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

# All requested packages already installed.

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′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 [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′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 [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	Coor
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	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.
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

# All requested packages already installed.
```

In [21]:

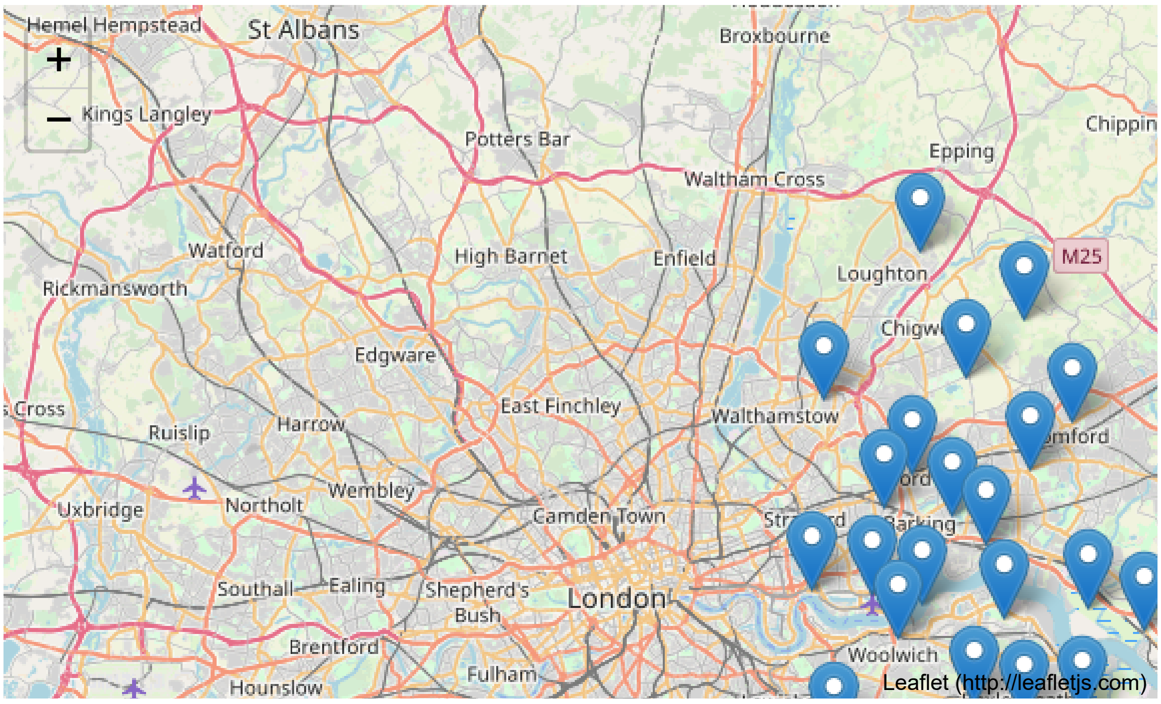
```
latitude = 51.5074
longitude = 0.1278

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 Art 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 Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Neighborhood						
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]:

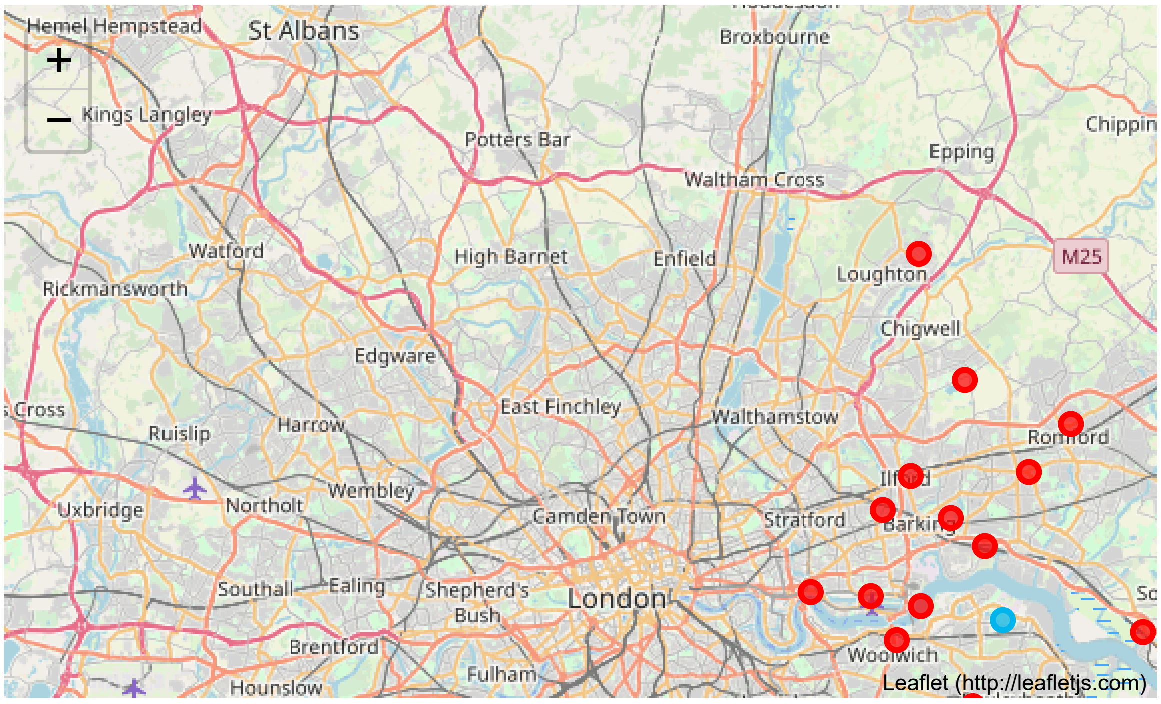
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=10)

# 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_mer
ged['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 Mos 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	Metr Static

	Local authority	Population	Longitude	Latitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Mos Commc Venu
16	Kingston upon Thames London Borough Council	166793	0.3064	51.4085	0	Clothing Store	Warehouse Store	Fast Foc Restaura
17	Lambeth London Borough Council	314242	0.1163	51.4607	0	Supermarket	Pub	Coffe Shc
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	Airpc
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 Foc Restaura
24	Sutton London Borough Council	195914	0.1945	51.3618	0	Historic Site	Tennis Court	Fast Foc 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 Foc 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	I

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	Dep

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]:

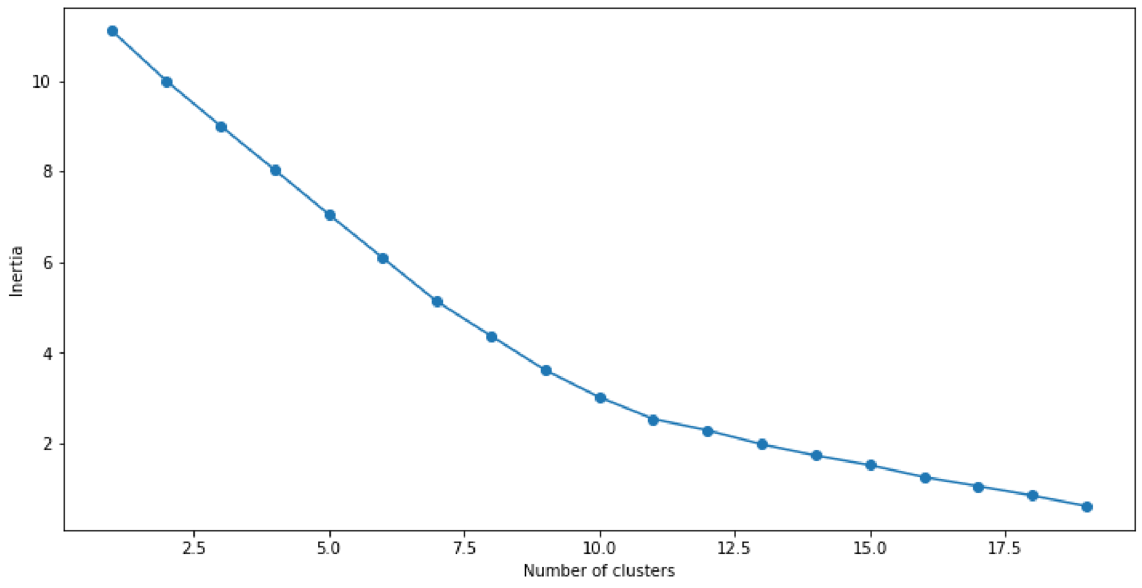
```
import matplotlib.pyplot as plt
%matplotlib inline

# 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