Identify A Strategic Location to Open a Brazilian take away restaurant in London, United Kingdom

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Capstone Project

1. Introduction

1.1 Background

The success of establishing a new restaurant depends on several factors: demand, brand loyalty, quality of food, competition, and so on. In most cases, a restaurant's location plays an essential determinant for its success. Hence, it is advantageous and of utmost importance to determine the most strategic location for establishment in order to maximize business profits.

Whether you're opening your first full-service restaurant, it's important to understand what to look out for when choosing a new restaurant location. For seasoned restaurateurs, you may have a successful location where you are but how much of that success is inadvertently down to accidental—or purposeful—restaurant location choice? The answer may be it has everything to do with it.

1.2 Problem Statement

- Brazilian family of chefs would like to open a Brazilian take away restaurants, selling Brazilian traditional food such as pizza katupiri', pastels, picanha in London.

-Objective is to identify the optimal neighborhood location to open. key factors to consider are: spending power of the London population, distribution of Brazilian restaurants, distance to public transport station.

- To identify the ideal London neighborhood clusters group, we are going to use Foursquare API, data scraping, geopy, pycaret to build the clustering model and matplotlib/seaborn to visualize data during our EDA (Exploratory Data Analysis).

1.3 Key Clients

- Brazilian Family of chefs, highly experienced in cooking for small to medium restaurants

2. Data Acquisition, Wrangling and Cleaning

2.1 Data Sources

The neighbourhoods alongside their respective postal codes, boroughs and the geographical coordinates, population and income for each neighborhood will be scraped from here:
https://www.doogal.co.uk/UKPostcodesCSV.ashx?area=London0 .
For returning the number of Brazilian restaurants in the vicinity of each neighborhood, we will use Foursquare API, more specifically, its *explore* function.

After cleaning, and apply exploratory analysis we will create a London map through Folium with an overview of the location of each neighborhood. From there we will implement some preprocessing steps to prepare the data for the clustering KMeans model to identify the neighborhood cluster with more potential to open a Brazilian restaurant.

2.2 Data Cleaning

After importing the file with postcodes and geospatial data, we can see that the dataset contains other useful data for our analysis. That is good as we don't have scrape other data.

Figure 1: Data with postcodes, neighbourhood and geospatial data.

	Postcode	In Use?	Latitude	Longitude	Easting	Northing	Grid Ref	County	District	Ward	District Code	Ward Code	Country	County Code	Constituency	Introduced	Terminated	Parish	National Park	Population
0	BR1 1AA	Yes	51.401546	0.015415	540291	168873	TQ402688	Greater London	Bromley	Bromley Town	E09000006	E05000109	England	E11000009	Bromley and Chislehurst	2016-05-01	NaN	Bromley, unparished area	NaN	NaN
1	BR1 1AB	Yes	51.406333	0.015208	540262	169405	TQ402694	Greater London	Bromley	Bromley Town	E09000006	E05000109	England	E11000009	Bromley and Chislehurst	2012-03-01	NaN	Bromley, unparished area	NaN	NaN
2	BR1 1AD	No	51.400057	0.016715	540386	168710	TQ403687	Greater London	Bromley	Bromley Town	E09000006	E05000109	England	E11000009	Bromley and Chislehurst	2014-09-01	2017-09-01	Bromley, unparished area	NaN	NaN
3	BR1 1AE	Yes	51.404543	0.014195	540197	169204	TQ401692	Greater London	Bromley	Bromley Town	E09000006	E05000109	England	E11000009	Bromley and Chislehurst	2008-08-01	NaN	Bromley, unparished area	NaN	34.0
4	BR1 1AF	Yes	51.401392	0.014948	540259	168855	TQ402688	Greater London	Bromley	Bromley Town	E09000006	E05000109	England	E11000009	Bromley and Chislehurst	2015-05-01	NaN	Bromley, unparished area	NaN	NaN

The dataset contains data for more than 30 neighborhood, that in the dataset are called District.

Next step summary of data cleaning:

- First, the columns that do not contain useful information for the EDA (Exploratory Data Analysis) and for the clustering model building after have been dropped.
- Second, the rows with null or non existent values have been dropped
- Third, the final dataframe has been simplified and sampled from more than 140000 rows to 100 rows because the folium library and the colab platform have crashed several times as the dataset was consuming quite a lot of memory.

Figure 2: Final Dataframe after data cleaning

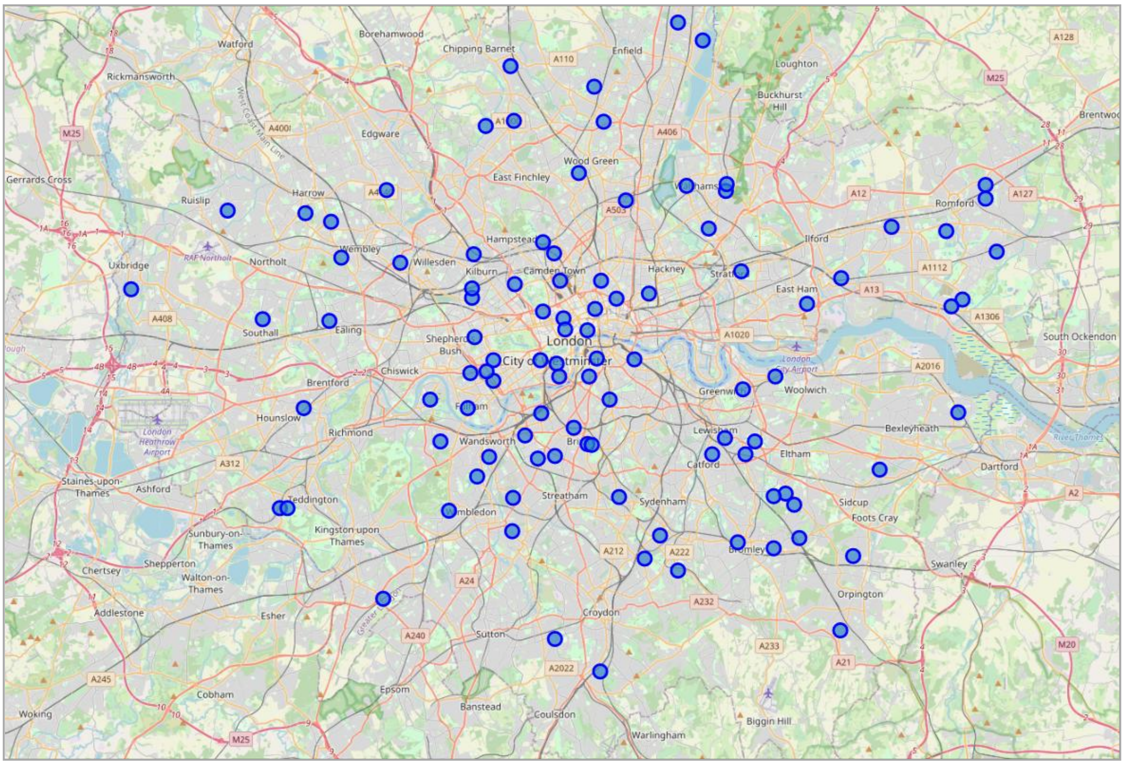
	District	Latitude	Longitude	Population	Households	Distance to station	Average Income
0	Bromley	51.404543	0.014195	34.0	21.0	0.462939	63100
1	Bromley	51.408058	0.015874	38.0	37.0	0.083058	63100
2	Bromley	51.409191	0.010068	1.0	1.0	0.489492	56100
3	Bromley	51.400462	0.016716	4.0	4.0	0.067905	63100
4	Bromley	51.401684	0.015705	14.0	6.0	0.219358	63100
...	...	...	...	...	...	...	...
140844	Hillingdon	51.623983	-0.495253	18.0	5.0	2.347240	54200
140845	Hillingdon	51.626955	-0.494143	22.0	15.0	2.048740	54200
140846	Hillingdon	51.628575	-0.499204	2.0	1.0	2.191290	54200
140847	Barnet	51.643292	-0.255958	11.0	6.0	1.960300	58000
140848	Barnet	51.642309	-0.256627	71.0	55.0	1.984360	58000

3. Exploratory Data Analysis

3.1 Folium Mapping

The folium library was called to help visualize, geographically, the location of each neighbourhood sampled in London.

Figure 3: London map with each neighbourhood

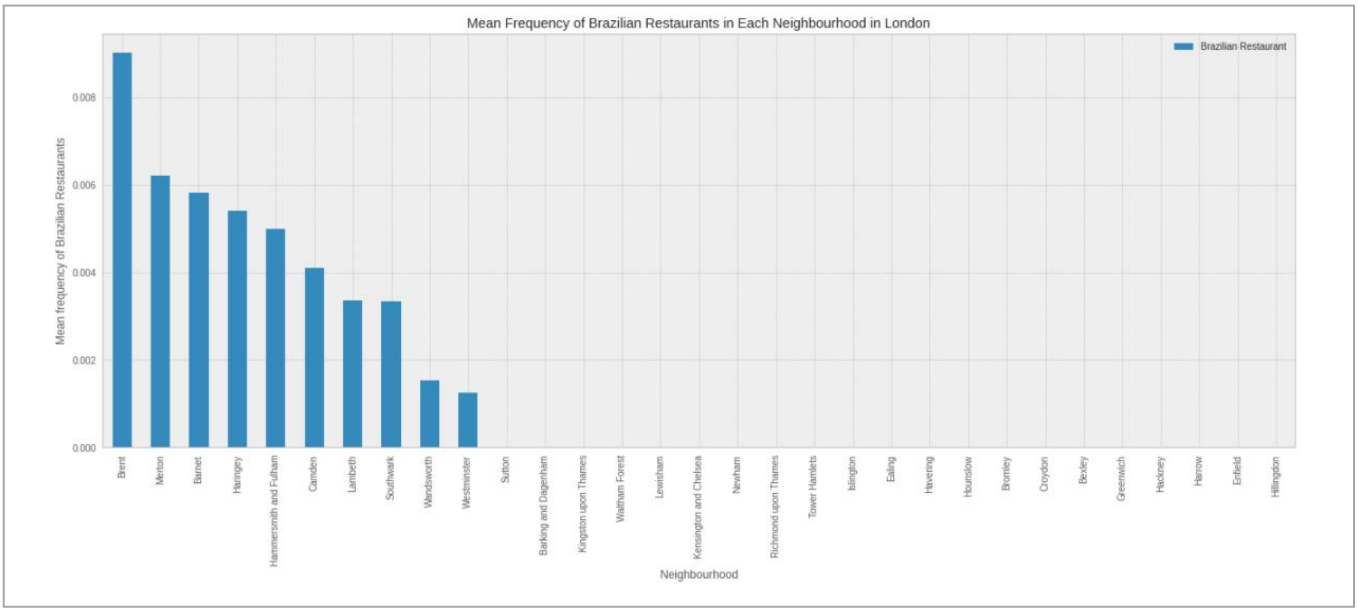


After plotting the map and each neighbourhood, it has been implemented a statistical analysis and overview of 3 factors useful for the final decision or recommendation to where is more suitable to open a restaurant: Distribution of Brazilian Restaurants, Median Income per neighbourhood and neighbourhood with the nearest distance to the station.

3.2 Frequency Distribution of Brazilian Restaurants

Using the Foursquare API's explore function, we could return the number of Brazilian restaurants located in each neighborhood. By calculating the mean respectively, it can give us a better understanding of the frequency of occurrence in each neighborhood. The argument for the use of frequency of Brazilian restaurants is based on the hypothesis that there would be a correlation between the number of Brazilian restaurants and competition. The higher the number of Brazilian restaurants in a neighborhood, the stronger the competition. The assumption of the analysis is that the barrier of entry to establish a new restaurant in a competitive market is high as existing Brazilian restaurants may have the competitive advantage of brand loyalty.
Though, counter intuitively, the presence of Brazilian restaurants may even be an indicator of demand for Brazilian cuisine; the presence of competition may even incentivize innovation to reduce cost and increase productivity.
Hence, it would be sound to establish business operations in a neighborhood that consists of a number of restaurants around the median value.

Figure 4: Neighbourhood with average frequency of Brazilian Restaurants

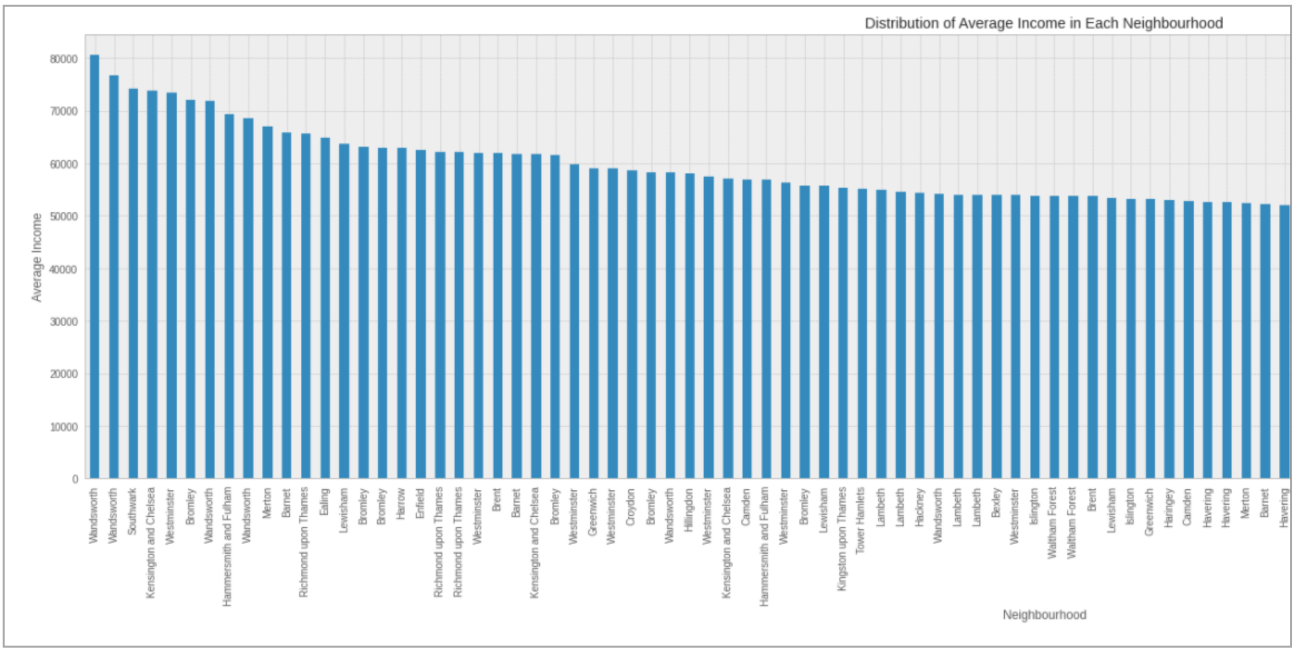


From the chart above we can infer that Brent is the neighborhood with the highest mean frequency of Brazilian restaurants, therefore it is advisable to don't open a Brazilian restaurant in that area.

3.3 Distribution of Median Household Income

As the Brazilian restaurant could be categorized as casual dining, the target audience is more geared towards the middle class/high class. As can be inferred from the bar chart below, neighborhoods distributed towards around the mean can readily afford and indulge themselves in the aforementioned Brazilian cuisine.

Figure 5: Distribution of Average Income in Each Neighbourhood

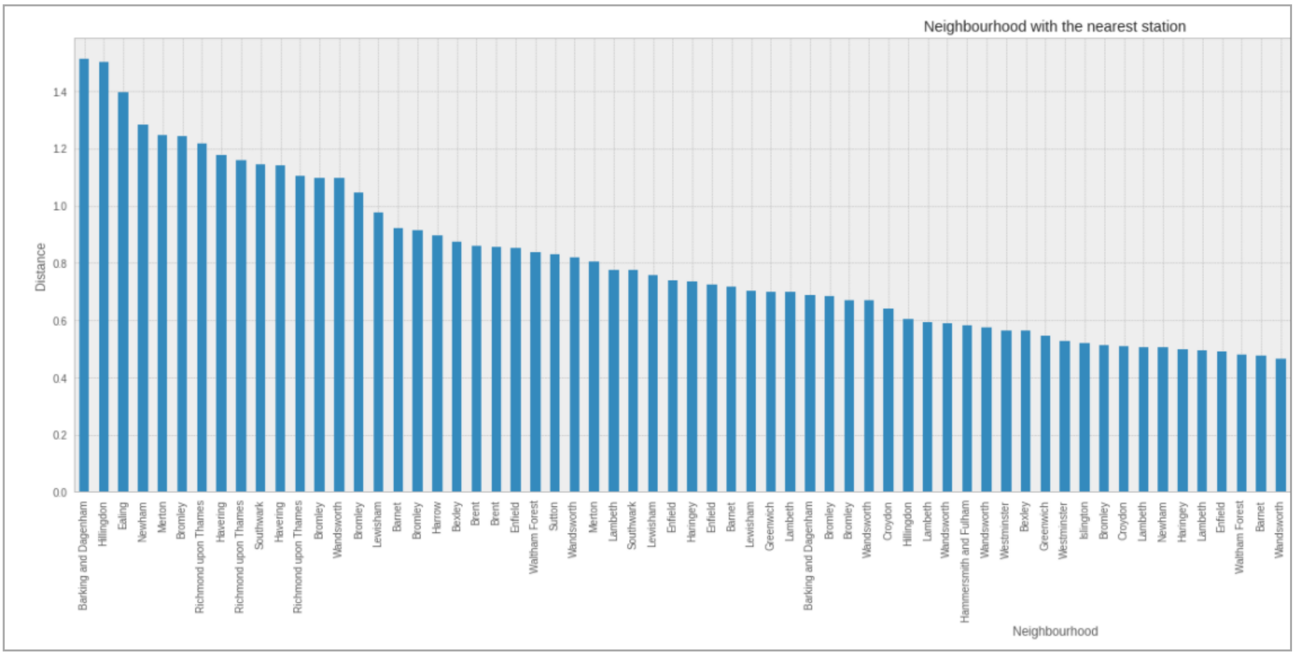


From the chart above we can see that the group of neighborhoods of Wandsworth, Southwark , Kensington and Chelsea are in the top 5 in terms of average income.

3.4 Distance to Station by neighborhoods

Another factor to consider when opening a restaurant in a big city like London is the distance to the nearest station. Most people live in London without having a car and the public transport is quite important to reach the areas and venues of preference. For an ethnic restaurant like a Brazilian one, the comfort to reach the venue with public transports is an important factor to motivate clients to visit and enjoy the venue.

Figure 6: Neighborhoods with the nearest station measured in distance.



Barking and Dagenham, Hillingdon and Ealing are in the top 3 in terms of distance to the nearest station.

4. Clustering Modeling

4.1 Data Pre-processing

The clustering model chosen is the kMeans clustering model. The machine learning API or library to build the model used is Pycaret. PyCaret is an open source low-code machine learning library in Python that aims to reduce the hypothesis to insights cycle time in a ML experiment. It enables data scientists to perform end-to-end experiments quickly and efficiently (source: https://pycaret.org).

The library allows to implement a simple preprocessing just with few lines of codes.

The scaling method used was the z-score, all implemented using the pycaret function to build the pre-processing pipeline named setup:

Figure 7: Pre-processing the model with Pycaret.

```
[ ] #we import the clustering model of pycaret

    from pycaret.clustering import *

    exp_clu101 = setup(df_final, normalize = True,
                       ignore_features = ['Neighbourhood'],
                       session_id = 123)
```

4.2 k-Means Clustering model

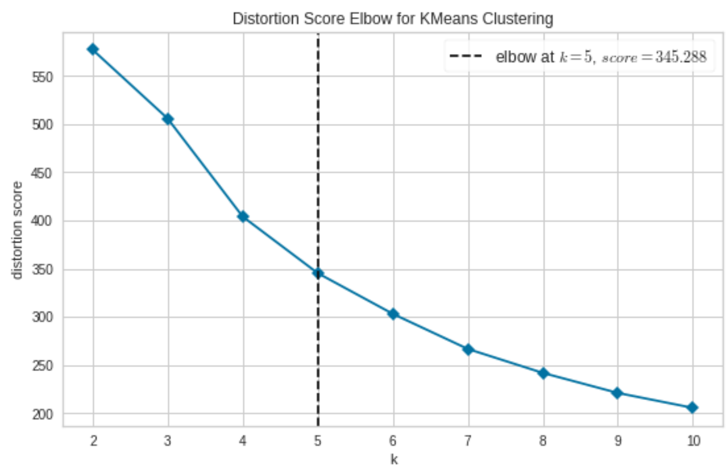
To implement a k-means model usually is important to assign a number of clusters the algorithm should label. To identify the optimal number clusters to use, with Pycaret first you fit the model with the standard number of clusters that is 4, after that with the function plot_model and choosing elbow method, Pycaret highlights the suitable number of clusters calculated with the squared error as a performance metric.

The suitable number of clusters is 5:

Figure 8: Elbow method chart with suitable number of k (clusters).

```
[ ] # Elbow method plotting to identify the right number of clusters

    plot_model(kmeans, plot= 'elbow')
```



After identifying the number of clusters, we will fit the standardized feature values into our k-Means algorithm. The results will be clusters of neighborhoods of similar characteristics.

4.2.1 Cluster Labels

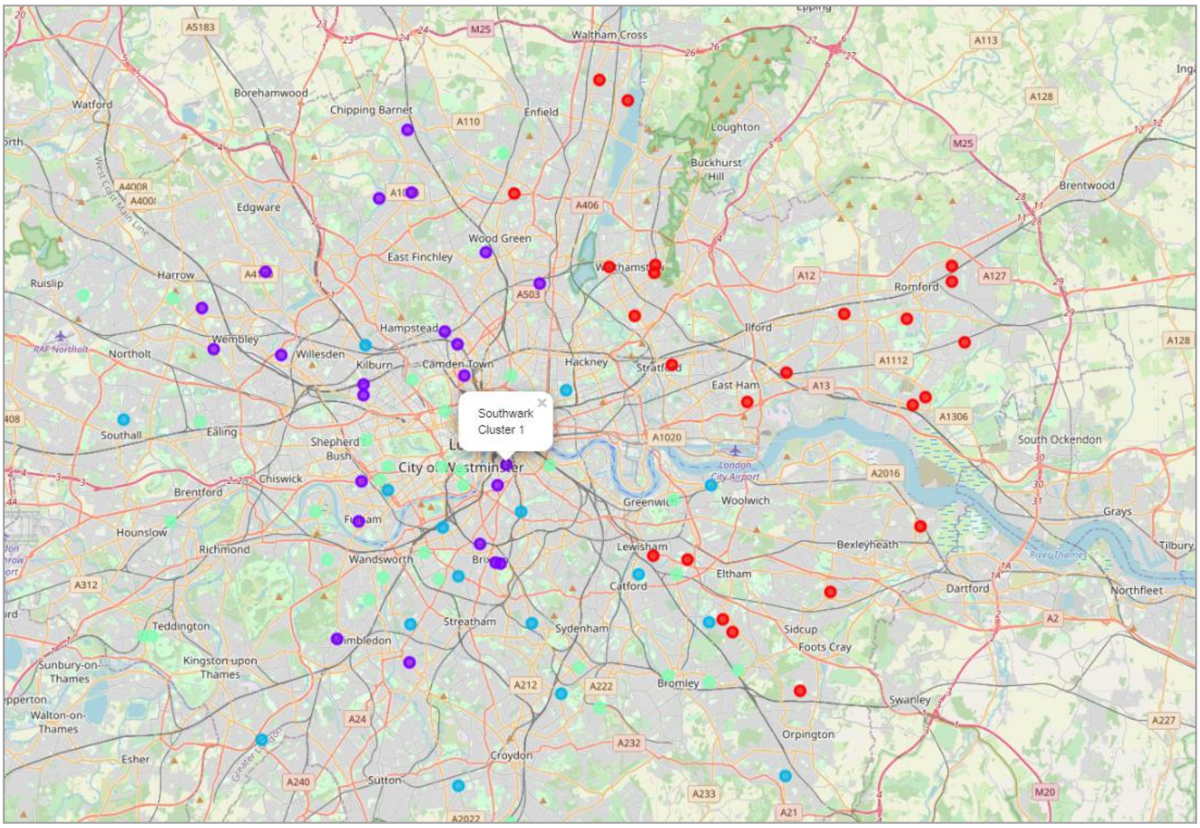
Here below we have the final data frame with the neighborhoods and the clusters (from 0 to 4 as in Python the counting starts from zero so 5 clusters: 0,1,2,3,4).

Figure 9: Dataframe with cluster labels.

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
0	Westminster	51.528918	-0.206048	71.0	20.0	0.565596	44500	0.00125	Cluster 1
1	Westminster	51.496019	-0.137685	46.0	27.0	0.433721	57500	0.00125	Cluster 3
2	Westminster	51.522106	-0.149017	3.0	1.0	0.316775	73500	0.00125	Cluster 3
3	Westminster	51.513050	-0.131427	5.0	3.0	0.294475	54000	0.00125	Cluster 3
4	Westminster	51.535685	-0.171829	6.0	2.0	0.180020	59900	0.00125	Cluster 3

Furthermore here below, the representation of the clusters in the London map using Folium:

Figure 10: Plot of the 5 clusters on the London map.



Cluster 0:

- Low spending power
- No presence of competition
- mid/high distance to the station

Figure 11: Cluster 0.

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
8	Bromley	51.425513	0.052632	34.0	17.0	1.098220	45800	0.0	0
9	Bromley	51.399587	0.100309	71.0	28.0	0.683057	42300	0.0	0
10	Bromley	51.430848	0.045822	35.0	11.0	1.045150	45800	0.0	0
32	Waltham Forest	51.584746	-0.033925	30.0	11.0	0.409922	50700	0.0	0
33	Waltham Forest	51.582277	-0.002204	89.0	31.0	0.478209	53700	0.0	0
34	Waltham Forest	51.563486	-0.015653	6.0	6.0	0.837416	46700	0.0	0
35	Waltham Forest	51.585813	-0.001676	58.0	29.0	0.097137	53700	0.0	0
40	Enfield	51.657057	-0.020592	1.0	1.0	0.723715	38700	0.0	0
42	Enfield	51.666158	-0.040539	76.0	30.0	0.853476	38300	0.0	0
43	Enfield	51.616572	-0.100123	16.0	5.0	0.737417	46200	0.0	0
47	Newham	51.542189	0.010360	36.0	15.0	0.503985	50200	0.0	0
48	Newham	51.525888	0.063026	95.0	33.0	1.283330	40400	0.0	0
66	Lewisham	51.458596	-0.002975	40.0	17.0	0.702157	53500	0.0	0
70	Havering	51.585085	0.206607	69.0	31.0	0.356473	52600	0.0	0
71	Havering	51.527812	0.188181	83.0	30.0	1.176440	44000	0.0	0
72	Havering	51.551881	0.215761	100.0	47.0	0.351363	52100	0.0	0
73	Havering	51.578145	0.206487	56.0	23.0	0.414984	52600	0.0	0
74	Havering	51.524680	0.179122	171.0	57.0	1.142380	44000	0.0	0
86	Greenwich	51.457183	0.021233	60.0	30.0	0.699302	53200	0.0	0
92	Bexley	51.443029	0.121412	88.0	39.0	0.874050	54000	0.0	0
93	Bexley	51.471565	0.185028	69.0	21.0	0.565264	44200	0.0	0
94	Barking and Dagenham	51.561947	0.175161	26.0	11.0	1.512370	43700	0.0	0
95	Barking and Dagenham	51.538752	0.090788	116.0	35.0	0.688178	49900	0.0	0
96	Barking and Dagenham	51.564448	0.131013	61.0	24.0	0.423293	40800	0.0	0

Cluster 1:

- Mid spending power
- Med/high presence of competition
- Medium distance to the station

Figure 12: Cluster 1

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
0	Westminster	51.528918	-0.206048	71.0	20.0	0.565596	44500	0.001250	1
18	Lambeth	51.455669	-0.113461	9.0	5.0	0.777299	54000	0.003367	1
21	Lambeth	51.455202	-0.109609	63.0	27.0	0.506102	54000	0.003367	1
22	Lambeth	51.489647	-0.112059	2.0	1.0	0.495755	54600	0.003367	1
23	Lambeth	51.463865	-0.124353	22.0	9.0	0.402040	54900	0.003367	1
24	Brent	51.582646	-0.274947	57.0	19.0	0.353669	50900	0.009009	1
25	Brent	51.533333	-0.206048	92.0	46.0	0.101633	53700	0.009009	1
26	Brent	51.566621	-0.319504	11.0	5.0	0.860764	61900	0.009009	1
27	Brent	51.549053	-0.310892	69.0	24.0	0.457962	47800	0.009009	1
28	Brent	51.546484	-0.263667	62.0	19.0	0.857033	40900	0.009009	1
44	Barnet	51.614525	-0.194904	70.0	23.0	0.715983	65800	0.005814	1
45	Barnet	51.644459	-0.175013	44.0	21.0	0.474490	61700	0.005814	1
46	Barnet	51.617341	-0.172074	37.0	16.0	0.923050	52200	0.005814	1
57	Southwark	51.498460	-0.105932	26.0	14.0	0.410530	48300	0.003333	1
64	Haringey	51.591314	-0.120335	43.0	16.0	0.734368	53100	0.005405	1
65	Haringey	51.577388	-0.082158	77.0	28.0	0.498445	44400	0.005405	1
75	Merton	51.422477	-0.224531	19.0	8.0	1.247450	67000	0.006211	1
76	Merton	51.411943	-0.173447	85.0	32.0	0.805762	52500	0.006211	1
79	Camden	51.518421	-0.132706	1.0	1.0	0.269255	46800	0.004098	1
81	Camden	51.537440	-0.135533	24.0	11.0	0.407740	48500	0.004098	1
82	Camden	51.551023	-0.139781	23.0	10.0	0.071352	57000	0.004098	1
83	Camden	51.556426	-0.148735	34.0	15.0	0.185730	52900	0.004098	1
98	Hammersmith and Fulham	51.491253	-0.207484	6.0	5.0	0.154938	56900	0.005000	1
99	Hammersmith and Fulham	51.473862	-0.209332	39.0	11.0	0.581015	69400	0.005000	1

Cluster 2:

- Mid spending power
- Low presence of competition
- Medium/high distance to the station

Figure 13: Cluster 2

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
14	Bromley	51.362141	0.090192	73.0	38.0	1.241690	61600	0.000000	2
19	Lambeth	51.449614	-0.139185	83.0	29.0	0.697894	49700	0.003367	2
20	Lambeth	51.429065	-0.088232	102.0	36.0	0.594626	50100	0.003367	2
38	Kensington and Chelsea	51.487289	-0.188915	109.0	81.0	0.458343	57100	0.000000	2
50	Wandsworth	51.428941	-0.172968	148.0	53.0	0.363703	51300	0.001538	2
52	Wandsworth	51.471192	-0.150287	77.0	36.0	0.465168	54100	0.001538	2
56	Southwark	51.478168	-0.095108	127.0	45.0	1.143710	44000	0.003333	2
61	Sutton	51.357886	-0.139529	117.0	38.0	0.832058	44600	0.000000	2
67	Lewisham	51.429587	0.036631	144.0	63.0	0.976703	44200	0.000000	2
68	Lewisham	51.450695	-0.012703	173.0	66.0	0.756707	55700	0.000000	2
78	Ealing	51.518183	-0.373996	108.0	27.0	1.395690	47700	0.000000	2
80	Camden	51.550415	-0.204611	186.0	105.0	0.385689	51400	0.004098	2
88	Greenwich	51.489310	0.038067	146.0	56.0	0.546876	52000	0.000000	2
90	Croydon	51.398141	-0.067555	188.0	85.0	0.509361	45200	0.000000	2
91	Kingston upon Thames	51.378398	-0.277722	173.0	70.0	0.209291	55400	0.000000	2
97	Tower Hamlets	51.530888	-0.063582	118.0	50.0	0.452014	55100	0.000000	2

Cluster 3:

- Mid/high spending power
- Low presence of competition
- Medium distance to the station

Figure 14: Cluster 3

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
1	Westminster	51.496019	-0.137685	46.0	27.0	0.433721	57500	0.001250	3
2	Westminster	51.522106	-0.149017	3.0	1.0	0.316775	73500	0.001250	3
3	Westminster	51.513050	-0.131427	5.0	3.0	0.294475	54000	0.001250	3
4	Westminster	51.535685	-0.171829	6.0	2.0	0.180020	59900	0.001250	3
5	Westminster	51.512436	-0.113124	4.0	1.0	0.160563	59000	0.001250	3
6	Westminster	51.497664	-0.151261	32.0	17.0	0.526160	56300	0.001250	3
7	Westminster	51.489636	-0.136115	9.0	6.0	0.208241	61900	0.001250	3
11	Bromley	51.406526	0.007654	36.0	17.0	0.353919	63100	0.000000	3
12	Bromley	51.403588	0.036137	55.0	21.0	0.669057	62900	0.000000	3
13	Bromley	51.408445	0.056699	26.0	11.0	0.321041	72000	0.000000	3
15	Bromley	51.392147	-0.040713	7.0	6.0	0.913357	58300	0.000000	3
16	Bromley	51.409708	-0.055161	52.0	20.0	0.511303	55700	0.000000	3
17	Hackney	51.528557	-0.089805	11.0	10.0	0.315468	54300	0.000000	3
29	Richmond upon Thames	51.423487	-0.360588	65.0	25.0	1.158880	62200	0.000000	3
30	Richmond upon Thames	51.423439	-0.354513	35.0	16.0	1.217460	62200	0.000000	3
31	Richmond upon Thames	51.477996	-0.239360	20.0	8.0	1.104870	65600	0.000000	3
36	Kensington and Chelsea	51.497809	-0.188800	52.0	18.0	0.376699	73900	0.000000	3
37	Kensington and Chelsea	51.508964	-0.204267	2.0	1.0	0.256720	61700	0.000000	3
39	Kensington and Chelsea	51.491967	-0.194232	13.0	8.0	0.068090	49800	0.000000	3
41	Enfield	51.634244	-0.107997	38.0	16.0	0.489925	62600	0.000000	3
49	Wandsworth	51.456981	-0.231109	80.0	25.0	1.096980	68500	0.001538	3
51	Wandsworth	51.459925	-0.163482	71.0	25.0	0.668297	80600	0.001538	3
53	Wandsworth	51.448371	-0.153267	29.0	16.0	0.574968	71800	0.001538	3
54	Wandsworth	51.449184	-0.192121	32.0	12.0	0.819897	58200	0.001538	3
55	Wandsworth	51.439621	-0.201794	69.0	31.0	0.588494	76700	0.001538	3
58	Southwark	51.498154	-0.075531	38.0	16.0	0.775141	74200	0.003333	3
59	Harrow	51.571271	-0.339808	35.0	13.0	0.897249	62900	0.000000	3
60	Hounslow	51.473786	-0.341075	97.0	35.0	0.294194	51600	0.000000	3
62	Hillingdon	51.572291	-0.402240	61.0	20.0	0.603354	58100	0.000000	3
69	Lewisham	51.450751	0.014012	74.0	35.0	0.116572	63700	0.000000	3
77	Ealing	51.517266	-0.320989	35.0	11.0	0.413129	64800	0.000000	3
84	Islington	51.523194	-0.107313	8.0	5.0	0.366736	53800	0.000000	3
85	Islington	51.537215	-0.102420	22.0	15.0	0.520079	53300	0.000000	3

Cluster 4:

- Low spending power
- No presence of competition
- Highest distance to the station

Figure 14: Cluster 3

	Neighbourhood	Latitude	Longitude	Population	Households	Distance to station	Average Income	Brazilian Restaurant	Cluster
63	Hillingdon	51.533017	-0.479713	1129.0	0.0	1.50396	45800	0.0	4

5. Conclusions

In this study, I have labeled the neighborhoods corresponding to their characteristics--spending power, percentage of Brazilian restaurants(competitors) and neighborhood with nearest distance to the station. The most promising group of neighborhoods for opening an Brazilian Restaurant, with a niche in Brazilian cuisine, appears to be ‘Cluster Label 3’.

The medium high spending power of the neighborhoods in this cluster allows them to readily afford the slightly upscaled prices of the client’s Brazilian restaurant menu.
The number of competitors is pretty low, that would definitely help build a brand in the area for people curious to try Brazilian cuisine.
Our client could more specifically consider Richmond and some areas of Kensington and Chelsea as a location of establishment for optimal results characterized by a medium high spending average.
However cluster 3 shows a medium distance to the station and that probably could be considered as an insight to activate a solid promotion to the locals to make sure there is a significant and remunerative client base to limit any potential issue of the less easy to reach of the restaurant from people of other areas of London.
In conclusion, the extensive analysis above would greatly increase the likelihood of the restaurant’s success. Similarly, we can use this project to analyze interchangeable scenarios, such as opening a restaurant of different cuisines.