Midterm Project Report
Computational Advertising
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Introduction:

This project is focused around building and implementing a recommendation prediction system using innovative and new machine learning algorithms and techniques. Specifically, our task is focused around taking data from Yelp, a social platform used for user reviews of businesses and restaurants that a user has interacted with. We are dealing with Yelp data from the state of Arizona. We are provided with information on which users have interacted with which restaurants, so user-restaurant data, information on which users interact with which users, so user-user data, and lastly categories for each restaurant, so restaurant-category data. From here we use these 3 points of data to create a recommendation prediction system that recommends restaurants to users. This problem is interesting because we don't have actual ratings from users, only that a user has rated a restaurant, and we don't know how users interact with other users, only that they have interacted with each other. This leaves us with the task of understanding and trying to predict these ratings and making generalized recommendations based off of them. It's a very complicated problem with lots of different variables to take into account, which is what makes it fun and interesting. I am using the baseline implementation of BPR (bayesian personalized ranking) with implicit feedback for my midterm progress report since it solves our problem, as it takes binary implicit feedback, as in whether a user has rated something or not and not the actual rating, and can still provide a reasonable recommendation.

Related Work:

Link: https://dl.acm.org/citation.cfm?id=3339370

For related work I have looked into the paper "Bi-Group Bayesian Personalized Ranking from Implicit Feedback". This paper abstracts beyond the original idea of Bayesian Personalized Ranking in a few interesting ways. The main difference is that we take into account implicit feedback by separating the data into 2 categories, a support group and an opposition group. Support group members will support feedback by rewarding item preference while opposition group members will object to feedback by penalizing item preference. This model has been shown to provide significantly better recommendation performance given the right circumstances. I was thinking we could incorporate this model of a support and opposition group by simply putting users that have rated a restaurant into the support group and users who have not rated a restaurant into the opposition group. This would work theoretically for our data set, but it might have lots of pitfalls. For example, since we don't know what exactly a user has rated a restaurant, by assuming that any user that has rated a place is in the support group could lead to us overpredicting restaurants that have lots of ratings even if the user might actually have given them a bad rating per say. But, as shown, it could also have better performance if the claim that users usually rate a restaurant if they have positive sentiment about it is true, since then we would get a better view of the support group, but this doesn't really do much for the opposition group, since a user might not have visited a restaurant simply because it was too far, or some factor like that, not that they necessarily wouldn't or didn't like it. So it is a pretty complex problem, and given the data provided it might not work too well, but I still think it is worth looking into.

Implementation:

My implementation for now is still the baseline BPR system which was provided to us, which I have attached in this zip file for reference.

Result Interpretation:

Since we are using the baseline implementation itself, our results do not outperform our standard baseline, and are simply the exact same as the baseline. Specifically, our results over 20 epochs on the training data set were:

Recall@50 : 0.3462490439414978
NDCG@50 : 0.27908894419670105

These results aren't bad given how abstract the problem is, but hopefully through approaches such as the Bi-Group Bayesian Personalized Feedback outlined above we can get better results than this baseline.