

Where to live in London?

Coursera Capstone Project Michael Ho-Hsin Hsiang

TABLE OF CONTENTS





Introduction and Background of Problem

London is one of the most common choices for international students in terms of tertiary education. According to the data published by the British Council, in the academic year 2018-2019 London has 286,235 international students to its higher education institutions. There are a lot of famous universities located in London, including Imperial College London (ICL), University College London (UCL), King's College London (KCL), London School of Economics (LSE) etc. One of the biggest concerns for international students when moving to a new city would be finding an accommodation. In terms of finding a good place to live, there are many criteria that we should concern, for example, living convenience, rent rate, crime rate etc. Therefore in this project, I intend to explore different neighborhoods of London and find the best area for international students to live in London.

This study will focus only on the safety, rental easiness and expenses and the general atmosphere of the neighborhood. For the safety part, I will make use of the London recorded crime data to analyze. For the rental easiness and expenses part, I will use data from London Datastore, and for the general atmosphere, Foursquare API and K means clustering will be used.



DATA

LONDON BOROUGHS

Wikipedia

https://en.wikipedia.org/wiki/List of London boroughs

List of boroughs and local authorities [edit]

Borough \$	Inner \$	Status +	Local authority \$	Political control	Headquarters \$	Area (sq ¢ mi)	Population (2013 \$ est) ^[1]	Co- ordinates	Nr. in \$
Barking and Dagenham [note 1]			Barking and Dagenham London Borough Council	Labour	Town Hall, 1 Town Square	13.93	194,352	51.5607°N 0.1557°E	25
Barnet			Barnet London Borough Council	Conservative	North London Business Park, Oakleigh Road South	33.49	369,088	51.6252°N 0.1517°W	31
Bexley			Bexley London Borough Council	Conservative	Civic Offices, 2 Watling Street	23.38	236,687	51.4549°N 0.1505°E	23
Brent			Brent London Borough Council	Labour	Brent Civic Centre, Engineers Way	16.70	317,264	51.5588°N 0.2817°W	12
Bromley			Bromley London Borough Council	Conservative	Civic Centre, Stockwell Close	57.97	317,899	51.4039°N 0.0198°E	20

London Datastore UK Crimestat

https://data.london.gov.uk/download/recor ded_crime_summary/d2e9ccfc-a054-41e3 -89fb-53c2bc3ed87a/MPS%20Borough% 20Level%20Crime%20%28most%20rece nt%2024%20months%29.csv

https://www.ukcrimestats.com/Police Forc e/City of London Police

LONDON CRIME DATA (past 24 months)

	MajorText	MinorText	Borough	201803	201804	201805	201806	201807	201808	201809
0	Arson and Criminal Damage	Arson	Barking and Dagenham	6	3	4	12	6	5	3
1	Arson and Criminal Damage	Criminal Damage	Barking and Dagenham	115	122	126	123	127	101	107
2	Burglary	Burglary - Business and Community	Barking and Dagenham	38	36	24	33	30	18	33
3	Burglary	Burglary - Residential	Barking and Dagenham	122	75	93	77	94	84	99
4	Drug Offences	Drug Trafficking	Barking and Dagenham	7	3	8	6	9	7	10

AVERAGE RENT IN DIFFERENT BOROUGHS (2011-2019)

London Datastore

https://data.london.gov.uk/downlo ad/average-private-rents-borough /73b9fb07-b5bb-4a53-88b7-c172 69879a08/voa-average-rent-boro ugh.xls

В	С	D	E	F	G	Н	1	J	K	L	
		12 m	onths to Q2	2 2011			12 m	onths to Q3	3 2011		
		Al	l categori	es		All categories					
Area	Count of rents	Average (£)	Lower quartile (£)	Median (£)	Upper quartile (£)	Count of rents	Average (£)	Lower quartile (£)	Median (£)	Upper quartile (£)	
City of London	109	1,713	1,365	1,647	1,950	106	1,720	1,365	1,690	1,972	
Barking and Dagenham	894	792	675	800	950	767	800	675	802	950	
Barnet	4,054	1,202	650	1,000	1,407	3,798	1,258	737	1,062	1,450	
Bexley	1,042	795	650	775	950	910	807	650	800	950	
Brent	1,989	1,218	750	1,105	1,500	1,779	1,242	750	1,148	1,517	
Bromley	1,677	983	750	875	1,100	1,969	1,021	775	916	1,125	
Camden	3,457	1,757	1,083	1,517	2,080	3,739	1,821	1,170	1,582	2,123	
Croydon	1,262	843	675	825	950	1,684	859	675	850	1,000	
Ealing	2,355	1,093	750	1,000	1,300	1,909	1,123	750	1,000	1,300	
Enfield	1,728	943	625	933	1,192	1,664	958	650	949	1,200	

LONDON POPULATION BY BOROUGH (2018)

CITYPOPULATION.de

https://www.citypopulation.de/en/uk/great erlondon/

Name	Status	Population Estimate 1981-06-30	Population Estimate 1991-06-30	Population Estimate 2001-06-30	Population Estimate 2011-06-30	Population Estimate 2018-06-30
Barking and Dagenham	Borough	161,300	155,500	165,700	187,029	211,998
Barnet	Borough	295,200	297,700	319,500	357,538	392,140
Bexley	Borough	217,400	218,100	218,800	232,774	247,258
Brent	Borough	248,300	240,800	269,600	312,245	330,795
Bromley	Borough	299,200	293,500	296,200	310,554	331,096
Camden	Borough	179,100	180,700	202,600	220,087	262,226
City of London	City	6,700	5,400	7,400	7,412	8,706
City of Westminster	Borough	188,400	185,000	203,300	219,582	255,324
Croydon	Borough	320,700	315,900	335,100	364,815	385,346
Ealing	Borough	285,300	283,800	307,300	339,314	341,982
Enfield	Borough	260,900	260,100	277,300	313,935	333,869
Greenwich	Borough	214,100	210,900	217,500	255,483	286,186
Hackney	Borough	185,200	185,000	207,200	247,182	279,665
Hammersmith and Fulham	Borough	150,200	153,800	169,400	182,445	185,426
Haringev	Borough	206.900	207.000	221.300	255.540	270.624

ANALYSIS



Data Cleaning



Data Cleaning

As there are lots of NaN, missing data and useless data in the datasets, we need to perform Data cleaning before using the data.



Crime Data

Crime Data consists of crime details such as type of crime which are useless. We need to drop out all these datas and keep only number of crimes.



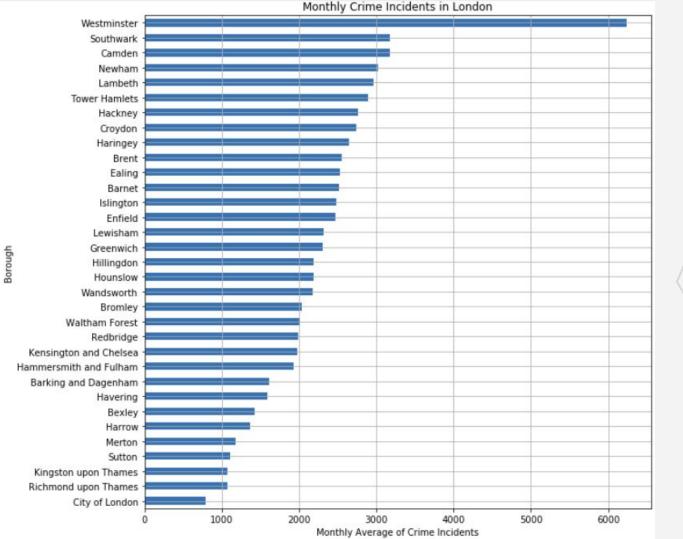
Rental Data

We only need the "Count of rents" and "Average(pounds)" data among the whole dataset.

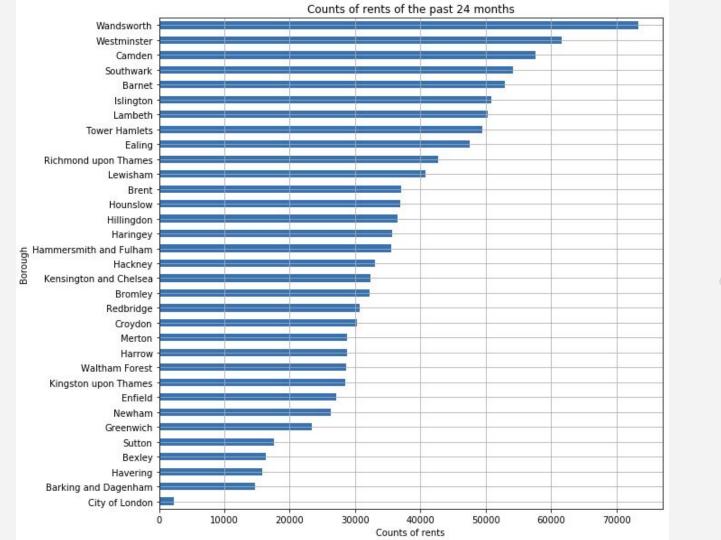


Population

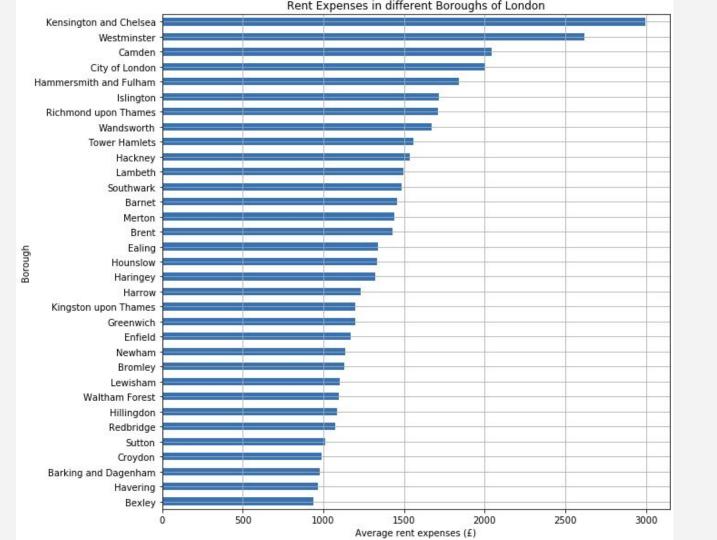
Population data consists of the estimate population of several different years. Only the data of 2018 was used.



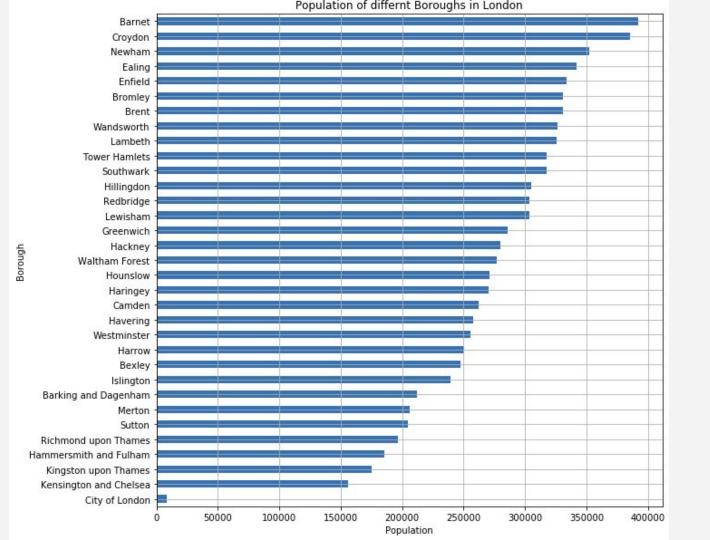






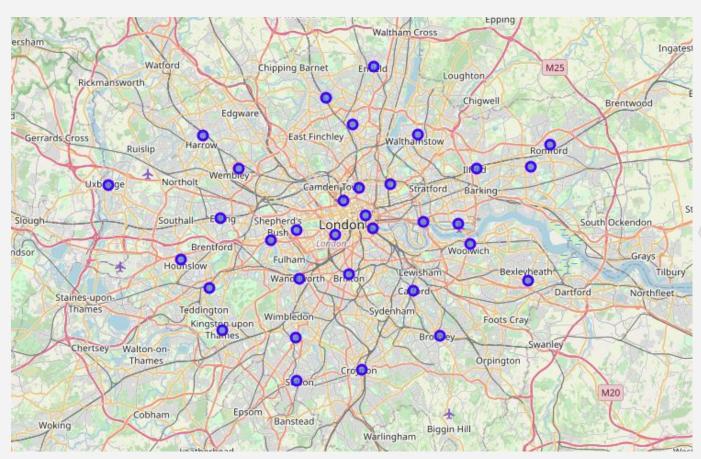








Map of Boroughs in London





RESULTS

Clustering of Boroughs (I)

Use Foursquare API to get top venues near each Borough

	BoroughName	Borough Latitude	Borough Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Barking and Dagenham	51.5607	0.1557	Central Park	51.559560	0.161981	Park
1	Barking and Dagenham	51.5607	0.1557	Lara Grill	51.562445	0.147178	Turkish Restaurant
2	Barking and Dagenham	51.5607	0.1557	Iceland	51.560578	0.147685	Grocery Store
3	Barking and Dagenham	51.5607	0.1557	Shell	51.560415	0.148364	Gas Station
4	Barking and Dagenham	51.5607	0.1557	Morrisons	51.559774	0.148752	Supermarket

Clustering of Boroughs (II)

Transform to onehot data based on different categories of venues

												5	
	BoroughName	Afghan Restaurant	African Restaurant	Airport	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Art Gallery	Art Museum	Arts & Crafts Store		Athletics & Sports
0	Barking and Dagenham	0	0	0	0	0	0	0	0	0	0	0	0
1	Barking and Dagenham	0	0	0	0	0	0	0	0	0	0	0	C
2	Barking and Dagenham	0	0	0	0	0	0	0	0	0	0	0	C
3	Barking and Dagenham	0	0	0	0	0	0	0	0	0	0	0	0
4	Barking and Dagenham	0	0	0	0	0	0	0	0	0	0	0	0

Clustering of Boroughs (III)

Calculate the mean of each category and group the data by Boroughs

	BoroughName	Afghan Restaurant	African Restaurant	Airport	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Art Gallery	Art Museum	Arts & Crafts Store
0	Barking and Dagenham	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.00
1	Barnet	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.00
2	Bexley	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.040000	0.000000	0.00	0.00
3	Brent	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.021277	0.000000	0.00	0.00
4	Bromley	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.00
5	Camden	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.030000	0.00	0.00
6	City of London	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.010000	0.010000	0.00	0.00
7	Croydon	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.00
8	Ealing	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.010000	0.00	0.00
9	Enfield	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00	0.00

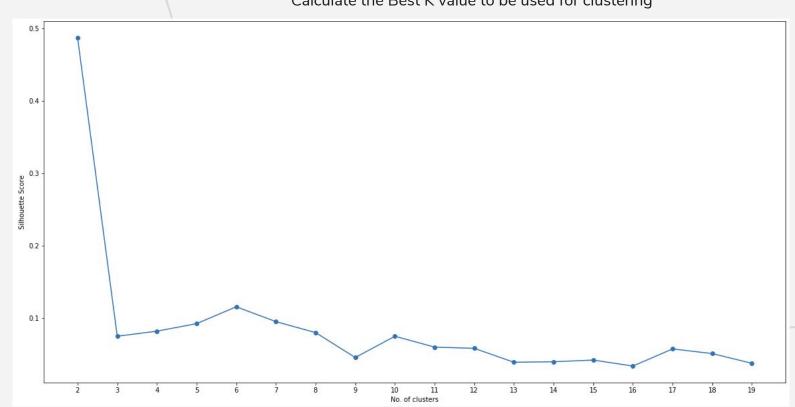
Clustering of Boroughs (IV)

Visualize the top-ranked categories in each Borough

	Borough	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Barking and Dagenham	Bus Stop	Sports Club	Bus Station	Gas Station	Park
1	Barnet	Pub	Park	Fish & Chips Shop	Bus Stop	Gym
2	Bexley	Pub	Clothing Store	Supermarket	Fast Food Restaurant	Coffee Shop
3	Brent	Coffee Shop	Hotel	Clothing Store	Bar	Grocery Store
4	Bromley	Clothing Store	Pub	Coffee Shop	Gym / Fitness Center	Café

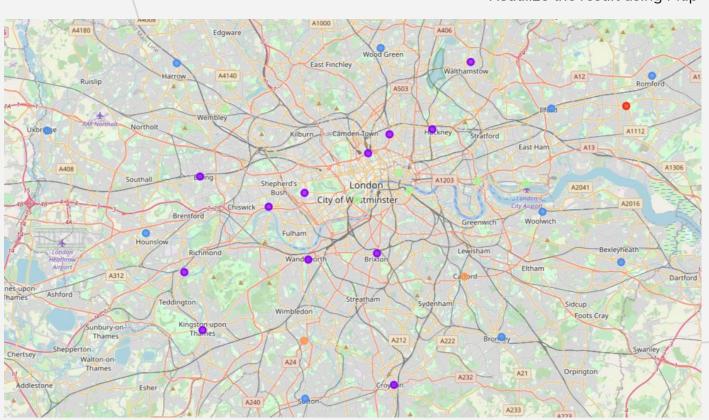
Clustering of Boroughs (V)





Clustering of Boroughs (VI)

Visualize the result using Map



Clustering of Boroughs (VII)

Camden

Croydon

Ealing

Hackney

5

6

7

10

Coffee Shop

Coffee Shop

Coffee Shop

Coffee Shop

# Cluster 0: Conve london_merged.loc[0, london_merged.	columns[[0] + lis	t(range(7, london	_merged.shape[1]))]]
Borough	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7tl

		venue	velide	velide	velide	venue	velide	
0	Barking and Dagenham	Bus Stop	Sports Club	Bus Station	Gas Station	Park	Supermarket	Golf

Café

Pub

Pub

Café

If Course

7th Most Common

Italian Restaurant

Indian Restaurant

Hotel

Brewery

Park

Bookstore

Flea Market

Italian Restaurant

Venue

Burger Joint

Burger Joint

Platform

Bakery

# Cluster 1: Lively london_merged.loc[l		1, london_merged	.columns[[0] + li	st(range(7, londo	n_merged.shape[1])	0)]]

# Cluster 1: Lively london_merged.loc[lo			1, london_merged	d.columns[[0] + li	st(range(7, londo	n_merged.shape[1]))]]
	2004242 0002	62500 ZIE. 095281	NEW 23 C 0 22 2	2759316 (1953)		\$50,000 (E.C.)	00/01/20 07/01

london_merged.loc[london_merged['Cluster Labels'] == 1, london_merged.columns[[0] + list(range(7, london_merged.shape[1]))]]									
Borough		2nd Most Common			5th Most Common				

						- 0	1
Borough	1st Most Common	2nd Most Common	3rd Most Common	4th Most Common	5th Most Common	6th Most Common	7th Most Common
	Venue						

Bookstore

Pub

Italian Restaurant

Thai Restaurant

Hotel

Bakery

Park

Clothing Store

Clustering of Boroughs (VIII)

Bromley

Enfield

Greenwich

Barnet

Cluster 2: Busy area (Coffee shops, Clothing stores)

Clothing Store

Pub

london_merged	.loc[london_merged	d['Cluster Labels']	== 2, london_mer	ged.columns[[0] +	list(range(7 , lo nd	on_merged.shape[1]))]]
Borough	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 (

	Borough	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
2	Bexley	Pub	Clothing Store	Supermarket	Fast Food Restaurant	Coffee Shop	Hotel	Italian Restaurant

	Borougn	Venue	Venue	Venue	Venue	٧
2	Bexley	Pub	Clothing Store	Supermarket	Fast Food Restaurant	Coffee

Pub	Coffee Shop	Gym / Fitness Center	Café	Electronics Store	Pizza Place
Shop	Clothing Store	Café	Department Store	Supermarket	Fish & Chips Shop
Store	Clothing Store	Coffee Shop	Fast Food Restaurant	Plaza	Supermarket
					2000

Gym

Film Studio

Café

Fish & Chips Shop	Supermarket	Department Store	Café	Clothing Store	Coffee Shop	Pub
Supermarket	Plaza	Fast Food Restaurant	Coffee Shop	Clothing Store	Grocery Store	Pub
Grocery Store	Pharmacy	Bakery	Fast Food Restaurant	Clothing Store	Café	Pub

Bus Stop

12	Haringey	Pub	Café	Clothing Store	Fast Food Restaurant	Bakery	Pharmacy	Grocery Store
13	Harrow	Coffee Shop	Indian Restaurant	Clothing Store	Sandwich Place	Fast Food Restaurant	Gym / Fitness Center	Pharmacy

13	Harrow	Coffee Shop	Indian Restaurant	Clothing Store	Sandwich Place	Fast Food Restaurant	Gym / Fitness Center	Pharmac
100	uster 3: Mix							

13	Harrow	Соптее эпор	indian Restaurant	Clothing Store	Sandwich Place	rast rood Restaurant	Gym / Fitness Center	Pharmac
# Ci	luster 3: Mix							
lone	don_merged.loc[lo	ondon_merged[<mark>'</mark> (Cluster Labels'] == 3	, london_merged.c	olumns[[0] +]	ist(range(7, londo	on_merged.shape[1]))]]	

# Cluster 3: Mix	
<pre>london_merged.loc[london_merged['Cluster Labels'] == 3, london_merged.columns[[0] + list(range(7, london_merged.shape[1]))]]</pre>	

ondon_merg	ed.loc[london_merg	ed['Cluster Labels	'] == 3, london_me	rged.columns[[0] +	list(range(7, lone	don_merged.shape[1]))]]
Borough		2nd Most Common					

TOTA OTT_THE B	ca. roc[rondon_mer e	Seal craster raters	j bj rondon_me	. Bearcoramis[[a] .	- 1135(/ angc(/) 15masn_mer gearsmape[1]/)]]		
Borough	1st Most Common	2nd Most Common	3rd Most Common	4th Most Common	5th Most Common	6th Most Common	7th Most Common

Fish & Chips Shop

Park

Borough	1st Most Common	2nd Most Common	3rd Most Common	4th Most Common	5th Most Common	6th Most Common	7th Most Common
Dorougii	Venue						

Clustering of Boroughs (IX)

Merton Fast Food Restaurant

22

		ravetter area Loc[london_merged[['Cluster Labels']	== 4, london_merge	ed.columns[[0] + 1	ist(range(7, londo	on_merged.shape[1]))]]
	Borough	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
3	Brent	Coffee Shop	Hotel	Clothing Store	Bar	Grocery Store	Pizza Place	Warehouse Store
23	Newham	Hotel	Light Rail Station	Coffee Shop	Park	Airport Service	Rental Car Location	Bus Station
12020	1221 12 20	2002	20.020 720	1997 19	72 12 25 32	E 61	U 12	10 No 9/27

Southwark Coffee Shop Italian Restaurant Hotel Scenic Lookout Park Beer Bar Seafood Restaurant

28	Tower Hamlets	Coffee Shop	Park	Hotel	Lounge	Bus Stop	Italian Restaurant	Café
# CL	uster 5: Groc	ery Store and superma	orket					

	Hamlets	conce onep	1 318	110001	counge	Балокор	realian neseautane	
# Cla	uster 5: Groce	ery Store and supermo	orket					
londe	on merged.loc[london merged['Clust	er Labels'1 == 5.	london merged.co	lumns[[0] + list(r	range(7, londor	merged.shape[1]))]]	

# Cluster 5: Grocery Store and supermarket	
<pre>london_merged.loc[london_merged['Cluster Labels'] == 5, london_merged.columns[[0] + list(range(7, london_merged.shape[1]))]]</pre>	

london_merged	.loc[london_merge	d['Cluster Labels'] == 5, london_mer	ged.columns[[0] +	list(range(7, lond	on_merged.shape[1]))]]
Darauah	1st Most Common	2nd Most Common	3rd Most Common	4th Most Common	5th Most Common	6th Most Common	7th Most Common

Borou	gh 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

Supermarket

Park

Train Station

Bar

	Borough	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
21	Lewisham	Grocery Store	Coffee Shop	Park	Supermarket	Pub	Café	Italian Restaurant

Grocery Store

Café

Results in terms of Crime rate and Rent data (I)

Join dataframe of borough info, crime data and rental data.

	Borough	Latitude	Longitude	CrimeToPop	Count of rents	Average
0	Barking and Dagenham	51.5607	0.1557	7.625072	14728.0	978.284623
1	Barnet	51.6252	-0.1517	6.432014	52966.0	1458,462446
2	Bexley	51.4549	0.1505	5.746191	16360.0	936.829586
3	Brent	51.5588	-0.2817	7.702908	37109.0	1426,499681
4	Bromley	51.4039	0.0198	6.142478	32242.0	1130.038838

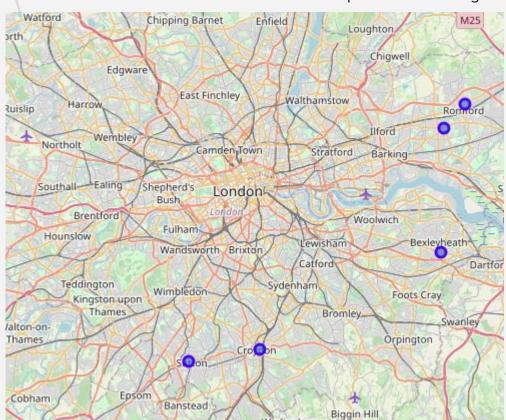
Results in terms of Crime rate and Rent data (II)

Transform the data into scores between 0-1 and sum up the scores

	Borough	Latitude	Longitude	Safety	Easy to Rent	Rent Expense	Total Score
2	Bexley	51.4549	0.1505	0.996084	0.802133	1.000000	2.798217
14	Havering	51.5812	0.1837	0.991141	0.809522	0.986665	2.787327
0	Barking and Dagenham	51.5607	0.1557	0.973936	0.825101	0.979865	2.778902
27	Sutton	51.3618	-0.1945	1.000000	0.785358	0.964182	2.749541
6	Croydon	51.3714	-0.0977	0.980030	0.605519	0.975116	2,560665

Results in terms of Crime rate and Rent data (III)

Calculate and Visualize the top-5 scored boroughs

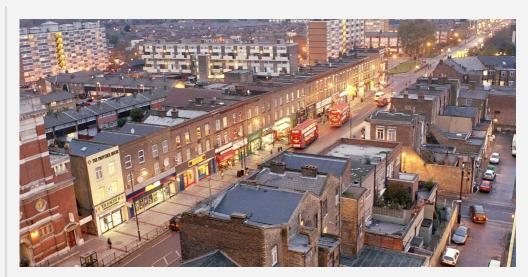




Conclusion

To conclude, there are lots of factors that need to be considered when choosing a place to live in a city. This project only takes Crime Rate, Rental Data, and living environment into account.

The results shows that **Bexley**, **Havering**, **Barking and Dagenham**, **Sutton** and **Croydon** are the top 5 choices to live as they have the combination of lowest crime rate, reasonable rental price and sufficient amount of rental choices. The living environment varies for different people so it's hard to get a conclusion based on this factor.



Barking and Dagenham



CREDITS

This is where you give credit to the ones who are part of this project.

- Presentation template by Slidesgo
- Icons by Flaticon
- Infographics by Freepik
- Images created by Freepik
- Image from https://unsplash.com/s/photos/london
- Text & Image slide photo created by Freepik.com