

Side Dish Store Recommendation System Utilizes A Collaborative Filtering Methodology

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Abstract–Side Dish Stores serve as traditional venues for buying and selling a diverse array of products, including fish, foodstuffs, beverages, kitchen spices, clothing, souvenirs, and more. In their pursuit of maximizing profits, traders use competitive strategies, such as online marketing, to expand their sales channels and promote products digitally. This research aims to generate recommendations for selling fish, and traditional supermarkets through a collaborative filtering method. The criteria used to generate recommendations for shops or fish sellers among 25 alternatives include product type, availability, service quality, shop cleanliness, product quality, and sales volume. The research results indicate that the highest predicted value is 0.70, where user 16 exhibits the highest similarity with user 14. Consequently, TSF 1= 4.17, TSF 5= 3.5, TSF 9= 3.33, TSF 13= 3.83, and TSF 15= 4.5. When ranked, TSF 15 will be the first recommendation for user 16, followed by TSF 1, TSF 13, TSF 5, and TSF 9. This recommendation system facilitates consumers in determining the appropriate shop or fish seller to visit when shopping at the Side Dish Store. Traders can easily market products to enhance sales. Moreover, the system streamlines buying and selling transactions for traders and consumers without the necessity of direct visits to the Side Dish Store.

Keywords: Collaborative Filtering; Recommendation System; Side Dish Stores; Similarity Value, Predicted Value

1. INTRODUCTION

Side Dish Stores serve as meeting places for sellers and buyers, where transactions and a culture of bargaining thrive [1]. These markets confront increasingly fierce competition from minimarkets, which offer superior quality facilities, comfort, and service in modern retail settings. This trend has led most consumers to transition to modern retail options, posing a potential threat to the sustainability of Side Dish Store [2].

Various products, including fish, food ingredients, beverages, kitchen spices, clothing, souvenirs, and more, are bought and sold in the Side Dish Store. Among these, sales of fresh fish are particularly sought after by consumers, especially at fish auctions. The Fish Landing Base (PPI) in Kec. Bontobahari, Kab. Bulukumba, South Sulawesi, serves as one of the fishermen's bases for marketing their catches. Between November and December 2023, fishermen in the area caught approximately 100 tons of fish of various types.

The marketing of fishermen's catches in Bontobahari typically involves auctioning the fish at the fish auction place either at the port or at the base. The fish auction process encompasses several stages, including receiving fish from fishermen, categorizing fish by type and size, and conducting a bidding or auction process. However, marketing through auctions like this can lead to losses for the auctioneer, as unsold fish may need to be stored for several days until their quality deteriorates, resulting in the auctioneer failing to maximize profits.

In addition to fish, consumers typically seek kitchen ingredients and basic food necessities, particularly kitchen spices, in Side Dish Stores. The variety of shops and fish traders offering essential goods motivates traders to enhance market services through competition. The current problem lies in consumers facing challenges in selecting an appropriate food vendor that matches their preferences. Furthermore, merchants have yet to embark on online marketing efforts to broaden their market reach and optimize profits. Through online marketing efforts, traders in Side Dish Store can digitally promote their products. With the assistance of a recommendation system integrated into the online marketing platform, customers will find it more convenient to discover a suitable shop or fish seller that aligns with their preferences.

Several previous studies have been conducted, including research by Nurul Muzayyana et al. in 2023, aimed at constructing a recommendation system within online shop applications to facilitate potential buyers in finding products that align with their preferences [3]. This recommendation system employs knowledge-based recommendations to prioritize users who have purchased the item and efficiently determine the similarity value between users' needs and the required items. Additionally, related research conducted by Yuli Murdianingsih and Isti Isbahatunnisa in 2020 focused on developing a recommendation system for laptop purchases, utilizing criteria such as laptop type, monitor screen width, price, memory capacity, and hard disk capacity, employing the fuzzy resistance method [4]. This system assists users in receiving recommendations for selecting a laptop based on their desired criteria.

Related research conducted by Suryani et al. in 2024 established a system that offers recommendations for candidates for the President of the Student Executive Board [5]. The criteria employed include communication skills, leadership attitudes, vision, and mission, as well as skills and organizational experience. This research highlights that



alternative 7, with the highest score of 4.35, stands as the top-ranked student candidate, thus being the most recommended choice for the position of Chair of the Student Executive Board.

Furthermore, in the research conducted by Zhiyun Ren et al. in 2021, a hybrid collaborative filtering model is being constructed to offer personalized search term recommendations to physicians for specific patients, leveraging insights from patients' clinical backgrounds and searches made during appointments [6]. Considering the increasing adoption and extensive use of electronic health records (EHR), along with the prevalence of recommender systems across various platforms like Netflix, Google, Facebook, Twitter, and numerous other services [7], it is prudent to contemplate their integration into EHRs. One notable constraint of the developed approaches is their inability to provide recommendations for patients lacking encounter information within the system.

In another related study by Putu Aditya Pratama and Gede Rai Utama in 2022, a decision support system was developed to aid in selecting an online shop that aligns with consumer expectations, utilizing the Simple Additive Weighting (SAW) method [8]. The system furnishes recommendations for online stores based on predetermined criteria and weights. As a result, consumers seeking to purchase goods, particularly sports equipment, can promptly make purchases according to their desired criteria without experiencing confusion in selecting the appropriate online store or shop.

Other related research conducted by Beiliang Cui et al. in 2019, proposes a recommendation service capable of predicting the proportion of stock ownership [7]. The study revealed that collaborative filtering algorithms, which incorporate user ranking similarity and frequently chosen item similarity, are proficient in managing sparse and missing data from listed companies. Conversely, collaborative filtering algorithms utilizing refill-based item-based collaborative filtering prove effective in addressing the prediction challenge of ownership ratios for newly listed companies.

The research aimed to construct a recommendation system for shops and fish sellers in Side Dish Store utilizing the collaborative filtering method. To apply the collaborative filtering method effectively, we need comprehensive data from each trader covering product type, availability, service quality, shop cleanliness, product standard, and sales volume. According to these criteria, customers will rate items as follows: No Rating = 0, Poor = 1, Fair = 2, Good = 3, Very Good = 4, and Excellent = 5. After compiling all data, the recommender system will necessitate 16 customers to rate each store, undergoing several iterations of collaborative filtering algorithms.

A similar methodology was employed in related research conducted by H. Februariyanti et al. in 2021, where the collaborative filtering method was utilized to offer recommendations for three product alternatives and suggest best-selling items based on the highest sales data for the month and year across three products [9]. Additionally, research undertaken by Abdullah 'Alim et al. in 2020, implemented the collaborative filtering method in a system designed to recommend information technology skills required by companies for job seekers [10]. This system suggests skills to users based on data processing results from job vacancies on employment websites, tailored to the skills possessed by the application users. The user approach operates by assessing the user's level of similarity with others who share similar preferences. This method assumes that items favored by similar users are likely to be appreciated by individuals with corresponding interests.

This research aims to develop a recommendation system to assist consumers in identifying the appropriate shop or fish seller to visit when shopping at the Side Dish Store. Recommendation systems have demonstrated their effectiveness and widespread use in suggesting products on E-commerce platforms [11]. The significance of recommendation systems lies in their ability to help users discover content that aligns with their preferences and enhance business marketing and sales strategies [12]. Moreover, recommendation systems strive to optimize efficiency and minimize operational costs [13]. Traders can readily promote products to boost sales. Furthermore, the system facilitates traders and buyers in conducting transactions without the need to visit the traditional market in person.

2. RESEARCH METHODOLOGY

The recommendation system comprises users $U = \{u_1, \dots, u_{|U|}\}$ and items $I = \{i_1, \dots, i_{|I|}\}$. Each user $u_i \in U$ interacts with some items $ij \in I$ [14]. The method employed in the recommendation system for shops and fish sellers in Side Dish Store is collaborative filtering. Collaborative Filtering (CF) is a technique frequently integrated into recommendation systems, allowing for the delivery of personalized recommendations based on users' historical behavior and preferences [15] [16]. The fundamental principle of the CF algorithm is to furnish relevant recommendations to users by leveraging their preferences and experiences to enhance satisfaction [17]. Examining user-item similarity, the algorithm identifies correlations among users, discerns patterns, and suggests items that closely align with users' tastes. One of the primary advantages of the CF method is its domain independence, which generally renders it more accurate than the Content-Based (CB) Filtering approach [18]. The collaborative filtering approach exhibits adaptability across diverse domains and the capability to detect changes in user interests over time [19].

The Figure 1 below illustrates the process of Collaborative Filtering in delivering recommendations to users [20]:

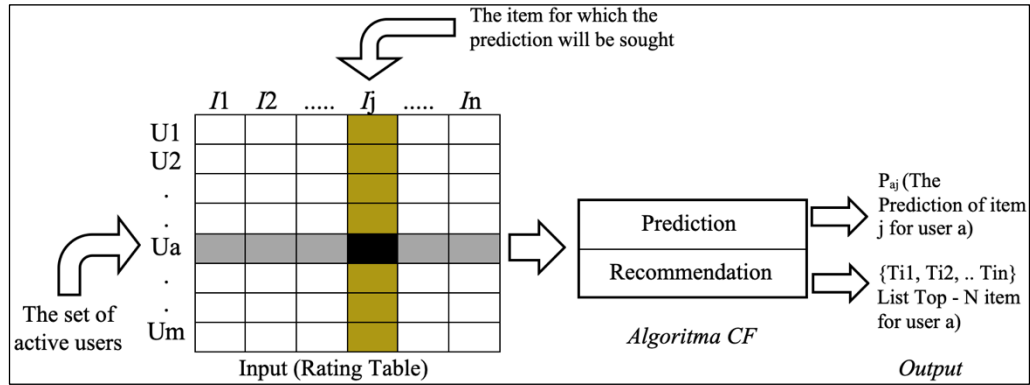


Figure 1. The Collaborative Filtering Scheme

Figure 1 illustrates the diagrammatic representation of the collaborative filtering process. The CF algorithm depicts the entire $m \times n$ user-item matrix as a rating matrix, where each cell signifies the rating given by the user for each item. Active users (U_a) are users for whom items they might prefer will be identified using the CF algorithm.

When implementing collaborative filtering algorithms, attention must be given to the following aspects. First, It's crucial to devise a reasonable scoring matrix to accurately gauge the similarity between target users and recommended items. Second, Define a rational threshold to control how responsive recommendation results are to changes in time and space. Finally, Revise the evaluation matrix according to current circumstances.

The following illustrates the CF recommendation model framework that was constructed can be seen in figure 2:

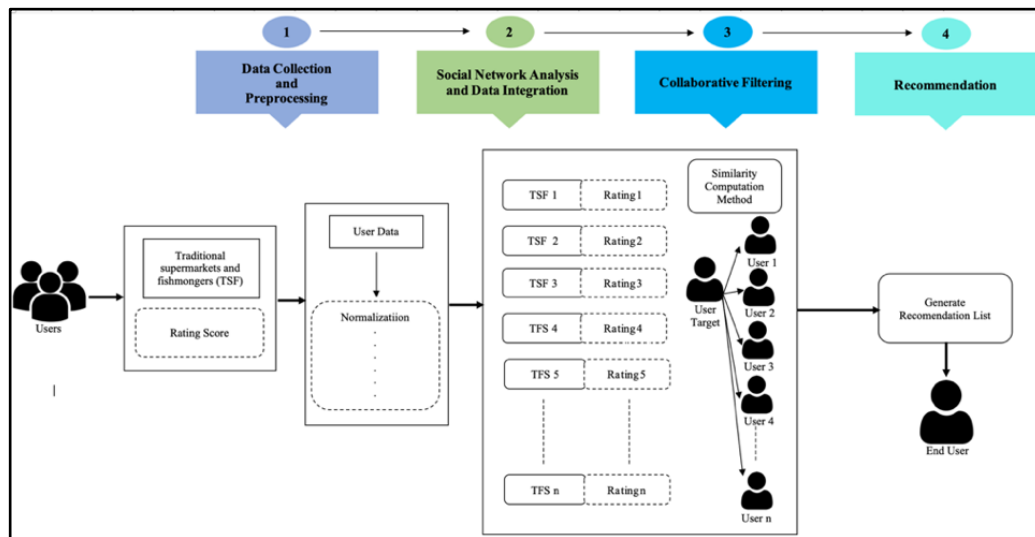


Figure 2. Framework of The collaborative filtering recommendation model

In the initial stage, referred to as data collection and processing, we gather data from diverse sources and then filter, format, and prepare it for subsequent analysis. This data includes user behaviors like ratings, reviews, and purchase histories. In the next phase, we utilize network visualization methods to examine social network data and identify key users and communities within the network. Subsequently, we merge the insights from the CF recommendation system and social network analysis to enhance the precision and significance of recommendations.

The third stage involves collaborative filtering, which comprises the following steps [21]:

- Assign a rating to each object i .
- Compute the average rating and aggregate them.
- Establish the minimum threshold for product similarity values and filter similar products accordingly.
- Calculate the similarity value between objects using the Pearson Correlation Coefficient (PCC) formula as depicted in equation 1 below:

$$S_{(i,j)} = \frac{\sum_{u \in U} (R_{u,i} - \hat{R}_u)(R_{u,j} - \hat{R}_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - \hat{R}_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \hat{R}_u)^2}} \quad (1)$$

Where $S_{(i,j)}$ represents the similarity value between item i and item j , and $u \in U$ is the set of users who rated both item i and item j . $R_{u,i}$ denotes the user's rating on item i , \hat{R}_i is the average rating value, $R_{u,j}$ signifies the user rating on item j , and \hat{R}_j is the average rating value for item j . The Pearson Correlation Coefficient (PCC) calculates

similarity within the range of -1 to +1 [22]. In this range, a value of 1 signifies a robust positive correlation, -1 denotes a significant negative correlation, and 0 denotes a complete absence of correlation [23].

e. The determination of the prediction results' values is then made.

In the fourth stage, the similarity between the target user and other users is calculated, taking into account the target user's impact. Subsequently, items exhibiting the highest collective preference level are chosen to generate a recommendation list. Finally, the system presents the selected recommendations to the user.

3. RESULT AND DISCUSSION

The results of this research include a recommendation system for sales in traditional supermarkets and fishmongers, as depicted in the use case shown in Figure 3:

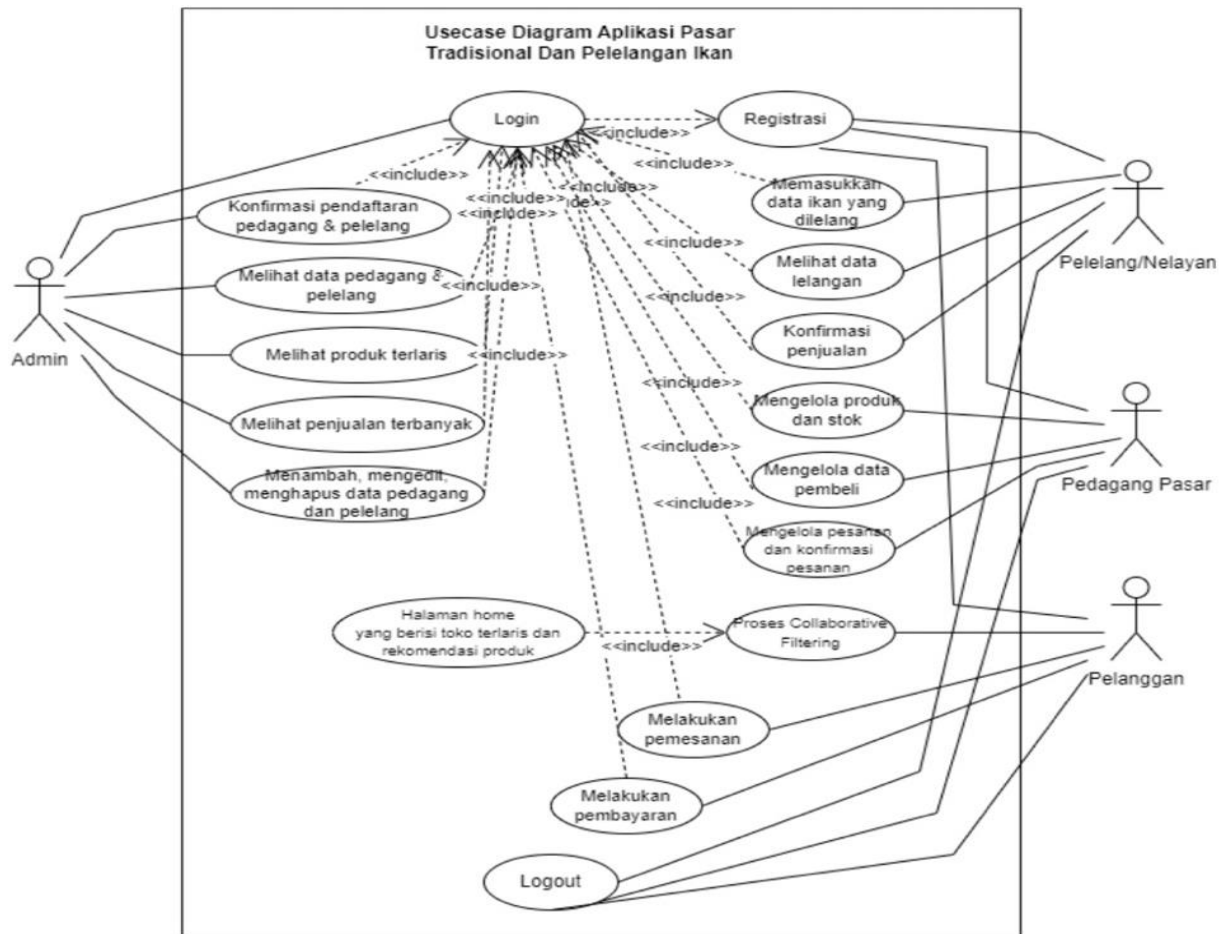


Figure 3. Use case diagram system

In Figure 3 above, the system comprises four distinct access levels: Admin, Customer, Merchant, and Auctioneer. Admin actors are required to log in initially to access trader and auctioneer data, confirm registration by traders and auctioneers, view best-selling products, track sales metrics, and manage trader, auctioneer, or fisherman data by adding, editing, or deleting entries. Auction actors or fishermen need to register an account and subsequently log in. Upon login, the auctioneer can input the fish intended for auction, access auction data, and confirm orders for the products being sold. Merchant actors, similar to fishermen, must register and then log in to their accounts to manage products, inventory, and customer orders. Meanwhile, customers are prompted to register or log in first to access all features on the web application, allowing them to browse products, place orders, and complete payments.

The implementation of the collaborative filtering method in this research necessitates data on criteria that, according to field surveys, exert the most influence on the selection of traditional supermarkets and fishmongers' sales in Side Dish Stores. These criteria encompass product type (C1), product availability (C2), service (C3), store cleanliness (C4), product quality (C5), and number of sales (C6). Meanwhile, the alternative data used includes 25 alternatives, comprising 10 traditional supermarkets and five fishmongers' sales (A1, A2, A3, ... A15).

The number of users after filtering was only 16 customers who had visited the ten traditional supermarkets and 5 fishmongers' stalls at the traditional market. These users will rate alternatives based on their shopping experiences thus far. Ratings from users can be seen in the following Table 1:



Table 1. User Rating Value

| Value | Description |
|-------|-------------|
| 1 | Poor |
| 2 | Sufficient |
| 3 | Fair |

a. Assign a rating to each object i

The rating for each object can be seen in the following Table 2:

Table 2. The rating for each object

| | TSF 1 | TSF 2 | TSF 3 | TSF 4 | TSF 5 | TSF 6 | TSF 7 | TSF 8 | TSF 9 | TSF 10 | TSF 11 | TSF 12 | TSF 13 | TSF 14 | TSF 15 |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|--------|--------|--------|--------|--------|
| U1 | 3,33 | 2,83 | 3,67 | 4,50 | 3,50 | 4,00 | 3,00 | 1,83 | 2,67 | 2,00 | 2,50 | 4,33 | 3,83 | 4,17 | 3,33 |
| U2 | 3,67 | 2,83 | 3,33 | 4,67 | 3,33 | 4,00 | 3,00 | 1,83 | 2,83 | 2,00 | 2,83 | 4,50 | 4,33 | 3,00 | 3,50 |
| U3 | 3,33 | 2,67 | 3,67 | 4,83 | 3,67 | 4,00 | 3,00 | 1,67 | 2,67 | 2,00 | 2,67 | 4,50 | 4,17 | 3,00 | 3,50 |
| U4 | 2,67 | 3,67 | 5,00 | 3,67 | 4,00 | 3,00 | 1,67 | 2,67 | 2,00 | 2,67 | 4,67 | 4,33 | 3,00 | 3,67 | 3,33 |
| U5 | 3,00 | 2,83 | 4,50 | 4,33 | 3,83 | 3,50 | 2,17 | 2,50 | 2,17 | 2,50 | 3,50 | 4,67 | 3,17 | 3,17 | 3,33 |
| U6 | 3,33 | 2,50 | 3,67 | 4,83 | 3,50 | 4,00 | 3,00 | 3,83 | 2,67 | 4,33 | 2,50 | 4,50 | 4,00 | 3,00 | 3,33 |
| U7 | 3,50 | 2,50 | 3,50 | 4,67 | 3,33 | 4,00 | 3,00 | 4,33 | 2,67 | 4,17 | 2,50 | 4,33 | 3,83 | 3,00 | 3,33 |
| U8 | 3,17 | 2,83 | 4,00 | 4,33 | 3,67 | 3,67 | 2,67 | 3,50 | 2,33 | 4,83 | 3,17 | 4,33 | 3,67 | 3,33 | 4,00 |
| U9 | 3,50 | 3,33 | 4,67 | 4,00 | 4,00 | 3,33 | 2,33 | 2,33 | 3,33 | 4,33 | 4,67 | 4,17 | 3,17 | 3,67 | 3,17 |
| U10 | 3,67 | 3,33 | 4,50 | 4,00 | 4,50 | 3,33 | 4,33 | 4,50 | 4,17 | 5,00 | 3,67 | 4,17 | 3,17 | 4,00 | 3,83 |
| U11 | 3,33 | 2,83 | 3,83 | 4,50 | 3,67 | 3,83 | 2,83 | 2,17 | 4,67 | 4,17 | 2,83 | 4,67 | 3,83 | 3,17 | 3,33 |
| U12 | 3,67 | 2,67 | 3,33 | 4,67 | 3,33 | 4,00 | 3,00 | 4,00 | 2,67 | 2,00 | 2,67 | 4,67 | 4,33 | 3,00 | 3,33 |
| U13 | 4,67 | 4,00 | 3,67 | 3,67 | 2,67 | 4,50 | 2,33 | 4,33 | 3,17 | 4,33 | 3,67 | 3,33 | 3,33 | 4,00 | 3,17 |
| U14 | 4,17 | 3,50 | 3,50 | 4,00 | 3,50 | 3,17 | 3,33 | 4,67 | 3,33 | 3,17 | 3,17 | 4,17 | 3,83 | 3,67 | 4,50 |
| U15 | 2,83 | 3,17 | 4,33 | 4,17 | 4,00 | 3,50 | 2,50 | 3,67 | 3,83 | 2,33 | 3,33 | 4,33 | 3,17 | 3,17 | 3,50 |
| U16 | ? | 3,83 | 4,33 | 4,17 | ? | 3,50 | 4,17 | ? | ? | 3,67 | 3,33 | 4,33 | ? | 4,50 | ? |

b. The average rating can be seen in the following table 3:

Table 3. The average user rating

| User | Average rating value |
|-------|----------------------|
| U1 | 3,30 |
| U2 | 3,31 |
| U3 | 3,29 |
| U4 | 3,33 |
| U5 | 3,28 |
| U6 | 3,53 |
| U7 | 3,51 |
| U8 | 3,57 |
| U9 | 3,60 |
| U10 | 4,01 |
| U11 | 3,58 |
| U12 | 3,42 |
| U13 | 3,66 |
| U14 | 3,71 |
| U15 | 3,46 |
| U16 | 3,98 |
| Total | 56,54 |

The average rating value for U1 is obtained from:

$$U1 = \left(\frac{3,33 + 2,50 + 3,67 + 4,83 + 3,50 + 4 + 3 + 1,83 + 2,67 + 2 + 2,50 + 4,50 + 4 + 3 + 3,33}{15} \right)$$

$$U1 = 3.24$$

c. Establish the minimum threshold for product similarity values and filter similar products accordingly.

Each user provides a rating for every merchant they have visited and whose products they have purchased. If there is a new user (U16) and there are 6 traders who have never been visited and whose products have never been purchased, the question arises: which shop is more suitable to recommend to U16 (TSF 1, TSF 5, TSF 8, TSF 9, TSF 13, or TSF 15)? If the recommendation employs collaborative filtering, then we need to identify the user who has the highest proximity to U16. Therefore, the columns TSF 1, TSF 5, TSF 8, TSF 9, TSF 13, and TSF 15 are initially removed to yield the following tables 4 and 5:



Table 4. Data Cleansing

| | TSF 2 | TSF 3 | TSF 4 | TSF 6 | TSF 7 | TSF 10 | TSF 11 | TSF 12 | TSF 14 | Average rating value |
|-------|-------|-------|-------|-------|-------|--------|--------|--------|--------|----------------------|
| U1 | 2,83 | 3,67 | 4,50 | 4,00 | 3,00 | 2,00 | 2,50 | 4,33 | 4,17 | 3,44 |
| U2 | 2,83 | 3,33 | 4,67 | 4,00 | 3,00 | 2,00 | 2,83 | 4,50 | 3,00 | 3,35 |
| U3 | 2,67 | 3,67 | 4,83 | 4,00 | 3,00 | 2,00 | 2,67 | 4,50 | 3,00 | 3,37 |
| U4 | 3,67 | 5,00 | 3,67 | 3,00 | 1,67 | 2,67 | 4,67 | 4,33 | 3,67 | 3,59 |
| U5 | 2,83 | 4,50 | 4,33 | 3,50 | 2,17 | 2,50 | 3,50 | 4,67 | 3,17 | 3,46 |
| U6 | 2,50 | 3,67 | 4,83 | 4,00 | 3,00 | 4,33 | 2,50 | 4,50 | 3,00 | 3,59 |
| U7 | 2,50 | 3,50 | 4,67 | 4,00 | 3,00 | 4,17 | 2,50 | 4,33 | 3,00 | 3,52 |
| U8 | 2,83 | 4,00 | 4,33 | 3,67 | 2,67 | 4,83 | 3,17 | 4,33 | 3,33 | 3,69 |
| U9 | 3,33 | 4,67 | 4,00 | 3,33 | 2,33 | 4,33 | 4,67 | 4,17 | 3,67 | 3,83 |
| U10 | 3,33 | 4,50 | 4,00 | 3,33 | 4,33 | 5,00 | 3,67 | 4,17 | 4,00 | 4,04 |
| U11 | 2,83 | 3,83 | 4,50 | 3,83 | 2,83 | 4,17 | 2,83 | 4,67 | 3,17 | 3,63 |
| U12 | 2,67 | 3,33 | 4,67 | 4,00 | 3,00 | 2,00 | 2,67 | 4,67 | 3,00 | 3,33 |
| U13 | 4,00 | 3,67 | 3,67 | 4,50 | 2,33 | 4,33 | 3,67 | 3,33 | 4,00 | 3,72 |
| U14 | 3,50 | 3,50 | 4,00 | 3,17 | 3,33 | 3,17 | 3,17 | 4,17 | 3,67 | 3,52 |
| U15 | 3,17 | 4,33 | 4,17 | 3,50 | 2,50 | 2,33 | 3,33 | 4,33 | 3,17 | 3,43 |
| U16 | 3,83 | 4,33 | 4,17 | 3,50 | 4,17 | 3,67 | 3,33 | 4,33 | 4,50 | 3,98 |
| Total | 49,33 | 63,50 | 69,00 | 59,33 | 46,33 | 53,50 | 51,67 | 69,33 | 55,50 | 57,50 |

Table 5. Filtered Data Results

| User | Average rating | Subtracted value |
|------|----------------|------------------|
| U1 | 3,44 | 0,54 |
| U2 | 3,35 | 0,63 |
| U3 | 3,37 | 0,61 |
| U4 | 3,59 | 0,39 |
| U5 | 3,46 | 0,52 |
| U6 | 3,59 | 0,39 |
| U7 | 3,52 | 0,46 |
| U8 | 3,69 | 0,30 |
| U9 | 3,83 | 0,15 |
| U10 | 4,04 | -0,06 |
| U11 | 3,63 | 0,35 |
| U12 | 3,33 | 0,65 |
| U13 | 3,72 | 0,26 |
| U14 | 3,52 | 0,46 |
| U15 | 3,43 | 0,56 |
| U16 | 3,98 | 0,00 |

Data with a subtracted value close to 0 represent users' data that are most similar to U16's data. These data will be evaluated for their similarity values.

d. The similarity value between objects

The resulting value ranges from +1.0 to -1.0. A similarity value of 0 indicates that the two items are uncorrelated (independent). A similarity value close to +1.0 suggests that the two items are highly similar to each other. Therefore, if the rank of one item is known, the rank of other items can be inferred with high probability. A similarity value can be seen in the following table 6:

Table 6. Similarity

| Similarity | Numerator Value | Divider Value | Sim(Ui, U16) |
|------------|-----------------|---------------|--------------|
| (U1, U16) | 1,768518519 | 2,932715984 | 0,603030954 |
| (U2, U16) | 0,919753086 | 2,873521435 | 0,320078728 |
| (U3, U16) | 1,200617284 | 3,09270964 | 0,38820886 |
| (U4, U16) | 0,320987654 | 3,420889413 | 0,093831637 |
| (U5, U16) | 0,910493827 | 2,94270337 | 0,309407274 |
| (U6, U16) | 0,598765432 | 2,89531837 | 0,206804695 |
| (U7, U16) | 0,50308642 | 2,669351643 | 0,188467646 |
| (U8, U16) | 0,197530864 | 2,448213829 | 0,080683665 |
| (U9, U16) | -0,305555556 | 2,487279021 | -0,122847317 |
| (U10, U16) | 0,617283951 | 1,796497804 | 0,343604066 |
| (U11, U16) | 0,577160494 | 2,422397144 | 0,238260062 |



| | | | |
|------------|--------------|-------------|--------------|
| (U12, U16) | 1,111111111 | 3,058640418 | 0,36326961 |
| (U13, U16) | -0,851851852 | 2,091854999 | -0,407223183 |
| (U14, U16) | 0,864197531 | 1,211198572 | 0,713506068 |
| (U15, U16) | 0,87654321 | 2,443072317 | 0,358787255 |
| (U16, U16) | 1,358024691 | 1,358024691 | 1 |

An example of calculating the similarity between U9 and U16 is as follows:

$$Sim(U9, U16) = \frac{(3.33 - 3.83)(4.67 - 3.98) + (4.67 - 3.83)(4.33 - 3.98) + (4 - 3.83)(4.17 - 3.98) + (3.33 - 3.83)(3.50 - 3.98) + (2.33 - 3.83)(4.17 - 3.98) + (4.33 - 3.83)(3.67 - 3.98) + (4.67 - 3.83)(3.33 - 3.98) + (4.17 - 3.83)(4.33 - 3.98) + (3.67 - 3.83)(4.50 - 3.98)}{\sqrt{((3.33 - 3.83)^2 + (4.67 - 3.83)^2 + (4 - 3.83)^2 + (3.33 - 3.83)^2 + (2.33 - 3.83)^2 + (4.33 - 3.83)^2 + (4.67 - 3.83)^2) \times ((4.67 - 3.98)^2 + (4.33 - 3.98)^2 + (4.17 - 3.98)^2 + (3.50 - 3.98)^2 + (4.17 - 3.98)^2 + (3.67 - 3.98)^2 + (3.33 - 3.98)^2 + (4.33 - 3.98)^2 + (4.50 - 3.98)^2}}$$

$Sim(U9, U16) = -0,122847317$

The visualization of the similarity values between each user and U16 can be seen in the following Figure 3:



Figure 3. Visualization of Similarity Each User

The visualization above indicates that the similarity value (U14, U16) is closest to 1, meaning U16 tends to be similar to U14. This can be observed in the following Figure 4:

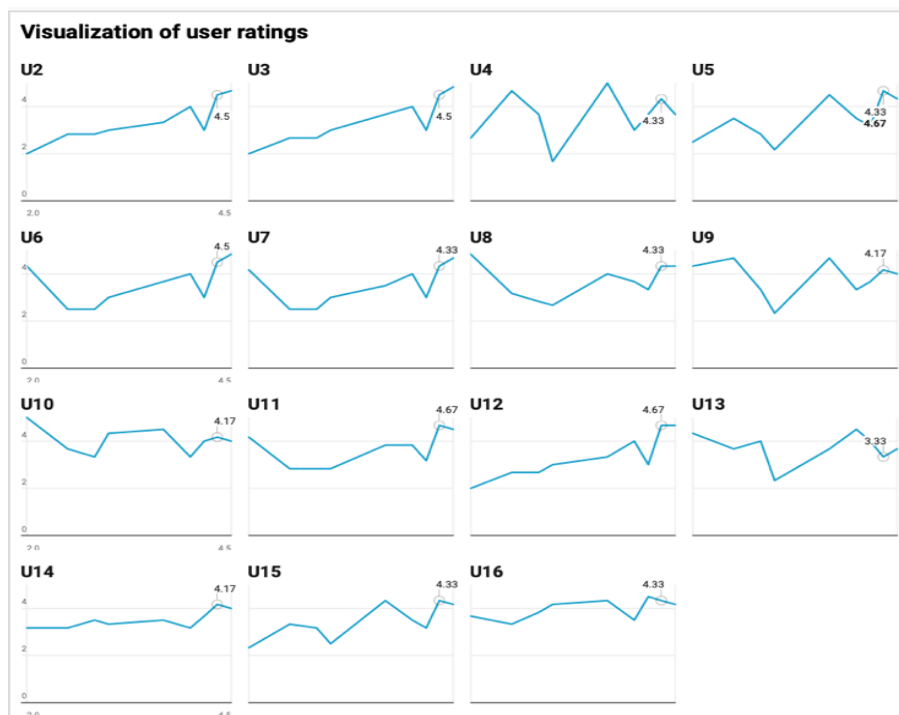


Figure 4. Visualization of the Comparison of Ratings for Each User



e. Prediction result value

Based on similarity, U14 is closest to 1 or exhibits the strongest positive correlation, indicating that U16 is more recommended to visit TSF 8, followed by TSF 15, TSF 1, TSF 13, TSF 5, and finally TSF 9, based on the ratings that U14 has provided for all objects. Meanwhile, U13 is closest to -1 or shows the strongest negative correlation.

4. CONCLUSION

The research results show that the highest prediction value using the Collaborative Filtering method is 0.70, where user 16 exhibits the highest similarity with user 14. U14 has the strongest positive correlation because the similarity value (U14, U16) is 0.70 closest to 1, implying that user 16 has the highest similarity with user 14. Consequently, TSF 1= 4.17, TSF 5= 3.5, TSF 9= 3.33, TSF 13= 3.83, and TSF 15= 4.5. If ranked, TSF 15 will be recommended first for user 16, followed by TSF 1, TSF 13, TSF 5, and TSF 9. User 16 has the second highest similarity with user 1. U1 has the strongest positive correlation after U14 because the similarity value (U1, U16) is 0.6, meaning user 16 has the second highest similarity with user 1. As a result, TSF 1= 3.33, TSF 5= 3.5, TSF 9= 2.67, TSF 13= 3.83, and TSF 15= 3.33. If ranked, TSF 13 will be recommended first for 16 users, followed by TSF 5, TSF 1, TSF 15, and TSF 9. This recommendation system facilitates consumers in determining the right shop or fish seller to visit when shopping at the Side Dish Store. Traders can easily market products to boost sales. Moreover, the system streamlines transactions between traders and consumers, eliminating the need to visit Side Dish Store directly.

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