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RESEARCH ARTICLE

Recommender System for Group of Users Using Matrix Factorization for Tourism Domain (Case Study: Bali)

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Abstract: Choosing a product that suits a customer's needs requires a recommendation system to provide suggestions on a collection of items of interest to the user. Recommendations can be applied in various fields such as entertainment, shopping sites, social networking, job portals, discovery of relevant web pages, and so on. There are many circumstances where recommendations are needed for a group such as in tourism and entertainment purposes. The development of a Group Recommendation System (GRS) was carried out in response to the need to provide several recommendations to a group of users. We conducted this research to build a GRS that can provide item recommendations using the Collaborative Filtering (CF) method with Matrix Factorization Technique, as well as three approaches, i.e., After Factorization (AF), Before Factorization (BF), and Weighted Before Factorization (WBF). Determine the best approach for the three categories of groups formed, i.e., small groups (three members), medium groups (five members), and large groups (ten members). The focus of this research is the tourism destination domain in Bali. The evaluation methods used are Precision and Recall for various group sizes. In the evaluation results of the precision calculation, the medium group obtained the highest score for the AF, BF, and WBF approaches of 0.944. Meanwhile, in calculating recall, the small group achieved the highest scores for the AF, BF, and WBF approaches of 0.294, 0.259, and 0.259. From the results of this study, it appears that small groups are suitable for using the BF approach, while the AF method is more effective for large groups, and the best approach for medium groups is the WBF. The precision and recall score are presented on a scale from 0 to 1, where 1 signifies perfect performance.

Keywords: After Factorization, Bali Tourism, Before Factorization, Group Recommender System, Tourism Recommender System, Weighted Before Factorization

1 Introduction

Technological advances make all information easy to access and obtain via the internet. The amount of information can make it difficult for users to determine a suitable product or service. To choose a product that suits the customer's needs, a recommendation system is implemented to provide suggestions regarding a collection of items that are of interest to active users. These recommendations can be applied in various fields such as entertainment, shopping sites, social networks, job portals, discovery of relevant web pages, and others [1, 2]. Recommendation systems play a role in collecting user interaction data, such as user ratings, browsing history, demographic data, social aspects such as friends, tags, trust, or trusted parties, as well as contextual information such as time or location to provide suggestions [3]. However, in life, many recommendation systems are used for the needs of a group of users, and it is impossible to create a customized recommender system for each person, with user preferences in a group may vary [3].

Collaborative Filtering (CF) is widely adopted in developing recommender systems by utilizing similarity measurements as a tool for providing recommendations [3]. Using collaborative filtering techniques, one of the main objectives is to identify user preferences by observing how multiple users engage in activities on user items simultaneously [4]. CF has many advantages, including that this system is not focused on content, because in CF the user provides an explicit assessment, so that the original quality assessment of the item can be carried out and can provide effective recommendations because it is based on user similarity rather than item similarity [5]. MF is one of the popular methods in CF, that represent users and items through latent factors derived from the matrix containing user-item ratings [6].

There are many circumstances where recommendations are needed for a group rather than an individual, such as for tourism and entertainment purposes [7]. In a GRS, the main task is to overcome differences in interests among group members to provide recommendations for items that are most relevant to the entire group [4]. In [8] developed a GRS for the film domain, with the MF method and incorporating three distinct aggregation strategies approach, i.e., AF, BF, and WBF. Many studies discuss recommendation systems for the tourism domain [9]. In [10] built a GRS using a Hybrid method by combining Content Based Filtering (CB), CF, and Knowledge-Based Filtering (KB) methods with user recommendation ratings processed using Borda Method calculations. In its development, with the tourism domain, in [11] built a GRS called Influence-Based Group Recommendation (IBGR) using the Fuzzy C-Means (FCM) clustering method and Pearson Correlation Coefficient (PCC) Similarity, getting average evaluation results which uses Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Precision is 0.574, 0.733, and 85.35%. By using a hybrid method to build GRS, in [12] succeeded in providing recommendations for tourist attractions with a group selection process recommended to users using the borda method. In [13] built a group recommender system by implementing STSGroup. With usability evaluation results using the System Usability Scale (SUS) of 76 points.

Tourism activities are more frequently organized in groups with friends or family. The GRS was developed in response to the need to provide several recommendations to a group of users [14]. This study focuses on the tourist destination of Bali, which is famous for its popularity among tourists due to its abundant natural resources and rich cultural diversity, making it a unique and attractive location. In this study, we construct a GRS capable of offering item suggestions through the Collaborative Filtering (CF) method utilizing Matrix

Factorization (MF). We use Single Value Decomposition, known as SVD++, for performing MF and use Stochastic Gradient Descent (SGD) that is applied to iteratively update the factored matrix to minimize the error or loss function. Furthermore, a combination of approaches such as AF, BF, and WBF were implemented across different group categorizations. CF plays a crucial role in enhancing recommendations by employing MF, a proven and effective strategy for providing recommendations [15]. The GRS created through the utilization of three approaches is implemented across three distinct group categories, intending to identify the most effective approach for each specific category.

2 Research Method

Recommender systems play a role in aiding users in decision-making by analyzing user preference data and suggesting products that align with their preferences [16, 17]. In obtaining user preferences, recommender systems obtain user information from two kinds of ratings i.e., implicit rating and explicit rating [18]. Implicit rating refers to the process of inferring a user's preferences or feedback based on their behavior or interactions with a system. In other words, their preferences are deduced from their actions, such as clicks, views, purchase history, time spent on a page, or other behavioral patterns. Explicit rating refers to the direct and intentional feedback given by users to express their opinions, preferences, or satisfaction with a product, service, or content. Explicit rating involves users providing direct input or feedback in the form of numerical ratings, reviews, likes, thumbs up or down, or other explicit expressions of their opinion. The increasing need for information in social activities, such as listening to music, watching movies, traveling, attending social events, and various other activities, makes recommendation systems for groups more significant [19].

2.1 System Design

GRS will be built for tourism recommendations in Bali using the MF method. Figure 1 shows the basic design system model for constructing GRS in this study. We pre-processed the dataset to ensure optimal accuracy when using it in the development of GRS. Furthermore, groups were established by generating a user-item rating matrix. Following this process, MF was employed with the AF, BF, and WBF approaches. Evaluation was conducted on all three methods to ascertain the most effective approach tailored to each group.

2.2 Dataset

We use data from the Kaggle[1] website and presented in CSV file format. This dataset involves ratings of tourist sites in Bali and includes elements such as the *place_id*, *user_id*, and *ratings* as listed in Table 1. The attribute *user_id*, *place_id*, and *rating* are important for building an effective group recommender system using MF. These attributes enable personalization, capture user preferences, and facilitate the collaborative filtering process to provide relevant and accurate recommendations for both individuals and groups.

[1]kaggle datasets download -d utarasetyaw/data-set-destination-in-bali

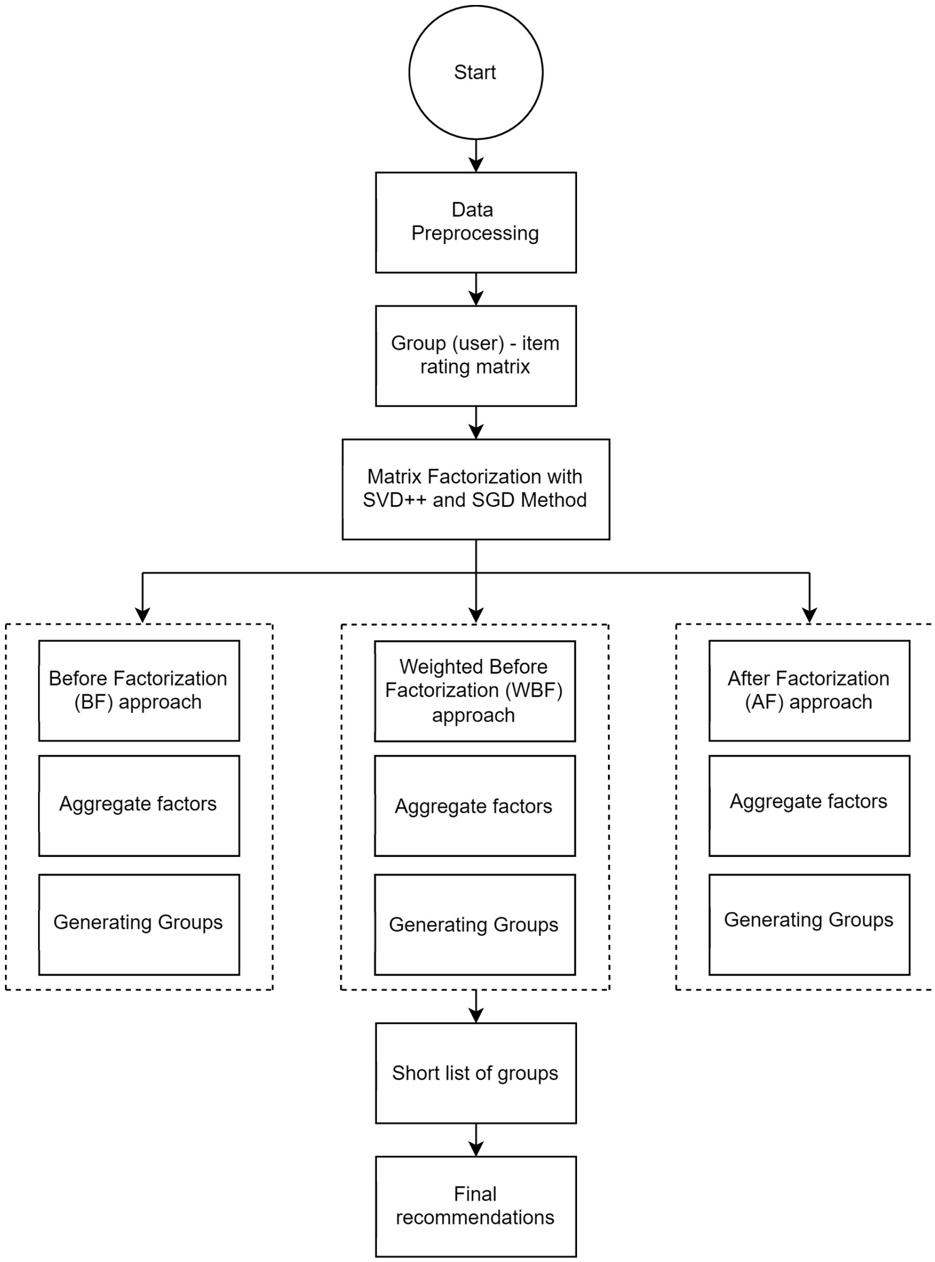

Figure 1: System design overview.

The *place_id* attribute ranges from ID 1 to 75, while the *user_id* is in the range of ID 1 to 100. Each user contributes ratings to the dataset, where each user provides ratings for at least five tourist attractions. This is necessary in such a way as to produce recommendations for tourist attractions that are correct and appropriate also to avoid the cold start problem.

Table 1: The initial dataset before processing

place_id	user_id	rating
1	2	4
1	19	1
1	42	2
1	55	5
1	65	2

The scope of the dataset was narrowed by changing the *user_id* range from 1-100 to 1-75. Priority is given to the user who gives the highest rating to the item. This resulted in a total of 2250 entries, in contrast to the initial 3000 entries. Furthermore, re-indexing *place_id* and *user_id*. Instead, reset the starting point to 0 and use *user_id* as the position of the *place_id* column. The dataset was then divided into 80:20 for training and test data. The results of the data pre-processing can be seen in Table 2.

Table 2: The dataset after preprocessing

place_id	user_id	rating
1	0	3
6	0	5
7	0	5
11	0	2
12	0	5

The *user_id* is essential to uniquely identify each user in the system. On the other hand, the *place_id* serves as a unique identifier for each destination or item in the recommender system. For example, *place_id* = 1 refers to Satria Agrotourism, *place_id* = 2 refers to Agung Bali Oleh - Oleh, *place_id* = 6 refers to Tukad Cepung Waterfall tourist spot, and *place_id* = 7 refers to Aloha Ubud Swing tourist spot. This explanation is taken from the same Kaggle[2] website as the dataset used in this study.

The rating itself is numerical value assigned by the user to each *place_id* for the name of a tourist destination located on the island of Bali. In the dataset, this rating feature has a *rating* scale from 1 to 5 assigned by the user to a particular place as a direct indicator of the user's preference or satisfaction level. MF techniques leverage this numerical information to decompose the user-item interaction matrix into latent factors, enabling the system to understand and predict user preferences for unrated items.

2.3 Collaborative Filtering

Collaborative Filtering (CF) selects items based on the interests of other users that have similar preferences or based on reviews addressed by other users. This approach uses

[2]kaggle datasets download -d utarasetyaw/data-set-destination-in-bali

statistical methods to find similarities between vectors of users or items [1]. Recommender Systems (RS) that rely on collaborative filtering (CF) work based on ratings given by a group of users against various items.

The system proposes items that have not been considered by the target user but are likely to be appreciated. Ratings are a matrix of size $a \times b$, where a represents user's number and b represents item's number. If the new user has joined the system, then an empty row will be added to the matrix [20].

Table 3: The dataset after preprocessing

User/Item	Kuta Beach	Pura Tanah Lot	Bali Bird Park	Garuda Wisnu Kencana
Caca	4	3	?	4
Vita	?	5	5	3
Adit	5	?	1	5
Windhi	3	4	5	?

CF systems provide recommendations by using relationships and similarities between users or items. This relationship is formed through the interaction between users and items run by RS. Therefore, RS can project the possible ratings given by users that have yet to rate an item. The item is then organized based on the estimated rating score, and the higher-ranked item is recommended to the corresponding user [20].

There are two primary categories of CF algorithms: memory and model based. Memory-based algorithms use heuristics on the scoring matrix to generate recommendations, while model-based algorithms use models derived from the scoring matrix to provide item recommendations. Memory-based algorithms are commonly associated with the Nearest Neighbor (NN) strategy, while model-based algorithms work with MF. Memory-based algorithms typically entail three steps:

(a) compute the similarity between users or items,

(b) create groups consisting of similar users or items, and

(c) generate recommendations by selecting similar items.

In addition, MF shows that matrix valuation can be calculated using the original method by multiplying the latent feature matrix, recognizing the implied data pattern. SVD++, SGD, and ALS have proven successful in CF. Further details on this subject can be explored in additional sources [21].

2.4 Matrix Factorization

The Matrix Factorization (MF) model depicts user-item interactions by mapping users and items into a shared latent factor space [8]. In its implementation, the MF model is used by factorizing the rank matrix.

Define $\vec{d}_a = (d_(a,1), \ldots, d_{i,K})$ as the vector that represents the factors associated with a. Meanwhile, b_a refers to the item-a bias which is independent of any interaction. Furthermore, $\vec{p}_u = (p_{u,1}, \ldots, p_{u,K})$ is the vector that represents the factors associated with user u, and b_u is the bias of user u that is not related to any interaction.

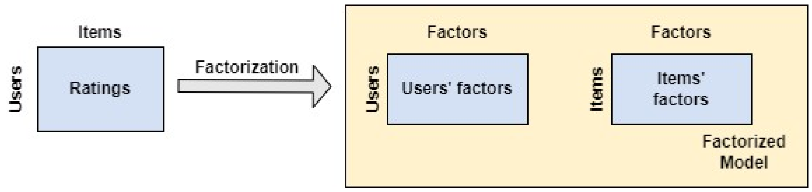

Figure 2: Illustration of the matrix factorization process [15].

The system optimizes the vectors representing factors ($\vec{d}_a$ and $\vec{p}_u$) and bias (b_a also b_u) by minimizing the following expression for a given number of ratings:

$$\min_{\vec{p}_u,\vec{d}_a,b_u,b_a} \sum_{r_{u,a}\neq\bullet} (r_{u,a} - \mu - b_u - b_a - (\vec{p}_u)^{\intercal}\vec{d}_a)^2 + \lambda(\|\vec{p}_u\|^2 + \|\vec{d}_a\|^2 + b_u^2 + d_a^2) \tag{1}$$

The training rating $r_{u,a}$ reflects the user's assessment of item a with μ the average rank of the dataset and λ is a parameter that affects the training process. After the MF model is trained, the calculation of the prediction for the rating of item a by user u ($m_{u,a}$) can be performed using the subsequent formula:

$$m_{u,a} = \mu + b_a + b_u + \vec{p}_u\vec{d}_a \tag{2}$$

To generate group predictions, the first necessary step is to calculate the vector representing group factors ($\vec{p}_G$) and the bias specific to the group (b_G). The process of calculating these values will be detailed in the upcoming sections. After factoring in the group, the computation for predicting the rating of group G for item i :

$$m_{G,a} = \mu + b_a + b_G + \vec{p}_G\vec{d}_a \tag{3}$$

Recommendations for group G (R_G) are determined based on predicted values, specifically, this represents S items with predicted value that have not been ranked for each group member. The following conditions need to be satisfied:

$$\#R_G \leq S \tag{4}$$

$$\forall a \in R_G, \forall u \in G : r_{u,a} = \bullet \tag{5}$$

$$\forall a \in R_G, \forall j \notin R_G : m_{G,a} \geq m_{G,j} \tag{6}$$

2.5 After Factorization

The AF method involves the process of factoring user groups by combining users in groups. For this approach, the information generated after factorization is used instead of the ranking information, so the users become unified in the group when the MF model is built [8].

Consider $G = u_1, \ldots, u_n$ as the set of users within group G, where $\vec{p}_u = (p_{u,1}, \ldots, p_{u,K})$ represents the factor vector of user u, and b_u signifies the bias value for user u. We denote $\vec{p}_G$ as group G factor vector:

$$\vec{p}_G = \begin{pmatrix} h(p_{u_1,1}) & \ldots & (p_{u_n,1}) \\ \vdots & \ddots & \vdots \\ h(p_{u_1,K}) & \ldots & (p_{u_n,K}) \end{pmatrix} \tag{7}$$

b_G refers to a group of G bias,

$$b_G = h(b_{u_1}, \dots, b_{u_n}) \tag{8}$$

2.6 Before Factorization

BF is based on the concept of representing the group preferences of a user, $G = u_1, \dots, u_n$, through a virtual user, u_G, collects ratings given from all users in the group G. This aggregation is done using information that already exists before the Matrix Factorization process (ratings) [8]. This approach consists of two stages:

(a) Simulate the ratings given by virtual users u_G on items, $r_{G,a}$. This step is performed using a specific aggregation function h with the following formula:

$$r_{G,a} = h(r_{u_1,a}, r_{u_2,a}, \dots, r_{u_n,a}) \tag{9}$$

where $r_{u_1,a}, r_{u_2,a}, \dots, r_{u_n,a}$ are the ratings that have been observed by users in group G for item a.

(b) Calculate the virtual user factor vector ($\vec{p}_G = (p_{G,1}, \dots, p_{G,k})$) and virtual user bias (b_G) after the rank ($r_{G,a}$) is known. The process can be explained using the following mathematical notations,

$$\min_{\vec{p}_G, \vec{b}_G} \sum_{r_{G,i} \neq \bullet} (r_{G,a} - \mu - b_G - b_a - (\vec{p}_G)^\intercal \vec{d}_a)^2 + \lambda(\|\vec{p}_{u_G}\|^2 + \|\vec{d}_a\|^2 + b_{u_G}^2 + d_a^2) \tag{10}$$

Using the values of q_1, b_i, and μ. The math notation is simplified to,

$$\min_{\vec{p}_G, \vec{b}_G} \sum_{r_{G,i} \neq \bullet} ((r_{G,a} - \mu - b_a) - ((\vec{p}_G)^\intercal \vec{d}_a + b_G))^2 + \lambda(\|\vec{p}_G\|^2 + b_G^2) \tag{11}$$

We give the following definition:

$$s_{G,a} = r_{G,a} - \mu - b_i \tag{12}$$

$$\vec{p}_G^* = (\vec{p}_G, b_G) = (p_{G,1}, \dots, p_{G,K}, b_G) \tag{13}$$

$$\vec{d}_a^* = (\vec{d}_{a,1} = (d_{a,1}, \dots, d_{a,K}, 1) \tag{14}$$

Based on the definition, the previous expression can be obtained in the following way:

$$\min_{\vec{p}_G^*} \sum_{s_{G,a} \neq \bullet} (s_{G,a} - ((\vec{p}_G^*)^\intercal \vec{d}_G^*)^2 + \lambda(\|\vec{p}_G\|^2) \tag{15}$$

It can be concluded that this minimization process corresponds to the concept of ridge regression. For simplicity of notation, we will assume that the virtual user u_G has ranked the items $1, \dots, u_G$, and we will define the matrix A:

$$A = \begin{pmatrix} d_{1,1} & \dots & d_{1,K} & 1 \\ d_{2,1} & \dots & d_{2,K} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ d_{n_G,1} & \dots & d_{n_G,K} & 1 \end{pmatrix} \tag{16}$$

We can conclude that:

$$\begin{pmatrix} \vec{p}_G \\ b_G \end{pmatrix} = \begin{pmatrix} p_{G,1} \\ p_{G,2} \\ \vdots \\ p_{G,K} \\ b_G \end{pmatrix} = \left(A^T W A + \lambda I\right)^{-1} A^T W \begin{pmatrix} s_{G,1} \\ s_{G,2} \\ \vdots \\ s_{G,n_G} \end{pmatrix} \tag{17}$$

2.7 Weighted Before Factorization

The WBF method allocates a weight to each item depending on the ratings provided by the users in the group [8]. In this case, we put more emphasis on the items that are most frequently rated by the users and exhibit comparable ratings to those of the group's users. The weight $W_{G,a}$ defined as the weight of item a for group G:

$$W_{G,a} = \frac{\#\{u \in G | r_{u,a} \neq \bullet\}}{\#G} \cdot \frac{1}{1 + \sigma_{G,a}} \tag{18}$$

The sign states of subset cardinality dan $\sigma_{G,a}$ the average deviation of the ranks of the members in the G on the items a.

This method differs from the BF approach solely in the second phase, where the computation of a virtual user vector $\vec{p}_G$ and virtual user bias (b_G) takes place. In this instance, objective function is as follows:

$$\min_{\vec{p}_G, \vec{b}_G} \sum_{r_{G,a} \neq \bullet} (r_{G,a} - \mu - b_G - b_a - (\vec{p}_G)^\intercal \vec{d}_a)^2 + \lambda(\|\vec{p}_G\|^2 + \|\vec{d}_a\|^2 + b_{u_G}^2 + d_a^2) \tag{19}$$

Utilizing a similar approach as in the preceding section, we can infer that this expression is akin to weighted ridge regression. Consequently, we obtain:

$$\begin{pmatrix} \vec{p}_G \\ b_G \end{pmatrix} = \begin{pmatrix} p_{G,1} \\ p_{G,2} \\ \vdots \\ p_{G,K} \\ b_G \end{pmatrix} = \left(A^\intercal W A + \lambda I\right)^{-1} A^\intercal W \begin{pmatrix} s_{G,1} \\ s_{G,2} \\ \vdots \\ s_{G,n_G} \end{pmatrix} \tag{20}$$

2.8 Evaluation Metrics

The most frequently used classification metrics in recommender systems are precision and recall [22], [23]. Precision represents the fraction of the recommended items that are relevant among all the items recommended to the user, while recall represents the number of recommended items that match the total number of items that should have been recommended [23].

In assessing the quality of recommendations generated for a user group, we set the definition of precision and recall for group G as follows:

$$precision_G = \frac{\#TP_G}{\#(TP_G \cup FP_G)} \tag{21}$$

$$recall_G = \frac{\#TP_G}{\#T_G} \tag{22}$$

TP_G represents the collection of actual positive recommendations, FP_G shows various false positive suggestions, and T_G denotes the set of anticipated recommendations, as outlined in the notations that follow.

$$FP_G = \{a \in R_G \mid \exists g \in G, \text{such that } \hat{r}_{g,a} \leq \theta\} \tag{23}$$

$$TP_G = \{a \in R_G \mid \exists g \in G, \text{such that } \hat{r}_{g,a} \neq \bullet \text{ and } \forall u \in G : r_{u,a} = \bullet \rightarrow r_{u,a} \geq \theta\} \tag{24}$$

$$T_G = \{a \in I \mid \exists g \in G, \text{such that } r_{g,a} \neq \bullet \text{ and } \forall u \in G : r_{u,a} = \bullet \rightarrow r_{u,a} \geq \theta\} \tag{25}$$

Parameter θ is defined as the limit used to judge whether a user is likely to like or dislike an item. The dataset comes with a rating feature that scales from 1 to 5. In this study, we set the value of θ to 4. User test ratings for items i is denoted as $\hat{r}_{u,a}$, and R_G constitutes the set of recommended items for group G (test ratings are not considered in the determination of recommended items).

3 Results

3.1 Dataset

The results of preprocessing the dataset, obtained 2250 data with a total of 75 users and 75 tourist attractions given in Figure 3. Then, split the data into 80:20 for the training data and testing data given in Figure Figure 3. From the dataset, it will be used to generate groups according to the existing sizes, such as small, medium, and large using the approaches used in the research are AF, BF, and WBF.

	userID	placeID	rating
505	0	1	3
1064	0	37	4
284	0	12	5
1010	0	46	3
1100	0	58	1
...	...	...	...
263	74	55	4
1095	74	25	5
226	74	72	2
53	74	62	3
1394	74	28	5

[1575 rows x 3 columns]

Figure 3: Data train result.

```
      userID  placeID  rating
1615       0       11       2
1748       0       34       4
1920       0       32       4
1834       0       38       3
1947       0        7       5
...      ...      ...     ...
2064      74        0       1
2215      74       57       3
...
1857      74       34       5
1792      74       36       5

[675 rows x 3 columns]
```

Figure 4: Data test result.

3.2 Generating Group

We need to ensure that the number of items tested is sufficient to obtain the optimal evaluation outcomes from each method applied in this study. Therefore, we set a minimum limit of 10, which basically means that in the test dataset there are at least ten tourist attractions that have received ratings from at least one group member. We group these members into three categories where the small group, the medium group consists, and the large group [15].

```
******* Running for  small  groups *************
generated groups (only first 3 are getting printed here):
[4, 46, 71]
[19, 21, 32]
[22, 53, 55]

******* Running for  medium  groups *************
generated groups (only first 3 are getting printed here):
[2, 5, 10, 23, 61]
[24, 29, 32, 68, 70]
[40, 46, 53, 57, 66]

******* Running for  large  groups *************
generated groups (only first 3 are getting printed here):
[3, 11, 23, 24, 30, 33, 34, 59, 60, 67]
[0, 6, 27, 42, 44, 47, 53, 56, 65, 70]
[8, 22, 31, 32, 40, 41, 50, 63, 64, 72]
```

Figure 5: Generate groups result.

3.3 Evaluation

The following three functions are used for the evaluation of each of the three methods AF, BF, and WBF. For evaluation we use Precision and Recall for various group sizes. The evaluation results are presented in Table 4 and Table 5. The AF, BF, and WBF were evaluated by randomly creating 50 groups, with the possibility of one member belonging to multiple groups.

The precision and recall result are presented in Table 4 and Table 5 for the respective values of three types of groups i.e., small, medium, and large groups in each approach. The precision and recall score are presented on a scale from 0 to 1, where 1 signifies perfect performance. In Table 4, the three approaches, i.e., AF, BF, and WBF generally provide better results for the medium group, while for the small group the best approach is BF, and for the large group the best approach is AF. Based on the results in Table 5, the three approaches also show the best results or performance for small groups. WBF is the best approach for medium-sized groups. AF is reasonably effective in large groups. Therefore, the AF approach is suitable for large groups. In medium groups, the best approach is WBF. Meanwhile, for small groups the best approach is the BF approach.

Table 4: Precision

Methods	Small Group (M=3)	Medium Group (M=5)	Large Group (M=10)
AF	0.866	0.944	0.790
BF	0.916	0.944	0.644
WBF	0.866	0.944	0.698

Algorithm 1 Evaluate_AF Function

function EVALUATE_AF($self, is\_debug = False$)
    tp ← intersection size of self.actual_recos and self.reco_list_af
    fp ← intersection size of self.actual_recos and self.reco_list_af
    try
    precision_af ← tp / (tp + fp)
    except ZeroDivisionError
    try
    recall_af ← tp / size of self.actual_recos
    except ZeroDivisionError
    recall_af ← NaN
    if is_debug is True **then**
        print tp, fp, precision_af, recall_af
    end if
    return precision_af, recall_af, tp, fp
end function

Algorithm 2 Evaluate_BF Function

```
function EVALUATE_BF(self, is_debug = False)
    tp ← intersection size of self.actual_recos and self.reco_list_bf
    fp ← intersection size of self.actual_recos and self.reco_list_bf
    try
    precision_bf ← tp / (tp + fp)
    except ZeroDivisionError
    try
    recall_bf ← tp / size of self.actual_recos
    except ZeroDivisionError
    recall_bf ← NaN
    if is_debug is True then
        print tp, fp, precision_bf, recall_bf
    end if
    return precision_bf, recall_bf, tp, fp
end function
```

Algorithm 3 Evaluate_WBF Function

```
function EVALUATE_WBF(self, is_debug = False)
    tp ← intersection size of self.actual_recos and self.reco_list_wbf
    fp ← intersection size of self.actual_recos and self.reco_list_wbf
    try
    precision_wbf ← tp / (tp + fp)
    except ZeroDivisionError
    try
    recall_wbf ← tp / size of self.actual_recos
    except ZeroDivisionError
    recall_wbf ← NaN
    if is_debug is True then
        print tp, fp, precision_wbf, recall_wbf
    end if
    return precision_wbf, recall_wbf, tp, fp
end function
```

Table 5: Recall

Methods	Small Group (M=3)	Medium Group (M=5)	Large Group (M=10)
AF	0.294	0.179	0.147
BF	0.259	0.179	0.091
WBF	0.259	0.189	0.107

4 Discussion

We built a group recommender system for the tourism sector in Bali using the CF method by applying the MF technique. We employ three methods, i.e., AF, BF, and WBF, which will be implemented across three distinct group categories. These categories encompass diverse members, with the small group comprising three users, the medium group comprising five users, and the large group consisting of ten users.

Ortega, et.al. [9] categorized groups into smaller groups of two until four members, medium of five until eight members, and large of nine until twelve members. Furthermore, these approaches underwent a comparison to identify the most effective approach for each group category. Research results may vary depending on the dataset used. To get better evaluation results, the dataset used has gone through preprocessing techniques. It must be ensured that there are enough items to be tested. In this study, the testing dataset includes a minimum of ten tourist attractions that have received ratings from at least one member of the group.

5 Conclusion

We develop the GRS provides tourism recommendations on the island of Bali using the CF method by applying the MF technique. The research used 2250 data which were then divided in a ratio of 80:20 for training data and testing data with a total of 75 users and 75 tourist attractions. The *user_id* enabling the recommender system to personalize suggestions by considering each user's historical preferences and behavior within the group. The *place_id* empowers the model to comprehend user preferences for destinations by linking them to unique identifiers. The user-assigned *rating* to a specific place directly reflects their preference or satisfaction.

Our system utilizes three distinct approaches to identify the most suitable method for research. Furthermore, various group categorizations incorporate combined approaches such as AF, BF, and WBF. The three approaches had their evaluation results assessed in several category groups: a small group, a medium group, and a large group.

The aim of this research is to determine the best approach for the three group categories formed, which can show optimal results when applied to a dataset of tourist destinations on the island of Bali. In the evaluation results for precision calculations, for the AF, BF and WBF approaches, the highest score was in the medium group, i.e., 0.944. Meanwhile, for the recall calculation, the highest score for the AF, BF, and WBF is 0.294, 0.259, and 0.259, respectively, in the small group. From the results of this study, it appears that small groups are suitable for using the BF, while the AF is more effective for large groups, and the best approach for medium groups is the WBF.

We hope that there will be further research in providing recommendations for a group in selecting tourist destinations in areas that have not been considered by adding features such as considering costs, tourist categories, addresses, and others for further research.

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