Recommending Crowdsourced Trips on wOndary

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ABSTRACT

Making recommendations for tourist trips is a challenging task due to the intrinsic complexity of the domain. The characterization of itineraries is non-trivial, because there is a lack of open destination databases such as regions, islands, cities or attractions that would help to understand the characteristics of destinations within a trip. For this purpose, we present wOndary, which supports the planning and sharing of worldwide trips based on crowdsourcing. We sidestep item discovery and routing challenges of the tourist trip design problem by performing content-based recommendation by facilitating a novel structured representation of itineraries. We share our experiences in the establishment of the core model for our travel recommender system and discuss future developments.

KEYWORDS

recommender systems, user modeling, crowdsourcing, explaining recommendations, critiquing

1 INTRODUCTION

Independent travel planning is very complex. Today's connected world offers a myriad of choices of where to travel to, and there is unlimited information based on which one can make a decision. wOndary[1] has developed a platform for independent travelers to plan their trips. Initially, it started as a planning tool to create personal itineraries that can be shared privately with friends and co-travelers or that can be published as a public trip on the platform. In this paper, we describe how we transition the wOndary platform to a personalized recommender system for crowdsourced trips and describe the future potential of this work.

Our proposed solution involves the following contributions. We present a data model for structuring trips into blocks that are both useful for users and for segmenting trips. Furthermore, we present an attractions categorization that enables content-based recommendations via implicitly elicited preference. Utilizing this novel data model for structured itineraries, we provide recommendations for complete trips, and for parts of trips, i.e., blocks. The approach was driven by the following research questions (RQs):

RQ 1: What is a suitable recommendation model that masters the complexities of travel and enables future innovation regarding the user experience within wOndary?

RQ 2 How can crowdsourced trips be structured and characterized to enable content-based recommendations?

RQ 3: How can user preferences be elicited without requiring much effort by the user?

In the following section, we describe wOndary and the core of the novel content-based travel recommender. Then, in Section 3 we survey prior literature on personalized travel recommendation and further discuss avenues to improve the current basic system in Section 4. We conclude this paper in Section 5.

[1] https://wondary.com

2 TRAVEL RECOMMENDATION FOR INDEPENDENT TRAVELERS

wOndary is a platform that allows users to save, organize and share details about their trips. The platform helps with the structuring of personal itineraries, enables collaboration between group travelers, and encourages the publishing of personal itineraries so that others can reuse and customize these crowdsourced trips for their own purposes. wOndary currently focuses on young urbans (23–30 year olds) that strive for unique experiences during independently planned trips.

The user journey on wOndary reflects the *travel micro-moments* as defined by Google as "*dreaming*, *planning*, *booking*, and *experiencing*" [11]. When users dream of going away, they browse crowdsourced itineraries on wOndary or read travel-related stories. Online travel media, such as travel blogs can include wOndary's widget to refer users to unique itineraries that have been created by other travelers. In the planning phase the users save activities or copy itineraries to quickly create their own, customized trip. The users can search for specific locations and activities on and off the platform and collaborate with their co-travelers. By synchronizing the wOndary itinerary to the calendar app on their phone, the trip info becomes available when a user is offline to experience the foreign culture, but can be adapted at any time if there is Internet connectivity. Once the users return from their trip, they can privately share their itinerary with friends and colleagues or decide to publish it to all other users within the platform.

wOndary features a web application that is currently available in open beta on https://wondary.com. It is implemented as a single-page-application that runs on the Google Cloud Platform, and therefore, works in web browsers on all types of devices.

2.1 Finding Inspiration with the "Explore" Page

The users need a structured way to access the growing number of crowdsourced itineraries. To answer our first research question, wOndary provides a location-based *"Explore"* feature that allows querying a location, and filtering by geographical bounds and attributes, such as trip duration. Filtering is possible by adjusting the trip duration (72 hours, 1 week, or 2+weeks), the season, and the query area by adjusting the map excerpt. We chose this visual representation for the recommendations because a complex domain, like global travel, requires an intuitive user interface instead of a simple list. Therefore, matching items are displayed on a map and as a list, where their ranking depends on the distance to the queried location constituting the baseline for future improvements.

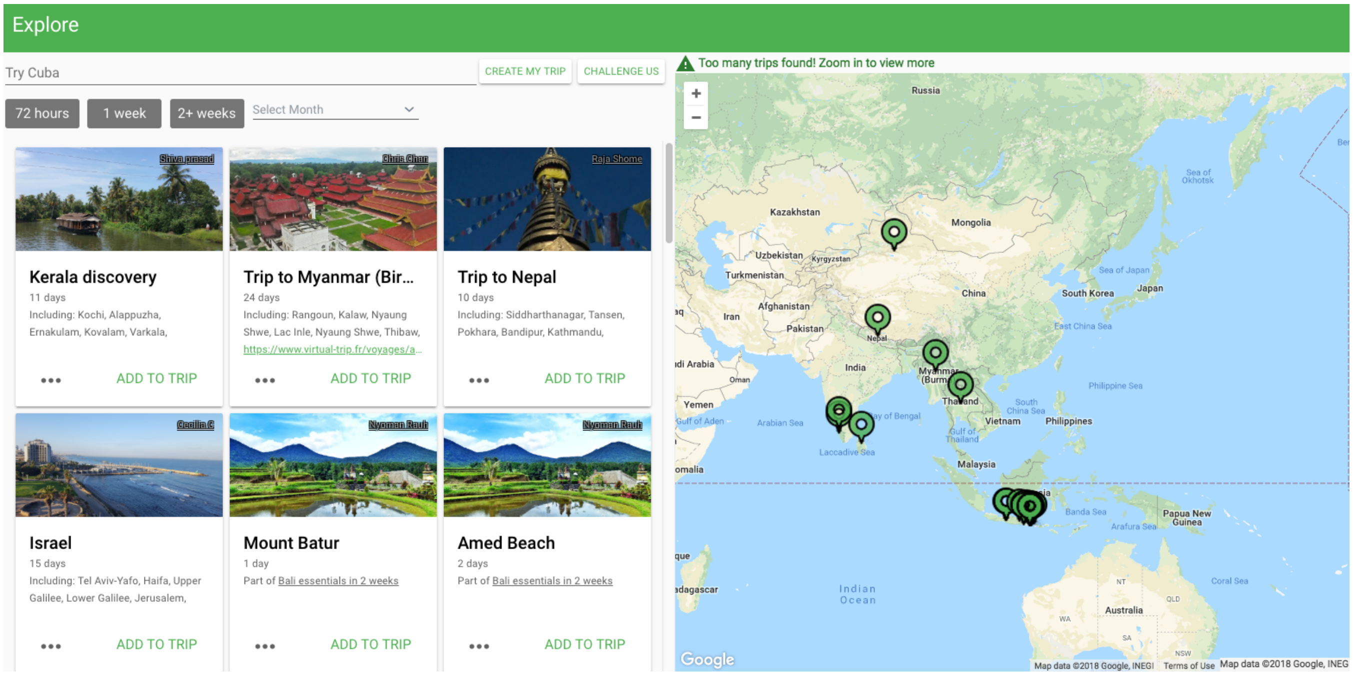

Figure 1: Explore Page, https://wondary.com/explore

The recommended items are both full itineraries as well as blocks, as defined below. As can be seen in Figure 1, the interface allows users to zoom into a geographical region. The users can also view high-level information about itineraries and focus on the ones they would like to see further details about, or they can copy them as a basis for their own customized trip.

With an increasing number of trips being published on the platform, it has become difficult for users to identify itineraries that fit their travel requirements. For example, itineraries are diverse in terms of included activities, and a user who loves sightseeing may not be interested in a trip that features primarily beaches or a multi-day hike through the mountains. Additionally, the users expect websites to support them in finding relevant content. Last, the number of trips for a popular region make it tedious for users to review all itineraries. Therefore, recommendations are playing an increasingly important role in wOndary's Explore feature because showing relevant content to the user improves their engagement and general satisfaction with the application.

2.2 A Data Model for Structured Itineraries

wOndary's data model for trips is based on insights from the domain. When travelers plan their trips, they often think of destinations, e.g., cities that they want to connectively visit. For example, a trip to Italy would start with several days in Rome, then, a day in Florence, visiting friends in Bologna over the weekend, and finish with three more days in Venice. To capture this, wOndary structures trips into blocks. A block acts as a descriptor of a partial trip that has a duration of one or more consecutive days and links to a location. Thus, trips are modeled as a sequence of one or more blocks. This structure was designed using user feedback and matches the way travelers approach planning. Additionally, it allows the normalization of trips spanning longer periods of time (several weeks or months) into portions that are transferable between trips of different travelers. wOndary heavily relies on blocks, not only when recommending items but also when presenting structured information about trips to users.

The next lower level of the data model is the day, consisting of three types of entries: transportation, lodging, and activities. Having a good overview of how to get from one place to another and where to stay overnight is essential for planning travel, whereas, instead, travelers define their trips based on the attractions they visit during the day. Currently, the users can input the attractions using venues from Google Places to ensure that they actually exist; typos are corrected, and duplicates are eliminated. Furthermore, the Google Places service provides further information, such as an image, opening hours, or ratings.

To perform content-based recommendations, it is necessary to classify items and the users into some meaningful categories. Therefore, our answer to RQ2 is the aforementioned data model using the five categories listed below, which are influenced by the target audience of the platform and the available attraction information. We compiled them based on an analysis of the platform's trips combined with our expert knowledge on individual travel.

- **Food** Mainly comprises restaurants and cafés, but also grocery stores and food markets.
- **Culture** Describes activities and places with cultural or historical attributes. For example, museums, galleries, churches and theaters fall under this category.
- **Nightlife** Categorizes places that are commonly related to nightlife such as bars, night markets, and jazz clubs.

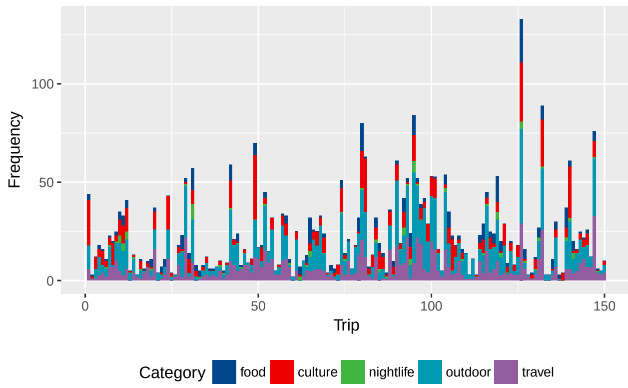

Figure 2: Frequencies of Categories per Trip

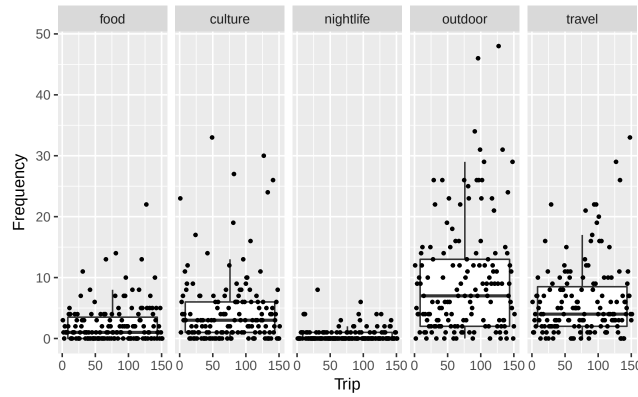

Figure 3: Classification of Trips per Category

- **Outdoor** Includes attributes associated with natural scenery or outdoor activities, such as parks, nature preserves, beaches, mountains and trails.
- **Transport & Travel** Consists of travel-related attractions, such as ferries, train stations and airports. This indicates that a relevant portion of the day is spent on transportation and that the transfer itself is an attraction.

2.3 Content-Based Travel Recommendations

To categorize the attractions, we query the Google Places types[2] and directly map them into our five categories. However, the returned place types are not primarily meant for travelers. For example, the type query for the Colosseum of Rome, Italy returns:

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"types": ["point_of_interest", "establishment"]
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While these types are not totally off mark, the information is insufficient to categorize this monument into one of our categories. Therefore, we augment the types from Google with an additional lookup of the attraction via the Foursquare API to allow one attraction to be a member of several categories. Foursquare has a rich hierarchical region categorization[3] with 923 categories that are organized in a tree to model specialized subcategories. To locate a Google Place on Foursquare, we performed a query by name using the exact location. By doing a bulk comparison, we found that most attractions also exist in Foursquare, except for political entities, such as city names. Conveniently, due to the bounded local search, the first result for Foursquare was the correct result for the corresponding Google Place. Recalling our example, we found that Colosseum was categorized as a *"Historic Site"*, which is within the *"Arts & Entertainment"* category of Foursquare. Using static mapping of all Google types and Foursquare categories, we can determine the wOndary categorization. The Colosseum would be categorized into *Culture* because the Google types (*'point_of_interest'* and *'establishment'*) are not part of the mapping, whereas a *'Historic Site'* maps to the *Culture* category. One attraction can have several wOndary categories; however, not all venue types are relevant for travelers. For example, hospitals are not mapped to any of our categories, because we argue that they are not relevant for planning a trip.

Figure 2 shows the distribution of categories of a representative sample of 150 trips from wOndary based on the top trips according to user interactions. A closer look into the distribution of the categories in Figure 3 shows that most venues are categorized into the *Outdoor* category, whereas *Nightlife* is the least frequent.

Having classified the items, it is also necessary to know the user's preferences to do content-based recommendation. The default method would be to explicitly ask the user to indicate her preferences regarding the five travel categories, e.g., on a scale from 1 (not interesting) to 5 (highly interesting). However, this would require a manual interaction, which we can avoid by using synergy effects from the categorization of attractions. To answer RQ3, we aggregated all attractions from a user's saved trips to create a user preference profile. While this can be refined further with more detailed click stream data, it is a straightforward metric for classifying user travel preferences within wOndary.

The actual ranking for the recommendations is performed by calculating the cosine similarity using the five dimensional vector of distinctive travel interests. Here we exploit the structure of our data model to recommend complete trips and trip parts, i.e., blocks or specific days. Currently, the Explore page features trips and blocks as recommendations. In the first step, the system filters out all trips that are not within the bounds of the map or do not match the temporal filters (see Figure 1). When a trip is only partially in the query region, the blocks within the area will be included. Then, all past trips of the user are removed because we assume they are not of interest for future travel plans. Trips and blocks as ranked by the cosine similarity with respect to the user profile and also listed left of the map. To keep clarity in the interface, only the top 30 items are displayed.

For new users that have not yet copied any trips, the content-based recommender cannot compute a ranking for the trips. Therefore, the trips displayed on the Explore page will be ranked by the geographic distance to the center of the map.

[2]https://developers.google.com/places/web-service/supported_types
[3]https://developer.foursquare.com/docs/resources/categories

3 STATE OF THE ART OF PERSONALIZED TRAVEL RECOMMENDATION

The tourism domain is a popular branch of recommender system (RS) research because it is a highly emotional, personal, and inherently complex topic. Early systems recommended single items, such as attractions or bundled travel packages [17], and there are big commercial players, such as hotels, restaurants, airlines, and activities. In their survey, Borràs et al. [3] categorized an intelligent tourism RS into four functionalities: travel destination and tourist packs, suggested attractions, trip planners, and social aspects. In 2014, most approaches focused on the attraction suggestion category; however, currently, the trend is on complex recommendations [30], such as sequences of attractions [29], composite travel regions [6, 13], and group recommendations [5] for tourism. When it comes to complex recommendations such as enjoyable routes, the challenge is to identify relevant points of interest (POIs) and then connect them in a coherent trip. This problem is called the Tourist Trip Design Problem (TTDP) [9], which is algorithmically interesting and has been widely investigated [28].

However, in this paper, we tackled the complexities of travel using a crowdsourcing approach by performing personalized travel recommendations using actual trips from users. Crowdsourcing has the advantage of being able to vary the length of travel, such as a multi-month world trip, a week trip to an island, or a weekend in a city, and this is an unsolved challenge in the tourist RS for solving the TTDP. Furthermore, the structured representation of trips allows the combination of several independent blocks into a prolonged trip or the possibility of selecting parts of a trip if the traveler is short on time. Determining the duration of stay at each location can be further personalized with additional information about the traveler, such as tourist mobility patterns [7] from past trips.

The RS of static travel items utilizes ratings as one factor of a hybrid recommendation algorithm [4]. However, because we exploit the trip structures to aggregate and reassemble trips, ratings are not of much use due to their high sparsity. Furthermore, we are concerned that users are not motivated to provide ratings for trips and blocks, and the platform's user experience could decline if it required users to rate trips. Therefore, we have employed the content-based recommendation paradigm [23] to match items to users. Content-based recommendations are commonplace as a hybrid factor in complex domains, such as in scientific publications [1], news articles [15, 16] or tourism [14]. However, for a purely content-based recommendation, it is often challenging to model the user after the very same features as the items to compute a similarity measure, e.g., the cosine distance, for ranking items. When investigating potential classification schemes of touristic items for content-based recommendations, the work of Neidhardt et al. is an established alternative to wOndary's categorization. Based on the Big Five Factor Model [18] from personality psychology and prior research on tourist roles [10, 31], Neidhardt et al. developed the *Seven Factor Model* of tourist behavioral patterns [21]. In a follow-up study [22], they showed that this can be used to elicit user preferences via pictures classified by domain experts. However, the final step of using these tourist behavioral patterns to recommend items was only recently performed [25] and required a very big commercial data set of 30,000 tourist destinations classified along 27 motivational and 14 geographical attributes.

Commercial approaches for travel recommendations range from merchants focusing on the sale of travel-related services, such as activities, transport and lodging, to review platforms with a business model based on commissions. Depending on the type of business, travel recommendations are a side-product or a main feature in which the recommendation can include a single product or service or complete trips. Big platforms, such as TripAdvisor and Google Maps, recommend separate activities to users based on ratings, reviews, and behavior on the platform. Social networks, such as Facebook, provide less structured ways to ask friends for travel recommendations as a way to provide crowd-sourcing recommendations. Google Trips recommends single- or multi-day tours [8] in the vicinity based on user behavior and by scanning the user's booking confirmations in Gmail.

Mafengwo[4] and Qyer[5] (both solely available in Mandarin) are the closest platforms to our approach and provide travel-related services, as well as trip planning, and sharing functionalities.

4 AUGMENTING WONDARY'S TRAVEL RECOMMENDATIONS

As described in this paper, its core functionality is the first step in wOndary's travel RS. To answer the second part of RQ1, this section discusses wOndary's future agenda concerning trip recommendations. We plan to improve the item categorization, to enable explanations and critiquing of our recommendations, and to explicitly support the travel decision-making process for groups.

As discussed at the end of Section 2, currently, new users are not provided with content-based recommendations. We believe we can overcome the cold start problem with an elaborate click stream analysis and an initial preference elicitation phase in which users provide their feedback for the five categories e.g., through small games.

The current categorization is based on expert knowledge and data sources for categorization. It would be useful to do a thorough investigation of the attraction's attributes with unsupervised learning to obtain data-backed clusters. Furthermore, a latent factor analysis of the trips would be interesting to evaluate the explicit categories. As we have rich information about the trips, the core of our recommender system is content-based. This could be improved in the future with more hybrid factors, e.g., knowledge-based recommendations and collaborative ratings of items. To provide transparency and improve trust in the recommendations, it would be highly interesting to provide explanations of the recommendations [27] to the user. These explanations could be based on the classification of items (*"because you liked … "*), the users (*"travelers similar to you also liked … "*), or by taking the social network on the platform into account (*"your friend traveled to … "*) [2]. Another promising technique to improve recommendations is critiquing [19]. A conversational element [20] within the presentation of results would enable active learning of user needs [24]. This is useful because we think that it is unlikely that recommendations in such a complex domain are perfect on the first iteration, e.g., because

[4] http://www.mafengwo.cn/
[5] http://www.qyer.com/

travelers may want to go on a different type of holiday than they went on before.

Since travel planning on wOndary is already collaborative, it is a logical step to extend the recommendations to groups to support the decision-making process. However, we acknowledge that this issue has not been resolved and is still of high interest to the research community in this area [5, 12, 26].

5 CONCLUSIONS

In this paper, we described our approach for recommending high-quality crowdsourced trips. We presented a novel structure for itineraries that is both useful for users to obtain an understanding of trip characteristics and for software systems to work with. This data model structures user-submitted trips, thereby defining items based on different lengths, i.e., trips, blocks, and days. Second, we have automatically classified the aforementioned item types using wOndary's categorization scheme. We exploited this categorization scheme to perform user modeling without explicit elicitation of preferences using the user's past trips. Finally, we showcased a user interface for intuitively presenting recommendations for trips across the globe.

The current version is the core part of the content-based recommender system and will be extended with advanced features in the future. While the recommendations of this platform are more personalized than ranking trips by distance to the center of the map, we want to confirm the perceived accuracy by utilizing an automated A/B testing framework, which we will also use to continuously measure future changes in the algorithm, of which we have sketched several in our future work section. This will establish wOndary's test setup for travel recommendations to provide informed decisions regarding improvement of the product.

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