Capstone Project - The Battle of Neighborhoods

By Pankaj Kumar,IBM

Business Problem section

Background

According to Bloomberg News, the London Housing Market is in a rut. It is now facing a number of different headwinds, including the prospect of higher taxes and a warning from the Bank of England that U.K. home values could fall as much as 30 percent in the event of a disorderly exit from the European Union. More specifically, four overlooked cracks suggest that the London market may be in worse shape than many realize: hidden price falls, record-low sales, homebuilder exodus and tax hikes addressing overseas buyers of homes in England and Wales.

Business Problem In this scenario, it is urgent to adopt machine learning tools in order to assist homebuyers clientele in London to make wise and effective decisions. As a result, the business problem we are currently posing is: how could we provide support to homebuyers clientele in to purchase a suitable real estate in London in this uncertain economic and financial scenario?

To solve this business problem, we are going to cluster London neighborhoods in order to recommend venues and the current average price of real estate where homebuyers can make a real estate investment. We will recommend profitable venues according to amenities and essential facilities surrounding such venues i.e. elementary schools, high schools, hospitals & grocery stores.

Data section

Data on London properties and the relative price paid data were extracted from the HM Land Registry (http://landregistry.data.gov.uk/ (http://landregistry.data.gov.uk/)). The following fields comprise the address data included in Price Paid Data: Postcode; PAON Primary Addressable Object Name. Typically the house number or name; SAON Secondary Addressable Object Name. If there is a sub-building, for example, the building is divided into flats, there will be a SAON; Street; Locality; Town/City; District; County.

To explore and target recommended locations across different venues according to the presence of amenities and essential facilities, we will access data through FourSquare API interface and arrange them as a dataframe for visualization. By merging data on London properties and the relative price paid data from the HM Land Registry and data on amenities and essential facilities surrounding such properties from FourSquare API interface, we will be able to recommend profitable real estate investments.

Methodology section

The Methodology section will describe the main components of our analysis and predication system. The Methodology section comprises four stages:

1. Collect Inspection Data
2. Explore and Understand Data
3. Data preparation and preprocessing
4. Modeling

1. Collect Inspection Data

After importing the necessary libraries, we download the data from the HM Land Registry website as follows:

In [1]:

```
import os # Operating System
import numpy as np
import pandas as pd
import datetime as dt # Datetime
import json # library to handle JSON files

!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # convert an address into latitude and l
ongitude values

import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas d
ataframe

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

!conda install -c conda-forge folium=0.5.0 --yes
import folium #import folium # map rendering library

print('Libraries imported.')
```

```
Collecting package metadata (current_repodata.json): ...working... done
Solving environment: ...working... done

## Package Plan ##

  environment location: C:\Users\Manju\anaconda3

  added / updated specs:
    - geopy


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    geographiclib-1.50         |             py_0          34 KB  conda-forge
    geopy-1.22.0               |     pyh9f0ad1d_0          63 KB  conda-forge
    ------------------------------------------------------------
                                           Total:          97 KB

The following NEW packages will be INSTALLED:

  geographiclib      conda-forge/noarch::geographiclib-1.50-py_0
  geopy              conda-forge/noarch::geopy-1.22.0-pyh9f0ad1d_0



Downloading and Extracting Packages

geopy-1.22.0         | 63 KB     |            |   0%
geopy-1.22.0         | 63 KB     | ##5        |  26%
geopy-1.22.0         | 63 KB     | ########## | 100%

geographiclib-1.50   | 34 KB     |            |   0%
geographiclib-1.50   | 34 KB     | ########## | 100%
Preparing transaction: ...working... done
Verifying transaction: ...working... done
Executing transaction: ...working... done
Collecting package metadata (current_repodata.json): ...working... done
Solving environment: ...working... done

# All requested packages already installed.

Libraries imported.
```

In [2]:
```
#Read the data for examination (Source: http://landregistry.data.gov.uk/)
df_ppd = pd.read_csv("http://prod2.publicdata.landregistry.gov.uk.s3-website-e
u-west-1.amazonaws.com/pp-2018.csv")
```

Before using data, we will have to explore and understand it.

2. Explore and Understand Data

We read the dataset that we collected from the HM Land Registry website into a pandas' data frame and display the first five rows of it as follows:

In [4]:
```
df_ppd.head(5)
```

Out[4]:

	{79A74E21-D11E-1289-E053-6B04A8C01627}	770000	2018-09-25 00:00	SK7 1AR	D	N	F	5	Unnamed: 8	OAK MEADOW	BRAMHALL
0	{79A74E21-D11F-1289-E053-6B04A8C01627}	253500	2018-09-24 00:00	M6 8GQ	D	N	F	1	NaN	RIVINGTON ROAD	NaN
1	{79A74E21-D120-1289-E053-6B04A8C01627}	231950	2018-09-28 00:00	WA3 2UE	D	Y	F	35	NaN	STONEACRE CLOSE	LOWTON
2	{79A74E21-D121-1289-E053-6B04A8C01627}	112500	2018-08-29 00:00	OL6 6RJ	S	N	F	102	NaN	THORNFIELD GROVE	NaN
3	{79A74E21-D122-1289-E053-6B04A8C01627}	184995	2018-06-15 00:00	M46 0TW	S	Y	F	37	NaN	THREADNEEDLE PLACE	ATHERTON
4	{79A74E21-D123-1289-E053-6B04A8C01627}	214995	2018-09-28 00:00	M28 3XS	D	Y	L	9	NaN	MARPLE GARDENS	WORSLEY

In [6]:
```
df_ppd.shape
```

Out[6]: (1029749, 16)

3. Data preparation and preprocessing

At this stage, we prepare our dataset for the modeling process, opting for the most suitable machine learning algorithm for our scope. Accordingly, we perform the following steps:

- Rename the column names
- Format the date column
- Sort data by date of sale
- Select data only for the city of London
- Make a list of street names in London
- Calculate the street-wise average price of the property
- Read the street-wise coordinates into a data frame, eliminating recurring word London from individual names
- Join the data to find the coordinates of locations which fit into client's budget
- Plot recommended locations on London map along with current market prices

In [7]:
```
# Assign meaningful column names
df_ppd.columns = ['TUID', 'Price', 'Date_Transfer', 'Postcode', 'Prop_Type',
'Old_New', 'Duration', 'PAON', \
                  'SAON', 'Street', 'Locality', 'Town_City', 'District', 'Coun
ty', 'PPD_Cat_Type', 'Record_Status']
```

In [8]:
```
# Format the date column
df_ppd['Date_Transfer'] = df_ppd['Date_Transfer'].apply(pd.to_datetime)

# Delete all obsolete transactions which were done before 2016
df_ppd.drop(df_ppd[df_ppd.Date_Transfer.dt.year < 2016].index, inplace=True)

# Sort by Date of Sale
df_ppd.sort_values(by=['Date_Transfer'],ascending=[False],inplace=True)
```

In [9]:
```
df_ppd_london = df_ppd.query("Town_City == 'LONDON'")

# Make a list of street names in LONDON
streets = df_ppd_london['Street'].unique().tolist()
```

In [10]:
```
df_grp_price = df_ppd_london.groupby(['Street'])['Price'].mean().reset_index()

# Give meaningful names to the columns
df_grp_price.columns = ['Street', 'Avg_Price']
```

In [11]:
```
#Input your Budget's Upper Limit and Lower Limit - Find the locations df_grp_p
rice which fits your budget
df_affordable = df_grp_price.query("(Avg_Price >= 2200000) & (Avg_Price <= 250
0000)")
```

In [15]:
```
# Display the dataframe
df_affordable
```

Out[15]:

	Street	Avg_Price
196	ALBION SQUARE	2450000.0
390	ANHALT ROAD	2435000.0
405	ANSDELL TERRACE	2250000.0
422	APPLEGARTH ROAD	2400000.0
855	BARONSMEAD ROAD	2375000.0
...	...	...
13722	WILFRED STREET	2410538.5
13748	WILLOW BRIDGE ROAD	2425000.0
13768	WILSON STREET	2257500.0
13796	WINCHENDON ROAD	2350000.0
13833	WINGATE ROAD	2206400.0

162 rows × 2 columns

In [16]:
```
import pandas as pd
import numpy as np
import datetime as DT
import hmac
from geopy.geocoders import Nominatim
from geopy.distance import vincenty
# import k-means from clustering stage
from sklearn.cluster import KMeans
```

In [17]:
```
for index, item in df_affordable.iterrows():
    print(f"index: {index}")
    print(f"item: {item}")
    print(f"item.Street only: {item.Street}")
```

```
index: 196
item: Street       ALBION SQUARE
Avg_Price         2.45e+06
Name: 196, dtype: object
item.Street only: ALBION SQUARE
index: 390
item: Street       ANHALT ROAD
Avg_Price      2.435e+06
Name: 390, dtype: object
item.Street only: ANHALT ROAD
index: 405
item: Street       ANSDELL TERRACE
Avg_Price           2.25e+06
Name: 405, dtype: object
item.Street only: ANSDELL TERRACE
index: 422
item: Street       APPLEGARTH ROAD
Avg_Price            2.4e+06
Name: 422, dtype: object
item.Street only: APPLEGARTH ROAD
index: 855
item: Street       BARONSMEAD ROAD
Avg_Price          2.375e+06
Name: 855, dtype: object
item.Street only: BARONSMEAD ROAD
index: 981
item: Street       BEAUCLERC ROAD
Avg_Price          2.48e+06
Name: 981, dtype: object
item.Street only: BEAUCLERC ROAD
index: 1102
item: Street       BELVEDERE DRIVE
Avg_Price           2.34e+06
Name: 1102, dtype: object
item.Street only: BELVEDERE DRIVE
index: 1215
item: Street       BICKENHALL STREET
Avg_Price           2.2085e+06
Name: 1215, dtype: object
item.Street only: BICKENHALL STREET
index: 1253
item: Street       BIRCHLANDS AVENUE
Avg_Price            2.217e+06
Name: 1253, dtype: object
item.Street only: BIRCHLANDS AVENUE
index: 1553
item: Street       BRAMPTON GROVE
Avg_Price       2.45688e+06
Name: 1553, dtype: object
item.Street only: BRAMPTON GROVE
index: 1632
item: Street       BRIARDALE GARDENS
Avg_Price          2.39713e+06
Name: 1632, dtype: object
item.Street only: BRIARDALE GARDENS
index: 1797
item: Street       BROOKWAY
```

```
Avg_Price     2.4e+06
Name: 1797, dtype: object
item.Street only: BROOKWAY
index: 1914
item: Street       BURBAGE ROAD
Avg_Price       2.445e+06
Name: 1914, dtype: object
item.Street only: BURBAGE ROAD
index: 1980
item: Street        BURY WALK
Avg_Price    2.4925e+06
Name: 1980, dtype: object
item.Street only: BURY WALK
index: 2068
item: Street       CALLCOTT STREET
Avg_Price          2.375e+06
Name: 2068, dtype: object
item.Street only: CALLCOTT STREET
index: 2129
item: Street       CAMPDEN HILL ROAD
Avg_Price          2.37965e+06
Name: 2129, dtype: object
item.Street only: CAMPDEN HILL ROAD
index: 2136
item: Street       CAMPION ROAD
Avg_Price       2.461e+06
Name: 2136, dtype: object
item.Street only: CAMPION ROAD
index: 2158
item: Street       CANNING PLACE
Avg_Price        2.425e+06
Name: 2158, dtype: object
item.Street only: CANNING PLACE
index: 2225
item: Street       CARLISLE ROAD
Avg_Price          2.2e+06
Name: 2225, dtype: object
item.Street only: CARLISLE ROAD
index: 2230
item: Street       CARLTON GARDENS
Avg_Price         2.4835e+06
Name: 2230, dtype: object
item.Street only: CARLTON GARDENS
index: 2242
item: Street       CARLYLE COURT
Avg_Price          2.3e+06
Name: 2242, dtype: object
item.Street only: CARLYLE COURT
index: 2406
item: Street       CHALCOT SQUARE
Avg_Price       2.28668e+06
Name: 2406, dtype: object
item.Street only: CHALCOT SQUARE
index: 2484
item: Street       CHARLES LANE
Avg_Price       2.414e+06
Name: 2484, dtype: object
```

```
item.Street only: CHARLES LANE
index: 2562
item: Street       CHELSEA CRESCENT
Avg_Price           2.495e+06
Name: 2562, dtype: object
item.Street only: CHELSEA CRESCENT
index: 2606
item: Street       CHESTER CLOSE NORTH
Avg_Price               2.45e+06
Name: 2606, dtype: object
item.Street only: CHESTER CLOSE NORTH
index: 2638
item: Street       CHEYNE COURT
Avg_Price        2.25e+06
Name: 2638, dtype: object
item.Street only: CHEYNE COURT
index: 2641
item: Street       CHEYNE ROW
Avg_Price      2.41e+06
Name: 2641, dtype: object
item.Street only: CHEYNE ROW
index: 2686
item: Street       CHISWICK MALL
Avg_Price       2.2875e+06
Name: 2686, dtype: object
item.Street only: CHISWICK MALL
index: 2761
item: Street         CITY ROAD
Avg_Price    2.46834e+06
Name: 2761, dtype: object
item.Street only: CITY ROAD
index: 2808
item: Street       CLARENDON STREET
Avg_Price            2.25e+06
Name: 2808, dtype: object
item.Street only: CLARENDON STREET
index: 2900
item: Street       CLONCURRY STREET
Avg_Price         2.38833e+06
Name: 2900, dtype: object
item.Street only: CLONCURRY STREET
index: 2944
item: Street       COLBECK MEWS
Avg_Price      2.3675e+06
Name: 2944, dtype: object
item.Street only: COLBECK MEWS
index: 2995
item: Street       COLLEGE CRESCENT
Avg_Price            2.44e+06
Name: 2995, dtype: object
item.Street only: COLLEGE CRESCENT
index: 3202
item: Street       CORNWALL TERRACE MEWS
Avg_Price                 2.35e+06
Name: 3202, dtype: object
item.Street only: CORNWALL TERRACE MEWS
index: 3255
```

```
item: Street       COURT LANE GARDENS
Avg_Price              2.36e+06
Name: 3255, dtype: object
item.Street only: COURT LANE GARDENS
index: 3377
item: Street       CRESCENT GROVE
Avg_Price         2.298e+06
Name: 3377, dtype: object
item.Street only: CRESCENT GROVE
index: 3583
item: Street       DALEBURY ROAD
Avg_Price          2.4e+06
Name: 3583, dtype: object
item.Street only: DALEBURY ROAD
index: 3848
item: Street       DEWHURST ROAD
Avg_Price        2.425e+06
Name: 3848, dtype: object
item.Street only: DEWHURST ROAD
index: 3929
item: Street       DORIA ROAD
Avg_Price    2.3625e+06
Name: 3929, dtype: object
item.Street only: DORIA ROAD
index: 3980
item: Street       DOWNSHIRE HILL
Avg_Price         2.225e+06
Name: 3980, dtype: object
item.Street only: DOWNSHIRE HILL
index: 4035
item: Street       DUCHESS WALK
Avg_Price      2.4775e+06
Name: 4035, dtype: object
item.Street only: DUCHESS WALK
index: 4232
item: Street       ECCLESTON SQUARE MEWS
Avg_Price                2.3355e+06
Name: 4232, dtype: object
item.Street only: ECCLESTON SQUARE MEWS
index: 4285
item: Street       EGBERT STREET
Avg_Price        2.265e+06
Name: 4285, dtype: object
item.Street only: EGBERT STREET
index: 4289
item: Street       EGERTON PLACE
Avg_Price          2.2e+06
Name: 4289, dtype: object
item.Street only: EGERTON PLACE
index: 4375
item: Street       ELM PARK ROAD
Avg_Price      2.32042e+06
Name: 4375, dtype: object
item.Street only: ELM PARK ROAD
index: 4894
item: Street       FLORAL STREET
Avg_Price      2.22722e+06
```

```
Name: 4894, dtype: object
item.Street only: FLORAL STREET
index: 5016
item: Street       FRANK DIXON WAY
Avg_Price         2.2125e+06
Name: 5016, dtype: object
item.Street only: FRANK DIXON WAY
index: 5098
item: Street       FULTON MEWS
Avg_Price      2.299e+06
Name: 5098, dtype: object
item.Street only: FULTON MEWS
index: 5241
item: Street       GERARD ROAD
Avg_Price     2.2585e+06
Name: 5241, dtype: object
item.Street only: GERARD ROAD
index: 5244
item: Street       GERRARD ROAD
Avg_Price      2.2425e+06
Name: 5244, dtype: object
item.Street only: GERRARD ROAD
index: 5289
item: Street       GIRDLERS ROAD
Avg_Price      2.44167e+06
Name: 5289, dtype: object
item.Street only: GIRDLERS ROAD
index: 5382
item: Street       GLOUCESTER CRESCENT
Avg_Price            2.35083e+06
Name: 5382, dtype: object
item.Street only: GLOUCESTER CRESCENT
index: 5450
item: Street       GORDON PLACE
Avg_Price       2.477e+06
Name: 5450, dtype: object
item.Street only: GORDON PLACE
index: 5486
item: Street       GRAFTON SQUARE
Avg_Price          2.27e+06
Name: 5486, dtype: object
item.Street only: GRAFTON SQUARE
index: 5493
item: Street       GRAHAM TERRACE
Avg_Price         2.325e+06
Name: 5493, dtype: object
item.Street only: GRAHAM TERRACE
index: 5952
item: Street       HARMAN DRIVE
Avg_Price      2.2625e+06
Name: 5952, dtype: object
item.Street only: HARMAN DRIVE
index: 5976
item: Street       HARRIS STREET
Avg_Price      2.47177e+06
Name: 5976, dtype: object
item.Street only: HARRIS STREET
```

```
index: 6039
item: Street       HAVANNAH STREET
Avg_Price        2.21731e+06
Name: 6039, dtype: object
item.Street only: HAVANNAH STREET
index: 6111
item: Street       HAZLEWELL ROAD
Avg_Price           2.5e+06
Name: 6111, dtype: object
item.Street only: HAZLEWELL ROAD
index: 6227
item: Street       HEREFORD MEWS
Avg_Price         2.31e+06
Name: 6227, dtype: object
item.Street only: HEREFORD MEWS
index: 6247
item: Street       HERONDALE AVENUE
Avg_Price           2.475e+06
Name: 6247, dtype: object
item.Street only: HERONDALE AVENUE
index: 6344
item: Street       HIGHGATE HIGH STREET
Avg_Price               2.211e+06
Name: 6344, dtype: object
item.Street only: HIGHGATE HIGH STREET
index: 6359
item: Street       HIGHWOOD HILL
Avg_Price       2.2525e+06
Name: 6359, dtype: object
item.Street only: HIGHWOOD HILL
index: 6395
item: Street       HILLGATE PLACE
Avg_Price           2.2e+06
Name: 6395, dtype: object
item.Street only: HILLGATE PLACE
index: 6506
item: Street       HOLLYCROFT AVENUE
Avg_Price          2.36138e+06
Name: 6506, dtype: object
item.Street only: HOLLYCROFT AVENUE
index: 6510
item: Street       HOLLYWOOD MEWS
Avg_Price          2.35e+06
Name: 6510, dtype: object
item.Street only: HOLLYWOOD MEWS
index: 6555
item: Street       HONEYWELL ROAD
Avg_Price       2.27833e+06
Name: 6555, dtype: object
item.Street only: HONEYWELL ROAD
index: 6611
item: Street       HORTENSIA ROAD
Avg_Price       2.27592e+06
Name: 6611, dtype: object
item.Street only: HORTENSIA ROAD
index: 6640
item: Street       HOXTON SQUARE
```

```
Avg_Price      2.23429e+06
Name: 6640, dtype: object
item.Street only: HOXTON SQUARE
index: 6666
item: Street       HUNTER ROAD
Avg_Price        2.3e+06
Name: 6666, dtype: object
item.Street only: HUNTER ROAD
index: 6825
item: Street       JACKSONS LANE
Avg_Price       2.3625e+06
Name: 6825, dtype: object
item.Street only: JACKSONS LANE
index: 6885
item: Street       JOHN STREET
Avg_Price      2.235e+06
Name: 6885, dtype: object
item.Street only: JOHN STREET
index: 7190
item: Street       KINNERTON STREET
Avg_Price          2.4856e+06
Name: 7190, dtype: object
item.Street only: KINNERTON STREET
index: 7224
item: Street       KNARESBOROUGH PLACE
Avg_Price              2.325e+06
Name: 7224, dtype: object
item.Street only: KNARESBOROUGH PLACE
index: 7244
item: Street       KNOX STREET
Avg_Price       2.25e+06
Name: 7244, dtype: object
item.Street only: KNOX STREET
index: 7264
item: Street       LADBROKE GROVE
Avg_Price        2.4833e+06
Name: 7264, dtype: object
item.Street only: LADBROKE GROVE
index: 7333
item: Street       LANCASTER MEWS
Avg_Price        2.3125e+06
Name: 7333, dtype: object
item.Street only: LANCASTER MEWS
index: 7403
item: Street       LANSDOWNE ROAD
Avg_Price       2.36488e+06
Name: 7403, dtype: object
item.Street only: LANSDOWNE ROAD
index: 7432
item: Street       LATIMER INDUSTRIAL ESTATE
Avg_Price                             2.4e+06
Name: 7432, dtype: object
item.Street only: LATIMER INDUSTRIAL ESTATE
index: 7485
item: Street       LAXTON PLACE
Avg_Price         2.5e+06
Name: 7485, dtype: object
```

```
item.Street only: LAXTON PLACE
index: 7687
item: Street       LINCOLN AVENUE
Avg_Price        2.2035e+06
Name: 7687, dtype: object
item.Street only: LINCOLN AVENUE
index: 7716
item: Street       LINGFIELD ROAD
Avg_Price       2.24875e+06
Name: 7716, dtype: object
item.Street only: LINGFIELD ROAD
index: 7745
item: Street       LISSON STREET
Avg_Price       2.4625e+06
Name: 7745, dtype: object
item.Street only: LISSON STREET
index: 7779
item: Street       LIVERPOOL GROVE
Avg_Price          2.288e+06
Name: 7779, dtype: object
item.Street only: LIVERPOOL GROVE
index: 7871
item: Street       LONGWOOD DRIVE
Avg_Price         2.375e+06
Name: 7871, dtype: object
item.Street only: LONGWOOD DRIVE
index: 7877
item: Street       LONSDALE SQUARE
Avg_Price         2.3575e+06
Name: 7877, dtype: object
item.Street only: LONSDALE SQUARE
index: 8415
item: Street       MAZE HILL
Avg_Price     2.25e+06
Name: 8415, dtype: object
item.Street only: MAZE HILL
index: 8550
item: Street       MIDDLESEX PASSAGE
Avg_Price             2.28e+06
Name: 8550, dtype: object
item.Street only: MIDDLESEX PASSAGE
index: 8714
item: Street       MONTPELIER AVENUE
Avg_Price              2.5e+06
Name: 8714, dtype: object
item.Street only: MONTPELIER AVENUE
index: 8724
item: Street       MONTPELIER WALK
Avg_Price           2.32e+06
Name: 8724, dtype: object
item.Street only: MONTPELIER WALK
index: 8872
item: Street       MULTON ROAD
Avg_Price        2.3e+06
Name: 8872, dtype: object
item.Street only: MULTON ROAD
index: 8877
```

```
item: Street       MUNDEN STREET
Avg_Price         2.25e+06
Name: 8877, dtype: object
item.Street only: MUNDEN STREET
index: 9151
item: Street       NORFOLK CRESCENT
Avg_Price         2.22333e+06
Name: 9151, dtype: object
item.Street only: NORFOLK CRESCENT
index: 9174
item: Street       NORTH CIRCULAR ROAD
Avg_Price            2.39314e+06
Name: 9174, dtype: object
item.Street only: NORTH CIRCULAR ROAD
index: 9250
item: Street       NOTTINGHAM STREET
Avg_Price           2.2275e+06
Name: 9250, dtype: object
item.Street only: NOTTINGHAM STREET
index: 9325
item: Street       OAKLEY STREET
Avg_Price      2.38129e+06
Name: 9325, dtype: object
item.Street only: OAKLEY STREET
index: 9336
item: Street       OAKWOOD COURT
Avg_Price      2.34875e+06
Name: 9336, dtype: object
item.Street only: OAKWOOD COURT
index: 9344
item: Street       OBSERVATORY GARDENS
Avg_Price               2.42e+06
Name: 9344, dtype: object
item.Street only: OBSERVATORY GARDENS
index: 9379
item: Street       OLD COURT PLACE
Avg_Price          2.395e+06
Name: 9379, dtype: object
item.Street only: OLD COURT PLACE
index: 9440
item: Street       ONSLOW MEWS WEST
Avg_Price             2.3e+06
Name: 9440, dtype: object
item.Street only: ONSLOW MEWS WEST
index: 9572
item: Street       PALACE PLACE
Avg_Price         2.3e+06
Name: 9572, dtype: object
item.Street only: PALACE PLACE
index: 9601
item: Street       PANTON STREET
Avg_Price        2.475e+06
Name: 9601, dtype: object
item.Street only: PANTON STREET
index: 9620
item: Street       PARK CRESCENT
Avg_Price         2.44e+06
```

```
Name: 9620, dtype: object
item.Street only: PARK CRESCENT
index: 9629
item: Street        PARK LANE
Avg_Price    2.2415e+06
Name: 9629, dtype: object
item.Street only: PARK LANE
index: 9650
item: Street       PARKE ROAD
Avg_Price    2.2625e+06
Name: 9650, dtype: object
item.Street only: PARKE ROAD
index: 9653
item: Street       PARKFIELDS
Avg_Price       2.2e+06
Name: 9653, dtype: object
item.Street only: PARKFIELDS
index: 9690
item: Street       PARTHENIA ROAD
Avg_Price       2.20057e+06
Name: 9690, dtype: object
item.Street only: PARTHENIA ROAD
index: 9722
item: Street       PAVILION ROAD
Avg_Price          2.2e+06
Name: 9722, dtype: object
item.Street only: PAVILION ROAD
index: 9783
item: Street       PEMBRIDGE MEWS
Avg_Price         2.251e+06
Name: 9783, dtype: object
item.Street only: PEMBRIDGE MEWS
index: 9785
item: Street       PEMBRIDGE ROAD
Avg_Price           2.4e+06
Name: 9785, dtype: object
item.Street only: PEMBRIDGE ROAD
index: 9794
item: Street       PEMBROKE STUDIOS
Avg_Price            2.45e+06
Name: 9794, dtype: object
item.Street only: PEMBROKE STUDIOS
index: 9799
item: Street       PENCOMBE MEWS
Avg_Price          2.2e+06
Name: 9799, dtype: object
item.Street only: PENCOMBE MEWS
index: 9879
item: Street       PETERSHAM PLACE
Avg_Price            2.3e+06
Name: 9879, dtype: object
item.Street only: PETERSHAM PLACE
index: 9894
item: Street       PHILLIMORE GARDENS
Avg_Price           2.48467e+06
Name: 9894, dtype: object
item.Street only: PHILLIMORE GARDENS
```

```
index: 9902
item: Street       PHYSIC PLACE
Avg_Price         2.5e+06
Name: 9902, dtype: object
item.Street only: PHYSIC PLACE
index: 9940
item: Street       PITFIELD STREET
Avg_Price        2.48333e+06
Name: 9940, dtype: object
item.Street only: PITFIELD STREET
index: 10150
item: Street       PRINCES GATE
Avg_Price     2.40333e+06
Name: 10150, dtype: object
item.Street only: PRINCES GATE
index: 10178
item: Street       PRIORY ROAD
Avg_Price    2.24826e+06
Name: 10178, dtype: object
item.Street only: PRIORY ROAD
index: 10189
item: Street       PROTHERO GARDENS
Avg_Price          2.2025e+06
Name: 10189, dtype: object
item.Street only: PROTHERO GARDENS
index: 10225
item: Street       PUTNEY HIGH STREET
Avg_Price            2.3486e+06
Name: 10225, dtype: object
item.Street only: PUTNEY HIGH STREET
index: 10242
item: Street       QUARRENDON STREET
Avg_Price          2.43775e+06
Name: 10242, dtype: object
item.Street only: QUARRENDON STREET
index: 10275
item: Street       QUEENS GATE TERRACE
Avg_Price            2.39944e+06
Name: 10275, dtype: object
item.Street only: QUEENS GATE TERRACE
index: 10329
item: Street       RADSTOCK STREET
Avg_Price         2.2175e+06
Name: 10329, dtype: object
item.Street only: RADSTOCK STREET
index: 10374
item: Street       RANELAGH AVENUE
Avg_Price            2.3e+06
Name: 10374, dtype: object
item.Street only: RANELAGH AVENUE
index: 10482
item: Street       REDCLIFFE ROAD
Avg_Price       2.44875e+06
Name: 10482, dtype: object
item.Street only: REDCLIFFE ROAD
index: 10507
item: Street       REEVES MEWS
```

```
Avg_Price       2.45e+06
Name: 10507, dtype: object
item.Street only: REEVES MEWS
index: 10564
item: Street       RHEIDOL MEWS
Avg_Price        2.31e+06
Name: 10564, dtype: object
item.Street only: RHEIDOL MEWS
index: 10619
item: Street       RINGWOOD AVENUE
Avg_Price          2.275e+06
Name: 10619, dtype: object
item.Street only: RINGWOOD AVENUE
index: 10700
item: Street       RODERICK ROAD
Avg_Price          2.4e+06
Name: 10700, dtype: object
item.Street only: RODERICK ROAD
index: 10757
item: Street       ROPEMAKERS FIELDS
Avg_Price              2.5e+06
Name: 10757, dtype: object
item.Street only: ROPEMAKERS FIELDS
index: 10872
item: Street       ROYAL CRESCENT
Avg_Price       2.34833e+06
Name: 10872, dtype: object
item.Street only: ROYAL CRESCENT
index: 10878
item: Street       ROYAL HILL
Avg_Price    2.2525e+06
Name: 10878, dtype: object
item.Street only: ROYAL HILL
index: 10935
item: Street       RUSSELL GARDENS MEWS
Avg_Price                 2.3e+06
Name: 10935, dtype: object
item.Street only: RUSSELL GARDENS MEWS
index: 11182
item: Street       SETTLES STREET
Avg_Price        2.4875e+06
Name: 11182, dtype: object
item.Street only: SETTLES STREET
index: 11257
item: Street       SHELDON AVENUE
Avg_Price       2.34954e+06
Name: 11257, dtype: object
item.Street only: SHELDON AVENUE
index: 11491
item: Street       SOUTH END ROW
Avg_Price         2.47e+06
Name: 11491, dtype: object
item.Street only: SOUTH END ROW
index: 11568
item: Street       SOUTHWOOD LAWN ROAD
Avg_Price               2.35e+06
Name: 11568, dtype: object
```

```
item.Street only: SOUTHWOOD LAWN ROAD
index: 11571
item: Street       SOVEREIGN PARK
Avg_Price           2.5e+06
Name: 11571, dtype: object
item.Street only: SOVEREIGN PARK
index: 11788
item: Street       ST MARGARETS CRESCENT
Avg_Price               2.2165e+06
Name: 11788, dtype: object
item.Street only: ST MARGARETS CRESCENT
index: 11824
item: Street       ST OSWALDS PLACE
Avg_Price            2.25e+06
Name: 11824, dtype: object
item.Street only: ST OSWALDS PLACE
index: 11844
item: Street       ST PETERS SQUARE
Avg_Price         2.46873e+06
Name: 11844, dtype: object
item.Street only: ST PETERS SQUARE
index: 11881
item: Street       STAFFORD TERRACE
Avg_Price           2.355e+06
Name: 11881, dtype: object
item.Street only: STAFFORD TERRACE
index: 12221
item: Street       SUTHERLAND PLACE
Avg_Price           2.456e+06
Name: 12221, dtype: object
item.Street only: SUTHERLAND PLACE
index: 12283
item: Street       SYDNEY STREET
Avg_Price      2.24083e+06
Name: 12283, dtype: object
item.Street only: SYDNEY STREET
index: 12425
item: Street       THAMES BANK
Avg_Price        2.4e+06
Name: 12425, dtype: object
item.Street only: THAMES BANK
index: 12487
item: Street       THE HEXAGON
Avg_Price      2.335e+06
Name: 12487, dtype: object
item.Street only: THE HEXAGON
index: 12766
item: Street       TREDEGAR SQUARE
Avg_Price        2.43667e+06
Name: 12766, dtype: object
item.Street only: TREDEGAR SQUARE
index: 12828
item: Street       TRINITY STREET
Avg_Price        2.3175e+06
Name: 12828, dtype: object
item.Street only: TRINITY STREET
index: 12978
```

```
item: Street       UPPER HAMPSTEAD WALK
Avg_Price                 2.5e+06
Name: 12978, dtype: object
item.Street only: UPPER HAMPSTEAD WALK
index: 13240
item: Street       WALPOLE GARDENS
Avg_Price         2.3035e+06
Name: 13240, dtype: object
item.Street only: WALPOLE GARDENS
index: 13242
item: Street       WALPOLE STREET
Avg_Price        2.2425e+06
Name: 13242, dtype: object
item.Street only: WALPOLE STREET
index: 13316
item: Street       WARWICK SQUARE
Avg_Price       2.43227e+06
Name: 13316, dtype: object
item.Street only: WARWICK SQUARE
index: 13415
item: Street       WELBECK WAY
Avg_Price      2.267e+06
Name: 13415, dtype: object
item.Street only: WELBECK WAY
index: 13427
item: Street       WELLESLEY TERRACE
Avg_Price              2.41e+06
Name: 13427, dtype: object
item.Street only: WELLESLEY TERRACE
index: 13438
item: Street       WELLINGTON STREET
Avg_Price          2.29316e+06
Name: 13438, dtype: object
item.Street only: WELLINGTON STREET
index: 13570
item: Street       WESTMORELAND PLACE
Avg_Price                2.3e+06
Name: 13570, dtype: object
item.Street only: WESTMORELAND PLACE
index: 13677
item: Street       WHITFIELD STREET
Avg_Price           2.451e+06
Name: 13677, dtype: object
item.Street only: WHITFIELD STREET
index: 13722
item: Street       WILFRED STREET
Avg_Price       2.41054e+06
Name: 13722, dtype: object
item.Street only: WILFRED STREET
index: 13748
item: Street       WILLOW BRIDGE ROAD
Avg_Price              2.425e+06
Name: 13748, dtype: object
item.Street only: WILLOW BRIDGE ROAD
index: 13768
item: Street       WILSON STREET
Avg_Price       2.2575e+06
```

```
Name: 13768, dtype: object
item.Street only: WILSON STREET
index: 13796
item: Street       WINCHENDON ROAD
Avg_Price           2.35e+06
Name: 13796, dtype: object
item.Street only: WINCHENDON ROAD
index: 13833
item: Street       WINGATE ROAD
Avg_Price      2.2064e+06
Name: 13833, dtype: object
item.Street only: WINGATE ROAD
```

In [18]:
```
geolocator = Nominatim()
```

```
C:\Users\Manju\anaconda3\lib\site-packages\ipykernel_launcher.py:1: Deprecati
onWarning: Using Nominatim with the default "geopy/1.22.0" `user_agent` is st
rongly discouraged, as it violates Nominatim's ToS https://operations.osmfoun
dation.org/policies/nominatim/ and may possibly cause 403 and 429 HTTP error
s. Please specify a custom `user_agent` with `Nominatim(user_agent="my-applic
ation")` or by overriding the default `user_agent`: `geopy.geocoders.options.
default_user_agent = "my-application"`. In geopy 2.0 this will become an exce
ption.
  """Entry point for launching an IPython kernel.
```

In [19]:
```
df_affordable['city_coord'] = df_affordable['Street'].apply(geolocator.geocode
).apply(lambda x: (x.latitude, x.longitude))
```

```
C:\Users\Manju\anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [20]:
```
df_affordable
```

Out[20]:

	Street	Avg_Price	city_coord
196	ALBION SQUARE	2450000.0	(-41.27375755, 173.28939323910353)
390	ANHALT ROAD	2435000.0	(51.4803164, -0.1668011)
405	ANSDELL TERRACE	2250000.0	(51.4998899, -0.1891027)
422	APPLEGARTH ROAD	2400000.0	(53.7486539, -0.3266704)
855	BARONSMEAD ROAD	2375000.0	(51.4773147, -0.239457)
...	...	...	...
13722	WILFRED STREET	2410538.5	(51.442178, 0.372743)
13748	WILLOW BRIDGE ROAD	2425000.0	(53.6408743, -1.2004617)
13768	WILSON STREET	2257500.0	(42.286454, -71.4009814)
13796	WINCHENDON ROAD	2350000.0	(42.645331, -71.954714)
13833	WINGATE ROAD	2206400.0	(51.092557, 1.1794554)

162 rows × 3 columns

In [21]:
```
df_affordable[['Latitude', 'Longitude']] = df_affordable['city_coord'].apply(p
d.Series)
```

```
C:\Users\Manju\anaconda3\lib\site-packages\pandas\core\frame.py:2963: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[k1] = value[k2]
```

In [22]:
```
df_affordable
```

Out[22]:

	Street	Avg_Price	city_coord	Latitude	Longitude
196	ALBION SQUARE	2450000.0	(-41.27375755, 173.28939323910353)	-41.273758	173.289393
390	ANHALT ROAD	2435000.0	(51.4803164, -0.1668011)	51.480316	-0.166801
405	ANSDELL TERRACE	2250000.0	(51.4998899, -0.1891027)	51.499890	-0.189103
422	APPLEGARTH ROAD	2400000.0	(53.7486539, -0.3266704)	53.748654	-0.326670
855	BARONSMEAD ROAD	2375000.0	(51.4773147, -0.239457)	51.477315	-0.239457
...	...	...	...	...	...
13722	WILFRED STREET	2410538.5	(51.442178, 0.372743)	51.442178	0.372743
13748	WILLOW BRIDGE ROAD	2425000.0	(53.6408743, -1.2004617)	53.640874	-1.200462
13768	WILSON STREET	2257500.0	(42.286454, -71.4009814)	42.286454	-71.400981
13796	WINCHENDON ROAD	2350000.0	(42.645331, -71.954714)	42.645331	-71.954714
13833	WINGATE ROAD	2206400.0	(51.092557, 1.1794554)	51.092557	1.179455

162 rows × 5 columns

In [23]:
```
df = df_affordable.drop(columns=['city_coord'])
```

In [24]:
```
df
```

Out[24]:

	Street	Avg_Price	Latitude	Longitude
196	ALBION SQUARE	2450000.0	-41.273758	173.289393
390	ANHALT ROAD	2435000.0	51.480316	-0.166801
405	ANSDELL TERRACE	2250000.0	51.499890	-0.189103
422	APPLEGARTH ROAD	2400000.0	53.748654	-0.326670
855	BARONSMEAD ROAD	2375000.0	51.477315	-0.239457
...	...	...	...	...
13722	WILFRED STREET	2410538.5	51.442178	0.372743
13748	WILLOW BRIDGE ROAD	2425000.0	53.640874	-1.200462
13768	WILSON STREET	2257500.0	42.286454	-71.400981
13796	WINCHENDON ROAD	2350000.0	42.645331	-71.954714
13833	WINGATE ROAD	2206400.0	51.092557	1.179455

162 rows × 4 columns

In [25]:
```
address = 'London, UK'

geolocator = Nominatim()
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of London City are {}, {}.'.format(latitude,
longitude))
```

```
C:\Users\Manju\anaconda3\lib\site-packages\ipykernel_launcher.py:3: Deprecati
onWarning: Using Nominatim with the default "geopy/1.22.0" `user_agent` is st
rongly discouraged, as it violates Nominatim's ToS https://operations.osmfoun
dation.org/policies/nominatim/ and may possibly cause 403 and 429 HTTP error
s. Please specify a custom `user_agent` with `Nominatim(user_agent="my-applic
ation")` or by overriding the default `user_agent`: `geopy.geocoders.options.
default_user_agent = "my-application"`. In geopy 2.0 this will become an exce
ption.
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

```
The geograpical coordinate of London City are 51.5073219, -0.1276474.
```

In [26]:
```
# create map of London using latitude and longitude values
map_london = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to map
for lat, lng, price, street in zip(df['Latitude'], df['Longitude'], df['Avg_Pr
ice'], df['Street']):
    label = '{}, {}'.format(street, price)
    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_london)

map_london
```

Out[26]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [27]:
```
#Define Foursquare Credentials and Version

CLIENT_ID = 'KI3TR0QO4JOKMFELOMF3WSOOI3HFNBF5YLW354MYWBKDHEX3' # Foursquare ID
CLIENT_SECRET = 'QF4ZBLJRBV4BQX52DVWUPEHJ14A2UJABPCZARZQZYTKIISUD' # Foursquar
e Secret
VERSION = '20181206' # Foursquare API version

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

```
Your credentails:
CLIENT_ID: KI3TR0QO4JOKMFELOMF3WSOOI3HFNBF5YLW354MYWBKDHEX3
CLIENT_SECRET:QF4ZBLJRBV4BQX52DVWUPEHJ14A2UJABPCZARZQZYTKIISUD
```

In [43]:
```
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?&client_id={}&clie
nt_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 = ['Street',
                  'Street Latitude',
                  'Street Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

In [44]:
```
# Run the above function on each location and create a new dataframe called lo
cation_venues and display it.
location_venues = getNearbyVenues(names=df['Street'],
                                  latitudes=df['Latitude'],
                                  longitudes=df['Longitude'] )
```

```
ALBION SQUARE
ANHALT ROAD
ANSDELL TERRACE
APPLEGARTH ROAD
BARONSMEAD ROAD
BEAUCLERC ROAD
BELVEDERE DRIVE
BICKENHALL STREET
BIRCHLANDS AVENUE
BRAMPTON GROVE
BRIARDALE GARDENS
BROOKWAY
BURBAGE ROAD
BURY WALK
CALLCOTT STREET
CAMPDEN HILL ROAD
CAMPION ROAD
CANNING PLACE
CARLISLE ROAD
CARLTON GARDENS
CARLYLE COURT
CHALCOT SQUARE
CHARLES LANE
CHELSEA CRESCENT
CHESTER CLOSE NORTH
CHEYNE COURT
CHEYNE ROW
CHISWICK MALL
CITY ROAD
CLARENDON STREET
CLONCURRY STREET
COLBECK MEWS
COLLEGE CRESCENT
CORNWALL TERRACE MEWS
COURT LANE GARDENS
CRESCENT GROVE
DALEBURY ROAD
DEWHURST ROAD
DORIA ROAD
DOWNSHIRE HILL
DUCHESS WALK
ECCLESTON SQUARE MEWS
EGBERT STREET
EGERTON PLACE
ELM PARK ROAD
FLORAL STREET
FRANK DIXON WAY
FULTON MEWS
GERARD ROAD
GERRARD ROAD
GIRDLERS ROAD
GLOUCESTER CRESCENT
GORDON PLACE
GRAFTON SQUARE
GRAHAM TERRACE
HARMAN DRIVE
HARRIS STREET
```

```
HAVANNAH STREET
HAZLEWELL ROAD
HEREFORD MEWS
HERONDALE AVENUE
HIGHGATE HIGH STREET
HIGHWOOD HILL
HILLGATE PLACE
HOLLYCROFT AVENUE
HOLLYWOOD MEWS
HONEYWELL ROAD
HORTENSIA ROAD
HOXTON SQUARE
HUNTER ROAD
JACKSONS LANE
JOHN STREET
KINNERTON STREET
KNARESBOROUGH PLACE
KNOX STREET
LADBROKE GROVE
LANCASTER MEWS
LANSDOWNE ROAD
LATIMER INDUSTRIAL ESTATE
LAXTON PLACE
LINCOLN AVENUE
LINGFIELD ROAD
LISSON STREET
LIVERPOOL GROVE
LONGWOOD DRIVE
LONSDALE SQUARE
MAZE HILL
MIDDLESEX PASSAGE
MONTPELIER AVENUE
MONTPELIER WALK
MULTON ROAD
MUNDEN STREET
NORFOLK CRESCENT
NORTH CIRCULAR ROAD
NOTTINGHAM STREET
OAKLEY STREET
OAKWOOD COURT
OBSERVATORY GARDENS
OLD COURT PLACE
ONSLOW MEWS WEST
PALACE PLACE
PANTON STREET
PARK CRESCENT
PARK LANE
PARKE ROAD
PARKFIELDS
PARTHENIA ROAD
PAVILION ROAD
PEMBRIDGE MEWS
PEMBRIDGE ROAD
PEMBROKE STUDIOS
PENCOMBE MEWS
PETERSHAM PLACE
PHILLIMORE GARDENS
```

```
PHYSIC PLACE
PITFIELD STREET
PRINCES GATE
PRIORY ROAD
PROTHERO GARDENS
PUTNEY HIGH STREET
QUARRENDON STREET
QUEENS GATE TERRACE
RADSTOCK STREET
RANELAGH AVENUE
REDCLIFFE ROAD
REEVES MEWS
RHEIDOL MEWS
RINGWOOD AVENUE
RODERICK ROAD
ROPEMAKERS FIELDS
ROYAL CRESCENT
ROYAL HILL
RUSSELL GARDENS MEWS
SETTLES STREET
SHELDON AVENUE

---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-44-c904c4dbc53e> in <module>
      2 location_venues = getNearbyVenues(names=df['Street'],
      3                                    latitudes=df['Latitude'],
----> 4                                   longitudes=df['Longitude'] )

<ipython-input-43-cfef04f74480> in getNearbyVenues(names, latitudes, longitud
es, radius, LIMIT)
     16 
     17         # make the GET request
---> 18         results = requests.get(url).json()["response"]['groups'][0][
'items']
     19 
     20         # return only relevant information for each nearby venue

KeyError: 'groups'
```

In [47]:
```
location_venues
```

Out[47]:

	Street	Street Latitude	Street Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	ALBION SQUARE	-41.273758	173.289393	The Free House	-41.273340	173.287364	Bar
1	ALBION SQUARE	-41.273758	173.289393	The Indian Cafe	-41.273308	173.286530	Indian Restaurant
2	ALBION SQUARE	-41.273758	173.289393	Queen's Gardens	-41.273671	173.291383	Park
3	ALBION SQUARE	-41.273758	173.289393	Urban	-41.274355	173.286317	New American Restaurant
4	ALBION SQUARE	-41.273758	173.289393	Fish Stop	-41.276010	173.289592	Fish & Chips Shop
...	...	...	...	...	...	...	...
4386	WILSON STREET	42.286454	-71.400981	restaurante grego em framingham	42.282605	-71.401414	Greek Restaurant
4387	WINGATE ROAD	51.092557	1.179455	Currys PC World	51.093848	1.179104	Electronics Store
4388	WINGATE ROAD	51.092557	1.179455	The Hungry Horse	51.089400	1.180624	Gastropub
4389	WINGATE ROAD	51.092557	1.179455	Nisa Local	51.095157	1.184555	Supermarket
4390	WINGATE ROAD	51.092557	1.179455	Booker	51.092661	1.172383	Warehouse Store

4391 rows × 7 columns

In [49]:
```
location_venues.groupby('Street').count()
```

Out[49]:

Street	Street Latitude	Street Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
ALBION SQUARE	28	28	28	28	28	28
ANHALT ROAD	15	15	15	15	15	15
ANSDELL TERRACE	47	47	47	47	47	47
APPLEGARTH ROAD	4	4	4	4	4	4
BARONSMEAD ROAD	14	14	14	14	14	14
...	...	...	...	...	...	...
WESTMORELAND PLACE	17	17	17	17	17	17
WHITFIELD STREET	46	46	46	46	46	46
WILFRED STREET	23	23	23	23	23	23
WILSON STREET	3	3	3	3	3	3
WINGATE ROAD	4	4	4	4	4	4

151 rows × 6 columns

In [48]:
```
# get the List of Unique Categories
print('There are {} uniques categories.'.format(len(location_venues['Venue Cat
egory'].unique())))
```

```
There are 338 uniques categories.
```

In [46]:
```
location_venues.shape
```

Out[46]: (4391, 7)

In [50]:
```
# one hot encoding
venues_onehot = pd.get_dummies(location_venues[['Venue Category']], prefix="",
prefix_sep="")

# add street column back to dataframe
venues_onehot['Street'] = location_venues['Street']

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

#fixed_columns
venues_onehot = venues_onehot[fixed_columns]

venues_onehot.head()
```

Out[50]:

	Street	ATM	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	American Restaurant	Antique Shop	Arcade
0	ALBION SQUARE	0	0	0	0	0	0	0	0
1	ALBION SQUARE	0	0	0	0	0	0	0	0
2	ALBION SQUARE	0	0	0	0	0	0	0	0
3	ALBION SQUARE	0	0	0	0	0	0	0	0
4	ALBION SQUARE	0	0	0	0	0	0	0	0

5 rows × 339 columns

In [51]:
```
london_grouped = venues_onehot.groupby('Street').mean().reset_index()
london_grouped
```

Out[51]:

	Street	ATM	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	American Restaurant	Antique Shop
0	ALBION SQUARE	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
1	ANHALT ROAD	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
2	ANSDELL TERRACE	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
3	APPLEGARTH ROAD	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
4	BARONSMEAD ROAD	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
...	...	...	...	...	...	...	...	..
146	WESTMORELAND PLACE	0.0	0.0	0.0	0.0	0.0	0.058824	0.(
147	WHITFIELD STREET	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
148	WILFRED STREET	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
149	WILSON STREET	0.0	0.0	0.0	0.0	0.0	0.000000	0.(
150	WINGATE ROAD	0.0	0.0	0.0	0.0	0.0	0.000000	0.(

151 rows × 339 columns

In [52]:
```
london_grouped.shape
```

Out[52]: (151, 339)

In [53]:
```
# What are the top 5 venues/facilities nearby profitable real estate investmen
ts?#

num_top_venues = 5

for hood in london_grouped['Street']:
    print("----"+hood+"----")
    temp = london_grouped[london_grouped['Street'] == 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).hea
d(num_top_venues))
    print('\n')
```

```
----ALBION SQUARE----
              venue  freq
0              Café  0.25
1       Coffee Shop  0.07
2               Pub  0.07
3  Indian Restaurant  0.07
4        Restaurant  0.07


----ANHALT ROAD----
                 venue  freq
0                  Pub  0.27
1        Grocery Store  0.13
2    French Restaurant  0.13
3  Gym / Fitness Center  0.07
4               Garden  0.07


----ANSDELL TERRACE----
            venue  freq
0      Restaurant  0.09
1  Clothing Store  0.09
2       Juice Bar  0.06
3             Pub  0.06
4           Hotel  0.06


----APPLEGARTH ROAD----
                    venue  freq
0                     Pub  0.25
1               Nightclub  0.25
2                     Bar  0.25
3                  Casino  0.25
4  New American Restaurant  0.00


----BARONSMEAD ROAD----
                 venue  freq
0  Indie Movie Theater  0.07
1      Thai Restaurant  0.07
2     Community Center  0.07
3           Restaurant  0.07
4          Pizza Place  0.07


----BEAUCLERC ROAD----
             venue  freq
0              Spa  0.25
1  Harbor / Marina  0.25
2  Automotive Shop  0.25
3      Pizza Place  0.25
4              ATM  0.00


----BELVEDERE DRIVE----
                           venue  freq
0                           Pool   0.5
```

```
1                   Playground   0.5
2                          ATM   0.0
3               Organic Grocery   0.0
4  Paper / Office Supplies Store   0.0


----BICKENHALL STREET----
                venue  freq
0         Pizza Place  0.05
1           Gastropub  0.05
2                Café  0.05
3               Hotel  0.05
4  Italian Restaurant  0.05


----BIRCHLANDS AVENUE----
                venue  freq
0                 Pub   0.2
1                Lake   0.1
2      Breakfast Spot   0.1
3  Chinese Restaurant   0.1
4   French Restaurant   0.1


----BRAMPTON GROVE----
                           venue  freq
0                   Home Service   1.0
1                            ATM   0.0
2            Other Great Outdoors   0.0
3                           Park   0.0
4  Paper / Office Supplies Store   0.0


----BRIARDALE GARDENS----
                     venue  freq
0      Sporting Goods Shop   0.2
1            Grocery Store   0.2
2  Health & Beauty Service   0.2
3              Coffee Shop   0.2
4     Gym / Fitness Center   0.2


----BROOKWAY----
                  venue  freq
0                   Spa   0.5
1           Art Gallery   0.5
2                   ATM   0.0
3  Other Great Outdoors   0.0
4                  Park   0.0


----BURBAGE ROAD----
                venue  freq
0                 Bar  0.25
1       Grocery Store  0.25
2        Dance Studio  0.25
3  Athletics & Sports  0.25
```

```
4   Outdoor Sculpture  0.00


----BURY WALK----
                venue  freq
0         Supermarket  0.20
1    English Restaurant  0.13
2         Coffee Shop  0.07
3                Café  0.07
4  Fast Food Restaurant  0.07


----CALLCOTT STREET----
              venue  freq
0               Pub  0.14
1     Grocery Store  0.04
2  Indian Restaurant  0.04
3       Yoga Studio  0.04
4            Bakery  0.04


----CAMPDEN HILL ROAD----
              venue  freq
0               Pub  0.15
1     Grocery Store  0.06
2            Bakery  0.06
3  Indian Restaurant  0.04
4       Coffee Shop  0.04


----CAMPION ROAD----
                venue  freq
0                Food   0.5
1               Trail   0.5
2                 ATM   0.0
3  Outdoor Event Space   0.0
4                Park   0.0


----CANNING PLACE----
              venue  freq
0    Clothing Store  0.25
1  Convenience Store  0.08
2   Department Store  0.08
3   Stationery Store  0.08
4               Gym  0.08


----CARLTON GARDENS----
               venue  freq
0  Italian Restaurant  0.23
1                Café  0.06
2        Dessert Shop  0.05
3   Convenience Store  0.03
4               Hotel  0.03
```

```
----CARLYLE COURT----
                        venue  freq
0  Construction & Landscaping  0.67
1                        Farm  0.33
2           Outdoor Sculpture  0.00
3                 Pastry Shop  0.00
4                        Park  0.00


----CHALCOT SQUARE----
                venue  freq
0                Café  0.07
1  Italian Restaurant  0.07
2                 Pub  0.06
3                 Bar  0.06
4         Coffee Shop  0.06


----CHARLES LANE----
                  venue  freq
0                   Spa  0.33
1   American Restaurant  0.33
2    Photography Studio  0.33
3                   ATM  0.00
4  Other Great Outdoors  0.00


----CHESTER CLOSE NORTH----
                    venue  freq
0                    Park  0.17
1                  Garden  0.08
2            Cocktail Bar  0.08
3  Furniture / Home Store  0.04
4                   Hotel  0.04


----CHEYNE COURT----
         venue  freq
0  Coffee Shop  0.08
1        Hotel  0.08
2       Bakery  0.08
3    Gift Shop  0.08
4  Supermarket  0.08


----CHEYNE ROW----
                  venue  freq
0                  Café  0.09
1    Italian Restaurant  0.05
2                   Pub  0.05
3  Gym / Fitness Center  0.05
4           Pizza Place  0.03


----CHISWICK MALL----
                  venue  freq
0                   Pub  0.33
```

```
1             Brewery  0.17
2          Art Museum  0.17
3           Gift Shop  0.17
4  Gym / Fitness Center  0.17


----CITY ROAD----
           venue  freq
0            Pub  0.25
1    Coffee Shop  0.11
2  Sandwich Place  0.07
3    Art Gallery  0.07
4      Gastropub  0.04


----CLARENDON STREET----
               venue  freq
0        Pizza Place  0.09
1  Italian Restaurant  0.06
2               Café  0.03
3      Fishing Store  0.03
4               Bank  0.03


----CLONCURRY STREET----
           venue  freq
0           Café  0.16
1           Park  0.10
2            Bar  0.06
3    Coffee Shop  0.06
4  Soccer Stadium  0.03


----COLBECK MEWS----
               venue  freq
0              Hotel  0.24
1                Pub  0.07
2             Garden  0.05
3               Café  0.04
4  Italian Restaurant  0.04


----COLLEGE CRESCENT----
               venue  freq
0  Italian Restaurant  0.06
1         Laundromat  0.06
2   Department Store  0.06
3             Resort  0.06
4        Coffee Shop  0.06


----CORNWALL TERRACE MEWS----
            venue  freq
0            Café  0.11
1          Garden  0.09
2            Park  0.07
3  Thai Restaurant  0.05
```

```
4      Pizza Place  0.05


----COURT LANE GARDENS----
                   venue  freq
0                    Pub  0.15
1          Grocery Store  0.15
2     Italian Restaurant  0.08
3       Food & Drink Shop  0.08
4  Furniture / Home Store  0.08


----CRESCENT GROVE----
                          venue  freq
0                         Hotel   1.0
1                           ATM   0.0
2           Other Great Outdoors   0.0
3                          Park   0.0
4  Paper / Office Supplies Store   0.0


----DALEBURY ROAD----
                      venue  freq
0               Coffee Shop  0.09
1               Pizza Place  0.09
2                       Bar  0.09
3                       Spa  0.09
4  Middle Eastern Restaurant  0.09


----DEWHURST ROAD----
                 venue  freq
0                  Pub  0.50
1         Grocery Store  0.25
2    Weight Loss Center  0.25
3  Other Great Outdoors  0.00
4                 Park  0.00


----DORIA ROAD----
                venue  freq
0  Italian Restaurant  0.11
1                Café  0.08
2                 Pub  0.06
3         Coffee Shop  0.06
4              Bakery  0.06


----DOWNSHIRE HILL----
                venue  freq
0                Café  0.18
1                 Pub  0.13
2              Museum  0.05
3  Italian Restaurant  0.05
4     Thai Restaurant  0.05
```

```
----DUCHESS WALK----
                venue  freq
0                 Pub  0.07
1         Coffee Shop  0.07
2                 Bar  0.06
3        Cocktail Bar  0.05
4  Italian Restaurant  0.04


----ECCLESTON SQUARE MEWS----
                venue  freq
0               Hotel  0.11
1                 Pub  0.09
2         Coffee Shop  0.06
3                Café  0.05
4  Italian Restaurant  0.05


----EGBERT STREET----
                 venue  freq
0    Convenience Store   0.5
1                  Pub   0.5
2  Outdoor Event Space   0.0
3          Pastry Shop   0.0
4                 Park   0.0


----EGERTON PLACE----
               venue  freq
0                Pub  0.14
1      Grocery Store  0.14
2  Indian Restaurant  0.14
3    Thai Restaurant  0.14
4     Sandwich Place  0.14


----ELM PARK ROAD----
           venue  freq
0            Pub  0.11
1    Gas Station  0.11
2  Train Station  0.11
3    Auto Garage  0.11
4    Supermarket  0.11


----FLORAL STREET----
                 venue  freq
0        Deli / Bodega  0.33
1       Cosmetics Shop  0.33
2       Clothing Store  0.33
3  Outdoor Event Space  0.00
4          Pastry Shop  0.00


----FRANK DIXON WAY----
                  venue  freq
0  Gym / Fitness Center  0.17
```

```
1                 Park  0.17
2           Playground  0.17
3                 Farm  0.17
4                 Café  0.17


----FULTON MEWS----
               venue  freq
0              Hotel  0.18
1                Pub  0.08
2        Coffee Shop  0.06
3               Café  0.05
4  Chinese Restaurant  0.05


----GERARD ROAD----
               venue  freq
0  Convenience Store  0.17
1  Indian Restaurant  0.17
2      Grocery Store  0.17
3  Fish & Chips Shop  0.17
4   Business Service  0.17


----GERRARD ROAD----
                           venue  freq
0           Fast Food Restaurant   0.5
1                            Pub   0.5
2                            ATM   0.0
3                           Park   0.0
4  Paper / Office Supplies Store   0.0


----GIRDLERS ROAD----
               venue  freq
0                Pub  0.12
1          Gastropub  0.06
2     Sandwich Place  0.06
3              Hotel  0.06
4  Convention Center  0.06


----GORDON PLACE----
                           venue  freq
0                       Bus Stop   1.0
1            Outdoor Event Space   0.0
2                    Pastry Shop   0.0
3                           Park   0.0
4  Paper / Office Supplies Store   0.0


----GRAFTON SQUARE----
          venue  freq
0           Pub  0.09
1           Bar  0.06
2    Restaurant  0.04
3          Café  0.04
```

```
4  Burger Joint  0.04


----GRAHAM TERRACE----
                venue  freq
0    Indian Restaurant   0.5
1                 Café   0.5
2                  ATM   0.0
3  Outdoor Event Space   0.0
4                 Park   0.0


----HARMAN DRIVE----
                venue  freq
0                 Park  0.33
1       Shopping Plaza  0.33
2               Bakery  0.33
3                  ATM  0.00
4  Outdoor Event Space  0.00


----HARRIS STREET----
                venue  freq
0                  ATM   0.2
1           Donut Shop   0.2
2          Pizza Place   0.2
3                 Park   0.2
4  Indie Movie Theater   0.2


----HAVANNAH STREET----
               venue  freq
0  Italian Restaurant  0.13
1                 Bar  0.10
2             Brewery  0.10
3                Café  0.06
4         Supermarket  0.06


----HAZLEWELL ROAD----
                 venue  freq
0   Japanese Restaurant  0.25
1  Gym / Fitness Center  0.12
2           Coffee Shop  0.12
3          Tennis Court  0.12
4             Gastropub  0.12


----HEREFORD MEWS----
                 venue  freq
0                   Pub  0.08
1                  Café  0.07
2  Gym / Fitness Center  0.05
3    Persian Restaurant  0.04
4     Indian Restaurant  0.04
```

```
----HERONDALE AVENUE----
                        venue  freq
0           French Restaurant  0.50
1  Construction & Landscaping  0.25
2              Clothing Store  0.25
3          Outdoor Event Space  0.00
4                 Pastry Shop  0.00


----HIGHGATE HIGH STREET----
           venue  freq
0            Pub  0.27
1         Bakery  0.09
2  Historic Site  0.05
3          Plaza  0.05
4    Pizza Place  0.05


----HIGHWOOD HILL----
                   venue  freq
0     Athletics & Sports   1.0
1                    ATM   0.0
2  Performing Arts Venue   0.0
3            Pastry Shop   0.0
4                   Park   0.0


----HILLGATE PLACE----
               venue  freq
0      Grocery Store  0.14
1                Pub  0.07
2        Coffee Shop  0.07
3        Pizza Place  0.07
4  Indian Restaurant  0.07


----HOLLYCROFT AVENUE----
                     venue  freq
0                      Pub  0.25
1                    Hotel  0.25
2                      Gym  0.25
3            Grocery Store  0.25
4  New American Restaurant  0.00


----HOLLYWOOD MEWS----
                  venue  freq
0                Garden  0.07
1         Grocery Store  0.07
2  Gym / Fitness Center  0.07
3                Bakery  0.07
4    Italian Restaurant  0.07


----HONEYWELL ROAD----
          venue  freq
0          Café  0.27
```

```
1           Pub  0.20
2  Tennis Court  0.07
3    Playground  0.07
4   Coffee Shop  0.07


----HORTENSIA ROAD----
                venue  freq
0  Italian Restaurant  0.10
1      Soccer Stadium  0.06
2      Sandwich Place  0.06
3                 Pub  0.06
4       Grocery Store  0.06


----HOXTON SQUARE----
                venue  freq
0         Coffee Shop  0.09
1                Café  0.06
2        Cocktail Bar  0.05
3               Hotel  0.05
4  Italian Restaurant  0.04


----JACKSONS LANE----
                venue  freq
0                 Pub  0.35
1                Café  0.12
2  Italian Restaurant  0.06
3            Bus Stop  0.06
4  Seafood Restaurant  0.06


----JOHN STREET----
                 venue  freq
0  Austrian Restaurant  0.08
1          Supermarket  0.08
2   Chinese Restaurant  0.08
3         Tram Station  0.08
4     Asian Restaurant  0.08


----KINNERTON STREET----
               venue  freq
0  Indian Restaurant   0.2
1               Park   0.2
2        Pizza Place   0.2
3        Bus Station   0.2
4                Gym   0.2


----KNARESBOROUGH PLACE----
                venue  freq
0               Hotel  0.28
1                 Pub  0.07
2  Italian Restaurant  0.06
3              Garden  0.04
```

```
4  Chinese Restaurant  0.04


----KNOX STREET----
                  venue  freq
0     Convenience Store   0.2
1        Sandwich Place   0.2
2           Coffee Shop   0.2
3  Gym / Fitness Center   0.2
4  Fast Food Restaurant   0.2


----LADBROKE GROVE----
                  venue  freq
0    Italian Restaurant  0.09
1  Gym / Fitness Center  0.07
2             Juice Bar  0.05
3           Record Shop  0.05
4           Pizza Place  0.05


----LANCASTER MEWS----
                venue  freq
0                Café  0.14
1                 Pub  0.08
2  Italian Restaurant  0.05
3                 Bar  0.05
4         Coffee Shop  0.05


----LANSDOWNE ROAD----
               venue  freq
0              Hotel  0.17
1               Café  0.14
2                Pub  0.07
3          Gastropub  0.07
4  Convenience Store  0.03


----LATIMER INDUSTRIAL ESTATE----
                  venue  freq
0  Gym / Fitness Center  0.18
1                  Park  0.12
2          Soccer Field  0.12
3                   Pub  0.06
4        Breakfast Spot  0.06


----LAXTON PLACE----
               venue  freq
0                Pub  0.09
1        Coffee Shop  0.09
2  Indian Restaurant  0.09
3              Plaza  0.04
4               Café  0.04
```

```
----LINCOLN AVENUE----
                venue  freq
0                 Bar  0.22
1         Pizza Place  0.11
2         Pet Service  0.11
3       Train Station  0.11
4  Mexican Restaurant  0.11


----LINGFIELD ROAD----
           venue  freq
0         Bakery   0.2
1       Pharmacy   0.2
2  Grocery Store   0.2
3           Park   0.2
4            Pub   0.2


----LISSON STREET----
                       venue  freq
0                Coffee Shop  0.07
1             Sandwich Place  0.07
2                        Pub  0.07
3  Middle Eastern Restaurant  0.03
4                      Hotel  0.03


----LIVERPOOL GROVE----
      venue  freq
0      Café  0.07
1  Pharmacy  0.07
2       Pub  0.04
3       Gym  0.04
4    Bakery  0.04


----LONGWOOD DRIVE----
                       venue  freq
0                   Pharmacy  0.15
1                Pizza Place  0.15
2              Big Box Store  0.08
3             Discount Store  0.08
4  Middle Eastern Restaurant  0.08


----LONSDALE SQUARE----
                      venue  freq
0                       Pub  0.08
1         French Restaurant  0.06
2  Mediterranean Restaurant  0.06
3                    Bakery  0.06
4    Furniture / Home Store  0.05


----MIDDLESEX PASSAGE----
                venue  freq
0   Italian Restaurant  0.07
```

```
1           Coffee Shop  0.06
2              Wine Bar  0.06
3  Gym / Fitness Center  0.06
4           Art Gallery  0.04


----MONTPELIER AVENUE----
            venue  freq
0             Pub   0.2
1           Hotel   0.2
2  Discount Store   0.2
3     Supermarket   0.2
4   Grocery Store   0.2


----MONTPELIER WALK----
                venue  freq
0  Italian Restaurant  0.14
1                Café  0.11
2               Hotel  0.05
3            Boutique  0.04
4              Garden  0.04


----MULTON ROAD----
                           venue  freq
0                            Pub  0.33
1                 Breakfast Spot  0.33
2                   Tennis Court  0.33
3           Other Great Outdoors  0.00
4  Paper / Office Supplies Store  0.00


----MUNDEN STREET----
               venue  freq
0               Café  0.12
1                Pub  0.10
2              Hotel  0.08
3  Indian Restaurant  0.06
4           Bus Stop  0.06


----NORTH CIRCULAR ROAD----
         venue  freq
0          Pub   0.2
1        Hotel   0.2
2     Bus Stop   0.2
3  Supermarket   0.2
4         Park   0.2


----NOTTINGHAM STREET----
                 venue  freq
0               Bakery   0.2
1            Wine Shop   0.2
2            Locksmith   0.2
3                Trail   0.2
```

```
4  Sporting Goods Shop   0.2


----OAKLEY STREET----
                venue  freq
0                Pool   0.5
1              Lounge   0.5
2                 ATM   0.0
3  Outdoor Event Space   0.0
4                Park   0.0


----OAKWOOD COURT----
         venue  freq
0   Smoke Shop  0.25
1         Food  0.25
2  Golf Course  0.25
3  Video Store  0.25
4          ATM  0.00


----OBSERVATORY GARDENS----
            venue  freq
0            Café  0.09
1             Pub  0.05
2  Clothing Store  0.05
3      Restaurant  0.04
4       Juice Bar  0.04


----OLD COURT PLACE----
            venue  freq
0           Hotel  0.11
1          Garden  0.06
2  Clothing Store  0.06
3         Exhibit  0.05
4       Juice Bar  0.05


----ONSLOW MEWS WEST----
                venue  freq
0               Hotel  0.11
1              Bakery  0.05
2  Italian Restaurant  0.05
3        Burger Joint  0.04
4      Sandwich Place  0.04


----PALACE PLACE----
                    venue  freq
0  Health & Beauty Service   0.5
1               Restaurant   0.5
2                      ATM   0.0
3      Outdoor Event Space   0.0
4                     Park   0.0
```

```
----PANTON STREET----
         venue  freq
0          Pub  0.12
1  Coffee Shop  0.08
2   Restaurant  0.08
3        Hotel  0.08
4          Bar  0.08


----PARK CRESCENT----
                venue  freq
0       Moving Target   0.5
1        Camera Store   0.5
2                 ATM   0.0
3  Outdoor Event Space   0.0
4                Park   0.0


----PARK LANE----
                 venue  freq
0  Fast Food Restaurant  0.08
1    Mexican Restaurant  0.06
2             Nightclub  0.06
3        Discount Store  0.04
4        Sandwich Place  0.04


----PARKE ROAD----
                venue  freq
0                 Pub   0.4
1      Breakfast Spot   0.2
2            Gym Pool   0.2
3                Lake   0.2
4  Outdoor Event Space   0.0


----PARKFIELDS----
            venue  freq
0   Historic Site  0.33
1     Supermarket  0.17
2  Harbor / Marina  0.17
3           Hotel  0.17
4           Diner  0.17


----PARTHENIA ROAD----
           venue  freq
0  Grocery Store  0.13
1    Coffee Shop  0.13
2            Pub  0.10
3           Café  0.08
4   Climbing Gym  0.05


----PAVILION ROAD----
             venue  freq
0    Grocery Store   0.5
```

```
1             Lake   0.5
2  Pedestrian Plaza   0.0
3       Pastry Shop   0.0
4             Park   0.0


----PEMBRIDGE MEWS----
                venue  freq
0                 Pub  0.07
1  Italian Restaurant  0.05
2          Restaurant  0.04
3   Indian Restaurant  0.03
4              Bakery  0.03


----PEMBRIDGE ROAD----
                           venue  freq
0                   Soccer Field   0.5
1                           Café   0.5
2            Outdoor Event Space   0.0
3                           Park   0.0
4  Paper / Office Supplies Store   0.0


----PEMBROKE STUDIOS----
                venue  freq
0          Restaurant  0.14
1                 Pub  0.10
2         Supermarket  0.07
3          Sports Bar  0.07
4  Italian Restaurant  0.03


----PENCOMBE MEWS----
                venue  freq
0  Italian Restaurant  0.09
1                 Pub  0.05
2              Bakery  0.05
3      Clothing Store  0.04
4                Café  0.04


----PETERSHAM PLACE----
                   venue  freq
0                    Pub  0.67
1             Sports Bar  0.33
2  Portuguese Restaurant  0.00
3                   Park  0.00
4                 Palace  0.00


----PHILLIMORE GARDENS----
                venue  freq
0                Café  0.16
1      Ice Cream Shop  0.05
2      Harbor / Marina  0.04
3                 Pub  0.04
```

```
4  Italian Restaurant  0.04


----PHYSIC PLACE----
                venue  freq
0                Café  0.08
1                 Pub  0.08
2         Coffee Shop  0.05
3  Japanese Restaurant  0.05
4         Art Gallery  0.05


----PITFIELD STREET----
         venue  freq
0          Pub  0.20
1  Post Office  0.07
2         Café  0.07
3         Bank  0.07
4       Bakery  0.07


----PRINCES GATE----
                         venue  freq
0                    Gift Shop   1.0
1                          ATM   0.0
2          Outdoor Event Space   0.0
3                         Park   0.0
4  Paper / Office Supplies Store   0.0


----PRIORY ROAD----
               venue  freq
0                Pub  0.27
1         Restaurant  0.13
2  French Restaurant  0.07
3        Pizza Place  0.04
4       Cocktail Bar  0.02


----PROTHERO GARDENS----
              venue  freq
0     Grocery Store  0.19
1       Coffee Shop  0.12
2          Bus Stop  0.06
3  Sushi Restaurant  0.06
4       Pizza Place  0.06


----PUTNEY HIGH STREET----
                venue  freq
0         Coffee Shop  0.09
1                Café  0.05
2      Clothing Store  0.05
3      Sandwich Place  0.04
4  Japanese Restaurant  0.04
```

```
----QUARRENDON STREET----
                venue  freq
0         Coffee Shop  0.11
1  Italian Restaurant  0.09
2                 Pub  0.09
3       Grocery Store  0.09
4                Park  0.07


----QUEENS GATE TERRACE----
                  venue  freq
0                  Food  0.15
1  Fast Food Restaurant  0.15
2     Convenience Store  0.08
3    Mexican Restaurant  0.08
4         Shopping Mall  0.08


----RADSTOCK STREET----
                 venue  freq
0                  Pub  0.31
1        Grocery Store  0.15
2    French Restaurant  0.15
3  Japanese Restaurant  0.08
4         Cocktail Bar  0.08


----RANELAGH AVENUE----
                 venue  freq
0                 Park  0.19
1  Indie Movie Theater  0.06
2                Track  0.06
3          Pizza Place  0.06
4           Restaurant  0.06


----REDCLIFFE ROAD----
                  venue  freq
0        Breakfast Spot  0.25
1          Burger Joint  0.12
2  Fast Food Restaurant  0.12
3  Gym / Fitness Center  0.12
4     Convenience Store  0.12


----REEVES MEWS----
               venue  freq
0              Hotel  0.14
1  French Restaurant  0.06
2               Café  0.06
3          Hotel Bar  0.05
4       Cocktail Bar  0.05


----RHEIDOL MEWS----
                      venue  freq
0                       Pub  0.12
```

```
1              Coffee Shop  0.05
2  Mediterranean Restaurant  0.04
3        French Restaurant  0.04
4                   Bakery  0.04


----RINGWOOD AVENUE----
               venue  freq
0  Convenience Store   0.2
1          Gastropub   0.1
2   Sushi Restaurant   0.1
3       Burger Joint   0.1
4                Spa   0.1


----RODERICK ROAD----
                  venue  freq
0     Convenience Store  0.14
1            Restaurant  0.14
2  Pakistani Restaurant  0.14
3           Supermarket  0.14
4           Pizza Place  0.14


----ROPEMAKERS FIELDS----
                  venue  freq
0           Pizza Place  0.10
1    Italian Restaurant  0.10
2     Indian Restaurant  0.10
3  Gym / Fitness Center  0.10
4        Breakfast Spot  0.05


----ROYAL CRESCENT----
                venue  freq
0  Italian Restaurant  0.09
1               Hotel  0.09
2                 Pub  0.09
3                Café  0.09
4                Park  0.09


----RUSSELL GARDENS MEWS----
               venue  freq
0              Hotel  0.20
1                Pub  0.08
2  Convention Center  0.08
3  Indian Restaurant  0.08
4          Gastropub  0.08


----SETTLES STREET----
                venue  freq
0          Smoke Shop  0.25
1  Italian Restaurant  0.25
2       Jewelry Store  0.25
3         Tailor Shop  0.25
```

```
4                 ATM  0.00


----SHELDON AVENUE----
                  venue  freq
0                   Bar  0.15
1         Sandwich Place  0.08
2  Fast Food Restaurant  0.08
3           Pizza Place  0.05
4             Nightclub  0.05


----SOUTH END ROW----
            venue  freq
0      Restaurant  0.08
1           Hotel  0.08
2  Clothing Store  0.08
3       Juice Bar  0.06
4          Bakery  0.04


----SOUTHWOOD LAWN ROAD----
                venue  freq
0                 Pub  0.30
1                Café  0.09
2              Bakery  0.06
3   Indian Restaurant  0.06
4  Italian Restaurant  0.06


----SOVEREIGN PARK----
                venue  freq
0   Indian Restaurant  0.25
1  Chinese Restaurant  0.25
2         Pizza Place  0.25
3                 Gym  0.25
4                 ATM  0.00


----ST OSWALDS PLACE----
                venue  freq
0                Café  0.12
1                 Pub  0.12
2      Cricket Ground  0.07
3             Gay Bar  0.07
4  Italian Restaurant  0.05


----ST PETERS SQUARE----
                venue  freq
0  Italian Restaurant  0.21
1      Ice Cream Shop  0.10
2               Hotel  0.08
3                Café  0.06
4         Pizza Place  0.04
```

```
----STAFFORD TERRACE----
                 venue  freq
0          Supermarket  0.38
1                  Pub  0.12
2  Fast Food Restaurant  0.12
3   Rental Car Location  0.12
4          Pizza Place  0.12


----SUTHERLAND PLACE----
                          venue  freq
0                          Park   0.5
1                         Hotel   0.5
2                           ATM   0.0
3           Other Great Outdoors   0.0
4  Paper / Office Supplies Store   0.0


----THAMES BANK----
                 venue  freq
0        Grocery Store  0.25
1         Burger Joint  0.25
2          Pizza Place  0.25
3  Gym / Fitness Center  0.25
4                  ATM  0.00


----THE HEXAGON----
               venue  freq
0     Clothing Store  0.11
1                Pub  0.08
2  Italian Restaurant  0.08
3        Coffee Shop  0.08
4    Asian Restaurant  0.05


----TREDEGAR SQUARE----
          venue  freq
0           Pub  0.19
1      Bus Stop  0.15
2   Pizza Place  0.12
3  Burger Joint  0.08
4   Coffee Shop  0.08


----TRINITY STREET----
            venue  freq
0  Clothing Store  0.12
1           Hotel  0.06
2        Pharmacy  0.06
3   Train Station  0.06
4     Coffee Shop  0.06


----UPPER HAMPSTEAD WALK----
               venue  freq
0                Pub  0.11
```

```
1               Café  0.11
2             Bakery  0.07
3  Italian Restaurant  0.05
4        Coffee Shop  0.04


----WALPOLE GARDENS----
               venue  freq
0                Pub  0.25
1  Convenience Store  0.12
2               Park  0.12
3    Thai Restaurant  0.12
4      Train Station  0.12


----WALPOLE STREET----
                           venue  freq
0                            ATM   1.0
1           Other Great Outdoors   0.0
2                           Park   0.0
3  Paper / Office Supplies Store   0.0
4                         Palace   0.0


----WARWICK SQUARE----
             venue  freq
0   Sandwich Place  0.25
1           Bakery  0.12
2    Grocery Store  0.12
3         Platform  0.12
4  Automotive Shop  0.12


----WELBECK WAY----
                venue  freq
0         Yoga Studio  0.25
1  Chinese Restaurant  0.25
2     Warehouse Store  0.25
3   Fish & Chips Shop  0.25
4                 ATM  0.00


----WELLESLEY TERRACE----
               venue  freq
0      Grocery Store   0.3
1        Supermarket   0.2
2  Indian Restaurant   0.1
3        Pizza Place   0.1
4               Park   0.1


----WELLINGTON STREET----
            venue  freq
0     Coffee Shop  0.18
1           Hotel  0.08
2      Restaurant  0.05
3  Sandwich Place  0.03
```

```
4            Café  0.03


----WESTMORELAND PLACE----
            venue  freq
0  Breakfast Spot  0.06
1  Ice Cream Shop  0.06
2   Grocery Store  0.06
3        Pharmacy  0.06
4          Bakery  0.06


----WHITFIELD STREET----
                venue  freq
0               Hotel  0.17
1              Hostel  0.07
2  Japanese Restaurant  0.04
3                 Bar  0.04
4          Steakhouse  0.04


----WILFRED STREET----
                 venue  freq
0                  Pub  0.22
1    Italian Restaurant  0.09
2  Fast Food Restaurant  0.09
3                Bakery  0.04
4      Department Store  0.04


----WILSON STREET----
                venue  freq
0      Baseball Field  0.33
1    Greek Restaurant  0.33
2        Home Service  0.33
3                 ATM  0.00
4  Outdoor Event Space  0.00


----WINGATE ROAD----
                    venue  freq
0       Electronics Store  0.25
1         Warehouse Store  0.25
2               Gastropub  0.25
3             Supermarket  0.25
4  New American Restaurant  0.00
```

In [54]:
```
# Define a function to return the most common venues/facilities nearby real es
tate investments#

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

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

In [55]:
```
num_top_venues = 10

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

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

In [56]:
```
# create a new dataframe
venues_sorted = pd.DataFrame(columns=columns)
venues_sorted['Street'] = london_grouped['Street']

for ind in np.arange(london_grouped.shape[0]):
    venues_sorted.iloc[ind, 1:] = return_most_common_venues(london_grouped.ilo
c[ind, :], num_top_venues)
```

In [57]:
```
venues_sorted.head()
```

Out[57]:

	Street	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue
0	ALBION SQUARE	Café	Indian Restaurant	Bar	Pub	Restaurant	Coffee Shop	French Restaurant
1	ANHALT ROAD	Pub	Grocery Store	French Restaurant	Diner	Plaza	English Restaurant	Japanese Restaurant
2	ANSDELL TERRACE	Clothing Store	Restaurant	Hotel	Pub	Juice Bar	Italian Restaurant	Bakery
3	APPLEGARTH ROAD	Pub	Bar	Nightclub	Casino	Zoo	Falafel Restaurant	Electronics Store
4	BARONSMEAD ROAD	Farmers Market	Café	Restaurant	Park	Nature Preserve	Breakfast Spot	Coffee Shop

In [58]:
```
venues_sorted.shape
```
Out[58]: (151, 11)

In [59]:
```
london_grouped.shape
```
Out[59]: (151, 339)

In [60]:
```
london_grouped=df
```

After our inspection of venues/facilities/amenities nearby the most profitable real estate investments in London, we could begin by clustering properties by venues/facilities/amenities nearby

In [61]:
```
#Distribute in 5 Clusters

# set number of clusters
kclusters = 5

london_grouped_clustering = london_grouped.drop('Street', 1)

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:50]
```
Out[61]:
```
array([1, 4, 2, 4, 3, 1, 3, 2, 2, 1, 4, 4, 1, 1, 3, 3, 1, 4, 2, 1, 0, 0,
       4, 1, 1, 2, 4, 0, 1, 2, 4, 3, 4, 3, 3, 0, 4, 4, 3, 2, 1, 3, 0, 2,
       0, 2, 2, 0, 2, 2])
```

In [62]:
```
#Dataframe to include Clusters

london_grouped_clustering=df
london_grouped_clustering.head()
```
Out[62]:

	Street	Avg_Price	Latitude	Longitude
196	ALBION SQUARE	2450000.0	-41.273758	173.289393
390	ANHALT ROAD	2435000.0	51.480316	-0.166801
405	ANSDELL TERRACE	2250000.0	51.499890	-0.189103
422	APPLEGARTH ROAD	2400000.0	53.748654	-0.326670
855	BARONSMEAD ROAD	2375000.0	51.477315	-0.239457

In [63]:
```
london_grouped_clustering.shape
```
Out[63]: (162, 4)

In [64]:
```
df.shape
```

Out[64]:
```
(162, 4)
```

In [65]:
```
london_grouped_clustering.dtypes
```

Out[65]:
```
Street        object
Avg_Price    float64
Latitude     float64
Longitude    float64
dtype: object
```

In [66]:
```
# add clustering labels
london_grouped_clustering['Cluster Labels'] = kmeans.labels_

# merge london_grouped with london_data to add latitude/longitude for each nei
ghborhood
london_grouped_clustering = london_grouped_clustering.join(venues_sorted.set_i
ndex('Street'), on='Street')

london_grouped_clustering.head(30) # check the last columns!
```

Out[66]:

	Street	Avg_Price	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue
196	ALBION SQUARE	2.450000e+06	-41.273758	173.289393	1	Café	Indian Restaurant
390	ANHALT ROAD	2.435000e+06	51.480316	-0.166801	4	Pub	Grocery Store
405	ANSDELL TERRACE	2.250000e+06	51.499890	-0.189103	2	Clothing Store	Restaurant
422	APPLEGARTH ROAD	2.400000e+06	53.748654	-0.326670	4	Pub	Bar
855	BARONSMEAD ROAD	2.375000e+06	51.477315	-0.239457	3	Farmers Market	Café
981	BEAUCLERC ROAD	2.480000e+06	30.211452	-81.617981	1	Spa	Automotive Shop
1102	BELVEDERE DRIVE	2.340000e+06	38.072818	-78.458796	3	Pool	Playground
1215	BICKENHALL STREET	2.208500e+06	51.521201	-0.158908	2	Café	Gastropub
1253	BIRCHLANDS AVENUE	2.217000e+06	51.448394	-0.160468	2	Pub	Breakfast Spot
1553	BRAMPTON GROVE	2.456875e+06	51.589961	-0.318525	1	Home Service	Zoo
1632	BRIARDALE GARDENS	2.397132e+06	51.560175	-0.195431	4	Sporting Goods Shop	Health & Beauty Service
1797	BROOKWAY	2.400000e+06	45.432185	-122.802812	4	Spa	Art Gallery
1914	BURBAGE ROAD	2.445000e+06	52.538507	-1.353674	1	Bar	Athletics & Sports
1980	BURY WALK	2.492500e+06	52.145529	-0.423593	1	Supermarket	English Restaurant
2068	CALLCOTT STREET	2.375000e+06	51.508350	-0.198328	3	Pub	Indian Restaurant
2129	CAMPDEN HILL ROAD	2.379653e+06	51.508111	-0.199667	3	Pub	Grocery Store
2136	CAMPION ROAD	2.461000e+06	43.623321	-70.236225	1	Food	Trail
2158	CANNING PLACE	2.425000e+06	52.641027	-1.135223	4	Clothing Store	Convenience Store
2225	CARLISLE ROAD	2.200000e+06	43.399438	-79.973215	2	NaN	NaN
2230	CARLTON GARDENS	2.483500e+06	-37.801943	144.971970	1	Italian Restaurant	Café

	Street	Avg_Price	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue
2242	CARLYLE COURT	2.300000e+06	32.972701	-97.173392	0	Construction & Landscaping	Farm
2406	CHALCOT SQUARE	2.286679e+06	51.541088	-0.155928	0	Café	Italian Restaurant
2484	CHARLES LANE	2.414000e+06	40.257626	-75.093891	4	Spa	American Restaurant
2562	CHELSEA CRESCENT	2.495000e+06	34.522443	-85.443891	1	NaN	NaN
2606	CHESTER CLOSE NORTH	2.450000e+06	51.529205	-0.145081	1	Park	Cocktail Bar
2638	CHEYNE COURT	2.250000e+06	52.035905	0.727612	2	Restaurant	Café
2641	CHEYNE ROW	2.410000e+06	51.483717	-0.169603	4	Café	Gym / Fitness Center
2686	CHISWICK MALL	2.287500e+06	51.487994	-0.246605	0	Pub	Gift Shop
2761	CITY ROAD	2.468340e+06	51.529697	-0.097763	1	Pub	Coffee Shop
2808	CLARENDON STREET	2.250000e+06	42.284961	-71.345534	2	Pizza Place	Italian Restaurant

In [67]:
```
# Create Map

map_clusters = folium.Map(location=[latitude, longitude], 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(london_grouped_clustering['Latitude'], londo
n_grouped_clustering['Longitude'], london_grouped_clustering['Street'], london
_grouped_clustering['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=Tru
e)
    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[67]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [68]:
```
london_grouped_clustering.loc[london_grouped_clustering['Cluster Labels'] == 0
, london_grouped_clustering.columns[[1] + list(range(5, london_grouped_cluster
ing.shape[1]))]].head()
```

Out[68]:

	Avg_Price	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7 C
2242	2.300000e+06	Construction & Landscaping	Farm	Farmers Market	Electronics Store	English Restaurant	Ethiopian Restaurant	Ever
2406	2.286679e+06	Café	Italian Restaurant	Bar	Pub	Coffee Shop	French Restaurant	Conv
2686	2.287500e+06	Pub	Gift Shop	Gym / Fitness Center	Art Museum	Brewery	Flea Market	
3377	2.298000e+06	Hotel	Zoo	Farmers Market	Electronics Store	English Restaurant	Ethiopian Restaurant	Ever
4285	2.265000e+06	Pub	Convenience Store	Farmers Market	Electronics Store	English Restaurant	Ethiopian Restaurant	Ever

In [69]:
```
london_grouped_clustering.loc[london_grouped_clustering['Cluster Labels'] == 1
, london_grouped_clustering.columns[[1] + list(range(5, london_grouped_cluster
ing.shape[1]))]].head()
```

Out[69]:

	Avg_Price	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue
196	2450000.0	Café	Indian Restaurant	Bar	Pub	Restaurant	Coffee Shop	French Restaurant
981	2480000.0	Spa	Automotive Shop	Pizza Place	Harbor / Marina	Farm	Electronics Store	English Restaurant
1553	2456875.0	Home Service	Zoo	Farmers Market	Electronics Store	English Restaurant	Ethiopian Restaurant	Event Space
1914	2445000.0	Bar	Athletics & Sports	Dance Studio	Grocery Store	Zoo	Farm	English Restaurant
1980	2492500.0	Supermarket	English Restaurant	Dry Cleaner	Café	Park	Pub	American Restaurant

In [70]:

```
london_grouped_clustering.loc[london_grouped_clustering['Cluster Labels'] == 2
, london_grouped_clustering.columns[[1] + list(range(5, london_grouped_cluster
ing.shape[1]))]].head()
```

Out[70]:

	Avg_Price	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue
405	2250000.0	Clothing Store	Restaurant	Hotel	Pub	Juice Bar	Italian Restaurant	Bakery
1215	2208500.0	Café	Gastropub	Hotel	Italian Restaurant	Restaurant	Pizza Place	Movie Theater
1253	2217000.0	Pub	Breakfast Spot	Brewery	Bakery	French Restaurant	Coffee Shop	Chinese Restaurant
2225	2200000.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2638	2250000.0	Restaurant	Café	Hotel	Gift Shop	Pizza Place	Theater	Bakery

In [71]:

```
london_grouped_clustering.loc[london_grouped_clustering['Cluster Labels'] == 3
, london_grouped_clustering.columns[[1] + list(range(5, london_grouped_cluster
ing.shape[1]))]].head()
```

Out[71]:

	Avg_Price	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Mo Commc Venu
855	2375000.0	Farmers Market	Café	Restaurant	Park	Nature Preserve	Breakfast Spot	Coffee Shc
1102	2340000.0	Pool	Playground	Zoo	Farm	Egyptian Restaurant	Electronics Store	Englis Restaura
2068	2375000.0	Pub	Indian Restaurant	Ice Cream Shop	Grocery Store	Park	Yoga Studio	Bake
2129	2379652.7	Pub	Grocery Store	Bakery	Indian Restaurant	Park	Hotel	Ice Crea Shc
2944	2367500.0	Hotel	Pub	Garden	Café	Coffee Shop	Italian Restaurant	Mediterranea Restaura

In [72]:
```
london_grouped_clustering.loc[london_grouped_clustering['Cluster Labels'] == 4
, london_grouped_clustering.columns[[1] + list(range(5, london_grouped_cluster
ing.shape[1]))]].head()
```

Out[72]:

	Avg_Price	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue
390	2435000.0	Pub	Grocery Store	French Restaurant	Diner	Plaza	English Restaurant	Japanese Restaurant
422	2400000.0	Pub	Bar	Nightclub	Casino	Zoo	Falafel Restaurant	Electronics Store
1632	2397132.0	Sporting Goods Shop	Health & Beauty Service	Grocery Store	Gym / Fitness Center	Coffee Shop	Egyptian Restaurant	Electronics Store
1797	2400000.0	Spa	Art Gallery	Zoo	Farmers Market	Electronics Store	English Restaurant	Ethiopian Restaurant
2158	2425000.0	Clothing Store	Convenience Store	Stationery Store	Basketball Court	Gym	Chinese Restaurant	Department Store

Results and Discussion section

First of all, even though the London Housing Market may be in a rut, it is still an "ever-green" for business affairs.

We may discuss our results under two main perspectives.

First, we may examine them according to neighborhoods/London areas. It is interesting to note that, although West London (Notting Hill, Kensington, Chelsea, Marylebone) and North-West London (Hampsted) might be considered highly profitable venues to purchase a real estate according to amenities and essential facilities surrounding such venues i.e. elementary schools, high schools, hospitals & grocery stores, South-West London (Wandsworth, Balham) and North-West London (Isliington) are arising as next future elite venues with a wide range of amenities and facilities. Accordingly, one might target under-priced real estates in these areas of London in order to make a business affair.

Second, we may analyze our results according to the five clusters we have produced. Even though, all clusters could praise an optimal range of facilities and amenities, we have found two main patterns. The first pattern we are referring to, i.e. Clusters 0, 2 and 4, may target home buyers prone to live in 'green' areas with parks, waterfronts. Instead, the second pattern we are referring to, i.e. Clusters 1 and 3, may target individuals who love pubs, theatres and soccer.

Conclusion

To sum up, according to Bloomberg News, the London Housing Market is in a rut. It is now facing a number of different headwinds, including the prospect of higher taxes and a warning from the Bank of England that U.K. home values could fall as much as 30 percent in the event of a disorderly exit from the European Union. In this scenario, it is urgent to adopt machine learning tools in order to assist homebuyers clientele in London to make wise and effective decisions. As a result, the business problem we were posing was: how could we provide support to homebuyers clientele in to purchase a suitable real estate in London in this uncertain economic and financial scenario?

To solve this business problem, we clustered London neighborhoods in order to recommend venues and the current average price of real estate where homebuyers can make a real estate investment. We recommended profitable venues according to amenities and essential facilities surrounding such venues i.e. elementary schools, high schools, hospitals & grocery stores.

First, we gathered data on London properties and the relative price paid data were extracted from the HM Land Registry (http://landregistry.data.gov.uk/ (http://landregistry.data.gov.uk/)). Moreover, to explore and target recommended locations across different venues according to the presence of amenities and essential facilities, we accessed data through FourSquare API interface and arranged them as a data frame for visualization. By merging data on London properties and the relative price paid data from the HM Land Registry and data on amenities and essential facilities surrounding such properties from FourSquare API interface, we were able to recommend profitable real estate investments.

Second, The Methodology section comprised four stages: 1. Collect Inspection Data; 2. Explore and Understand Data; 3. Data preparation and preprocessing; 4. Modeling. In particular, in the modeling section, we used the k-means clustering technique as it is fast and efficient in terms of computational cost, is highly flexible to account for mutations in real estate market in London and is accurate.

Finally, we drew the conclusion that even though the London Housing Market may be in a rut, it is still an "ever-green" for business affairs. We discussed our results under two main perspectives. First, we examined them according to neighborhoods/London areas. although West London (Notting Hill, Kensington, Chelsea, Marylebone) and North-West London (Hampsted) might be considered highly profitable venues to purchase a real estate according to amenities and essential facilities surrounding such venues i.e. elementary schools, high schools, hospitals & grocery stores, South-West London (Wandsworth, Balham) and North-West London (Isliington) are arising as next future elite venues with a wide range of amenities and facilities. Accordingly, one might target under-priced real estates in these areas of London in order to make a business affair. Second, we analyzed our results according to the five clusters we produced. While Clusters 0, 2 and 4 may target home buyers prone to live in 'green' areas with parks, waterfronts, Clusters 1 and 3 may target individuals who love pubs, theatres and soccer.

Thank for Reviewing!!!