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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 Millennials. 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 activities that may compete in terms of time. 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.

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.

∗D. Nurbakova held a doctoral fellowship from la Région Auvergne-Rhône-Alpes.
We distinguish 5 essential characteristics (given in italics 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.

### 3.1 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 activities. 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 activities. 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 activities. 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 activities. 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 activities.

### 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 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). The chart shows evidence that individuals miss many activities that represent interest to them. Thus, the number of Interested & 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 descending 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.

---

   challenge
2. https://github.com/jalberthowden/foursquare-user-dataset
3. http://disneycruiselineblog.com/2015/07/personal-navigators-7-night-eastern-
   caribbean-cruise-on-disney-fantasy-itinerary-a-june-20-2015/
Table 1: Comparison of the available datasets.

<table>
<thead>
<tr>
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</thead>
<tbody>
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<td>Time windows</td>
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</tr>
<tr>
<td></td>
<td>Coordinates</td>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Service Time</td>
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<td>✓</td>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Sequence</td>
<td>Time windows</td>
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<td>✓</td>
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<td>✓</td>
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</tr>
<tr>
<td></td>
<td>Starting/Ending Point</td>
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<td>✓</td>
</tr>
<tr>
<td></td>
<td>Tour Additional Attributes</td>
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<td>✓</td>
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<td>✓</td>
</tr>
<tr>
<td>User</td>
<td>User’s personal data</td>
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<td>✓</td>
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<tr>
<td>User-Item</td>
<td>Historical Data</td>
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<td></td>
<td>Score</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>✓</td>
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<td>✓</td>
</tr>
<tr>
<td>User-User</td>
<td>Social links</td>
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<td>✓</td>
<td>✓</td>
<td></td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 2: Description of the parts of the survey. Qnt denotes the number of questions in a section.

<table>
<thead>
<tr>
<th>Section</th>
<th>Qnt</th>
<th>Description</th>
<th>Question Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Profile</td>
<td>10</td>
<td>Questions on basic user’s features and their cruising experience</td>
<td>Your gender: ☐ Female ☒ Male</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Have you already experienced DCL (Disney Cruise Line)?</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Are you aiming to attend the maximum amount of activities mentioned in your Personal Navigator or just a few must-see?</td>
</tr>
<tr>
<td>Users Preferences</td>
<td>311</td>
<td>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</td>
<td></td>
</tr>
<tr>
<td>Itinerary Planner</td>
<td>593</td>
<td>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”.</td>
<td>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 aboard the Disney Fantasy. Available: Day 1, 16:30-17:15, Location: Deck Stage Never ○ ○ ○ ○ ○ • Won’t miss</td>
</tr>
<tr>
<td>Afterwards</td>
<td>5</td>
<td>Conclusion questions</td>
<td>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?</td>
</tr>
</tbody>
</table>

- **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.
To the best of our knowledge, this is the first attempt to classify and them with the performed data analysis. Moreover, we have discussed the challenges faced of users' behaviour while on board of a cruise or while attending a distributed event. Moreover, we have summarized the existing datasets, and describe them with respect to the aforementioned characteristics. The undertaken user study reveals general trends in activity selection process. Though the discussed dataset is not large-scale, the undertaken user study presents some data that helps to understand individuals' behaviour in activity selection process. However, 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.

### REFERENCES


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.

### Table 3: Participants Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td># Female users</td>
<td>7</td>
</tr>
<tr>
<td># Users already experienced DCL</td>
<td>1</td>
</tr>
<tr>
<td># Users already experienced any cruise</td>
<td>4</td>
</tr>
<tr>
<td>Users considering the distance between venues</td>
<td>8</td>
</tr>
</tbody>
</table>

### Table 4: Dataset Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td># Activities</td>
<td>593</td>
</tr>
<tr>
<td># Days</td>
<td>7</td>
</tr>
<tr>
<td># Users</td>
<td>23</td>
</tr>
<tr>
<td># Locations</td>
<td>47</td>
</tr>
<tr>
<td># Categories</td>
<td>52</td>
</tr>
</tbody>
</table>

![Figure 2: Precision w.r.t. the number of history days.](image-url)

The algorithms were evaluated in terms of their precision. We returned top-20 activities for each day 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.