HEC Montreal

MATH 80600A

Project Proposal

A Comparative Analysis of Recommendation Systems

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March 22, 2021

1 Context and Motivation

While the Internet offers an ever increasing amount of data, it becomes harder for users to find relevant and engaging content. Over several decades, there has been a significant research on computer applications that offer tailored content to users. Recommender systems are an example of applications that cater to the user's personal information needs and want [Schafer et al., 2001].

Indeed , recommender systems (RS) represent an effective information retrieval tool that enable highly personalized recommendation. Although the main recommender systems (content based, collaborative filtering, hybrid) are successful in generating satisfactory recommendations, they suffer still from various challenges such as the cold start problem, accuracy, scalability, and sparsity of the matrix. Several of the above mentioned obstacles could be addressed with the help of matrix factorization (MF) techniques. However, MF techniques still suffer from sparsity and do not fully cover all intricate user item interactions.

Deep Learning (DL) approaches have been successful in many research fields such as computer vision and natural language processing due to improved performance and the ability to learn feature representations from scratch. Recently, the application of numerous DL approaches in RS started to grow [Zhang et al., 2019]. They enable RS to cater to specific input data such as unstructured text (with RNN) or images (with CNN). In the context of interaction only setting (matrix completion or collaborative ranking problem), deep neural networks are justified when dimensionality and interactions are very high and when the dataset is very large. Approaches have showed that a MLP had better performance than traditional methods such as MF [He et al., 2017].

More specifically, Deep Learning based recommendation models present the following strengths:

- Nonlinear Transformation: DL can model non linear user item interaction patterns through non linear activation such as relu, sigmoid, tanh, etc.
- Representation Learning: DL is efficient in learning underlying explanataroy factors and helps us understand the interaction between users and items, towards a better recommender with fewer efforts in feature engineering
- Sequence Modelling: RNN and CNN play critical roles in integrating the temporal dynamics in state of the art recommender systems (ie. next-item/basket prediction)
- Flexibility: DL techniques have high flexbility since they are developed in DL frameworks that are modular.

However, DL approaches have some drawbacks. While traditional RD can be clearly interpreted, DL usually behave as black boxes, preventing a good understanding of the recommendation to the user. Further, DL RS are data hungry since they require sufficient data to fully support its abundant parametrization. A third challenge is the need for more extensive fine tuning of the hyperparameters compared to traditional RS.

Thus, DL approaches present exciting opportunities to improve traditional RS performance with less feature design while possibly limiting the level of clarity of the recommendation explanability. Our problem definition is then to do a comparative approach of the performance, computational efficiency, scalability, and interpretability of the tradtional RS versus DL RS.

2 Project Description and Goals

Our project aims at undertaking a comparative analysis of the strengths and limitations of traditional recommendation models versus deep neural network based recommenders.
After a thorough survey of the current machine learning and deep learning techniques, we will compare the performance, scalability, and computational efficiency of traditional and deep learning approaches on three different datasets.
The goals are as follows:

1. Cataloging the strengths and limitations of traditional RS and deep learning approaches
2. Providing insights on the scenarios that warrant a traditional RS or a deep learning approach
3. Providing a clear picture of the best implementation of these techniques through sound data exploration, data wrangling potential normalization, clear modeling approach including hyperparameter fine tuning
4. Providing a clear understanding of the RS metrics available and an approach to use the most adequate fitting with the context and data

3 Data Description

In order to adequately implement, assess and analyse the different recommendations, we must first discuss the datasets upon which we aim to develop, test and refine the various recommendation systems. In this age of rapid change and shift to online behaviour we have opted to focus our efforts on 3 key datasets which we believe represents key behaviours in the post-covid world ie relaxing, purchasing and socializing.

The first dataset is the movielens set, it contains three kinds of information: 5-star rating on movies by users; demographic characteristics of users and descriptive characteristics of the movie. We plan to use MovieLens Latest Datasets(Small version for prototyping and Full version for training/testing) The full version of MovieLens Latest dataset has 27,000,000 ratings and 1,100,000 tag applications applied to 58,000 movies by 280,000 users. The dataset contains 6 files: genome-scores.csv, genome-tags.csv, links.csv, movies.csv, ratings.csv and tags.csv.

The second dataset is the Amazon product reviews dataset. This dataset is taken directly from the product reviews on the popular ecommerce website Amazon.com compiled in 2018. It contains the textual reviews and ratings of a wide range of products on the Amazon platform. Furthermore, the dataset is subdivided into smaller sets each pertaining to a particular category such as fashion, books, electronics etc. We intend to model our recommendation systems on only 1 of these product category in this case Sports. The dataset contains two files for any given category. The first includes the reviews as well as the star rating for a given product and the second includes product metadata such as descriptions, price, features and links between products such as viewed/bought.

The third dataset is the Epinions Dataset. This dataset is based on a general consumer review site Epinions.com. It allows users to rate items, browse/write reviews, and add friends to their 'Circle of Trust'. Hence, it provide a large amount of rating information and social information. It contains two files: Ratings data(ratings given by users to items) and Trust data(trust statements issued by users).

4 Study Plan

In the preparation phase, we will first make a survey of existing approaches and analysis techniques in the field of reccomendation system in order to isolate three techniques to be applied to our datasets.

For data exploration, we will inspect and understand the statistics of the datasets and the structure of the different variables. After that we will do preprocessing (data cleaning, normalization, etc) on the data.

Next we need to determine the metrics such as MSE, RMSE, F1 etc. that are going to be used to assess the performance of our models this could vary based on the type of recommendation system chosen and is not static

In the training phase, we begin with our first dataset MovieLens and implement a machine learning technique such as Matrix Factorization [Koren et al., 2009] technique and use it as our baseline. Next we would implement a deep learning technique like autoencoders.

If time permits, we plan to implement other recommendation models (RNN based [Kang and McAuley, 2018] or GNN [Fan et al., 2019]) and test all above models on different datasets(Amazon product review, Epinions).

Finally, we would compare the performances of different models on different dataset and give a comprehensive analysis on the results.The last step is to catalog and create a comparative table.

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