Parts Franck Report

Introduction

With the ever-increasing amount of online information, recommender systems have become a go-to strategy to overcome information overload. Recommender systems facilitate personalization through e-commerce and have grown significantly in terms of public awareness since its rise in the nineties, in parallel to the Web debut. Indeed, may conferences and workshops are exclusively dedicated to this topic, such as the *ACM Conference on Recommender Systems (RecSys)*.

Recommender systems are also very diverse because they may leverage various types of user-preferences and user-requirement data to make the recommendations. The most classical methods in recommender systems include collaborative filtering methods, knowledge-based methods, and content-based methods. They form the fundamental pillars of machine learning based recommender systems.

These methods evolved to fit various scenarios, data domains, and contexts, such as time, location (ie. gps signal) and social media information. Numerous breakthroughs have been found such as the application of Matrix Factorization (MF) and Restricted Boltzmann Machines (RBM), not only for movie recommendation during the 2006 Netflix contest, but also query log mining, news recommendations, and computational advertising.

Conventional methods such as MF are considered state of the art and have been favored over content-based methods, due to dealing better with sparsity, scalability, and predictions. However, they face several challenges such as the cold start problem (new items or users are difficult to predict), very high data sparsity (most of the items are not rated by a user), scalability issues with O(m\*n) complexity in MF, difficulty to boost diversity of the recommended items, and the obstacles to learn latent implicit features.

The last decade has witnessed the Deep Learning (DL) revolution with powerful applications in computer vision, speech recognition, and natural language processing. Currently, it is also revolutionizing the state-of-the-art recommendation architectures by bringing more opportunities to improve performance, which can be generically quantified through RMSE for rating predictions. Indeed, DL approaches have overcome some of the obstacles faced by conventional recommender systems. These approaches can capture the non-trivial and non-linear user-item relationships, and they allow for the representation learning of more complex abstractions as data representations in the higher layers. Further, DL identifies intricate relationships within the data from the abundant sources available at hand such as textual, contextual, and visual information. Thus, the number of published papers has increased exponentially in the recent years. Even RecSys started to organize frequent seminars and workshops on the matter since the year 2016. It is to be noted that DL recommenders also face the following challenges: lack of interpretability, large data requirements, extensive hyperparameter tuning.

As a result, we intend to compare the strengths and limitations of Matrix Factorization (MF), one of the state-of-the-art conventional recommender systems, with DL approaches such as AutoRec and GNN. Other DL algorithms have been studied but we limited our analysis to these two for brevity. First, we will undertake a survey of the literature and explain these methods. Then, we will briefly describe the datasets we used. Third we will describe our experiments with MF, Autorec, and GNC with the goal to optimize prediction rating in user-item context. Finally, we will discuss the results before touching upon the limitations.

Literature Review

Matrix Factorization (MF) is one of the Collaborative Filtering approaches characterized by the reliance on both items and users’ vectors as opposed to Neighborhood based approach [1] that relies on the preferences of the user’s neighbor. Koren et al. have showed The items and users’ vectors are used to infer latent factors of item ratings [2], also referred to as features. MF represents the relation between items and users through that set of latent factors and forms two low rank matrices. Each of them represents the relation between users or the items and the latent features. Finally, the multiplication of these two matrices helps us estimate the user’s future preferences [3]. Mathematically, the rating prediction is: =

For prediction, the loss function is as follows with regularization terms on the users and items vectors:

. The goal of this function to minimize the loss.

It is to be noted there is no common evaluation framework that can be applied to all recommender systems. A variety of measures exist to assess the rating prediction strength of MF techniques and other recommenders in general. There exist three types of metrics to evaluate the power of an algorithm: classification, prediction, and rank accuracy. The classification accuracy assesses the quality of the algorithm to differentiate good items from bad ones. Examples are Precision, Recall, ROC, AUC [4]. The prediction accuracy evaluates the difference between predicted rating and actual rating is the type of metric we chose. Typical prediction metrics are the MAE, normalized MAE, MSE, and RMSE. RMSE has been chosen across our experiments. Rank accuracy measures whether the algorithm sorts the recommended items like the user.

Research in MF and Context Aware MF are abundant. Matrix decomposition has risen as a tool to show latent structures in the data. Some commonly used MF techniques are Singular Value Decomposition [5], PCA, Probabilistic Matrix Factorization [6], and Non-Negative Matrix Factorization [7]. In specific settings, it was showed the SVD could be improved by adding biases to users and items. SVD++ was proposed by Koren et al. to use implicit feedback. It demonstrated a high accuracy but expensive computational costs. Tensor Factorization extends the two-dimensional MF problem into an n-dimensional version by including contextual information [8]. The multi-dimensional matrix is factored into a lower-dimensional one, where each contextual dimension, the item, and the user are represented with a lower dimensional feature vector [9]. Karatzoglou et al suggested a multiverse recommendation system by using CF methods on Tensor Factorization. Additional contextual aware MF models have been studied. Comparative analysis of Boolean Matrix Factorization (BMF) with SVD is undertaken by Akhmatnurov et al [10].

Experiments with the Boolean matrix dot product of binary matrices with or without contextual information with an SVD showed a higher precision for the BMF where the number of user neighbors is not high. Tensor Factorization based on a fuzzy mapping between the latent and contextual factors is proposed by Fang et al [11]. In their paper, movie tags and release time were used as contextual variables and their use led to a higher RMSE and HLU while diminishing the number of iterations by 25%. Finally, we may mention the use of Sparse Linear Method (SLIM) by Zheng et al as Contextual SLIM that incorporates contextual information in a Matrix Factorization approach for Top-N recommendations.

Datasets

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. For our experiments on the Movie Lens data, we restricted our investigation on the ratings set and did not add contextual information. The 100k, 1 Million and the 25 Million (later downsized to 2.5 Million) movie lens datasets were used to compare Matrix Factorization performance with Deep Learning approaches such as AutoRec and GNN.

Experiment

Results/Discussion

References

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