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Analysis of the Indonesian Tourist Destination Recommendation System Using User Profile-Based Collaborative Filtering

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Abstract

Tourism recommendation systems in Indonesia are challenged by highly heterogeneous user preferences and severe rating sparsity, which undermine the effectiveness of conventional collaborative filtering methods. However, prior studies predominantly rely on rating-based interactions and often utilize generic datasets, limiting their ability to capture the contextual and behavioural diversity of Indonesian tourism. Although user profile information is known to influence preferences, its integration with latent factor models is still fragmented and rarely evaluated in a unified, context-aware framework. Consequently, existing approaches often produce suboptimal accuracy and lack robustness in sparse and imbalanced data environments. This study proposes a unified user profile-enriched collaborative filtering framework that integrates Singular Value Decomposition (SVD), Jaccard similarity, and K-Nearest Neighbor (KNN) to jointly model latent preferences and contextual user characteristics. This integration constitutes the main novelty of this work, enabling simultaneous mitigation of sparsity and enhancement of personalization in a single pipeline. Experiments are conducted on an Indonesian tourism dataset, with performance evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and execution time. The results show that the proposed method consistently outperforms the rating-based baseline, achieving lower MAE (1.6994 vs. 1.7355) and RMSE (2.0653 vs. 2.1148), while maintaining comparable computational efficiency. Furthermore, the model demonstrates greater stability across varying neighbor sizes, indicating improved scalability and robustness. Practically, this approach provides a scalable and context-aware recommendation framework that can support more adaptive and personalized tourism services in Indonesia, particularly in real-world scenarios characterized by sparse and heterogeneous data.

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1. Introduction

Indonesia is an archipelagic country with many tourist destinations that are culturally and geographically attractive to travelers. Due to advances in information technology, especially in the digital era, the tourism sector must shift toward data-driven services [1]. Recommendations are a popular method for helping customers choose tourist destinations that match their preferences, needs, and characteristics. With the increasing availability of user and destination data, manual or static, information-based approaches are no longer effective for optimal travel decision-making [2][3]. Recommendation systems often use collaborative filtering, which leverages similar user behavior patterns or preferences [4]. This method is considered better at providing more relevant recommendations because it draws on the experiences of other users with similar features. Collaborative filtering has great potential for Indonesia's tourism sector due to the diverse preferences of tourists, including types of natural, cultural, religious, and man-made tourism, as well as demographic factors and travel behavior. However, the destination recommendation system still faces many problems when using collaborative filtering. The local context of the destination and limited user profile data are the most important [5]. In addition to collaborative filtering, content-based and hybrid filtering are recommendation system methods that have also been used by researchers in the field of tourism [6][7][8]. Generally, some researchers use only historical user rating data without examining user demographic data, such as user profiles. Additionally, many studies still rely on general datasets or simulations that do not adequately capture the specific characteristics of Indonesian tourism. Therefore, the tourism recommendation system has not yet fully met the needs of tourists [9].

Given these conditions, research on destination recommendation systems in Indonesia that use collaborative filtering enriched by user profile information remains relatively limited. User demographic characteristics, such as age, region of origin, travel interests, and travel patterns, significantly influence travel preferences; however, in many studies, these aspects have not been fully utilized or are still used in limited ways. Moreover, studies that comprehensively examine the performance of collaborative filtering on highly heterogeneous Indonesian tourism data remain rare, so potential issues such as high preference variation and data imbalance have not been fully addressed [10].

Despite the growing number of studies on tourism recommendation systems, several critical limitations remain. First, most prior works predominantly rely on rating-based collaborative filtering and tend to overlook the integration of rich user profile information, resulting in limited personalization capability, particularly in domains with high preference heterogeneity. Second, existing approaches often utilize generic or non-contextual datasets, which fail to capture the unique characteristics of Indonesian tourism, such as diverse cultural preferences, geographical variation, and travel behavior patterns. Third, although latent factor models such as Singular Value Decomposition (SVD) have been widely used to address data sparsity, their integration with user profile-based similarity measures is still fragmented and rarely evaluated within a unified framework. As a result, current systems often exhibit suboptimal performance, limited robustness, and poor adaptability when applied to sparse and imbalanced real-world tourism data.

To address these gaps, this study proposes a user profile-enriched collaborative filtering framework that integrates SVD, Jaccard similarity, and K-Nearest Neighbor (KNN) in a unified modeling pipeline. The main contribution of this research is threefold. First, it introduces a hybrid representation that combines latent factors with user demographic profiles to improve recommendation accuracy under sparse data conditions. Second, it provides a contextual evaluation using an Indonesian tourism dataset, enabling a more realistic assessment compared to prior studies that rely on generic datasets. Third, it offers a comprehensive performance analysis across multiple evaluation metrics, including MAE, RMSE, and execution time, to demonstrate the trade-off between accuracy and computational efficiency. The purpose of this research is to assess the effectiveness of an Indonesian tourist destination recommendation system that uses user-profile-based collaborative filtering. Compared to conventional collaborative filtering methods that rely solely on ratings or interaction history, an analysis is conducted to determine how well the recommendations made thru user profile integration perform. As a result, this research is expected to provide a clearer picture of how effective these techniques are at building a tourism recommendation system that better aligns with each individual's needs and preferences.

In this study, we investigate the potential use of user profile elements in the collaborative filtering process at Indonesian tourist destinations. By considering local characteristics and tourist behavior in Indonesia, this research adjusts the recommendation system model used. This approach differs from previous studies that generally apply generic recommendation methods without considering the local context of users. Additionally, this research not only builds the model but also analyzes the results of the recommendations produced. The findings of this research are expected to serve as a reference in the development of data-based tourism recommendation systems that are more contextual, adaptive, and capable of being tailored to various conditions and user needs.

2. Research Methodology

2.1. Research Flowchart

This research aims to analyze the performance of similarity algorithms in the collaborative filtering approach combined with user profile data. The methodology of this research consists of three stages: the first is the input stage, which involves determining the dataset to use. In this study, the main dataset is the Indonesian tourism dataset from the public Kaggle repository [11]. Next, the dataset undergoes preprocessing to prevent distortion. The second stage of the process, after the dataset is ready, is to be processed using Singular Value Decomposition (SVD) [12], continued calculating user profile similarity using the Jaccard similarity method [13] until the next prediction process using the K-nearest Neighbor (KNN) method [14]. Finally, the analysis uses evaluation metrics aimed at assessing the accuracy of the travel recommendation system using the Mean Absolute Error (MAE) metric [15], and Root Mean Square Error (RMSE) [16], and execution time [17]. The flow of this research method is presented in Figure 1.

2.2. Dataset

At the initial stage, the Indonesian tourism dataset was collected and prepared as the primary data source for this study. The dataset consists of three main components: user information, tourist destination data, and user–destination interactions. User information includes basic attributes that represent individual characteristics, while the tourist destination data contains information related to various types of attractions. The interaction data captures user preferences in the form of ratings or visit histories, which serve as the basis for modelling user behaviour.

The dataset reflects the diversity of tourism preferences in Indonesia, encompassing various categories such as natural, cultural, and man-made destinations. This heterogeneity makes the dataset suitable for evaluating recommendation systems in a real-world context, particularly in handling variations in user preferences and interactions across different types of destinations. Furthermore, the structure of the dataset enables the representation of relationships between users and destinations in a matrix form, where each interaction indicates the level of user preference toward a specific destination.

2.3. Method

This study employs a collaborative filtering framework that integrates dimensionality reduction, similarity computation, and neighborhood-based prediction. The overall method consists of three main stages: latent factor extraction using Singular Value Decomposition (SVD), similarity measurement, and neighbor selection using K-Nearest Neighbor (KNN). In the first stage, dimensionality reduction is performed using Singular Value Decomposition (SVD) to address the sparsity problem in the user–destination interaction matrix. Given a rating matrix RRR, SVD decomposes it into three matrices as follows:

$$R = U\Sigma V^T \quad (1)$$

where U represents the user latent factor matrix, Σ is a diagonal matrix containing singular values, and V^T represents the latent factor matrix of tourist destinations. By retaining only the top-k singular values, the model obtains a low-dimensional latent representation that captures the most significant underlying patterns of user preferences and destination characteristics.

In the second stage, similarity between users (or destinations) is computed based on their latent representations. Cosine similarity is employed to measure the similarity between two latent vectors, defined as:

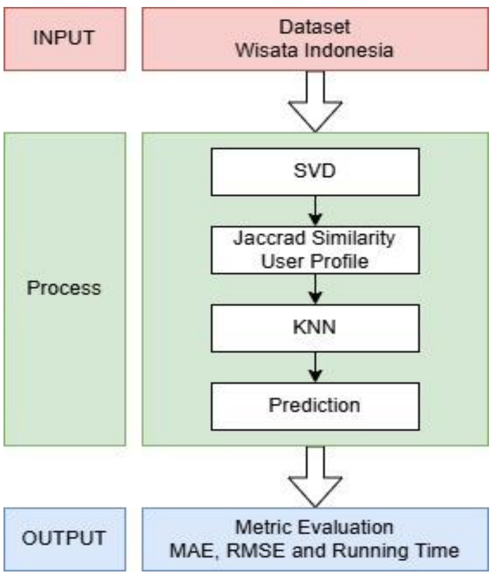

Figure 1. Research Flowchart

$$\text{Sim}(a,b) = \frac{a \cdot b}{\| a \| \times \| b \|} \quad (2)$$

where a and b denote the latent vectors of two users or destinations. The similarity value ranges from 0 to 1, where higher values indicate greater similarity.

In the final stage, the K-Nearest Neighbor (KNN) method is applied to identify the most relevant neighbors for a target user. Based on the computed similarity scores, the top-k most similar users (or destinations) are selected. These neighbors are then used as the basis for predicting unknown ratings, under the assumption that similar users exhibit similar preference patterns. This integrated approach enables the model to leverage both latent structural information (via SVD) and local similarity relationships (via KNN), thereby improving the robustness and accuracy of the recommendation process, particularly in sparse data environments.

2.4. Testing

The evaluation stage is conducted to assess the performance of the proposed recommendation system in predicting user preferences. In this stage, the model generates predicted ratings for user–destination pairs that are not observed in the training data. The prediction process is based on the ratings of the selected nearest neighbors, weighted by their similarity scores. The predicted rating for user uuu on destination iii is computed as:

$$\hat{r}_{u,i} = \frac{\sum_{v \in N(u)} \text{Sim}(u,v) \times r_{v,i}}{\sum_{v \in N(u)} | \text{Sim}(u,v) |} \quad (3)$$

where $\hat{r}_{u,i}$s the predicted rating of user u toward destination i, $N(u)$ is the set of nearest neighbors of the user u, $\text{Sim}(u,v)$the similarity score between users u and v, serta $r_{v,i}$ is the rating given by user v toward destination i.

To measure the performance of the generated recommendation system, an evaluation is conducted using several metrics. Mean Absolute Error (MAE) is used to measure the average absolute error between actual ratings and predicted ratings, which is formulated as:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} | r_i - \hat{r}_i | \quad (4)$$

Additionally, Root Mean Square Error (RMSE) is used to impose a greater penalty on larger prediction errors, with the formula:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (r_i - \hat{r}_i)^2} \quad (5)$$

Furthermore, computational efficiency is evaluated by measuring the execution time of the recommendation process. This metric is essential to assess the feasibility of the proposed method in real-world applications, where response time is a critical factor.

3. Results and Discussions

3.1. Results

The experimental results show that increasing the number of nearest neighbors (k) significantly affects the recommendation system's accuracy in both tested approaches: the Jaccard method based on ratings and the proposed SVD + Jaccard method based on user profiles. At relatively small k values, both methods still produce relatively high errors, as measured by MAE and RMSE. This condition indicates that the limited number of neighbors is not yet able to adequately represent user preferences. With a small number of neighbors, the recommendation system relies on information from only a small subset of similar users, which can lead to rating predictions influenced by noise and high individual variation. As a result, the stability of predictions has not yet been optimally achieved at this stage. As k increases, the MAE and RMSE for both methods show a consistent downward trend. This decrease indicates that the more neighbors involved in the prediction process, the richer the preference information the system can use. With a wider coverage of neighbors, the system can aggregate similar preference patterns, thereby gradually reducing prediction errors.

This phenomenon aligns with the basic principle of collaborative filtering, where the quality of recommendations is greatly influenced by the quantity and diversity of information sources from other relevant users. However, in the Jaccard method based on ratings, the trend of error reduction begins to slow and tends to plateau in the k range of 80 to 100. In this range, the MAE and RMSE values no longer improve significantly, even though the number of neighbors continues to increase. This indicates that adding neighbors at that stage no longer provides relevant information for the prediction process. The additional neighbors involved tend to be less similar, making the information they contribute redundant or even introducing noise. Thus, the pure rating-based method has limitations when the number of neighbor increases and the data structure becomes sparser, as the homogeneity of preferences among users decreases. Unlike the aforementioned approach, the proposed SVD + Jaccard method based on user profiles shows more stable and consistent performance across the entire range of k values. Although at small k values this method produces slightly higher MAE and RMSE than the Jaccard method based on ratings, the error reduction is sharper at medium to large k values.

This condition indicates that integrating latent factors from SVD decomposition with user profile information yields increasingly significant contributions as the number of neighbors increases. The latent representation produced by SVD can capture hidden preference patterns not directly reflected in the rating data, making user similarities more meaningful and informative. Moreover, using user profiles allows the recommendation system to consider relevant non-rating characteristics, such as users' interests and general preferences. With this combination, the system becomes more robust to data sparsity, a common characteristic of the tourism domain. When the number of neighbors increases, the proposed method not only relies on explicit similarity based on ratings but also utilizes latent structures and user profile context, resulting in more stable and accurate predictions. Quantitatively, the superiority of the proposed method is reflected in lower average MAE and RMSE than the rating-based Jaccard method. The average MAE for the rating-based method was recorded at 1.7355, while the SVD + Jaccard method based on user profiles achieved an average MAE of 1.6994. A similar pattern is observed in the RMSE values: the rating-based method had an average RMSE of 2.1148, while the proposed method achieved a lower value of 2.0653.

Although the difference in values is not significant, the consistent reduction in errors across the entire range of k values indicates that the user profile-based approach yields a stable, sustainable improvement in recommendation quality. From the perspective of a tourist destination recommendation system, this finding has important implications. The tourism domain is generally characterized by limited rating data and high variability in user preferences, so relying solely on ratings often yields suboptimal recommendations. The results of this study indicate that integrating user profile information with latent factors from SVD can reduce this dependency and help the system capture more complex preference patterns. Thus, the recommendation system becomes more adaptive to differences in user characteristics and better able to provide relevant, personalized travel destination recommendations. Overall, this analysis confirms that the SVD + Jaccard method based on user profiles not only excels in average accuracy but also shows greater performance stability as the number of neighbors increases. This reinforces the argument that enriching user representation thru latent factors and contextual profiles is an effective approach to improving the quality of tourism recommendation systems. A comparison of MAE and RMSE for both methods across various k values is shown in Figures 2 and 3, clearly illustrating the trend of error reduction and performance differences between the approaches. In addition to accuracy, the aspect of computational efficiency was also analyzed thru the measurement of average execution time. The test results show that both methods have relatively comparable execution times, as shown in Table 1.

These results indicate that adding an SVD decomposition stage and using user profiles do not significantly increase computation time. Thus, the proposed method not only improves recommendation accuracy but also remains efficient in terms of execution time. This is an important advantage in developing a tourism destination recommendation system for real-world applications, where system efficiency and responsiveness are crucial.

Table 1. Average Running Time

Method	Average Execution Time (seconds)
Jaccard (Rating Based)	1,3259
SVD + Jaccard (User Profile)	1,3226

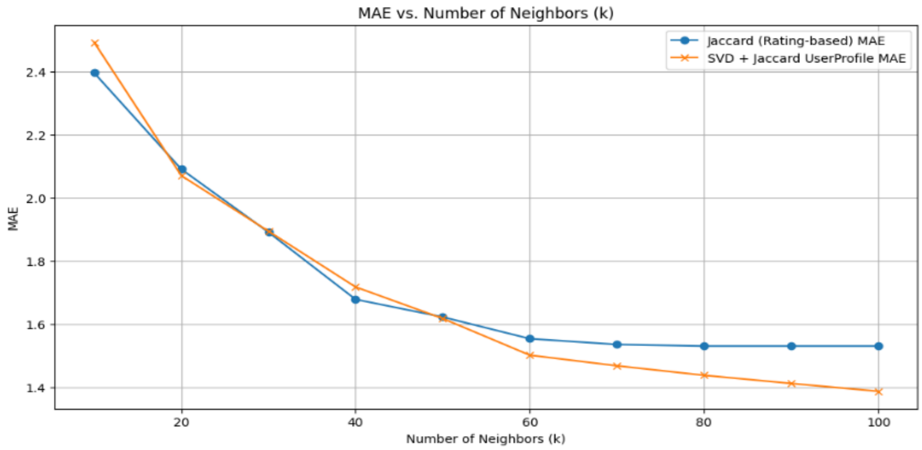

Figure 2. Mean Absolute Error (MAE) Results

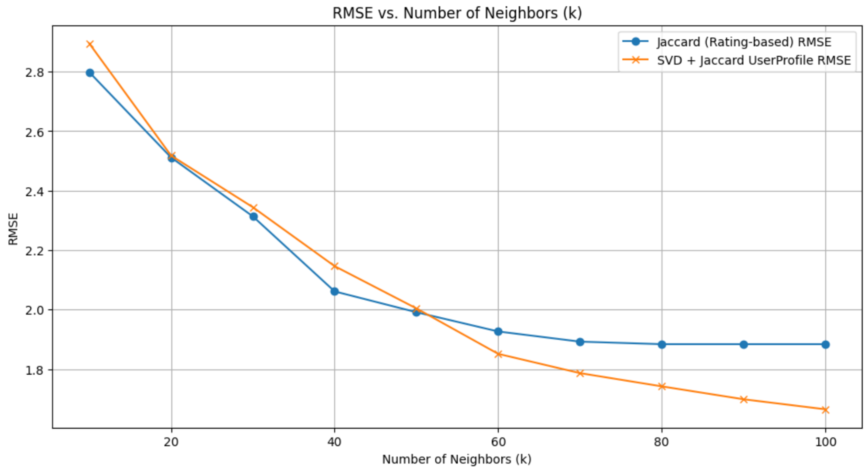

Figure 3. Root Mean Square Error (RMSE) Results

3.2. Discussions

The experimental results demonstrate that the proposed user profile-enriched collaborative filtering approach consistently achieves better performance compared to the conventional rating-based method. This improvement can be analytically explained by the complementary roles of latent factor modeling and user profile information. The SVD component effectively reduces sparsity by projecting the user–item interaction matrix into a lower-dimensional latent space, enabling the model to capture hidden preference structures that are not explicitly observable in the rating data. At the same time, the incorporation of user profile similarity using Jaccard coefficient introduces contextual information that enhances the semantic meaning of user similarity. This combination allows the system to generate more informative and stable neighborhood relationships, particularly when dealing with sparse and heterogeneous data.

A key finding of this study is the difference in performance behavior as the number of nearest neighbors (k) increases. In the rating-based approach, the improvement in MAE and RMSE tends to plateau at higher k values, indicating that additional neighbors contribute less relevant information and may introduce noise. In contrast, the proposed method maintains a more stable performance trend across varying k values. This suggests that the integration of latent factors and user profiles improves the robustness of similarity measurement, allowing the model to better filter out irrelevant neighbors even when k increases. This behavior is particularly important in real-world recommendation systems, where selecting an optimal k is often challenging due to data variability.

Another important insight is related to the trade-off between accuracy and computational efficiency. The results show that the proposed method achieves improved accuracy without a significant increase in execution time. This indicates that the additional computational cost introduced by SVD and user profile processing is effectively balanced by the reduction in noise and improved convergence of similarity calculations. From a system design perspective, these finding highlights that enhancing model complexity does not necessarily compromise efficiency if the added components contribute meaningful information.

From a domain-specific perspective, the results confirm that tourism recommendation systems require more than purely interaction-based modeling. The high diversity of tourist preferences—shaped by demographic, cultural, and behavioral factors—makes it essential to incorporate contextual user information. The proposed approach demonstrates that combining latent representations with user profiles can better capture this complexity, resulting in more adaptive and personalized recommendations. This finding reinforces the importance of context-aware recommendation strategies, particularly in domains characterized by high variability and limited interaction data.

Despite these contributions, several limitations remain. First, the dataset used in this study is relatively limited in scale and may not fully represent the diversity of real-world tourism data in Indonesia. Larger and more heterogeneous datasets could further validate the robustness of the proposed approach. Second, the user profile features considered in this study are still relatively basic and may not capture more complex behavioral patterns, such as temporal dynamics, travel sequences, or contextual factors like seasonality. Third, the model relies on traditional similarity and neighborhood-based methods, which may have limitations in capturing highly non-linear relationships compared to deep learning-based approaches. Therefore, future research can extend this work by incorporating richer contextual features, such as temporal and spatial information, and by exploring advanced models such as deep learning or hybrid architectures. Additionally, evaluating the system using user-centric metrics, such as user satisfaction or ranking-based measures (e.g., Precision, Recall, or NDCG), would provide a more comprehensive assessment of recommendation quality in real-world applications.

4. Conclusion

Based on the experimental results, it can be concluded that increasing the number of nearest neighbors (value k) significantly affects the accuracy of the recommendation system in both tested approaches: the Jaccard-based approach on ratings and the proposed SVD + Jaccard-based approach on user profiles. At low k values, both methods yield relatively high MAE and RMSE due to the limited preference information used in the prediction process. As k increases, the errors in both methods consistently decrease, indicating that including more neighbors can enrich user preference information.

However, the Jaccard rating-based method tends to stagnate at high k values, where adding more neighbors no longer yields a significant increase in accuracy. On the other hand, the SVD + Jaccard method based on user profiles shows more stable and consistent performance across the entire range of k values, with a sharper decrease in error at medium to high k values. Quantitatively, the proposed method yields lower average MAE and RMSE values compared to rating-based methods, indicating that the integration of SVD latent factors and user profile information is capable of development from this research can be conducted using larger and more varied datasets, and deep learning-based research can be carried out by integrating tourism-related content such as location and visit time, in order to enhance the adaptability and accuracy of the tourism recommendation system.

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