Capstone Project

The Battle of Neighbourhoods

Report

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Location for opening a restaurant chain in London

1. Introduction

To find the safer districts of London for opening a restaurant

1.1 Target Audience and Background:

A lot of investors look at investing in major cities around the world. This investment could see many forms. One such common area tends to be investing in the food business. This tends to be a relatively safe form of investment. Before carrying out any investment, the business owner would have created a business plan looking at various aspects of the business.

1.2 Location: One critical area of the business would be the choice of area with regards to safety. This itself would invite more customers to the restaurant, staff willing to work in the location of the restaurant, access to logistical support services and the cost of premises to buy or to rent the restaurant premises.

1.3 Transport links and other venues: The other aspects in the restaurant business would include kind of neighbourhood in the vicinity that one might expect to see typically in areas where good restaurants are located. This includes other types of businesses in the area and how accessible this location is for people to visit and dine. This will include transport links.

In this project, I have chosen the City of London to get valuable insights and provide this information to any potential investor who would like to open a chain of restaurants.

1.4 The problem/task at hand

An investor as outlined above has decided to invest in a restaurant business. He wants to open a chain of restaurants in the City of London. The restaurant owner has asked the advice to carry out research using the designs to find one of the safest district of London. A safe district is likely to house generally the more affluent in society. This might mean less chances of vandalism and store break-ins for the business. It will also mean relatively higher selling prices of houses. This means the social attitudes and buying power of this neighbourhood is likely going to be high. This might be more customers will be visiting the restaurant and hence therefore more business for the restaurant owner.

The neighbourhood would be explored with reference to transportable links and the general suitability as a business venture.

1.5 Criteria

The crime statistics dataset with the breakdown of crimes in each of the boroughs will be looked at. This will be a period up till 2016. This will give a good indication of the trend, even though we are in 2020.

The research aims to get the safest burrow in London exploring the number of crimes in each of the neighbourhood. As a means of statistical inference, k-means clustering will be actually used to study the data.

1.6 Why Data?

Without leveraging data to make decisions about new restaurant locations, the chain owner could spend countless hours walking around districts, consulting many real estate agents with their own district biases, and end up opening in yet another location that is not ideal.

Data will provide better answers and better solutions to their task at hand.

1.7 Outcomes

The goal is to identify the best areas of London to open new restaurants as part of the chain's plan. The results will be translated to management in a simple form that will convey the data-driven analysis for the best location to open a restaurant.

2. Description of the Data and how it used to solve the problem

2.1 Data Acquisition and cleaning

2.2 Data Sources and consists of the following:

The data required for the project will be taken from the following sources

i) Section 1: London crime data

ii)Section 2: List of London boroughs

iii) Section 3: Wikipedia, list of neighbourhoods in the Royal Borough of Kingston.

The cleansed data will then be used alongside Foursquare data, which is readily available. Foursquare location data will be leveraged to explore or compare boroughs around London

2.3 Data purposes:

- The London crime data will find the following: lsoa_code, borough, major_category, minor_category, value, year, month
- The list of London Borough will provide the following:Borough,Inner,Status,Local authority, Political control,Headquarters,Area, Population,Co ordinates, Nr in map.
- The list of neighbourhoods will provide the following:Neighbourhood, Borough,Latitude,Longitude

2.4 Data cleaning

Data downloaded or scraped from multiple sources were combined into one table.

This is done in the following sequences

The London crime data is accessed from Kaggle and this is then uploaded to Amazon S3 bucket.

This then downloaded into the notebook and into a dataframe.

The data was then processed to take off the null entries and the most recent data since 2016 kept.

2.4.1 Pre processing data for recent crimes

Table 1: London Crime after pre-processing

In three sections, data will be handled separately. From the London crime data, recent crimes are in selected. The major categories of crime are pivoted to get the total crimes per Borough

Out[12]:

	lsoa_code	borough	major_category	minor_category	value	year	month
0	E01004177	Sutton	Theft and Handling	Theft/Taking of Pedal Cycle	1	2016	8
1	E01000733	Bromley	Criminal Damage	Criminal Damage To Motor Vehicle	1	2016	4
2	E01003989	Southwark	Theft and Handling	Theft From Shops	4	2016	8
3	E01002276	Havering	Burglary	Burglary in a Dwelling	1	2016	8
4	E01003674	Redbridge	Drugs	Possession Of Drugs	2	2016	11

Change the column names

2.4.2 Scraping Data for List of Borough using beautiful soup

Table 2: List of London Boroughs

The second data scraped a Wikipedia page using the Beautiful soup library in Python.This helps us to extract the data in the tabular form as shown on the website. After web scraping, string manipulation is required the names of the boroughs in the correct form. This is important because of the merging of the datasets using borough names.

Out[61]:

	Borough	Inner	Status	Local authority	Political control	Headquarters	Area (sq mi)	Population (2013 est)[1]	Co-ordinates	Nr. in map
0	Barking and Dagenham [note 1]	NaN	NaN	Barking and Dagenham London Borough Council	Labour	Town Hall, 1 Town Square	13.93	194352	51°33′39″N 0°09′21″E / 51.5607°N 0.1557°E	25
1	Barnet	NaN	NaN	Barnet London Borough Council	Conservative	Barnet House, 2 Bristol Avenue, Colindale	33.49	369088	51°37′31″N 0°09′06″W / 51.6252°N 0.1517°W	31
2	Bexley	NaN	NaN	Bexley London Borough Council	Conservative	Civic Offices, 2 Watling Street	23.38	236687	51°27′18″N 0°09′02″E / 51.4549°N 0.1505°E	23
3	Brent	NaN	NaN	Brent London Borough Council	Labour	Brent Civic Centre, Engineers Way	16.70	317264	51°33′32″N 0°16′54″W / 51.5588°N 0.2817°W	12
4	Bromley	NaN	NaN	Bromley London Borough Council	Conservative	Civic Centre, Stockwell Close	57.97	317899	51°24′14″N 0°01′11″E / 51.4039°N 0.0198°E	20
5	Camden	NaN	NaN	Camden London Borough Council	Labour	Camden Town Hall, Judd Street	8.40	229719	51°31′44″N 0°07′32″W / 51.5290°N 0.1255°W	11
6	Croydon	NaN	NaN	Croydon London Borough Council	Labour	Bernard Weatherill House, Mint Walk	33.41	372752	51°22′17″N 0°05′52″W / 51.3714°N 0.0977°W	19
7	Ealing	NaN	NaN	Ealing London Borough Council	Labour	Perceval House, 14-16 Uxbridge Road	21.44	342494	51°30′47″N 0°18′32″W / 51.5130°N 0.3089°W	13
8	Enfield	NaN	NaN	Enfield London Borough Council	Labour	Civic Centre, Silver Street	31.74	320524	51°39′14″N 0°04′48″W / 51.6538°N 0.0799°W	30
9	Greenwich [note 2]	[note 3]	Royal	Greenwich London Borough Council	Labour	Woolwich Town Hall, Wellington Street	18.28	264008	51°29′21″N 0°03′53″E / 51.4892°N 0.0648°E	22
10	Hackney	NaN	NaN	Hackney London Borough Council	Labour	Hackney Town Hall, Mare Street	7.36	257379	51°32′42″N 0°03′19″W / 51.5450°N 0.0553°W	9
11	Hammersmith and Fulham [note 4]	NaN	NaN	Hammersmith and Fulham London Borough Council	Labour	Town Hall, King Street	6.33	178685	51°29′34″N 0°14′02″W / 51.4927°N 0.2339°W	4
12	Haringey	[note 3]	NaN	Haringey London Borough Council	Labour	Civic Centre, High Road	11.42	263386	51°36′00″N 0°06′43″W / 51.6000°N 0.1119°W	29
13	Harrow	NaN	NaN	Harrow London Borough Council	Labour	Civic Centre, Station Road	19.49	243372	51°35′23″N 0°20′05″W / 51.5898°N 0.3346°W	32
14	Havering	NaN	NaN	Havering London Borough Council	Conservative (council NOC)	Town Hall, Main Road	43.35	242080	51°34′52″N 0°11′01″E / 51.5812°N 0.1837°E	24
15	Hillingdon	NaN	NaN	Hillingdon London Borough Council	Conservative	Civic Centre, High Street	44.67	286806	51°32′39″N 0°28′34″W / 51.5441°N 0.4760°W	33
16	Hounslow	NaN	NaN	Hounslow London Borough Council	Labour	Hounslow House, 7 Bath Road	21.61	262407	51°28′29″N 0°22′05″W / 51.4746°N 0.3680°W	14
17	Islington	NaN	NaN	Islington London Borough Council	Labour	Customer Centre, 222 Upper Street	5.74	215667	51°32′30″N 0°06′08″W / 51.5416°N 0.1022°W	10
18	Kensington and Chelsea	NaN	Royal	Kensington and Chelsea London Borough Council	Conservative	The Town Hall, Hornton Street	4.68	155594	51°30′07″N 0°11′41″W / 51.5020°N 0.1947°W	3
19	Kingston upon Thames	NaN	Royal	Kingston upon Thames London Borough Council	Liberal Democrat	Guildhall, High Street	14.38	166793	51°24′31″N 0°18′23″W / 51.4085°N 0.3064°W	16
20	Lambeth	NaN	NaN	Lambeth London Borough Council	Labour	Lambeth Town Hall, Brixton Hill	10.36	314242	51°27′39″N 0°06′59″W / 51.4607°N 0.1163°W	6
21	Lewisham	NaN	NaN	Lewisham London Borough Council	Labour	Town Hall, 1 Catford Road	13.57	286180	51°26′43″N 0°01′15″W / 51.4452°N 0.0209°W	21
22	Merton	NaN	NaN	Merton London Borough Council	Labour	Civic Centre, London Road	14.52	203223	51°24′05″N 0°11′45″W / 51.4014°N 0.1958°W	17

2.4.3 Merging dataframes to get a single dataframe.

Table 3: London Borough Crime

The two datasets are merged on the borough names form a new dataset that combines the necessary information. Purpose of this dataset is to visualise the crime rates in each borough and identify the borough with the least crimes recorded during 2016.

	Borough	Local authority	Political control	Headquarters	Area (sq mi)	Population (2013 est)[1]	Co-ordinates	Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	Total
0	Barking and Dagenham	Barking and Dagenham London Borough Council	Labour	Town Hall, 1 Town Square	13.93	194352	51°33′39″N 0°09′21″E / 51.5607°N 0.1557°E /...	1287	1949	919	378	534	5607	6067	16741
1	Barnet	Barnet London Borough Council	Conservative	North London Business Park, Oakleigh Road South	33.49	369088	51°37′31″N 0°09′06″W / 51.6252°N 0.1517°W /...	3402	2183	906	499	464	9731	7499	24684
2	Bexley	Bexley London Borough Council	Conservative	Civic Offices, 2 Watling Street	23.38	236687	51°27′18″N 0°09′02″E / 51.4549°N 0.1505°E /...	1123	1673	646	294	209	4392	4503	12840
3	Brent	Brent London Borough Council	Labour	Brent Civic Centre, Engineers Way	16.70	317264	51°33′32″N 0°16′54″W / 51.5588°N 0.2817°W /...	2631	2280	2096	536	919	9026	9205	26693
4	Bromley	Bromley London Borough Council	Conservative	Civic Centre, Stockwell Close	57.97	317899	51°24′14″N 0°01′11″E / 51.4039°N 0.0198°E /...	2214	2202	728	417	369	7584	6650	20164

2.2.4 Finding the neighbourhood with the safest borough.

Table 4: Neighbourhoods of the safest borough

After visualising the crime in each borough, we will find the lowest crime rate and hence rate that borough as the safest borough. Third source of data is acquired from the list of neighbourhoods in the safest borough on Wikipedia. This dataset is created from scratch. The pandas dataframe is created with the names of the neighbourhoods the name of the borough with the latitude and longitude are left blank.

	Neighborhood	Borough	Latitude	Longitude
0	Berrylands	Kingston upon Thames		
1	Canbury	Kingston upon Thames		
2	Chessington	Kingston upon Thames		
3	Coombe	Kingston upon Thames		
4	Hook	Kingston upon Thames		

Using Google Maps API geocoding for the final dataset

2.2.5 Merging dataframes to get a single dataframe.

Table 5: Neighbourhoods with safest borough

The coordinates of the neighbourhoods are obtained using Google Maps API geocoding get the final dataset

	Neighborhood	Borough	Latitude	Longitude
0	Berrylands	Kingston upon Thames	51.393781	-0.284802
1	Canbury	Kingston upon Thames	51.417499	-0.305553
2	Chessington	Kingston upon Thames	51.358336	-0.298622
3	Coombe	Kingston upon Thames	51.419450	-0.265398
4	Hook	Kingston upon Thames	51.367898	-0.307145

This will be used to get the venues for each neighbourhood using the Foursquare API.

Foursquare location data will be leveraged to explore or compare boroughs around London.

Data manipulation and analysis to derive subsets of the initial data.

2.5 Feature Selection

After data cleaning, the following features will be kept and the others dropped.

Feature selection during data cleaning

Kept features	Dropped features	Reason for dropping features
Categories of Crime (major , minor)	lsoa code	This did not add value to the prediction
Borough		
Number of crimes		
Year (recent)	Month, years before 2016 rejected	This is to give a recent set of figures to work with

3. Methodology

3.1 Exploratory Data Analysis

The methodology in this project consists of two parts:

1. Exploratory Data Analysis: Visualise the crime rates in the London boroughs for chain restaurant owners to identify the safest borough and extract the neighborhoods in that borough to find the 10 most common venues in each neighborhood.
2. Modelling and unsupervised Machine Learning: To help chain restaurant owners to find other amenities in the safest boroughs. We will be clustering similar neighborhoods using k - means clustering which is a form of unsupervised machine learning algorithm that clusters data based on predefined cluster size. We will use a cluster size of 5 for this project that will cluster the 15 neighborhoods into 5 clusters. The reason to conduct a K- means clustering is to cluster neighborhoods with similar amenities. This is so that chain

restaurant owners can look at other amenities that go hand in hand whilst running a food business, such as transport and other businesses in the area.

3.1.1 Statistical summary of the crimes committed in London

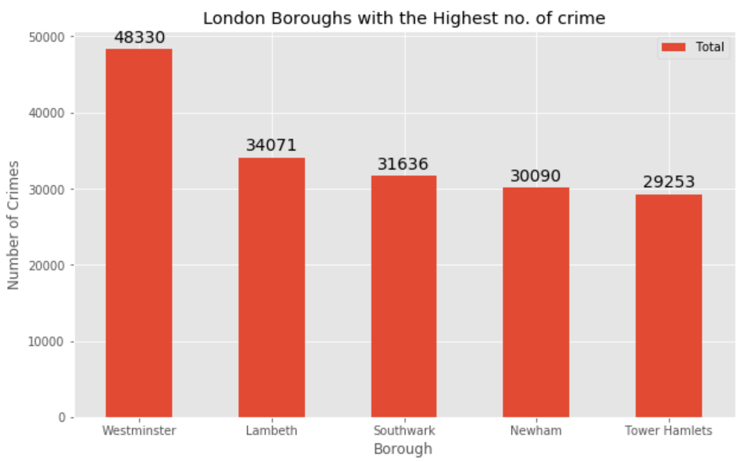
The function' describe' in Python provides the statistics of the dataframe. The following function will give us the mean, standard deviation, minimum, maximum, 1st quartile (25%) 2nd quartile (50%) and the 3rd quartile (75%) for each of the major categories of crime.

Out[19]:

	Borough							No_of_Crimes	Total
Major_Category		Burglary	Criminal Damage	Drugs	Other Notifiable Offences	Robbery	Theft and Handling	Violence Against the Person	
0	Barking and Dagenham	1287	1949	919	378	534	5607	6067	16741
1	Barnet	3402	2183	906	499	464	9731	7499	24684
2	Bexley	1123	1673	646	294	209	4392	4503	12840
3	Brent	2631	2280	2096	536	919	9026	9205	26693
4	Bromley	2214	2202	728	417	369	7584	6650	20164
5	Camden	2652	1935	1493	490	899	14088	7626	29183
6	City of London	2	2	10	6	4	129	25	178
7	Croydon	2738	3219	1367	718	1139	9229	10302	28712
8	Ealing	2492	2562	1355	613	669	10040	9396	27127
9	Enfield	2541	2136	1063	492	807	8037	7409	22485
10	Greenwich	1780	2476	867	521	486	8010	8590	22730
11	Hackney	2719	1981	1353	499	1030	11851	8832	28265
12	Hammersmith and Fulham	1531	1408	1321	474	397	8925	6118	20174

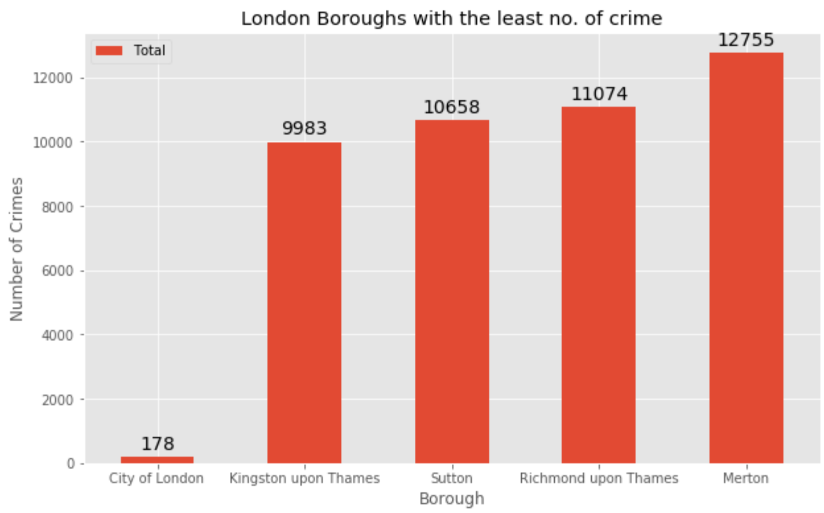
The count for each of the major categories gives the value of 33 which is the number of London boroughs. 'Violence against the person' is the highest reported, followed by 'Theft and Handling' followed by 'Robbery. Lowest recorded crimes included 'Burglary', 'Criminal Damage' and ' Drugs'

3.1.2 Boroughs which stored the highest of crime rates

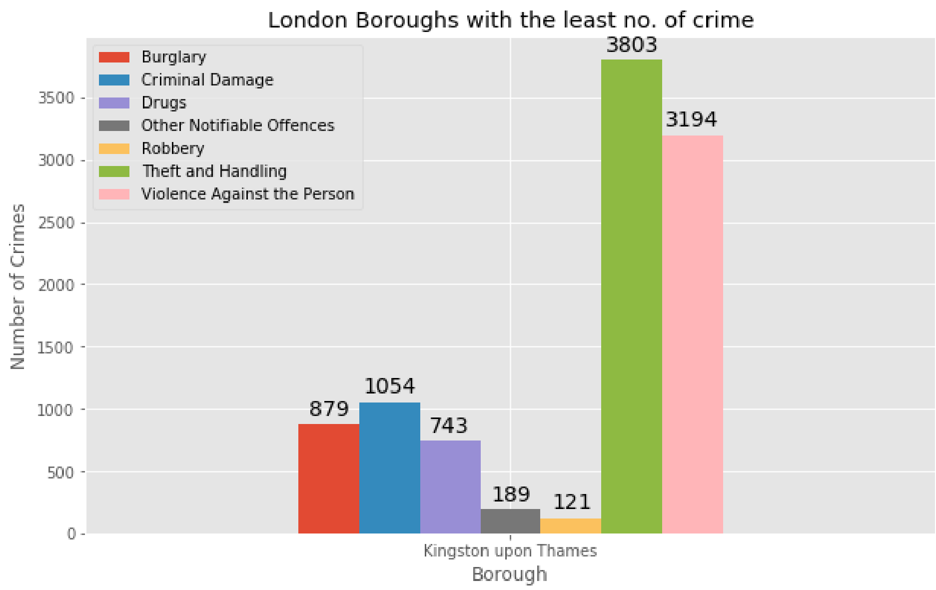


When we compare the boroughs with the highest crime rate, it is evident that Westminster has the highest recorded crimes followed by the boroughs of Lambeth Southwork, Newham and Tower Hamlets. It is also to be noted that the crime rates at Westminster is higher than the other four boroughs. Based on this advice would be not open any chain of restaurants in this area.

3.1.3 Boroughs which scored the least of crime rates

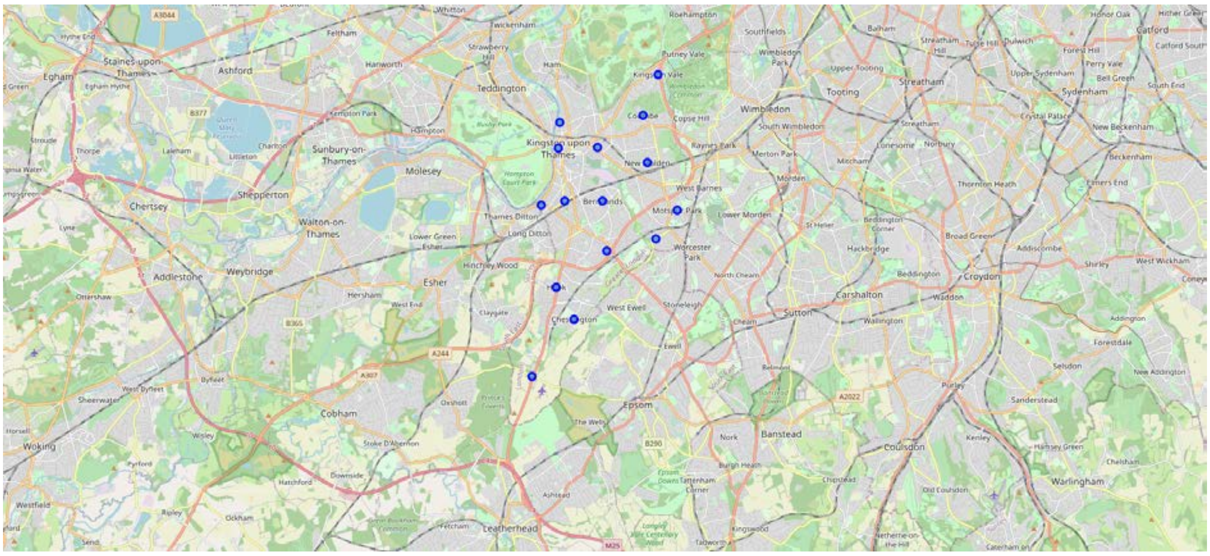


Kingston upon Thames is the safest borough



We can see Kingston upon Thames is the safest borough. We will explore this in the next section.

3.1.3 Neighbourhoods in the Kingston upon Thames



There are 15 neighbourhoods in the number of Kingston upon Thames. They have been visualised on a map using the folium library on Python.

3.2 Modelling and Machine Learning (unsupervised)

Using the final dataset containing the neighbourhoods in Kingston upon Thames and finding the latitude and longitude, we can then use the Foursquare developer API to find venues within 500 m radius of each of the neighbourhoods. The output will be adjacent file containing all the venues in the neighbourhood. This is then converted into a pandas dataframe. The dataframe contains all the venues along with the coordinates and their categories

Out[95]:

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Berrylands	4	4	4	4	4	4
Canbury	14	14	14	14	14	14
Coombe	1	1	1	1	1	1
Hook	4	4	4	4	4	4
Kingston Vale	4	4	4	4	4	4
Kingston upon Thames	30	30	30	30	30	30
Malden Rushett	4	4	4	4	4	4
Motspur Park	5	5	5	5	5	5
New Malden	6	6	6	6	6	6
Norbiton	27	27	27	27	27	27
Old Malden	3	3	3	3	3	3
Seething Wells	20	20	20	20	20	20
Surbiton	30	30	30	30	30	30
Tolworth	18	18	18	18	18	18

One hot coding is done on the venues data. This is a process by which categorical values are converted into a form which can be interpreted by machine learning algorithms to do a better job in prediction. The venues data is then grouped by the neighbourhood and the mean of the venues is calculated. As a final task, the 10 common venues are calculated for each of the neighbourhoods.

To help restaurant chain owners find similar neighbourhoods in the safest borough, will use clustering similar neighbourhoods using k- means clustering which is a form of unsupervised machine learning algorithm that clusters data based on predefined cluster size. We will use a cluster size of five for this project that will cluster 15 neighbourhoods into five clusters. The reason to conduct a k- means clustering is to cluster venues with similar venues so that restaurant owners can shortlist area of interest based on the venues/transport links/amenities around each neighbourhood.

4. Results

Implementing the k- means clustering we can access each cluster to see which neighbourhoods were assigned to each of the five clusters. We will examine the neighbourhoods in sequence.

<u>Examining cluster one</u>:

Out[75]:

	Neighborhood	Borough	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
6	Kingston Vale	Kingston upon Thames	51.431850	-0.258138	0	Grocery Store	Sandwich Place	Bar	Soccer Field	Department Store	Discount Store	Farmers Market	Fast Food Restaurant	Fish & Chips Shop	Food
7	Malden Rushett	Kingston upon Thames	51.341052	-0.319076	0	Grocery Store	Pub	Garden Center	Restaurant	Fish & Chips Shop	Deli / Bodega	Department Store	Discount Store	Farmers Market	Fast Food Restaurant
11	Old Malden	Kingston upon Thames	51.382484	-0.259090	0	Construction & Landscaping	Grocery Store	Food	Train Station	Bagel Shop	Department Store	Golf Course	Gift Shop	German Restaurant	Gastropub
14	Tolworth	Kingston upon Thames	51.378876	-0.282860	0	Grocery Store	Restaurant	Pharmacy	Pizza Place	Train Station	Hotel	Indian Restaurant	Italian Restaurant	Discount Store	Coffee Shop

Cluster one is the biggest cluster with 9 of the 15 neighborhoods in the borough Kingston upon Thames. Upon closely examining these neighborhoods we can see that the most common venues in these neighborhoods are Stores, Pubs, Restaurants and Train Station

Looking at the second and the fourth cluster we can see that these clusters have only one neighbourhood each. This is because of the unique venues in each of the neighbourhoods and hence they could be clustering similar neighbourhoods.

<u>Examining cluster two</u>:

	Neighborhood	Borough	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
2	Chessington	Kingston upon Thames	51.358336	-0.298622	1	Construction & Landscaping	Food	Deli / Bodega	Department Store	Discount Store	Farmers Market	Fast Food Restaurant	Fish & Chips Shop	French Restaurant	Grocery Store

The second cluster has one neighborhood which consists of Venues such as Construction, Food Shops and Departmental Stores.

<u>Examining cluster three</u>:

Out[77]:

	Neighborhood	Borough	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
4	Hook	Kingston upon Thames	51.367898	-0.307145	2	Bakery	Supermarket	Indian Restaurant	Fish & Chips Shop	Turkish Restaurant	Food	Department Store	Discount Store	Farmers Market	Fast Food Restaurant
9	New Malden	Kingston upon Thames	51.405335	-0.263407	2	Gym	Gastropub	Office	Sushi Restaurant	Supermarket	Bar	Korean Restaurant	Indian Restaurant	Fast Food Restaurant	Department Store

The third cluster neighborhoods which consists of Venues such as Gyms, Pubs and Restaurants

Examining cluster four:

Out[78]:

	Neighborhood	Borough	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
0	Berrylands	Kingston upon Thames	51.393781	-0.284802	3	Gym / Fitness Center	Park	Bus Stop	Turkish Restaurant	Fish & Chips Shop	Department Store	Discount Store	Farmers Market	Fast Food Restaurant	Food
8	Motspur Park	Kingston upon Thames	51.390985	-0.248898	3	Gym	Park	Bus Stop	Soccer Field	Fish & Chips Shop	Department Store	Discount Store	Farmers Market	Fast Food Restaurant	Food

The fourth cluster has two neighborhood in it, this has common venues such as Train Stations, Pubs, Restaurants, Electronics Stores etc.

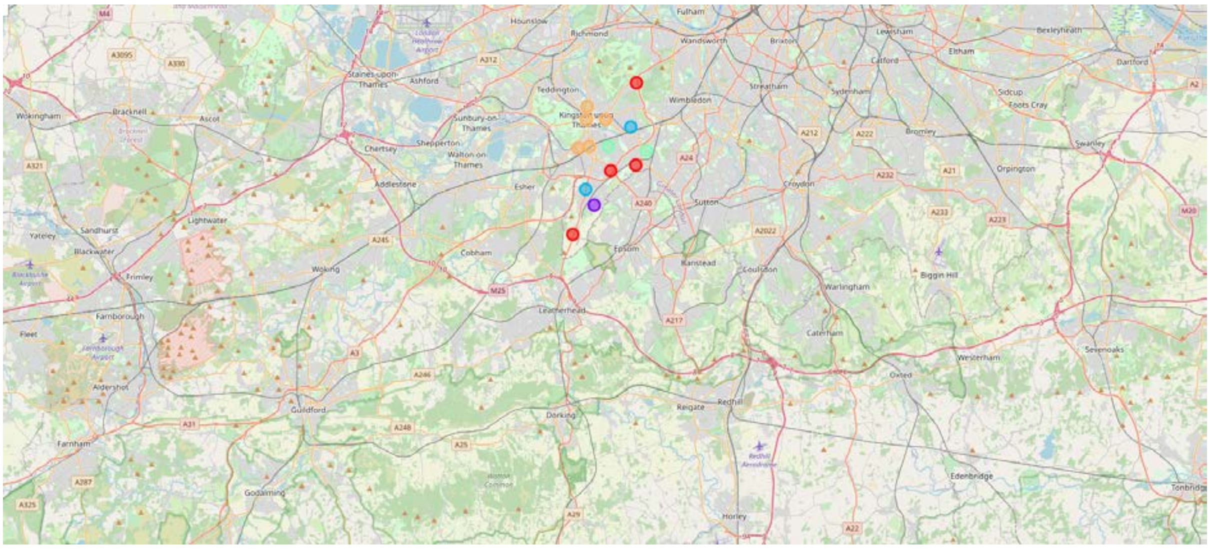
Examining cluster five:

Out[80]:

	Neighborhood	Borough	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
1	Canbury	Kingston upon Thames	51.417499	-0.305553	4	Pub	Park	Café	Supermarket	Spa	Gym / Fitness Center	Shop & Service	Fish & Chips Shop	Plaza	Hotel
5	Kingston upon Thames	Kingston upon Thames	51.409627	-0.306262	4	Café	Pub	Burger Joint	Sushi Restaurant	Coffee Shop	Turkish Restaurant	French Restaurant	Gym / Fitness Center	Gift Shop	German Restaurant
10	Norbiton	Kingston upon Thames	51.409999	-0.287396	4	Indian Restaurant	Italian Restaurant	Food	Platform	Pub	Japanese Restaurant	Hotel	Coffee Shop	Hardware Store	Café
12	Seething Wells	Kingston upon Thames	51.392642	-0.314366	4	Indian Restaurant	Coffee Shop	Pub	Café	Gym	Chinese Restaurant	Fast Food Restaurant	Fish & Chips Shop	Restaurant	Italian Restaurant
13	Surbiton	Kingston upon Thames	51.393756	-0.303310	4	Coffee Shop	Pub	Pharmacy	Grocery Store	Italian Restaurant	Breakfast Spot	French Restaurant	Train Station	Gym / Fitness Center	Hotel

The fifth cluster has two neighborhood which consists of Restaurants, Coffee Shops, Pubs.

Visualising the cluster neighbourhoods on a map using the folium library:



Each cluster is colour-coded for the ease of presentation. We can see the majority of the neighbourhood falls in the red cluster which is the first cluster. Three neighbourhoods have their own cluster, i.e., blue purple and yellow. These are clusters 2, 3 and 5 the green cluster consists of two neighbourhoods which is 4th cluster.

5. Discussion

The aim of the project was to help business investors who would like to invest in chain of restaurants in the safest borough of London. They would also like to examine the neighbourhoods giving them the idea whether it is a sustainable for restaurant business. This could be looking at transport links and the nature of other businesses in the area.

If a business owner is looking for good connectivity then cluster 1 and cluster 4 would be the choice.

If a business owner is looking for the presence of other business in the area, including pubs restaurants and coffee shops then clusters 2, 3, 5 would be the ideal choice.

Based on the recommendations, a business owner would be able to decide where to invest the location where to invest in restaurant.

6.Conclusion

This project helps to get holistic view into the investment decisions that might be critical before investing in a hospitality business. Not only the venue has got to be safe with regards to crime, it also has to be a place where the potential customers would be able to visit easily. It should also mean the staff work in the restaurant should also be able to commute and get to work in the easiest possible manner. This project has given the options restaurant owner in terms of the safest boroughs in London and also the location details where are prospective restaurant might thrive the City of London.