

Modeling Customer Behavior for efficient recommendation systems

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Abstract: Maintaining good relationships with customers is the need of the day for many companies. For maintain this relationship and loyalty, it is always preferred to design a good recommendation system which would always attract new customers and also retain the old ones. Current systems take the choice of customers and also measures similarity of the customer to different customers for recommendations. But reviews of the customers are not taken into consideration for recommendations. Hence, the proposed approach takes reviews of the buyers (textual and nontextual) and combines it with the current systems for an efficient recommendation.

Keywords : Recommendation systems, Sentiment Analysis, Hybrid recommendation systems, etc.

1 INTRODUCTION

Customer satisfaction and customer loyalty has played a keen role in maintaining customers relationships with the companies. It is a kind of qualitative and quantitative analysis as to how a customer behaves with your company. This kind of analysis helps us to identify the needs of our customers. It informs us regarding the decision making methods used by the customer for finalizing his purchase. This is becoming very important for B2B as well as B2C companies. This is happening due to the growing needs of personalization of customers. To maintain customer retention, it is needed that the customer be satisfied with the services of a given company. One of such service is known as a recommendation system. As good personalized recommendations can add another dimension to the user experience, e-commerce leaders like Amazon.com and Netflix have made recommender systems a salient part of their websites [1].

2 RELATED WORK

Earlier, research is mainly focused on the content of the recommender system which analyzed the characteristics of the object itself to complete the recommendation task (content based recommendation) [1]. However, this recommendation method can only be confined to content analysis, which makes researchers and practitioners invest great efforts in designing new recommender systems. Researchers have proposed recommender systems based on collaborative filtering, association rules [2], utility, knowledge, social network [3], multiobjective programming [4], clustering [5], and other theories and techniques. Zheng et al. utilized GPS trajectory data to solve mobile recommendation problems [6] Park et al. recommended users with restaurants using Bayesian networks based on location and some other information [7]. A similar system for movie recommendation system has been proposed by [8].

3 TYPES OF RECOMMENDATION SYSTEMS

Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user. There are in all three different types of recommendation systems. They are collaborative filtering, content based recommendation systems and hybrid recommendation systems. The content based filtering relies on the content of an item that user has purchased or seen before. The content based recommendation has proven to be effective while giving recommendations for new items or new users. However, content based filtering has some limitations. It is difficult to provide appropriate recommendation since it relies only on the previous history of candidates and does not take into consideration changes in taste of the given customer.

Moreover, it recommends all the related items instead of the particular item liked by the user.

The collaborative-filtering aims to identify users who have similar interests and preferences by calculating similarities and dissimilarities between their profiles. The idea behind this method is to find similarities between different users and accordingly give recommendations. The collaborative filtering overcomes some of the limitations of the content based filtering. The system can suggest items to the user, based on the rating of items, instead of the content of the items which can improve the quality of recommendations. However, collaborative filtering has some drawbacks. The first drawback is that the coverage of rating could be very sparse thereby resulting in poor quality recommendation. In the case of the addition of new items into database, the system would not be able to recommend until that item is served to a substantial number of users known as cold-start. Secondly, when new users are added, the system must learn the user preferences from the rating of users, in order to make accurate recommendations. The third variety is a hybrid recommendation system which is a combination of both types of recommendation. As a result it tries to eradicate the limitations of the two recommendation systems. This paper takes into consideration a hybrid approach which combines the sentiments of the users along with the utility matrix generated by the previous said system to generate an efficient recommendation system.

4 SENTIMENT ANALYSIS

Sensing the mood and the preferences of user through text analysis techniques is a research area that has been quite active in recent years. This is known as opinion mining or sentiment analysis. Adding this to the current recommendation systems will provide an extra dimension to the existing systems. However, it is not sufficient to classify specific statements as positive, negative or neutral but to be able to correlate such statements in the form of ratings. One of the most important tasks in sentiment analysis is to identify which words express a sentiment [2]. Words which have some sentiment intensity are referred as opinion words. Opinion words can be recognized either by manual, corpus-based or dictionary-based approaches. As manual approaches are very time-consuming, it is sufficient to combine with other automated methods. SentiWordNet dictionary is a popular linguistic resource in sentiment analysis which provides an answer to the “how and which words people use to express preferences?” [5]. Previous studies using the lexicon of SentiWordNet have shown promising results as discussed in [6].

5 PROPOSED APPROACH

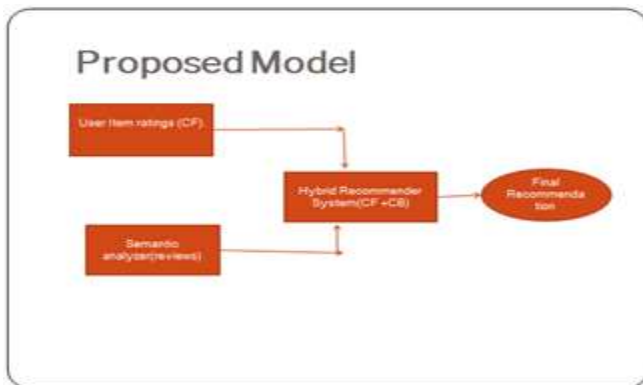


Fig 1: Proposed model architecture

The aim is to overcome the issue of data sparseness in recommender system by integrating textual review (sentiments) into Collaborative recommendation. Most of the recommender systems do not consider sentiments for their calculations and hence this leads to data sparseness. It is not always necessary that a user will tend to give a review. Also it may happen that a user may give some reviews on social media, blogs etc. Considering this too, along with the ratings will prove to generate a better recommendation system. Research in sentiment analysis have shown that such information can produce better sentiment accuracy [7] to help in improving the data sparseness problem. Figure 1 illustrates the problem issued by the data sparseness in recommender systems and the proposed solution by integrating the rating items and textual reviews. Users can express their feelings. Similarity between

users can be calculated using various distance measures metrics. Out of these, euclidean distance proves to be the best distance measure.

5.1 Hybrid recommender module

The formula $sim(x, y) = \frac{1}{\sqrt{(x_1 - x_2)^2}}$ being where x_1 and x_2 are two different customers. If this measure is close to 0 then the two users are similar. Along with this the comments of user x_1 and x_2 are to be considered for further recommendations. Hence the equation for hybrid recommendation system is

$$score(hybrid) = sim(x_1, x_2) * R_{m1} + R_p * sim(p_s, p_q)_u$$

Where $sim(x_1, x_2) * R_{m1}$ indicates the similarity between x_1 and x_2 . R_{m1} denotes the ratings given to a product by user 1 (Collaborative filtering). R_p indicates $sim(p_s, p_q)_u$ rating of a given product whereas indicates similarity between different products which the user u has rated previously.

The sentiment analysis module will receive the sentiments of users regarding a product and then along with the hybrid recommendation system be combined for the final recommendation.

5.2 Sentiment analysis module

The sentiments may be long enough where data preprocessing techniques need to be applied for stemming only important words which convey the sentiments of the users. The sentiments of the users can be classified into positive, negative and neutral comments. Here, we can consider only positive and negative comments. (neutral to be considered as positive only). A comment can be considered as negative or positive according to the number of words signifying this sentiment.

We first classify the reviews into positive and negative parts according to the sentiment lexicon.

The lexicon is built according to the field of items being purchased. Words such as “good” and “wonderful” in reviews indicate that the user had a positive impression for the product. If most users

have positive evaluation for the product, the movie should be deemed as a priori one to be recommended to users who have not bought it

After doing this the final equation to be considered is

$$Score_{final_u} = Score_{hybrid} + Score_{SA}$$

Where Score hybrid is the recommendation score out of hybrid recommendation system and SA score is the score out of Sentiment analysis.

.Final recommendation list is generated according to the new score. Due to this score, the system generates optimized list of recommendations for the user.

Challenges faced here are

A. Sarcastic Comments

Sarcasm is known as “the activity of saying or writing the opposite of what you mean, or of speaking in a way intended to make someone else feel stupid or show them that you are angry” (Macmillan, 2007). For example, let us consider the tweet “It’s Sunday and it’s freezing! It’s raining! How better can this day be??”

This will be classified as a normal tweet since only the word “better” is recognized as a positive word from the whole tweet. However, other approach can say it is a negative tweet due to the word “bad” into it. In addition, we should also consider “coherence”; that is, the relationships across multiple sentences. Generally, sarcastic tweets should contain expressions which clearly show the relationships or references to some words across sentences. For example, in the tweet “And I just found out that my other pap fell and broke his hip. Awesome day thus far”, the word “awesome” (positive) refers to the action “fell” and “broke” (both are negative words), that is a contradiction of sentiments in the sarcastic tweet. However, when a tweet contains contradiction of sentiment polarity without coherence between them, it could be regarded as non-sarcastic tweet. For example, in the tweet “He likes dogs. She hates cats.”, the word “love” (positive) and “hates” (negative) refer to the different subjects in two sentences. Although the tweet contains contradictions in sentiment polarity, the two sentences are not coherent. Therefore, it should not be classified as a sarcastic tweet. In this way, coherence is important for the recognition of sarcasm. Finally, Support Vector Machine is used to train a classifier that judges if a tweet is sarcastic.

B. Fake Reviews

To handle this we may consider the agreement value that illustrates how similar the feature and its opinion orientation resulted from the polarity generation process with the other reviews (discussed earlier). This process uses Jaccard similarity. Results from Jaccard similarity was in the range of (0,1), 0 means that the second review didn’t have the same opinion orientation for any feature, 1 means both reviews had the same opinion orientation for all the features.

5 CONCLUSION

In this paper, an efficient approach for building a recommendation system has been proposed. Also care has been taken to handle sarcastic reviews and also fake reviews.

REFERENCES

- [1] C. Basu, H. Hirsh, and W. Cohen, “Recommendation as classification: Using social and content-based information in recommendation,” in *Proceedings of the 1998 15th National Conference on Artificial Intelligence, AAAI*, pp. 714–720, July 1998.
- [2] W. Xu, J. Wang, Z. Zhao, C. Sun, and J. Ma, “A Novel Intelligence Recommendation Model for Insurance Products with Consumer Segmentation,” *Journal of Systems Science and Information*, vol. 2, no. 1, pp. 16–28, 2014.
- [3] Y. Xu, X. Guo, J. Hao, J. Ma, R. Y. K. Lau, and W. Xu, “Combining social network and semantic concept analysis for personalized academic researcher recommendation,” *Decision Support Systems*, vol. 54, no. 1, pp. 564–573, 2012.
- [4] D. Guo, Z. Zhao, W. Xu et al., “How to find a comfortable bus route - Towards personalized information recommendation services,” *Data Science Journal*, vol. 14, article no. 14, 2015.
- [5] D. Guo, Y. Zhu, W. Xu, S. Shang, and Z. Ding, “How to find appropriate automobile exhibition halls: Towards a personalized recommendation service for auto show,” *Neurocomputing*, vol. 213, pp. 95–101, 2016.
- [6] V. W. Zheng, B. Cao, Y. Zheng, X. Xie, and Q. Yang, “Collaborative filtering meets mobile recommendation: a user-centered approach,” in *Proceedings of the 24th AAAI Conference on Artificial Intelligence*, pp. 236–241, 2010.
- [7] V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang, “Towards mobile intelligence: learning from GPS history data for collaborative recommendation,” *Artificial Intelligence*, vol. 184/185, pp. 17–37, 2012.
- [8] YiBo Wang, Mingming Wang, and Wei Xu, “A Sentiment-Enhanced Hybrid Recommender System for Movie Recommendation: A Big Data Analytics Framework”, *Wireless Communications and Mobile Computing* Volume 2018, Article ID 8263704