# Introduction

We intend to analyze the neighborhoods in City of London and will try to understand and explore neighborhoods.Our intention is to get the most common venue categories in each neighborhood, and then use this feature to group the neighborhoods into clusters. We will use the Foursquare API to explore neighborhoods and get the relevant data for each neighborhood. We will use the k-means clustering algorithm to complete this task. Finally, we will use the Folium library to visualize the neighborhoods in London City and their emerging clusters. This project will be useful for people coming in the City of London , which will help them with an idea of how similar and diverse different neighborhoods in the City of London are. It would help them choose/pick the places of their choice easily , for the different activities they would like to do in the City of London.

## Table of Contents



Before we get the data and start exploring it, let's download all the dependencies that we will need :

In [1]:

```
!conda install -c conda-forge lxml --yes
import numpy as np # library to handle data in a vectorized manner
import pandas as pd # library for data analsysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
import json # library to handle JSON files
import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe
# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors
# import k-means from clustering stage
from sklearn.cluster import KMeans
print('Libraries imported.')
```

```
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - lxml


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    lxml-4.4.1                 |   py36h7ec2d77_0         1.6 MB  conda-fo
rge
    openssl-1.1.1d             |       h516909a_0         2.1 MB  conda-fo
rge
    certifi-2019.11.28         |           py36_0         149 KB  conda-fo
rge
    ca-certificates-2019.11.28 |       hecc5488_0         145 KB  conda-fo
rge
    ------------------------------------------------------------
                                           Total:         3.9 MB

The following packages will be UPDATED:

    ca-certificates: 2019.11.27-0         --> 2019.11.28-hecc5488_0 conda-
forge
    certifi:         2019.11.28-py36_0    --> 2019.11.28-py36_0     conda-
forge
    lxml:            4.3.1-py36hefd8a0e_0 --> 4.4.1-py36h7ec2d77_0  conda-
forge

The following packages will be DOWNGRADED:

    openssl:         1.1.1d-h7b6447c_3    --> 1.1.1d-h516909a_0     conda-
forge


Downloading and Extracting Packages
lxml-4.4.1           | 1.6 MB    | ##################################### | 
100% 
openssl-1.1.1d       | 2.1 MB    | ##################################### | 
100% 
certifi-2019.11.28   | 149 KB    | ##################################### | 
100% 
ca-certificates-2019 | 145 KB    | ##################################### | 
100% 
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Libraries imported.
```

# 1. Download and Explore Dataset

Here we are creating a DataFrame from the London data available on : "https://en.wikipedia.org/wiki/List_of_London_boroughs (https://en.wikipedia.org/wiki/List_of_London_boroughs)"

In [2]:

```
tables = pd.read_html("https://en.wikipedia.org/wiki/List_of_London_boroughs")
df1 = pd.DataFrame(tables[0])
df1.head()
```

Out[2]:

| | Borough | Inner | Status | Local authority | Political control | Headquarters | Area (sq mi) | Population (2013 est) [1] | ordir |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham [note 1] | NaN | NaN | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 51°33' 0°09'2 51.56 0.15 |
| **1** | Barnet | NaN | NaN | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 51°37' 0°09'( 51.62 0.15' |
| **2** | Bexley | NaN | NaN | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 51°27' 0°09'0 51.45 0.15 |
| **3** | Brent | NaN | NaN | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 51°33' 0°16'! 51.55 0.28' |
| **4** | Bromley | NaN | NaN | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 51°24' 0°01'1 51.40 0.01 |

In [3]:

```
df1.rename(columns = {'Population (2013 est)[1]':'Population'}, inplace = True)
```

In [4]:

```
df1=df1.drop(columns=['Nr. in map'])
```

Cleaning data in Column - Borough

In [5]:

```
import re

def remove_all_digits(borough):
    new_borough = re.sub('\d', '', borough)
    return new_borough


def remove_all_brackets(borough):
    new_borough = re.sub('\[]', '', borough)
    return new_borough

def remove_all_note(borough):
    new_borough = re.sub('\[', '', borough)
    return new_borough
```

In [6]:

```
df1['Borough'] = df1['Borough'].apply(remove_all_digits)
df1['Borough'] = df1['Borough'].apply(remove_all_brackets)
df1.head()
```

Out[6]:

| | Borough | Inner | Status | Local authority | Political control | Headquarters | Area (sq mi) | Population | ordir |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham [note ] | NaN | NaN | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 51°33' 0°09'2 51.56 0.15 |
| **1** | Barnet | NaN | NaN | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 51°37' 0°09' 51.62 0.15 |
| **2** | Bexley | NaN | NaN | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 51°27' 0°09'C 51.45 0.15 |
| **3** | Brent | NaN | NaN | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 51°33' 0°16' 51.55 0.28 |
| **4** | Bromley | NaN | NaN | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 51°24' 0°01'1 51.40 0.01 |

In [7]:

```
df1.iloc[0,0] = 'Barking and Dagenham'
df1.iloc[11,0] = 'Hammersmith and Fulham'
df1.iloc[9,0] = 'Greenwich'
```

Changing name of column Co-ordinates to Coordinates and Creating 2 separate columns from column --> Coordinates

In [8]:

```
df1.rename(columns = {'Co-ordinates':'Coordinates'}, inplace = True)
df1[['Cordinate1','Cordinate2']] = df1.Coordinates.str.split("/",expand=True,)
df1.head()
```

Out[8]:

| | Borough | Inner | Status | Local authority | Political control | Headquarters | Area (sq mi) | Population | Coorc |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | NaN | NaN | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 51°3 0°09 51.5 0.1 |
| **1** | Barnet | NaN | NaN | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 51°3 0°09 51.6 0.1 |
| **2** | Bexley | NaN | NaN | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 51°2 0°09 51.4 0.1 |
| **3** | Brent | NaN | NaN | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 51°3 0°16 51.5 0.2 |
| **4** | Bromley | NaN | NaN | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 51°2 0°0 51.4 0.0 |

Drop irrelevant Columns and retaining Column containing Latitude and Longitude of Places in degrees.

In [9]:

```
df1=df1.drop(columns=['Coordinates'])
df1=df1.drop(columns=['Cordinate1'])
```

Now separating Latitudes and Longitudes from the last Column and then putting them in separate columns

In [10]:

```
column1 = df1.Cordinate2
sub_df1 = pd.DataFrame(column1.str.split(expand=True,))
df1[['Latitude','Longitude']] = sub_df1
df1.head()
```

Out[10]:

| | Borough | Inner | Status | Local authority | Political control | Headquarters | Area (sq mi) | Population | Cordi |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Barking and Dagenham | NaN | NaN | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 51.56 0.15 |
| 1 | Barnet | NaN | NaN | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 51.62 0.15 |
| 2 | Bexley | NaN | NaN | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 51.45 0.15 |
| 3 | Brent | NaN | NaN | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 51.55 0.28 |
| 4 | Bromley | NaN | NaN | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 51.40 0.01 |

Next we are removing the Irrelavant columns- Cordinate2/Inner and Status

In [11]:

```
df1=df1.drop(columns=['Cordinate2'])
df1=df1.drop(columns=['Inner'])
df1=df1.drop(columns=['Status'])
```

Having done that we clean data in Columns Latitude & Longitude(removing degress and letter 'W' , 'E' and 'N')

In [12]:

```
df1['Latitude'] = df1['Latitude'].replace('\u00b0','', regex=True)
df1['Longitude'] = df1['Longitude'].replace('\u00b0','', regex=True)
def remove_characterN(Latitude):
    new_lat = re.sub('N', '', Latitude)
    return new_lat
def remove_characterW(Longitude):
    new_lon = re.sub('W', '', Longitude)
    return new_lon
def remove_characterE(Longitude):
    new_lon = re.sub('E', '', Longitude)
    return new_lon
```

In [13]:

```
df1['Latitude'] = df1['Latitude'].apply(remove_characterN)
df1['Longitude'] = df1['Longitude'].apply(remove_characterW)
df1['Longitude'] = df1['Longitude'].apply(remove_characterE)
df1.head()
```

Out[13]:

| | Borough | Local authority | Political control | Headquarters | Area (sq mi) | Population | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 51.5607 | 0.1557 |
| **1** | Barnet | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 51.6252 | 0.1517 |
| **2** | Bexley | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 51.4549 | 0.1505 |
| **3** | Brent | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 51.5588 | 0.2817 |
| **4** | Bromley | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 51.4039 | 0.0198 |

In [14]:

```
df1.dtypes
```

Out[14]:

```
Borough              object
Local authority      object
Political control    object
Headquarters         object
Area (sq mi)        float64
Population            int64
Latitude             object
Longitude            object
dtype: object
```

In [15]:

```
df1['Longitude'] = df1['Longitude'].astype(float)
```

***df1['Latitude'] = df1['Latitude'].astype(float) ---> This throws error -ValueError: could not convert string to float: '\ufeff51.5607'***

***This is because each value in Column "Latitude" has extra masking of \ufeff***

Here is how we get rid of that :

In [16]:

```
my_list = []
my_list = df1.Latitude

new_list = []
for i in my_list:
    i = i.replace('\ufeff', '')
    new_list.append(i)

new_list
```

Out[16]:

```
['51.5607',
 '51.6252',
 '51.4549',
 '51.5588',
 '51.4039',
 '51.5290',
 '51.3714',
 '51.5130',
 '51.6538',
 '51.4892',
 '51.5450',
 '51.4927',
 '51.6000',
 '51.5898',
 '51.5812',
 '51.5441',
 '51.4746',
 '51.5416',
 '51.5020',
 '51.4085',
 '51.4607',
 '51.4452',
 '51.4014',
 '51.5077',
 '51.5590',
 '51.4479',
 '51.5035',
 '51.3618',
 '51.5099',
 '51.5908',
 '51.4567',
 '51.4973']
```

In [17]:

```
df_newest = pd.DataFrame(new_list)
df_newest.columns = ['Latitudes']
df_newest['Latitudes'] = df_newest['Latitudes'].astype(float)
df_newest
```

Out[17]:

| | Latitudes |
|---|---|
| 0 | 51.5607 |
| 1 | 51.6252 |
| 2 | 51.4549 |
| 3 | 51.5588 |
| 4 | 51.4039 |
| 5 | 51.5290 |
| 6 | 51.3714 |
| 7 | 51.5130 |
| 8 | 51.6538 |
| 9 | 51.4892 |
| 10 | 51.5450 |
| 11 | 51.4927 |
| 12 | 51.6000 |
| 13 | 51.5898 |
| 14 | 51.5812 |
| 15 | 51.5441 |
| 16 | 51.4746 |
| 17 | 51.5416 |
| 18 | 51.5020 |
| 19 | 51.4085 |
| 20 | 51.4607 |
| 21 | 51.4452 |
| 22 | 51.4014 |
| 23 | 51.5077 |
| 24 | 51.5590 |
| 25 | 51.4479 |
| 26 | 51.5035 |
| 27 | 51.3618 |
| 28 | 51.5099 |
| 29 | 51.5908 |
| 30 | 51.4567 |
| 31 | 51.4973 |

Next step of ours is to add this new correct dataframe as a Column to our master DataFrame and remove old one

In [18]:

```
df1=df1.drop(columns=['Latitude'])
df1['Latitude'] = df_newest
df1.head()
```

Out[18]:

| | Borough | Local authority | Political control | Headquarters | Area (sq mi) | Population | Longitude | Latitude |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 0.1557 | 51.5607 |
| **1** | Barnet | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 0.1517 | 51.6252 |
| **2** | Bexley | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 0.1505 | 51.4549 |
| **3** | Brent | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 0.2817 | 51.5588 |
| **4** | Bromley | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 0.0198 | 51.4039 |

Now we have cleaned all relevant data in DataFrame and we have our final desired DataFrame on which we will perform our further analysis.

In [19]:

```
df1.dtypes
```

Out[19]:

```
Borough               object
Local authority       object
Political control     object
Headquarters          object
Area (sq mi)         float64
Population             int64
Longitude            float64
Latitude             float64
dtype: object
```

**Create a map of London with neighborhoods superimposed on top.**

In [20]:

```
!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you haven't c
ompleted the Foursquare API lab
import folium # map rendering library
```

```
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - folium=0.5.0


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    altair-4.0.0               |             py_0         606 KB  conda-fo
rge
    vincent-0.4.4              |             py_1          28 KB  conda-fo
rge
    branca-0.3.1               |             py_0          25 KB  conda-fo
rge
    folium-0.5.0               |             py_0          45 KB  conda-fo
rge
    ------------------------------------------------------------
                                           Total:         704 KB

The following NEW packages will be INSTALLED:

    altair:  4.0.0-py_0 conda-forge
    branca:  0.3.1-py_0 conda-forge
    folium:  0.5.0-py_0 conda-forge
    vincent: 0.4.4-py_1 conda-forge


Downloading and Extracting Packages
altair-4.0.0         | 606 KB    | ##################################### |
100%
vincent-0.4.4        | 28 KB     | ##################################### |
100%
branca-0.3.1         | 25 KB     | ##################################### |
100%
folium-0.5.0         | 45 KB     | ##################################### |
100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

In [21]:

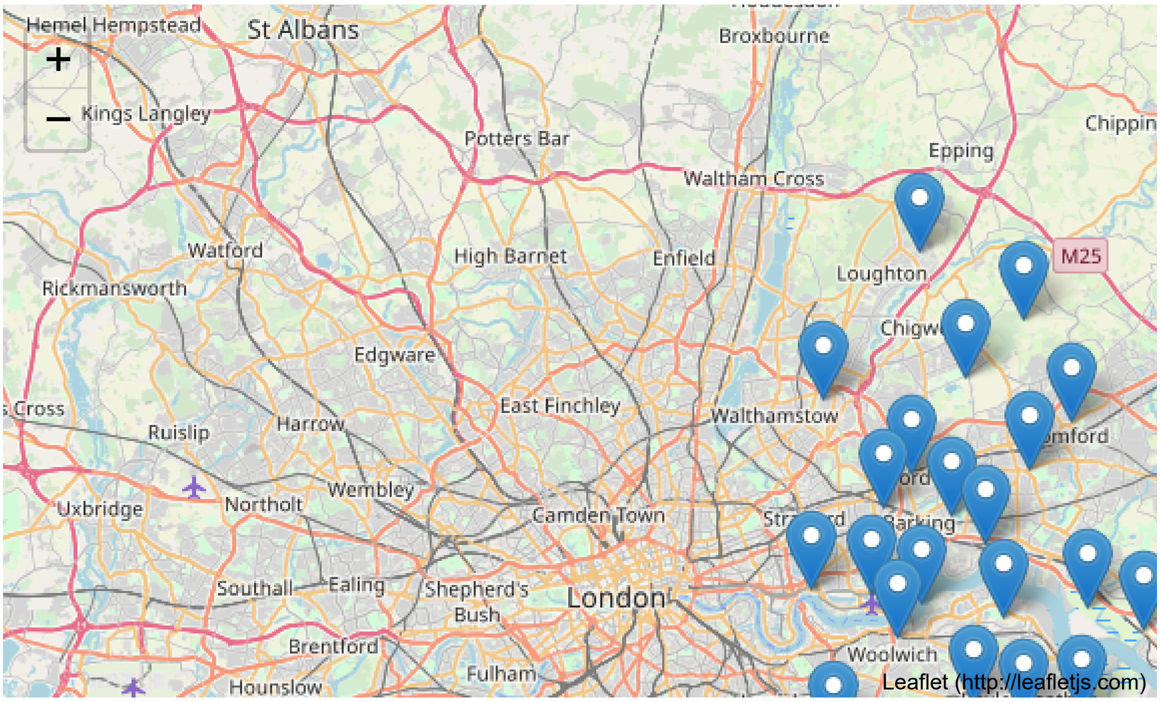
```
latitude = 51.5074
longitude = 0.1278

map_london = folium.Map(location=[latitude, longitude], zoom_start=10)

# add markers to map
for lat, lng, borough in zip(df1['Latitude'], df1['Longitude'], df1['Borough']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.Marker(
        [lat, lng],
        #radius=5,
        popup=label
        ).add_to(map_london)
        #color='blue',
        #fill=True,
        #fill_color='#3186cc',
        #fill_opacity=0.7,
        #parse_html=False)

map_london
```

Out[21]:




## 2. Explore Neighborhoods in London

**Let's create a function to repeat the same process to all the neighborhoods in London**

In [22]:

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

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        #print("Started Loop")

        # 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']['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 [23]:

```
CLIENT_ID = '00K4WO0241PHMV3NXQX2EKYFPWDNWPXBIH4AVRYAI0DOER1Q' # your Foursquare ID
CLIENT_SECRET = '5Y3CJGQUGEOQ24M5HRGTCC0BIY3JD03UUUEI2FXTJKXHVCGS' # your Foursquare Se
cret
VERSION = '20180605' # Foursquare API version

print('Your credentails:')
```

Your credentails:

In [24]:

```
LIMIT = 100 # limit of number of venues returned by Foursquare API
```

In [25]:

```
df_venues = getNearbyVenues(names=df1['Borough'],
                                   latitudes=df1['Latitude'],
                                   longitudes=df1['Longitude']
                                  )
```

### Let's check the size of the resulting dataframe

In [26]:

```
print(df_venues.shape)
df_venues.head()
```

(284, 7)

Out[26]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venu Categor |
|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | 51.5607 | 0.1557 | Central Park | 51.559560 | 0.161981 | Par |
| **1** | Barking and Dagenham | 51.5607 | 0.1557 | Crowlands Heath Golf Course | 51.562457 | 0.155818 | Golf Cours |
| **2** | Barking and Dagenham | 51.5607 | 0.1557 | Robert Clack Leisure Centre | 51.560808 | 0.152704 | Martial Ar Doj |
| **3** | Barking and Dagenham | 51.5607 | 0.1557 | Beacontree Heath Leisure Centre | 51.560997 | 0.148932 | Gym Fitnes Cente |
| **4** | Barking and Dagenham | 51.5607 | 0.1557 | Morrisons Becontree Heath | 51.559774 | 0.148752 | Supermarke |

Let's check how many venues were returned for each neighborhood

In [27]:

```
df_venues.groupby('Neighborhood').count()
```

Out[27]:

| Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|
| **Barking and Dagenham** | 7 | 7 | 7 | 7 | 7 | 7 |
| **Bexley** | 27 | 27 | 27 | 27 | 27 | 27 |
| **Brent** | 2 | 2 | 2 | 2 | 2 | 2 |
| **Bromley** | 40 | 40 | 40 | 40 | 40 | 40 |
| **Camden** | 4 | 4 | 4 | 4 | 4 | 4 |
| **Croydon** | 7 | 7 | 7 | 7 | 7 | 7 |
| **Ealing** | 2 | 2 | 2 | 2 | 2 | 2 |
| **Enfield** | 4 | 4 | 4 | 4 | 4 | 4 |
| **Greenwich** | 42 | 42 | 42 | 42 | 42 | 42 |
| **Hackney** | 7 | 7 | 7 | 7 | 7 | 7 |
| **Hammersmith and Fulham** | 3 | 3 | 3 | 3 | 3 | 3 |
| **Haringey** | 2 | 2 | 2 | 2 | 2 | 2 |
| **Havering** | 38 | 38 | 38 | 38 | 38 | 38 |
| **Hillingdon** | 1 | 1 | 1 | 1 | 1 | 1 |
| **Hounslow** | 1 | 1 | 1 | 1 | 1 | 1 |
| **Islington** | 4 | 4 | 4 | 4 | 4 | 4 |
| **Kingston upon Thames** | 1 | 1 | 1 | 1 | 1 | 1 |
| **Lambeth** | 9 | 9 | 9 | 9 | 9 | 9 |
| **Lewisham** | 4 | 4 | 4 | 4 | 4 | 4 |
| **Merton** | 2 | 2 | 2 | 2 | 2 | 2 |
| **Newham** | 15 | 15 | 15 | 15 | 15 | 15 |
| **Redbridge** | 38 | 38 | 38 | 38 | 38 | 38 |
| **Richmond upon Thames** | 4 | 4 | 4 | 4 | 4 | 4 |
| **Southwark** | 1 | 1 | 1 | 1 | 1 | 1 |
| **Sutton** | 3 | 3 | 3 | 3 | 3 | 3 |
| **Tower Hamlets** | 14 | 14 | 14 | 14 | 14 | 14 |
| **Wandsworth** | 1 | 1 | 1 | 1 | 1 | 1 |
| **Westminster** | 1 | 1 | 1 | 1 | 1 | 1 |

### Let's find out how many unique categories can be curated from all the returned venues

In [28]:

```
print('There are {} uniques categories.'.format(len(df_venues['Venue Category'].unique
())))
```

```
There are 90 uniques categories.
```

# 3. Analyze Each Neighborhood

In [29]:

```
# one hot encoding
df_onehot = pd.get_dummies(df_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
df_onehot['Neighborhood'] = df_venues['Neighborhood']

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

df_onehot.head()
```

Out[29]:

| | Neighborhood | African Restaurant | Airport | Airport Lounge | Airport Service | American Restaurant | Asian Restaurant | Bakery | Bar |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | Barking and Dagenham | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | Barking and Dagenham | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | Barking and Dagenham | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | Barking and Dagenham | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

And let's examine the new dataframe size.

In [30]:

```
df_onehot.shape
```

Out[30]:

```
(284, 91)
```

**Next, let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each category**

In [31]:

```
df_grouped = df_onehot.groupby('Neighborhood').mean().reset_index()
df_grouped
```

Out[31]:

| | Neighborhood | African Restaurant | Airport | Airport Lounge | Airport Service | American Restaurant | Asian Restaurant | Bake |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **1** | Bexley | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.037037 | 0.00000 | 0.0370 |
| **2** | Brent | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **3** | Bromley | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.02500 | 0.0250 |
| **4** | Camden | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **5** | Croydon | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **6** | Ealing | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **7** | Enfield | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **8** | Greenwich | 0.02381 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.02381 | 0.02381 |
| **9** | Hackney | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **10** | Hammersmith and Fulham | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **11** | Haringey | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **12** | Havering | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0526 |
| **13** | Hillingdon | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **14** | Hounslow | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **15** | Islington | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **16** | Kingston upon Thames | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **17** | Lambeth | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **18** | Lewisham | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **19** | Merton | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **20** | Newham | 0.00000 | 0.066667 | 0.066667 | 0.133333 | 0.000000 | 0.00000 | 0.0000 |
| **21** | Redbridge | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0789 |
| **22** | Richmond upon Thames | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.250000 | 0.00000 | 0.0000 |
| **23** | Southwark | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **24** | Sutton | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **25** | Tower Hamlets | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **26** | Wandsworth | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |
| **27** | Westminster | 0.00000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00000 | 0.0000 |

### Let's confirm the new size

In [32]:

```
df_grouped.shape
```

Out[32]:

```
(28, 91)
```

### Let's print each neighborhood along with the top 5 most common venues

In [33]:

```
num_top_venues = 5

for hood in df_grouped['Neighborhood']:
    print("----"+hood+"----")
    temp = df_grouped[df_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_index(drop=True).head(num_top
_venues))
    print('\n')
```

```
----Barking and Dagenham----
                 venue  freq
0                 Pool  0.14
1          Bus Station  0.14
2     Martial Arts Dojo  0.14
3  Gym / Fitness Center  0.14
4          Supermarket  0.14


----Bexley----
                 venue  freq
0                  Pub  0.11
1       Clothing Store  0.11
2          Supermarket  0.07
3  Fast Food Restaurant  0.07
4          Coffee Shop  0.07


----Brent----
            venue  freq
0             Pub   0.5
1     Golf Course   0.5
2  Nature Preserve   0.0
3           Plaza   0.0
4      Playground   0.0


----Bromley----
                 venue  freq
0       Clothing Store  0.12
1          Coffee Shop  0.12
2  Gym / Fitness Center  0.05
3          Pizza Place  0.05
4                  Bar  0.05


----Camden----
               venue  freq
0       Home Service  0.25
1        Rugby Pitch  0.25
2                Gym  0.25
3         Skate Park  0.25
4  African Restaurant  0.00


----Croydon----
               venue  freq
0  Italian Restaurant  0.14
1        Coffee Shop  0.14
2                Bar  0.14
3  Chinese Restaurant  0.14
4        Pizza Place  0.14


----Ealing----
               venue  freq
0       Home Service   0.5
1   Business Service   0.5
2  African Restaurant   0.0
3    Nature Preserve   0.0
4              Plaza   0.0
```

```
----Enfield----
               venue  freq
0               Park  0.50
1            Dog Run  0.25
2      Shopping Plaza  0.25
3  African Restaurant  0.00
4   Outdoor Sculpture  0.00


----Greenwich----
                 venue  freq
0          Coffee Shop  0.07
1       Clothing Store  0.07
2  Fast Food Restaurant  0.07
3          Supermarket  0.07
4                  Pub  0.07


----Hackney----
              venue  freq
0  Indian Restaurant  0.43
1                Pub  0.14
2      Train Station  0.14
3               Park  0.14
4              Hotel  0.14


----Hammersmith and Fulham----
                       venue  freq
0  Construction & Landscaping  0.33
1                        Café  0.33
2                 Bus Station  0.33
3          African Restaurant  0.00
4                         Pub  0.00


----Haringey----
               venue  freq
0          Skate Park   0.5
1                Park   0.5
2  African Restaurant   0.0
3     Nature Preserve   0.0
4               Plaza   0.0


----Havering----
                 venue  freq
0          Coffee Shop  0.11
1       Clothing Store  0.11
2        Shopping Mall  0.08
3            Bookstore  0.05
4  Fast Food Restaurant  0.05


----Hillingdon----
               venue  freq
0             Stables   1.0
1  African Restaurant   0.0
2               Plaza   0.0
```

```
3          Playground   0.0
4            Platform   0.0


----Hounslow----
                   venue  freq
0   Fast Food Restaurant   1.0
1     African Restaurant   0.0
2  Portuguese Restaurant   0.0
3                  Plaza   0.0
4             Playground   0.0


----Islington----
                venue  freq
0   Fish & Chips Shop  0.25
1   Martial Arts Dojo  0.25
2       Metro Station  0.25
3                Café  0.25
4  African Restaurant  0.00


----Kingston upon Thames----
                venue  freq
0      Clothing Store   1.0
1  African Restaurant   0.0
2   Outdoor Sculpture   0.0
3                Pool   0.0
4               Plaza   0.0


----Lambeth----
         venue  freq
0          Pub  0.22
1  Coffee Shop  0.22
2  Supermarket  0.22
3   Playground  0.11
4         Café  0.11


----Lewisham----
             venue  freq
0              Pub  0.25
1            Hotel  0.25
2             Café  0.25
3             Park  0.25
4  Nature Preserve  0.00


----Merton----
                   venue  freq
0                    Pub   1.0
1  Portuguese Restaurant   0.0
2                  Plaza   0.0
3             Playground   0.0
4               Platform   0.0


----Newham----
                venue  freq
0               Hotel  0.33
```

```
1     Airport Service  0.13
2            Rafting  0.07
3  Chinese Restaurant  0.07
4            Airport  0.07


----Redbridge----
                  venue  freq
0  Fast Food Restaurant  0.11
1        Clothing Store  0.11
2                Bakery  0.08
3         Grocery Store  0.05
4        Sandwich Place  0.05


----Richmond upon Thames----
                 venue  freq
0  American Restaurant  0.25
1          Coffee Shop  0.25
2       Soccer Stadium  0.25
3  Sporting Goods Shop  0.25
4   African Restaurant  0.00


----Southwark----
                venue  freq
0     Harbor / Marina   1.0
1  African Restaurant   0.0
2     Nature Preserve   0.0
3               Plaza   0.0
4          Playground   0.0


----Sutton----
                venue  freq
0       Historic Site  0.67
1        Tennis Court  0.33
2  African Restaurant  0.00
3     Nature Preserve  0.00
4               Plaza  0.00


----Tower Hamlets----
               venue  freq
0  Food & Drink Shop  0.14
1           Platform  0.14
2    Nature Preserve  0.07
3              Diner  0.07
4        Coffee Shop  0.07


----Wandsworth----
                venue  freq
0                 Gym   1.0
1  African Restaurant   0.0
2     Nature Preserve   0.0
3               Plaza   0.0
4          Playground   0.0


----Westminster----
```

```
               venue  freq
0     Breakfast Spot   1.0
1  African Restaurant   0.0
2     Nature Preserve   0.0
3                Pool   0.0
4               Plaza   0.0
```

### Let's put that into a *pandas* dataframe

First, let's write a function to sort the venues in descending order.

In [34]:

```
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]
```

Now let's create the new dataframe and display the top 10 venues for each neighborhood.

In [35]:

```
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'] = df_grouped['Neighborhood']

for ind in np.arange(df_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(df_grouped.il
oc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[35]:

| | Neighborhood | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Co |
|---|---|---|---|---|---|---|---|---|
| 0 | Barking and Dagenham | Pool | Gym / Fitness Center | Golf Course | Park | Supermarket | Martial Arts Dojo | Bus S |
| 1 | Bexley | Pub | Clothing Store | Italian Restaurant | Fast Food Restaurant | Coffee Shop | Supermarket | C Rest |
| 2 | Brent | Pub | Golf Course | Warehouse Store | Electronics Store | Cosmetics Shop | Department Store | D |
| 3 | Bromley | Coffee Shop | Clothing Store | Gym / Fitness Center | Bar | Pizza Place | Burger Joint | Elec |
| 4 | Camden | Home Service | Gym | Rugby Pitch | Skate Park | Duty-free Shop | Cosmetics Shop | Depa |

# 4. Cluster Neighborhoods - Methodology and Machine Learning algorithm of K- means Clustering

Run *k*-means to cluster the neighborhood into 5 clusters.

In [36]:

```
# set number of clusters
kclusters = 5

df_grouped_clustering = df_grouped.drop('Neighborhood', 1)

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

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

Out[36]:

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

In [37]:

```
df1_new = df1
df1_new.rename(columns = {'Borough':'Neighborhood'}, inplace = True)
df1_new.head()
```

Out[37]:

| | Neighborhood | Local authority | Political control | Headquarters | Area (sq mi) | Population | Longitude | Latitu |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 0.1557 | 51.56 |
| **1** | Barnet | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 0.1517 | 51.62 |
| **2** | Bexley | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 0.1505 | 51.45 |
| **3** | Brent | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 0.2817 | 51.55 |
| **4** | Bromley | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 0.0198 | 51.40 |

Let's create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood.

In [38]:

```
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

df_merged = df1_new

# merge toronto_grouped with toronto_data to add latitude/longitude for each neighborho
od
df_merged = df_merged.join(neighborhoods_venues_sorted.set_index('Neighborhood'), on='N
eighborhood')

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

Out[38]:

| | Neighborhood | Local authority | Political control | Headquarters | Area (sq mi) | Population | Longitude | Latitu |
|---|---|---|---|---|---|---|---|---|
| 0 | Barking and Dagenham | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 0.1557 | 51.56 |
| 1 | Barnet | Barnet London Borough Council | Conservative | North London Business Park, Oakleigh Road South | 33.49 | 369088 | 0.1517 | 51.62 |
| 2 | Bexley | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 0.1505 | 51.45 |
| 3 | Brent | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 0.2817 | 51.55 |
| 4 | Bromley | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 0.0198 | 51.40 |

In [39]:

```
df_merged = df_merged.dropna()
df_merged['Cluster Labels'] = df_merged['Cluster Labels'].astype(int)
df_merged = df_merged.reset_index(drop=True)
df_merged.head()
```

Out[39]:

| | Neighborhood | Local authority | Political control | Headquarters | Area (sq mi) | Population | Longitude | Latitu |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham | Barking and Dagenham London Borough Council | Labour | Town Hall, 1 Town Square | 13.93 | 194352 | 0.1557 | 51.56 |
| **1** | Bexley | Bexley London Borough Council | Conservative | Civic Offices, 2 Watling Street | 23.38 | 236687 | 0.1505 | 51.45 |
| **2** | Brent | Brent London Borough Council | Labour | Brent Civic Centre, Engineers Way | 16.70 | 317264 | 0.2817 | 51.55 |
| **3** | Bromley | Bromley London Borough Council | Conservative | Civic Centre, Stockwell Close | 57.97 | 317899 | 0.0198 | 51.40 |
| **4** | Camden | Camden London Borough Council | Labour | Camden Town Hall, Judd Street | 8.40 | 229719 | 0.1255 | 51.52 |

Finally, let's visualize the resulting clusters

In [40]:

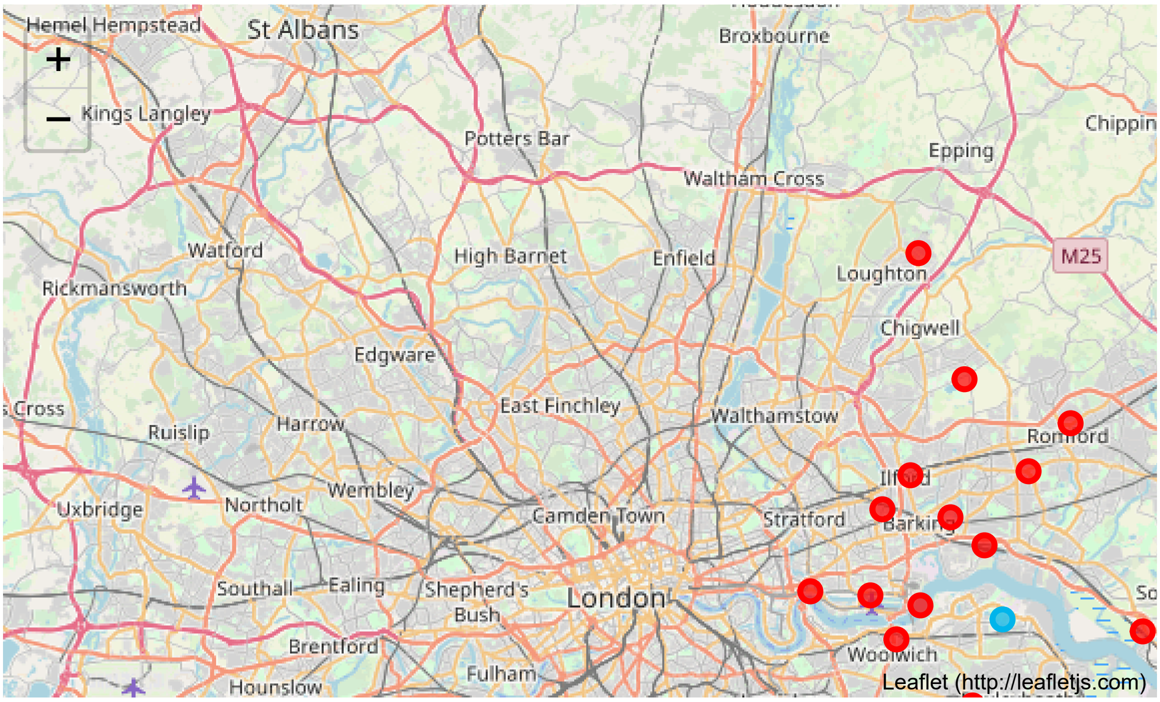
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=10)

# 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(df_merged['Latitude'], df_merged['Longitude'], df_merged['Neighborhood'], df_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=0.7).add_to(map_clusters)

map_clusters
```

Out[40]:




## 5. Examine Clusters

Now, we can examine each cluster and determine the discriminating venue categories that distinguish each cluster. Based on the defining categories, we can then assign a name to each cluster. Here we can clearly see below how distinct and clearly similar/dissimilar the different clusters are amongst themselves.

**Cluster 1 : Seems like a place for Cafe , Pubs , Pools and Supermarkets**

In [41]:

```
df_merged.loc[df_merged['Cluster Labels'] == 0, df_merged.columns[[1] + list(range(5, d
f_merged.shape[1]))]]
```

Out[41]:

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Mo: Commo Venu |
|---|---|---|---|---|---|---|---|---|
| **0** | Barking and Dagenham London Borough Council | 194352 | 0.1557 | 51.5607 | 0 | Pool | Gym / Fitness Center | Gc Cours |
| **1** | Bexley London Borough Council | 236687 | 0.1505 | 51.4549 | 0 | Pub | Clothing Store | Italia Restaura |
| **3** | Bromley London Borough Council | 317899 | 0.0198 | 51.4039 | 0 | Coffee Shop | Clothing Store | Gym Fitnes Cent |
| **4** | Camden London Borough Council | 229719 | 0.1255 | 51.5290 | 0 | Home Service | Gym | Rugk Pitc |
| **5** | Croydon London Borough Council | 372752 | 0.0977 | 51.3714 | 0 | Pizza Place | Coffee Shop | Pu |
| **6** | Ealing London Borough Council | 342494 | 0.3089 | 51.5130 | 0 | Home Service | Business Service | Fast Foc Restaura |
| **7** | Enfield London Borough Council | 320524 | 0.0799 | 51.6538 | 0 | Park | Dog Run | Shoppir Plaz |
| **8** | Greenwich London Borough Council | 264008 | 0.0648 | 51.4892 | 0 | Fast Food Restaurant | Clothing Store | Coffe Shc |
| **9** | Hackney London Borough Council | 257379 | 0.0553 | 51.5450 | 0 | Indian Restaurant | Hotel | Tra Static |
| **10** | Hammersmith and Fulham London Borough Council | 178685 | 0.2339 | 51.4927 | 0 | Construction & Landscaping | Café | Bu Static |
| **11** | Haringey London Borough Council | 263386 | 0.1119 | 51.6000 | 0 | Park | Skate Park | Warehous Stor |
| **12** | Havering London Borough Council | 242080 | 0.1837 | 51.5812 | 0 | Clothing Store | Coffee Shop | Shoppir Ma |
| **15** | Islington London Borough Council | 215667 | 0.1022 | 51.5416 | 0 | Café | Martial Arts Dojo | Metı Static |

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Mos Commo Venu |
|---|---|---|---|---|---|---|---|---|
| **16** | Kingston upon Thames London Borough Council | 166793 | 0.3064 | 51.4085 | 0 | Clothing Store | Warehouse Store | Fast Foo Restaura |
| **17** | Lambeth London Borough Council | 314242 | 0.1163 | 51.4607 | 0 | Supermarket | Pub | Coffe Sho |
| **18** | Lewisham London Borough Council | 286180 | 0.0209 | 51.4452 | 0 | Hotel | Pub | Ca |
| **20** | Newham London Borough Council | 318227 | 0.0469 | 51.5077 | 0 | Hotel | Airport Service | Airpo |
| **21** | Redbridge London Borough Council | 288272 | 0.0741 | 51.5590 | 0 | Clothing Store | Fast Food Restaurant | Bake |
| **22** | Richmond upon Thames London Borough Council | 191365 | 0.3260 | 51.4479 | 0 | Sporting Goods Shop | American Restaurant | Socc Stadiu |
| **23** | Southwark London Borough Council | 298464 | 0.0804 | 51.5035 | 0 | Harbor / Marina | Warehouse Store | Fast Foo Restaura |
| **24** | Sutton London Borough Council | 195914 | 0.1945 | 51.3618 | 0 | Historic Site | Tennis Court | Fast Foo Restaura |
| **25** | Tower Hamlets London Borough Council | 272890 | 0.0059 | 51.5099 | 0 | Platform | Food & Drink Shop | Hot |
| **26** | Wandsworth London Borough Council | 310516 | 0.1910 | 51.4567 | 0 | Gym | Warehouse Store | Fast Foo Restaura |

### Cluster 2 Seems like a place for Pubs ,Golf Courses and Electronics and Warehouses

In [42]:

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

Out[42]:

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4t Co |
|---|---|---|---|---|---|---|---|---|---|
| 2 | Brent London Borough Council | 317264 | 0.2817 | 51.5588 | 1 | Pub | Golf Course | Warehouse Store | Ele |
| 19 | Merton London Borough Council | 203223 | 0.1958 | 51.4014 | 1 | Pub | Warehouse Store | Electronics Store | Co |

**Cluster 3 Seems like a place for Breakfast spots and Small shops and stores**

In [43]:

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

Out[43]:

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4t Co |
|---|---|---|---|---|---|---|---|---|---|
| 27 | Westminster City Council | 226841 | 0.1372 | 51.4973 | 2 | Breakfast Spot | Fish & Chips Shop | Department Store | |

**Cluster 4 Seems like a place for Fast Foods , eateries and some construction/ landscape along with warehousing places**

In [44]:

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

Out[44]:

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue |
|---|---|---|---|---|---|---|---|---|
| **14** | Hounslow London Borough Council | 262407 | 0.368 | 51.4746 | 3 | Fast Food Restaurant | Warehouse Store | Construction & Landscaping |

**Cluster 5 Seems like a place for Distinct with Stables , Cosmetics and Departmental stores**

In [45]:

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

Out[45]:

| | Local authority | Population | Longitude | Latitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4t Cc |
|---|---|---|---|---|---|---|---|---|---|
| **13** | Hillingdon London Borough Council | 286806 | 0.476 | 51.5441 | 4 | Stables | Fast Food Restaurant | Cosmetics Shop | Depa |

Possible K values for optimal analysis of clusters --> {Elbow point Observation} :

We can also go ahead and try to analyse what K values we can choose to define different types of Clusters. There is a popular method known as elbow method which is used to determine the optimal value of K to perform the K-Means Clustering Algorithm. The basic idea behind this method is that it plots the various values of cost with changing k. As the value of K increases, there will be fewer elements in the cluster. So average distortion will decrease. The lesser number of elements means closer to the centroid. So, the point where this distortion declines the most is the elbow point.

In [46]:

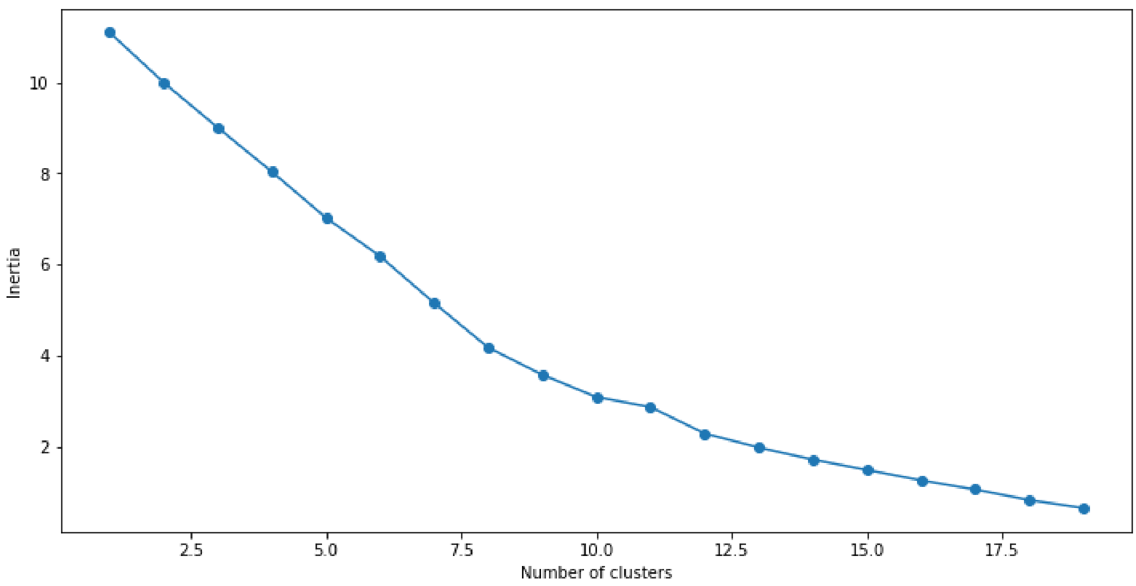
```
import matplotlib.pyplot as plt
%matplotlib inline

# fitting multiple k-means algorithms and storing the values in an empty list
SSE = []
for cluster in range(1,20):
    kmeans = KMeans(n_jobs = -1, n_clusters = cluster, init='k-means++')
    kmeans.fit(df_grouped_clustering)
    SSE.append(kmeans.inertia_)

# converting the results into a dataframe and plotting them
frame = pd.DataFrame({'Cluster':range(1,20), 'SSE':SSE})
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

Out[46]:

```
Text(0, 0.5, 'Inertia')
```




## Results : Conclusion on K- means , K values :

Here we can clearly see that a possible range of values from 5-8 seems optimum for K - means clustering anaysis here

## Discussion :

Since we discussed during start of this project will be useful for people coming in the City of London , which will help them with an idea of how similar and diverse different neighborhoods in the City of London are. It would help them choose/pick the places of their choice easily , for the different activities they would like to do in the City of London. Based on our analysis above for using K - means clustering with K=5 , we have below classifications to help people:

Cluster 1 : Seems like a place for Cafe , Pubs , Pools and Supermarkets
Cluster 2 : Seems like a place for Pubs ,Golf Courses and Electronics and Warehouses
Cluster 3 : Seems like a place for Breakfast spots and Small shops and stores
Cluster 4 : Seems like a place for Fast Foods , eateries and some construction/ landscape along with warehousing places
Cluster 5 : Seems like a place for Distinct with Stables , Cosmetics and Departmental store

Now coming to value of K , we see that , we can go till K=8 for more clusters in classifications as inferred above.

## Conclusion:

Our conclusion is 2 folds here:

We have identified that we can go for K=8 for optimum results on K-means clustering.We can then easily identify the clusters and their different categories for (Cafe , Pubs , Pools and Supermarkets) or (Pubs ,Golf Courses and Electronics and Warehouses) or (Breakfast spots and Small shops and stores) or (Fast Foods , eateries and some construction/ landscape along with warehousing places) or (Distinct with Stables , Cosmetics and Departmental store).

Another point is that , we had used above, value of LIMIT = 100 # limit of number of venues returned by Foursquare API. If we increase this number to a larger value, then we would have more data and venues to cluster and which would refine our data and analysis, both. This would result in crisp and much detailed findings.

# Thank you