**Capstone Project - The Battle of Neighborhoods (Week 1-2)**

**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/>). 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 longitude values*

**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**

!conda install -c conda-forge folium=0.5.0 --yes

**import** **folium** *#import folium # map rendering library*

print('Libraries imported.')

Solving environment: done

## Package Plan ##

environment location: /home/jupyterlab/conda

added / updated specs:

- geopy

The following packages will be downloaded:

package | build

---------------------------|-----------------

geopy-1.17.0 | py\_0 49 KB conda-forge

geographiclib-1.49 | py\_0 32 KB conda-forge

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Total: 82 KB

The following NEW packages will be INSTALLED:

geographiclib: 1.49-py\_0 conda-forge

geopy: 1.17.0-py\_0 conda-forge

Downloading and Extracting Packages

geopy-1.17.0 | 49 KB | ##################################### | 100%

geographiclib-1.49 | 32 KB | ##################################### | 100%

Preparing transaction: done

Verifying transaction: done

Executing transaction: done

Solving environment: done

## Package Plan ##

environment location: /home/jupyterlab/conda

added / updated specs:

- folium=0.5.0

The following packages will be downloaded:

package | build

---------------------------|-----------------

vincent-0.4.4 | py\_1 28 KB conda-forge

branca-0.3.1 | py\_0 25 KB conda-forge

altair-2.3.0 | py36\_1001 533 KB conda-forge

pandas-0.23.4 | py36hf8a1672\_0 27.8 MB conda-forge

folium-0.5.0 | py\_0 45 KB conda-forge

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Total: 28.4 MB

The following NEW packages will be INSTALLED:

altair: 2.3.0-py36\_1001 conda-forge

branca: 0.3.1-py\_0 conda-forge

folium: 0.5.0-py\_0 conda-forge

vincent: 0.4.4-py\_1 conda-forge

The following packages will be UPDATED:

pandas: 0.23.4-py37h04863e7\_0 --> 0.23.4-py36hf8a1672\_0 conda-forge

Downloading and Extracting Packages

vincent-0.4.4 | 28 KB | ##################################### | 100%

branca-0.3.1 | 25 KB | ##################################### | 100%

altair-2.3.0 | 533 KB | ##################################### | 100%

pandas-0.23.4 | 27.8 MB | ##################################### | 100%

folium-0.5.0 | 45 KB | ##################################### | 100%

Preparing transaction: done

Verifying transaction: done

Executing transaction: done

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-eu-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 [3]:

df\_ppd.head(5)

Out[3]:

|  | **{6DA0844A-2DB9-30F2-E053-6B04A8C05F3B}** | **597000** | **2018-05-04 00:00** | **W2 6BN** | **F** | **N** | **L** | **58B** | **Unnamed: 8** | **GLOUCESTER GARDENS** | **Unnamed: 10** | **LONDON** | **CITY OF WESTMINSTER** | **GREATER LONDON** | **A** | **A.1** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | {6DA0844A-2DBA-30F2-E053-6B04A8C05F3B} | 3400000 | 2018-05-23 00:00 | NW6 1HS | D | N | F | 37 | NaN | CREDITON HILL | NaN | LONDON | CAMDEN | GREATER LONDON | A | A |
| **1** | {6DA0844A-2DBB-30F2-E053-6B04A8C05F3B} | 431000 | 2018-04-17 00:00 | SW1P 4HN | F | N | L | DUKES HOUSE | FLAT 17 | VINCENT STREET | NaN | LONDON | CITY OF WESTMINSTER | GREATER LONDON | A | A |
| **2** | {6DA0844A-2DBC-30F2-E053-6B04A8C05F3B} | 430000 | 2018-05-11 00:00 | N5 2UA | F | N | L | 50 | NaN | HIGHBURY QUADRANT | NaN | LONDON | ISLINGTON | GREATER LONDON | A | A |
| **3** | {6DA0844A-2DBD-30F2-E053-6B04A8C05F3B} | 462000 | 2018-05-09 00:00 | N19 4JR | F | N | L | 73C | NaN | LANDSEER ROAD | NaN | LONDON | ISLINGTON | GREATER LONDON | A | A |
| **4** | {6DA0844A-2DBE-30F2-E053-6B04A8C05F3B} | 585000 | 2018-05-02 00:00 | W12 0AD | T | N | F | 204 | NaN | WULFSTAN STREET | NaN | LONDON | HAMMERSMITH AND FULHAM | GREATER LONDON | A | A |

In [4]:

df\_ppd.shape

Out[4]:

(726020, 16)

Our dataset consists of over 700000 rows and 16 columns. We will now prepare and preprocess data accordingly.

**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 [5]:

*# Assign meaningful column names*

df\_ppd.columns = ['TUID', 'Price', 'Date\_Transfer', 'Postcode', 'Prop\_Type', 'Old\_New', 'Duration', 'PAON', \

'SAON', 'Street', 'Locality', 'Town\_City', 'District', 'County', 'PPD\_Cat\_Type', 'Record\_Status']

In [6]:

*# 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 [7]:

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 [8]:

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 [9]:

*#Input your Budget's Upper Limit and Lower Limit - Find the locations df\_grp\_price which fits your budget*

df\_affordable = df\_grp\_price.query("(Avg\_Price >= 2200000) & (Avg\_Price <= 2500000)")

In [10]:

*# Display the dataframe*

df\_affordable

Out[10]:

|  | **Street** | **Avg\_Price** |
| --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 |
| **178** | ALBION SQUARE | 2.450000e+06 |
| **355** | ANHALT ROAD | 2.435000e+06 |
| **368** | ANSDELL TERRACE | 2.250000e+06 |
| **381** | APPLEGARTH ROAD | 2.400000e+06 |
| **617** | AYLESTONE AVENUE | 2.286667e+06 |
| **753** | BARONSMEAD ROAD | 2.375000e+06 |
| **867** | BEAUCLERC ROAD | 2.480000e+06 |
| **1079** | BICKENHALL STREET | 2.351667e+06 |
| **1094** | BILLING ROAD | 2.200000e+06 |
| **1108** | BIRCHLANDS AVENUE | 2.217000e+06 |
| **1310** | BOWERDEAN STREET | 2.300000e+06 |
| **1371** | BRAMPTON GROVE | 2.475833e+06 |
| **1439** | BRIARDALE GARDENS | 2.397132e+06 |
| **1605** | BROWNING CLOSE | 2.320000e+06 |
| **1820** | CALLCOTT STREET | 2.375000e+06 |
| **1871** | CAMPDEN HILL ROAD | 2.352889e+06 |
| **1889** | CANFIELD GARDENS | 2.278000e+06 |
| **1894** | CANNING PLACE | 2.425000e+06 |
| **1950** | CARLISLE ROAD | 2.200000e+06 |
| **1963** | CARLYLE COURT | 2.300000e+06 |
| **2105** | CHALCOT SQUARE | 2.286679e+06 |
| **2171** | CHARLES LANE | 2.414000e+06 |
| **2237** | CHELSEA CRESCENT | 2.495000e+06 |
| **2278** | CHESTER CLOSE NORTH | 2.450000e+06 |
| **2306** | CHEYNE COURT | 2.250000e+06 |
| **2352** | CHISWICK MALL | 2.287500e+06 |
| **2468** | CLARENDON STREET | 2.250000e+06 |
| **2512** | CLEVELAND SQUARE | 2.437500e+06 |
| **2544** | CLONCURRY STREET | 2.388333e+06 |
| **...** | ... | ... |
| **9151** | RANELAGH AVENUE | 2.300000e+06 |
| **9268** | REEVES MEWS | 2.450000e+06 |
| **9318** | RHEIDOL MEWS | 2.310000e+06 |
| **9367** | RINGWOOD AVENUE | 2.275000e+06 |
| **9438** | RODERICK ROAD | 2.400000e+06 |
| **9544** | ROTHBURY ROAD | 2.371700e+06 |
| **9585** | ROYAL CRESCENT | 2.348333e+06 |
| **9590** | ROYAL HILL | 2.436250e+06 |
| **9602** | ROYSTON ROAD | 2.250000e+06 |
| **9641** | RUSSELL GARDENS MEWS | 2.300000e+06 |
| **9935** | SHEPHERDS BUSH ROAD | 2.391450e+06 |
| **10117** | SOUTH END ROW | 2.470000e+06 |
| **10123** | SOUTH LAMBETH ROAD | 2.400944e+06 |
| **10185** | SOUTHWOOD LAWN ROAD | 2.350000e+06 |
| **10188** | SOVEREIGN PARK | 2.500000e+06 |
| **10414** | ST OSWALDS PLACE | 2.250000e+06 |
| **10428** | ST PETERS SQUARE | 2.468730e+06 |
| **10457** | STAFFORD TERRACE | 2.355000e+06 |
| **10875** | TAVISTOCK STREET | 2.300000e+06 |
| **11007** | THE PARK | 2.277146e+06 |
| **11143** | TITE STREET | 2.447730e+06 |
| **11293** | TRINITY STREET | 2.317500e+06 |
| **11434** | UPPER HAMPSTEAD WALK | 2.500000e+06 |
| **11822** | WELBECK WAY | 2.267000e+06 |
| **11907** | WEST TEMPLE SHEEN | 2.325000e+06 |
| **12104** | WILLIAM MEWS | 2.248125e+06 |
| **12130** | WILSON STREET | 2.257500e+06 |
| **12155** | WINCHENDON ROAD | 2.350000e+06 |
| **12382** | WRENTHAM AVENUE | 2.232500e+06 |
| **12401** | WYCOMBE SQUARE | 2.200000e+06 |

131 rows × 2 columns

In [11]:

**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 [12]:

**for** index, item **in** df\_affordable.iterrows():

print(f"index: **{index}**")

print(f"item: **{item}**")

print(f"item.Street only: **{item.Street}**")

index: 20

item: Street ABBOTSBURY CLOSE

Avg\_Price 2.36709e+06

Name: 20, dtype: object

item.Street only: ABBOTSBURY CLOSE

index: 178

item: Street ALBION SQUARE

Avg\_Price 2.45e+06

Name: 178, dtype: object

item.Street only: ALBION SQUARE

index: 355

item: Street ANHALT ROAD

Avg\_Price 2.435e+06

Name: 355, dtype: object

item.Street only: ANHALT ROAD

index: 368

item: Street ANSDELL TERRACE

Avg\_Price 2.25e+06

Name: 368, dtype: object

item.Street only: ANSDELL TERRACE

index: 381

item: Street APPLEGARTH ROAD

Avg\_Price 2.4e+06

Name: 381, dtype: object

item.Street only: APPLEGARTH ROAD

index: 617

item: Street AYLESTONE AVENUE

Avg\_Price 2.28667e+06

Name: 617, dtype: object

item.Street only: AYLESTONE AVENUE

index: 753

item: Street BARONSMEAD ROAD

Avg\_Price 2.375e+06

Name: 753, dtype: object

item.Street only: BARONSMEAD ROAD

index: 867

item: Street BEAUCLERC ROAD

Avg\_Price 2.48e+06

Name: 867, dtype: object

item.Street only: BEAUCLERC ROAD

index: 1079

item: Street BICKENHALL STREET

Avg\_Price 2.35167e+06

Name: 1079, dtype: object

item.Street only: BICKENHALL STREET

index: 1094

item: Street BILLING ROAD

Avg\_Price 2.2e+06

Name: 1094, dtype: object

item.Street only: BILLING ROAD

index: 1108

item: Street BIRCHLANDS AVENUE

Avg\_Price 2.217e+06

Name: 1108, dtype: object

item.Street only: BIRCHLANDS AVENUE

index: 1310

item: Street BOWERDEAN STREET

Avg\_Price 2.3e+06

Name: 1310, dtype: object

item.Street only: BOWERDEAN STREET

index: 1371

item: Street BRAMPTON GROVE

Avg\_Price 2.47583e+06

Name: 1371, dtype: object

item.Street only: BRAMPTON GROVE

index: 1439

item: Street BRIARDALE GARDENS

Avg\_Price 2.39713e+06

Name: 1439, dtype: object

item.Street only: BRIARDALE GARDENS

index: 1605

item: Street BROWNING CLOSE

Avg\_Price 2.32e+06

Name: 1605, dtype: object

item.Street only: BROWNING CLOSE

index: 1820

item: Street CALLCOTT STREET

Avg\_Price 2.375e+06

Name: 1820, dtype: object

item.Street only: CALLCOTT STREET

index: 1871

item: Street CAMPDEN HILL ROAD

Avg\_Price 2.35289e+06

Name: 1871, dtype: object

item.Street only: CAMPDEN HILL ROAD

index: 1889

item: Street CANFIELD GARDENS

Avg\_Price 2.278e+06

Name: 1889, dtype: object

item.Street only: CANFIELD GARDENS

index: 1894

item: Street CANNING PLACE

Avg\_Price 2.425e+06

Name: 1894, dtype: object

item.Street only: CANNING PLACE

index: 1950

item: Street CARLISLE ROAD

Avg\_Price 2.2e+06

Name: 1950, dtype: object

item.Street only: CARLISLE ROAD

index: 1963

item: Street CARLYLE COURT

Avg\_Price 2.3e+06

Name: 1963, dtype: object

item.Street only: CARLYLE COURT

index: 2105

item: Street CHALCOT SQUARE

Avg\_Price 2.28668e+06

Name: 2105, dtype: object

item.Street only: CHALCOT SQUARE

index: 2171

item: Street CHARLES LANE

Avg\_Price 2.414e+06

Name: 2171, dtype: object

item.Street only: CHARLES LANE

index: 2237

item: Street CHELSEA CRESCENT

Avg\_Price 2.495e+06

Name: 2237, dtype: object

item.Street only: CHELSEA CRESCENT

index: 2278

item: Street CHESTER CLOSE NORTH

Avg\_Price 2.45e+06

Name: 2278, dtype: object

item.Street only: CHESTER CLOSE NORTH

index: 2306

item: Street CHEYNE COURT

Avg\_Price 2.25e+06

Name: 2306, dtype: object

item.Street only: CHEYNE COURT

index: 2352

item: Street CHISWICK MALL

Avg\_Price 2.2875e+06

Name: 2352, dtype: object

item.Street only: CHISWICK MALL

index: 2468

item: Street CLARENDON STREET

Avg\_Price 2.25e+06

Name: 2468, dtype: object

item.Street only: CLARENDON STREET

index: 2512

item: Street CLEVELAND SQUARE

Avg\_Price 2.4375e+06

Name: 2512, dtype: object

item.Street only: CLEVELAND SQUARE

index: 2544

item: Street CLONCURRY STREET

Avg\_Price 2.38833e+06

Name: 2544, dtype: object

item.Street only: CLONCURRY STREET

index: 2581

item: Street COLBECK MEWS

Avg\_Price 2.3675e+06

Name: 2581, dtype: object

item.Street only: COLBECK MEWS

index: 2628

item: Street COLLEGE CRESCENT

Avg\_Price 2.225e+06

Name: 2628, dtype: object

item.Street only: COLLEGE CRESCENT

index: 2817

item: Street CORNWALL TERRACE MEWS

Avg\_Price 2.35e+06

Name: 2817, dtype: object

item.Street only: CORNWALL TERRACE MEWS

index: 2862

item: Street COURT LANE GARDENS

Avg\_Price 2.36e+06

Name: 2862, dtype: object

item.Street only: COURT LANE GARDENS

index: 2947

item: Street CRAVEN STREET

Avg\_Price 2.39e+06

Name: 2947, dtype: object

item.Street only: CRAVEN STREET

index: 3157

item: Street DALEBURY ROAD

Avg\_Price 2.4e+06

Name: 3157, dtype: object

item.Street only: DALEBURY ROAD

index: 3390

item: Street DEWHURST ROAD

Avg\_Price 2.425e+06

Name: 3390, dtype: object

item.Street only: DEWHURST ROAD

index: 3459

item: Street DORIA ROAD

Avg\_Price 2.325e+06

Name: 3459, dtype: object

item.Street only: DORIA ROAD

index: 3502

item: Street DOWNSHIRE HILL

Avg\_Price 2.225e+06

Name: 3502, dtype: object

item.Street only: DOWNSHIRE HILL

index: 3517

item: Street DRAX AVENUE

Avg\_Price 2.4e+06

Name: 3517, dtype: object

item.Street only: DRAX AVENUE

index: 3552

item: Street DUCHESS WALK

Avg\_Price 2.28688e+06

Name: 3552, dtype: object

item.Street only: DUCHESS WALK

index: 3719

item: Street ECCLESTON SQUARE MEWS

Avg\_Price 2.3355e+06

Name: 3719, dtype: object

item.Street only: ECCLESTON SQUARE MEWS

index: 3767

item: Street EGBERT STREET

Avg\_Price 2.265e+06

Name: 3767, dtype: object

item.Street only: EGBERT STREET

index: 3771

item: Street EGERTON PLACE

Avg\_Price 2.2e+06

Name: 3771, dtype: object

item.Street only: EGERTON PLACE

index: 4264

item: Street FIRECREST DRIVE

Avg\_Price 2.375e+06

Name: 4264, dtype: object

item.Street only: FIRECREST DRIVE

index: 4292

item: Street FLASK WALK

Avg\_Price 2.435e+06

Name: 4292, dtype: object

item.Street only: FLASK WALK

index: 4416

item: Street FRANK DIXON WAY

Avg\_Price 2.2125e+06

Name: 4416, dtype: object

item.Street only: FRANK DIXON WAY

index: 4611

item: Street GERARD ROAD

Avg\_Price 2.2585e+06

Name: 4611, dtype: object

item.Street only: GERARD ROAD

index: 4626

item: Street GIBSON SQUARE

Avg\_Price 2.2e+06

Name: 4626, dtype: object

item.Street only: GIBSON SQUARE

index: 4738

item: Street GLOUCESTER AVENUE

Avg\_Price 2.208e+06

Name: 4738, dtype: object

item.Street only: GLOUCESTER AVENUE

index: 4797

item: Street GORDON PLACE

Avg\_Price 2.32833e+06

Name: 4797, dtype: object

item.Street only: GORDON PLACE

index: 5161

item: Street HAMPSTEAD WAY

Avg\_Price 2.34333e+06

Name: 5161, dtype: object

item.Street only: HAMPSTEAD WAY

index: 5243

item: Street HARMAN DRIVE

Avg\_Price 2.45e+06

Name: 5243, dtype: object

item.Street only: HARMAN DRIVE

index: 5377

item: Street HAZLEWELL ROAD

Avg\_Price 2.5e+06

Name: 5377, dtype: object

item.Street only: HAZLEWELL ROAD

index: 5476

item: Street HEREFORD MEWS

Avg\_Price 2.31e+06

Name: 5476, dtype: object

item.Street only: HEREFORD MEWS

index: 5496

item: Street HERONDALE AVENUE

Avg\_Price 2.475e+06

Name: 5496, dtype: object

item.Street only: HERONDALE AVENUE

index: 5636

item: Street HILLGATE PLACE

Avg\_Price 2.2e+06

Name: 5636, dtype: object

item.Street only: HILLGATE PLACE

index: 5694

item: Street HOLDEN AVENUE

Avg\_Price 2.31e+06

Name: 5694, dtype: object

item.Street only: HOLDEN AVENUE

index: 5736

item: Street HOLLYWOOD MEWS

Avg\_Price 2.35e+06

Name: 5736, dtype: object

item.Street only: HOLLYWOOD MEWS

index: 5813

item: Street HORNTON STREET

Avg\_Price 2.28083e+06

Name: 5813, dtype: object

item.Street only: HORNTON STREET

index: 5873

item: Street HUNTER ROAD

Avg\_Price 2.3e+06

Name: 5873, dtype: object

item.Street only: HUNTER ROAD

index: 6009

item: Street JACKSONS LANE

Avg\_Price 2.3625e+06

Name: 6009, dtype: object

item.Street only: JACKSONS LANE

index: 6056

item: Street JOHN ISLIP STREET

Avg\_Price 2.41333e+06

Name: 6056, dtype: object

item.Street only: JOHN ISLIP STREET

index: 6381

item: Street KNOX STREET

Avg\_Price 2.25e+06

Name: 6381, dtype: object

item.Street only: KNOX STREET

index: 6459

item: Street LANCASTER MEWS

Avg\_Price 2.3125e+06

Name: 6459, dtype: object

item.Street only: LANCASTER MEWS

index: 6594

item: Street LAXTON PLACE

Avg\_Price 2.5e+06

Name: 6594, dtype: object

item.Street only: LAXTON PLACE

index: 6750

item: Street LILLIE SQUARE

Avg\_Price 2.24538e+06

Name: 6750, dtype: object

item.Street only: LILLIE SQUARE

index: 6770

item: Street LINCOLN AVENUE

Avg\_Price 2.2035e+06

Name: 6770, dtype: object

item.Street only: LINCOLN AVENUE

index: 6820

item: Street LISSON STREET

Avg\_Price 2.4625e+06

Name: 6820, dtype: object

item.Street only: LISSON STREET

index: 6849

item: Street LIVERPOOL GROVE

Avg\_Price 2.288e+06

Name: 6849, dtype: object

item.Street only: LIVERPOOL GROVE

index: 6931

item: Street LONGWOOD DRIVE

Avg\_Price 2.375e+06

Name: 6931, dtype: object

item.Street only: LONGWOOD DRIVE

index: 6935

item: Street LONSDALE SQUARE

Avg\_Price 2.3575e+06

Name: 6935, dtype: object

item.Street only: LONSDALE SQUARE

index: 7223

item: Street MANSFIELD STREET

Avg\_Price 2.5e+06

Name: 7223, dtype: object

item.Street only: MANSFIELD STREET

index: 7417

item: Street MAZE HILL

Avg\_Price 2.25e+06

Name: 7417, dtype: object

item.Street only: MAZE HILL

index: 7658

item: Street MONTAGU MEWS NORTH

Avg\_Price 2.2e+06

Name: 7658, dtype: object

item.Street only: MONTAGU MEWS NORTH

index: 7687

item: Street MONTPELIER WALK

Avg\_Price 2.32e+06

Name: 7687, dtype: object

item.Street only: MONTPELIER WALK

index: 7814

item: Street MULTON ROAD

Avg\_Price 2.3e+06

Name: 7814, dtype: object

item.Street only: MULTON ROAD

index: 7972

item: Street NEW KENT ROAD

Avg\_Price 2.35533e+06

Name: 7972, dtype: object

item.Street only: NEW KENT ROAD

index: 8061

item: Street NORFOLK CRESCENT

Avg\_Price 2.3625e+06

Name: 8061, dtype: object

item.Street only: NORFOLK CRESCENT

index: 8146

item: Street NOTTINGHAM STREET

Avg\_Price 2.31667e+06

Name: 8146, dtype: object

item.Street only: NOTTINGHAM STREET

index: 8221

item: Street OAKWOOD COURT

Avg\_Price 2.475e+06

Name: 8221, dtype: object

item.Street only: OAKWOOD COURT

index: 8260

item: Street OLD COURT PLACE

Avg\_Price 2.395e+06

Name: 8260, dtype: object

item.Street only: OLD COURT PLACE

index: 8313

item: Street ONSLOW MEWS WEST

Avg\_Price 2.3e+06

Name: 8313, dtype: object

item.Street only: ONSLOW MEWS WEST

index: 8314

item: Street ONSLOW SQUARE

Avg\_Price 2.33328e+06

Name: 8314, dtype: object

item.Street only: ONSLOW SQUARE

index: 8429

item: Street PALACE PLACE

Avg\_Price 2.3e+06

Name: 8429, dtype: object

item.Street only: PALACE PLACE

index: 8455

item: Street PANTON STREET

Avg\_Price 2.475e+06

Name: 8455, dtype: object

item.Street only: PANTON STREET

index: 8473

item: Street PARK CRESCENT

Avg\_Price 2.2375e+06

Name: 8473, dtype: object

item.Street only: PARK CRESCENT

index: 8499

item: Street PARKE ROAD

Avg\_Price 2.2625e+06

Name: 8499, dtype: object

item.Street only: PARKE ROAD

index: 8501

item: Street PARKFIELDS

Avg\_Price 2.2e+06

Name: 8501, dtype: object

item.Street only: PARKFIELDS

index: 8537

item: Street PARTHENIA ROAD

Avg\_Price 2.348e+06

Name: 8537, dtype: object

item.Street only: PARTHENIA ROAD

index: 8565

item: Street PAVILION ROAD

Avg\_Price 2.2e+06

Name: 8565, dtype: object

item.Street only: PAVILION ROAD

index: 8621

item: Street PEMBRIDGE ROAD

Avg\_Price 2.4e+06

Name: 8621, dtype: object

item.Street only: PEMBRIDGE ROAD

index: 8630

item: Street PEMBROKE STUDIOS

Avg\_Price 2.45e+06

Name: 8630, dtype: object

item.Street only: PEMBROKE STUDIOS

index: 8633

item: Street PENCOMBE MEWS

Avg\_Price 2.2e+06

Name: 8633, dtype: object

item.Street only: PENCOMBE MEWS

index: 8704

item: Street PETERSHAM PLACE

Avg\_Price 2.3e+06

Name: 8704, dtype: object

item.Street only: PETERSHAM PLACE

index: 8723

item: Street PHYSIC PLACE

Avg\_Price 2.5e+06

Name: 8723, dtype: object

item.Street only: PHYSIC PLACE

index: 8845

item: Street PORCHESTER TERRACE

Avg\_Price 2.5e+06

Name: 8845, dtype: object

item.Street only: PORCHESTER TERRACE

index: 8985

item: Street PROTHERO GARDENS

Avg\_Price 2.2e+06

Name: 8985, dtype: object

item.Street only: PROTHERO GARDENS

index: 9033

item: Street QUARRENDON STREET

Avg\_Price 2.43775e+06

Name: 9033, dtype: object

item.Street only: QUARRENDON STREET

index: 9064

item: Street QUEENS GATE GARDENS

Avg\_Price 2.49232e+06

Name: 9064, dtype: object

item.Street only: QUEENS GATE GARDENS

index: 9113

item: Street RADSTOCK STREET

Avg\_Price 2.31e+06

Name: 9113, dtype: object

item.Street only: RADSTOCK STREET

index: 9151

item: Street RANELAGH AVENUE

Avg\_Price 2.3e+06

Name: 9151, dtype: object

item.Street only: RANELAGH AVENUE

index: 9268

item: Street REEVES MEWS

Avg\_Price 2.45e+06

Name: 9268, dtype: object

item.Street only: REEVES MEWS

index: 9318

item: Street RHEIDOL MEWS

Avg\_Price 2.31e+06

Name: 9318, dtype: object

item.Street only: RHEIDOL MEWS

index: 9367

item: Street RINGWOOD AVENUE

Avg\_Price 2.275e+06

Name: 9367, dtype: object

item.Street only: RINGWOOD AVENUE

index: 9438

item: Street RODERICK ROAD

Avg\_Price 2.4e+06

Name: 9438, dtype: object

item.Street only: RODERICK ROAD

index: 9544

item: Street ROTHBURY ROAD

Avg\_Price 2.3717e+06

Name: 9544, dtype: object

item.Street only: ROTHBURY ROAD

index: 9585

item: Street ROYAL CRESCENT

Avg\_Price 2.34833e+06

Name: 9585, dtype: object

item.Street only: ROYAL CRESCENT

index: 9590

item: Street ROYAL HILL

Avg\_Price 2.43625e+06

Name: 9590, dtype: object

item.Street only: ROYAL HILL

index: 9602

item: Street ROYSTON ROAD

Avg\_Price 2.25e+06

Name: 9602, dtype: object

item.Street only: ROYSTON ROAD

index: 9641

item: Street RUSSELL GARDENS MEWS

Avg\_Price 2.3e+06

Name: 9641, dtype: object

item.Street only: RUSSELL GARDENS MEWS

index: 9935

item: Street SHEPHERDS BUSH ROAD

Avg\_Price 2.39145e+06

Name: 9935, dtype: object

item.Street only: SHEPHERDS BUSH ROAD

index: 10117

item: Street SOUTH END ROW

Avg\_Price 2.47e+06

Name: 10117, dtype: object

item.Street only: SOUTH END ROW

index: 10123

item: Street SOUTH LAMBETH ROAD

Avg\_Price 2.40094e+06

Name: 10123, dtype: object

item.Street only: SOUTH LAMBETH ROAD

index: 10185

item: Street SOUTHWOOD LAWN ROAD

Avg\_Price 2.35e+06

Name: 10185, dtype: object

item.Street only: SOUTHWOOD LAWN ROAD

index: 10188

item: Street SOVEREIGN PARK

Avg\_Price 2.5e+06

Name: 10188, dtype: object

item.Street only: SOVEREIGN PARK

index: 10414

item: Street ST OSWALDS PLACE

Avg\_Price 2.25e+06

Name: 10414, dtype: object

item.Street only: ST OSWALDS PLACE

index: 10428

item: Street ST PETERS SQUARE

Avg\_Price 2.46873e+06

Name: 10428, dtype: object

item.Street only: ST PETERS SQUARE

index: 10457

item: Street STAFFORD TERRACE

Avg\_Price 2.355e+06

Name: 10457, dtype: object

item.Street only: STAFFORD TERRACE

index: 10875

item: Street TAVISTOCK STREET

Avg\_Price 2.3e+06

Name: 10875, dtype: object

item.Street only: TAVISTOCK STREET

index: 11007

item: Street THE PARK

Avg\_Price 2.27715e+06

Name: 11007, dtype: object

item.Street only: THE PARK

index: 11143

item: Street TITE STREET

Avg\_Price 2.44773e+06

Name: 11143, dtype: object

item.Street only: TITE STREET

index: 11293

item: Street TRINITY STREET

Avg\_Price 2.3175e+06

Name: 11293, dtype: object

item.Street only: TRINITY STREET

index: 11434

item: Street UPPER HAMPSTEAD WALK

Avg\_Price 2.5e+06

Name: 11434, dtype: object

item.Street only: UPPER HAMPSTEAD WALK

index: 11822

item: Street WELBECK WAY

Avg\_Price 2.267e+06

Name: 11822, dtype: object

item.Street only: WELBECK WAY

index: 11907

item: Street WEST TEMPLE SHEEN

Avg\_Price 2.325e+06

Name: 11907, dtype: object

item.Street only: WEST TEMPLE SHEEN

index: 12104

item: Street WILLIAM MEWS

Avg\_Price 2.24812e+06

Name: 12104, dtype: object

item.Street only: WILLIAM MEWS

index: 12130

item: Street WILSON STREET

Avg\_Price 2.2575e+06

Name: 12130, dtype: object

item.Street only: WILSON STREET

index: 12155

item: Street WINCHENDON ROAD

Avg\_Price 2.35e+06

Name: 12155, dtype: object

item.Street only: WINCHENDON ROAD

index: 12382

item: Street WRENTHAM AVENUE

Avg\_Price 2.2325e+06

Name: 12382, dtype: object

item.Street only: WRENTHAM AVENUE

index: 12401

item: Street WYCOMBE SQUARE

Avg\_Price 2.2e+06

Name: 12401, dtype: object

item.Street only: WYCOMBE SQUARE

In [13]:

geolocator = Nominatim()

/home/jupyterlab/conda/lib/python3.6/site-packages/geopy/geocoders/osm.py:143: UserWarning: Using Nominatim with the default "geopy/1.17.0" `user\_agent` is strongly discouraged, as it violates Nominatim's ToS https://operations.osmfoundation.org/policies/nominatim/ and may possibly cause 403 and 429 HTTP errors. Please specify a custom `user\_agent` with `Nominatim(user\_agent="my-application")` or by overriding the default `user\_agent`: `geopy.geocoders.options.default\_user\_agent = "my-application"`. In geopy 2.0 this will become an exception.

UserWarning

In [14]:

df\_affordable['city\_coord'] = df\_affordable['Street'].apply(geolocator.geocode).apply(**lambda** x: (x.latitude, x.longitude))

/home/jupyterlab/conda/lib/python3.6/site-packages/ipykernel\_launcher.py:1: SettingWithCopyWarning:

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: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy

"""Entry point for launching an IPython kernel.

In [15]:

df\_affordable

Out[15]:

|  | **Street** | **Avg\_Price** | **city\_coord** |
| --- | --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 | (51.5322588, -0.0061531) |
| **178** | ALBION SQUARE | 2.450000e+06 | (-41.27375755, 173.289393239104) |
| **355** | ANHALT ROAD | 2.435000e+06 | (51.4803265, -0.1667607) |
| **368** | ANSDELL TERRACE | 2.250000e+06 | (51.4998899, -0.1891027) |
| **381** | APPLEGARTH ROAD | 2.400000e+06 | (53.7486539, -0.3266704) |
| **617** | AYLESTONE AVENUE | 2.286667e+06 | (51.5409157, -0.2178742) |
| **753** | BARONSMEAD ROAD | 2.375000e+06 | (51.4773147, -0.239457) |
| **867** | BEAUCLERC ROAD | 2.480000e+06 | (51.4995771, -0.2290331) |
| **1079** | BICKENHALL STREET | 2.351667e+06 | (51.5211969, -0.1589341) |
| **1094** | BILLING ROAD | 2.200000e+06 | (51.4818833, -0.1878624) |
| **1108** | BIRCHLANDS AVENUE | 2.217000e+06 | (51.4483941, -0.1604676) |
| **1310** | BOWERDEAN STREET | 2.300000e+06 | (51.4727099, -0.1924853) |
| **1371** | BRAMPTON GROVE | 2.475833e+06 | (51.5703648, -0.2833944) |
| **1439** | BRIARDALE GARDENS | 2.397132e+06 | (51.5601748, -0.1954305) |
| **1605** | BROWNING CLOSE | 2.320000e+06 | (51.8858497, 0.8560813) |
| **1820** | CALLCOTT STREET | 2.375000e+06 | (51.5083499, -0.1983276) |
| **1871** | CAMPDEN HILL ROAD | 2.352889e+06 | (51.5064605, -0.1988955) |
| **1889** | CANFIELD GARDENS | 2.278000e+06 | (51.5467987, -0.1797091) |
| **1894** | CANNING PLACE | 2.425000e+06 | (51.4995696, -0.1842477) |
| **1950** | CARLISLE ROAD | 2.200000e+06 | (42.5490988, -71.4166686) |
| **1963** | CARLYLE COURT | 2.300000e+06 | (32.6264366, -83.717601) |
| **2105** | CHALCOT SQUARE | 2.286679e+06 | (51.5414545, -0.1552649) |
| **2171** | CHARLES LANE | 2.414000e+06 | (43.8161668, -79.4182871) |
| **2237** | CHELSEA CRESCENT | 2.495000e+06 | (34.524738, -85.448539) |
| **2278** | CHESTER CLOSE NORTH | 2.450000e+06 | (51.5292054, -0.1450813) |
| **2306** | CHEYNE COURT | 2.250000e+06 | (51.599677, 0.5256231) |
| **2352** | CHISWICK MALL | 2.287500e+06 | (51.4879942, -0.2466045) |
| **2468** | CLARENDON STREET | 2.250000e+06 | (42.3494188, -71.0745938) |
| **2512** | CLEVELAND SQUARE | 2.437500e+06 | (31.75991915, -106.491294431738) |
| **2544** | CLONCURRY STREET | 2.388333e+06 | (51.4737632, -0.2162442) |
| **...** | ... | ... | ... |
| **9151** | RANELAGH AVENUE | 2.300000e+06 | (51.4716287, -0.2399743) |
| **9268** | REEVES MEWS | 2.450000e+06 | (51.5097077, -0.1540986) |
| **9318** | RHEIDOL MEWS | 2.310000e+06 | (51.5348497, -0.097876) |
| **9367** | RINGWOOD AVENUE | 2.275000e+06 | (51.5936992, -0.1555817) |
| **9438** | RODERICK ROAD | 2.400000e+06 | (51.5548113, -0.1582001) |
| **9544** | ROTHBURY ROAD | 2.371700e+06 | (52.5736459, 1.1145307) |
| **9585** | ROYAL CRESCENT | 2.348333e+06 | (50.8183538, -0.1253598) |
| **9590** | ROYAL HILL | 2.436250e+06 | (50.5370393, -3.9525672) |
| **9602** | ROYSTON ROAD | 2.250000e+06 | (55.8819805, -4.1734339) |
| **9641** | RUSSELL GARDENS MEWS | 2.300000e+06 | (51.4998689, -0.2118904) |
| **9935** | SHEPHERDS BUSH ROAD | 2.391450e+06 | (51.5028895, -0.2229598) |
| **10117** | SOUTH END ROW | 2.470000e+06 | (51.4987463, -0.1890787) |
| **10123** | SOUTH LAMBETH ROAD | 2.400944e+06 | (51.4731911, -0.1215633) |
| **10185** | SOUTHWOOD LAWN ROAD | 2.350000e+06 | (51.5746267, -0.146238) |
| **10188** | SOVEREIGN PARK | 2.500000e+06 | (-27.4937089, 153.210145350143) |
| **10414** | ST OSWALDS PLACE | 2.250000e+06 | (51.4872071, -0.1185341) |
| **10428** | ST PETERS SQUARE | 2.468730e+06 | (41.9022353, 12.4578392797771) |
| **10457** | STAFFORD TERRACE | 2.355000e+06 | (51.5009379, -0.1960492) |
| **10875** | TAVISTOCK STREET | 2.300000e+06 | (51.5123714, -0.119919) |
| **11007** | THE PARK | 2.277146e+06 | (30.3308401, 71.247499) |
| **11143** | TITE STREET | 2.447730e+06 | (51.4859494, -0.16108) |
| **11293** | TRINITY STREET | 2.317500e+06 | (52.2058864, 0.118053) |
| **11434** | UPPER HAMPSTEAD WALK | 2.500000e+06 | (51.558467, -0.1774529) |
| **11822** | WELBECK WAY | 2.267000e+06 | (52.5580269, -0.2627633) |
| **11907** | WEST TEMPLE SHEEN | 2.325000e+06 | (51.4601389, -0.275404) |
| **12104** | WILLIAM MEWS | 2.248125e+06 | (50.8768344, 0.2653067) |
| **12130** | WILSON STREET | 2.257500e+06 | (-19.264566, 146.8046701) |
| **12155** | WINCHENDON ROAD | 2.350000e+06 | (51.4329074, -0.3484547) |
| **12382** | WRENTHAM AVENUE | 2.232500e+06 | (51.3597581, 1.0946807) |
| **12401** | WYCOMBE SQUARE | 2.200000e+06 | (51.5062978, -0.2003163) |

131 rows × 3 columns

In [16]:

df\_affordable[['Latitude', 'Longitude']] = df\_affordable['city\_coord'].apply(pd.Series)

/home/jupyterlab/conda/lib/python3.6/site-packages/pandas/core/frame.py:3140: SettingWithCopyWarning:

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: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy

self[k1] = value[k2]

In [17]:

df\_affordable

Out[17]:

|  | **Street** | **Avg\_Price** | **city\_coord** | **Latitude** | **Longitude** |
| --- | --- | --- | --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 | (51.5322588, -0.0061531) | 51.532259 | -0.006153 |
| **178** | ALBION SQUARE | 2.450000e+06 | (-41.27375755, 173.289393239104) | -41.273758 | 173.289393 |
| **355** | ANHALT ROAD | 2.435000e+06 | (51.4803265, -0.1667607) | 51.480326 | -0.166761 |
| **368** | ANSDELL TERRACE | 2.250000e+06 | (51.4998899, -0.1891027) | 51.499890 | -0.189103 |
| **381** | APPLEGARTH ROAD | 2.400000e+06 | (53.7486539, -0.3266704) | 53.748654 | -0.326670 |
| **617** | AYLESTONE AVENUE | 2.286667e+06 | (51.5409157, -0.2178742) | 51.540916 | -0.217874 |
| **753** | BARONSMEAD ROAD | 2.375000e+06 | (51.4773147, -0.239457) | 51.477315 | -0.239457 |
| **867** | BEAUCLERC ROAD | 2.480000e+06 | (51.4995771, -0.2290331) | 51.499577 | -0.229033 |
| **1079** | BICKENHALL STREET | 2.351667e+06 | (51.5211969, -0.1589341) | 51.521197 | -0.158934 |
| **1094** | BILLING ROAD | 2.200000e+06 | (51.4818833, -0.1878624) | 51.481883 | -0.187862 |
| **1108** | BIRCHLANDS AVENUE | 2.217000e+06 | (51.4483941, -0.1604676) | 51.448394 | -0.160468 |
| **1310** | BOWERDEAN STREET | 2.300000e+06 | (51.4727099, -0.1924853) | 51.472710 | -0.192485 |
| **1371** | BRAMPTON GROVE | 2.475833e+06 | (51.5703648, -0.2833944) | 51.570365 | -0.283394 |
| **1439** | BRIARDALE GARDENS | 2.397132e+06 | (51.5601748, -0.1954305) | 51.560175 | -0.195431 |
| **1605** | BROWNING CLOSE | 2.320000e+06 | (51.8858497, 0.8560813) | 51.885850 | 0.856081 |
| **1820** | CALLCOTT STREET | 2.375000e+06 | (51.5083499, -0.1983276) | 51.508350 | -0.198328 |
| **1871** | CAMPDEN HILL ROAD | 2.352889e+06 | (51.5064605, -0.1988955) | 51.506461 | -0.198896 |
| **1889** | CANFIELD GARDENS | 2.278000e+06 | (51.5467987, -0.1797091) | 51.546799 | -0.179709 |
| **1894** | CANNING PLACE | 2.425000e+06 | (51.4995696, -0.1842477) | 51.499570 | -0.184248 |
| **1950** | CARLISLE ROAD | 2.200000e+06 | (42.5490988, -71.4166686) | 42.549099 | -71.416669 |
| **1963** | CARLYLE COURT | 2.300000e+06 | (32.6264366, -83.717601) | 32.626437 | -83.717601 |
| **2105** | CHALCOT SQUARE | 2.286679e+06 | (51.5414545, -0.1552649) | 51.541455 | -0.155265 |
| **2171** | CHARLES LANE | 2.414000e+06 | (43.8161668, -79.4182871) | 43.816167 | -79.418287 |
| **2237** | CHELSEA CRESCENT | 2.495000e+06 | (34.524738, -85.448539) | 34.524738 | -85.448539 |
| **2278** | CHESTER CLOSE NORTH | 2.450000e+06 | (51.5292054, -0.1450813) | 51.529205 | -0.145081 |
| **2306** | CHEYNE COURT | 2.250000e+06 | (51.599677, 0.5256231) | 51.599677 | 0.525623 |
| **2352** | CHISWICK MALL | 2.287500e+06 | (51.4879942, -0.2466045) | 51.487994 | -0.246605 |
| **2468** | CLARENDON STREET | 2.250000e+06 | (42.3494188, -71.0745938) | 42.349419 | -71.074594 |
| **2512** | CLEVELAND SQUARE | 2.437500e+06 | (31.75991915, -106.491294431738) | 31.759919 | -106.491294 |
| **2544** | CLONCURRY STREET | 2.388333e+06 | (51.4737632, -0.2162442) | 51.473763 | -0.216244 |
| **...** | ... | ... | ... | ... | ... |
| **9151** | RANELAGH AVENUE | 2.300000e+06 | (51.4716287, -0.2399743) | 51.471629 | -0.239974 |
| **9268** | REEVES MEWS | 2.450000e+06 | (51.5097077, -0.1540986) | 51.509708 | -0.154099 |
| **9318** | RHEIDOL MEWS | 2.310000e+06 | (51.5348497, -0.097876) | 51.534850 | -0.097876 |
| **9367** | RINGWOOD AVENUE | 2.275000e+06 | (51.5936992, -0.1555817) | 51.593699 | -0.155582 |
| **9438** | RODERICK ROAD | 2.400000e+06 | (51.5548113, -0.1582001) | 51.554811 | -0.158200 |
| **9544** | ROTHBURY ROAD | 2.371700e+06 | (52.5736459, 1.1145307) | 52.573646 | 1.114531 |
| **9585** | ROYAL CRESCENT | 2.348333e+06 | (50.8183538, -0.1253598) | 50.818354 | -0.125360 |
| **9590** | ROYAL HILL | 2.436250e+06 | (50.5370393, -3.9525672) | 50.537039 | -3.952567 |
| **9602** | ROYSTON ROAD | 2.250000e+06 | (55.8819805, -4.1734339) | 55.881980 | -4.173434 |
| **9641** | RUSSELL GARDENS MEWS | 2.300000e+06 | (51.4998689, -0.2118904) | 51.499869 | -0.211890 |
| **9935** | SHEPHERDS BUSH ROAD | 2.391450e+06 | (51.5028895, -0.2229598) | 51.502890 | -0.222960 |
| **10117** | SOUTH END ROW | 2.470000e+06 | (51.4987463, -0.1890787) | 51.498746 | -0.189079 |
| **10123** | SOUTH LAMBETH ROAD | 2.400944e+06 | (51.4731911, -0.1215633) | 51.473191 | -0.121563 |
| **10185** | SOUTHWOOD LAWN ROAD | 2.350000e+06 | (51.5746267, -0.146238) | 51.574627 | -0.146238 |
| **10188** | SOVEREIGN PARK | 2.500000e+06 | (-27.4937089, 153.210145350143) | -27.493709 | 153.210145 |
| **10414** | ST OSWALDS PLACE | 2.250000e+06 | (51.4872071, -0.1185341) | 51.487207 | -0.118534 |
| **10428** | ST PETERS SQUARE | 2.468730e+06 | (41.9022353, 12.4578392797771) | 41.902235 | 12.457839 |
| **10457** | STAFFORD TERRACE | 2.355000e+06 | (51.5009379, -0.1960492) | 51.500938 | -0.196049 |
| **10875** | TAVISTOCK STREET | 2.300000e+06 | (51.5123714, -0.119919) | 51.512371 | -0.119919 |
| **11007** | THE PARK | 2.277146e+06 | (30.3308401, 71.247499) | 30.330840 | 71.247499 |
| **11143** | TITE STREET | 2.447730e+06 | (51.4859494, -0.16108) | 51.485949 | -0.161080 |
| **11293** | TRINITY STREET | 2.317500e+06 | (52.2058864, 0.118053) | 52.205886 | 0.118053 |
| **11434** | UPPER HAMPSTEAD WALK | 2.500000e+06 | (51.558467, -0.1774529) | 51.558467 | -0.177453 |
| **11822** | WELBECK WAY | 2.267000e+06 | (52.5580269, -0.2627633) | 52.558027 | -0.262763 |
| **11907** | WEST TEMPLE SHEEN | 2.325000e+06 | (51.4601389, -0.275404) | 51.460139 | -0.275404 |
| **12104** | WILLIAM MEWS | 2.248125e+06 | (50.8768344, 0.2653067) | 50.876834 | 0.265307 |
| **12130** | WILSON STREET | 2.257500e+06 | (-19.264566, 146.8046701) | -19.264566 | 146.804670 |
| **12155** | WINCHENDON ROAD | 2.350000e+06 | (51.4329074, -0.3484547) | 51.432907 | -0.348455 |
| **12382** | WRENTHAM AVENUE | 2.232500e+06 | (51.3597581, 1.0946807) | 51.359758 | 1.094681 |
| **12401** | WYCOMBE SQUARE | 2.200000e+06 | (51.5062978, -0.2003163) | 51.506298 | -0.200316 |

131 rows × 5 columns

In [18]:

df = df\_affordable.drop(columns=['city\_coord'])

In [19]:

df

Out[19]:

|  | **Street** | **Avg\_Price** | **Latitude** | **Longitude** |
| --- | --- | --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 | 51.532259 | -0.006153 |
| **178** | ALBION SQUARE | 2.450000e+06 | -41.273758 | 173.289393 |
| **355** | ANHALT ROAD | 2.435000e+06 | 51.480326 | -0.166761 |
| **368** | ANSDELL TERRACE | 2.250000e+06 | 51.499890 | -0.189103 |
| **381** | APPLEGARTH ROAD | 2.400000e+06 | 53.748654 | -0.326670 |
| **617** | AYLESTONE AVENUE | 2.286667e+06 | 51.540916 | -0.217874 |
| **753** | BARONSMEAD ROAD | 2.375000e+06 | 51.477315 | -0.239457 |
| **867** | BEAUCLERC ROAD | 2.480000e+06 | 51.499577 | -0.229033 |
| **1079** | BICKENHALL STREET | 2.351667e+06 | 51.521197 | -0.158934 |
| **1094** | BILLING ROAD | 2.200000e+06 | 51.481883 | -0.187862 |
| **1108** | BIRCHLANDS AVENUE | 2.217000e+06 | 51.448394 | -0.160468 |
| **1310** | BOWERDEAN STREET | 2.300000e+06 | 51.472710 | -0.192485 |
| **1371** | BRAMPTON GROVE | 2.475833e+06 | 51.570365 | -0.283394 |
| **1439** | BRIARDALE GARDENS | 2.397132e+06 | 51.560175 | -0.195431 |
| **1605** | BROWNING CLOSE | 2.320000e+06 | 51.885850 | 0.856081 |
| **1820** | CALLCOTT STREET | 2.375000e+06 | 51.508350 | -0.198328 |
| **1871** | CAMPDEN HILL ROAD | 2.352889e+06 | 51.506461 | -0.198896 |
| **1889** | CANFIELD GARDENS | 2.278000e+06 | 51.546799 | -0.179709 |
| **1894** | CANNING PLACE | 2.425000e+06 | 51.499570 | -0.184248 |
| **1950** | CARLISLE ROAD | 2.200000e+06 | 42.549099 | -71.416669 |
| **1963** | CARLYLE COURT | 2.300000e+06 | 32.626437 | -83.717601 |
| **2105** | CHALCOT SQUARE | 2.286679e+06 | 51.541455 | -0.155265 |
| **2171** | CHARLES LANE | 2.414000e+06 | 43.816167 | -79.418287 |
| **2237** | CHELSEA CRESCENT | 2.495000e+06 | 34.524738 | -85.448539 |
| **2278** | CHESTER CLOSE NORTH | 2.450000e+06 | 51.529205 | -0.145081 |
| **2306** | CHEYNE COURT | 2.250000e+06 | 51.599677 | 0.525623 |
| **2352** | CHISWICK MALL | 2.287500e+06 | 51.487994 | -0.246605 |
| **2468** | CLARENDON STREET | 2.250000e+06 | 42.349419 | -71.074594 |
| **2512** | CLEVELAND SQUARE | 2.437500e+06 | 31.759919 | -106.491294 |
| **2544** | CLONCURRY STREET | 2.388333e+06 | 51.473763 | -0.216244 |
| **...** | ... | ... | ... | ... |
| **9151** | RANELAGH AVENUE | 2.300000e+06 | 51.471629 | -0.239974 |
| **9268** | REEVES MEWS | 2.450000e+06 | 51.509708 | -0.154099 |
| **9318** | RHEIDOL MEWS | 2.310000e+06 | 51.534850 | -0.097876 |
| **9367** | RINGWOOD AVENUE | 2.275000e+06 | 51.593699 | -0.155582 |
| **9438** | RODERICK ROAD | 2.400000e+06 | 51.554811 | -0.158200 |
| **9544** | ROTHBURY ROAD | 2.371700e+06 | 52.573646 | 1.114531 |
| **9585** | ROYAL CRESCENT | 2.348333e+06 | 50.818354 | -0.125360 |
| **9590** | ROYAL HILL | 2.436250e+06 | 50.537039 | -3.952567 |
| **9602** | ROYSTON ROAD | 2.250000e+06 | 55.881980 | -4.173434 |
| **9641** | RUSSELL GARDENS MEWS | 2.300000e+06 | 51.499869 | -0.211890 |
| **9935** | SHEPHERDS BUSH ROAD | 2.391450e+06 | 51.502890 | -0.222960 |
| **10117** | SOUTH END ROW | 2.470000e+06 | 51.498746 | -0.189079 |
| **10123** | SOUTH LAMBETH ROAD | 2.400944e+06 | 51.473191 | -0.121563 |
| **10185** | SOUTHWOOD LAWN ROAD | 2.350000e+06 | 51.574627 | -0.146238 |
| **10188** | SOVEREIGN PARK | 2.500000e+06 | -27.493709 | 153.210145 |
| **10414** | ST OSWALDS PLACE | 2.250000e+06 | 51.487207 | -0.118534 |
| **10428** | ST PETERS SQUARE | 2.468730e+06 | 41.902235 | 12.457839 |
| **10457** | STAFFORD TERRACE | 2.355000e+06 | 51.500938 | -0.196049 |
| **10875** | TAVISTOCK STREET | 2.300000e+06 | 51.512371 | -0.119919 |
| **11007** | THE PARK | 2.277146e+06 | 30.330840 | 71.247499 |
| **11143** | TITE STREET | 2.447730e+06 | 51.485949 | -0.161080 |
| **11293** | TRINITY STREET | 2.317500e+06 | 52.205886 | 0.118053 |
| **11434** | UPPER HAMPSTEAD WALK | 2.500000e+06 | 51.558467 | -0.177453 |
| **11822** | WELBECK WAY | 2.267000e+06 | 52.558027 | -0.262763 |
| **11907** | WEST TEMPLE SHEEN | 2.325000e+06 | 51.460139 | -0.275404 |
| **12104** | WILLIAM MEWS | 2.248125e+06 | 50.876834 | 0.265307 |
| **12130** | WILSON STREET | 2.257500e+06 | -19.264566 | 146.804670 |
| **12155** | WINCHENDON ROAD | 2.350000e+06 | 51.432907 | -0.348455 |
| **12382** | WRENTHAM AVENUE | 2.232500e+06 | 51.359758 | 1.094681 |
| **12401** | WYCOMBE SQUARE | 2.200000e+06 | 51.506298 | -0.200316 |

131 rows × 4 columns

In [20]:

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))

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

In [21]:

*# 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\_Price'], 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[21]:

In [22]:

*#Define Foursquare Credentials and Version*

CLIENT\_ID = 'KI3TR0QO4JOKMFELOMF3WSOOI3HFNBF5YLW354MYWBKDHEX3' *# Foursquare ID*

CLIENT\_SECRET = 'QF4ZBLJRBV4BQX52DVWUPEHJ14A2UJABPCZARZQZYTKIISUD' *# Foursquare 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

We can now proceed to the Modeling phase. We will analyze neighborhoods to recommend real estates where home buyers can make a real estate investment. We will then recommend profitable venues according to amenities and essential facilities surrounding such venues i.e. elementary schools, high schools, hospitals & grocery stores.

**4. Modeling**

After exploring the dataset and gaining insights into it, we are ready to use the clustering methodology to analyze real estates. We will use 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.

In [23]:

**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=**{}**&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 = ['Street',

'Street Latitude',

'Street Longitude',

'Venue',

'Venue Latitude',

'Venue Longitude',

'Venue Category']

**return**(nearby\_venues)

In [24]:

*# Run the above function on each location and create a new dataframe called location\_venues and display it.*

location\_venues = getNearbyVenues(names=df['Street'],

latitudes=df['Latitude'],

longitudes=df['Longitude']

)

ABBOTSBURY CLOSE

ALBION SQUARE

ANHALT ROAD

ANSDELL TERRACE

APPLEGARTH ROAD

AYLESTONE AVENUE

BARONSMEAD ROAD

BEAUCLERC ROAD

BICKENHALL STREET

BILLING ROAD

BIRCHLANDS AVENUE

BOWERDEAN STREET

BRAMPTON GROVE

BRIARDALE GARDENS

BROWNING CLOSE

CALLCOTT STREET

CAMPDEN HILL ROAD

CANFIELD GARDENS

CANNING PLACE

CARLISLE ROAD

CARLYLE COURT

CHALCOT SQUARE

CHARLES LANE

CHELSEA CRESCENT

CHESTER CLOSE NORTH

CHEYNE COURT

CHISWICK MALL

CLARENDON STREET

CLEVELAND SQUARE

CLONCURRY STREET

COLBECK MEWS

COLLEGE CRESCENT

CORNWALL TERRACE MEWS

COURT LANE GARDENS

CRAVEN STREET

DALEBURY ROAD

DEWHURST ROAD

DORIA ROAD

DOWNSHIRE HILL

DRAX AVENUE

DUCHESS WALK

ECCLESTON SQUARE MEWS

EGBERT STREET

EGERTON PLACE

FIRECREST DRIVE

FLASK WALK

FRANK DIXON WAY

GERARD ROAD

GIBSON SQUARE

GLOUCESTER AVENUE

GORDON PLACE

HAMPSTEAD WAY

HARMAN DRIVE

HAZLEWELL ROAD

HEREFORD MEWS

HERONDALE AVENUE

HILLGATE PLACE

HOLDEN AVENUE

HOLLYWOOD MEWS

HORNTON STREET

HUNTER ROAD

JACKSONS LANE

JOHN ISLIP STREET

KNOX STREET

LANCASTER MEWS

LAXTON PLACE

LILLIE SQUARE

LINCOLN AVENUE

LISSON STREET

LIVERPOOL GROVE

LONGWOOD DRIVE

LONSDALE SQUARE

MANSFIELD STREET

MAZE HILL

MONTAGU MEWS NORTH

MONTPELIER WALK

MULTON ROAD

NEW KENT ROAD

NORFOLK CRESCENT

NOTTINGHAM STREET

OAKWOOD COURT

OLD COURT PLACE

ONSLOW MEWS WEST

ONSLOW SQUARE

PALACE PLACE

PANTON STREET

PARK CRESCENT

PARKE ROAD

PARKFIELDS

PARTHENIA ROAD

PAVILION ROAD

PEMBRIDGE ROAD

PEMBROKE STUDIOS

PENCOMBE MEWS

PETERSHAM PLACE

PHYSIC PLACE

PORCHESTER TERRACE

PROTHERO GARDENS

QUARRENDON STREET

QUEENS GATE GARDENS

RADSTOCK STREET

RANELAGH AVENUE

REEVES MEWS

RHEIDOL MEWS

RINGWOOD AVENUE

RODERICK ROAD

ROTHBURY ROAD

ROYAL CRESCENT

ROYAL HILL

ROYSTON ROAD

RUSSELL GARDENS MEWS

SHEPHERDS BUSH ROAD

SOUTH END ROW

SOUTH LAMBETH ROAD

SOUTHWOOD LAWN ROAD

SOVEREIGN PARK

ST OSWALDS PLACE

ST PETERS SQUARE

STAFFORD TERRACE

TAVISTOCK STREET

THE PARK

TITE STREET

TRINITY STREET

UPPER HAMPSTEAD WALK

WELBECK WAY

WEST TEMPLE SHEEN

WILLIAM MEWS

WILSON STREET

WINCHENDON ROAD

WRENTHAM AVENUE

WYCOMBE SQUARE

In [25]:

location\_venues

Out[25]:

|  | **Street** | **Street Latitude** | **Street Longitude** | **Venue** | **Venue Latitude** | **Venue Longitude** | **Venue Category** |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | ABBOTSBURY CLOSE | 51.532259 | -0.006153 | Pie Crust Cafe | 51.536489 | -0.004051 | Thai Restaurant |
| **1** | ABBOTSBURY CLOSE | 51.532259 | -0.006153 | Three Mills Green | 51.528840 | -0.006834 | Park |
| **2** | ABBOTSBURY CLOSE | 51.532259 | -0.006153 | Tesco Express | 51.535118 | -0.005973 | Grocery Store |
| **3** | ABBOTSBURY CLOSE | 51.532259 | -0.006153 | Holiday Inn Express | 51.536332 | -0.004623 | Hotel |
| **4** | ABBOTSBURY CLOSE | 51.532259 | -0.006153 | Bow Riviera | 51.528684 | -0.010352 | Waterfront |
| **5** | ALBION SQUARE | -41.273758 | 173.289393 | The Free House | -41.273340 | 173.287364 | Bar |
| **6** | ALBION SQUARE | -41.273758 | 173.289393 | The Indian Cafe | -41.273308 | 173.286530 | Indian Restaurant |
| **7** | ALBION SQUARE | -41.273758 | 173.289393 | Fish Stop | -41.276010 | 173.289592 | Fish & Chips Shop |
| **8** | ALBION SQUARE | -41.273758 | 173.289393 | Urban | -41.274355 | 173.286317 | New American Restaurant |
| **9** | ALBION SQUARE | -41.273758 | 173.289393 | The Bridge Street Collective | -41.272520 | 173.285517 | Café |
| **10** | ALBION SQUARE | -41.273758 | 173.289393 | Deville Cafe | -41.271941 | 173.285535 | Beer Garden |
| **11** | ALBION SQUARE | -41.273758 | 173.289393 | Fresh Choice | -41.272194 | 173.287218 | Supermarket |
| **12** | ALBION SQUARE | -41.273758 | 173.289393 | Queen's Gardens | -41.273671 | 173.291383 | Park |
| **13** | ALBION SQUARE | -41.273758 | 173.289393 | cod and lobster | -41.275203 | 173.283747 | Seafood Restaurant |
| **14** | ALBION SQUARE | -41.273758 | 173.289393 | Hopgood's | -41.274749 | 173.283831 | Restaurant |
| **15** | ALBION SQUARE | -41.273758 | 173.289393 | Mango | -41.274460 | 173.285345 | Indian Restaurant |
| **16** | ALBION SQUARE | -41.273758 | 173.289393 | The Vic Mac's Brew Bar | -41.274757 | 173.283914 | Pub |
| **17** | ALBION SQUARE | -41.273758 | 173.289393 | Sprig & Fern | -41.274508 | 173.286527 | Brewery |
| **18** | ALBION SQUARE | -41.273758 | 173.289393 | La Gourmandise | -41.274262 | 173.286211 | French Restaurant |
| **19** | ALBION SQUARE | -41.273758 | 173.289393 | Lambretta's Cafe & Bar | -41.274372 | 173.284462 | Café |
| **20** | ALBION SQUARE | -41.273758 | 173.289393 | Columbus Coffee | -41.274759 | 173.285391 | Coffee Shop |
| **21** | ALBION SQUARE | -41.273758 | 173.289393 | Morrison Street Cafe | -41.274505 | 173.285461 | Café |
| **22** | ALBION SQUARE | -41.273758 | 173.289393 | The Kitchen | -41.272360 | 173.285500 | Café |
| **23** | ALBION SQUARE | -41.273758 | 173.289393 | East Street Cafe | -41.275689 | 173.284927 | Vegetarian / Vegan Restaurant |
| **24** | ALBION SQUARE | -41.273758 | 173.289393 | Ford's Restaurant & Bar | -41.274637 | 173.283851 | Restaurant |
| **25** | ALBION SQUARE | -41.273758 | 173.289393 | 7010 | -41.270045 | 173.286959 | Café |
| **26** | ALBION SQUARE | -41.273758 | 173.289393 | Robert Harris Coffee | -41.272941 | 173.283876 | Café |
| **27** | ALBION SQUARE | -41.273758 | 173.289393 | Suter Art Gallery | -41.273665 | 173.291377 | Art Gallery |
| **28** | ALBION SQUARE | -41.273758 | 173.289393 | 623 In the City | -41.274049 | 173.285020 | Bar |
| **29** | ALBION SQUARE | -41.273758 | 173.289393 | The Nelson Provincial Museum | -41.274486 | 173.283911 | Museum |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **4839** | WYCOMBE SQUARE | 51.506298 | -0.200316 | The Castle | 51.506934 | -0.206818 | Pub |
| **4840** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Starbucks | 51.509785 | -0.197193 | Coffee Shop |
| **4841** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Flat three | 51.506870 | -0.207079 | Japanese Restaurant |
| **4842** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Clarke's | 51.507059 | -0.194539 | Restaurant |
| **4843** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Pizza sugo pasta | 51.508884 | -0.198349 | Pizza Place |
| **4844** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Farina Pizzeria Napoletana | 51.508594 | -0.198539 | Pizza Place |
| **4845** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Safestay | 51.502797 | -0.201773 | Hostel |
| **4846** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Tesco | 51.507032 | -0.206243 | Grocery Store |
| **4847** | WYCOMBE SQUARE | 51.506298 | -0.200316 | VQ Notting Hill | 51.509663 | -0.197294 | Café |
| **4848** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Da Maria | 51.508793 | -0.197319 | Italian Restaurant |
| **4849** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Starbucks | 51.508727 | -0.199236 | Coffee Shop |
| **4850** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Uxbridge Arms | 51.508333 | -0.198832 | Pub |
| **4851** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Black & Blue | 51.508419 | -0.195127 | Steakhouse |
| **4852** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Bowden | 51.509604 | -0.200982 | Hostel |
| **4853** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Ravna Gora Hotel London | 51.507693 | -0.203656 | Hotel |
| **4854** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Jeroboams | 51.507209 | -0.207171 | Cheese Shop |
| **4855** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Feng Sushi | 51.508832 | -0.197857 | Sushi Restaurant |
| **4856** | WYCOMBE SQUARE | 51.506298 | -0.200316 | McDonald's | 51.508857 | -0.198051 | Fast Food Restaurant |
| **4857** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Uli | 51.509773 | -0.197798 | Asian Restaurant |
| **4858** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Caffè Nero | 51.509093 | -0.196379 | Coffee Shop |
| **4859** | WYCOMBE SQUARE | 51.506298 | -0.200316 | The Old Swan | 51.508958 | -0.195254 | Pub |
| **4860** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Wycombe Square | 51.506081 | -0.199988 | Plaza |
| **4861** | WYCOMBE SQUARE | 51.506298 | -0.200316 | campden hill lawn tennis club | 51.506303 | -0.201113 | Tennis Court |
| **4862** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Lord Holland's Pond | 51.504066 | -0.203464 | Monument / Landmark |
| **4863** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Holland Park Station (HL) | 51.507400 | -0.204891 | Bus Stop |
| **4864** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Tesco | 51.507569 | -0.206355 | Grocery Store |
| **4865** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Holland Park London Underground Station | 51.507261 | -0.205511 | Metro Station |
| **4866** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Japanese Gallery | 51.505183 | -0.193709 | Art Gallery |
| **4867** | WYCOMBE SQUARE | 51.506298 | -0.200316 | The Abbey Court Notting Hill Hotel | 51.510046 | -0.197004 | Hotel |
| **4868** | WYCOMBE SQUARE | 51.506298 | -0.200316 | Fukushima Garden | 51.502893 | -0.204592 | Garden |

4869 rows × 7 columns

In [26]:

location\_venues.groupby('Street').count()

Out[26]:

|  | **Street Latitude** | **Street Longitude** | **Venue** | **Venue Latitude** | **Venue Longitude** | **Venue Category** |
| --- | --- | --- | --- | --- | --- | --- |
| **Street** |  |  |  |  |  |  |
| **ABBOTSBURY CLOSE** | 5 | 5 | 5 | 5 | 5 | 5 |
| **ALBION SQUARE** | 27 | 27 | 27 | 27 | 27 | 27 |
| **ANHALT ROAD** | 14 | 14 | 14 | 14 | 14 | 14 |
| **ANSDELL TERRACE** | 56 | 56 | 56 | 56 | 56 | 56 |
| **APPLEGARTH ROAD** | 5 | 5 | 5 | 5 | 5 | 5 |
| **AYLESTONE AVENUE** | 5 | 5 | 5 | 5 | 5 | 5 |
| **BARONSMEAD ROAD** | 13 | 13 | 13 | 13 | 13 | 13 |
| **BEAUCLERC ROAD** | 30 | 30 | 30 | 30 | 30 | 30 |
| **BICKENHALL STREET** | 95 | 95 | 95 | 95 | 95 | 95 |
| **BILLING ROAD** | 63 | 63 | 63 | 63 | 63 | 63 |
| **BIRCHLANDS AVENUE** | 8 | 8 | 8 | 8 | 8 | 8 |
| **BOWERDEAN STREET** | 25 | 25 | 25 | 25 | 25 | 25 |
| **BRAMPTON GROVE** | 4 | 4 | 4 | 4 | 4 | 4 |
| **BRIARDALE GARDENS** | 5 | 5 | 5 | 5 | 5 | 5 |
| **BROWNING CLOSE** | 2 | 2 | 2 | 2 | 2 | 2 |
| **CALLCOTT STREET** | 50 | 50 | 50 | 50 | 50 | 50 |
| **CAMPDEN HILL ROAD** | 53 | 53 | 53 | 53 | 53 | 53 |
| **CANFIELD GARDENS** | 69 | 69 | 69 | 69 | 69 | 69 |
| **CANNING PLACE** | 33 | 33 | 33 | 33 | 33 | 33 |
| **CARLISLE ROAD** | 2 | 2 | 2 | 2 | 2 | 2 |
| **CHALCOT SQUARE** | 59 | 59 | 59 | 59 | 59 | 59 |
| **CHARLES LANE** | 4 | 4 | 4 | 4 | 4 | 4 |
| **CHESTER CLOSE NORTH** | 20 | 20 | 20 | 20 | 20 | 20 |
| **CHEYNE COURT** | 3 | 3 | 3 | 3 | 3 | 3 |
| **CHISWICK MALL** | 7 | 7 | 7 | 7 | 7 | 7 |
| **CLARENDON STREET** | 100 | 100 | 100 | 100 | 100 | 100 |
| **CLEVELAND SQUARE** | 50 | 50 | 50 | 50 | 50 | 50 |
| **CLONCURRY STREET** | 26 | 26 | 26 | 26 | 26 | 26 |
| **COLBECK MEWS** | 100 | 100 | 100 | 100 | 100 | 100 |
| **COLLEGE CRESCENT** | 5 | 5 | 5 | 5 | 5 | 5 |
| **...** | ... | ... | ... | ... | ... | ... |
| **QUEENS GATE GARDENS** | 5 | 5 | 5 | 5 | 5 | 5 |
| **RADSTOCK STREET** | 12 | 12 | 12 | 12 | 12 | 12 |
| **RANELAGH AVENUE** | 18 | 18 | 18 | 18 | 18 | 18 |
| **REEVES MEWS** | 92 | 92 | 92 | 92 | 92 | 92 |
| **RHEIDOL MEWS** | 82 | 82 | 82 | 82 | 82 | 82 |
| **RINGWOOD AVENUE** | 6 | 6 | 6 | 6 | 6 | 6 |
| **RODERICK ROAD** | 14 | 14 | 14 | 14 | 14 | 14 |
| **ROTHBURY ROAD** | 4 | 4 | 4 | 4 | 4 | 4 |
| **ROYAL CRESCENT** | 29 | 29 | 29 | 29 | 29 | 29 |
| **ROYSTON ROAD** | 3 | 3 | 3 | 3 | 3 | 3 |
| **RUSSELL GARDENS MEWS** | 24 | 24 | 24 | 24 | 24 | 24 |
| **SHEPHERDS BUSH ROAD** | 88 | 88 | 88 | 88 | 88 | 88 |
| **SOUTH END ROW** | 61 | 61 | 61 | 61 | 61 | 61 |
| **SOUTH LAMBETH ROAD** | 27 | 27 | 27 | 27 | 27 | 27 |
| **SOUTHWOOD LAWN ROAD** | 36 | 36 | 36 | 36 | 36 | 36 |
| **SOVEREIGN PARK** | 4 | 4 | 4 | 4 | 4 | 4 |
| **ST OSWALDS PLACE** | 42 | 42 | 42 | 42 | 42 | 42 |
| **ST PETERS SQUARE** | 90 | 90 | 90 | 90 | 90 | 90 |
| **STAFFORD TERRACE** | 67 | 67 | 67 | 67 | 67 | 67 |
| **TAVISTOCK STREET** | 100 | 100 | 100 | 100 | 100 | 100 |
| **TITE STREET** | 38 | 38 | 38 | 38 | 38 | 38 |
| **TRINITY STREET** | 90 | 90 | 90 | 90 | 90 | 90 |
| **UPPER HAMPSTEAD WALK** | 58 | 58 | 58 | 58 | 58 | 58 |
| **WELBECK WAY** | 3 | 3 | 3 | 3 | 3 | 3 |
| **WEST TEMPLE SHEEN** | 6 | 6 | 6 | 6 | 6 | 6 |
| **WILLIAM MEWS** | 2 | 2 | 2 | 2 | 2 | 2 |
| **WILSON STREET** | 4 | 4 | 4 | 4 | 4 | 4 |
| **WINCHENDON ROAD** | 14 | 14 | 14 | 14 | 14 | 14 |
| **WRENTHAM AVENUE** | 1 | 1 | 1 | 1 | 1 | 1 |
| **WYCOMBE SQUARE** | 82 | 82 | 82 | 82 | 82 | 82 |

125 rows × 6 columns

In [27]:

*# get the List of Unique Categories*

print('There are **{}** uniques categories.'.format(len(location\_venues['Venue Category'].unique())))

There are 313 uniques categories.

In [28]:

location\_venues.shape

Out[28]:

(4869, 7)

In [29]:

*# 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[29]:

|  | **Street** | **Accessories Store** | **Adult Boutique** | **Afghan Restaurant** | **African Restaurant** | **American Restaurant** | **Antique Shop** | **Argentinian Restaurant** | **Art Gallery** | **Art Museum** | **...** | **Vegetarian / Vegan Restaurant** | **Video Game Store** | **Vietnamese Restaurant** | **Warehouse Store** | **Waterfront** | **Wine Bar** | **Wine Shop** | **Women's Store** | **Yoga Studio** | **Zoo** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | ABBOTSBURY CLOSE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | ABBOTSBURY CLOSE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | ABBOTSBURY CLOSE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | ABBOTSBURY CLOSE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | ABBOTSBURY CLOSE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

5 rows × 314 columns

In [30]:

london\_grouped = venues\_onehot.groupby('Street').mean().reset\_index()

london\_grouped

Out[30]:

|  | **Street** | **Accessories Store** | **Adult Boutique** | **Afghan Restaurant** | **African Restaurant** | **American Restaurant** | **Antique Shop** | **Argentinian Restaurant** | **Art Gallery** | **Art Museum** | **...** | **Vegetarian / Vegan Restaurant** | **Video Game Store** | **Vietnamese Restaurant** | **Warehouse Store** | **Waterfront** | **Wine Bar** | **Wine Shop** | **Women's Store** | **Yoga Studio** | **Zoo** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | ABBOTSBURY CLOSE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.200000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **1** | ALBION SQUARE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.037037 | 0.000000 | ... | 0.037037 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **2** | ANHALT ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **3** | ANSDELL TERRACE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.017857 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.017857 | 0.000000 | 0.0 |
| **4** | APPLEGARTH ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **5** | AYLESTONE AVENUE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **6** | BARONSMEAD ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **7** | BEAUCLERC ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **8** | BICKENHALL STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010526 | 0.000000 | 0.000000 | 0.010526 | 0.0 |
| **9** | BILLING ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.015873 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **10** | BIRCHLANDS AVENUE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **11** | BOWERDEAN STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **12** | BRAMPTON GROVE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **13** | BRIARDALE GARDENS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **14** | BROWNING CLOSE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **15** | CALLCOTT STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.020000 | 0.000000 | 0.000000 | 0.040000 | 0.0 |
| **16** | CAMPDEN HILL ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.018868 | 0.000000 | 0.000000 | 0.037736 | 0.0 |
| **17** | CANFIELD GARDENS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.014493 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **18** | CANNING PLACE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **19** | CARLISLE ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **20** | CHALCOT SQUARE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.033898 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.016949 | 0.0 |
| **21** | CHARLES LANE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **22** | CHESTER CLOSE NORTH | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.050000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **23** | CHEYNE COURT | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **24** | CHISWICK MALL | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.142857 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **25** | CLARENDON STREET | 0.01 | 0.000000 | 0.000000 | 0.0 | 0.050000 | 0.000000 | 0.000000 | 0.010000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.020000 | 0.030000 | 0.010000 | 0.0 |
| **26** | CLEVELAND SQUARE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.020000 | 0.000000 | 0.000000 | 0.020000 | 0.020000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **27** | CLONCURRY STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.038462 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.038462 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **28** | COLBECK MEWS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.010000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **29** | COLLEGE CRESCENT | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **95** | QUEENS GATE GARDENS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **96** | RADSTOCK STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **97** | RANELAGH AVENUE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **98** | REEVES MEWS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.010870 | 0.000000 | 0.000000 | 0.010870 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010870 | 0.010870 | 0.032609 | 0.000000 | 0.0 |
| **99** | RHEIDOL MEWS | 0.00 | 0.012195 | 0.012195 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.012195 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.012195 | 0.0 |
| **100** | RINGWOOD AVENUE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.166667 | 0.000000 | 0.000000 | 0.0 |
| **101** | RODERICK ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **102** | ROTHBURY ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **103** | ROYAL CRESCENT | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **104** | ROYSTON ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **105** | RUSSELL GARDENS MEWS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **106** | SHEPHERDS BUSH ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.011364 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.011364 | 0.000000 | 0.022727 | 0.000000 | 0.0 |
| **107** | SOUTH END ROW | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.016393 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.016393 | 0.000000 | 0.0 |
| **108** | SOUTH LAMBETH ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **109** | SOUTHWOOD LAWN ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **110** | SOVEREIGN PARK | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **111** | ST OSWALDS PLACE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.023810 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **112** | ST PETERS SQUARE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.022222 | 0.011111 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.033333 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **113** | STAFFORD TERRACE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.029851 | 0.014925 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.014925 | 0.014925 | 0.000000 | 0.0 |
| **114** | TAVISTOCK STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.020000 | 0.000000 | 0.000000 | 0.000000 | 0.010000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010000 | 0.010000 | 0.000000 | 0.000000 | 0.0 |
| **115** | TITE STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.026316 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.026316 | 0.000000 | 0.0 |
| **116** | TRINITY STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.011111 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.011111 | 0.011111 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.011111 | 0.011111 | 0.000000 | 0.0 |
| **117** | UPPER HAMPSTEAD WALK | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.017241 | 0.000000 | 0.017241 | 0.000000 | 0.000000 | ... | 0.017241 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.017241 | 0.000000 | 0.000000 | 0.0 |
| **118** | WELBECK WAY | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **119** | WEST TEMPLE SHEEN | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **120** | WILLIAM MEWS | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **121** | WILSON STREET | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **122** | WINCHENDON ROAD | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **123** | WRENTHAM AVENUE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **124** | WYCOMBE SQUARE | 0.00 | 0.000000 | 0.000000 | 0.0 | 0.000000 | 0.000000 | 0.000000 | 0.012195 | 0.000000 | ... | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.012195 | 0.000000 | 0.000000 | 0.024390 | 0.0 |

125 rows × 314 columns

In [31]:

london\_grouped.shape

Out[31]:

(125, 314)

In [32]:

*# What are the top 5 venues/facilities nearby profitable real estate investments?#*

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**).head(num\_top\_venues))

print('**\n**')

----ABBOTSBURY CLOSE----

venue freq

0 Thai Restaurant 0.2

1 Park 0.2

2 Waterfront 0.2

3 Grocery Store 0.2

4 Hotel 0.2

----ALBION SQUARE----

venue freq

0 Café 0.22

1 Bar 0.07

2 Pub 0.07

3 Indian Restaurant 0.07

4 Coffee Shop 0.07

----ANHALT ROAD----

venue freq

0 Pub 0.29

1 Japanese Restaurant 0.07

2 Gym / Fitness Center 0.07

3 Pizza Place 0.07

4 Diner 0.07

----ANSDELL TERRACE----

venue freq

0 Clothing Store 0.07

1 Italian Restaurant 0.07

2 Juice Bar 0.05

3 Hotel 0.05

4 Indian Restaurant 0.05

----APPLEGARTH ROAD----

venue freq

0 Bar 0.4

1 Nightclub 0.2

2 Casino 0.2

3 Pub 0.2

4 New American Restaurant 0.0

----AYLESTONE AVENUE----

venue freq

0 Park 0.4

1 Movie Theater 0.2

2 Bus Stop 0.2

3 Café 0.2

4 Optical Shop 0.0

----BARONSMEAD ROAD----

venue freq

0 Food & Drink Shop 0.15

1 Restaurant 0.15

2 Pub 0.08

3 Coffee Shop 0.08

4 Breakfast Spot 0.08

----BEAUCLERC ROAD----

venue freq

0 Coffee Shop 0.17

1 Hotel 0.13

2 Pub 0.13

3 Thai Restaurant 0.07

4 Chinese Restaurant 0.07

----BICKENHALL STREET----

venue freq

0 Hotel 0.07

1 Chinese Restaurant 0.04

2 Gastropub 0.04

3 Restaurant 0.04

4 Pizza Place 0.03

----BILLING ROAD----

venue freq

0 Pub 0.10

1 Soccer Stadium 0.05

2 Italian Restaurant 0.05

3 Grocery Store 0.05

4 Park 0.03

----BIRCHLANDS AVENUE----

venue freq

0 Pub 0.25

1 French Restaurant 0.12

2 Train Station 0.12

3 Chinese Restaurant 0.12

4 Bakery 0.12

----BOWERDEAN STREET----

venue freq

0 Italian Restaurant 0.12

1 Pub 0.12

2 Coffee Shop 0.12

3 Mediterranean Restaurant 0.08

4 Park 0.08

----BRAMPTON GROVE----

venue freq

0 Bar 0.25

1 Lake 0.25

2 Middle Eastern Restaurant 0.25

3 Men's Store 0.25

4 Accessories Store 0.00

----BRIARDALE GARDENS----

venue freq

0 Gym / Fitness Center 0.2

1 Food Truck 0.2

2 Indian Restaurant 0.2

3 Grocery Store 0.2

4 Coffee Shop 0.2

----BROWNING CLOSE----

venue freq

0 Bakery 0.5

1 Gastropub 0.5

2 Accessories Store 0.0

3 Optical Shop 0.0

4 Paella Restaurant 0.0

----CALLCOTT STREET----

venue freq

0 Pub 0.14

1 Bakery 0.06

2 Grocery Store 0.04

3 Park 0.04

4 Hotel 0.04

----CAMPDEN HILL ROAD----

venue freq

0 Pub 0.11

1 Bakery 0.08

2 Pizza Place 0.04

3 Yoga Studio 0.04

4 Hotel 0.04

----CANFIELD GARDENS----

venue freq

0 Coffee Shop 0.07

1 Café 0.06

2 Italian Restaurant 0.06

3 Japanese Restaurant 0.04

4 Pizza Place 0.04

----CANNING PLACE----

venue freq

0 Hotel 0.21

1 Pub 0.06

2 Clothing Store 0.06

3 Italian Restaurant 0.06

4 French Restaurant 0.06

----CARLISLE ROAD----

venue freq

0 Soccer Field 0.5

1 Nightlife Spot 0.5

2 North Indian Restaurant 0.0

3 Outdoors & Recreation 0.0

4 Outdoor Supply Store 0.0

----CHALCOT SQUARE----

venue freq

0 Café 0.10

1 Italian Restaurant 0.08

2 Bar 0.08

3 Pub 0.07

4 Pizza Place 0.07

----CHARLES LANE----

venue freq

0 Coffee Shop 0.75

1 Bus Station 0.25

2 Accessories Store 0.00

3 Organic Grocery 0.00

4 Pakistani Restaurant 0.00

----CHESTER CLOSE NORTH----

venue freq

0 Cocktail Bar 0.10

1 Garden 0.10

2 Gym / Fitness Center 0.10

3 Park 0.10

4 Playground 0.05

----CHEYNE COURT----

venue freq

0 Health & Beauty Service 0.33

1 Construction & Landscaping 0.33

2 Gastropub 0.33

3 Accessories Store 0.00

4 Optical Shop 0.00

----CHISWICK MALL----

venue freq

0 Pub 0.43

1 Gym / Fitness Center 0.14

2 Brewery 0.14

3 Art Museum 0.14

4 Gift Shop 0.14

----CLARENDON STREET----

venue freq

0 Spa 0.06

1 American Restaurant 0.05

2 Sandwich Place 0.04

3 Italian Restaurant 0.04

4 Gym 0.04

----CLEVELAND SQUARE----

venue freq

0 Bar 0.08

1 Lounge 0.08

2 Mexican Restaurant 0.06

3 Gay Bar 0.06

4 Pizza Place 0.06

----CLONCURRY STREET----

venue freq

0 Café 0.15

1 Park 0.12

2 Sporting Goods Shop 0.04

3 Bar 0.04

4 Spa 0.04

----COLBECK MEWS----

venue freq

0 Hotel 0.24

1 Pub 0.08

2 Restaurant 0.04

3 Italian Restaurant 0.04

4 Garden 0.04

----COLLEGE CRESCENT----

venue freq

0 College Hockey Rink 0.2

1 Business Service 0.2

2 Bar 0.2

3 Diner 0.2

4 College Cafeteria 0.2

----CORNWALL TERRACE MEWS----

venue freq

0 Café 0.08

1 Museum 0.05

2 Pub 0.05

3 Coffee Shop 0.05

4 Garden 0.05

----COURT LANE GARDENS----

venue freq

0 Pub 0.18

1 Grocery Store 0.18

2 Bakery 0.09

3 Italian Restaurant 0.09

4 Pizza Place 0.09

----CRAVEN STREET----

venue freq

0 Hotel 0.07

1 Theater 0.06

2 Pub 0.05

3 Ice Cream Shop 0.04

4 Wine Bar 0.04

----DALEBURY ROAD----

venue freq

0 Asian Restaurant 0.33

1 Bus Stop 0.17

2 Café 0.17

3 Indian Restaurant 0.17

4 Grocery Store 0.17

----DEWHURST ROAD----

venue freq

0 Hotel 0.17

1 Pub 0.14

2 Italian Restaurant 0.07

3 Indian Restaurant 0.07

4 Coffee Shop 0.07

----DORIA ROAD----

venue freq

0 Café 0.10

1 Italian Restaurant 0.10

2 Coffee Shop 0.07

3 Pub 0.05

4 Bakery 0.05

----DOWNSHIRE HILL----

venue freq

0 Café 0.18

1 Pub 0.13

2 Italian Restaurant 0.08

3 Bakery 0.05

4 Coffee Shop 0.05

----DRAX AVENUE----

venue freq

0 Rugby Pitch 1.0

1 Accessories Store 0.0

2 Palace 0.0

3 Paella Restaurant 0.0

4 Outdoors & Recreation 0.0

----DUCHESS WALK----

venue freq

0 Coffee Shop 0.08

1 Pub 0.07

2 Bar 0.05

3 Italian Restaurant 0.05

4 Cocktail Bar 0.04

----ECCLESTON SQUARE MEWS----

venue freq

0 Hotel 0.11

1 Pub 0.09

2 Italian Restaurant 0.07

3 Sandwich Place 0.06

4 Café 0.06

----EGBERT STREET----

venue freq

0 Pub 1.0

1 Opera House 0.0

2 Paella Restaurant 0.0

3 Outdoors & Recreation 0.0

4 Outdoor Supply Store 0.0

----EGERTON PLACE----

venue freq

0 Café 0.14

1 Italian Restaurant 0.10

2 Hotel 0.06

3 Garden 0.04

4 Boutique 0.04

----FIRECREST DRIVE----

venue freq

0 Pub 0.11

1 Coffee Shop 0.11

2 Lake 0.11

3 History Museum 0.11

4 Gym 0.11

----FLASK WALK----

venue freq

0 Café 0.10

1 Pub 0.08

2 Italian Restaurant 0.07

3 Bakery 0.05

4 French Restaurant 0.03

----FRANK DIXON WAY----

venue freq

0 Farm 0.17

1 Gym / Fitness Center 0.17

2 Park 0.17

3 Tennis Court 0.17

4 Café 0.17

----GERARD ROAD----

venue freq

0 Pub 0.12

1 Recording Studio 0.12

2 Fast Food Restaurant 0.12

3 Mediterranean Restaurant 0.12

4 Sandwich Place 0.12

----GIBSON SQUARE----

venue freq

0 Pub 0.06

1 French Restaurant 0.06

2 Gastropub 0.05

3 Mediterranean Restaurant 0.04

4 Burger Joint 0.04

----GLOUCESTER AVENUE----

venue freq

0 Bakery 0.5

1 Indian Restaurant 0.5

2 Accessories Store 0.0

3 Optical Shop 0.0

4 Pakistani Restaurant 0.0

----GORDON PLACE----

venue freq

0 Bus Stop 0.09

1 Café 0.09

2 Middle Eastern Restaurant 0.09

3 Tram Station 0.09

4 Restaurant 0.09

----HAMPSTEAD WAY----

venue freq

0 Café 0.33

1 Zoo 0.17

2 Park 0.17

3 Garden 0.17

4 Pub 0.17

----HARMAN DRIVE----

venue freq

0 Bus Station 0.25

1 Coffee Shop 0.25

2 Gym / Fitness Center 0.25

3 Middle Eastern Restaurant 0.25

4 New American Restaurant 0.00

----HAZLEWELL ROAD----

venue freq

0 Grocery Store 0.3

1 Japanese Restaurant 0.1

2 Café 0.1

3 Tennis Court 0.1

4 Gym / Fitness Center 0.1

----HEREFORD MEWS----

venue freq

0 Pub 0.09

1 Café 0.06

2 Coffee Shop 0.05

3 Hotel 0.05

4 Gym / Fitness Center 0.05

----HERONDALE AVENUE----

venue freq

0 French Restaurant 0.50

1 Tennis Court 0.25

2 Grocery Store 0.25

3 Museum 0.00

4 Outdoors & Recreation 0.00

----HILLGATE PLACE----

venue freq

0 Pub 0.15

1 Bakery 0.06

2 Indian Restaurant 0.04

3 Park 0.04

4 Grocery Store 0.04

----HOLDEN AVENUE----

venue freq

0 Indian Restaurant 0.25

1 Grocery Store 0.25

2 Pizza Place 0.25

3 Fish & Chips Shop 0.25

4 Accessories Store 0.00

----HOLLYWOOD MEWS----

venue freq

0 Pizza Place 0.07

1 Italian Restaurant 0.07

2 Pub 0.07

3 Garden 0.07

4 Bakery 0.07

----HORNTON STREET----

venue freq

0 Clothing Store 0.05

1 Café 0.05

2 Pub 0.05

3 Restaurant 0.04

4 Bakery 0.04

----HUNTER ROAD----

venue freq

0 Playground 1.0

1 Accessories Store 0.0

2 Opera House 0.0

3 Paella Restaurant 0.0

4 Outdoors & Recreation 0.0

----JACKSONS LANE----

venue freq

0 Pub 0.30

1 Trail 0.05

2 Italian Restaurant 0.05

3 Indian Restaurant 0.05

4 Hotel 0.05

----JOHN ISLIP STREET----

venue freq

0 Art Gallery 0.17

1 Café 0.08

2 Plaza 0.06

3 Garden 0.06

4 Restaurant 0.06

----KNOX STREET----

venue freq

0 Bar 0.25

1 Gas Station 0.25

2 Deli / Bodega 0.25

3 Greek Restaurant 0.25

4 Accessories Store 0.00

----LANCASTER MEWS----

venue freq

0 Hotel 0.25

1 Pub 0.10

2 Café 0.07

3 Italian Restaurant 0.06

4 Coffee Shop 0.05

----LAXTON PLACE----

venue freq

0 Pub 0.09

1 Coffee Shop 0.08

2 Indian Restaurant 0.08

3 Sandwich Place 0.03

4 Park 0.03

----LILLIE SQUARE----

venue freq

0 Pub 0.21

1 Farmers Market 0.11

2 Pizza Place 0.11

3 Indian Restaurant 0.11

4 Hotel 0.11

----LINCOLN AVENUE----

venue freq

0 Mexican Restaurant 0.2

1 New American Restaurant 0.1

2 Sports Bar 0.1

3 Pizza Place 0.1

4 Café 0.1

----LISSON STREET----

venue freq

0 Coffee Shop 0.07

1 Pub 0.07

2 Sandwich Place 0.05

3 Gym / Fitness Center 0.04

4 Pharmacy 0.04

----LIVERPOOL GROVE----

venue freq

0 Café 0.13

1 Fried Chicken Joint 0.07

2 Pharmacy 0.07

3 Department Store 0.03

4 Bagel Shop 0.03

----LONGWOOD DRIVE----

venue freq

0 Gym / Fitness Center 0.17

1 Japanese Restaurant 0.08

2 Furniture / Home Store 0.08

3 Gym 0.08

4 Sporting Goods Shop 0.08

----LONSDALE SQUARE----

venue freq

0 Pub 0.08

1 Gastropub 0.06

2 Mediterranean Restaurant 0.06

3 French Restaurant 0.06

4 Furniture / Home Store 0.05

----MANSFIELD STREET----

venue freq

0 Café 0.07

1 Coffee Shop 0.05

2 Italian Restaurant 0.05

3 Burger Joint 0.04

4 French Restaurant 0.03

----MONTAGU MEWS NORTH----

venue freq

0 Hotel 0.09

1 Pub 0.04

2 Restaurant 0.04

3 Chinese Restaurant 0.04

4 Italian Restaurant 0.03

----MONTPELIER WALK----

venue freq

0 Café 0.15

1 Italian Restaurant 0.12

2 Hotel 0.07

3 Boutique 0.04

4 Japanese Restaurant 0.03

----MULTON ROAD----

venue freq

0 Indian Restaurant 0.50

1 Café 0.25

2 Grocery Store 0.25

3 Accessories Store 0.00

4 Opera House 0.00

----NEW KENT ROAD----

venue freq

0 Bus Stop 0.14

1 Grocery Store 0.10

2 Pub 0.10

3 Bike Rental / Bike Share 0.07

4 Middle Eastern Restaurant 0.07

----NOTTINGHAM STREET----

venue freq

0 Hotel 0.06

1 Café 0.06

2 Sandwich Place 0.04

3 French Restaurant 0.04

4 Chinese Restaurant 0.04

----OAKWOOD COURT----

venue freq

0 Smoke Shop 0.25

1 Pizza Place 0.25

2 Food 0.25

3 Golf Course 0.25

4 Accessories Store 0.00

----OLD COURT PLACE----

venue freq

0 Hotel 0.09

1 Garden 0.07

2 Clothing Store 0.05

3 Italian Restaurant 0.05

4 Pub 0.04

----ONSLOW MEWS WEST----

venue freq

0 Hotel 0.13

1 Ice Cream Shop 0.05

2 Bakery 0.05

3 Italian Restaurant 0.04

4 Burger Joint 0.04

----ONSLOW SQUARE----

venue freq

0 Hotel 0.09

1 Italian Restaurant 0.09

2 Bakery 0.04

3 Ice Cream Shop 0.04

4 Burger Joint 0.04

----PALACE PLACE----

venue freq

0 Insurance Office 0.17

1 Hobby Shop 0.17

2 Food 0.17

3 Gift Shop 0.17

4 Latin American Restaurant 0.17

----PANTON STREET----

venue freq

0 Theater 0.07

1 Hotel 0.05

2 Ice Cream Shop 0.04

3 Cocktail Bar 0.04

4 Seafood Restaurant 0.03

----PARK CRESCENT----

venue freq

0 Café 0.20

1 Pub 0.13

2 Coffee Shop 0.10

3 Fish & Chips Shop 0.07

4 Pizza Place 0.07

----PARKE ROAD----

venue freq

0 Pub 0.50

1 River 0.25

2 Park 0.25

3 Playground 0.00

4 Platform 0.00

----PARKFIELDS----

venue freq

0 Historic Site 0.4

1 Harbor / Marina 0.2

2 Supermarket 0.2

3 Hotel 0.2

4 Outdoors & Recreation 0.0

----PARTHENIA ROAD----

venue freq

0 Coffee Shop 0.14

1 Grocery Store 0.11

2 Café 0.11

3 Pub 0.08

4 Climbing Gym 0.05

----PAVILION ROAD----

venue freq

0 Boutique 0.10

1 Café 0.10

2 Italian Restaurant 0.08

3 Hotel 0.07

4 Japanese Restaurant 0.04

----PEMBRIDGE ROAD----

venue freq

0 Soccer Field 1.0

1 North Indian Restaurant 0.0

2 Outdoors & Recreation 0.0

3 Outdoor Supply Store 0.0

4 Outdoor Sculpture 0.0

----PEMBROKE STUDIOS----

venue freq

0 Restaurant 0.14

1 Pub 0.07

2 Supermarket 0.07

3 Café 0.07

4 Italian Restaurant 0.04

----PENCOMBE MEWS----

venue freq

0 Italian Restaurant 0.09

1 Pub 0.08

2 Coffee Shop 0.05

3 Café 0.04

4 Clothing Store 0.04

----PETERSHAM PLACE----

venue freq

0 Sports Bar 0.25

1 Athletics & Sports 0.25

2 BBQ Joint 0.25

3 Pub 0.25

4 Playground 0.00

----PHYSIC PLACE----

venue freq

0 Pub 0.10

1 Coffee Shop 0.05

2 Ice Cream Shop 0.05

3 Art Gallery 0.05

4 Gym / Fitness Center 0.05

----PORCHESTER TERRACE----

venue freq

0 Hotel 0.17

1 Pub 0.08

2 Coffee Shop 0.07

3 Chinese Restaurant 0.06

4 Greek Restaurant 0.04

----PROTHERO GARDENS----

venue freq

0 Grocery Store 0.15

1 Coffee Shop 0.15

2 Japanese Restaurant 0.05

3 Hotel 0.05

4 Noodle House 0.05

----QUARRENDON STREET----

venue freq

0 Coffee Shop 0.12

1 Italian Restaurant 0.09

2 Mediterranean Restaurant 0.07

3 Café 0.07

4 Pub 0.07

----QUEENS GATE GARDENS----

venue freq

0 Pub 0.4

1 Italian Restaurant 0.2

2 Indian Restaurant 0.2

3 Gastropub 0.2

4 Opera House 0.0

----RADSTOCK STREET----

venue freq

0 Pub 0.33

1 Cocktail Bar 0.08

2 Gym / Fitness Center 0.08

3 Grocery Store 0.08

4 French Restaurant 0.08

----RANELAGH AVENUE----

venue freq

0 Restaurant 0.11

1 Park 0.11

2 Food & Drink Shop 0.11

3 Italian Restaurant 0.06

4 Bakery 0.06

----REEVES MEWS----

venue freq

0 Hotel 0.11

1 Italian Restaurant 0.05

2 Restaurant 0.05

3 French Restaurant 0.05

4 Clothing Store 0.04

----RHEIDOL MEWS----

venue freq

0 Pub 0.15

1 Park 0.05

2 Café 0.05

3 Coffee Shop 0.05

4 French Restaurant 0.05

----RINGWOOD AVENUE----

venue freq

0 Forest 0.17

1 Wine Shop 0.17

2 Café 0.17

3 Indian Restaurant 0.17

4 Gym / Fitness Center 0.17

----RODERICK ROAD----

venue freq

0 Café 0.21

1 Museum 0.07

2 Gastropub 0.07

3 Gym / Fitness Center 0.07

4 Grocery Store 0.07

----ROTHBURY ROAD----

venue freq

0 Pub 0.25

1 Market 0.25

2 Fast Food Restaurant 0.25

3 Supermarket 0.25

4 Optical Shop 0.00

----ROYAL CRESCENT----

venue freq

0 Café 0.21

1 Pub 0.14

2 Deli / Bodega 0.07

3 Hotel 0.07

4 Music Venue 0.03

----ROYSTON ROAD----

venue freq

0 Business Service 0.33

1 Grocery Store 0.33

2 Lake 0.33

3 Accessories Store 0.00

4 Organic Grocery 0.00

----RUSSELL GARDENS MEWS----

venue freq

0 Hotel 0.17

1 Pub 0.12

2 Italian Restaurant 0.08

3 Convention Center 0.08

4 Persian Restaurant 0.08

----SHEPHERDS BUSH ROAD----

venue freq

0 Hotel 0.08

1 Grocery Store 0.06

2 Coffee Shop 0.05

3 Thai Restaurant 0.03

4 Café 0.03

----SOUTH END ROW----

venue freq

0 Hotel 0.08

1 Clothing Store 0.07

2 Italian Restaurant 0.07

3 Café 0.05

4 Indian Restaurant 0.05

----SOUTH LAMBETH ROAD----

venue freq

0 Convenience Store 0.19

1 Grocery Store 0.11

2 Coffee Shop 0.07

3 Fast Food Restaurant 0.04

4 Metro Station 0.04

----SOUTHWOOD LAWN ROAD----

venue freq

0 Pub 0.28

1 Café 0.08

2 Indian Restaurant 0.06

3 Bakery 0.06

4 Plaza 0.03

----SOVEREIGN PARK----

venue freq

0 Gym / Fitness Center 0.25

1 Indian Restaurant 0.25

2 Café 0.25

3 Pizza Place 0.25

4 Accessories Store 0.00

----ST OSWALDS PLACE----

venue freq

0 Pub 0.10

1 Café 0.10

2 Nightclub 0.07

3 Gay Bar 0.07

4 Italian Restaurant 0.07

----ST PETERS SQUARE----

venue freq

0 Italian Restaurant 0.23

1 Café 0.09

2 Ice Cream Shop 0.09

3 Hotel 0.08

4 Pizza Place 0.03

----STAFFORD TERRACE----

venue freq

0 Café 0.10

1 Italian Restaurant 0.04

2 Garden 0.04

3 Clothing Store 0.04

4 Bakery 0.04

----TAVISTOCK STREET----

venue freq

0 Theater 0.06

1 Coffee Shop 0.05

2 Restaurant 0.04

3 Burger Joint 0.04

4 Italian Restaurant 0.04

----TITE STREET----

venue freq

0 Pub 0.11

1 Pizza Place 0.05

2 Ice Cream Shop 0.05

3 Café 0.05

4 Coffee Shop 0.05

----TRINITY STREET----

venue freq

0 Pub 0.08

1 Coffee Shop 0.07

2 Clothing Store 0.06

3 Café 0.06

4 Burger Joint 0.04

----UPPER HAMPSTEAD WALK----

venue freq

0 Café 0.10

1 Pub 0.09

2 Bakery 0.05

3 Italian Restaurant 0.05

4 Ice Cream Shop 0.03

----WELBECK WAY----

venue freq

0 Gym Pool 0.33

1 Warehouse Store 0.33

2 Fast Food Restaurant 0.33

3 Accessories Store 0.00

4 Optical Shop 0.00

----WEST TEMPLE SHEEN----

venue freq

0 Bar 0.33

1 Pub 0.17

2 Middle Eastern Restaurant 0.17

3 Tennis Court 0.17

4 Park 0.17

----WILLIAM MEWS----

venue freq

0 Building 0.5

1 Flower Shop 0.5

2 Nail Salon 0.0

3 Optical Shop 0.0

4 Paella Restaurant 0.0

----WILSON STREET----

venue freq

0 Athletics & Sports 0.25

1 Liquor Store 0.25

2 Dance Studio 0.25

3 Gay Bar 0.25

4 Opera House 0.00

----WINCHENDON ROAD----

venue freq

0 Pizza Place 0.14

1 Garden Center 0.07

2 Bakery 0.07

3 Diner 0.07

4 Fast Food Restaurant 0.07

----WRENTHAM AVENUE----

venue freq

0 Locksmith 1.0

1 Accessories Store 0.0

2 Optical Shop 0.0

3 Pakistani Restaurant 0.0

4 Paella Restaurant 0.0

----WYCOMBE SQUARE----

venue freq

0 Pub 0.10

1 Coffee Shop 0.05

2 Grocery Store 0.05

3 Pizza Place 0.05

4 Italian Restaurant 0.04

In [33]:

*# Define a function to return the most common venues/facilities nearby real estate 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 [34]:

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 [35]:

*# 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.iloc[ind, :], num\_top\_venues)

In [36]:

venues\_sorted.head()

Out[36]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **0** | ABBOTSBURY CLOSE | Grocery Store | Park | Waterfront | Hotel | Thai Restaurant | Farm | Eastern European Restaurant | Electronics Store | English Restaurant | Event Space |
| **1** | ALBION SQUARE | Café | Restaurant | Indian Restaurant | Bar | Coffee Shop | Pub | New American Restaurant | Seafood Restaurant | Fish & Chips Shop | Brewery |
| **2** | ANHALT ROAD | Pub | Plaza | Pizza Place | Grocery Store | Japanese Restaurant | French Restaurant | English Restaurant | Gym / Fitness Center | Diner | Garden |
| **3** | ANSDELL TERRACE | Clothing Store | Italian Restaurant | Café | English Restaurant | Pub | Juice Bar | Hotel | Indian Restaurant | Bakery | Garden |
| **4** | APPLEGARTH ROAD | Bar | Pub | Casino | Nightclub | Fast Food Restaurant | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm |

In [37]:

venues\_sorted.shape

Out[37]:

(125, 11)

In [38]:

london\_grouped.shape

Out[38]:

(125, 314)

In [39]:

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 [40]:

*#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\_clustering)

*# check cluster labels generated for each row in the dataframe*

kmeans.labels\_[0:50]

Out[40]:

array([2, 0, 4, 1, 4, 3, 2, 0, 2, 1, 1, 3, 0, 4, 3, 2, 2, 3, 4, 1, 3, 3,

4, 0, 0, 1, 3, 1, 4, 4, 2, 1, 2, 2, 4, 4, 4, 3, 1, 4, 3, 2, 3, 1,

2, 4, 1, 1, 1, 1], dtype=int32)

In [41]:

*#Dataframe to include Clusters*

london\_grouped\_clustering=df

london\_grouped\_clustering.head()

Out[41]:

|  | **Street** | **Avg\_Price** | **Latitude** | **Longitude** |
| --- | --- | --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 | 51.532259 | -0.006153 |
| **178** | ALBION SQUARE | 2.450000e+06 | -41.273758 | 173.289393 |
| **355** | ANHALT ROAD | 2.435000e+06 | 51.480326 | -0.166761 |
| **368** | ANSDELL TERRACE | 2.250000e+06 | 51.499890 | -0.189103 |
| **381** | APPLEGARTH ROAD | 2.400000e+06 | 53.748654 | -0.326670 |

In [42]:

london\_grouped\_clustering.shape

Out[42]:

(131, 4)

In [43]:

df.shape

Out[43]:

(131, 4)

In [44]:

london\_grouped\_clustering.dtypes

Out[44]:

Street object

Avg\_Price float64

Latitude float64

Longitude float64

dtype: object

In [45]:

df.dtypes

Out[45]:

Street object

Avg\_Price float64

Latitude float64

Longitude float64

dtype: object

In [46]:

*# add clustering labels*

london\_grouped\_clustering['Cluster Labels'] = kmeans.labels\_

*# merge london\_grouped with london\_data to add latitude/longitude for each neighborhood*

london\_grouped\_clustering = london\_grouped\_clustering.join(venues\_sorted.set\_index('Street'), on='Street')

london\_grouped\_clustering.head(30) *# check the last columns!*

Out[46]:

|  | **Street** | **Avg\_Price** | **Latitude** | **Longitude** | **Cluster Labels** | **1st Most Common Venue** | **2nd Most Common Venue** | **3rd Most Common Venue** | **4th Most Common Venue** | **5th Most Common Venue** | **6th Most Common Venue** | **7th Most Common Venue** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **20** | ABBOTSBURY CLOSE | 2.367093e+06 | 51.532259 | -0.006153 | 2 | Grocery Store | Park | Waterfront | Hotel | Thai Restaurant | Farm | Eastern European Restaurant | Electronics Store | English Restaurant | Event Space |
| **178** | ALBION SQUARE | 2.450000e+06 | -41.273758 | 173.289393 | 0 | Café | Restaurant | Indian Restaurant | Bar | Coffee Shop | Pub | New American Restaurant | Seafood Restaurant | Fish & Chips Shop | Brewery |
| **355** | ANHALT ROAD | 2.435000e+06 | 51.480326 | -0.166761 | 4 | Pub | Plaza | Pizza Place | Grocery Store | Japanese Restaurant | French Restaurant | English Restaurant | Gym / Fitness Center | Diner | Garden |
| **368** | ANSDELL TERRACE | 2.250000e+06 | 51.499890 | -0.189103 | 1 | Clothing Store | Italian Restaurant | Café | English Restaurant | Pub | Juice Bar | Hotel | Indian Restaurant | Bakery | Garden |
| **381** | APPLEGARTH ROAD | 2.400000e+06 | 53.748654 | -0.326670 | 4 | Bar | Pub | Casino | Nightclub | Fast Food Restaurant | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm |
| **617** | AYLESTONE AVENUE | 2.286667e+06 | 51.540916 | -0.217874 | 3 | Park | Movie Theater | Bus Stop | Café | Fish & Chips Shop | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |
| **753** | BARONSMEAD ROAD | 2.375000e+06 | 51.477315 | -0.239457 | 2 | Food & Drink Shop | Restaurant | Breakfast Spot | Nature Preserve | Bookstore | Farmers Market | Thai Restaurant | Park | Coffee Shop | Pizza Place |
| **867** | BEAUCLERC ROAD | 2.480000e+06 | 51.499577 | -0.229033 | 0 | Coffee Shop | Pub | Hotel | Thai Restaurant | Grocery Store | Chinese Restaurant | Cocktail Bar | Gastropub | Ice Cream Shop | Fish & Chips Shop |
| **1079** | BICKENHALL STREET | 2.351667e+06 | 51.521197 | -0.158934 | 2 | Hotel | Chinese Restaurant | Gastropub | Restaurant | Italian Restaurant | Pizza Place | Pub | Café | Thai Restaurant | Greek Restaurant |
| **1094** | BILLING ROAD | 2.200000e+06 | 51.481883 | -0.187862 | 1 | Pub | Soccer Stadium | Italian Restaurant | Grocery Store | Park | Gym / Fitness Center | Lounge | Gastropub | Café | Sandwich Place |
| **1108** | BIRCHLANDS AVENUE | 2.217000e+06 | 51.448394 | -0.160468 | 1 | Pub | French Restaurant | Train Station | Bakery | Lake | Coffee Shop | Chinese Restaurant | Flower Shop | Electronics Store | English Restaurant |
| **1310** | BOWERDEAN STREET | 2.300000e+06 | 51.472710 | -0.192485 | 3 | Coffee Shop | Pub | Italian Restaurant | Mediterranean Restaurant | Park | Thai Restaurant | Café | Furniture / Home Store | Gastropub | Chinese Restaurant |
| **1371** | BRAMPTON GROVE | 2.475833e+06 | 51.570365 | -0.283394 | 0 | Bar | Lake | Middle Eastern Restaurant | Men's Store | Fish & Chips Shop | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |
| **1439** | BRIARDALE GARDENS | 2.397132e+06 | 51.560175 | -0.195431 | 4 | Food Truck | Indian Restaurant | Grocery Store | Gym / Fitness Center | Coffee Shop | Farmers Market | Electronics Store | English Restaurant | Event Space | Exhibit |
| **1605** | BROWNING CLOSE | 2.320000e+06 | 51.885850 | 0.856081 | 3 | Bakery | Gastropub | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |
| **1820** | CALLCOTT STREET | 2.375000e+06 | 51.508350 | -0.198328 | 2 | Pub | Bakery | Park | Hotel | Pizza Place | Indian Restaurant | Yoga Studio | Grocery Store | Hostel | Seafood Restaurant |
| **1871** | CAMPDEN HILL ROAD | 2.352889e+06 | 51.506461 | -0.198896 | 2 | Pub | Bakery | Pizza Place | Hotel | Grocery Store | Indian Restaurant | Yoga Studio | Hostel | Farmers Market | Movie Theater |
| **1889** | CANFIELD GARDENS | 2.278000e+06 | 51.546799 | -0.179709 | 3 | Coffee Shop | Café | Italian Restaurant | Bookstore | Japanese Restaurant | Grocery Store | Pizza Place | Hotel | Supermarket | Sandwich Place |
| **1894** | CANNING PLACE | 2.425000e+06 | 51.499570 | -0.184248 | 4 | Hotel | Indian Restaurant | French Restaurant | Chinese Restaurant | Italian Restaurant | Pub | Clothing Store | Bar | Park | Garden |
| **1950** | CARLISLE ROAD | 2.200000e+06 | 42.549099 | -71.416669 | 1 | Nightlife Spot | Soccer Field | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |
| **1963** | CARLYLE COURT | 2.300000e+06 | 32.626437 | -83.717601 | 3 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2105** | CHALCOT SQUARE | 2.286679e+06 | 51.541455 | -0.155265 | 3 | Café | Bar | Italian Restaurant | Pizza Place | Pub | French Restaurant | Restaurant | Vegetarian / Vegan Restaurant | Coffee Shop | Belgian Restaurant |
| **2171** | CHARLES LANE | 2.414000e+06 | 43.816167 | -79.418287 | 4 | Coffee Shop | Bus Station | Zoo | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |
| **2237** | CHELSEA CRESCENT | 2.495000e+06 | 34.524738 | -85.448539 | 0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2278** | CHESTER CLOSE NORTH | 2.450000e+06 | 51.529205 | -0.145081 | 0 | Garden | Cocktail Bar | Gym / Fitness Center | Park | Beer Bar | Buffet | Bar | Coffee Shop | Mexican Restaurant | Performing Arts Venue |
| **2306** | CHEYNE COURT | 2.250000e+06 | 51.599677 | 0.525623 | 1 | Gastropub | Construction & Landscaping | Health & Beauty Service | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |
| **2352** | CHISWICK MALL | 2.287500e+06 | 51.487994 | -0.246605 | 3 | Pub | Brewery | Art Museum | Gift Shop | Gym / Fitness Center | Zoo | Fast Food Restaurant | English Restaurant | Event Space | Exhibit |
| **2468** | CLARENDON STREET | 2.250000e+06 | 42.349419 | -71.074594 | 1 | Spa | American Restaurant | Sandwich Place | Italian Restaurant | Gym | Gym / Fitness Center | Cosmetics Shop | Hotel | Seafood Restaurant | Women's Store |
| **2512** | CLEVELAND SQUARE | 2.437500e+06 | 31.759919 | -106.491294 | 4 | Lounge | Bar | Pizza Place | Mexican Restaurant | Gay Bar | Coffee Shop | Fast Food Restaurant | Hotel | History Museum | Theater |
| **2544** | CLONCURRY STREET | 2.388333e+06 | 51.473763 | -0.216244 | 4 | Café | Park | Tea Room | Coffee Shop | Soccer Stadium | Fish & Chips Shop | Spa | Garden | Sporting Goods Shop | Farmers Market |

In [47]:

*# 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'], london\_grouped\_clustering['Longitude'], london\_grouped\_clustering['Street'], london\_grouped\_clustering['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[47]:

In [48]:

london\_grouped\_clustering.loc[london\_grouped\_clustering['Cluster Labels'] == 0, london\_grouped\_clustering.columns[[1] + list(range(5, london\_grouped\_clustering.shape[1]))]].head()

Out[48]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **178** | 2.450000e+06 | Café | Restaurant | Indian Restaurant | Bar | Coffee Shop | Pub | New American Restaurant | Seafood Restaurant | Fish & Chips Shop | Brewery |
| **867** | 2.480000e+06 | Coffee Shop | Pub | Hotel | Thai Restaurant | Grocery Store | Chinese Restaurant | Cocktail Bar | Gastropub | Ice Cream Shop | Fish & Chips Shop |
| **1371** | 2.475833e+06 | Bar | Lake | Middle Eastern Restaurant | Men's Store | Fish & Chips Shop | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |
| **2237** | 2.495000e+06 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2278** | 2.450000e+06 | Garden | Cocktail Bar | Gym / Fitness Center | Park | Beer Bar | Buffet | Bar | Coffee Shop | Mexican Restaurant | Performing Arts Venue |

In [49]:

london\_grouped\_clustering.loc[london\_grouped\_clustering['Cluster Labels'] == 1, london\_grouped\_clustering.columns[[1] + list(range(5, london\_grouped\_clustering.shape[1]))]].head()

Out[49]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **368** | 2250000.0 | Clothing Store | Italian Restaurant | Café | English Restaurant | Pub | Juice Bar | Hotel | Indian Restaurant | Bakery | Garden |
| **1094** | 2200000.0 | Pub | Soccer Stadium | Italian Restaurant | Grocery Store | Park | Gym / Fitness Center | Lounge | Gastropub | Café | Sandwich Place |
| **1108** | 2217000.0 | Pub | French Restaurant | Train Station | Bakery | Lake | Coffee Shop | Chinese Restaurant | Flower Shop | Electronics Store | English Restaurant |
| **1950** | 2200000.0 | Nightlife Spot | Soccer Field | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |
| **2306** | 2250000.0 | Gastropub | Construction & Landscaping | Health & Beauty Service | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |

In [50]:

london\_grouped\_clustering.loc[london\_grouped\_clustering['Cluster Labels'] == 2, london\_grouped\_clustering.columns[[1] + list(range(5, london\_grouped\_clustering.shape[1]))]].head()

Out[50]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **20** | 2.367093e+06 | Grocery Store | Park | Waterfront | Hotel | Thai Restaurant | Farm | Eastern European Restaurant | Electronics Store | English Restaurant | Event Space |
| **753** | 2.375000e+06 | Food & Drink Shop | Restaurant | Breakfast Spot | Nature Preserve | Bookstore | Farmers Market | Thai Restaurant | Park | Coffee Shop | Pizza Place |
| **1079** | 2.351667e+06 | Hotel | Chinese Restaurant | Gastropub | Restaurant | Italian Restaurant | Pizza Place | Pub | Café | Thai Restaurant | Greek Restaurant |
| **1820** | 2.375000e+06 | Pub | Bakery | Park | Hotel | Pizza Place | Indian Restaurant | Yoga Studio | Grocery Store | Hostel | Seafood Restaurant |
| **1871** | 2.352889e+06 | Pub | Bakery | Pizza Place | Hotel | Grocery Store | Indian Restaurant | Yoga Studio | Hostel | Farmers Market | Movie Theater |

In [51]:

london\_grouped\_clustering.loc[london\_grouped\_clustering['Cluster Labels'] == 3, london\_grouped\_clustering.columns[[1] + list(range(5, london\_grouped\_clustering.shape[1]))]].head()

Out[51]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **617** | 2.286667e+06 | Park | Movie Theater | Bus Stop | Café | Fish & Chips Shop | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market |
| **1310** | 2.300000e+06 | Coffee Shop | Pub | Italian Restaurant | Mediterranean Restaurant | Park | Thai Restaurant | Café | Furniture / Home Store | Gastropub | Chinese Restaurant |
| **1605** | 2.320000e+06 | Bakery | Gastropub | Fish & Chips Shop | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |
| **1889** | 2.278000e+06 | Coffee Shop | Café | Italian Restaurant | Bookstore | Japanese Restaurant | Grocery Store | Pizza Place | Hotel | Supermarket | Sandwich Place |
| **1963** | 2.300000e+06 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

In [52]:

london\_grouped\_clustering.loc[london\_grouped\_clustering['Cluster Labels'] == 4, london\_grouped\_clustering.columns[[1] + list(range(5, london\_grouped\_clustering.shape[1]))]].head()

Out[52]:

|  | **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** | **8th Most Common Venue** | **9th Most Common Venue** | **10th Most Common Venue** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **355** | 2435000.0 | Pub | Plaza | Pizza Place | Grocery Store | Japanese Restaurant | French Restaurant | English Restaurant | Gym / Fitness Center | Diner | Garden |
| **381** | 2400000.0 | Bar | Pub | Casino | Nightclub | Fast Food Restaurant | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm |
| **1439** | 2397132.0 | Food Truck | Indian Restaurant | Grocery Store | Gym / Fitness Center | Coffee Shop | Farmers Market | Electronics Store | English Restaurant | Event Space | Exhibit |
| **1894** | 2425000.0 | Hotel | Indian Restaurant | French Restaurant | Chinese Restaurant | Italian Restaurant | Pub | Clothing Store | Bar | Park | Garden |
| **2171** | 2414000.0 | Coffee Shop | Bus Station | Zoo | English Restaurant | Event Space | Exhibit | Falafel Restaurant | Farm | Farmers Market | Fast Food Restaurant |

**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/>). 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.