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CityRec — A Data-Driven Conversational Destination Recommender System

In today's age of information, recommender systems have evolved to a must have feature for many platforms, especially in the area of travel and tourism. Destination recommender systems is a challenging domain, since unlike restaurants and points of interests, the items are not so well defined and no reliable rating information is available. Thus, we propose a data-driven characterization of cities, which is then directly used in a conversational recommender system. Through this, we overcome the costly elicitation of expert-based destination characterization, as well as the cold start problem of recommender systems. The recommender system can be used at http://cityrec.cm.in.tum.de/ and the source code has been published.

Key words: Tourism recommendation, Conversational recommender systems, Destination characterization

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Introduction and Related Work

Recommender systems have become popular in the tourism domain as a solution to help prospective travelers evaluate the overwhelming amount of information and choices they are presented with (Borràs, Moreno, & Valls, 2014). Such systems utilize personalization techniques to create an understanding of tourists' preferences and enable them to make informed decisions when planning their trips. Typically, travel recommender systems focus on assisting the user on a specific step of the planning, e.g., choosing a destination, creating a route plan, or finding POIs (points of interest) when the tourist is already at the destination (Herzog, Dietz, & Wörndl, 2019).

Thus, an important aspect of recommender systems revolves around the elicitation of user preferences. This is especially challenging in the tourism domain, as the tourism items to be recommended are usually complex to characterize and users may not always be able to tell their preferences to the system in a clear way. In fact, they might not explicitly know these preferences themselves (Neidhardt, Seyfang, Schuster, & Werthner, 2015). Given that the accuracy of recommendations also depends on how well the system understands the user preferences, it is particularly worthwhile to investigate what viable preference elicitation methods are appropriate when building a travel recommender system (Dietz, 2018).

Conversational human-computer interaction and critiquing have been suggested in previous studies as a way to address preference elicitation and enrich the user's experience with the recommender system (Averjanova, Ricci, & Nguyen, 2008; Ricci & Nguyen, 2007). These methods work through gradually refining the user profile and eliciting user preferences through multiple interaction steps (Chen & Pu, 2012); however, this is not a one-size-fits-all solution for preference elicitation and it is important to evaluate how it affects the perceived quality of recommendations before employing it in a travel recommender system.

In this paper, we present a newly developed destination recommender system that aims to overcome the cold start problem by combining a destination characterization approach with the conversational user interaction paradigm. The cold start phase of a recommender is the early phase, where it has none or very little information about its users and items (Braunhofer, Elahi, & Ricci, 2014). Traditionally, a recommender system would overcome this by, for example, recommending the most popular items, which results in nonpersonalized recommendations. The solution we employ allows users to explore the item space and to improve the recommendations using a directed search for more preferred items attributes.

System Overview

The basic task of a recommender system is to match users to items. Traditionally, this has been done with Collaborative Filtering, i.e., utilizing ratings to recommend items that similar users have rated highly. Since there are no ratings of cities available, we aim to embed users and items into the same vector space, by characterizing the cities along eight dimensions. We derive four features — "Food", "Arts & Entertainment", "Outdoors & Recreation", and "Nightlife" — from the relative frequencies of venues in the cities. The underlying assumption is that these frequencies are reasonable indicators for the association level of the city with the corresponding feature. For example, if the number of bars and clubs is high in the distribution of the venues of a city, it might be more suitable for nightlife activities than one that only has a few venues in this category, relative to the other categories in the distribution. This venue information is enriched with climate data, such as temperature and precipitation, and a cost index, as these factors also play an important role for deciding where to travel to. The details of this approach are described in (Dietz, Myftija, & Wörndl, 2019). Figure 1 shows the normalized values of five characteristic cities in the data set.

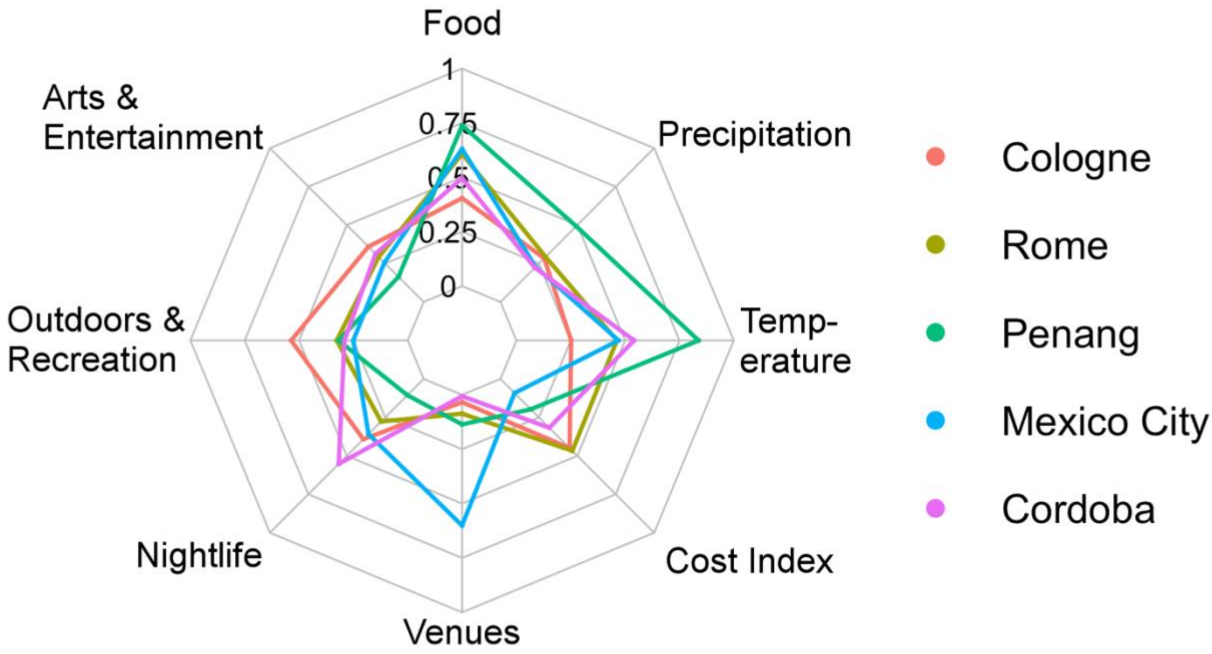

Figure 1: Spider plot of normalized feature values

Having characterized the items to be recommended, we need to develop a recommender system that is capable of eliciting the users' preferences and to find suitable cities to travel to. Such a system would need to provide a pleasant user interface and a strategy for overcoming the cold start problem, since there is no previous user information, such as ratings, available. Our solution to these challenges is CityRec[1], a destination recommender system which is served through a web application. To allow fellow researchers to use the system as the foundation for their experiments, we released the application's source code to Github[2].

We overcome the cold start problem by allowing users to directly interact with the items and select 3-5 cities they find interesting. This step, depicted in Figure 2, allows them to make an initial choice for expressing their preferences. The sample cities are a diverse representation of the item space; thus, the users can already make their preferences clear. We calculate an initial user profile by using the mean value of each feature.

1 http://cityrec.cm.in.tum.de/
2 https://github.com/divino5/cityrec-prototype

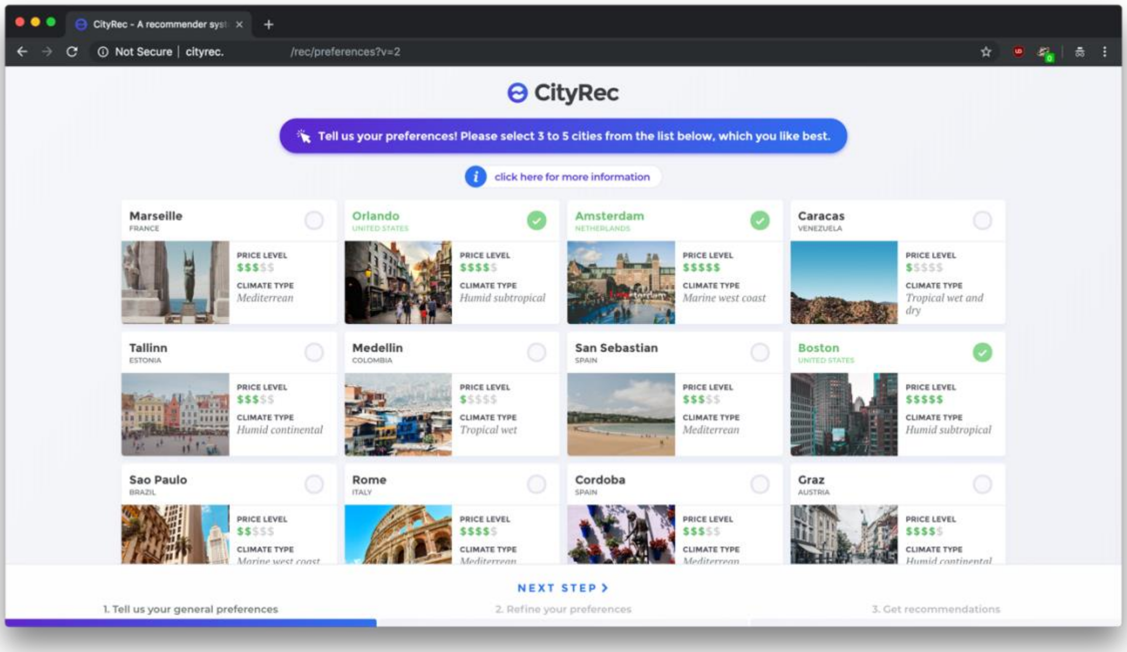

Figure 2: Initial preference elicitation step

Based on this initial profile, the system displays four initial recommendations with a greater level of detail to the user. Since this first user profile might not yet be accurate, in this step, the users can critique the initial city recommendations by adjusting each of the features using a five-point scale: *"much lower"*, *"lower"*, *"just right"*, *"higher"*, and *"much higher."* This would shift the user's profile towards the respective dimension. Thus, the user interacts with the items and is able to adjust the user profile within the item space. This increases the understanding the user's of the item space and also leads to more accurate recommendations.

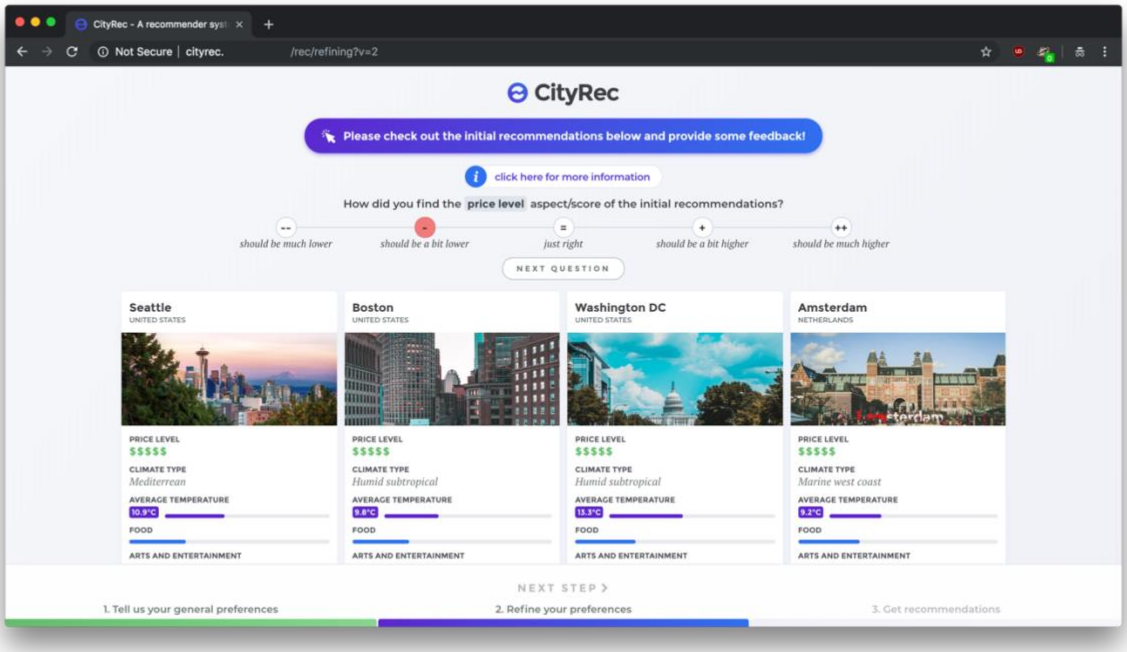

Figure 3 Recommendation refinement step

In a preliminary evaluation using 104 online users in a between-subjects study design, we found that the correlation between the final user profile of the system with critiquing to a self-reported importance of the features was significantly higher than the baseline system, which did not employ the aforementioned refinement step. Although the critiquing system was more effort to use, the users were significantly (p=0.037) more satisfied and also rated the recommendation accuracy significantly higher (p=0.043). More details on the study can be found in (Dietz et al., 2019).

Conclusions

This paper described CityRec, a data-driven conversational destination recommender system for destinations all over the world. Recommending cities to travel to is currently still an under-researched topic, as cities as items are intangible, hard to characterize, and not of direct business interest compared to recommending hotels or restaurants for a commission. Nevertheless, such systems are important for users who seek advice where to travel to. Our system marks a first step, which is to be expanded in terms of cities offered (currently 180). Furthermore, we plan to improve the user interaction to make it easier and more enjoyable to use. Future recommendations could be extended by also recommending the duration of stay at a city (Dietz & Wörndl, 2019) or by characterizing users based on their past trips (Dietz & Weimert, 2018).

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