

## 1. INTRODUCTION

### 1.1 Overview

Particularly when dining out with friends, family, and coworkers, people are beginning to appreciate restaurant recommendations more and more. Friends' recommendations are frequently restricted to their previous trips, and consumers might not enjoy the locations they are suggested. A content-based recommendation system seeks to develop a system in which users enter the name of a restaurant, the system examines reviews of other restaurants, and then recommends comparable restaurants based on those evaluations. This technique is especially useful for residents who may use it to identify new restaurants based on their activity and tourists who frequently visit famous restaurants while they are in town.

### 1.2 Purpose

Our project aims to create a system that assists users in discovering new restaurants by leveraging the power of online reviews and recommendations. The process involves users inputting the name of a restaurant they are interested in, and the system then analyzes reviews of other restaurants to generate comparable recommendations. This technique proves particularly valuable for both local residents and tourists.

For local residents, the system provides an avenue for exploring new dining options. By entering the name of a known restaurant, users can receive recommendations for similar establishments that have received positive reviews. This allows residents to expand their culinary experiences and try out different venues based on the feedback and evaluations of others.

Tourists, on the other hand, often encounter challenges when trying to find suitable dining options while visiting unfamiliar places. By utilizing this system, tourists can input the name of a renowned restaurant they have heard of or have already visited. The system then examines reviews of other restaurants to identify similar establishments that may match their preferences. This enables tourists to discover alternative dining choices that align with their tastes and interests, even if they are not familiar with the local food scene.

The system's recommendations are generated by analyzing various aspects of the reviews, such as the overall rating, specific comments about the food quality, service, ambiance, and other relevant factors. By aggregating and processing this information, the system can determine which restaurants share similar characteristics and offer

comparable experiences.

The underlying idea behind this project is to harness the collective wisdom of online reviewers to provide personalized recommendations. By considering the evaluations and opinions of others, the system can guide users towards restaurants that align with their preferences, thereby enhancing their dining experiences. Overall, this system offers a user-friendly and efficient way for both residents and tourists to explore new restaurants based on the evaluations of other establishments, facilitating the discovery of unique dining experiences and expanding culinary horizons.

The methods for developing a recommendation system covered in this project include Content-Based Filtering, data pre-processing, data visualisation for insights, algorithm application, model correctness, and web application construction utilising the Flask framework. Through visualisation, we will attempt to analyse data, apply algorithms depending on the dataset, and create a web application using the Flask framework.

## 2. LITERATURE SURVEY

### 2.1 Existing problem

A restaurant recommendation system data science project can address several existing problems related to dining experiences.

This system can filter and present personalized recommendations based on user preferences, making it easier for users to find suitable dining options. It can introduce users to new and lesser-known restaurants, helping them discover diverse dining experiences they may not have considered otherwise. Restaurant reviews can vary greatly in terms of reliability and relevance. A recommendation system can aggregate and analyze reviews from multiple sources to provide more accurate and reliable recommendations, reducing the risk of relying on biased or uninformative reviews. People with dietary restrictions or specific dietary preferences often struggle to find suitable dining options. Our project can take into account factors like vegetarian, vegan, gluten-free, or other dietary preferences, ensuring that recommendations align with the user's specific requirements.

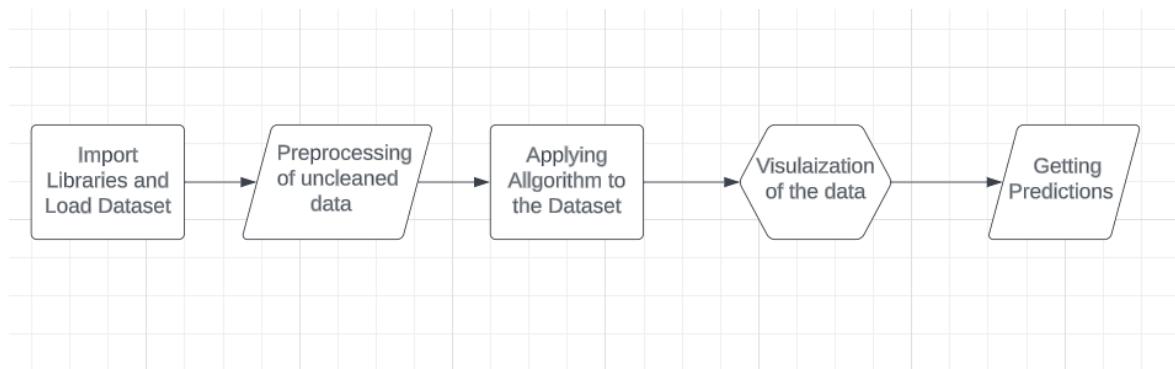
### 2.2 Proposed solution

Through Analysis Model, we have calculated the prediction values using regression algorithms. We have done Data Visualisation and have derived the bar plots for various categories like the restaurant allows online deliveries or not, they allow table booking or not etc. These informations will allow users to plan their dining experience

with ease. We have also designed a Prediction Model to help users find the best restaurants as per their choices. We have used TF-IDF Vectorization create the model. The model functions in a way that for a searched restaurant the model will recommend 10 more such restaurants with similar rating.

### 3. THEORETICAL ANALYSIS

#### 3.1 Block diagram



**Diagrammatic overview of the project**

#### 3.2 Hardware / Software designing

For successful execution of the project we have the following requirements:

- An environment to write and test codes successfully. For that, we can use either Anaconda IDE (Integrated Developing Environment) or Anaconda Navigator.
- To implement Machine Learning Algorithms, following packages are to be installed:
  - Numpy - a powerful Python library for scientific computing and numerical operations, offering high-performance multidimensional array objects and a wide range of mathematical functions.
  - Matplotlib - a comprehensive Python library for creating static, animated, and interactive visualizations, enabling the generation of diverse plots and charts.
  - Seaborn - a Python data visualization library that builds upon Matplotlib, providing a high-level interface for creating attractive statistical graphics with minimal code.
  - Flask - a lightweight and flexible Python web framework that allows developers to build web applications quickly and easily.

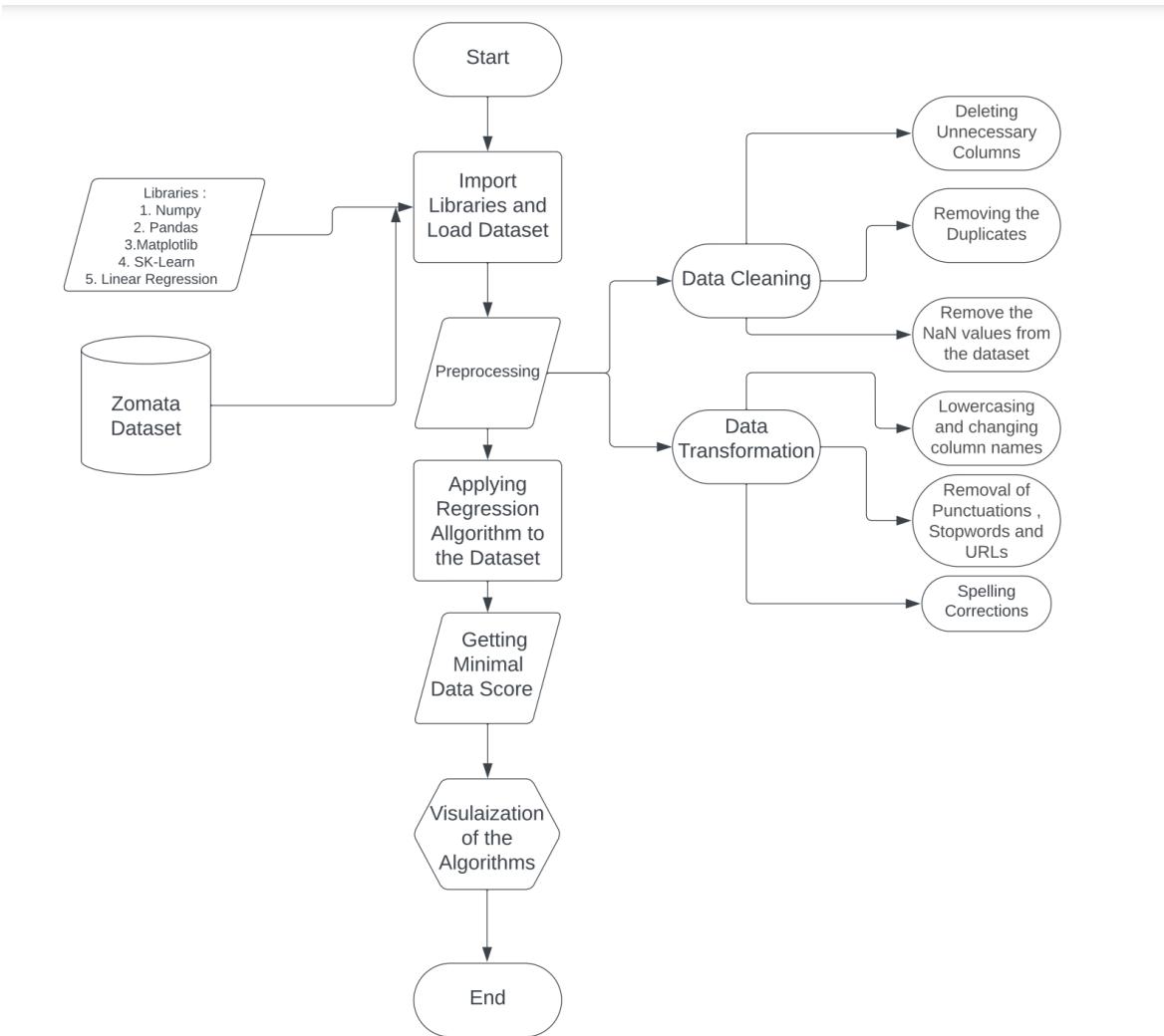
## 4. EXPERIMENTAL INVESTIGATIONS

The approach we took was centred on using natural language processing methods to process user comment material and extract the necessary meal names. Conceptually clustering food names has been accomplished using the semantic similarity approach. The Wu-Palmer approach produced more precise clustering findings. Sentiment analysis has been carried out to ascertain the user's opinion of each food and to show whether it is favourable or unfavourable.

Group-based restaurant suggestion is a major potential direction for this research because consumers typically go to restaurants in groups. In order to do this, it is important to specify how closely user preferences and their preferred foods in each restaurant align.

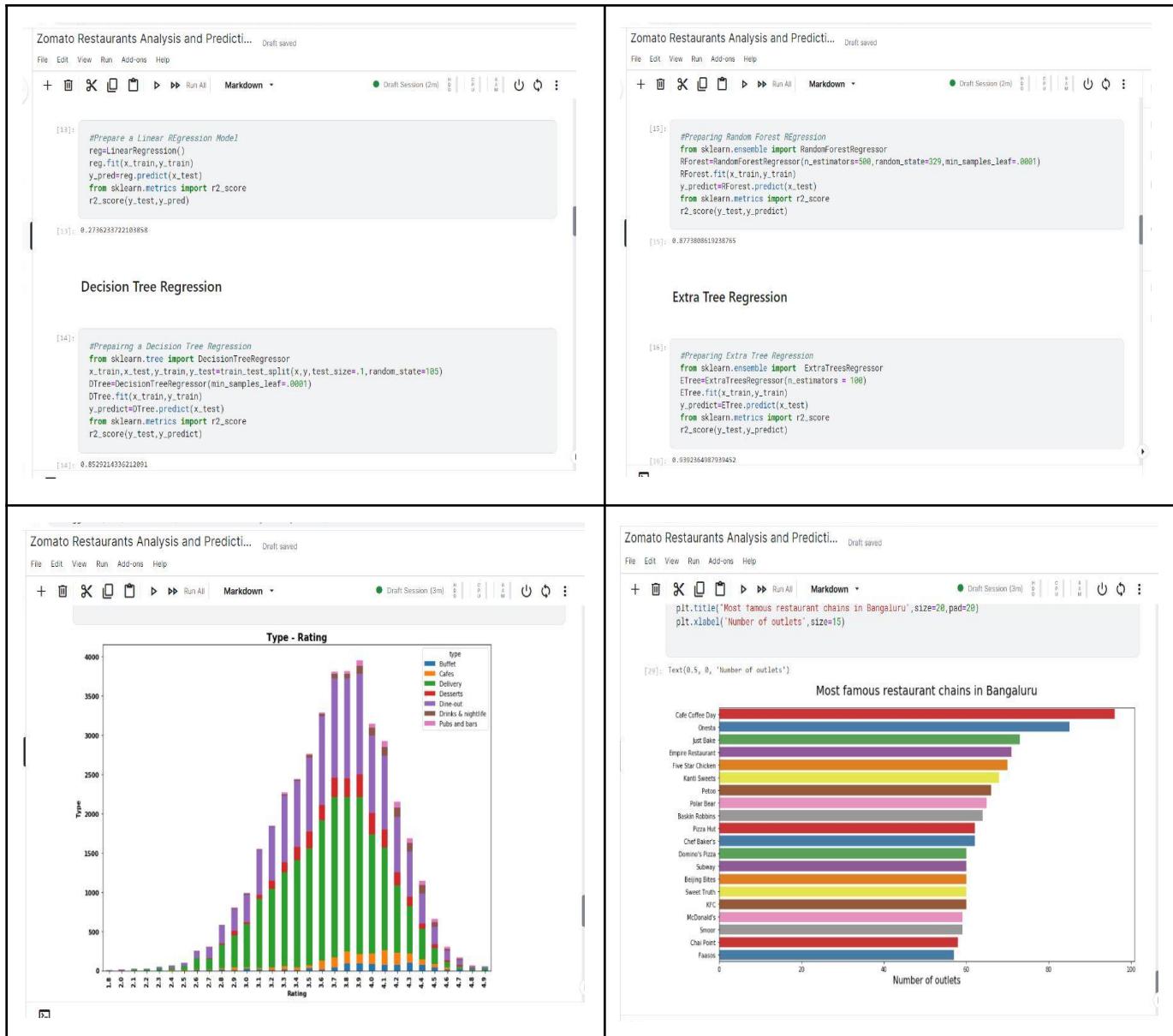
## 5. FLOWCHART

Diagram showing the control flow of the solution



## 6. RESULT

- Analysis Model Output Screenshots:



- Prediction Model Output Screenshot:

Restaurant Recommendation System Using ML 🔥 ... Draft saved

File Edit View Run Add-ons Help

+ 🗑️ ✎ 🖨️ ➡️ Run All Code

```
for each in recommend_restaurant:
    df_new = df_new.append(pd.DataFrame(df_percent[['cuisines','Mean Rating', 'cost']][df_percent.index

# Drop the same named restaurants and sort only the top 10 by the highest rating
df_new = df_new.drop_duplicates(subset=['cuisines', 'Mean Rating', 'cost'], keep=False)
df_new = df_new.sort_values(by='Mean Rating', ascending=False).head(10)

print('TOP %s RESTAURANTS LIKE %s WITH SIMILAR REVIEWS: ' % (str(len(df_new)), name))

return df_new
recommend('Pai Vihar')
```

TOP 10 RESTAURANTS LIKE Pai Vihar WITH SIMILAR REVIEWS:

	cuisines	Mean Rating	cost
Skoolroom	Cafe, Continental, Italian, Burger, Beverages	4.23	700.0
Cravy Wings	American, Burger, Fast Food	4.11	400.0
Ilyazsab The House Of Chicken	Rolls, Kebab	3.84	250.0
Andhra Ruchulu	Andhra, Biryani, North Indian, Chinese	3.72	1.0
Green Pepper	Seafood, South Indian, Chinese, Kerala	3.65	600.0
King Of Spices	South Indian, North Indian, Chinese, Biryani, ...	3.45	500.0
Chowpatty	North Indian, Fast Food, Street Food	3.43	300.0
Chicken Corner	Biryani, North Indian, Fast Food, Chinese	3.35	400.0
Queen Pearls	Pizza	3.32	500.0
Spice Affair	North Indian, Chinese	3.32	600.0

## **7. ADVANTAGES & DISADVANTAGES**

List of advantages and disadvantages of the proposed solution are :

## **Advantages :**

1. Simplicity : The algorithm we have implemented is a straight forward and easy to understand statistical technique .
  2. Predictive Power : Linear Regression allows you to identify and quantify relationships between variables . By analyzing historical data , such as customer count , sales and other parameters you can predict outcomes with reasonable accuracy .
  3. Relationship Identification : Linear Regression helps you to determine the strength and direction of relationships between independent and dependent variables . For instance you can assess how factors affect sales.
  4. Feature Importance : By examining regression coefficients , you can prioritize and focus on the most influential factors impacting the performance .

### **Dis-Advantages :**

1. Linearity Assumption : In most cases relationships in real life are more complex patterns and can be non-linear. Using linear regression in such cases will lead to incorrect predictions .
  2. Overfitting or Underfitting : Both cases will result in suboptimal scenarios .

3. Sensitivity to Outliners : Outliners can disproportionately influence regression line , leading to biased predictions .

## 8. APPLICATIONS

This project can be applied in various areas to enhance the dining experience and support decision-making processes. Here are some areas discussed :

- **Online Food Delivery Platforms:** Restaurant recommendation systems can be integrated into online food delivery platforms like Uber Eats, Grubhub, or DoorDash. By providing personalized recommendations, these platforms can help users discover new restaurants and cuisines that align with their preferences, increasing user satisfaction and engagement.
- **Restaurant Discovery Apps:** Dedicated restaurant discovery apps can leverage recommendation systems to help users explore new dining options and can provide tailored suggestions based on user preferences, location, dietary restrictions, or other relevant factors thus promoting culinary variety and encourages users to try different restaurants.
- **Travel and Tourism Websites/Apps:** When users are traveling to new cities or countries, a restaurant recommendation system can assist them in finding local dining experiences. Travel and tourism websites or apps can integrate recommendation systems to suggest restaurants based on the user's location, preferences, and reviews from fellow travelers.
- **Review and Rating Platforms:** Restaurant recommendation systems can enhance review and rating platforms like Yelp or TripAdvisor. By providing personalized recommendations alongside user reviews and ratings, these platforms can offer a more comprehensive and informative experience to users seeking restaurant information.
- **Smart Home Devices:** Recommendation systems can be integrated into smart home devices such as voice assistants. Users can ask for restaurant recommendations based on their preferences, location, or other criteria, and receive instant suggestions, making it convenient for them to plan dining experiences at home.
- **Corporate Dining Services:** Large organizations or companies with on-site dining facilities can utilize restaurant recommendation systems to offer diverse and

personalized dining options to their employees. By integrating the system into their internal portals or cafeteria apps, employees can receive recommendations based on their preferences, dietary restrictions, or proximity to the workplace.

- **Personalized Loyalty Programs:** Restaurants with loyalty programs can leverage recommendation systems to enhance their offerings. By analyzing customer preferences and dining history, the system can provide personalized recommendations to loyalty program members, increasing customer satisfaction and engagement.

## 9. CONCLUSION

Overall, a restaurant recommendation system data science project has wide-ranging applications in online food delivery platforms, restaurant discovery apps, travel and tourism websites, review platforms, smart home devices, corporate dining services, and personalized loyalty programs. By incorporating the system in these areas, users can benefit from personalized and relevant restaurant recommendations, leading to increased satisfaction, exploration, and culinary variety.

We can solve various problems faced by users, such as information overload, limited awareness, lack of personalization, inconsistent reviews, and the long decision-making process. The system assists users in discovering new and diverse dining options, saving time in decision-making, and providing relevant and tailored recommendations. With continuous learning and feedback mechanisms, a restaurant recommendation system can adapt to evolving user preferences and provide up-to-date recommendations.

## 10. FUTURE SCOPE

The future scope of this project is promising, with several potential areas for further development and enhancement. Some of the future directions to explore are as follows:

- **Integration of Advanced Techniques:** Incorporating advanced machine learning and deep learning techniques into the recommendation system. For example, exploring the use of reinforcement learning, natural language processing (NLP), or graph-based models to improve recommendation accuracy and personalization.
- **Contextual Recommendations:** Consider incorporating contextual information

such as time of day, weather, or social context into the recommendation process. This can help provide more relevant and timely recommendations based on the user's current situation or preferences and thus improving efficiency of the project.

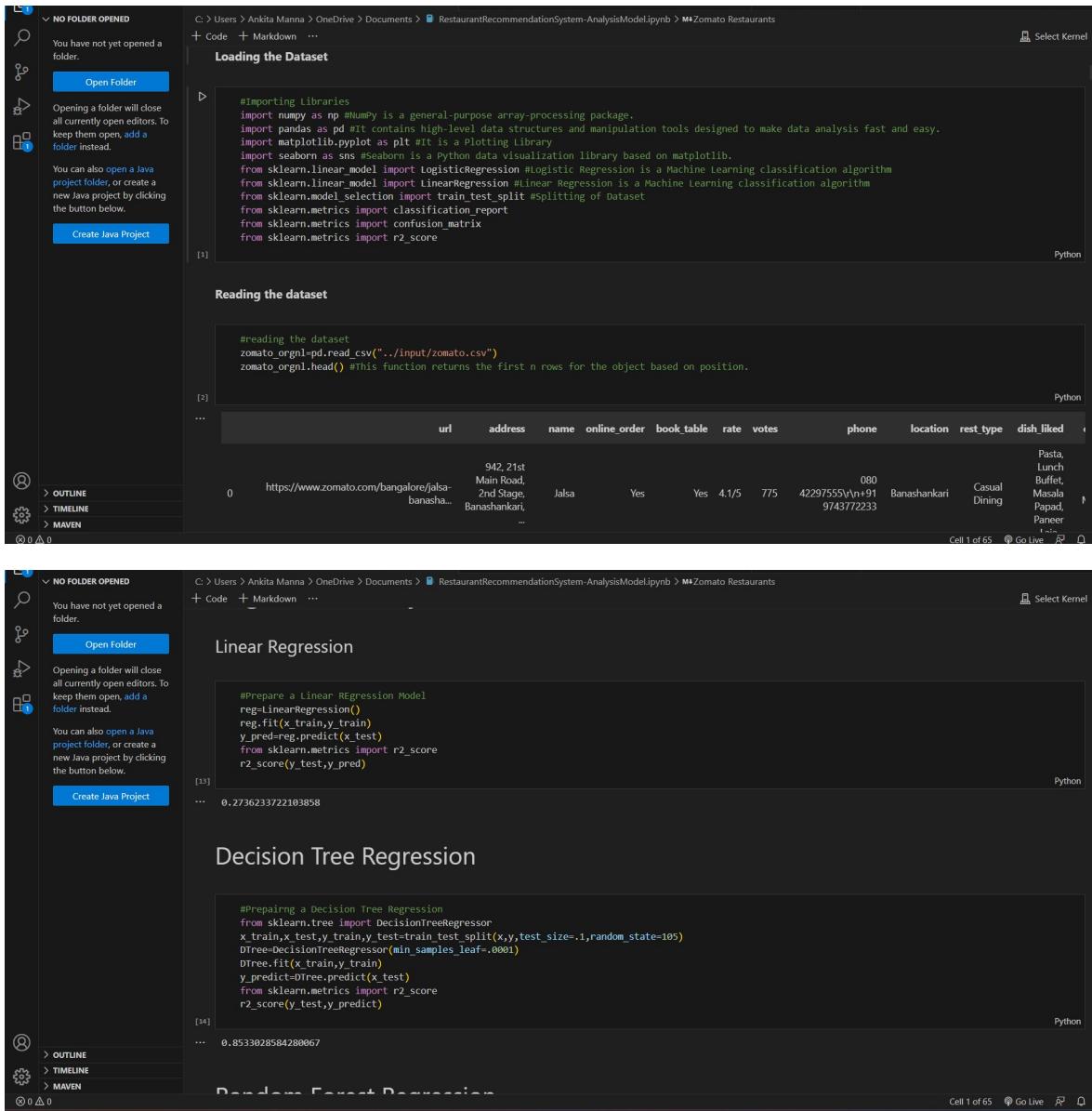
- **Multi-modal Recommendations:** Extend the recommendation system to incorporate multi-modal data sources such as images, videos, or audio. For instance, using image recognition techniques, the system can recommend restaurants based on the ambiance or visually appealing dishes.
- **Hybrid Recommendation Systems:** Hybrid approaches that combine different recommendation techniques, such as collaborative filtering, content-based filtering, and knowledge-based systems. Hybrid models can leverage the strengths of multiple approaches to provide more accurate and diverse recommendations.
- **Explainable Recommendations:** Develop methods to provide explanations for the recommended choices. Users often appreciate transparency and want to understand why a particular restaurant is suggested to them. Explainable recommendation techniques can increase user trust and engagement with the system.
- **Multi-objective Recommendations:** Incorporate multiple objectives into the recommendation system, such as diversity, serendipity, novelty, and user constraints. Optimize the recommendations to balance these objectives and provide a more holistic dining experience.
- **Mobile and Voice-based Interfaces:** Adapt the recommendation system for mobile platforms and voice-based interfaces , making it convenient for users to receive personalized restaurant suggestions on the go.
- **Continuous Learning and Feedback:** Implement mechanisms for continuous learning and feedback. Regularly update the recommendation system with new data, user feedback, and evolving preferences. Adaptive learning techniques can ensure that the system stays up-to-date and provides accurate recommendations over time.

## 11. BIBILOGRAPHY

- Kaggle
- YouTube ([https://youtu.be/1YoD0fg3\\_EM](https://youtu.be/1YoD0fg3_EM))
- SmartBridge Applied Data Science Course Resources
- Mentors and other fellow course members

## APPENDIX

### ● Analysis Model Source Code:



The screenshot shows two Jupyter Notebook cells. Cell [1] displays code for loading the dataset and reading the dataset. Cell [2] displays the resulting DataFrame.

```

[1]: 
#Importing libraries
import numpy as np #NumPy is a general-purpose array-processing package.
import pandas as pd #It contains high-level data structures and manipulation tools designed to make data analysis fast and easy.
import matplotlib.pyplot as plt #It is a Plotting Library
import seaborn as sns #Seaborn is a Python data visualization library based on matplotlib.
from sklearn.linear_model import LogisticRegression #Logistic Regression is a Machine Learning classification algorithm
from sklearn.linear_model import LinearRegression #Linear Regression is a Machine Learning classification algorithm
from sklearn.model_selection import train_test_split #Splitting of Dataset
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import r2_score

[2]: 
#reading the dataset
zomato_orgnlpd.read_csv("../input/zomato.csv")
zomato_orgnlpd.head() #This function returns the first n rows for the object based on position.

```

Cell [2] output:

	url	address	name	online_order	book_table	rate	votes	phone	location	rest_type	dish_liked
0	https://www.zomato.com/bangalore/jalsa-banash...	942, 21st Main Road, 2nd Stage, Banashankari	Jalsa	Yes	Yes	4.1/5	775	080 974372233	Banashankari	Casual Dining	Pasta, Lunch Buffet, Masala Papad, Paneer

Cell 1 of 65    Go Live    ⚙️

**Linear Regression**

```

[1]: 
#Prepare a Linear Regression Model
reg=LinearRegression()
reg.fit(x_train,y_train)
y_pred=reg.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_pred)

[2]: 
0.2736233722103858

```

**Decision Tree Regression**

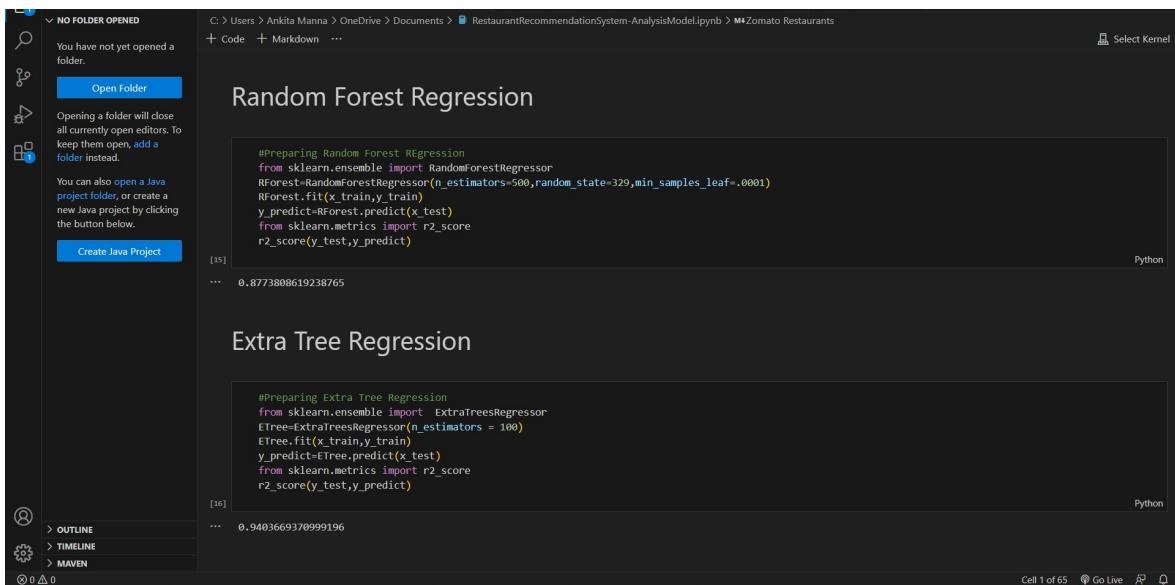
```

[1]: 
#Preparing a Decision Tree Regression
from sklearn.tree import DecisionTreeRegressor
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.1,random_state=105)
DTree=DecisionTreeRegressor(min_samples_leaf=.0001)
DTree.fit(x_train,y_train)
y_predict=DTree.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_predict)

[2]: 
0.8533028584280067

```

Cell 1 of 65    Go Live    ⚙️



**Random Forest Regression**

```
#Preparing Random Forest Regression
from sklearn.ensemble import RandomForestRegressor
RForest=RandomForestRegressor(n_estimators=500,random_state=329,min_samples_leaf=.0001)
RForest.fit(x_train,y_train)
y_predict=RForest.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_predict)
```

[15] ... 0.8773808619238765

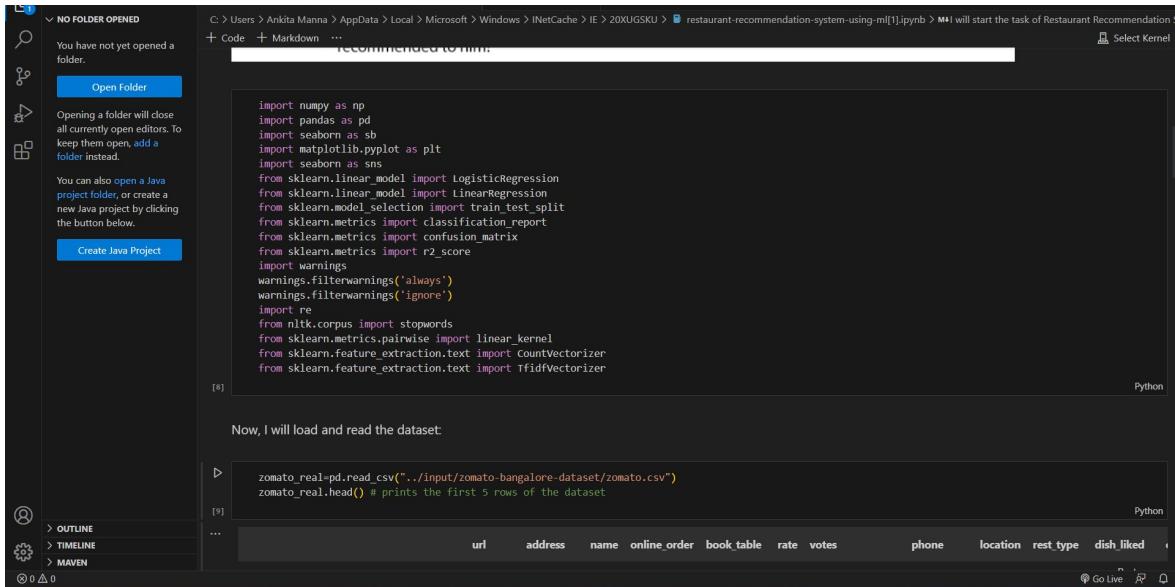
**Extra Tree Regression**

```
#Preparing Extra Tree Regression
from sklearn.ensemble import ExtraTreesRegressor
ETree=ExtraTreesRegressor(n_estimators = 100)
ETree.fit(x_train,y_train)
y_predict=ETree.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_predict)
```

[16] ... 0.9403669370999196

Cell 1 of 65 ⏪ Go Live ⏴

## ● Prediction Model Source Code:



**RECOMMENDED TO HIM:**

```
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import r2_score
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')
import re
from nltk.corpus import stopwords
from sklearn.metrics.pairwise import linear_kernel
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

[8] ...

Now, I will load and read the dataset:

```
zomato_real=pd.read_csv("../input/zomato-bangalore-dataset/zomato.csv")
zomato_real.head() # prints the first 5 rows of the dataset
```

[9] ...

url	address	name	online_order	book_table	rate	votes	phone	location	rest_type	dish_liked
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Cell 1 of 1 ⏪ Go Live ⏴

# Restaurant Recommendation System

**NO FOLDER OPENED**

You have not yet opened a folder.

**Open Folder**

Opening a folder will close all currently open editors. To keep them open, add a folder instead.

You can also open a Java project folder, or create a new Java project by clicking the button below.

**Create Java Project**

C:\> Users > Ankita Manna > AppData > Local > Microsoft > Windows > INetCache > IE > 20XUGSKU > restaurant-recommendation-system-using-ml[1].ipynb > **M+1** will start the task of Restaurant Recommendation S

+ Code + Markdown ...

```
zomato=zomato.drop(['address','rest_type', 'type', 'menu_item', 'votes'],axis=1)
import pandas

# Randomly sample 60% of your dataframe
df_percent = zomato.sample(frac=0.5)
```

[12]

Select Kernel Python

## TF-IDF Vectorization

TF-IDF (Term Frequency-Inverse Document Frequency) vectors for each document. This will give you a matrix where each column represents a word in the general vocabulary (all words that appear in at least one document) and each column represents a restaurant, as before.

TF-IDF is the statistical method of assessing the meaning of a word in a given document. Now, I will use the TF-IDF vectorization on the dataset:

```
df_percent.set_index('name', inplace=True)
indices = pd.Series(df_percent.index)

# Creating tf-idf matrix
tfidf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0, stop_words='english')
tfidf_matrix = tfidf.fit_transform(df_percent['reviews_list'])

cosine_similarities = linear_kernel(tfidf_matrix, tfidf_matrix)
```

[13]

Select Kernel Python

Now the last step for creating a Restaurant Recommendation System is to write a function that will recommend restaurants:

```
def recommend(name, cosine_similarities = cosine_similarities):
    # Create a list to put top restaurants
    recommend_restaurant = []

    # Find the index of the hotel entered
    idx = indices[indices == name].index[0]

    # Find the restaurants with a similar cosine-sim value and order them from biggest number
    score_series = pd.Series(cosine_similarities[idx]).sort_values(ascending=False)

    # Extract top 30 restaurant indexes with a similar cosine-sim value
    top30_indexes = list(score_series.iloc[0:30].index)

    # Names of the top 30 restaurants
    for each in top30_indexes:
        recommend_restaurant.append(list(df_percent.index)[each])

    # Creating the new data set to show similar restaurants
    df_new = pd.DataFrame(columns=['cuisines', 'Mean Rating', 'cost'])

    # Create the top 30 similar restaurants with some of their columns
    for each in recommend_restaurant:
        df_new = df_new.append(pd.DataFrame([df_percent[['cuisines', 'Mean Rating', 'cost']][df_percent.index == each].sample()]))
```

[14]

Select Kernel Python