Itinerary Recommendation for Cruises: User Study

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ABSTRACT

Vacations and leisure activities constitute an important part of human life. Nowadays, a lot of attention is paid to cruising, that is reported to be a favourite vacation choice for families with kids and for Millenials. Like other distributed events (events that gather multiple activities distributed in space and time under one umbrella) such as big festivals, conventions, conferences etc., cruises offer a vast variety of simultaneous on-board activities for all ages and tastes. This results in a cruiser's information overload, in particular given a very limited availability of activities. Recommender systems appear as a desirable solution in such an environment. Due to the number of time constraints, it is more convenient to get a personalised itinerary of activities rather than a list of top-*n*. In this paper, we present a user study conducted in order to create a preliminary dataset that simulates users' attendance of a cruise and sheds the light on the activity selection behaviour. We discuss challenges faced by the itinerary recommendation and illustrate them with user study examples.

CCS CONCEPTS

• **Information systems → Personalization**;

KEYWORDS

recommendation of leisure activities, itinerary recommendation

1 INTRODUCTION

Nowadays, the field of leisure activities experiences a substantial growth. In this context, a rising phenomenon we are witnessing 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.

Attendees of distributed events are overwhelmed with the number of ongoing parallel activities and are looking for personalised experience. Recommender systems appear as a natural solution in such an environment. It is to note that given the density of activities and their limited availability, participants are interested in a personalised itinerary (a sequence of activities to undertake) rather than in a list of top-*n* activities that may compete in terms of time.

In this work, we consider a case of a cruise. According to Florida-Caribbean Cruise Association (F-CCA) [6], 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 [6] 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.

In this paper, we focus on the itinerary recommendation and present a user study based on a 7-night Disney Fantasy cruise. More precisely, we aim at answering the following research questions.

RQ1: What is itinerary recommendation and what makes it challenging?

RQ2: What are the characteristics of the data treated by itinerary recommendation? Is there any dataset that could be used as is?

The remainder of the paper is organised as follows. In Section 2 we define the itinerary recommendation problem and the challenges it faces. Section 3 gives an overview of existing datasets, presents our user study that simulates users' attendance of a cruise and discussion over conducted analysis. Section 4 concludes the paper.

2 PROBLEM STATEMENT AND CHALLENGES

In this paper, we aim at finding a personalised itinerary for a given user that maximises his satisfaction and takes into account spatio-temporal constraints. More precisely, given a set of activities with their locations, descriptions, time windows of their availability, duration, and a vector of categories, a set of users, and users' history (attendance) binary matrix, find a feasible sequence of activities (or itinerary) that maximises the user's satisfaction for every given user. User's satisfaction with respect to an itinerary is defined as the sum of the user's satisfaction scores regarding all the activities within the itinerary. For more details on the itinerary recommendation problem, see [9].

Itinerary recommendation faces the following **challenges**.

C-1: Implicit Feedback. Given that activities are happening in future as in the case of event recommendation [8], 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

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item is not known. The use of multiple contexts may increase the recommendation performance of the algorithms.

C-2: Interest vs. Attendance. Due to the limited availability and multiple parallel activities, we deal with attendance bias, as 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.

C-3: List vs. Itinerary. Activities are competitive and short-lived, which results in the user's preference for one activity over the others in a given time slot. In this context, an itinerary (a feasible sequence of activities) is more desirable than a list of interesting activities.

We will illustrate the challenges in the next section.

3 USER STUDY

In this section, we formulate a list of characteristics of a dataset satisfying the needs of the target problem, provide a comparison of available datasets (see Tab. 1) and describe a user study conducted in order to collect data with desirable characteristics.

3.1 Data Characteristics and Existing Datasets

We categorise the existing datasets w.r.t. the focus of data into 3 groups: *Single Item*, *Schedule*, and *Sequence*. We define a list of characteristics (column "Characteristics" in Tab. 1) based on the activity attributes and consecutive nature of performed activities during distributed events. We cluster the characteristics into 5 types w.r.t. the entity they describe: item (unit under consideration), sequence (ordered sequence of items), user (information about users), user-item (user-item interactions), and user-user (relations between users). We distinguish 5 essential characteristics (given in italics in Tab. 1): (1) time windows (start and end time of activity availability), (2) coordinates (geographical location of an activity), (3) service time (duration of an activity), (4) categories (associated categories), (5) users historical data. Though we indicate only 5 elements as essentials, all the others listed in Tab. 1 are also important as they may enhance the recommendation. As it can be seen, none of the existing datasets contains all the essential characteristics. Thus, we have made an attempt to create an integral dataset that contains all the required features and provides an insight into users' behaviour.

3.2 Data Collection

In order to collect required data, we have performed a user study via online survey. Participants were recruited via a link to the online questionnaire sent by email to several research and university mailing lists. The claimed aim of the study was to create a dataset that simulates cruise attendance and could be used in order to make personalised recommendations of itineraries. The list of activities used in the survey was 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 online[3]. The deck plan of the ship can be found on the web[4]. The questionnaire consisted of 4 parts. The overview of the survey with examples of questions is given in Tab. 2.

Thus, 23 contributions were collected. Statistics concerning the participants are provided in Tab. 3. The main statistics of the dataset are given in Tab. 4. The average duration of an activity is 45 minutes. The average number of ongoing simultaneous activities is 5.

[1] Yelp challenge dataset, http://www.yelp.com/dataset_challenge
[2] https://github.com/jalbertbowden/foursquare-user-dataset
[3] http://disneycruiselineblog.com/2015/07/personal-navigators-7-night-eastern-caribbean-cruise-on-disney-fantasy-itinerary-a-june-20-2015/
[4] http://disneycruiselineblog.com/ships/deck-plans-disney-dream-disney-fantasy/

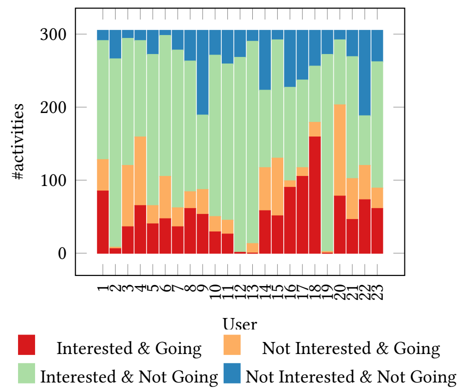

Figure 1: Distribution of interest in activities and attendance per user.

3.3 Data Analysis

The conducted user study gives a more practical insight into personalised itinerary recommendation and the activity selection process. In the following, we illustrate the challenges from Section 2.

C-2: Interest vs. Attendance. Figure 1 displays the user-wise distribution of the number of activities a user: (1) 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*), (2) was interested in but did not join (*Interested & Not Going*), (3) was not interested in but joined (*Not Interested & Going*), and (4) was not interested in and did not join (*Not Interested & Not Going*)[5]. The chart shows evidence that individuals miss many activities that represent 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.

C-3: List vs. Itinerary. Let us consider the following settings. We compare several top-n item recommendation algorithms against itinerary recommendation from the literature. As history data we consider a binary attendance matrix.

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

- *Content-based*: 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*: We fed a vector of aforementioned scores into a logistic regression model.

[5] Ratings are used only for this part of the study. We do not consider them in estimation of user's interest in activities, as we assume there exist only binary attendance matrix.

Table 1: Comparison of the available datasets.

		Single Item									Schedule			Sequence	
Entity	Characteristic	TREC CS'13 [3]	TREC CS'14 [4]	TREC CS'15 [2]	Yelp [1]	Foursquare_1 [14]	Foursquare_2 [2]	Flickr [11]	Twitter [5]	Meetup [7]	MCTOPMTW [10]	Other OP-TW [12]	Other OP-based [12]	TripBuilder [1]	GeoLife [15]
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				✓	✓	✓			✓					

Table 2: 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?

- *ILS+Scores*: We also tested a state-of-the-art itinerary construction algorithm [9] that is based on the Iterated Local Search (ILS) algorithm [13] with activities scores calculated using hybrid scores (content-based, category-based and time-based) and transition probabilities between activities.

Table 3: 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

Table 4: Dataset Statistics

# Activities	# Days	# Users	# Locations	# Categories
593	7	23	47	52

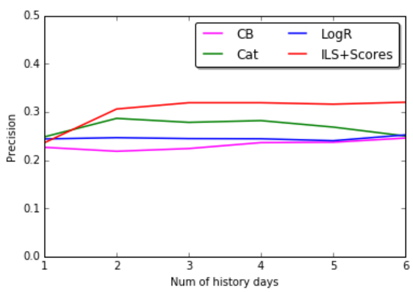

Figure 2: Precision w.r.t. the number of history days.

The algorithms were evaluated in terms of their precision. We returned top-20 activities for each day[6] using top-n recommendation algorithms. Figure 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.

4 DISCUSSION AND CONCLUSION

In this paper we have considered the problem of personalised itinerary recommendation with special interest for cruises. We have distinguished the characteristics of data used in itinerary recommendation and have presented an overview of available datasets. To the best of our knowledge, this is the first attempt to classify and summarise the existing datasets, and describe them with respect to the aforementioned characteristics. Moreover, we have undertaken a user study in order to build a preliminary dataset that satisfies all the characteristics and that helps to understand individuals' behaviour in activity selection process. Though the discussed dataset is not large-scale, the undertaken user study reveals general trends of users' behaviour while on board of a cruise or while attending a distributed event. Moreover, we have discussed the challenges faced by the problem of itinerary recommendation and have illustrated them with the performed data analysis.

As future work, we plan to create a dataset via crowdsourcing using CrowdFlower platform. The characteristics presented in Sec. 3.1 will serve as the basis for the new dataset. Another direction of future work consists in proposing more accurate solution for the itinerary recommendation that would embrace all the sides and address all the challenges of the itinerary recommendation.

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

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