3rd International Conference and Workshops on Recent Advances and Innovations in Engineering, 22-25 November 2018
(IEEE Conference Record # 43534)

Improving Performance of Product Recommendations Using User Reviews

Rahul Kumar Chaurasiya
Department of Electronics & Telecommunication
National Institute of Technology Raipur, India
rkchaurasiya@nitrr.ac.in

Utkarsh Sahu
Department of Electronics & Telecommunication
National Institute of Technology Raipur, India
utk.set@gmail.com

***Abstract*—Recommendation systems have gained importance with the rapid growth in e-commerce industry. Recommendation system utilizes user feedbacks to suggest products that might be useful to the user and also help in accessing the long tail products. Traditional recommendation systems rely on ratings provided by users. However, with advancement in data acquisition, most e-commerce websites today capture other useful feedbacks such as review and review helpfulness, etc. This paper proposes an approach to improve the performance of recommendation systems using user reviews. The experiments are performed on Amazon product dataset which consists of product ratings and reviews. A comparison between traditional rating-based and the proposed recommendation system shows improvement in the recall and root mean square error (RMSE) scores of recommendation system.**

Keywords— Recommendation system, User reviews, Collaborative filtering, Sentiment analysis, Review-based profile.

I. INTRODUCTION

The exponential growth in e-commerce industry has provided the users with a wide variety of products to choose from. E-commerce websites are modern day departmental stores with wide range of products. Recommender systems play the role of sales-person who would understand customers' requirements and suggest products to them. Today almost all e-commerce websites use recommender systems to help its users enhanced user experiences by providing suggestions which the user might like [1]. The success of any recommender system depends on whether it can continuously provide its users with products that they might like [2]. With advancement in data acquisition and reduced costs of data storage,various types of user's activity and feedbacks can be recorded easily. In recent years, various recommendation algorithms have been developed[3], like content-based, collaborative filtering [12], matrix factorization and domain specific systems like case-based, contextual recommender systems. Location-based systems have also been applied to enhance social networking services [11].

However, the performance of any recommender system depends on the quality of feedbacks or user opinions it uses for generating recommendations. It is generally observed that the present day recommender systems are able to process large quantity of data, but the quality of recommendations has a large scope of improvement. Typical recommendation systems use user rating to generate recommendations, but users are not much bothered while rating the products and this leads to poor recommendations. With advancement in text mining and sentiment analysis, reviews have become a valuable feedback by users which can be processed and used for multiple purposes. This paper proposes an improvised review based recommendation system that uses reviews as user feedbacks to generate recommendations. The result section verifies the importance of proposed method as we can observe a significant improvement in recommendations by using reviews as user feedbacks over using ratings as user feedbacks.

The rest of the paper is organized as follows: Section 2 describes about the dataset. The existing Collaborative filtering based recommendation systems are discussed in section 3. The methodology of the proposed review – based recommendation system has been presented in section 4. Section 5 is devoted to experiments and results. Finally, we conclude the paper in section 6.

II. DATASET

We have used the data from Amazon product dataset [4, 5]. The dataset contains user feedbacks for 24 different categories of products such as musical instruments (10,261 reviews), office products (53,258 reviews), Amazon videos (37,126 reviews), digital music (64,706 reviews), automotives (20,473 reviews) etc. spanning from May-1996 to July 2014. The features included in dataset are: reviewer ID, product ID, ratings, reviews text, helpfulness votes and timestamp. The 5-core dataset is a subset of Amazon product dataset in which each user and item has at least 5 reviews and ratings.

This dataset consists of both user ratings and user reviews, thus helps to have a comparative study between traditional recommendation systems and the proposed recommendation system using reviews.

III. COLLABORATIVE FILTERING-BASED RECOMMENDATION SYSTEMS

Collaborative filtering is the most common approach used in many successful recommendation systems[6]. Collaborative filtering looks for patterns in user activity by considering user feedbacks to generate recommendations. The basic idea of this approach is that unspecified feedbacks of users can be imputed due to high correlation among the users and items. Memory-based approach uses the entire user-product data to compute predictions or recommendations. There are two types of memory-based collaborative filtering approaches: user-based collaborative filtering and item-based collaborative filtering. The working principles of these methods have been described in this section.

A. User-based collaborative filtering

User based approach computes similarity amongst users to find neighbors (a set of users having similar activity history) and then generates predictions[7]. The algorithm then predicts the ratings of items not known to users and recommends the top-K items.

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Let u &v be two users, $R_{u,i}$&$R_{v,i}$be the ratings feedback provided by user u&user v to product i.$\bar{R}_u$&$\bar{R}_v$be the average rating provided by user u and *user v*. The adjusted cosine similarity between user u& v, denoted by $UserSimilarity_{u,v}$ is given by (1):

$$UserSimilarity_{u,v} = \frac{\sum_{users}(R_{u,i}-\bar{R}_u)(R_{v,i}-\bar{R}_v)}{\sqrt{\sum_{users}(R_{u,i}-\bar{R}_u)^2}\cdot\sqrt{\sum_{users}(R_{v,i}-\bar{R}_v)^2}} \quad (1)$$

The prediction of product j for user v is denoted by $predictions_{v,j}$ and is given by (2), where $R_{u,j}$ is the rating provided by user u for product j.

$$predictions_{v,j} = \frac{\sum_{v\in U}(UserSimilarity_{u,v})\cdot R_{u,j}}{|\sum_{v\in U}(UserSimilarity_{u,v})|} \quad (2)$$

B. Item-based collaborative filtering

Item-based approach uses the set of items that user has rated and computes their similarity to other items to generate predictions[8]. It computes similar items based on the ratings provided by all the users to a particular item J with respect to target item I. Let i &j be two items, $R_{i,u}$&$R_{j,u}$be the ratings feedback provided by user u to product i &j.$\bar{R}_u$be the average rating provided by user u. The adjusted cosine similarity between items i &j, denoted by $ItemSimilarity_{i,j}$ is given by (3):

$$ItemSimilarity_{i,j} = \frac{\sum_{items}(R_{i,u}-\bar{R}_u)(R_{j,u}-\bar{R}_u)}{\sqrt{\sum_{items}(R_{i,u}-\bar{R}_u)^2}\cdot\sqrt{\sum_{items}(R_{j,u}-\bar{R}_u)^2}} \quad (3)$$

The prediction of product k for user u is denoted by $predictions_{u,k}$ and is given by (4), where $R_{u,j}$ is the rating provided by user u for product j.

$$predictions_{k,u} = \frac{\sum_{j\in I}(ItemSimilarity_{j,k})\cdot R_{u,j}}{|\sum_{j\in I}(ItemSimilarity_{j,k})|} \quad (4)$$

IV. Proposed Review-Based Recommendation System

Traditional recommendation algorithms build user and item profile based on ratings data to generate recommendations. However the performance of such systems typically depends on the quality of feedback data being used as input to the system. With advancement in the field of data mining, a variety of techniques have been proposed which try to improve the quality of both implicit and explicit feedbacks. Reviews are an important explicit feedback that can be used to improve the quality of feedbacks for recommendation generation.

This paper proposes a review-based profile for users and items that uses various text analysis and sentiment analysis techniques to extract valuable information from user reviews. User ratings provide a quantitative measure of feedback for an item but reviews can provide both quantitative as well as qualitative measure of feedbacks. Figure 1 describes the steps involved in the proposed review-based recommendation system.

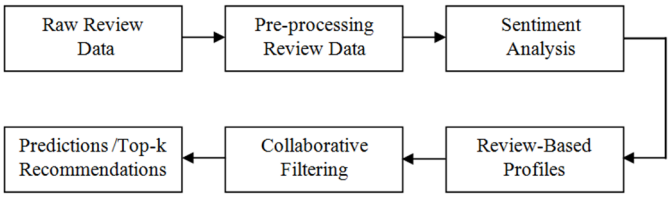

Fig.1. Flowchart for proposed review-based approach.

A. Preprocessing review data

Pre-processing of raw review text is done using the natural language processing techniques namely tokenization and stopword removal. Tokenization refers to breaking the review text into separate terms, called tokens, which can be treated as individual identity for further analysis. Tokenization is followed by stopword removal to obtain just the terms that contain useful insights of user feedbacks and discards the redundant terms.

B. Sentiment analysis

Sentiment analysis provides a quantitative measure of user's opinion about the product [9]. It uses various text mining and natural language processing techniques to extract useful information from reviews. Sentiment analyzer classify the textual data based on various benchmark dictionaries that have well established set of positive, neutral and negative emotion words. Sentiment intensity analyzer uses the tokens obtained from the text data and provides a compound value for user's sentiment for the product.

C. Review-based user and item profile

User and item profiles are built based on the sentiment scores obtained for the reviews. The reviews provided by the user determine the preferences of that particular user. Users with similar activity history are considered neighbors and activity of one user in the neighborhood provides. Review-based user profile takes into account a more detailed analysis of user feedback as ratings are in an integral scale and rating patterns of different users may be very different but reviews provide a precise description about user's opinion of the product.

Item receives review from users which can describe the experience of using the product, the good features about the product, drawbacks and challenges faced while using the product or any similar experience. The sentiment score describes the polarity of the review which gives a precise feedback about the user's experience of the product. The keywords obtained from the reviews are used as features of the product with relative positive or negative sentiment scores. These features are used as descriptions and tags for the product by applying feature extraction techniques.

D. Generating predictions/top-k recommondations

In this paper, item-based collaborative filtering algorithm is used to generate predictions. Item-based similarity is obtained for each item a particular user has reviewed, using adjusted cosine similarity approach. The prediction scores for unknown items are then calculated using the similarity scores. The top-k items, i.e. items with high prediction scores are recommended to the particular user. User and item profiles are updated after every new review given by the user to a new item.

V. EXPERIMENTS AND RESULTS

The experiments were performed on Amazon product dataset. The dataset consists of 24 categories of products reviewed by customers of Amazon.com. We used a subset of the dataset consisting of 5 categories of products i.e. Amazon instant videos, digital music, automotives, and office products & musical instruments. The 5-core dataset consists of subset of Amazon product dataset with a minimum of 5 reviews and ratings per user and per product. The dataset consists of both ratings and review text as feedback from the users.

TABLE I. COMPARISON BETWEEN USER RATINGS AND REVIEW SCORE (OBTAINED BY PROPOSED METHOD)

Reviewer ID	Product ID	Ratings	Review Score
A1J5KCZC8CMW9I	B0000AKCLJ	3	4.46568
A103W7ZPKGOCC9	B000001E58	5	3.69258
A10CBLMJD1OQL7	B000002IWQ	4	4.31797
A10LII7OFFN1GX	B00005O54Q	2	0.16771
A11CNSUROWGLEG	B00006ZCFJ	1	0.07203
A11ED8O95W2103	B000002KHB	5	4.49523
A11J3144NAHA2Y	B0000026J6	5	1.19079
A12WON27MLDXNI	B0000029DD	1	3.25626
A1FFPPPIOSI36M	B000002HDG	2	4.39592
A1IDNJ1Y42GMLS	B00000IAU3	4	4.54363

A. Evalution matrix

Predictions were generated using ratings and sentiment scores provided by users to products. The evaluation predictions generated for each user was done by dividing the dataset into train data and test data. The train data consisted of 70% of the samples and the test data consists of 30% of samples.

We then used the train dataset to generate predictions for the users and items in test dataset. The item-based collaborative filtering was applied to both ratings score and sentiment score over the entire train dataset. Predictions generated were than to be evaluated with the actual rating score and sentiment scores present in the test dataset.

We used recall score and root mean squared error (RMSE) score to evaluate the performance of the predictions generated for each category of products [10]. Recall score is the ratio of *true positives* andthe sum of *true positives* and *false negatives*. *True positives* represent the relevant items recommended to the user, *false negatives* represents the relevant items that are not recommended to the user.

$$Recall = \frac{truepositives}{truepositives + falsenegatives} \quad (5)$$

RMSE score finds the root mean squared error between the R_{pred} (predicted ratings) and R_{actual} (actual ratings provided by user).

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(R_{pred} - R_{actual})^2} \quad (6)$$

A comparative analysis is done between the RMSE score and recall score obtained using ratings score and review score.

B. Results

The results for *RMSE score* and *recall score* for rating-based approach and proposed review-based approach for respective product categories have been tabulated in the tables below.

TABLE II. RMSE SCORES USING RATING & REVIEW-BASED PROFILES

RMSE Score			
S.No.	**Product Category**	**Rating**	**Review**
1.	Amazon Videos	0.5667	0.5427
2.	Digital Music	0.6521	0.6375
3.	Office Products	0.5811	0.5639
4.	Music Instruments	0.6555	0.6335
5.	Automotives	0.8183	0.8072

TABLE III. RECALL SCORE USING RATING & REVIEW-BASED PROFILES

Recall Score			
S.No.	**Product Category**	**Rating**	**Review**
1.	Amazon Videos	0.7011	0.7369
2.	Digital Music	0.5521	0.5641
3.	Office Products	0.6645	0.6816
4.	Music Instruments	0.5568	0.5788
5.	Automotives	0.3287	0.3327

VI. CONCLUSION

In this paper, a review-based recommendation approach is proposed to generate recommendations. The proposed approach processes review text as user feedback to generate predictions using the benchmark item-based collaborative filtering algorithm. The raw review dataset which represents a detailed feedback of user to the product is pre-processed, followed by obtaining sentiment intensity scores.

An increase in the recall score and decrease in RMSE score is observed using the proposed recommendation model as compared to the traditional rating based model.

The future scope of this paper lies in utilizing the review keywords (obtained during preprocessing user reviews) in content-based recommendation algorithm to obtain recommendations. Further, review helpfulness can also be used to give proportionate weight-age to review.

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