A

Project Phase-I Report

On

"Project Title-

"Restaurant Recommendation System"

Submitted by,

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Under the guidance of

Prof R.D.Mane

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Dr. J. J. Magdum College of Engineering, Jaysingpur

Academic Year

2022-2023

Dr. J. J. Magdum Trust's

Dr. J. J. Magdum college of Engineering, Jaysingpur.

C E R T I F I C A T E

This is to certify that,

Mr.Dapale Yogesh Yashvant

Mr. Farakte Pratik Sanjay

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satisfactorily completed the Project Phase –I entitled **"Restaurant Recommendation System "** in partial fulfillment for award of Bachelor of Engineering Degree in Computer Science & Engineering by Shivaji University, Kolhapur in Academic Year-2022-23 Semester-I.

Prof. _____________

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Head

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Department of Computer Science & Engineering

CERTIFICATE

This is to certify that, the project entitled,

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is presented before Department Research Committee (DRC) by,

Sr. No.	Student Name	Roll No.
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Under the guidance of Prof. R.D.Mane for the academic year 2022-23.The DRC has consented to give the approval for the said project.

Head,

Department Research Committee, (DRC)

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ACKNOWLEGEMENT

First of all I would like to thank Prof. (R.D.Mane*)* who is presently working as an Assistant Professor of Computer Science & Engineering Department for guiding me through this project work. I am extremely grateful to him for all his invaluable guidance and kind suggestions during the Phase-I of my project work. His ever encouraging attitude, guidance and whole hearted help were biggest motivation for me in completing this project work.

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Lastly I thank all the people who have guided and helped me directly or indirectly.

Signature

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Mr.Dapale Yogesh Yashvant

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Mr. Gadad Mahammed Azhar Mahammed Gous

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INDEX

Chapter 2:-Introduction

The proposed topic for this project report centers around the development of a Restaurant Recommendation System, a cutting-edge solution designed to revolutionize the dining experience for individuals in an increasingly dynamic and diverse culinary landscape. In today's fast-paced world, people are often faced with the daunting task of choosing a restaurant from an overwhelming number of options, each offering a unique dining experience. This recommendation system aims to streamline the decision-making process by harnessing the power of data analysis and user preferences to provide personalized restaurant suggestions.

The motivation behind selecting this topic is rooted in the growing importance of technology in shaping consumer choices and enhancing user experiences. With the advent of smartphones and the proliferation of digital platforms, consumers now have access to a vast array of restaurant options, which can be both exciting and overwhelming. We believe that a well-designed Restaurant Recommendation System can simplify this process, making it more enjoyable for individuals to discover and select dining establishments that align with their tastes and preferences.

While there are several restaurant recommendation applications available in the market, our project seeks to distinguish itself through innovative features and enhanced accuracy. Many existing systems rely solely on user ratings or reviews, which can be biased and inconsistent. In contrast, our system will incorporate a wider range of data sources, including user preferences, location, cuisine type, and real-time feedback to offer more refined and personalized recommendations. Additionally, we plan to implement a user-friendly interface, allowing users to easily customize their preferences and access real-time updates on restaurant availability and special offers. By combining these elements, our Restaurant Recommendation System aims to provide a more comprehensive and user-centric dining experience, setting it apart from existing solutions in the market.

2.1:-Literature Review

1. **"A Collaborative Filtering Recommendation Algorithm for Restaurants" by J. Lee and S. Kim (2019)**

In this paper, the authors focus on collaborative filtering as the core algorithm for restaurant recommendations. They utilize user reviews and ratings to identify patterns and preferences, ultimately providing personalized restaurant suggestions. The study achieves promising results in terms of user satisfaction and recommendation accuracy. However, it acknowledges the challenge of data sparsity and scalability as limitations and suggests future research to address these issues for better system performance.

2. **"A Content-Based Restaurant Recommendation System" by M. Chen and L. Zhang (2018)**

Chen and Zhang present a content-based recommendation system for restaurants, which relies on analyzing restaurant attributes such as cuisine type, location, and price range to make personalized recommendations. The paper discusses the advantages of content-based methods, highlighting their effectiveness in providing diverse recommendations. It acknowledges the limitation of limited user feedback and suggests potential enhancements to incorporate user-generated content for improved recommendations.

3. **"Location-Based Restaurant Recommendation Using Deep Learning" by A. Gupta and R. Verma (2020)**

Gupta and Verma propose a location-based recommendation system that employs deep learning techniques. Their model considers user location and preferences to suggest nearby restaurants, achieving high accuracy in recommendations. The paper highlights the potential for integrating real-time location data and user mobility patterns for future improvements, while also mentioning privacy concerns associated with location-based systems.

4. **"Hybrid Restaurant Recommendation System Using Deep Learning and Collaborative Filtering" by S. Park and H. Kim (2017)**

Park and Kim present a hybrid recommendation system that combines deep learning and collaborative filtering. By utilizing neural networks, they capture complex user preferences and supplement them with collaborative filtering for improved recommendations. The paper demonstrates enhanced recommendation accuracy compared to single-method approaches. It discusses the need for handling cold-start problems and scalability challenges in hybrid models as future research directions.

5. "Enhancing Restaurant Recommendation through Sentiment Analysis of User-Generated Reviews" by E. Johnson and K. Smith (2016)

Johnson and Smith propose a recommendation system that incorporates sentiment analysis of user-generated restaurant reviews. By analyzing sentiment, they aim to provide more nuanced and emotionally relevant recommendations. The study shows that considering user sentiments can lead to higher user satisfaction and engagement. The paper acknowledges the challenge of sentiment analysis accuracy and suggests refining sentiment analysis techniques as a future research direction.

These selected papers encompass various technologies and algorithms, such as collaborative filtering, content-based approaches, deep learning, and sentiment analysis, highlighting their respective strengths and limitations. They emphasize user satisfaction and recommendation accuracy as primary goals and provide valuable insights into potential enhancements and future research directions to address the mentioned limitations, including data sparsity, privacy concerns, and scalability issues.

2.1.1:-EXISTING SYSTEM

While many existing recommender systems mainly target individuals, there is a remarkable increase of recommender systems which generate suggestions for groups. Some early systems were developed in a variety of domains, such as, group web page recommendation (Lieberman et al. 1999), tour packages for groups of tourists (Ardissono et al. 2003), music tracks and playlists for large groups of many listeners (Crossen et al. 2002), movies and TV programs for friends and family (O'Connor et al. 2001; Yu et al. 2006). Group scenarios are especially popular in the food domain in which a group of family members, friends or colleagues wants to make a party or simply have a meal together. However, the complexity significantly increases when food recommender systems need to take into account the preferences of all group members and strategies for achieving the consensus within group members. From the survey, we have inferred that they have developed a recommended system just to search for food. However, the complexity significantly increases when food recommender systems need to take into account the preferences of all group members and strategies for achieving the consensus within group members. Many Restaurants stores and maintain their day to day transactions manually. But some of them are having automation system which is helping them to store the data. But such restaurants are storing the information about the orders and the customer information. They don't have facility to store the information of feedbacks and favourite orders of customers over some period of time. Restaurants are having standalone applications so at one time, they have the facility of many screens or many operations which is happening at one time. So they are storing them and then at last, the restaurant managers will able to see the data of last day

2.1.2:-Limitations of Existing System

Based on the literature review, the limitations of existing restaurant recommendation systems can be summarized as follows:

- **Data Dependency:** Many existing systems, such as deep learning-based models, require a substantial amount of user data to provide accurate recommendations. This poses a limitation as it may be challenging to acquire sufficient data, especially for new users or in the case of sparse datasets.
- **Scalability Issues:** Collaborative filtering algorithms, although effective, face scalability challenges, particularly with large datasets. As the number of users and restaurants grows, these algorithms may struggle to provide timely recommendations, affecting user experience.
- **Cold-Start Problem:** Several systems encounter difficulties when dealing with new users or restaurants, often referred to as the cold-start problem. These users lack historical data or reviews, making it challenging to provide relevant recommendations.
- **Data Quality and Accuracy:** Systems that rely on geographical information or user-generated reviews may suffer from inaccuracies in data. Inaccurate location data or biased user reviews can lead to suboptimal recommendations.
- **Real-Time Processing:** Some recommendation systems incorporate sentiment analysis of user reviews, but processing and analyzing large volumes of textual data in real-time can be computationally intensive and may introduce delays in providing recommendations.
- **Privacy Concerns:** Systems that leverage social network data or user preferences to improve recommendations must address privacy concerns. Users may be hesitant to share personal information or connect their social profiles with the recommendation system due to privacy considerations.
- **Critical Mass of Social Connections:** For systems that explore social network influence, the need for a critical mass of social connections can be a limitation. Users with a limited social network may not benefit as much from social-based recommendations.

Understanding these limitations is crucial for the development of an effective Restaurant Recommendation System. Addressing these challenges can lead to more accurate, efficient, and user-friendly recommendation solutions.

2.1.3:-PROPOSED SYSTEM

We are proposing a system, which uses streamlit to develop a small web app. Our main aim is to build a restaurant recommendation system that provides personalized restaurant recommendations to users. Since different people have different food preferences and dietary restrictions, we perform careful feature selection to take advantage of the information reflected in a user's reviews.we develop a restaurant recommendation system using the Latent Factor Collaborative Filtering Optimization. This system recommends restaurants for users or group of users based on their preferences such as beautiful ambience, good food, tasteful desserts and so. Our system provides personalized restaurant recommendations to users. The recommendation for new user is done by considering the user's location by tracking his location through gps, and by the ratings we got from Zomato's API. The restaurant which is nearby to the user, whose ratings are high will be recommended. For the old user we will consider his behaviour while using the application along with his location and restaurant popularity.

Chapter 3:-Methodology

3.1:-Problem Statement and Motivation:

Restaurants is one of the major industry that has close ties with humans' necessity & offers a variety of experiences and food from specialty cuisines (e.g. Mexican, Italian etc.) to taste, décor & services. Yelp users give rating to the restaurant based on their preferences so one rating for a restaurant that all users see. Yelp has a single star rating which is not enough to address different user preferences. Customized rankings are imperatives to any business and people will benefit more from this service. So, we can build a recommendation system that can identify a user's preferences and provide customized rankings for each individual user.

This recommender system focuses on predicting the rating that a user would have given to a certain restaurant, which is used to rank all the restaurants including those that have not been rated by the user.

3.2:-Proposed Experiment Work

EXPERIMENTAL AND MATERIALS AND METHODS; ALGORITHMS USED

SOFTWARE ENVIRONMENT: The software requirements are the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity. Operating system: Windows 10. Used: Python, Jupyter Notebook and Anaconda Prompt.

HARDWARE ENVIRONMENT:

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It shows what the systems do and not how it should be implemented. Hardware: Intel i5 Core RAM: 8GB

3.3:-Techniques to be used

MODULE DESCRIPTION

Recommender Systems or Recommendation Systems are simple algorithms that aim to provide the most relevant and accurate items (products, movies, events, articles) to the user (customers, visitors, app users, readers) by filtering useful stuff from a huge pool of information base. Recommendation engines discover data patterns in the data set by learning consumers' choices and produces the outcomes that co-relates to their needs and interests. Unlike offline stores, online stores have no sales people, they have huge number of products on their websites and users on other hand have 9 limited time and patience to navigate to the items that they are looking for. Recommendation systems solve these kinds of problems by exploiting the user preferences and prioritize the items based on all other users' past behaviour. Recommendation engines discover data patterns in the data set by learning consumers' choices and produces the outcomes that co-relates to their needs and interests. There are two types of Recommendation Systems. They are: 1) Content-Based Filtering 2) Collaborative Filtering 1. Content-Based Filtering: - Content-based filtering refers to such methods that provide recommendations by comparing representations of content describing an item to representations of content that interest the user pairs. This system recommends based on comparison between the descriptors of the items and a user profile. 2) Collaborative Filtering: - Unlike content-based filtering, this system doesn't require description of the data hence it recommends without knowing anything about the products. Collaborative filtering is the type of recommendation algorithm that bases its predictions and recommendations on the rating or behavior of other users in the system. The fundamental idea of collaborative filtering is to find other users in the community that share opinions. There are two popular

Approaches of collaborative filtering:

A. User-based approach Recommendation System uses the user ratings of other users with similar preferences to recommend a food item to a certain user. User-based recommendation algorithms firstly identify the k most similar users to the active user in which each user is treated as a vector and the similarities between the active user and other users are computed. B. Item-based approach Though user- based approach is useful, it suffers from the scalability problem as the user base grows. Searching from the 10 neighbours of a user becomes time-consuming. To extend collaborativefiltering to the large user base, a more scalable version of collaborative filtering, the i.e. item based approach was introduced. The overall structure of this approach seems to be similar to that of content based approach to recommendation and personalization, but item similarity is deduced from user preference patterns rather than extracted from the item data. Matrix factorization: - It is a class of collaborative filtering algorithms used in recommender systems. Matrix factorization algorithms work by decomposing the user-item interaction matrix into the product of two lower dimensionality rectangular matrices. A Recommendation System is an information filtering system that seeks to predict the rating a user would give for the item (in this case a restaurant). We can break down the large matrix of ratings from users and items into two smaller matrixes of userfeature and item-feature. We have two matrixes (user-features, business-features) that we can multiply to predict the ratings that a user gives to a restaurant. Later, we need to update the values in the features of our two matrixes according to the Error. To optimize the predictions, we need to calculate the error using the function below. Given P is the users-features matrix and Q is the business-features matrix. If we subtract the real ratings (r) with the predicted ratings (P.Q) and we square it, we get the LSE(Least Square Error). To avoid overfitting we have to add regularization to our LSE formula and it will become the formula written below. We apply the equation to minimize the error using Gradient Decent to update the values of each feature in matrix P and matrix Q.

LIBRARIES

- **Sklearn**- Scikit Learn additionally called sklearn could be a free code machine learning library for python programming. It options varied classification, clustering, regression machine learning algorithms. during this it's used for mercantilism machine learning models, get accuracy, get confusion matrix.

- **Pandas**- Pandas could be a quick, powerful, versatile and easy to use, engineered on prime of the Python programming language. It is open source used for knowledge analysis and manipulation tool. In this, it's accustomed scan the dataset.

- **Matplotlib**- Matplotlib could be a plotting library for the Python programing language and its numerical mathematical extension NumPy. In this, it's used for knowledge visualization.

- **NumPy**- Numpy could be a python library used for working with arrays. additionally has functions for domain of algebra, fourier rework, and matrices. Numpy stands for Numerical Python.In this it's accustomed amendment 2- dimensional array into contiguous plantearray.

- **Streamlit** is associate degree ASCII text file Python library that produces it Straight forward to make and share lovely, custom internet apps for machine learning and information science. in only a number of minutes you'll be able to build and deploy powerful information apps. The best issue concerning Streamlit is it does not need any data of internet development.

- **Seaborn** could be a library for creating applied mathematics graphics in Python. it's designed on prime of matplotlib and closely integrated with pandas knowledge structures. It aims to form visual image a central a part of exploring and understanding knowledge.

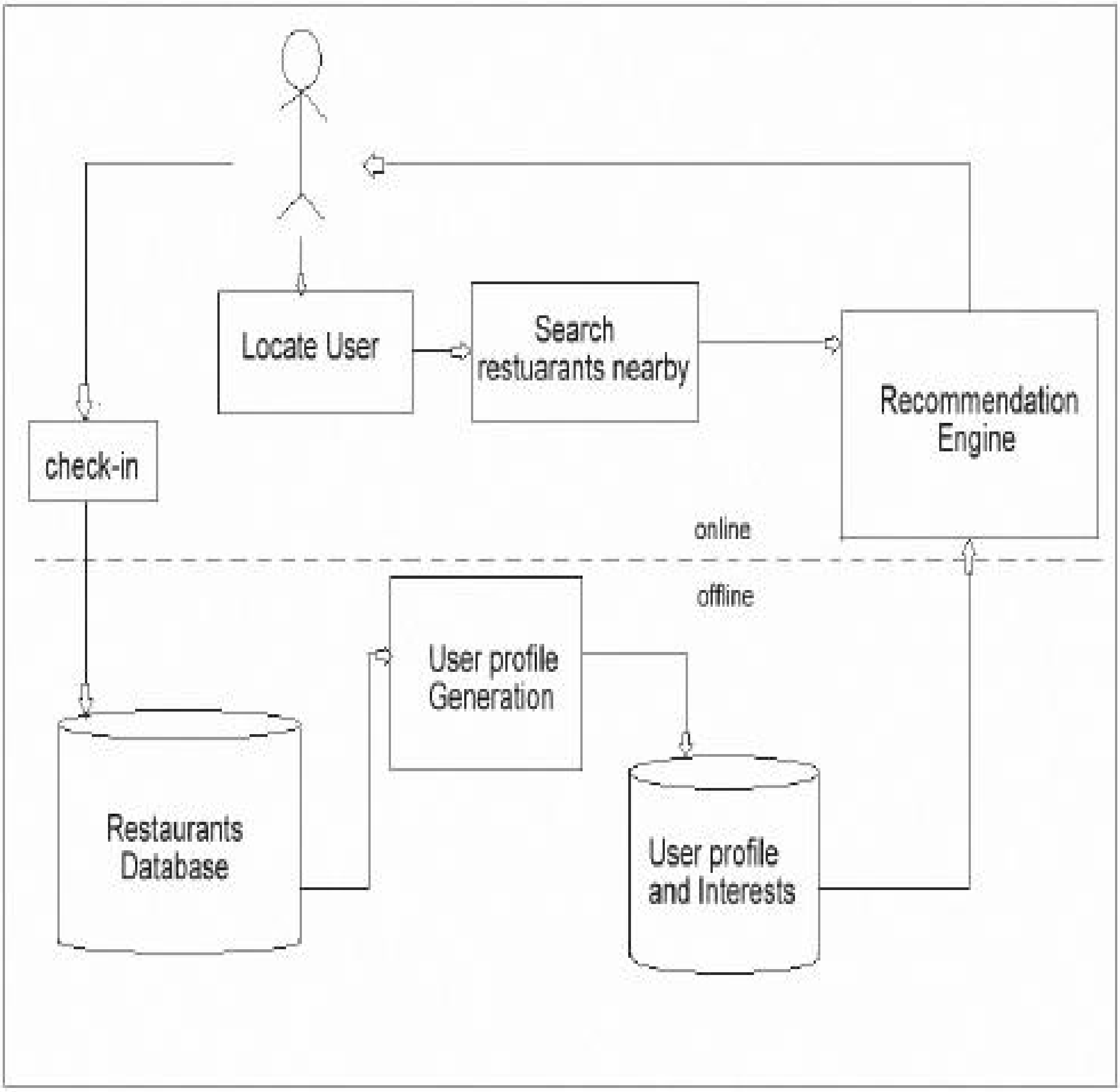
3.4:-SYSTEM ARCHITECTURE

ALGORITHMS

Matrix factorization algorithms work by decomposing the original matrix into two matrices one is the upper triangle (U), and the other is the lower triangle (L). Algorithm: Step 1: Take the input matrix as U and an empty diagonal matrix as L Step 2: n be length of matrix U Step 3: for col in range (1, n): a. for row in range (2, n): a-1. if row > col mul = U [[row, col]]/U [[col, col]] L [row, col] = mul U[row,] = U[row,] – mul * U[col,] Return U Dataset collection Import the necessary libraries Data visualisation Training and Testingof model Deploy the model using Streamlit Search the restaurant according to the user taste 13

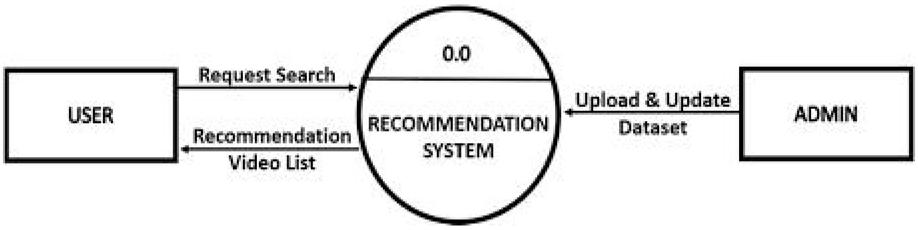
METHODOLOGY Project contain three components: 1. Dataset assortment 2. Train and check the model. 3. Deploy the model mistreatment streamlit. ✓ Dataset assortment: - we tend to had collected dataset from **kaggle notebooks**. The dataset contains userid, review, ratings. It contains 192609 rows. ✓ Train and test method: - we had used a machine algorithm to train the model and after training, we had tested the model. ✓ Deploy the model using streamlit: - In this we have created a web application to search the restaurant according to customers tastes and also it shows some recommendations according to the reviews and rating.

Sytem Archtechture Diagram :

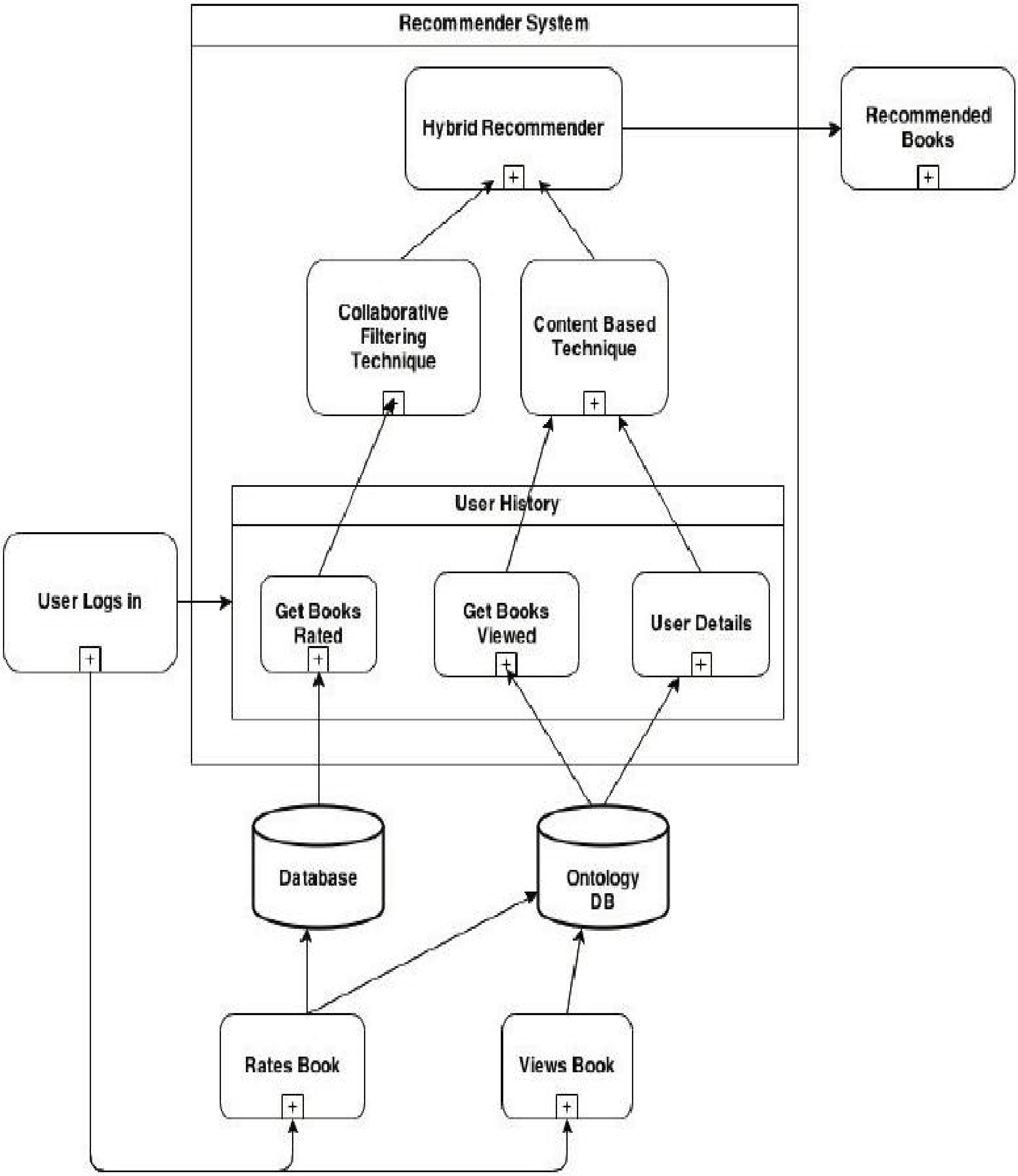


DFD(data flow diagram)

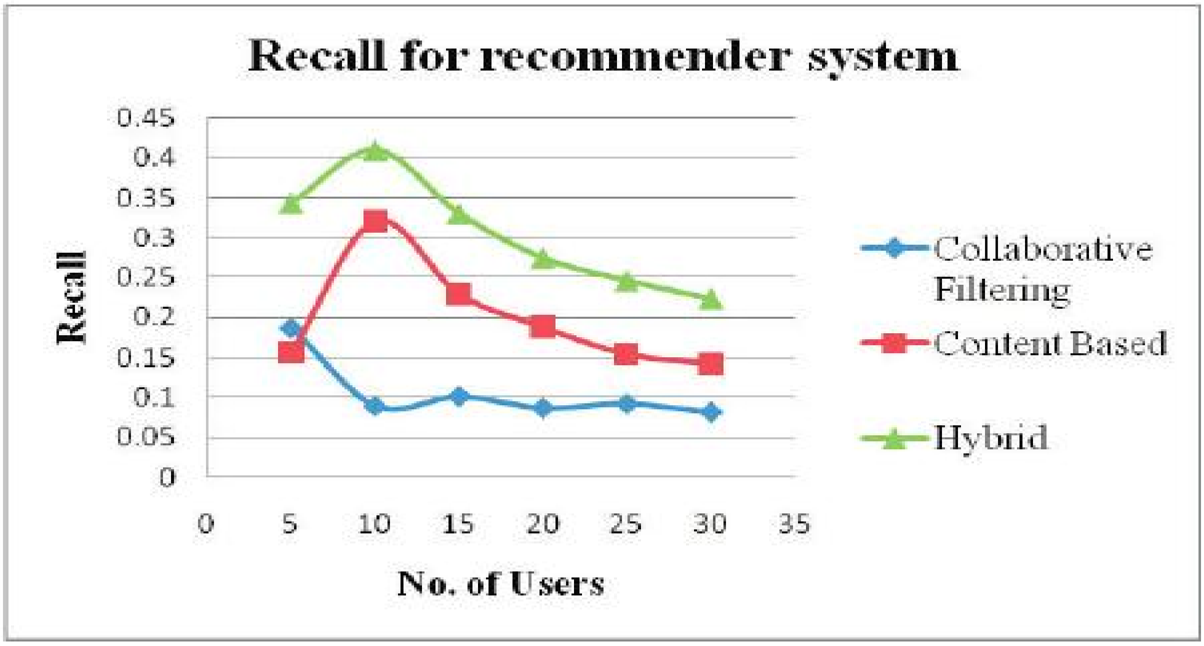
0 level DFD:-

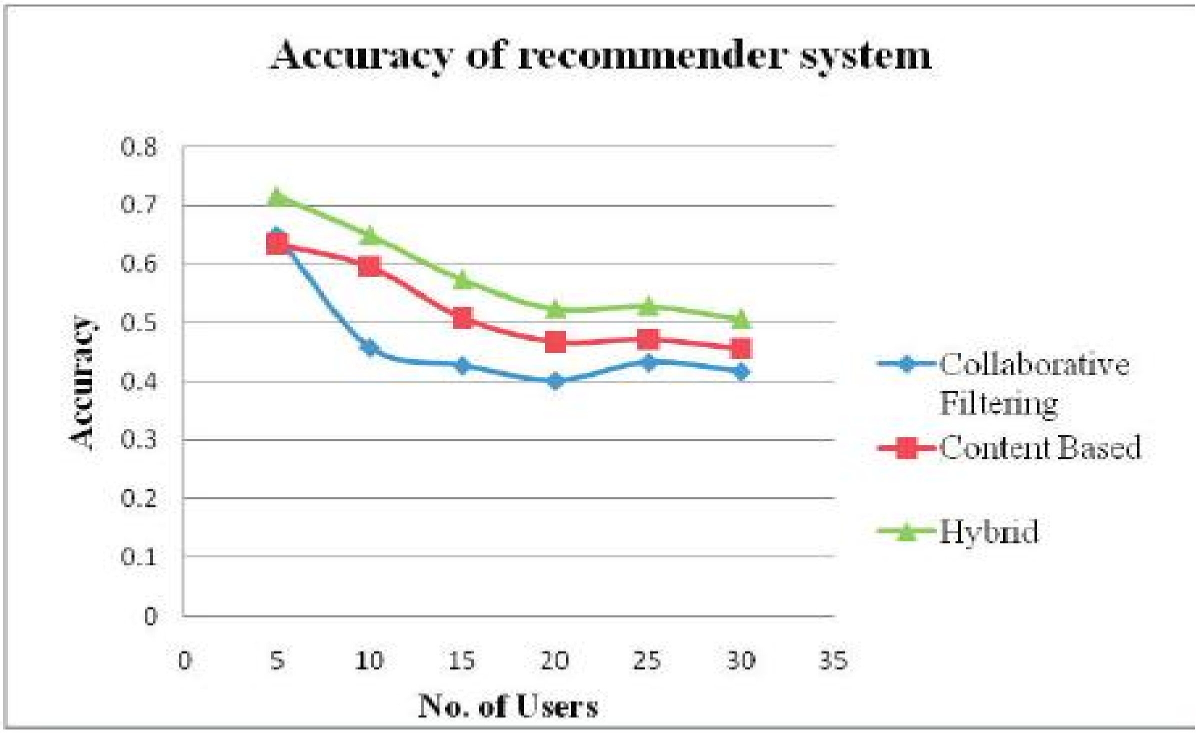


Block Diagram of Restaurant Recommender System

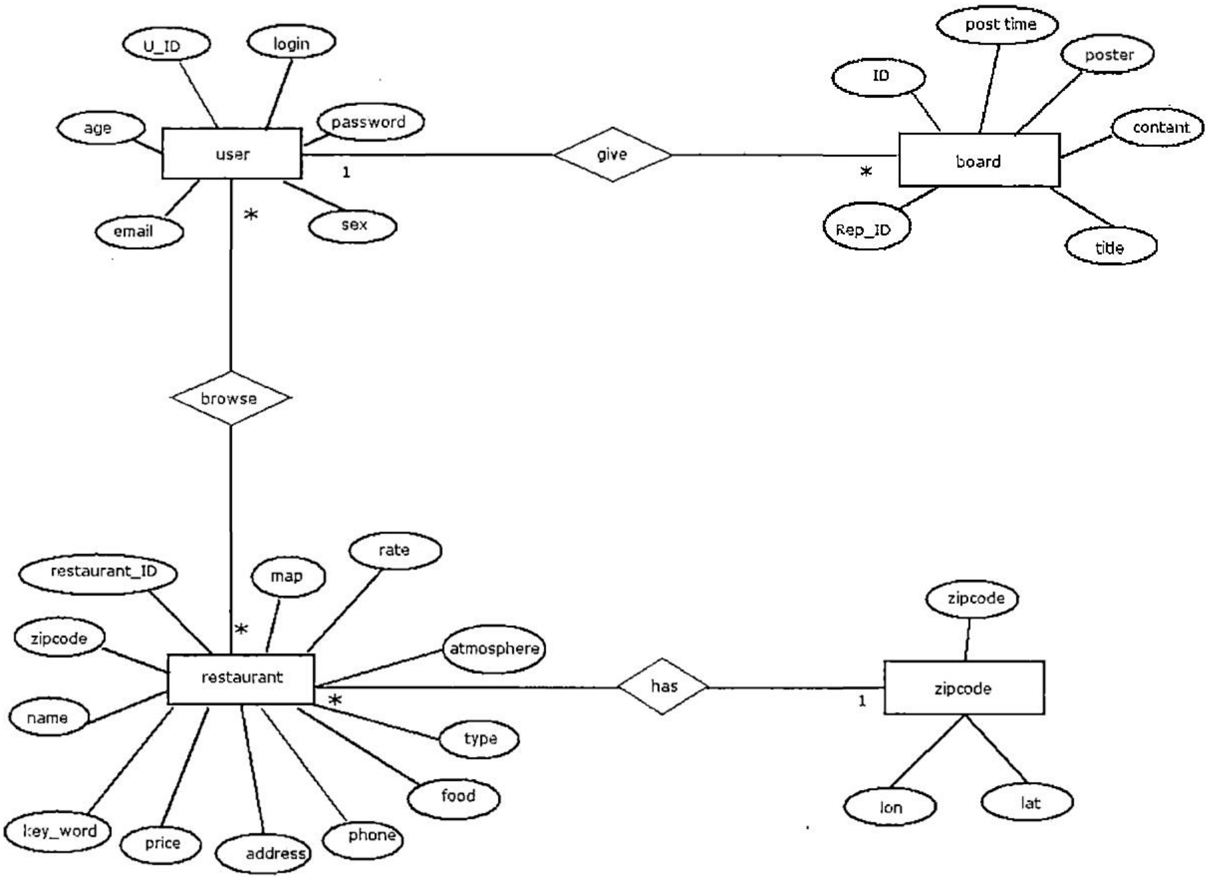


Recall And Accuracy Graph

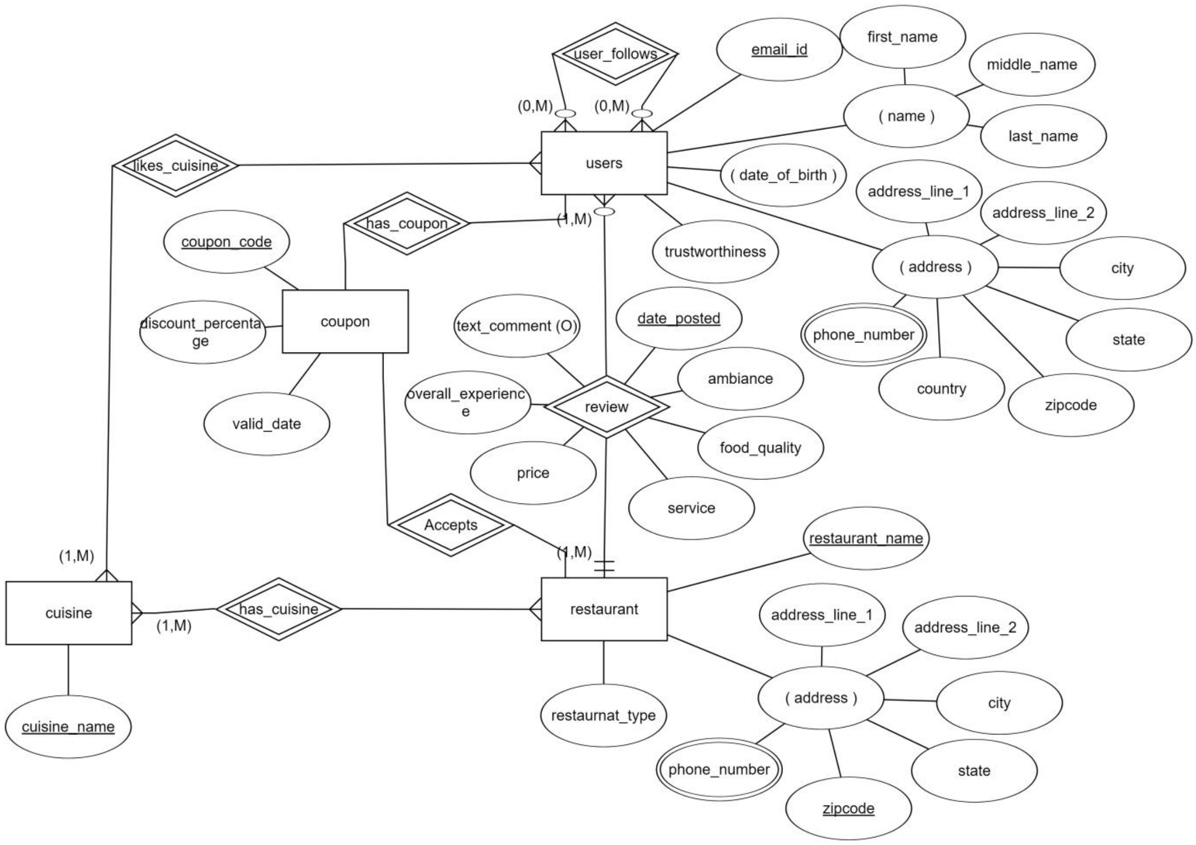




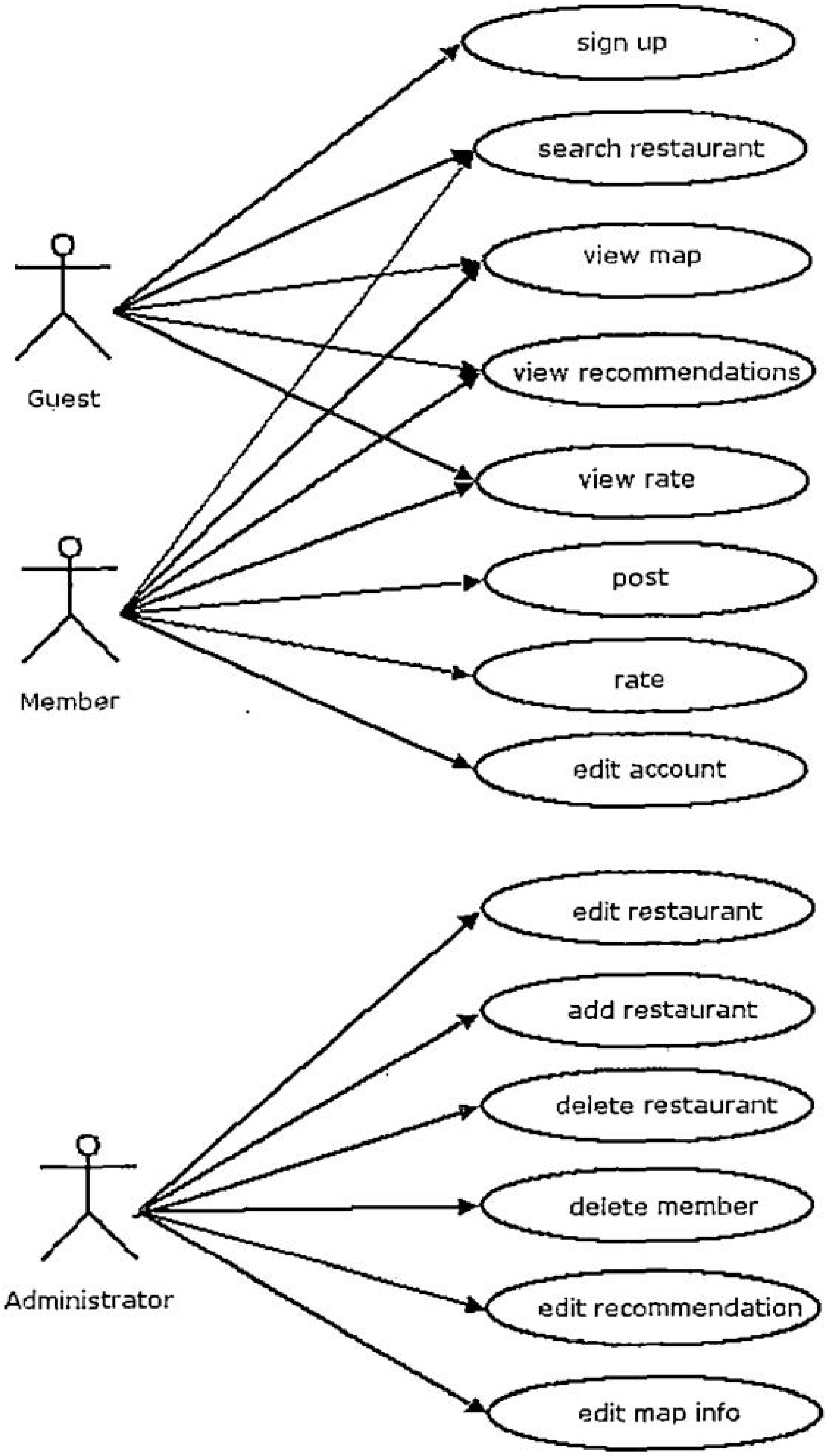
Database Relation Diagram



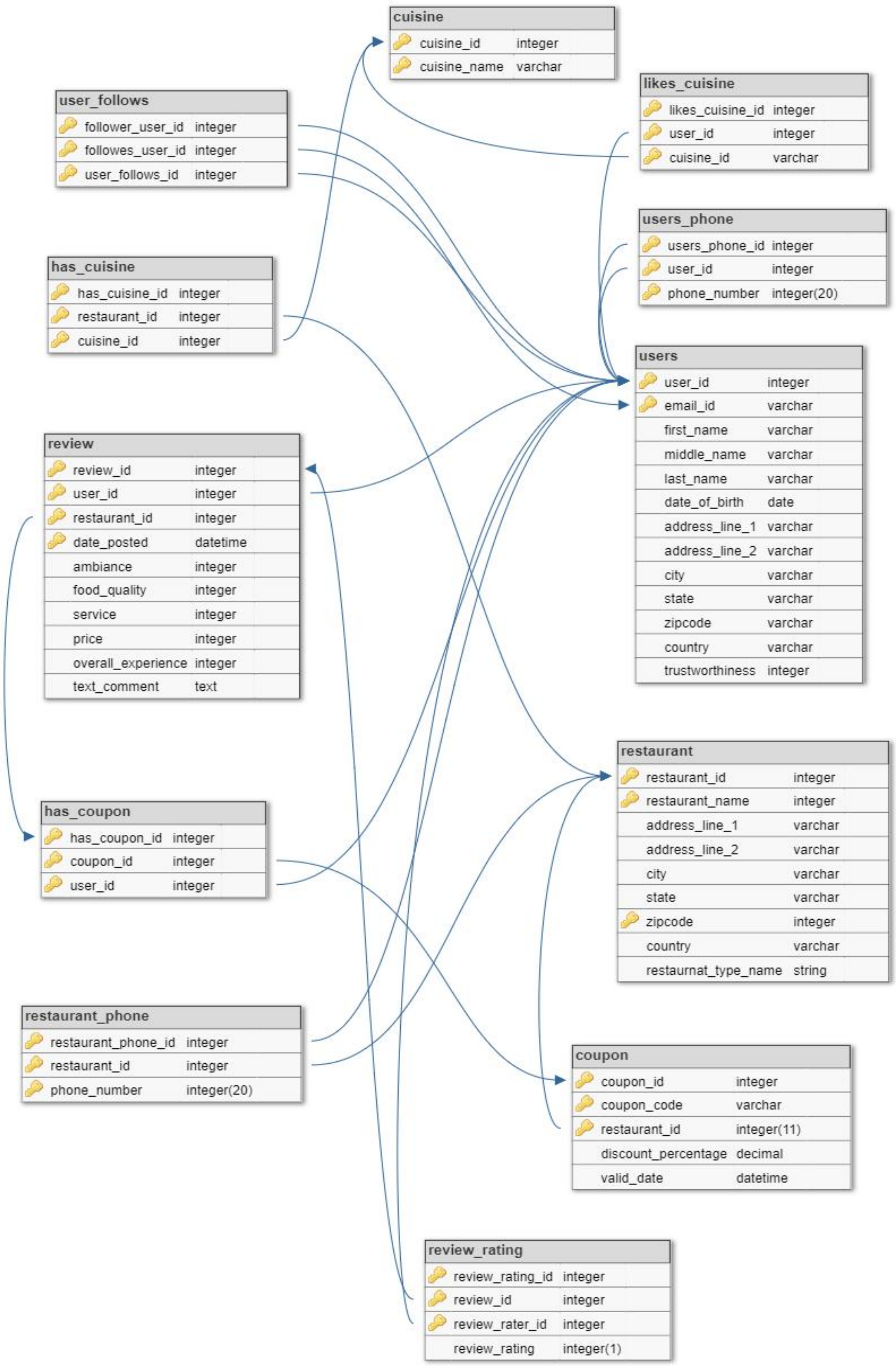
Entity Relation Diagram



UseCase Diagram



Database Architecture Diagram



Database Tables Formate

User Table

field	Type	null	key	default	extra
Name	varchar(15)	Yes		null	
Password	varchar(30)	Yes		null	
Sex	char(1)	Yes		null	
Email	varchar(30)	Yes		null	
Age	Int(2)	Yes		null	
user_id	Int(11)		PRI	0	auto_ increment

Restaurant Table

field	type	null	key	default	extra
RestName	varchar(30)				
type	varchar(15)	Yes		null	
area	varchar(15)	Yes		null	
Phone	varchar(12)	Yes		null	
address	varchar(50)	Yes		null	
zipcode	Int(5)	Yes		null	
map	varchar(255)	Yes		null	
id			PRI	0	auto_ increment
foodrate	Float(10,2)	Yes		null	
atmosrate	Float(10,2)	Yes		null	
ratecount	Int(11)	Yes		null	
price	Int(11)	Yes		null	

Chapter 4:-Implementation tools & module developed

Recommendation Model

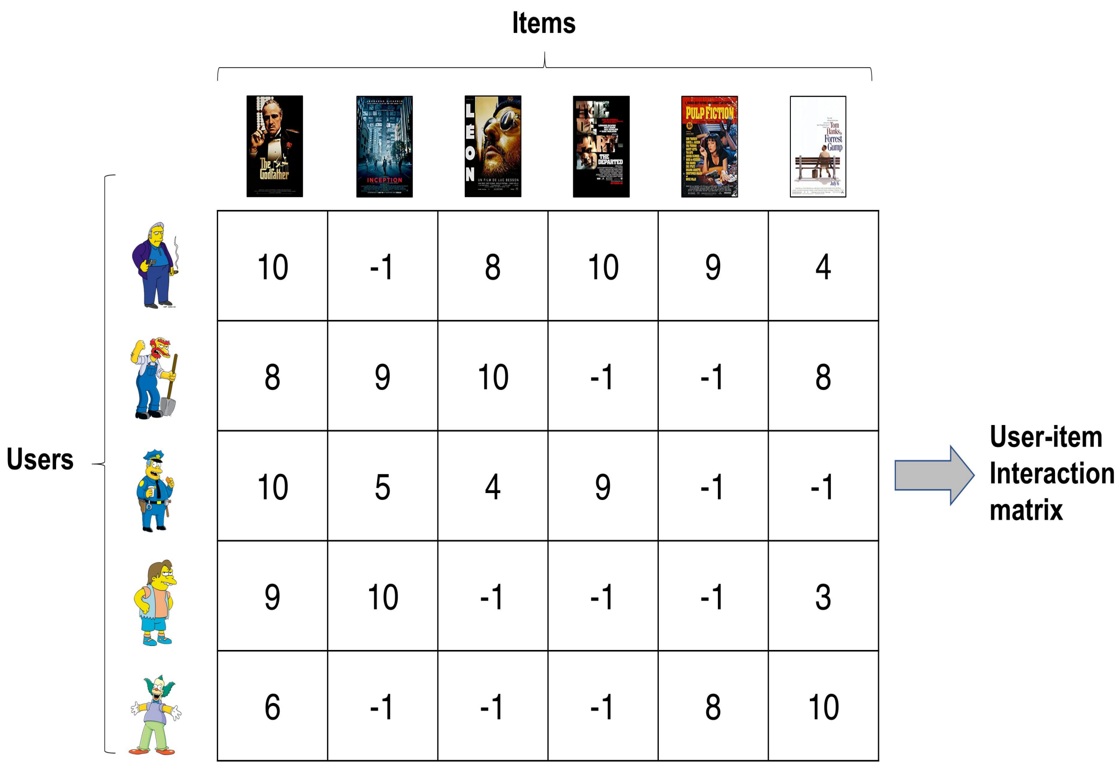
Collaborative Filtering

Collaborative filtering is widely adopted in recommender systems. Netflix and Amazon all use collaborative filtering to create customized experience for their users. This technique predicts the missing entries of a user-item association matrix. In general, collaborative filtering uses the following intuitions:

▪ Personal tastes correlate.

▪ Users who agreed with each other before are more likely to agree in future

▪ To predict the rating of the user, use users who have similar taste



10	-1	8	10	9	4
8	9	10	-1	-1	8
10	5	4	9	-1	-1
9	10	-1	-1	-1	3
6	-1	-1	-1	8	10

The underlying assumption is that if A agrees with B on some issues, A is likely to share B's opinions on other issues. To predict the user rating for an unrated item, collaborative filtering algorithm looks into on the ratings from other users with similar rating histories (users with green rows). Because of this logic, the field marked with "?" should be updated to thumb down. Mathematically, the underlying mechanics of collaborative filtering is matrix factorization combining with cost minimization problem. The user-item matrix M is as the following, where r is actual rating value:

$Rui = \{ r, if\ user\ u\ rate\ item\ i\ 0, if\ user\ u\ did\ not\ rate\ item\ i$

The user-item matrix R is U x M, where U is a matrix of factors that describes each user and M is a matrix of factors that describes each item. Since we do not know either variable, alternative least squares(ALS) with regularization is used to approximate R. ALS first estimates the item factor matrix using the user factor matrix and vice versa. After enough iterations, a convergence point will be reached where either matrix changes much. To ensure U x M approximates R, the following cost function is minimized:

$f(U, M) = \sum Wi,j(ri,j - vi \times mj)\ 2 + \lambda\ (\sum nvi\ ||vi\ ||\ 2 + \sum nmj\ ||mi\ ||\ 2\ j\ )\ i,j$ �

ALGORITHMS

Matrix factorization algorithms work by decomposing the original matrix into two matrices one is the upper triangle (U), and the other is the lower triangle (L).

Algorithm:

Step 1: Take the input matrix as U and an empty diagonal matrix as L

Step 2: n be length of matrix U

Step 3: for col in range (1, n):

a. for row in range (2, n):

a-1. if row > col

mul = U [[row, col]]/U [[col, col]]

L [row, col] = mul

U[row,] = U[row,] – mul * U[col,]

Return U

CONCLUSION

In this project, we developed a web app which recommend the restaurant based on the choice of your interest. This is used for the users to predict the suitable and best restaurant as per their tastes. The content based filtering and collaborative based filtering makes the recommendation more efficient so that each user can use this application for their easy prediction of restaurant.

The project Restaurant Recommendation System was successfully completed by using latent factor collaborative filtering or matrix factorization. In this project, we developed a model that could recommend the restaurant based on the choiceofinterest

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6. Hybrid Restaurant Recommendation System Using Deep Learning and Collaborative Filtering by S. Park and H. Kim (2017)
7. Enhancing Restaurant Recommendation through Sentiment Analysis of User-Generated Reviews by E. Johnson and K. Smith (2016)

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