Introduction/Business Problem

Background

When a business is successful in a local scale and sees a notorious increase in their retained profit in a short amount of time, a usual reaction is to expand the business further in order to maximise earnings.

However, what is successful locally may not be welcomed in the same way in other wards. After all, different citizens have different needs and what works with a sector of the population may not work in the same way in a different geographical area due to competition there or differences regarding interests.

It is therefore important when choosing a new, additional location for the business to select the premise that is most similar to their current one in order to maximise the odds of being successful.

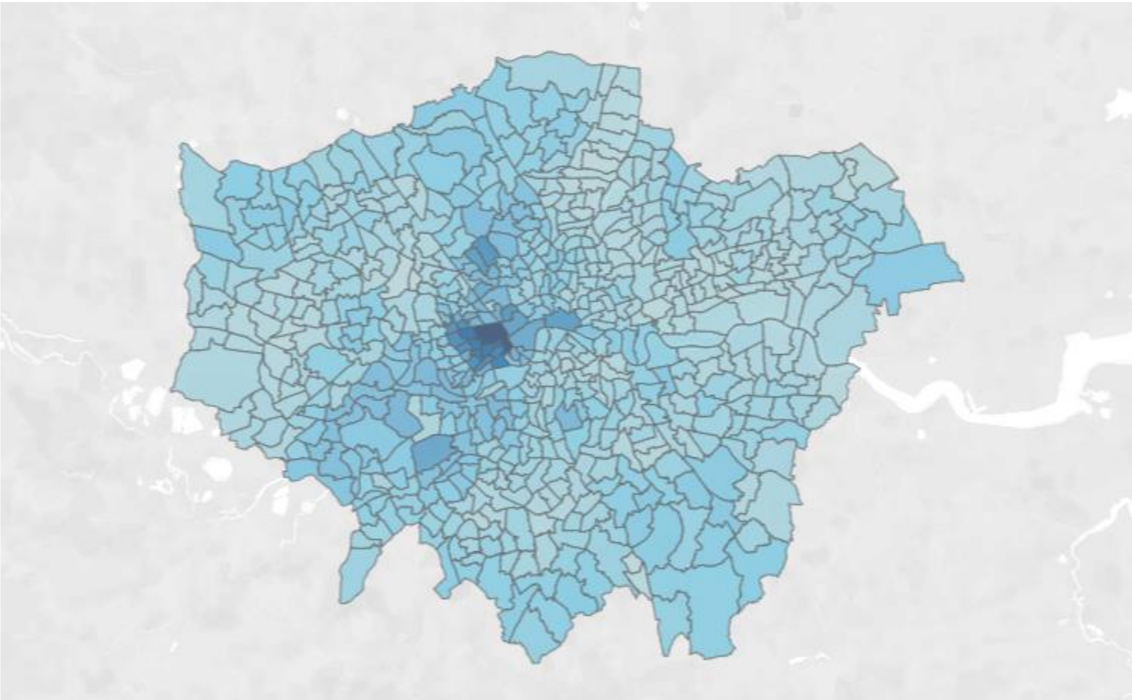
There are several factors to consider when selecting the ward to set up. These can be summed up in two categories: other venues and the possible customer base.

The existence of other venues is a double-edged sword that I will study in depth. If there are other businessmen that have set up successful venues of the same category as the one studied, it is likely that the neighbours there enjoy that type of venue. However, if they are already loyal customers of the existing venue, they may not feel like switching to the new alternative. This depends on the type of venue, as customers like to try different restaurants, but will be more reluctant to switch hairdresser salon.

I will look at the possible customer base in terms of the mean and median income for each ward. The higher the earnings of the population, the higher the chance of investing in normal goods and services and the lower the chance of investing in inferior goods. I will examine both mean and median earnings to reduce the effect of inequality between neighbours on the dataset, as a mean income of £2000 per month is not a useful figure if this ward has thousands of citizens on very low income and a couple of rich businessmen. This figure will give a wrong impression of the type of customer existing there. Moreover, median incomes in the area are also important in the sense that lower median incomes mean the businessman will have to pay lower wages and so the costs of setting up there are reduced. However, this means lower disposable income and so lower prices must be charged to still sell.

Problem description

I will use figures from London to compare setting up businesses in its different wards. By looking on websites such as TripAdvisor, I will choose a few venues to study from different wards and different categories. The project aims to choose a ward to set up another instance for each of the companies.



[*London wards shaded by mean income- source: data.gov.uk*]

Interest

The information gathered will be useful for businessmen wishing to expand within London.

Data

Data gathered

1. I will collect information on London's division into wards.
2. I will choose a number of venues from different wards to study.
3. I will look at the mean and median income from each of the wards.
4. I will study the venues in each ward and their categories.

Sources

I aimed to choose well-informed and reliable sources for this study.

1. I will get this data from a Wikipedia table. Even though Wikipedia is a crowd-sourced website, this table is a frequent search. This makes it unlikely for there to be mistakes, as it is commonly checked.
2. I will choose these from the TripAdvisor search function. Owners are the ones that create a profile for their business in TripAdvisor and customers are the ones that write the reviews. Therefore, a profile of a venue that has many reviews must exist in real life.
3. I will take the earnings per ward from the data.gov.uk website. Being the British Government's official website for data collection and visualization, the source is guaranteed to be reliable, as the government is the organization that has the most information on citizens and their earnings. Otherwise, interviewees could lie regarding how much they earn per month or could possibly not know an exact figure. This data comes from the information on all citizens, so there is no possible sampling bias.
4. I will obtain the information on venues from the Foursquare API. This API is updated every few minutes or seconds, which means its information regarding available venues is up-to-date. Even though it is also a crowd-sourced website, the intense traffic that looks at the data (especially that from a big city, such as London) and can find mistakes makes the information on it almost certainly correct.

Methodology

Data cleaning and feature selection

The dataset on the division of London was obtained from a Wikipedia table (https://en.wikipedia.org/wiki/List_of_areas_of_London). The division into wards was complete, meaning all wards in London had been collected. I extracted the data using the Python library BeautifulSoup. There were no missing values, so I did not have to fill these in. The only problem was that the column that stated the borrow contained numbers in the format [n] to link to other pages. I deleted these from my table using a Python string manipulation function that I programmed for this task. I deleted the columns regarding boroughs, post codes, dial numbers and references as I did not see any utility for them in my study. I renamed the wards column to make sure it was the same as that in the second table. I then obtained the coordinates of each ward with the GeoPy library and created two extra columns for each ward: Latitude and Longitude. There were some values that GeoPy could not obtain. There were only a few, so I printed out the concrete neighbourhoods missing coordinates and filled them in by hand.

The dataset on the mean and median income was obtained from the official British Government website. This again contained no empty cells, so I did not have to work with NaN values. I dropped the columns that were not necessary for my study and kept the numerical data. I renamed the column with the wards to make sure that it was the same as that in the first table.

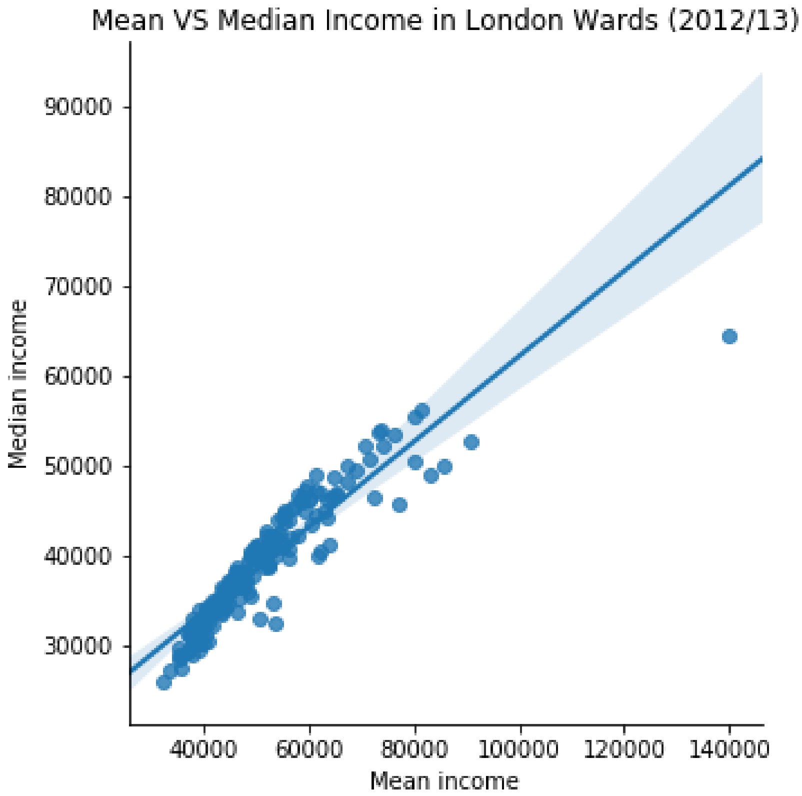
I then merged these two data frames to have a new table with the location of each ward (for future use with the Foursquare API) and the mean and median income for each year in the time between 2001 and 2013. I dropped the Borough column and made the ward name the index, as it is a unique identifier for each ward and will save up time compared to working with the numerical indices. The income is stored in string format with pound signs. We must therefore convert these values to integers to work with them later on. For the income, I decided to keep the most recent figures (2012/13), as they are the most useful for the study. After this cleaning my DataFrame looks like this:

	Latitude	Longitude	Mean 2012/13	Median 2012/13
Ward				
Abbey Wood	51.487621	0.114050	39630	31540
Addiscombe	51.379692	-0.074282	46520	38070
Alperton	51.537768	-0.297924	38550	31250
Balham	51.442828	-0.151443	76280	53420
Barkingside	51.585818	0.088624	49040	39620
Barnehurst	51.462687	0.161757	45990	38200
Barnes	51.471896	-0.238744	80160	55450
Barnsbury	51.538935	-0.114735	62770	44970
Bayswater	51.512414	-0.187632	85610	49960
Beckton	51.516080	0.059426	40180	34100

I saved the DataFrame in a csv file for future usage.

Exploratory data analysis

The first thing I did was plot median against mean income per ward. The objective of this was to show that I indeed needed both variables and that one did not do the job of the other.



Indeed, it can be seen that, for low incomes, the mean and median income are very similar. For these values, there is a straight, concentrated line of best fit. However, as the mean income increases, the median income increases at a lower rate, showing that both variables are needed. This difference for higher values is due to the nature of both statistics. A few rich people increase the value of the mean, yet the median is unaffected, as it is based on the value in the middle and does not take the rest into account. I now know the variables I will need to take into account for the model.

I made sure there were no duplicate entries in the dataset by removing rows with the same ward name.

Model

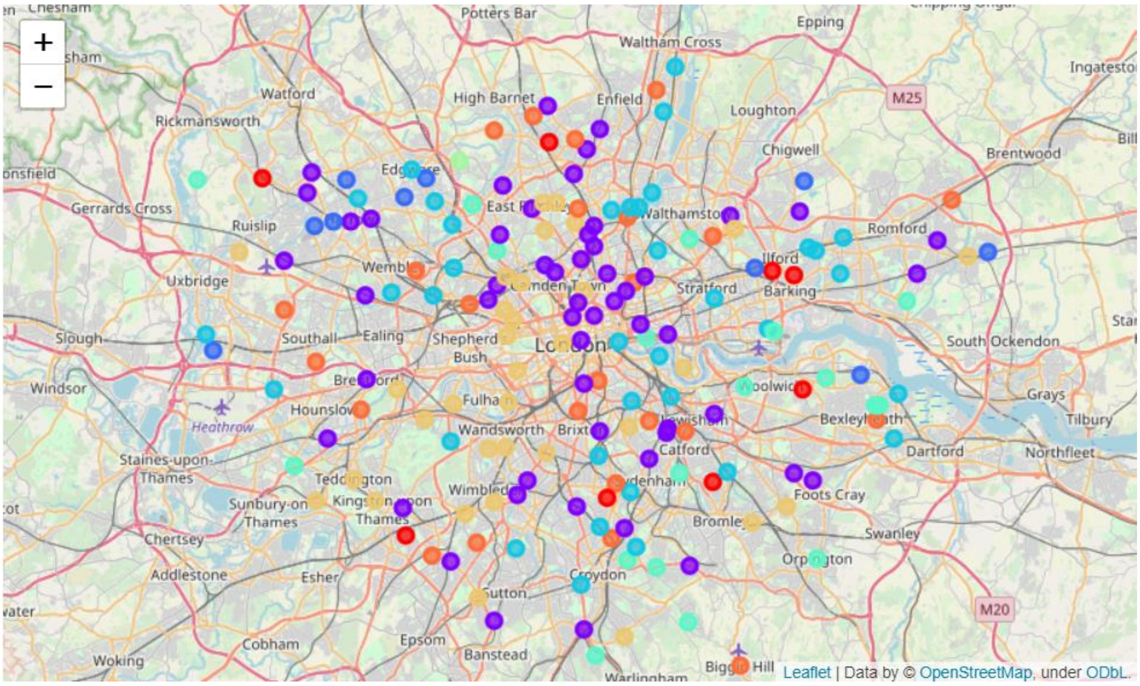
To cluster the wards in London, I used the Foursquare API. When training the model, I used a radius value of 2.5km for each ward, as I thought this would give the venues in the ward and just outside it, which are the ones the neighbours living in the ward are most likely to visit frequently. Knowing this, I obtained the venues visited by the neighbours in each ward using the Foursquare API. I then grouped these into categories and stored these values as a fraction of the total number of venues visited by neighbours of that ward. I included the mean and median income as variables to take into account too for clustering, yet the values were much larger than the proportion figures, which were smaller than 1. This meant that I had to adjust the income figures so that they too were smaller or equal to 1.

I tried several numbers of clusters until I found the number that separated the wards into the most sensible clusters to my judgement. I then visualised these clusters onto a Folium map.

Results

I finally decided for 8 clusters. More than that just ended with clusters with 1 ward and less than that led to clusters that were too large to provide any useful information.

I sorted the wards as follows:



Discussion

By showing the first few rows of each cluster and examining the values of the wards, I will interpret each of the groups.

Cluster 1:

Mean 2012/13	Median 2012/13	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
54530	42330	Bus Stop	Gym / Fitness Center	Park	Yoga Studio	Fish Market	Fast Food Restaurant	Field	Film Studio
46940	36310	Bus Stop	Café	Park	Yoga Studio	Flea Market	Fast Food Restaurant	Field	Film Studio
37320	30880	Park	Gym / Fitness Center	Café	Grocery Store	Yoga Studio	Fish Market	Fast Food Restaurant	Field
35280	29730	Park	Yoga Studio	Falafel Restaurant	Farmers Market	Fast Food Restaurant	Field	Film Studio	Fish & Chips Shop
35150	28500	Park	Furniture / Home Store	Pool	Yoga Studio	Fish Market	Farmers Market	Fast Food Restaurant	Field
57970	46550	Park	Gym / Fitness Center	Golf Course	Yoga Studio	Fish & Chips Shop	Farmers Market	Fast Food Restaurant	Field
40660	32390	Park	Bus Stop	Fast Food Restaurant	Convenience Store	Yoga Studio	Fish Market	Farmers Market	Field
45670	37430	Bar	Park	English Restaurant	Fish Market	Farmers Market	Fast Food Restaurant	Field	Film Studio

The neighbours in the first cluster have incomes a bit above the London average (39,100- median and 51,770-mean). There is a large number of parks, cafés and markets, showing an interest in outdoors activities. Restaurants are not as common as in other clusters, so businesses set up could focus on outdoors activities, such as sporting events.

Cluster 2:

Mean 2012/13	Median 2012/13	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
49040	39620	Soccer Field	Café	Supermarket	Metro Station	Yoga Studio	Farmers Market	Fast Food Restaurant	Field
55230	44260	Pub	Bus Stop	Park	Train Station	Electronics Store	Asian Restaurant	Yoga Studio	Fish Market
55200	44870	Café	Pub	Bakery	French Restaurant	Indian Restaurant	Pizza Place	Restaurant	Train Station
62190	40340	Coffee Shop	Café	Hotel	Pub	Exhibit	Bookstore	Sandwich Place	Plaza
44700	34550	Pub	Coffee Shop	Campground	Breakfast Spot	Beer Bar	Café	Grocery Store	Bakery
44100	35040	Coffee Shop	Gym	Deli / Bodega	Convenience Store	Bus Stop	English Restaurant	Movie Theater	Sandwich Place
46130	38100	Grocery Store	Café	Coffee Shop	Convenience Store	Diner	Malay Restaurant	Flower Shop	Brewery
56130	40590	Pub	Café	Bus Stop	Fruit & Vegetable Store	Trail	Train Station	Modern European Restaurant	Sushi Restaurant
57150	45410	Indian Restaurant	Turkish Restaurant	Pub	Coffee Shop	Café	Supermarket	Pizza Place	Japanese Restaurant
60270	43350	Pub	Coffee Shop	Pizza Place	Hotel	Café	Vietnamese Restaurant	Bar	Italian Restaurant
55190	43570	Italian Restaurant	Café	Turkish Restaurant	Greek Restaurant	French Restaurant	Fish & Chips Shop	Indian Restaurant	Metro Station
52340	38780	Clothing Store	Coffee Shop	Italian Restaurant	Hotel	Department Store	Bookstore	Middle Eastern Restaurant	Park
52020	42560	Convenience Store	Coffee Shop	Pub	Newsstand	Gourmet Shop	Grocery Store	Theater	Café
55480	41160	Coffee Shop	Pub	Café	Platform	Grocery Store	Sandwich Place	Health & Beauty Service	Park
41990	34730	Bakery	Convenience Store	Grocery Store	Pharmacy	Coffee Shop	Pizza Place	Metro Station	Café
53940	43790	Theater	Café	Garden	Grocery Store	Train Station	Turkish Restaurant	Yoga Studio	Film Studio

Neighbours in Cluster 2 have incomes significantly above average. Restaurants, coffee shops and cafés are common. Higher prices could be charged here and businesses offering more exclusive or special products could be set up here.

Cluster 3:

Mean 2012/13	Median 2012/13	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
40110	33510	Grocery Store	Train Station	Indian Restaurant	Eastern European Restaurant	Yoga Studio	Fish & Chips Shop	Farmers Market	Fast Food Restaurant
39000	29400	Bakery	Wings Joint	Grocery Store	Coffee Shop	Indian Restaurant	Metro Station	Fish & Chips Shop	Farm
51810	42250	Cupcake Shop	Grocery Store	Fast Food Restaurant	Indian Restaurant	Home Service	Park	Yoga Studio	Fish & Chips Shop
38700	31520	Burger Joint	Indian Restaurant	Metro Station	Bus Stop	Flower Shop	Fast Food Restaurant	Field	Film Studio
46390	36940	Indian Restaurant	Grocery Store	Thai Restaurant	Supermarket	Yoga Studio	Fish Market	Farmers Market	Fast Food Restaurant
37310	31580	Indian Restaurant	Gym / Fitness Center	Pub	Restaurant	Train Station	Fast Food Restaurant	Film Studio	Exhibit
43850	35030	Indian Restaurant	Bus Stop	Breakfast Spot	Supermarket	Yoga Studio	Flower Shop	Fast Food Restaurant	Field
51060	40310	Indian Restaurant	Grocery Store	Pizza Place	Coffee Shop	Pub	Fast Food Restaurant	Sandwich Place	Vegetarian / Vegan Restaurant
39500	32680	Construction & Landscaping	Grocery Store	Indian Restaurant	Bed & Breakfast	Flea Market	Farmers Market	Fast Food Restaurant	Field
50910	40210	Grocery Store	Indian Restaurant	Warehouse Store	Park	Metro Station	Yoga Studio	Film Studio	Farm

Neighbours in Cluster 3 have incomes slightly below average for London. Foreign, presumably cheap restaurants are frequent, as well as fast food and fish and chips. This shows a preference for simple, cheap ideas, rather than more elaborate ones, which could indicate the trend to follow here.

Cluster 4:

Mean 2012/13	Median 2012/13	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
38550	31250	Hookah Bar	Asian Restaurant	Gym / Fitness Center	Bus Stop	Fast Food Restaurant	Hardware Store	Electronics Store	Sandwich Place
40180	34100	Supermarket	Light Rail Station	Bus Station	Grocery Store	Pub	Discount Store	Gym / Fitness Center	Hotel
37860	33000	Construction & Landscaping	Park	Plaza	Flea Market	Farmers Market	Fast Food Restaurant	Field	Film Studio
38860	33920	Supermarket	Pub	Park	Train Station	Gym	Platform	Grocery Store	Breakfast Spot
39990	30170	Supermarket	Fast Food Restaurant	Clothing Store	Food Court	Pub	Gym / Fitness Center	Chinese Restaurant	Bubble Tea Shop
38790	30860	Bus Stop	Hotel	Restaurant	Fried Chicken Joint	Asian Restaurant	Fruit & Vegetable Store	Fast Food Restaurant	Park
41810	34900	Supermarket	Bus Stop	Sporting Goods Shop	Fast Food Restaurant	Mediterranean Restaurant	Clothing Store	Coffee Shop	Electronics Store
42730	34060	Platform	Breakfast Spot	History Museum	Sculpture Garden	Park	Café	Outdoor Sculpture	Track Stadium
37610	31840	Hotel	Coffee Shop	Gym / Fitness Center	Castle	Scenic Lookout	Garden	French Restaurant	Hotel Bar
38230	30990	Thai Restaurant	Deli / Bodega	Food & Drink Shop	Music Venue	Restaurant	Cosmetics Shop	Bakery	Hostel
41980	33600	Coffee Shop	Pizza Place	Supermarket	Fast Food Restaurant	Platform	Sushi Restaurant	Café	Sandwich Place
37780	30240	Coffee Shop	Fish & Chips Shop	Trail	Train Station	Park	Film Studio	Farm	Farmers Market
39690	33160	Gym / Fitness Center	Café	Grocery Store	Furniture / Home Store	Warehouse Store	Clothing Store	Supermarket	Pizza Place

41520	33820	Chinese Restaurant	Irish Pub	Fast Food Restaurant	Warehouse Store	Yoga Studio	Fish Market	Farm	Farmers Market
43660	36150	Platform	Grocery Store	Fried Chicken Joint	Train Station	Coffee Shop	Chinese Restaurant	Park	Fast Food Restaurant
33620	27030	Pub	Movie Theater	Train Station	Middle Eastern Restaurant	Outdoors & Recreation	Rental Car Location	Food & Drink Shop	Food
37560	31450	Nature Preserve	Park	Pub	Grocery Store	Skating Rink	Yoga Studio	Fish & Chips Shop	Fast Food Restaurant
38070	31520	Coffee Shop	Café	Pub	Grocery Store	Gastropub	Cocktail Bar	Plaza	Supermarket
38900	30030	Grocery Store	Pub	Coffee Shop	Italian Restaurant	Bus Stop	Bar	Cocktail Bar	Supermarket
35810	28560	Train Station	Pub	Supermarket	Playground	Fast Food Restaurant	Turkish Restaurant	Film Studio	Falafel Restaurant
40880	30320	Pub	Bakery	Café	Supermarket	Food & Drink Shop	Grocery Store	Bus Stop	Bar
47830	36970	Café	Park	Gym	Athletics & Sports	Metro Station	Scenic Lookout	Grocery Store	Food Truck
42350	34480	Irish Pub	Pub	Fast Food Restaurant	Train Station	Supermarket	Yoga Studio	Fish Market	Farm
37720	31040	Breakfast Spot	Coffee Shop	River	Park	Yoga Studio	Fish Market	Farmers Market	Fast Food Restaurant
32250	25800	Brewery	Café	Park	Canal Lock	Yoga Studio	Flower Shop	Field	Film Studio
40960	33720	Platform	Mediterranean Restaurant	Massage Studio	Gym Pool	Pharmacy	Train Station	Coffee Shop	Sandwich Place
37600	28920	Turkish Restaurant	Café	Coffee Shop	Bus Stop	Grocery Store	Fried Chicken Joint	Park	Chinese Restaurant
35720	27340	Platform	Café	Gym	Park	Coffee Shop	Clothing Store	Bar	Fast Food Restaurant

Neighbours in Cluster 4 have incomes significantly below the average for London. However, there is still a lot of activity. There are many pubs, restaurants and sports centres for the neighbours. This could be an option for a businessman wishing to open a company relating to sport, yet it should be noted that the prices should likely be low for the venue to be successful.

Cluster 5:

Mean 2012/13	Median 2012/13	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
39630	31540	Playground	Grocery Store	Campground	Cosmetics Shop	Flea Market	Farmers Market	Fast Food Restaurant	Field
46520	38070	Park	Fast Food Restaurant	Café	Grocery Store	Chinese Restaurant	Tram Station	Bakery	Yoga Studio
37860	31340	Grocery Store	Gym	Event Service	Train Station	Park	Yoga Studio	Farm	Fast Food Restaurant
47740	37940	Grocery Store	Construction & Landscaping	Thai Restaurant	Bus Stop	Park	Coffee Shop	Historic Site	Soccer Stadium
52190	38960	Bus Stop	Health & Beauty Service	Food Truck	Grocery Store	Coffee Shop	Fish & Chips Shop	Farmers Market	Fast Food Restaurant
41250	34450	Grocery Store	Chinese Restaurant	Electronics Store	Fish Market	Farmers Market	Fast Food Restaurant	Field	Film Studio
39140	31150	Grocery Store	Fast Food Restaurant	Restaurant	Park	Yoga Studio	Fish Market	Farmers Market	Field
46190	37990	Kids Store	Café	Grocery Store	Gastropub	Yoga Studio	Flea Market	Fast Food Restaurant	Field
51560	38530	Grocery Store	Pizza Place	Chinese Restaurant	Middle Eastern Restaurant	Irish Pub	Turkish Restaurant	Plaza	Coffee Shop
54850	44160	Platform	Cricket Ground	Grocery Store	Train Station	Fish Market	Farmers Market	Fast Food Restaurant	Field
37090	31040	Hotel	Farm	Grocery Store	Restaurant	Park	Fish & Chips Shop	Farmers Market	Fast Food Restaurant
35060	28770	Grocery Store	Bakery	Gas Station	Convenience Store	Tram Station	Fish & Chips Shop	Farm	Farmers Market
44610	37130	Grocery Store	Chinese Restaurant	Electronics Store	Fish Market	Farmers Market	Fast Food Restaurant	Field	Film Studio

Citizens in Cluster 5 have median incomes below average yet have quite high mean incomes. This shows a considerable amount of high-income families and a poor counterpart. Either of these two sectors could be targeted. There are expensive venues, such as soccer stadiums and gastropubs, as well as cheap ones, such as fish and chips shops and fast food restaurants.

Cluster 6:

Ward	Latitude	Longitude	Mean 2012/13	Median 2012/13	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
Mill Hill	51.615442	-0.233068	56660	41920	Pharmacy	Park	Athletics & Sports	Yoga Studio	Falafel Restaurant	Farmers Market	Fast Food Restaurant	Field

Cluster 6 is formed by a unique ward: Mill Hill. Businessmen should study it carefully before setting up there, as the average income is very high and there are a variety of venues already set up.

Cluster 7:

Mean 2012/13	Median 2012/13	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
76280	53420	Coffee Shop	Pub	Pizza Place	Bakery	Café	Indian Restaurant	Supermarket	Steakhouse
80160	55450	Park	Food & Drink Shop	Restaurant	Bookstore	Thai Restaurant	Café	Coffee Shop	Bakery
62770	44970	Grocery Store	Park	Pub	Café	Gastropub	Caucasian Restaurant	African Restaurant	Bar
85610	49960	Hotel	Pub	Coffee Shop	Chinese Restaurant	Café	Greek Restaurant	Garden	Persian Restaurant
61330	47190	Bus Stop	Cricket Ground	Train Station	Home Service	Yoga Studio	Fish Market	Farmers Market	Fast Food Restaurant
139710	64320	Hotel	Bakery	Burger Joint	Ice Cream Shop	Pizza Place	Café	Garden	Italian Restaurant
58070	46220	Italian Restaurant	Pub	Grocery Store	Coffee Shop	American Restaurant	Train Station	Soccer Field	Gastropub
59910	46250	Pub	Italian Restaurant	Indian Restaurant	Memorial Site	Pizza Place	Gastropub	Food & Drink Shop	Food
70560	52070	Pub	Coffee Shop	Café	Grocery Store	Bakery	Indie Movie Theater	Japanese Restaurant	Pizza Place
61190	44360	Pub	Thai Restaurant	Grocery Store	Lounge	Platform	Pharmacy	Performing Arts Venue	Café
64860	48670	Café	Pub	Indian Restaurant	Ice Cream Shop	Gastropub	Burger Joint	Indie Movie Theater	Fish Market
81320	56090	Coffee Shop	Pub	Pizza Place	Café	Italian Restaurant	Grocery Store	Creperie	Chinese Restaurant
67140	49950	Italian Restaurant	Pub	Wine Shop	Café	Deli / Bodega	Furniture / Home Store	Indian Restaurant	Mediterranean Restaurant

The neighbours of Cluster 7 are the ones with the highest average income. This is reflected in the venues offered, as there are bodegas and Persian restaurants, for example, which are more select than the fast food restaurants offered in other wards. Cluster 7 is the opportunity for businessmen with more special ideas to succeed, as the high costs of production these usually have can be covered by the high price that can be charged here.

Cluster 8:

Mean 2012/13	Median 2012/13	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
45990	38200	Pizza Place	Pub	Grocery Store	Middle Eastern Restaurant	Train Station	Fish Market	Farmers Market	Fast Food Restaurant
52070	40930	Airport Terminal	Convenience Store	Pub	Café	Grocery Store	Music Venue	Flea Market	Fast Food Restaurant
46500	38230	Pub	Wine Shop	Restaurant	Café	Music Venue	Modern European Restaurant	Creperie	Gastropub
53550	39870	Café	Chinese Restaurant	Pub	Grocery Store	Coffee Shop	Fish Market	Farmers Market	Fast Food Restaurant
36850	29450	Pub	Sports Club	Grocery Store	Fast Food Restaurant	Flea Market	Farmers Market	Field	Film Studio
46160	36650	Café	Pub	Indian Restaurant	Nature Preserve	Breakfast Spot	Train Station	Yoga Studio	Flea Market
44860	37010	Pub	Café	Grocery Store	Automotive Shop	Yoga Studio	Fish Market	Farmers Market	Fast Food Restaurant
52520	40260	Pub	Hotel	Supermarket	Farmers Market	Park	Thai Restaurant	Bakery	Pizza Place
43770	34790	Pub	Breakfast Spot	Grocery Store	Fast Food Restaurant	Memorial Site	Coffee Shop	Chinese Restaurant	Gym / Fitness Center
42750	34640	Pub	Bakery	Indian Restaurant	Park	Train Station	Restaurant	Brazilian Restaurant	Wine Shop
48990	40290	Pub	Bakery	Park	Grocery Store	Coffee Shop	Gym / Fitness Center	Café	Food & Drink Shop
46400	38700	Pub	Café	Pharmacy	Supermarket	Fast Food Restaurant	Metro Station	Mediterranean Restaurant	Grocery Store
52260	38730	Pub	Garden Center	Yoga Studio	Fish Market	Farm	Farmers Market	Fast Food Restaurant	Field

The neighbours in Cluster 8 have incomes close to the average in London. Pubs are the most common type of venue in this cluster, as well as a group of culture-related activities, such as memorial sites, nature preserves, wine shops and film studios. Businessmen in the culture sector, as well as ones looking to set up, could find what they were looking for in Cluster 8.

Conclusion

There are nearly 200 wards in London. There are therefore many communities where businesses could be set up. However, these differ in terms of income and venues already available. For existing business owners, it is important to look for wards similar to that where the business is already successful to try to reproduce that elsewhere. It is more complex for entrepreneurs wishing to set up a new company, as the characteristics of the different clusters could be seen as positive or negative due to competition. These people should decide based on the type of venue they wish to set up.