CBCF WITH THE IPU MODEL IS TO IMPROVE RECOMMENDATION PERFORMANCE WITH THE EVALUATIONS GIVEN BY CLIENTS

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ABSTRACT:

A new clustering based CF (CBCF) method using an incentivized/penalized user (IPU) model only with the ratings given by users, which is thus easy to implement. We aim to design such a simple clustering-based approach with no further prior information while improving the recommendation accuracy. To be precise, the purpose of CBCF with the IPU model is to improve recommendation performance such as precision, recall, and F1 score by carefully exploiting different preferences among users. Specifically, we formulate a constrained optimization problem in which we aim to maximize the recall (or equivalently F1 score) for a given precision. To this end, users are divided into several clusters based on the actual rating data and Pearson correlation coefficient. Afterward, we give each item an incentive/penalty according to the preference tendency by users within the same cluster. Our experimental results show a significant performance improvement over the baseline CF scheme without clustering in terms of recall or F1 score for a given precision.

KEYWORDS: collaborative filtering (CF), clustering based CF (CBCF), incentivized/penalized user (IPU) model.

INTRODUCTION

collaborative filtering (CF) is one of the most prominent and popular techniques used for recommender systems. CF methods are generally classified into memory-based CF and model-based CF. In model-based CF, training datasets are used to develop a model for predicting user preferences. Different machine learning techniques such as Bayesian networks, clustering, and rule-based approaches can also be utilized to build models. An alternating least squares with weighted λ-regularization (ALS-

WR) scheme is a representative example of model-based CF. ALS-WR is performed based on a matrix factorization algorithm and is tolerant of the data sparsity and scalability [6], [7]. The main advantages of model-based CF are an improvement of prediction performance and the robustness against the data sparsity. However, it has some shortcomings such as an expensive cost for building a model [5]. On the other hand, memory-based CF does not build a specific model, but directly computes the similarity between users or items using the entire rating matrix or its samples. Hence, memory-based CF is easy to implement and effective to manage. However, it has also some drawbacks such as dependence on human ratings, performance decrement when data are sparse, and disability of recommendation for new users (i.e., cold-start users) and items [5]. Memory-based CF approaches are again classified into user-based CF and item-based CF. The main ideas behind the user-based CF and item-based CF approaches are to find the user similarity and the item similarity, respectively, according to the ratings (or preferences). After finding similar users, called neighbors, user-based CF recommends the top-N most preferable items that an active user has not accessed yet. User-based CF has limitations related to scalability, especially when the number of users is much larger than the number of items. Item-based CF was proposed to mitigate this scalability problem, but cannot still entirely solve the problem when the numbers of users and items are large. Despite such limitations, CF has been employed as one of the most representative recommender systems leveraged in online commerce.

LITERATURE SURVEY

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A common task of recommender systems is to improve customer experience through personalized recommendations based on prior implicit feedback. These systems passively track different sorts of user behavior, such as purchase history, watching habits and browsing activity, in order to model user preferences. Unlike the much more extensively researched explicit feedback, we do not have any direct input from the users regarding their preferences. In particular, we lack substantial evidence on which products consumer dislike. In this work we identify unique properties of implicit feedback datasets. We propose treating the data as indication of positive and negative preference associated with vastly varying confidence levels. This leads to a factor model which is especially tailored for implicit feedback recommenders. We also suggest a scalable optimization procedure, which scales linearly with the data size. The algorithm is used successfully within a recommender system for television shows. It compares favorably with well tuned implementations of other known methods. In addition, we offer a novel way to give explanations to recommendations given by this factor model.

PROBLEM DEFINTION

On the other hand, several companies, e.g., Pandora Internet Radio, Netflix, and Artsy, have developed their own clustering-based recommendation methods, called Music Genome Project, Micro-Genres of Movies, and Art Genome Project, respectively. These clustering-based recommendation methods have successfully led to satisfactory performance, but the processing cost for clustering is very expensive.

Unlike the aforementioned clustering-based recommendation methods that take long processing time to recommend items, we aim to design a simple but novel clustering-based CF (CBCF) method only with ratings given by users, which is thus easy to implement.

On the other hand, memory-based CF does not build a specific model, but directly computes the similarity between users or items using the entire rating matrix or its samples. Hence, memory-based CF is easy to implement and effective to manage. However, it has also some drawbacks such as dependence on human ratings, performance decrement when data are sparse, and disability of recommendation for new users and items.

Disadvantages of Existing system

- There is no accurate analysis on lack of Classification.

PROPOSED APPROACH

- An easy-to-implement CBCF method using the IPU model is proposed to further enhance the performance related to UX.
- To design our CBCF method, we first formulate a constrained optimization problem, in which we aim to maximize the recall (or equivalently F1 score) for a given precision.
- We numerically find the amount of incentive/penalty that is to be given to each item according to the preference tendency by users within the same cluster.
- We evaluate the performance of the proposed method via extensive experiments and demonstrate that F1 score of the CBCF method using the IPU model is improved compared with the baseline CF method without clustering, while recall for given (fixed) precision

can be significantly improved by up to about 50%.

CONCLUSION:

Specifically, in the proposed CBCF method, we formulated a constrained optimization problem in terms of maximizing the recall (or equivalently F1 score) for a given precision. To this end, clustering was applied so that not only users are divided into several clusters based on the actual rating data and Pearson correlation coefficient but also an incentive/penalty is given to each item according to the preference tendency by users within a same cluster. As a main result, it was demonstrated that the proposed CBCF method using the IPU model brings a remarkable gain in terms of recall or F1 score for a given precision. A possible direction of future research in this area includes the design of a new clustering-based CF method by exploiting the properties of model-based CF approaches (e.g., matrix factorization).

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