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. 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.

∗D. Nurbakova held a doctoral fellowship from la Région Auvergne-Rhône-Alpes.

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
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 consequent 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 on-line 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 dataset.

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 did not join (Interested & Not 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 & 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.

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.

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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>
</table>
| User Profile        | 10  | Questions on basic user’s features and their cruising experience             | Your gender: ☐ Male ☐ Female  
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?  
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 o o o o o  won’t miss  
Going o o o o  don’t miss  
Not going o o o o o  miss  |
| 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  
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”.  
Afterwards           | 5   | Conclusion questions  

- 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 using CrowdFlower platform. The characteristics presented in Sec. 6. Itinerary recommendation algorithm shows higher precision, each algorithm with varying number of history days (from 1 to 6). Table 3: Participants Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
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<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>

Managing Activities. Not-to-miss List : Daily planning : No planning

Age group: 21-30 : > 30

14 : 4 : 5

 table 4: Dataset Statistics

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

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 day6 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.

REFERENCES