International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Mathematical Modelling of Engineering Problems
Vol. 11, No. 7, July, 2024, pp. 1922-1928
Journal homepage: http://iieta.org/journals/mmep

Comparison of User Based and Item Based Collaborative Filtering in Restaurant Recommendation System

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Kurniawan Eka Permana

Department of Informatics, University of Trunojoyo Madura, Bangkalan 69162, Indonesia

Corresponding Author Email: kurniawan@trunojoyo.ac.id

https://doi.org/10.18280/mmep.110723

Received: 5 December 2023
Revised: 18 March 2024
Accepted: 30 March 2024
Available online: 31 July 2024

Keywords:
collaborative filtering, recommendation system, tourism recommendation system, User-Based, Item-Based

ABSTRACT

In today's rapidly evolving digital landscape, the success of the restaurant industry hinges not only on culinary excellence but also on the ability to deliver personalized and memorable dining experiences. To achieve this, recommendation systems have emerged as indispensable tools, with Collaborative Filtering standing out as a promising method. This study aims to assess the effectiveness of Item-Based and User-Based methodologies within the context of a restaurant recommendation system. The research methodology involves loading and manipulating data within a matrix framework, followed by normalization. Both Item-Based and User-Based approaches are then applied to the normalized matrix, using Pearson Correlation and Cosine Similarity as comparative metrics. Through a comprehensive evaluation, the study identifies the User-Based technique as superior, demonstrating a Pearson Correlation coefficient of 0.012391 and yielding the lowest Mean Absolute Error (MAE) value. Furthermore, analysis using Spearman correlation data reveals significant correlations within the User-Based approach algorithm, with a notable proportion falling within specific ranges. Specifically, 50% of correlations fall within the ranges of 0.96-0.99 and 0.96-0.97. These findings underscore the effectiveness of the User-Based approach in refining the precision and reliability of restaurant recommendations, particularly when compared to the Item-Based approach. In conclusion, this research sheds light on the efficacy of different recommendation methodologies within the restaurant industry's digital landscape. The findings have implications for enhancing personalized dining experiences and improving the overall customer satisfaction within the industry.

1. INTRODUCTION

In today's dynamic and digitally-driven era, the restaurant industry has transcended its traditional role of merely serving delectable cuisine. It now pivots towards curating bespoke and unforgettable dining encounters tailored to the unique preferences of each patron. In this pursuit of personalized service, recommendation systems have emerged as indispensable assets for both consumers seeking tailored dining experiences and restaurant managers aiming to enhance customer satisfaction and loyalty. Among the various recommendation systems, Collaborative Filtering stands out as a particularly potent tool [1-3].

The notion of collaborative filtering is based on the premise that users who have demonstrated similar preferences or behaviors in the past might provide useful insights into the preferences of a target user. In the context of restaurant, this means that users who share same interests or have visited similar restaurant may help steer others toward options that match their preferences.

There are two types of collaborative filtering: User-Based and Item-Based. User-Based Collaborative Filtering is based on locating users who display similar patterns of behavior to the individual in question [4, 5]. After identifying comparable users, the algorithm offers restaurant-related things based on the tastes of these 'neighboring' users. It's a suggestion system that stresses personalisation and taps into the collective expertise of people.

On the other hand, Item-Based Collaborative Filtering focuses on establishing connections between restaurant-related items based on user interactions. By detecting similarities between products and recommending goods that closely resemble those previously favored by the user, this approach prioritizes item characteristics over extensive user data, thereby offering better scalability and resilience in addressing the "cold start" problem commonly encountered in recommendation systems [6, 7]. However, it may deliver less tailored recommendations than the User-Based method.

Meanwhile, the selection of similarity measures, such as Cosine Similarity and Pearson Correlation, is critical in influencing the efficiency of these Collaborative Filtering in this recommendation system [8, 9]. The purpose of this research is to disentangle the complexities of these collaborative filtering approaches, as well as the impact of Cosine Similarity and Pearson Correlation on a restaurant recommendation system. We hope to provide insights into which combination of method and metric is most effective for suggesting restaurants by systematically comparing User-

Based and Item-Based approaches and the respective similarity metrics, thereby contributing to an improved dining experience for patrons and facilitating the restaurant industry's success.

2. LITERATURE REVIEW

User-Based Collaborative Filtering is a recommendation methodology that operates on the premise of personalizing suggestions through the analysis of user behavior and preferences [10, 11]. It hinges on the principle that individuals who have exhibited akin interests and behaviors in the past are predisposed to share similar preferences in the future. This approach entails the computation of user similarity by scrutinizing prior interactions, encompassing actions like ratings, reviews, or purchase history. Subsequently, recommendations are tailored based on the preferences and choices of analogous users. By leveraging the collective wisdom of individuals with comparable tastes and behaviors, User-Based Collaborative Filtering aims to offer recommendations that are attuned to the unique preferences of each user. Through this process, the system endeavors to enhance user satisfaction and engagement by providing personalized and relevant suggestions, thus augmenting the overall user experience within the recommendation ecosystem.

1. In the realm of restaurant recommendation systems, User-Based Collaborative Filtering emerges as a pivotal tool, leveraging the collective wisdom of users with similar dining preferences to curate tailored suggestions. Its relevance is underscored by its ability to analyze past interactions, such as restaurant visits, ratings, and reviews, to identify patterns and trends among users, thereby facilitating the delivery of recommendations that resonate with each individual's unique tastes [12, 13].

2. User-Based collaboration for personalized dining suggestions filtering meticulously scrutinizes a user's dining history, including past meal selections, ratings, and reviews. By identifying users with akin tastes, it suggests eateries that have garnered approval from these similar users, thereby enhancing the dining experience through tailored recommendations aligned with individual preferences [14]. This level of customization significantly enhances the dining experience for users, ensuring that they receive recommendations tailored specifically to their tastes and preferences. As a result, users are more likely to discover and enjoy dining options that align perfectly with their individual preferences, leading to greater satisfaction and enjoyment overall.

3. Improved user pleasure [15]. By suggesting eateries that align with an individual's interests and preferences, this technique amplifies user satisfaction and loyalty. Users are inclined to trust and revisit a restaurant recommendation platform that consistently caters to their preferences. This fosters a sense of reliability and connection, enhancing user engagement and long-term loyalty to the platform.

4. User-Based Collaborative Filtering introduces individuals to new culinary delights by facilitating the discovery of novel dining experiences. By analyzing user preferences and behaviors, this technique recommends restaurants and cuisines that users may not have encountered before, broadening their culinary horizons and enriching their dining experiences with exciting new options [12, 14, 15]. It suggests restaurants not only with similar cuisines or menu items, but also with similar ambience, price, and service quality, widening consumers' eating horizons.

5. Personalized suggestions derived from User-Based Collaborative Filtering actively engage users, motivating them to explore fresh dining alternatives and regularly make reservations through the platform. By tailoring recommendations to individual preferences, users feel valued and empowered to discover new culinary experiences, fostering a sense of excitement and anticipation that drives frequent engagement with the site [15].

Conversely, Item-Based Collaborative Filtering is a recommendation approach reliant on item similarity rather than user similarity. It operates on the principle that users demonstrating a preference for a particular item, such as a restaurant or meal, are likely to favor related items. To generate recommendations, this strategy identifies associations between objects, often employing methods like Cosine Similarity or Pearson Correlation to establish connections and offer personalized suggestions.

1. Item-Based Collaborative Filtering might propose comparable restaurants or meals to what a user has previously loved in the context of restaurants [15-17]. For example, if a customer often dines at Italian restaurants, the system may recommend additional Italian restaurants with comparable features.

2. It can also deliver various suggestions by detecting objects that have certain characteristics with the user's interests. This guarantees that the consumer is exposed to a wide range of eating experiences, which is especially significant in the restaurant business, where culinary and ambience diversity is valued.

3. Item-Based Collaborative Filtering can handle "cold start" issues, where new eateries with little or no user contact history must be recommended [18]. The algorithm may efficiently propose new restaurants by assessing item-item correlations based on factors such as cuisine type, price range, location, and reviews.

4. Item-Based Collaborative Filtering can be used to supplement User-Based Filtering in restaurant recommendation systems [19]. Item-Based Filtering focuses on the intrinsic traits and links of restaurants and meals, whereas User-Based Filtering is based on user preferences and their resemblance.

Previous research suggests that both User-Based Collaborative Filtering and Item-Based Collaborative Filtering have distinct advantages in the context of restaurant recommendation systems [12, 13, 19]. While User-Based Collaborative Filtering excels in providing personalized recommendations based on user behavior, Item-Based Collaborative Filtering is effective in addressing the "cold start" problem and complementing User-Based Collaborative Filtering by focusing on item similarities. By incorporating these insights, the current study aims to provide a comprehensive comparison of User-Based Collaborative Filtering and Item-Based Collaborative Filtering methodologies and their respective implications for restaurant recommendation systems.

Meanwhile, in User-Based or Item-Based Collaborative Filtering, typical similarity metrics include Cosine Similarity or Pearson Correlation [8, 9]:

1. Cosine Similarity: The Cosine Similarity metric is used to compare the similarity of two non-zero vectors in a multidimensional space. It computes the cosine of the angle formed by these vectors and returns a number between -1 and 1. Cosine Similarity is used in the context of recommendation

systems, especially restaurant recommendation systems, to analyze the similarity of users, things, or any combination of qualities or attributes.

The Cosine Similarity between two vectors A and B is obtained mathematically as:

$$cosine\_similarity\ (A, B) = \frac{A.B}{\|A\|.\|B\|} \tag{1}$$

where, $A.B$ represents the dot product of vectors A and B; $\|A\|.\|B\|$ represent the magnitudes (or lengths) of vectors A and B.

2. Pearson Correlation, often known as Pearson's r, is a metric for determining the linear relationship between two sets of data points. It examines how two variables, X and Y, move in a linear pattern. Pearson Correlation is used in restaurant recommendation systems to assess the correlation between user preferences or interactions with products (restaurants).

$$pearson\_correlation\ (A, B) = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 (Y_i - \bar{Y})^2}} \tag{2}$$

where, X_i and Y_i are data points (e.g., user ratings or interactions); $\bar{X}$ and $\bar{Y}$ are the means of X and Y, respectively.

By assessing the similarity between items or users, Cosine Similarity and Pearson Correlation are important in User-Based or Item-Based Collaborative Filtering [8, 20]. Based on user interactions and traits, these metrics are utilized to identify related things, allowing the system to deliver appropriate restaurant recommendations that correlate with a user's prior tastes and features of previously appreciated restaurants or dishes. The choice of these similarity measures is determined by the recommendation system's unique requirements and features.

Existing research on User-Based and Item-Based Collaborative Filtering in restaurant recommendation systems has provided valuable insights into their effectiveness [12, 13, 19]. However, several limitations have been identified, which our study aims to address.

One limitation of previous studies is the lack of comprehensive comparison between User-Based and Item-Based Collaborative Filtering methodologies. While some research has focused on the strengths and weaknesses of each approach individually, few studies have conducted a direct comparison to determine which method is more effective in the context of restaurant recommendations.

Our study addresses these limitations by conducting a comprehensive comparison of User-Based and Item-Based Collaborative Filtering methodologies within the context of restaurant recommendation systems. We utilize a diverse and extensive dataset containing real-world user interactions and restaurant attributes to ensure the robustness and validity of our findings.

Furthermore, by incorporating both Cosine Similarity and Pearson Correlation in our research methodology, we are able to compare their performance and effectiveness in the context of restaurant recommendation systems. This comparative analysis allows us to evaluate the strengths and weaknesses of each similarity measure and determine which approach yields more accurate and reliable recommendations.

3. RESEARCH METHODOLOGY

The recommendation system used in this study is depicted in Figure 1.

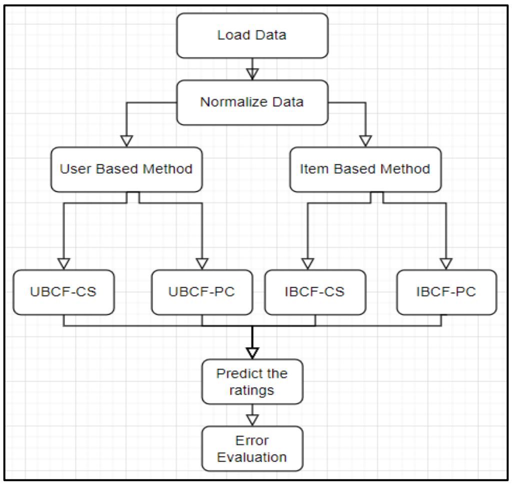

Figure 1. Proposed method

1. Load data

For our study, we utilize the Yelp dataset sourced from Kaggle, a widely used platform for accessing datasets. The dataset we employ is freely accessible at the following link: (http://www.kaggle.com) [21]. Specifically, our analysis focuses on importing the yelp_academic_dataset_review.json file from this dataset. This file contains a wealth of review data pertinent to our research objectives, enabling us to conduct a thorough examination of User-Based and Item-Based Collaborative Filtering methodologies within the context of restaurant recommendations.

Before commencing analysis, preprocessing of the data is imperative to ensure that our focus remains solely on restaurants within the dataset. By refining the dataset to exclusively encompass restaurant-related information, we can facilitate a more targeted and meaningful analysis. This preprocessing stage involves several steps:

- The choice of Tucson as the study site is deliberate, considering its vibrant culinary scene and the presence of renowned establishments such as "Prep & Pastry" among others. This selection ensures a diverse and representative sample of restaurant data for analysis.
- From the dataset, three key attributes are selected for analysis: *user_id*, *business_id*, and *stars*. These attributes provide essential information for examining user interactions with restaurants, including user preferences and ratings.
- Upon selecting the relevant restaurant data from Tucson, preprocessing steps are applied to ensure data quality and relevance. This includes filtering out non-restaurant entities and cleaning the data to remove any inconsistencies or errors.
- Furthermore, to facilitate the comparison between User-Based or Item-Based Collaborative Filtering methodologies, the dataset is structured to represent user-item interactions. Specifically, the data is organized into a matrix format where rows represent users, columns represent restaurants, and cells contain corresponding ratings or interactions. In cases where a user has not provided a rating for a restaurant, the matrix cell will display 'NaN', indicating missing data.

2. Normalize data

To account for variations in rating behavior among users, we normalize the matrix by computing the average rating of each user. This normalization step helps to mitigate biases introduced by users who consistently provide higher or lower ratings than others. After normalization, restaurants with ratings lower than the user's average are assigned negative values, while restaurants with ratings higher than the user's average are assigned positive values. This adjustment ensures that ratings are balanced across users and facilitates fair comparisons between restaurants based on user preferences.

By normalizing the matrix in this manner, we aim to create a standardized representation of user-item interactions that accounts for individual user tendencies and preferences. This normalized matrix serves as the foundation for implementing collaborative filtering algorithms and conducting comparative analyses between User-Based and Item-Based recommendation approaches.

3. Calculate similarity with Cosine Similarity or Pearson Correlation

a. User based collaborative filtering - Cosine Similarity (UBCF-CS)

We calculated Cosine Similarity to measure how similar user preferences are to other user's preferences.

b. User based collaborative filtering - Pearson Correlation (UBCF-PC)

We used Pearson Correlation to determine how closely one user's preferences match those of other users.

c. Item based collaborative filtering - Cosine Similarity (IBCF-CS)

The Cosine Similarity measure is used in this technique to compute similarities between two restaurants.

d. Item based collaborative filtering - Pearson Correlation (IBCF-PC)

The Pearson Correlation is calculated to measure correlation between two restaurants.

e. Predict ratings

In this phase, a selection of restaurants will be selected to recommend to the target user. The recommended restaurants are determined by the average of the user similarity score and restaurant rating. Restaurants with a higher degree of similarity are given more rank in the restaurant list suggestion.

f. Error evaluation

The mean absolute error (MAE) is one of the most commonly used metrics for validating continuous variable correctness. These measurements tell us how accurate our forecasts are and how much they differ from the actual numbers. The MAE is used to validate a model's error rate while predicting a numerical result. The smaller the MAE score, the more accurate the model is at predicting.

$$MAE = \frac{\sum_{i=1}^{N} |y_i - \hat{y}|}{N} \quad (3)$$

where, Y_i=actual value of y; $\hat{y}$=predicted value of y; N=amount of data.

Meanwhile, Spearman correlation will be used to compare between true rank and predicted rank. Spearman's rank correlation is a way of comparing two variables by assigning rankings to them and then calculating their correlation. A Spearman's rank correlation coefficient has a value between 1 and +1. When the rank of one variable grows, the rank of the other variable similarly increases in the case of '1'. When the rank of one variable grows, the rank of the other variable drops. When '0' is used, the rank of one variable does not correspond with the rank of the other variable.

$$S = 1 - \frac{6 * \sum D^2}{n * (n^2 - 1)} \quad (4)$$

The Spearman's rank correlation coefficient is shown in Formula (4). D is the difference in the ranks of two variables, and n denotes the sample size.

4. EXPERIMENTAL RESULT

In this part, we validate the error of the UBCF-CS, UBCF-PC, IBCF-CS, and IBCF-PC algorithms using the MAE. The error performance of the algorithms is contrasted in order to forecast and achieve a Top-N recommendation.

4.1 Comparison of algorithms

The MAE performance of each method is depicted in Figure 2. Every process also follows a predetermined procedure that includes six different scenarios for the number of neighbors. The number of neighbors is 10, 20, 30, 40 and 50.

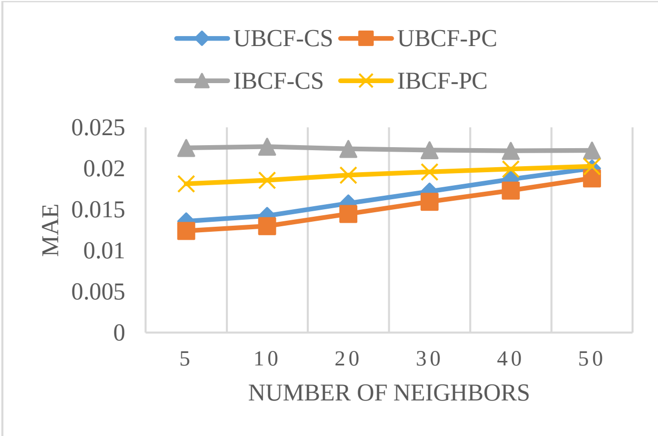

Figure 2. MAE performance

Many instances are meticulously studied to evaluate the recommendation system, each with a different number of top neighbors included in the prediction process. Table 1 displays the algorithm performance as measured by the MAE value.

Table 1. MAE performance on each algorithm

NoN	UBCF-CS	UBCF-PC	IBCF-CS	IBCF-PC
5	**0,013563**	**0,012391**	0,022493	**0,018125**
10	0,014226	0,012977	0,022652	0,018575
20	0,015732	0,014449	0,022386	0,019174
30	0,017188	0,015945	0,02224	0,019571
40	0,01866	0,017295	**0,022146**	0,019915
50	0,020004	0,01881	0,022188	0,020251

Notes: NoN is an abbreviation for the number of neighbors.

The MAE values for UBCF-CS, range from 0.013563 to 0.020004 across different NoN values. Generally, UBCF-CS performs reasonably well, with lower MAE values compared to some other configurations.

The MAE values for UBCF-PC, range from 0.012391 to 0.01881 across different NoN values. UBCF-PC generally exhibits lower MAE values compared to UBCF-CS, indicating slightly better predictive accuracy.

Meanwhile, the MAE values for IBCF-CS, range from 0.022493 to 0.022188 across different NoN values. IBCF-CS consistently has higher MAE values compared to both UBCF configurations, suggesting lower predictive accuracy.

On the other hand, the MAE values for IBCF-PC, range from 0.018125 to 0.020251 across different NoN values. Similar to IBCF-CS, IBCF-PC also exhibits higher MAE values compared to UBCF configurations.

Overall, the results suggest that UBCF-PC tends to outperform other configurations in terms of predictive accuracy, as it consistently yields lower MAE values across different NoN values.

The MAE values exhibit clear trends across different configurations and NoN values. For example, both UBCF-PC and IBCF-PC consistently yield lower MAE values compared to their counterparts using Cosine Similarity (CS). This trend highlights the influence of similarity metrics on recommendation accuracy.

By varying the number of neighbors considered in the collaborative filtering algorithms, the study evaluates how algorithm performance changes with different levels of neighborhood size. This sensitivity analysis provides valuable insights into the optimal NoN value for each algorithm configuration.

While the MAE values provide a relative measure of prediction accuracy within the study's context, they do not offer an absolute benchmark for evaluating the overall effectiveness of the recommendation algorithms. Without a reference point, it is challenging to assess whether the observed MAE values represent satisfactory performance levels in real-world scenarios.

4.3 Comparison of spearman correlation

Subsequently, a comprehensive Spearman correlation comparison was conducted, following matrix normalization, to further assess the performance of each algorithm. The results of this comparison are visually represented in Figure 3. Notably, User-Based Collaborative Filtering with Cosine Similarity (UBCF-CS) and User-Based Collaborative Filtering with Pearson Correlation (UBCF-PC) exhibited median Spearman correlations of 0.980372426 and 0.980281616, respectively. These findings underscore the robust consistency and reliability of both User-Based approaches in generating restaurant recommendations.

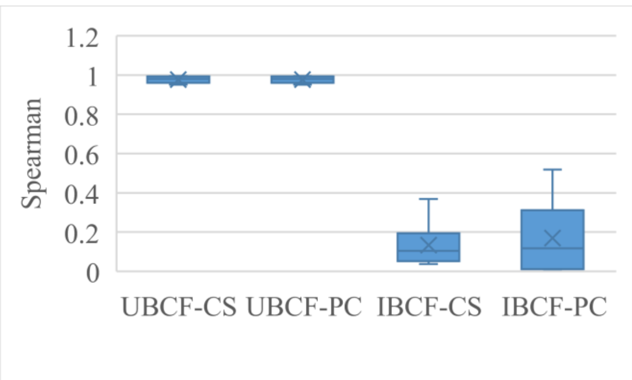

Figure 3. Spearman correlation between methods

In contrast, the Item-Based method displayed markedly lower median Spearman correlation values, with UBCF-CS and UBCF-PC showcasing median correlations of 0.103881168 and 0.116378504, respectively. This substantial disparity highlights the inherent limitations of Item-Based collaborative filtering techniques in achieving consistency and accuracy in recommendation generation.

Further analysis of the interquartile ranges provides additional insights into the variability and spread of the Spearman correlation values. UBCF-CS demonstrated a narrow interquartile range of 0.961331266 to 0.992486325, indicating a high degree of consistency in its recommendation outputs. Conversely, UBCF-PC exhibited a slightly wider interquartile range of 0.961468421 to 0.977996966, yet still maintained a robust level of consistency and reliability in its recommendations.

On the other hand, the Item-Based collaborative filtering methods, both with Cosine Similarity (IBCF-CS) and Pearson Correlation (IBCF-PC), displayed considerably broader interquartile ranges. IBCF-CS showed an interquartile range spanning from 0.051408117 to 0.311813922, indicative of greater variability in recommendation outputs compared to the User-Based approaches. Similarly, IBCF-PC showcased an interquartile range ranging from 0.011036075 to 0.139586024, underscoring the inherent challenges associated with achieving consistency and reliability in Item-Based recommendation generation.

Overall, the Spearman correlation comparison reaffirms the superiority of User-Based collaborative filtering methodologies, particularly those utilizing Cosine Similarity and Pearson Correlation, in delivering consistent and reliable restaurant recommendations. These findings underscore the importance of leveraging user-centric approaches to enhance recommendation accuracy and user satisfaction within restaurant recommendation systems.

The Spearman correlation comparison provides valuable insights into the consistency and reliability of the collaborative filtering algorithms in generating restaurant recommendations. Let's discuss the implications of the results:

Strengths of User-Based Collaborative Filtering (UBCF):

i. Both UBCF-CS and UBCF-PC exhibit high median Spearman correlations, indicating strong monotonic relationships between the predicted and actual rankings of restaurant preferences.
ii. The narrow interquartile ranges for UBCF-CS and UBCF-PC suggest consistent performance across different subsets of the dataset, reflecting robustness and stability in recommendation accuracy.
iii. Weaknesses of Item-Based Collaborative Filtering (IBCF):
iv. In contrast to UBCF, the Item-Based methods (IBCF-CS and IBCF-PC) display significantly lower median Spearman correlations, indicating weaker monotonic relationships between predicted and actual rankings.
v. The wide interquartile ranges for IBCF-CS and IBCF-PC suggest variability in recommendation accuracy across different subsets of the dataset. This inconsistency may undermine user confidence in the recommendations provided by the Item-Based methods.

The Spearman correlation comparison provides valuable insights for algorithm selection in restaurant recommendation systems. System developers may favor User-Based collaborative filtering algorithms, such as UBCF-CS and UBCF-PC, over Item-Based methods to optimize recommendation accuracy and user experience.

5. CONCLUSION

In this study, we have undertaken a comprehensive evaluation of item- and User-Based approaches within the realm of restaurant recommendation systems. Our analysis has revealed compelling insights, with the User-Based Collaborative Filtering with Pearson Correlation (UBCF-PC) configuration emerging as the frontrunner in terms of predictive accuracy. Across various configurations and numbers of neighbors (NoN), UBCF-PC consistently demonstrated superior performance, boasting lower Mean Absolute Error (MAE) values compared to alternative methodologies.

The User-Based technique, specifically employing a Pearson Correlation coefficient of 0.012391, exhibited the most favorable MAE value upon comparison with its Item-Based counterpart. Moreover, our investigation into Spearman correlation data unveiled that User-Based approaches exhibit heightened consistency and reliability in generating restaurant recommendations when juxtaposed with Item-Based methods. Notably, the Spearman correlation analysis underscored a significant correlation within the User-Based approach, with approximately 50% of the correlations falling within the range of 0.96-0.99 and 0.96-0.97, reinforcing the algorithm's efficacy.

From a practical standpoint, our findings carry several implications for the development and optimization of restaurant recommendation systems. Firstly, prioritizing User-Based collaborative filtering algorithms, particularly those leveraging Pearson Correlation, may lead to more accurate and reliable recommendations. Enhanced recommendation accuracy, in turn, contributes to heightened user satisfaction and engagement with recommendation platforms, thereby enriching the overall user experience. Additionally, while MAE serves as a valuable metric for prediction accuracy, the incorporation of supplementary evaluation measures such as Spearman correlation allows for a more holistic assessment of recommendation system performance.

Looking ahead, we recommend further exploration into the underlying factors contributing to the performance disparities between User-Based and Item-Based collaborative filtering algorithms. Such investigations hold the potential to yield valuable insights for algorithm refinement and enhancement. Furthermore, the exploration of hybrid recommendation approaches, amalgamating the strengths of both User-Based and Item-Based methodologies, presents an avenue for advancing recommendation accuracy and robustness. By pursuing these avenues of research, we can continue to propel the evolution of restaurant recommendation systems, ultimately optimizing their efficacy and utility for end-users.

ACKNOWLEDGMENT

This work was supported by Research and Community Service Institutions, University of Trunojoyo Madura, Research of Penelitian Grup Riset, Penelitian Mandiri LPPM UTM.

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