# Capstone Project - Applied Data Science

## 1. Introduction/Business Problem

Currently Brexit is affecting the City of London and many financial institutions are moving to other cities in Europe (a popular one is Paris) in order to continue servicing the European customers without interruptions and amendments. As a result many financial institutions are asking their employees to move to these cities. Let's explore which areas of these cities are similar to the areas of London, so the employers can give an informed advice to the employees.

The goal of these project is to examine which areas of the other two cities are similar to areas of London. Based on this clustering the employees will be able either to choose the most similar area to the one they live now, or have an informed comparison while choosing the area of their new home.

The approach we will follow is to cluster the areas of each city based on the venue types they are near. By clustering the areas of London we can identify the common features of each area. To do this we will utilise the k-means clustering algorithm. Once we create the main clusters we will run the algorithm for areas in Paris and classify each area based on the clusters created earlier. Someone can use this results to look for areas during the transition to look for areas similar to the her/his current location.

## 2. Data Requirements and Collection

The data we are going to need are the several districts of London and Paris. We are going to acquire these form the following links:

- London: https://www.milesfaster.co.uk/london-postcodes-list.htm (https://www.milesfaster.co.uk/london-postcodes-list.htm)
- Paris: https://www.annuaire-administration.com/code-postal/region/ile-de-france.html (https://www.annuaire-administration.com/code-postal/region/ile-de-france.html)

Additionally, we will need the data related with the venues in its city. We are going to acquire these by using the Foursquare API as required by the instructions of this project.

Importing Libraries.

In [1]:

```
import requests

import pandas as pd
import numpy as np

from geopy.geocoders import Nominatim
from geopy.extra.rate_limiter import RateLimiter

import matplotlib.cm as cm
import matplotlib.colors as colors

import json
from pandas.io.json import json_normalize

# import k-means from clustering stage
from sklearn.cluster import KMeans
```

In [2]:

```
url='https://www.milesfaster.co.uk/london-postcodes-list.htm'
url
```

Out[2]:

```
'https://www.milesfaster.co.uk/london-postcodes-li
st.htm'
```

In [3]:

```
raw_data=requests.get(url).text
```

We import BeautifulSoup to arrange the data we downloaded as HTML.

In [4]:

```
from bs4 import BeautifulSoup

soup = BeautifulSoup(raw_data,'lxml')
#print(soup.prettify())
```

We use find attribute to find the table in the website.

In [5]:

```
my_table = soup.find('table',{'class':'noborder'})
#my_table
```

We define the columns of our new table which will include the postcodes and district names.

In [6]:

```
headings=('Postcodes','Districts')
postcodes=[]
districts=[]
```

We extract the raw data from the lxml format.

In [7]:

```
for i in range(0,len(my_table.findAll('td'))-1,2):
    if (my_table.findAll('td')[i].text.replace('\n','').strip(
)!=''):
        postcodes.append(my_table.findAll('td')[i].text.replac
e('\n','').strip())
        districts.append(my_table.findAll('td')[i+1].text.repl
ace('\n','').strip())
```

We create a pandas dataframe where we store the postcode and district data for London.

In [8]:

```
data_london={headings[0]:postcodes,headings[1]:districts}
df_ldn=pd.DataFrame(data_london)
df_ldn
```

Out[8]:

| | Postcodes | Districts |
|---|---|---|
| 0 | E1 | Whitechapel, Stepney, Mile End |
| 1 | SE1 | Waterloo, Bermondsey, Southwark, Borough |
| 2 | E1W | Wapping |
| 3 | SE2 | Abbey Wood |
| 4 | E2 | Bethnal Green, Shoreditch |
| ... | ... | ... |
| 116 | NW10 | Willesden, Harlesden, Kensal Green |
| 117 | W12 | Shepherds Bush |
| 118 | NW11 | Golders Green, Hampstead Gdn Suburb |
| 119 | W13 | West Ealing |
| 120 | W14 | West Kensington |

121 rows × 2 columns

We notice that for some Districts there are more than one areas. We expand the table to examine each area separately.

In [9]:

```
headings2=('Postcodes','Areas')
postcodes2=[]
areas=[]
for postcode in df_ldn['Postcodes']:
    for area in df_ldn.loc[df_ldn['Postcodes']==postcode,'Dist
ricts'].item().split(','):
        postcodes2.append(postcode)
        areas.append(area.strip())
data_london={headings2[0]:postcodes2,headings2[1]:areas}
df_ldn2=pd.DataFrame(data_london)
df_ldn2
```

```
/Users/markoslolos/anaconda3/lib/python3.6/site-pa
ckages/ipykernel_launcher.py:5: FutureWarning: `it
em` has been deprecated and will be removed in a f
uture version
  """
```

Out[9]:

| | Postcodes | Areas |
|---|---|---|
| 0 | E1 | Whitechapel |
| 1 | E1 | Stepney |
| 2 | E1 | Mile End |
| 3 | SE1 | Waterloo |
| 4 | SE1 | Bermondsey |
| ... | ... | ... |
| 201 | W12 | Shepherds Bush |
| 202 | NW11 | Golders Green |
| 203 | NW11 | Hampstead Gdn Suburb |
| 204 | W13 | West Ealing |
| 205 | W14 | West Kensington |

206 rows × 2 columns

Let's find now the latitude and longitude of each area. We also update the dataframe with the data from London with the geographical coordinates of each area.

In [10]:

```
latitudes=[]
longitudes=[]
```

Below is the code we created to download the data using Nominatim. However, this function has download restrictions so we saved the data later to have access at any time without the need to call the function every time.

In [11]:

```
#geolocator = Nominatim(user_agent="my-application")
#for i in range(0,len(df_ldn2)):
#    location = geolocator.geocode(df_ldn2['Areas'][i]+' '+df_
ldn2['Postcodes'][i]+' '+'London'+' '+'United Kingdom',timeout
=60)
#    if (location is None):
#        location = geolocator.geocode(df_ldn2['Areas'][i]+' '
+'United Kingdom',timeout=60)
#    if (location is None):
#        location = geolocator.geocode(df_ldn2['Postcodes'][i]
+' '+'London'+' '+'United Kingdom',timeout=60)
#    latitudes.append(location.latitude)
#    longitudes.append(location.longitude)
#df_ldn2['Latitude']=latitudes
#df_ldn2['Longitude']=longitudes
```

We export the dataframe to csv so we don't have to use the Nominatim() service again as it has usage constriants.

In [12]:

```
#df_ldn2.to_csv('###Applied Data Science Capstone/Applied-Data
-Science-Capstone/df_ldn2.csv',index=False)
```

In [13]:

```
df_ldn2=pd.read_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/df_ldn2.csv')
df_ldn2
```

Out[13]:

| | Postcodes | Areas | Latitude | Longitude |
|---|---|---|---|---|
| 0 | E1 | Whitechapel | 51.518623 | -0.062081 |
| 1 | E1 | Stepney | 51.517402 | -0.046219 |
| 2 | E1 | Mile End | 51.525091 | -0.035047 |
| 3 | SE1 | Waterloo | 51.502881 | -0.112090 |
| 4 | SE1 | Bermondsey | 51.497700 | -0.064345 |
| ... | ... | ... | ... | ... |
| 201 | W12 | Shepherds Bush | 51.505314 | -0.222901 |
| 202 | NW11 | Golders Green | 51.571832 | -0.195522 |
| 203 | NW11 | Hampstead Gdn Suburb | 51.580508 | -0.180616 |
| 204 | W13 | West Ealing | 51.510413 | -0.323524 |
| 205 | W14 | West Kensington | 51.490993 | -0.207486 |

206 rows × 4 columns

In [14]:

```
df_ldn2.dtypes
```

Out[14]:

```
Postcodes     object
Areas         object
Latitude     float64
Longitude    float64
dtype: object
```

Create a map of London using Folium library.

In [15]:

```
#!pip install folium
import folium # map rendering library
```

Let's get the coordinates of London to create the London map.

In [16]:

```
address = 'London, United Kingdom'

geolocator = Nominatim(user_agent="my-application")
location = geolocator.geocode(address)
ldn_latitude = location.latitude
ldn_longitude = location.longitude
print('The geograpical coordinate of London are {}, {}.'.forma
t(ldn_latitude, ldn_longitude))
```

```
The geograpical coordinate of London are 51.507321
9, -0.1276474.
```

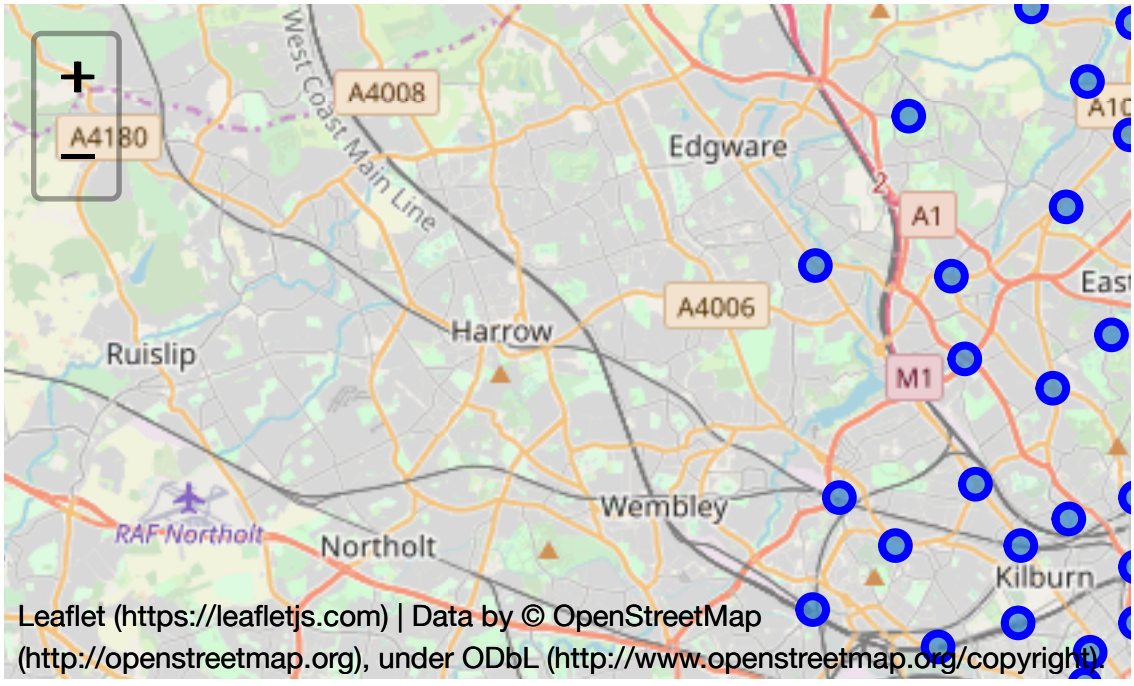
In [17]:

```
# create map of London using latitude and longitude values
map_ldn = folium.Map(location=[ldn_latitude, ldn_longitude], z
oom_start=11)

# add markers to map
for lat, lng, label in zip(df_ldn2['Latitude'], df_ldn2['Longi
tude'], df_ldn2['Areas']):
    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_ldn)

map_ldn
```

Out[17]:




Next, we are going to start utilizing the Foursquare API to explore the neighborhoods and segment them.

In [18]:

```
CLIENT_ID = 'R220KWCO4PCAQ3WTYQPMTC4YUQ4LAEXXYINCG4NZBK54Y3BQ'
# your Foursquare ID
CLIENT_SECRET = 'N14IIZ4HPQNHO3WDKTPCRDH5ON00CTZ4LDHLOCYZ0F1XJ
HZA' # your Foursquare Secret
VERSION = '20180605' # Foursquare API version

print('Your credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: R220KWCO4PCAQ3WTYQPMTC4YUQ4LAEXXYINCG4N
ZBK54Y3BQ
CLIENT_SECRET:N14IIZ4HPQNHO3WDKTPCRDH5ON00CTZ4LDHL
OCYZ0F1XJHZA
```

Let's create a function to find the top 100 venues within 500 metres of an area.

In [19]:

```
def getNearbyVenues(names, latitudes, longitudes, radius=500,
LIMIT=100):

    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?&c
lient_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 ven
ue
```

```
        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 resu
lts])

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

    return(nearby_venues)
```

Now let's write the code to run the above function on each area and create a new dataframe which includes the nearby venues. As before, because the free version of Foursquare API has restrcictions, we download the data using this code and then we save the data to access them many times.

In [20]:

```
#ldn_venues = getNearbyVenues(names=df_ldn2['Areas'],
#                              latitudes=df_ldn2['Latitud
e'],
#                              longitudes=df_ldn2['Longit
ude']
#                             )
#ldn_venues.head()
```

In [21]:

```
#ldn_venues.to_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/ldn_venues.csv',index=False)
ldn_venues=pd.read_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/ldn_venues.csv')
ldn_venues.head()
```

Out[21]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude |
|---|---|---|---|---|---|
| 0 | Whitechapel | 51.518623 | -0.062081 | Tayyabs | 51.517240 |
| 1 | Whitechapel | 51.518623 | -0.062081 | Mouse Tail Coffee Stories | 51.519471 |
| 2 | Whitechapel | 51.518623 | -0.062081 | New Road Hotel | 51.517575 |
| 3 | Whitechapel | 51.518623 | -0.062081 | Needoo Grill | 51.517070 |
| 4 | Whitechapel | 51.518623 | -0.062081 | Zaza's | 51.518066 |

# 3. Methodology

## 3.1 Data Wrangling

# London

Firstly, we will need to transform the categorical variables into numerical variables. We need to do this to facilitate the training of our model.

Let's vectorise neiborhoods with one hot encoding. In other words, let's transform the categorical variables to numerical ones to allow the training of the model.

In [22]:

```
#create dummie variable
ldn_onehot=pd.get_dummies(ldn_venues[['Venue Category']],prefi
x="",prefix_sep="")

#add Neighborhood column
ldn_onehot['Neighborhood'] = ldn_venues['Neighborhood']

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

ldn_onehot.head()
```

Out[22]:

| | Zoo Exhibit | ATM | Accessories Store | Afghan Restaurant | African Restaurant | American Restaurant | A |
|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | |

5 rows × 361 columns

In [23]:

```
ldn_onehot.shape
```

Out[23]:

```
(7745, 361)
```

In [24]:

```
ldn_grouped = ldn_onehot.groupby('Neighborhood').mean().reset_
index()
ldn_grouped
```

Out[24]:

| | Neighborhood | Zoo Exhibit | ATM | Accessories Store | Afghan Restaurant | Afric Restaura |
|---|---|---|---|---|---|---|
| 0 | Abbey Wood | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 1 | Acton | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 2 | Aldgate | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 3 | Alexandra Palace | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 4 | Anerley | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| ... | ... | ... | ... | ... | ... | |
| 197 | Winchmore Hill | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 198 | Wood Green | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 199 | Woodside Park | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 200 | Woolwich | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 201 | Worlds End | 0.0 | 0.0 | 0.0 | 0.0 | 0 |

202 rows × 361 columns

Let's print each neighborhood along with the top 5 most common venues. This is optional as it requires a lot of space on the final report.

In [25]:

```
#num_top_venues = 10

#for hood in ldn_grouped['Neighborhood']:
#    print("----"+hood+"----")
#    temp = ldn_grouped[ldn_grouped['Neighborhood'] == hood].T
.reset_index()
#    temp.columns = ['venue','freq']
#    temp = temp.iloc[1:]
#    temp['freq'] = temp['freq'].astype(float)
#    temp = temp.round({'freq': 2})
#    print(temp.sort_values('freq', ascending=False).reset_ind
ex(drop=True).head(num_top_venues))
#    print('\n')
```

Let's put that into a pandas dataframe to be more organised.

In [26]:

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

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

In [27]:

```
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
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = ldn_grouped['Nei
ghborhood']

for ind in np.arange(ldn_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_co
mmon_venues(ldn_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[27]:

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue |
|---|---|---|---|---|---|
| 0 | Abbey Wood | Campground | Playground | Grocery Store | Yoga Studio |
| 1 | Acton | Pub | Gym / Fitness Center | Brewery | Fast Food Restaurant |
| 2 | Aldgate | Hotel | Coffee Shop | Cocktail Bar | Pub |
| 3 | Alexandra Palace | Indie Theater | Gym / Fitness Center | Event Space | Garden Center |
| 4 | Anerley | Grocery Store | Supermarket | Fast Food Restaurant | Park |

# Paris

In [28]:

```
url2= 'https://www.annuaire-administration.com/code-postal/region/ile-de-france.html'
url2
```

Out[28]:

```
'https://www.annuaire-administration.com/code-postal/region/ile-de-france.html'
```

In [29]:

```
raw_data2=requests.get(url2).text
```

In [30]:

```
soup2 = BeautifulSoup(raw_data2,'lxml')
#print(soup2.prettify())
```

We can see that the wanted table with all the postcodes and the area names is the second table, which apears in the text. (the print statement cover a very long part of the page)

In [31]:

```
my_table2 = soup2.findAll('table')[1]
#my_table2
```

Extracting the raw data.

In [32]:

```
headings=('Postcodes','Districts')
postcodes=[]
districts=[]
```

In [33]:

```
for i in range(8,531):
    for j in range(0,len(soup2.findAll('table')[1].findAll('tr
')[i].findAll('a'))):
            postcodes.append(soup2.findAll('table')[1].findAll
('tr')[i].findAll('strong')[0].text)
            districts.append(soup2.findAll('table')[1].findAll
('tr')[i].findAll('a')[j].text)
```

In [34]:

```
df_prs={headings[0]:postcodes,headings[1]:districts}
df_prs=pd.DataFrame(df_prs)
df_prs
```

Out[34]:

| | Postcodes | Districts |
|---|---|---|
| 0 | 75001 | Paris 1er Arrondissement |
| 1 | 75002 | Paris 2e Arrondissement |
| 2 | 75003 | Paris 3e Arrondissement |
| 3 | 75004 | Paris 4e Arrondissement |
| 4 | 75005 | Paris 5e Arrondissement |
| ... | ... | ... |
| 1295 | 95840 | Villiers-Adam |
| 1296 | 95850 | Jagny-sous-Bois |
| 1297 | 95850 | Mareil-en-France |
| 1298 | 95870 | Bezons |
| 1299 | 95880 | Enghien-les-Bains |

1300 rows × 2 columns

Let's find now the latitude and longitude of each area.(We used this algorithm once to download the data and saved them in a local file for convenience).

In [35]:

```
#latitudes=[]
#longitudes=[]
```

In [36]:

```
#geolocator = Nominatim(user_agent="my-application")
#geocode = RateLimiter(geolocator.geocode, min_delay_seconds=1
)
#for i in range(1208,len(df_prs)):
#    location = geolocator.geocode(df_prs['Districts'][i]+' '+
df_prs['Postcodes'][i]+' '+'Paris'+' '+'France',timeout=60)
#    if (location is None):
#        location = geolocator.geocode(df_prs['Districts'][i]+
' '+'France',timeout=60)
#    if (location is None):
#        location = geolocator.geocode(df_prs['Postcodes'][i]+
' '+'Paris'+' '+'France',timeout=60)
#    latitudes.append(location.latitude)
#    longitudes.append(location.longitude)
#df_prs['Latitude']=latitudes
#df_prs['Longitude']=longitudes
```

We update the dataframe with the geographical coordinates of each area.

In [37]:

```
#df_prs.to_csv('###Applied Data Science Capstone/Applied-Data-
Science-Capstone/df_prs.csv',index=False)
```

In [38]:

```
df_prs=pd.read_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/df_prs.csv')
df_prs
```

Out[38]:

| | Postcodes | Districts | Latitude | Longitude |
|---|---|---|---|---|
| 0 | 75001 | Paris 1er Arrondissement | 48.862158 | 2.337036 |
| 1 | 75002 | Paris 2e Arrondissement | 48.867684 | 2.343126 |
| 2 | 75003 | Paris 3e Arrondissement | 48.862683 | 2.358685 |
| 3 | 75004 | Paris 4e Arrondissement | 48.854156 | 2.356786 |
| 4 | 75005 | Paris 5e Arrondissement | 48.845419 | 2.352582 |
| ... | ... | ... | ... | ... |
| 1295 | 95840 | Villiers-Adam | 49.064253 | 2.234209 |
| 1296 | 95850 | Jagny-sous-Bois | 49.078432 | 2.444024 |
| 1297 | 95850 | Mareil-en-France | 49.068166 | 2.425619 |
| 1298 | 95870 | Bezons | 48.925002 | 2.210549 |
| 1299 | 95880 | Enghien-les-Bains | 48.969973 | 2.306848 |

1300 rows × 4 columns

Let's get the Paris coordinates and create a map for the area of Paris.

In [40]:

```
address = 'Paris, France'

geolocator = Nominatim(user_agent="my-application")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Paris are {}, {}.'.format(latitude, longitude))
```

```
The geograpical coordinate of Paris are 48.8566101
, 2.3514992.
```

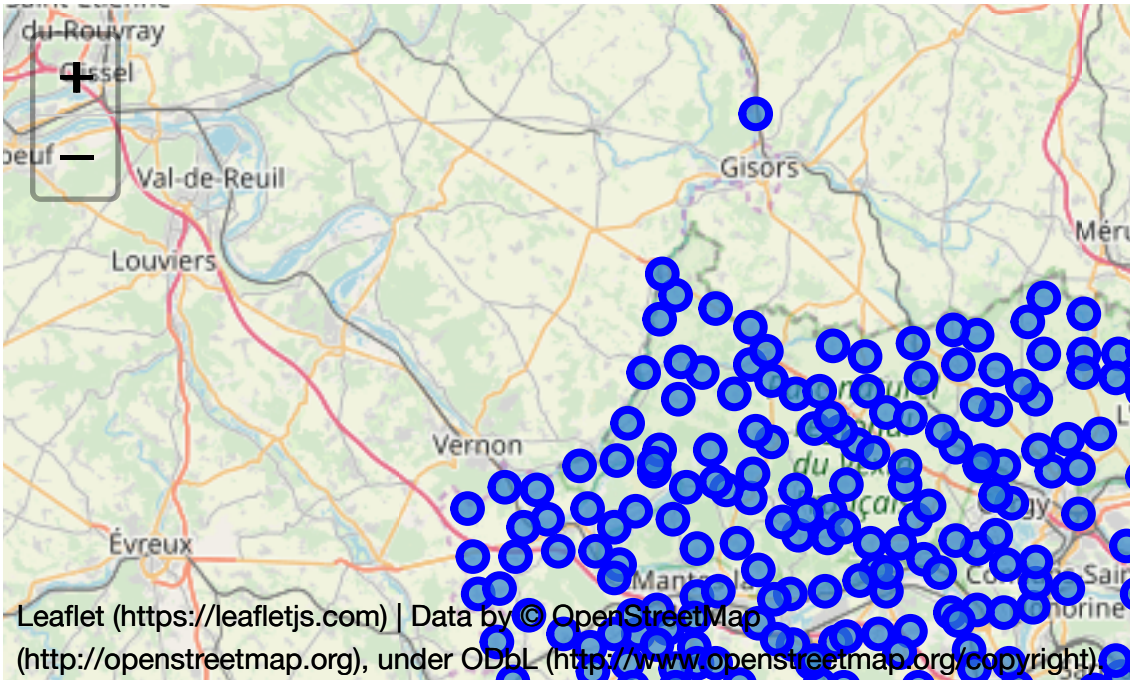
In [41]:

```
# create map of Paris using latitude and longitude values
map_ldn = folium.Map(location=[latitude, longitude], zoom_start=9)

# add markers to map
for lat, lng, label in zip(df_prs['Latitude'], df_prs['Longitude'], df_prs['Districts']):
    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_ldn)

map_ldn
```

Out[41]:




Let's add in the dataframe all the nearby the 100 most popular locations.

In [42]:

```
#prs_venues1 = getNearbyVenues(names=df_prs['Districts'][0:650],
#                                        latitudes=df_prs['Latitude'][0:650],
#                                        longitudes=df_prs['Longitude'][0:650]
#                                       )
#prs_venues1.head()
```

In [43]:

```
#prs_venues1.to_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/prs1_venues.csv',index=False)
prs_venues1=pd.read_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/prs1_venues.csv')
prs_venues1
```

Out[43]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | V Lati |
|---|---|---|---|---|---|
| 0 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Musée du Louvre | 48.86 |
| 1 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Palais Royal | 48.86 |
| 2 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Comédie-Française | 48.86 |
| 3 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Cour Napoléon | 48.86 |
| 4 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Place du Palais Royal | 48.86 |
| ... | ... | ... | ... | ... | |
| 3248 | Porcheville | 48.971703 | 1.776663 | Gymnase Davot | 48.97 |
| 3249 | Porcheville | 48.971703 | 1.776663 | Guilmin Franck | 48.96 |
| 3250 | Chavenay | 48.853387 | 1.987669 | La Caravelle | 48.85 |
| 3251 | Villepreux | 48.831600 | 2.014560 | Pharmacie Nguyen | 48.83 |
| 3252 | Villepreux | 48.831600 | 2.014560 | Le Virginie | 48.83 |

3253 rows × 7 columns

In [44]:

```
#prs_venues2 = getNearbyVenues(names=df_prs['Districts'][650:len(df_prs)],
#                               latitudes=df_prs['Latitude'][650:len(df_prs)],
#                               longitudes=df_prs['Longitude'][650:len(df_prs)]
#                              )
#prs_venues2.head()
```

In [45]:

```
#prs_venues2.to_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/prs2_venues.csv',index=False)
prs_venues2=pd.read_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/prs2_venues.csv')
prs_venues2
```

Out[45]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | La |
|---|---|---|---|---|---|
| 0 | Chevreuse | 48.707249 | 2.048661 | Auberge La Brunoise | 48.7 |
| 1 | Chevreuse | 48.707249 | 2.048661 | Quinthésens | 48.7 |
| 2 | Choisel | 48.687263 | 2.018512 | H B SERVICES | 48.6 |
| 3 | Milon-la-Chapelle | 48.725918 | 2.050415 | Hotel de la Chapelle | 48.7 |
| 4 | Saint-Rémy-lès-Chevreuse | 48.705489 | 2.071109 | RER Saint-Rémy-lès-Chevreuse [B] | 48.7 |
| ... | ... | ... | ... | ... | |
| 3263 | Enghien-les-Bains | 48.969973 | 2.306848 | Grand Hôtel Barrière | 48.9 |
| 3264 | Enghien-les-Bains | 48.969973 | 2.306848 | Hanoï | 48.9 |
| 3265 | Enghien-les-Bains | 48.969973 | 2.306848 | Marché d'Enghien | 48.9 |
| 3266 | Enghien-les-Bains | 48.969973 | 2.306848 | Energie Forme | 48.9 |
| 3267 | Enghien-les-Bains | 48.969973 | 2.306848 | Lac d'Enghien-les-Bains | 48.9 |

3268 rows × 7 columns

In [46]:

```
prs_venues=pd.concat([prs_venues1, prs_venues2], ignore_index=True)
#prs_venues.to_csv('###Applied Data Science Capstone/Applied-Data-Science-Capstone/prs_venues.csv',index=False)
prs_venues
```

Out[46]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | V Lat |
|---|---|---|---|---|---|
| 0 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Musée du Louvre | 48.86 |
| 1 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Palais Royal | 48.86 |
| 2 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Comédie-Française | 48.86 |
| 3 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Cour Napoléon | 48.86 |
| 4 | Paris 1er Arrondissement | 48.862158 | 2.337036 | Place du Palais Royal | 48.86 |
| ... | ... | ... | ... | ... | |
| 6516 | Enghien-les-Bains | 48.969973 | 2.306848 | Grand Hôtel Barrière | 48.96 |
| 6517 | Enghien-les-Bains | 48.969973 | 2.306848 | Hanoï | 48.97 |
| 6518 | Enghien-les-Bains | 48.969973 | 2.306848 | Marché d'Enghien | 48.96 |
| 6519 | Enghien-les-Bains | 48.969973 | 2.306848 | Energie Forme | 48.96 |
| 6520 | Enghien-les-Bains | 48.969973 | 2.306848 | Lac d'Enghien-les-Bains | 48.96 |

6521 rows × 7 columns

Let's vectorise again each location type.

In [47]:

```
#create dummie variable
prs_onehot=pd.get_dummies(prs_venues[['Venue Category']],prefi
x="",prefix_sep="")

#add Neighborhood column
prs_onehot['Neighborhood'] = prs_venues['Neighborhood']

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

#We keep only the common columns that it has with London locat
ion
common_cols=ldn_grouped.columns.intersection(prs_onehot.column
s)
prs_onehot=prs_onehot[common_cols]
prs_onehot.head()
```

Out[47]:

| | Neighborhood | Zoo Exhibit | ATM | Accessories Store | Afghan Restaurant | African Restaurant |
|---|---|---|---|---|---|---|
| 0 | Paris 1er Arrondissement | 0 | 0 | 0 | 0 | 0 |
| 1 | Paris 1er Arrondissement | 0 | 0 | 0 | 0 | 0 |
| 2 | Paris 1er Arrondissement | 0 | 0 | 0 | 0 | 0 |
| 3 | Paris 1er Arrondissement | 0 | 0 | 0 | 0 | 0 |
| 4 | Paris 1er Arrondissement | 0 | 0 | 0 | 0 | 0 |

5 rows × 283 columns

Let's group them now to add the number of the most popular locations

In [48]:

```
prs_grouped = prs_onehot.groupby('Neighborhood').mean().reset_
index()
prs_grouped
```

Out[48]:

| | Neighborhood | Zoo Exhibit | ATM | Accessories Store | Afghan Restaurant | Afric Restaura |
|---|---|---|---|---|---|---|
| 0 | Ablis | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 1 | Ablon-sur-Seine | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 2 | Aigremont | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 3 | Alfortville | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 4 | Amponville | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| ... | ... | ... | ... | ... | ... | |
| 855 | Éragny | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 856 | Étampes | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 857 | Étiolles | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 858 | Étréchy | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| 859 | Ézanville | 0.0 | 0.0 | 0.0 | 0.0 | 0 |

860 rows × 283 columns

Let's put the 5 most common venues of each area into a dataframe.

In [49]:

```
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
prs_neighborhoods_venues_sorted = pd.DataFrame(columns=columns
)
prs_neighborhoods_venues_sorted['Neighborhood'] = prs_grouped[
'Neighborhood']

for ind in np.arange(ldn_grouped.shape[0]):
    prs_neighborhoods_venues_sorted.iloc[ind, 1:] = return_mos
t_common_venues(prs_grouped.iloc[ind, :], num_top_venues)

prs_neighborhoods_venues_sorted.head()
```

Out[49]:

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | |
|---|---|---|---|---|---|---|
| 0 | Ablis | Photography Studio | Kebab Restaurant | Falafel Restaurant | Eastern European Restaurant | E |
| 1 | Ablon-sur-Seine | Pharmacy | Hotel | Athletics & Sports | Train Station | |
| 2 | Aigremont | Construction & Landscaping | Pharmacy | Golf Course | Sporting Goods Shop | ( |
| 3 | Alfortville | Supermarket | Pool | Bakery | Convenience Store | F |
| 4 | Amponville | Yoga Studio | Farm | Electronics Store | Ethiopian Restaurant | |

Let's predict the cluster allocation for each area of Paris based on London clusters.

In [50]:

```
#dropping the neiborhood column
prs_grouped_clustering = prs_grouped.drop('Neighborhood', 1)
```

In [51]:

```
ldn_grouped_clustering = ldn_grouped[common_cols].drop('Neighborhood', 1)
```

## Let's train our model with *k*-means to cluster the neighborhoods of London using only the common location categories.

In [52]:

```
# set number of clusters
kclusters = 5

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0,n_init=20
).fit(ldn_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

Out[52]:

```
array([1, 4, 0, 0, 1, 0, 0, 0, 0, 2], dtype=int32)
```

In [53]:

```
# add clustering labels
neighborhoods_venues_sorted['Cluster Labels']=kmeans.labels_

ldn_merged = df_ldn2

#merging the two tables
ldn_merged = ldn_merged.join(neighborhoods_venues_sorted.set_i
ndex('Neighborhood'), on='Areas')

ldn_merged.head() # check the last columns!
```

Out[53]:

| | Postcodes | Areas | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue |
|---|---|---|---|---|---|---|
| 0 | E1 | Whitechapel | 51.518623 | -0.062081 | Hotel | Pub |
| 1 | E1 | Stepney | 51.517402 | -0.046219 | Park | Fried Chicken Join |
| 2 | E1 | Mile End | 51.525091 | -0.035047 | Pub | Coffee Shop |
| 3 | SE1 | Waterloo | 51.502881 | -0.112090 | Bar | Coffee Shop |
| 4 | SE1 | Bermondsey | 51.497700 | -0.064345 | Coffee Shop | Pub |

Finally, let's visualize the resulting clusters.

In [54]:

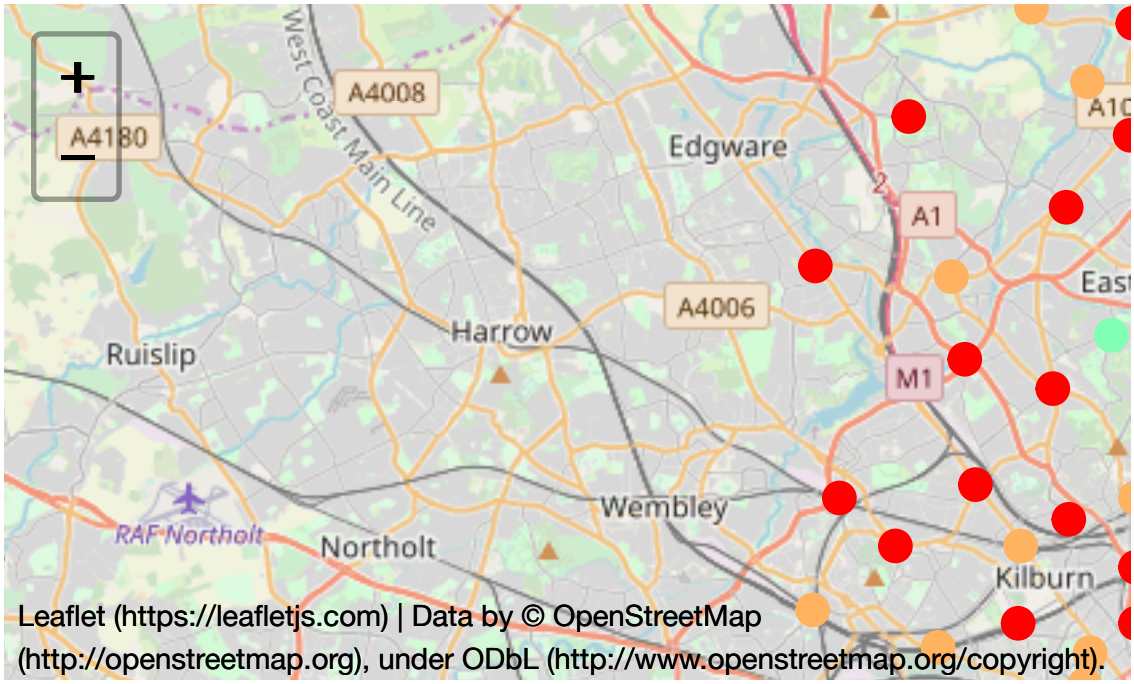
```
# create map
map_clusters = folium.Map(location=[ldn_latitude, ldn_longitud
e], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
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(ldn_merged['Latitude'], ldn_
merged['Longitude'], ldn_merged['Areas'], ldn_merged['Cluster
Labels']):
    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=1).add_to(map_clusters)

map_clusters
```

Out[54]:



Let's see how amy areas each of the classes include.

In [55]:

```
ldn_merged.groupby('Cluster Labels').count()
```

Out[55]:

| Cluster Labels | Postcodes | Areas | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue |
|---|---|---|---|---|---|---|
| 0 | 111 | 111 | 111 | 111 | 111 | 111 |
| 1 | 6 | 6 | 6 | 6 | 6 | 6 |
| 2 | 11 | 11 | 11 | 11 | 11 | 11 |
| 3 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4 | 76 | 76 | 76 | 76 | 76 | 76 |

Let's predict now the cluster of each area in Paris for the same parameters.

In [56]:

```
# run a test for k-means prediction
kmeans.predict(prs_grouped_clustering)[0:20]
```

Out[56]:

```
array([0, 0, 0, 0, 0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 0
, 0, 0, 2, 0, 0],
      dtype=int32)
```

In [57]:

```
# add clustering labels
prs_neighborhoods_venues_sorted['Cluster Labels']=kmeans.predi
ct(prs_grouped_clustering)
prs_merged = df_prs
prs_neighborhoods_venues_sorted.head()
```

Out[57]:

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | |
|---|---|---|---|---|---|---|
| 0 | Ablis | Photography Studio | Kebab Restaurant | Falafel Restaurant | Eastern European Restaurant | E |
| 1 | Ablon-sur-Seine | Pharmacy | Hotel | Athletics & Sports | Train Station | |
| 2 | Aigremont | Construction & Landscaping | Pharmacy | Golf Course | Sporting Goods Shop | ( |
| 3 | Alfortville | Supermarket | Pool | Bakery | Convenience Store | F |
| 4 | Amponville | Yoga Studio | Farm | Electronics Store | Ethiopian Restaurant | |

In [58]:

```
#merging the two tables
prs_merged=df_prs
prs_merged = prs_merged.join(prs_neighborhoods_venues_sorted.s
et_index('Neighborhood'), on='Districts')
prs_merged.dropna(inplace=True)
prs_merged['Cluster Labels']=prs_merged['Cluster Labels'].asty
pe(int)
prs_merged.head(30) # check the last columns!
```

Out[58]:

| | Postcodes | Districts | Latitude | Longitude | 1st Most Common Venue |
|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| 24 | 77090 | Collégien | 48.836211 | 2.673176 | Lake | |
| 34 | 77115 | Blandy | 48.567401 | 2.782429 | Farm | |
| 43 | 77120 | Coulommiers | 48.812130 | 3.084382 | Mobile Phone Shop | S |
| 62 | 77130 | Cannes-Écluse | 48.364105 | 2.992034 | Pharmacy | |
| 91 | 77144 | Chalifert | 48.889642 | 2.772546 | Hotel | |
| 126 | 77167 | Bagneaux-sur-Loing | 48.231468 | 2.704271 | Train Station | |
| 127 | 77167 | Châtenoy | 48.232954 | 2.626251 | Yoga Studio | |
| 131 | 77169 | Boissy-le-Châtel | 48.826800 | 3.135700 | Auto Workshop | |
| 135 | 77170 | Brie-Comte-Robert | 48.690452 | 2.616674 | Pool | R |
| 136 | 77170 | Coubert | 48.672607 | 2.695454 | Restaurant | |
| 142 | 77173 | Chevry-Cossigny | 48.724446 | 2.661709 | Park | |
| 147 | 77177 | Brou-sur-Chantereine | 48.885684 | 2.628900 | Portuguese Restaurant | Me |
| 150 | 77181 | Courtry | 48.915800 | 2.602480 | Construction & Landscaping | |
| 159 | 77210 | Avon | 48.404887 | 2.720722 | Bakery | |
| 179 | 77240 | Cesson | 48.112633 | -1.602294 | French Restaurant | |
| 198 | 77290 | Compans | 48.875598 | 2.395068 | Bar | |
| 201 | 77310 | Boissise-le-Roi | 48.528036 | 2.573765 | Hotel | |
| | | Choisy-en- | | | French | |

| | | | | | | |
|---|---|---|---|---|---|---|
| 209 | 77320 | Brie | 48.759215 | 3.217024 | Restaurant | |
| 228 | 77350 | Boissettes | 48.520592 | 2.610324 | Recreation Center | |
| 229 | 77350 | Boissise-la-Bertrand | 48.533894 | 2.593044 | Restaurant | |
| 245 | 77380 | Combs-la-Ville | 48.664699 | 2.564877 | Construction & Landscaping | F |
| 250 | 77390 | Chaumes-en-Brie | 48.664775 | 2.842398 | Arcade | |
| 251 | 77390 | Courquetaine | 48.677387 | 2.743935 | Yoga Studio | |
| 259 | 77400 | Carnetin | 48.900646 | 2.704690 | Yoga Studio | |
| 268 | 77410 | Charny | 48.971648 | 2.760863 | Pharmacy | |
| 269 | 77410 | Claye-Souilly | 48.946087 | 2.688370 | Comedy Club | |
| 277 | 77420 | Champs-sur-Marne | 48.852630 | 2.603806 | Japanese Restaurant | |
| 281 | 77440 | Congis-sur-Thérouanne | 49.006476 | 2.974228 | Botanical Garden | |
| 302 | 77470 | Boutigny | 48.744573 | 1.585516 | Auto Workshop | |
| 309 | 77480 | Baby | 48.849259 | 2.373977 | French Restaurant | |

In [59]:

```
prs_merged.groupby('Cluster Labels').count()
```

Out[59]:

| Cluster Labels | Postcodes | Districts | Latitude | Longitude | 1st Most Common Venue | 2n Mos Commo Venu |
|---|---|---|---|---|---|---|
| 0 | 174 | 174 | 174 | 174 | 174 | 17 |
| 1 | 5 | 5 | 5 | 5 | 5 | |
| 2 | 13 | 13 | 13 | 13 | 13 | 1 |
| 4 | 11 | 11 | 11 | 11 | 11 | 1 |

In [60]:

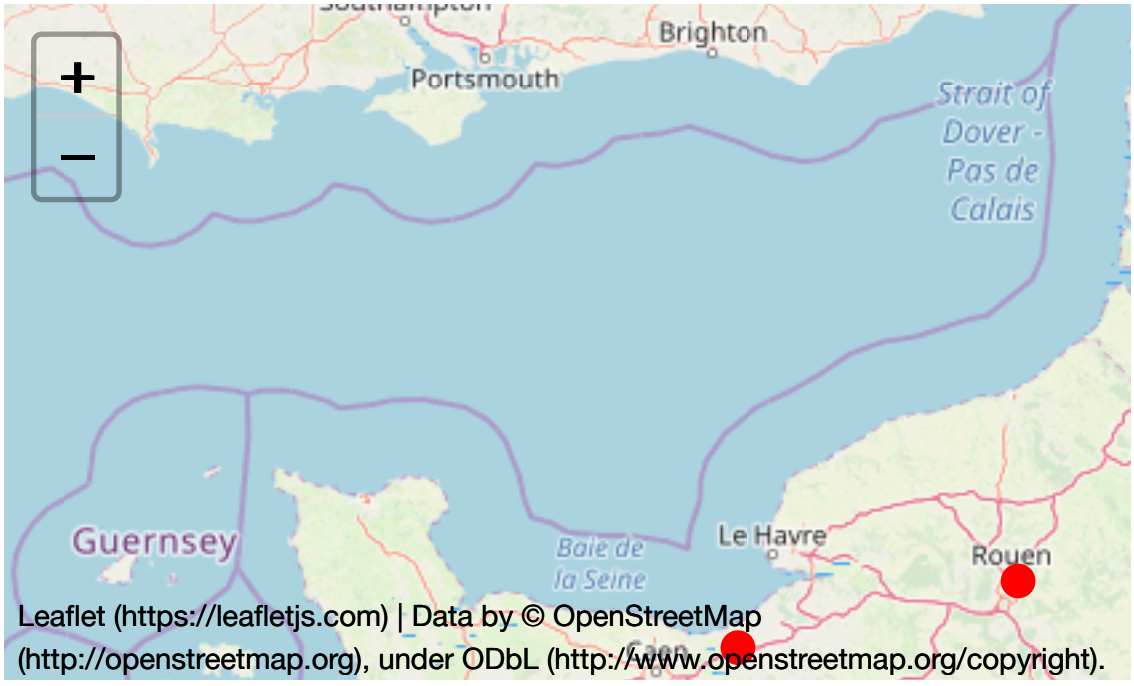
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom
_start=7)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
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(prs_merged['Latitude'], prs_
merged['Longitude'], prs_merged['Districts'], prs_merged['Clus
ter Labels']):
    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=1).add_to(map_clusters)

map_clusters
```

Out[60]:



# 4. London Machine Learning and Paris Prediction Results

## Let's interepret each of the cluster characteristics that were creted by using the London location data

We notice that the there are three clusters that gather the majotiry of the locations in London. Let's examine the characteristics of each cluster to learn more about these locations.

In [61]:

```
ldn_merged.groupby('Cluster Labels').count()
```

Out[61]:

| Cluster Labels | Postcodes | Areas | Latitude | Longitude | 1st Most Common Venue | 2nd Most Common Venue |
|---|---|---|---|---|---|---|
| 0 | 111 | 111 | 111 | 111 | 111 | 111 |
| 1 | 6 | 6 | 6 | 6 | 6 | 6 |
| 2 | 11 | 11 | 11 | 11 | 11 | 11 |
| 3 | 2 | 2 | 2 | 2 | 2 | 2 |
| 4 | 76 | 76 | 76 | 76 | 76 | 76 |

## Cluster 0

In [62]:

```
ldn_merged.loc[ldn_merged['Cluster Labels'] == 0, ldn_merged.columns[[1] + list(range(4, ldn_merged.shape[1]))]]
```

Out[62]:

| | Areas | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5t Co |
|---|---|---|---|---|---|---|
| 0 | Whitechapel | Hotel | Pub | Indian Restaurant | Coffee Shop | Ice |
| 3 | Waterloo | Bar | Coffee Shop | Hotel | Bakery | |
| 5 | Southwark | Pub | Hotel | Coffee Shop | Gym / Fitness Center | Res |
| 9 | Bethnal Green | Coffee Shop | Pub | Cocktail Bar | Café | |
| 10 | Shoreditch | Coffee Shop | Hotel | Restaurant | Cocktail Bar | Res |
| ... | ... | ... | ... | ... | ... | |
| 198 | Willesden | Grocery Store | Bakery | Cosmetics Shop | Breakfast Spot | |
| 201 | Shepherds Bush | Clothing Store | Coffee Shop | Supermarket | Grocery Store | Bo |
| 202 | Golders Green | Coffee Shop | Grocery Store | Korean Restaurant | Café | Res |
| 204 | West Ealing | Grocery Store | Coffee Shop | Hotel | Supermarket | Fas Res |
| 205 | West Kensington | Café | Hotel | Grocery Store | Coffee Shop | |

111 rows × 12 columns

Cluster 0 includes rural areas that have great access to shopping stores, grocery stores, activities, and restaurants. We can say that these areas are best suited to people who like to be near active day life for convenience. These places also look extremely central. with great access to gym, theatres and in some occassions hotels.

## Cluster 1

In [63]:

```
ldn_merged.loc[ldn_merged['Cluster Labels'] == 1, ldn_merged.c
olumns[[1] + list(range(4, ldn_merged.shape[1]))]]
```

Out[63]:

| | Areas | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | |
|---|---|---|---|---|---|---|
| 8 | Abbey Wood | Campground | Playground | Grocery Store | Yoga Studio | |
| 24 | Bellingham | Grocery Store | Gym | Train Station | Park | |
| 72 | Anerley | Grocery Store | Supermarket | Fast Food Restaurant | Park | Cor |
| 129 | Friern Barnet | Grocery Store | Italian Restaurant | Dessert Shop | Yoga Studio | R |
| 130 | New Southgate | Grocery Store | Fish & Chips Shop | Train Station | Metro Station | |
| 138 | Castelnau | Lake | Nature Preserve | Grocery Store | Yoga Studio | R |

Cluster 1 includes areas which look to be more decentralised with popular locations being, grocery stores, train stations and restaurants.

## Cluster 2

In [64]:

```
ldn_merged.loc[ldn_merged['Cluster Labels'] == 2, ldn_merged.columns[[1] + list(range(4, ldn_merged.shape[1]))]]
```

Out[64]:

| | Areas | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | |
|---|---|---|---|---|---|---|
| 1 | Stepney | Park | Fried Chicken Joint | Chinese Restaurant | Thrift / Vintage Store | |
| 29 | Deptford | Park | Pub | Playground | Restaurant | F R |
| 37 | Leyton | Hotel | Park | Grocery Store | Farm | F R |
| 55 | West Ham | Park | Bulgarian Restaurant | Asian Restaurant | Bus Station | |
| 58 | Surrey Docks | Park | Farm | Gym | Scenic Lookout | |
| 66 | Plumstead | Social Club | Convenience Store | Lake | Kebab Restaurant | |
| 73 | Dulwich | Art Gallery | Flower Shop | Gym / Fitness Center | Restaurant | |
| 96 | Thamesmead | Park | Supermarket | Pub | Flower Shop | |
| 98 | Barnsbury | Park | Grocery Store | Pub | Café | G |
| 123 | Lower Edmonton | Pub | Pizza Place | Event Service | Park | V |
| 146 | Stamford Hill | Brazilian Restaurant | Pizza Place | Bus Station | Betting Shop | |

Cluster 2 most common area are the parks of London, however they are locations around the city rather than parks in central London. Other popular areas are pubs, restaurants, pizza places and dry cleaners.

## Cluster 3

In [65]:

```
ldn_merged.loc[ldn_merged['Cluster Labels'] == 3, ldn_merged.columns[[1] + list(range(4, ldn_merged.shape[1]))]]
```

Out[65]:

| | Areas | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|---|
| 65 | Woolwich | Park | Coffee Shop | Pet Store | Child Care Service | Indian Restaurant |
| 203 | Hampstead Gdn Suburb | Park | Coffee Shop | Yoga Studio | Farm | Electronics Store |

Cluster 3 includes areas similar to the ones in Cluster 2. Probably these two clusters could have been classified as one.

## Cluster 4

In [66]:

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

Out[66]:

| | Areas | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5t Co |
|---|---|---|---|---|---|---|
| 2 | Mile End | Pub | Coffee Shop | Bus Stop | Pizza Place | ( |
| 4 | Bermondsey | Coffee Shop | Pub | Grocery Store | Cheese Shop | |
| 6 | Borough | Pub | Café | Bar | Coffee Shop | |
| 7 | Wapping | Pub | Park | Coffee Shop | Italian Restaurant | Conve |
| 11 | Blackheath | Pub | Café | Bakery | Indian Restaurant | Pizz |
| ... | ... | ... | ... | ... | ... | |
| 189 | Maida Vale | Deli / Bodega | Pub | Thai Restaurant | Grocery Store | Coffe |
| 190 | Warwick Avenue | Café | Pub | Park | Grocery Store | Res |
| 197 | Holland Park | Pub | Grocery Store | Pizza Place | Indian Restaurant | Coffe |
| 199 | Harlesden | Pub | Rental Car Location | Middle Eastern Restaurant | Train Station | Auto |
| 200 | Kensal Green | Portuguese Restaurant | Train Station | Bakery | Pub | |

76 rows × 12 columns

Cluster 4 has areas which most popular locations are pubs. Other popular areas are convinience stores, coffee shops, gyms and restaurants. We can conclude that these areas are central, but residential friendly for young professionals as they are not as crowded by restaurants as cluster 3 and have many ammenities near them.

## Prediction review for Paris based on London classification

In [67]:

```
prs_merged.groupby('Cluster Labels').count()
```

Out[67]:

| Cluster Labels | Postcodes | Districts | Latitude | Longitude | 1st Most Common Venue | 2r Mo Commc Venu |
|---|---|---|---|---|---|---|
| 0 | 174 | 174 | 174 | 174 | 174 | 17 |
| 1 | 5 | 5 | 5 | 5 | 5 | |
| 2 | 13 | 13 | 13 | 13 | 13 | 1 |
| 4 | 11 | 11 | 11 | 11 | 11 | 1 |

A problem that we faced which we will discuss later on in this assignment is that the two locations had only 282 type of locations similar, which made it impossible to get a result for some of the areas in Paris, because they had completely different popular locations.

Let's plot the clusters of the two areas side by side.

Firstly, we create the new dataframe in a format friendly for plotting.

In [68]:

```
clusters=ldn_merged['Cluster Labels'].unique()
clusters.sort()
clusters
```

Out[68]:

```
array([0, 1, 2, 3, 4])
```

In [69]:

```
df_comp={'Cluster Labels':clusters}
df_comp=pd.DataFrame(df_comp)
df_comp=df_comp.join(pd.DataFrame(ldn_merged.groupby('Cluster
Labels').count()['Postcodes']),on='Cluster Labels')
df_comp=df_comp.join(pd.DataFrame(prs_merged.groupby('Cluster
Labels').count()['Districts']),on='Cluster Labels')
df_comp.rename(columns={'Postcodes':'London','Districts':'Pari
s'},inplace=True)
df_comp.set_index('Cluster Labels',inplace=True)
```

Plotting the results using the artist layer.

In [71]:

```
ax1 = df_comp.plot.bar(rot=0,figsize=(15,5))
ax1.set_title('Number of locations per cluster')
```

Out[71]:

```
Text(0.5, 1.0, 'Number of locations per cluster')
```

In [72]:

```
df_comp_pct=df_comp
df_comp_pct[['London', 'Paris']] = df_comp[['London', 'Paris']
].apply(lambda x: x/x.sum(), axis=0)
df_comp_pct
```

Out[72]:

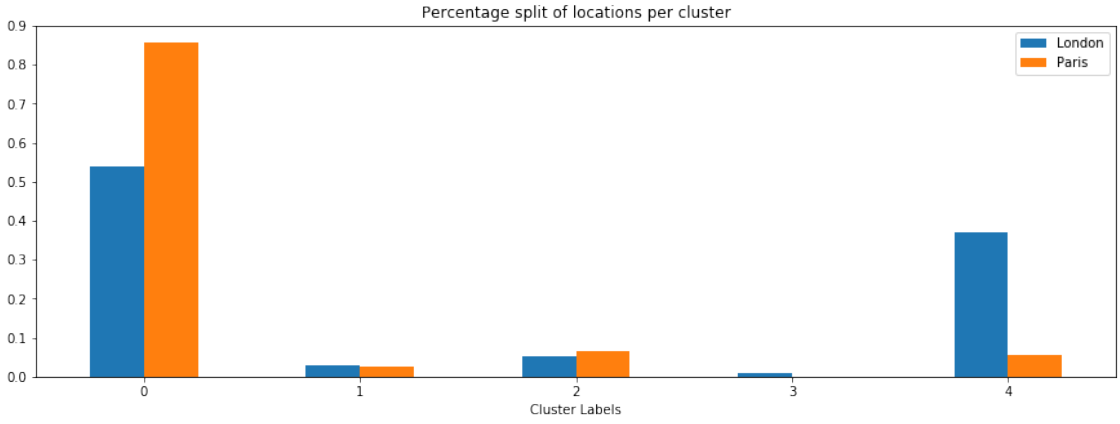
| Cluster Labels | London | Paris |
|---|---|---|
| 0 | 0.538835 | 0.857143 |
| 1 | 0.029126 | 0.024631 |
| 2 | 0.053398 | 0.064039 |
| 3 | 0.009709 | NaN |
| 4 | 0.368932 | 0.054187 |

In [73]:

```
ax2 = df_comp_pct.plot.bar(rot=0,figsize=(15,5))
ax2.set_title('Percentage split of locations per cluster')
```

Out[73]:

```
Text(0.5, 1.0, 'Percentage split of locations per
cluster')
```




# 5. Discussion

We can conclude that the first category is the dominant category in areas of London and Paris too. This category represents central shopping areas good for people who would like to be in the centre of their neiborhoods.

The biggest difference is that for London these location account for approximately half the areas of London. On the other hand for Paris the percentage is much higher close to 85%.

This is probably because the prediction algorithm took out most of the areas of Paris as the common location with London were not satisfactory to make a prediction. But we will explain this at the end of this section.

From the sample reviewed, the second category (Cluster 1) being the decentralised areas are almost equally weighted for both cities at a level of 2.5-3.0%.

The third category (Cluster 2) being the areas near the parks are also almost equally weighted for the two cities.

As mentioned earlier at the algorithm training paragraph, Cluster 2 and 3 should probably be the same category. This is also reflected in the fact that there were 0 predicted areas in Paris for Cluster 3.

Given this facts and assuming that these two clusters converge on the type of areas we can say that these clusters are similar in percentage content for the two cities. More specifically by adding the percentages they approximately 6.2-6.4%.

Again these results assumes that the sample reviewed can be representative.

Lastly, the last category (Cluster 4) is what looks to significantly differentiate the two cities. Cluster 4 is heavy in Pubs inclusion. This is a cultural element of the UK (and respectively London), which makes London so more different than the other cities of Europe. The content of pub doinated areas in London is 35-40% . On the other hand Paris only has approximately 5% of its areas being pub dominated.

## Limitations

In the process of completing this assignment we met a challenge; in some occassions the most popular places in London were completely different than popular areas in Paris and vice versa. This resulted to only use a small sample of mutually existing locations ("common_cols") to train the algorithm and predict the areas of Paris. This smaple obviously was not representative enough as in the process many areas of Paris were dropped. This is because there were not satisfactory mutually existing areas to use for the prediction. This limitation is something that we can look into exploring in the future to make the algorithm more resilient in predict areas which might have similarities but are not strictlyb identical.

# 6. Conclusions

In this assignment we developed an algorithm to predict the areas in Paris that are suitable of employeed who are currently located in London and need to move because of Brexit. This algorithm could be used by employers, real estate agents or other parties who are interested in providing advisory on such a switch of locations.

We came up with the results that the two cities are pretty similar in Neighborhood type content. However, their main difference is the cultural way of socialising and entertainment.Additionally this algorithm can be further developed to procide a more resilient way of prediction rather than the identical matching of locations.

# Disclaimer