Restaurant Recommendation System Using Machine Learning Algorithms

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Abstract: The essential nature of recommendation systems becomes apparent when making purchasing decisions or exploring unfamiliar locales. Restaurants, in particular, benefit from these systems both in terms of managerial efforts to attract a larger customer base and in assisting customers in discovering their preferred and renowned dishes. Navigating diverse food options, particularly in new locations, poses a considerable challenge. This paper introduces a restaurant recommendation system that relies on distributing food and service ratings, assessing matrix density for improved accuracy. Additionally, a popularity-based recommender model is developed to propose restaurants to customers, utilizing a ranking scheme based on scores. The model's output includes suggestions for the most popular restaurants and their standout dishes. Collaborative filtering is integrated with singular value decomposition to enhance the model's effectiveness. Model evaluation is conducted using Root Mean Square Error (RMSE), leveraging a Kaggle dataset. Furthermore, a practical web-based application is constructed using Python's Flask web framework.

Keywords: - Recommender system; Machine Learning; Collaborative filtering; User inputs and behaviors; User feature, Ranking.

I.INTRODUCTION

Recommendation systems have garnered widespread popularity across diverse domains due to their versatile applications. These systems, driven by a set of algorithms, derive insights from input data to provide personalized suggestions to users. Essentially, they act as tools for recommending products to customers by taking into account factors like search history, user similarities, patterns, and ratings. Noteworthy examples in real-time applications include YouTube, Amazon, and Facebook, all of which heavily rely on historical data for their functionality.

The operation of these systems primarily involves analyzing past data. Items are ranked based on available data, and users receive the most pertinent recommendations. Recommendation systems can be divided into two categories:

- Content-Based
- Collaborative Filtering (CF)

1. Collaborative Filtering:

Collaborative Filtering is exclusively grounded in past interactions between customers and products. It relies on historical data encompassing all transactions involving user engagement with targeted products. A matrix serves as the repository for this data, where rows represent customers and columns represent products. This technique relies solely on historical data, overlooking contemporary trends and cultural influences. [5]

At its core, Collaborative Filtering can be categorized into memory-based and model-based methods.The memory-based method is straightforward, leveraging only historical data with uncomplicated distance measurements. In contrast, the model-based approach utilizes a model to align with potential outcomes.[2]-[3]

2. Content-Based Filtering:

Content-Oriented Using more information about clients and items is the process of filtering. It needs more data, such as gender, region, and date of birth, to improve predictions. The goal is to predict consumer characteristics and behavior concerning a product based on favorable or unfavorable responses.[1]

People of all ages are drawn to food because it is a global emblem of cultures, values, and customs. Even if there are a lot of eateries that can accommodate a range of budgets and sizes, choosing the appropriate one is crucial to satisfying dietary requirements, guaranteeing excellence, and providing well-known meals in a certain area. This variety plays a significant role in the varying degrees of restaurant profitability. By successfully satisfying these requirements, some businesses can increase their earnings; similarly, eateries with lower profitability might benefit from the same approach.

Restaurants provide good cuisine, but at the same time, patrons are looking for tasty, high-quality meals. An interface becomes essential to ensure customer and restaurant owner satisfaction. Customers are methodically suggested the restaurant's distinctive features using this interface.[4]-[5]

It addresses problems about consumers' ignorance of both neighboring eateries and well-liked dishes. When visiting foreign countries, tourists frequently have significant trouble locating restaurants that serve traditional, well-regarded, high-quality local cuisine. Under these conditions, a useful workaround is to incorporate a machine algorithm using reviews into the recommender system.[4]

The study looks at an online restaurant recommendation system using real-time data. This application's main objective is to recommend the best foods to users based on their dietary restrictions and the specified location.

II. REVIEW OF RELATED WORK

Several approaches exist for creating a restaurant recommendation system. Numerous existing systems operate based on the following methods.

Within the framework of this recommender system, recommendations are tailored according to user preferences, deriving insight from the realization that a user's affinity for an item is molded by various factors articulated in reviews. The initial exploration entails a deep dive into topic modeling, unveiling concealed elements within the review text. [6]

Ultimately, the application of regression models facilitates the identification and comprehension of the intricate relationship between users and restaurants.

They underscored the widespread acclaim of the restaurant recommendation system, highlighting its continuous advancements in precision and intricacy. Their presentation showcased a personalized recommendation system based on location, seamlessly integrated into mobile technology. The in-depth study scrutinized user behavior patterns within recommendation systems, proposing various methods for refinement and improvement.[1][6]

In this study, they explained how the restaurant recommendation system works with fancy machine learning stuff. They tried different ways to find a good model that predicts how much you might like a restaurant. They used methods like Slope One, k-Nearest Neighbors, and something called multiclass SVM classification. After checking everything, they found that the multiclass SVM thing worked better than the others.[7]

They contrast item-based and user-based collaborative filtering methods for rating prediction. At last, architecture is provided to facilitate the construction of a real-time recommendation system.[7]

According to the user's location, the restaurant was predicted using SVM in the proposed system. It can be extremely helpful and fulfilling for a user to save a lot of time, money, and effort by having a suggestion system that could assist them in choosing which restaurant to attend.[5]

There exist multiple elements that influence a user's decision to visit a restaurant, such as a restaurant's cuisine, location, ambiance, price range, popularity, ratings, and so on. On websites like Yelp and Zomato, this kind of data is gathered and made accessible.[5]

Utilizing a comprehensive, open-source dataset from Yelp that includes user-level data on their favorite restaurants in addition to restaurant reviews, the goal is to develop an effective software application recommendation system for Yelp users that will assist them in making predictions about whether or not they will enjoy dining out by utilizing machine learning techniques and algorithms.[6][10]

The study conducted in this research examined the various reasons why consumers utilize internet reviews. There are a lot of reviews available for many goods and services, making it challenging for buyers to choose which ones to read. According to an earlier study, internet review sites may be able to offer a personalized approach for ranking reviews based on the preferences of individual users.

III. METHODOLOGY

The Recommendation system under consideration, as outlined in this proposal, employs statistical techniques and exploratory data analysis to address the subsequent inquiries: determining the number of distinct users and restaurants, as well as assigning ratings that encompass aspects like cuisine, service, and quality.[6][9]

To enhance the model, we analyzed the occurrence of user reviews, the overall count of restaurant ratings, and the distribution of evaluations for food, service, and quality individually.

```
Unique users:  138
Unique restaurant:  130
Total no.of ratings given:  1161
Total no.of food ratings given:  1161
Total no.of service ratings given:  1161
```

Fig 1. Find out unique values of the entity.

```
U1061      18
U1106      18
U1134      16
U1024      15
U1022      14
```

Fig 2. Find Number of times user rated.

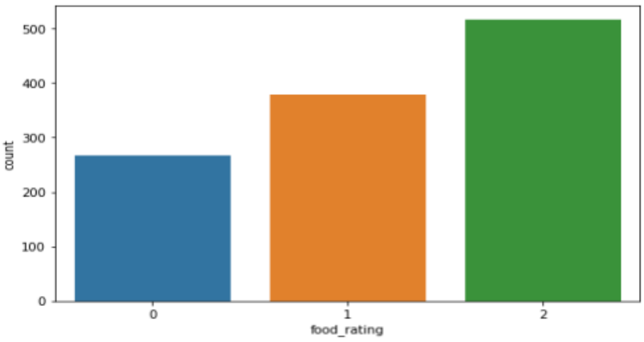


Fig 3. Food Rating.

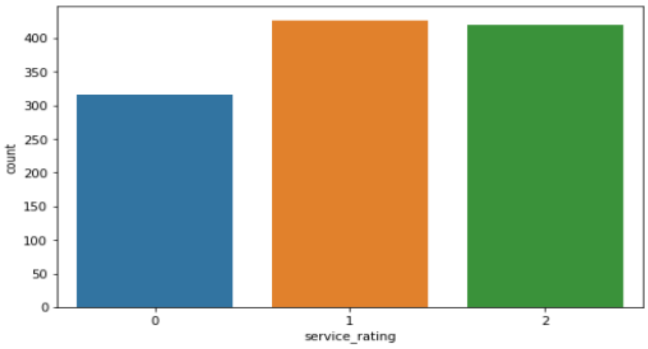


Fig 4. Service Rating.

	userID	placeID	rating	food_rating	service_rating
0	U1077	135085	2	2	2
1	U1077	135038	2	2	1
2	U1077	132825	2	2	2
3	U1077	135060	1	2	2
4	U1068	135104	1	1	2

Fig 5. Retrieving Users with food/Service Rating.

```
given_num_of_ratings:  884
possible_num_of_ratings:  16640
density: 5.31%
```

Fig 6. Density Matrix for the data set.

1. **Dataset:**
   The application will use the central dataset for this recommendation system, which comes from Kaggle, to provide restaurant recommendations.

   There are nine CSV files in the collection that cover different topics including user payments, food, and ratings. We concentrate on the rating file, which has 1161 instances and five attributes in particular. This dataset integrates seamlessly with our platform, allowing the machine learning algorithm to generate customer-relevant results.[4]

2. **Popularity-Based Recommendation:**
   This is the typical baseline methodology. Rather than prioritizing a personalized strategy, the model provides clients with explicit suggestions for the top meals within a specific location, during specific hours of the day, or at appropriate dining establishments. As a result, customers are free to decide whether or not to use the product, depending on their preferences. The recommendations are predicated on what is in style or popular right now in the community.[4][6]

   This recommendation type proves especially valuable in scenarios where there is no available historical data for a particular user. It functions on the principles of popularity and stays aligned with current trends. The benefits of this approach include its ability to overcome the cold start problem and its independence from the need for customer historical data.

However, a drawback is its non-personalized nature, potentially recommending similar popular products to every customer.[8]-[9]

	placeID	score
123	135085	36
31	132825	32
80	135032	28
98	135052	25
33	132834	25

Fig 7. Assign score to the most popular places.

	placeID	score	Rank
123	135085	36	1.0
31	132825	32	2.0
80	135032	28	3.0
98	135052	25	4.0
33	132834	25	5.0

Fig 8. Rank based on the scores.

	placeID	score	Rank
123	135085	36	1.0
31	132825	32	2.0
80	135032	28	3.0
98	135052	25	4.0
33	132834	25	5.0

Fig 9. Prediction for most popular restaurants in popularity-based recommendation.

3. Collaborative Filtering:
Collaborative filtering has emerged as a contemporary algorithm in recommendation systems. This method leverages inputs derived from various users with akin preferences, encompassing both user-based collaborative filtering and item-based collaborative filtering.[10]

This approach taps into users' inherent preferences by analyzing the latent features that characterize the input values. We employed a collaborative filtering model based on singular value decomposition.

placeID	132560	132561	132564	132572	132583	132584	132594	132608	132609
userID									
U1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig 10. Pivot table.

```
Below are the recommended places for user(user_id = 12):

                    user_ratings  user_predictions
Recommended Places
135046                       0.0          0.780975
135026                       0.0          0.465279
135058                       0.0          0.458938
135055                       0.0          0.455777
135045                       0.0          0.440416
```

Fig 11. Recommend places based on ratings and user

	Avg_actual_ratings	Avg_predicted_ratings	place_index
placeID			
132560	0.015625	-1.171132e-18	0
132561	0.023438	3.334107e-18	1
132564	0.023438	-1.491341e-18	2
132572	0.117188	9.900262e-02	3
132583	0.031250	3.323385e-02	4

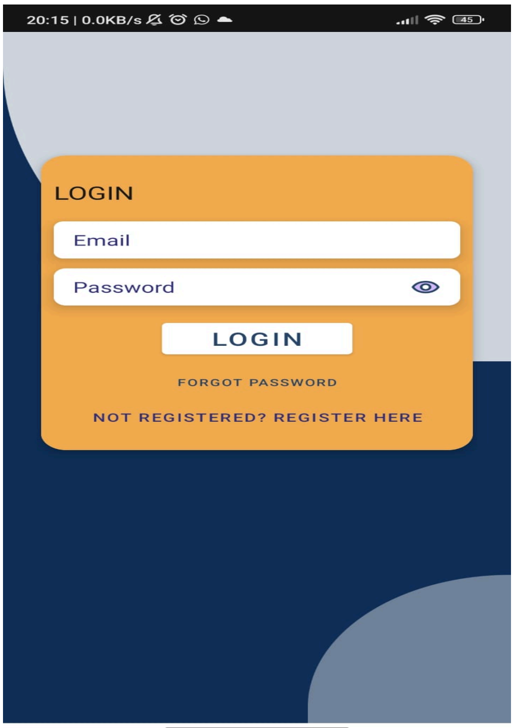
Fig 12. Actual ratings and Predicted ratings.

```
RMSE SVD Model = 0.01874
```

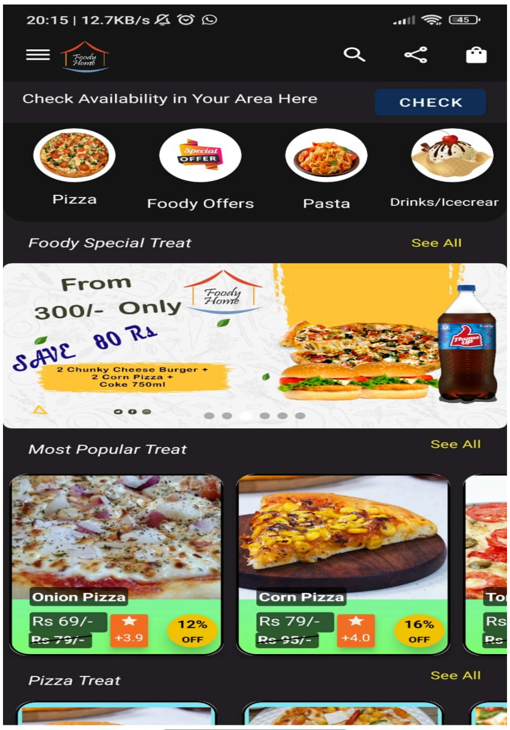
Fig 13. Evaluating the model with RMSE.

Python is utilized in this work to develop our machine learning algorithm, taking advantage of its extensive ecosystem of machine learning libraries. Python's versatility is demonstrated by its ability to display results in several formats, such as table view, graph view, and chart view. We use HTML, CSS, and JavaScript in conjunction with the Flask framework to construct the front end. Flask was chosen because it is simple to integrate with Python and offers a productive and smooth development environment.

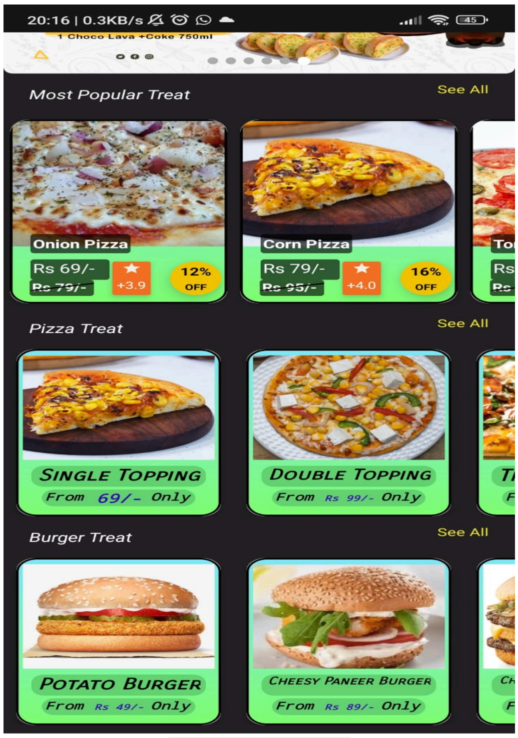
When in use, the display is incredibly responsive and fast. We use SQLite for the database, creating unique tables for every client to keep track of logs, reviews, ratings, comments, and browsing history.



Login Page



Home Page



Menu

Payment options

IV. CONCLUSION

The primary goal of the research is to create a web-based application for clients that serves as a restaurant recommendation system with the integration of machine learning.

Users use this app to find restaurants that suit their needs, find famous foods in particular areas, and for personal preferences. Customers are assured of

having access to ratings.
By combining collaborative and popularity-based filtering, the effectiveness of recommendations is enhanced, making it easier for every user to predict restaurants when utilizing this program.
Users look for eateries around a lot of the time. We address this issue by adding restaurant locations to our dataset. This enables our machine learning algorithm to predict the best eateries for clients based on their current location with ease.

The web application for restaurant recommendations aims to enhance the user experience by facilitating quick and efficient searches for neighboring eateries. By reducing user effort and time, this simplified method increases the experience's overall value.

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