# An Inside into London through its Boroughs

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## 1. Introduction:

*1.1.* *Background:* In this era of Globalization, borders are limited to maps on the papers. With the increasing movement of peoples across the borders, it becomes essential to get some knowledge about the place where one is planning to move. Different people have different situations and reasons for migrating from one country to another, and thus they have different needs. This project is an attempt to cater to the spectrum of such different needs for the people moving to London, UK. In this project, I try to describe the 32 boroughs of London based on the data of various parameters provided by the UK government. Foursquare API is used to get the information on Venues in the neighborhoods of different boroughs.

*1.2.* *Problem:* Expats coming to London to settle down should have a broad perspective of the city's demographics, economics, and financial standards of various parts of the city. Without a proper understanding of the place, they may find it challenging to find a place suitable for their settlement with the neighborhood that meets their requirements.

*1.3.* *Interest:* People of different age groups, gender, occupation status, students, or anyone who is planning to settle down for a considerable amount of time in London will find this piece of information useful in making up their minds and getting familiar with features of various boroughs of London.

## 2. Data:

2.1. *Data Sources:* For the list of areas in London, the Wikipedia page for London areas, https://en.wikipedia.org/wiki/List_of_areas_of_London was scrapped using BeautifulSoup library of Python. Data regarding the profiles of London Boroughs was obtained from the link https://old.datahub.io/dataset/london-borough-profiles ,it is the official data provided by the government authorities of the United Kingdom.

2.2. *__Data Cleaning and Data Preparation:__* After getting the data from the Wikipedia page, it was then converted to a tabular format into a Pandas Dataframe, which looked like:

| | Neighborhood | London borough | Post town | Postcode district |
|---|---|---|---|---|
| 0 | Abbey Wood | Bexley, Greenwich | LONDON | SE2 |
| 1 | Acton | Ealing, Hammersmith and Fulham | LONDON | W3, W4 |
| 2 | Addington | Croydon | CROYDON | CR0 |
| 3 | Addiscombe | Croydon | CROYDON | CR0 |
| 4 | Albany Park | Bexley | BEXLEY, SIDCUP | DA5, DA14 |
| 5 | Aldborough Hatch | Redbridge | ILFORD | IG2 |
| 6 | Aldgate | City | LONDON | EC3 |

Before using the above data with the FOURSQUARE API, the Neighborhoods must be linked with their respective Latitude and Longitude. For this purpose, NOMINATIM was used to get the google coordinates for each Neighborhood location, and they were populated to the above Dataframe to give the following result:

| | Neighborhood | London borough | Post town | Postcode district | Neighborhood Latitude | Neighborhood Longitude |
|---|---|---|---|---|---|---|
| 0 | Abbey Wood | Bexley, Greenwich | LONDON | SE2 | 51.4876 | 0.11405 |
| 1 | Acton | Ealing, Hammersmith and Fulham | LONDON | W3, W4 | 51.5081 | -0.273261 |
| 2 | Addington | Croydon | CROYDON | CR0 | 51.3586 | -0.0316347 |
| 3 | Addiscombe | Croydon | CROYDON | CR0 | 51.3797 | -0.0742821 |
| 4 | Albany Park | Bexley | BEXLEY, SIDCUP | DA5, DA14 | 51.4354 | 0.125965 |
| 5 | Aldborough Hatch | Redbridge | ILFORD | IG2 | 51.5855 | 0.0988 |

The second set of Data regarding the London Borough Profile was directly downloaded from the website (link provided above). The raw Data looked initially like this:

| | Code | Area_name | Inner/_Outer_London | GLA_Population_Estimate_2017 | GLA_Household_Estimate_2017 | Inland_Area_(Hectares) | Population_density_(per_hectare)_2017 | Average_Age,_201 |
|---|---|---|---|---|---|---|---|---|
| 0 | E09000001 | City of London | Inner London | 8800 | 5326 | 290 | 30.3 | 43 |
| 1 | E09000002 | Barking and Dagenham | Outer London | 209000 | 78188 | 3,611 | 57.9 | 32 |
| 2 | E09000003 | Barnet | Outer London | 389600 | 151423 | 8,675 | 44.9 | 37 |
| 3 | E09000004 | Bexley | Outer London | 244300 | 97736 | 6,058 | 40.3 | 39 |
| 4 | E09000005 | Brent | Outer London | 332100 | 121048 | 4,323 | 76.8 | 35 |

In this Data, missing values were replaced by NaN values, data-type of columns were converted from object-type to float-type, and finally, Latitude and Longitude columns were created and populated using the GEOLOCATOR-NOMINATIM. Then only columns required for analysis were kept, and the rest were dropped before plotting each feature as Heat-Map.

# 3. Methodology:

After getting the Data on the Neighborhood venues from FOURSQUARE API, it was grouped by venue categories. There were a total of 410 venue categories found. These 410 venue categories were further divided into 14 different Venue Types, and then these venue-types were again repopulated into the Dataframe:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category | Venue Type |
|---|---|---|---|---|---|---|---|---|
| 0 | Abbey Wood | 51.487621 | 0.114050 | Co-op Food | 51.487650 | 0.113490 | Grocery Store | Grocery_daily |
| 1 | Abbey Wood | 51.487621 | 0.114050 | Bostal Gardens | 51.486670 | 0.110462 | Playground | Sports_fitness |
| 2 | Abbey Wood | 51.487621 | 0.114050 | Abbey Wood Caravan Club | 51.485502 | 0.120014 | Campground | Sports_fitness |
| 3 | Acton | 51.508140 | -0.273261 | London Star Hotel | 51.509624 | -0.272456 | Hotel | Hotels_boarding |
| 4 | Acton | 51.508140 | -0.273261 | The Aeronaut | 51.508376 | -0.275216 | Pub | Pubs_bars |

The 14 Venue Types and the number of venues in each category is as follows:

| | Venue Type | Count |
|---|---|---|
| 0 | Cafe_fastfood | 3016 |
| 1 | Restaurants | 2418 |
| 2 | Pubs_bars | 1453 |
| 3 | Shopping_retail | 1154 |
| 4 | Grocery_daily | 882 |
| 5 | Entertainment_recreation | 702 |
| 6 | Sports_fitness | 572 |
| 7 | Hotels_boarding | 436 |
| 8 | Transportation | 432 |
| 9 | Tourists_landmarks | 315 |
| 10 | Pharmacy | 145 |
| 11 | Personal_care | 45 |
| 12 | Business_office | 25 |
| 13 | Education_school | 5 |

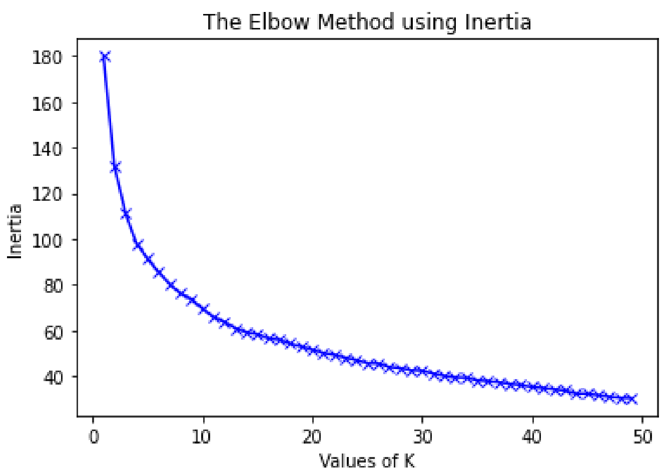
As London is a metropolitan state, the number of restaurants, pubs, bars, and cafes will overpower the other venue types. Thus, weights were assigned to each venue-type to neutralize this bias, which can have a drastically adverse impact on clustering of neighborhoods based on these venue types:

| | Venue Type | Count | Weight |
|---|---|---|---|
| 0 | Business_office | 25 | 0.464000 |
| 1 | Cafe_fastfood | 3016 | 0.003846 |
| 2 | Education_school | 5 | 2.320000 |
| 3 | Entertainment_recreation | 702 | 0.016524 |
| 4 | Grocery_daily | 882 | 0.013152 |
| 5 | Hotels_boarding | 436 | 0.026606 |
| 6 | Personal_care | 45 | 0.257778 |
| 7 | Pharmacy | 145 | 0.080000 |
| 8 | Pubs_bars | 1453 | 0.007983 |
| 9 | Restaurants | 2418 | 0.004797 |
| 10 | Shopping_retail | 1154 | 0.010052 |
| 11 | Sports_fitness | 572 | 0.020280 |
| 12 | Tourists_landmarks | 315 | 0.036825 |
| 13 | Transportation | 432 | 0.026852 |

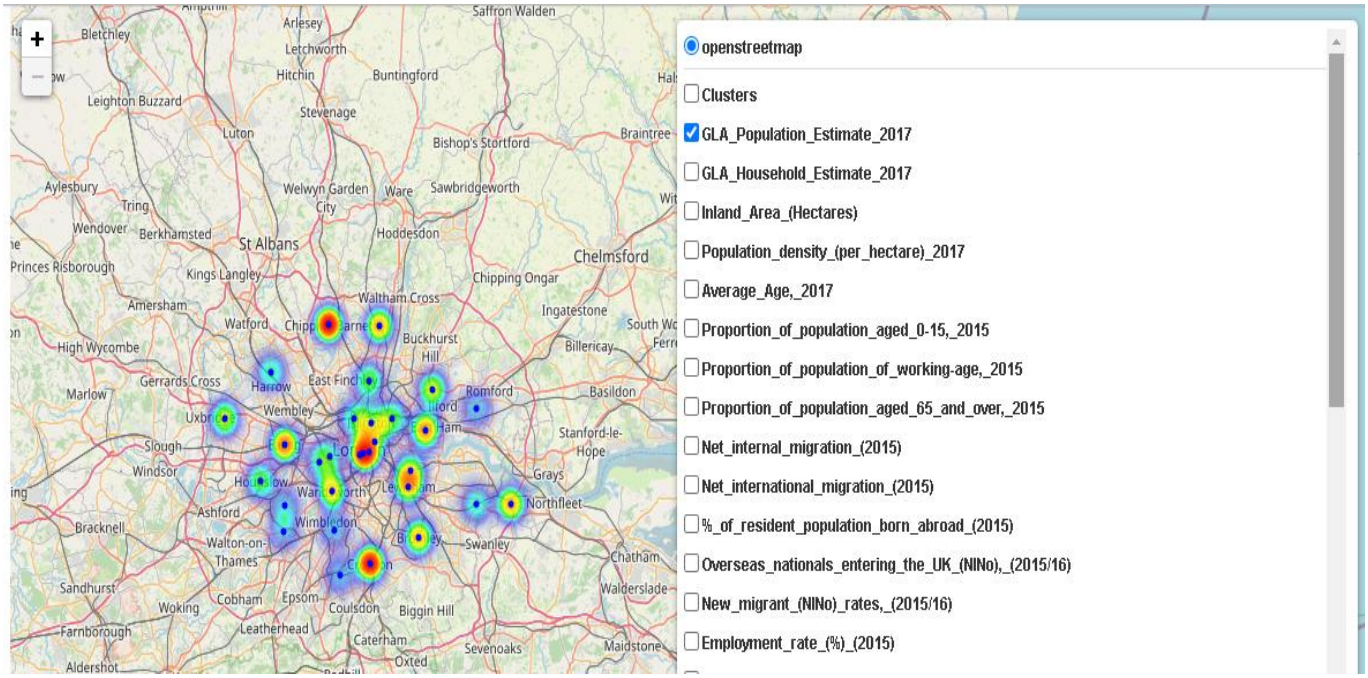
Furthermore, the neighborhoods were one-hot encoded as per the venue-types, and the sum was multiplied by the weights calculated above, thereafter *features were standardized* using Min-Max scaler from Scikit-learn library:

| | Neighborhood | Business_office | Cafe_fastfood | Education_school | Entertainment_recreation | Grocery_daily | Hotels_boarding | Personal_care | P |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Abbey Wood | 0.0 | 0.000 | 0.0 | 0.000000 | 0.125 | 0.000000 | 0.0 | |
| 1 | Acton | 0.0 | 0.100 | 0.0 | 0.000000 | 0.125 | 0.045455 | 0.0 | |
| 2 | Addington | 0.0 | 0.000 | 0.0 | 0.066667 | 0.000 | 0.000000 | 0.0 | |
| 3 | Addiscombe | 0.0 | 0.075 | 0.0 | 0.133333 | 0.250 | 0.000000 | 0.0 | |
| 4 | Albany Park | 0.0 | 0.000 | 0.0 | 0.000000 | 0.125 | 0.000000 | 0.0 | |

The above data prepared for clustering is then used for *K-Means clustering*. *Elbow method* was used to select the appropriate number of clusters (which came out to be TEN):



On the other hand, with the second set of data, Folium was used to create different FeatureGroups for different features for each borough. These FeatureGroups were then finally added *'as_child'* to the base Map of the London State. LayerControl Feature of the Folium library was also added to the base map for flexible and easy interpretation of the borough profiles:




# 4. RESULT:

After clustering the neighborhood-venues data, ten clusters were formed:

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No. of Neighborhoods in Cluster 1:  31
No. of Neighborhoods in Cluster 2:  254
No. of Neighborhoods in Cluster 3:  24
No. of Neighborhoods in Cluster 4:  5
No. of Neighborhoods in Cluster 5:  32
No. of Neighborhoods in Cluster 6:  39
No. of Neighborhoods in Cluster 7:  35
No. of Neighborhoods in Cluster 8:  5
No. of Neighborhoods in Cluster 9:  19
No. of Neighborhoods in Cluster 10:  66
```

These clusters were then analyzed based on the number of venue types in each cluster. Thereafter, cluster profiling was done, and each cluster was named based on what distinct feature it represents:

| Venue Type | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | SUM |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Business_office | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 1 | 19 | 0 | 25 |
| Cafe_fastfood | 115 | 375 | 420 | 108 | 302 | 302 | 774 | 89 | 91 | 440 | 3016 |
| Education_school | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 5 |
| Entertainment_recreation | 30 | 144 | 67 | 18 | 87 | 40 | 208 | 16 | 18 | 74 | 702 |
| Grocery_daily | 47 | 177 | 117 | 17 | 48 | 107 | 67 | 9 | 30 | 263 | 882 |
| Hotels_boarding | 18 | 60 | 53 | 37 | 41 | 24 | 129 | 18 | 16 | 40 | 436 |
| Personal_care | 4 | 8 | 4 | 1 | 6 | 2 | 12 | 3 | 0 | 5 | 45 |
| Pharmacy | 4 | 5 | 44 | 5 | 3 | 59 | 6 | 3 | 4 | 12 | 145 |
| Pubs_bars | 50 | 250 | 170 | 64 | 142 | 123 | 335 | 41 | 55 | 223 | 1453 |
| Restaurants | 86 | 320 | 349 | 102 | 240 | 250 | 579 | 70 | 75 | 347 | 2418 |
| Shopping_retail | 34 | 122 | 254 | 39 | 79 | 133 | 321 | 41 | 40 | 91 | 1154 |
| Sports_fitness | 30 | 121 | 83 | 13 | 130 | 28 | 66 | 12 | 23 | 66 | 572 |
| Tourists_landmarks | 22 | 41 | 15 | 11 | 47 | 8 | 132 | 9 | 15 | 15 | 315 |
| Transportation | 137 | 113 | 50 | 5 | 15 | 26 | 11 | 5 | 21 | 49 | 432 |
| TOTAL | 577 | 1736 | 1626 | 425 | 1140 | 1102 | 2640 | 322 | 407 | 1625 | 11600 |

**Percentage Distribution of *Venue-Types* across Clusters (Row-wise):**

| Venue Type | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Business_office | 0.000000 | 0.000000 | 0.000000 | 20.000000 | 0.000000 | 0.000000 | 0.000000 | 4.000000 | 76.000000 | 0.000000 |
| Cafe_fastfood | 3.812997 | 12.433687 | 13.925729 | 3.580902 | 10.013263 | 10.013263 | 25.663130 | 2.950928 | 3.017241 | 14.588859 |
| Education_school | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 100.000000 | 0.000000 | 0.000000 |
| Entertainment_recreation | 4.273504 | 20.512821 | 9.544160 | 2.564103 | 12.393162 | 5.698006 | 29.629630 | 2.279202 | 2.564103 | 10.541311 |
| Grocery_daily | 5.328798 | 20.068027 | 13.265306 | 1.927438 | 5.442177 | 12.131519 | 7.596372 | 1.020408 | 3.401361 | 29.818594 |
| Hotels_boarding | 4.128440 | 13.761468 | 12.155963 | 8.486239 | 9.403670 | 5.504587 | 29.587156 | 4.128440 | 3.669725 | 9.174312 |
| Personal_care | 8.888889 | 17.777778 | 8.888889 | 2.222222 | 13.333333 | 4.444444 | 26.666667 | 6.666667 | 0.000000 | 11.111111 |
| Pharmacy | 2.758621 | 3.448276 | 30.344828 | 3.448276 | 2.068966 | 40.689655 | 4.137931 | 2.068966 | 2.758621 | 8.275862 |
| Pubs_bars | 3.441156 | 17.205781 | 11.699931 | 4.404680 | 9.772884 | 8.465244 | 23.055747 | 2.821748 | 3.785272 | 15.347557 |
| Restaurants | 3.556658 | 13.234078 | 14.433416 | 4.218362 | 9.925558 | 10.339123 | 23.945409 | 2.894955 | 3.101737 | 14.350703 |
| Shopping_retail | 2.946274 | 10.571924 | 22.010399 | 3.379549 | 6.845754 | 11.525130 | 27.816291 | 3.552860 | 3.466205 | 7.885615 |
| Sports_fitness | 5.244755 | 21.153846 | 14.510490 | 2.272727 | 22.727273 | 4.895105 | 11.538462 | 2.097902 | 4.020979 | 11.538462 |
| Tourists_landmarks | 6.984127 | 13.015873 | 4.761905 | 3.492063 | 14.920635 | 2.539683 | 41.904762 | 2.857143 | 4.761905 | 4.761905 |
| Transportation | 31.712963 | 26.157407 | 11.574074 | 1.157407 | 3.472222 | 6.018519 | 2.546296 | 1.157407 | 4.861111 | 11.342593 |

**Percentage Distribution of Venue-Types within each *Cluster* (Column-wise):**

| Venue Type | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Business_office | 0.000000 | 0.000000 | 0.000000 | 1.176471 | 0.000000 | 0.000000 | 0.000000 | 0.310559 | 4.668305 | 0.000000 |
| Cafe_fastfood | 19.930676 | 21.601382 | 25.830258 | 25.411765 | 26.491228 | 27.404719 | 29.318182 | 27.639752 | 22.358722 | 27.076923 |
| Education_school | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1.552795 | 0.000000 | 0.000000 |
| Entertainment_recreation | 5.199307 | 8.294931 | 4.120541 | 4.235294 | 7.631579 | 3.629764 | 7.878788 | 4.968944 | 4.422604 | 4.553846 |
| Grocery_daily | 8.145581 | 10.195853 | 7.195572 | 4.000000 | 4.210526 | 9.709619 | 2.537879 | 2.795031 | 7.371007 | 16.184615 |
| Hotels_boarding | 3.119584 | 3.456221 | 3.259533 | 8.705882 | 3.596491 | 2.177858 | 4.886364 | 5.590062 | 3.931204 | 2.461538 |
| Personal_care | 0.693241 | 0.460829 | 0.246002 | 0.235294 | 0.526316 | 0.181488 | 0.454545 | 0.931677 | 0.000000 | 0.307692 |
| Pharmacy | 0.693241 | 0.288018 | 2.706027 | 1.176471 | 0.263158 | 5.353902 | 0.227273 | 0.931677 | 0.982801 | 0.738462 |
| Pubs_bars | 8.665511 | 14.400922 | 10.455105 | 15.058824 | 12.456140 | 11.161525 | 12.689394 | 12.732919 | 13.513514 | 13.723077 |
| Restaurants | 14.904679 | 18.433180 | 21.463715 | 24.000000 | 21.052632 | 22.686025 | 21.931818 | 21.739130 | 18.427518 | 21.353846 |
| Shopping_retail | 5.892548 | 7.027650 | 15.621156 | 9.176471 | 6.929825 | 12.068966 | 12.159091 | 12.732919 | 9.828010 | 5.600000 |
| Sports_fitness | 5.199307 | 6.970046 | 5.104551 | 3.058824 | 11.403509 | 2.540835 | 2.500000 | 3.726708 | 5.651106 | 4.061538 |
| Tourists_landmarks | 3.812825 | 2.361751 | 0.922509 | 2.588235 | 4.122807 | 0.725953 | 5.000000 | 2.795031 | 3.685504 | 0.923077 |
| Transportation | 23.743501 | 6.509217 | 3.075031 | 1.176471 | 1.315789 | 2.359347 | 0.416667 | 1.552795 | 5.159705 | 3.015385 |

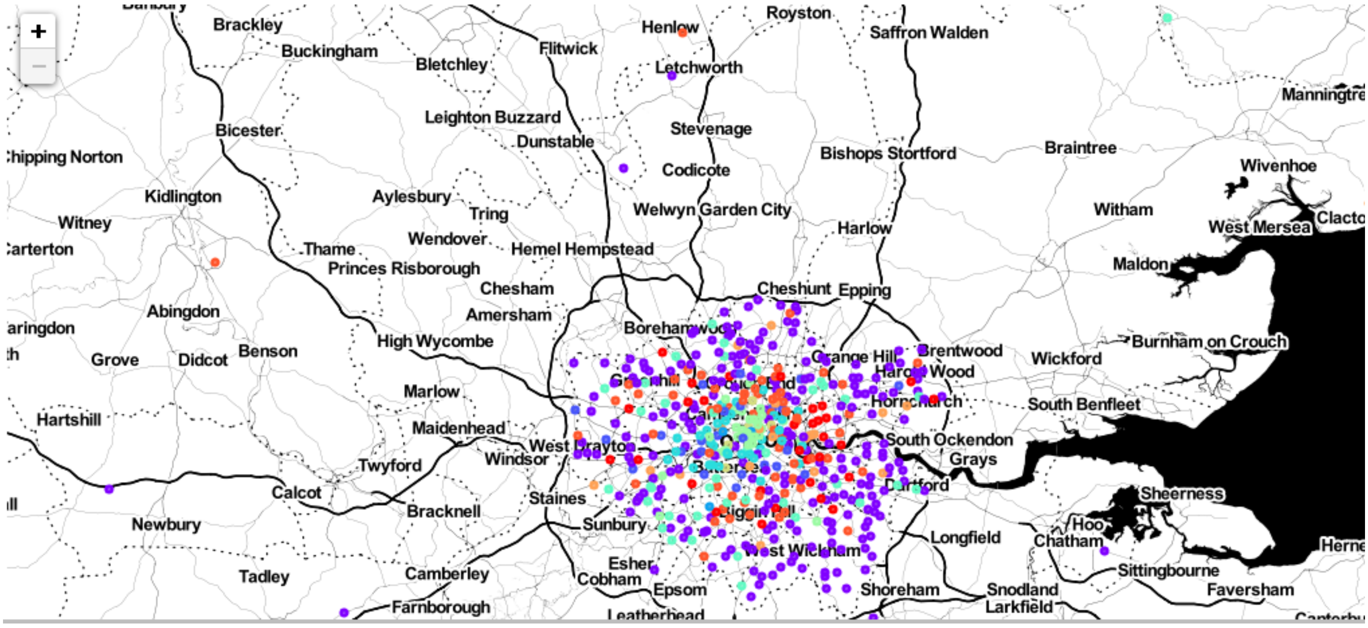
Based on the analysis from the above visualization of the distribution of Venue-Types across and within clusters, 9 out of 10 clusters were profiled. Following profiling has been deduced ***(high prevalence of Restaurants, Pubs_bars, and Cafe_fastfood was neglected while profiling the clusters):***

1) *CLUSTER-1:* Transportation Cluster.
2) *CLUSTER-2:* Common Neighborhood Cluster. It contains Grocery, Shopping Retail, etc. in moderation.
3) *CLUSTER-3:* Shopping Retail Cluster.
4) *CLUSTER-4:* Ambiguous, thus, cannot be profiled.
5) *CLUSTER-5:* Sports & Fitness Cluster.
6) *CLUSTER-6:* Pharmacy Cluster.
7) *CLUSTER*-7: Master Cluster, as it contains almost everything in a significant proportion.
8) *CLUSTER-8:* Education Cluster.
9) *CLUSTER*-9: Business & Office Cluster.
10) *CLUSTER*-10: Grocery Daily Cluster along with Cafe, Fastfood, and Restaurants.

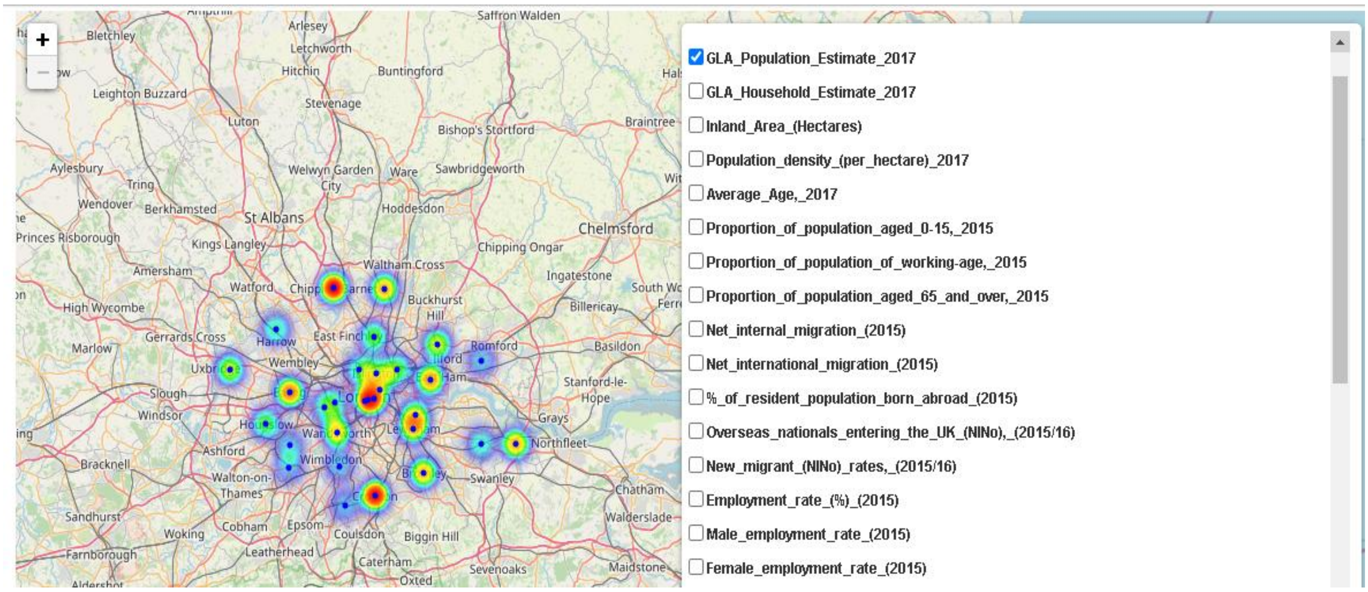
Most neighborhood falls in Cluster-2, and as it the Common neighborhood cluster, these neighborhoods are mostly outside central London.

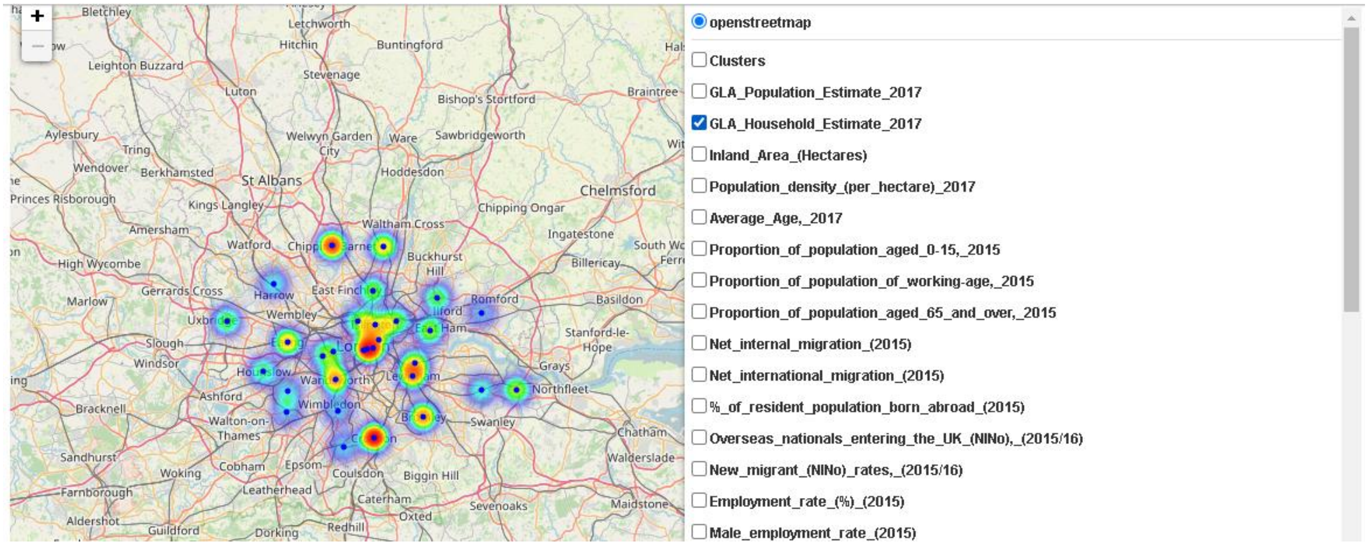
# 5. Discussion:

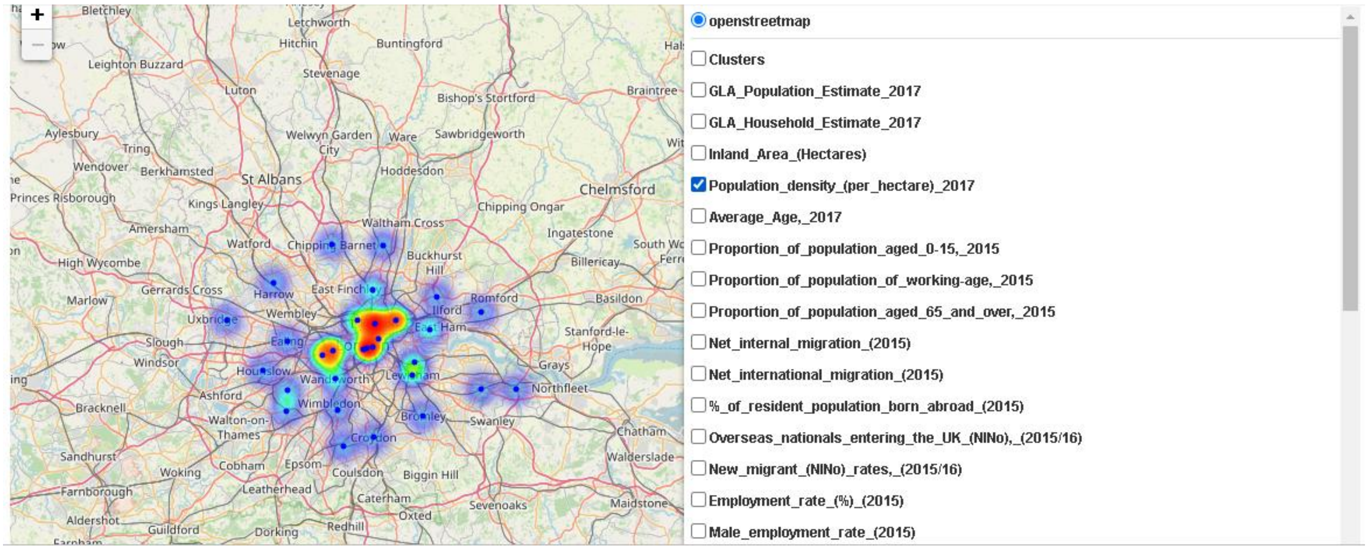
The clustering graph, as shown below, along with the Heat-Maps of various features, allows us to deduce some insights regarding various London Boroughs.



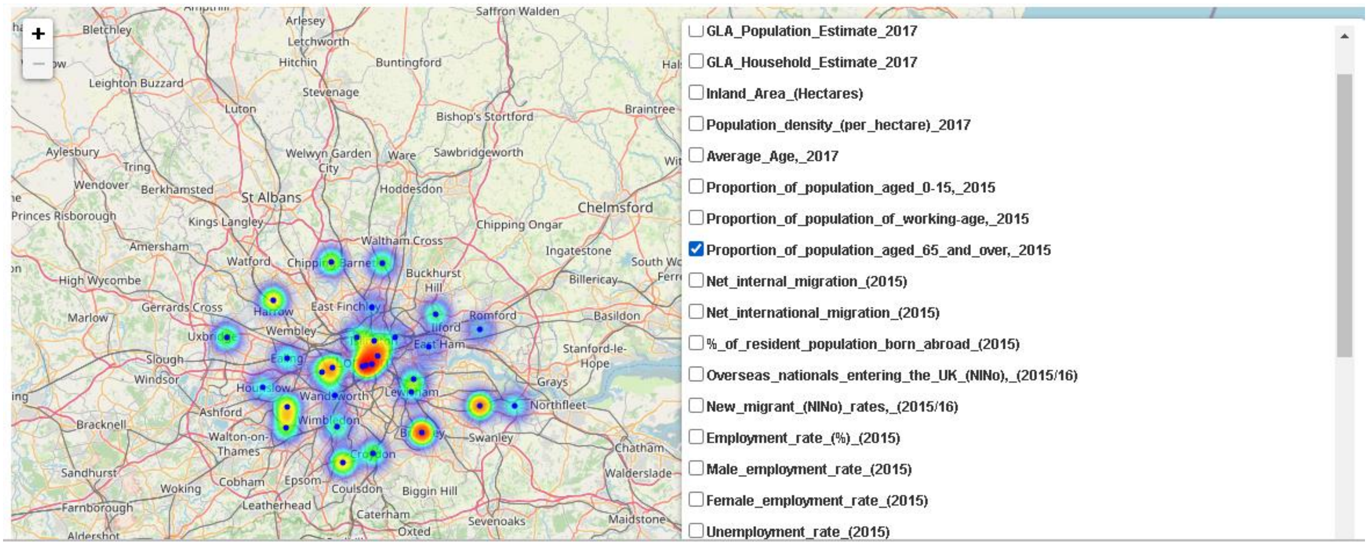

Barnet, Croydon, and Lambeth are the most populated boroughs with the most number of households as well. Barnet and Croydon, located in Northern and Southern London, respectively, the neighborhoods in these boroughs belong to Cluster no. 2 (Common Neighborhood Cluster) and Cluster no. 1 (Transportation Cluster). Apart from this, Lambeth is in central London; thus, its neighborhood is dominated by Cluster no. 7 (Master Cluster) and Cluster no. 5 (Sports and Fitness Cluster). With smaller inland-area and more population, Central London is the most densely populated among all boroughs:-

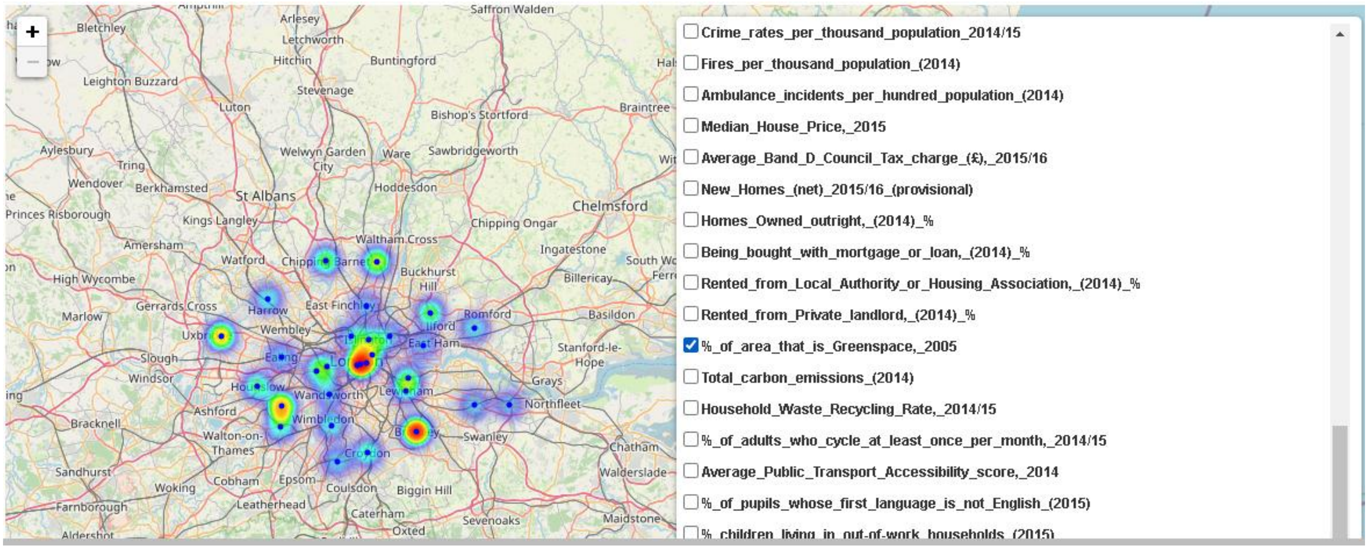


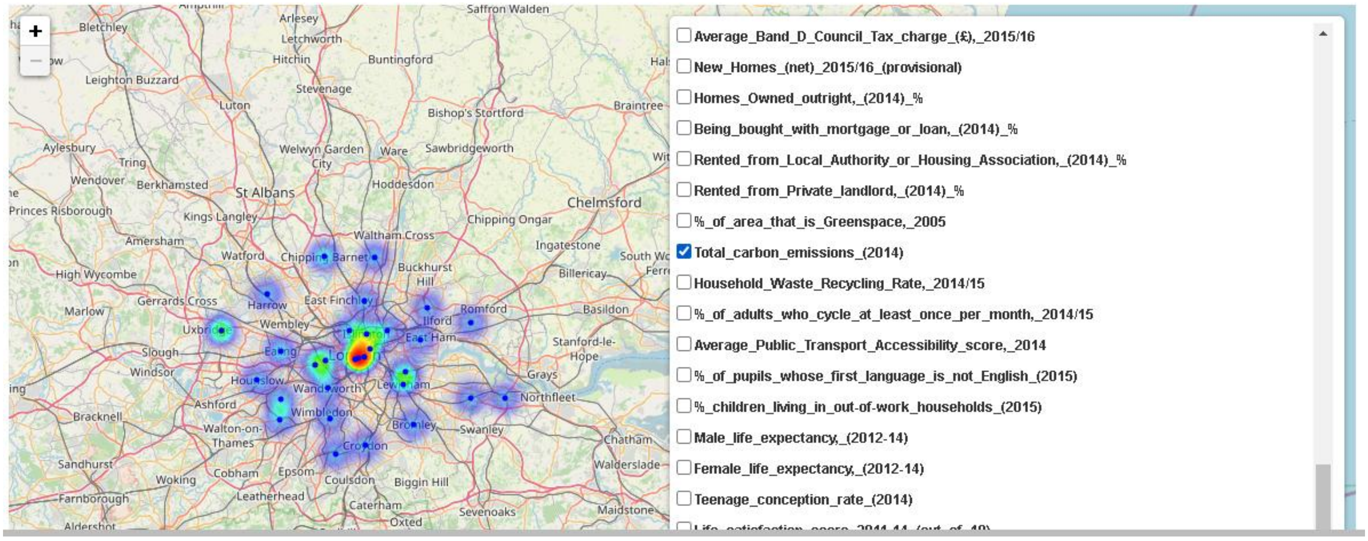


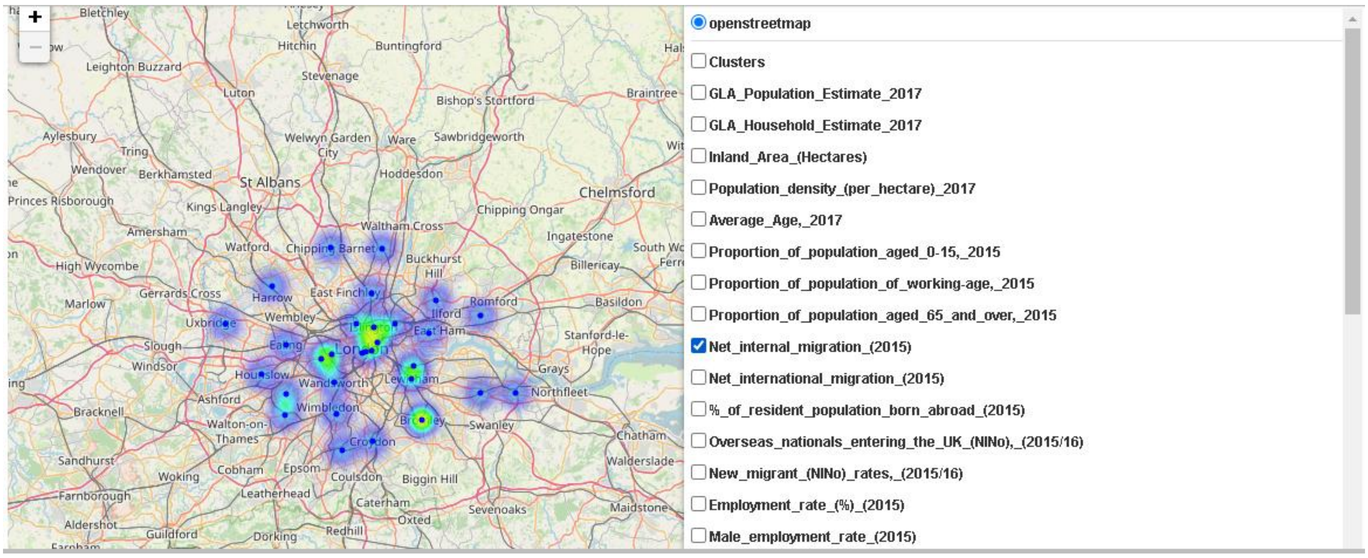




Bromley, along with Bexley and the City of London, have a significant chunk of the population, which is 65 years or above; therefore, the neighborhoods in these boroughs also include Cluster no. 6 (Pharmacy Cluster). Bromley, which is one of the 13 metropolitan centers of Greater London has the largest inland area in London with lesser population and households as compared to the other major centers like Croydon and Central Parts of London. It has the highest percentage of green space coverage and one of the least amount of carbon emission. As a result, Bromley sees most of the internal migration of the rest of the UK into London. Bromley and Bexley also saw the most number of houses bought outright (without and loan or mortgage):-

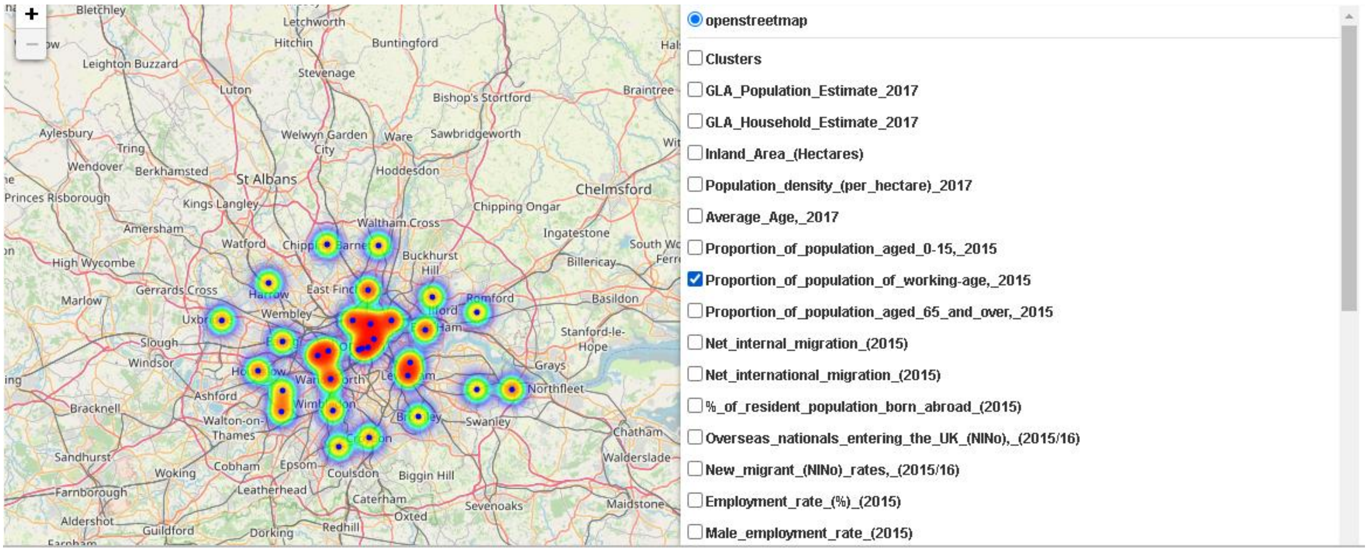


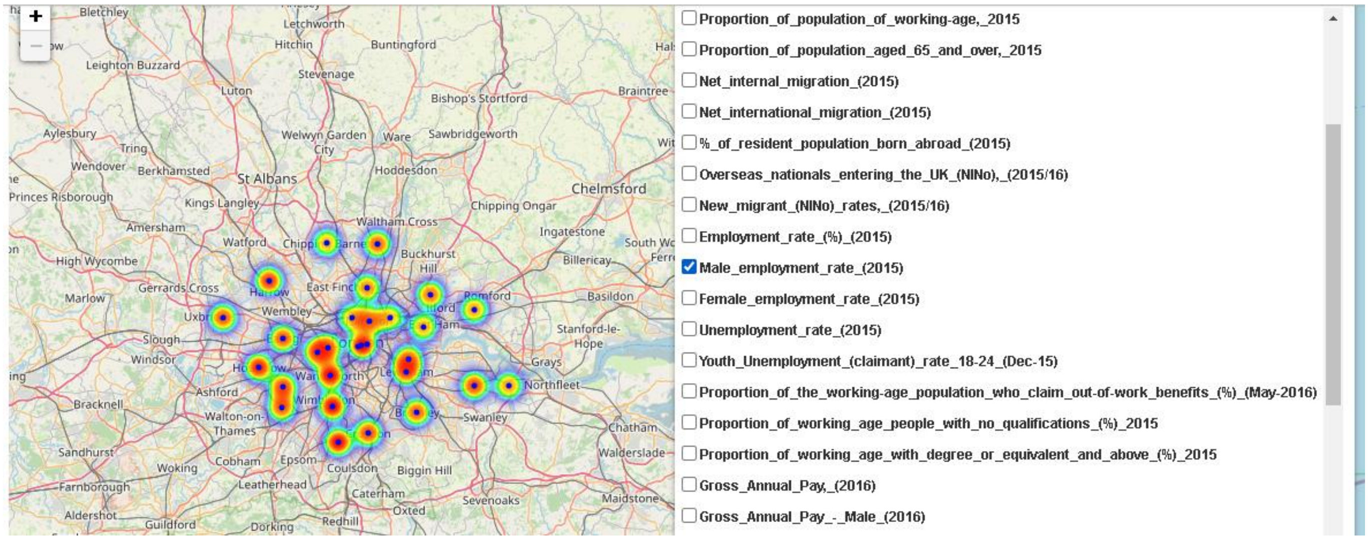


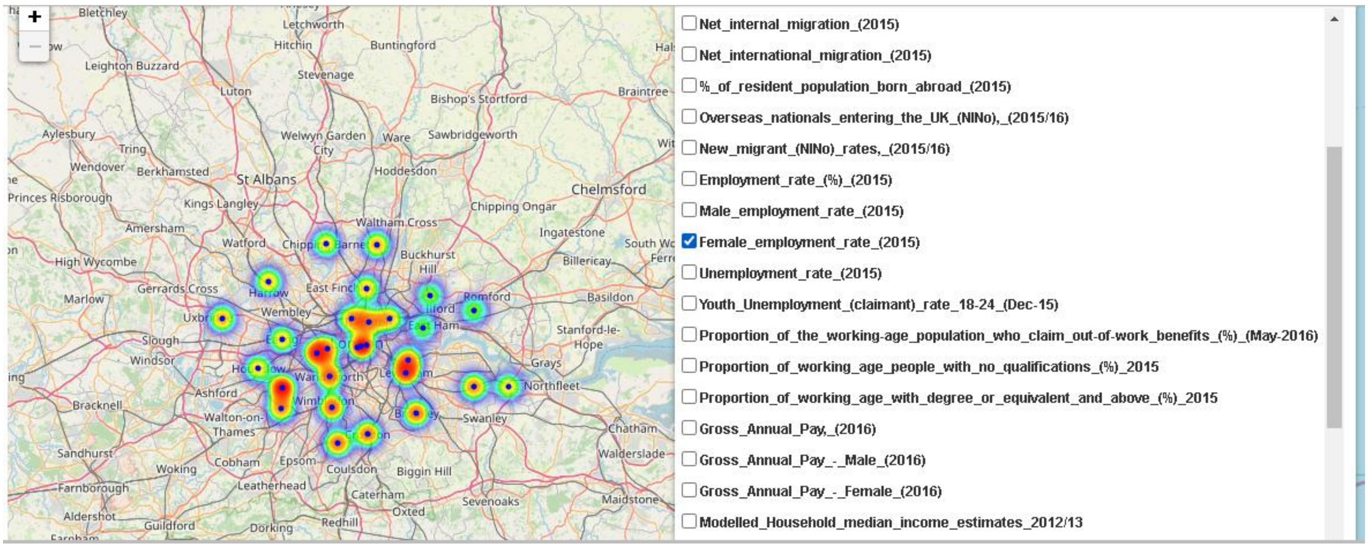



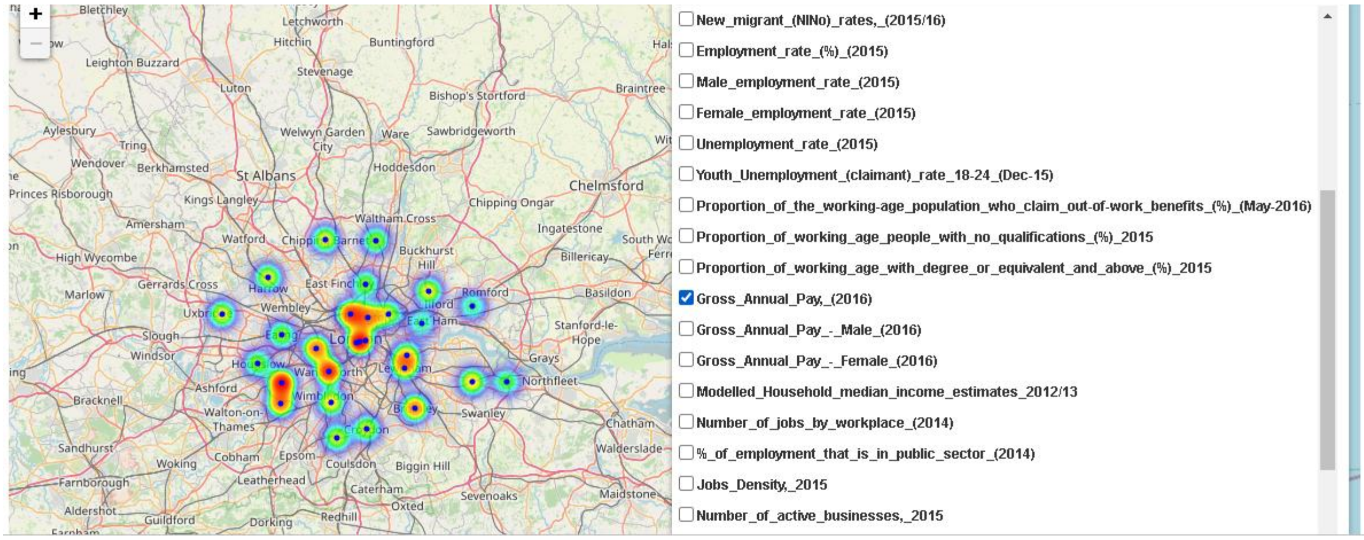




The majority of the working-age population resides in and around the areas of Central London, like the City of London, Islington, Westminster, Lambeth, Southwark, Camden, Hackney, Hammersmith, and Fulham etc. There are umpteen employment opportunities for both the genders in Central London. Apart from Central London, male employment opportunities are equitably available across London, with a significant chunk in the South-western part of London. On the other hand, Female employment is concentrated majorly at 'Richmond upon Thames' and 'Hammersmith & Fulham' boroughs. Thus female employment plays a crucial role in deciding Gross Annual Pay, and therefore 'Richmond upon Thames' has one of the highest Gross Annual Pay:-

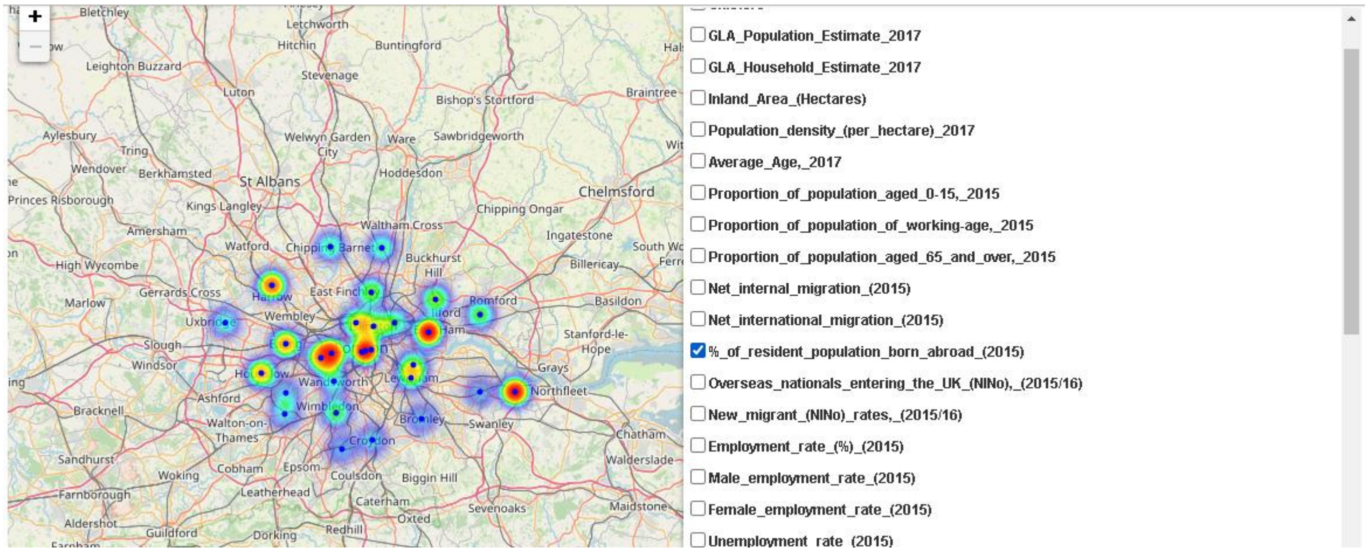

openstreetmap
Clusters
GLA_Population_Estimate_2017
GLA_Household_Estimate_2017
Inland_Area_(Hectares)
Population_density_(per_hectare)_2017
Average_Age,_2017
Proportion_of_population_aged_0-15,_2015
Proportion_of_population_of_working-age,_2015
Proportion_of_population_aged_65_and_over,_2015
Net_internal_migration_(2015)
Net_international_migration_(2015)
%_of_resident_population_born_abroad_(2015)
Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)

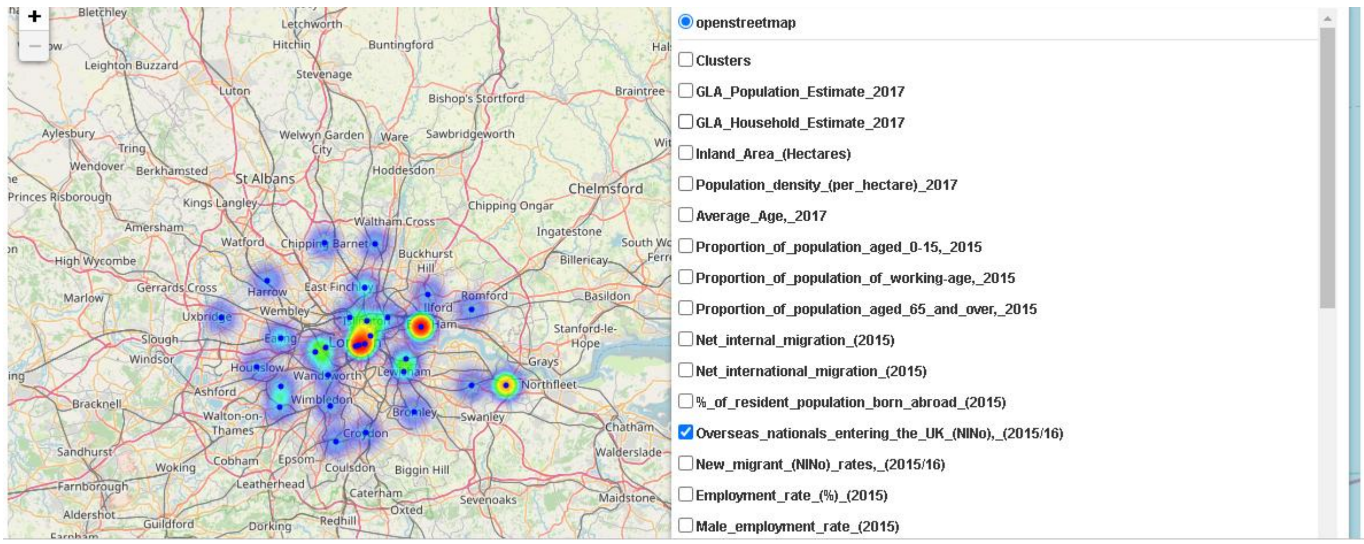

Proportion_of_population_of_working-age,_2015
Proportion_of_population_aged_65_and_over,_2015
Net_internal_migration_(2015)
Net_international_migration_(2015)
%_of_resident_population_born_abroad_(2015)
Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)

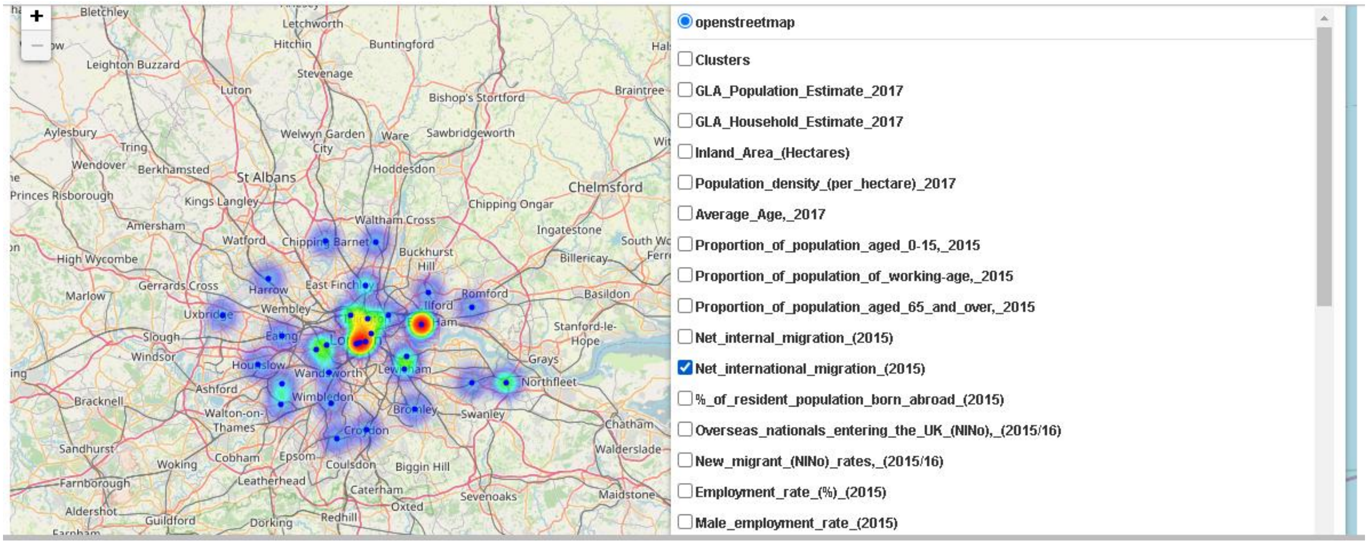

Net_internal_migration_(2015)
Net_international_migration_(2015)
%_of_resident_population_born_abroad_(2015)
Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)
Gross_Annual_Pay_-_Female_(2016)
Modelled_Household_median_income_estimates_2012/13



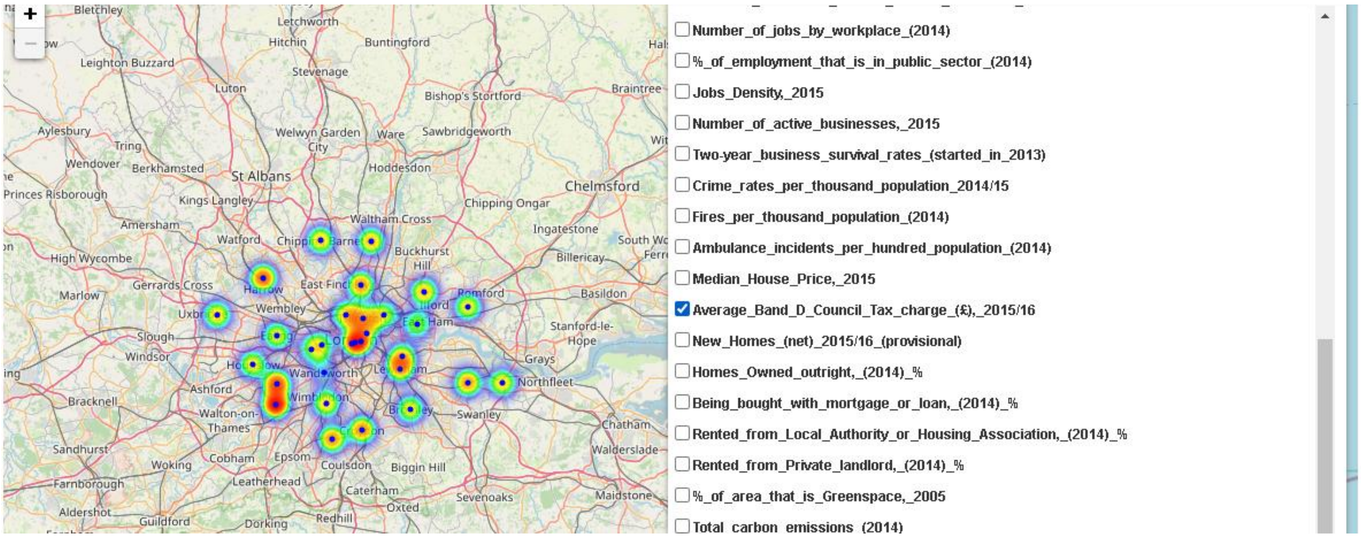

Westminster, Newham, Kensington & Chelsea, Harrow, and Brent have the most number of the resident population who are born abroad. Apart from Westminster, which is in central London and attracts international migration, Newham saw the most number of overseas nationals and international migration in the past few years. The neighborhood of Newham majorly contains venues from Cluster no. 1 (Transportation Cluster) and Cluster no. 10 (Grocery along with Cafe and Fastfood cluster):-

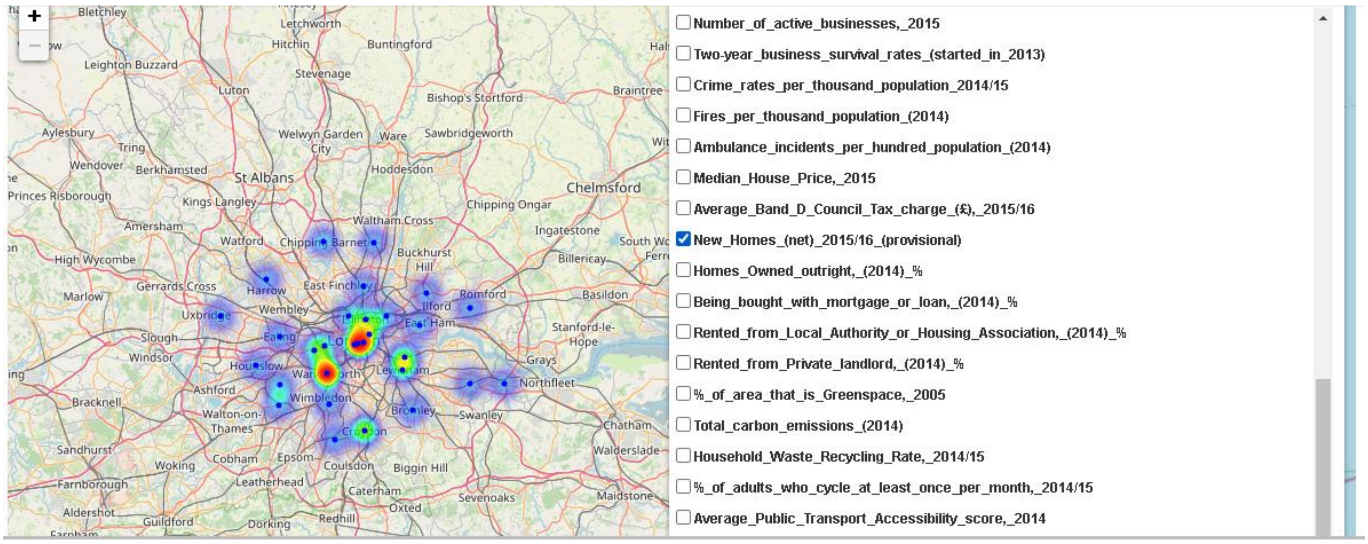


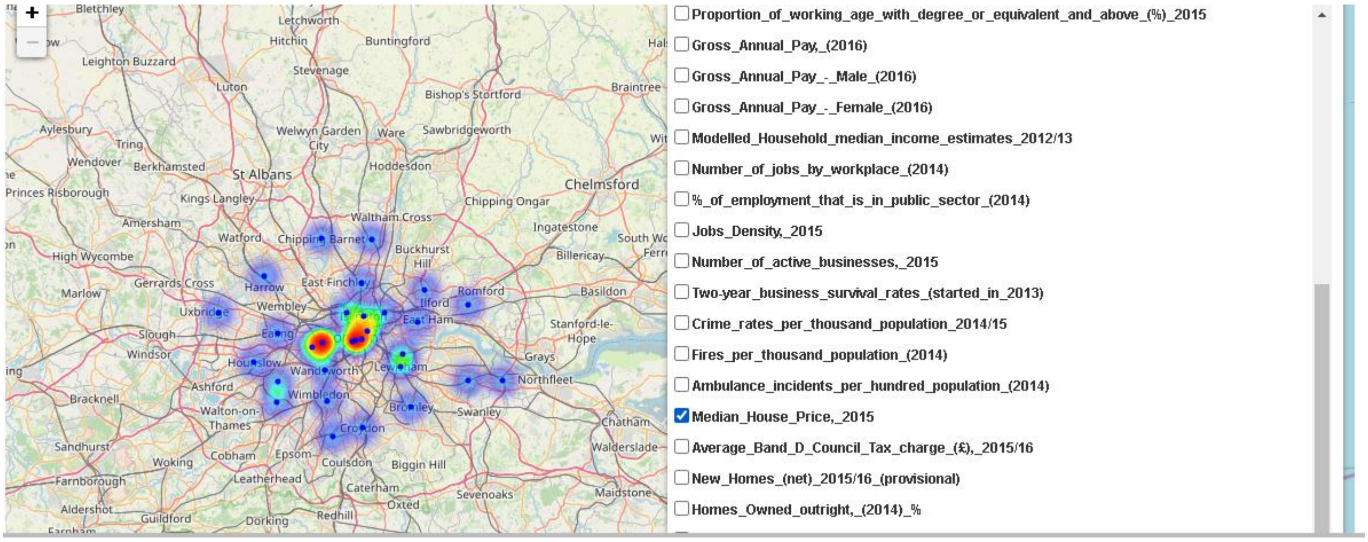



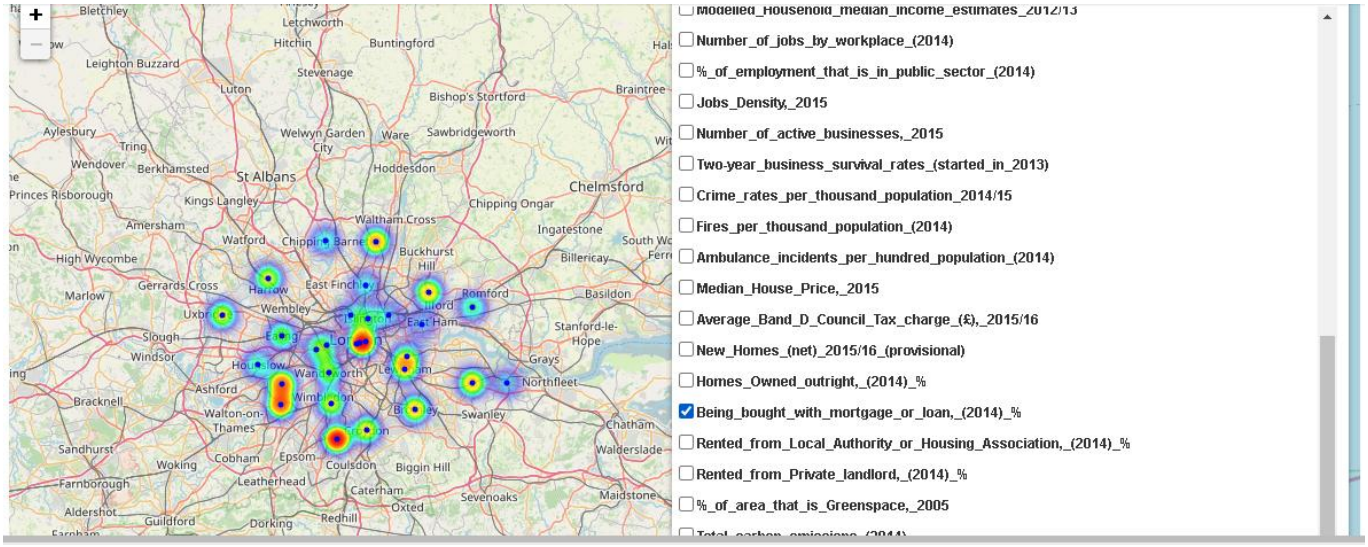


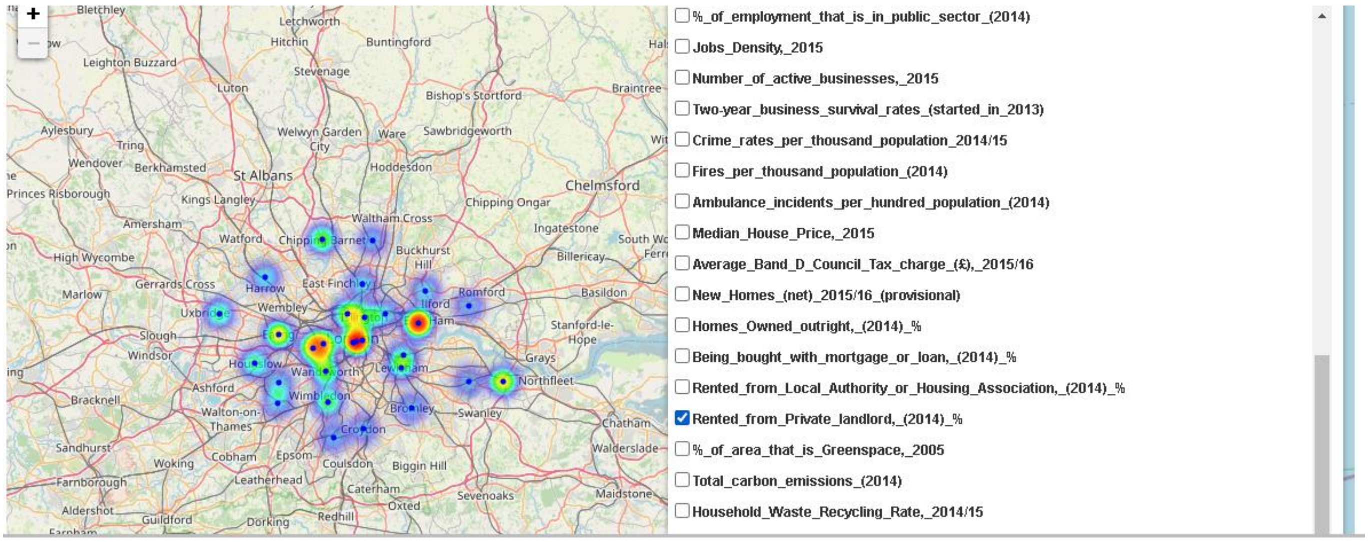

Wandsworth had the lowest average for the Band-D council tax charge, and thus it has the highest number of net New Homes. Kensington & Chelsea borough has the highest Median House Price since it is just around central London with Clusters no. 7 (Master Cluster), no. 5 (Sports & Fitness) and no. 10 (Grocery with Cafe and Fastfood) around it. On the other hand, Sutton in Southern London has the most number of houses bought on mortgage or loan. Newham has one of the most numbers of houses rented from private landlords. In comparison, Hackney has the most numbers of houses rented from Local Authority or Housing Associations:-

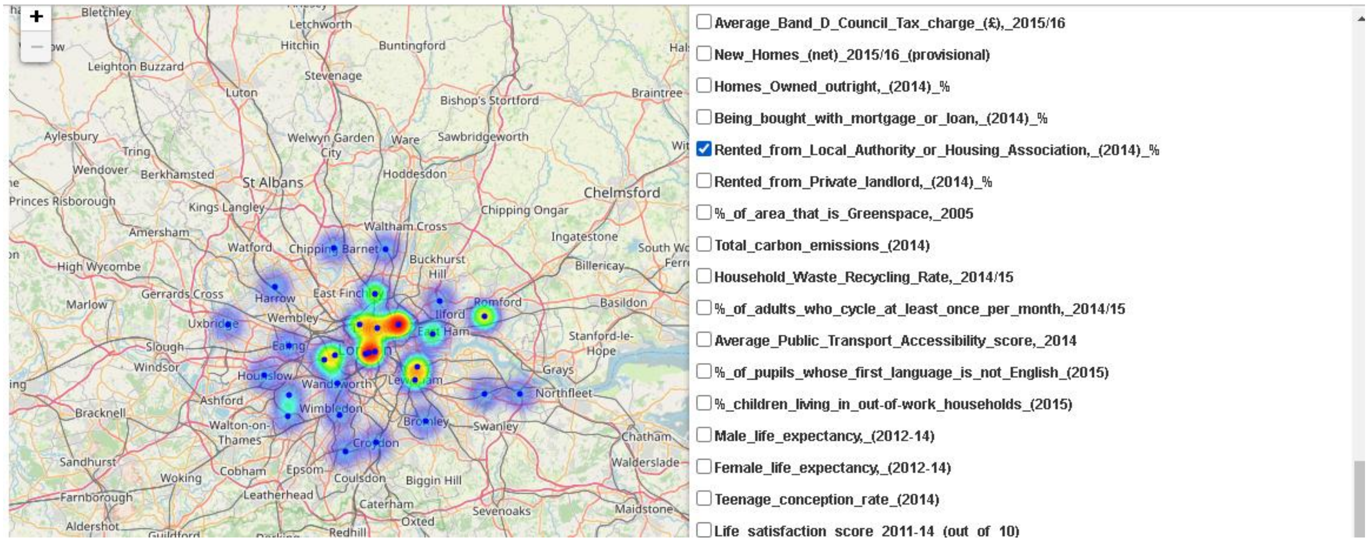



Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)
Gross_Annual_Pay_-_Female_(2016)
Modelled_Household_median_income_estimates_2012/13
Number_of_jobs_by_workplace_(2014)
%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015
Number_of_active_businesses,_2015
Two-year_business_survival_rates_(started_in_2013)
Crime_rates_per_thousand_population_2014/15
Fires_per_thousand_population_(2014)
Ambulance_incidents_per_hundred_population_(2014)
Median_House_Price,_2015
Average_Band_D_Council_Tax_charge_(£),_2015/16
New_Homes_(net)_2015/16_(provisional)
Homes_Owned_outright,_(2014)_%


Number_of_jobs_by_workplace_(2014)
%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015
Number_of_active_businesses,_2015
Two-year_business_survival_rates_(started_in_2013)
Crime_rates_per_thousand_population_2014/15
Fires_per_thousand_population_(2014)
Ambulance_incidents_per_hundred_population_(2014)
Median_House_Price,_2015
Average_Band_D_Council_Tax_charge_(£),_2015/16
New_Homes_(net)_2015/16_(provisional)
Homes_Owned_outright,_(2014)_%
Being_bought_with_mortgage_or_loan,_(2014)_%
Rented_from_Local_Authority_or_Housing_Association,_(2014)_%
Rented_from_Private_landlord,_(2014)_%
%_of_area_that_is_Greenspace,_2005

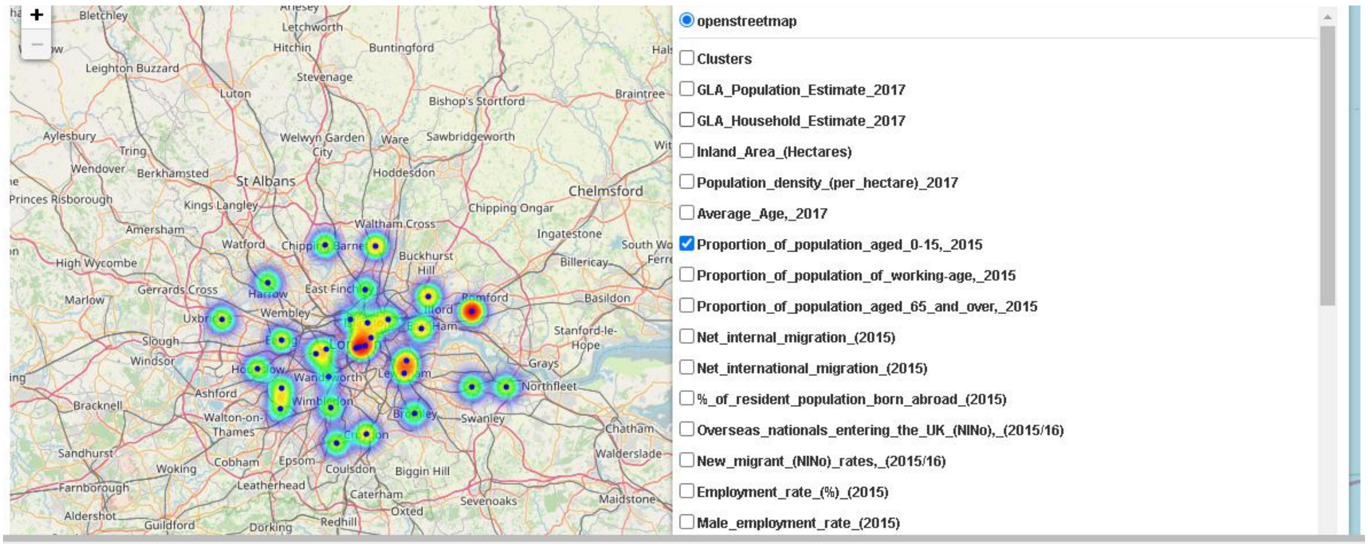

%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015
Number_of_active_businesses,_2015
Two-year_business_survival_rates_(started_in_2013)
Crime_rates_per_thousand_population_2014/15
Fires_per_thousand_population_(2014)
Ambulance_incidents_per_hundred_population_(2014)
Median_House_Price,_2015
Average_Band_D_Council_Tax_charge_(£),_2015/16
New_Homes_(net)_2015/16_(provisional)
Homes_Owned_outright,_(2014)_%
Being_bought_with_mortgage_or_loan,_(2014)_%
Rented_from_Local_Authority_or_Housing_Association,_(2014)_%
Rented_from_Private_landlord,_(2014)_%
%_of_area_that_is_Greenspace,_2005
Total_carbon_emissions_(2014)
Household_Waste_Recycling_Rate,_2014/15

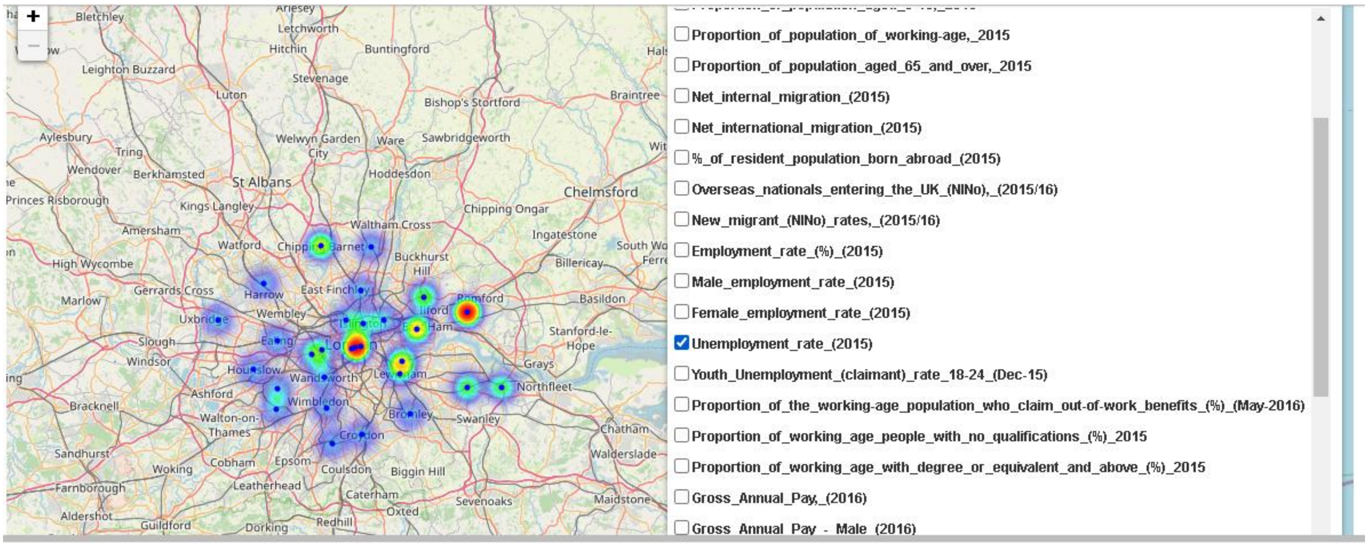


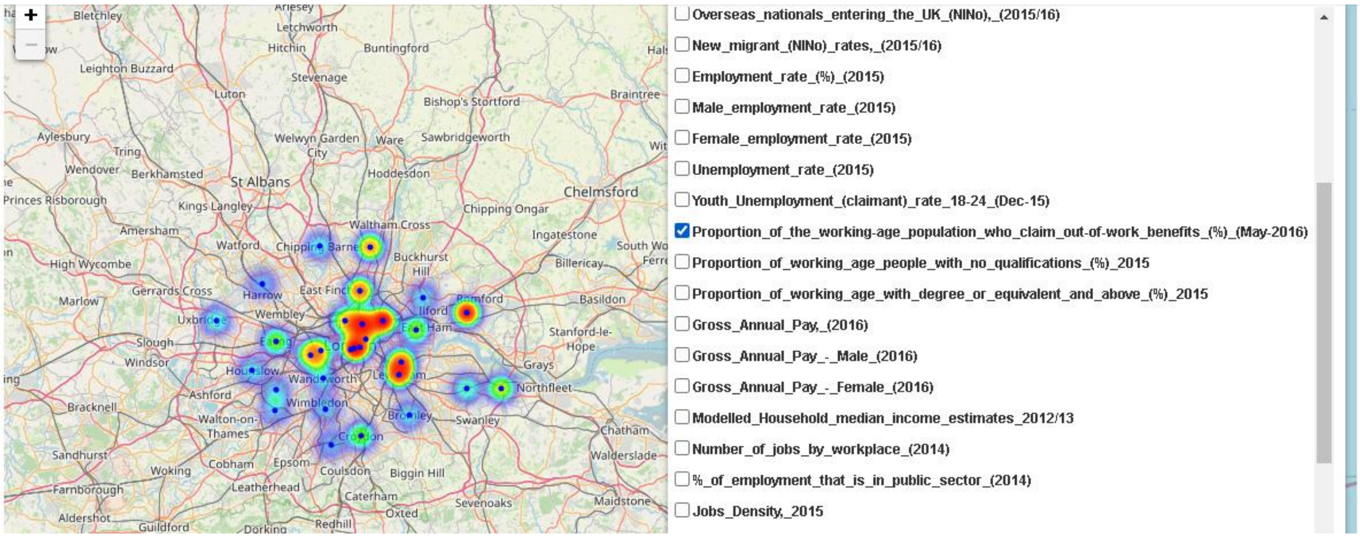

***Problems of 'Barking and Dagenham' borough:-***

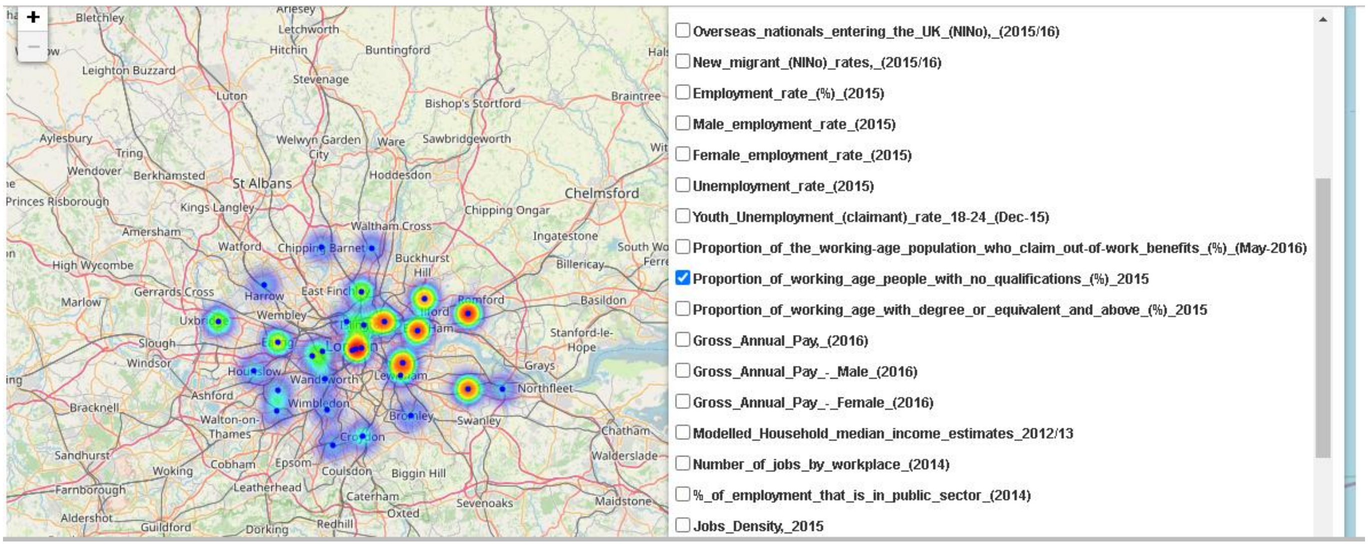
It is situated in the far eastern part of London and has the highest percentage share of the population aged between 0-15 years with One in every five jobs is in the public sector. there are following challenges with this borough:-

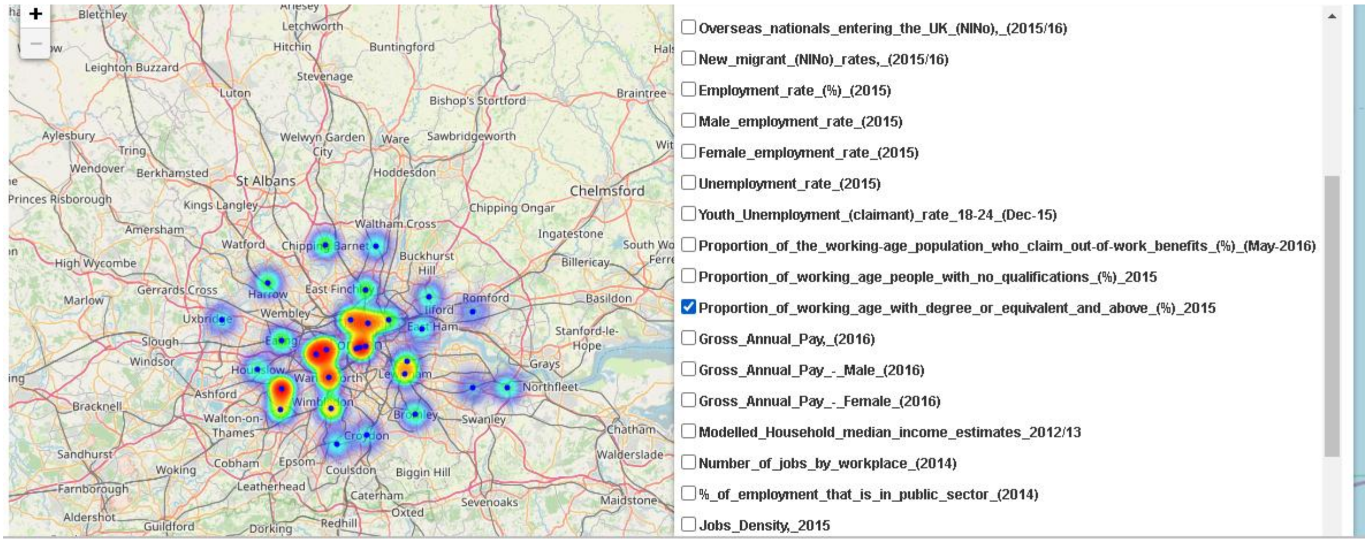
a. Highest rate of unemployment, with every tenth person of the working-age population claiming out of work benefits.
b. One of the highest percentages of the population, which is of working-age but has no qualification.
c. One of the lowest proportion of the working-age population with a degree equivalent or above.
d. Very high teenage conception rate.
e. Very high childhood obesity prevalence.
f. A high Mortality rate in which preventable causes cause deaths.



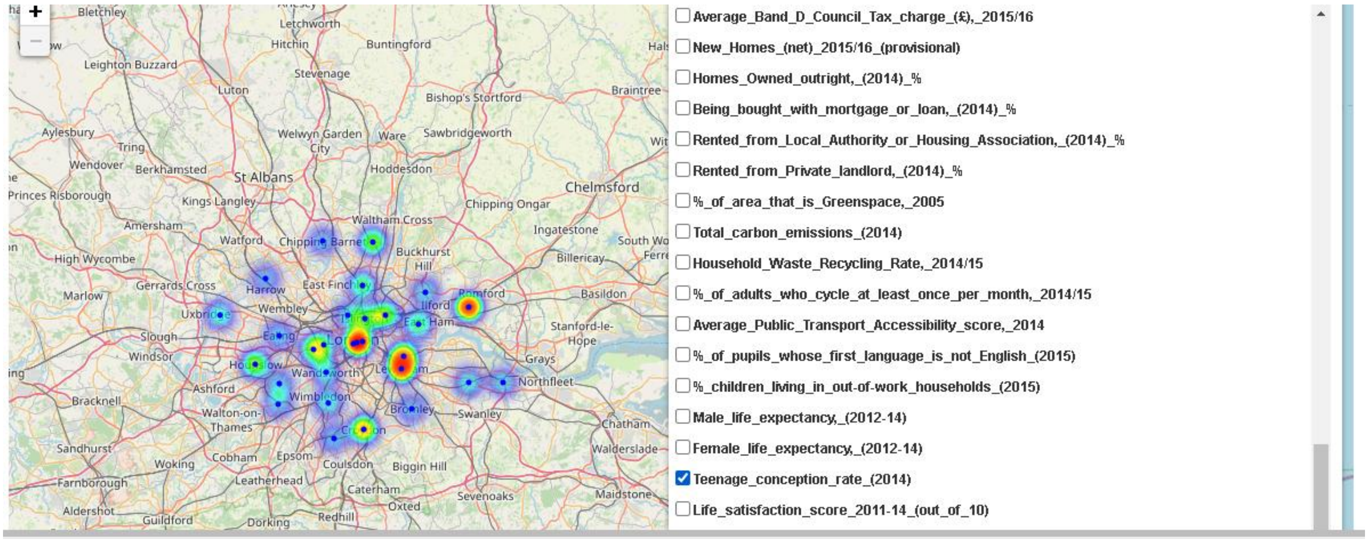

Proportion_of_population_of_working-age,_2015
Proportion_of_population_aged_65_and_over,_2015
Net_internal_migration_(2015)
Net_international_migration_(2015)
%_of_resident_population_born_abroad_(2015)
Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)


Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)
Gross_Annual_Pay_-_Female_(2016)
Modelled_Household_median_income_estimates_2012/13
Number_of_jobs_by_workplace_(2014)
%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015

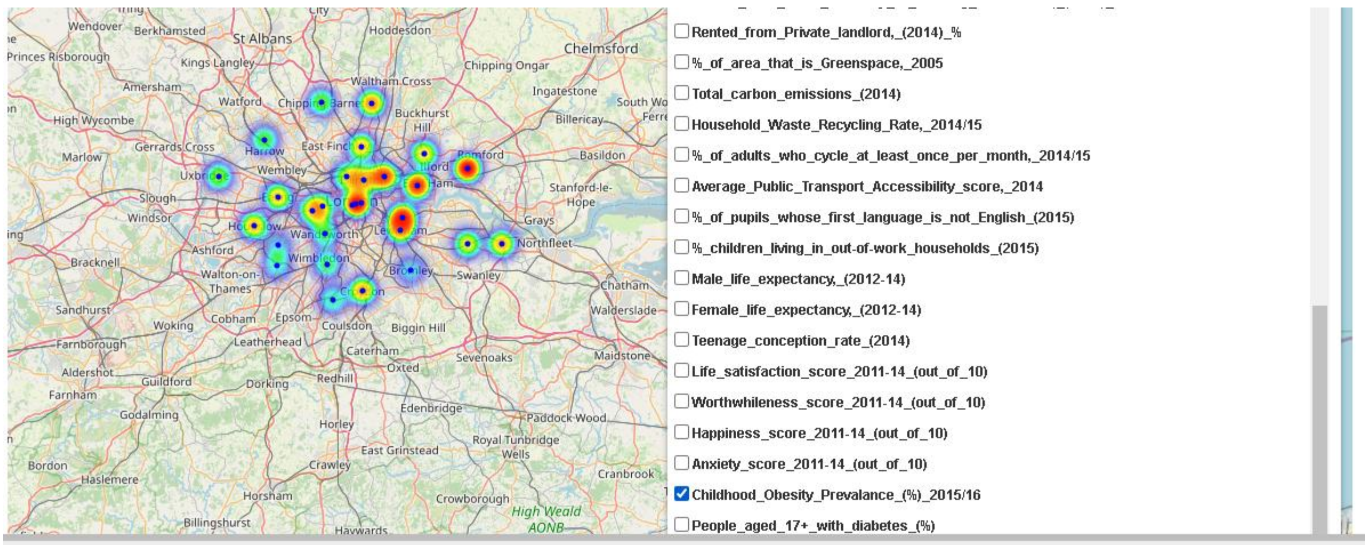

Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)
Gross_Annual_Pay_-_Female_(2016)
Modelled_Household_median_income_estimates_2012/13
Number_of_jobs_by_workplace_(2014)
%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015



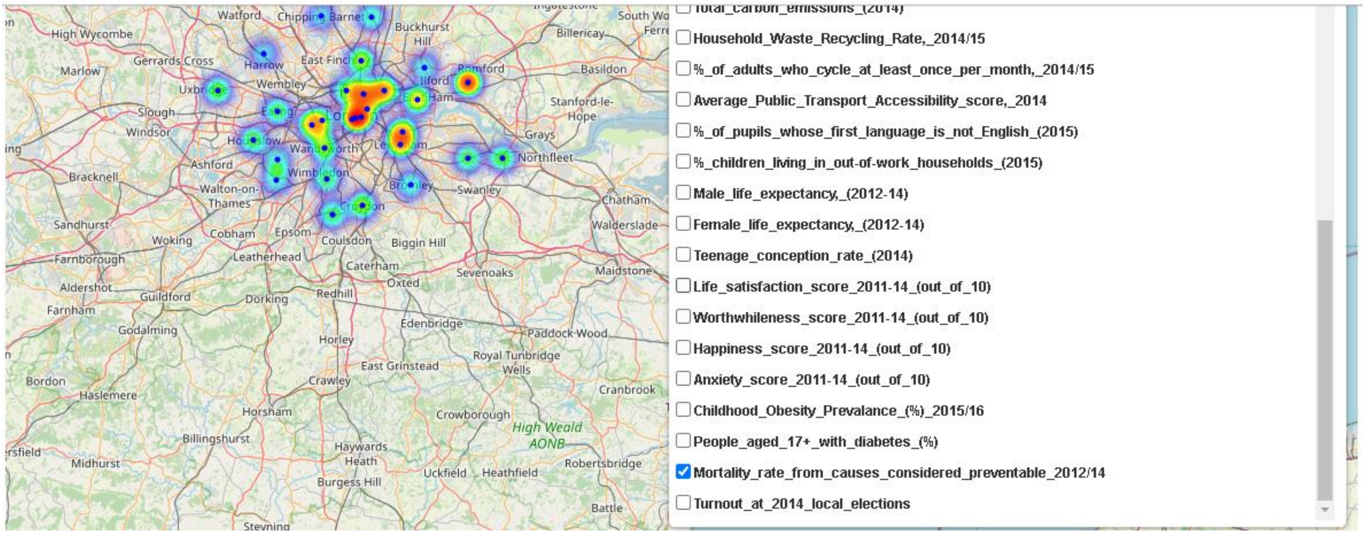
Overseas_nationals_entering_the_UK_(NINo),_(2015/16)
New_migrant_(NINo)_rates,_(2015/16)
Employment_rate_(%)_(2015)
Male_employment_rate_(2015)
Female_employment_rate_(2015)
Unemployment_rate_(2015)
Youth_Unemployment_(claimant)_rate_18-24_(Dec-15)
Proportion_of_the_working-age_population_who_claim_out-of-work_benefits_(%)_(May-2016)
Proportion_of_working_age_people_with_no_qualifications_(%)_2015
Proportion_of_working_age_with_degree_or_equivalent_and_above_(%)_2015
Gross_Annual_Pay,_(2016)
Gross_Annual_Pay_-_Male_(2016)
Gross_Annual_Pay_-_Female_(2016)
Modelled_Household_median_income_estimates_2012/13
Number_of_jobs_by_workplace_(2014)
%_of_employment_that_is_in_public_sector_(2014)
Jobs_Density,_2015

Average_Band_D_Council_Tax_charge_(£),_2015/16
New_Homes_(net)_2015/16_(provisional)
Homes_Owned_outright,_(2014)_%
Being_bought_with_mortgage_or_loan,_(2014)_%
Rented_from_Local_Authority_or_Housing_Association,_(2014)_%
Rented_from_Private_landlord,_(2014)_%
%_of_area_that_is_Greenspace,_2005
Total_carbon_emissions_(2014)
Household_Waste_Recycling_Rate,_2014/15
%_of_adults_who_cycle_at_least_once_per_month,_2014/15
Average_Public_Transport_Accessibility_score,_2014
%_of_pupils_whose_first_language_is_not_English_(2015)
%_children_living_in_out-of-work_households_(2015)
Male_life_expectancy,_(2012-14)
Female_life_expectancy,_(2012-14)
Teenage_conception_rate_(2014)
Life_satisfaction_score_2011-14_(out_of_10)

Rented_from_Private_landlord,_(2014)_%
%_of_area_that_is_Greenspace,_2005
Total_carbon_emissions_(2014)
Household_Waste_Recycling_Rate,_2014/15
%_of_adults_who_cycle_at_least_once_per_month,_2014/15
Average_Public_Transport_Accessibility_score,_2014
%_of_pupils_whose_first_language_is_not_English_(2015)
%_children_living_in_out-of-work_households_(2015)
Male_life_expectancy,_(2012-14)
Female_life_expectancy,_(2012-14)
Teenage_conception_rate_(2014)
Life_satisfaction_score_2011-14_(out_of_10)
Worthwhileness_score_2011-14_(out_of_10)
Happiness_score_2011-14_(out_of_10)
Anxiety_score_2011-14_(out_of_10)
Childhood_Obesity_Prevalance_(%)_2015/16
People_aged_17+_with_diabetes_(%)




# 6. CONCLUSION:

As the Happiness-Score and Life-Satisfaction score, which are evenly distributed almost across the entire state, it is evident that London is a perfect right choice to move for any reason, be it studies, business, job, or just staying. Apart from that, it is not like there are problems with only one borough *(Barking and Dagenham),* and rest other boroughs have no problems at all. Other boroughs too have their problems, but they are distributed, whereas, in this particular borough, most of the problems are concentrated.