London-Paris-compare

Introduction and Business Problem

London and Paris are two of the most ancient city in the world. This project is aim to try to analysis the two cities, more specifically I aimed to analysis how the cities can be separated to several section(cluster) with similar shops and facilities. By doing so, I believe we can have betting understanding of the two cities.

The Reason for choosing London and Paris is because both cities have a lot of data available to the public and make it very easy to collect data for both of the cities.

Data Description

London

I get the data from https://en.wikipedia.org/wiki/List_of_London_boroughs

The dataframe contain data of London consist:

1. Borough : Name of Borough
2. Latitude : Latitude
3. Longitude : Longitude

Paris

I get the data from https://en.wikipedia.org/wiki/Arrondissements_of_Paris and from https://www.data.gouv.fr/fr/datasets/r/e88c6fda-1d09-42a0-a069-606d3259114e.

I preprocess the data into a cvs file already.

The dataframe contain data of Paris consist:

1. District : Name of District
2. Latitude : Latitude
3. Longitude : Longitude

Foursquare API Data

I will get data from foursquare API to analysis each distrinct in London and in Paris

In [1]:
```
import requests
import pandas as pd
import numpy as np
import urllib.request
from geopy.geocoders import Nominatim
import folium
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import matplotlib.colors as colors
from sklearn.cluster import KMeans
```

In [2]:
```
CLIENT_ID = '32MVT5TKDCXDFDDR0DUTZTUKTE1J02ZOCSTRSFZ4V3RTV5VN' # your Foursquare ID
CLIENT_SECRET = 'POM4TH0RJ3U0NAEHV4VLSNGS2RGS2Q0BMWYXPF10AVXANF1E' # your Foursquare Secret
VERSION = '20180605' # Foursquare API version
LIMIT = 100 # A default Foursquare API limit value
```

In [3]:
```
## URL to extract City neighbourhood information
urlL = "https://en.wikipedia.org/wiki/List_of_London_boroughs"
pageLondon = urllib.request.urlopen(urlL)
wikitablesL = pd.read_html(urlL,  attrs={"class":"wikitable"})
dfL0 = wikitablesL[0]
dfL1 = wikitablesL[1]
```

In [4]:
```
dfL0=dfL0.rename(columns={'Population (2019 est)[1]':'Population(2019 est)',}).drop(columns=['Nr. in map'])
dfL1=dfL1.drop(columns=['Nr. inmap'])
dfl=pd.concat([dfL0,dfL1]).reset_index().drop(columns=['index'])
dfl=dfl.drop(columns=['Inner','Status','Local authority','Political control','Headquarters','Area (sq mi)','
dfl['Co-ordinates'][0]='51.5607°N 0.1557°E'
lat_list=[51.5607]
log_list=[0.1557]
for i in range(1,dfl.shape[0]):
    index=dfl['Co-ordinates'][i].find('/')
    dfl['Co-ordinates'][i]=dfl['Co-ordinates'][i][index+1:]
    coord=dfl['Co-ordinates'][i].split(' ')
    lat=float(coord[1][:8].encode('utf-8').decode('utf-8-sig'))
    if coord[2][-1]=='W':
        flag=-1
    else:
        flag=1
    log=flag*float(coord[2][:6])
    lat_list.append(lat)
    log_list.append(log)
dfl['Latitude']=lat_list
dfl['Longitude']=log_list
dfl.drop(columns=['Co-ordinates'],inplace=True)
dfl.loc[0,'Borough']='Barking and Dagenham'
dfl.loc[9,'Borough']='Greenwich'
dfl.loc[11,'Borough']='Hammersmith and Fulham'
dfl.head()
```

Out[4]:

	Borough	Latitude	Longitude
0	Barking and Dagenham	51.5607	0.1557
1	Barnet	51.6252	-0.1517
2	Bexley	51.4549	0.1505
3	Brent	51.5588	-0.2817
4	Bromley	51.4039	0.0198

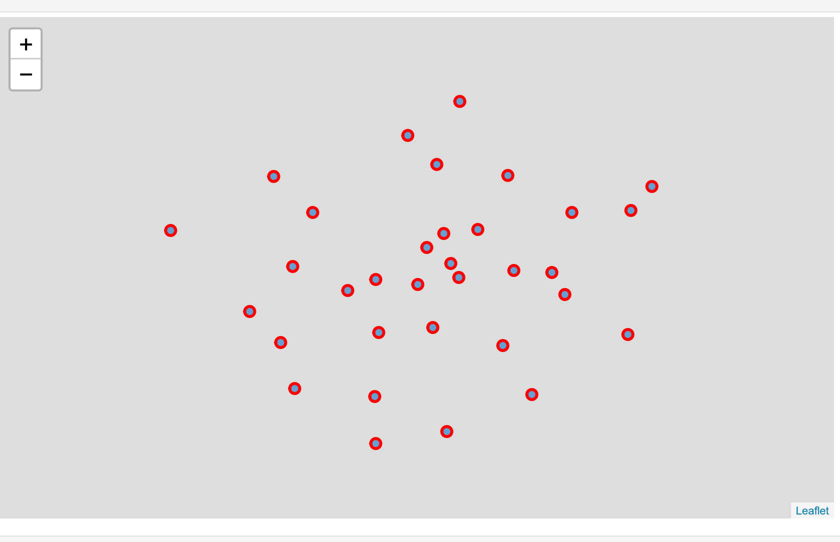
In [5]:
```
dfp=pd.read_csv(R"C:\Users\lautszchun\Desktop\projects_and_resources\coursera-data-science\London-Paris-camp
dfp.head()
```

Out[5]:

	postal_code	district	nom_dept	Latitude	Longitude
0	75001	Louvre	PARIS	48.862630	2.336293
1	75002	Bourse	PARIS	48.867903	2.344107
2	75003	Temple	PARIS	48.863054	2.359361
3	75004	Hotel-de-Ville	PARIS	48.854228	2.357362
4	75005	Pantheon	PARIS	48.844509	2.349859

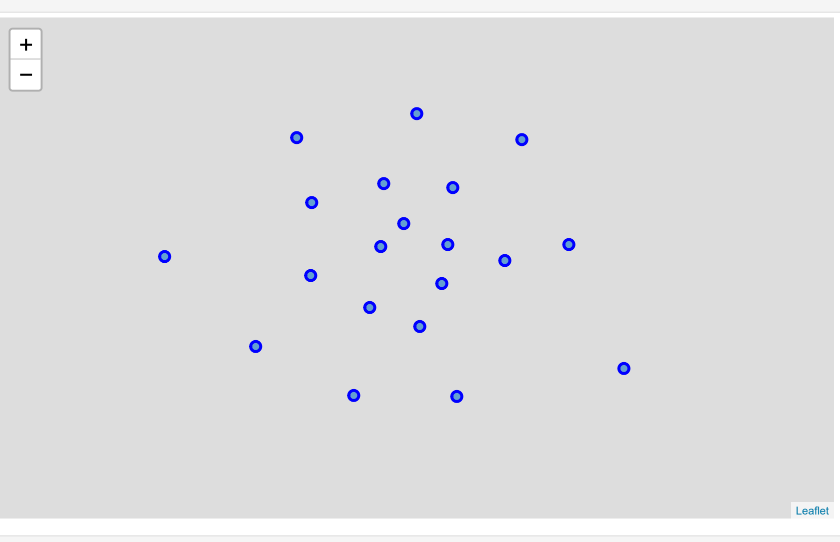
In [6]:
```
address = 'London'

geolocator = Nominatim(user_agent="ny_explorer")
location = geolocator.geocode(address)
london_latitude = location.latitude
london_longitude = location.longitude

map_london = folium.Map(location=[london_latitude, london_longitude], zoom_start=10)

for lat, lng, borough in zip(dfl['Latitude'],dfl['Longitude'],dfl['Borough']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_london)

map_london
```

Out[6]:



In [7]:
```
address = 'Paris'

geolocator = Nominatim(user_agent="ny_explorer")
location = geolocator.geocode(address)
paris_latitude = location.latitude
paris_longitude = location.longitude

map_paris = folium.Map(location=[paris_latitude, paris_longitude], zoom_start=12)

for lat, lng, borough in zip(dfp['Latitude'],dfp['Longitude'],dfp['district']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_paris)

map_paris
```

Out[7]:



In [8]:
```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={},{}&rad
            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']['location']['lat'],
            v['venue']['location']['lng'],
            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 = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

In [9]:
```
London_venues=getNearbyVenues(dfl['Borough'],dfl['Latitude'],dfl['Longitude'])
```

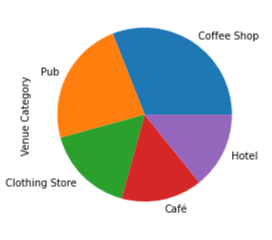
In [10]:
```
Paris_venues = getNearbyVenues(dfp['district'],dfp['Latitude'],dfp['Longitude'])
```

In [20]:
```
# one hot encoding
london_onehot = pd.get_dummies(London_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
london_onehot['Neighborhood'] = London_venues['Neighborhood']

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

# one hot encoding
paris_onehot = pd.get_dummies(Paris_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
paris_onehot['Neighborhood'] = Paris_venues['Neighborhood']

# move neighborhood column to the first column
fixed_columns = [paris_onehot.columns[-1]] + list(paris_onehot.columns[:-1])
paris_onehot = paris_onehot[fixed_columns]
```

Showing the top 5 venue in London

In [21]:
```
ld_venue_count=London_venues['Venue Category'].value_counts()
ld_venue_count[:5].plot(kind = 'pie')
```

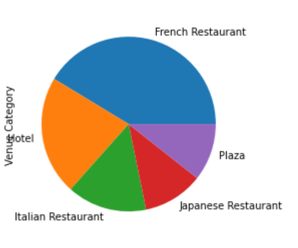
Out[21]: <AxesSubplot:ylabel='Venue Category'>



Showing the top 5 venue in Paris

In [22]:
```
pr_venue_count=Paris_venues['Venue Category'].value_counts()
pr_venue_count[:5].plot(kind = 'pie')
```

Out[22]: <AxesSubplot:ylabel='Venue Category'>



In [23]:
```
london_grouped = london_onehot.groupby('Neighborhood').mean().reset_index()
paris_grouped = paris_onehot.groupby('Neighborhood').mean().reset_index()
```

In [25]:
```
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]
```

In [52]:
```
num_top_venues = 10

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

# create columns according to number of top venues
columns = ['Neighborhood']
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))

# create a new dataframe
london_venues_sorted = pd.DataFrame(columns=columns)
london_venues_sorted['Neighborhood'] = london_grouped['Neighborhood']

for ind in np.arange(london_grouped.shape[0]):
    london_venues_sorted.iloc[ind, 1:] = return_most_common_venues(london_grouped.iloc[ind, :], num_top_venu

columns = ['Neighborhood']
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))

paris_venues_sorted = pd.DataFrame(columns=columns)
paris_venues_sorted['Neighborhood'] = paris_grouped['Neighborhood']

for ind in np.arange(paris_grouped.shape[0]):
    paris_venues_sorted.iloc[ind, 1:] = return_most_common_venues(paris_grouped.iloc[ind, :], num_top_venues
```

In [38]:
```
two_city=pd.concat([london_grouped,paris_grouped],ignore_index=True)
two_city=two_city.fillna(0)
```

In [40]:
```
k=3
london_grouped_clustering = london_grouped.drop('Neighborhood', 1)
london_kmeans = KMeans(n_clusters=k, random_state=0).fit(london_grouped_clustering)

paris_grouped_clustering = paris_grouped.drop('Neighborhood', 1)
paris_kmeans = KMeans(n_clusters=k, random_state=0).fit(paris_grouped_clustering)

two_city_clustering = two_city.drop('Neighborhood',1)
two_city_kmeans=KMeans(n_clusters=k, random_state=0).fit(two_city_clustering)
```

In [46]:
```
two_city_kmeans.labels_[0:33]
```

Out[46]:
```
array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [47]:
```
two_city_kmeans.labels_[34:]
```

Out[47]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2, 2])
```

In [53]:
```
london_venues_sorted.insert(0, 'Cluster Labels', two_city_kmeans.labels_[0:33])
```

In [57]:
```
london_merged = dfl

london_merged = london_merged.join(london_venues_sorted.set_index('Neighborhood'), on='Borough')

london_merged.head()
```

Out[57]:

	Borough	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 Most Common Venue
0	Barking and Dagenham	51.5607	0.1557	0	Gym / Fitness Center	Pool	Bus Station	Supermarket	Park	Martial Arts School	Golf Course	Outdoors & Recreation
1	Barnet	51.6252	-0.1517	1	Café	Bus Stop	Business Service	African Restaurant	Outlet Store	Nightclub	Okonomiyaki Restaurant	Optical Shop
2	Bexley	51.4549	0.1505	0	Clothing Store	Pub	Coffee Shop	Fast Food Restaurant	Pharmacy	Supermarket	Shopping Mall	Furniture / Home Store
3	Brent	51.5588	-0.2817	0	Hotel	Coffee Shop	Bar	Clothing Store	Sporting Goods Shop	Grocery Store	Indian Restaurant	Burger Joint
4	Bromley	51.4039	0.0198	0	Clothing Store	Coffee Shop	Bar	Gym / Fitness Center	Burger Joint	Pizza Place	Donut Shop	Supermarket

In [59]:
```
paris_venues_sorted.insert(0, 'Cluster Labels', two_city_kmeans.labels_[33:])

paris_merged = dfp

paris_merged = paris_merged.join(paris_venues_sorted.set_index('Neighborhood'), on='district')

paris_merged.head()
```

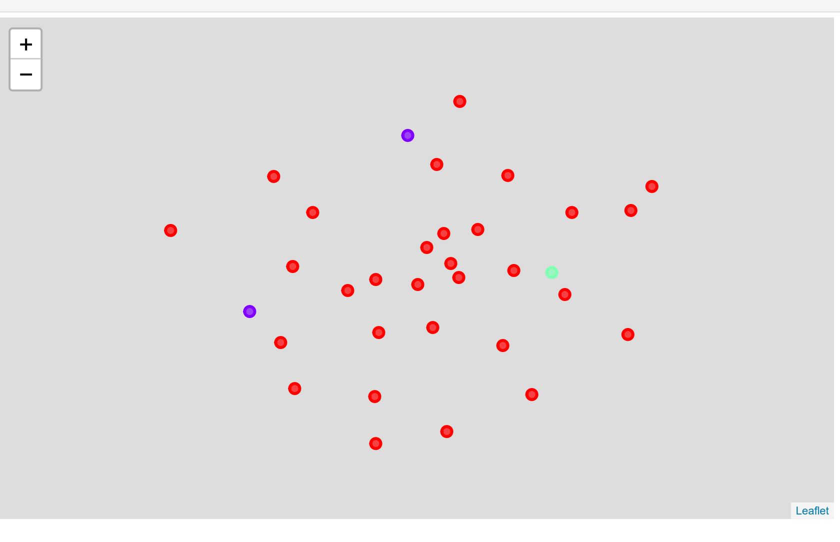
Out[59]:

	postal_code	district	nom_dept	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 Co
0	75001	Louvre	PARIS	48.862630	2.336293	2	French Restaurant	Japanese Restaurant	Hotel	Plaza	Italian Restaurant	Art Museum	Rest
1	75002	Bourse	PARIS	48.867903	2.344107	2	French Restaurant	Cocktail Bar	Wine Bar	Bakery	Italian Restaurant	Plaza	
2	75003	Temple	PARIS	48.863054	2.359361	2	French Restaurant	Japanese Restaurant	Coffee Shop	Art Gallery	Gourmet Shop	Italian Restaurant	W
3	75004	Hotel-de-Ville	PARIS	48.854228	2.357362	2	French Restaurant	Ice Cream Shop	Clothing Store	Hotel	Italian Restaurant	Plaza	(
4	75005	Pantheon	PARIS	48.844509	2.349859	2	French Restaurant	Hotel	Italian Restaurant	Plaza	Bar	Bakery	

Showing the Clusters of London

In [60]:
```
# create map
london_map_clusters = folium.Map(location=[london_latitude, london_longitude], zoom_start=10)

# set color scheme for the clusters
x = np.arange(k)
ys = [i + x + (i*x)**2 for i in range(k)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(london_merged['Latitude'], london_merged['Longitude'], london_merged['Boro
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(london_map_clusters)

london_map_clusters
```

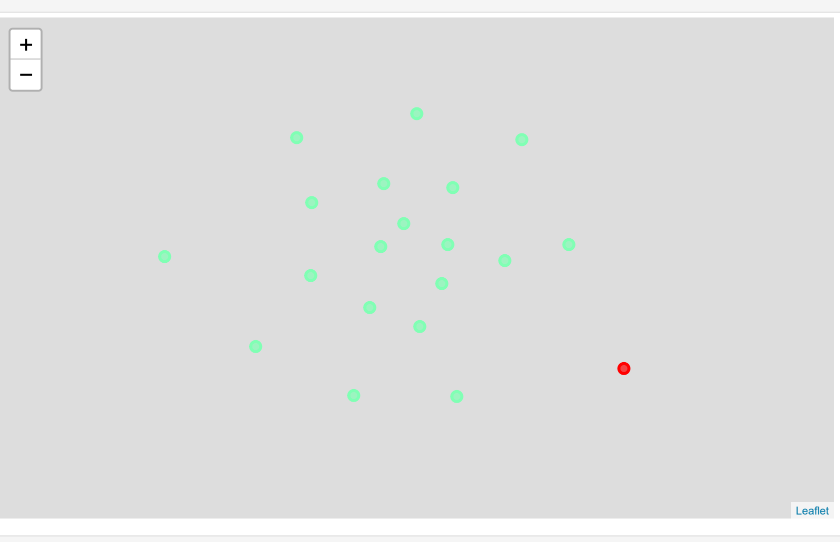
Out[60]:



Showing the Clusters of Paris

In [61]:
```
# create map
paris_map_clusters = folium.Map(location=[paris_latitude, paris_longitude], zoom_start=12)

# set color scheme for the clusters
x = np.arange(k)
ys = [i + x + (i*x)**2 for i in range(k)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(paris_merged['Latitude'], paris_merged['Longitude'], paris_merged['distric
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(paris_map_clusters)

paris_map_clusters
```

Out[61]:



In [62]:
```
(london_merged.loc[london_merged['Cluster Labels'] == 0])
```

Out[62]:

	Borough	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 Mo Comm Ven
0	Barking and Dagenham	51.5607	0.1557	0	Gym / Fitness Center	Pool	Bus Station	Supermarket	Park	Martial Arts School	Golf Cour
2	Bexley	51.4549	0.1505	0	Clothing Store	Pub	Coffee Shop	Fast Food Restaurant	Pharmacy	Supermarket	Shoppi M
3	Brent	51.5588	-0.2817	0	Hotel	Coffee Shop	Bar	Clothing Store	Sporting Goods Shop	Grocery Store	Indi Restaura
4	Bromley	51.4039	0.0198	0	Clothing Store	Coffee Shop	Bar	Gym / Fitness Center	Burger Joint	Pizza Place	Donut Sh
5	Camden	51.5290	-0.1255	0	Coffee Shop	Hotel	Café	Pub	Breakfast Spot	Train Station	De Bode
6	Croydon	51.3714	-0.0977	0	Pub	Coffee Shop	Korean Restaurant	Asian Restaurant	Portuguese Restaurant	Mediterranean Restaurant	Clothi Sto
7	Ealing	51.5130	-0.3089	0	Coffee Shop	Clothing Store	Park	Pub	Bakery	Italian Restaurant	Pizza Pla
8	Enfield	51.6538	-0.0799	0	Coffee Shop	Clothing Store	Pub	Supermarket	Department Store	Pharmacy	Booksto
9	Greenwich	51.4892	0.0648	0	Coffee Shop	Fast Food Restaurant	Pub	Clothing Store	Supermarket	Grocery Store	Ho
10	Hackney	51.5450	-0.0553	0	Pub	Coffee Shop	Café	Brewery	Cocktail Bar	Bakery	Clothi Sto
11	Hammersmith and Fulham	51.4927	-0.2339	0	Pub	Café	Indian Restaurant	Coffee Shop	Italian Restaurant	Gastropub	Chine Restaura
12	Haringey	51.6000	-0.1119	0	Park	Turkish Restaurant	Bakery	Bus Station	Movie Theater	Supermarket	Groce Sto
13	Harrow	51.5898	-0.3346	0	Indian Restaurant	Train Station	Grocery Store	Coffee Shop	Supermarket	Thai Restaurant	Indie Mov Theat
14	Havering	51.5812	0.1837	0	Clothing Store	Coffee Shop	Shopping Mall	Café	Fast Food Restaurant	Pub	Supermark
15	Hillingdon	51.5441	-0.4760	0	Coffee Shop	Clothing Store	Fast Food Restaurant	Pub	Pharmacy	Italian Restaurant	Toy / Gar Sto
17	Islington	51.5416	-0.1022	0	Pub	Mediterranean Restaurant	Cocktail Bar	Boutique	Ice Cream Shop	Burger Joint	Bake
18	Kensington and Chelsea	51.5020	-0.1947	0	Juice Bar	Café	Bakery	Hotel	Clothing Store	Restaurant	Fren Restaura
19	Kingston upon Thames	51.4085	-0.3064	0	Coffee Shop	Café	Clothing Store	Pub	Italian Restaurant	Sushi Restaurant	Bake
20	Lambeth	51.4607	-0.1163	0	Caribbean Restaurant	Coffee Shop	Market	Pub	Gym / Fitness Center	Pizza Place	Ca
21	Lewisham	51.4452	-0.0209	0	Supermarket	Grocery Store	Coffee Shop	Platform	Bus Stop	Train Station	Itali Restaura
22	Merton	51.4014	-0.1958	0	Café	Diner	Supermarket	Pizza Place	Indian Restaurant	Coffee Shop	Burger Jo
24	Redbridge	51.5590	0.0741	0	Clothing Store	Fast Food Restaurant	Supermarket	Grocery Store	Coffee Shop	Hotel	Bake
25	Richmond upon Thames	51.4479	-0.3260	0	Coffee Shop	Pub	Italian Restaurant	Indian Restaurant	Grocery Store	Pharmacy	Steakhou
26	Southwark	51.5035	-0.0804	0	Coffee Shop	Pub	Restaurant	Bar	Scenic Lookout	Cocktail Bar	Fren Restaura
27	Sutton	51.3618	-0.1945	0	Café	Clothing Store	Coffee Shop	Pub	Pizza Place	Bar	Itali Restaura
28	Tower Hamlets	51.5099	-0.0059	0	Sandwich Place	Italian Restaurant	Coffee Shop	Hotel	Chinese Restaurant	Boat or Ferry	Gyn Fitne Cent
29	Waltham Forest	51.5908	-0.0134	0	Pub	Social Club	Vegetarian / Vegan Restaurant	Gym / Fitness Center	Beer Store	Coffee Shop	Concert H
30	Wandsworth	51.4567	-0.1910	0	Pub	Coffee Shop	Clothing Store	Indian Restaurant	Supermarket	Asian Restaurant	Optic Sh
31	Westminster	51.4973	-0.1372	0	Hotel	Coffee Shop	Theater	Pub	Sandwich Place	Sushi Restaurant	Itali Restaura
32	City of London	51.5155	-0.0922	0	Coffee Shop	Wine Bar	Clothing Store	Italian Restaurant	Steakhouse	Seafood Restaurant	Art Galle

In [63]:
```
(london_merged.loc[london_merged['Cluster Labels'] == 1])
```

Out[63]:

	Borough	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 Most Common Venue	9th Cor
1	Barnet	51.6252	-0.1517	1	Café	Bus Stop	Business Service	African Restaurant	Outlet Store	Nightclub	Okonomiyaki Restaurant	Optical Shop	O G
16	Hounslow	51.4746	-0.3680	1	Bed & Breakfast	Café	Metro Station	Park	Outlet Store	New American Restaurant	Nightclub	Okonomiyaki Restaurant	C

In [64]:
```
(london_merged.loc[london_merged['Cluster Labels'] == 2])
```

Out[64]:

	Borough	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 Most Common Venue	9th Most Common Venue
23	Newham	51.5077	0.0469	2	Hotel	Airport Service	Sandwich Place	Currency Exchange	Chinese Restaurant	Airport	Light Rail Station	Pharmacy	Rafting

In [65]:
```
paris_merged.loc[paris_merged['Cluster Labels'] == 0]
```

Out[65]:

	postal_code	district	nom_dept	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 Co
11	75012	Reuilly	PARIS	48.835156	2.419807	0	Zoo Exhibit	Zoo	Supermarket	Monument / Landmark	Bistro	Pedestrian Plaza	Am Rest

In [66]:
```
paris_merged.loc[paris_merged['Cluster Labels'] == 1]
```

Out[66]:

postal_code	district	nom_dept	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	8 C

In [67]:
```
paris_merged.loc[paris_merged['Cluster Labels'] == 2]
```

Out[67]:

	postal_code	district	nom_dept	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 Mos Commo Venu
0	75001	Louvre	PARIS	48.862630	2.336293	2	French Restaurant	Japanese Restaurant	Hotel	Plaza	Italian Restaurant	A Museu
1	75002	Bourse	PARIS	48.867903	2.344107	2	French Restaurant	Cocktail Bar	Wine Bar	Bakery	Italian Restaurant	Plaz
2	75003	Temple	PARIS	48.863054	2.359361	2	French Restaurant	Japanese Restaurant	Coffee Shop	Art Gallery	Gourmet Shop	Italia Restaurant
3	75004	Hotel-de-Ville	PARIS	48.854228	2.357362	2	French Restaurant	Ice Cream Shop	Clothing Store	Hotel	Italian Restaurant	Plaz
4	75005	Pantheon	PARIS	48.844509	2.349859	2	French Restaurant	Hotel	Italian Restaurant	Plaza	Bar	Baker
5	75006	Luxembourg	PARIS	48.848968	2.332671	2	Chocolate Shop	French Restaurant	Bakery	Restaurant	Pastry Shop	Fountai
6	75007	Palais-Bourbon	PARIS	48.856083	2.312439	2	Hotel	French Restaurant	Italian Restaurant	Café	Plaza	Bistr
7	75008	Elysse	PARIS	48.872527	2.312583	2	French Restaurant	Hotel	Spa	Art Gallery	Corsican Restaurant	Italia Restaurant
8	75009	Opera	PARIS	48.876896	2.337460	2	French Restaurant	Hotel	Bistro	Japanese Restaurant	Cocktail Bar	Restaurar
9	75010	Entrepot	PARIS	48.876029	2.361113	2	French Restaurant	Bistro	Hotel	Café	Coffee Shop	India Restaurant
10	75011	Popincourt	PARIS	48.859415	2.378741	2	Restaurant	Café	Italian Restaurant	French Restaurant	Bakery	Asia Restaurant
12	75013	Gobelins	PARIS	48.828718	2.362468	2	Vietnamese Restaurant	Asian Restaurant	Chinese Restaurant	French Restaurant	Thai Restaurant	Juice Ba
13	75014	Observatoire	PARIS	48.828993	2.327101	2	French Restaurant	Hotel	Bakery	Italian Restaurant	Brasserie	Food & Drin Sho
14	75015	Vaugirard	PARIS	48.840155	2.293559	2	Italian Restaurant	Hotel	French Restaurant	Thai Restaurant	Japanese Restaurant	India Restaurant
15	75016	Passy	PARIS	48.860399	2.262100	2	Lake	Plaza	Trail	French Restaurant	Bus Station	A Museu
16	75017	Batignolles-Monceau	PARIS	48.887337	2.307486	2	French Restaurant	Hotel	Italian Restaurant	Japanese Restaurant	Bakery	Caf
17	75018	Butte-Montmartre	PARIS	48.892735	2.348712	2	Bar	French Restaurant	Italian Restaurant	Plaza	Pizza Place	Restaurar
18	75019	Buttes-Chaumont	PARIS	48.886869	2.384694	2	French Restaurant	Bar	Bistro	Hotel	Sushi Restaurant	Seafoo Restaurant
19	75020	Menilmontant	PARIS	48.863187	2.400820	2	Bakery	Plaza	Bistro	Japanese Restaurant	French Restaurant	Italia Restaurant

Final Conculsion

In the two cities, they are not quite similar. But Newham in London is quite the same with the majority of Paris. And Reuilly in Paris is quite the same with the majority of London. Barnet and Hounslow in London is the outliers among the two cities.