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Research Article

Recommendation Systemfor Daily Consumer Purchases List Usingspecial Hybrid Approach

Sanaa Al Rawahi[1], Nasser Al Musalhi[2*], Erbug Celebi[3]

[1]Department of Information Technologies, Cyprus International University, Nicosia, North Cyprus, TURKEY Mersin 99258
[2*]Department of Information Technology, University of Technology and Applied Sciences (Ibra-Branch), Ibra, Sultanate of Oman.
[3]Artificial Intelligence Application and Research Center, Cyprus International University, Nicosia, North Cyprus, TURKEY Mersin 99258

***Corresponding Author:** Nasser Al Musalhi
Email: nhsoman2015@gmail.com

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ARTICLE INFO	ABSTRACT
	Recommendation systems have attained widespread prevalence in the current digital world, providing consumers with specific recommendations for a diverse range of products, services, and information. These systems have a significant role in shaping customer behavior, particularly in the realm of online shopping. This study aims to evaluate the performance of a hybrid recommendation system in suggesting daily purchase items to consumers by examining three different recommendation system methods: collaborative filtering (CF), Content-based filtering (C-B), and Hybrid. Then we assess their efficiency in delivering suggested items to consumers through the utilization of recall, precision, and F1 metrics. The study reveals that each strategy exhibited distinct strengths. However, the hybrid approach is considered the most effective method for recommending items for new users who do not have a history profile.

1. Introduction

System recommendations refer to software tools and methodologies that offer suggestions for products and services that could potentially capture the user's interest. These activities encompass a variety of decision-making processes, including the selection of things for purchase, the consumption of music, and the perusal of online news articles. The recommendations have been categorized into three distinct groups. When users are provided with suggestions by the system, these suggestions are commonly referred to as "items" in a general sense. Recommender Systems often exhibit specialization towards a specific category of items, such as music or news. Consequently, the system's design, graphical user interface, and core recommendation technique are customized to offer valuable and efficient suggestions for the given item category[1].The understanding of referral systems, also known as recommender systems or recommendation engines, might provide difficulties in terms of comprehension. All these systems serve a comparable purpose, as they leverage customers' historical behavior and current preferences to anticipate their future preferences. Gaining insights into consumer expectations can be achieved by examining their purchase behaviors. Understanding the factors that influence consumer purchasing behavior is of utmost significance. Prior to its release onto the market, a comprehensive evaluation of a product is important to ascertain its acceptance among consumers. Marketers could get knowledge regarding the preferences and aversions of their intended audience, which can then be utilized to strategize and execute their marketing initiatives. Research on consumer purchasing behavior, encompassing the analysis of individuals' product preferences, the underlying motivations driving their purchases, the timing of their buying decisions, the frequency of their purchases, and related factors, is widely prevalent in academic literature. [2]. A recommendation system is a crucial component of many modern platforms, designed to predict and suggest items that users might be interested in, based on their preferences and behaviors. These systems leverage various algorithms and techniques to analyze large amounts of data, typically including user interactions, item attributes, and contextual information. There are three primary types of recommendation systems: content-based, collaborative filtering, and hybrid systems.
This study assesses the efficacy of three recommendation system approaches in providing clients with suggestions for daily consumable products. By using historical data, these systems may optimize customer buying patterns by suggesting the most relevant products for daily needs. Moreover, the research examines the use of recommendation algorithms to provide customized shopping rosters by leveraging consumer

purchase records. Furthermore, the exploration of machine learning approaches may be undertaken to enhance the precision of suggestions by considering specific times.

1.1 Content-Based Filtering

Content-based filtering, also known as cognitive filtering, recommends products by comparing the product's properties with the buyer's characteristics. Tags and labels describe the product's features, and user interactions create a customer profile. This profile outlines the user's interests, such as music preferences or cosmetic choices, which the system uses to search for relevant recommendations within its database. Content-based systems focus on a user's explicit and implicit input to build their profile and suggest items based on their past purchases or preferences. Unlike collaborative filtering, content-based systems do not consider other users' activities. Both user and item qualities play a crucial role in content recommendation systems, contributing to accurate predictions[3]–[5]. Figure 1 shows how the content-based approach works.

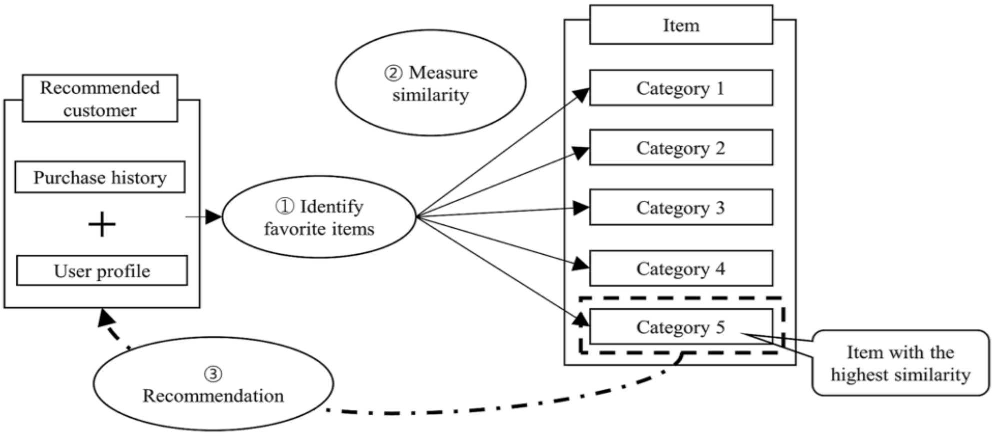

Figure 1: Content-based filtering

Content-based filtering in recommender systems offers several advantages, including enabling users to create personalized profiles based on their ratings, educating users about the system's functioning, and recommending items not yet rated by any user, which is particularly beneficial for new users. However, there are limitations to content-based filtering, such as the challenge of generating certain item qualities, the potential for overspecialization in recommending similar items, and the reliance on user ratings, which may be sparse and make evaluation challenging[5].

1.2 Collaborative Filtering

Collaborative filtering (CF) improves upon content-based filtering by recommending items based on similarities between users and items. CF suggests items to users based on the preferences of others who share similar interests. It's a widely used technique in recommendation systems, particularly for predicting and recommending products based on user ratings or activity. CF leverages the idea that users who have liked similar products in the past are likely to have similar preferences in the future. This approach has been successful in various applications, such as e-commerce and online movie platforms. Notable examples include Amazon increasing sales by 29%, Netflix boosting movie rentals by 60%, and Google News improving click-through rates by 30.9%, showcasing the effectiveness of collaborative filtering [6], [7].Collaborative-filtering recommender systems employ two fundamental methods: user-based and item-based approaches.

(A) User-Based Approach: User-based filtering suggests products based on the preferences of individuals who have shown similar tastes in the past. Users with comparable preferences are identified, and products liked by one user are recommended to others with similar tastes. For example, if User X and User Z both enjoy strawberries and watermelons, the system recommends grapes and oranges to User Z, assuming that users with shared preferences tend to have similar interests[8], [9].

(B) Item-Based Approach: While user-based filtering is effective, it encounters scalability issues with a growing user base. Item-based collaborative filtering (IB CF) addresses this by connecting products based on users' existing ratings and recommending new, related items[7]–[9]. If many users have given similar ratings to two different items, those items are considered comparable. For instance, watermelon and grapes might form a neighborhood in IB CF, so if a user likes watermelon, the system suggests grapes from the same neighborhood.

Collaborative filtering (CF) offers several advantages, including simplified recommendation system deployment, the flexibility to incorporate new data seamlessly, and improved prediction accuracy. However, CF has limitations, including the "Cold Start" problem, where substantial historical data is needed for accurate recommendations; scalability challenges due to the vast number of users and items; and the issue of sparsity, where only a small fraction of products in extensive databases receive frequent ratings from users. These considerations highlight the trade-offs in using collaborative filtering for recommendation systems[4], [10].

1.3 Hybrid Filtering

Hybrid filtering strategies combine multiple recommendation algorithms to enhance system performance and overcome the limitations of individual methods. This approach acknowledges that a mix of algorithms can provide more effective suggestions by leveraging the strengths of each. Various recommendation approaches are integrated to mitigate the shortcomings of standalone strategies. Integration methods include implementing techniques separately and combining results, blending content-based and collaborative filtering, or creating a unified recommendation system that combines both approaches, offering a versatile solution to recommendation system optimization[11]. Figure 2 shows the hybrid filtering approach.

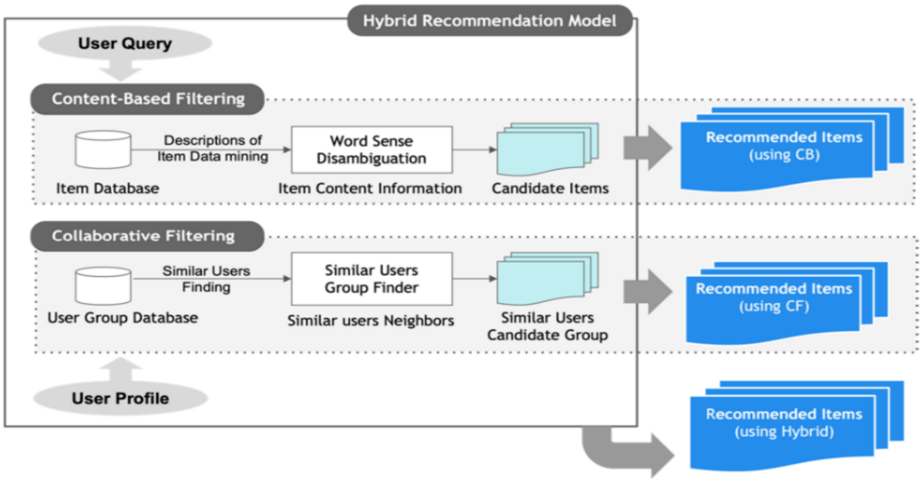

Figure 2: Hybrid Model Architecture[12]

Hybrid filtering offers advantages including overcoming the limitations of individual methods, leading to improved recommendation outcomes, and the ability to work effectively with sparse data. However, it also presents drawbacks, such as increased expenses, heightened complexity in system design and management, and the occasional need for external data that may not always be readily accessible. These considerations underline the trade-offs associated with the use of hybrid recommendation systems.

1.4 Recommendation Systems Algorithms

Recommendation system algorithms are computational methods used to predict and generate recommendations for users based on their preferences, historical interactions, and contextual information. These algorithms are essential components of recommendation systems and are responsible for analyzing large datasets to identify relevant items for users. There are several types of recommendation system algorithms, each with its approach to generating recommendations

(A) Nearest Neighbor is a vector-based method that employs object attributes as dimensions, making it suitable for modeling unknown or challenging-to-validate concepts. It finds application in machine learning tasks as well. This technique is instrumental in recommender systems, particularly in implementing collaborative filtering. It operates under the assumption of data stability, classifying data based on the closest neighbor. Measuring the distance between individual items or groups of items, using a distance metric like Euclidean distance, determines the degree of resemblance between them [13]. Euclidean distance can be calculated with the following Eq:

$$\text{sim}\,(i,j) = \sqrt{\sum_{k=1}^{n} \left(R_{k,i} - R_{k,i}\right)^2} \quad (1)$$

Rk, i denotes the User k's assessments of the target item i, while *Rk,j* represents the User k rating of Item j. The variable 'n' represents the overall count of people who have rated both items i and j. This method establishes coordinates to assign preference ratings to objects and calculates the distance between each pair using the Euclidean distance metric. When the computed distance between two points, referred to as sim*(i,j)* is substantial, it signifies that these two points lack comparability. Conversely, when the value of *sim(i,j)* is small, it suggests that the two points are indeed comparable [6].

(B) Cosine similarity: widely recognized as the most precise measure, has established itself as the standard choice [14]. This metric calculates the similarity between two n-dimensional vectors by examining the angle of intersection between them. It finds extensive application in information retrieval and text mining, especially for comparing text documents represented as word vectors. Formally, the similarity between two vectors, a and b, is defined as follows Eq.2.

$$\text{sim}\ (\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| * |\vec{b}|} \tag{2}$$

Where $(\vec{a}, \vec{b})$ are the two neighbor vectors.

(C) Pearson Correlation Coefficient: PCC stands as one of the most employed techniques in Recommender Systems (RSS) [6]. This coefficient aids in gauging the extent to which a value in one series surpasses its corresponding value in another series. It evaluates the probability that when two sets of integers are aligned one-to-one, they move in the same direction. A strong relationship between two vectors is indicated when the correlation coefficient, denoted as sim(i,j), approaches one. Conversely, when there is little alignment in the trends of two vectors, the sim(i,j) function approaches zero. In cases where two vectors exhibit opposing trends, the value of sim(i,j) approaches -1. The formula for this calculation is displayed below Eq3:

$$\text{sim}(i, j) = \frac{\langle R_{k,i} - A_i, R_{k,j} - A_j \rangle}{\| R_{k,i} - A_i \| \| R_{k,j} - A_j \|} = \frac{\sum_{k=1}^{n} \left(R_{k,i} - A_i\right)\left(R_{k,j} - A_j\right)}{\sqrt{\sum_{k=1}^{n} \left(R_{k,i} - A_i\right)^2 \times \sum_{k=1}^{n} \left(R_{k,j} - A_j\right)^2}} \tag{3}$$

2. Related Work

Lakshmi Tharun Ponnam and colleagues utilized an approach called item-based collaborative filtering in their study. To compare the user's recommendation for each item, they first evaluate the user's item rating matrix to uncover the links between things. Item-based collaborative filtering was found to produce simple, trustworthy, and defendable recommendations. When the number of people in the system exceeds the number of items, an item-based approach is the most practical[15].In a study conducted by Chengxin Yin et al, the objective was to enhance customer satisfaction through the implementation of a unique recommendation system. This system was designed based on consumer initiative decisions and employed an associative categorization approach, which aimed to provide innovative and effective recommendations. The experimental study provides clear evidence that the online personalized recommendation system enhances customer satisfaction during the online suggestion process through the utilization of a distinct associative categorization mechanism that relies on consumer initiative[16].

The study conducted by Wang and Hou focused on the development of a book recommendation algorithm that utilizes collaborative filtering and interest degree as its basis. The paper by [17] introduces a system for book recommendation that combines collaborative filtering with interest-based approaches. The book's level of interest serves as a noteworthy metric, alongside factors such as search frequency, duration of borrowing, intervals between borrowings, and instances of renewal. The findings of the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) analyses indicate that the proposed methodology in this study exhibits a faster convergence rate compared to the conventional method.

Numerous research studies have delved into the efficacy of recommendation systems across diverse domains. N. A. Osman et alproposed a sentiment-based model for electrical device recommendations, leveraging user comments and preferences for context-aware suggestions[18]. Sylvain Senecal and Jacques Nantel found that individuals who frequently sought product suggestions were more likely to follow expert recommendations[19]. Bruno Pradel and colleagues [20]conducted a case study on a recommender system using purchase data, highlighting the significant impact of algorithmic parameters and domain information on recommendation performance. Hyunwoo Hwangbo and his team developed a collaborative filtering recommendation system for a Korean fashion corporation, outperforming alternative suggestions in terms of product engagement and sales[21]. Nursultan Kurmashov and colleagues devised an effective book recommendation system using collaborative filtering[22]. Rohit Dwivedi and colleagues explored various recommendation systems and assessment approaches using Amazon data, developing popularity-based and collaborative filtering-based recommender engines[23]. Mingyue Zhang and Jesse Bockstedt examined online product recommendations and their influence on consumers' willingness to pay, revealing the importance of timing and recommendation type on consumer decisions, contingent on the decision phase. Collectively, these studies underscore the diverse applications and approaches in recommendation systems, highlighting the critical role of context, user behavior, and algorithmic parameters in optimizing performance across different domains[24].

3. Methodology:

In this research, we have selected the dataset and examined the three types of RS to specify the efficiency of each model of RS. Figure 3 shows the methodology sequences for this research.

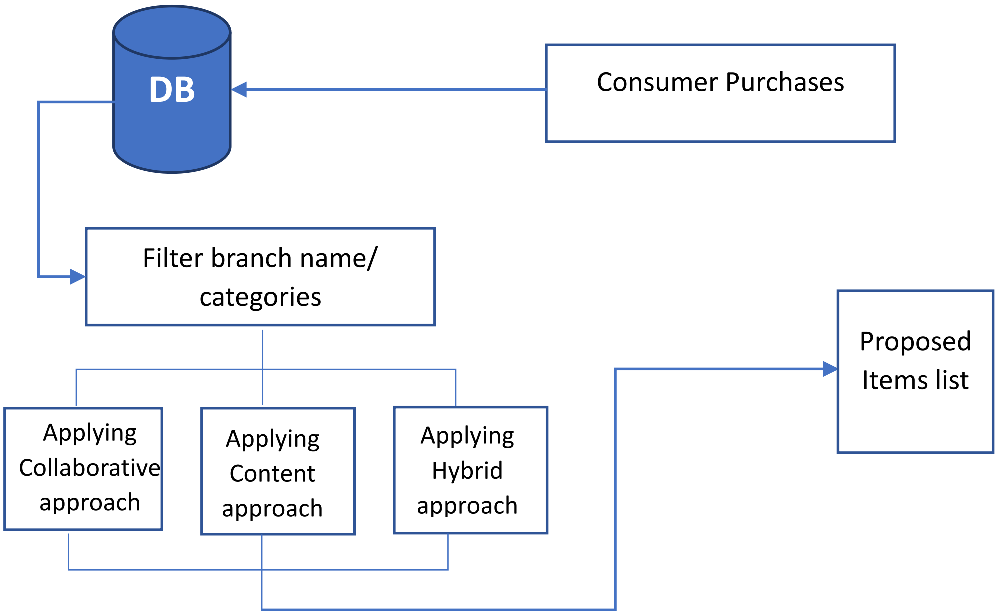

Figure 3: Methodology sequences

3.1 Data Preparation

To achieve the methodology approaches, we used in this research the Turkish market sales dataset with +9000 items[25]. This Turkish-language dataset encompasses supermarket data, featuring over 600,000 sales entries, 52,000+ distinct Turkish customer profiles with attributes like names, gender, age, and birthdates, 9,000+ categorized and subcategorized items grouped into categories 1 through 4, information on 81 store locations, a workforce of +1,200 sales personnel, geographical coordinates (latitude and longitude), and records spanning a three-month sales period. It's important to note that all the data within thisdataset is synthetic; the sales records were randomly generated based on city population distributions, and the customer names are entirely artificial and unrelated to real individuals.To prepare the dataset we have normalizedit and chose to work with a single branch based on thehighest total number of transactions that have been recorded in the branchas appears in Figure 4:

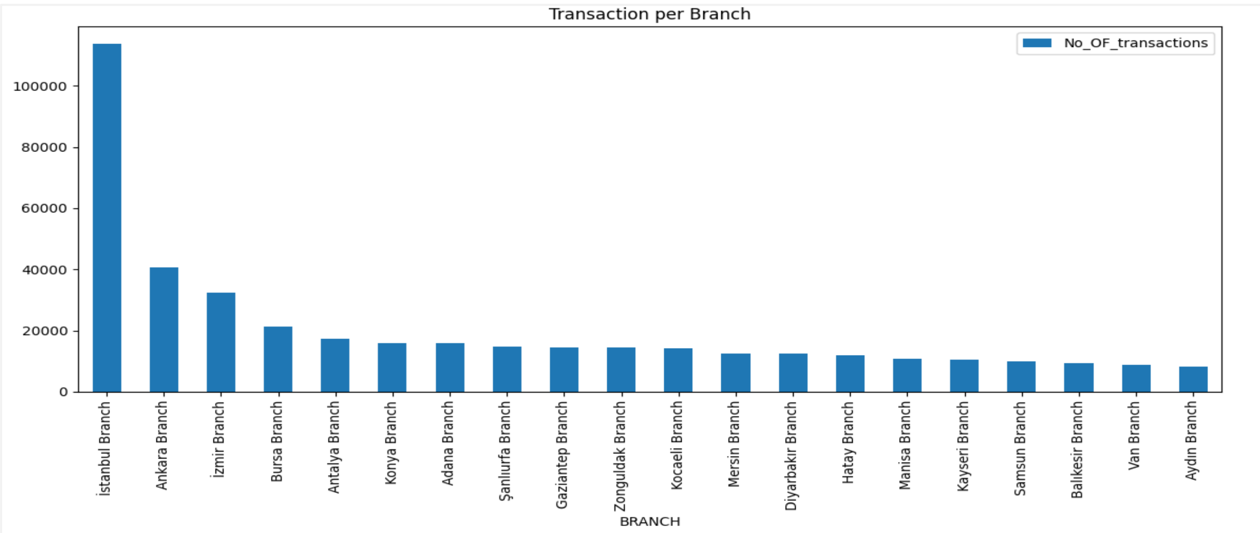

Figure 4: Transaction per branch for the top 20 branches

3.2 Implementation

The experiment was conducted using the Python programming language in order to assess the efficacy of hybrid recommendation methodologies. Three different experiments were conducted, whereby content-based filtering (CB) and item-based collaborative filtering (CF) were combined in various configurations.

3.2.1 Collaborative Filtering Implementation

Firstly, we have experimented withthe CF model with the user-based and item-based. To find the relation between the user and the item, we have normalized the data and calculated the corresponding usersusing the PCC algorithm as it appears in Eq.3. It is possible to give recommendations to the user based on item popularity and also based on the other user's histories. In this experiment, we selected a random user ID 209.We find the similarity matrix between the items, then find the correlation between the selected user and similar users as it appearsin Table1and accordingly, we find the recommended list by getting the highest score resulting by the PCC among all similar users andafter we eliminated the products that had been boughed by the target user (user ID 209 in this case), and we only kept the items that were purchased by similar people to the target user. Then, we calculate the average item bought by the user in the case by calculating the most similar items to be recommended as shown in Table2 for a selected user.

Table1: Correlation between a selected user and recommended users

CLIENT CODE	ITEM CODE												
	0	7	8	11	13	40	41	68	91	104	107	143	147
209	0.983173	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	0.983173	-0.016827	-0.016827	-0.016827
LIST OF SIMILAR USERS													
9440	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615	-0.009615
100329	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827	-0.016827
135453	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846	-0.028846
236986	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654
467575	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019	-0.012019
701569	-0.033654	-0.033654	0.966346	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654	-0.033654

982171	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731	-0.081731

Table2: Top 10 Recommendations list fora selected user

ITEMCODE	ITEMNAME	item score	predicted buying
5362	MAGIC HANDS CIG MEATBALL 200GR	0.739860	1.906527
11004	SEK MILK 1 LT. SIMPLE	0.727273	1.893939
23467	30 LARGE SIZE COVERED EGGS FROM HERE	0.692308	1.858974
20885	OSMANCIK PIRINC KG.	0.692308	1.858974
17964	DERYA FRESH BLEACHER 700GR	0.692308	1.858974
14486	DOGUS KUP SEKER 750GR	0.692308	1.858974
5701	ORANGE	0.692308	1.858974
3190	F NEFFIS MILK HALF OIL 1 LT	0.209790	1.376457
5716	ONION	-0.200000	0.966667
6262	ROCKET	-0.200000	0.966667

3.3 Content-Based Filtering Implementation

The content-based approach generates recommendations for particular products by analyzing a user's profile. In doing so, we merge item categories with item names to extract the distinctive features of each item, resulting in a column named "combined category." This amalgamation enables us to provide personalized recommendations. We used the cosine similarity function in Eq.2 to calculate the vector distance between the user and the item.Figure 5 shows the vector for user history items. Table3 shows the top 10 user recommendation list using the cosine similarity approach score.

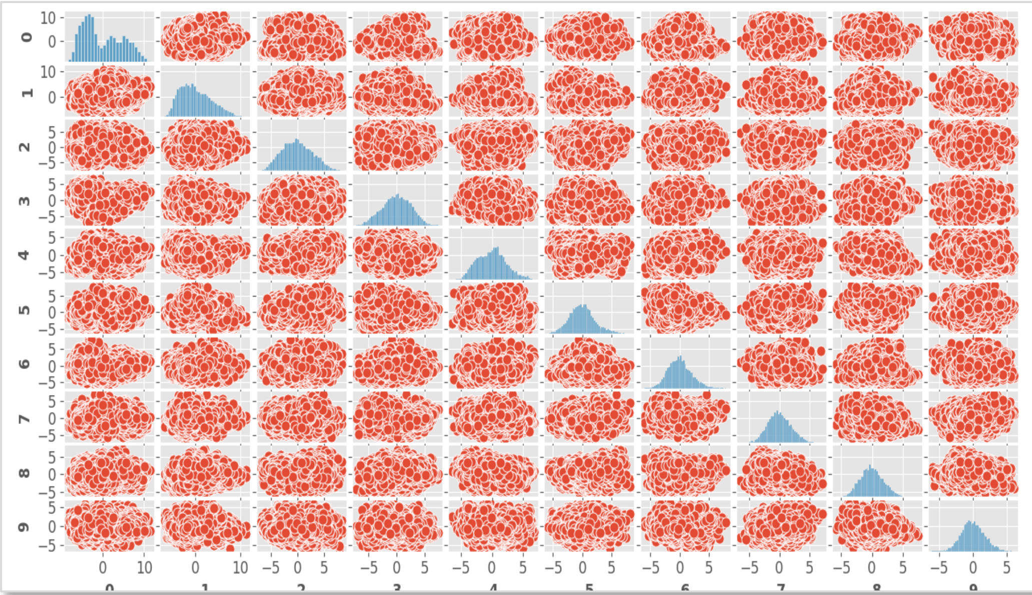

Figure 5: User profile vectors graph

Table 3: Top 10 Content-based approach recommended list for aselected user

ITEMCODE	ITEMNAME	Score
12636	ACTIVEX 4 PIECE SOAP 280GR SENSITIVE PROTECTION	0.997313
14605	S.BRITE ERGONOMIC BRUSH AND FARAS SET	0.976936
20343	S.BRITE HANDLE MAT	0.973667
20278	S.BRITE SILSUPUR MAT	0.969267

20289	S.BRITE COMFORT SUNGER	0.967664
20335	S.BRITE CLEANING MAT	0.967258
20354	S.BRITE DETERGENT CONTAINER CLEANING SYSTEM	0.966667
20351	S.BRITE PRACTICAL MOP SYSTEM	0.966434
3230	F NEFFIS PILAVLIK BULGUR 2 KG.	0.965338
20306	S.BRITE MAXI ROLL CLOTH	0.965026

3.4 Hybrid Filtering ModelImplementation

To implement the hybrid filtering model, concern that the limitations of CF and CBfiltering are not as effective as individual models. Therefore, we have considered the following factors to implement the efficient model:

- The number of sales: represents how many items are sold.
- The sum of item sales:represents the total quantity of sales for an item.
- The average sales: Find out how often people buy this item on average.

The following recommended list can be used as a suggestion that is effective since all these factors are subject to vary depending on the amount of by a single user or the often used by various users. So, we can recommend a list based on the number of sales as shown in Figure6. Also, we can recommend an average number of sales as shown in Figure 7 below.

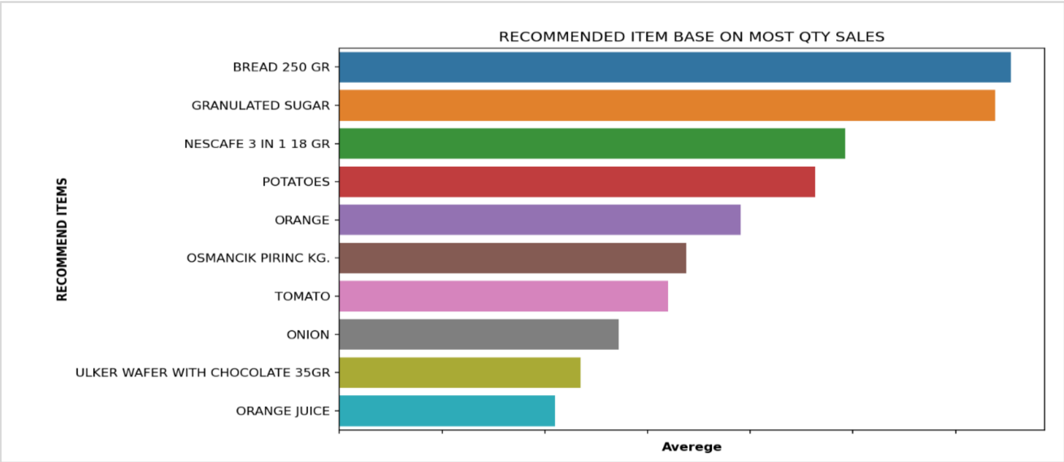

Figure6: Recommended items based on the number of sales

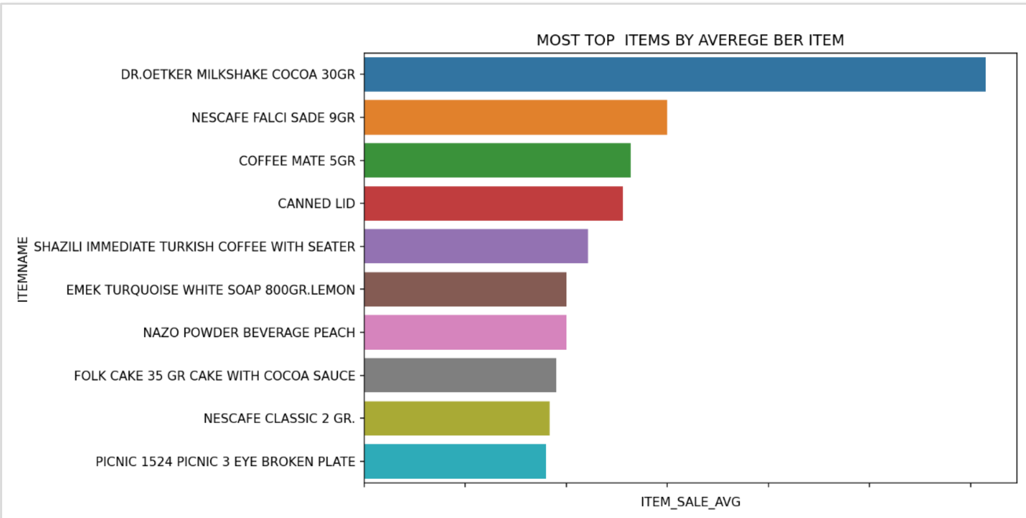

Figure7: Recommended items based on the average number of sales.

A deep looking at the overall number of sales operations for a particular item, we observed that some of the items were sold in bulk, but just a few times. This might cause the system to be inefficient. As a result of this restriction, we employed theweighted average (WA)concept to computean average of sales and employed a threshold to consider the minimum number of sales operations for an item byusing the following Eq.4 and the result of calculation shows top 10 recommended items represent in Table.4 bellow:

$$\mathrm{w} = \frac{\mathrm{I.S} + \mathrm{O.m}}{S + m} \quad (4)$$

where:
I = Average item sales (average sales in an item).
S = Number of sales for a particular item (count sales in item (qty)).
m = Minimum sales required to be counted.
O = The Overall mean of whole items average (Sum of item average / by count of items).

Table 4: Recommended list based on proposed weighted average.

ITEMCODE	ITEM SALE COUNT	ITEM SALE AVG	ITEM SALE SUM	ITEMNAME	Weighted Avg
2375	4	30.750000	123.000	DR.OETKER MILKSHAKE COCOA 30GR	15.931179
19195	17	11.058824	188.000	SHAZILI IMMEDIATE TURKISH COFFEE WITH SEATER	9.164258
2680	6	13.166667	79.000	COFFEE MATE 5GR	8.344943
2250	19	9.157895	174.000	NESCAFE CLASSIC 2 GR.	7.758671
17	5	12.800000	64.000	CANNED LID	7.605492
18253	89	7.415708	659.998	PASAKOY AYRAN 200GR	7.144596
1557	6	9.500000	57.000	FOLK CAKE 35 GR CAKE WITH COCOA SAUCE	6.144943
2573	30	6.733333	202.000	NESCAFE 3 IN 1 LOTS OF COFFEE TASTE 18 GR	6.872842
2510	411	5.990268	2462.000	NESCAFE 3 IN 1 18 GR	5.943252
2627	2	15.000000	30.000	NESCAFE FALCI SADE 9GR	5.741571

Occasionally, a specific item may be purchased in large quantities but with a relatively low number of sales operations which may fall under minimum sales required to be counted. This situation suggests that the item could be a preferred choice, but it might be overlooked when using the weighted average formula, which places more emphasis on the number of sales rather than the quantity sold. To enhance the accuracy of our recommendations, we adopt a balanced approach, allocating 50 percent weight to the weighted average and 50 percent weight to the number of sales for each item Eq.5. To achieve this, we employ a scaling technique to standardize the quantity units, thereby streamlining the dataset and addressing the minimum sales issue. In Figure 7, we illustrate the final recommended system, which effectively combines the weighted average and the number of sales for each item as a combined weighted average (CWA), resulting in a hybrid recommendation approach.

$$\mathrm{CWA} = \frac{0.5.\mathrm{avg} + 0.5.\mathrm{sum}}{2} \quad (5)$$

Where avg is the average after normalizing and sum is the sum of sales after normalization.
Table5 shows the result of CWA and the visualized result shows in Figure8 below.

Table 5: Recommended items based on a combined weighted average

ITEM CODE	SALE COUNT	ITEM SALE AVG	ITEM SALE SUM	ITEM NAME	Weighted Avg	Normalize Avg	Normalize sum	score
6980	20	4.700000	94.0	ETI PUF 18 GR. COLORED	4.102060	0.200639	0.976145	0.588392
2250	19	9.157895	174.0	NESCAFE CLASSIC 2 GR.	7.758671	0.364842	0.752892	0.558867
19205	14	2.500000	35.0	TURKISH COFFEE WITH SHAZILI READY MILK WITH SUGAR	2.191635	0.112790	1.000000	0.556395
2375	4	30.750000	123.0	DR.OETKER MILKSHAKE COCOA 30GR	15.931179	1.000000	0.037565	0.518782
12328	18	2.888889	52.0	CAFE CROWN 3 IN 1 IN ACTION	2.565883	0.124857	0.708509	0.416683
11006	49	2.387755	117.0	SEQUENT BEAUTIFUL MILK 200 ML.	2.291499	0.107696	0.597548	0.352622

17722	2	10.000000	20.0	NAZO POWDER BEVERAGE PEACH	4.074905	0.441238	0.201793	0.321516
2704	41	2.682927	110.0	CAFE CROWN LATTE	2.543321	0.120723	0.516041	0.318382
2627	2	15.000000	30.0	NESCAFE FALCI SADE 9GR	5.741571	0.569674	0.057443	0.313559
5056	17	1.529412	26.0	ULUDAG SODA GLASS BOTTLE 250ML	1.449973	0.076915	0.489516	0.283215

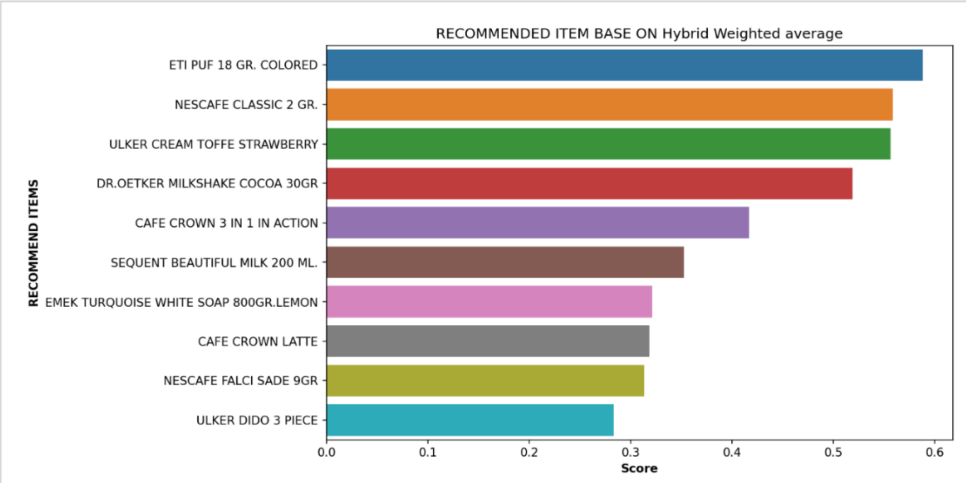

Figure8: Graph of Recommended list based on the weighted average and number of sales for each item.

3.5 Evaluation of models

Evaluations are used extensively inside recommender systems in order to determine the degree to which certain suggestion strategies are successful. Measuring a recommender system typically entails looking for evidence that the system is effective as well as gaining a better understanding of who our target audience is[11], [26], [27].Many evaluation metrics are available to calculate the accuracy of RS models such as precision, Recall, and F1 accuracy metrics. The performance of a recommendation algorithm may be judged based on a variety of assessments, such as accuracy or coverage. Both kinds of measurements are examples of possible evaluation criteria. The kind of filtering strategy that is used determines the metrics that are put to use.we tested the accuracy of the RS working using Top-N metrics, which measure the accuracy of the top suggestions provided to a user by comparing them to the products the user has engaged within the test set. The following is how this evaluation technique works:

- For every single user.
- For every product in the test set with which the user has interacted as follows:
  - Take twenty items that the user has never interacted with. These non-interactive items are either irrelevant to the user or the user is just unaware that they exist. Both possibilities are possible.
  - Request that the recommender model provide a ranked list of items to be suggested, using a set that consists of one item that interacts with other items and 20 items that do not interact ("non-relevant" items).
  - Calculate the Top-N accuracy metrics for this user and the item with which the user interacted, using the ranked list of suggestions.
- Compile an aggregate of the Top-N accuracy metrics.

After that, we examined both Recall @ N and Precision @N, as decision-support metrics, when N stands for the size of the suggestion list, whether the item to which the user had reacted was one of the top-N suggested products in the 21 ranked list suggestions for a user. Then, we evaluated F1@N to measure the performance in terms of accuracy for both Precision and Recall, with equal weight. Table 6 shows the accuracy score result for all the types.

Table 6: Comparison between all approaches using Recall, Precision, and F1 Metrics

Approach Name	Recall@10	Precision@10	F1@10
Collaborative	79 %	82 %	80 %
Content-based	36 %	53 %	43 %
Hybrid using Popularity	91 %	86 %	88 %
proposed WA	93 %	90 %	91%
proposed CWA	94%	93%	93 %

4. Result Discussion

Recommendation systems, categorized into content-based, collaborative filtering, and hybrid systems, leverage historical data and algorithms to predict user preferences. The evaluation method entails comparing top suggestions with user interactions in the test set, utilizing metrics like Recall@N, Precision@N, and F1@N. Results from the assessment, depicted in Table 6, reveal that collaborative filtering achieves high recall (79%) and precision (82%), yielding an F1 score of 80%, while content-based filtering shows lower recall (36%) but higher precision (53%), resulting in an F1 score of 43%. Hybrid systems, particularly those employing popularity, demonstrate strong performance with high recall (91%), precision (86%), and F1 score (88%). Additionally, the proposed approaches, WA and CWA, outshine others, boasting even higher scores across all metrics, indicating their potential to enhance recommendation accuracy. These findings underscore the importance of selecting appropriate algorithms to optimize recommendation system efficacy, with implications for improved user satisfaction and engagement in various applications like e-commerce and personalized content delivery platforms.

5. Conclusion

In conclusion, Recommender systems are crucial in guiding consumer behavior and enhancing purchasing decisions. Driven by historical data and machine learning, these systems can analyze consumer preferences and introduce new, relevant products. Personalizing recommendations based on user history and context reduces decision fatigue and fosters brand loyalty. Evaluating recommender system models using metrics like recall, precision, and F1 score helps understand the effectiveness of different approaches. Content-based models may not always perform as well as collaborative or popularity-based models, but each approach has strengths. Recommender systems are valuable tools in today's digital landscape, guiding consumers, and businesses towards more informed and satisfying choices. Understanding user behavior and continuously refining recommendation algorithms are essential for harnessing their full potential for enhancing user experiences and driving business success.

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