A Restaurant Recommendation System based on Collaborative Filtering using Machine Learning Algorithms and the Multi-Criteria Method.*

Maroua Chemlal[1,*,†], Amina Zedadra[1,†], Med Nadjib Kouahla[1,†] and Ouarda ZEDADRA[1,†]

[1]*LabSTIC Laboratory,University 8 May 1945, BP 401, Guelma 24000, Algeria*

Abstract

Recommendation systems have become complex algorithms that analyze user data and preferences, to provide personalized recommendations. These systems play an important role in helping users make decisions in many different fields. Recently, a significant difference in restaurant selection preferences has been observed among individuals. To this end, this paper presents an innovative system named a restaurant recommendation system based on collaborative filtering using machine learning algorithms and the multi-criteria method (CRMS) that uses machine learning and the Analytical Hierarchy Process (AHP), to enhance dining experiences through personalized restaurant recommendations. The CRMS provides a framework for comparing user preferences with restaurant attributes, allowing data-driven decisions to be made in choosing restaurants, taking into account other users' ratings and location. The primary goal of this system is to develop an application that attempts to recommend restaurants that match the user's preferences using the multi-criteria Ahp method, as well as their geographical location and user ratings using machine learning algorithms based on collaborative filtering. The results of the proposed system show that it helps users find restaurants according to their preferences and aspirations to provide better recommendations.

Keywords

Recommender System, Preferences, multi-criteria methods, machine learning, Restaurant Recommendation, locations, Rating

1. Introduction

Recommender systems are vital tools for enhancing user experiences by offering personalized and relevant information. These intelligent tools employ sophisticated algorithms and techniques to analyze user preferences, historical behavior, and contextual data, with the goal of providing personalized suggestions and recommendations. Moreover, these systems analyze users data and preferences in order to match users with suitable products, services, or content, leading to increased customer satisfaction and engagement [1]. To build our recommendation system, we first need to create a user model that allows us to define which features to include in the system. These characteristics are presented through three profiles: demographic profile, preference profile, and location profile. Following this modeling, we developed our solution based on three factors: first, the user preference factor that allows knowing the most similar and relevant restaurants with respect to these preferences using different decision-making mechanisms, including the Ahp method, which is defined as a special attribute classification technique. By user similarity to target, it is a method of multi-criteria decision analysis. A set of alternatives is compared based on an initially defined criterion. They are used in many fields, especially commercial ones, to make decisions about products that have several characteristics, i.e. making an analytical decision based on collected data [2], secondly an evaluation factor where the user rating is predicted based on similar users using collaborative filtering by Machine learning algorithms and finally the location factor that facilitates smart navigation in the city in order to find the closest restaurants in

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*Corresponding author.
†These authors contributed equally.
chemlal.maroua@univ-guelma.dz (M. Chemlal); zedadra.amina@univ-guelma.dz (A. Zedadra); kouahla.nadjib@univ-guelma.dz (M. N. Kouahla); zedadra.ouarda@univ-guelma.dz (O. ZEDADRA)
0009-0002-4156-4016 (M. Chemlal)

terms of distance. The results are then integrated into our system to improve suggestions based on these three factors.
In the remainder of the paper, Section 2 presents previous studies of food and restaurant recommendation systems. Then Section 3, Methods and materials, which details the components and algorithms used in the proposed approach. Section 4 describes the experimental results including the system implementation . Section 5 describes deployment of website and the final section concludes the research and presents future directions for the work.

2. Related works

Restaurant recommendation systems play a pivotal role in enhancing individuals' well-being by tailoring recommendations based on their food preferences and convenience. Our review categorizes related works into four sections: Traditional Collaborative Filtering (CF) Systems (Section 2.1), Content-Based Recommendation Systems (Section 2.2), Hybrid Recommendation Systems (Section 2.3), and Multi-Criteria Decision Making (MCDM) Systems (Section 2.4).

2.1. Traditional Collaborative Filtering (CF) Systems:

Daniel and Amalia.[3] proposed a Restaurant recommendation system employing advanced collaborative filtering and review text analysis. The proposed approach combines Natural Language Processing (NLP) sentiment analysis with previous ratings and customer clustering for optimized recommendations. Alabduljabbar [4] introduced a matrix factorization collaborative-based recommender system tailored for Riyadh city restaurants, utilizing user reviews and ratings. This innovative system employs three distinct machine learning algorithms to predict user preferences and offer personalized recommendations. Gurung. [5] proposed a restaurant recommendation system utilizes collaborative filtering with SVD, ALS, and Neural Networks via Keras, evaluated on the Yelp dataset for diverse restaurant reviews. The model incorporates sentiment analysis to quantify positive and negative reviews, aiding in categorizing new reviews for restaurants. Karabila et al. [6] introduced a novel recommendation system combining sentiment analysis and collaborative filtering through ensemble learning. Their approach involved GloVe vectorization for text data and a Bidirectional LSTM model for sentiment analysis. Additionally, a collaborative filtering recommendation model was developed and integrated with the sentiment analysis component. Kouahla et al.[7] proposed a recommendation system integrating sentiment analysis, user preferences, and ratings. Utilizing Yelp datasets, to reprocess and filter POIs, integrating sentiment analysis. the proposed system optimizes POI recommendations by combining factors and LightGCN modeling for enhanced user experience.

2.2. Content-Based Recommendation Systems:

Gupta et al. [8] proposed a model leveraging Zomato data to recommend food based on users' current mood from top-rated restaurants. Integrating attributes like cuisine, location, mood, and nutrition, it utilizes the K-Means Algorithm for restaurant grouping and combines content-based and collaborative filtering methods for personalized recommendations. Kosim and Prihandi. [9] proposed a Recommendation System for drink selection at Mubtada Kopi cafe, employing non-personalized and content-based filtering methods. Content-based filtering prompts users to choose preferences from six predefined categories, calculating the match between user preferences and menu items using a dot matrix formula. Parihar. [10] proposed a recommendation system leveraging Machine Learning algorithms, utilizing data scraped from a popular food application in India, encompassing restaurant reviews. Their research aims to foster positive and promote new businesses by creating multiple recommendation models: one based on similar place reviews, another on user-defined ideal review inputs, and the last incorporating past restaurant visits and location preferences for tailored suggestions. Pérez-Almaguer et al. [11] introduced a novel content-based group recommendation approach (CB-GRS) tailored for restaurant recommendations, incorporating distinct stages such as feature imputation, virtual group profile generation, feature weighting, and automatic aggregation selection. Evaluated specifically in the context of Havana City's restaurants, their proposal demonstrates the significance of its components and surpasses previous works.

2.3. Hybrid Recommendation Systems:

Shirisha et al. [12] presented recommender systems in the food industry, using sentiment analysis from user comments to offer recommendations based on dietary preferences. Through categorizing food names in reviews, the system accurately gauges sentiment and suggests nearby eateries meeting users' needs. Nandan and Gupta. [13] introduced the ExtraTreeRegressor algorithm, leveraging hybrid filtration for restaurant recommendations. This novel approach aims to enhance accuracy and accessibility in providing restaurant suggestions. Keya et al.[14] introduced a restaurant recommendation method, combining collaborative filtering with user preference-based approaches utilizing bidirectional encoder representations of transformers and a recursive module. Utilizing the Kzomato dataset comprising 9552 samples and 21 features, the system achieved impressive metrics with an F1-score, precision, and recall of 86%.

2.4. Multi-Criteria Decision Making (MCDM) Systems:

Amari et al.[15]proposed a Multi-Criteria Decision Making (MCDM) model for parking space allocation, comparing CODA, EDAS, TOPSIS, and WASPAS methods. They employ the criticism method to objectively determine criterion weights and calculate the "average correlation between elements SW" for evaluation. Alwedyan. [16] presented a recommendation system employs the Analytical Hierarchy Process (AHP) to determine the optimal location for a casual restaurant, considering seven criteria and twenty-five sub-criteria. Expert opinions are solicited to rank the criteria, with costs, location, and traffic patterns identified as the most influential factors. Shu et al.[17]proposed a multi-criteria decision support model for restaurant ranking based on user demand. Utilizing the Linguistic Weighted Average (2LOWA) clustering operator and Importance Weights (IW) method, the model generates customized composite scores from user ratings sourced from Dianping.com.

We noticed that the realm of dining recommendation systems, research by (Danielle and Amalia, Abdul-Jabbar, Gurung, Karabila et al. and Kouahla et al.) highlights the efficacy of traditional collaborative filtering (CF) techniques such as user-based collaborative filtering, matrix factorization, and sentiment analysis, tailored for the restaurant domain. However, traditional CF systems often fall short in considering multiple criteria and user preferences beyond ratings, leading to the emergence of content-based recommendation systems emphasized by (Gupta et al., Kosem and Prihandi., Parihar and Pérez-Almaguer et al.) accommodating user preferences and dietary requirements. To address these limitations, hybrid recommendation systems integrating CF, content-based filtering, sentiment analysis, and AI algorithms, as demonstrated by(Sherisha et al., Nandan and Gupta and Keya et al.) deliver personalized and diverse restaurant recommendations catering to users' preferences and health conditions. Additionally, multi-criteria decision-making (MCDM) systems, exemplified by works from (Amari et al., Al-Wedyan and Shu et al.,) leverage approaches like the Analytic Hierarchy Process (AHP) and linguistic weighting to rank restaurant locations or create customized meal plans, considering factors such as dietary requirements, user preferences, and location-based preferences.

The CRMS restaurant recommendation system integrates collaborative filtering with AHP and ML algorithms, surpassing traditional CF and content-based systems by considering diverse criteria and user preferences.

3. Materials and Methods

3.1. Dataset

For the development of our restaurant recommendation system, we utilized the extensive restaurant dataset from 'Restaurant Data with Consumer Ratings', a widely recognized platform offering diverse datasets for academic and non-commercial use. This comprehensive dataset encompasses a rich array of information, including user reviews, business details, ratings, and more, providing a robust foundation for our system's development and evaluation.

3.2. CRMS: A Restaurant Recommendation System based on Collaborative Filtering using ML algorithms and AHP Method

The proposed approach is illustrated in Figure 1 and consists of the following steps. CRMS system has

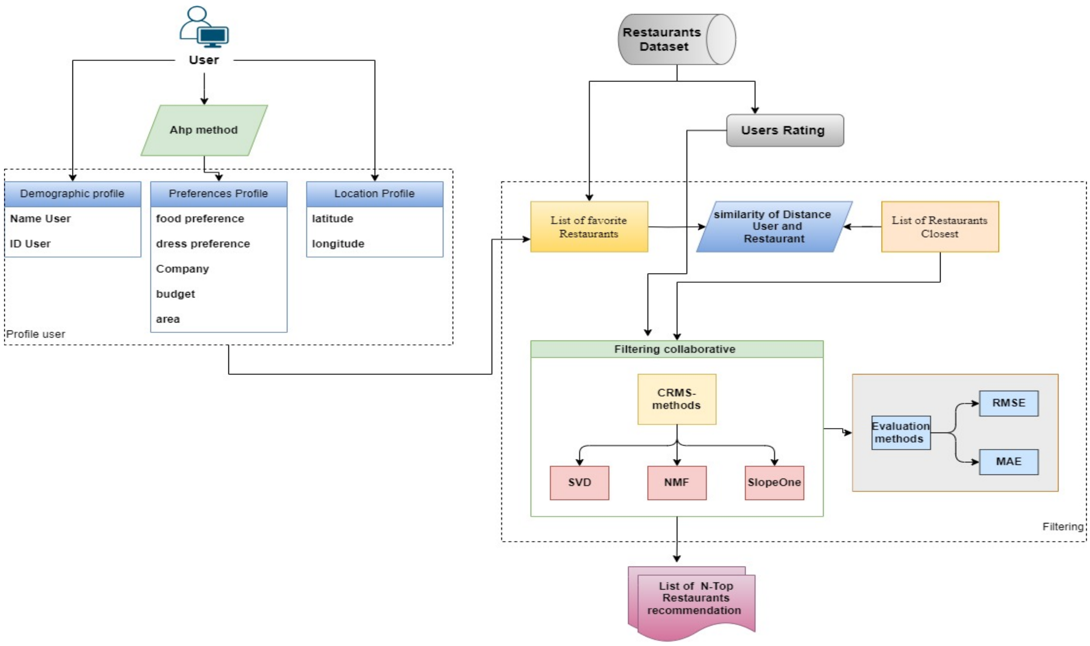


Figure 1: System architecture

two main phases: *(1) user profile:* where personal data such as ID name and user name are collected and preferences profile are calculated using the AHP method and *(2) Filtering:* where recommendations are given to the user's based on their profile and location.

3.2.1. User profiling

Creating a user profile in the first step in the personalized recommendation process. It Builds a rough description of the user, by taking into account not only their preferences and geographic location, but also the ratings of other similar users.
We obtain a global profile for each user which composed of three profiles:

1. *Demographic Profile:* It represents the initial user profile section created during registration, comprising the user's identifier and personal details like name. This data, collected through a registration form, constitutes personal .
2. *Preference Profile:* It is formed from user input on various restaurant criteria including food, dress code, company, budget, transportation, and area preferences. Users must accurately specify their preferences.
3. *Location Profile:* It represents the dynamic segment of the profile, crucial for defining the user's current location, primarily conveyed through latitude and longitude coordinates.

3.2.2. Filtering

This phase is as a pivotal mechanism for recommending restaurants to the user's. It involves calculating the similarity between the user's location and potential restaurants, factoring in distance and proximity. Subsequently, machine learning algorithms, including Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), and Slope One, leverage the user's historical ratings to refine recommendations. By analyzing past ratings , these algorithms generate personalized recommendations, enhancing the overall user experience with precision and relevance.
The goal of collaborative filtering is to predict its rating by collecting ratings from other users. Matrix decomposition is a common technique used in collaboration-based filtering, which distinguishes items and users through factor vectors inferred from item classification patterns. The concept behind matrix factorization is straightforward. This involves decomposing the user and restaurant classification matrix into two parts. Example of user ratings and system recommendations for preference-based filtering method. User ratings for a group of restaurants are filtered, based on the top 10 recommendations generated by the system based on the user's preferences. The recommendations are sorted in descending order based on their expected scores, with the highest scores listed at the top.
CRMS System implemented a collaborative-based recommender system using three matrix factorization-based algorithms. In particular, we implemented and compared three algorithms: Non-negative Matrix Factorization (NMF), Singular Value Decomposition (SVD), and Slope One. NMF decomposes when implicit feedback is taken into account. Implicit comments include information about other users' rating history, which provides details about the items for which the user has expressed a preference, either explicitly or implicitly. Algorithm 1 presents the main steps of Restaurant Recommendation System.

Algorithm 1 Restaurant Recommendation Algorithm

```
Input: User preferences, restaurant attributes, ratings data
Output: Top 10 recommended restaurants for each user
Construct pairwise comparison matrix for criteria
Calculate priority weights from pairwise comparison matrix
Check consistency of pairwise comparisons
Calculate overall priorities for each alternative
Analyze sensitivity to assess robustness of results
Sort list of restaurants and select top 10
Predict user ratings using machine learning algorithms (e.g., SVD, NMF, Slope One)
Split data into training and testing sets
Train selected algorithms (SVD, NMF, Slope One) on training data
Aggregate predicted ratings to generate ranked list of recommended restaurants
Evaluate trained models using metrics such as MAE, RMSE
Return top_list_10 list of restaurants
```

To handle the computational requirements for modeling large datasets, we used Google Colab to take advantage of shared resources and ensure consistent performance. All algorithms have been implemented in Python using popular libraries such as NumPy and pandas. PyCharm was used as an integrated development environment (IDE) for managing and deploying packages, and additional libraries including arbitrary math and os.path were used. A website is created using the Laravel framework and JavaScript.

4. Model Evaluation

To evaluate the performance of our system, we used the AHP method. first, we calculated the similarity scores between characteristics restaurants with users preferences. The results showed that our algorithm gives an average similarity score of 0.60 for the top recommended restaurants. Also, we calculated error comparison and analysis tests using the two measures RMSE (Root Mean Squared Error) and MAE

(Mean Absolute Error) for the evaluation of the final results of the prediction. We compared our method with Sun et al.'s Method. Evaluation metrics are:
RMSE measures the square root of the average of the squares of the differences between actual values y_i and predicted values $\hat{y}_i$:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

MAE computes the average absolute differences between actual values y_i and predicted values $\hat{y}_i$:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

Based on the provided information, we can summarize the performance results of different recommendation algorithms in terms of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error)in the table 1 :

Table 1
Performance Comparison of Recommendation Algorithms

Algorithm	RMSE	MAE
RMSQ-MF	0.9800	0.7900
CRMS-SVD	0.5777	0.6821
CRMS-NMF	0.7458	0.6090
CRMS-SlopOne	0.7150	0.5084

According to the results, the CRMS-SVD method exhibits the lowest RMSE, while the CRMS-SlopOne method achieves the lowest MAE. The choice between these algorithms may depend on the specific application requirements and priorities. As shown in the table 1. Compared to other methods, the SVD algorithm gives the best results, with RMSE = 0.5777, MAE = 0.6821. To this end, we create a learning model based on this method that construct and provide RMSE and MAE values for the recommendation system.

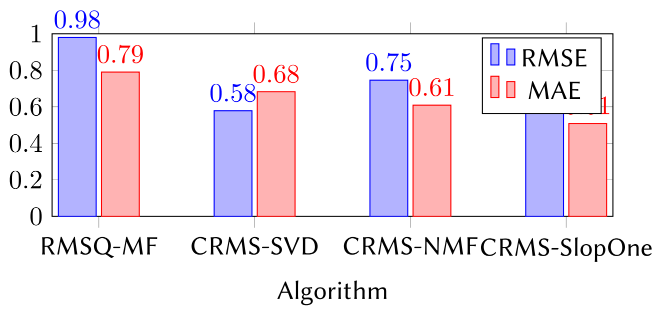


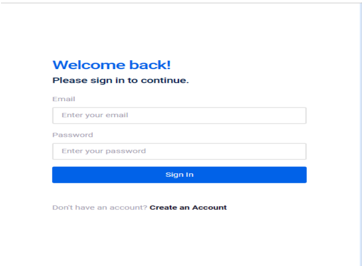
Figure 2: Performance Comparison of Recommendation Algorithms

5. Deployment

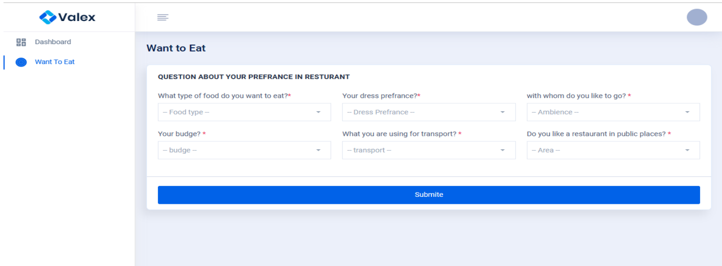
After developing and evaluating the system, we deployed it for use by users. This involves integrating the system into a website that users can browse to find the recommendation. website boasts an intuitive interface crafted specifically to recommend closest restaurants, facilitating their dining experiences by offering tailored restaurant suggestions aligned with their preferences. Our system goes beyond to accurately predict user ratings. In addition, it recommends restaurants closest to users, the proposed system ensure that users receive recommendations precisely attuned to their preferences, enhancing their overall dining satisfaction and well-being.

1. Users log in using their email and password.
2. When logging in, users are required to enter personal data such as ID, Name.
3. The user answers questions to find out his preferences
4. The system calculates the user's priority preferences for choosing restaurants
5. Predict user ratings
6. Get his location from the GPS device
7. Taking advantage of the data collected, our system creates personalized recommendations for suitable restaurants that match the user's needs, location and rating .
8. Recommendations take into account all this user profile .

Figures 3a ,3b and 3c shows the interface of the web application.



(a) User registration interface



(b) the user input form where they can fill in their preferences.

```
###########################################################
{'restaurant': "Culver's branch 44", 'distance': 0.43734033985217924}
{'restaurant': 'Baskin Robbins branch 44', 'distance': 0.48863957732063323}
{'restaurant': 'Bob Evans branch 44', 'distance': 0.5645684908179109}
{'restaurant': 'Perkins branch 44', 'distance': 0.7954213638786367}
###########################################################
```

(c) Recommendation results of the best restaurants

Figure 3: User interface and recommendation results

This web application provides users with a complete solution to find suitable restaurant options, with their preferences.

6. Conclusion and future works

This paper presents a personalized approach to food and restaurant recommendations for individuals based on their health status, especially those with diabetes and obesity. We offer an innovative recommendation system designed to enhance the user experience by looking at individual profiles, preferences, and applying the AHP method to generate personalized recommendations based on the user's current location and predictive rating using machine learning algorithms. This approach takes into account the user's diabetes status and optimal nutrient intake. It provides a user-friendly interface and requires users to enter relevant personal details. The system calculates the nutritional content. Overall, the program aims to support individuals in making healthy food choices when dining out. The system skillfully evaluates and prioritizes restaurant options based on multi-criteria, including user ratings and other relevant factors.
As a future work, we want to develop mechanisms for dynamically updating user profiles based on user feedback, behavior, or changes in preferences over time. This adaptive approach ensures that recommendations stay relevant and reflective of evolving user preferences.

Declaration on Generative AI

During the preparation of this work, the author(s) used GPT-4 in order to correct grammatical errors, typos, and other writing mistakes. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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