North-East UK region

Property buyer guide.

June 2020.

1. Introduction.

North-East of UK region covers Northumberland, County Durham, Tyne and Wear, and the area of the former county of Cleveland in North Yorkshire.

Its fast growing region with several big international company's offices/plants locations.

Quite often employees from another countries/regions are coming to work in local locations of international companies. That means finding best property location to live is one of key questions they face.

1.1 Business problem

For people coming to the region it’s hard to determinate which area is best to rent/buy property in without deep analysis. To combine analysis potential buyer should use multiple sources of information which is time consuming. However such analysis is required to be done as many factors need to be taken into account (price, travel time to work, shops, parks, school locations, crime rates, ect.). List of the factors and their weight obviously different for every person. There are more than 130 postcode districts to choose from and this guide is aimed to provide data driven approach for finding optimum property location in area.

Data acquisition and cleaning

1.2 Data sources

Following Data sources are used in analysis.

1. For study I require basic information about the region – postcode list (for example NE22 5HF), post code district (contains multiple postcodes, for example NE22), area name linked to postcode data (for example - Cramlington). Also I require some demographic information and geographic coordinates to visualize areas on the map.

   Source used: NE UK postcode list CSV file with areas name, demographic and coordinates available for free use from multiple resources, including data.service.gov.uk

2. I require historic data of property prices.

   Source used: Latest property sale prices in England and Wales - UK Price Paid Data from data.service.gov.uk

3. Crime rate data per postcode district

Source used: Crime rate data from Police from data.police.uk

4. To explore selected areas Foursquare API will be used.

2.2 Prepressing/ Data Cleansing.

Due to large amount of data/ inconsistency of variables, data cleansing was required

It was also used to determinate optimum variable between post code, post code district, Town/area, area name, general area name. Postcode district was used to progress with study. So to reduce data noise other parameters were dropped/ merged. Also actions to reduce/drop missing and zero data was removed. Renaming of particular columns was arranged.

3. Methodology section

Mostly during analysis data was taken from CSV files, using pandas read.csv.

As a first step, analysis on NE postcode data was done to come up with dataframe which contains required data for further steps.

	PCD	miles	Avg asking price	Crime rate	Area Name	General_Area_name
0	CA8	44.383	201660	55	Brampton, Gilsland, Greenhead, Slaggyford	Other
1	CA9	40.512	176904	50	Alston, Garrigill, Nenthead	Other
2	DH1	9.562	223730	127	Durham	Other
3	DH2	5.703	119902	97	Chester-le-Street, Ouston, Pelton, Birtley	CHESTER LE STREET
4	DH3	4.636	171267	139	Chester-le-Street, Great Lumley, Birtley	Other

Totally 132 unique postcodes areas were listed.

132	TS29	54.7112	-1.41995	437470	535286	NZ374352	Trimdon Station	County Durham	208	193	6313.0

133 rows × 18 columns

```
In [139]: df_combi['PCD'].unique()
Out[139]: array(['CA8', 'CA9', 'DH1', 'DH2', 'DH3', 'DH4', 'DH5', 'DH6', 'DH7',
       'DH8', 'DH9', 'DH97', 'DH98', 'DH99', 'DL1', 'DL2', 'DL3', 'DL4',
       'DL5', 'DL11', 'DL12', 'DL13', 'DL14', 'DL15', 'DL16', 'DL17',
       'DL98', 'NE1', 'NE2', 'NE3', 'NE4', 'NE5', 'NE6', 'NE7', 'NE8',
       'NE9', 'NE10', 'NE11', 'NE12', 'NE13', 'NE15', 'NE16', 'NE17',
       'NE18', 'NE19', 'NE20', 'NE21', 'NE22', 'NE23', 'NE24', 'NE25',
       'NE26', 'NE27', 'NE28', 'NE29', 'NE30', 'NE31', 'NE32', 'NE33',
       'NE34', 'NE35', 'NE36', 'NE37', 'NE38', 'NE39', 'NE40', 'NE41',
       'NE42', 'NE43', 'NE44', 'NE45', 'NE46', 'NE47', 'NE48', 'NE49',
       'NE61', 'NE62', 'NE63', 'NE64', 'NE65', 'NE66', 'NE67', 'NE68',
       'NE69', 'NE70', 'NE71', 'NE82', 'NE83', 'NE85', 'NE88', 'NE92',
       'NE98', 'NE99', 'SR1', 'SR2', 'SR3', 'SR4', 'SR5', 'SR6', 'SR7',
       'SR8', 'TD5', 'TD12', 'TD15', 'TS1', 'TS2', 'TS3', 'TS4', 'TS5',
       'TS6', 'TS7', 'TS8', 'TS9', 'TS10', 'TS11', 'TS12', 'TS13', 'TS14',
       'TS15', 'TS16', 'TS17', 'TS18', 'TS19', 'TS20', 'TS21', 'TS22',
       'TS23', 'TS24', 'TS25', 'TS26', 'TS27', 'TS28', 'TS29'],
      dtype=object)
```

Next step was to start applying some additional factors which influence person decision.

First factor was travel distance to work location. For analysis purposes major manufacturing facility was used with postcode district SR5. I used his location to determinate distance between all of 132 postcodes and mentioned one. Next criteria is less 15 miles distance was applied.

	PCD	Latitude	Longitude	Easting	Northing	Grid Reference	Town/Area	Region	Postcodes	Active postcodes	Popul
2	DH1	54.7826	-1.56261	428229	543165	NZ282431	Durham	County Durham	1966	1298	49987

That allowed us to narrow choice to 74 postcodes districts.

```
In [147]: df_close_location['PCD'].unique()

Out[147]: array(['DH1', 'DH2', 'DH3', 'DH4', 'DH5', 'DH6', 'DH7', 'DH9', 'DH97',
                 'DH98', 'DH99', 'DL98', 'NE1', 'NE2', 'NE3', 'NE4', 'NE5', 'NE6',
                 'NE7', 'NE8', 'NE9', 'NE10', 'NE11', 'NE12', 'NE13', 'NE15',
                 'NE16', 'NE17', 'NE18', 'NE20', 'NE21', 'NE23', 'NE24', 'NE25',
                 'NE26', 'NE27', 'NE28', 'NE29', 'NE30', 'NE31', 'NE32', 'NE33',
                 'NE34', 'NE35', 'NE36', 'NE37', 'NE38', 'NE39', 'NE40', 'NE41',
                 'NE44', 'NE67', 'NE69', 'NE82', 'NE83', 'NE85', 'NE88', 'NE92',
                 'NE98', 'NE99', 'SR1', 'SR2', 'SR3', 'SR4', 'SR5', 'SR6', 'SR7',
                 'SR8', 'TD5', 'TD12', 'TD15', 'TS2', 'TS28', 'TS29'], dtype=object)

In [153]: df_close_location['PCD'].nunique()

Out[153]: 74
```

Next factor/parameter which was used is price. Looking at average income in region and some surveys held, 150k GBP was used as entry price for around 80% of potential buyers.

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33 entries, 3 to 132
Data columns (total 18 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   PCD                33 non-null     object
 1   Latitude           33 non-null     float64
 2   Longitude          33 non-null     float64
 3   Easting            33 non-null     int64
 4   Northing           33 non-null     int64
 5   Grid Reference     33 non-null     object
 6   Town/Area          33 non-null     object
 7   Region             33 non-null     object
 8   Postcodes          33 non-null     int64
 9   Active postcodes   33 non-null     int64
 10  Population         33 non-null     float64
 11  Households         33 non-null     float64
 12  Nearby districts   33 non-null     object
 13  miles              33 non-null     float64
 14  Avg asking price   33 non-null     float64
 15  Crime rate         33 non-null     float64
 16  Area Name          33 non-null     object
 17  General_Area_name  33 non-null     object
dtypes: float64(7), int64(4), object(7)
memory usage: 4.9+ KB
```

So now we narrowed our search for 33 postcode districts

Next step in exploratory data analysis is to determinate if there are some particular areas which has much higher crime rate compared to others.

Using Csv data with crime rate included, new data frame was created.

Out[158]:

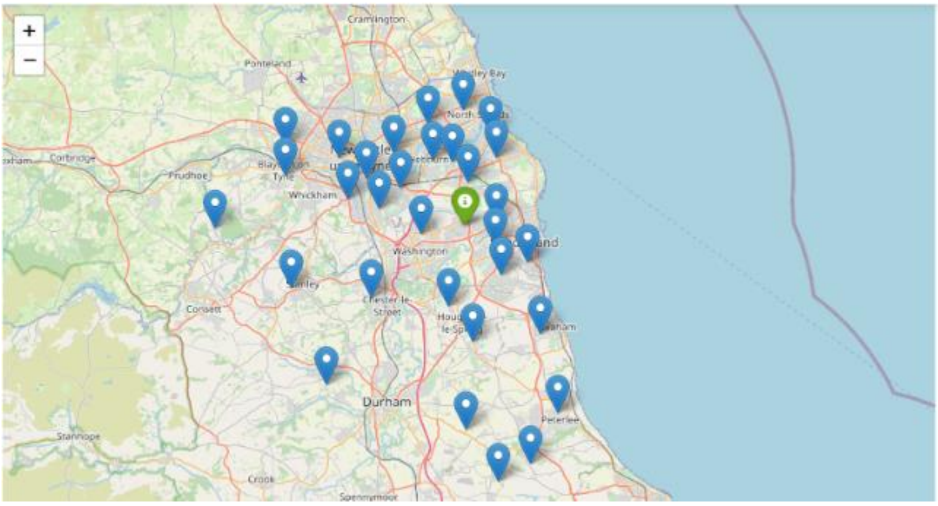
sting	Northing	Postcodes	Active postcodes	Population	Households	miles	Avg asking price	Crime rate
000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000	33.000000
995.484848	557160.636364	974.090909	744.939394	29247.181818	12940.575758	7.322121	117322.666667	164.454545
8.941157	10028.893171	386.518706	307.873953	13111.054702	5831.251083	3.745897	20053.057148	128.733273
711.000000	535286.000000	157.000000	131.000000	4890.000000	2255.000000	1.869000	63903.000000	92.000000
885.000000	551753.000000	726.000000	533.000000	20159.000000	9019.000000	4.289000	104299.000000	117.000000
824.000000	558709.000000	1052.000000	831.000000	33367.000000	14394.000000	5.972000	120457.000000	135.000000
020.000000	564228.000000	1236.000000	972.000000	37590.000000	16533.000000	9.818000	130257.000000	169.000000
784.000000	581039.000000	1547.000000	1245.000000	52220.000000	23285.000000	14.417000	145719.000000	854.000000

We can see that max rate is 854 which is far away from mean , and 75% of data. So will sort dataframe to see the values and eliminate related postcode areas from further study

So postcode SR1 was excluded from further study.

As I finalized list to 32 postcodes, it’s time to establish deep analysis on area.

Using Folium, locations were added to the map, including work location for reference.



Explore selected postcodes using Foursquare API.

1) Explore top venues within specific radius of postcode coordinates
2) Finding q-ty of venues per postcode area
3) Explore most common venues for each postcode district.

In [265]:
```
df_dataincl_venues
```

Out[265]:

	Name	Grid Reference	Latitude	Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	DURHAM_DH7	NZ218438	54.7895	-1.66153	New Board Inn	54.793065	-1.668720	Restaurant
1	Trimdon Station_TS29	NZ374352	54.7112	-1.41995	Chisholm Bookmakers	54.716614	-1.410735	Gaming Cafe
2	Trimdon Station_TS29	NZ374352	54.7112	-1.41995	Bus Stop	54.718554	-1.412110	Bus Stop
3	CHESTER LE STREET _DH2	NZ258517	54.8599	-1.59829	Bodywell Chip	54.862821	-1.601266	Mobile Phone Shop
4	CHESTER LE STREET _DH2	NZ258517	54.8599	-1.59829	Orchard Roofing	54.863375	-1.603886	Construction & Landscaping
...	...	...	...	...	...	...	...	...
304	Gateshead_NE8	NZ253624	54.9563	-1.60503	Sanctuary Artspace	54.961932	-1.600646	Art Gallery
305	Gateshead_NE8	NZ253624	54.9563	-1.60503	Aldi	54.958737	-1.594837	Supermarket
306	Gateshead_NE8	NZ253624	54.9563	-1.60503	Shipley Art Gallery	54.950109	-1.600080	Art Gallery
307	Gateshead_NE8	NZ253624	54.9563	-1.60503	Life Health & Fitness	54.949089	-1.598779	Gym
308	Gateshead_NE8	NZ253624	54.9563	-1.60503	Last Days Of The Raj	54.948851	-1.599012	Indian Restaurant

In [266]:
```
#finding how many venues for each postcode area
df_dataincl_venues.groupby('Name').count()
```

Out[266]:

	Grid Reference	Latitude	Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Name							
BLYTH_NE24	15	15	15	15	15	15	15
Blaydon-on-Tyne_NE21	11	11	11	11	11	11	11
Boldon Colliery_NE35	10	10	10	10	10	10	10
CHESTER LE STREET _DH2	6	6	6	6	6	6	6
DURHAM_DH6	1	1	1	1	1	1	1
DURHAM_DH7	1	1	1	1	1	1	1
Gateshead_NE10	10	10	10	10	10	10	10
Gateshead_NE11	10	10	10	10	10	10	10
Gateshead_NE8	28	28	28	28	28	28	28
Gateshead_NE9	15	15	15	15	15	15	15
HOUGHTON LE SPRING_DH4	4	4	4	4	4	4	4

Adding type of venue.

	Name	American Restaurant	Art Gallery	Athletics & Sports	Auto Garage	Bakery	Bar	Bed & Breakfast	Bistro	Bowling Alley	...	Stadium	Station Store
0	DURHAM_DH7	0	0	0	0	0	0	0	0	0	...	0	0
1	Trimdon Station_TS29	0	0	0	0	0	0	0	0	0	...	0	0
2	Trimdon Station_TS29	0	0	0	0	0	0	0	0	0	...	0	0
3	CHESTER LE STREET _DH2	0	0	0	0	0	0	0	0	0	...	0	0
4	CHESTER LE STREET _DH2	0	0	0	0	0	0	0	0	0	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
304	Gateshead_NE8	0	1	0	0	0	0	0	0	0	...	0	0
305	Gateshead_NE8	0	0	0	0	0	0	0	0	0	...	0	0
306	Gateshead_NE8	0	1	0	0	0	0	0	0	0	...	0	0
307	Gateshead_NE8	0	0	0	0	0	0	0	0	0	...	0	0
308	Gateshead_NE8	0	0	0	0	0	0	0	0	0	...	0	0

Finding most common venues for specific postcode areas

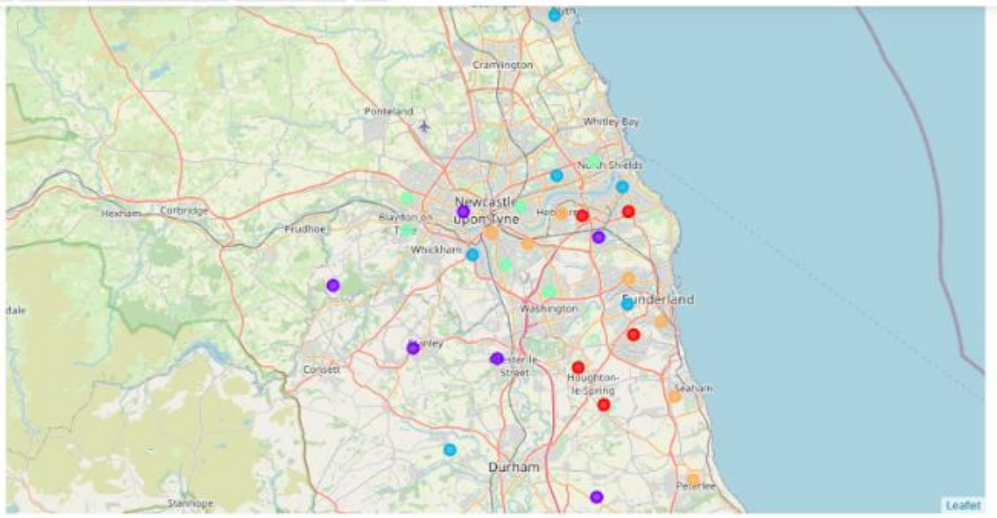
	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	BLYTH_NE24	Supermarket	Warehouse Store	Soccer Stadium	Grocery Store	Italian Restaurant
1	Blaydon-on-Tyne_NE21	Grocery Store	Coffee Shop	Supermarket	Business Service	Shopping Mall
2	Boldon Colliery_NE35	American Restaurant	Soccer Field	Gastropub	Light Rail Station	Movie Theater
3	CHESTER LE STREET _DH2	Construction & Landscaping	Mobile Phone Shop	Indian Restaurant	Doctor's Office	Home Service
4	DURHAM_DH6	Campground	Warehouse Store	Dance Studio	Doctor's Office	Dog Run
5	DURHAM_DH7	Restaurant	Warehouse Store	Convenience Store	Discount Store	Doctor's Office
6	Gateshead_NE10	Supermarket	Gym Pool	Train Station	Gym	Grocery Store
7	Gateshead_NE11	Hotel	Warehouse Store	Coffee Shop	Gym	Go Kart Track
8	Gateshead_NE8	Gym	Art Gallery	Sandwich Place	Supermarket	Warehouse Store
9	Gateshead_NE9	Coffee Shop	Grocery Store	Pub	Indian Restaurant	Pharmacy
10	HOUGHTON LE SPRING_DH4	Bar	Italian Restaurant	Martial Arts Dojo	Soccer Field	Warehouse Store
11	HOUGHTON LE SPRING_DH5	Indian Restaurant	Stadium	Sports Club	Pet Store	Warehouse Store
12	Hebburn_NE31	Soccer Field	Bar	Supermarket	Pub	Italian Restaurant
13	Jarrow_NE32	History Museum	Track	Bar	Light Rail Station	Warehouse Store
14	Newcastle upon Tyne_NE15	Golf Course	Supermarket	Restaurant	Chinese Restaurant	Warehouse Store
15	Newcastle upon Tyne_NE17	Construction & Landscaping	Convenience Store	Pub	Discount Store	Doctor's Office
16	Newcastle upon Tyne_NE4	Grocery Store	Hotel	Indian Restaurant	Shopping Mall	Fried Chicken Joint
17	Newcastle upon Tyne_NE6	Fish & Chips Shop	Discount Store	Supermarket	Climbing Gym	Warehouse Store
18	North Shields_NE29	Furniture / Home Store	Grocery Store	Pharmacy	Chinese Restaurant	Soccer Field
19	Peterlee_SR8	Warehouse Store	Bus Station	Video Game Store	Fast Food Restaurant	Pharmacy
20	STANLEY_DH9	Bus Station	Dog Run	Bakery	Supermarket	Discount Store
21	SUNDERLAND_SR2	Park	Bar	Supermarket	Pub	Italian Restaurant
22	SUNDERLAND_SR3	Convenience Store	Park	Athletics & Sports	Grocery Store	Supermarket
23	SUNDERLAND_SR4	Pizza Place	Sandwich Place	Fried Chicken Joint	Convenience Store	Discount Store
24	SUNDERLAND_SR5	Supermarket	Fast Food Restaurant	Coffee Shop	Warehouse Store	Bowling Alley
25	Seaham_SR7	Gym	Grocery Store	Pub	Outdoors & Recreation	Other Great Outdoors
26	South Shields+NE33	Pub	Supermarket	Italian Restaurant	Coffee Shop	Grocery Store
27	South Shields_NE34	Grocery Store	Indian Restaurant	Italian Restaurant	Pub	Sandwich Place
28	Trimdon Station_TS29	Bus Stop	Gaming Cafe	Dance Studio	Doctor's Office	Dog Run
29	WASHINGTON_NE37	Clothing Store	Grocery Store	Pharmacy	Chinese Restaurant	Music Store

22	SUNDERLAND_SR3	Convenience Store	Park	Athletics & Sports	Grocery Store	Supermarket
23	SUNDERLAND_SR4	Pizza Place	Sandwich Place	Fried Chicken Joint	Convenience Store	Discount Store
24	SUNDERLAND_SR5	Supermarket	Fast Food Restaurant	Coffee Shop	Warehouse Store	Bowling Alley
25	Seaham_SR7	Gym	Grocery Store	Pub	Outdoors & Recreation	Other Great Outdoors
26	South Shields+NE33	Pub	Supermarket	Italian Restaurant	Coffee Shop	Grocery Store
27	South Shields_NE34	Grocery Store	Indian Restaurant	Italian Restaurant	Pub	Sandwich Place
28	Trimdon Station_TS29	Bus Stop	Gaming Cafe	Dance Studio	Doctor's Office	Dog Run
29	WASHINGTON_NE37	Clothing Store	Grocery Store	Pharmacy	Chinese Restaurant	Music Store

30	WINGATE_TS28	Health & Beauty Service	Gas Station	Doctor's Office	Dog Run	Fast Food Restaurant
31	Wallsend_NE28	Supermarket	Park	Shopping Mall	Convenience Store	Light Rail Station

Next step in analysis is clustering - grouping together a set of objects (postcode areas) in a way that objects in the same cluster are more similar to each other than to objects in other clusters.

K-Means Clustering Algorithm was used.



Finally each cluster was exanimated and named.

Results Section

For new buyer potential list of post codes areas numbers was decreased from 132 to 32**.**

Based on buyers priority further on following Clusters characteristics can be used to proceed with particular houses details/viewings.

First Cluster – Has significant amount of restaurants.

	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	Latitude	Longitude
10	HOUGHTON LE SPRING_DH4	Bar	Italian Restaurant	Martial Arts Dojo	Soccer Field	Warehouse Store	54.8529	-1.49028
11	HOUGHTON LE SPRING_DH5	Indian Restaurant	Stadium	Sports Club	Pet Store	Warehouse Store	54.8246	-1.45587
13	Jarrow_NE32	History Museum	Track	Bar	Light Rail Station	Warehouse Store	54.9697	-1.48439
22	SUNDERLAND_SR3	Convenience Store	Park	Athletics & Sports	Grocery Store	Supermarket	54.8779	-1.41645
27	South Shields_NE34	Grocery Store	Indian Restaurant	Italian Restaurant	Pub	Sandwich Place	54.9728	-1.42321

Second Cluster – More rural area with less restaurants, probably more ‘laidback lifestyle’

	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	Latitude	Longitude
2	Boldon Colliery_NE35	American Restaurant	Soccer Field	Gastropub	Light Rail Station	Movie Theater	54.9529	-1.46282
3	CHESTER LE STREET _DH2	Construction & Landscaping	Mobile Phone Shop	Indian Restaurant	Doctor's Office	Home Service	54.8599	-1.59829
4	DURHAM_DH6	Campground	Warehouse Store	Dance Studio	Doctor's Office	Dog Run	54.7535	-1.46490
15	Newcastle upon Tyne_NE17	Construction & Landscaping	Convenience Store	Pub	Discount Store	Doctor's Office	54.9158	-1.81885
16	Newcastle upon Tyne_NE4	Grocery Store	Hotel	Indian Restaurant	Shopping Mall	Fried Chicken Joint	54.9728	-1.64380
20	STANLEY_DH9	Bus Station	Dog Run	Bakery	Supermarket	Discount Store	54.8678	-1.71096
28	Trimdon Station_TS29	Bus Stop	Gaming Cafe	Dance Studio	Doctor's Office	Dog Run	54.7112	-1.41995
30	WINGATE_TS28	Health & Beauty Service	Gas Station	Doctor's Office	Dog Run	Fast Food Restaurant	54.7255	-1.37499

Third Cluster – Quite in a middle between clusters 1 and 2. Has restaurants/shops but has sport facilities and park as well.

	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	Latitude	Longitude
0	BLYTH_NE24	Supermarket	Warehouse Store	Soccer Stadium	Grocery Store	Italian Restaurant	55.1228	-1.52140
5	DURHAM_DH7	Restaurant	Warehouse Store	Convenience Store	Discount Store	Doctor's Office	54.7895	-1.66153
7	Gateshead_NE11	Hotel	Warehouse Store	Coffee Shop	Gym	Go Kart Track	54.9401	-1.63176
23	SUNDERLAND_SR4	Pizza Place	Sandwich Place	Fried Chicken Joint	Convenience Store	Discount Store	54.9016	-1.42472
26	South Shields+NE33	Pub	Supermarket	Italian Restaurant	Coffee Shop	Grocery Store	54.9920	-1.43125
31	Wallsend_NE28	Supermarket	Park	Shopping Mall	Convenience Store	Light Rail Station	55.0007	-1.51887

Fourth Cluster - Store areas with big malls and supermarkets

	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	Latitude	Longitude
1	Blaydon-on-Tyne_NE21	Grocery Store	Coffee Shop	Supermarket	Business Service	Shopping Mall	54.9588	-1.71977
9	Gateshead_NE9	Coffee Shop	Grocery Store	Pub	Indian Restaurant	Pharmacy	54.9316	-1.58767
14	Newcastle upon Tyne_NE15	Golf Course	Supermarket	Restaurant	Chinese Restaurant	Warehouse Store	54.9832	-1.71906
17	Newcastle upon Tyne_NE6	Fish & Chips Shop	Discount Store	Supermarket	Climbing Gym	Warehouse Store	54.9772	-1.56735
18	North Shields_NE29	Furniture / Home Store	Grocery Store	Pharmacy	Chinese Restaurant	Soccer Field	55.0117	-1.46933
29	WASHINGTON_NE37	Clothing Store	Grocery Store	Pharmacy	Chinese Restaurant	Music Store	54.9114	-1.52838

Fifth Cluster – Sports/outdoor areas.

	Name	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	Latitude	Longitude
6	Gateshead_NE10	Supermarket	Gym Pool	Train Station	Gym	Grocery Store	54.9484	-1.55697
8	Gateshead_NE8	Gym	Art Gallery	Sandwich Place	Supermarket	Warehouse Store	54.9563	-1.60503
12	Hebburn_NE31	Soccer Field	Bar	Supermarket	Pub	Italian Restaurant	54.9717	-1.51259
19	Peterlee_SR8	Warehouse Store	Bus Station	Video Game Store	Fast Food Restaurant	Pharmacy	54.7666	-1.33657
21	SUNDERLAND_SR2	Park	Bar	Supermarket	Pub	Italian Restaurant	54.8886	-1.37865
24	SUNDERLAND_SR5	Supermarket	Fast Food Restaurant	Coffee Shop	Warehouse Store	Bowling Alley	54.9217	-1.42208
25	Seaham_SR7	Gym	Grocery Store	Pub	Outdoors & Recreation	Other Great Outdoors	54.8309	-1.36058

Conclusion section

In this study, I analysed north-east UK postcode locations to narrow the choice potential buyer needs to make in terms of buying a property.

Postcodes were choosing based on criteria's and clustering was made.

Based on lifestyle, potential buyer can now choose the cluster and explore details of particular houses in this area. So instead of exploring more than 130 postcode districts, buyer can start exploring 6-7 districts

Discussion section / Observations /Future actions.

Using APIs available from Property selling websites, we also can add specific properties which are on sale.

As some of the clusters are quite close to each other, recommendation will be to explore 2-3 clusters to list the properties. Using APIs it should be quick process.