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Recommender System with User-Based and Item-Based Collaborative Filtering on Twitter using K-Nearest Neighbors Classification

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Abstract−Netflix is one of the most widely used applications for watching movies online. There are various movie titles that can be watched by users, so a recommendation system is needed to help users who feel confused in choosing movie titles. Twitter is a social media used to express ideas, thoughts, and feelings. Not a few Twitter users who conduct movie discussions, with the movie discussion can be converted into a rating that can be used in the recommendation system. Collaborative Filtering is one of the methods of the recommendation system, by recommending based on the similarity between users (user-based) and based on items that have similarities with user-selected items (item-based). In this research, the Collaborative Filtering method is combined with K-Nearest Neighbors classification which obtains an RMSE value for user-based 1.8244 and item-based 0.5449. K-Nearest Neighbors gets 91.22% precision and 91.07% recall for user-based, while item-based gets 89.44% precision and 91.22% recall with the optimal K as a parameter is 3.

Keywords: Recommender System, Collaborative Filtering, User-Based, Item-Based , K-Nearest Neighbors

1. INTRODUCTION

Netflix is an application for watching movies online, Netflix was founded in 1999 as an electronic video store which is currently a very frequently used application. Netflix is used in up to 190 countries in the world with approximately 100 million users [1]. Netflix has a variety of movie titles and their types, so users will feel confused to choose movie titles. Therefore, the solution that can be given is a recommendation system that can provide the best movies.

Many Netflix users leave reviews on social media. One of the most popular social media to date is Twitter. Twitter is intended to provide an expression such as ideas, thoughts and feelings with a limited number of words [2]. Of course, many Twitter users give their opinions about various things, such as movies that are currently circulating. This information can provide a rating from each Twitter user, where tweets containing opinions, suggestions, and criticisms can provide consideration whether this movie is worth watching or not [3]. Data from twitter still uses non-standard language, abbreviated language, writing errors and some sentences that are not used to generate recommendations, so a process is needed to convert it into a rating. Tweets containing movie data or reviews given by twitter users of a movie are so many, so that the data can be used as a reference for a recommendation rating.

With the large number of films in this world, of course everyone has their own favorite films and genres. A recommendation system is needed to provide movies with ratings that have been given by other movie viewers who make movies with the most choices so that users do not feel confused to choose which movie to watch [4]. With this recommendation system, users can choose the recommended movie. The recommendation system also has several methods, one of which is the Collaborative Filtering method.

Collaborative Filtering has two categories, namely memory-based and model-based. Memory-based provides recommendations using user-items directly. There are two approaches in memory-based, namely user-based and item-based. User-based finds similarities between users to provide recommendations for items that users will like. On the other hand, item-based prediction is based on items that are similar to items favored by users [5]. Recommendation systems have several drawbacks, one of which is Data Sparsity. Data sparsity is a problem where when users do not give values to items, in this case to movie ratings. Therefore, we will look at the RMSE and MAE values whether this system successfully overcomes data sparsity or not [6].

Several studies have tried to combine Collaborative Filtering and K-Nearest Neighbors methods. One of them is research by Pooja Mudgil, et al. Who tried to combine the Collaborative Filtering method with Naïve Bayes and K-Nearest Neighbors [7]. This research compares 4 methods where, the combined method of Collaborative Filtering and Naïve Bayes and K-Nearest Neighbors, Collaborative Filtering, K-Nearest Neighbors and Nave Bayes. Where the results of the hybrid method predict with 96% results, followed by Collaborative Filtering 92%, KNN 87% and Naïve Bayes 81%. It can be seen that the KNN method can predict greater results than the Naïve Bayes method. While in this reaserch combining Collaborative Filtering with KNN and the final result are precision and recall.

In a study conducted by Dawei Yang, et al [8]. Collaborative Filtering was combined with K-Nearest Neighbors classification by using Item-based and Rating-based which resulted in RMSE and MAE values increasing by 1%. While in this research not using rating-based but using User-Based and Item-Based Collaborative Filtering with performance evaluation is carried out by using precision and recall. Because the data that has been obtained in the form of ratings on a scale of 0-5 is converted into a binary metric, class 0 and class 1

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or not recommended and recommended. The use of precision is to get recommended movie results based on all existing movies, while recall is used to get recommended movie results based on all recommended movies.

In the next research written by Yusuf Fadila Rachman, et al. Discusses the comparison of the KNN method with C4.5 [9]. Where the KNN method gets greater results than C4.5 with a precision value of 62.5% and recall 52.5% for KNN and precision 57.41% and recall 53.49% for C4.5. The accuracy value of C4.5 is lower because of the many attributes in this study, making it difficult to build a comparison tree. Based on related research, the author will build a recommendation system by combining the Collaborative Filtering method with the K-Nearest Neighbors method. The purpose of this research is to find out whether the accuracy value of combining the Collaborative Filtering and KNN methods can get better results than the Collaborative method alone.

The purpose of this research is to look at combining collaborative filtering with K-Nearest Neighbors classification with several K as parameters, with precision and recall as performance measures. From a twitter dataset that is converted into a 1-5 rating and then converted into two classes, namely 0-1, so that KNN classification can be carried out.

2. RESEARCH METHOD

The system design will be explained at this stage. Where in this research there will be two methods, namely the memory-based Collaborative Filtering method and the combination of memory-based Collaborative Filtering with K-Nearest Neighbors classification. There are several stages to complete this research, such as data crawling, data preprocessing, user and item-based Collaborative Filtering, user and item-based modeling evaluation using RMSE, and K-Nearest Neighbors classification and modeling evaluation using precision and recall. The system design can be seen in Figure 1 and Figure 2.

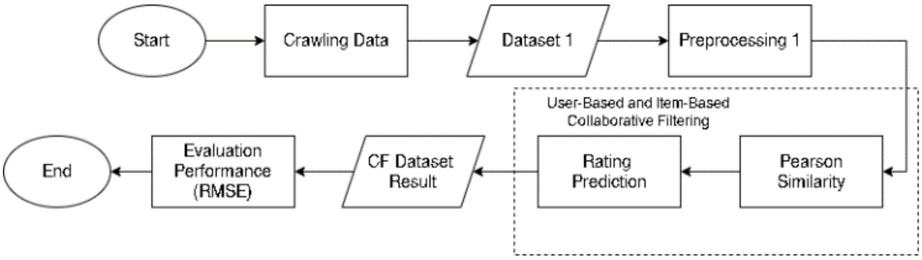

Figure 1. Collaborative Filtering System

In stage 1 or Collaborative Filtering System, the data crawling stage is carried out to get data from Twitter where the data will be preprocessed to get clean data so that it can be converted into a rating from 1-5, using polarity. Then Collaborative Filtering is done by looking for Pearson similarity from each User and Movie, and Rating Prediction is done. Then the Performance Evaluation is done using RMSE.

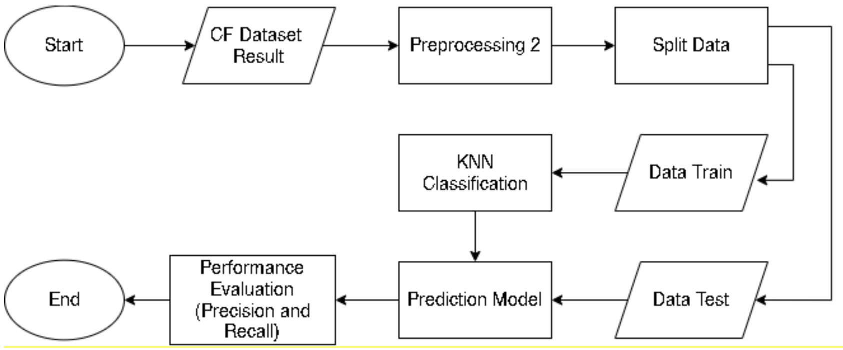

Figure 2. K-Nearest Neighbors System

After obtaining the database from Collaborative Filtering, the database will be carried out Preprocessing stage 2, namely changing the results of reviews 1-5 into two classes so that classification can be carried out. Then split the data by changing it into Train Data and Test Data which will be carried out K-Nearest Neighbors Classification. Once obtained, Performance Evaluation will be carried out using Precision and Recall.

2.1 Crawling Data

The data used is tweet data on Twitter based on several trusted film reviewer accounts, so that information in the form of criticism and suggestions from them can provide a rating that will be useful for the dataset. With the addition of using data containing movie titles on Netflix from 2005-2016, the data that has been collected will become a dataset containing id_tweet, username, title, date and tweet.

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After getting a tweet containing a film review, the tweet with the best rating will be selected and according to the film being discussed. Then the rating will also be added based on reviewer websites such as IMDB, Rotten Tomatoes, and Metacritic with movie titles on Netflix. The crawled data managed to get 35 users and 785 titles.

2.2. Data Preprocessing

The preprocessing stage is very important because the data obtained is data in the form of a review or sentence, where a recommendation system uses numbers for the rating, at this stage the dataset will be changed from tweets in the form of a review to a rating of 1-5. The preprocessing stage is divided into two, with the first stage cleaning data and creating a data structure by deleting numbers, emoticons, URLs, hashtags, and punctuation marks so that they can be converted into ratings. After that, the polarity calculation is carried out, where polarity is a step to see whether the text is positive or negative. At the polarity stage, the python library, namely TextBlob, is used to identify the meaning of each sentence. After obtaining the polarity results, proceed with the labeling stage, namely changing the rating that has been polarized into a rating with a ratio of 0 to 5. Polarity calculations can be used using equation 1:

$$\text{Rating} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \times 5 \quad (1)$$

With the value of x_i is the polarity result, the min(x) value is the smallest polarity value of -1 and the max(x) value is the largest polarity value of 1, then multiplied by the rating scale value of 5. In the second preprocessing stage, changing the rating from 0-5 to rating 0 and 1, with the aim that rating 0 is a film that does not recommended and rating 1 is the recommended movie. This stage is carried out after Collaborative Filtering, with a rating of 0-1 being a rating of 0, and a rating of 3-5 being a rating of 1.

2.3. Collaborative Filtering

Collaborative Filtering is a method where the recommendation system uses opinions from other users to predict the items that will be given to the user. Collaborative Filtering usually uses a collection of information from several users to assign a rating to an item [10]. There are two methods that exist in Collaborative Filtering, namely by looking at the similarities between users (user-based) and similarities between items (item-based). User-Based is intended to provide recommendations to users who select items based on ratings by other users. Item-Based, on the other hand, makes recommendations based on items that have a lot in common with other items. [11]. At this stage, the similarity value is calculated using the Pearson correlation method to determine top-n so that the empty rating can be filled by using a rating. Using equation 2:

$$PC = \frac{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)^2 \sum_{i \in I_{uv}} (r_{vi} - \bar{r}_v)^2}} \quad (2)$$

Then after obtaining top-n we can fill in the empty rating using the user-based method by entering equation 3:

$$x_{i,j} = \bar{x}_i + \frac{\sum_{u' \in \hat{u}} sim(i,u') \times (x_{u',j} - \bar{x}_{u'})}{\sum_{u' \in \hat{u}} |sim(i,u')|} \quad (3)$$

And so is item-based, here is equation 4 for the item-based method.

$$x_{i,j} = \bar{x}_j + \frac{\sum_{i' \in \hat{\imath}} sim(j,i') \times (x_{i',i} - \bar{x}_{i'})}{\sum_{i' \in \hat{\imath}} |sim(j,i')|} \quad (4)$$

2.4. K-Nearest Neighbors

K-Nearest Neighbors or commonly abbreviated as KNN is a classification method that is most often used because it is very easy to implement and easy to understand and explain [12]. KNN is used as a classification method that trains the model in the form of supervised learning. Defines a new class based on an equality function, where the value of K refers to the number of neighbors or neighbors [13]. The goal of KNN is to find the minimum distance between data evaluated by the nearest k (neighbors). [14]. In this research, KNN is used to make two classes, namely recommended and not recommended films to get precision and recall with the best results. By comparing several K parameters, of course, you will get various precision and recall results.

2.5. Performance Evaluation

Calculate the performance evaluation value for Collaborative Filtering using the results from RMSE. Root Mean Squared Error (RMSE) is a performance evaluation to calculate the average value that has a squared difference in the actual value and the predicted rating value. RMSE calculates the value of the power rooted by the result RMSE is a matrix that has a very high yield matrix when a very high error is not desired [15]. It can be seen in equation 5:

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$$RMSE= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|pi - qi|)^2} \quad (5)$$

At the classification evaluation stage, the authors use the Confusion Matrix to determine the accuracy that has been carried out by the system, the effectiveness of the recommendations given and whether they are appropriate. with the recommended. There are results obtained from several equations in the confusion matrix, namely: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). If the recommended film is appropriate, a True Positive (TP) value will be given and if the recommended film is not appropriate, a True Negative (TN) value will be given. If the film is not recommended and is not suiTable, it will be given a False Negative (FN) value and if the film is not recommended and appropriate, it will be given a False Positive (FP) value [16]. Precision is the comparison of the positive category value divided by the total number of correct positive data or not, it can be calculated by equation 6:

$$precision= \frac{TP}{TP+FP} \quad (6)$$

Recall shows the total number of correct results given by the system, can be calculated by equation 7:

$$recall= \frac{TP}{TP+FN} \quad (7)$$

3. RESULT AND DISCUSSION

In this research there are several stages to get recommended and not recommended film results, in the first stage the data that has been crawled will be data cleaning first so that the data used has a good rating, after in cleaning the data will be carried out to the stage of the Collaborative Filtering method to get the RMSE results. The next stage is to make a classification of K-Nearest Neighbors to get recommended and not recommended films, after that calculate the precision and recall values.

3.1 Data Result

In this research, data has been crawled with 785 movie titles and 30 twitter users was carried out using the Python snscrape library, resulting in 3134 data. Which is taken from every review related to the title of the film. The example of crawled data result will be displayed in Table 1.

Tabel 1. Example of Data Crawling Result

Username	Text	Title
HabisNontonFilm	#ALIVE Seorang gamer terjebak sendirian di apartemennya saat seluruh kota kacau-balau karna virus mematikan. Satu lagi film zombie dari Korea yg cukup relate dengan keadaan sekarang. Betapa bosannya di rumah, tapi betapa ngerinya di luar rumah. Tinggal pilih aja. https://t.co/rZ5rWumzi4	#Alive

After the data is successfully crawled, we will proceed with data cleaning, to remove URLs, mention & hashtags, punctuation marks, numbers, and emoticons. Which can be seen in Table 2, that we only removing unused text like URL to cleaning the text from tweet.

Tabel 2. Example of Data Cleaning Result

	Text
Before	#ALIVE Seorang gamer terjebak sendirian di apartemennya saat seluruh kota kacau-balau karna virus mematikan. Satu lagi film zombie dari Korea yg cukup relate dengan keadaan sekarang. Betapa bosannya di rumah, tapi betapa ngerinya di luar rumah. Tinggal pilih aja. https://t.co/rZ5rWumzi4
After	#ALIVE Seorang gamer terjebak sendirian di apartemennya saat seluruh kota kacau-balau karna virus mematikan. Satu lagi film zombie dari Korea yg cukup relate dengan keadaan sekarang. Betapa bosannya di rumah, tapi betapa ngerinya di luar rumah. Tinggal pilih aja.

After the data is clean, we will proceed with making polarity. Polarity is used to convert text into rating. By making the polarity ratio -1 to 1, it will change where the polarity -1 will be a rating of 0 to 2.4, polarity 1 will be a rating of 2.6 to 5 and polarity 0 is a rating of 2.5. In Table 3 the movie #Alive has a polarity of 0 which we can calculate into a rating equal to 2.50 using equation 1, by entering the polarity value of 0.

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Tabel 3. Example of Polarity Result

Text	Title	Polarity	Rating
Seorang gamer terjebak sendirian di apartemennya saat seluruh kota kacau-balau karna virus mematikan. Satu lagi film zombie dari Korea yg cukup relate dengan keadaan sekarang. Betapa bosannya di rumah, tapi betapa ngerinya di luar rumah. Tinggal pilih aja.	#Alive	0	2.50

Dataset will be combined with the ratings provided by website reviewer such as IMDB, Rotten Tomatoes, and Metacritic. The data that has been combined will have 6184 reviews, 35 users, and 785 movie titles. In Table 4 we can see the example of combination dataset with the website reviewer, the data from website reviewer are manually crawled by the author, website reviewer give the exact rating provided by movie reviewer.

Tabel 4. Example of Combination Dataset and Data from Website Reviewer

Username	Title	Rating
HabisNontonFilm	#Alive	0
IMDB	#FriendsButMarried2	2.955
Metacritic Metascore	10 Days in Sun City	0
Metacritic User Score	14 Cameras	1.75

Dataset will be converted into a pivot Table which has User, Film , and ratings. With an empty rating of 21487 and 5988 ratings that have been filled. The results can be seen in Table 5.

Tabel 5. Example of Pivot Table

Film User	#Alive	#FriendsButMarried2	10 Days in Sun City	14 Cameras
HabisNontonFilm	2.50	0	0	0
IMDB	3.15	2.95	2.55	2.30
Metacritic Metascore	0	0	0	1.25
Metacritic User Score	0	0	0	1.75

3.2 Collaborative Filtering Result

At this stage, a Pearson similarity calculation is performed to see the similarity of user-based and item-based where closer to the value of 1 the data will be more similar. The results of the Pearson similarity for user-based can be seen in Table 6, we can see in Table 6 that Metacritic User Score and Metacritic Metascore has the highest similarity because the value where closer to 1. And also for the item-based.

Tabel 6. User-Based Similarity

User	HabisNontonFilm	IMDB	Metacritic Metascore	Metacritic User Score
HabisNontonFilm	1	0.1206	0.0652	0.0138
IMDB	0.1206	1	0.3409	0.3165
Metacritic Metascore	0.0652	0.3409	1	0.8018
Metacritic User Score	0.0138	0.3165	0.8018	1

The data that has obtained similarity can calculate empty rating based on the neighbors of each user and their items. In Table 7 we can see the empty rating has been filled with the top-n neighbors using User-Based, in this stage we compute rating based on users top-n neighbors for User-Based and rating items based on film top-n neighbors for Item-Based. In this experiment top-n neighbors are assigning to 10, that's mean the empty rating will be filled with the ratings of 10 neighbors that has the highest similarity. It can be seen at Table 5 Metacritic Metascore does not give a rating to the movie #Alive or has a rating of 0, but after Collaborative Filtering the results of the movie #Alive changed to 3.53 using the rating of the 10 nearest neighbors.

Tabel 7. User-Based Result

Film User	#Alive	#FriendsButMarried2	10 Days in Sun City	14 Cameras
HabisNontonFilm	2.5	0	0	0
IMDB	3.15	2.95	2.55	2.30
Metacritic Metascore	3.53	0	0	1.25
Metacritic User Score	3.47	0	0	1.75

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After the empty rating was successfully obtained, initially the empty rating was 21487 after the Collaborative Filtering method succeeded in reducing the sparsity data with the number of empty ratings for user-based to 11049 or 48.5% of the previous data. For item-based ratings, the empty rating reduced to 20397 or 5.07%.

The data will be evaluated to see the RMSE value, the RMSE value will be better if it is close to 0. In this study, top-n is taken with a value of 10 which produces an RMSE value for user-based of 1.8224 and for item-based of 0.5449. Datasets that have predictive values will continue to combine the Collaborative Filtering method with the K-Nearest Neighbors classification.

3.3 K-Nearest Neighbors Result

Dataset that has a predictive value will be converted into a class form of 0 and 1, by getting the median value is 3.19 for user-based and 3.2 for items, then the separating value is 3. resulting in values greater than 3 or rating of 3 to 5 will enter class 1 and values smaller than 3 or rating of 0 to 1 will enter class 0. Class of 0 is a film that is not recommended because it has a rating of 0 to 1 and class of 1 is a recommended film because it has a rating of 3 to 5 which is considered a good rating. It can be seen in Table 8 for user-based. And we did the same method for item-based.

Tabel 8. User-Based KNN Dataset

User Film	#Alive	#FriendsButMarried2	10 Days in Sun City	14 Cameras
HabisNontonFilm	0	0	0	0
IMDB	1	0	0	0
Metacritic Metascore	1	0	0	0
Metacritic User Score	1	0	0	0

After the data has been changed to two classes, the data will be classified by K-Nearest Neighbors with several parameters, K = 3 to 10. The results of precision and recall with each K as user-based are as follows Figure 3. Meanwhile, the results of precision and recall for item-based can be seen in Figure 4.

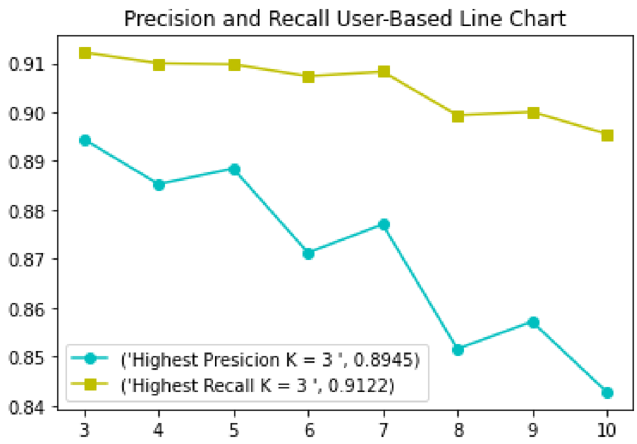

Figure 3. Precision and Recall Result for User-Based

In Figure 3, it can be seen that the results of the K-Nearest Neighbors classification get Precision and Recall with parameter K = 3 as the highest result with Precision 0.8945 and Recall 0.9122.

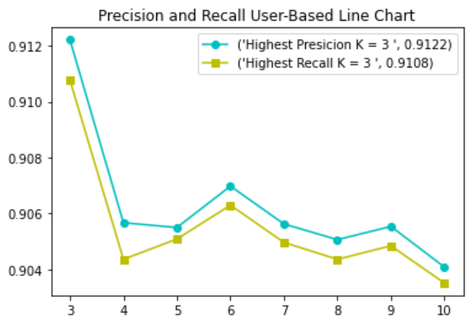

Figure 4. Precision and Recall Result for Item-Based

In Figure 4, it can be seen that the results of the K-Nearest Neighbors classification get Precision and Recall with the parameter K = 3 as the highest result with the results of Precision 0.9122 and Recall 0.9108.

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4. CONCLUSION

Based on the research that the author has done on Collaborative Filtering testing and combining Collaborative Filtering and K-Nearest Neighbors classification methods, with the dataset obtained from Twitter and given additional ratings from IMBD, Rotten Tomatoes, and Metacritic. It was found that the test results for user-based with a value of top-n = 10 got an RMSE result of 1.8244 and item-based got an RMSE result of 0.5449, after that it was entered into the K-Nearest Neighbors classification with several K as a comparison parameter for the results for precision and recall, where K = 3 to 10. The results of user-based and item-based tests on K with optimal results are K = 3 with 91.22% precision and 91.07% recall for user-based for item-based getting precision results of 89.44% and 91.22% recalls. It can be concluded that the combination of Collaborative Filtering and K-Nearest Neighbors methods can be done to get recommended and not recommended films, by looking at the comparison of precision and recall results to find the optimal K.

REFERENCES

[1] S. Postmus, "Recommender system techniques applied to Netflix movie data," no. c, pp. 16–18, 2018.
[2] Sarosa Castrena Abadi, M. A. Hidayat, and P. T. Asmoro, "Sistem Rekomendasi Film Berbasis Jejaring Sosial (Twitter) Menggunakan Ibm Bluemix," *J. Teknol. Inf. Univ. Lambung Mangkurat*, vol. 5, no. 1, pp. 31–38, 2020, doi: 10.20527/jtiulm.v5i1.45.
[3] F. Rahutomo, P. Y. Saputra, and M. A. Fidyawan, "Implementasi Twitter Sentiment Analysis Untuk Review Film Menggunakan Algoritma Support Vector Machine," *J. Inform. Polinema*, vol. 4, no. 2, p. 93, 2018, doi: 10.33795/jip.v4i2.152.
[4] K. R. Sari, W. Suharso, and Y. Azhar, "Pembuatan Sistem Rekomendasi Film dengan Menggunakan Metode Item Based Collaborative Filtering pada Apache Mahout," *J. Repos.*, vol. 2, no. 6, p. 767, 2020, doi: 10.22219/repositor.v2i6.936.
[5] D. Valcarce, A. Landin, J. Parapar, and Á. Barreiro, "Collaborative filtering embeddings for memory-based recommender systems," *Eng. Appl. Artif. Intell.*, vol. 85, no. June 2021, pp. 347–356, 2019, doi: 10.1016/j.engappai.2019.06.020.
[6] T. Anwar, V. Uma, M. I. Hussain, and M. Pantula, "Collaborative filtering and kNN based recommendation to overcome cold start and sparsity issues: A comparative analysis," *Multimed. Tools Appl.*, no. March, 2022, doi: 10.1007/s11042-021-11883-z.
[7] P. Mudgil, S. Gautam, U. Chhabra, M. Jadaun, P. Jain, and V. Singh, "Analysing Huge Data Collection And Comparing Through Algorithms: KNN, Naive And Collaborative Filtering and Hybrid," *Int. J. Sci. Technol. Res.*, vol. 8, no. 7, pp. 220–224, 2019.
[8] D. Wang, Y. Yih, and M. Ventresca, "Improving neighbor-based collaborative filtering by using a hybrid similarity measurement," *Expert Syst. Appl.*, vol. 160, p. 113651, 2020, doi: 10.1016/j.eswa.2020.113651.
[9] Y. F. Rachman, R. Saptono, and Winarno, "Comparison of C4.5 Algorithm and K-Nearest Neighbors on the Classification of Multiple Intelligence Test Results for Recommended Student Lectures," *J. Ilm. Teknol. dan Inf.*, vol. 7, no. 2, pp. 108–114, 2018.
[10] A. E. Wijaya and D. Alfian, "Sistem Rekomendasi Laptop Menggunakan Collaborative Filtering Dan Content-Based Filtering," *J. Comput. Bisnis*, vol. 12, no. 1, pp. 11–27, 2018.
[11] R. M. A. Rojasi Fadilla, Roni Andarsyah, "Data Analytics : Peningkatan Performa Algoritmma Rekomendasi Collaborative Filtering Menunakan K-Means Clustering." 2020. page 8
[12] S. Rajarajeswari, S. Naik, S. Srikant, M. K. Sai Prakash, and P. Uday, "Movie Recommendation System," *Adv. Intell. Syst. Comput.*, vol. 882, no. 11, pp. 329–340, 2019, doi: 10.1007/978-981-13-5953-8_28.
[13] A. Tripathi and A. K. Sharma, "Recommending Restaurants: A Collaborative Filtering Approach," *ICRITO 2020 - IEEE 8th Int. Conf. Reliab. Infocom Technol. Optim. (Trends Futur. Dir.*, pp. 1165–1169, 2020, doi: 10.1109/ICRITO48877.2020.9197946.
[14] KPM, R. A. Ramadhani, and e D. LiceFrense, "K-Nears Neigbours Risa Helilintar , Risky Aswi Ramadhani Siti Rochana," *Python "Belajar Pemrograman Python Dasar,"* vol. 84, no. December, pp. 487–492, 2017, [Online]. Available: http://www.ask-jansen.com/wp-content/uploads/2014/04/Kontroversi-Kalori-ebook.pdf%0Ahttp://ir.obihiro.ac.jp/dspace/handle/10322/3933. page 36
[15] L. Al Hassanieh, C. A. Jaoudeh, J. B. Abdo, and J. Demerjian, "Similarity measures for collaborative filtering recommender systems," *2018 IEEE Middle East North Africa Commun. Conf. MENACOMM 2018*, no. April, pp. 1–5, 2018, doi: 10.1109/MENACOMM.2018.8371003.
[16] S. D. Nurhayati and W. Widayani, "Sistem Rekomendasi Wisata Kuliner di Yogyakarta dengan Metode Item-Based Collaborative Filtering," vol. 1, no. 2, pp. 10–18, 2021.