

**RESTAURANT RECOMMENDER SYSTEM
USING ITEM BASED COLLABORATIVE FILTERING
AND ADJUSTED COSINE ALGORITHM SIMILARITY**

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ABSTRACT

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In 2018, the Ministry of Industry (Kemenperin) stated that the food and beverage sector contributed 6.34% of the national gross domestic product (GDP). Currently, culinary information can be easily found, both in print and online. The amount of information available sometimes makes people over-informed, making it difficult to choose a restaurant based on their preferences. To assist consumers in selecting a restaurant, we need a system that can provide several recommendations. This study aims to implement the item-based Collaborative Filtering method using the Adjusted Cosine Similarity algorithm on a restaurant recommendation system. The test was carried out with 40 samples from UIN Syarif Hidayatullah Jakarta using purposive sampling because the sample was selected based on specific criteria, and 40 respondents can be said to be correct because of the minimum number of respondents is 30. The accuracy test uses precision, and the determination of the error value uses MAE. The analysis of the research results used three scenarios, which are 5, 20, and 40 users. The third scenario produces the best precision and MAE values. Precision is better if the precision value is close to 1, and MAE is getting better if the MAE value is getting closer to 0. So it can be concluded that the Item-Based method with the Adjusted Cosine algorithm has the best accuracy and error values when the number of users grows.

Keywords: *Recommender system, Restaurant, Item based, Collaborative filtering, Adjusted cosine similarity*

I. INTRODUCTION

The growth of the food and beverage industry began to be a mainstay supporting national economic development and manufacturing. In 2018 the Ministry of Industry (Kemenperin) mentioned the food and beverage sector has contributed to the national gross domestic product (GDP) of 6.34%. The achievement of the Kemenperin was 0.23% from 2017 to 6.21%. Since 2018 the food and beverage industry has made it into the top five Largest GDP contributors alongside other sectors such as the chemical industry, transport equipment, textiles, and technology [1]. In 2019 the food and beverage sector were believed to continue to be excellent, especially in the tourism industry that develops culinary tourism.

There is a lot of information about the culinary tour found, both in print and electronic media. Even on social media, we often have information about the culinary tour or a review of someone about a culinary object. The information helps the community (culinary connoisseur) in obtaining the necessary information. However, increasing the amount of information does not necessarily facilitate the community in determining the restaurant or food menu to be eaten. Too much information and easy to obtain will make someone confused in choosing the options. In this case, someone will experience overload information or too much information [2]. It is supported by a survey that has been done. Based on the survey with the distribution of the poll against 100 respondents, 85% of respondents still feel the difficulty in determining the restaurant that suits their preference. To determine the problem, a system that can provide convenience to consumers in deciding the restaurant efficiently.

A recommendation system can help users discover that information by giving them personalized advice. A recommendation system can adapt its output to a specific user's characteristics, implying that the system should conclude what the user needs based on previous activities or interactions with other similar users [3]. Two approaches are commonly used in making a system of recommendations, namely content-based filtering and collaborative filtering. First, based on similarities in their content, content-based filtering compares the proximity of an item recommended to users to

an item that another user has already taken. In comparison, collaborative filtering is used to predict the usability of items based on later user ratings [4]. The collaborative filtering approach is divided into two categories, i.e., user-based collaborative filtering called memory-based, and item-based collaborative filtering is also called model-based. The system will calculate similarities between items viewed from the user's rating provided for the item on the item-based approach. To measure similarities between the items used a similarity algorithm.

Several types of research on recommendation systems using collaborative filtering have been done before. In research [5], the recommendation system on the XYZ e-commerce web uses a user-based collaborative filtering approach and cosine similarity algorithm. The best recommendations are generated when testing with the smallest number of neighbors. In research [6], a tourism agenda recommendation system using an item-based collaborative filtering approach and a cosine similarity algorithm. This study successfully used the collaborative filtering method, as evidenced by the 100% success in the black box testing.

The algorithm of adjusted cosine similarity is an algorithm made to overcome the weaknesses of its basic algorithm, namely the cosine algorithm similarity. In research [7], the researchers have tested accuracy cosine similarity with adjusted cosine similarity. From the MAE test done, adjusted cosine similarity produces the best accuracy value.

In this research, the authors are interested in implementing collaborative filtering methods with an item-based approach and using the adjusted cosine algorithm similarity on the restaurant's recommendation system. By implementing a recommendation system, users can easily specify a restaurant that suits user preferences more efficiently.

II. RESEARCH METHOD

2.1 Method of Collecting Data

This research conducted data collection in the form of library studies, observation, and dissemination of questionnaires. Literature study collection was obtained from various sources, including journals, books, and websites

about the recommendation system, collaborative filtering method, and restaurants. Observation and dissemination of the questionnaire aimed to obtain information in data that become objects in the research.

2.2 System Development Method

In this research, we used the Rapid Application Development (RAD) method. There are three phases in the RAD method involving analysts and users in the assessment, design, and deployment phases.

- a. Terms and Conditions (requirements planning).
- b. Workshop Design (workshop design).
- c. Implementation.

2.3 The Proposed Method

After collecting data and references from several previous studies, this research proposed the item-based collaborative filtering approach using the adjusted cosine similarity algorithm for prediction and recommended weights.

2.3.1 Item-Based Collaborative Filtering

The fundamental difference between User-based CF with Item-based CF is the correlation sought by a user or item. ICF models have almost the same scheme as UCF. Suppose the previously searched UCF is a correlation between users. If the ICF correlation is sought between the user's items, the correlated items are recommended against Several other users [8].

Item-based collaborative filtering has several advantages [9]:

1. Scalability
By using collaborative filtering, the scalability problem can be handled, and it is better than user-based filtering.
2. Prediction Speed
It is faster than user-based method because the dataset used in the predictive process is much smaller.
3. Data Characteristic
It is better to use data characteristics where there is a difference in the number of significant items between one user.

2.3.2 Adjusted Cosine Similarity

Adjusted algorithm cosine similarity is an algorithm made to overcome the weaknesses of its basic algorithm, namely cosine algorithm similarity. Adjusted algorithm cosine similarity

is an algorithm made to overcome the weaknesses of its basic algorithm, namely cosine algorithm similarity. Adjusted algorithm cosine similarity tries to overcome the algorithm's weakness because the user has a schema difference in rating. There's a high rating for an item, then giving it a low rating on other items. Then, for the same item, the item is assigned a regular and low rating. To balance the rating value, then calculate the average of each user [10].

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

Note :

Sim (i, j): Value of similarity between item I and item J

$u \in U$: Set user U

R_{ui} : Rating user U on item I.

R_{uj} : Rating user U on item J.

\bar{R}_u : Average value of user rating U

To calculate the similarity value between 2 items, a user set is required to rate the item. The resulting value in the adjusted-cosine similarity is ranged from + 1.0 to 1.0. Items are correlated if the Similarity value between the two items is close to + 1, and the reverse item is deemed unrelated if its similarity value is approaching -1 [11].

2.3.3 Weighted Sum

The method of prediction calculation for the non-cold-start problem is a weighted average of deviation. However, less can be calculated on the issue of new items that have not been rated because the average value in the item is zero (because there is no rating). Therefore, a weighted sum method is used to calculate a rating prediction on a new case item [4]. Weighted sum calculates the predicted rating of these items by comparing the rating that a user has ever given to an item with similarities between the items and other items [6].

$$P(u,j) = \frac{\sum_{i \in I} (R_{u,i} * S_{i,j})}{\sum_{i \in I} |S_{i,j}|} \quad (2)$$

Information:

$P(u, j)$: Prediction for u user on J product
 $i \in I$: A product set similar to J product
 $R_{u, I}$: Rate u users on the product I
 $S_{i, j}$: The value of similarity between a product I and product J.
 If a rating prediction has been calculated, the item recommendation can also be.

III. RESULT AND DISCUSSION

The recommendation system generally consists of content and a collaborative filtering method. This research implements collaborative filtering methods with an item-based approach. At this stage, the design process of system work is depicted on the following flowcharts.

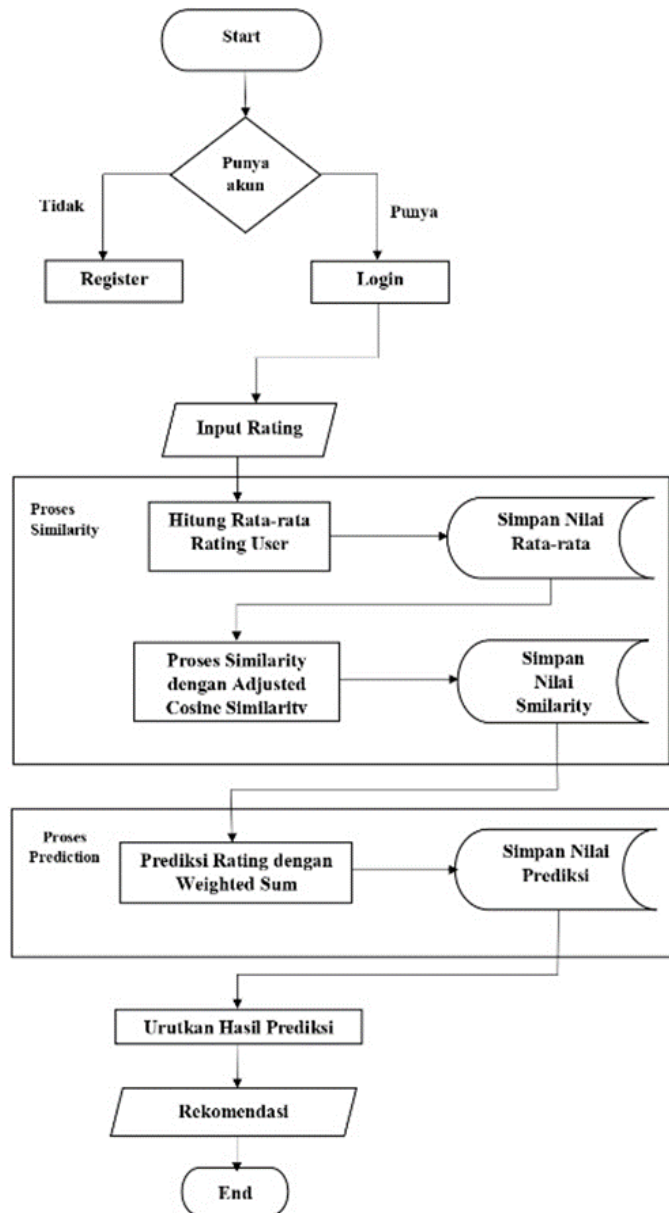


Fig 1. Flowchart system

The resulting recommendation process is divided into two stages:

1. Calculating Similarity Process

The similarity is the process of calculating similarity values between items. The basic calculation of similarity on item-based is looking for any user that gives a rating on two items to be searched similarity. The rating used is explicit, meaning the user provides a conscious rating on the system. At the restaurant's recommendation system, similarity calculates the value of similarities between one restaurant and another, usually called a similarity between objects. The similarity value is calculated using the adjusted cosine equation similarity. User-provided rating of 1 for the worst value up to 5 for the best value.

2. Prediction Process

Following the determination of the similarity value between the items, the next specified prediction item will be suggested. The predicted value is calculated using a weighted sum algorithm. In the prediction stage, several conditions must be met to determine the predicted rating given to the user, namely:

- a. The neighbor is a restaurant that has been rating by the user.

- b. The similarity value between items must be larger than 0. After calculating the rating prediction value, the value will be taken from the largest to the smallest. The restaurant with the highest prediction rating will be the highly recommended restaurant system, so vice versa.

3.1 Implementation

The item-based collaborative filtering method that has been designed is then implemented into the system. Recommendations will be generated when the similarity process with the adjusted cosine similarity algorithm and prediction with weighted sum is successfully carried out. Testing of adjusted cosine similarity on the recommendation system has not been doing much. To find out how accurate the resulting recommendations are, testing is carried out.

3.2 Result

Implementing a collaborative filtering method with an item-based approach consists of 28 restaurant datasets equipped with rating data from 40 users. The system's main menu display is a list of 28 restaurants like the following figure 2.

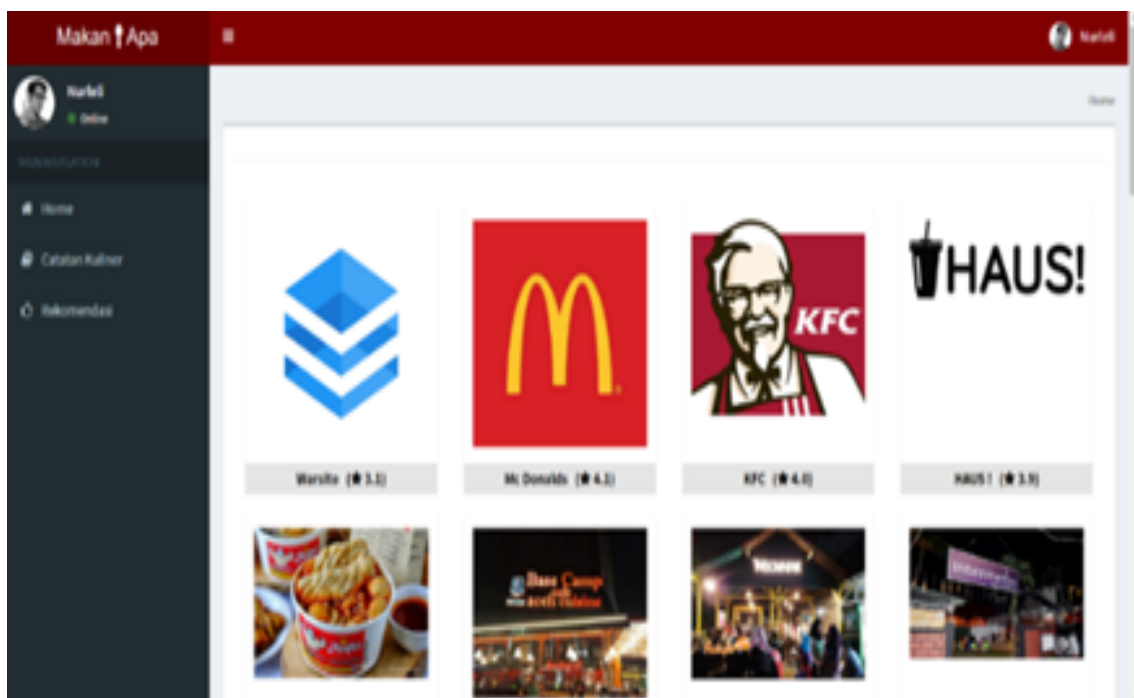


Fig 2. Restaurant recommendation main page

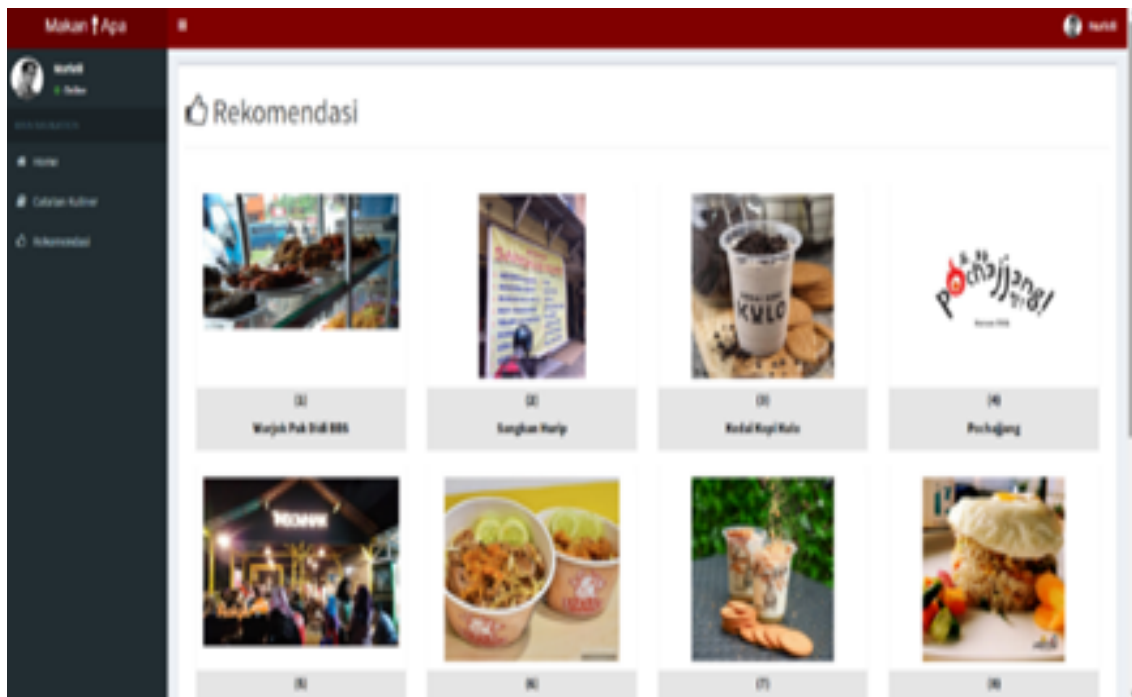


Fig 3. Recommendation result page

3.3 Testing

Testing can be done when the user has given the rating and got the recommendation result. This test is done to calculate the accuracy of the recommendation results, whether the system's recommendation is provided according to the user. This test is also done to determine the level of error or system error. The test consists of 3 different scenarios. They were testing with the first scenario, using five users who gave ratings to restaurants that have been visited. Meanwhile, the second and third scenarios used 20 and 40 users.

3.3.1 Precision Testing

The first test is the precision test; the precision calculations calculate how relevant the system is given to the user. The user will respond from the given recommendation data. The feedback given is the user's opinion, whether the recommendation provided by the system is appropriate or not.

Table 1. Precision value table

Scenario	User	Precision
Scenario 1	5	0,678
Scenario 2	20	0,723
Scenario 3	40	0,732

The more the user, the precision value will be increased. The increasing value is because the increasing user increases the rating data so that the recommended restaurant is more and more. The more restaurant that is recommended, the more data the user can receive. It is supported by [12] which states that at least interaction data per user is also the cause of low precision value.

3.3.2 Mean Absolute Error

The next test is calculating system accuracy based on the magnitude of the error value. To calculate the system error value, use the mean absolute error (MAE). The calculation is done by requesting user feedback in the form of the predictive value of the user towards the recommended restaurant. The predicted value of the user's response is compared to the system's prediction value, yielding the system error value. The smaller the MAE value, the better the system is made.

Table 2. Table MAE value

Scenario	Amount of Users	MAE
Scenario 1	5 with 46 data rating	0,672
Scenario 2	20 with 238 data rating	0,653
Scenario 3	40 with 571 data rating	0,623

Based on the testing process that has been done, the method of collaborative filtering with the item-based approach using the adjusted cosine algorithm similarity was successfully applied to the restaurant's recommendation system. It is seen from the precision value, and MAE is produced quite well. From the 3 test scenarios that have been done, more and more meal rating data will affect the precision value and MAE. The more data rating, the smaller the MAE value and the greater the precision value, likewise vice versa. Many of the rating data is influential to the level of architecture or data vacancy.

IV. CONCLUSION

Based on the testing process that has been conducted, the method of collaborative filtering with the item-based approach using the adjusted cosine algorithm similarity was successfully applied to the restaurant's recommendation system. It is showed from the precision value, and MAE is produced quite well. From the three scenarios that have been conduct, more meal rating data will affect the precision value and MAE. The more data, the smaller the MAE value and the greater the precision value, likewise vice versa. Many of the rating data is influential to the level of architecture or data vacancy. For further research, it is recommended that the rating is not explicitly given. Users can provide ratings implicitly or a combination of explicit and implicit. It is hoped that other methods can be used that can produce more effective precision and lower error rates.

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