Balancing Preferences, Popularity and Location in Context-Aware Restaurant Deal Recommendation: A Bristol, Cardiff and Brighton Case Study

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Abstract

We propose a personalisation solution to recommend tailored restaurant deals for residents or visitors in a city. Unlike previous work on recommendations in the restaurant sector where actual venues are recommended, we focus on suggesting specific products in the form of deals offered by such restaurants. This is done by jointly filtering relevant information for the end-user based on their food-drink preferences, the popularity of the restaurant, its proximity to the user’s location and temporal constraints on the availability of deals. A real case study has been conducted upon datasets provided by Wriggle, a platform for discovering local deals in various cities across England.

Data Preparation

The anonymised datasets provided by Wriggle contain a history of purchased deals by every user over a period of five years, describing deals associated to food categories/cuisines. Deals are offered by over 2 thousand restaurant and consumed by nearly 150 thousand users in the cities of Bristol, Cardiff and Brighton. There is also data about every user’s profile, including dietary requirements if any (vegetarian, vegan), and restaurant profiles. We filtered users who have at least one purchase in the last 5 months of purchase dataset because real location data exists only for that particular period. Then, we split the user history dataset into a training and test set for three aforesaid cities.

We consider three different time span settings for the user purchase history: 6 Months, 12 Months and entire history since 2014.

Results

- The experiments were aiming at predicting whether the latest deal purchased or restaurant visited by the user appears in the recommendation list of size K=10 generated by our model. We measures Avg_Recall and Avg_NDCG at 10 to evaluate predictive power of the model.
- The model with optimised weight scheme tends to slightly outperform the version with same weights, in almost all cases, specially when considering 6 months time span.
- Both two versions of our model generally outperform the three baseline approaches, however a location based recommendation has better predictive power in two of the three cities for the 6-month case. The reason behind this might be the scarce purchase history.
- The user preference baseline gently improves for longer time spans which is suggesting that the more purchase history data are available, the more reliable the extracted (implicit) preference information is.

What’s Next

- Considering people often visit restaurants in groups, future work involves investigating preference aggregation for consensual group recommendations.
- Harnessing the capabilities of data networks in smart cities to enable highly situation-aware recommendations in real time for tourists visiting a city.
- Modeling users’ preferences on food-drink categories more flexibly and under several decision criteria.
- Applying improved models on open datasets to make this research more reproducible.

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Fig 1 A deal presentation on the Wriggle App.

Fig 2 Data Processing Model Representation

\[ \alpha + \beta + \gamma = 1 \]

Fig 3 Experiment results for three cities.

Item pre-filtering

In our model given an item set X (i.e. restaurant deals) context information C is firstly used to extract a subset of relevant deals to the current user and their context, accomplishing:

(i) Start-End Time: most deals are periodical or limited and have a start-end time, therefore the currently available deals must be filtered;
(ii) Location: We calculated average travel distance for purchases and used this figure to filter deals within a distance; and
(iii) Dietary Requirements: although this is a user profile feature, we pre-filter suitable deals for users who are vegetarian or vegan.

Model

Weighted filtering

(i) Preference Matching(\(\alpha\)): It calculates the similarity between preferences on food-drink categories, and the specific categorical features of a deal.
(ii) Popularity Matching(\(\beta\)): This process takes the restaurant popularity into account, based on the average customer rating given to the restaurant.
(iii) Location Matching(\(\gamma\)): It takes the distance between restaurants within a predefined radius and the current user location, thereby prioritising deals from closer restaurants.

Fig:3 Experiment results for three cities.