

Designing and Developing a Personalised Recommender System

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I. INTRODUCTION

A. Domain of application

The domain of this application is a recommender system for bars, using the Yelp dataset. Decide whether I want to define the time-span for the date, depends on if there is too much data from all available time period. I am also taking into accounts Covid-19 data when generating recommendations.

B. Related work review

Some related work

C. Purpose/Aim

The purpose of this application is to give suitable suggestions for a user to go to. Using information about the user such as their location and personal preferences.

II. METHODS

A. Data description

The data I am using is taken from the Yelp dataset, it includes user reviews of different businesses and services in a specific location. There are 10 cities included in the dataset: Montreal, Calgary, Toronto, Pittsburgh, Charlotte, Urbana-Champaign, Phoenix, Las Vegas, Madison, and Cleveland. These user reviews include ratings, text feedback, and other such information.

B. Data preparation and feature selection

Prepare data Of the 209,393 businesses in the dataset, 168,903 are still open. There are 43,980 restaurants which are open and contain 'Restaurant' as one of the categories. 502 businesses in the overall dataset don't list anything in their categories section. 43,052 businesses had at least 1 check-in. There are 4,223,201 reviews of restaurants. 695,951 tips for these restaurants. 1,968,703 users. 43,992 restaurants listed with covid features, 8 restaurants which make up 12 duplicate entries (8 have 2 entries and 4 have 3 entries), the only difference between their entries being in the "Virtual Services Offered" section. Allow to pick user ID of 10 users with most reviews made, to avoid cold start problem 4 users have over 10,000 reviews, the most is 14,455 (Victor, 8k3aOmPeyhbR5HUucA5aA). I actually want to select the most reviews of the places I am accepting, restaurants. When taking the most reviews of restaurants in the dataset, a threshold of

600 reviews gives a list of 10 users, with the most being 1747. I then checked each of these for how many different restaurants they had reviewed and the greatest number of times they had reviewed a single restaurant to check that none of them were just users who reviewed a small number of restaurants a huge amount of times each. All 10 users passed this criteria, with even the least active user having reviewed 496 unique restaurants, which will certainly avoid any cold-start problems. I split the businesses into 10 groups, by the city which they are closest to, I did this by using latitude and longitude rather than State or City since this does not give actual distance and restaurants close to a border could then be mis-categorised. The entire Yelp dataset is huge and much of it is not necessary for my domain of bars. As such I prepared the data by eliminating any data not relevant to my domain. I selected features such as user ratings and a particular user's average rating, since if a user typically rates places they go highly, but rates a particular bar low, this is more significant than a user who always rates places low.

C. Hybrid scheme

Which two algorithms A hybrid scheme is a good way to design a recommender system, since you can get the best of both algorithms if done properly. Meaning better recommendations than either algorithm could achieve individually.

D. Recommendation techniques/algorithms

The first recommender system is collaborative filtering. I am using item-based collaborative filtering, since the number of users is larger than the number of items (1,968,703 users vs 209,393 businesses in the entire dataset), this gives greater accuracy of predictions. In this case the list of available items does not change, so a user-based method would be unnecessary. One of the requirements for this system is justifiability, and item-based methods make it much easier to explain why certain predictions were made. Item-item collaborative filtering looks for restaurants that are similar, in terms of how people rate them, to the restaurants that the user has already rated and recommend the most similar restaurants.

I am using a weighted mixed combination of these two systems in order to produce the results of my hybrid recommender system.

E. Evaluation methods

How to evaluate

III. IMPLEMENTATION

A. Input interface

The input interface is the command line. The program offers users opportunities to input information about themselves, as well as make choices from a selection of items which the system provides or suggests.

B. Recommendation algorithm

What algorithm

C. Output interface

The output interface is the command line. The system can output recommendations for bars which the user might like, as well as information about how the system works and why certain suggestions were made, at the user's request.

IV. EVALUATION RESULTS

A. Comparison against baseline implementation

Compare vs generic suggestions

B. Comparison against hybrid recommenders in related studies

Read some papers

C. Ethical issues

People's personal data

V. CONCLUSION

A. Limitations

What can it not do?

B. Further developments

What could I do in the future [1].

REFERENCES

- [1] L. Martinez, R. M. Rodriguez, and M. Espinilla, "Reja: A georeferenced hybrid recommender system for restaurants," in *2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*, vol. 3, 2009, pp. 187–190.