

Recommendation System Algorithm Content-Based Filtering Method to Provide Drink Menu Recommendations

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ABSTRACT

Overchoice is a cognitive disorder in which people have difficulty making decisions when faced with many choices, that make the problem in this study. This over-choice phenomenon often occurs in choosing drinks in cafes and restaurants. This research aims to create a Recommendation System (RS) to assist in choosing the drink you want to order. Making a non-personalized hospital at the Muftada Kopi cafe uses the best-rated and content-based filtering methods. The content-based filtering method tries to retrieve user preferences explicitly, asking the user to choose the preferences the user wants from the six content made before calculating the match between the user's preferences and the six contents in each item using the dot matrix formula. The results will be converted into a rating to match the best-rated hospital approach, which is made on a non-personalized basis. This rating matches the user's preferences and the Muftada Kopi menu list items. The higher the rating, the better it matches the user's preferences. The order RS recommends with the Content-based filtering method is rosella tea, chocolate, lemon tea, blossom tea, and spice tea.

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1. INTRODUCTION

Culinary tourism is a problem currently prevalent in the development of Indonesian society. Information regarding the culinary world can be easily obtained through electronic media. This amount of information does not necessarily make it easier for culinary consumers to make menu choices according to their wishes and expectations. Search engines can help users who already have references about what dishes they want to consume at that time. Users encounter difficulties without reference to what will be served. A search engine alone is still insufficient, so a recommendation system is needed to provide suggestions according to user needs.

In 2004, American psychologist Barry Schwartz's book "The Paradox of Choice Why More is Less" said that having choices in all aspects of life: education, career, friendship, romance, parenting, and so on, can improve one's quality of life. These choices can allow a person to control life goals and to get what he wants from any situation. On the other hand, the fact that having several choices is "good" does not mean that having more choices is "better"; having too many choices (overload of choices) also results in bad decisions, anxiety, stress, and dissatisfaction even to the point of impact on depression [1]. Overload of choice or Overchoice is a cognitive disorder in which people have difficulty making decisions when faced with many choices; having too many equal choices is very mentally draining because each choice must consider several alternatives to choose the best option [2]–[5].

In this period of technological development where every day everyone is faced with countless choices, this phenomenon of overload of choice often occurs in everyday life, such as choosing a drink at a cafe. Visitors are faced with several menu choices ranging from drinks containing coffee, without coffee, juices, soft drinks, tea, etc. Each of these drinks has its distinctive taste and different prices. These considerations increase the complexity of choosing a drink, where visitors must invest more time and energy. Apart from that, self-doubt sometimes arises, anxiety about choosing a drink you do not like, and fear of being disappointed with your choice; therefore, a Recommendation System (RS) is needed to assist in choosing the drink you want to order and select other menu options.

A recommendation System (RS) is a subclass of machine learning which is generally concerned with ranking or evaluating products or users [6]. These recommendations relate to the decision-making process, such as what items to buy, what music to listen to, or what online news to read. This "item" is a general term that indicates what the system recommends to users. RS usually focuses on a specific type of item, and its design, graphical user interface, and core recommendation techniques used to generate recommendations are all tailored to provide valuable and practical suggestions for specific item types [7].

RS techniques or RS algorithms can be divided into three categories, namely content-based Filtering, collaborative Filtering, and hybrid systems. Collaborative Filtering takes the input or input values from various users and performs various comparisons on these inputs. Content-based Filtering takes advantage of the user's interests and tries to match user preferences with the attributes or content possessed by various items to be recommended, while the hybrid system combines the two previous algorithms [8]. This hospital can also be combined with other fields in machine learning and Artificial Intelligence (AI) to produce more optimal recommendations.

RS is aimed at individuals who do not have sufficient experience and competence to evaluate or assess each of the "items" offered so that it has the potential to make the individual feel overwhelmed. A popular website, Amazon.com, this website makes RS help individual online visitors who will read books; because RS is generally built on a personalized basis, online visitors get different recommendation results from other online visitors. In addition, some hospitals are not made individually or non-personalized. Non-personalized RS is generally found in newspapers and magazines. As one example of the

top ten books that are often read, although non-personalized RS can be used and is effective in certain situations, non-personalized RS is rarely discussed by researchers [7].

RS is an information processing system that collects various data to develop recommendations. The primary data is data about the item to be recommended and data from the user or users who will receive the recommendation. However, because the data and knowledge sources available to hospitals as recommenders vary widely, it ultimately depends on the recommendation technique used. In general, there are recommended techniques that do not require knowledge sources. This technique uses specific data, such as the user rating of an item. Other recommendation techniques rely heavily on knowledge sources, such as descriptions of users or items. Some techniques also require correlations or relationships and activities between users. In all cases, as a general classification, the data used to create RS refers to three objects: items, users, and transactions [7]. In addition, this technology has been widely adopted by companies in serious e-commerce like Amazon, Netflix, and Pandora. This recommendation system is essential for e-commerce because it can deliver references that the customer likes, create strategic marketing, and increase customer loyalty [9].

One company that uses a recommendation system to help its users is NETFLIX, which uses its own RS technique, the Netflix Recommendation Engine (NRE). NRE helps its users find movies that users will watch with minimal effort; NRE estimates the likelihood that users will watch movies that NETFLIX provides based on user history, how users rate a film, and other users with similar preferences. Similar, based on the film category, and so on. In addition, to get the best NETFLIX recommendations, consider when the user watches a movie, the device the user uses, and how long the user watches a particular film [10].

In its simplest form, individually generated RSs offer suggestions for items selected in a ranking list. In making this ranking list, RS tries to predict which Product or service is most suitable based on the preferences and limitations given by the user. To accomplish the computational task of making these ratings, RS takes the user's preferences explicitly, for example, by rating a product or interpreting the user's actions. RS might conclude that the user will be interested in the Product if the user goes to the page about the Product [7]. Several approaches are commonly applied to real-world scenarios in building non-personalized hospitals. Approach - this approach is the popularity often bought, best rated (best rating), recent items (just purchased), and random popularity. Popularity is the primary approach often used to create non-personalized hospitals [11]. This study built a non-personalized hospital at the Mubtada Kopi cafe with the best-rated approach and content-based filtering techniques. Recommender system performance can impact the commercial success of many companies in terms of revenue and user satisfaction [12].

The content-based filtering method has the principle of providing recommendations based on the similarity of the item profile. When the user selects a restaurant, a recommendation will be given as a list of restaurants with profile items similar to the selected restaurant [13]. Similar research has been conducted by Maharani and Gunawan [14] by comparing the two methods used for recommendation systems. The parameters used to form the user profile are still not precise, but research results show that the content-

based filtering method is superior to demographics. Another study was conducted by Huda [15] by forming a classification of content features based on the taste characteristics of food as a basis for determining recommendations. User tastes are described by nine attributes: sweet, savory, salty, sour, bitter, sauce, spicy, vegetable, and meat. Pearson correlation is used to calculate content feature similarity between foods. The same is the case with restaurants; another example that displays a row of menus is a coffee shop.

A coffee shop is a place that provides a variety of coffee drinks and other drinks, either hot or cold, and some cafes even sell some snacks. Cafes also function like bars, restaurants, or workspaces but differ from cafeterias. Mubtada Kopi is a cafe that provides coffee and various other drinks, including snacks, founded in 2016.

The many drink menus available at Mubtada Kopi can make visitors who come to the Mubtada cafe find it challenging to choose drinks, and the phenomenon of over-choice cannot be avoided. One solution to this is for the waiter to recommend the menu to visitors, which also creates ignorance because the waiter does not know each visitor's drink preferences. Not all visitors have the same drink preferences with service, especially since each visitor has preferences that are not the same as one another, and the length of time needed by some visitors who experience the over-choice phenomenon will hinder the waiter from serving drink orders from other visitors. At Mubtada Kopi, visitors can ask for drink recommendations directly from the barista on duty to take drink orders. However, this will affect the speed of the barista in completing his work in making the ordered drink. Therefore, hospitals must recommend drinks available at Mubtada Kopi to their visitors to help them choose the drinks offered, save time for visitors in ordering menus, and help Mubtada Kopi understand their visitors better. In this study, all food menus in the cafe were ignored because the number of food menus available at Mubtada Kopi only had five and were considered too few to be included in the new system. Difficulties are encountered for users without references, and using a search engine is still not enough, so a recommendation system is needed to provide suggestions according to user needs, one of which is Content-based Filtering.

Content-based Filtering takes advantage of the user's specific interests and seeks to match the user's preferences with the attributes or content possessed by the various items to be recommended. The built RS will try to recommend items by fetching user preferences explicitly. After that, these user preferences will be matched with the content of each item in the menu list. Previously, each item on the menu would be given six contents, namely the composition of the ingredients needed to make one drink. These contents, namely: soda, fruit, coffee, milk, tea, and spices. The six contents were determined based on research conducted by Javier Livio and Rania Hodhod, who said that the assessment came from the Specialty Coffee Association of America (SCAA), which instructed assessors (baristas) to assess coffee drinks using a numerical scale to store ten essential flavors for coffee. , namely: Fragrant/Aroma, Flavor, Aftertaste, Acidity, Body, Balance, Uniformity, Clean Cup, Sweetness, Overall, and stores the value of a coffee's defects [16].

After providing content for each item on the drink list, a value will be given to each content based on the value reference given by the SCAA. The assessment is carried out by considering what ingredients are used to make one item on the drink list with a maximum

total value of the six contents, which is 5. After all, items are given a value, and the content-based filtering technique will try to retrieve user preferences explicitly, namely asking the user to choose the preferences that the user wants from the six previously created content and then calculating the suitability of the user's preferences with the six contents in each item using the dot matrix formula. After getting the results, these numbers will be converted into a rating to match the RS approach, namely the best rating made in a non-personalized manner. This rating indicates the suitability of the user's preferences with the items on the Mubtada Kopi menu list. The higher the rating, the better it matches the user's preferences.

This technique does not require data in the form of knowledge sources as a reference for making recommendations and is very easy to scale due to the low amount of data. However, this method requires more specific knowledge from the developer who will provide features or content for each Product. So, the accuracy of this recommendation system is highly dependent on the accuracy of knowledge from the developer who will provide features or content for each Product [16]. Along with the development of information technology, system information plays an essential role in processing many available data and valuable information and can be used as a system that can help users to decide [17]. Many multiple system developers have used Recommendation Systems to build a system that can provide convenience to users, one of which uses a filtering algorithm to provide recommendations to users [18].

2. METHOD

The method used in this research is a qualitative research method. Qualitative research produces descriptive data in speech or writing from the things observed [19]. Collecting data directly can be as follows: 1. Asking the user to rate an item. 2. Ask the user to rank favorite items and at least choose one favorite item. 3. Provide several choices of items to the user and ask him to choose the best. 4. Ask the user to list the items he likes the most or the items he does not like [20].

A recommendation system is a software tool and a technique that provides valuable item recommendations to users. Recommendations are based on various decision-making processes, such as what items to buy, what music to listen to, what food to eat, or what online news to read [7]. A recommendation system with a content-based filtering method recommends items similar to the previous item the user likes or chooses. Item similarity is calculated based on the features of the items being compared [7]. Recommender systems use several data mining techniques and algorithms to identify user preferences for items in a system out of millions of choices available [21]. This method is user-independent and does not depend on whether the item is a new item that has never been selected by any user or is not new. If a user has ordered a menu of dishes in a particular category, the system will try to recommend a menu of dishes with similar categories available at other restaurants that the user might also like [22].

The approach to the Content-Based Filtering method can be divided into: two, namely using an analysis of the content description and user-item interaction [23], supported by statements Aggarwal [24] regarding two sources of the data used by the

Content-Based Filtering system, namely descriptive data represents an item and the second data source is the user profile, associated user interaction and action on an item. Content-based Filtering gives recommendations by exploring the contents of user profiles, product descriptions, or matters relating to the formation of user choice of an item [25].

The CBF method focuses on comparing user interests with product features or content. Products with the most similar features to the user's interests will be recommended. Given the importance of product features in this system, discussing how users' favorite features are decided is essential. Two methods can be used. First, users can be given a list of features that can be selected according to user preferences. Second, the algorithm can track the products the user has previously selected and add those features to the user data. Likewise, product features can be identified by the product developer himself. In addition, users can be asked what features they believe fit best with the Product [13]. The weakness of the content-based filtering method is that recommendations are limited to similar items, so there is no opportunity to get unexpected items. The following are the steps for creating Content-based Filtering: First, create a table that lists all products and features and then assign values as shown in Figure 1.

	Feature 1	Feature 2	Feature 3	Feature 4
Product 1	1		1	2
Product 2		1	4	
Product 3	3			1
User Data	2		1	1

Figure 1. Product matrix table

Furthermore, after being given a value, be it binary numbers 1 and 0 or free numbers. A method to identify similarities between products and user interests needs to be done. The most basic formula uses the dot product method shown in Equation 1.

$$\sum_{i=1}^n p_i u_i \tag{1}$$

where:

p = Product features

u = User interests

i = Drink list iteration starting from 1

n = number of drink lists

After calculating using the equation above, the value of similarity between products and the most considerable user interest will be recommended to users.

3. RESULTS AND DISCUSSION

The content-based filtering method has the principle of providing recommendations based on the similarity of the item profile. After the next preprocessing stage, the appropriate profile items are compared to look for similarities. In identifying the features and values to be created by the barista, this report refers to research conducted by Javier Livio and Rania Hodhod, who said that the assessment came from the Specialty Coffee Association of America (SCAA), which instructed the assessors (baristas) to assess coffee drinks using a scale numeric to store ten essential flavors for coffee, namely: Fragrant/Aroma, Flavor, Aftertaste, Acidity, Body, Balance, Uniformity, Clean Cup, Sweetness, Overall and also stores the value of a coffee's defects as shown in Figure 2 [26].

The figure shows a SCAA Cupping Form with several sections. On the left, there is a 'Roast Level or Sample' section with a grid for recording data. The main body of the form contains five scales, each with a 'Score:' box and a 6-10 scale. The scales are: 'Fragrance/Aroma', 'Flavor', 'Acidity', 'Aftertaste', and 'Intensity'. The 'Intensity' scale has 'High' and 'Low' labels. Below the 'Fragrance/Aroma' scale, there are three vertical scales labeled 'Dry', 'Qualities', and 'Break'. The 'Qualities' scale has a horizontal line drawn across it, and the 'Break' scale has a vertical line drawn through it.

Figure 2. SCAA Cupping Form

The list of drinks available at Mubtada Kopi does not all contain coffee, so appropriate changes are made to all existing drink menus to make it easier for visitors or consumers to understand. Therefore, the division of the list of available drinks menus into six different contents, and each is assessed based on the composition of the ingredients, namely soda, fruit, coffee, milk, tea, and spices, on a scale of 1 to 5, with one as a score lowest and five as the highest score. The steps in building a hospital are as follows:

The first thing to do is create a table to list all available products and features/content, and then an assessment is given, the results of which are shown in Table 1.

Table 1. A snippet from the rated drink list

No	Drink menu list	Category					
		Soda	Fruit	Coffee	Milk	Tea	Spices
1	Spice tea	0	0	0	0	2,5	2,5
2	Rosella tea	0	0	0	0	5	0
3	Tarik tea	0	0	0	3,5	1,5	0
4	Wedang uwuh	0	0	0	0	0	5
5	Chocolate	0	5	0	0	0	0
6	Choco latte	0	1,5	0	3,5	0	0
7	Red velvet latte	0	1,5	0	3,5	0	0
8	Green tea latte	0	0	0	3,5	1,5	0
9	Milkshake Chocolate	0	1,5	0	3,5	0	0
10	Milkshake banana	0	1,5	0	3,5	0	0
11	Milkshake strawberry	0	1,5	0	3,5	0	0

No	Drink menu list	Category					
		Soda	Fruit	Coffee	Milk	Tea	Spices
12	Milkshake Oreo	0	1,5	0	3,5	0	0

Each value obtained is taken from the composition of each ingredient needed to make the drink. After that, the user provides an assessment with a value of zero or one for each category, as shown in Table 2.

Table 2. User interest category

User interest	Category					
	Soda	Fruit	Coffee	Milk	Tea	Spices
	0	1	0	0	1	0

After being given a value, the dot product formula is used to identify similarities between products and user interests, as shown in Table 2. As an example spice tea, the value of 2,5 is obtained from

$$\sum_{i=1}^6 p_i u_i = (0 \times 0 + 0 \times 1 + 0 \times 0 + 0 \times 0 + 2,5 \times 1 + 2,5 \times 0) = 2,5$$

In the same way, values will be obtained, as shown in the following table.

Table 3. Results of Dot Product calculations

Drink Menu List	Result	Rank
Spice tea	2,5	5
Rosella tea	5	1
Tarik tea	1,5	8
Wedang uwuh	0	25
Chocolate	5	2
Choco latte	1,5	9
Red velvet latte	1,5	10
Green tea latte	1,5	11
Milkshake Chocolate	1,5	12
Milkshake banana	1,5	13
Milkshake Strawberry	1,5	14
Milkshake Oreo	1,5	15

After calculating using the equation above, the highest similarity value between products and user interests that will be recommended to users is shown in Table 4.

Table 4. Menu order to be recommended

Rank	Drink Menu List
1	Rosella tea
2	Chocolate
3	Lemon tea
4	Blossom tea
5	Spice tea

From Table 4 above, it explains that consumers, in this case, have the most recommendations for the tendency to choose a drink menu, namely rosella tea, followed by

chocolate, lemon tea, blossom tea, and spice tea, or cafe waitpersons can provide recommendations to consumers on drink menus starting with the first rank rosella tea and then followed by the others in the order recommended.

There are many benefits of having a list like in Table 4 above, such as making it easier for consumers to choose the most recommended drink at the cafe, or what is commonly called a mainstay menu, and for the cafe, having this list is used to anticipate the availability of the stock of ingredients used. Besides that, on a broader scale, Content-Based Filtering allows for high personalization in providing user recommendations based on their preferences. This method analyzes content users have previously consumed and looks for similarities with other content to generate recommendations that match their interests. This can increase user satisfaction and engagement with the platform [27]. Content-Based Filtering does not require data from other users or user behavior information. This method can provide relevant recommendations even to new users with no history of interaction with the platform. This helps maintain user privacy and avoids the problem of leakage of personal information [28]. By analyzing the characteristics of the content consumed by users, Content-Based Filtering can generate particular and relevant recommendations. This method considers content features such as genre, author, or artist and matches them with similar content to provide recommendations that match user preferences [29]. Furthermore, Content-Based Filtering tends to be easier to implement and scale than other recommendation methods. This method does not require complex calculations involving other user data, making it more efficient in handling large volumes of data, and it can be implemented quickly on different platforms and services [30].

4. CONCLUSION

In conclusion, with the creation of this recommendation system to choose drinks available at Mubtada Kopi, visitors will no longer experience the over-choice phenomenon; visitors who use this recommendation system application can choose their preferences; visitors who come to order drinks at Mubtada Kopi need a relatively short time when using the application that has been built; and by making this recommendation system, baristas can focus on doing their job in making drinks ordered by customers without having to provide drink recommendations to customers and customers still get their recommendations from the system made. The order RS recommends with the Content-based filtering method is rosella tea, chocolate, lemon tea, blossom tea, and spice tea.

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