ENHANCING COLLABORATIVE FILTERING TAG-BASED RECOMMENDATION WITH NEURAL NETWORK MODEL

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ABSTRACT

Social tagging becomes more significant when the use of these tags can benefit the searching and browsing capabilities. In the recommendation systems, the use of information such as tags can improve the accuracy of the traditional recommendation by considering social interests and social trusts between users. However, sparsity is one of the major problems in tag-based recommendation system because users do not always want to volunteer to contribute tags because it not compulsory. Therefore, this research proposes a neural network tag-based recommendation that makes used of available tags to further support relationships with properties of items and users. The evaluation experiments show that the proposed approach improves the recommendation quality.

Keywords: Data Sparsity; Social Tagging; Neural Network; Recommender Systems

1. INTRODUCTION

The emergence of Web 2.0, which offers a social and interactive platform for users to online participation, collaboration and interaction, contribute tremendous impact of the availability of heterogeneous information available on the web. The increasing amount of this kind of information brings the difficulties in recommending suitable items that meet the user needs

[1]. Due to this situation, the Recommender System (RS) is introduced to help users to overcome this problem by providing a recommendation that is predicted to be the most relevant to the users based on their interest. This prediction process is done by using various kinds of recommendation techniques based on the availability of data and domain characteristic. Since the mid-1990s, when the first RS was introduced, a number of studies have been conducted but then it still requires further improvements to make recommendation techniques more effective, practical and applicable to an even wider range of real-life applications.

1.1. Recommender System Approaches

Typically, recommender systems are classified as Collaborative Filtering (CF), Content-based(CB), Knowledge-based(KB) and hybrid which depend on the different set of knowledge sources and the algorithmic approach employed by the recommender system. Despite CF recommendation approach became the most adopted techniques for RS, the increasing popularity of collaborative tagging systems pushed towards to tags being integrated into the process of recommendation production. Although the use of tags has been found very convenient for managing and organizing people's digital material, from the research perspective it seems to have attracted much interest in Recommender Systems (RS) in the recent years, with literature rapidly expanding[2].

1.2 Motivation

Sparsity problem is one of the major problems encountered by a recommender system [3]. Data sparsity has great influence on the quality of recommendation. The main reason behind data sparsity is that most users do not rate most of the items and the available ratings are usually sparse. Collaborative Filtering suffers from this problem because it depends on the rating matrix. As well as for tag-based approach, the sparsity of tag also gives effect on the accuracy of recommendation. Users do not always want to volunteer to contribute the tag because it is not compulsory. They can use any other language, word, short form or even an expression in order to tag an online item. This situation leads to idiosyncrasy, ambiguity and redundancy problem when there is no or little information which can help to improve the accuracy of personalized recommendation.

Collaborative Filtering (CF) can give promising result of the recommendation. However, the problem such as cold start and data sparsity have limited the capability of CF since it relies on overall ratings only. Recently, lots of researches try to overcome the problem by integrating CF with other techniques so that the recommendation accuracy can be improved. One of the approaches is by utilizing other textual features such as user-defined tag since there are many web applications nowadays; provide the ability to users to label their resources. However, based on the analysis done to the social tagging dataset such as Movielens, the tag is also suffered from the sparsity issues. This situation becomes worst when the personalized recommendation also takes into consideration the overlapping tag among same users to the same item to measure the similarity preferences between user.

2. RESULTS AND DISCUSSION

In this section, the effectiveness of the approach will be evaluated based on the movie domain dataset with the aim to study: (1) the performance of our approaches in comparison with popular approaches in recommender systems and (2) the impact of different optimization techniques in the recommendation process

Experiments were conducted to investigate the performance of popular approaches in a recommender system called Matrix Factorization (MF). Matrix Factorization (MF) [4, 5] is a representative of CF that has been proven successful in solving recommendation problems [6, 7].

Each dataset was randomly divided into 80% training and 20% test set. The latent factors of each user and items were initialized randomly. When compared with MF and NN without tags our model which has integrated the Neural Network with tags has achieved better performance. Figure 4 shows the performance gap between these three different models.

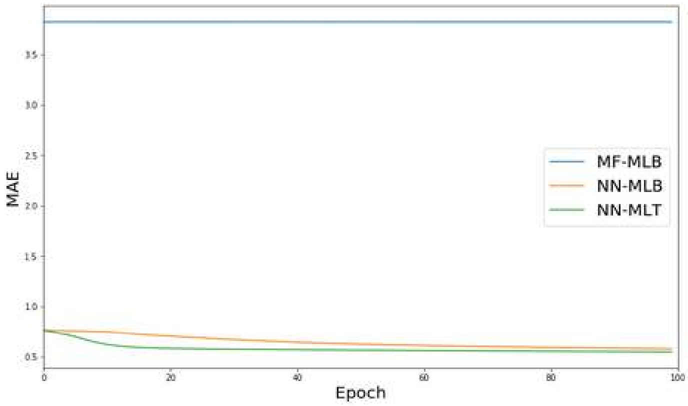
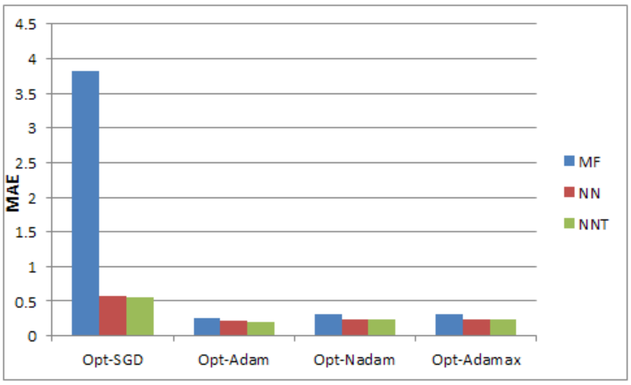


Fig.1. Comparison for the MF (MF-MLB), NN(NN_MLB) and NN with Tag (NN-MLT)

From Figure 1, MF achieved at best 3.825 for MAE and not much different for all epochs. The use of Neural Network has given a great impact when this measurement metric was improvised to 0.5795. Furthermore, when the tags are integrated into the input neuron in the Neural Network input layer, the MAE improved to 0.5502.

This suggests that considering tags is more effective in the recommendation compared to the use of the ratings only.



	MF	NN	NNT
Opt-SGD	3.8225	0.5795	0.5502
Opt-Adam	**0.2526**	**0.2105**	**0.207**
Opt-Nadam	0.3205	0.231	0.2333
Opt-Adamax	0.3189	0.2328	0.2307

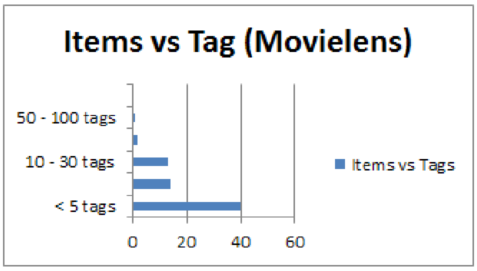
Fig.2. The different optimization techniques in the recommendation

According to Figure 2, the optimizer does give such an impact to the recommendation process. Adam optimizer achieved the best MAE but Stochastic Gradient Descent has shown the lowest. ADAM which is an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments is the best optimizer to be used in this research.

3. EXPERIMENTAL

In this section, we will explain the dataset evaluation metric, competing methods as well as the parameter settings.

Dataset: Movielens dataset by Grouplens was used for data analysis and later the experiments in section 2. The dataset is consisted of 12 743 of users, 15 268 movies, 498 963 ratings and 39 653 tags. Fig.3. shows the distributions of users and items over the tags. We split the dataset into two subsets, where 80% was adopted as a training set and the rest 20% was used as a test.



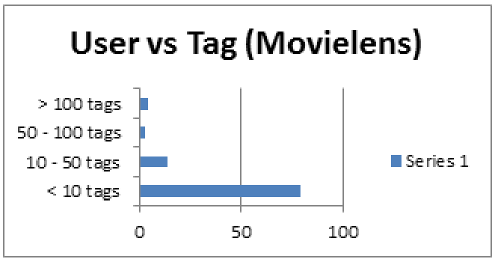


Fig.3. Movielens data distributions

Evaluation Metric: Mean absolute error (MAE) was adopted to measure the performance of the proposed method. As the name suggests, the MAE is an average of the absolute errors $|e_i| = |y_i - x_i|$, where y_i is the prediction and x_i the true value.

Competing methods: The following approaches have been implemented and compare with to justify the effectiveness of our approach. (1) Matrix Factorization (MF) is a well-known CF method for a recommendation with explicit feedback user ratings; and (2) Neural network with a rating only. The implementation of this method is based on the package and library in TensorFlow(Python).

Parameter Settings: The optimal settings of parameters were either determined by experiments or suggested by the literature. For simplicity, the number of latent features was fixed at 30. For all competing methods, we apply 100 epochs and 0.01 learning rates. The optimizer by default is set to Stochastic Gradient Descent (SGD)

4. CONCLUSION

In this article, a neural network tag-based recommendation model was presented to improve the recommendation accuracy. The problem of prediction ratings by utilizing tags information from users and items information was considered. Through experiments with the real-world public dataset Movielens, we demonstrated that our model significantly outperforms the baseline method such as MF on rating prediction accuracy.

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