

Meta-Algorithmic Approach for Development of Recommender System

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Abstract: Recommender systems are applied in a variety of applications like movies, music, research articles, social tags and restaurants etc. As these systems have become extremely common in recent years. Providing the good recommendations to the customer based on their usage patterns is the major focus of this paper. Prior research has reported that desired property of recommendation algorithm is the stability and has important implications on user's trust and acceptance of recommendation. Two scalable, general purpose meta algorithmic approaches based on bagging and iterative smoothing that can be used in conjunction with different traditional recommendation algorithms to improve their stability are introduced in [1]. The proposed system is not only for improving the recommendation stability, but are actually able to provide good recommendations based on user's usage patterns.

Keywords: Bagging, Collaborative Filtering, Iterative Smoothing, Recommender Systems, Recommendation Stability.

I. INTRODUCTION

Recommender system represent technologies that assist users in finding a set of interesting or relevant items, typically by predicting the rating (i.e., an indicator of preference) that users would give to an item they had not yet considered [1]. Recommender systems play an important role in many application most prominently ecommerce. Many companies use recommender systems to suggest alternative or cross-selling products to their customers. For example, Netflix has reported that roughly 75 percent of what their subscribers watch (including both DVDs by mail and videos streamed online) has been recommended to customers by its recommender system [2]. So, offering good recommendations to customers is critical in order to retain users and it can also contribute to the enhancement of product sales. Desired property of recommendation algorithm is the stability and has important implications on users trust and acceptance of recommendation introduced in [2],[3]. It is the consistent agreement of predictions made on the same items by the same algorithm, when any new incoming ratings are in complete agreement to systems prior estimations. Thus, stability is designed to capture the level of internal consistency among predictions made by a given recommendation algorithm. Consider an example for two items i_1, i_2 the system makes rating predictions for user u , and that both predictions are of 5 stars, and suppose prediction for i_1 is precisely accurate (i.e., user u completely agrees with the system) and, after user u consumes item i_1 , this 5-star rating gets added to the system as a known ratings. The recommendation algorithm then re-computes all other predictions in light of the newly added data. If the newly calculated rating for item i_2 suddenly changes dramatically (even though the newly incoming data is exactly as the system has already

been predicting), it is considered as an indication of an unstable system. The degree to which such change occur reflects the level of instability of the recommendation algorithm [2], [3]. To improve stability bootstrap aggregation and iterative smoothing these two approaches are introduced in [1]. These approaches can be used as wrappers in conjunction with any traditional recommendation technique therefore they serve as meta-algorithms. In various data mining and machine learning applications, bootstrap aggregation (or bagging) is an already widely used approach. Due to the aggregating nature of bagging, to improve stability authors proposed to employ bagging as a natural initial meta algorithmic approach. Another approach iterative smoothing is uses multiple iterations for repeatedly and collectively adjusting the rating predictions of a recommendation algorithm based on its other predictions therefore it aimed more directly at the stability improvement by using multiple iterations.

This paper also provides a comprehensive perform an evaluation of the approaches mentioned above in conjunction with a number of popular and widely used recommendation algorithms in terms of their stability as well as accuracy on several real-world datasets. The results show that the proposed system provide good recommendations to the customers based on their usages pattern.

II. RELATED WORK

G. Adomavicius and A. Tuzhilin [2] they provided the review of current generation of recommendation methods that are categories into three main categories as follows:

- Content-based recommendations: The user will be recommended items similar to the ones the user preferred in the past.
- Collaborative recommendations: The user will be recommended items that people with similar tastes and preferences liked in the past.
- Hybrid approaches: These methods combine content-based and collaborative methods.

This paper also describes various limitations such as new user and item problem and possible extensions of current recommendation methods. These extensions include of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multicriteria ratings, and a provision of more flexible and less intrusive types of recommendations that are useful to improve recommendation capabilities and make recommender systems applicable to an even broader range of applications.

G. Adomavicius and J. Zhang [3] they focused on the consistency of recommendation system predictions. Here the author investigates an issue that some popular recommendation algorithms can suffer from a high degree of instability.

G.Adomavicius and J.Zhang[4] They suggested that stability is an interesting theoretical and desired property of recommendation algorithms, because unstable recommendations can potentially decreases user’s trust in recommender systems and, as a result, reduce user’s acceptance of recommendations. In this article, they also provided an extensive empirical evaluation of stability for six popular dataset.

C. Basu, H. Hirsh, and W. Cohen [5] they provided inductive learning approach to use both rating information and other information about artifact for stable prediction and user preferences.

M.Deshpande and G.Karypis [6] they presented a class of model-based recommendation algorithms that first determines the similarities between the various items and then uses them to identify the set of items to be recommended.

J.L.Herlocker, J.A.Konstan, K.Terveen and J.T.Riedl [7] they focused on the key decisions in evaluating collaborative filtering recommender systems: The user tasks being evaluated, the types of analysis and datasets are used, the ways in which prediction quality is measured, the evaluation of prediction attributes other than quality and the user-based evaluation of the system.

From the above survey it can be easily concluded that, major focus in recommender system’s literature is predictive accuracy. As unstable or inconsistent recommendations could lead to user’s confusion and may have negative impact on user’s trust of the recommender system. To address the challenges, proposed system explores two meta-algorithmic approaches based on the bagging and iterative smoothing technique that can be used to improve stability of a wide variety of recommendation algorithms.

III. PROPOSED SYSTEM

The details of overall proposed system architecture, breakdown structure and mathematical model are covered in this section.

A. System Architecture

The For offering good recommendations to the customers and to improve the stability of recommender system in the proposed system as shown in Fig.1

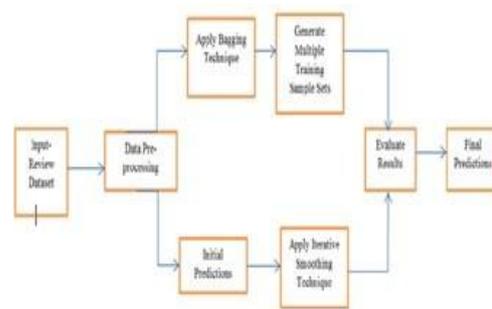


Fig.1 System Architecture

We used two general purpose meta-algorithmic approaches which are introduced in[1] in conjunction with traditional recommendation algorithms. Measure focus of the proposed system is user behavior study in which we are going to consider Timestamp i.e. how much time user spend for particular product e.g here we consider the movie ,how much time user have spent for particular movie depending on that timestamp value predictions can generate.

• Input: Review dataset-List of recommendations are get produced by recommender systems depending on the user’s past behavior (items previously purchased or selected and/or numerical ratings given to those items) as well as similar decisions made by the other users. So for implementing the system the input dataset will be review of ratings given by the users.

• Data Pre-processing: After all the non-trivial work is done, the module then uses a data preprocessing technique which involves the data cleaning, data integration, data transformation, data reduction, data discretization steps. Also it involves the major task of the system i.e Timestamp value which is the part of user behavior study. This timestamp value can help to generate strong predictions. Following two scalable, general purpose meta algorithmic approaches used in conjunction with different traditional recommendation algorithms to improve their stability.

• Bagging Technique: This technique combines predictions made from different models into one output. It can be used with both classification and numeric prediction models to improve their accuracy and the major focus of bagging is to

build a set of models for the same predictive task and have them vote with equal weight. Multiple training sub-datasets are generated by randomly sampling the overall training data.

• **Iterative Smoothing Technique:** This technique uses multiple iterations to repeatedly and explicitly adjust predictions of a recommendation algorithm based on its other predictions in order to make them more consistent with each other.

The proposed system is mainly focused on the following terms:

- 1) Input datasets
- 2) Data preprocessing
- 3) Two meta-algorithmic approaches

The implementation details of the proposed system are explained by the following modules:

• **Module 1:** This module is responsible for accepting the input (review data) generated based on the user's ratings. Then this module performs analysis on the above-mentioned data set. After all the non-trivial work is done, the module then uses a data preprocessing technique which involves the following steps:

Data Cleaning-Processes such as missing values, smoothing the noisy data or resolving the inconsistencies in the data are used to clean the data.

Data Integration-Different data representation techniques are used to put data together and conflicts within the data are resolved.

Data Transformation-Data is normalized, aggregated and generalized.

Data Reduction-Representation of a data is reduced in a data warehouse.

Data Discretization-It involves reduction of a number of values of a continuous attribute by dividing the range of attributes into intervals.

• **Module 2 and Module 3:** In these modules, two Bagging and Iterative smoothing techniques are used in conjunction with different traditional recommendation algorithms to improve their stability.

B. Algorithm

Input : Review data set

Process: Data Pre-processing, Bagging and Iterative smoothing

Output: Predictions with high stability

• **Step 1:** In this, input to the system is selected from real world datasets which includes reviews given by users.

• **Step 2:** In this, processing techniques are applied on the selected input dataset to get pre-processed data.

• **Step 3:** Here, two meta-algorithmic approaches are used in conjunction with traditional recommendation algorithms in the following manner:

Bagging Technique: It extracts M random equal-sized samples from training data. Then for each

sample $D_{m,m} = 1, \dots, M$ build model f_m on sample D_m using algorithm T and use this model f_m to predict unknown ratings. Then compute all final predictions.

Iterative Smoothing: It directly builds model f_0 on known ratings D using some standard recommendation algorithm T . Then apply model f_0 to compute predictions P_0 for unknown ratings. For each iteration $k=1, 2, \dots$, for each unknown rating pair construct dataset $D_{k,u,i}$ by including all known ratings P_{k-1} and all predicted ratings from the previous iteration, except for ratings $P_{k-1}(u,i)$ and build model $f_{k,u,i}$ on dataset $D_{k,u,i}$ using T and make prediction on (u,i) and store in P_k . Output prediction made in the final iteration P_k .

C. Stability Computation

According to G. Adomavicius and J. Zhang in [3], for stability computation it is necessary to define the predictive model to be stable if its predictions for the same items are consistent over a period of time, assuming that any new ratings that have been submitted to the recommender system over that period are in complete agreement with systems prior predictions. Hence, quantifying stability of the predictive model involves multiple time periods to compare predictions. In this study, a two-phase approach to compute the stability of a recommender algorithm, which is illustrated in Figure 2.

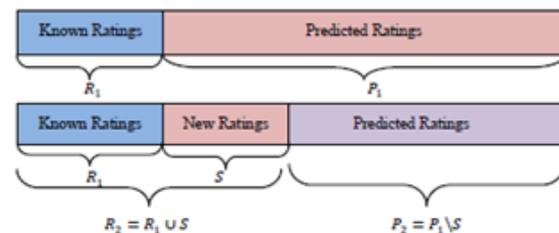


Fig. 2. Stability computation approach with two stages

In phase 1, set of known ratings R_1 is given, using R_1 a predictive model is built, and for all unknown ratings predictions are made and denoted as P_1 , where $P_1(u,i)$ represents a system-predicted rating for user u and item i . Then, by assuming that the recommendation system was highly accurate and was able to make predictions P_1 that are identical to user's true preferences a set of hypothetical incoming ratings is added to the original set of known ratings R_1 .

Therefore, in phase 2, some subset S of predictions P_1 is added as the newly incoming known ratings. Thus, in phase 2 the set of known ratings becomes $R_2 = R_1 \cup S$ and the set of unknown ratings becomes $P_2 = P_1 \setminus S$. Based on R_2 , a second predictive model is built using the same recommendation algorithm, and predictions on unknown ratings P_2 are made. Then by comparing the two predictions stability is then measured, i.e., P_1 and P_2 , to compute their mean absolute difference or root mean squared difference, which we call mean absolute shift (MAS) or root mean squared shift (RMSS), respectively.

$$RMSS = \sqrt{\frac{\sum (P1(u,i) - P2(u,i))^2}{|P1 \cap P2|}} \quad (1)$$

Where P1 and P2 are the predictions made in Phases 1 and 2 respectively, i.e., the stability metrics capture the shift in predictions made by the same recommendation algorithm.

IV. CONCLUSION

The proposed system offers the good recommendations based on users usage patterns. It explores two meta-algorithmic approaches based on the bagging and iterative smoothing technique that can be used to improve stability of a wide variety of state-of-the-art recommendation algorithms. We examined the performance of meta-algorithmic approaches which are mentioned earlier on four real world datasets by considering the user's usage pattern. Our results show that both approaches demonstrates effectiveness in their stability it is verified by final predictions generated by both the approaches.

ACKNOWLEDGMENT

The authors would like to thank the researchers as well as publishers for making their resources available. Also the authorities of Sajivani College of Engineering ,Koparga on for providing the required infrastructure and support. Finally, we would like to extend a heartfelt gratitude to friends and family members.

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BIOGRAPHYIES



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