Capstone Project - The Battle of Neighborhoods

1. Introduction

A Tale of Two cities, a novel written by Charles Dickens was set in London and Paris which takes place during the French Revolution. These cities were both happening then and now. A lot has changed over the years and we now take a look at how the cities have grown.

London and Paris are quite the popular tourist and vacation destinations for people all around the world. They are diverse and multicultural and offer a wide variety of experiences that is widely sought after. We try to group the neighbourhoods of London and Paris respectively and draw insights to what they look like now.

2. Business Problem

The aim is to help tourists choose their destinations depending on the experiences that the neighbourhoods have to offer and what they would want to have. This also helps people make decisions if they are thinking about migrating to London or Paris or even if they want to relocate neighbourhoods within the city. Our findings will help stakeholders make informed decisions and address any concerns they have including the different kinds of cuisines, provision stores and what the city has to offer.

3. Data Description

We require geographical location data for both London and Paris. Postal codes in each city serve as a starting point. Using Postal codes we use can find out the neighborhoods, boroughs, venues and their most popular venue categories.

3.1 London

To derive our solution, We scrape our data from
https://en.wikipedia.org/wiki/List_of_areas_of_London

This wikipedia page has information about all the neighbourhoods, we limit it London.

1. *borough* : Name of Neighbourhood
2. *town* : Name of borough
3. *post_code* : Postal codes for London.

This wikipedia page lacks information about the geographical locations. To solve this problem we use ArcGIS API

3.2 ArcGIS API

ArcGIS Online enables you to connect people, locations, and data using interactive maps. Work with smart, data-driven styles and intuitive analysis tools that deliver location intelligence. Share your insights with the world or specific groups.

More specifically, we use ArcGIS to get the geo locations of the neighbourhoods of London. The following columns are added to our initial dataset which prepares our data.

1. *latitude* : Latitude for Neighbourhood
2. *longitude* : Longitude for Neighbourhood

3.3 Paris

To derive our solution, We leverage JSON data available at https://www.data.gouv.fr/fr/datasets/r/e88c6fda-1d09-42a0-a069-606d3259114e

The JSON file has data about all the neighbourhoods in France, we limit it to Paris.

1. *postal_code* : Postal codes for France
2. *nom_comm* : Name of Neighbourhoods in France
3. *nom_dept* : Name of the boroughs, equivalent to towns in France
4. *geo_point_2d* : Tuple containing the latitude and longitude of the Neighbourhoods.

3.4 Foursquare API Data

We will need data about different venues in different neighbourhoods of that specific borough. In order to gain that information we will use "Foursquare" locational information. Foursquare is a location data provider with information about all manner of venues and events within an area of interest. Such information includes venue names, locations, menus and even photos. As such, the foursquare location platform will be used as the sole data source since all the stated required information can be obtained through the API.

After finding the list of neighbourhoods, we then connect to the Foursquare API to gather information about venues inside each and every neighbourhood. For each neighbourhood, we have chosen the radius to be 500 meters.

The data retrieved from Foursquare contained information of venues within a specified distance of the longitude and latitude of the postcodes. The information obtained per venue as follows:

1. *Neighbourhood* : Name of the Neighbourhood
2. *Neighbourhood Latitude* : Latitude of the Neighbourhood
3. *Neighbourhood Longitude* : Longitude of the Neighbourhood
4. *Venue* : Name of the Venue
5. *Venue Latitude* : Latitude of Venue
6. *Venue Longitude* : Longitude of Venue
7. *Venue Category* : Category of Venue

Based on all the information collected for both London and Paris, we have sufficient data to build our model. We cluster the neighbourhoods together based on similar venue categories. We then present our observations and findings. Using this data, our stakeholders can take the necessary decision.

4. Methodology

We will be creating our model with the help of Python so we start off by importing all the required packages.

```
import pandas as pd
import requests
import numpy as np
import matplotlib.cm as cm
import matplotlib.colors as colors
import folium
from sklearn.cluster import KMeans
```

Package breakdown:

- *Pandas* : To collect and manipulate data in JSON and HTMl and then data analysis
- *requests* : Handle http requests
- *matplotlib* : Detailing the generated maps
- *folium* : Generating maps of London and Paris
- *sklearn* : To import Kmeans which is the machine learning model that we are using.

The approach taken here is to explore each of the cities individually, plot the map to show the neighbourhoods being considered and then build our model by clustering all of the similar neighbourhoods together and finally plot the new map with the clustered neighbourhoods. We draw insights and then compare and discuss our findings.

4.1 Data Collection

In the data collection stage, we begin with collecting the required data for the cities of London and Paris. We need data that has the postal codes, neighbourhoods and boroughs specific to each of the cities.

To collect data for London, we scrape the List of areas of London wikipedia page to take the 2nd table using the following code:

```
url_london = "https://en.wikipedia.org/wiki/List_of_areas_of_London"
wiki_london_url = requests.get(url_london)
wiki_london_data = pd.read_html(wiki_london_url.text)
wiki_london_data = wiki_london_data[1]
wiki_london_data
```

The data looks like this:

	Location	London borough	Post town	Postcode district	Dial code	OS grid ref
0	Abbey Wood	Bexley, Greenwich [7]	LONDON	SE2	020	TQ465785
1	Acton	Ealing, Hammersmith and Fulham[8]	LONDON	W3, W4	020	TQ205805
2	Addington	Croydon[8]	CROYDON	CR0	020	TQ375645
3	Addiscombe	Croydon[8]	CROYDON	CR0	020	TQ345665
4	Albany Park	Bexley	BEXLEY, SIDCUP	DA5, DA14	020	TQ478728
...	...	...	...	...	...	...
526	Woolwich	Greenwich	LONDON	SE18	020	TQ435795
527	Worcester Park	Sutton, Kingston upon Thames	WORCESTER PARK	KT4	020	TQ225655
528	Wormwood Scrubs	Hammersmith and Fulham	LONDON	W12	020	TQ225815
529	Yeading	Hillingdon	HAYES	UB4	020	TQ115825
530	Yiewsley	Hillingdon	WEST DRAYTON	UB7	020	TQ063804

531 rows × 6 columns

To collect data for Paris, we download the JSON file containg all the postal codes of France from https://www.data.gouv.fr/fr/datasets/r/e88c6fda-1d09-42a0-a069-606d3259114e

Using Pandas we load the table after reading the JSON file:

```
!wget -q -O 'france-data.json' https://www.data.gouv.fr/fr/datasets/r/e88c6fda-1d09-42a0-a069-606d3259114e
print("Data Downloaded!")
paris_raw = pd.read_json('france-data.json')
paris_raw.head()
```

	datasetid	recordid	fields	geometry	record_timestamp
0	correspondances-code-insee-code-postal	2bf36b38314b6c39dfbcd09225f97fa532b1fc45	{'code_comm': '645', 'nom_dept': 'ESSONNE', 's...	{'type': 'Point', 'coordinates': [2.2517129721...	2016-09-21T00:29:06.175+02:00
1	correspondances-code-insee-code-postal	7ee82e74e059b443df18bb79fc5a19b1f05e5a88	{'code_comm': '133', 'nom_dept': 'SEINE-ET-MAR...	{'type': 'Point', 'coordinates': [3.0529405055...	2016-09-21T00:29:06.175+02:00
2	correspondances-code-insee-code-postal	e2cd3186f07286705ed482a10b6aebd9de633c81	{'code_comm': '378', 'nom_dept': 'ESSONNE', 's...	{'type': 'Point', 'coordinates': [2.1971816504...	2016-09-21T00:29:06.175+02:00
3	correspondances-code-insee-code-postal	868bf03527a1d0a9defe5cf4e6fa0a730d725699	{'code_comm': '243', 'nom_dept': 'SEINE-ET-MAR...	{'type': 'Point', 'coordinates': [2.7097808131...	2016-09-21T00:29:06.175+02:00
4	correspondances-code-insee-code-postal	21e809b1d4480333c8b6fe7addd8f3b06f343e2c	{'code_comm': '003', 'nom_dept': 'VAL-DE-MARNE...	{'type': 'Point', 'coordinates': [2.3335102498...	2016-09-21T00:29:06.175+02:00

4.2 Data Preprocessing

For London, We replace the spaces with underscores in the title.The *borough* column has numbers within square brackets that we remove using:

```
wiki_london_data.rename(columns=lambda x: x.strip().replace(" ", "_"), inplace=True)
wiki_london_data['borough'] = wiki_london_data['borough'].map(lambda x:
x.rstrip(']').rstrip('0123456789').rstrip('['))
```

For Paris, we break down each of the nested fields and create the dataframe that we need:

```
paris_field_data = pd.DataFrame()
for f in paris_raw.fields:
    dict_new = f
    paris_field_data = paris_field_data.append(dict_new, ignore_index=True)

paris_field_data.head()
```

4.3 Feature Selection

For both of our datasets, we need only the borough, neighbourhood, postal codes and geolocations (latitude and longitude). So we end up selecting the columns that we need by:

```
df1 = wiki_london_data.drop( [ wiki_london_data.columns[0],
wiki_london_data.columns[4], wiki_london_data.columns[5] ], axis=1)

df_2 = paris_field_data[['postal_code','nom_comm','nom_dept','geo_point_2d']]
```

4.4 Feature Engineering

Both of our Datasets actually contain information related to all the cities in the country. We can narrow down and further process the data by selecting only the neighbourhoods pertaining to 'London' and 'Paris'

```
df1 = df1[df1['town'].str.contains('LONDON')]
```

```
df_paris = df_2[df_2['nom_dept'].str.contains('PARIS')].reset_index(drop=True)
```

Looking over our London dataset, we can see that we don't have the geolocation data. We need to extrapolate the missing data for our neighbourhoods. We perform this by leveraging the ArcGIS API. With the Help of ArcGIS API we can get the latitude and longitude of our London neighbourhood data.

```
from arcgis.geocoding import geocode
from arcgis.gis import GIS
gis = GIS()
```

Defining London arcgis geocode function to return latitude and longitude

```
def get_x_y_uk(address1):
  lat_coords = 0
  lng_coords = 0
  g = geocode(address='{}, London, England, GBR'.format(address1))[0]
  lng_coords = g['location']['x']
  lat_coords = g['location']['y']
  return str(lat_coords) +","+ str(lng_coords)
```

Passing postal codes of london to get the geographical co-ordinates

```
coordinates_latlng_uk = geo_coordinates_uk.apply(lambda x: get_x_y_uk(x))
```

We proceed with Merging our source data with the geographical co-ordinates to make our dataset ready for the next stage

```
london_merged = pd.concat([df1,lat_uk.astype(float), lng_uk.astype(float)], axis=1)
london_merged.columns= ['borough','town','post_code','latitude','longitude']
london_merged
```

	borough	town	post_code	latitude	longitude
0	Bexley, Greenwich	LONDON	SE2	51.49245	0.12127
1	Ealing, Hammersmith and Fulham	LONDON	W3, W4	51.51324	-0.26746
6	City	LONDON	EC3	51.51200	-0.08058
7	Westminster	LONDON	WC2	51.51651	-0.11968
9	Bromley	LONDON	SE20	51.41009	-0.05683
...	...	...	...	...	...
521	Redbridge	LONDON	IG8, E18	51.58977	0.03052
522	Redbridge, Waltham Forest	LONDON, WOODFORD GREEN	IG8	51.50642	-0.12721
525	Barnet	LONDON	N12	51.61592	-0.17674
526	Greenwich	LONDON	SE18	51.48207	0.07143
528	Hammersmith and Fulham	LONDON	W12	51.50645	-0.23691

308 rows × 5 columns

As for our Paris dataset, we don't need to get the geo coordinates using an external data source or collect it with the `ArcGIS` API call since we already have it stored in the *geo_point_2d* column as a tuple in the df_paris dataframe.

We just need to extract the latitude and longitude for the column:

```
paris_lat = paris_latlng.apply(lambda x: x.split(',')[0])
paris_lat = paris_lat.apply(lambda x: x.lstrip('['))

paris_lng = paris_latlng.apply(lambda x: x.split(',')[1])
paris_lng = paris_lng.apply(lambda x: x.rstrip(']'))

paris_geo_lat  = pd.DataFrame(paris_lat.astype(float))
paris_geo_lat.columns=['Latitude']

paris_geo_lng = pd.DataFrame(paris_lng.astype(float))
paris_geo_lng.columns=['Longitude']
```

We then create our Paris dataset with the required information:

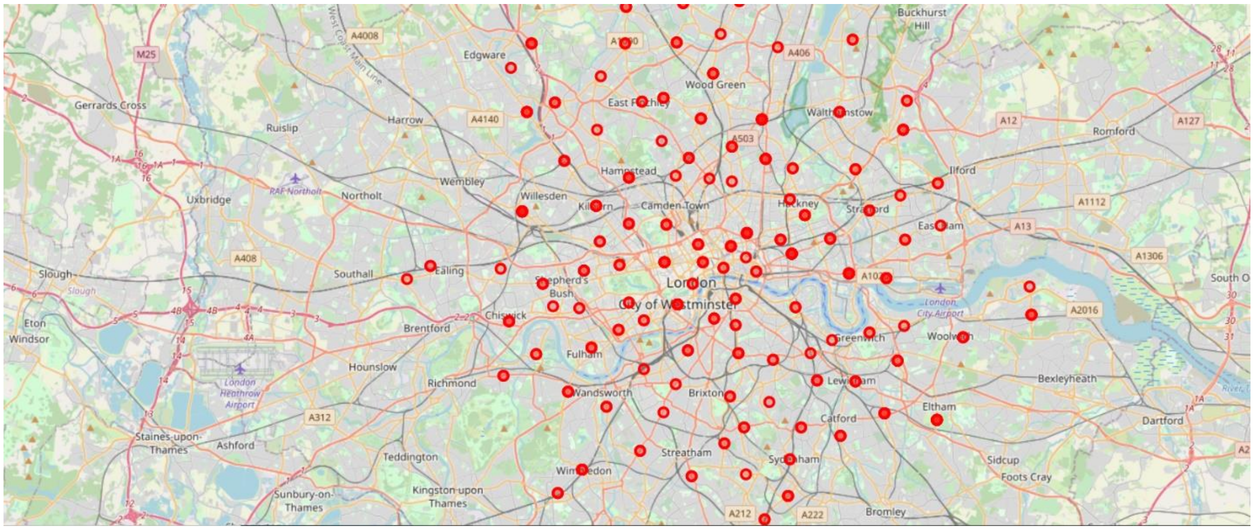
```
paris_combined_data = pd.concat([df_paris.drop('geo_point_2d', axis=1),
paris_geo_lat, paris_geo_lng], axis=1)
paris_combined_data
```

	postal_code	nom_comm	nom_dept	Latitude	Longitude
0	75009	PARIS-9E-ARRONDISSEMENT	PARIS	48.876896	2.337460
1	75002	PARIS-2E-ARRONDISSEMENT	PARIS	48.867903	2.344107
2	75011	PARIS-11E-ARRONDISSEMENT	PARIS	48.859415	2.378741
3	75003	PARIS-3E-ARRONDISSEMENT	PARIS	48.863054	2.359361
4	75006	PARIS-6E-ARRONDISSEMENT	PARIS	48.848968	2.332671
5	75004	PARIS-4E-ARRONDISSEMENT	PARIS	48.854228	2.357362
6	75001	PARIS-1ER-ARRONDISSEMENT	PARIS	48.862630	2.336293
7	75017	PARIS-17E-ARRONDISSEMENT	PARIS	48.887337	2.307486
8	75008	PARIS-8E-ARRONDISSEMENT	PARIS	48.872527	2.312583
9	75013	PARIS-13E-ARRONDISSEMENT	PARIS	48.828718	2.362468
10	75012	PARIS-12E-ARRONDISSEMENT	PARIS	48.835156	2.419807
11	75005	PARIS-5E-ARRONDISSEMENT	PARIS	48.844509	2.349859
12	75019	PARIS-19E-ARRONDISSEMENT	PARIS	48.886869	2.384694
13	75020	PARIS-20E-ARRONDISSEMENT	PARIS	48.863187	2.400820
14	75010	PARIS-10E-ARRONDISSEMENT	PARIS	48.876029	2.361113
15	75016	PARIS-16E-ARRONDISSEMENT	PARIS	48.860399	2.262100
16	75018	PARIS-18E-ARRONDISSEMENT	PARIS	48.892735	2.348712
17	75007	PARIS-7E-ARRONDISSEMENT	PARIS	48.856083	2.312439
18	75015	PARIS-15E-ARRONDISSEMENT	PARIS	48.840155	2.293559
19	75014	PARIS-14E-ARRONDISSEMENT	PARIS	48.828993	2.327101

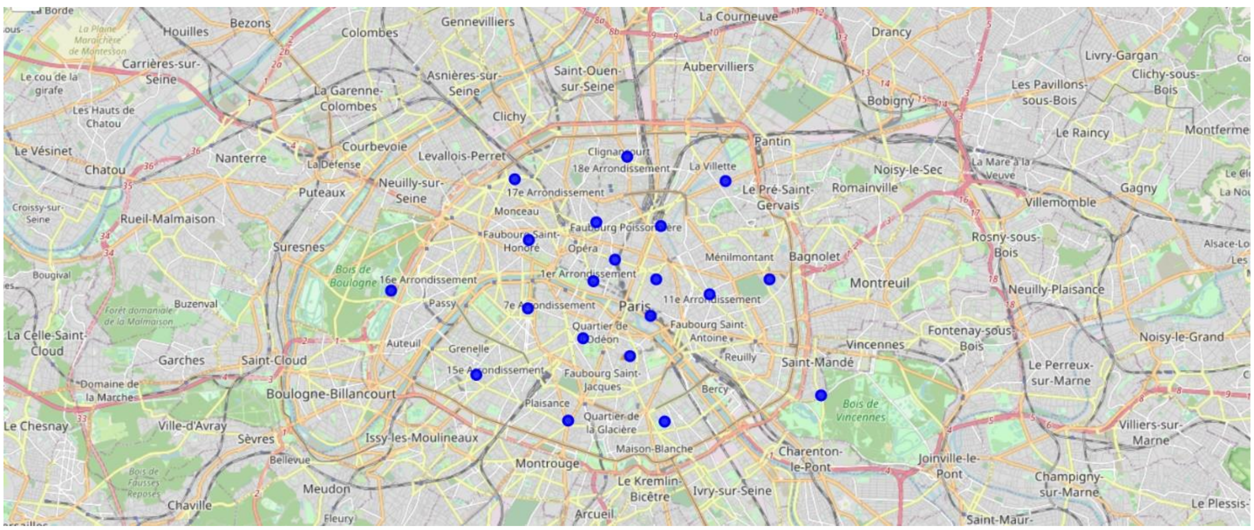
4.5 Visualizing the Neighbourhoods of London and Paris

Now that our datasets are ready, using the Folium package, we can visualize the maps of London and Paris with the neighbourhoods that we collected.

Neighbourhood map of London:



Neighbourhood map of Paris:



Now that we have visualized the neighbourhoods, we need to find out what each neighbourhood is like and what are the common venue and venue categories within a 500m radius.

This is where Foursquare comes into play. With the help of Foursquare we define a function which collects information pertaining to each neighbourhood including that of the name of the neighbourhood, geo-coordinates, venue and venue categories.

```
LIMIT=100

def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
```

```
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url =
'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&l
l={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT
            )

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in
venue_list])
    nearby_venues.columns = ['Neighbourhood',
                  'Neighbourhood Latitude',
                  'Neighbourhood Longitude',
                  'Venue',
                  'Venue Category']

    return(nearby_venues)
```

Resulting data looks like:

	Neighbourhood	Neighbourhood Latitude	Neighbourhood Longitude	Venue	Venue Category
0	Bexley, Greenwich	51.49245	0.12127	Lesnes Abbey	Historic Site
1	Bexley, Greenwich	51.49245	0.12127	Sainsbury's	Supermarket
2	Bexley, Greenwich	51.49245	0.12127	Lidl	Supermarket
3	Bexley, Greenwich	51.49245	0.12127	Abbey Wood Railway Station (ABW)	Train Station
4	Bexley, Greenwich	51.49245	0.12127	Bean @ Work	Coffee Shop

4.6 One Hot Encoding

Since we are trying to find out what are the different kinds of venue categories present in each neighbourhood and then calculate the top 10 common venues to base our similarity on, we use the One Hot Encoding to work with our categorical datatype of the venue categories. This helps to convert the categorical data into numeric data.

We won't be using label encoding in this situation since label encoding might cause our machine learning model to have a bias or a sort of ranking which we are trying to avoid by using One Hot Encoding.

We perform one hot encoding and then calculate the mean of the grouped venue categories for each of the neighbourhoods.

```
# One hot encoding
London_venue_cat = pd.get_dummies(venues_in_London[['Venue Category']],
prefix="", prefix_sep="")

# Adding neighbourhood to the mix
London_venue_cat['Neighbourhood'] = venues_in_London['Neighbourhood']

# moving neighborhood column to the first column
fixed_columns = [London_venue_cat.columns[-1]] + list(London_venue_cat.columns[:-
1])
London_venue_cat = London_venue_cat[fixed_columns]

# Grouping and calculating the mean
London_grouped = London_venue_cat.groupby('Neighbourhood').mean().reset_index()
```

	Neighbourhood	Accessories Store	Adult Boutique	African Restaurant	American Restaurant	Antique Shop	Arcade	Arepa Restaurant	Argentinian Restaurant	Art Gallery	...	Vietnamese Restaurant	Warehouse Store	Whisky Bar	Win Bar
0	Bexley, Greenwich	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1	Bexley, Greenwich	0	0	0	0	0	0	0	0	0	...	0	0	0	0
2	Bexley, Greenwich	0	0	0	0	0	0	0	0	0	...	0	0	0	0
3	Bexley, Greenwich	0	0	0	0	0	0	0	0	0	...	0	0	0	0
4	Bexley, Greenwich	0	0	0	0	0	0	0	0	0	...	0	0	0	0

5 rows × 301 columns

4.7 Top Venues in the Neighbourhoods

In our next step, We need to rank and label the top venue categories in our neighborhood.

Let's define a function to get the top venue categories in the neighbourhood

```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

    return row_categories_sorted.index.values[0:num_top_venues]
```

There are many categories, we will consider top 10 categories to avoid data skew.

Defining a function to label them accurately

```
num_top_venues = 10

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Neighbourhood']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))
```

Getting the top venue categories in the neighbourhoods of London

```
# create a new dataframe for London
neighborhoods_venues_sorted_london = pd.DataFrame(columns=columns)
```

neighborhoods_venues_sorted_london['Neighbourhood'] =
London_grouped['Neighbourhood']

for ind in np.arange(London_grouped.shape[0]):
    neighborhoods_venues_sorted_london.iloc[ind, 1:] =
return_most_common_venues(London_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted_london.head()

	Neighbourhood	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	Barnet	Coffee Shop	Café	Grocery Store	Pub	Italian Restaurant	Bus Stop	Supermarket	Pharmacy	Sushi Restaurant	Turkish Restaurant
1	Barnet, Brent, Camden	Bakery	Gym / Fitness Center	Clothing Store	Hardware Store	Supermarket	Fish & Chips Shop	Falafel Restaurant	Farmers Market	Fast Food Restaurant	Filipino Restaurant
2	Bexley	Supermarket	Historic Site	Platform	Convenience Store	Coffee Shop	Train Station	Golf Course	Bus Stop	Park	Construction & Landscaping
3	Bexley, Greenwich	Daycare	Construction & Landscaping	Sports Club	Bus Stop	Massage Studio	Golf Course	Historic Site	Park	Convenience Store	Diner
4	Bexley, Greenwich	Supermarket	Convenience Store	Platform	Train Station	Historic Site	Coffee Shop	Zoo Exhibit	Fish & Chips Shop	Falafel Restaurant	Farmers Market

4.8 Model Building - KMeans

Moving on to the most exicitng part **- Model Building!** We will be using KMeans Clustering Machine learning algorithm to cluster similar neighbourhoods together. We will be going with the number of clusters as 5.

# set number of clusters
k_num_clusters = 5

London_grouped_clustering = London_grouped.drop('Neighbourhood', 1)

# run k-means clustering
kmeans_london = KMeans(n_clusters=k_num_clusters,
random_state=0).fit(London_grouped_clustering)

Our model has labelled each of the neighbourhoods, we add the label into our dataset.

neighborhoods_venues_sorted_london.insert(0, 'Cluster Labels', kmeans_london.labels_
+1)

We then join London_merged with our neighbourhood venues sorted to add latitude & longitude for each of the neighborhood to prepare it for visualization.

london_data = london_merged

london_data = london_data.join(neighborhoods_venues_sorted_london.set_index('Neighbourhood'), on='borough')

london_data.head()

	borough	town	post_code	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	7th Most Common Venue	8th Mo: Comm Venue
0	Bexley, Greenwich	LONDON	SE2	51.49245	0.12127	4	Supermarket	Convenience Store	Platform	Train Station	Historic Site	Coffee Shop	Zoo Exhibit	Fish & Chips Shop
1	Ealing, Hammersmith and Fulham	LONDON	W3, W4	51.51324	-0.26746	2	Grocery Store	Indian Restaurant	Train Station	Park	Breakfast Spot	Hotel Bar	Fish & Chips Shop	Exhibit
6	City	LONDON	EC3	51.51200	-0.08058	1	Hotel	Coffee Shop	Italian Restaurant	Gym / Fitness Center	Pub	Restaurant	Sandwich Place	Wine B
7	Westminster	LONDON	WC2	51.51651	-0.11968	1	Hotel	Coffee Shop	Café	Pub	Sandwich Place	Italian Restaurant	Theater	Restau
9	Bromley	LONDON	SE20	51.41009	-0.05683	1	Supermarket	Hotel	Fast Food Restaurant	Grocery Store	Convenience Store	Park	Pharmacy	Bistro

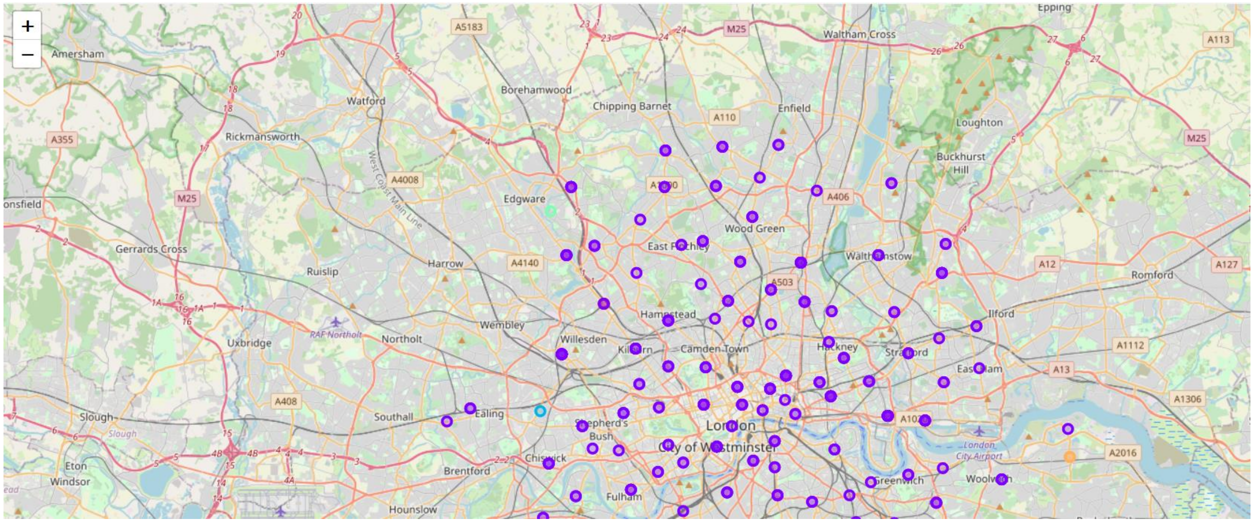
4.9 Visualizing the clustered Neighbourhoods

Our data is processed, missing data is collected and compiled. The Model is built. All that's remaining is to see the clustered neighbourhoods on the map. Again, we use Folium package to do so.

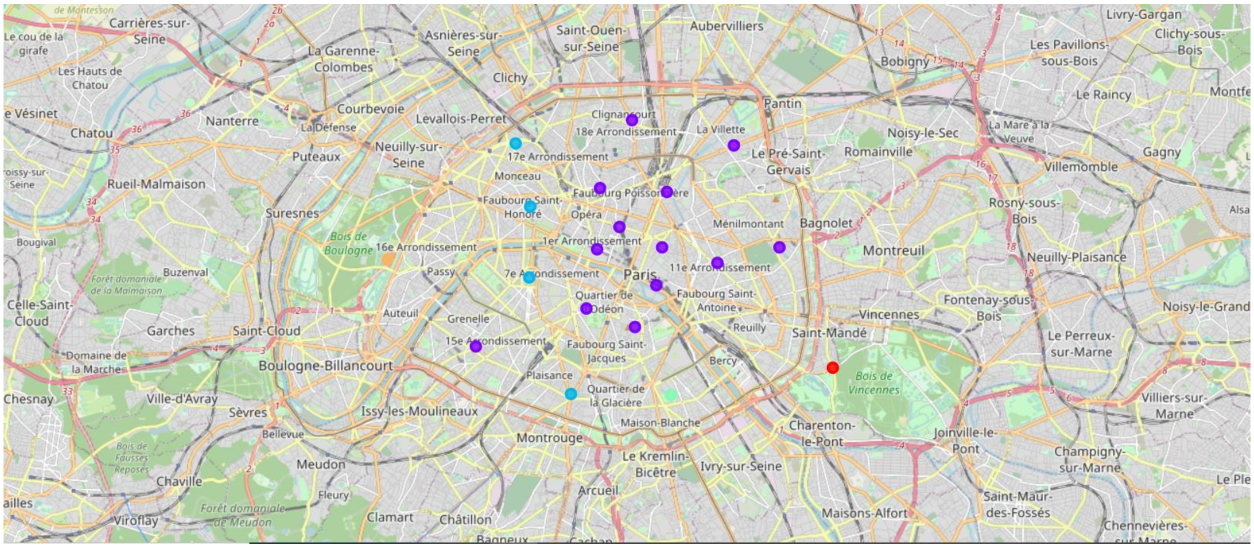
We drop all the NaN values to prevent data skew

london_data_nonan = london_data.dropna(subset=['Cluster Labels'])

Map of clustered neighbourhoods of London:



Map of clustered neighbourhoods of Paris



4.9.1 Examining our Clusters

We could examine our clusters by expanding on our code using the Cluster Labels column:

Cluster 1

london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 1, london_data_nonan.columns[[1] + list(range(5, london_data_nonan.shape[1]))]]

Cluster 2

```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 2,
london_data_nonan.columns[[1] + list(range(5, london_data_nonan.shape[1]))]]
```

Cluster 3

```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 3,
london_data_nonan.columns[[1] + list(range(5, london_data_nonan.shape[1]))]]
```

Cluster 4

```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 4,
london_data_nonan.columns[[1] + list(range(5, london_data_nonan.shape[1]))]]
```

Cluster 5

```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 5,
london_data_nonan.columns[[1] + list(range(5, london_data_nonan.shape[1]))]]
```

5. Results and Discussion

The neighbourhoods of London are very mulitcultural. There are a lot of different cusines including Indian, Italian, Turkish and Chinese. London seems to take a step further in this direction by having a lot of Restaurants, bars, juice bars, coffee shops, Fish and Chips shop and Breakfast spots. It has a lot of shopping options too with that of the Flea markets, flower shops, fish markets, Fishing stores, clothing stores. The main modes of transport seem to be Buses and trains. For leisure, the neighbourhoods are set up to have lots of parks, golf courses, zoo, gyms and Historic sites. Overall, the city of London offers a multicultural, diverse and certainly an entertaining experience.

Paris is relatively small in size geographically. It has a wide variety of cusines and eateries including French, Thai, Cambodian, Asian, Chinese etc. There are a lot of hangout spots including many Restaurants and Bars. Paris has a lot of Bistro's. Different means of public transport in Paris which includes buses, bikes, boats or ferries. For leisure and sight seeing, there are a lot of Plazas, Trails, Parks, Historic sites, clothing shops, Art galleries and Museums. Overall, Paris seems like the relaxing vacation spot with a mix of lakes, historic spots and a wide variety of cusines to try out.

6. Conclusion

The purpose of this project was to explore the cities of London and Paris and see how attractive it is to potential tourists and migrants. We explored both the cities based on their postal codes and then extrapolated the common venues present in each of the neighbourhoods finally concluding with clustering similar neighbourhoods together.

We could see that each of the neighbourhoods in both the cities have a wide variety of experiences to offer which is unique in it's own way. The cultural diversity is quite evident which also gives the feeling of a sense of inclusion.

Both Paris and London seem to offer a vacation stay or a romantic getaway with a lot of places to explore, beautiful landscapes, amazing food and a wide variety of culture. Overall, it's upto the stakeholders to decide which experience they would prefer more and which would more to their liking.