐	☐
14:00 - 15:30. Brave (PG). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
15:30 - 16:15. Family Crafts . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
16:00 - 17:45. Toy Story 3 (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
16:00 - 17:21. Monkey Kingdom (G). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
16:00 - 17:00. Daisy . *Category*: Characters. *Location*: Gangway	☐	☐
16:15 - 17:00. Digestive Management Seminar . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐
16:30 - 17:00. Sea Ya' Real Soon! . *Category*: Characters. *Location*: Lobby Atrium. Don't Miss Event	☐	☐
16:30 - 17:30. Beer Tasting (21+). *Category*: Adults. *Location*: O'Gills Pub. Nominal fee. Reservation required	☐	☐
17:00 - 17:30. Footprint Analysis . *Category*: Adults. *Location*: Senses Spa & Salon	☐	☐

Event	**Going**	**Not going**
17:15 - 18:00. Live Music with Rob Sanders . *Category*: Fun for all ages. *Location*: La Piazza	☐	☐
17:15 - 17:45. Jewish Sabbath . *Category*: Fun for all ages. *Location*: Outlook	☐	☐
17:15 - 18:00. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
17:30 - 17:45. Donald . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
17:30 - 17:45. The Disney Fantasy's Whistle . *Category*: Fun for all ages. *Location*: Deck 12. Don't Miss Event	☐	☐
17:45 - 19:27. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
18:00 - 19:00. The Emperor's New Groove (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
18:15 - 19:00. Disney Cruise Line: An Unforgettable Journey . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
19:00 - 20:15. Family Dance Party . *Category*: Fun for all ages. *Location*: The Tube	☐	☐
19:15 - 19:30. Goofy . *Category*: Characters. *Location*: Preludes	☐	☐
19:30 - 19:45. Minnie . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
19:30 - 20:15. Family Talent Show . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
19:30 - 20:15. Live Music with Andrea & Rafaela . *Category*: Adults. *Location*: La Piazza	☐	☐

Event	**Going**	**Not going**
19:45 - 20:00. Pluto . *Category*: Characters. *Location*: Preludes	☐	☐
20:00 - 21:15. Movie Prem Ear: Teen Beach Movie 2 (TV-G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
20:00 - 20:15. Mickey . *Category*: Characters. *Location*: Deck 4, Balcony	☐	☐
20:15 - 21:57. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
20:30 - 21:30. Disney Cruise Line: An Unforgettable Journey . *Category*: Fun for all ages. *Location*: Walt Disney Theatre. Event of the Day	☐	☐
20:30 - 21:15. Live Music with Rob Sanders . *Category*: Adults. *Location*: La Piazza	☐	☐
21:30 - 22:15. Live Music with FireLites . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
21:30 - 22:15. DJ Requests . *Category*: Adults. *Location*: The Tube	☐	☐
21:45 - 22:30. Family Dance Party . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
22:00 - 00:00. Fantasia (G). *Category*: Funnel Vision. *Location*: Funnel Vision	☐	☐
22:00 - 22:30. 1820 Society: Farewell . *Category*: Adults. *Location*: The Tube	☐	☐
22:15 - 22:45. Sea Ya' Real Soon! . *Category*: Characters. *Location*: Lobby Atrium. Don't Miss Event	☐	☐
22:15 - 22:45. Ice Breakers . *Category*: Adults. *Location*: The Tube	☐	☐

Event	Going	Not going
22:30 - 23:45. Family Superstar Karaoke . *Category*: Fun for all ages. *Location*: D Lounge	☐	☐
22:45 - 00:27. Inside Out (PG). *Category*: Buena Vista Theatre. *Location*: Buena Vista Theatre	☐	☐
22:45 - 23:15. Rob Sanders LIVE . *Category*: Fun for all ages. *Location*: Lobby Atrium	☐	☐
22:45 - 23:15. The Comedy & Jugging of Michael Dubois . *Category*: Adults. *Location*: The Tube	☐	☐
23:15 - 00:15. Club DJ Mike Sincere . *Category*: Adults. *Location*: The Tube	☐	☐

PART IV. AFTERWARDS

This part contains some conclusion questions.

Could you, please, select the categories of activities that represented the most interest for you

Please, select the categories of activities that you tried not to miss

☐ Animation Classes

☐ Bingo

☐ Board Games

☐ Clubbing

☐ Cooking Workshops

☐ Crafts

☐ Dance Party

☐ Game Show

☐ Guided Tour

☐ Karaoke

☐ Live Music

☐ Meeting Characters

☐ Movies

☐ Seminars

☐ Sport

☐ Tasting Classes

☐ Theatre

☐ Trivia

☐ Variety Show

☐ Other:

When you were having a choice among different activities of your interest, did you consider the distance to the venue while making your choice?
If you prefer a nearby activity rather than an activity on the opposite part of the ship, please select yes. It the distance doesn't matter for you, please select no.

◯ Yes

◯ No

How do you usually manage the list of activities to perform during your vacations?
Please, select the answer that best describes you.

○ Daily planning of all activities

○ Making a list of not-to-miss activities

○ No planning

Please, mention your favourite onboard activities or activities you remember to visit

Additional information

Please, feel free to provide any other information/comments

B

Appendix. Questionnaire for DESIR_db

Description: This research study aims to explore how individuals feel about their life, and how their behavioural orientations influence their selection and experience of leisure and vacation activities. We investigate how the pursuits of Pleasure, Meaning, and Engagement, and Personality traits correlate with the portfolio of activities that individuals are engaged in most.

B.1 Use of Data

This section contains a statement about the use of data and the user's consent of it.
'By clicking this check box, I certify that I voluntarily consent to take part in this research study and that I accept that the data I provide will be used in academic purpose.'

B.2 Part I. Demographic Profile

Q1. **What is your gender?**

○ Female

○ Male

Q2. **What is your age?**

○ Under 18

○ 18-24

○ 25-34

○ 35-44

○ 45-54

○ 55-64

○ 65-74

○ 75-84

Q3. **What is the highest level of your qualification/education?**

○ No Qualification

○ General Certificate of Education (A Level or equivalent)

○ Bachelor Degree

○ Masters Degree

○ Doctorate Degree

○ Don't Know

Q4. **What is your marital status?**

○ Married or civil partnership

○ Widowed

○ Divorced

◯ Separated

◯ Never married

Q5. **Are you currently...?**

◯ Employed full time

◯ Employed part time

◯ Unemployed looking for work

◯ Unemployed not looking for work

◯ Retired

◯ Student

◯ Disabled

◯ Self-employed

◯ Homemaker

B.3 Part II. Psychological Profile: Well-Being

Q6. **Please indicate the box that best describes your experience of each over the last 2 weeks.**

	1 - None of the time	2 - Rarely	3 - Some of the time	4 - Often	5 - All of the time
I've been feeling optimistic about the future	◯	◯	◯	◯	◯
I've been feeling useful	◯	◯	◯	◯	◯
I've been feeling relaxed	◯	◯	◯	◯	◯

	1 - None of the time	2 - Rarely	3 - Some of the time	4 - Often	5 - All of the time
I've been feeling interested in other people	◯	◯	◯	◯	◯
I've had energy to spare	◯	◯	◯	◯	◯
I've been dealing with problems well	◯	◯	◯	◯	◯
I've been thinking clearly	◯	◯	◯	◯	◯
I've been feeling good about myself	◯	◯	◯	◯	◯
I've been feeling close to other people	◯	◯	◯	◯	◯
I've been feeling confident	◯	◯	◯	◯	◯
I've been able to make up my own mind about things	◯	◯	◯	◯	◯
I've been feeling loved	◯	◯	◯	◯	◯
I've been interested in new things	◯	◯	◯	◯	◯
I've been feeling cheerful	◯	◯	◯	◯	◯

Q7. **Please read each item and indicate to what extent you feel this way at the present moment or over the past week**

	1 - Very Slightly or Not at All	2 - A Little	3 - Moderately	4 - Quite a Bit	5 - Extremely
Interested	◯	◯	◯	◯	◯
Distressed	◯	◯	◯	◯	◯

	1 - Very Slightly or Not at All	2 - A Little	3 - Moderately	4 - Quite a Bit	5 - Extremely
Excited	○	○	○	○	○
Upset	○	○	○	○	○
Strong	○	○	○	○	○
Guilty	○	○	○	○	○
Scared	○	○	○	○	○
Hostile	○	○	○	○	○
Enthusiastic	○	○	○	○	○
Proud	○	○	○	○	○
Irritable	○	○	○	○	○
Alert	○	○	○	○	○
Ashamed	○	○	○	○	○
Inspired	○	○	○	○	○
Nervous	○	○	○	○	○
Determined	○	○	○	○	○
Attentive	○	○	○	○	○
Jittery	○	○	○	○	○
Active	○	○	○	○	○
Afraid	○	○	○	○	○

Q8. **Below are five statements that you may agree or disagree with. Using a 7-point scale below, please indicate your agreement with each item.**

	1 - Strongly disagree	2 - Disagree	3 - Slightly disagree	4 - Neither agree nor disagree	5 - Slightly agree	6 - Agree	7 - Strongly agree
In most ways my life is close to my ideal	○	○	○	○	○	○	○
The conditions of my life are excellent	○	○	○	○	○	○	○
I am satisfied with my life	○	○	○	○	○	○	○
So far I have gotten the important things I want in life	○	○	○	○	○	○	○
If I could live my life over, I would change almost nothing	○	○	○	○	○	○	○

B.4 Part III. Psychological Profile: Orientations to Happiness

Q9. **Please indicate on a 5-point scale the degree to which the item applies to you.**

1. My life serves a higher purpose

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

2. In choosing what to do, I always take into account whether it will benefit other people

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

3. I have a responsibility to make the world a better place
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

4. My life has a lasting meaning
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

5. What I do matters to society
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

6. I have spent a lot of time thinking about what life means and how I fit into its big picture
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

7. Life is too short to postpone the pleasures it can provide
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

8. I go out of my way to feel euphoric
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

9. In choosing what to do, I always take into account whether it will be pleasurable
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

10. I agree with this statement: "Life is short - eat dessert first"
○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

11. I love to do things that excite my senses

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

12. For me, the good life is the pleasurable life

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

13. Regardless of what I am doing, time passes very quickly

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

14. I seek out situations that challenge my skills and abilities

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

15. Whether at work or play, I am usually "in a zone" and not conscious of myself

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

16. I am always very absorbed in what I do

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

17. In choosing what to do, I always take into account whether I can lose myself in it

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

18. I am rarely distracted by what is going on around me

○ 1 = very much unlike me ○ 2 ○ 3 ○ 4 ○ 5 = very much like me

B.5 Part IV. Psychological Profile: Personality

Q10. **Please indicate on a 5-point scale the degree to which each item applies to you.**

	1 - Very Inaccurate	2 - Moderately Inaccurate	3 - Neither Inaccurate nor Accurate	4 -Moderately Accurate	5 - Very Accurate
Am the life of the party	○	○	○	○	○
Talk to a lot of different people at parties	○	○	○	○	○
Don't talk a lot	○	○	○	○	○
Keep in the background	○	○	○	○	○
Sympathize with other's feelings	○	○	○	○	○
Feel others' emotions	○	○	○	○	○
Am not really interested in others	○	○	○	○	○
Am not interested in other people's problems	○	○	○	○	○
Get chores done right away	○	○	○	○	○
Like order	○	○	○	○	○
Often forget to put things back in their proper place	○	○	○	○	○
Make a mess of things	○	○	○	○	○
Have frequent mood swings	○	○	○	○	○
Get upset easily	○	○	○	○	○

	1 - Very Inaccurate	2 - Moderately Inaccurate	3 - Neither Inaccurate nor Accurate	4 -Moderately Accurate	5 - Very Accurate
Am relaxed most of the time	○	○	○	○	○
Seldom feel blue	○	○	○	○	○
Have a vivid imagination	○	○	○	○	○
Have difficulty understanding abstract ideas	○	○	○	○	○
Am not interested in abstract ideas	○	○	○	○	○
Do not have a good imagination	○	○	○	○	○

B.6 Part V. Leisure Activities Preferences

Q11. **Please select the categories of activities you usually perform or are interested in performing. Please rate each selected activity to which degree it (1) involves social contact; (2) requires effort; (3) is structured; (4) is pleasurable; (5) is engaging; (6) is meaningful.**

"Social contact" range: 1 = I always do it alone ; 6 = I always do it with others.

"Effort" range: 1 = It requires no effort and/or skill when I do it ; 6 = It requires heaps of effort and/or skill when I do it.

"Structure" range: 1 = It has no rules, time-limits, uniforms, etc. when I do it ; 6 = It has heaps of rules, time-limits, uniforms, etc. when I do it.

"Pleasurable" means how much you are experiencing enjoyment or positive emotion. "Pleasure" range: 1 = not at all ; 5 = moderately ; 9 = extremely.

"Engaging" means how much you feel the activity has you focused, challenged, or in zone. "Engagement" range: 1 = not at all ; 5 = moderately ; 9 = extremely.

"Meaningful" means how much you feel the activity is rewarding, helping you to advance your goals, or is worthwhile. "Meaning" range: 1 = not at all ; 5 = moderately ; 9 = extremely.

Category	Like	Contact	Effort	Structure	Pleasure	Engagement	Meaning
Outdoors & Adventures	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Tech	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐

Category	Like	Contact	Effort	Structure	Pleasure	Engagement	Meaning
Family	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Health & Wellness	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Sports & Fitness	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Learning	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Photography	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Food & Drink	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Writing	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Language & Culture	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Music	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Movements	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
LGBTQ	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Film	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Sci-Fi & Games	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Beliefs	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Arts	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Book Clubs	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Dance	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Hobbies & Crafts	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐

Category	Like	Contact	Effort	Structure	Pleasure	Engagement	Meaning
Fashion & Beauty	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Social	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Career & Business	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Gardening & Outdoor housework	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Cooking	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Theatre, Show, Performance & Concerts	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Drinking alcohol & Partying	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐
Sex & Love Making	☐	1-6 ☐	1-6 ☐	1-6 ☐	1-9 ☐	1-9 ☐	1-9 ☐

Q12. **Number of leisure activities you do per day:**

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4+

Q13. **Number of leisure activities you do per week:**

- ○ 0
- ○ 1
- ○ 2-3
- ○ 4-5
- ○ 5+

Q14. **Number of leisure activities you do per weekend:**

- ○ 0
- ○ 1
- ○ 2-3
- ○ 4-5
- ○ 5+

Q15. **Average duration of activities, min:**

- ○ 0-5
- ○ 5-20
- ○ 20-40

◯ 46-60

◯ 60+

Q16. **Think about your usual weekend. Please indicate your priority (preference) concerning the choices provided. When replying, please mind that you are choosing between activities that are happening at the same time, and that they represent interest for you. Long-term vs. Multiple short-term activities: One Full Weekend Activity or Multiple activities. Example: A festival in another city or Multiple events (regular or/and unique) in your city**

◯ Full Weekend Activity

◯ Multiple Activities

Q17. **Think about your usual weekend. Please indicate your priority (preference) concerning the choices provided. When replying, please mind that you are choosing between activities that are happening at the same time, and that they represent interest for you. Regular activity or New activity. Do you cancel your regular activities in order to join smth new? Example: your regular gym class vs. a new beginner workshop of wine/chocolate tasting or thai massage**

◯ Regular

◯ New

B.7 Part VI. Vacation Preferences

Q18. **Please select the answer that best describes you:**
Q19. **Please for each of the following types of holidays indicate the frequency with which you have been endorsed with it:**

	Yes	No
Have you been on holiday of two nights and more in the last 6 years?	☐	☐
Have you been on holiday of two nights and more in the last 2-3 years?	☐	☐
Have you been on holiday of two nights and more in the last year?	☐	☐
When on holiday, do you intent to do as much as you can (maximising the number of things you do, places you visit) -YES or to select very few activities to do-NO?	☐	☐
When on holiday, do you often try new kinds of activities you have never done before - YES or you prefer to do something you are sure that you will like - NO?	☐	☐

	Always	Most of the time	About half the time	Sometimes	Never
Beach holiday	○	○	○	○	○
Sightseeing	○	○	○	○	○
In a city	○	○	○	○	○
Nature based	○	○	○	○	○
Friends/family visits	○	○	○	○	○
Package based	○	○	○	○	○
Festivals (2 and more days)	○	○	○	○	○
Cruise (2 and more days)	○	○	○	○	○
Other	○	○	○	○	○

Q20. **Please, select the type of group you went on the last holiday with:**

☐ alone

☐ with your significant other

☐ with a group of friends

☐ with family (i.e. different generations)

Q21. **When on holiday, do you plan your days, making an itinerary?**

○ Daily planning of all activities

○ Making a list of not-to-miss activities

○ No planning

B.8 Part VII. Psychological Profile: Fear of Missing Out

Q22. **Below is a collection of statements about your everyday experience. Using the scale provided please indicate how true each statement is of your general experience. Please answer according to what really reflects your experiences rather than what you think your experiences should be. Please treat each item separately from every other item.**

	1 - Not at all true of me	2 - Slightly true of me	3 - Moderately true of me	4 - Very true of me	5 - Extremely true of me
I fear others have more rewarding experiences than me.	○	○	○	○	○
I fear my friends have more rewarding experiences than me.	○	○	○	○	○
I get worried when I find out what my friends are up to.	○	○	○	○	○
It is important that I understand my friends "in jokes".	○	○	○	○	○
Sometimes, I wonder if I spend too much time keeping up with what is going on.	○	○	○	○	○
It bothers me when I miss an opportunity to meet up with friends.	○	○	○	○	○
When I have a good time it is important for me to share the details online (eg. updating status).	○	○	○	○	○
When I miss out on a planned get-together it bothers me.	○	○	○	○	○

	1 - Not at all true of me	2 - Slightly true of me	3 - Moderately true of me	4 - Very true of me	5 - Extremely true of me
When I go on vacation, I continue to keep tabs on what my friends are doing.	○	○	○	○	○

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Colophon

FAR OVER THE MISTY STANDARD GOLD
To the deepest likes that are untold
We must perceive the tastes, beliefs
To seek the best results to hold.

The maths of yore made mighty spell,
While matrices seem come from hell
Too sparse, too big, too hard to twig.
Might we compute in parallel?

To find the clue what's on your mind
We do research of any kind
Some item-based, some model-based
We mesh the light of all of them.

For content-based approach referred
We look at weight of each keyword
To set profile and then compile
To find the top *k* things preferred.

We find the candidate selection priors
By means of novel qualifiers
Sometimes we fuse, sometimes refuse.
All to satisfy the user's undisclosed desires.

Far over the misty standard gold
To the deepest likes that are untold
We must perceive the tastes, beliefs
To claim to almost have the truth unfold.

What shall I do to capture this alert?
Or maybe here'd better to use the invert?
You see the steam, even in dream.
The normal life for introvert.

The deadlines come unlike the snails,
And men they look up with faces pale;
We hurry up to not blow up
To overcome the runs that fail.

Far over the misty standard gold
To the deepest likes that are untold
We must perceive the tastes, beliefs
To get the best feedback and win!

FOLIO ADMINISTRATIF

THESE DE L'UNIVERSITE DE LYON OPEREE AU SEIN DE L'INSA LYON

NOM : NURBAKOVA DATE de SOUTENANCE : 13.12.2018
(avec précision du nom de jeune fille, le cas échéant)

Prénoms : Diana

TITRE : Recommendation of Activity Sequences during Distributed Events

NATURE : Doctorat Numéro d'ordre : 2018LYSEI115

Ecole doctorale : ED n° 512 Informatique et Mathématiques

Spécialité : Informatique

RESUME :
Multi-day events such as conventions, festivals, cruise trips, to which we refer to as *distributed events*, have become very popular in recent years, attracting hundreds or thousands of participants. Their programs are usually very dense, making it challenging for the attendees to make a decision which events to join. Recommender systems appear as a common solution in such an environment. While many existing solutions deal with personalised recommendation of single items, recent research focuses on the recommendation of consecutive items that exploits user's behavioural patterns and relations between entities, and handles geographical and temporal constraints.

In this thesis, we first **formulate the problem of recommendation of activity sequences**, classify and discuss the types of influence that have an impact on the estimation of the user's interest in items.

Second, we propose an approach (**ANASTASIA**) to solve this problem, which aims at **providing an integrated support for users to create a personalised itinerary of activities**. ANASTASIA brings together three components, namely: (1) estimation of the user's interest in single items, (2) use of sequential influence on activity performance, and (3) building of an itinerary that takes into account spatio-temporal constraints. Thus, the proposed solution makes use of the methods based on sequence learning and discrete optimisation.

Moreover, stating the lack of publicly available datasets that could be used for the evaluation of event and itinerary recommendation algorithms, we have created two datasets, namely: (1) **event attendance on board of a cruise (Fantasy_db)** based on a conducted user study, and (2) **event attendance at a major comic book convention (DEvIR)**. This allows to perform evaluation of recommendation methods, and contributes to the reproducibility of results.

MOTS-CLÉS : sequence-aware recommender systems, distributed events, event recommendation

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