PAPER • OPEN ACCESS

Weighted hybrid technique for recommender system

To cite this article: S. Suriati *et al* 2017 *J. Phys.: Conf. Ser.* **930** 012050

IOP Conf. Series: Journal of Physics: Conf. Series **930** (2017) 012050 doi:10.1088/1742-6596/930/1/012050

Weighted hybrid technique for recommender system

Suriati[1], Meisyarah Dwiastuti[2], Tulus[3]

[1]Department of Informatics, STT Harapan Medan, Medan, Indonesia
[2]Department of Computer Science and Electronics, Universitas Gadjah Mada, Yogyakarta, Indonesia
[3] Department of Mathematics, Universitas Sumatera Utara, Medan, Indonesia

[1]suriati_19@yahoo.com, [2]meisyarah.dwiastuti@gmail.com, [3]tulus@usu.ac.id

Abstract. Recommender system becomes very popular and has important role in an information system or webpages nowadays. A recommender system tries to make a prediction of which item a user may like based on his activity on the system. There are some familiar techniques to build a recommender system, such as content-based filtering and collaborative filtering. Content-based filtering does not involve opinions from human to make the prediction, while collaborative filtering does, so collaborative filtering can predict more accurately. However, collaborative filtering cannot give prediction to items which have never been rated by any user. In order to cover the drawbacks of each approach with the advantages of other approach, both approaches can be combined with an approach known as hybrid technique. Hybrid technique used in this work is weighted technique in which the prediction score is combination linear of scores gained by techniques that are combined.The purpose of this work is to show how an approach of weighted hybrid technique combining content-based filtering and item-based collaborative filtering can work in a movie recommender system and to show the performance comparison when both approachare combined and when each approach works alone. There are three experiments done in this work, combining both techniques with different parameters. The result shows that the weighted hybrid technique that is done in this work does not really boost the performance up, but it helps to give prediction score for unrated movies that are impossible to be recommended by only using collaborative filtering.

1. Introduction

Recommender system becomes an important component in an information system or webpages nowadays. In e-commerce and social networking websites, recommender system has substantial role in developing their business [1,2,3]. The recommender system can help user to find things that he might not expect to look for before, for example a book that matches user preference but not quite popular [4]. A good recommender system can make the user trust and rely on the recommendation given so he keeps using it in the future. This is an essential reason to escalate a business.

Recommendation given by a system can be either personalized or non-personalized. Non-personalized recommender system gives general recommendation for all users. For example, it recommends the 10 top movies for ones whose average ratings are the highest. A personalized recommenderbuilds a profile for each user by predicting his score of preference towards the item. The preferences can be retrieved by user's action on the system, either implicitly or explicitly. Implicit action is activity user does on the system that unintentionally influences the preference score because the system record and compute it. For instance, clicking, opening a product page, closing a product page, etc. Explicit action is activity that user intentionally does to show his preference towards a product. For instance, giving a rating for a product.

There are some familiar approaches to build a recommender system, namely content-based filtering[5] and collaborative filtering[6]. Content-based filtering analyzes relation between user preference and item description. It builds a profile for user to show his preference based on characteristics of the items. Opinions from other users are not involved in making the prediction. A drawback of this approach is that it cannot distinguish the quality of item. Two items with the same characteristics will be considered have the same quality even though human can easily categorize them as different items. As the number of items increases, the number of items in the same category grows. It makes ineffectiveness of content-based approach.

Collaborative filteringgives recommendation to a user by examining rating behavior of other users [6]. It assumes that other users' opinions can be aggregated in such a way as to predict the preference of a user. Thus, the prediction is not influenced by item features. Since human's opinion is involved, the quality of information gained becomes better and more accurate if it compares to approach that only depends on computer intelligence. However, this approach also has drawbacks. Pure collaborative filtering cannot deal with early rater problem. It cannot provide a prediction for a new item or an item that has not been rated by any user since there is no users' ratings to compute the prediction.

There are two known types of collaborative approach: user-based and item-based collaborative filtering. In user-based collaborative filtering, the prediction for a certain user is influenced by opinions from other users similar to him. As the number of users increases, the amount of system work also rises. However, in a small community, there are users whose opinions do not consistently agree with any group of people so they do not get benefit from collaborative filtering [7]. Item-based collaborative filtering, which analyzes items relationship instead of users relationship, can be the alternative approach since it provides a better quality than user-based collaborative approach [8].

In order to balance the advantages and drawback of each recommendation approach, hybrid approach can be implemented [9]. Hybrid approach is a combination of two or more approaches in building a recommender system. There are some hybrid techniques, such as weighted, switching, mixed, feature combination, cascade, feature augmentation, and meta-level technique [9].

Since collaborative approach uses ratings as information, it cannot recommend item which has never been rated by any user. On the other hand, content-based approach involves item's features to compute rating prediction. Even if the item has not been rated, but it has feature that a user likes, it can be recommended by the system. The combination of both approaches using hybridization, hopefully, can increase the quality of recommendation. Weighting technique is used to combine those recommendation approaches.

In this paper, we implementthe combination of content-based and item-based collaborative approaches using weighted hybrid technique. The objective of this work is to show, firstly, how an approach of weighted hybrid technique can work in a movie recommender system and, secondly, the performance comparison when both approaches are combined and when each approach works alone.

2. Related Work

Researches concerning recommender system have shown a great interest since last two decades. In [5], Pazzani did some surveys on implementation of content-based recommender system, including the possible techniques and algorithms used. Tapestry [10], known as the earliest recommender system using collaborative filtering, was designed to recommend documents to a collection of users in which user's annotations on documents are used for filtering. The GroupLens research system [11, 12]introduced a collaborative filtering solution for Usenet news and movies.

Burke [9] did surveys and experiments on possible methods to perform a hybrid recommender system. He mentioned 6 known methods of giving recommendation and 7 possible techniques to combine two or more of them. The summary shows that 6 out of 7 hybrid techniques can be implemented to combine content-based filtering and collaborative filtering and there are some researches have been done for those techniques. His work also shows combinations which are impossible and redundant.

Claypool et al. [7] has ever worked on combining collaborative and content-based filtering through a linear combination for an online newspaper recommender system. They consider collaborative filtering as a good approach to make accurate prediction which is personalized by combining opinions by humans and content-based filtering can make a fast prediction. Therefore, combining both of them will hopefully result a fast and accurate prediction.

Another work on combining those techniques is done by Melville et al. [13]. They introduced a framework where a sparse user ratings matrix can be converted into a full ratings matrix by implementing content-based predictions, and collaborative-filtering technique is used to provide recommendations.

3. Methods

3.1. Content-based filtering

Content-based filtering (CB) technique gives recommendation to user by computing similarity between user and item based on item features. Supposed that we have item matrix **A** with element $a_{i,j}$ representing relationship between item i and item feature j, and rating matrix **R** with element $r_{u,i}$ representing ratings that user u give to item i, we want to build user profile matrix **B** with element $b_{u,j}$ representing relationship between user u and item feature j. The user profile matrix is obtained by computing matrix multiplication of rating matrix and item matrix, as shown in equation (1).

$$\boldsymbol{B} = \boldsymbol{R} \times \boldsymbol{A} \tag{1}$$

Since it is too large to compute the whole user profile matrix at once, we get $b_{u,j}$ by computing dot product of vector $\boldsymbol{a}_j$ and $\boldsymbol{r}_u$. Before applying dot product, the ratings in user vector $\boldsymbol{r}_u$ is subtracted by a threshold. Threshold is a number or point that distinguishes range of rating considered as ‘like’ and ‘unlike’. We experiment different values for threshold that will be explained in the subsequent section. Rating that is lower than the threshold will have minus value after subtraction. After applying dot product, the result must be normalized in order to have the same scale for all features. Normalization can be done by dividing the result by product of norm of the vectors. In other word, it is the same as we apply cosine similarity formulation over those two vectors, the subtracted user vector $\boldsymbol{r}_u$ and feature vector $\boldsymbol{a}_j$.

Rating prediction can be computed then by finding similarity between a user and items that he has not rated. If both item profile $\boldsymbol{a}_i$ and user profile $\boldsymbol{b}_u$ are represented as vector with item features as the indices, cosine similarity can be used to compute how close both vectors are, that represents how likely the user and the item are. the range of the score is between -1 and 1. Rating prediction of user u to item i can be computed using equation (2). In the equation, x is the highest rating value on the system.

$$p_{u,i} = (x - t)sim(\boldsymbol{b}_u, \boldsymbol{a}_i) + t \tag{2}$$

3.2. Item-based collaborative filtering

The concept is: if a user likes items, the system assumes that he will like items similar to those he likes. Unlike CB technique, this technique does not use item features as information. It is interested in other users’ opinion to find similar items. This technique predicts rating given by user u to item i by examining similarity between item i to items that have been rated by user u, selecting k similar items, and computing the weighted average of user's rating on these similar items. The computation of prediction pu,i can be done as follows:

$$p_{u,i} = \frac{\sum_{j \in S} sim(i,j) r_{u,j}}{\sum_{j \in S} |sim(i,j)|} \tag{3}$$

in which S is a set of k similar items to i, j is a member of S, and $r_{u,j}$is the rating user u has given to item j. The k similar items are selected using k-nearest neighborhood (k-nn) algorithmwith $k = 30$. The similarity metric used is cosine similarity.

3.3. Weighted hybrid technique

Weighted technique computes the prediction score as results of all recommendation approaches by considering them as variables in a linear combination. This technique gives each of them weight and summing up the weighted results. Supposed that there are *c* recommendation approaches to be combined using weighted strategy, the prediction score of user *u* to item *i*can be computed as follow:

$$p_{u,i} = \sum_{f}^{c} \sigma_f p_{u,i}^{(f)} \tag{4}$$

where σ_f denotes weight of algorithm $p_{u,i}$

Since we are interested in combining 2 recommendation approaches, we set c=2. According to [14], if c = 2, the computation of prediction score can be written as:

$$p_{u,i} = \sigma_1 \cdot p_{u,i}^{(1)} + (1 - \sigma_1) \cdot p_{u,i}^{(2)} \tag{5}$$

and the optimized weight can be gained by compute:

$$\sigma_1 = \frac{\sum_u \sum_i \left(p_{ui} - p_{ui}^{(2)}\right)\left(p_{ui}^{(1)} - p_{ui}^{(2)}\right)}{\sum_u \sum_i \left(p_{ui}^{(1)} - p_{ui}^{(2)}\right)^2} \tag{6}$$

4. Experiment

4.1. Data preparation

Dataset used in this experiment is MovieLens dataset [8]. There are 2 datasets contained, namely ratings dataset and movies dataset. The ratings dataset has 4 attributes: u*serId, movieId, rating*, and *timestamp*. It contains 1,000,209 anonymous ratings of approximately 3,900 movies made by 6,040 users. Each user has at least 20 ratings, in which the rating is within the range of 1 to 5. The movies dataset has information about the movies: id, title, and genres. Each movie may have one or more genres or no genre. The representation of movie genres is converted into binary representation, in which the genre or the feature is represented as either 1, if the movie has the genre, or 0 otherwise.

The ratings dataset is randomly splited into 2 sets, 80% of the dataset as training set, and 20% as testing set. The training set is used to compute prediction score in this experiment using three approaches: content-based filtering, item-based collaborative filtering, and weighted hybrid approach. The testing set is used to evaluate performance of the methods.

4.2. Implementation

Our experiment is implemented using Python and ran on a Linux PC with Intel Core i3-2350M processor having speed of 2.30GHz and RAM of 4GB. In order to find the best performance of the hybrid technique, there are three experiments performing different combinations of method used on content-based filtering (CB) and item-based collaborative filtering (CF). The first experiment performs CB with 2.5 as threshold and CF without applying threshold. The second experiment performs CB with 2.5 as threshold and CF with user rating mean as threshold. The third experiment performs combination of CB and CF using user rating mean as threshold for each prediction computation.

Those three experiments are implemented to training set in order to build a model for each approach (CB and CF). After the models are built, the weight of CB σ is computed. Consequently, weight of CF is also found by computing $1-\sigma$. Once the σ is obtained, prediction score by hybrid method can be computed using equation (5). The n items with the best prediction score become the output of the recommender system.

Table 1. Experiments for combination of CB and CF and σ value obtained.

No.	**CB Threshold**	**CF Threshold**	σ
1	2.5	0	0.932
2	2.5	user rating mean	1.108
3	user rating mean	user rating mean	1.269

Table 2. Performance evaluation of three experiments.

Measurement\exp.	**1st**	**2nd**	**3rd**
MAPE CB	0.93	0.93	0.90
MAPE CF	2.13	0.73	0.73
MAPE Hybrid	0.969	0.972	1.031

For each experiment, the prediction score is predicted by three approaches, which are CB, CF, and hybrid, in order to be able to compare the performance for each approach as well. Since the score obtained by the algorithm implemented is continuous, it has to be rounded to discrete value. By using models that have been built, the performance can be evaluated by predicting user rating on the testing set. The evaluation metric used is Mean Absolute Percentage Error (MAPE). MAPEisan error measurement comparing the real ratings value and the prediction score. We expect the value of MAPE as small as possible. Value of zero means there is no error in our prediction.

5. Result and Discussion

In this section, we describe the recommendation performance from our experiments.

Table 1 shows the value of σ, weight of CB approach, obtained on each experiment. On the first experiment, both weights of CB and CF have positive value. But CB weight seems to be much higher. It means that CB score is pretty close to the real rating that it becomes dominant in the combination. On the other hand, the second and the third experiments have σ value more than 1 which makes CF weight negative. It means that most CB scores are less than the real rating and in contrary, most CF scores are more than the real rating.

The performance evaluation can be seen on Table 2. It shows that for CB, the performance is better on the first and second experiments when we set threshold as universal rating mean. For CF, it shows that the system performs much better when we set threshold for each user as his rating mean. From the table, we can also infer that when we set threshold for CF, it works better than CB. Moreover, it seems like the second experiment that combines best performance of CB and best performance of CF does not yield the best performance of hybrid technique. If we consider hybrid performance based on both measurement, the first experiment results the best, even though its CF performance is really bad. Overall, we can see CF technique with threshold seems to be the best technique for the system since it yields the least error. Hybrid technique used in this work does not seem really helpful to boost the performance.

6. Conclusion

This work is trying to combine content-based filtering approach and item-based collaborative filtering approach using weighted hybrid technique. There are three experiments performed in order to see which approach shows the best performance. The best performance of content-based approach and collaborative filtering is when we set the threshold as user rating mean that result MAPE 0.90 and 0.73 respectively. However, the best performance of the hybrid approach is when we set 2.5 as threshold for the content-based filtering approach and do not set threshold for the collaborative filtering that results MAPE 0.969. Overall, the weighted hybrid technique that is done in this work does not really boost the performance up, since the result shows that the error gained by each technique is still less than the error gained by the hybrid one. But it helps to give prediction score for unrated items that are impossible to be recommended by only using collaborative filtering. For future work, we encourage to try applying a new approach to optimize the weights or implementing different hybrid approach.

References

[1] Linden G, Smith B, and York J 2003Amazon.com recommendations: item-to-item collaborative filtering*IEEE Internet Computing***7**76-80
[2] Rogers S K 2016Item-to-item Recommendations at Pinterest*Proc. of the 10th ACM Conference on Recommender Systems* (Boston)
[3] Wu L "Browsemap: Collaborative Filtering At LinkedIn," 23 October 2014. [Online]. Available: https://engineering.linkedin.com/recommendersystems/browsemap-collaborative-filtering-linkedin
[4] Rajaraman A, and Ullman J D 2011*Mining Massive Datasets* (New York: Cambridge University Press)
[5] Pazzani M J, and Billsus D 2007Content-based recommendation systems *The Adaptive Web: Methods and Strategies of Web Personalization* (Heidelberg: Springer Verlag Berlin) pp 325-41
[6] Ekstrand M D, Riedl J T, and Konstan J A 2011 Collaborative Filtering Recommender Systems*Foundations and Trends® in Human–Computer Interaction***4** 81-173
[7] Claypool M, Gokhale A, Miranda T, Murnikov P, Netes D,and Sartin M1999Combining content-based and collaborative filters in an online newspaper*SIGIR99: Proceedings of the ACM SIGIR Workshop on Recommender Systems*
[8] Sarwar B, Karypis J, Konstan J, and Riedl R 2001 Item-based Collaborative Filtering Recommendation Algorithms *Proc. of the 10th International Conference on World Wide Web* pp 285-95

[9] Burke R 2002. Hybrid Recommender Systems: Survey and Experiments*User Modeling and User-Adapted Interaction* **12**331-70

[10] Goldberg D, Nichols D, Oki B, and Terry D 1992 Using collaborative filtering to weave an information tapestry. *Communications of the ACM* vol 35 pp 61-70

[11] Konstan J, Miller B, Maltz D, Herlocker J, Gordon L, and Riedl J 1997 GroupLens: Applying Collaborative Filtering to Usenet News*Communications of the ACM* vol 40 pp 77-87

[12] Resnick P, Iacovou N, Suchak M, Bergstrom P, and Riedl J 1994 GroupLens: An Open Architecture for Collaborative Filtering of Netnews *Proceedings of CSCW '94* pp 175-86

[13] Melville P, Mooney R, and Nagarajan R 2002. Content-boosted collaborative filtering for improved recommendations *Proc. of the Eighteenth National Conference on Artificial Intelligence* (AAAI- 02) pp 187–92

[14] Lin W, Li Y, Feng S, and Wang Y 2014 The optimization of weights in weighted hybrid recommendation algorithm *Proc. of the 2014 IEEE/ACIS 13th International Conference on Computer and Information Science (ICIS)* pp 415-18