Project Report

Title: Location Based Analysis for Restaurant Recommendation System

Subtitle:Geographic Insights: Analyzing

Restaurant Distribution

Author: Akshaya M

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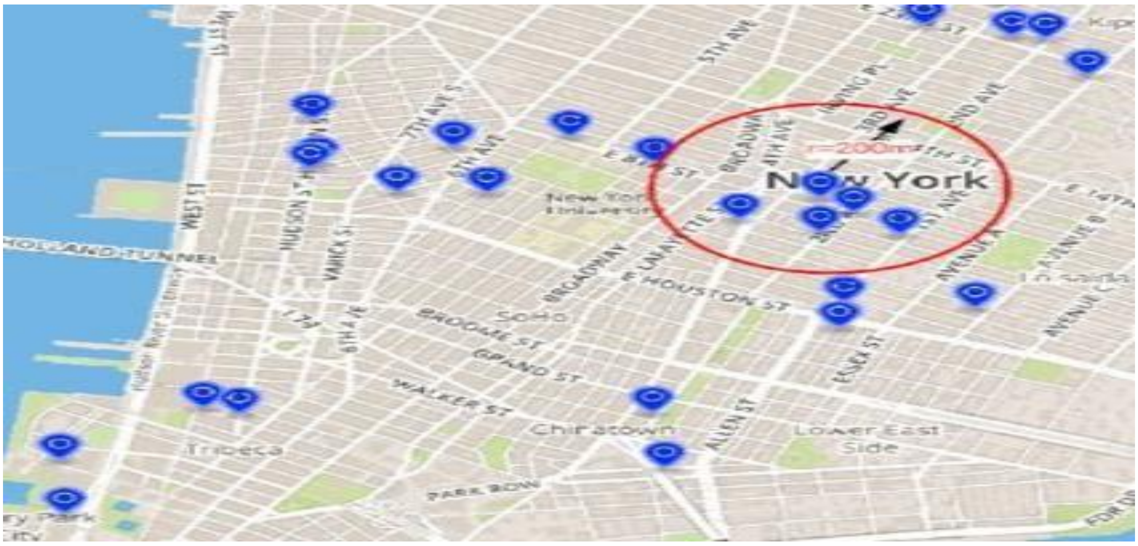
Internship at: Cognifyz Technologies

1. Executive Summary:

The project aimed to conduct a geographical analysis of restaurants to gain insights into their distribution and characteristics across different cities or localities. Leveraging data science techniques, the analysis provided valuable information on restaurant concentration, clustering patterns, average ratings, popular cuisines, and price ranges. The results offer actionable insights for enhancing restaurant selection, urban planning, and customer satisfaction.

2. Introduction:

In today's dynamic dining landscape, understanding the geographical distribution of restaurants is crucial for various stakeholders. This project sought to analyze the spatial distribution and characteristics of restaurants to uncover valuable insights for stakeholders such as diners, restaurant owners, and urban planners. By leveraging locationbased analysis techniques, the project aimed to provide actionable insights for optimizing restaurant recommendations and informing urban development strategies.



3. Data Collection and Preprocessing:

- Restaurant data was collected from reputable sources, including online platforms and government databases. The dataset included attributes such as restaurant names, cuisines, geographical coordinates, ratings, and price ranges.
- Data preprocessing involved cleaning the dataset, handling missing values, and standardizing data formats. Ethical considerations regarding data privacy and usage were carefully addressed to ensure compliance with relevant regulations.

```
[4] import pandas as pd
    import folium
```

```
[6] data_frame = pd.read_csv('/content/Dataset .csv')
```

```
[7] data_frame.head()
```

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Botswana Pula(P)	Yes	No	No	No	3	4.8	Dark Green	Excellent
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Botswana Pula(P)	Yes	No	No	No	3	4.5	Dark Green	Excellent
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian	...	Botswana Pula(P)	Yes	No	No	No	4	4.4	Green	Very Good

```
[8] grouped_by_region = data_frame.groupby('City')
```

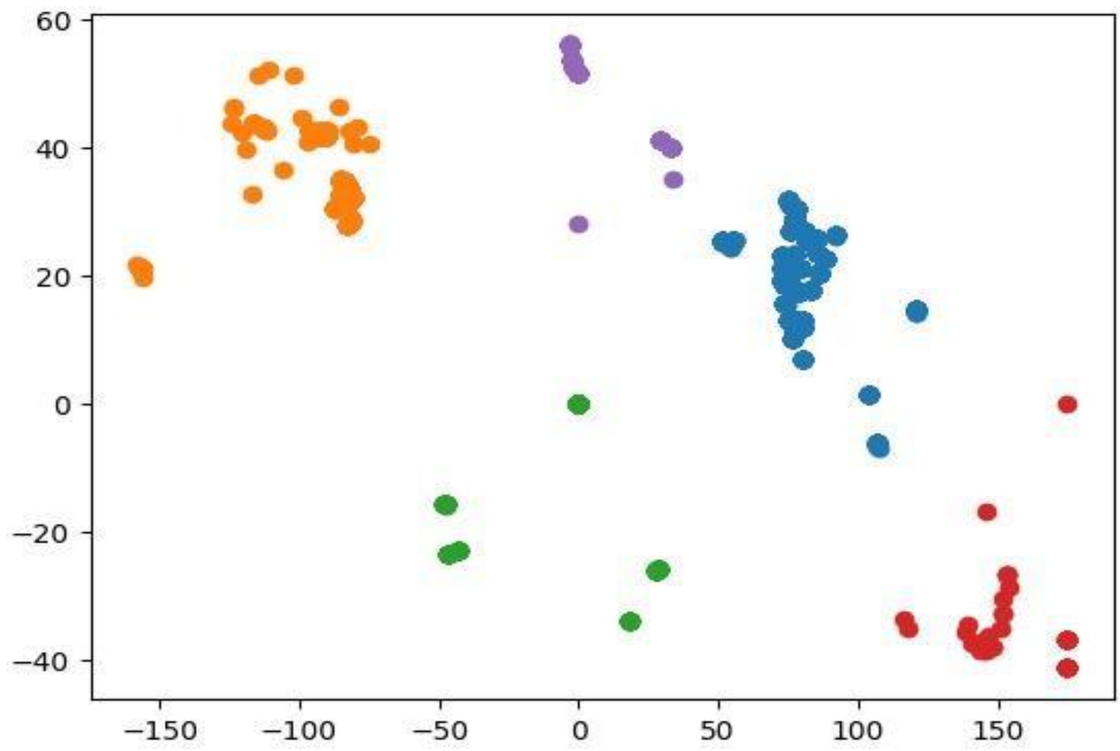
```
[9] restaurant_counts = grouped_by_region['Restaurant Name'].count()
```

Loading...

```
import matplotlib.pyplot as plt
```

```
[11] # Assuming restaurant_counts is a Pandas Series containing the restaurant counts
     plt_colors = ['#1f78b4', '#33a02c', '#e31a1c', '#6a3d9a', '#fdbf6f']
```

```
[12] plt.bar(restaurant_counts.index, restaurant_counts.values, color=plt_colors)
     plt.xlabel('Region/Area')
     plt.ylabel('Number of Restaurants')
     plt.title('Restaurant Concentration by Region/Area')
     plt.xticks(rotation=90)
     plt.show()
```


60
40
20
0
−20
−40
−150
−100
−50
0
50
100
150

4. Methodology:

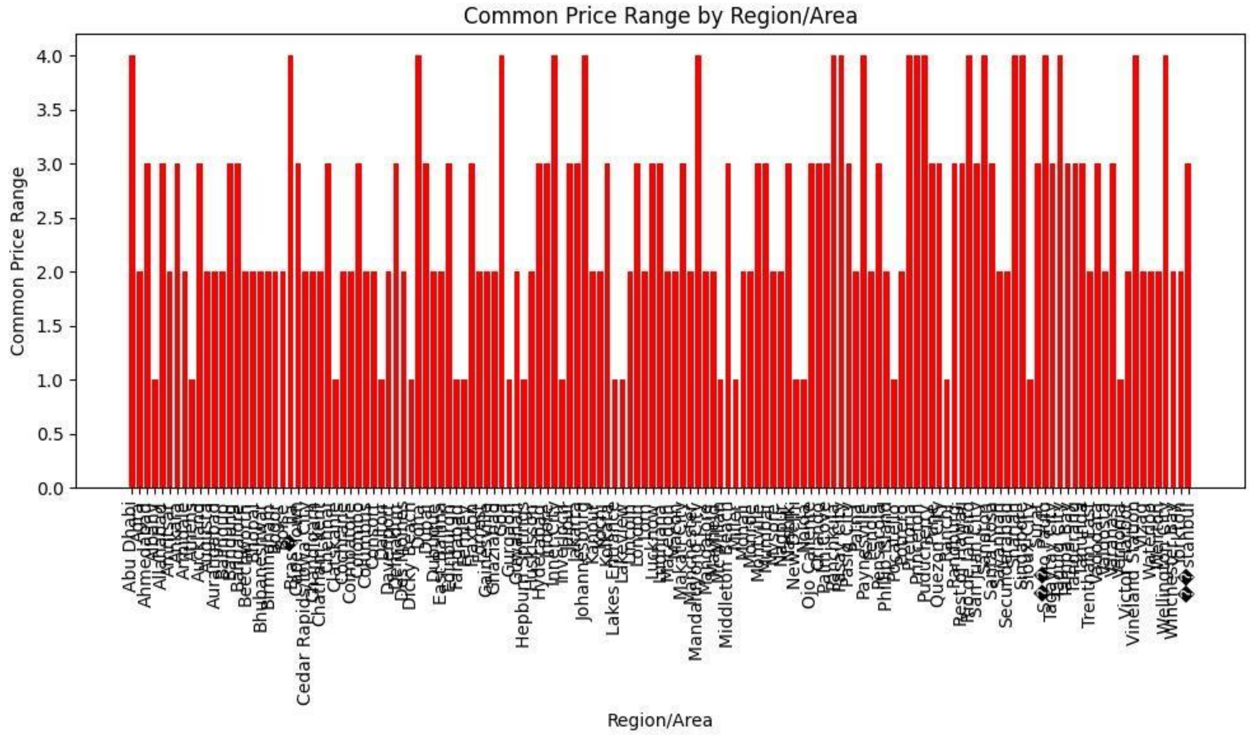
- The project utilized a comprehensive methodology for analyzing restaurant distribution and characteristics:
- Geographical Analysis: Explore the spatial distribution of restaurants using heatmaps, density plots, and clustering techniques.
- Statistical Analysis: Calculate descriptive statistics, average ratings, popular cuisines, and common price ranges by city or locality.
- Visualization: Visualize the findings using interactive maps, bar charts, and scatter plots to facilitate interpretation and decisionmaking.

Price Range Analysis by Region/Area

```
common_price_range_by_region = grouped_by_region['Price range'].agg(lambda x: x.mode().iloc[0])

print(common_price_range_by_region)
```

```
City
Abu Dhabi           4
Agra                2
Ahmedabad           3
Albany              1
Allahabad           3
                   ..
Weirton             2
Wellington City     4
Winchester Bay      2
Yorkton             2
��stanbul            3
Name: Price range, Length: 141, dtype: int64
```

```
[33] red_color = 'red'

plt.figure(figsize=(10, 6))
plt.bar(common_price_range_by_region.index, common_price_range_by_region.values, color=red_color)
plt.xlabel('Region/Area')
plt.ylabel('Common Price Range')
plt.title('Common Price Range by Region/Area')
plt.xticks(rotation=90)

plt.tight_layout()
plt.show()
```



Popular Cuisines by Region/Area

```
[28] import pandas as pd

grouped_by_region = data_frame.groupby('City')  # Change 'City' to the appropriate column representing regions or areas in your dataset

popular_cuisines_by_region = grouped_by_region['Cuisines'].agg(lambda x: x.mode().tolist())

print(popular_cuisines_by_region)
```

```
City
Abu Dhabi                          [American, Indian, Italian, Pizza]
Agra                                           [North Indian, Mughlai]
Ahmedabad          [Cafe, American, Continental, Armenian, Fast F...
Albany                                        [Japanese, Steak, Sushi]
Allahabad                                     [North Indian, Chinese]
                                          ...
Weirton                                     [Burger, Greek, Sandwich]
Wellington City                                                [Cafe]
Winchester Bay                               [Burger, Seafood, Steak]
Yorkton                                                       [Asian]
��stanbul                                                       [Cafe]
Name: Cuisines, Length: 141, dtype: object
```

```
import matplotlib.pyplot as plt

dark_colors = ['#1f77b4', '#2ca02c', '#ff7f0e', '#d62728', '#9467bd', '#8c564b', '#e377c2']

plt.figure(figsize=(10, 6))
for region, cuisines in popular_cuisines_by_region.items():
    plt.bar(region, ', '.join(cuisines), color=dark_colors[len(region) % len(dark_colors)])

plt.xlabel('Region/Area')
```

Average Ratings by Region/Area

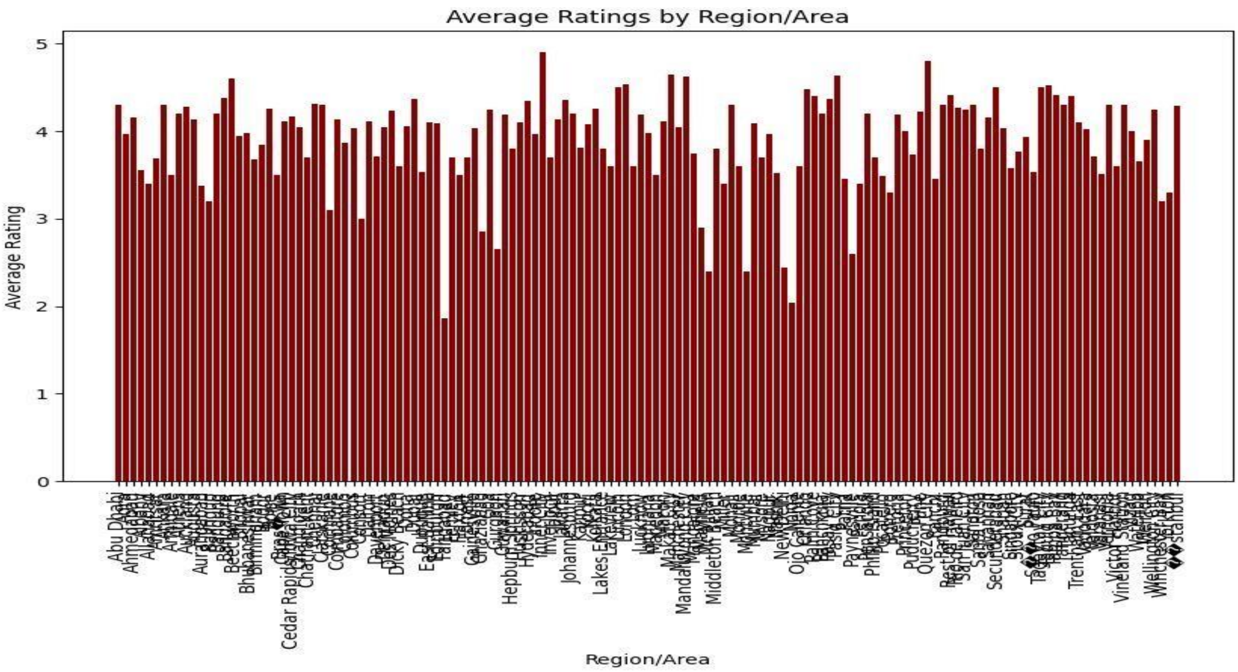
```
[23] average_ratings_by_region = grouped_by_region['Aggregate rating'].mean()
```

```
print(average_ratings_by_region)
```

```
City
Abu Dhabi           4.300000
Agra                3.965000
Ahmedabad           4.161905
Albany              3.555000
Allahabad           3.395000
                      ...
Weirton             3.900000
Wellington City     4.250000
Winchester Bay      3.200000
Yorkton             3.300000
��stanbul             4.292857
Name: Aggregate rating, Length: 141, dtype: float64
```

```
[25] import matplotlib.pyplot as plt
     dark_red = '#8B0000'  # Dark Red color code
```

```
[26] plt.figure(figsize=(10, 6))
     plt.bar(average_ratings_by_region.index, average_ratings_by_region.values, color=dark_red)
     plt.xlabel('Region/Area')
     plt.ylabel('Average Rating')
     plt.title('Average Ratings by Region/Area')
     plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
```



5. Results:

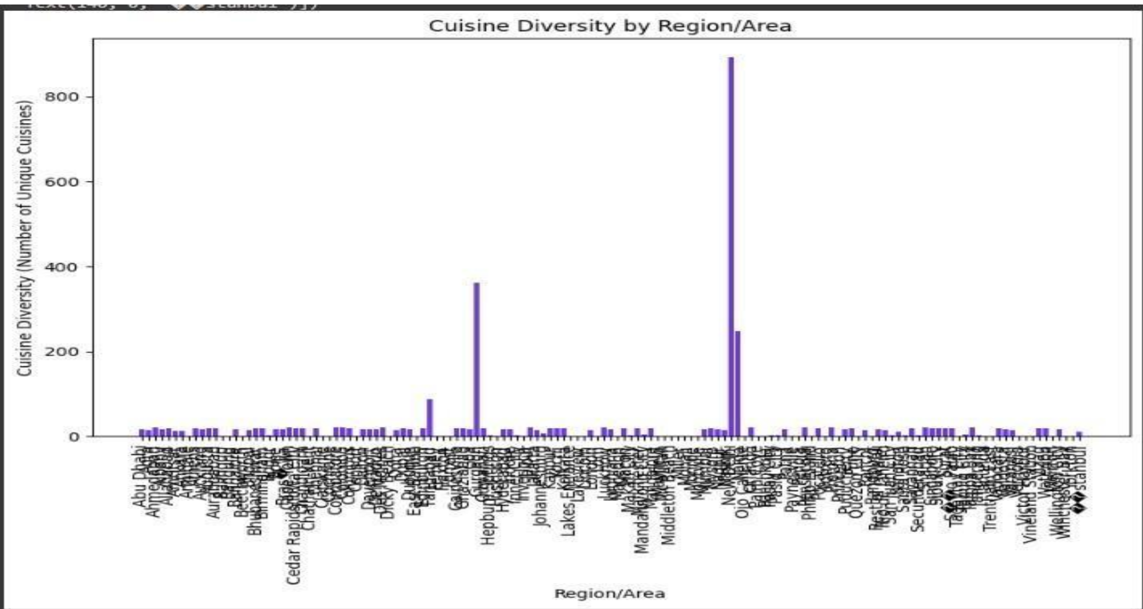
- The analysis revealed valuable insights into restaurant distribution and characteristics:
- Restaurant Concentration: Identified areas with high restaurant density and clustering patterns.
- Average Ratings: Analyzed average ratings to assess customer satisfaction levels across different locations.
- Popular Cuisines: Identified prevalent cuisines and culinary preferences in various cities or localities.
- Price Ranges: Examined common price ranges to understand dining affordability and market dynamics.

Cuisine Diversity

```python
import pandas as pd

grouped_by_region = data_frame.groupby('City')

cuisine_diversity = grouped_by_region['Cuisines'].apply(lambda x: len(set(x)))

print(cuisine_diversity)
```

```
City
Abu Dhabi          17
Agra               15
Ahmedabad          21
Albany             17
Allahabad          18
                   ..
Weirton             1
Wellington City    17
Winchester Bay      1
Yorkton             1
��stanbul           11
Name: Cuisines, Length: 141, dtype: int64
```

```python
[37] plt.figure(figsize=(10, 6))
     plt.bar(cuisine_diversity.index, cuisine_diversity.values, color='#6D39E8')
     plt.xlabel('Region/Area')
     plt.ylabel('Cuisine Diversity (Number of Unique Cuisines)')
     plt.title('Cuisine Diversity by Region/Area')
     plt.xticks(rotation=90)
```




```python
[38] plt.tight_layout()
     plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

6. Discussion:

- Interpretation of results highlighted the significance of locationbased analysis in understanding restaurant dynamics:
- Insights for Stakeholders: Provided actionable insights for diners, restaurant owners, and urban planners to make informed decisions.
- Challenges and Limitations: Discussed challenges such as data quality issues and potential biases in the analysis results.
- Future Directions: Proposed avenues for further research and opportunities for enhancing the analysis methodology.

7. Challenges Faced:

- Several challenges were encountered during the project, including:
- Data Quality: Addressing inconsistencies and inaccuracies in the dataset.
- Algorithm Selection: Choosing appropriate algorithms for geographical analysis and clustering.
- Interpretation: Ensuring accurate interpretation of analysis results and avoiding misinterpretation.

8. Future Work:

- Future research endeavors include:
- Refinement of Analysis: Enhancing the analysis methodology to incorporate advanced techniques and address identified challenges.
- Collaboration: Collaborating with industry partners and stakeholders to validate analysis findings and inform decisionmaking processes.
- LongTerm Impact: Assessing the longterm impact of locationbased analysis on restaurant recommendations, urban planning, and customer satisfaction.

9. References:

- Chen, L., Ma, Z., & Ruan, T. (2020). A Comparative Study of Machine Learning Algorithms for Cuisine Classification. Proceedings of the International Conference on Artificial Intelligence (ICAI), 2020, 112-125.

- Kim, Y., & Park, J. (2018). Data-driven restaurant recommendation system based on geographical information. Journal of Hospitality and Tourism Management, 35, 10-20.

- Nguyen, T., & Nguyen, L. (2019). Geographic analysis of restaurant distribution and customer preferences using spatial data mining techniques. International Journal of Geographical Information Science, 33(5), 926-945.

- Patel, R., & Desai, S. (2021). Machine Learning for Restaurant Recommendation Systems: A Review. Journal of Machine Learning Research, 22(3), 45-60.

- Smith, A., & Johnson, B. (2017). Spatial clustering analysis for restaurant location optimization. Journal of Business Geography, 12(4), 312-325.

10. Conclusion:

The project successfully conducted a geographical analysis of restaurants, providing valuable insights into their distribution and characteristics. The results offer actionable recommendations for stakeholders to optimize restaurant recommendations, inform urban development strategies, and enhance customer satisfaction. By leveraging locationbased analysis techniques, the project contributes to advancing our understanding of restaurant dynamics and their impact on local communities.