An Enhancement of Item-based Collaborative Filtering Utilizing K-Nearest Neighbors and Interquartile Range Theory

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Abstract

The Item-based Collaborative Filtering Technique is a recommendation algorithm that recommends things based on the similarity between items. This study will focus on enhancing the Item-based Collaborative Filtering algorithm concerning the diversity of the recommendations. This paper introduces an enhanced version of the algorithm in which K-Nearest Neighbors and Interquartile Range Theory was implemented, wherein this diversifies the final list of recommendations to the user. These methods prevent the researchers from recommending items from a narrow spectrum of users' interests. Compared to the typical IBCF, the study shows that the methods used effectively make the recommended items diversified.

Keywords: Item-based Collaborative Filtering; Interquartile Range; Recommendation Algorithm; k-nearest neighbor

1. Introduction

During the past ten years, it is evident that companies have invested heavily in recommender systems. The rise of YouTube, Netflix, and other web services has hugely impacted society and continuously takes more places in such lives. (Li, 2021). Recommender systems are made up of algorithms that were aimed to suggest related objects or items to users. This could recommend movies to watch, products to buy, food to order, and other things depending on their industry (Resnick et al., 1997). Content-Based Filtering, Collaborative Filtering, and Hybrid Systems are the three types of recommendation algorithms that currently exist. User-Based Collaborative Filtering and Item-Based Collaborative Filtering are the two types of collaborative filtering (Sarwar et al., 2001).

Item-Based Collaborative Filtering has gained popularity due to its ability to recommend items based on the similarity between items derived from the user's rating. Amazon invented and used it in 1998. (Smith & Linden, 2017). Unlike content-based systems, it filters for items of interest based on user interactions and other users' preferences, allowing it to predict what the user might be engaged in (Ponnam et al., 2016). The item-based collaborative filtering algorithm examines the collection of things that the user has rated and calculates how similar the target item and the ones closest to it are. Once similar items are collected, it then proceeds to prediction computation. There will be a list based on the prediction, and those items will be recommended to the user. In most Collaborative Filtering algorithms, popular items are more preferred because they have higher predicted ratings than less popular items. As a result, long-tail items are unlikely to be discovered, but popular items make for the majority of user recommendations. Over time, this disparity will worsen, trapping more items in the long tail (Ho et al., 2014).

The study aims to lessen the number of popular items to be recommended and provide users with a diverse range of items. By that means, researchers will use the K-nearest neighbor together with cosine-based similarity and weighted sum for prediction computation. To be able to recommend a diverse list of items, researchers will then use the Interquartile Range Theory (IQR).

2. Related Studies

The study of Herlocker et al. (2004) entitled "Evaluating Collaborative Filtering Recommender Systems" coined the phrase "There is an emerging understanding that good recommendation accuracy alone does not give users of recommender systems an effective and satisfying experience." Recommender systems must also focus on functionality over accuracy. Furthermore, a system that consistently recommends very popular items can almost certainly guarantee that the majority of the recommended items will be liked by the majority of the users. As a result, the proportions of the recommender system's effectiveness which go beyond precision and include user acceptability are affected. Accuracy alone in the recommendation systems does not guarantee user satisfaction. Moreover, recommendations that focus only on accuracy may disregard other qualities and produce recommendations that appear apparently "good" yet are inferior in user contentment. One great example is a recommendation of an entire set of Beatles songs, the system may be accurate, but users will indeed become bored with a similar number of items (Zhang et al., 2012).

According to Ho et al. (2014), accuracy is not the only factor in equalizing the user needs, and it may also be harmful. Previous studies also showed that it would be beneficial for the business model and customers if long-tail items have more sales. It is also important to consider novelty, unexpectedness, and diversity. Several recommendations deliver great results but are still ineffective in practice. The ultimate purpose of the recommender system is to offer users with relevant things with high accuracy. However, it appears way too obvious, and it gives a little help to the user due to the state of being ordinary. Hence, to measure the "non-obviousness" of a specific recommendation, Novelty and Serendipity might occur (Ziegler et al., 2005). According to Yu et al. (2009), the purpose of recommendation diversification appears to be to find a set of distinctive items, yet still relevant to the user's interests.

Wasilweski et al. (2018) proposed merging information about relevancy and user intent item-aspect associations to offer better recommendations in one step, rather than providing recommendations first and then reranking them to incorporate more aspects and closer choice of the user's taste. In order to accomplish this, they introduce customized item similarity, in which the item-based nearest-neighbor collaborative filtering algorithm was based on intent-aware personalized covariance.. Yang et al. (2018) used the MF model in their research to increase the diversity of recommendation results while preserving the required correlation with user preferences. The accuracy and diversity of the recommender system can be improved by incorporating a variance minimization regularization term, as well as merging bias and implicit feedback.

Unlike traditional item-based collaborative filtering, the intralist similarity metric is used to evaluate the topical diversity of the recommendation set and topic diversification to increase the diversity of the top recommendation list, which results in improved user satisfaction. The technique considers both the accuracy and the scope of the user's interests. (Ziegler, 2005). Researchers Wang and Yin (2013) proposed an artificially collaborative filtering approach that combines user-based and item-based collaborative filtering methods to improve recommendations diversity. Each user can modify the diversity of their own suggestion list based on the proposed approach by adjusting the prevalence rate and novelty rate parameters.

In (Ashkan et al., 2015), a modular function called diversity-weighted utility maximization was intended to improve the recommended list's dissimilarity and a greedy algorithm was used to maximize it. Similar to the study of Sha et al (2016), they proposed a framework in which they analyze and optimize search problems that take relevance of items, user-interest coverage, and diversity between items. Zhang et al (2021) suggested the Link-Based Collaborative Filtering strategy to handle the suggestion overfitting problem without the use of additional complex information in their study. Wang et al (2021) present a diversified recommendation approach that combines the LSH methodology and the CT method. To ensure the proposal's effectiveness, the LSH technique is employed to discover appropriate neighbors for the potential user.

The context of user-based collaborative filtering (UCBCF) is a new collaborative filtering approach proposed by Niemann and Wolpers (2013), in which frequent details are assigned to objects. Items are similar in this way if they frequently occur in a similar usage, but they do not always appear together in the same user profile. In research from Berbague et al. (2018), they proposed a similarity index adjusted for biased recommendations for greater diversity while maintaining good accuracy.

Li and Murata (2012) developed a hybrid recommendation system that integrates multidimensional clustering and collaborative filtering techniques to enhance the diversity of recommendations. The suggested approach, according to Eskandanian et al. (2017), consists of stages, namely data preprocessing and multidimensional clustering, segment selection, and recommendation phase for the target user. They employ a clustering method to group users based on their tolerance for diversity, and they test how effective the method is by calculating accuracy-diversity tradeoffs for each user cluster.

Singh et al. (2015) suggested a novel way for analyzing diversity in recommendation systems using the relative similarity index, with the goal of boosting aggregate diversity. When both methods (User-based and Item-based) are merged, Caixia Ren et al. (2016) claim that the recommender system can be accepted for a long period of time. Individual and aggregate diversity is increasing as more methods for recommending long-tail items to users are added. Predicted rating values are also used in their suggested technique in the recommendation organizer, which may then assure the degree of aggregated diversity (Ho et al., 2014).

3. Existing Item-Based Collaborative Filtering Algorithm

3.1. Overview

The Item-Based Collaborative Filtering Technique compares the target item to the things that are closest to it by verifying the set of objects that the user has rated. After collecting similar items, it will compute a prediction based on the weighted average of the target user's rating on these similar things (Sarwar et al., 2001). Collaborative Filtering is divided into two phases:

3.2. Item Similarity Computation

The initial step in an item-based collaborative filtering method is to determine item similarity before filtering the most similar things. The objective behind computing the similarity between items $_m$ and $_n$ is to separate the people who rated both things and use the similarity computation technique to get the s_{mn} (Sarwar et al., 2001). Cosine-Based Similarity is an equation for calculating the similarity among two items that uses the cosine of the angle between two matrices to calculate the similarity.

$$similarity(m,n) = \cos(\vec{m},\vec{n}) = \frac{\vec{m}\cdot\vec{n}}{\|m\| * \|n\|} \tag{1}$$

where,
m is the i_m; vector A
n is the i_n; vector B
similarity(m,n) is the similarity measure between vector A and B

3.3. Prediction Computation

The output is then generated using prediction. After the isolation of the most similar items using similarity metrics, the next step is to find the target user's ratings and use a strategy to make predictions. The Weighted Sum is one of the ways for calculating the prediction (Sarwar et al.,2001).

$$P(U, I_m) = \frac{\Sigma_n rating(U, I_m) * S_{mn}}{\Sigma_n S_{mn}} \tag{2}$$

Weighted sum is used to produce prediction through adding the sum of the ratings given by user U on items similar to I_m. Each rating is weighted based on the similarity of items $_m$ and $_n$. This technique shows how an active user rates relevant things.

3.3. The Problem in Item-based Collaborative Filtering

According to Kunaver and Požrl (2017), once the system is able to consistently generate recommendations for each user, new issues arise because the system can start recommending items from a very narrow range of user interests. A collaborative filter-based approach often prioritizes popular articles, and some long-tail items may not be recommended (Ashkan et al., 2015). To date, many approaches to improving diversity have been developed in the context of memory-based algorithms. In the paper of Wasilweski et al (2016), diversity improvement has been viewed as a separate post-processing step performed after the initial rating prediction was obtained. First, because the items suggested by the item-based technique are usually tightly tied to what the user already knows, other potentially interesting objects will be missed. Then, when a user first joins the system, the item-based strategy completely fails (Yu et al., 2009). To conclude, the traditional item-based collaborative filtering recommends items that are most likely top-rated and popular among the other items.

3.4. Pseudocode of IBCF

```
dataset([users][ratings],[item])
calculate n nearest neighbor using cosine similarity
put all item rated by user in a list
sort the list by rating
for item in list:
   get n nearest neighbor of rated items
   calculate predicted rating
   get the average of predicted rating per item
recommend most repeated nearest neighbor
show predicted rating
```

Figure 1. Algorithm of the Existing Item-Based Collaborative Filtering Technique

4. Methodology

4.1. The Proposed Method

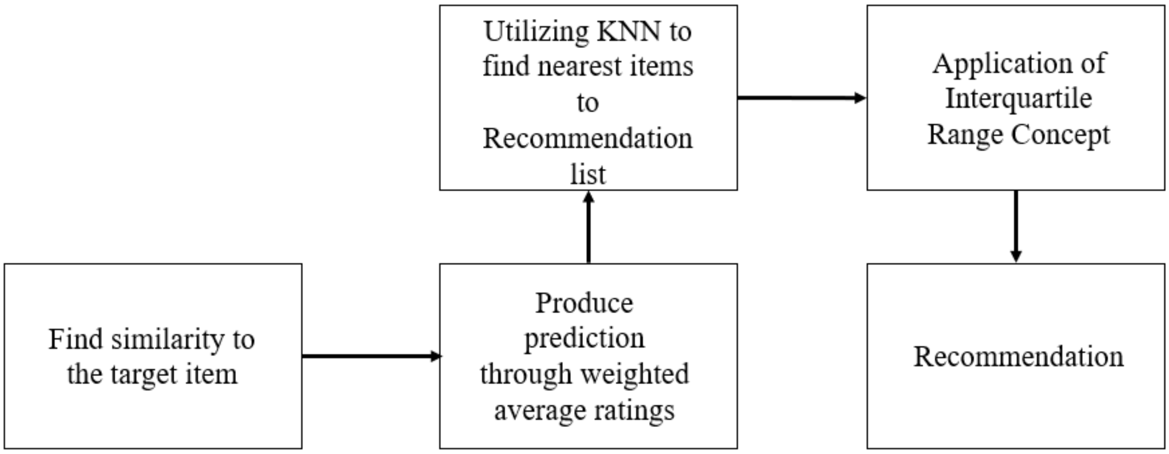

Figure 2. Framework of the Proposed Approach to the Item-based Collaborative Filtering

The next step after generating the prediction is to apply the proposed function to diversify the recommendation list that will be provided to the user. First, is to utilize K - Nearest Neighbor and the Cosine-based similarity metric to find the nearest items based on the generated top recommendation on the prediction computation. The KNN uses the following algorithm: (Ali et al., 2019)

1. Determine the number of nearest neighbors. (K -Value)
2. Calculate the distance between the test sample and the rest of the samples.
3. Determine the distance between the test sample and the other samples.
4. Arrange the categories of the closest neighbors.
5. Designate the new data object's prediction value based on the majority of its nearest neighbors' category.

Figure 3. KNN Algorithm

4.2. Application and Modification of the Interquartile Concept

After finding the similarity items on the top recommendation list, it is to perform the Interquartile concept to basically find the appropriate items for recommendation. The interquartile range is a basic estimator of data spread. (Buch, 2014). To calculate the interquartile range (IQR), the dataset must be sorted in ascending order, the list's median value determined, and values extracted from the 25th and 75th interquartile ranges extracted.

$$IQR = Upper\ Quartile - Lower\ Quartile = Q3 - Q1 \qquad (3)$$

However, we modified the concept. Instead of obtaining values from Quartile 1 to below Quartile 3, we reduced it to Quartile 2. The researchers find that it would be optimal to retrieve items from lower Quartile 1 up to the Quartile 2 since they are not most likely top-rated, and it is somehow closely related to the original recommendation list.

$$mIQR = Middle\ Quartile - Lower\ Quartile = Q2 - Q1 \qquad (4)$$

4.3. Pseudocode of Enhanced IBCF

```
dataset([users][ratings],[item])
calculate n nearest neighbor using cosine similarity
put all item rated by user in a list
sort the list by rating
for item in list:
   get n nearest neighbor of rated items
   calculate predicted rating
rec-item = most repeated nearest neighbor
near-rec-item = nearest neighbors of rec-items
interquartile-item = apply inter-quartile range concept to near-rec-item
get the average of predicted rating per item
recommend inter-quartile-item
show predicted rating of inter-quartile-item
```

Figure 4. Modified Algorithm of the Item-Based Collaborative Filtering Technique

5. Results and Discussion

5.1. Dataset

The researchers used an experimental approach to see if the improved algorithm will improve the existing item-based collaborative filtering system's performance. The MovieLens Data from Harper and Konstan (2015), with a size of 200k movies from 700 users, will be utilized during the experimentation. It comprises the user, item, rating, and timestamp. The rating is the user's opinion on a particular item which ranges from (0-5 star rating). The data set is often used to recommender systems such as collaborative filtering, which is basically dependent on the rating of the items.

5.2. Prediction - Recommendation List

After undergoing the phases of the item-based collaborative filtering: item similarity, and prediction computation, the top movies are produced. Table 1 presents the produced top movies that were based on the past opinions of the user, particularly on the ratings of the movies. The top five recommended movies have the same prediction rating. These movies will be the basis for the next stage of the proposed solution to the algorithm.

Table 1. Top movies for Recommendation

Movie Title	Prediction Rating
Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)	5.000000000000001
Armageddon (1998)	5.000000000000001
Dead Zone, The (1983)	5.000000000000001
Easy A (2010)	5.000000000000001
Election (1999)	5.000000000000001

5.3. Nearest Neighbor of the Recommended Items

In finding the nearest items or movies to the top-recommended movies the researchers utilized the K-Nearest Neighbor Algorithm along with a cosine-based similarity metric. The lower the value of the distance it means the movie is closer to the target movie. In this case, we take the top 5 movies with the highest prediction value to find their nearest neighbor.

Table 2. Nearest neighbors of Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)

Movie Title	Distance
Eternal Sunshine of the Spotless Mind (2004)	0.4117652546533712

Fight Club (1999)	0.44930880385885474
Memento (2000)	0.45401329318661054
Run Lola Run (Lola Rennt) (1998)	0.4878500936940715
Life Is Beautiful (La Vita è bella) (1997)	0.49474865449258754
...	...
Spider-Man (2002)	0.563903941618506
Truman Show, The (1998)	0.5671805855217615
Big Fish (2003)	0.5693941169851129
Minority Report (2002)	0.5697375833691802
Chocolat (2000)	0.5704124910183243

Table 3. Nearest neighbors of Armageddon (1998)

Movie Title	Distance
Men in Black (a.k.a. MIB) (1997)	0.4584504842239495
Sixth Sense, The (1999)	0.46465786955592403
Saving Private Ryan (1998)	0.4824194198340024
American Pie (1999)	0.49464011378583805
Star Wars: Episode I - The Phantom Menace (1999)	0.5024777738040417
...	...
Beetlejuice (1988)	0.5725913294697214
Catch Me If You Can (2002)	0.5731549252952814
Spider-Man (2002)	0.5733866344446223
Day After Tomorrow, The (2004)	0.5753073436650309
Minority Report (2002)	0.576043073284307

Table 4. Nearest neighbors of Dead Zone, The (1983)

Movie Title	Distance
Mission, The (1986)	0.5028822074128256
Buddy Holly Story, The (1978)	0.5043387414014455
Halloween III: Season of the Witch (1982)	0.5311752451952827
Oliver Twist (2005)	0.5329006335030863
Song of the South (1946)	0.5439236224513362
...	...
Something Wicked This Way Comes (1983)	0.622921392539076
Psycho II (1983)	0.6231688066895891
Swarm, The (1978)	0.6262122328108881
Mouse Hunt (1997)	0.631291398573588
Night Porter, The (Portiere di notte, Il) (1974)	0.6314768492501713

Table 5. Nearest neighbors of Easy A (2010)

Movie Title	Distance
Girl Next Door, The (2004)	0.4962028382837548
21 Jump Street (2012)	0.5052436767427515
Crazy, Stupid, Love. (2011)	0.5225699801504226
Holiday, The (2006)	0.5226484093914342
Ugly Truth, The (2009)	0.5330357257269386
...	...
Thor (2011)	0.6195357635798152
Super (2010)	0.621285315952143
Legally Blonde (2001)	0.625700485228093

Up (2009)	0.6259999504838062
Twilight Saga: Eclipse, The (2010)	0.6272634652151275

Table 6. Nearest neighbors of Election (1999)

Movie Title	Distance
Rushmore (1998)	0.47542158469254325
Raising Arizona (1987)	0.5275616836884149
Crimes and Misdemeanors (1989)	0.5444368309754648
Run Lola Run (Lola Rennt) (1998)	0.5497721929868087
Go (1999)	0.5510760529195168
...	...
Midnight Cowboy (1969)	0.6240432542708716
Crumb (1994)	0.6243453863081507
Shakespeare in Love (1998)	0.6255006695127188
Amadeus (1984)	0.6256602496168645
Grosse Pointe Blank (1997)	0.6270532782745935

The Tables 2 up to Table 6 show the listed nearest neighbor of every movie that has the highest prediction value. The list is in ascending order to easily recognize the closest movie to the top prediction value movies. In this case, we obtained values of the forty nearest neighbors for each of the top-recommended movies.

5.4. Interquartile Range Theory

The last stage of the proposed algorithm is selecting the movies which will be provided to the user. After selecting the nearest movies to the target movies, the researchers then used the Modified Interquartile Range Theory (mIRT) wherein the researchers chose the optimal spot on where to obtain movies that are not so much related to the top-recommended movies. The proposed solution offers a wide variety of selections wherein users may like.

Table 7. The final list of Recommendations

Movie Title
Shrek (2001)
O Brother, Where Art Thou? (2000)
Lord of the Rings: The Two Towers, The (2002)
Kill Bill: Vol. 2 (2004)
Beautiful Mind, A (2001)
...
Summer of Sam (1999)
Full Monty, The (1997)
American Beauty (1999)
Dog Day Afternoon (1975)
Notorious (1946)

Table 7 shows the final list of recommended movies for the user, this came from the application of mIRT in every list in which they are divided into Quartiles. The researchers pick the spot of lower Quartile 1 up to Quartile 2 in which the similarity to the top movies is relatively far enough but not too close. In this way, we lessen the similarity of movies but increase the diversification of the recommendation which will be provided to the user.

5.5. Comparative Analysis

The researchers utilized the personalization evaluation metric to evaluate whether the proposed algorithm improves the traditional collaborative filtering. It measures the similarity of recommendations between users. The higher the score indicates the recommendation list of the users is different, which presents good personalization, the lower the score indicates similarity in the recommendation of the users.

Table 8. Traditional IBCF vs. Enhanced IBCF personalization result

Algorithm	Average Personalization
Traditional IBCF	0.9511111111111108
Enhanced IBCF	0.9799494949494948

Table 8 presents the result of the personalization of two algorithms. The researchers used an experimental approach wherein users were randomly picked and compared whether their recommendation lists were similar. The average personalization value was obtained through an iterative method of personalization evaluation between the recommendation list of the users. The table indicated that the enhanced algorithm improves the diversification of the recommendation provided to the user.

6. Conclusion and Recommendation

This study shows that the methods applied are effective in diversifying the recommended items compared to the traditional IBCF. In this study, the researchers proposed an improvement to the Item-based Collaborative Filtering Technique. The K-Nearest Neighbor Algorithm and Interquartile Range Theory are implemented in the existing IBCF algorithm, resulting in more diversified recommended items. This proves that the method used successfully improved the algorithm's diversification factor.

The researchers recommend determining the best KNN value for future works and testing other Interquartile Range limits. In addition, the researchers suggest that the algorithm be implemented in another programming language, such as Java, to increase the diversification of item recommendations. To improve the study, it is also advised that this should be tested in an actual system with greater datasets and user comments.

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