SmartVenues: Recommending Popular and Personalised Venues in a City

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ABSTRACT

We present SmartVenues, a system that recommends nearby venues to a user who visits or lives in a city. SmartVenues models the variation over time of each venue's level of attendance, and uses state-of-the-art time series forecasting algorithms to predict the future attendance of these venues. We use the predicted levels of attendance to infer the popularity of a venue at future points in time, and to provide the user with recommendations at different times of the day. If the users log in with their Facebook account, the recommendations are personalised using the pages they *like*. In this demonstrator, we detail the architecture of the system and the data that we collect in real-time to be able to perform the predictions. We also present two different interfaces that build upon our system to display the recommendations: a web-based application and a mobile application.

Categories and Subject Descriptors: H.3.3 [Information Storage & Retrieval]: Information Search & Retrieval

Keywords: venue recommendation; location-based social network; attendance prediction; time series forecasting; Foursquare; Facebook

1. INTRODUCTION

Mobile technologies are changing the way we look for and consume information. Search is becoming increasingly local, and is now mostly performed using mobile devices[1]. Looking for venues while on the move is a new task that is receiving growing interest, demonstrated by the popularity of Location-Based Social Networks (LBSNs) [11] such as Foursquare[2], Yelp[3], or Google Places[4]. In these LBSNs, users can broadcast their location to their friends (or to other users), and can rate or comment the venues they visited. The preferences of users are derived from this implicit feedback, allowing the applications of the LBSNs to provide users with personalised venue recommendations [9, 10].

There are two main drawbacks in the current venue recommendation applications proposed by the leading LBSNs [3]. Firstly, they do not take the time of the day or the date into account. Indeed, the popularity of venues varies throughout the day, and can also depend on the day of the week or the season of the year. For example, bars are more likely to be crowded on week end nights, while parks are significantly more attractive during spring or summer time. Secondly, they require the users to rate large amounts of venues to perform accurate personalised recommendations. This drawback is also known as the cold start problem of recommender systems [8].

In this demonstrator, we present SmartVenues, a venue recommendation system for discovering popular and personalised venues in a city at different times of the day, without requiring the users to enter their preferences. SmartVenues aims at 1) modelling the popularity of individual venues over time by predicting their levels of attendance, 2) recommending personalised venues to the users by using the pages they *like* on Facebook, and 3) providing appropriate interfaces that are suitable for exploration (web-based) or discovery (mobile-based) scenarios. SmartVenues relies on a backend system that computes the predictions and recommendations (described in Section 2), on the top of which we have implemented the two different interfaces (Section 3). The web interface of SmartVenues can be accessed at `http://demos.terrier.org/SMART/venuesuggestion`, and the mobile application can be downloaded from the Google Play store at `https://play.google.com/store/apps/details?id=gla.ac.uk.entertainme.ui`.

2. DATA & ARCHITECTURE

The SmartVenues system is composed of two parts. The first one models the popularity of venues over time by querying Foursquare to obtain the levels of attendance for each venue in real-time, and by computing predictions of these levels of attendance. The second one is interactive and ranks the venues for a given Facebook user, at a given location and a given time. SmartVenues currently proposes recommendations for four cities: London, Amsterdam, San Francisco, and Glasgow.

2.1 Modelling and predicting the popularity of venues

We take a simple yet realistic definition of the popularity of a venue by considering its level of attendance: a venue that attracts a lot of people is more likely to be popular [5].

[1]`http://marketingland.com/nielsen-time-accessing-internet-smartphones-pcs-73683`
[2]`http://foursquare.com`
[3]`http://yelp.com`
[4]`http://maps.google.com/`

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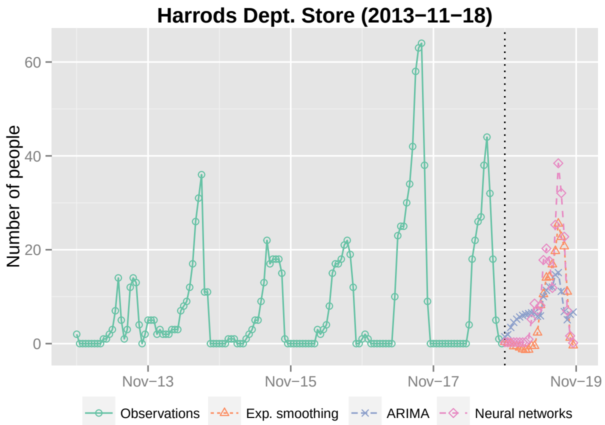

Figure 1: Predicting the attendance of the Harrods department store (London) on the 18^{th} November 2013, using three state-of-the-art time series forecasting models. Models were trained from the 12^{nd} to the 17^{th}.

We use the API of Foursquare[5], which allows to obtain the number of people currently visiting the venue. By querying the API every hour for each venue, we build comprehensive time series of venue attendance. An example of such time series can be seen in Figure 1, where the green line represents the observations made over a six days period for the Harrods department store in London.

We predict the future levels of attendance of venues using time series forecasting algorithms, such as ARIMA (Autoregressive integrated moving average), Exponential Smoothing, or Neural Networks [7]. These algorithms use past observations to learn trends, seasonal variations, and recurring patterns in the data. It suits perfectly our use case, for which we have large amounts of very precise (i.e. hourly) data. Moreover, they offer the advantage to predict not only the value of the next point of the time series, but the values of the next N points. In our case, we predict the levels of attendance of each venue for the next 24 hours. An example of these predictions is displayed in Figure 1, where we see the output values of three forecasting models for the seventh day, after having trained the models on the first six days. All of the time series forecasting models were built using the well-known `forecast` package of `R` [4]. The ARIMA algorithm was found to be the most accurate according to our preliminary experiments, and we logically use it as our default forecasting model.

2.2 Recommending venues

The other part of SmartVenues focuses on the actual retrieval and recommendation of venues. However, this process does not rely on traditional collaborative filtering approaches, and hence does not require the users to enter a list of preferences nor does it ask them to rate venues. We personalise the recommendations by asking the users to log in with their Facebook account, thereby using the pages they *like* on the social network as a surrogate for their personal interests. We used the authentication software development kit provided by Facebook[6] in order to obtain the pages that users like without storing any personal information.

We employ a simple and straightforward approach for personalising the recommendations. First, we indexed the homepages of the venues using the Terrier IR platform [6]. Then, when the users – logged in with their Facebook account – request recommendations, we use the category (e.g. "music", "author", "museum", ...) of each of the Facebook pages they like as a query to retrieve a ranked list of venues. In other words, the score of a venue v is computed as follows:

$$score(v) = \frac{1}{|\text{likes}(u)|} \sum_{p \in \text{likes}(u)} RSV(\text{cat}(p), v) \qquad (1)$$

where $\text{likes}(u)$ denotes the set of Facebook pages liked by the user u, and $\text{cat}(p)$ is the category of the page p. In this demonstrator, we use the DPH weighting model [1] as the RSV function. Finally, we only keep the venues that are close to the location that the user entered as an input parameter, in order to recommend nearby venues. More specifically, we do not recommend venues that are more than 500 meters away from their location.

3. INTERFACES

The web-based application allows the users to set custom locations and to explore the recommendations, as well as the venue popularity predictions. Conversely, the mobile application focuses on a real-time scenario, where the users are in the city and want to obtain entertaining suggestions. We detail their components in the following sections.

3.1 Web-based application

First, users need to log in with their Facebook account to receive personalised recommendations. We set a predefined list of locations, represented as links that the user can click on, in order to help users in their exploration. They can easily change their location by double-clicking on a specific point of the map, thus triggering a change in the recommendations. The interface, depicted in Figure 2, is composed of three main parts.

The first one is the map (A), on which the venues are displayed as red balloons. The location of the user is represented by a green arrow. The second part is the recommendation list (B). When users click on a venue in this list, the map is centered around this venue and an information window – containing venue information such as its categories, its URL in Foursquare, and a randomly selected image – is displayed. The last part (C) is a graph showing the forecasted attendance of a selected venue for the past and coming hours, and is the main originality of this interface. The users can then look at the current popularity of the venues, and see when the system predict their popularity to be at its maximum. Moreover, they can drag the slider of this graph further into the "future", which will automatically recompute the recommendations and re-rank the venues by taking their future popularity into account. This feature can be used to explore the popularity of different venues (or an entire area of the city) at different times of the day, and can hence help the users to take decisions and plan their day.

3.2 Mobile application

While the web-based application focuses on exploration and allows the users to see how the rankings change depending on the hour, the mobile application is centered on an "on-the-move" scenario. In this scenario, the user does not have to specify his location, it is automatically inferred from

[5]`http://developer.foursquare.com/docs/venues/herenow`
[6]`http://developers.facebook.com/docs/facebook-login`

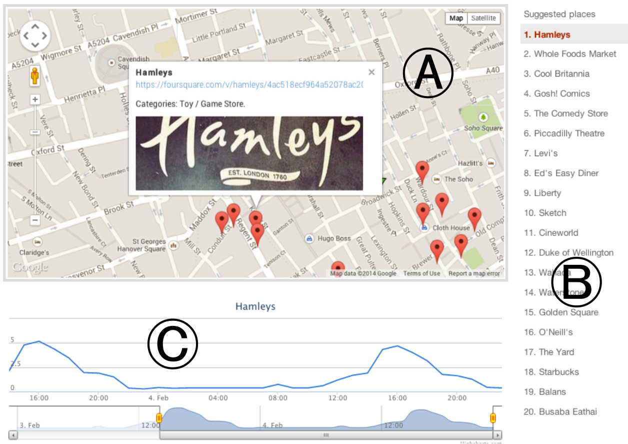

Figure 2: The web-based application is composed of three parts: (A) an interactive map, (B) a recommendation list, and (C) a graph showing the forecasted attendance of the selected venue.

the GPS or the mobile access data. Then, recommendations are provided using the approach detailed in Section 2.

Again, the users have to log in with their Facebook account to be able to see the personalised recommendations, as shown on the left-hand picture of Figure 3. The recommended venues are displayed on a map and are represented by icons associated to their categories (e.g. Food, Arts & Entertainment). A ranked list of recommendations is also presented to the user, showing information such as the total number of check-ins, the distance between the location of the user and the venue, or the rating. When clicking on a venue, the mobile application provides more detailed information, as shown on the right-hand picture of Figure 3. It includes a detailed map, along with pictures of the venue that have been taken by Foursquare users, some social information (number of likes, check-ins, and unique users), as well as the comments that have been provided by other users. The users can then choose to check in the venue, bookmark it, or ask the application to show them the directions towards the venue. Finally, when the users move to a new location (distant enough from the initial one), the application automatically sends them a notification and pushes new recommendation of nearby popular venues.

4. CONCLUDING DISCUSSION

We have described SmartVenues, a system that aims at providing popular and personalised venue recommendations to users, and we have presented two interfaces that we built on the top of this system. While the web-based interface is suitable for exploratory scenarios (e.g. "What will be the most interesting and popular venue in three hours around this location?"), the mobile application can be used whilst on the move and thereby can help to address increasing local and mobile information needs.

The context-aware suggestion of venues is still a challenge within the Information Retrieval community [2], especially in relation to the evaluation of such a complex task. Therefore, we envision several uses of the mobile application for evaluation purposes. Firstly, we could use the GPS function of the smartphones to actually see if a user visited a venue that was recommended, and derive several indicators such as the time spent in a venue. Secondly, we could use these information to perform A/B testing or interleaving evaluations

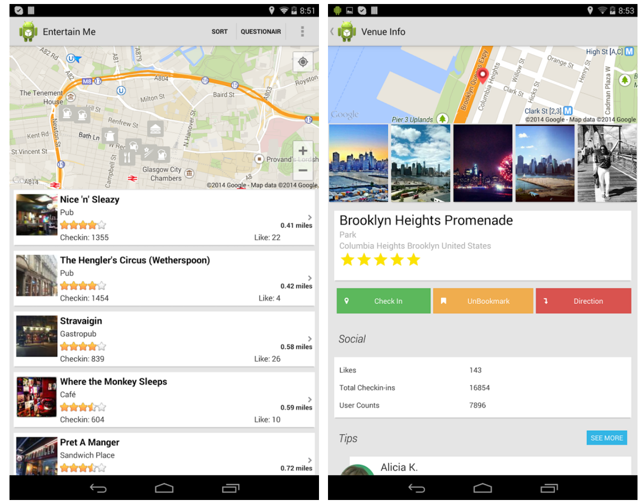

Figure 3: Two views of the mobile application. On the left-hand side, the recommended venues are displayed on the map and as a ranked list. Details about venues are provided when clicking on them, as shown on the right-hand side picture.

in order to compare the effectiveness of various recommendation or ranking algorithms. The interaction data could also be used to deploy algorithms that can learn over time if users prefer popular or personalised recommendations, and to re-rank venues accordingly. Finally, we could obtain city-wide data that would help us answer questions such as: why do people visit these venues? Are there areas of the city that need to be improved to attract more people?

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