TripRec – A Recommender System for Planning Composite City Trips Based on Travel Mobility Analysis

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ABSTRACT

Location-based social networks (LBSNs) are rich sources of studying travel mobility of people. With more users sharing updates about their activities in LBSNs, there is a high availability of data to learn about their travel mobility patterns. This can help to improve travel recommender systems, as we get a realistic impression of travelers' travel behavior. We propose a system that recommends personalised city trips to different users by employing data-driven approaches. Our web-based system recommends composite trips of 138 cities all around the world. The application elicits user information and preferences like home region, destination region, traveller type, maximum travel duration and fondness for different types of venues in a city, as inputs. Satisfying the user preferences and constraints, a suitable trip including an ordered list of cities with duration of stay at each is determined, to be recommended to the user.

KEYWORDS

Destination Recommender Systems, City Trips, Data Mining, Personalisation

1 INTRODUCTION AND RELATED WORK

Destination recommender systems (DRSs) can help travellers to discover destinations to travel to. Depending on the type of data utilised, a recommendation model can be collaborative filtering (CF) or content-based filtering (CBF). The former model is typically based on explicit or implicit user feedback. CBF-based recommender systems (RSs) use the characteristic features of the items and the preferences of a user before generating the recommendations for them. The design of RSs, which earlier relied only on intuition-based models, is now employing more data-driven approaches [4]. The latter involves analysis of large sets of data, interpreting and incorporating them for building better decision-making strategies.

City tourism, also known as urban tourism involves travelling to the urban cities of different countries. It facilitates the development of the cities to attract tourists. Moreover, with more than half of the world population staying in urban areas [16], city tourism is important for the economy as it brings employment to numerous individuals. On the other side, this is mainly interesting for tourists who prefer to visit locations including architectures & monuments, pubs & bars, restaurants & cafés etc. However, it is difficult for people to determine desirable top destination cities to be visited for their next trip. City RSs become useful in this context.

Google Trips[1] collects data from Gmail account of a user and combines it with other features like crowd-sourced reviews about destinations for suggesting trips to her. However, this is not personalised for users without prior Gmail accounts. Due to the inherent complexities, there is no application in the market that uses data-driven approaches for determining personalised, composite city trips for all users, motivating us to start working further in that direction. To tackle this challenge, we discover travel mobility patterns from LBSNs and utilise them for computing personalised composite city trips.

Traditionally, destination recommendation was subdivided into recommending regions [22], cities [7], point of interests (POIs) [1, 2, 12], activities [18] or events [15]. Recommending POIs can mean recommendation of next POI [12], top-k POIs using two common types of recommender systems, viz., CF-based [1] and CBF-based [2], or composite POIs. The conversational DRS called *CityRec* developed by Dietz et al. [7] recommended only individual cities to users. The RS developed by us recommends composite trips, specifically, multiple cities to be visited in order along with a recommended duration of stay. A composite trip consists of a sequence of travel destinations. Composite tourist recommender systems (CTRSs) deal with choosing a number of travel destinations, selecting the sequence of visit, and determining suitable duration of stay in each of the destination. Researchers in the past developed CTRSs recommending multiple countries [11, 22], or POIs [23, 24].

POI recommendations by Yu and Chang [24] were delivered to the users time-to-time, whereas, those provided by Wörndl et al. [23] were displayed together at a time. CTRSs for POIs can recommend composite POIs with [3, 20] or without [23] constructing timed paths. Those with the timed paths suggest the time of arrival and time to leave the POI along with the sequence of POIs, determining the duration of stay at each POI. CTRSs are mostly otherwise designed by solving tourist trip design problem (TTDP) [9, 10]. The CTRS designed by us also uses the approach of solving TTDP with the maximum travel duration constraint to recommend one or more cities to tourists.

2 SYSTEM OVERVIEW

We discuss the system in three broad stages – the data engineering & analysis (pre-processing), CBF-based recommendation (peri-processing), and user-centric evaluation of the web application (post-processing).

2.1 Data Engineering, Analysis & Pre-processing

Initially, we collect, analyse and clean the data to make it ready to be used for the CBF-based recommendation.

[1]https://www.google.com/travel/

2.1.1 Mapping of World Regions. We divide six continents of the world (except Antarctica) to 10 global regions, viz., North America, South America, North Europe, Southwest Europe, Southeast Europe, North Africa, South Africa, West Asia, East Asia and Oceania. Figure 1 displays these regions on the world map.

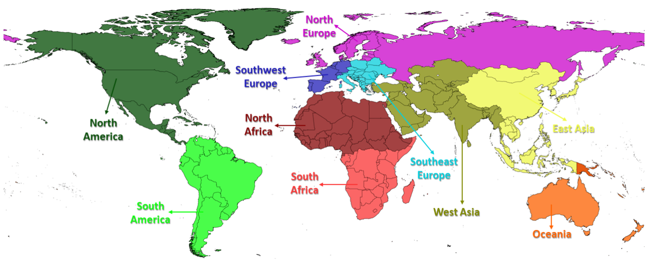

Figure 1: World map annotated with our customised world regions

2.1.2 Datasets – Cities & Trips. We consider 138 cities to be recommended to travellers of different types. The cities are attributed with different features. Those involving the frequencies of venues, with different types of touristic values located in the cities, are called *arts & entertainment (AE)*, *food (FD)*, *nightlife (NL)*, and *outdoors & recreation (OR)*. The types of these venues are based on four of the Foursquare venue categories[2]. We divide each of the frequency values by the total venue counts of all four types considered in the respective cities. This is done to avoid bias due to the varied range of venue counts in different cities and check the prevalence of the different types in each of the cities. Finally, for each city, stemming from a number derived from Numbeo[3], the *cost index (CI)* values are normalized between 0 and 100.

Trips are identified out of the check-ins from Twitter using a data-mining approach [5, 21]. Each trip is annotated with different characteristic features:

- Mobility-based features – the features that help in analysing mobility patterns of travelling in the respective trips. This includes *travel duration*, *displacement*, *radius of gyration*, *cities visited*, and *countries visited* [6].
- Traveller characteristics – the features that include information about the travellers of the identified trips. This includes *home region* of a traveller and the *home ratio*, providing the ratio of the number of check-ins at her home country to that at a location outside the home country.
- City-based features – features signifying the kind of places visited during the trip. Since there can be multiple cities in a trip, we calculate the average value F_i for each city-based feature within a trip i using Equation 1.

$$F_i = \frac{\sum_{j=1}^{n} \left(n_{b_j} * F_{b_j} \right)}{\sum_{j=1}^{n} n_{b_j}}, \qquad (1)$$

where n is the distinct number of blocks (cities) within the trip, n_{bj} denotes the number of times block b_j is visited within the trip, F_{bj} denotes value of the feature F for block b_j, and F designates AE, FD, NL, OR, or CI.

After this characterisation, some of these trips are removed based on their poor qualities to assure a better quality of the dataset.

2.1.3 Identification of Regional Traveller Types. Unlike the previous papers for clustering travellers [6, 8], in this paper, we segregate trips by travellers from different home regions before identifying the travel mobility patterns. We discover 10 prototype clusters for the types of travellers around the world, after characterising the trips followed by them. Next, we cluster the trip subsets and thus the travellers using k-means clustering into suitable number of groups chosen using silhouette index. This is followed by the identification of the traveller types found in different regions. The 47 traveller types so obtained from different regions of the world act as the possible options for traveller types to be chosen from by a user of our final RS application. The methodologies, traveller types and their analysis can further be found in the elaborated discussion in the master thesis by Roy [17].

2.1.4 Calculation of Duration of Stays. The number of days to stay at any city to be recommended to different types of travellers are pre-calculated and stored. At first, we compute the mean duration of stay at a city considering the trips by all the travellers of the same type having their home location in the same region. We do this for all the cities, for the different traveller types belonging to each of the 10 regions. Altogether, we obtain 47 different values for duration of stay at each city depending on the 47 traveller types.

In the trips we consider, not all traveller types visit all the cities. However, we can find visits to all of the 138 cities in our database, if we consider the travellers of all types. We do not intend to omit the possibility of recommendation of any of the 138 cities to any traveller type. We update the duration of stay at a city with the average stay by the travellers of all types belonging to the particular home region, if it is found to be zero by the current traveller type. If it is still zero, we update the duration again with the mean duration of stay in the city by the travellers of all types from all the home regions. This is done for every city, for the 47 traveller types.

2.2 Pre-processing & Content-based Recommendation

This section explains the user inputs, CBF-based recommendation algorithm and the overview of the web application.

2.2.1 User Inputs. A user needs to input her preferences based on which a CBF-based recommendation is provided to her. Following are the inputs required for our algorithm:

(1) Home region of the user, chosen from the 10 world regions.
(2) Traveller type of the user that suits her the best, chosen from the list of traveller types for those having their home same as the user's home region.
(3) Destination region for the user's desired trip, chosen again from the 10 world regions.
(4) Maximum duration for the desired trip.
(5) The preference levels for the different city-based features.

2.2.2 Recommendation Algorithm. After calculating the duration of stay at different cities for different traveller types, and after

[2]https://developer.foursquare.com/docs/resources/categories
[3]https://www.numbeo.com/cost-of-living/

having the inputs from one user, we utilise the following steps as part of the recommendation algorithm to plan a composite city trip for her:

(1) **Filtering Cities According to Destination Region** – From the 47 lists of cities with different duration of stays for different traveller types, we select the list based on the current user's home region and her travelling type. From that list of 138 cities, we remove the ones which do not belong to the region chosen by the user as her destination region. As a result, we are left with a subset of cities considered further for recommendation.
(2) **Assigning Scores to Cities** – For each city in the filtered subset, we find the Euclidean distance between the city-based feature vector ($C = [CI_{city}, AE_{city}, F_{city}, N_{city}, OR_{city}]$) and the user preference vector ($P = [P_{CI}, P_{AE}, P_F, P_N, P_{OR}]$). This is followed by using equation 2 to assign a score to each of them. The simple score metric used here serves the purpose of giving higher values to the cities whose feature values are closer to the preferences of a user.

$$score_{city} \leftarrow \frac{1}{distance_{city} + 1} \tag{2}$$

(3) **Selection of Cities** – The filtered cities are sorted based on the scores assigned to them. Then the greedy selection of the highly scored cities is done until the total duration of stay at the selected cities does not exceed the maximum travel duration input of the user. This constitutes the initial list of selected cities. Some of the cities, that are far away from others in the list and have only a single day as the duration of stay for the current user, are removed from the list. After the removal, if the constraints permit, more cities are considered to be added to form the final list of selected cities.
(4) **Ordering of Cities** – For ordering the selected list of cities, we initially find different orders starting from each city in the list as source and moving to the nearest one next. Then we calculate the total distances to be covered for visiting the cities in the different orders, and pick up the specific order with the shortest distance to be covered.

2.2.3 TripRec Web Application. We develop *TripRec* , a data-driven prototype web application to recommend composite city trips to different types of travellers using the discussed recommendation strategy. A user interface (UI) facilitates the interaction between a user and the system. Figure 2 shows the interaction flows between a user and the system through the UI for TripRec.

While prompting a user to provide different inputs for eliciting her preferences, the system also guides her with helpful information in every step while she uses the application. As a trip recommendation, the UI displays the cities, its corresponding countries, and the duration of stay at each city in the order returned by the recommendation algorithm. This is also accompanied by presenting the order of visits to the recommended cities using Google Maps[4]. If no recommendation is found for the specified inputs, the user is asked to modify them and try again. Figure 3 shows an exemplary recommendation result to a user from *Southwest Europe*, opting to

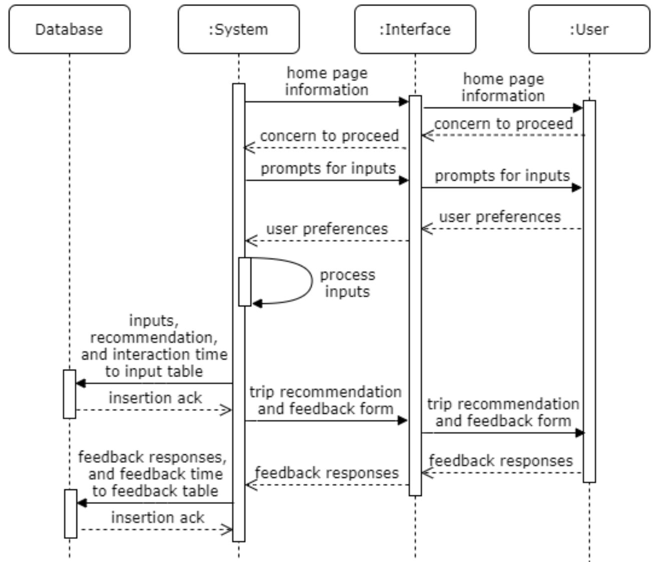

Figure 2: Interaction between user and system

visit some cities in *North Europe* within 16 days as *Eurotrotters* [17], who are travellers from Europe, travelling to many nearby cities and countries.

Figure 3: Exemplary recommendation by *TripRec*

The agreement questions in the feedback form follow the ResQue Questionnaire [14], a validated evaluation tool for RS:

(Q1) The individual travel destinations recommended to me matched my interests
(Q2) The composite travel destinations recommended to me matched my interests
(Q3) The recommended duration of stays at each city seems appropriate for me
(Q4) I understood why the travel destinations were recommended to me
(Q5) I found it easy to tell the system what my preferences are
(Q6) TripRec allows me to modify my taste profile
(Q7) The layout and labels of the recommender interface are clear
(Q8) Overall, I am satisfied with this recommender system
(Q9) I would use this recommender system again, when looking for travel destinations

[4]https://www.google.com/maps

The user needs to specify their level of agreement to the different statements on a five-point likert scale [13]. The responses check the RS on the basis of quality of the recommended items, transparency, ease of preference elicitation and revision, interface adequacy and attitudes of the user. There are also personal questions about the age and gender of the user and a place to add additional comments.

2.3 User-centric Evaluation of Web Application

We conducted a user study for *TripRec* to examine the behaviours of its users, their opinions about the system, and some characteristics of the services provided to them. Within a span of two weeks, we accumulated 217 recommendation requests from 113 unique users, 75 of whom provided feedback used for the evaluation of the application.

2.3.1 Different Users and their Behaviours. The application received the maximum number of requests by people from *West Asia*, followed by those from *Southwest Europe* and *Southeast Europe*, whereas there were no users from *Oceania*. Other than *West Asia*, users wanted to go to the European regions, viz., *Southwest Europe*, *Southeast Europe*, and *North Europe* the most. Irrespective of home regions, the users usually tend to visit cities with low to medium *cost index*. A lot of the users chose to follow the traveller type *vacationers* [17], who are travellers making a short trip not so far, possibly within their own home regions.

2.3.2 Analysing Recommendations Based on User Data. We analyse the recommendations provided to users by *TripRec* based on their preferences. We determine which cities are recommended the most by calculating the recommendation ratio (RR) of the cities within each destination region. RR of a city is the number of times it is recommended divided by the total number of recommendations within the corresponding destination region. We can see more variation of cities in the recommendation results when there are more cities under a destination region in our database. Using our user study data, we also find out, on an average, what proportion of the total travel duration is the recommended duration of stay at each city, for travellers from different regions. The recommended average duration of stay at a city divided by the average duration of a trip is called as the mean proportionate duration of stay (MPDS) at a city. Results show that the addition of more cities in the database with diverse duration of stays can balance the MPDS at different cities.

2.3.3 Quantitative Feedback Analysis. We find out how satisfied the users were with our system based on their age groups. We noticed that most of the users belonged to the age range between 21 and 30 years, and the users aged over 40 years tended to get more satisfied with the system.

Next, we compare the users' agreement levels to the various feedback questions. Users seem to have mostly agreed to the provided questions in favour of *TripRec*. However, looking at the responses closely, we note the following points:

(1) Most of the users were satisfied with the individual recommendations ($Q1$). However, the number of users satisfied with the composite recommendations ($Q2$) was comparatively lower.
(2) Users dissatisfied with the recommended duration of stays ($Q3$) were comparatively more than those dissatisfied with the recommended cities ($Q1$, $Q2$).
(3) Maximum number of users have strongly agreed to having clear layouts and labels for the interface ($Q7$), followed by those strongly agreeing to being able to specify their preferences to the system ($Q5$) and then modify them ($Q6$) as well.
(4) A lot of users have agreed to have overall liked *TripRec* ($Q8$). However, comparatively lesser people agreed to use the system again ($Q9$) in real-life. People were more neutral about the latter, possibly because of the system being a research prototype that can recommend from just 138 cities.

Finally, we determine how long the users interact with the system in terms of interaction time and feedback time. We consider only the final interaction time by each user. Eliminating an outlier record with interaction time of about *10 hours*, we plot the histogram for interaction time as shown in Figure 4:Left, the mean interaction time being *4 minutes and 40 seconds* with *6 minutes* standard deviation. Figure 4:Right shows the histogram for feedback time, the average being *5 minutes and 45 seconds* with standard deviation *12 minutes and 25 seconds*.

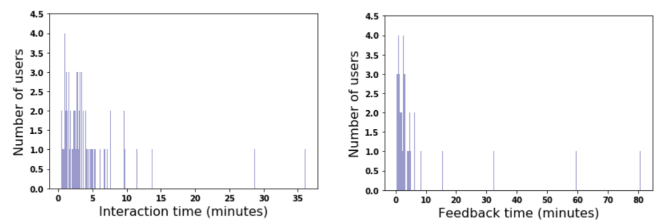

Figure 4: Left: Interaction time histogram. Right: Feedback time histogram

2.3.4 Qualitative Feedback Analysis. Some users gave additional comments expressing their concerns or providing suggestions to improve our system. Few notable ones are summarised below with our remarks on top of that:

(1) Exclude the countries already visited by a user from the recommendation list provided to her – this was out of scope, but can be considered later.
(2) Round sliders for providing preferences for city-based features were difficult to handle in some mobile devices – our prototype system was not yet designed for the specific needs of all types of devices, but can later be made more responsive.
(3) Nearby cities should be recommended – the prototype database had only 138 cities to check the functionalities of the system. With more cities added, the system is supposed to perform better.

More information about *TripRec* and its user-centric evaluation can be found in the master thesis by Roy [17].

3 CONCLUSION & FUTURE WORK

In this paper, we designed and developed the first destination recommender system for computing personalised, composite city trips for any user, after analysing mobility data from location based social networks. The overall complexity of composite destination recommendations is very high, which is reflected in our system, which employs various data engineering steps, including characterisation of cities and trips, mapping of the different cities to 10 world regions and identification of regional traveller types. We presented a novel algorithm for content-based composite city trip recommendations, which we deployed in prototype web application that served as an user-centric evaluation platform.

For the upcoming versions of TripRec, we can incorporate features like the budget information of the recommended trip and the flight booking options, which were out of scope for our present research and the prototype application. POIs specific to user preferences should be shown to the users, when demanded, for each of the recommended cities. This might enhance user satisfaction and ensure recommendation transparency. Furthermore, we plan to develop strategies for computing recommendations when the user has specified a set of preferences that would currently return an empty set. Such empty recommendations could happen due to the limited availability of only 138 cities for our prototype application. We can add more cities to our database to provide more realistic recommendations. The world divisions could then also be made more granular using a touristic region model [19], given that each region would have more cities. Moreover, with more options of cities in the database, we can take account of the distances between the cities from the beginning during their selection. Further improvement can be in terms of the duration of stays recommended to different users at the selected cities, making it more personalised.

Finally, we can also make our next prototype more responsive for more devices other than web. More options can be provided to the users to elicit their interests, priorities, and posteriorities, for greater user satisfaction.

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