A Tale of Two Cities

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

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 model also helps people make decisions if they are thinking about migrating to London or Paris or even if they wish 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.

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 can find out the neighbourhoods, boroughs, venues and their most popular venue categories.

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 to London.

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

This Wikipedia page lacks information about geographical locations. To solve this problem, we use *ArcGIS API*.

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 geographical locations of the neighbourhoods of London. Adding the following columns to our initial data set prepares our data.

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

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 Neighborhoods 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 Neighborhoods.

Foursquare API Data

We will need data about different venues in different neighbourhoods of that specific borough. To gain that information, we will use “Foursquare” location 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 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 Neighborhood
2. *Neighbourhood Latitude*: Latitude of the Neighborhood
3. *Neighbourhood Longitude*: Longitude of the Neighborhood
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.

Methodology

We will be creating our model with the help of Python, so we start by importing all the required packages. The code is available on GitHub to follow along.

```
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 K Means machine learning model.

The approach taken here is to explore each of the cities individually, plot the map to show the considered neighbourhoods 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.

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, using pandas, we scrape the List of areas of London Wikipedia page to take the 2nd table:

```
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
```

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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
...	...	...	...	...	...	...
528	Woolwich	Greenwich	LONDON	SE18	020	TQ435795
529	Worcester Park	Sutton, Kingston upon Thames	WORCESTER PARK	KT4	020	TQ225655
530	Wormwood Scrubs	Hammersmith and Fulham	LONDON	W12	020	TQ225815
531	Yeading	Hillingdon	HAYES	UB4	020	TQ115825
532	Yiewsley	Hillingdon	WEST DRAYTON	UB7	020	TQ063804

Data for London scrapped from the Wikipedia page.

To collect data for Paris, we download the JSON file containing 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	21e809b1d4480333c8b6fe7addd8f3b06f343e2c	{'code_comm': '003', 'nom_dept': 'VAL-DE-MARNE...	{'type': 'Point', 'coordinates': [2.3335102498...	2016-09-21T00:29:06.175+02:00
1	correspondances-code-insee-code-postal	c38925e974a8875071da3eb1391a6935d9c97e07	{'code_comm': '430', 'nom_dept': 'SEINE-ET-MAR...	{'type': 'Point', 'coordinates': [2.7879422114...	2016-09-21T00:29:06.175+02:00
2	correspondances-code-insee-code-postal	7c0aa8ba7a7b4320a9cf5abf12288eb76e3eead8	{'code_comm': '412', 'nom_dept': 'SEINE-ET-MAR...	{'type': 'Point', 'coordinates': [2.5107818983...	2016-09-21T00:29:06.175+02:00
3	correspondances-code-insee-code-postal	b123405b4d069c33725418aab20ca0b741f8a5d8	{'code_comm': '598', 'nom_dept': 'VAL-D'OISE',...	{'type': 'Point', 'coordinates': [2.3004997834...	2016-09-21T00:29:06.175+02:00
4	correspondances-code-insee-code-postal	33dea89ab43606076200134a51f2b9d2d7d62256	{'code_comm': '040', 'nom_dept': 'SEINE-ET-MAR...	{'type': 'Point', 'coordinates': [2.5699190953...	2016-09-21T00:29:06.175+02:00

JSON data containing postal codes of France

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()
```

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
']]
```

Feature Engineering

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

```
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
...	...	...	...	...	...
523	Redbridge	LONDON	IG8, E18	51.58977	0.03052
524	Redbridge, Waltham Forest	LONDON, WOODFORD GREEN	IG8	51.50642	-0.12721
527	Barnet	LONDON	N12	51.61592	-0.17674
528	Greenwich	LONDON	SE18	51.48207	0.07143
530	Hammersmith and Fulham	LONDON	W12	51.50645	-0.23691

The resulting feature engineered London Dataset

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 from 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	75010	PARIS-10E-ARRONDISSEMENT	PARIS	48.876029	2.361113
1	75016	PARIS-16E-ARRONDISSEMENT	PARIS	48.860399	2.262100
2	75009	PARIS-9E-ARRONDISSEMENT	PARIS	48.876896	2.337460
3	75015	PARIS-15E-ARRONDISSEMENT	PARIS	48.840155	2.293559
4	75002	PARIS-2E-ARRONDISSEMENT	PARIS	48.867903	2.344107
5	75011	PARIS-11E-ARRONDISSEMENT	PARIS	48.859415	2.378741
6	75005	PARIS-5E-ARRONDISSEMENT	PARIS	48.844509	2.349859
7	75019	PARIS-19E-ARRONDISSEMENT	PARIS	48.886869	2.384694
8	75020	PARIS-20E-ARRONDISSEMENT	PARIS	48.863187	2.400820
9	75003	PARIS-3E-ARRONDISSEMENT	PARIS	48.863054	2.359361
10	75006	PARIS-6E-ARRONDISSEMENT	PARIS	48.848968	2.332671
11	75018	PARIS-18E-ARRONDISSEMENT	PARIS	48.892735	2.348712
12	75008	PARIS-8E-ARRONDISSEMENT	PARIS	48.872527	2.312583
13	75013	PARIS-13E-ARRONDISSEMENT	PARIS	48.828718	2.362468
14	75012	PARIS-12E-ARRONDISSEMENT	PARIS	48.835156	2.419807
15	75007	PARIS-7E-ARRONDISSEMENT	PARIS	48.856083	2.312439

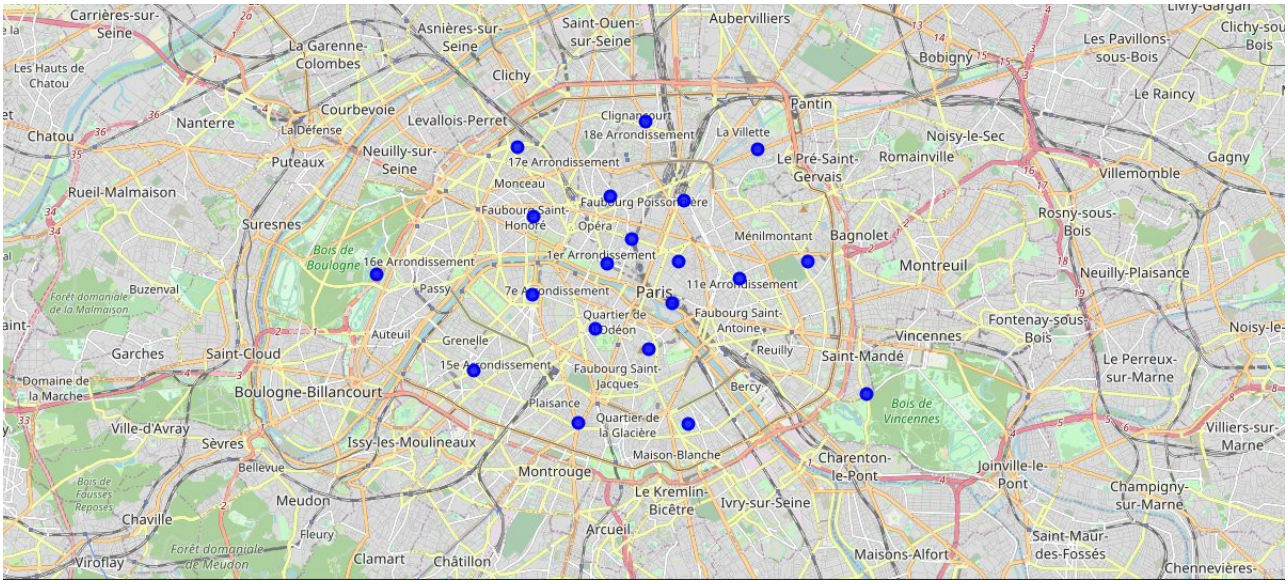
Resulting Feature engineered dataset of Paris

Note: Both the datasets have been properly processed and formatted. Since the same steps are applied to both the datasets of London and Paris, we will be discussing the code for only the London dataset for simplicity.

Visualizing the Neighborhoods 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.

Map of London showing the neighborhoods



Map of Paris showing the neighborhoods

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 500 m 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={}&ll={},{}&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)
```

	Neighbourhood	Neighbourhood Latitude	Neighbourhood Longitude	Venue	Venue Category
0	Bexley, Greenwich	51.49245	0.12127	Sainsbury's	Supermarket
1	Bexley, Greenwich	51.49245	0.12127	Lesnes Abbey	Historic Site
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

Data collected using Foursquare API

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 data type 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	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletics & Sports
0	Barnet	0.0	0.0	0.0	0.001887	0.0	0.0	0.0	0.007547	0.0	0.0	0.0	0.020755	0.0
1	Barnet, Brent, Camden	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0
2	Bexley	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0
3	Bexley, Greenwich	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0
4	Bexley, Greenwich	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.0

Data with the mean values for each of the Neighborhoods after one-hot encoding

Top Venues in the Neighborhoods

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

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 the 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	Supermarket	Pharmacy	Chinese Restaurant	Turkish Restaurant	Pizza Place
1	Barnet, Brent, Camden	Gym / Fitness Center	Music Venue	Clothing Store	Supermarket	Zoo Exhibit	Film Studio	Event Space	Exhibit	Falafel Restaurant	Farmers Market
2	Bexley	Supermarket	Historic Site	Train Station	Platform	Convenience Store	Coffee Shop	Bus Stop	Golf Course	Construction & Landscaping	Park
3	Bexley, Greenwich	Park	Construction & Landscaping	Sports Club	Bus Stop	Golf Course	Historic Site	Food Service	Convenience Store	Department Store	Cycle Studio
4	Bexley, Greenwich	Supermarket	Platform	Convenience Store	Historic Site	Train Station	Coffee Shop	Zoo Exhibit	Film Studio	Event Space	Exhibit

Top Common venues in each Neighborhood ranked.

Model Building — K Means

Moving on to the most exciting part — **Model Building!** We will be using K Means Clustering Machine learning algorithm to cluster similar neighbourhoods together. There are many different cluster sizes that we can select, we will be going with the number of clusters as 5 to keep it as optimized as possible.

```
# 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 dataframe* with our *neighborhood venues sorted dataframe* to add latitude & longitude for each of the neighbourhoods to prepare it for visualization.

```
london_data = london_merged

london_data =
london_data.join(neighborhoods_venues_sorted_london.set_index('Neig
hbourhood'), 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 M Comr Venu
0	Bexley, Greenwich	LONDON	SE2	51.49245	0.12127	4	Supermarket	Platform	Convenience Store	Historic Site	Train Station	Coffee Shop	Zoo Exhibit	Film Studi
1	Ealing, Hammersmith and Fulham	LONDON	W3, W4	51.51324	-0.26746	1	Grocery Store	Train Station	Breakfast Spot	Park	Indian Restaurant	Deli / Bodega	Fish Market	Exhib
6	City	LONDON	EC3	51.51200	-0.08058	2	Coffee Shop	Italian Restaurant	Hotel	Pub	Gym / Fitness Center	Food Truck	Sandwich Place	Beer
7	Westminster	LONDON	WC2	51.51651	-0.11968	2	Hotel	Coffee Shop	Pub	Sandwich Place	Café	Italian Restaurant	Restaurant	Theat
9	Bromley	LONDON	SE20	51.41009	-0.05683	2	Supermarket	Grocery Store	Convenience Store	Hotel	Fast Food Restaurant	Park	Italian Restaurant	Gym / Fitnes Cente

Labelled Clustered dataset of London

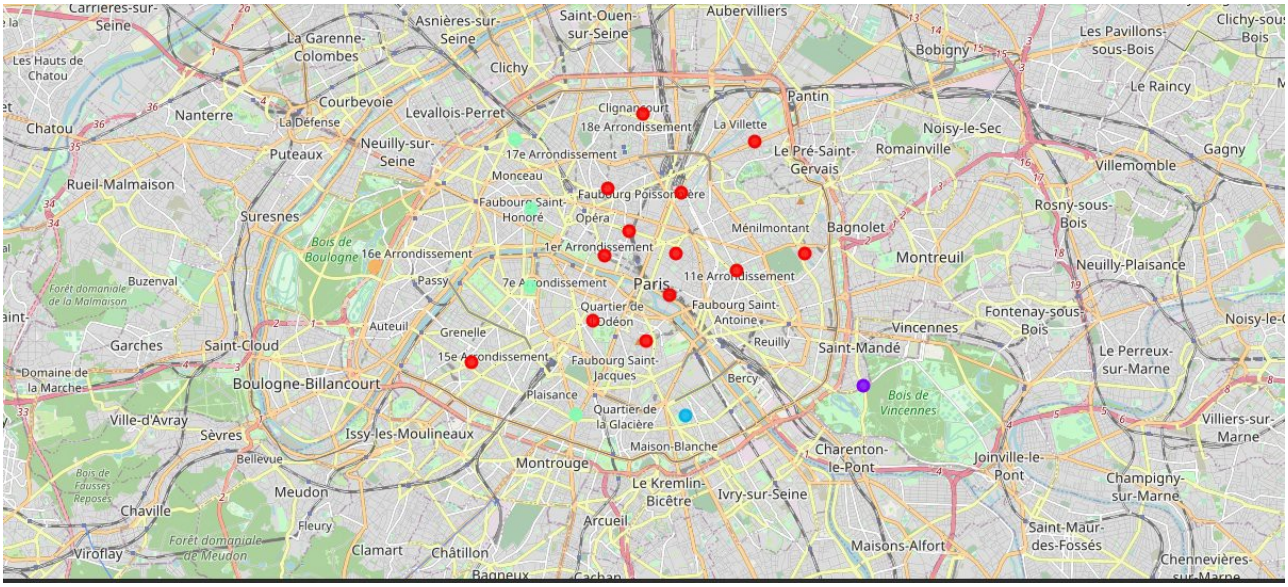
Visualizing the clustered Neighborhoods

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(Not a Number) 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

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]))]]
```

Results and Discussion

The neighbourhoods of London are very multicultural. There are a lot of different cuisines 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 entertaining experience.

Paris is relatively small in size geographically. It has a wide variety of cuisines 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 Bistros. Different means of public transport in Paris which includes buses, bikes, boats or ferries. For leisure and sightseeing, 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 cuisines to try out.

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 its 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 up-to-the stakeholders to decide which experience they would prefer more and which would more to their liking.

The detailed code is available on GitHub. Thanks for reading!

References

1. The Battle of Neighbourhood — My London's Perspective by Dayo John
2. The Battle of neighborhoods! What is the best place where can I start my restaurant business in Paris? by Zakaria BOUZIANE
3. Foursquare API
4. ArcGIS API