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Tourism Recommender System using Weighted Parallel Hybrid Method with Singular Value Decomposition

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Abstract

Presently, we often get suggestions for recommendations for tourist attractions from various sources such as the internet, magazines, newspapers, or travel agencies. Because there is numerous information, tourists become difficult to determine the tourism destination that suits their wishes. We created a tourism recommender system that can provide information in the form of recommendations for tourist attractions by the preference of tourists. The method used is a hybrid method that combines several recommendation methods, which are Content-Based Filtering (CB) and Collaborative Filtering (CF). We use tourism data of Lombok Island, West Nusa Tenggara, was taken from the TripAdvisor site. We apply the Singular Value Decomposition algorithm on CF and CB. The Hybrid Weighted Parallel Technique is used for Hybrid Method. The experimental results show that the hybrid method with the weighting technique provides higher prediction accuracy than when undergoing the recommendation system method separately with average values of 0.4140 (MAE), 0.2548 (MSE), 0.5006 (RMSE).

Keywords: Tourism Recommender System, Collaborative Filtering, Content-Based Filtering, Hybrid Method, Singular Value Decomposition, Weighted Technique.

Abstrak

Saat ini kita sering mendapatkan saran rekomendasi tempat wisata dari berbagai sumber seperti internet, majalah, koran, ataupun biro perjalanan. Karena banyaknya informasi, wisatawan menjadi sulit untuk menentukan destinasi wisata yang sesuai dengan keinginannya. Kami membuat sistem rekomendasi pariwisata yang dapat memberikan informasi berupa rekomendasi tempat wisata berdasarkan preferensi wisatawan. Metode yang digunakan adalah metode Hybrid yang menggabungkan beberapa metode rekomendasi, yaitu Content-Based Filtering (CB) dan Collaborative Filtering (CF). Kami menggunakan data pariwisata Pulau Lombok, Nusa Tenggara Barat, yang akan diambil dari situs TripAdvisor. Kami menerapkan algoritma Singular Value Decomposition pada CF dan CB. Teknik Hybrid Weighted Parallel digunakan untuk metode Hybrid-nya. Hasil percobaan menunjukkan bahwa metode hybrid dengan teknik pembobotan memberikan akurasi prediksi yang lebih tinggi daripada saat menjalani metode sistem rekomendasi secara terpisah dengan nilai rata-rata 0.4140 (MAE), 0.2548 (MSE), 0.5006 (RMSE).

Kata Kunci: Tourism Recommender System, Collaborative Filtering, Content-Based Filtering, Hybrid Method, Singular Value Decomposition, Weighted Technique.

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I. Introduction

Tourism has become one of the needs of most people. In general, tourism is an activity or trip undertaken by a person to a destination for vacation or recreation. According to Law of Indonesia No. 10/2009 on Tourism, tourism is implied by different sorts of tourism exercises which are bolstered by different facilities and services given by the society, vendors, authority, and municipality.

Someone who wants to travel somewhere needs to plan his trip by choosing an interesting destination to visit. A tourist gets information on tourism destinations from various sources such as the internet, magazines, newspapers, and travel agencies. The number of resources can make it easier for people to collect information, but the amount of data makes it difficult and confused for tourists to determine the destination that suits their wishes. Subsequently, we need a system that can filter knowledge so that it is relevant to that person.

The Recommender System is one of the solutions developed to solve this issue. There are several reasons for using a recommender system, including travel is not done every day, the costs incurred are not small, and require careful planning. Basically, recommender systems are developed to manage a lot of information and provide decisions [1]. One way that can be used to provide relevant information and can help make decisions is the recommender system. The recommender system in the tourism sector is one example of the application of decision-making to assist tourists in determining their tourist destinations [2].

In the recommender system, there are several approaches used, including demographic filtering (DF), knowledge-based filtering (KB), content-based filtering (CB), collaborative filtering (CF), and hybrid methods. The three recommender system approaches mentioned (DF, KB, and CB) are efficient but not personalized. The recommender system approach provides the same recommendation results to all users which should not happen in real cases because tourism destinations must be recommended based on the user's individual preference. Therefore, the CF approach is used by using preferences between users so that the destination recommendations given to each user are different. However, this method still has drawbacks, including in CB it has shortcomings when the selected item does not have a rating, then the item never be recommended to users or commonly called the cold-start problem [3]. In order to make the recommendations given more personalized, a hybrid approach was developed which combines the CB and CF methods.

The CB method uses user profile input where the profile has user preference information. The preferences of each user are vary depending on the information on the items that have been rated by the user [4]. There are many preferences that can be used as input such as articles, photos, videos, blogs, reviews, and others [17]. The results of the recommendations given in this system depend on the selection of previous items by the user which in this CB approach, recommends items by looking for item similarities from items that have been previously rated by the user [3].

The CF method plays a critical part in the world of recommender systems. It is not only used in e-commerce but also in the search for certain documents such as scientific work documents, articles, and magazines. The use of matrix factorization (MF) technology has proven to be a successful recommender system strategy used in the system [5]. This CF approach uses a history of user ratings and ratings from other users [6]. In model-based, a model built with MF for example with Singular Value Decomposition (SVD) [15]. SVD in the surprise library can be used because it is claimed to be powerful to minimize RMSE and provide relevant recommendations to users [12].

We apply Weighted Parallel Hybridization in building a recommender system that combines CB and CF which is expected to provide recommendations that are more relevant to users. In CB, we calculate the similarity of tourism content with cosine similarity which has previously been encoded using TF-IDF (Term Frequency-Inverse Document Frequency), then the rating is predicted for items that have not been rated by the user. In CB, we use the SVD algorithm to look for rating predictions that have not been rated by the user. The idea is that this algorithm creates a model based on historical rating data from other users which are used to predict the rating of an item.

II. LITERATURE REVIEW

A. *PREVIOUS STUDY*

Currently, many recommender systems have been developed, one of which is in the field of tourism. Research [1] proposes a recommender system and combines several methods, including Content-Based Filtering (CB), Collaborative Filtering (CF), and Demographic Filtering (DF). The implementation of the recommendation method in this study applies machine learning algorithms such as KNN for CB, CF, and Decision Tree for DF. The equation used to calculate the similarity is Euclidean Distance. The hybrid method using weighting and switching techniques. The performance results on the accuracy sideshow that the weighting and displacement hybridization method are greater than the other methods.

In research [5], proposed a recommender system that is different from previous studies. The proposed strategy is to apply Matrix Factorization (MF) to the Collaborative Filtering method. Using MF, it proved to be the most successful strategy recommendation applied to the MovieLens 100k dataset. The experimental results show that the recommendation prediction is better than the existing system.

Another study [12] proposed by S. Rajarajeswari, et al. build a film recommender system using switching hybridization technique. There are several recommendation methods that are used interchangeably, including simple recommendations, CB, and CF. In writing a simple recommendation, it calculates a weighted rating from the number of votes given by users and provides the highest rating recommendation. While in CB and CF, we use the Cosine Similarity equation for the similarity between film metadata and Yahoo Singular Value Decomposition which is known to be very effective in providing good recommendation results to users.

Research [2] proposed a combination of CF and KB methods for recommending tourist destinations to groups. The CF method used in this study uses item-based collaborative filtering where the method is used previous history ratings based on the similarity between items that have been rated. The similarity calculation used is Pearson Similarity. Subsequently, the KB formula is applied using the previously integrated information sources. In the final stage, the hybridization technique used to combine the two methods is the weighting technique. Based on statistical analysis using the Anova One Way Test to test the results of the recommendations produced 95% for the level of confidence and the HO value of 0.05.

We develop a tourism recommender system using the Weighted Hybrid Parallel Method with Singular Value Decomposition (SVD) at a tourist destination in Lombok, West Nusa Tenggara. We use data taken from the Tripadvisor website. In the third part, the writer explains the method used in this research by combining Content-Based Filtering and Collaborative Filtering methods. In the final stage, the writer uses MAE (Mean Absolute Error), MSE (Mean Square Error), and RMSE (Root Mean Square Error) to improve the performance of the method. It is hoped that using a hybridization technique can improve the accuracy of the results of the recommendations given to users.

B. *RECOMMENDER SYSTEM*

A recommender system is a system designed to provide users with a recommendation that they may like. In everyday life, we often find offers about recommendations for films, music, books, research articles, search queries, social tags, products, financial services, restaurants, Twitter pages, jobs, and universities [13],[14]. Too much information makes us confused to choose the product. Companies are forced to have intelligent systems to provide solutions in which to direct customers to products that they may be interested in [14]. A recommender system was developed with the point of overcoming the issue of decision-making [1]. Recommender system have been executed in numerous expansive companies such as Amazon, eBay, Netflix, and Google to recommend relevant products to their customers [13],[14],[15],[16].

In general, recommender system are classified into several paradigms. The most frequently used recommender system methods are Content-Based Filtering, Collaborative Filtering, Demographic Filtering, and Hybrid [1],[12],[17]. Information systems are also called data sifting instruments that utilize huge information according to user preferences and interests. A recommender system tries to predict the preference or rating that the user gives to an item [13]. In addition, this tool can match the tastes of users with other users who have the same interests [12].

C. CONTENT-BASED FILTERING

Content-Based Filtering (CB) Method is the foremost commonly used strategy of recommendation method for example for e-commerce domains [9]. This recommendation is based on a system that requires end-users to describe using natural language or other means such as ratings to indicate their preferences [18]. The CB method works on user profiles that have information about users and their preferences [4]. Substances can basically be classified into articles, photos, recordings, blogs, contentions, items, and composites, depending on how the metadata is extracted. [17]. This method works by finding the similarity of items from items that have been previously rated by the user [3].

This frame of CB is valuable for giving insights from unstructured content, for the most part from articles and reports [14]. The number of events of a word in an archive is decided by the Term Frequency (TF). In this study, the word "recommender" is very often encountered because this journal discusses the recommender system. Meanwhile, less common words are increased using Inverse Document Frequency (IDF) [17]. The IDF is calculated as follows:

$$idfi = log\left(\frac{n}{n_i}\right) \tag{1}$$

Where n indicates the number of records of interest and n_i shows to overall of terms in the document. This strategy aims is to recommend products acquired from the similarity of products that have been previously rated, for instance, when people like item A, the system learns and recommends other items similar to item A [10].

We use the CB method which basically recommends based on user history. There are several stages in this method, among others, in the first stage of calculating the TF-IDF on metadata and at the next stage calculating the item similarity value with Cosine Similarity. Cosine Similarity is utilized to calculate the likeness obtained from the rating given by the user. Cosine Similarity measures the likeness between two *n*-dimensional vectors based on the point between them [7]. The following formula (1) to calculate similarity with Cosine Similarity.

$$sim(p,q) = \frac{\vec{p} \cdot \vec{q}}{|\vec{p}| \times |\vec{q}|} = \frac{\sum_{c \in C} r_{cp} r_{cq}}{\sqrt{\sum_{c \in C} r_{cp}^2} \times \sqrt{\sum_{c \in C} r_{cq}^2}} \tag{2}$$

Where $sim(p,q)$ is the similarity between items p and q, r_{cp} and r_{cq} respectively indicate the user's rating on both p and q items, respectively. The range of results given in the calculation of cosine similarity is 0 to 1. A value of 0 implies that there is no similitude between the two things whereas a value near to 1 demonstrates a solid similitude [7]. Furthermore, the results of the cosine similarity on each item are searched for the cosine distance with the following equation:

$$cosine\ distance = 1 - sim(p,q) \tag{3}$$

Where the smaller the value of the cosine distance, the closer and similar to the item. To foresee the rating of user c item p, we use SVD (Singular-Value Decomposition) from which a dataset of user p is requested and the resulting model to predict item rating p. The researcher uses a cosine distance value limit of ≤ 6 which is definitely recommended to users who represent the item in accordance with the wishes of the user.

D. COLLABORATIVE FILTERING

In general, the Collaborative Filtering (CF) method aims to predict the rating of active users on products that have not been rated based on user preferences and the interests of other users [1],[18]. This method recommends products that have been selected by previous users with a similar model from active users [2]. CF is able to suggest multiform items more precisely since they are not on machine-analyzed content [14]. This method relies on the relationship between users and ratings where each element represents a certain rating on a particular item [10].

CF methods are classified into memory-based techniques and models. Memory-based techniques are divided into two, which are item-based and user-based. Within the user-based approach, the list of prescribed things is made based on the client, whereas within the item-based approach the list is made based on the item [16][19]. The model-based technique recommends items based on the built model. The foremost well known model-based procedures are Matrix Factorization, Fuzzy Systems, Bayesian Classifiers, and Neural Networks [15]. Large datasets and there are sparse data can take advantage of the Matrix Factorization technique [15]. Besides having high accuracy, model-based is said to be better in overcoming sparsity and scalability problems [15].

We use a Model-Based CF approach using SVD (Singular Value Decomposition). There are several stages in this method, including the first stage is to generate train data, then model it with SVD. SVD could be a matrix factorization strategy that's utilized as a CF calculation and most of the calculations are based on a user-item matrix where each row reveals to a client and each column reveals to an item [5]. This study, using a library from Surprise SVD which is claimed to be effective for experiencing RMSE (Root Mean Square Error). After getting the model, The next step is to calculate the predicted rating of all items that have not been evaluated by users.

$$R \approx (U) * (V^T) \tag{4}$$

Where R is the original matrix which is composed of two matrices such as U and V. The product of the two matrices is close to the original matrix. The rating matrix is made by using the Lombok Island destination dataset sourced from the TripAdvisor website which contains 3,639 users, 77 destinations, and 5,694 ratings. Users, destinations, and ratings are taken from the dataset and converted into a two-dimensional rating matrix containing users and items and the rating each user gave to the items they liked.

The following Pseudocode Collaborative Filtering is built:

Pseudocode 1. Collaborative Filtering

Input: user, destination, rating.

Begin

1 : Data = user, destination, rating

2 : Trainset = data.build_full_trainset()

3 : SVD = Surprise SVD

4 : Model evaluation with MAE, MSE and RMSE

5 : Rating prediction with SVD

6 : Return destination

End

Output: destinations that meet user preferences.

E. HYBRID METHOD

The hybrid method is a new trend in recommender system that uses two or more recommendation strategy [1]. The most objective of this method is to get higher exactness by overcoming the shortcomings of a few of the recommended strategy when applied separately. Each method has advantages depending on each condition, for example, if the condition is where other users have not given a rating, the Content-Based Filtering (CB) method works better, while if the condition is recommending relevant items to users, the Collaborative Filtering (CF) method works well [1].

In the hybrid method, there are several techniques that are often used. An explanation of the techniques on the hybrid is described in table (1) as follows [11].

TABLE I
Various hybridization techniques

No	Hybrid technique	Explanation
1	Weighting	Combines several recommendation values on several recommendation methods based on certain parameters.
2	Switching	Combines the two techniques alternately.
3	Mixed	A technique of interrelated recommendations to improve the results of other recommendations.
4	Cascade	A technique of interrelated recommendations to improve the results of other recommendations.
5	Feature Augmentation	The output of one technique is used for the input of another technique
6	Meta-Level	A model that is studied on a recommendation that is used for input to other recommenders.

We propose the Weighted Hybrid Method by combining two recommended methods, which are CB, and CF. Weighted Hybrid is a hybridization technique that combines the results of recommendations from several approaches and adds up the weights for each approach and adds up the weights to produce hybrid recommendations [2],[9]. The application of the hybrid method can overcome the cold-start problem in which are cold-start items and users [1]. The hybrid combination with CB and CF proved to be a good recommendation system after being applied with the weighted parallel technique with the highest F1-Score value of 9.99% [9]. In addition, the composition of CB and CF becomes a recommendation system that provides effective recommendation results according to user preferences [19].The use of this weighted hybrid is because all the advantages of each recommendation method are be used during the recommendation process [20]. The hybrid design that is suitable for use in this weighted hybrid method is a parallel hybridization design in which each recommendation method is run separately. From the calculation results of the two predictions, they are combined into a hybrid prediction by adding the final prediction results with weights. The hybrid weight used in the second method is 0.5 because the weight on the hybrid must be equal to 1 [1],[2],[9].

$$\hat{r}hybrid = wcf \ * \hat{r}cf + wcb \ * \hat{r}cb \tag{5}$$

$$wcf + wcb = 1 \tag{6}$$

Where $\hat{r}hybrid$ is a hybrid prediction, wcf and wcb are the weights of CF and CB, while $\hat{r}cf$ and $\hat{r}cb$ are rating predictions for CF and CB. The values of $\hat{r}cf$ and $\hat{r}cb$ are obtained from the predictions made by

Singular Value Decomposition (SVD), while wcb and wcf are each 0.5, which if added up is 1 according to formula (6).

III. RESEARCH METHOD

A. DATASET AND PRE-PROCESSING DATA

The dataset used in this study taken from the TripAdvisor site. We use WebHarvy for crawling this dataset which can convert HTML information into structured data. This application can retrieve related information such as destinations, users, and even the rating that has been given. The location of the destination taken is the area of Lombok Island, West Nusa Tenggara which is famous for its various tourist destinations. The data crawled on TripAdvisor is user rating data and details of tourism destinations including names, categories, and addresses. After collecting data, the results are automatically exported into (.xlsx) format.

The initial stage of data preprocessing is to divide the dataset into two part which are the destination dataset and user rating dataset. Firstly, destination dataset contains destination_id, destination, tourism_categories. The steps for this data pre-processing are:

1. Checking for missing values in the dataset.
2. Create metadata which is a combination of tourism_category and address features.
3. Change the metadata to lowercase
4. Eliminate numbers and punctuation in metadata

Secondly, the user rating dataset contains user_id, user_name, destination_id, destination, and rating. The pre-processing data for this data, it checks for missing values in the dataset.

B. GENERATING AND PRE-PROCESSING DATA

We extract the data collection from the TripAdvisor site with a web-crawler software called WebHarvy. We chose Lombok Island as a tourist destination because Lombok Island is one of the islands that has famous tourist attractions in Indonesia and even abroad. The dataset results obtained 5,694 ratings in 77 tourist attractions with 3,639 users. The data set that has been obtained is divided into two parts, in which the Collaborative Filtering approach uses rating data from users while the Content-Based Filtering approach uses tourism data. The user dataset contains user ratings for attractions. In data collections and categories that include detailed information on attractions such as tours and addresses. 19 tours obtained are Sacred and Religious Sites, Shopping Places, Nature and Wildlife Areas, Forests, Parks, Points of Interest and Southeast, Parks, Beaches, Specialty Museums, Waterfalls, Surrounding Areas, Areas, Monuments and Statues, Trails Hiking, Mountains, Volcanoes, Coral Reefs, Islands and Zoos. The stages of pre-processing the data before use are creating a metadata feature which is a combination of tourism features and addresses in the tourism dataset, changing the metadata to lowercase letters, removing numbers and punctuation marks in the metadata.

C. SYSTEM DESIGN

We propose this study to create a tourism recommender system that combines Content-Based Filtering (CB) and Collaborative Filtering (CF) methods. Figure (1) is a block diagram that explains the basic description of the system to be designed.

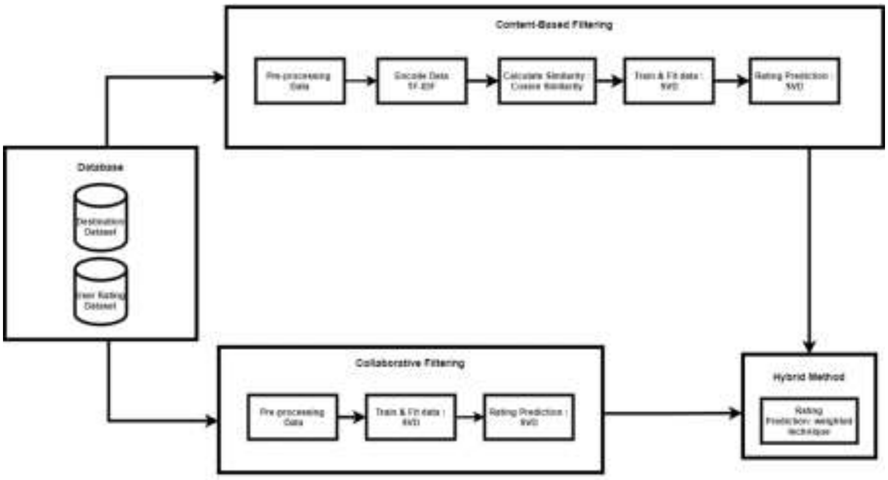

Fig. 1. Block Diagram

Firstly, the data is crawled using a web-crawler named WebHarvy. Furthermore, there is a data preprocessing stage before the data is used. The recommendation method used is the Hybrid Method which combines two recommendation methods, which are the CB, and the CF method. These two methods are run in parallel. The CB method uses TF-IDF (Term Frequency-Inverse Document Frequency) to encode the data and calculates the similarity using the Cosine Similarity equation. Based on the similarity results, the prediction results of the destination rating are searched using SVD (Singular-Value Decomposition). The CF method uses Surprise SVD to create a model that is used to generate rating predictions from preference items and other users. The Hybrid Method uses a weighting technique where the two predictions are combined into a hybrid rating prediction by adding the results of both predictions with weights and the result is a hybrid recommendation for tourist destinations.

D. PERFORMANCE EVALUATION

We use the MAE (Mean Absolute Error) metric. MAE is used to compare the predicted value with the actual value [3]. The range of ratings used in this study is from 1 to 5. The lower the MAE value, the higher the accuracy value of the recommendations produced [3],[8]. The following formula (7) MAE

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n} \tag{7}$$

Where MAE is the Mean Absolute Error, x_i is the predicted user rating on item i, y_i is the user's actual rating on item i, and n is the total number of rating pairs of x_i and y_i

In addition to the MAE metric, this pin uses the MSE (Mean Square Error) and RMSE (Root Mean Square Error) metrics. MSE and RMSE are widely used for evaluating the performance of the recommender system model [13], which are defined as for formula(7) and formula(8) :

$$MSE = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{9}$$

Where y_i is the actual rating of the user on item i , x_i is the predicted rating of the user on item i while n is the number of predicted values.

IV. RESULTS AND DISCUSSION

We perform scenario calculations on the results of each recommended method. Research testing in terms of accuracy using three metrics which are MAE (Mean Absolute Error), MSE (Mean Square Error), RMSE (Root Mean Square Error) and performed 3 cross-validations. The following are the test results for each recommended method.

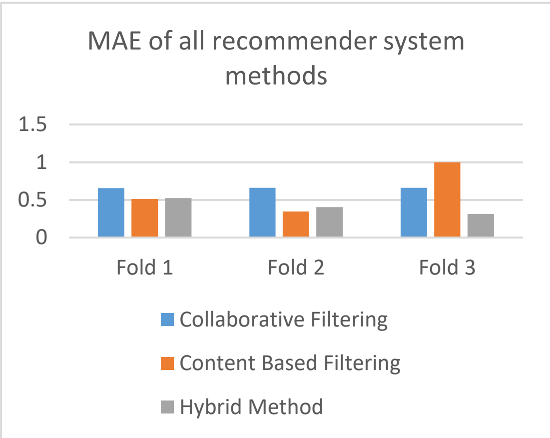

Fig. 2. MAE of all recommender system methods

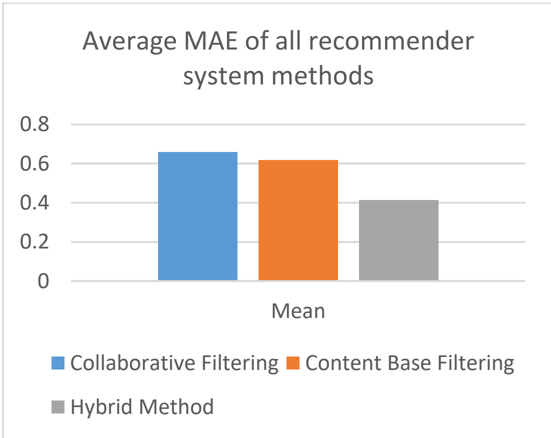

Fig. 3. Average MAE of all recommender system methods

The bar charts illustrate the testing result of all recommendation methods in terms of accuracy with MAE metric. Overall, in every fold of evaluation, the hybrid method shows the lowest value in terms of errors in the third fold, while the average result of this testing indicates the hybrid method performs better than the other methods.

In detail, based on Figure (2), all experiments carried out in three folds showed fluctuating values against all methods. The first fold shows that the CB method has a better performance of 0.5094 followed by the hybrid method and the Collaborative Filtering method with values of 0.5250 and 0.6574 respectively. The second fold CB still gets better accuracy where CB gets a value of 0.3445, the hybrid method gets 0.4044, and CF gets 0.6586. In the third fold, each method shows a significant change where the hybrid method has a value of 0.3125, CF of 0.6613, and CB of 0.9984.

Furthermore, the hybrid method with the weighting technique appears way better than CF and CB methods. This is indicated by the smallest average MAE value for the hybrid method. Based in Figure (3), the average value obtained from testing with this MAE is 0.414 for the hybrid method, 0.6174 for CB and 0.6591 for CF.

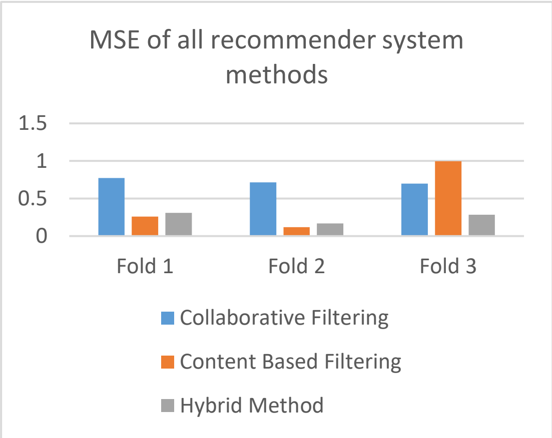

Fig. 4. MSE of all recommender system methods

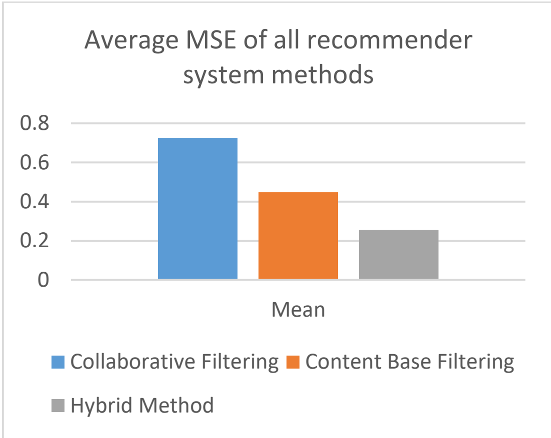

Fig. 5. Average MSE of all recommender system methods

The bar charts display the MSE comparison between CF, CB, and the hybrid method. Overall, all fold of the evaluation the hybrid method shows a significant change which has quite a large gap, while the hybrid method has the lowest average of error than the other methods.

In detail, based on Figure (4), CB is the method that has the smallest error with a value of 0.2595 followed by the hybrid method of 0.3107 and CF of 0.7711. In second fold, CB still has the smallest error value of 0.1187 and is followed by the hybrid method and CF of 0.1680 and 0.7130 respectively. In the last fold, CB shows the opposite of the previous fold which gets the highest error of 0.9968. CF gets a value of 0.6984 while the hybrid method gets a value of 0.2857.

Furthermore, evaluation with MSE metrics shows that the hybrid method gets the highest accuracy from other methods. Based on Figure (5) the average MSE value obtained by the hybrid method is 0.2548 while CB and CF get 0.4458 and 0.7262 respectively.

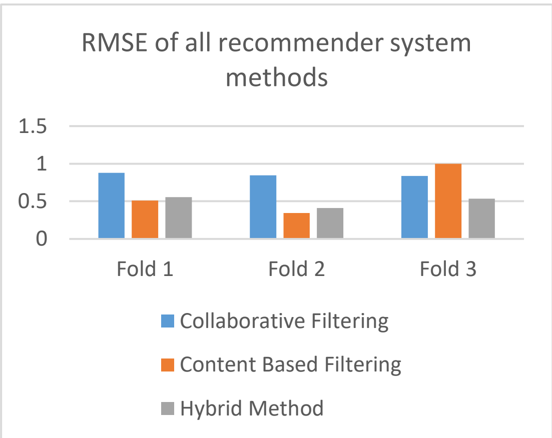

Fig. 6. RMSE of all recommender system methods

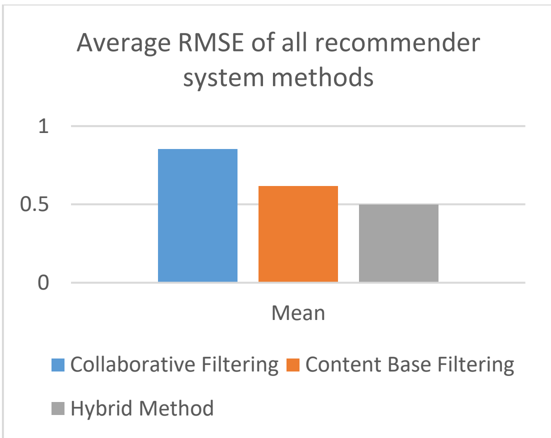

Fig. 7. Average RMSE of all recommender system methods

The bar charts depict the result of RMSE testing for all recommendation methods that we use in this research. Overall, each fold of the evaluation the hybrid method tends to have a high accuracy value than other methods, while the hybrid method gets the highest accuracy with the lowest average value of RMSE.

In detail, based on Figure (6), CB is the method that has the smallest error with a value of 0.5094 followed by the hybrid method of 0.5574 and CF of 0.8781. In the next fold, CB still has the smallest error value of 0.3445 and is followed by the hybrid method and CF of 0.4099 and 0.8444 respectively. In the last fold, the hybrid method becomes the highest accuracy of 0.5345, whereas CF and CB get 0.8357 and 0,9984 respectively.

Furthermore, based on Figures (7) RMSE is obtained which indicates that the Hybrid Method with a weighting technique has an average value of 0.5006 while 0.8527 for CF and 0.6174 for CB.

V. CONCLUSION

In our study, an experiment of the Hybrid Method with Weighting Techniques on the tourism recommender system has been carried out. We extricated information from TripAdvisor and took Lombok Island as a visitor goal. This recommender system is an integration of Collaborative Filtering (CF) and Content-Based Filtering (CB) approaches. Based on the evaluation with MAE (Mean Absolute Error), MSE (Mean Square Error), and RMSE (Root Mean Square Error) metrics, the exploratory results show that the Hybrid Method with weighting technique provides higher prediction accuracy than when undergoing the recommendation method separately. The test results are significantly shown in the MSE test which has the smallest average of 0.2548 compared to others, 0.7275 for CF and 0.4583, 0.6174 for CB. Suggestion for further research is to build a group recommender system that recommends items to groups. This recommender system is providing recommendations for tourist destinations that are suitable for group tours which can address the different needs that exist for each member of the tour group in determining tourist destinations [2].

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REFERENCES

[1] M. E. B. H. Kbaier, H. Masri, and S. Krichen, “A Personalized Hybrid Tourism Recommender System,” 2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA), 2017.
[2] Lutfi Ambarwati and Z.K.A Baizal, “Group Recommender System Using Hybrid Filtering for Tourism Domain,” Indonesia Journal on Computing (Indo-JC), vol. 4, no. 2, pp. 21–30, Sep. 2019.
[3] Q. R. Arvianti and Z.K.A. Baizal, “Tourism Recommender System Using Item-Based Hybrid Clustering Method (Case Study: Bandung Raya Region),” Journal of Data Science and Its Applications, vol. 2, no. 2, pp. 95–101, Nov. 2019.
[4] S. Sharma, A. Sharma, Y. Sharma, and M. Bhatia, “Recommender system using hybrid approach,” 2016 International Conference on Computing, Communication and Automation (ICCCA), 2016.
[5] R. Barathy and P. Chitra, “Applying Matrix Factorization In Collaborative Filtering Recommender Systems,” 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020.
[6] R. Subramaniam, R. Lee, and T. Matsuo, “Movie Master: Hybrid Movie Recommendation,” 2017 International Conference on Computational Science and Computational Intelligence (CSCI), 2017.
[7] O. Oyebode and R. Orji, “A hybrid recommender system for product sales in a banking environment,” Journal of Banking and Financial Technology, vol. 4, no. 1, pp. 15–25, 2020.
[8] R. Turnip, D. Nurjanah, and D. S. Kusumo, “Hybrid recommender system for learning material using content-based filtering and collaborative filtering with good learners rating,” 2017 IEEE Conference on e-Learning, e-Management and e-Services (IC3e), 2017.
[9] M. Aprilianti, R. Mahendra, and I. Budi, “Implementation of weighted parallel hybrid recommender systems for e-commerce in Indonesia,” 2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS), 2016.
[10] P. Darshna, “Music recommendation based on content and collaborative approach & reducing cold start problem,” 2018 2nd International Conference on Inventive Systems and Control (ICISC), 2018.
[11] S. Rahmawati, D. Nurjanah, and R. Rismala, “Analisis dan Implementasi pendekatan Hybrid untuk Sistem Rekomendasi Pekerjaan dengan Metode Knowledge Based dan Collaborative Filtering,” Indonesian Journal on Computing (Indo-JC), vol. 3, no. 2, p. 11, 2018.

[12] S. Rajarajeswari, S. Naik, S. Srikant, M. K. S. Prakash, and P. Uday, “Movie Recommendation System,” Emerging Research in Computing, Information, Communication and Applications Advances in Intelligent Systems and Computing, pp. 329–340, 2019.
[13] N. Nassar, A. Jafar, and Y. Rahhal, “A novel deep multi-criteria collaborative filtering model for recommendation system,” Knowledge-Based Systems, vol. 187, p. 104811, 2020.
[14] S. K. Raghuwanshi and R. K. Pateriya, “Collaborative Filtering Techniques in Recommendation Systems,” Data, Engineering and Applications, pp. 11–21, 2019.
[15] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, “Collaborative filtering and deep learning based recommendation system for cold start items,” Expert Systems with Applications, vol. 69, pp. 29–39, 2017.
[16] J. Jooa, S. Bangb, and G. Parka, “Implementation of a Recommendation System Using Association Rules and Collaborative Filtering,” Procedia Computer Science, vol. 91, pp. 944–952, 2016.
[17] G. Suganeshwari and S. P. S. Ibrahim, “A Survey on Collaborative Filtering Based Recommendation System,” Proceedings of the 3rd International Symposium on Big Data and Cloud Computing Challenges (ISBCC – 16’) Smart Innovation, Systems and Technologies, pp. 503–518, 2016.
[18] V. Subramaniyaswamy, R. Logesh, M. Chandrashekhar, A. Challa, and V. Vijayakumar, “A personalised movie recommendation system based on collaborative filtering,” International Journal of High Performance Computing and Networking, vol. 10, no. 1/2, p. 54, 2017.
[19] P. Mathew, B. Kuriakose, and V. Hegde, “Book Recommendation System through content based and collaborative filtering method,” 2016 International Conference on Data Mining and Advanced Computing (SAPIENCE), 2016.
[20] F. Isinkaye, Y. Folajimi, and B. Ojokoh, “Recommendation systems: Principles, methods and evaluation,” Egyptian Informatics Journal, vol. 16, no. 3, pp. 261–273, 2015.