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Recommender System Movie Netflix using Collaborative Filtering with Weighted Slope One Algorithm in Twitter

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Abstract−Movies are entertainment that many people enjoy filling their spare time. After watching a movie, people usually write reviews about the movie on social media such as Twitter. As the number of movies grows, people are often confused about which movie to watch next. Based on these problems, a helpful recommendation system was created to find movies they might like based on the movies they've seen before. This study developed a movie recommendation system using Collaborative Filtering (CF) with the Weighted Slope One (WSO) algorithm. The dataset used is taken from tweet data on Twitter. Then the tweet dataset is converted into a rating value which will later be used in the recommendation system. This study uses Mean Absolute Error (MAE) to measure accuracy. In Collaborative Filtering, the system gets the best MAE of 0.924. Then for Weighted Slope One, the system gets the best MAE of 0.568.

Keywords: Recommender System; Collaborative Filtering; Movie; Netflix; Twitter; Weighted Slope One

1. INTRODUCTION

In this digital era, industrial development is increasingly advanced and rapid, for example, in the movie and technology industry [1]. Based on data from IMDb, the average movie production in 2005 reached 4,584 and increased to 9,387 in 2015 [1]. With the increasingly sophisticated technology, watching movies can be easier through online streaming services such as Netflix that can be enjoyed anywhere and anytime [2]. Netflix is the world's largest online streaming service provider and has more than 148 million subscribers [3]. The more movies produced, the more different tastes of each user. Therefore, users often use social media, such as Twitter, to post reviews about what movies they have watched and what movies they like or dislike [4]. With the spread of many reviews on Twitter, users are often confused about finding the next movie they will watch based on the movie they have watched. One way to get what movies we might like is with a recommendation system.

The recommendation system is a method that allows users to find items that are suitable for that user [5]. Generally, there are four recommendation systems types: Collaborative Filtering, Content-Based, Knowledge-Based, and Hybrid-Based [6]. Ifada et al. [7], revealed that the Collaborative Filtering method could be superior to Hybrid-Based. Weighted Slope One is an algorithm of Collaborative Filtering based on linear regression and uses deviation to calculate the predicted rating of the item [6]. The Weighted Slope One algorithm has several advantages, such as easy maintenance, efficient query time, and accuracy [8].

Hu et al. [9], conducted research on Weighted Slope One using similarity, based on ratings and attributes with the tourist attractions dataset obtained from 'www.ilvping.com.' This study compares the best MAE values from several methods such as Weighted Slope One with the best MAE 0.779, Item-Similarity Slope One with the best MAE 0.767, and Item-Based Collaborative Filtering with the best MAE 0.782. Based on the results obtained, they concluded that the Item-Similarity Slope One matched the tourist attractions dataset.

Wang et al. [6], also conducted research on Weighted Slope One with the Movielens dataset. This study compares the MAE results of several methods such as User-Based Collaborative Filtering with the best MAE of 0.771, Weighted Slope One with the best MAE of 0.739, and Improved Weighted Slope One with the best MAE of 0.729. They concluded that their Improved Weighted Slope One algorithm was better than other methods.

Based on several previous studies that have been mentioned [6], [9], and as far as the author knows, no research has made a Netflix movie recommendation system using Collaborative Filtering with Weighted Slope One algorithm, whose dataset was obtained from Twitter. Tweet data obtained generally contains reviews in the form of text. Then tweet data is converted into numbers or ratings (0-5) using the Polarity method. Polarity measures the positivity, negativity, and neutrality of a tweet [10].

The purpose of this study was to implement a recommendation system using Collaborative Filtering with the Weighted Slope One algorithm, which was tested with the Netflix movie dataset, and to find out how accurate the recommendation system was using a text dataset obtained from Twitter.

The organizational structure of this research paper is as follows: section 2 describes the methods used in this research, section 3 describes the results and discussion, and section 4 contains conclusions

2. RESEARCH METHODOLOGY

2.1 System Design

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The following is Figure 1, which illustrates the stages of the system, starting from data crawling, after that data is pre-processed into ratings, then performing the Collaborative Filtering process, and finally running the Weighted Slope One algorithm.

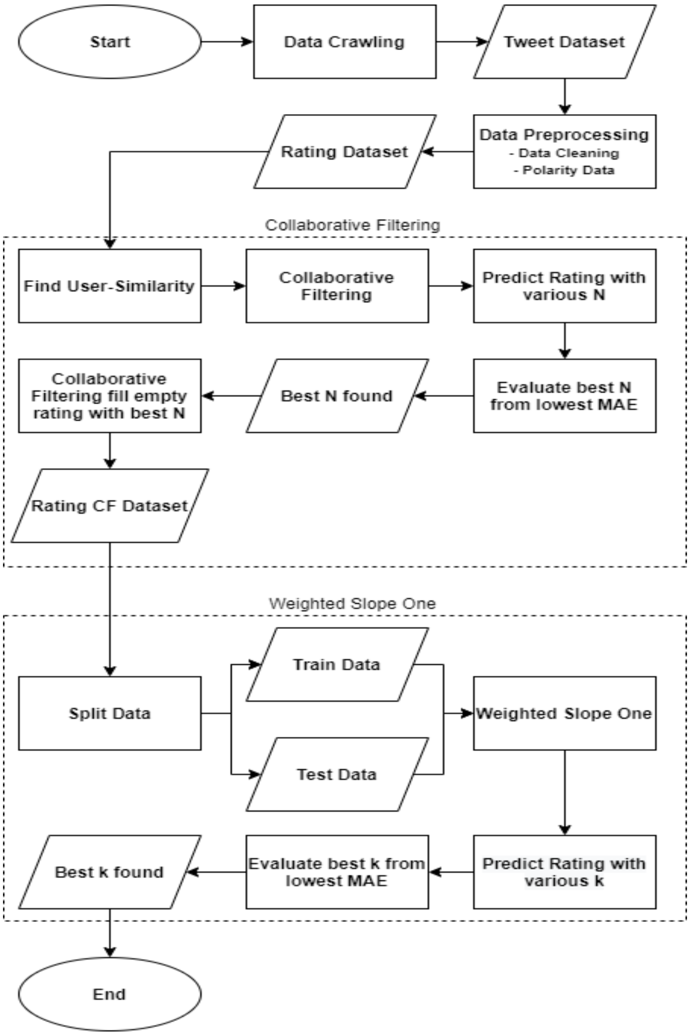

Figure 1. System Recommendation Design

2.2 Data Crawling

The first stage is data crawling. Data crawling is a process of retrieving data from a platform which in this research is social media, Twitter. This data retrieval is done by specifying whom the user wants to search for and what Netflix movies the user might have watched. The selected users come from Indonesia, and their tweets often contain movie reviews. This process is carried out using the Python programming language, assisted by the Snscrape library.

2.3 Data Preprocessing

After data is obtained at the data crawling stage, Data Tweet pre-processed first to meet the system requirements. There are two processes: Data Cleaning to clean data and Polarity Data to convert text data into ratings.

2.3.1 Data Cleaning

Due to the data taken from Twitter, the tweet contents are not entirely in the form of text. There are several tweets containing hashtags, mentions, website links, and other special characters. Therefore, the text that has these criteria is cleaned first. Some of the processes are removing mentions, hashtags, HTTP links, special characters, double spaces, and movie titles. The title of the movie is removed from the text due to eliminate the positive or negative bias contained in the title of the movie.

2.3.2 Polarity Data

After the data is clean from various special characters, emoji symbols, etc., the data will be processed again to find the polarity score. A polarity score is a value that can determine the sentiment of a sentence [10]. The polarity score range is -1 to 1, which means that close to -1 indicates negative and close to 1 indicates positive [11]. Polarity works by checking every word in the sentence. The words 'like' and 'hate' have different meanings. 'like' means positive, and

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'hate' means negative. For example, if a tweet says 'I love the Captain America movie,' then the polarity score will be close to 1. Conversely, if the tweet reads 'I hate the Captain America movie,' the polarity score will be close to -1. Therefore, at the data cleaning stage, the title of the movie is removed from the text data. This process is done to avoid bias from movie titles with positive or negative meanings, such as 'Happy Feet,' 'Bad Boy,' etc. The movie's title was removed because 'Happy feet' has the word 'Happy,' which means positive, while 'Bad Boy' has the word 'Bad,' which means negative.

2.4 Collaborative Filtering

Collaborative Filtering is one of the methods in the recommendation system. The way Collaborative Filtering works is by looking for similarities in a group by looking at its attributes and then looking for similarities from users who want to recommend [12]. Collaborative Filtering itself has several advantages, namely high speed, efficiency, good quality, and can produce accurate recommendations [13]. Collaborative Filtering works by looking for the similarity between users or items. The similarity between users is called User-Based Similarity, while the similarity between items is called Item-based Similarity. In this research, a Collaborative Filtering experiment was conducted using User-Based Similarity. One of the ways to find similarities is with Pearson Correlation. The following is the Pearson Correlation Similarity equation [14].

$$Sim(i,j) = \frac{\sum_{m\in I_{i,j}}(R_{i,m} - \bar{R}_i)(R_{j,m} - \bar{R}_j)}{\sqrt{\sum_{m\in I_{i,j}}(R_{i,m} - \bar{R}_i)^2}\sqrt{\sum_{m\in I_{i,j}}(R_{j,m} - \bar{R}_j)^2}} \tag{1}$$

In equation (1), i and j are users who want to find their similarities. $I_{i,j}$ is a collection of items rated by users i and j. $\bar{R}_i$ is the average rating of user i in $I_{i,j}$. $\bar{R}_j$ is the average rating of user j in $I_{i,j}$. $R_{i,m}$ is rating user i for item m. $R_{j,m}$ is rating user j for item m [14].

The similarity that has been obtained is then used in equation (2) to fill in the empty rating. The best n similarity will be selected based on the results of the lowest MAE value. Here is the prediction equation.

$$P(u,i) = \bar{r_u} + \frac{\sum_1^N sim(u,v) * (r_{vi} - \bar{r_v})}{\sum_1^N sim(u,v)} \tag{2}$$

Where in equation (2), $P(u,i)$ is the prediction of user u for item i. $\bar{r_u}$ is the average rating of user u. $\bar{r_v}$ is the average rating of user v. $sim(u,v)$ is the similarity between user u and user v. $r_{v,i}$ is rating user v for item i. N is the number of users based on the order of similarity from the highest to the lowest [15].

In this study, the best N search was carried out based on the lowest MAE results from each N. Then, the Collaborative Filtering prediction results using the best N were used to fill in the blank data.

Before Collaborative Filtering is used to predict an empty value, the best N will be searched first. The way to find the best N is by predicting the existing rating value. For example, as in Table 3, user 1 has rated item 2. Then Collaborative Filtering will predict the rating based on the number of N user similarities from user 1. This process is carried out for all ratings whose values are not empty. Then the process is repeated by trying various N values to find the best N that produces the lowest MAE value. The MAE value is generated from the comparison between the original rating of the dataset and the predicted rating using N user similarity. After the best N is found, the next process is to fill in the empty rating with N used as the best N.

2.5 Weighted Slope One

The Weighted Slope One algorithm is a branch of Collaborative Filtering which used to predict ratings. Weighted Slope One is an improved version of Slope One. Since Slope One has a weakness that assumes all ratings have the same level of relevance so that the level of relevance of the rating is not considered. Weighted Slope One was created to solve this problem. In this method, weight is added as a measure of the relevance of a rating. The weight will increase if the rating is considered to have high relevance. Otherwise, the weight will decrease if the rating is considered to have low relevance. An example of the problem is that 50000 users rate both item X and item Y, while only 5000 users rate both items X and Z. This shows that item Y will be more relevant to making predictions than item Z [16]. In addition, Weighted Slope One requires deviation between users, which later the deviation is processed again for an equation to find predictions [6], [14]. The following is the deviation equation.

$$dev_{j,i} = \sum_{u\in S_{j,i}(X)} \frac{u_j - u_i}{card(S_{j,i}(X))} \tag{3}$$

In equation (3), $dev_{j,i}$ is the deviation between item j and item i. u_j is the rating user u for item j. u_i is rating user u for item i. $S_{j,i}(X)$ is a collection of users who rate item i and item j. $card(\ )$ is the total in it [6].

This study conducted an experiment using Collaborative Filtering with the Weighted Slope One algorithm. This method works by finding the user similarity of the target user with equation (1), then taking the number of k

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users with the highest to lowest user-similarity to the user who wants to find predictions. The value of k is chosen by trying an experiment comparing the lowest MAE value for each k. The equation for predicting is as follows.

$$P(u)_j = \frac{\sum_{i \in S(k)} \left(dev_{j,i} + u_i\right) c_{j,i}}{\sum_{i \in S(k)} c_{j,i}} \tag{4}$$

In equation (4), $P(u)_j$ is the predicted rating user u for item j. $S(k)$ is the set of k users that have the highest to lowest user-similarity. $c_{j,i}$ is the total user who rate item i and item j [6].

2.6 Performance Evaluation

This study uses Mean Absolute Error (MAE) to measure accuracy. MAE works by comparing the predicted rating results with the original rating, and then the comparison is averaged [17]. The equation for predicting is as follows.

$$MAE = \frac{1}{|p|} \sum_{(u,i) \in p} |r_{u,i} - r'_{u,i}| \tag{5}$$

In equation (5), $|p|$ is the sum of the number of ratings. $r_{u,i}$ is the original rating. $r'_{u,i}$ is the predicted rating [18].

3. RESULT AND DISCUSSION

3.1 Tweet Dataset

After data crawling process, Tweet Dataset was created. Tweet Dataset contains 3133 records from 30 users and 791 movies. This dataset contains a unique idTweet which is the username who tweeted, the title of the movie being reviewed, and the content of the tweet containing the movie review. The following Table 1 is an example of the contents of the dataset.

Table 1. Tweet Dataset

idTweet	Username	Title	Text
8151719	AnakNonton	Snowden	'Snowden' sekali lagi membuktikan kalau Oliver Stone adalah maestronya biopic.
1377495	AnakNonton	Mr. Peabody & Sherman	[Ulasan] Mr. Peabody & Sherman: Film Animasi yang Indah dan Sarat Pengetahuan http://t.co/9AZ5duA23y ★★★★
1441234	MovieManID	Captain Fantastic	Captain Fantastic (2016) Setelah menonton ini, semakin yakin kalau tiap orang tua punya cara yg beda2 nan unik dalam membesarkan anak2 mereka. Scene "Sweet Child of Mine" di sini sungguh 👌👍👍
………	………	………	………
7740034	CenayangFilm	Jupiter Ascending	cu... JUPITER ASCENDING JELEK

3.2 Polarity Data

Polarity works by giving a score based on words that generate positive or negative sentiments. Since polarity score range is between -1 to 1, then the value is normalized to 0 to 5 to adjust to the rating that exist. An example of the results is as attached in Table 2. Then the normalized data is combined with the Tweet Dataset to proceed to the next process.

Table 2. Polarity Tweet Result

Text	Polarity	Rating
'Snowden' sekali lagi membuktikan kalau Oliver Stone adalah maestronya biopic.	0.30	3.25
[Ulasan] Mr. Peabody & Sherman: Film Animasi yang Indah dan Sarat Pengetahuan http://t.co/9AZ5duA23y ★★★★	0.60	4.00
Captain Fantastic (2016) Setelah menonton ini, semakin yakin kalau tiap orang tua punya cara yg beda2 nan unik dalam membesarkan anak2 mereka. Scene "Sweet Child of Mine" di sini sungguh 👌👍👍	0.28	3.21
………	………	………
cu... JUPITER ASCENDING JELEK	-0.70	0.75

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3.3 Rating Dataset

After the polarity stage is completed, the normalization results of the polarity score were combined with the Tweet Dataset, and became Rating Dataset. Rating Dataset contains 'idUser' which indicates the user index, 'idMovie' which indicates the index of the movie, and the user's rating for the movie. Then the tweet rating dataset was added with website rating dataset such as IMDb, Rotten Tomatoes, and Metacritic. So the total Rating Dataset used is 6183 records from 35 users and 791 Movies. An example of the contents of the Rating Dataset is attached in Table 3.

Table 3. Rating Dataset

idUser	idMovie	Rating
1	2	2.65
1	5	2.92
2	34	4.00
2	136	5.00
….	….	….
35	790	3.15
35	791	2.25

Then the Rating Dataset is converted into a user x movie sized matrix, which means 35 x 791. Based on Table 4, which displays the rating matrix, it turns out that there are still many ratings of 0, or it can be called data sparsity. Data sparsity is a condition where the user only rates a small part of the total items [19]. The sparsity data from the rating matrix is 72.4% of the total 27685 data.

Table 4. Matrix Rating

idUser	idMovie					
	1	2	3	4	….	791
1	0.00	2.65	0.00	0.00	….	0.00
2	0.00	0.00	0.00	0.00	….	0.00
3	0.00	3.5	0.00	0.00	….	3.50
4	0.00	5.00	0.00	3.38	….	0.00
….	….	….	….	….	….	….
34	0.00	4.25	0.00	3.65	….	2.05
35	0.00	3.75	0.00	3.95	….	2.25

3.4 Collaborative Filtering Experiment Result

Before Collaborative Filtering predicts an empty value, first find the best value of n for prediction. The best value of n is found by conducting experiments on the value of n. The value of n starts with n = 1 to n = 34. However, in Figure 2, only n = 1 to n = 10 is shown because when n > 10, the runtime is very time-consuming, and the MAE value does not show the best results. The following are the results of the experiment.

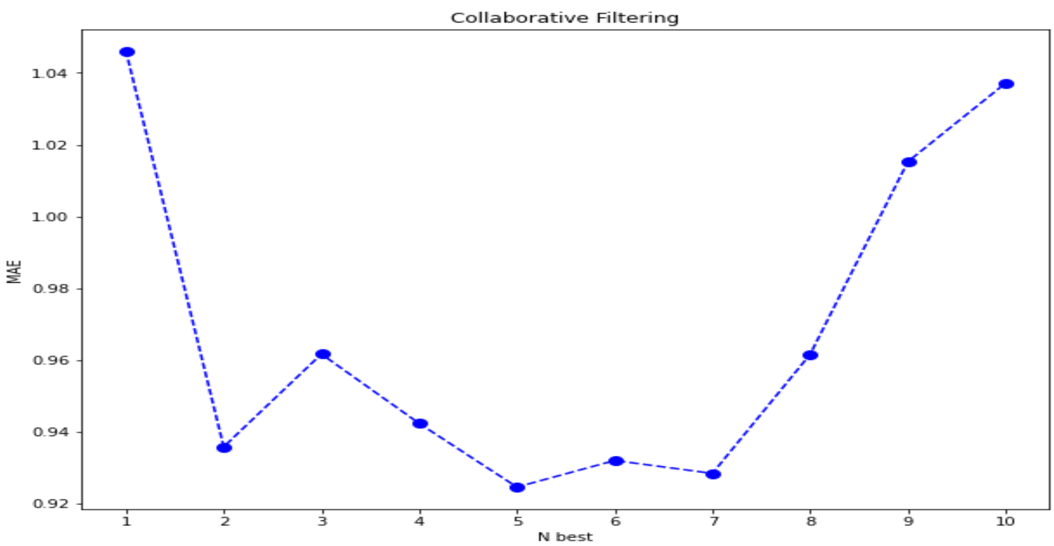

Figure 2. MAE Collaborative Filtering Result

Figure 2 shows that the lowest MAE result for Collaborative Filtering is at N = 5 with MAE value of 0.924. It could be concluded that the best N for Collaborative Filtering is N = 5. After finding the best N for Collaborative Filtering, then the best N is used to predict ratings that are still empty and become Rating CF Dataset.

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Table 7 shows a significant change in the amount of sparsity data. 70.8% of the total data was successfully predicted by Collaborative Filtering. Although there are still empty ratings, the numbers are relatively small.

Table 5. Data Sparsity

	Data Sparsity	Data Sparsity (%)
Rating Dataset	21698	72.4 %
Rating CF Dataset	444	1.6 %

3.5 Rating CF Dataset

After an empty rating in the Rating Matrix has been predicted, the dataset is turned into Rating CF Dataset. Rating CF Dataset contains a combination of the original rating data and the rating predicted by Collaborative Filtering with the best N. Furthermore, the order of the Rating CF Dataset is randomized and then divided into train data and test data to be used in the Weighted Slope One algorithm. The division ratio between these two data is 0.8/0.2. after that, a recommendation system using Weighted Slope One algorithm was created from train data to predict the rating value in test data based on idUser and idMovie. The following table 5 and table 6 show randomization and distribution of train data and test data.

Table 6. Train Data

idUser	idMovie	Rating
30	348	4.37
23	720	3.15
35	435	3.07
34	484	1.09
….	….	….
11	420	2.67
9	652	0.42

Table 7. Test Data

idUser	idMovie	Rating
12	410	1.31
18	789	2.33
28	693	3.42
26	380	1.63
….	…	….
7	548	1.86
13	312	4.50

3.6 Weighted Slope One Experiment Result

After Train Data and Test Data were obtained, the data is used for the Weighted Slope One method. In Weighted Slope One, an experiment was conducted on the value of k. The value of n starts with k = 1 to k = 34. However, in Figure 3, only k = 1 to k = 20 is displayed because the runtime when k > 20 is very time-consuming, and the MAE value does not show the best results.

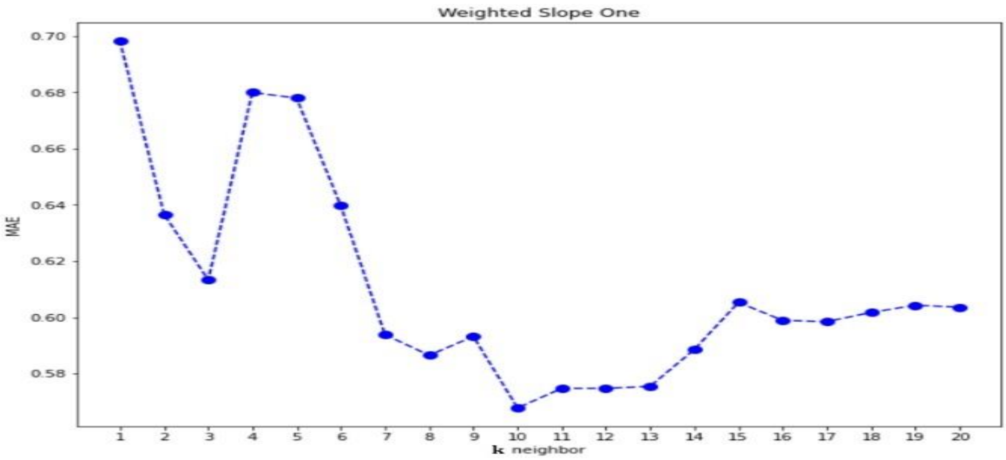

Figure 3. MAE Weighted Slope One Result

Figure 3 shows the lowest MAE value for Weighted Slope One is at k = 10 with MAE value of 0.568. It could be concluded that the best k for Weighted Slope One is k = 10.

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4. CONCLUSION

In this study, a recommendation system has been implemented using Collaborative Filtering with the Weighted Slope One algorithm. The dataset used is in the form of tweets from Twitter discussing Netflix movies. The dataset is 6183 records with 35 users and 791 movies. Based on the experiments that have been carried out, Collaborative Filtering is proven to be able to produce a fairly low MAE value of 0.924 with N = 5. Collaborative Filtering is also proven to be able to minimize the amount of data sparsity, however, not all empty data can be resolved. Weighted Slope One is also proven to be able to predict the rating quite well and can produce a fairly low MAE value of 0.568 with k = 10. It can be concluded that with the low MAE values generated, the system can work well using the dataset obtained from Twitter. Suggestions for further research to increase users and movies to become datasets and try to find data from different social media. In addition, different methods can be used for datasets originating from Twitter as well.

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