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Advancing Diversity in Recommendation Systems Through Collaborative Filtering: A Focus on Media Content

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Abstract

A recommendation system provides suggestions based on user preferences, interests, or behavior. However, a major challenge is its tendency to generate monotonous recommendations, reducing diversity and limiting new user experiences. Therefore, increasing diversity is essential to enhance user experience and satisfaction while maintaining recommendation accuracy. This research proposes to apply collaborative filtering method, which focuses on item-based filtering using KNN. This method focuses on item similarity using cosine similarity. To enhance diversity, the system filters results based on similarity and rating thresholds. The evaluation results confirm that applying a similarity threshold increases recommendation diversity, as indicated by consistently higher individual diversity values. Clustering further enhances individual diversity. Findings show that the highest individual diversity with clustering reaches 0.5719, compared to 0.5706 without clustering. These improvements suggest potential applications in domains such as e-commerce and music recommendation systems.

Keywords: Recommendation system, diversity, KNN clustering, item based collaborative filtering

1. INTRODUCTION

A recommendation system assists users in selecting products or services that align with their preferences from a multitude of available choices. These systems address the issue of information overload by automatically suggesting products or services that are likely to match the user's interests. Recommendation systems have also played a crucial and irreplaceable role in supporting decision making and reducing the risks of making those decisions [1], [2]. Recommendation systems play a crucial role in mitigating information overload by suggesting relevant products or services to users. However, a key issue in recommendation systems is the lack of diversity, leading to redundant recommendations that reduce user satisfaction and engagement. Prior research has highlighted that diverse recommendations contribute to increased user retention and improved experience [3], [4].

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One of the problems with recommendation systems is the problem of diversity. Diversity is a problem where the recommendations produced are still monotonous or not diverse so that they do not add to the quality of the user experience [5], [6]. So, it can be said that the diversity problem is a major problem in recommendation systems. Studies have shown that a lack of diversity in recommendations can negatively impact long-term user engagement, as users may find the system repetitive and uninspiring [7], [8] [9]. However, recommendations that are diverse in general often do not pay attention to user preferences when providing recommendations, thereby reducing the level of user satisfaction with the recommendations provided. This can also reduce the accuracy of the recommendation[10].

Research on diversity-enhanced recommendation systems has highlighted the importance of balancing accuracy and diversity to optimize user experience [11], [12]. For instance, in the context of movie recommendation systems, it has been found that users who receive a more diverse selection of recommendations are more likely to explore new genres and remain engaged with the platform [13], [14]. Similarly, studies in e-commerce suggest that increasing diversity in product recommendations can lead to higher conversion rates and customer satisfaction [15], [16].

To address this challenge, various techniques have been proposed, such as re-ranking methods, hybrid filtering, and diversification-based collaborative filtering [10], [17], [18], [19]. Prior research [20] has indicated that problems in recommendation systems, where the focus on recommendation accuracy has led to a lack of diversity and novelty in recommendations. To overcome this problem, this research proposes an improved Collaborative Filtering method, which combines User-Based and Item-Based Collaborative Filtering are employed to enhance diversity. This model assigns different weights to each algorithm and applies various diversity methods to generate recommendations list. The recommendation system then provides various recommendations to each user while maintaining accuracy.

Based on previous research, traditional recommendation systems prioritize accuracy, often at the expense of diversity. This study addresses the gap between accuracy and diversity by proposing an improved collaborative filtering method. Unlike previous approaches that focus solely on item similarity, this method incorporates clustering techniques and similarity thresholds to balance both diversity and accuracy. By applying item-based collaborative filtering with KNN, cosine similarity and similarity threshold, we aim to enhance recommendation diversity while maintaining relevance. By bridging the gap between accuracy and diversity in recommendation systems, this research contributes to the development of more user-centric and engaging recommendation methodologies. Future work

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may explore further optimizations by integrating real-time user feedback and deep learning techniques to refine diversity metrics.

2. METHODS

The research design was carried out based on several main stages shown in Figure 1. Research *Design*

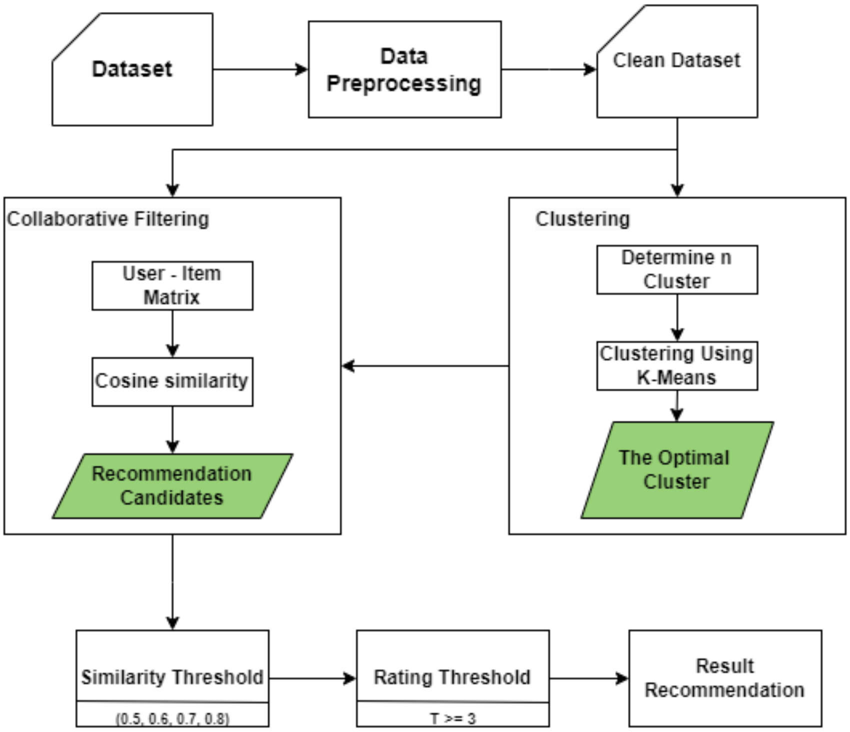

Figure 1. Research Design

2.1. Data Preprocessing

Before generating the list of recommendations, the data undergoes data preprocessing to produce clean, noise-free, and non-duplicated data. This preprocessing involves several steps, including attribute selection, data cleaning, and feature engineering. In the dataset, attributes such as review, picture, and metadata are not utilized, so these attributes are removed. In feature engineering, there is one hot encoding applied only for calculating Euclidean distance during the clustering process and was not used for experiments without clustering. The clustering process was employed to find the optimal cluster to generate diverse recommendations while maintaining accuracy. This optimal cluster was then

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converted into a new data frame for the next step, collaborative filtering. After determining the optimal cluster and creating the new data frame, the previously separated "cuisines" attribute via one hot encoding was combined back into a single attribute for use in collaborative filtering and threshold processes. This ensured the dataset had fewer attributes, retaining only restaurant, cost, cuisines, reviewer, reviewer_rating, id_restaurant, id_reviewer, and restaurant_rating. Duplication values were checked using df.duplicated().sum() with a result of 0 duplication values. Missing values in the dataset were examined, and any empty or NaN values were filled with appropriate values, like averages, or the rows containing nulls were removed.

2.2. Collaborative Filtering

Collaborative filtering is a recommendation technique that relies on user interactions, such as ratings or reviews from numerous users [21]. It operates by creating a database based on a user-item matrix that reflects users' preferences. By assessing the similarities between user profiles, the system can align users with comparable interests and preferences to provide recommendations. These recommendations may take the form of predictions or a list of the top N items that the user is likely to appreciate. A prediction involves a numerical score, which represents the expected rating of item j for user i, whereas a recommendation comprises a ranked list of items the user is anticipated to favor. There are two primary approaches to collaborative filtering: user-based collaborative filtering and item-based collaborative filtering. User-Based Collaborative Filtering is a technique that applies recommendations for attributes or similar preferences of other users who are similar to the user who wants to receive recommendations or is called the target user [22]. Item-Based Collaborative Filtering is a recommendation that provides recommendations based on similarities in items or products containing values (ratings) by users who have similar preferences and not similarities between users.

2.3. K-Nearest Neighbor (KNN)

KNN is a widely employed method in collaborative filtering for recommendation systems [21], [23]. The K-Nearest Neighbor algorithm categorizes data using a training dataset and groups similar users or items based on similarity measures such as cosine similarity. This approach involves finding the k closest neighbors for each user or item and then choosing the top k users or item. The classification is based on the majority proximity distances from these nearest neighbors, with similarity typically calculated using cosine similarity. The accuracy of KNN largely depends on the data source and the target objective, and it generally performs better in datasets with fewer missing values.

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2.4. Cosine Similarity

Cosine similarity measures the similarity between two vectors. In recommendation systems, it is often used to evaluate the similarity between the preferences of two users, two items, or a set of items [24], [25]. By calculating the similarity scores based on user or item preferences, cosine similarity helps generate personalized recommendations. Cosine similarity evaluates the similarity between two objects using real numbers, where a score of 0 indicates no similarity and a score of 1 indicates identical items. For instance, if user A and user B have a similarity score close to 1, it is likely that items rated highly by user B will also be of interest to user A [21], [23]. The calculation using formula as shown in Equation 1.

$$d=\sum_{j=1}^{k}\sum_{i=1}^{n}|x_i-c_j|^2 \quad (1)$$

In this context, vector A represents A, vector B represents B for comparing similarities, A.B denotes the dot product of vectors A and B, and ||A||B|| signifies the cross product of the magnitudes of A and B. The process as follow.

1) Justification for KNN and Cosine Similarity
   Unlike deep learning and matrix factorization methods, KNN and cosine similarity offer computational efficiency, making them suitable for real-time recommendations. KNN efficiently identifies similar items with minimal resource overhead, whereas cosine similarity ensures reliable similarity measures across varying datasets.
2) Biases and Limitations
   One challenge of KNN is its reliance on predefined neighbors, which may introduce bias in sparse datasets. To mitigate this, clustering is employed to refine recommendations and improve diversity without significantly impacting accuracy.

2.5. Evaluation Metrics

In this section, we measure the performance of recommendations based on the degree of diversity and accuracy resulting. In this research, we use individual diversity to measure the level of diversity in recommendation results and prove that recommendations have avoided providing recommendations that are too similar to the same user [21]. The calculation using formula as shown in Equation 2 and 3.

$$ID_u = \frac{1}{\frac{N(N-1)}{2}}\sum\sum_{i,j}d(i,j) \quad (2)$$

$$d(i,j)=1-sim(i,j) \quad (3)$$

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We also use precision to measure the accuracy of recommendation results, indicating how well the recommendations align with user preferences. True Positives (TP) are relevant recommendations, while False Positives (FP) are irrelevant recommendations.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{4}$$

In short, this paper aims to increase diversity by maintaining the accuracy of the recommendations provided. We set the threshold values as follows: Similarity Threshold, where the recommendation similarity value is smaller than the value of 0.5, 0.6, 0.7, and 0.8, and Rating Threshold, where the rating on the recommendation is $T \geq 3$.

3. RESULTS AND DISCUSSION

3.1. Dataset

The data for this restaurant recommendation system research is sourced from the Zomato Restaurants Hyderabad dataset available on Kaggle. It features restaurants in Hyderabad and covers the period all year in the dataset. The dataset includes 9706 ratings, ranging from 1 to 5, provided by 7385 users for 100 different restaurants. It also includes a variety of cuisines such as continental, Mexican, Italian, Chinese, and salads. The dataset we used consists of restaurants that have many reviews from users who have visited the restaurants. But, in this research we split the dataset into training and test sets, with 80% of the data used for training and 20% for testing. This split includes only users who have visited more than 5 restaurants. The training set helps the model learn user preferences based on their context, while the test set is used to evaluate the model's performance.

3.2. Experimental

We compare the collaborative filtering model without applying cluster with collaborative filtering by applying cluster using individual diversity and precision calculations. In this research, thresholds are applied in collaborative filtering, including similarity thresholds and rating thresholds, with the provisions of this research being the use of $k = 30$ for both single methods, which will later be combined. The k value is determined by the accuracy and variance of the recommendations made. Then, for the similarity threshold experiment, four threshold tests will be performed, including [0.5, 0.6, 0.7, 0.8], to discover the ideal threshold for promoting diversity while retaining accuracy. For the threshold rating determination, namely $T >= 3$, the value is chosen to produce recommendations with a good rating to be accepted by users. Then, we also looked at the influence of the number of user interactions on the resulting recommendations. We compare

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the recommendations produced when using data containing users who have interacted with more than 5 restaurants with users who have had fewer interactions, namely 2–4 restaurants.

3.3. Evaluation Threshold for One User

The research proposes using similarity thresholds and rating thresholds to enhance diversity and maintain accuracy in hybrid filtering. Four similarity thresholds are tested: 0.5, 0.6, 0.7, and 0.8, with a rating threshold of $T \geq 3$ applied to each similarity threshold. Recommendations are generated based on various top counts: top-10, top-15, top-20, top-25, and top-30.

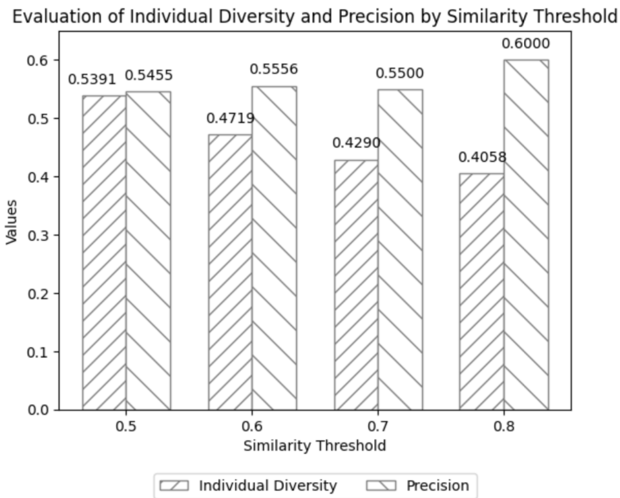

Figure 2. Evaluation similarity threshold for one user

Figure 2 shows two evaluation metrics, namely individual diversity and precision, where in several experiments the threshold values are different, 0.5, 0.6, 0.7 and 0.8. The bar chart shows that the best results are obtained at a similarity threshold of 0.5 where the recommendations given have the highest diversity compared to other experimental thresholds and have a balance between precision and individual diversity, which means that the recommendations given have a balance between accuracy and diversity. Diversity increases as the number of recommendations given increases. Analysis of the bar chart shows a clear trade-off between individual variability and precision. As precision increases, individual diversity tends to decrease. For example, in experiments at threshold similarity values of 0.6 and 0.8 where precision has reached the highest level but experienced a significant decrease in individual diversity. This means that, if precision is the primary metric to be optimized then a higher threshold similarity parameter value may be more appropriate. However, if you want to make individual diversity more optimal,

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consideration is needed by determining a low threshold similarity parameter value. Therefore, it is necessary to determine the most appropriate parameters to achieve a balance where the recommendation has a dryness that increases while maintaining precision.

3.4. Average Evaluation Threshold from All User

The research proposes using similarity thresholds and rating thresholds to enhance diversity and maintain accuracy in hybrid filtering. Four similarity thresholds are tested: 0.5, 0.6, 0.7, and 0.8, with a rating threshold of T ≥ 3 applied to each similarity threshold. Recommendations are generated based on various top counts: top 10, top 15, top 20, top 25, and top 30.

Table 1. Evaluation similarity threshold

Similarity Threshold	Top	Individual Diversity	Precision
	10	0, 5549	0, 5811
	15	0, 5662	0, 5959
Similarity Threshold = 0,5	20	0, 5702	0, 5915
	25	0, 5706	0, 5977
	30	**0, 5706**	**0, 5977**
	10	0, 4873	0, 5533
	15	0, 5112	0, 5511
Similarity Threshold = 0,6	20	0, 5256	0, 5704
	25	0, 5286	0, 5728
	30	0, 5286	0, 5728
	10	0, 4439	0, 5267
	15	0, 4750	0,5400
Similarity Threshold = 0,7	20	0, 4972	0, 5583
	25	0, 5036	0, 5666
	30	0, 5042	0, 5674
	10	0, 4227	0, 5367
	15	0, 4581	0, 5511
Similarity Threshold = 0,8	20	0, 4839	0, 5633
	25	0, 4923	0, 5727
	30	0, 4929	0, 5735

Based on Table 1, the individual results for diversity and precision show that thresholds of 0.7 and 0.8 in the Top-25 provide a small increase in both metrics. However, the best result in this research is achieved with a threshold of 0.7 in the Top-10 recommendations, as this configuration yields the highest diversity, despite a slight decrease in precision, which remains acceptable. The Top-10 recommendations are more user-friendly compared to the Top-25, as users are less likely to be overwhelmed by a limited number of choices. Additionally, the Top-

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10 recommendations show a significant increase in diversity, making them more effective for users. Although a similarity threshold of 0.5 could potentially offer greater diversity, it may result in some users not receiving any recommendations due to the lack of similar items below this threshold. Using a similarity threshold ensures that the recommendations are diverse, with higher dissimilarity values. Precision relies on the relevance of recommendations, so a higher number of recommendations increases the chances of relevance. While the number of recommendations doesn't significantly impact individual values of diversity and precision, it does enhance the likelihood of improving both metrics. Moreover, the speedup achieved by increasing the number of processor cores was constrained by the available computational resources. Specifically, as more threads were added, the expected improvement in performance (speedup) did not scale linearly. While there was some increase in speed when moving from 2 to 4 threads, the rate of this increase was lower compared to the speedup observed when initially increasing the number of threads. This implies that the system's ability to effectively utilize additional cores was limited, potentially due to overhead, resource contention, or other factors that prevented optimal scaling.

3.5. Recommendation

In this paper, we get the results and find that proves that our proposed method can perform better at increasing diversity and maintaining accuracy. The result would get from evaluation of the result of recommendation system based on the precision and individual diversity. From the result we know that the comparison of the recommendation with clustering and without clustering.

Table 2. Comparison results for each threshold

Similarity Threshold	Clustering Method		
	Top	Individual Diversity	Precision
0,5	10	**0,5578**	**0,8661**
	15	0,5675	0,8392
	20	0.5719	0,8162
	25	0,5719	0,8117
	30	**0,5719**	**0,8117**
0,6	10	0,4967	0,8571
	15	0,5184	0,8067
	20	0,5263	0,7806
	25	0,5294	0,7596
	30	0,5294	0,7596
0,7	10	0,4384	0,8666
	15	0,4705	0,8077
	20	0,4880	0,7708
	25	0,4923	0,7370

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Similarity Threshold	Clustering Method		
	Top	**Individual Diversity**	**Precision**
	30	0,4923	0,7370
	10	0,3820	0,8679
	15	0,4211	0,8042
0,8	20	0,4510	0,7615
	25	0,4577	0,7223
	30	0,4577	0,7223

Based on Table 2. Comparison results for each thresholdShown that using threshold 0,5 achieve higher individual diversity and precision score at the top 10 recommendation. This phenomenon occurs because we filtered the recommendation by taking only recommendations with only has 0,5 below of similarity which means the recommendation results will not show the very similar item with user preferences. We can see that by using threshold 0,8 achieves lower individual diversity then the lower threshold. This means that the item recommended is mostly like the item preference. This result will reduce the diversity of the recommendation.

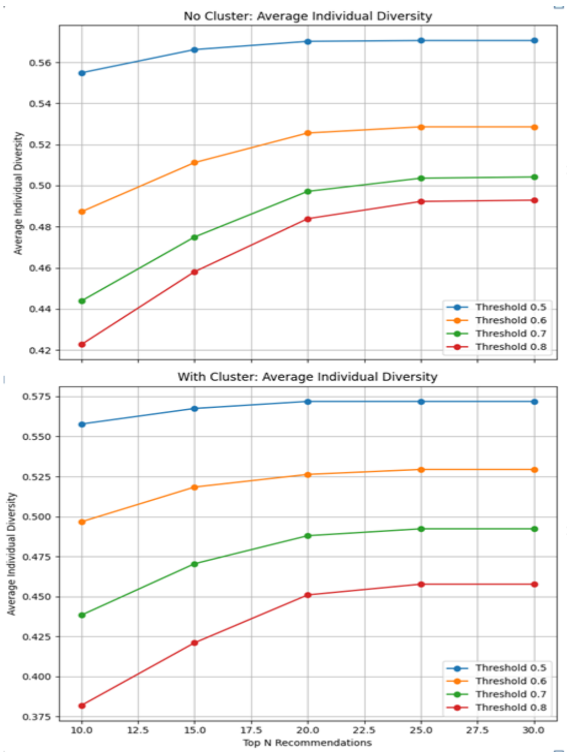

Figure 3. Individual diversity of different methods

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Based on Figure 3 the results indicate that applying a threshold improves recommendation diversity. The use of clustering consistently yields higher diversity than without clustering across various similarity thresholds (0.5, 0.6, 0.7, and 0.8). Each increase in the number of recommendations enhances diversity, with a notable improvement seen for each additional set of recommendations. Specifically, the method with clustering shows a significant boost in individual diversity, confirming its effectiveness in generating diverse recommendations.

In particular, the method incorporating clustering exhibits a significant boost in individual diversity. This confirms the effectiveness of clustering techniques in generating more diverse recommendations, which can better cater to the varied interests and preferences of users. The consistent performance across different similarity thresholds highlights the robustness of the clustering approach. Overall, these findings emphasize the importance of using clustering in recommendation systems to achieve a higher level of diversity, ultimately leading to a richer and more satisfying user experience.

Comparing k-means clustering with a non-clustering approach in recommendation systems is essential to demonstrate the added value of the clustering technique. While k-means clustering is known for enhancing recommendation diversity by grouping similar users or items together, the comparison with a non-clustering method serves to empirically validate this advantage. By evaluating both methods side by side, researchers can quantify how much the clustering improves diversity and whether it maintains accuracy compared to the traditional approach. This comparison also helps to identify specific scenarios where clustering offers the most benefit, ensuring that its implementation is justified and that it significantly contributes to a richer and more personalized user experience.

Figure 4 indicate that the method applying a threshold achieves the second-highest precision value, just after content-based filtering. The precision value of the threshold method increases as the number of recommendations increases, with the graph displaying consistent and linear improvements in precision. In other methods, increasing the number of recommendations does not necessarily ensure a high precision value. Precision in these methods depends on the relevance of the recommendations to the user's preferences or the fit with the dataset or collection of restaurants. The threshold method, therefore, shows a clear advantage in maintaining a high precision level as the number of recommendations grows, ensuring that users receive more relevant and accurate suggestions over time. Then the test was carried out again by looking at the evaluations produced recommendation between similarity threshold and without similarity threshold to see the impact threshold for the recommendation based on the accuracy and diversity of the recommendation.

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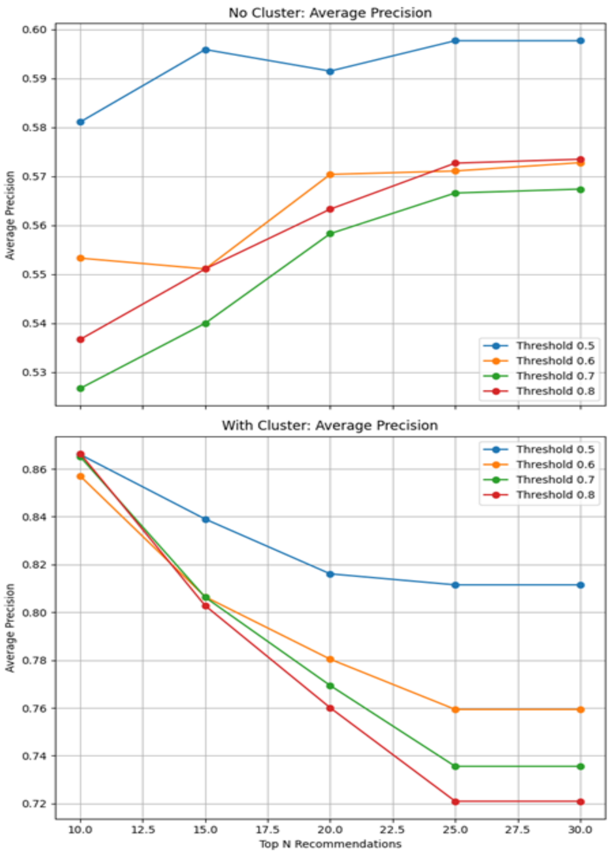

Figure 4. Precision of different methods

3.6. Discussion

The findings from this study offer valuable insights into how similarity thresholds and clustering techniques affect the performance of restaurant recommendation systems in terms of individual diversity and precision. Using the Zomato Hyderabad dataset, this research aimed to develop a more balanced recommendation model that not only delivers accurate suggestions but also introduces diversity into the recommendation list—a critical aspect of enhancing user satisfaction and discovery.

The analysis of similarity thresholds (Figure 2, Table 1) revealed a clear trade-off between precision and individual diversity. A lower threshold of 0.5 consistently provided the highest diversity in recommendations, which is essential for promoting varied content and reducing the repetitiveness commonly observed in standard collaborative filtering methods. However, precision slightly decreased at

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this threshold. Conversely, higher thresholds like 0.8 yielded greater precision but at the cost of diversity. This confirms the well-documented tension between accuracy and diversity in recommender systems. The Top-10 recommendation configuration proved optimal in many scenarios, striking a balance that favors user engagement by preventing overwhelming lists while maintaining effective recommendations.

Additionally, the evaluation across all users confirmed that while the total number of recommendations slightly influences diversity and precision, the impact of the similarity threshold is far more significant. The results showed that beyond a certain point (Top-20 or Top-30), diversity gains plateaued, while user relevance slightly improved with longer lists. These observations suggest that recommendation list length should be tailored not only based on system performance but also on user behavior and tolerance for cognitive load.

The integration of clustering techniques (Figure 3, Table 2) added a compelling dimension to the experiment. The clustering-enhanced model consistently outperformed the non-clustering approach across all similarity thresholds in terms of diversity. The use of k-means clustering grouped users or items based on shared attributes, which enabled the system to make more generalized, yet still personalized, suggestions. This was particularly effective at the 0.5 threshold, where diversity and precision both peaked (Top-10: 0.5578 and 0.8661, respectively). The clustering approach proved robust, improving diversity without compromising precision—addressing one of the primary limitations of traditional collaborative filtering.

Moreover, Figure 4 illustrated how the threshold-based method offered a stable and linear increase in precision with the number of recommendations, outperforming even clustering in precision at some stages, though not in diversity. The comparative evaluation highlights the strategic importance of applying thresholds for users with rich interaction histories. Users with more than five interactions saw more nuanced and useful recommendations, reinforcing the idea that interaction history plays a crucial role in model effectiveness.

The study demonstrates that carefully tuned similarity thresholds combined with clustering significantly improve recommendation quality by balancing diversity and precision. While content-based or high-similarity collaborative filtering excels at precision, the inclusion of diverse suggestions through threshold and clustering mechanisms contributes to better user engagement and satisfaction. For practical applications, this indicates that recommendation systems should dynamically adjust thresholds and apply clustering based on user profiles and interaction depth. These findings can guide developers and data scientists in designing recommendation systems that not only predict what users like but also introduce

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

them to options they might not have considered—enhancing the overall user experience.

4. CONCLUSION

This research found that when individual diversity increases, precision tends to decrease, and conversely, when precision increases, individual diversity tends to decrease. This indicates the trade-off between individual diversity and precision observed in this research, it is crucial to explore strategies that allow for maintaining high precision while increasing diversity, and vice versa. This can be achieved by fine-tuning the algorithms used or incorporating additional parameters that balance these two metrics effectively. The study also highlights the importance of selecting datasets that include user profiles, as these can offer valuable insights into user preferences and behaviors, thereby improving the relevance and accuracy of recommendations. By leveraging user profile data, collaborative filtering methods can be employed to deliver more personalized and relevant recommendations. Additionally, it is essential to use diverse and non-monotonous datasets to avoid generating repetitive or uninteresting recommendations. A more varied dataset can lead to innovative and engaging suggestions, enhancing user satisfaction and encouraging openness to new experiences. Future work should focus on exploring these strategies and refining the balance between precision and diversity, ensuring that recommendation systems can deliver both accurate and diverse results that cater to a wide range of user interests.

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