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RECOMMENDATION SYSTEM FOR SOLARIA FOOD MENU BASED ON CUSTOMER RATINGS USING SINGULAR VALUE DECOMPOSITION

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ABSTRACT

Solaria is a restaurant chain with a diverse menu, which can make it difficult for customers to choose food based on their preferences. This study aims to evaluate the influence of the retained components of the truncated Singular Value Decomposition (SVD) method on the development of a recommendation system, focusing on improving prediction accuracy. Data was collected through questionnaires from 153 respondents who rated 20 Solaria menu items. The analysis involved data preparation, matrix transformation, and duplicate data removal. The SVD method was employed to decompose the original rating matrix into three smaller matrices, thereby revealing latent patterns in the interactions between customers and menu items. The model was then optimized to predict ratings for items customers had not yet tried, using Mean Absolute Percentage Error (MAPE) as the performance metric. The results demonstrate that the SVD method is effective in recommending menu items aligned with customer preferences. Analysis of the retained components, i.e., the top singular values and their corresponding vectors preserved in the truncated SVD process, revealed their significant contribution to enhancing prediction accuracy. The system successfully recommended items based on personalized preference rankings, such as Seafood Fried Rice with the highest predicted rating and Chicken Soup Noodles with the lowest. This study highlights the importance of selecting an appropriate number of retained components to achieve optimal recommendation performance. The implementation of this system not only improves customer experience in selecting food but also offers valuable insights into Solaria into understanding customer trends and preferences.

Keywords: Food recommendation; Recommendation system; Singular value decomposition

1 Introduction

Solaria is one of the leading restaurant chains in Indonesia that offers a variety of menu choices, ranging from Indonesian cuisine to Asian dishes. This diversity provides flexibility for customers to select dishes according to their tastes and needs. However, the wide range of options can often lead to confusion, especially for first-time visitors or those who struggle to determine the most suitable food choices. Differences in individual preferences further complicate the challenge of offering relevant recommendations [1].

In the increasingly competitive culinary industry restaurant competition is intensifying, especially in urban centers such as Bogor. A study at the Solaria Botani Square Bogor branch indicated that while customer satisfaction was recorded at 71.45%, customer loyalty remained relatively low. Many customers are likely to switch to other restaurants if dissatisfied or if they

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find more appealing alternatives [2]. This trend presents a significant challenge for restaurant management to maintain and grow their customer base.

To address this issue, the application of technological innovations such as data-driven recommendation systems offer a promising solution. These systems predict customer preferences and provide personalized menu suggestions based on data [3]. In the context of Solaria, such a system can assist customers in making faster, preference-aligned choices while also enhancing their overall dining experience. Moreover, it provides strategic value to Solaria by uncovering customer behavior patterns and preference trends, which can inform menu design and promotional strategies.

One widely adopted technique in recommendation systems is Singular Value Decomposition (SVD). SVD is a mathematical method used to process large-scale data by decomposing the user–item interaction matrix into three smaller matrices. This decomposition reveals latent patterns, allowing the system to predict preferences even for items the user has not yet interacted with [4]. As part of machine learning within artificial intelligence, SVD-based recommendation systems learn from historical data to generate relevant predictions [5]. By applying this technique, Solaria can improve its recommendation accuracy and better tailor its menu to individual customer preferences.

Previous studies have demonstrated the effectiveness of recommendation systems in assisting decision-making. For example, Akbar et al. [6] applied collaborative filtering using SVD to produce book recommendations with strong accuracy. Similarly, Sitanggang [7] showed that a combination of SVD and Cosine Similarity could successfully recommend anime based on titles and genres. These examples highlight the broader applicability of recommendation technologies, including in the culinary sector.

This study focuses specifically on evaluating the retained components in the truncated SVD method, that is, the top singular values and their associated vectors preserved during dimensionality reduction. These retained components play a crucial role in determining the effectiveness of the recommendation system. Apart from this technical aspect, the quality of the data input also significantly influences performance. Historical data such as user ratings, menu preferences, or ordering history must be complete and accurate to ensure meaningful recommendations. Additionally, the size and diversity of the dataset are critical: limited or homogeneous datasets may hinder the SVD algorithm’s ability to detect nuanced customer preferences.

Another key implementation parameter is the number of retained components. Using too few components may result in underfitting and inaccurate predictions, whereas using too many increases computational complexity without notable gains in accuracy. Therefore, identifying the optimal number of retained components is essential for achieving a balance between performance and efficiency [4].

Furthermore, the performance of the recommendation system should be evaluated quantitatively. Metrics such as Mean Absolute Percentage Error (MAPE) offer valuable insight into how well the predicted ratings align with actual user preferences. This study aims to analyze how the number of retained components affects system accuracy, while also considering other contributing elements such as data quality and algorithm parameters. The goal is to ensure the recommendation system produces results that are not only accurate but also contextually relevant to the Solaria customer experience.

In summary, this study aims to evaluate and identify the most influential elements in the development of a recommendation system, with a specific focus on the role of retained components in enhancing prediction accuracy. The findings are expected to contribute to the optimization of recommendation system implementation and support Solaria in delivering a more satisfying and personalized dining experience to its customers.

2 METHODS AND DATASETS

2.1 Singular Value Decomposition

Suppose a matrix $A \in R_{m\times n}$ with rank r, there are orthogonal matrices $U_{m\times m}$, $V_{n\times n}$, and diagonal matrices $D_{r\times r} = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r)$ as follows.

$$A = U\Sigma V^T \text{ where } \sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r \geq 0.$$

The matrix $\sum = \begin{bmatrix} D & 0 \\ 0 & 0 \end{bmatrix}$ is an $m \times n$ matrix. The values of σ_i are the singular values of the matrix A. When $r < p = \min\{m, n\}$, A is said to have $p - r$ additional zero singular values. The factorization of this equation is called Singular Value Decomposition (SVD) of matrix A. The columns of U and V are the left and right singular vectors of A respectively [8], [9].

In the realm of machine learning, SVD can be used as a tool in recommendation systems. SVD helps in finding hidden patterns in the form of matrices U, Σ, and V. The diagonal matrix Σ contains singular values, each corresponding to a component that reflects a dimension of variation in the user-item interaction data. These are referred to as retained components when applying truncated SVD, as only the top singular values are preserved. The V^T matrix contains the feature vectors of items, where the rows represent items, and the columns correspond to the relationship of each item with the retained components. By multiplying these matrices, we can obtain the matrix A, which contains the predicted rating values between each user and item.

2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a widely used statistical technique for dimensionality reduction in recommendation systems. It works by transforming a large set of variables into a smaller set of principal components that still capture most of the important information. According to Sarwar et al. [10], PCA can extract key patterns in user behavior while minimizing information loss, such as rating history and consumption preferences. This dimensionality reduction helps simplify data structure, thereby making recommendation algorithms more efficient and faster in processing user preferences.

Although PCA and truncated SVD are based on different formulations, both aim to reduce data dimensionality by identifying and preserving the most relevant components. In this study, truncated SVD is applied to perform a similar role as PCA, with a focus on selecting the optimal number of retained components to ensure accurate recommendations.

2.3 Recommendation System with SVD-PCA Approach

The steps for modeling a recommendation system using the truncated SVD approach, inspired by PCA principles, are as follows:

1. Determine the number of retained components (modes), i.e., the number of singular values and their associated vectors to be preserved in the truncated SVD. Perform the SVD decomposition on the rating matrix accordingly.
2. Reconstruct the estimated rating matrix using:
   - Matrix U of size (number of rows × retained components),
   - Matrix Σ of size (retained components × retained components), and
   - Matrix V^T of size (retained components × number of columns).
3. Calculate the estimation error using the Mean Absolute Percentage Error (MAPE) between the reconstructed and original matrix, using the formula:

$$MAPE = \frac{\text{norm}(A_i - A_{i+1})}{\text{norm}(A_i)}$$

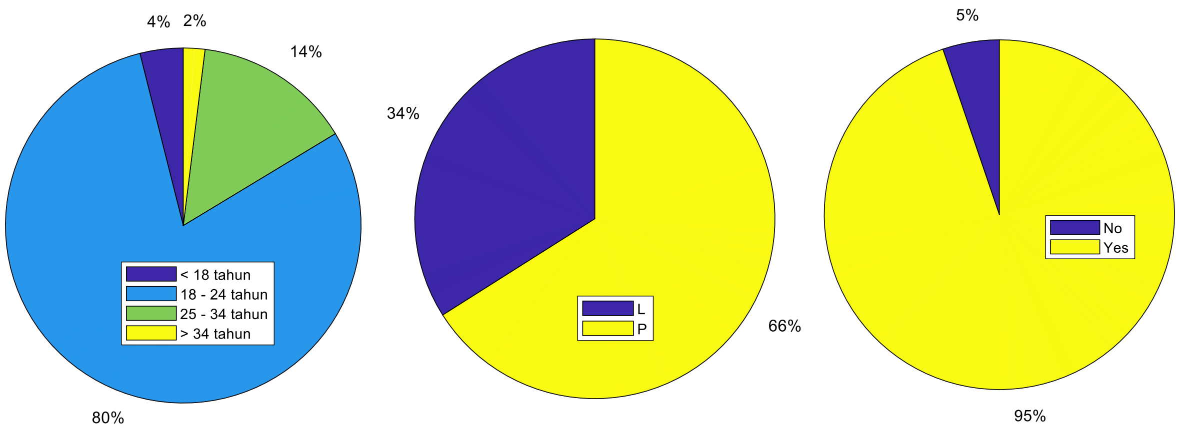
where A_i is the matrix at iteration i for $i = 0,1,2, \ldots$ [11].

4. Check whether the error is sufficiently small (i.e., if it meets the threshold $\varepsilon = 0.001$).
5. If the error does not meet the criterion, repeat the reconstruction using the updated estimated matrix from the previous iteration.
6. Generate recommendations for an individual user by:
   - Taking the corresponding row in the predicted rating matrix,
   - Sorting the predicted values in descending order,
   - Selecting the top three (3) items with the highest predicted ratings as the most recommended menus for that user.

2.4 Datasets

The data used in this study were collected through a structured questionnaire distributed to customers who had previously visited or were familiar with the Solaria restaurant. Respondents were asked to provide ratings for 20 items on the menu they had tried and to select their top three preferred dishes. A total of 153 valid responses were obtained and used to construct the rating matrix for further analysis in the recommendation model.

Before the modeling stage, an exploration of the demographic characteristics of the respondents was conducted to understand the background of the dataset. This demographic profiling provides insight into the composition of the users whose preferences inform the recommendation system. Figure 1 presents the distribution of respondents based on three demographic variables: age, gender, and visit history to Solaria.



a. age b. gender c. visit to Solaria

Figure 1. Distribution of respondents based on three demographic variables: a) age, b) gender, and c) visit history to Solaria.

Most respondents (80%) were in the 18–24 years age group, followed by 14% in the 25–34 age range. A small proportion of respondents were under 18 years (4%) or over 34 years (2%). This indicates that the primary audience of the recommendation system is young adults. The dataset consists of 66% female and 34% male respondents. This gender composition could influence menu preferences and should be considered when interpreting recommendation outcomes. A substantial 95% of respondents indicated that they had previously visited Solaria, while only 5% had not. This shows that the ratings and preferences gathered are mostly from users who have had direct experience with the food, lending credibility to the input data used for model training. These demographic insights help to contextualize the results of the recommendation system, ensuring that the model reflects the preferences of Solaria's actual customer base.

3 RESULTS AND DISCUSSION

3.1 Data Pre-processing

Data pre-processing is an essential first step in developing a recommendation system, as it ensures that the dataset is clean, structured, and suitable for matrix-based modeling methods such as truncated Singular Value Decomposition (SVD). In this study, the raw data collected from questionnaires were transformed into a rating matrix format and refined through a series of data-cleaning steps.

Initially, 153 respondents rated up to 20 Solaria menu items based on their individual experiences. These ratings were arranged into a matrix R with dimensions 153 × 20, where each row represents a unique respondent (user), and each column corresponds to a menu item. The element $r_{m,n}$ in the matrix denotes the rating given by user mmm to menu item n.

$$R = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m,1} & r_{m,2} & \cdots & r_{m,n} \end{bmatrix}$$

To improve the quality of the input for the recommendation model, the matrix underwent a filtering process to remove duplicate and inconsistent entries. This step helped reduce potential bias and ensured that each user contributed only once to the overall matrix. After cleaning, the resulting matrix R' contained 145 unique user records, forming a 145 × 20 matrix.

$$R' = \begin{bmatrix} r'_{1,1} & r'_{1,2} & \cdots & r'_{1,20} \\ r'_{2,1} & r'_{2,2} & \cdots & r'_{2,20} \\ \vdots & \vdots & \ddots & \vdots \\ r_{145,1'} & r_{145,2'} & \cdots & r'_{145,20} \end{bmatrix}$$

This cleaned matrix is then used as the foundation for the truncated SVD modeling process. In the next stage, this matrix will be factorized and reconstructed using a selected number of retained components, i.e., the most significant singular values and their associated vector, to approximate missing ratings and generate accurate menu recommendations.

3.2 Data Exploration

After completing the data pre-processing phase, exploratory data analysis was conducted to identify key patterns and characteristics within the dataset. This step is important to understand the distribution of user ratings across menu items and to uncover initial insights that may influence the performance of the recommendation model.

In this study, data exploration was performed using visualizations in the form of bar charts. These charts provide a summary of rating distributions and reveal which menu items are most and least favored by respondents. Such visualizations not only offer descriptive insights but also serve as a preliminary guide for the model in capturing user preferences more accurately.

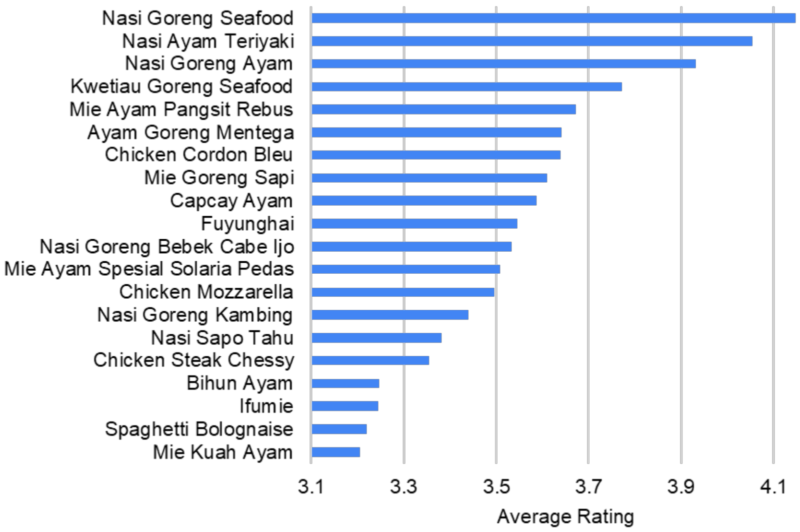


Figure 2. An average rating of 20 food menus at Solaria based on 153 respondents.

Figure 2 presents the average rating of all 20 Solaria menu items, arranged from the lowest to the highest. From this chart, Seafood Fried Rice received the highest average rating (4.15), while Chicken Soup Noodles received the lowest (3.21). The difference in average scores indicates varied customer satisfaction across menu items, which is valuable input for training the model to distinguish between highly and poorly rated dishes.

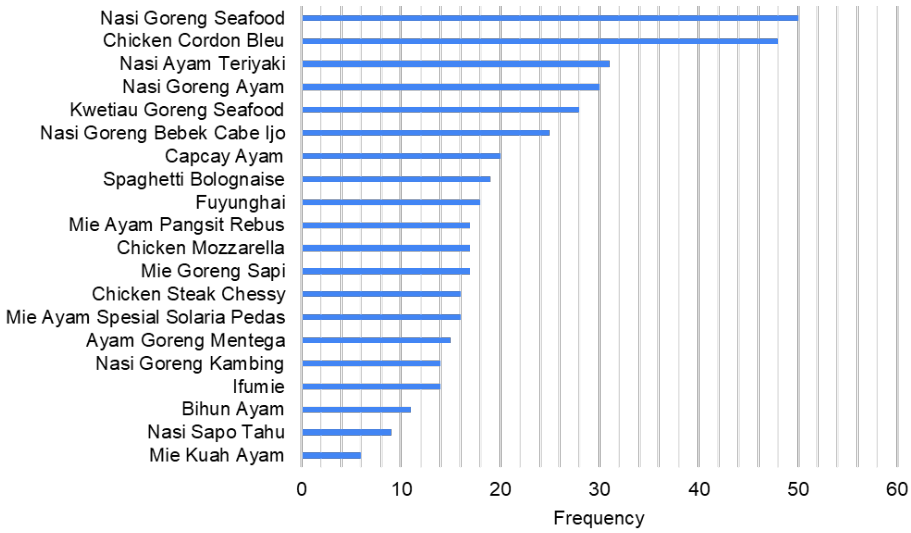


Figure 3. The top food menus at Solaria are based on 153 respondents.

Figure 3 shows the three most preferred menu items selected by respondents, based on their top choices. The top-ranking items are Seafood Fried Rice, Chicken Cordon Bleu, and Teriyaki Chicken Rice, while items such as Chicken Soup Noodles and Sapo Tahu Rice were less frequently chosen. These insights highlight key trends in customer preferences and are expected to be reflected in the modeling phase using truncated SVD.

Understanding these preference distributions is essential before applying dimensionality reduction techniques. When the truncated SVD model is applied in the next stage, it will aim to preserve these underlying patterns through the most informative retained components, allowing the system to make personalized recommendations even for unrated items.

3.3 Modeling of Recommendation Systems using Singular Value Decomposition

In this study, the recommendation model was developed using the truncated Singular Value Decomposition (SVD) technique, which aims to approximate the original user (item rating matrix by preserving only the most informative components) referred to as *retained components*. The goal of this modeling process is to predict missing ratings by reconstructing the matrix based on a reduced set of latent patterns found in the original data.

The modeling begins with the decomposition of the rating matrix into three matrices, i.e., the orthogonal matrix U, the diagonal matrix of singular values Σ, and the transpose of the orthogonal matrix V. The truncated SVD process retains only the top k singular values and their corresponding vectors, forming the retained components used for matrix reconstruction. This approach reduces computational complexity while preserving essential information needed for accurate recommendation generation.

The reconstruction process is performed iteratively. At each iteration, the missing entries in the rating matrix (initially marked as zeros) are estimated using the truncated matrices U_k, Σ_k, and V_k^T. The reconstruction error is then calculated using the Mean Absolute Percentage Error (MAPE), focusing only on the initially missing values. The process continues until the error drops below a predetermined threshold, in this case, $\varepsilon = 0.001$.

To evaluate the impact of the number of retained components on both accuracy and efficiency, several values of k were tested: 2, 3, 4, and 5. Modeling and simulations were conducted using Julia version 1.10.5. The results, summarized in Table 1, include the number of iterations required for convergence and the final MAPE value for each configuration.

Table 1. Iterations required and MAPE for different numbers of retained components in truncated SVD.

Retained Components	Iterations	MAPE
2	132	0.00097513
3	107	0.00096654
4	130	0.00099712
5	182	0.00099654

From Table 1, it can be observed that using 3 retained components resulted in the fewest iterations, indicating a faster convergence compared to the other configurations. On the other hand, using 5 retained components requires the longest modeling process. The progression of error reduction during iterations for each configuration is illustrated in Figure 4.

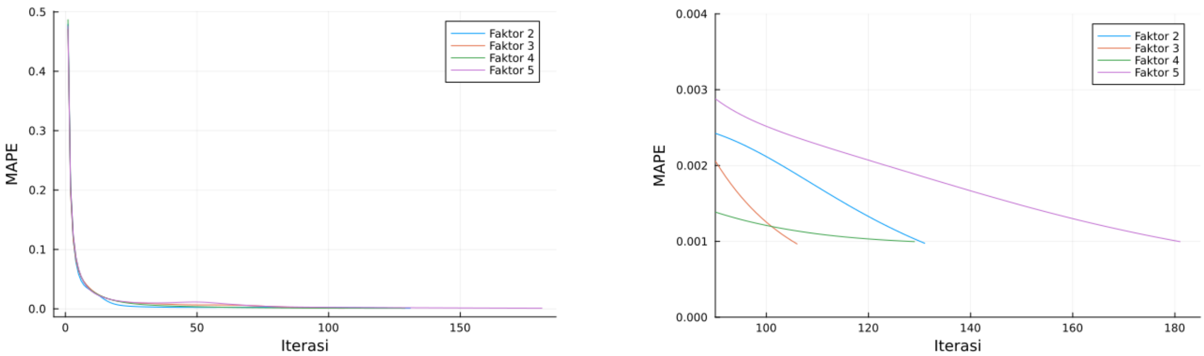


Figure 4. Error trends over iterations for different retained component values (2, 3, 4, 5).

As shown in the figure, the error values decreased significantly during the initial iterations and tended to converge after the 50th iteration. Although the convergence rate differs slightly across configurations, all tested values eventually met the error threshold. Interestingly, the model with 5 retained components achieved the error tolerance threshold slightly earlier than others, despite requiring more total iterations.

This experiment confirms that selecting the appropriate number of retained components is a crucial step in building an efficient and accurate recommendation model. The balance between convergence speed, computational cost, and prediction accuracy must be carefully considered in practical implementation.

3.4 Results of Recommendation Systems using Singular Value Decomposition

After the matrix reconstruction process using truncated SVD, the recommendation results were generated by evaluating the predicted rating matrix. For each user, the system ranks menu items based on the predicted ratings, which are derived from the matrix multiplication of the retained components. Items with the highest predicted values are then recommended to the user. To illustrate the output of the model, Table 2 presents the top three food menu recommendations for a sample user (User ID 4), using different values of retained components: 2, 3, 4, and 5.

Table 2. Food menu recommendation results for user ID 4 based on different numbers of retained components

No	2 Components	3 Components	4 Components	5 Components
1	Chicken Cordon Bleu	Chicken Cordon Bleu	Capcay Ayam	Chicken Cordon Bleu
2	Chicken Mozzarella	Nasi Goreng Kambing	Chicken Cordon Bleu	Capcay Ayam
3	Capcay Ayam	Capcay Ayam	Nasi Goreng Kambing	Nasi Goreng Kambing

As shown in the table, the recommended menus are relatively consistent across different configurations, with minor variations in the ranking order. For example, Chicken Cordon Bleu appears as the top recommendation for 2, 3, and 5 retained components, but Capcay Ayam ranks first when 4 components are used. Similarly, Chicken Mozzarella, which appears in the top three with 2 components, does not appear at all in the configurations with more retained components. These differences occur due to variations in the reconstruction process. Each value of k (the number of retained components) captures different latent structures in the rating matrix, which in turn affects the ranking of recommended items. To further evaluate model performance, prediction accuracy was assessed across a broader range of retained components, from $k = 2$ to $k = 19$. The resulting accuracy values are shown in Figure 5.

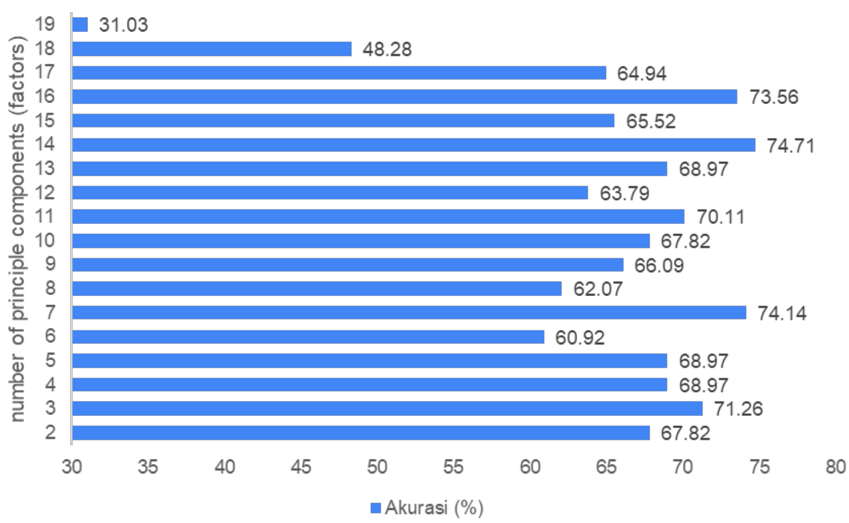


Figure 5. Accuracy of recommendation results for various numbers of retained components.

From the figure, it is evident that the model using 14 retained components achieved the highest prediction accuracy (74.71%), while the configuration with 19 retained components yielded the lowest (31.03%). This outcome highlights the importance of selecting an optimal number of retained components; more components do not necessarily lead to better accuracy and may even introduce noise or overfitting in the model. Based on this analysis, the configuration with 14 retained components was selected as the best-performing model. Table 3 presents the top three recommendations for User ID 4 using this configuration.

Table 3. Food menu recommendation results for user ID 4 using 14 retained components

No	Food Menu	Weight
1	Capcay Ayam	2.57
2	Ayam Goreng Mentega	2.21
3	Mie Ayam Spesial Solaria Pedas	2.17

The predicted weight reflects the degree of alignment between the user's preferences and the corresponding menu item. A higher weight indicates a stronger recommendation. In this case, Capcay Ayam emerged as the top recommendation for User ID 4 based on the model's analysis of the retained components. This modeling process demonstrates that the truncated SVD method can effectively capture customer preferences and provide personalized menu suggestions by selecting an appropriate number of retained components.

4 CONCLUSIONS

Based on the results of this study, the evaluation of various configurations of retained components in the truncated SVD model revealed significant differences in their contributions to prediction accuracy. The model configuration using 14 retained components achieved the highest accuracy, reaching 74.71%, while configurations with either fewer or excessive components resulted in lower performance.

These findings emphasize the importance of carefully selecting the appropriate number of retained components to achieve optimal performance in recommendation systems. Retained components, which represent the most significant latent patterns in the user–item interaction matrix, play a crucial role in accurately predicting user preferences. However, including too many components may introduce unnecessary complexity or noise, while too few may result in underfitting and poor personalization.

In addition to the component configuration, the quality and diversity of input data remain essential factors in supporting effective model training and reliable output, such as menu ratings and customer responses. Evaluation metrics such as Mean Absolute Percentage Error (MAPE) provided a useful benchmark for model performance and helped determine the point at which the model reached acceptable levels of predictive accuracy.

Overall, the implementation of a truncated SVD-based recommendation system has proven effective in generating personalized food menu recommendations at Solaria. The system not only improves customer experience by offering tailored suggestions but also provides valuable insights into Solaria's management in understanding customer trends and preferences. This contributes to both operational decision-making and long-term customer engagement strategies. Future work may explore the integration of additional features such as contextual data (e.g., time of visit, location, device used), hybrid models that combine collaborative and content-based filtering, or deep learning approaches to further enhance the performance and adaptability of the recommendation system.

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