

# Capstone project - Capstone London Restaurant

By Andy Brierly

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## Executive summary

This report describes the data science analysis performed on London districts to determine suitable candidates for locating a new Vegan takeaway restaurant.

The analysis focuses on two adjacent boroughs: Westminster and Camden, which are found to have relatively high consumer expenditure on food, high spending growth projections and large populations aged 16-29, which is my target demographic for this industry.

Having chosen these boroughs, I examined data for spending on takeaway food at a local postal district level to identify the optimal locations for a business that is likely to have a delivery range of 2 km. Clustering analysis was also applied to the data, in order to see how relative location and expenditure interacted.

The optimal locations were found to be around West Hampstead, Belsize Park and Bayswater.

I then utilized Foursquare's APIs to identify where existing Vegan can be found around my target areas. There is strong clustering around Camden Town and Bayswater, but limited offerings in Hampstead/Belsize Park. I therefore recommend the Hampstead/Bayswater area for further analysis, including costs to operate such a business and local consumer preferences through primary market research.

## 1. Problem & Background

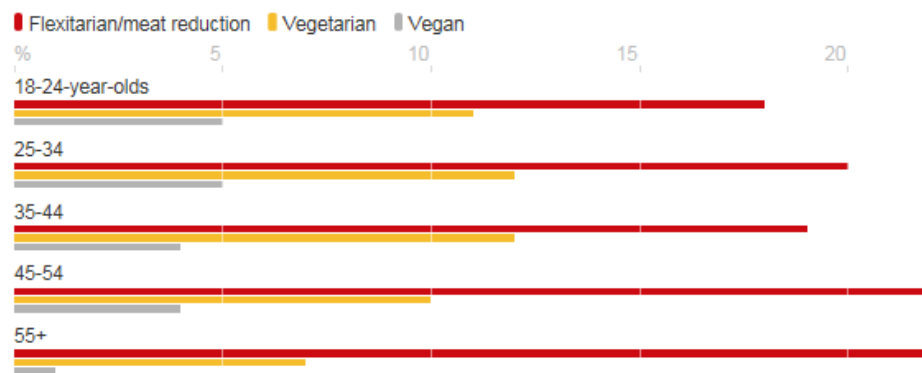
*Define a problem where you need to leverage the Foursquare location data. Describe the audience and why they would care about the problem.*

My client is looking to establish a new vegan restaurant business in London. The business will prepare vegan meals and deliver to homes, primarily within a 2km radius. The location of the business is key to its success, given the local nature of the business.

The client has chosen London as their target city, due to its young, multicultural and fast growing population, and wishes to identify the best area to set up, based on:

- Density of young residents;
- Propensity of local residents to spend on take-away food; and
- Economic growth prospects of the area.

The vegan restaurant sector is a fast growing market, and is particularly in demand with the younger demographics (18-34 year olds), as evidenced by research from the high-end supermarket chain Waitrose:



Guardian Graphic | Source: Waitrose food and drink report 2018-19

The client has requested an analysis of London to help them identify potential areas to establish the business. The analysis will be based on public data to identify postcodes with a large youth population, high consumer expenditure on food and takeaways and high growth projections. Foursquare will then be used to assess existing competition in these areas so that the client can judge where they are likely to be most successful.

For the purpose of this analysis, we will first identify London boroughs which best meet the three criteria set out by the client, and then look at a postcode level to assess which areas have the highest expenditure on take-away food. We can then select from these postal areas based on the Foursquare competitor data for 'Vegetarian & Vegan Restaurants'.

The analysis could later be extended to other cities or looking at the three criteria at a more granular postal level. This approach could also be used for other clients looking at different types of restaurant.

## 2. Data and how it will be used to solve the problem

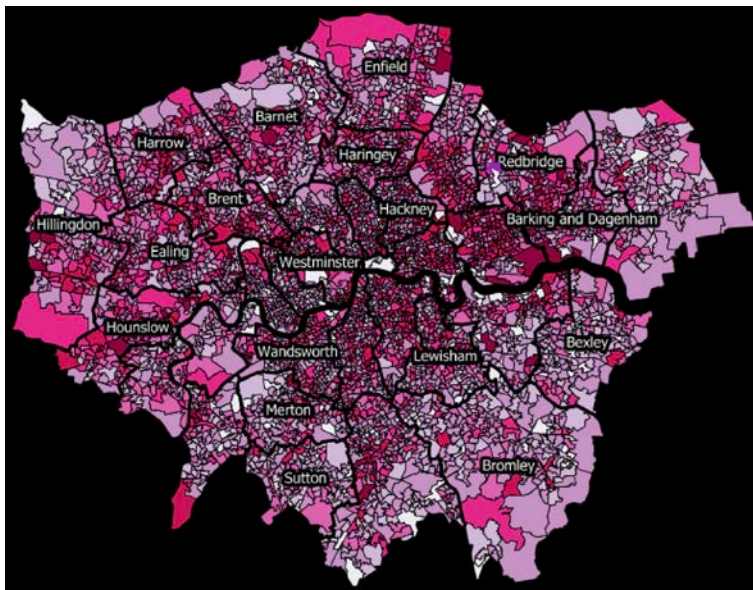
*Describe the data you will use to solve the problem. Need to include Foursquare data. Explain and discuss, with examples, data you will use.*

There are numerous sources of data on London demographics, economics and geography.

For this project, I will need data at a UK Borough level on population by age group, household expenditure on food and the local economic growth. I will then need data at a more granular postal code level showing spending on takeaway food. For both boroughs and postal areas, I will need data to map to longitude/latitude coordinates, in order to plot maps of the analysis.

Mango Map provides useful demographic data on London

(<https://mangomap.com/demographics/maps>) sourced from the Greater London Authority's Map Portal. The London Demographics Map Portal is a free and open data-sharing portal for demographic



data relating to the UK capital. The Portal provides a csv table with the following fields:

lsoallcd	object	hholds	int64	a_h_w_chil	int64
lsoallnm	object	avhholds	float64	a_h_wo_chi	int64
msoallcd	object	a_pop	int64	a_sing_par	int64
msoallnm	object	a_p0_15	int64	a_h_w_one	int64
ladl1cd	object	a_p16_29	int64	a_h_other	int64
ladl1nm	object	a_p30_44	int64	a_h_w_ch_1	float64
rgnl1cd	object	a_p45_64	int64	a_h_wo_c_1	float64
rgnl1nm	object	a_p65o	int64	a_sin_parp	float64
usualres	int64	a_working_	int64	a_h_w_onep	float64
hholdres	int64	a_area_h	float64	a_h_other_	float64
comestres	int64	a_peo_per_	int64		
popden	float64	a_househ	int64		

The fields we need are lad11nm (Local Authority District 2011 name) and a\_p16\_29 (Population of 16-29 year olds). We will use this age category as a close proxy for the desired 18-34 category.

For the economics of each borough, the UK Office for National Statistics (ONS) publishes lots of relevant data.



In particular, it provides comprehensive country-wide data on gross disposable household income (GDHI) per head for NUTS3 local areas (boroughs) at <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/bulletins/regionalgrossdisposablehouseholdincomegdhi/1997to2016> .

The ONS site provides a CSV table with 'NUTS3' local area name and gross disposable household income for each year from 1997 to 2017 (with a column for each year). We will just use the AREANM and the 2017 columns.

The third key source will be the London Government DataStore.

## LONDON DATASTORE

The London DataStore has current and projected data on expenditure by consumers in each London postal area on a range of categories, including Food, Restaurants and Takeaway food at <https://data.london.gov.uk/dataset/london-consumer-expenditure-estimates-2011-2036>. This will tell us both which areas spend the most on take-away food and which areas have the greatest growth prospects.

The site has a number of databases on London Consumer Expenditure projections from 2011 to 2036, each with a different level of granularity. The data was produced in 2011 so is a bit old, but the provision of projections gives a good proxy for 2019 and an approximation of 2019-2029 10-year growth prospects.

The data is provided as a spreadsheet with a worksheet for each city ('Greater London') for the regional level data and a worksheet for each Borough for the Postal Base level database. For the regional level database, the sheet has borough, sector and a column for expenditure projected for each year. The sectors covered are:

- |   |   |
|---|---|
| • Food  | • Household Goods and Services                    |
| • Non-alcoholic beverages                                 | • Medical Products                                |
| • Alcoholic beverages                                     | • Medical Services                                |
| • Tobacco   | • Purchase of vehicles                            |
| • Clothing and footwear                                   | • Operation of personal transport equipment       |
| • Actual rentals for housing                              | • Transport services                              |
| • Imputed rentals for housing                             | • Postal services                                 |
| • Maintenance and repair of the dwelling                  | • Telecommunications Services                     |
| • Water supply and miscellaneous services relating to the | • Audio-visual                                    |
| • Electricity, gas & other fuels                          | • Other major durables for recreation and culture |
| • Furniture & Textiles                                    | • Other recreational items and equipment          |

For the Postal Base data, each borough worksheet lists the abbreviated postcode (postcode area plus the first number of the postcode district), sector and a column for expenditure projected for each year.

Sectors include:

- Convenience
- Comparison – Bulky
- Comparison - Not Bulky
- DIY
- Gardening
- Accommodation Services
- Restaurants and Cafes
- Takeaway / Snack Spending
- On Licence (i.e. Pubs & Wine Bars)
- Leisure
- Other Goods and Services
- Other Spending (Mostly Household related, Health and Education)

Finally, I will use the ONS Postcode Directory from Open Postcode Geo, provided on the 'get the data' site (<https://www.getthedata.com/open-postcode-geo>), to get data to map boroughs and postal areas to longitude/latitude coordinates. The table is very big and lists every postcode in the UK. We will need to map our abbreviated postcodes to this data.

Foursquare will then provide the data we need to establish what other Vegetarian & Vegan restaurants exist in each area. Foursquare includes a category for Vegetarian & Vegan Restaurant venues (category ID: 4bf58dd8d48988d1d3941735). We will look for any such venues within 2km of our selected postal areas, as this is the typical delivery range for such a business.

### 3. Methodology

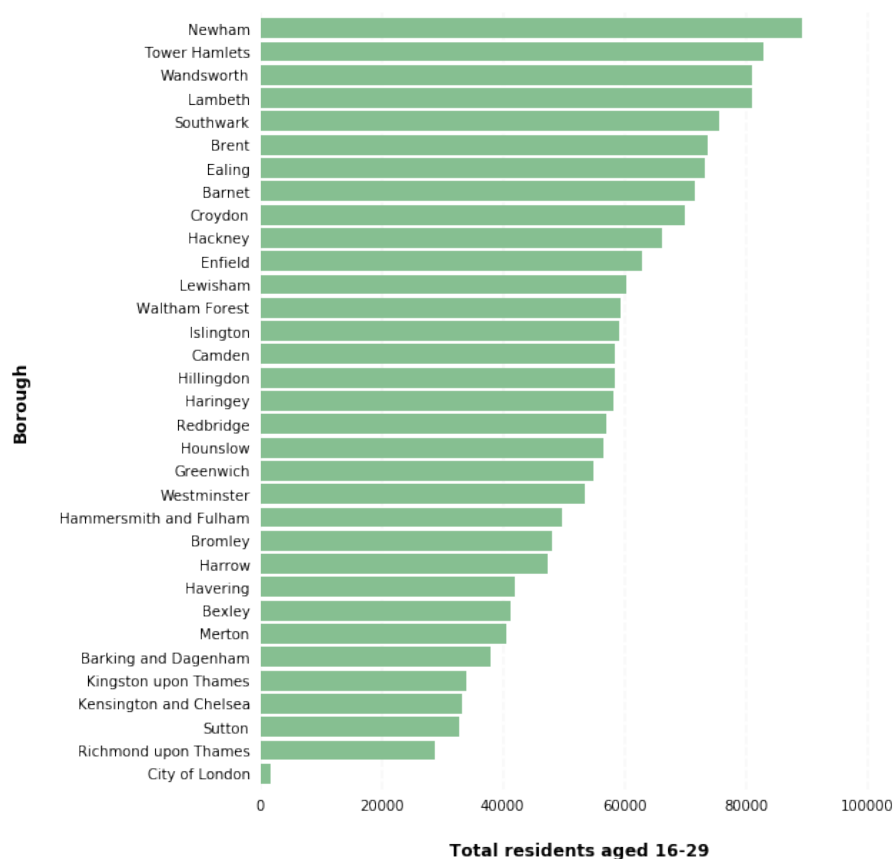
#### 3.1 Exploratory data analysis

Mango Map provides useful demographic data on London (<https://mangomap.com/demographics/maps>) sourced from the Greater London Authority's Map Portal. The London Demographics Map Portal is a free and open data-sharing portal for demographic

A CSV file was downloaded from MangoMap with the number of residents by age group and family size for each 'Lower Layer Super Output Area code' (Isoa11cd) in London – this was then grouped by 'Local Area District name' (lad11nm), which represents a borough and the column 'a\_p16\_29' selected to give number of residents between 16 and 29 (as a close proxy for the target 18-34 years target market).

Isoa11cd	Isoa11nm	lad11cd	lad11nm	...	a_h_w _ch_1	a_h_wo _c_1	a_sin _parp	a_h_w _onep	a_h _other_
E01000001	City of London 001A	E09000001	City of London	...	7.6	30.6	2.6	51.7	7.4
E01000002	City of London 001B	E09000001	City of London	...	10.4	30.7	2.7	50.4	5.9
E01000003	City of London 001C	E09000001	City of London	...	6.2	19.1	6.0	62.1	6.6
E01000005	City of London 001E	E09000001	City of London	...	13.1	14.3	9.4	48.8	14.3
E01000006	Barking and Dagenham 016A	E09000002	Barking and Dagenham	...	25.6	21.7	9.9	17.9	24.9

The bar graph below shows the dataset, sorted by young population size:



Gross disposable household income (GDHI) per head stats by Area District were then obtained from the UK office for National Statistics to data to the population dataset. The ONS provides a CSV file at <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/bulletins/regionalgrossdisposablehouseholdincomegdhi/1997to2016>, showing GDHI going back to 1997:

AREANM	AREACD	1997	1998	1999	2000	2001	...	2013	2014	2015	2016	2017
Hartlepool and Stockton-on-Tees	UKC11	9245	9332	9714	10238	10677	...	14717	15097	15498	15432	15782
South Teesside	UKC12	8961	8768	9146	9771	10239	...	14083	14572	14959	14835	14955
Darlington	UKC13	9612	9626	9699	10634	11483	...	14691	14828	15486	15916	15953
Durham CC	UKC14	9219	9547	9831	10423	10821	...	14391	14697	15276	15166	15445
Northumberland	UKC21	10279	10534	10957	11766	12219	...	17623	17810	18463	18498	18855

However, when this is merged with the youth population dataset, it can be seen that the ONS data does not exist for over half of the boroughs. Further investigation found that collection of this data by the UK Government has been sporadic and many of the London boroughs were grouped together:

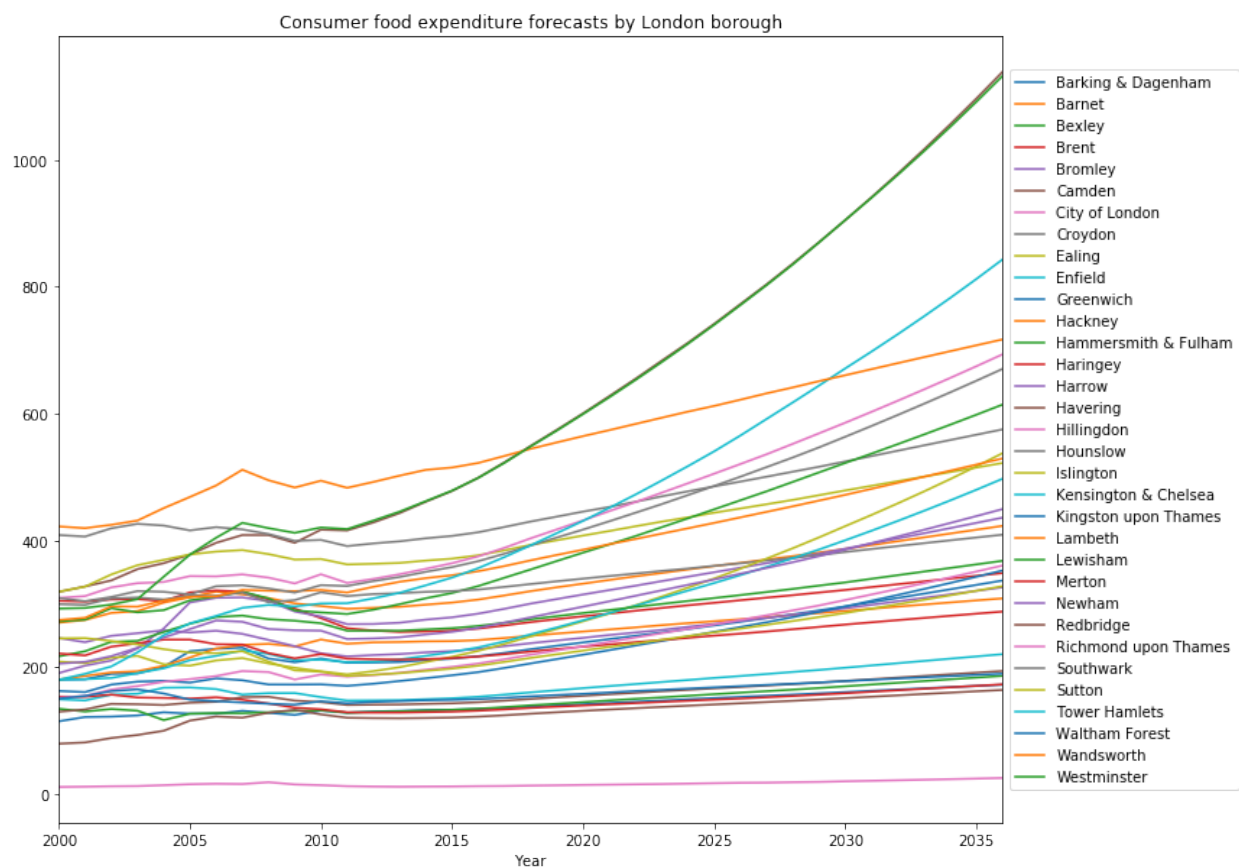
Borough	YoungPop	HH Income
City of London	1665	NaN
Richmond upon Thames	28810	NaN
Sutton	32859	NaN
Kensington and Chelsea	33262	NaN
Kingston upon Thames	33928	NaN
Barking and Dagenham	38075	NaN
Merton	40596	NaN
Bexley	41350	NaN
Havering	41864	NaN
Harrow	47384	NaN
Bromley	48100	28338.0
Hammersmith and Fulham	49666	NaN
Westminster	53409	53101.0
Greenwich	55021	NaN
Hounslow	56556	NaN
Redbridge	56956	NaN
Haringey	58201	NaN
Hillingdon	58448	NaN
Camden	58504	NaN
Islington	59162	NaN
Waltham Forest	59297	NaN
Lewisham	60276	NaN
Enfield	62941	23084.0
Hackney	66195	NaN
Croydon	69937	22608.0
Barnet	71568	28950.0
Ealing	73200	26705.0
Brent	73764	23568.0
Southwark	75703	NaN
Lambeth	80940	27393.0
Wandsworth	81078	37129.0
Tower Hamlets	82938	24748.0
Newham	89345	NaN

Accordingly, an alternative data source needed to be found.

The London Government also collects data, which is available from a number of sites, including the London Datastore. A number of spreadsheets are available for download with consumer spending data by Area/District and by Sector. The data is 6 years old, but includes projections out to 2036 and for my purposes is sufficient to get an estimate of which London boroughs spend more and what their growth prospects look like.

A spreadsheet by UK Borough is available at <https://data.london.gov.uk/dataset/london-consumer-expenditure-estimates-2011-2036>, and has a worksheet for 'Greater London'. The data has numerous Sector classifications, but of particular interest are 'Food' expenditure and 'Restaurant/Hotel' expenditure.

The line graph below gives a sense of the overall data, although the large number of boroughs plotted makes it difficult to form conclusions on individual boroughs. This graph just looks at the 'Food' sector.



To make use of this data, I pulled the projected 2019 expenditure by borough and the 10 year growth projection from 2019 to 2029, for both the 'Food' and 'Restaurant/Hotel' sectors. I then averaged the spending and growth data for the two sectors.



Before manipulating the data, some cleansing was required to take ‘\xa0’ markers out of the sector names:

```
exp_df_summ['Sector'].unique().tolist():
- 'Food',
- 'Non-alcoholic beverages',
- 'Alcoholic beverages',
- 'Tobacco',
- 'Clothing and footwear\xa0\xa0\xa0\xa0\xa0 ',
- 'Actual rentals for housing\xa0\xa0\xa0\xa0\xa0 ',
- 'Imputed rentals for housing\xa0\xa0\xa0\xa0\xa0 ',
- 'Maintenance and repair of the dwelling\xa0\xa0\xa0 ',
- 'Water supply and miscellaneous services relating to the\xa0 ',
- 'Electricity, gas & other fuels\xa0 ',
- 'Furniture & Textiles',
- 'Household Goods and Services',
- 'Medical Products',
- 'Medical Services',
- 'Purchase of vehicles\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Operation of personal transport equipment\xa0\xa0\xa0\xa0 ',
- 'Transport services\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Postal services\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Telecommunications Services',
- 'Audio-visual\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Other major durables for recreation and culture\xa0\xa0 ',
- 'Other recreational items and equipment\xa0\xa0\xa0\xa0 ',
- 'Recreational and cultural services\xa0\xa0\xa0\xa0\xa0 ',
- 'Newspapers\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Education\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Restaurants and hotels\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Personal care\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Personal effects n.e.c.\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Social protection\xa0\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Insurance\xa0\xa0\xa0\xa0\xa0\xa0\xa0 \xa0\xa0\xa0',
- 'Other services n.e.c.\xa0\xa0\xa0\xa0\xa0\xa0\xa0 ',
- 'Financial services not elsewhere classified\xa0\xa0\xa0\xa0 '
```

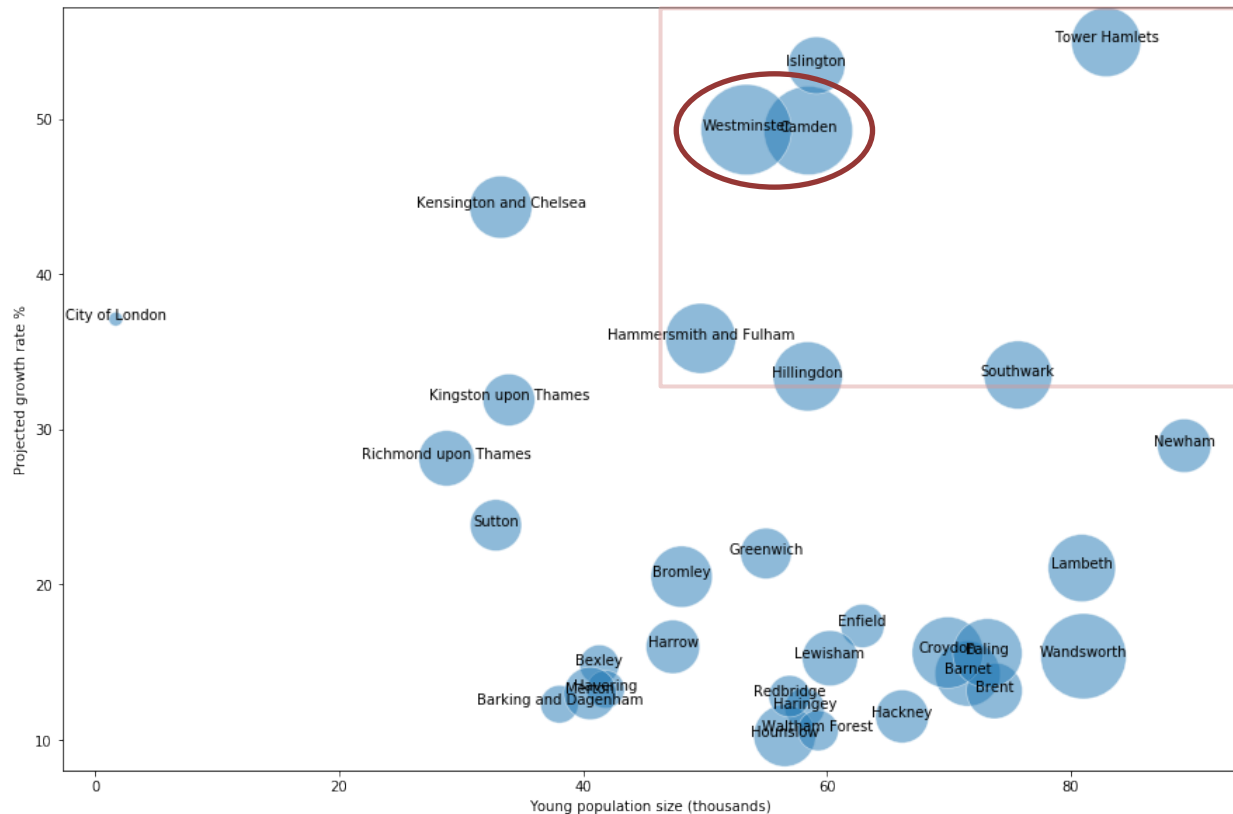
The data for the two sectors of interest were then merged, using:

```
exp_by_sect_df=pd.merge(exp_df_summ.loc[exp_df_summ['Sector']=='Food'].drop(['Sector'],axis=1),exp_df_summ.loc[exp_df_summ['Sector']=='Restaurants and hotels'].drop(['Sector'],axis=1), on='Borough', how='left')
```

After cleaning up the resulting headers and replacing ‘&’ with ‘and’ in the borough names, I had a good of dataset to which I could pull in the Young Population data:

Borough	Food expense 2019 (£m)	Food expense 10- year growth %	Restaurant/h otel expense 2019 (£m)	Restaurant/ hotel expense 10- yr growth %	YoungPop	Proxy target expend (£m)	Proxy target growth (%)
<b>Barking and Dagenham</b>	139.459832	13.632997	150.136859	10.961922	38075.0	144.798345	12.297460
<b>Barnet</b>	325.729451	16.839942	536.230612	11.694674	71568.0	430.980031	14.267308
<b>Bexley</b>	142.054816	17.470357	173.469754	12.230595	41350.0	157.762285	14.850476
<b>Brent</b>	275.468368	15.245147	359.809723	11.087088	73764.0	317.639045	13.166117
<b>Bromley</b>	307.162455	23.295505	458.088407	17.730780	48100.0	382.625431	20.513142
<b>Camden</b>	574.056731	51.546955	1016.272700	46.945783	58504.0	795.164715	49.246369
<b>City of London</b>	13.486068	39.832934	26.132142	34.380094	1665.0	19.809105	37.106514

This dataset was then plotted as a bubble chart, with growth on the y-axis, young population on the x-axis and expenditure driving the bubble size:



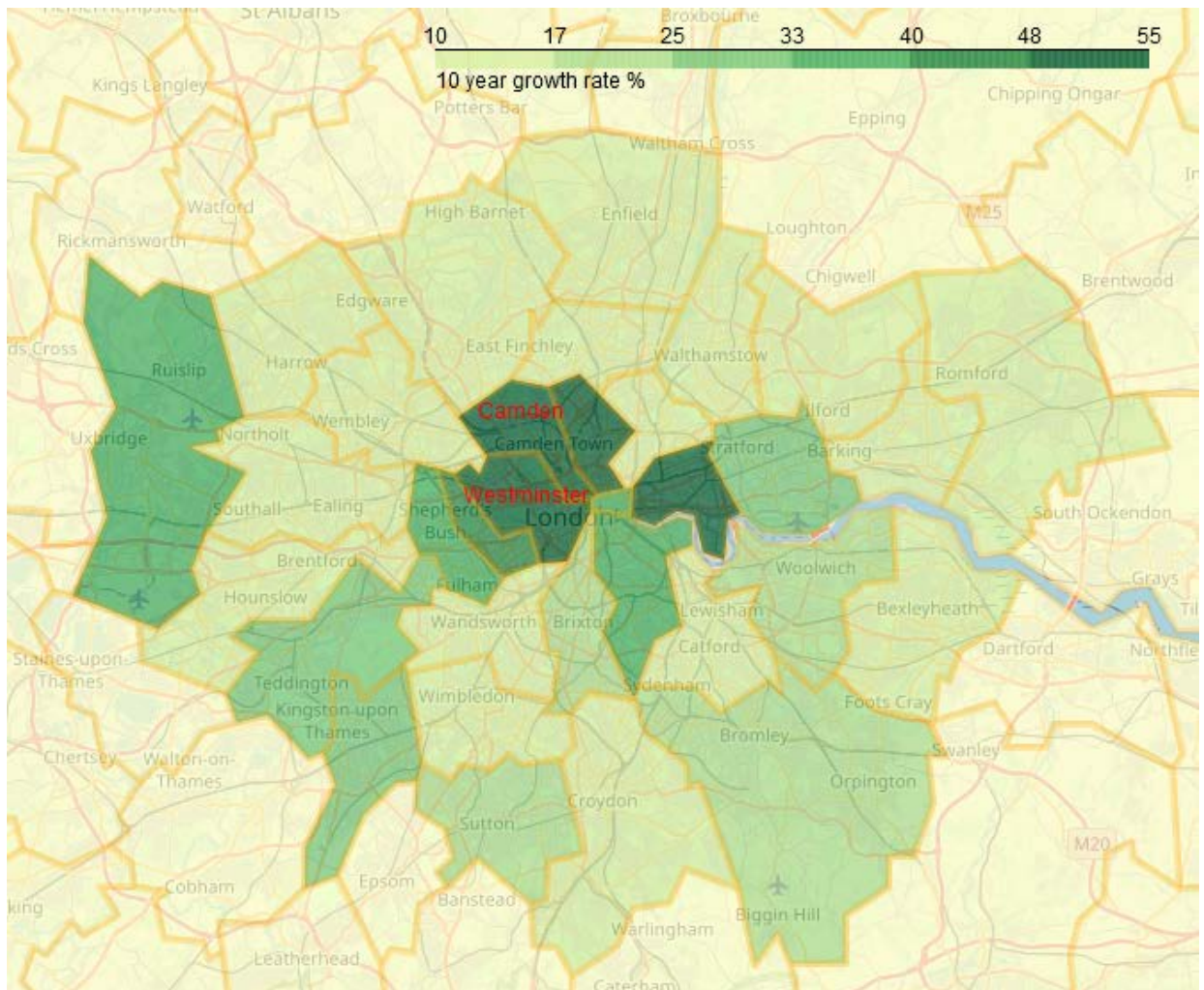
Based on the analysis, I will select Westminster and Camden from the upper quartile as the two boroughs to pursue, as they both have a large young population (over 50,000), high growth prospects (around 50% over the next 10 years) and large current household expenditure on food/restaurants (around £800m forecast for in 2019).

However, if these two boroughs prove to be unsuitable when the analysis moves to the more granular level, there is clearly an opportunity to go back and run the detailed analysis on the smaller markets: Tower Hamlets, Islington and potentially Hammersmith, Hillingdon and Southwark.

### 3.2 Inferential statistical testing/mapping London

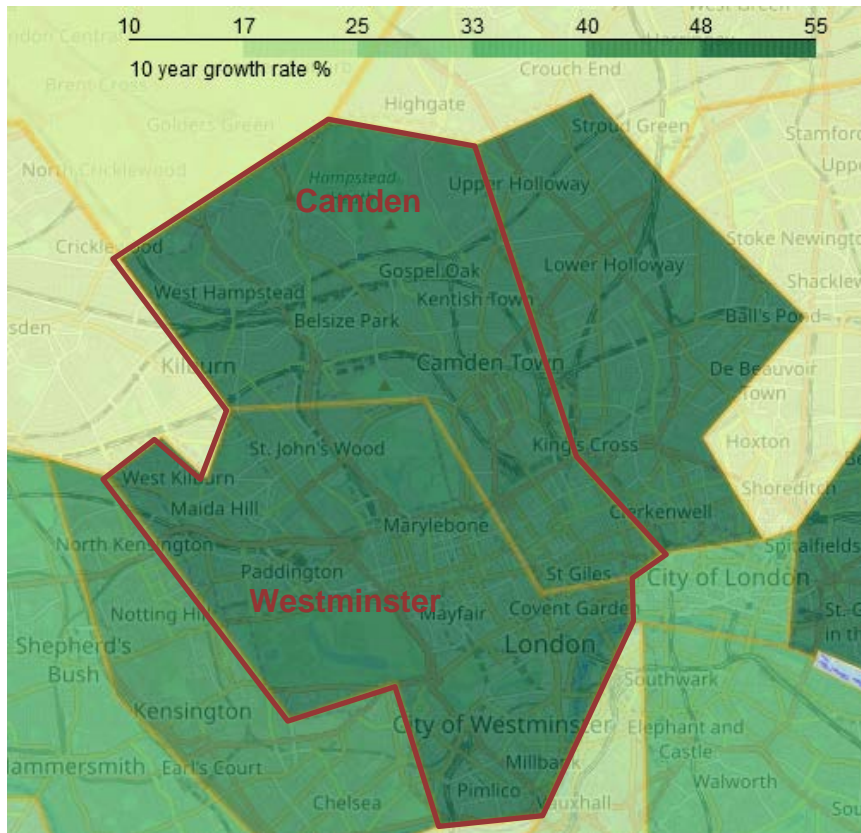
The initial data analysis pointed at Westminster and Camden as the target boroughs. The next step was to analyze the geography at a more granular level and map the findings.

The first step was to obtain GeoData to visualize the trends on maps. A GeoData geojson file was obtained from the UK Office for National Statistics Open Geography Portal (<https://geoportal.statistics.gov.uk/datasets/local-authority-districts-april-2019-boundaries-uk-buc>) and plotted using the folium map choropleth methods. The chart below uses the growth data for the choropleth shading:



Camden and Westminster clearly stand out as two of four higher growth boroughs. Islington and Tower Hamlets are the other two, but we know from the bubble chart they both have lower current expenditure.

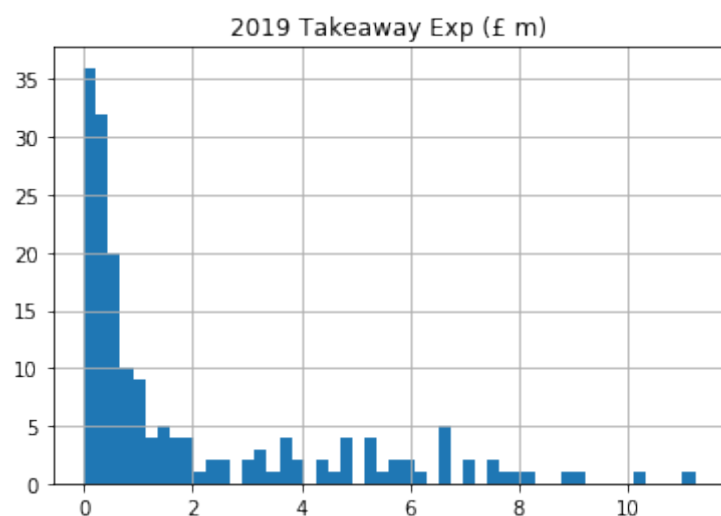
Next we hone in on Camden and Westminster, and analyse expenditure at a local level, before locating existing vegan restaurants:



The 'London Consumer Expenditure Estimates 2011-2036' datasets on the London Datastore site includes projections by postal district for Greater London, including a sector for 'Takeaways and snacks' in a spreadsheet with worksheets for each borough (aggregated-postal-base-greater-london.xls).

I read in the 2019 Takeaway data from the Camden and Westminster worksheets, cleansed the data and combined the two tables to get expenditure for each postal district. This is then illustrated in a histogram of expenditure by postal districts in the combined boroughs.

The histogram shows the vast majority of postcodes spend less than a million. Camden and Westminster together have 174 postcodes, but only 26 spend £5m or more. I therefore focused on those postal districts spending at least £5m on Takeaway food.





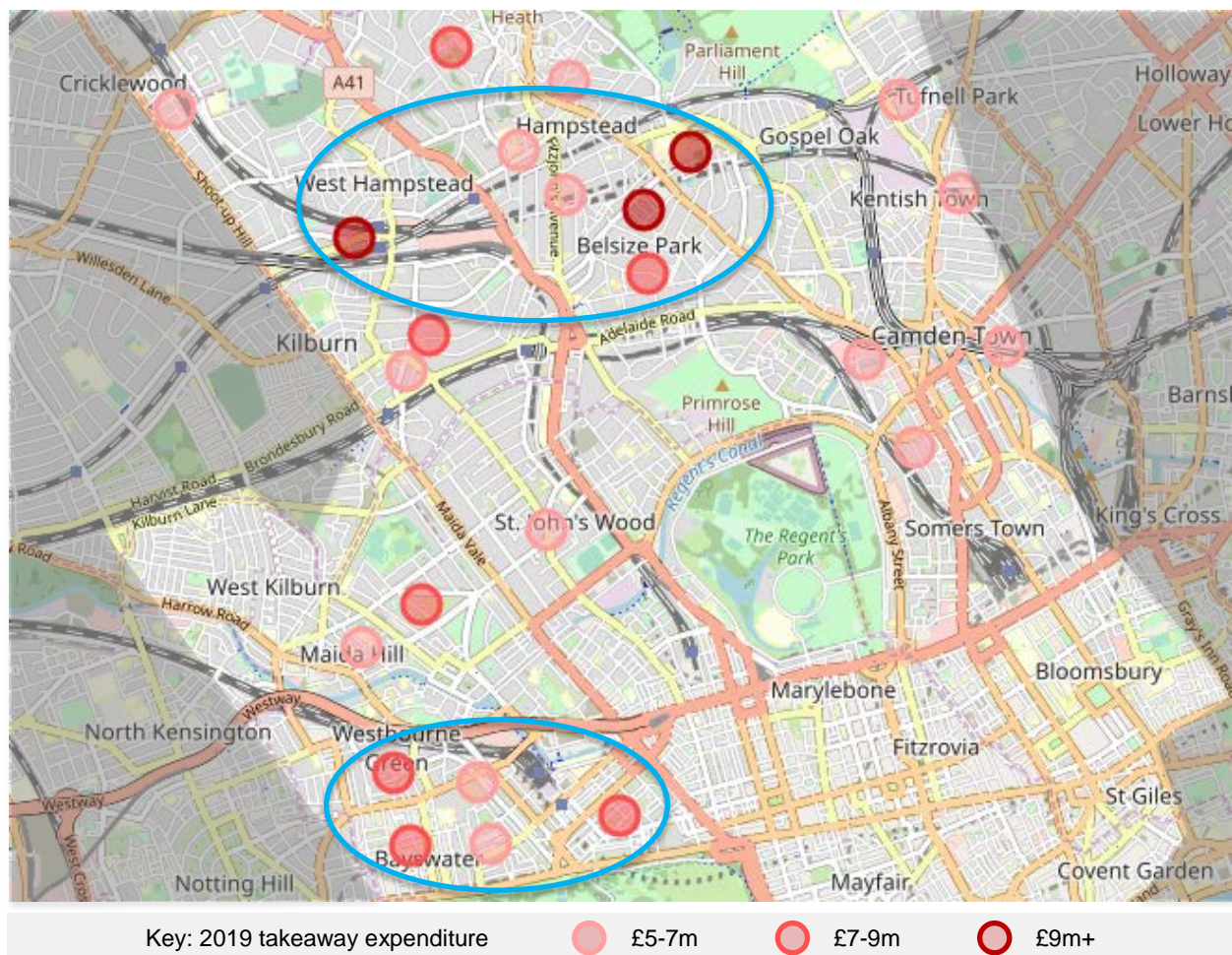
In order to show these 26 locations on a map, I needed to add longitude/latitude coordinates for the center points of each postal district in the table. For this, I used the ONS Postcode Directory from Open Postcode Geo, provided on the 'get the data' site (<https://www.getthedata.com/open-postcode-geo>), which gives coordinates for every postal district (and sub-district) across the UK.

The index of the Postcode directory required some processing to map the summarized 5-digit postcodes used for my Postal Districts to the 7-digit full postcodes in the ONS data. Some longitude/latitude fields of the ONS data also included noise in the data which needed cleansing.

However, after processing, the result was a clean table of Takeaway expenditure by postal district and longitude/latitude coordinates:

	Postcode	Takeaway Exp (£ m)	Latitude	Longitude
0	EC1M3	0.150362	51.521129	-0.107445
1	EC1N6	0.000618	51.518867	-0.107598
2	EC1N7	0.803023	51.520733	-0.110733
3	EC1N8	0.570774	51.520619	-0.108745
4	EC1R5	0.400891	51.522533	-0.110597

This data was then added to the folium map as red circles for each postal district over £5m in Takeaway expenditure (darker reds representing higher spend) - the higher spending postcodes are around Hampstead/Belsize Park and Bayswater.



Finally, I needed to plot existing Vegan restaurants from FourSquare on the map. FourSquare has a venue category for Vegetarian and Vegan Restaurants, making it straight forward to pull a list of relevant competitors within 2km of each £5m+ postal district:

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude
NW17/ NW18	51.535875	-0.142984	Purezza	51.538154	-0.144345
NW17	51.535875	-0.142984	What The Pitta	51.537937	-0.140377
NW17/ NW18	51.535875	-0.142984	Dou Dou Restaurant	51.539656	-0.142405
NW18	51.540880	-0.147668	Mildred's Camden	51.540560	-0.144939
NW18	51.540880	-0.147668	Young Vegans	51.541454	-0.146686
NW18	51.540880	-0.147668	Hawraman Cafe Bar	51.542902	-0.148172
NW18	51.540880	-0.147668	Rudy's Dirty Vegan Diner	51.542488	-0.148512
NW18	51.540880	-0.147668	Campbell's Canal Café	51.541387	-0.144801
NW18	51.540880	-0.147668	VBurger	51.541721	-0.146278
NW19	51.541688	-0.134729	Buttercream Dreams	51.543477	-0.140240
NW19	51.541688	-0.134729	veg vegan	51.540951	-0.141377
NW31/ NW37	51.556845	-0.174824	Bunny Yawn	51.557831	-0.178493
NW51	51.555750	-0.144381	L'express	51.555248	-0.141580
NW51/ NW52	51.555750	-0.144381	Funky Bean	51.552017	-0.141290
NW64	51.540226	-0.189767	Happy Vegetarian	51.536638	-0.191597
SW1V2	51.491286	-0.136988	Veg As You Go	51.492111	-0.138528
W23	51.513262	-0.181896	Cafe Forty One	51.512266	-0.186687
W23	51.513262	-0.181896	Raw La Suite West	51.512228	-0.186997
W24/ W25	51.513150	-0.189393	Farmacy	51.515334	-0.192749
W24/ W25	51.513150	-0.189393	Redemption	51.515516	-0.195184
W24	51.513150	-0.189393	Planet Organic	51.515504	-0.191166
W25	51.517288	-0.190838	Jusu Brothers	51.514804	-0.196389
W25	51.517288	-0.190838	Planet Organic	51.515504	-0.191166

This information could then be plotted on to the folium map to show locations of competitors versus the high spending postal districts, as shown in the results section.

### 3.3 Machine learnings used and why

As a whole, the £5m+ postcodes seem to be clustered. We can use KNN to confirm this.

Postcode	Cluster Labels	2019 Takeaway Exp (£ m)	Latitude	Longitude
EC1M3	0	0.150362	51.521129	-0.107445
EC1N6	0	0.000618	51.518867	-0.107598
EC1N7	0	0.803023	51.520733	-0.110733
EC1N8	0	0.570774	51.520619	-0.108745
EC1R5	0	0.400891	51.522533	-0.110597
N1C4	0	0.004112	51.536228	-0.125727
N66	1	3.620494	51.565931	-0.145130
NW10	1	3.634475	51.536981	-0.136518
NW11	3	2.600682	51.531383	-0.133893
NW12	0	0.724253	51.528802	-0.133043
NW13	3	2.005628	51.527065	-0.140761
NW14	1	3.364002	51.529999	-0.140153
NW17	2	5.530978	51.535875	-0.142984
NW18	2	6.708044	51.540880	-0.147668
NW19	2	6.285765	51.541688	-0.134729
NW23	2	6.055137	51.555208	-0.211006
NW31	2	5.651684	51.556845	-0.174824
NW32	4	11.235776	51.552731	-0.163620
NW33	2	7.039947	51.545792	-0.167485
NW34	4	10.140354	51.549438	-0.167921

The KMeans method from sklearn was applied to the table of Takeaway expenditure and location data, using 5 kclusters – the table above shows the first 20 rows of results.

The folium map was then re-created using cluster values to drive the colours of the postal district circles. As can be seen from the map below, the clustering has produced very similar trends to the previous folium map plot of expenditure values.

Although these expenditure values do form part of the KMeans clustering, the similarity of results does provide further evidence of the natural clustering of high spending districts. This could be expected as wealthy and young areas tend to cluster within boroughs beyond postal areas.



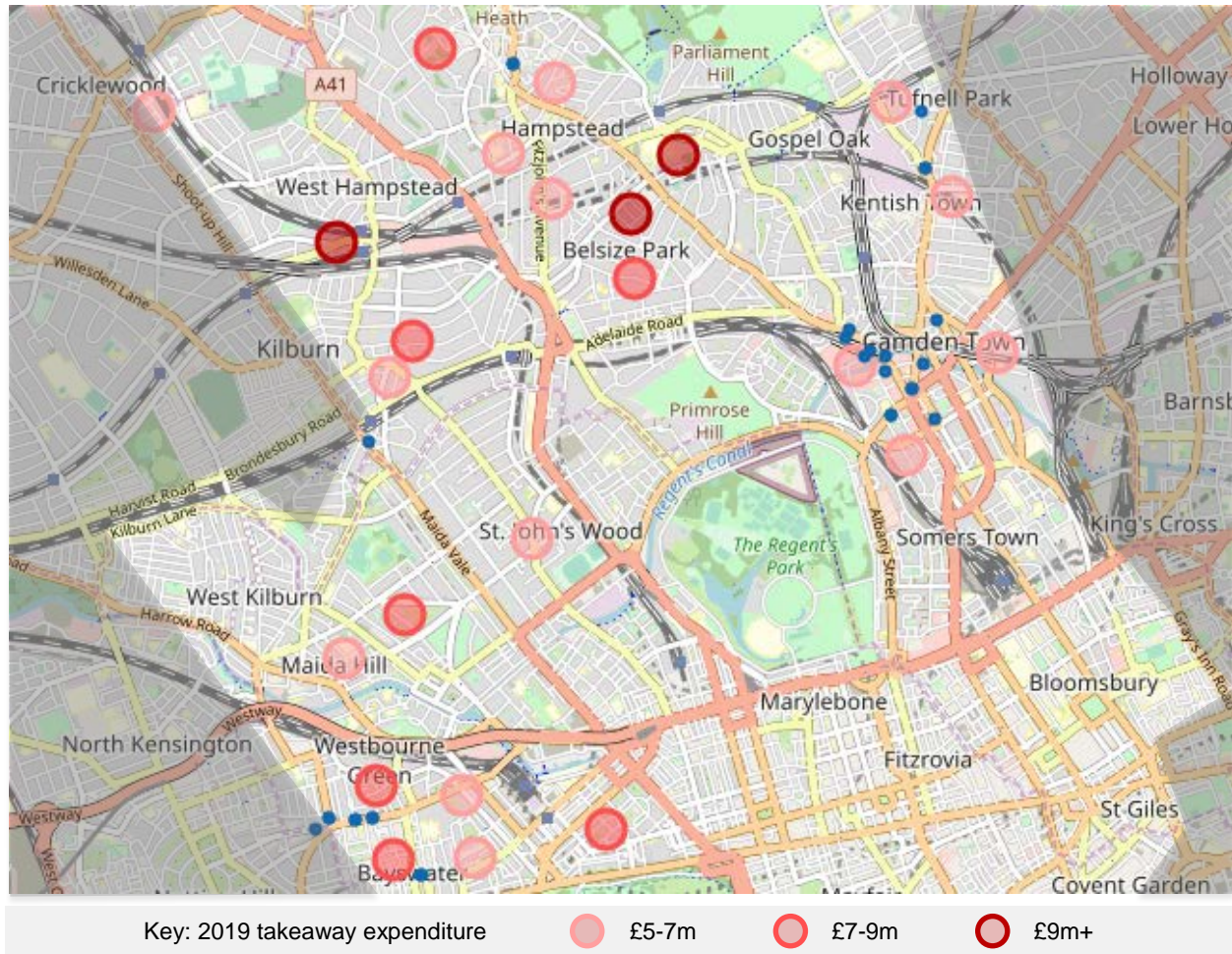




#### 4. Results

The postal districts with Takeaway spending over £5m are shown overlaid on the Westminster /Camden map. There appear to be clusters around West Hampstead/ Belsize Park and Bayswater.

Plotting the existing restaurants from Foursquare on our Westminster/Camden map (as blue dots) shows they are clustered around Camden Town and Bayswater.



The map shows that there are numerous Vegetarian/Vegan restaurants around Camden Town and several around the Bayswater area, but little in the Hampstead/Belsize Park area.

It would therefore seem sensible to target Hampstead/Belsize Park for the Vegan delivery restaurant service based on this analysis.

## **5. Discussion – observations and recommendations (based on results)**

The initial analysis highlights Hampstead/Belsize Park as optimal locations for a new Vegan restaurant in terms of consumer spending on takeaways and demographics.

As a next step, the area needs to be assessed in terms of the cost and practicalities of establishing such a business. These areas do have especially high real estate costs and no research has been done at this stage around feasibility of setting up such a business in this area.

Further primary market research also needs to be carried out on the local interest in vegan food in these areas before they are selected. This would ideally involve targeted questionnaires / surveys performed on the specific neighborhoods.

The analysis set out in this presentation could be extended to other London boroughs if these locations are found to be unsuitable or impractical, such as Islington or Tower Hamlets, as noted earlier.

## **6. Conclusion**

Based on consumer expenditure and population demographics, the data analysis provides a clear indication that Hampstead/Belsize Park would be good candidates for establishing a new Vegan business. Further analysis could be undertaken using a broader range of databases which may identify other locations (there is a large amount of data available on London).

This analysis could be extended to other cities across the UK and further research could be done on other London boroughs.

However, the results of the data analysis appear robust and form a good basis for further investigation.