

IBM - Data Science - Project

Applied Data Science Capstone - Battle of Neighborhoods

Finding Restaurants in Lagos, Nigeria

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Source: www.pulse.ng

1. Introduction / Business Problem

Exploring restaurants is important for tourists/visitors, as many travelers consider where to eat and what to eat when planning a trip. Lagos is a globally recognized technology hub and the entertainment heartbeat of West Africa. The biggest names in Afrobeat are mostly Lagosians, and the food scene here pulsates with equal force. In this city, a majority of the visitors are often left with the widest choices of venues and restaurants to explore, which is very difficult, especially for people visiting Lagos for the first time. Most people often look for the best restaurants by making comparisons. Although different people emphasize different categories of restaurants, the question is: in which areas of Lagos can we find these restaurants? This project aims to answer

this question using data science concepts learned in the IBM Data Science Professional Certificate Course: <https://www.coursera.org/professional-certificates/ibm-data-science>.



Source: [www. google.com](http://www.google.com)

This project **targets** visitors/tourists in Lagos, Nigeria. Information from the analysis done in this project will serve as a guide for **tourists** in finding preferable restaurants in the neighborhoods. This project can also be used by **entrepreneurs** and investors who plan to engage in restaurants business in the city of Lagos. The methods we will use in the analysis can be employed to explore other cities or countries in solving related real-world problems.

2. Datasets and Methods

Datasets from various sources were retrieved to carry out analysis in this project. Here, we will describe the datasets used as well as the tools and methods utilized to retrieve the datasets.

2.1 Lagos state data from Wikipedia

Lagos state data from Wikipedia: https://en.wikipedia.org/wiki/Lagos_State, was obtained to explore the neighborhoods information. The dataset contains the Local Government Areas (LGAs) which cover the cities and towns in the state. Other information such as the area, population,

administrative capital, and postal codes are also available in the file. The data was scraped from the HTML table in the webpage into a Pandas DataFrame as shown below:

| | LGA name | Area (km2) | Census 2006 population | Administrative capital | Postalcode |
|----|-----------------|-------------------|-------------------------------|-------------------------------|-------------------|
| 0 | Agege | 11 | 459939 | Agege | 100.0 |
| 1 | Alimosho | 185 | 1277714 | Ikotun | 100.0 |
| 2 | Ifako-Ijaye | 27 | 427878 | Ifako | 100.0 |
| 3 | Ikeja | 46 | 313196 | Ikeja | 100.0 |
| 4 | Kosofe | 81 | 665393 | Kosofe | 100.0 |
| 5 | Mushin | 17 | 633009 | Mushin | 100.0 |
| 6 | Oshodi-Isolo | 45 | 621509 | Oshodi/Isolo | 100.0 |
| 7 | Shomolu | 12 | 402673 | Shomolu | 101.0 |
| 8 | Ikeja Division | 424 | 4801311 | NaN | NaN |
| 9 | Apapa | 27 | 217362 | Apapa | 101.0 |
| 10 | Eti-Osa | 192 | 287785 | Ikoyi | 101.0 |

Data cleaning was performed on the file by dropping the rows with NaN values, renaming columns, and changing the format of the postal code from float to integer. The result can be observed in the following DataFrame.

2.2 Geospatial data using geocoder

The geocoder was enabled to get geospatial information of the areas. The nominatim function in geocoder package was utilized to fetch the geographical coordinates (i.e. latitude and longitude) of the areas and added in the DataFrame as follows:

| | LGA | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude |
|---|-------------|-------------------|-------------------|-------------------------------|-------------------|-----------------|------------------|
| 0 | Agege | 11 | 459939 | Agege | 100 | 6.625256 | 3.311209 |
| 1 | Alimosho | 185 | 1277714 | Ikotun | 100 | 6.584343 | 3.257631 |
| 2 | Ifako-Ijaye | 27 | 427878 | Ifako | 100 | 6.660436 | 3.321539 |
| 3 | Ikeja | 46 | 313196 | Ikeja | 100 | 6.604859 | 3.353204 |
| 4 | Kosofe | 81 | 665393 | Kosofe | 100 | 6.581974 | 3.414836 |

2.3 Venue data using Foursquare API

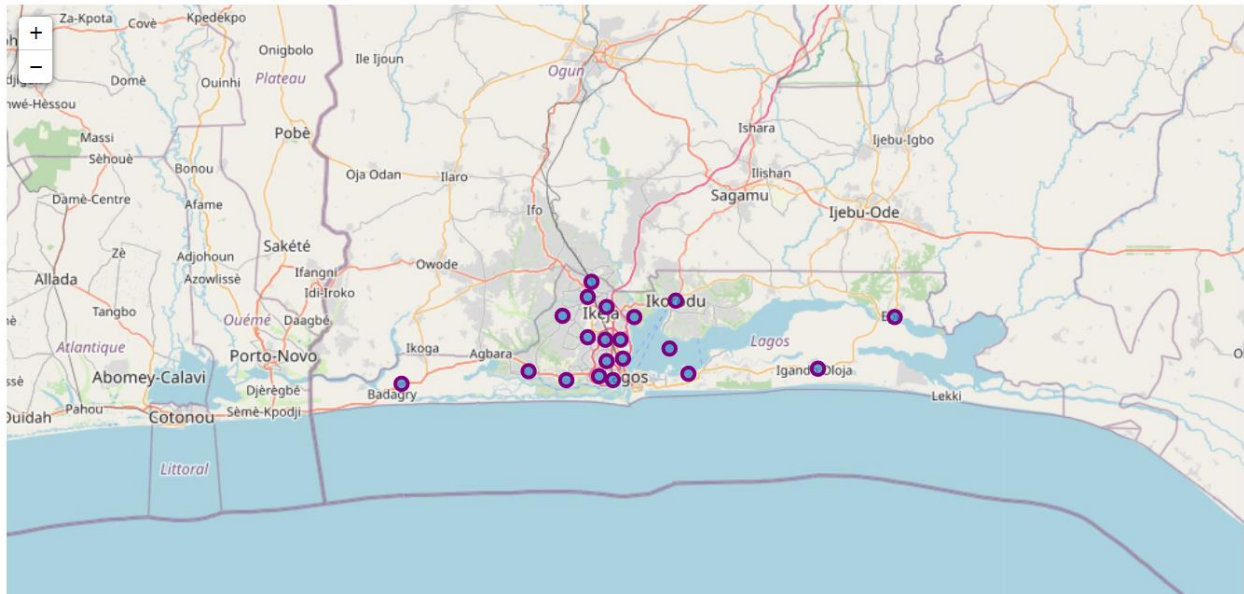
Foursquare API was employed to obtain data for all venues on foursquare within 5000 meters radius from each LGA. The venue data was merged in the DataFrame below:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|--------------|-----------------------|------------------------|----------------------|----------------|-----------------|----------------------|
| 0 | Agege | 6.625256 | 3.311209 | KFC | 6.620788 | 3.317968 | Fast Food Restaurant |
| 1 | Agege | 6.625256 | 3.311209 | Shoprite Ikeja | 6.614340 | 3.331319 | Shopping Mall |
| 2 | Agege | 6.625256 | 3.311209 | Tastee Fried Chicken | 6.631432 | 3.339814 | Fast Food Restaurant |
| 3 | Agege | 6.625256 | 3.311209 | NYSC Camp (Lagos) | 6.624946 | 3.302899 | Campground |
| 4 | Agege | 6.625256 | 3.311209 | KFC | 6.604590 | 3.308936 | Fast Food Restaurant |

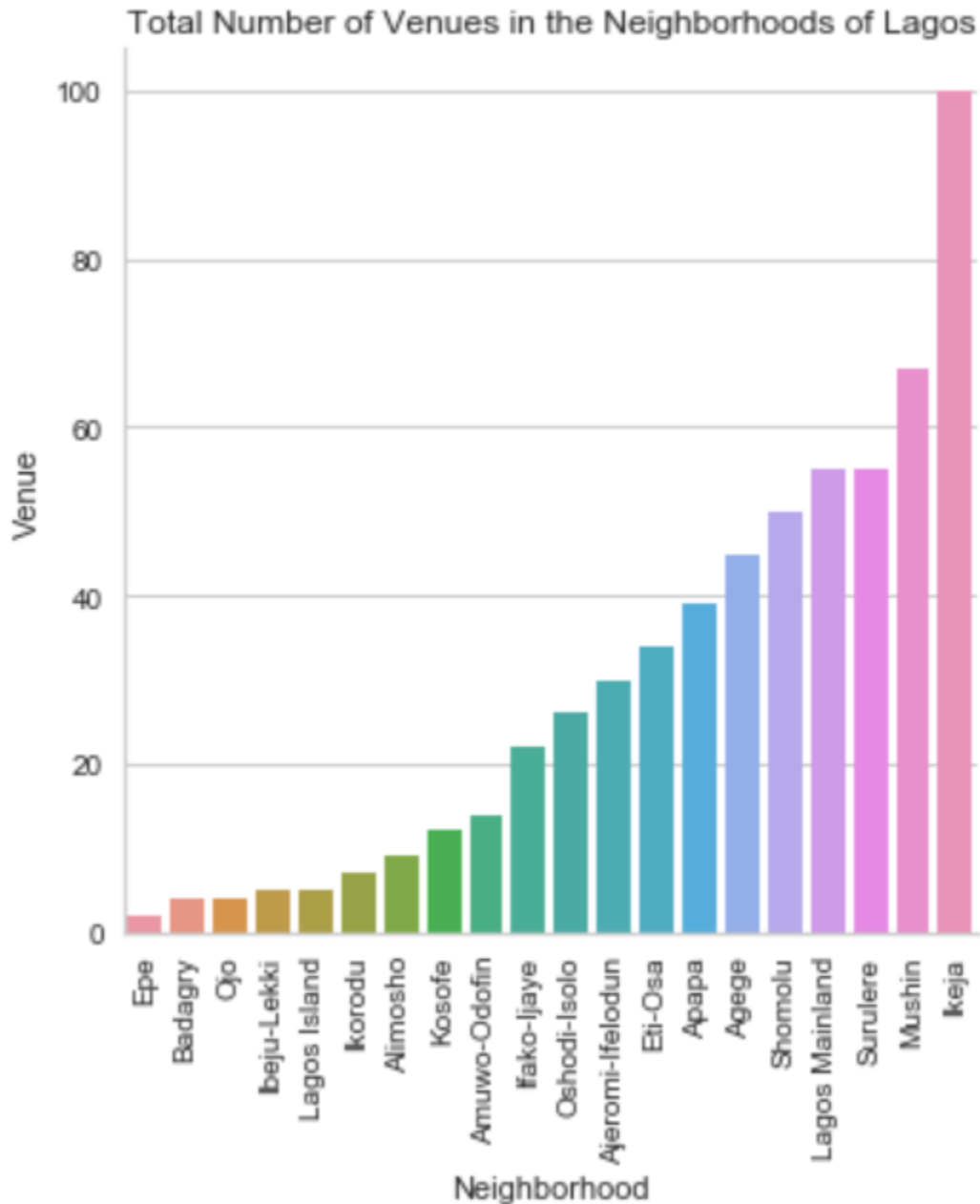
3. Results

3.1 Neighborhood exploration and analysis

First, Folium package was enabled to create a map displaying the distribution of the 20 LGAs.



Then, we processed the venues information (such as restaurants, convenient stores, campgrounds, shopping malls, etc.) returned by Foursquare API. A bar chart was created using Seaborn and Matplotlib packages to view the information.

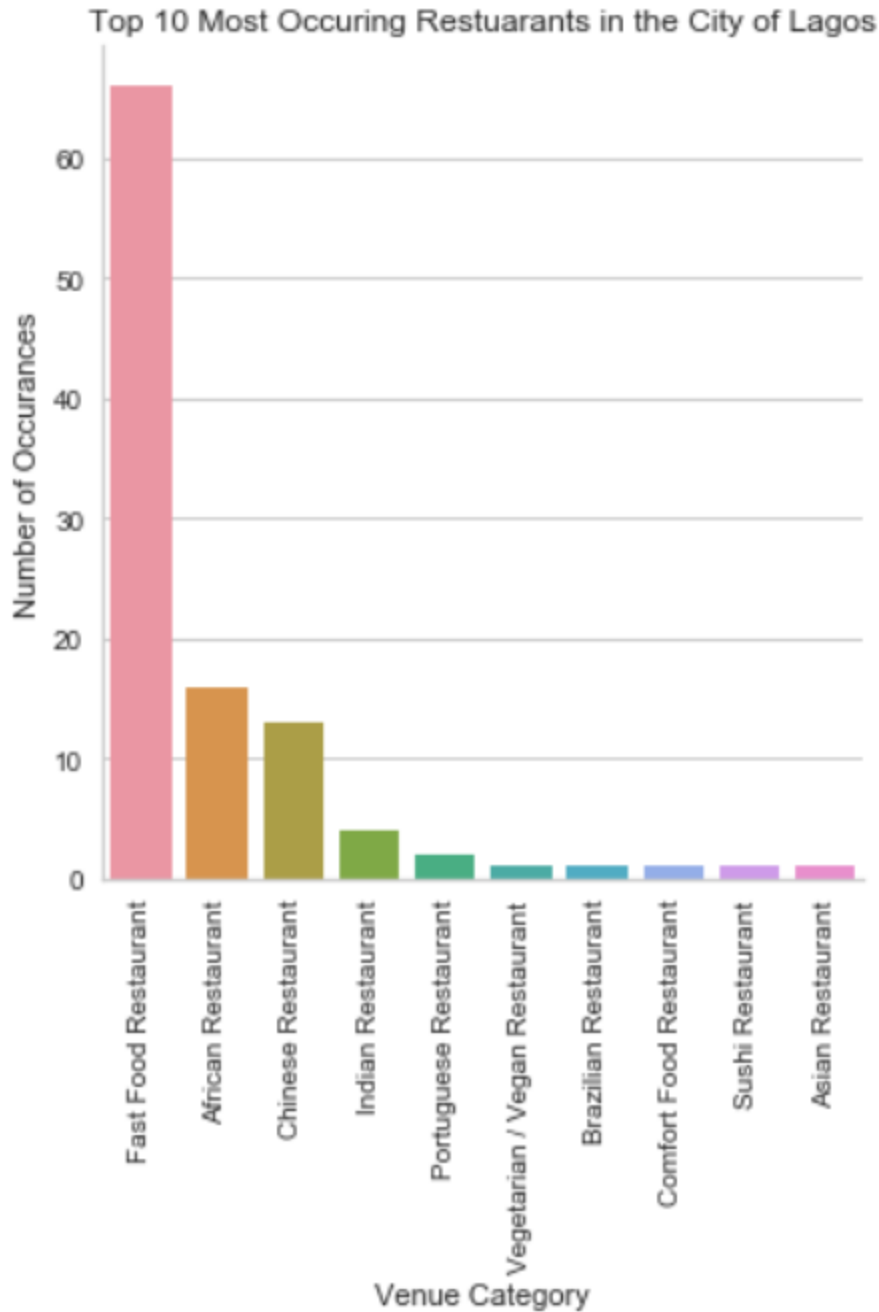


The bar chart above shows a dominating number of 100 venues returned for Ikeja and over 60 venues for Mushin. Surulere, Lagos Mainland, Shomolu and Agege have between 40 and 60 venues returned. Apapa, Eti-Osa, Ajeromi-Ifelodun, Oshodi-Isolo, and Ifako-Ijaye have between 20 and 40 venues. Meanwhile, from Amowo-Odofin to Epe, the venues returned in our given coordinates and radius are less than 20 in number.

To find the venue categories present in various LGAs neighborhoods, one hot encoding method was applied. This method transformed the categorical data into numerical data. The frequency of occurrences of individual venues was measured and returned for each neighborhood. The resultant venues were analyzed in descending order to show the most common venues. This is a preliminary analysis carried out to explore the availability of our venue category target in the neighborhoods, which is the **Restaurant**.

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | 9th Most Common Venue | 10th Most Common Venue |
|---|------------------|-----------------------|-----------------------|-------------------------------|-----------------------|-------------------------------|-----------------------|-----------------------|-----------------------|-------------------------------|-------------------------|
| 0 | Agege | Fast Food Restaurant | Bus Station | Hotel | Convenience Store | Boutique | Chinese Restaurant | Helipoint | Department Store | Electronics Store | Ice Cream Shop |
| 1 | Ajeromi-Ifelodun | Shopping Mall | Fast Food Restaurant | Chinese Restaurant | Pizza Place | Flea Market | Bakery | Multiplex | Clothing Store | Jewelry Store | Indian Restaurant |
| 2 | Alimosho | Fast Food Restaurant | Basketball Court | Park | Market | Hotel | Shopping Mall | Pizza Place | Bar | Vegetarian / Vegan Restaurant | Café |
| 3 | Amuwo-Odofin | Hotel | African Restaurant | Park | Beach | Bakery | Boat or Ferry | Shopping Mall | Pool | Mobile Phone Shop | Fast Food Restaurant |
| 4 | Apapa | Hotel | Shopping Mall | Fast Food Restaurant | Market | Lounge | Pizza Place | Indian Restaurant | Harbor / Marina | Chinese Restaurant | Gym / Fitness Center |
| 5 | Badagry | Museum | History Museum | Fast Food Restaurant | Beer Garden | Vegetarian / Vegan Restaurant | Department Store | Campground | Chinese Restaurant | Clothing Store | Coffee Shop |
| 6 | Epe | Hotel | Resort | Vegetarian / Vegan Restaurant | Diner | Café | Campground | Chinese Restaurant | Clothing Store | Coffee Shop | Comfort Food Restaurant |
| 7 | Eti-Osa | Hotel | Shopping Mall | Pizza Place | Lounge | Vegetarian / Vegan Restaurant | Flea Market | Ice Cream Shop | Hotel Pool | Gym | Gas Station |
| 8 | Ibeju-Lekki | Farm | Business Service | Beach | River | Department Store | Café | Campground | Chinese Restaurant | Clothing Store | Coffee Shop |
| 9 | Ifako-Ijaye | Fast Food Restaurant | Convenience Store | Grocery Store | Bar | Farmers Market | Hotel | Ice Cream Shop | Light Rail Station | Chinese Restaurant | Campground |

As expected, among the venue categories returned, a vast number of restaurants appeared among the most commonly occurring venue in Lagos. The information returned was applied to create a data frame that shows the most common restaurant categories for each LGA. We sorted the venues in descending order to create the top 10 most common restaurants. We used a bar chart to display the result.



The result above shows that the Fast Food Restaurant is the most frequently occurring restaurant category in Lagos, which seems pretty reasonable, as Lagos has a relatively high proportion of Fast Food restaurants. Using this data, one hot encoding is employed, this time, to obtain the frequency of occurrences of restaurants for each neighborhood.

| | Neighborhood | African Restaurant | Asian Restaurant | Brazilian Restaurant | Chinese Restaurant | Comfort Food Restaurant | European Restaurant | Fast Food Restaurant | Indian Restaurant | Portuguese Restaurant | Sushi Restaurant | Vegetarian / Vegan Restaurant |
|---|--------------|--------------------|------------------|----------------------|--------------------|-------------------------|---------------------|----------------------|-------------------|-----------------------|------------------|-------------------------------|
| 1 | Agege | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 2 | Agege | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 3 | Agege | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 4 | Agege | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 5 | Agege | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

We grouped the data by restaurants and by taking the mean frequency of occurrences of each category. This can be seen in the following DataFrame.

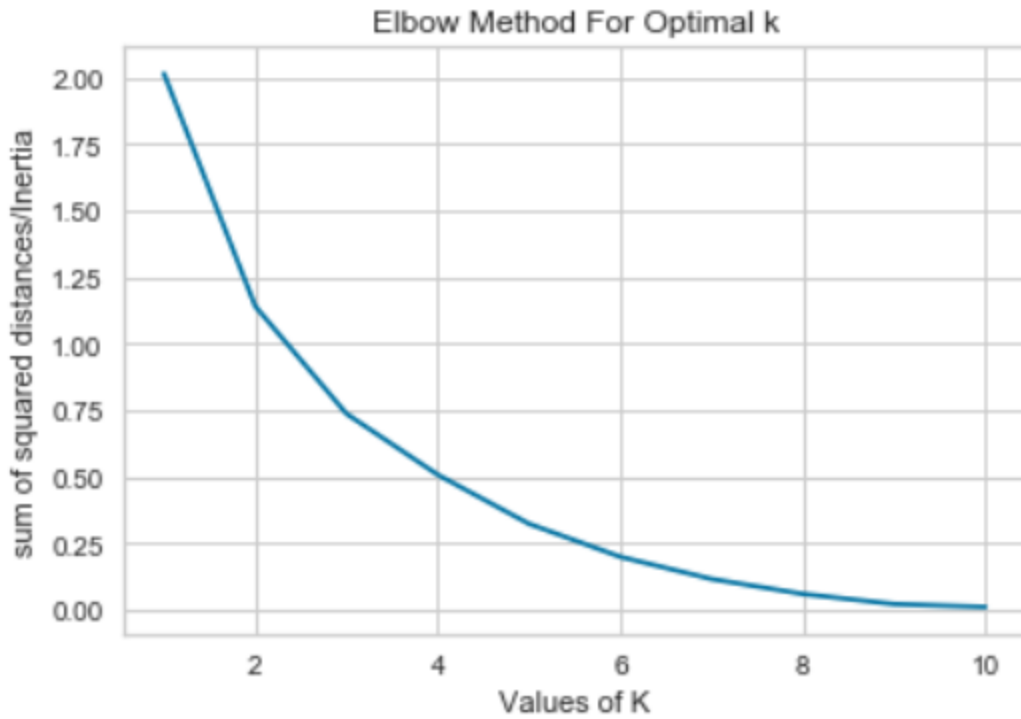
| | Neighborhood | African Restaurant | Asian Restaurant | Brazilian Restaurant | Chinese Restaurant | Comfort Food Restaurant | European Restaurant | Fast Food Restaurant | Indian Restaurant | Portuguese Restaurant | Sushi Restaurant | Vegetarian / Vegan Restaurant |
|---|------------------|--------------------|------------------|----------------------|--------------------|-------------------------|---------------------|----------------------|-------------------|-----------------------|------------------|-------------------------------|
| 0 | Agege | 0.000000 | 0.0 | 0.0 | 0.222222 | 0.0 | 0.0 | 0.777778 | 0.000000 | 0.0 | 0.0 | 0.0 |
| 1 | Ajeromi-Ifelodun | 0.000000 | 0.0 | 0.0 | 0.333333 | 0.0 | 0.0 | 0.500000 | 0.166667 | 0.0 | 0.0 | 0.0 |
| 2 | Alimosho | 0.000000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 1.000000 | 0.000000 | 0.0 | 0.0 | 0.0 |
| 3 | Amuwo-Odofin | 0.500000 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | 0.500000 | 0.000000 | 0.0 | 0.0 | 0.0 |
| 4 | Apapa | 0.142857 | 0.0 | 0.0 | 0.142857 | 0.0 | 0.0 | 0.428571 | 0.285714 | 0.0 | 0.0 | 0.0 |

Next, we sorted the resultant venues in descending order and added them to the data frame to show the most common venues.

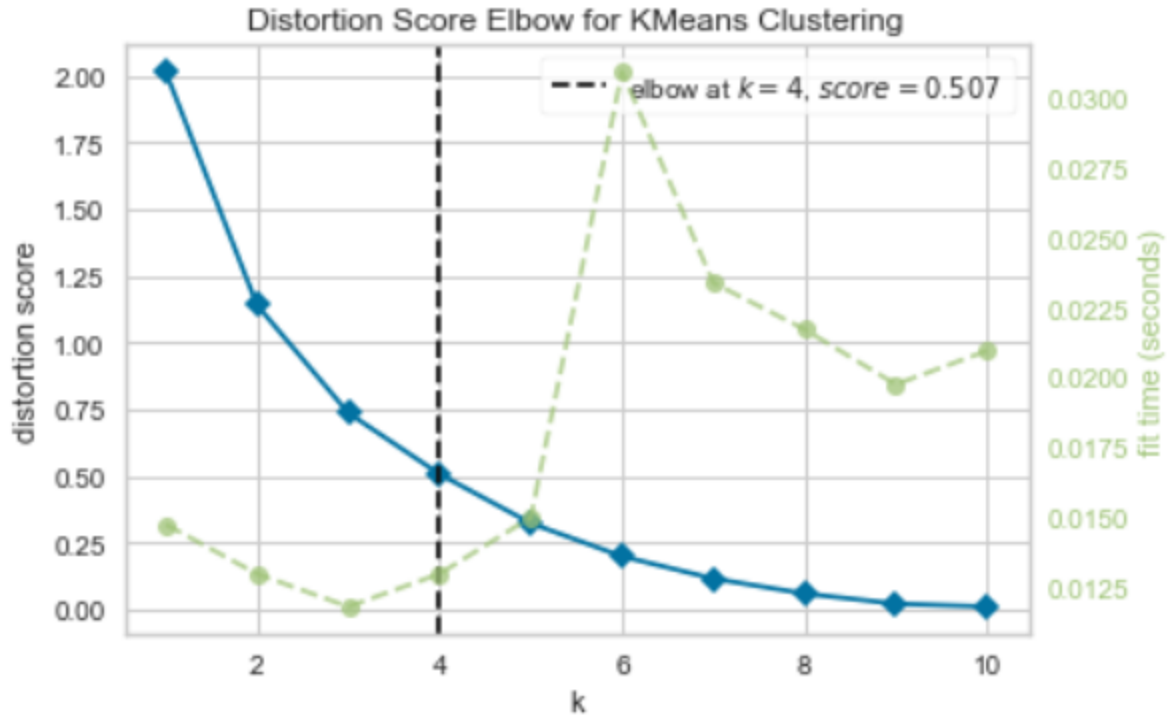
| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | 9th Most Common Venue | 10th Most Common Venue |
|---|------------------|-----------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-----------------------|-------------------------|-------------------------|-------------------------|------------------------|
| 0 | Agege | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant | Asian Restaurant |
| 1 | Ajeromi-Ifelodun | Fast Food Restaurant | Chinese Restaurant | Indian Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant | Asian Restaurant |
| 2 | Alimosho | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Chinese Restaurant | Brazilian Restaurant | Asian Restaurant |
| 3 | Amuwo-Odofin | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Chinese Restaurant | Brazilian Restaurant |
| 4 | Apapa | Fast Food Restaurant | Indian Restaurant | Chinese Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant |

3.2 K-Means Clustering

K-Means clustering was applied to analyze the data by clustering neighborhoods with similar averages of restaurants. First, the elbow curve method was applied to obtain the optimum K for the clustering. The reason for this is to avoid overfitting and underfitting the model. Using the elbow method, we ran K-Means clustering on the dataset for a given range of values of K. The average distances to the centroid across all data points are calculated and plotted to find the point where the average distance from the centroid suddenly falls (ie. the elbow)



Here, the elbow point at $K = 4$ was obtained i.e., the sum squared distances suddenly fall at this point, which indicates that the optimal K for this dataset is 4. To verify the accuracy of the elbow point, the `KElbowVisualizer` function in Yellowbrick package was enabled to fit the resultant K-Means to the elbow visualizer. We ran a model to fit the error and calculated the distortion score.



The above result displayed the score and indicated the elbow point using the dotted line. Here we can see that the elbow is at $K = 4$. Hence, 4 was selected as the number of clusters.

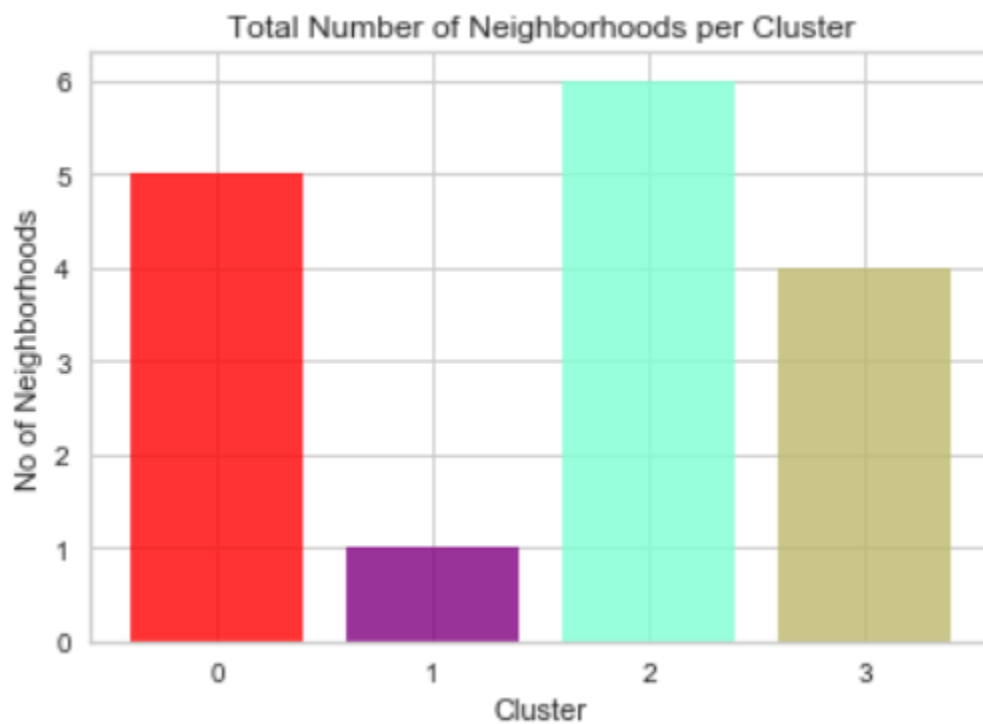
Then, we ran the K-Means clustering which grouped the neighborhoods based on the mean frequency of restaurants in 4 clusters. Each of these clusters was labeled from 0 to 3, with 0,1,2,3 being the first, second, third, and fourth clusters respectively.

| Cluster Labels | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8th Most Common Venue | 9th Most Common Venue | 10th Most Common Venue | |
|----------------|--------------|-----------------------|-----------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-----------------------|-------------------------|-------------------------|-------------------------|----------------------|
| 0 | 2 | Agege | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant | Asian Restaurant |
| 1 | 3 | Ajeromi-Ifeelodun | Fast Food Restaurant | Chinese Restaurant | Indian Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant | Asian Restaurant |
| 2 | 2 | Alimosho | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Chinese Restaurant | Brazilian Restaurant | Asian Restaurant |
| 3 | 0 | Amuwo-Odofin | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant | Comfort Food Restaurant | Chinese Restaurant | Brazilian Restaurant |
| 4 | 3 | Apapa | Fast Food Restaurant | Indian Restaurant | Chinese Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | European Restaurant | Comfort Food Restaurant | Brazilian Restaurant |

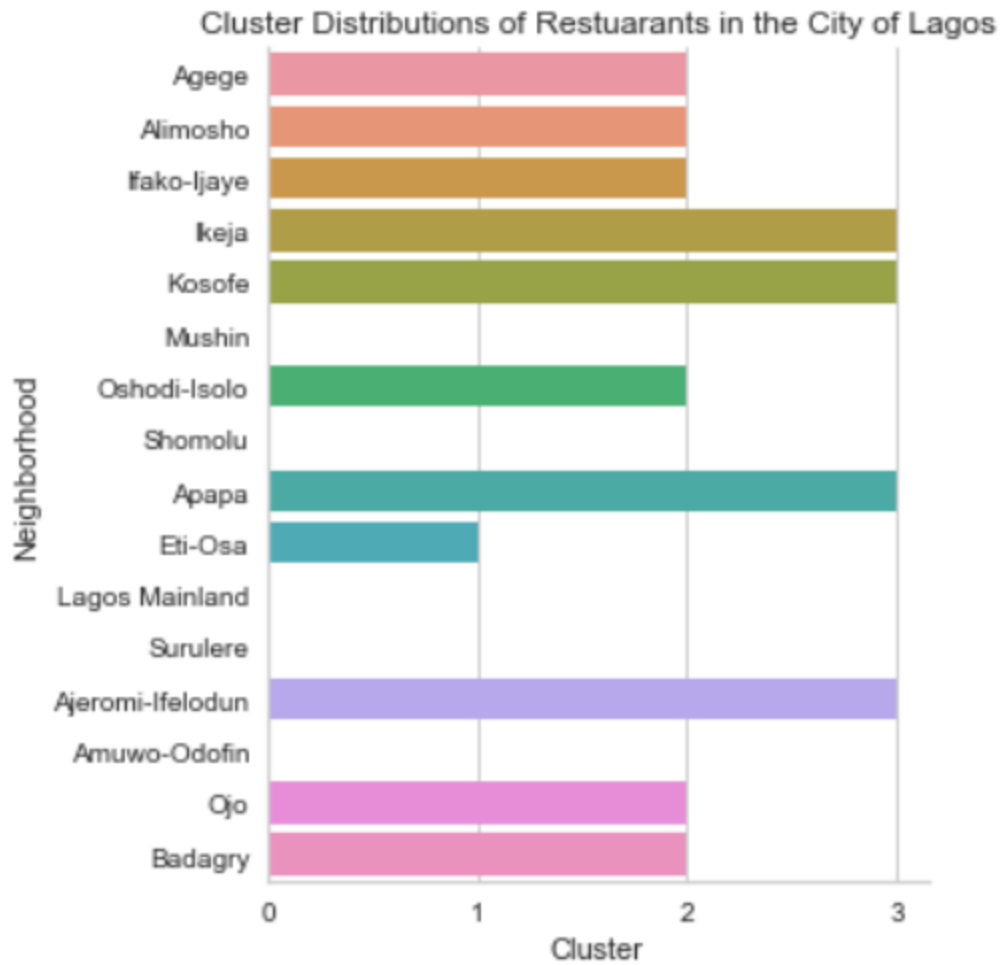
Next, we added the 4 cluster labels to the table, merged the files, and created a new DataFrame for cluster analysis as seen in the table.

| | Neighborhood | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue |
|---|--------------|------------|------------|------------------------|------------|----------|-----------|----------------|-----------------------|-------------------------------|-------------------------------|-------------------------------|-----------------------|-----------------------|
| 0 | Agege | 11 | 459939 | Agege | 100 | 6.625256 | 3.311209 | 2.0 | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant |
| 1 | Alimosho | 185 | 1277714 | Ikotun | 100 | 6.584343 | 3.257631 | 2.0 | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | Euro Restaurant |
| 2 | Ifako-Ijaye | 27 | 427878 | Ifako | 100 | 6.660436 | 3.321539 | 2.0 | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant |
| 3 | Ikeja | 46 | 313196 | Ikeja | 100 | 6.604859 | 3.353204 | 3.0 | Fast Food Restaurant | African Restaurant | Chinese Restaurant | Portuguese Restaurant | Indian Restaurant | Euro Restaurant |
| 4 | Kosofe | 81 | 665393 | Kosofe | 100 | 6.581974 | 3.414836 | 3.0 | Portuguese Restaurant | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Indian Restaurant |

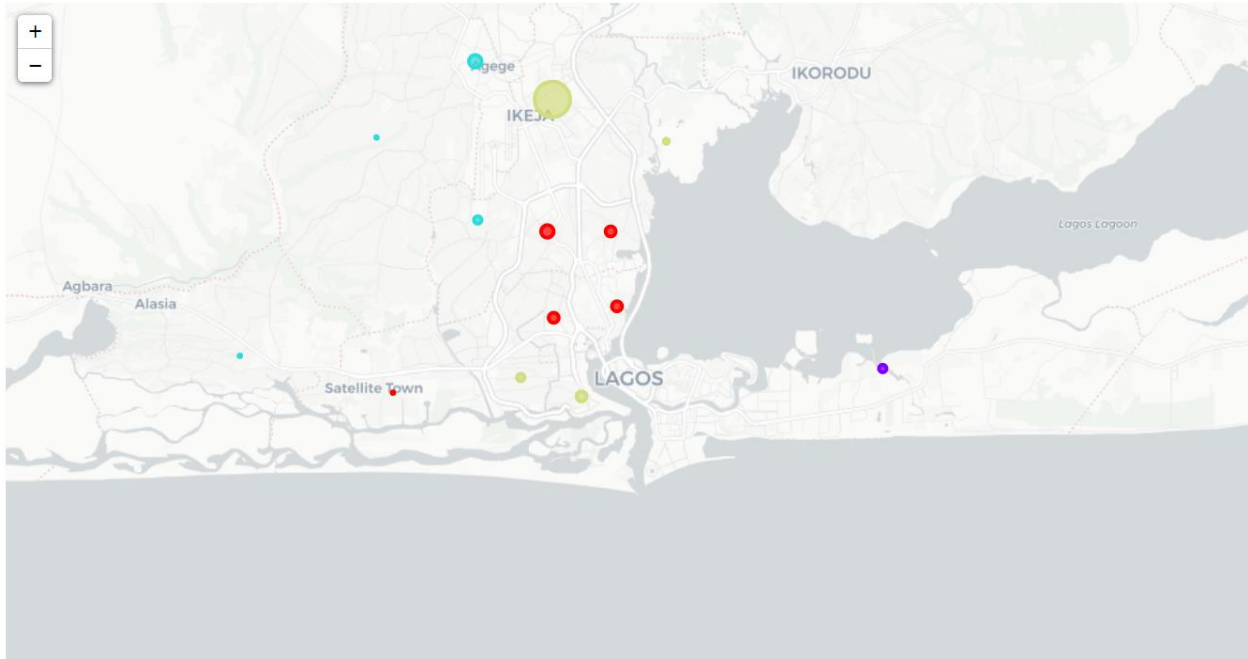
We visualized the DataFrame information using two bar charts. The first bar chart shows the number of neighborhoods in each cluster.



The second one displayed cluster distributions of restaurants in Lagos. The result can be seen below.



Finally, a map was created using the Folium package to visualize the 4 clusters distributions of the restaurants in the neighborhoods. Each cluster on the map indicates neighborhoods with a similar mean frequency of restaurants in each neighborhood.



The map above shows the distributions of the clusters. For example, we can see the third clusters in yellow indicating a dominating number of venues at Ikeja and the least venues at Ajeromi-Ifelodun.

3.3 Cluster Analysis

Among the 4 clusters, Cluster 0, 1, 2, 3 has 5, 1, 6, 4 number of neighborhoods returned respectively. Fast Food Restaurant appeared as the 1st most common restaurant category in the first (Cluster 0), third (Cluster 2), and fourth clusters (Cluster 3). This is not surprising as there is a vast number of Fast Food restaurants in Lagos. However, the second cluster is topped by the Vegetarian/Vegan Restaurant. The 2nd most common venues are topped by different restaurants among the clusters. Hence, considering the Fast Food Restaurant which is undoubtedly very common in the areas, the clusters can be described as follows:

1. The first cluster (Cluster 0)

| | Neighborhood | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue |
|----|----------------|------------|------------|------------------------|------------|----------|-----------|----------------|-----------------------|-----------------------|-------------------------------|-------------------------------|-----------------------|-----------------------|
| 5 | Mushin | 17 | 633009 | Mushin | 100 | 6.533331 | 3.349999 | 0.0 | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 7 | Shomolu | 12 | 402673 | Shomolu | 101 | 6.533565 | 3.384161 | 0.0 | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 12 | Lagos Mainland | 19 | 317720 | Lagos Mainland | 101 | 6.493061 | 3.388250 | 0.0 | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 13 | Surulere | 23 | 503975 | Surulere | 101 | 6.487201 | 3.353259 | 0.0 | Fast Food Restaurant | African Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portu Restaurant |
| 16 | Amuwo-Odofin | 135 | 318166 | Festac Town | 102 | 6.447023 | 3.266280 | 0.0 | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |

This is the Fast Food-African cluster. Here, visitors/ tourists who want to have a taste of different African dishes can easily locate the African Restaurant at Mushin, Shomolu, Lagos Mainland, Surulere, and Amuwo-Odofin areas.

2. The second cluster (Cluster 1)

| | Neighborhood | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue |
|----|--------------|------------|------------|------------------------|------------|----------|-----------|----------------|-------------------------------|-----------------------|-------------------------|-----------------------|-----------------------|-----------------------|
| 10 | Eti-Osa | 192 | 287785 | Ikoyi | 101 | 6.460231 | 3.532181 | 1.0 | Vegetarian / Vegan Restaurant | Sushi Restaurant | Comfort Food Restaurant | Chinese Restaurant | Asian Restaurant | Portug Restaurant |

In this cluster, the Vegetarian/ Vegan Restaurant is the first most common venue, followed by Sushi. It can be called the Vegetarian/ Vegan-Sushi cluster located at Eti-Osa.

3. The third cluster (Cluster 2)

| | Neighborhood | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue |
|----|--------------|------------|------------|------------------------|------------|----------|-----------|----------------|-----------------------|-------------------------------|-------------------------------|-----------------------|-----------------------|-----------------------|
| 0 | Agege | 11 | 459939 | Agege | 100 | 6.625256 | 3.311209 | 2.0 | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 1 | Alimosho | 185 | 1277714 | Ikotun | 100 | 6.584343 | 3.257631 | 2.0 | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | Euro Restaurant |
| 2 | Ifako-Ijaye | 27 | 427878 | Ifako | 100 | 6.660436 | 3.321539 | 2.0 | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 6 | Oshodi-Isolo | 45 | 621509 | Oshodi/Isolo | 100 | 6.540010 | 3.312415 | 2.0 | Fast Food Restaurant | Chinese Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Resto |
| 17 | Ojo | 158 | 598071 | Ojo | 102 | 6.466665 | 3.183333 | 2.0 | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | Euro Restaurant |
| 18 | Badagry | 441 | 241093 | Badagry | 103 | 6.439322 | 2.905844 | 2.0 | Fast Food Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant | Indian Restaurant | Euro Restaurant |

This cluster can be named the Fast Food-Chinese-Vegetarian/ Vegan cluster. Tourists can easily get Chinese Restaurant at Agege, Ifako, and Oshodi-Isolo. Vegetarian/ Vegan restaurants are highly distributed around Alimosho, Ojo and Badagry.

4. The fourth cluster (Cluster 3)

| | Neighborhood | Area (km2) | Population | Administrative Capital | Postalcode | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue |
|----|-------------------|------------|------------|------------------------|------------|----------|-----------|----------------|-----------------------|-----------------------|-----------------------|-------------------------------|-------------------------------|-----------------------|
| 3 | Ikeja | 46 | 313196 | Ikeja | 100 | 6.604859 | 3.353204 | 3.0 | Fast Food Restaurant | African Restaurant | Chinese Restaurant | Portuguese Restaurant | Indian Restaurant | European Restaurant |
| 4 | Kosofe | 81 | 665393 | Kosofe | 100 | 6.581974 | 3.414836 | 3.0 | Portuguese Restaurant | Fast Food Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Res |
| 9 | Apapa | 27 | 217362 | Apapa | 101 | 6.445187 | 3.368373 | 3.0 | Fast Food Restaurant | Indian Restaurant | Chinese Restaurant | African Restaurant | Vegetarian / Vegan Restaurant | Res |
| 15 | Ajeromi-Ifeelodun | 12 | 684105 | Ajeromi/Ifeelodun | 102 | 6.455122 | 3.335946 | 3.0 | Fast Food Restaurant | Chinese Restaurant | Indian Restaurant | Vegetarian / Vegan Restaurant | Sushi Restaurant | Portuguese Restaurant |

This cluster has a variety of restaurants. It can be known as the Fast Food-Portuguese/Afro-Asian cluster. Portuguese Restaurant is easily located at Kosofe. African, Indian and Chinese Restaurant are mainly distributed at Ikeja, Kosofe, Apapa and Ajeromi-Ifeelodun.

4. Discussion

We employed data science methods to carry out this project. This involves preprocessing, processing, analysis, and visualization of data. These processes are covered in the IBM Data Science Professional Certificate courses, both in theory as well as in practice through hands-on experiences on Skill Network Lab. The Python packages used for all the analyses are open source and cost-free. Using these tools and methods, we carried out an analysis to solve a real-world problem. We employed various packages to retrieve the data information, cleaned/filter, transformed, and visualized data. We scraped the neighborhoods data about Lagos from Wikipedia using the web scraping libraries. We retrieved geographical coordinates using geocoder libraries. We utilized the Foursquare API to fetch Restaurant and venues information. We employed machine learning to analyze the neighborhood by clustering, and the final result of clustered neighborhoods was visualized using the Seaborn and Matplotlib packages, in addition to Folium maps. Finally, cluster analysis was done on the basis of guiding tourists in Lagos in finding preferable restaurants in the neighborhoods.

5. Conclusions

We managed a business problem using data science approaches. We achieved a goal by providing a guide for tourists in Lagos. The results of this project will help tourists in Lagos where to find preferable restaurants in the neighborhood. This will also help them narrow down their choices of restaurants at the venues nearby. The methods applied in the analysis can be employed to explore other cities or countries to solve related real-world problems.

This project can also be used by entrepreneurs and investors who plan to engage in restaurants business in the city of Lagos. From this analysis, we can see that there are too many Fast Food Restaurants in the neighborhoods, some of which are serving unhealthy, junk food. Entrepreneurs can consider setting up restaurants that serve only healthy meals, such as gluten-free snacks made with coconut flour or almond flour, low-fat meals, low-carb meals, and other healthy recipes. A lot of people who are on diets can easily enjoy healthy, gluten-free treats at the restaurant.

This is also important for Lagosians, as most people in Lagos are of the working class with long work hours leaving little or no time to cook for themselves. They often buy foods from available restaurants and mostly eat at Fast Food Restaurants. Hence, starting a healthy restaurant and food delivery business in certain neighborhoods in Lagos is bound to be profitable if planned properly using the analysis in this project as a guide.