# Battle of the Neighbourhoods : The Hunt for Hipsters

# 1. Introduction / Business Problem

My partner is a jewellery designer/maker, with a successful shop in a trendy part of London. She has expressed an interest in opening a second shop, and her usual strategy for this might be to go do some market research. Rather than simply ask the coolest people we know, I'd like to use data science to identify an appropriate location.

The question is this: can we work out which are the hippest areas in London, and the areas that are on the verge of becoming hip? And given that where would be a good place to open a cool jewelry shop?

This approach could apply to anyone interested in opening an independent store or brand in London, and if successful could by applied to any city for which we have the appropriate data.

# 2. Data

We'll break this down into 2 components: quantifying trendiness into clusters, and finding competitive advantage.

To quantify trendiness we'll explore different options, among them identifying whether there are a large number of chain (non-independent) stores in the area, or stores with particular or unusual categories. We'll look at the frequency and density of specific category types such as record stores and coffee shops.

To find competitive advantage, we'll look at details of the specific jewelry shops, including rating and price. Consideration should be given to the number of total shops and restaurants in the area (which would generate more footfall and be a positive influence), as well as other jewellery shops (which would mean more competition and be a negative influence).

The data we'll need includes:

- **Geocoding** - to identify the specific locations
- **Foursquare API** - to identify the qualifying places (jewelry stores, restaurants etc.) and essential details around them

## 2.2. Geocoding

[Geonames.org (https://www.geonames.org/)](https://www.geonames.org/) is a fantastic free resource that publishes geocoded names and their latitudes/longitudes many countries around the world. The GeoNames geographical database is available for download free of charge under a creative commons attribution license. The resource includes an explicit accuracy for the latitude/longitude, which will be useful for filtering out bad/inaccurate/duplicate data.

Below is a sample of the resulting data. Note the available Latitude/Longitude, and the Accuracy record.

Out[2]:

| | Countrycode | Postalcode | Placename | Adminname1 | Admincode1 | Adminname2 | Admincod |
|---|---|---|---|---|---|---|---|
| **0** | GB | DN14 | Goole | England | ENG | East Riding of Yorkshire | 116090 |
| **1** | GB | DN14 | Pollington | England | ENG | East Riding of Yorkshire | 116090 |
| **2** | GB | DN14 | Faxfleet | England | ENG | East Riding of Yorkshire | 116090 |
| **3** | GB | DN14 | Laxton | England | ENG | East Riding of Yorkshire | 116090 |
| **4** | GB | DN14 | Old Goole | England | ENG | East Riding of Yorkshire | 116090 |

According to the documentation, 'Accuracy' is defined as below:

```
Accuracy is an integer, the higher the better :
1 : estimated as average from numerically neigbouring postal codes
3 : same postal code, other name
4 : place name from geonames db
6 : postal code area centroid
```

Consequently we'll want to limit ourselves to codes with an Accuracy of greater or equal to 3 (averages of neighboring postal codes isn't useful). And because we're going to be using the Latitude/Longitude, we'll remove duplicate records of that and use only the first name. Postalcode will be tricky to use as it bridges Placenames, but we'll want to keep it around for reference and collapse it into a single column joined by a comma.

Finally, we'll be limiting ourselves to Greater London.

Below is a resulting sample of the data we'll use:

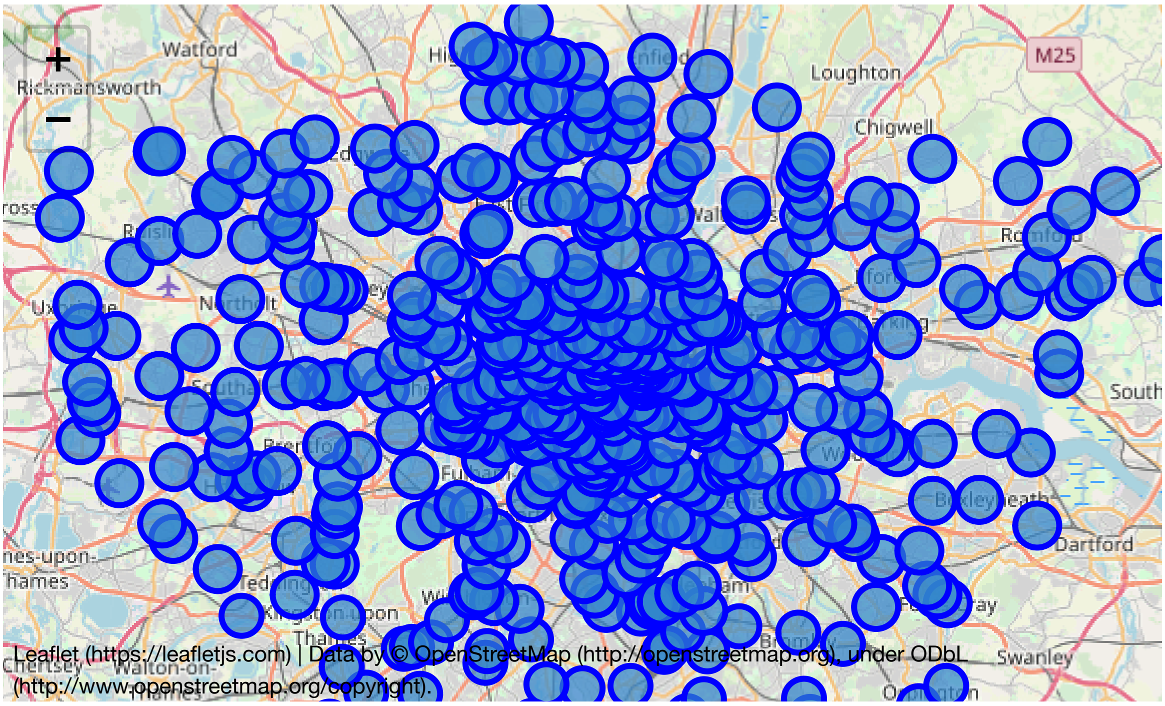
Out[3]:

| | Latitude | Longitude | Placename | Postalcode |
|---|---|---|---|---|
| **0** | 51.3133 | 0.0343 | Biggin Hill | TN16 |
| **1** | 51.3148 | -0.1570 | Hooley | CR5 |
| **2** | 51.3192 | 0.0712 | Cudham | TN14 |
| **3** | 51.3200 | -0.1409 | Coulsdon | CR5 |
| **4** | 51.3264 | -0.1011 | Kenley | CR8 |

```
There are 468 Places we will evaluate in London
```

A review of a map of London with the locations marked at a radius of 1000m exposes the amount of overlapping areas and the high coverage for central London. This should be sufficient for our evaluation.

Out[5]:




## 2.2. Foursquare API

We will retrieve both the places and necessary details from the Foursquare API. We'll get the precise location and category of the shop, as well as details such as price and rating where necessary. Some of these calls will be necessarily premium calls, so to keep ourselves within the boundaries of free usage we'll limit them.

When using the search and explore endpoints the Foursquare API will naturally constrain the responses, presumably to keep people from scraping/farming locations. We'll need to keep this in mind, as it means that our results will not be "complete" for a given radius.

We'll begin by retrieving the full list of categories from Foursquare and identifying which of them corresponds to jewelry (note in the UK this is spelled "jewellery").

Out[7]:

| | id | name |
|---|---|---|
| **746** | 4bf58dd8d48988d111951735 | Jewelry Store |

We want to focus on a specific types of venues, and the Foursquare API allows us to break things down into category "sections": shops, food, drinks, coffee, arts. We'll make separate calls for each of these venue sections and collect the relavant details. Although this may not get us everything, narrowing the search on sections will get us significantly more options.

Then we'll grab all the Jewelry Shop category venues in London exclusively. Below is a sample of these stores, and a heatmap of all the stores across London.

Out[17]:

| | Placename | Latitude | Longitude | Venue ID | Venue | Venue Latitude | Venu Longitud |
|---|---|---|---|---|---|---|---|
| 0 | Warren Street | 51.5136 | -0.1498 | 4ac518eff964a52063ad20e3 | Grays Antiques | 51.513622 | -0.14875 |
| 1 | Mayfair | 51.5095 | -0.1490 | 4ac518eff964a52066ad20e3 | Montblanc Boutique | 51.508787 | -0.14084 |
| 2 | Soho | 51.5144 | -0.1354 | 4ac518eff964a5208aad20e3 | Storm | 51.513183 | -0.13876 |
| 3 | Mayfair | 51.5095 | -0.1490 | 4ac518f0f964a520aaad20e3 | Tiffany & Co. | 51.509579 | -0.14130 |
| 4 | Oxford Circus | 51.5154 | -0.1414 | 4ac518f0f964a520c9ad20e3 | H. Samuel | 51.515108 | -0.14325 |

Out[18]:

# 3. Methodology

As our interest is in finding the most interesting areas in London, we will use an unstructured approach, and after some initial exploratory work we will apply clustering strategies to the data, with the aim of uncovering patterns that we'll be able to use.

## 3.1. Exploratory Analysis

There are some basic principles of being a hipster, that we should be able to reflect in our preparation.

1. Chain stores are bad. Be they coffee shops, book stores or otherwise, if it's a major brand (with few exceptions) then they should be avoided.
2. Funky independent shops are good. Particularly those of a specific type, such as record stores or organic markets.
3. Variety is important. The more options for shopping, food and drink, the better.
4. Don't forget culture. An area that has an interest beyond consumerism is cool, so arts and sights are key.

Let's begin by looking at the data and seeing whether we can extract features from it.

### 3.1.1. Venue Frequency

As a possible metric for understanding whether a given venue is a chain, we'll look at the occurrence of the venue with the same name throughout London. We want to easily identify the difference between actual independent stores, stores that might have 2-3 franchises across the city, and massive chains. We want to severely penalise the latter.

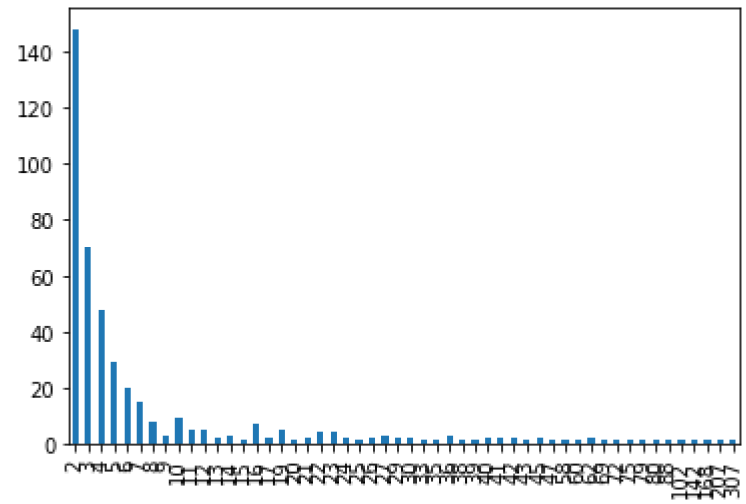
We'll begin by looking at venues in the following Foursquare "sections": Shops, Coffee, Food, and Drinks.

#### Shops

Looking at the frequency distribution of all venues in the Shops group (focusing on incidence > 2), we can see a fairly high incidence of chains. And if we look at the shops themselves we note that there are quite a few grocery store chains as well as other usual suspects. Note that there are some cases where a venue has a different category, but looking at the available samples these are acceptable categorizations and not an error.

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x11ad8df60>




Out[21]:

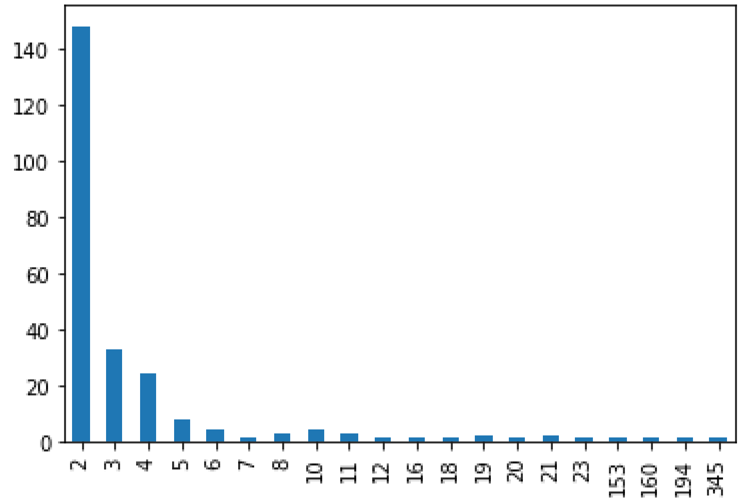
```
Venue              Venue Categories
Tesco Express      Grocery Store        307
Sainsbury's Local  Convenience Store    207
                   Supermarket          207
                   Grocery Store        207
Boots              Pharmacy             168
Co-op Food         Grocery Store        142
Paddy Power        Betting Shop         102
WHSmith            Bookstore             88
                   Stationery Store      88
Carphone Warehouse Mobile Phone Shop     80
Superdrug          Cosmetics Shop        79
                   Pharmacy              79
Iceland            Grocery Store         75
Sainsbury's        Supermarket           72
                   Grocery Store         72
Lidl               Discount Store        69
                   Supermarket           69
M&S Simply Food    Grocery Store         62
                   Convenience Store     62
                   Food & Drink Shop     62
Name: count, dtype: int64
```

### Coffee

Next we'll look at venues in the Coffee group. These have a less dramatic frequency curve, but are there are still quite a few chains of reasonable size. The ubiquitous Starbucks is present, although not at the top of the list.

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11d198a20>
```




Out[23]:

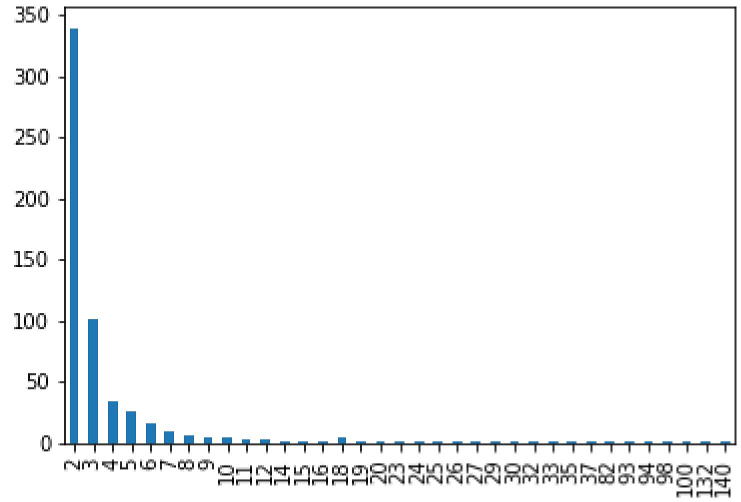
```
Venue                Venue Categories
Costa Coffee         Coffee Shop          345
Starbucks            Coffee Shop          194
Pret A Manger        Coffee Shop          160
                     Sandwich Place       160
Caffè Nero           Coffee Shop          153
JOE & THE JUICE      Juice Bar             23
Patisserie Valerie   Café                  21
Black Sheep Coffee   Coffee Shop           21
Paul                 Café                  20
                     Bakery                20
                     Sandwich Place        20
Benugo               Sandwich Place        19
                     Bakery                19
                     Food Truck            19
                     Deli / Bodega         19
                     Coffee Shop           19
                     Café                  19
GAIL's Bakery        Bakery                19
Wild Bean Cafe       Café                  18
Krispy Kreme         Donut Shop            16
Name: count, dtype: int64
```

### Food

Third up is the Food group. Also a significant number of chains showing up.

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11a815cc0>
```




Out[25]:

```
Venue            Venue Categories
Pret A Manger    Sandwich Place          140
Subway           Sandwich Place          132
McDonald's       Fast Food Restaurant    100
KFC              Fried Chicken Joint      98
                 Fast Food Restaurant     98
Greggs           Bakery                   94
Nando's          Portuguese Restaurant    93
PizzaExpress     Pizza Place              82
Domino's Pizza   Pizza Place              82
GAIL's Bakery    Bakery                   37
itsu             Sushi Restaurant         37
Franco Manca     Pizza Place              35
Pizza Hut        Pizza Place              33
wagamama         Asian Restaurant         33
Leon             Fast Food Restaurant     32
                 Restaurant               32
                 Café                     32
Byron            Burger Joint             30
Paul             Bakery                   29
                 Café                     29
Name: count, dtype: int64
```

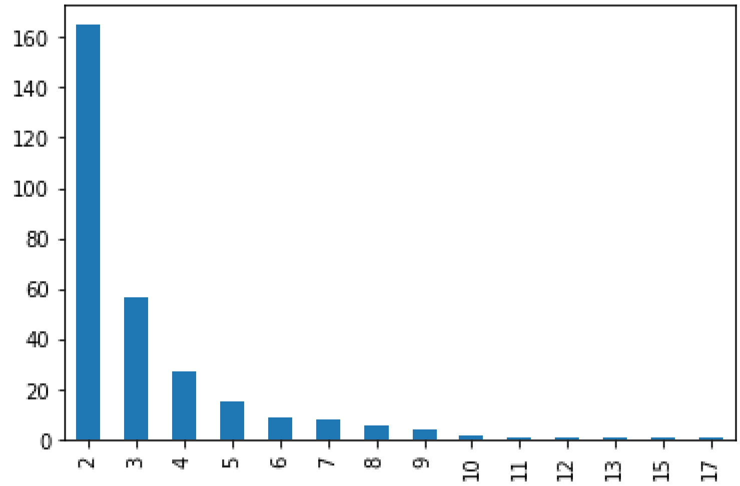
### Drinks

The Drinks group is a stranger outcome, as there are not as many clear chains. Doing a little research reveals that **All Bar One**, **Slug and Lettuce** and **Executive Lounge Hilton** are definitely part of a chain, but many of the others have the same name as a coincidence. Or due to the lack of creativity in pub names.

Consequently we won't be able to use this approach to easily identify whether a bar is a chain, so we'll need to exclude this feature from the list.

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11d47ad30>
```




Out[27]:

```
Venue                     Venue Categories
All Bar One               Bar                   17
The Crown                 Pub                   15
                          Gastropub             15
Slug & Lettuce            Bar                   13
Be At One                 Bar                   12
                          Cocktail Bar          12
The White Hart            Gastropub             11
                          Pub                   11
                          Hotel                 11
The Red Lion              Pub                   10
The George                Bar                   10
                          Pub                   10
Simmons Bar               Bar                    9
                          Cocktail Bar           9
Executive Lounge Hilton   Hotel Bar              9
The Royal Oak             Gastropub              9
                          Pub                    9
Simmons Bar               Pub                    9
The Victoria              Pub                    9
                          Gastropub              9
Name: count, dtype: int64
```

### 3.1.2. Hipster Factor

We'll establish some basic criteria for what qualifies as a hipster shop. It will need to be one of a selected set of categories listed below, and it will need to have a 'Venue Frequency' less than 10 - this will exclude obvious chain stores (which can occur with Bookstores and Thift / Vintage Stores, while maintaining flexibility for independents of a certain size.

Out[30]:

```
['Bookstore',
 'Thrift / Vintage Store',
 'Market',
 'Farmers Market',
 'Arts & Crafts Store',
 'Flea Market',
 'Record Shop',
 'Street Food Gathering',
 'Beer Store',
 'Organic Grocery',
 'Antique Shop']
```

Out[31]:

| | Latitude | Longitude | Placename | Number of Hip Venues |
|---|---|---|---|---|
| **178** | 51.5251 | -0.0769 | Shoreditch | 32 |
| **123** | 51.5085 | -0.1257 | London | 25 |
| **140** | 51.5134 | -0.1234 | Embankment | 24 |
| **124** | 51.5085 | -0.1249 | Charing Cross | 24 |
| **147** | 51.5142 | -0.1247 | Covent Garden | 24 |
| **160** | 51.5175 | -0.1204 | Holborn | 23 |
| **215** | 51.5431 | -0.1499 | Chalk Farm | 22 |
| **168** | 51.5225 | -0.0857 | Bank | 21 |
| **125** | 51.5095 | -0.1958 | Notting Hill Gate | 20 |
| **210** | 51.5406 | -0.1433 | Camden Town | 20 |

### 3.1.3. Culture

Counting the number of venues by area that are "arts" or "sights" venues will give us a good measure of the cultural options.

Sample of "arts":

Out[32]:

| | Latitude | Longitude | Placename | Number of Art Venues |
|---|---|---|---|---|
| **219** | 51.5134 | -0.1234 | Embankment | 161 |
| **228** | 51.5144 | -0.1354 | Soho | 157 |
| **200** | 51.5085 | -0.1249 | Charing Cross | 154 |
| **199** | 51.5085 | -0.1257 | London | 154 |
| **226** | 51.5142 | -0.1247 | Covent Garden | 153 |
| **237** | 51.5166 | -0.1308 | Tottenham Court Road | 146 |
| **231** | 51.5154 | -0.1414 | Oxford Circus | 111 |
| **242** | 51.5175 | -0.1204 | Holborn | 110 |
| **230** | 51.5148 | -0.1461 | Oxford Street | 85 |
| **269** | 51.5268 | -0.1333 | Euston | 79 |

## 3.2. Clustering

Our features of interest then should are:

1. number of shops
2. number of coffee venues
3. number of food venues
4. uniqueness of shops
5. uniqueness of coffee venues
6. uniqueness of food venues
7. number of hip venues
8. uniquenesss of hip venues
9. number of drinks venues
10. number of arts venues
11. number of sights

As a metric to reflect the uniqueness of a venue, we'll take the 'Venue Frequency' and square it, and take the average of this across all the venues within a given location. We'll call this the Mean Frequency Squared (MFS for short). A lower value means the shops in the location are more unique / independent, whereas a higher value will mean the shops are more likely to be chains.

We will then apply k-means clustering to the locations and their feature data, to discern patterns within the data and to identify locations that are most like each other. Once this task is completed, we'll review the individual clusters and determine which is the cluster most interesting to us to open a shop, and look at possible next steps.

Our data (in advance of normalization) looks like this:

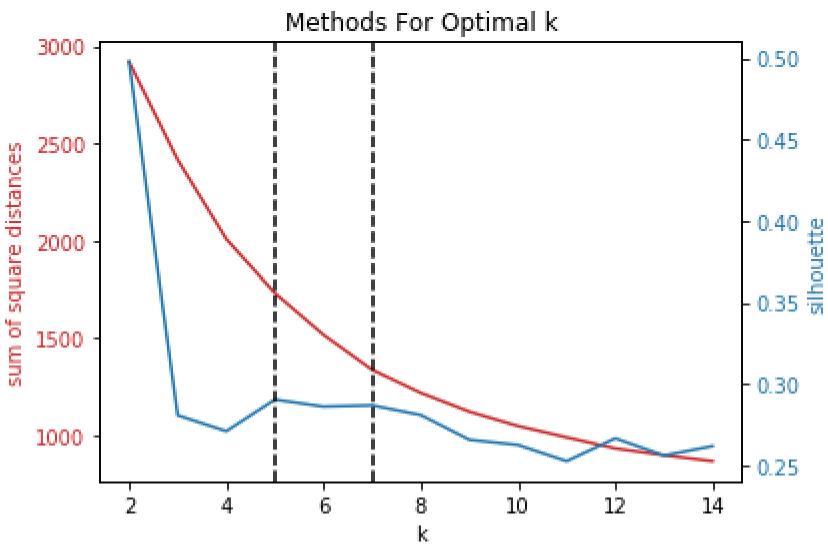
Out[33]:

| | Latitude | Longitude | Shops Count | Shops MFS | Coffee Count | Coffee MFS | Food Count | Food MFS | Drinks Count | Art Cour |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 51.3133 | 0.0343 | 7 | 17111.428571 | 4.0 | 29757.0 | 4.0 | 1.000000 | 2.0 | 2. |
| **1** | 51.3148 | -0.1570 | 3 | 1.000000 | 0.0 | 0.0 | 4.0 | 1.750000 | 2.0 | 2. |
| **2** | 51.3192 | 0.0712 | 4 | 1.000000 | 0.0 | 0.0 | 0.0 | 0.000000 | 1.0 | 1. |
| **3** | 51.3200 | -0.1409 | 12 | 10634.166667 | 5.0 | 4682.6 | 11.0 | 6.363636 | 4.0 | 4. |
| **4** | 51.3264 | -0.1011 | 2 | 10082.500000 | 0.0 | 0.0 | 10.0 | 1.000000 | 2.0 | 4. |

When we run k-means clustering against the data, we trial several different cluster numbers and review the resulting metrics to choose a good value for k.

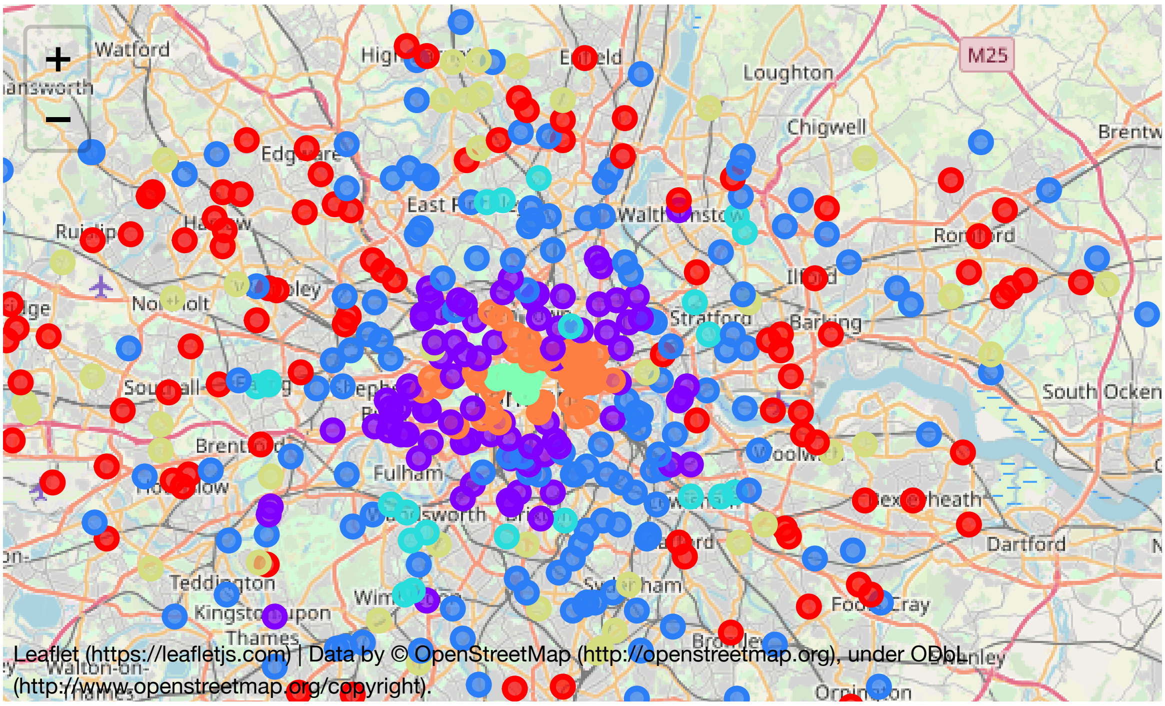
As we review the sum of square differences, there's not a sufficiently clear "elbow" to decide the value of k. Instead we use the silhouette score as a different metric and this gives us a bit more clarity.

Remarkably 2 metrics for k=5 and k=7 are quite close to each other, and we choose the slightly higher one rather than the one with the best score - the differnce is marginal and the outcome is more finely tuned to our purposes.




We then run the clustering for the value of k=7, and produce a map of London overlaid with different locations color-coded with their cluster. Below follows a review of the individual clusters and their prospective value to us.

Out[39]:




**Cluster 0**

Our first cluster is the second worst candidate to open a shop. It's the second least hip, and although it has more shops and these are slightly more independent, the food and coffee options are the most likely to be chains. This is likely to be a suburban area with slightly more activity, but an unwise place to open a hip store.

```
### cluster number: 0 has 98 locations:
Shops Count          25.489796
Shops MFS          6196.007732
Coffee Count          7.122449
Coffee MFS        34730.426611
Food Count           17.336735
Food MFS           2333.200831
Drinks Count          6.234694
Arts Count            2.765306
Sights Count         30.428571
Hipster Count         0.520408
Hipster MFS           0.945578
dtype: float64

# sample locations:
5           Sanderstead
7                Purley
20     South Beddington
25            Orpington
28        Worcester Park
29             Tolworth
30               Sutton
31              Croydon
45              Bromley
55           Chislehurst
Name: Placename, dtype: object
```

**Cluster 1**

This cluster is the most likely candidate for us to open a shop. It has a reasonable cultural profile, a good number of coffee, food places and shops with independence. It also has decent number of hipster options with a good score.

```
### cluster number: 1 has 82 locations:
Shops Count        70.195122
Shops MFS        7039.706114
Coffee Count       45.902439
Coffee MFS       9282.302691
Food Count         98.914634
Food MFS          865.451266
Drinks Count       43.634146
Arts Count         13.865854
Sights Count      142.012195
Hipster Count       6.951220
Hipster MFS         4.253009
dtype: float64

# sample locations:
49     Kingston upon Thames
60          South Wimbledon
103              Tulse Hill
105    Richmond upon Thames
107                Richmond
110                 Lambeth
111                 Clapham
114        Clapham Junction
117                 Brixton
118           Clapham North
Name: Placename, dtype: object
```

**Cluster 2**

This cluster is one of the weaker candidate for opening a shop. It has few shops, coffee and food options, and culturally it's poor compared to some of the stronger clusters.

```
### cluster number: 2 has 162 locations:
Shops Count        19.882716
Shops MFS        6009.353817
Coffee Count        9.049383
Coffee MFS       8100.492138
Food Count         21.129630
Food MFS          537.102504
Drinks Count        8.425926
Arts Count          3.283951
Sights Count       34.839506
Hipster Count       1.296296
Hipster MFS         1.149544
dtype: float64

# sample locations:
1           Hooley
2           Cudham
3         Coulsdon
4           Kenley
6            Downe
8           Sutton
10      Addington
13     Chelsfield
14    Farnborough
15          Keston
Name: Placename, dtype: object
```

**Cluster 3**

This cluster is a step up from our three weakest. It has a small amount of hip and cultural activity, a reasonable number of shops with decent independence, but it's the second most likely to have coffee and food options that are chains. Based purely on our metrics this is a slightly more urbanized suburbia, and it's telling that the weakest clusters for our purposes are all around the edge of London.

```
### cluster number: 3 has 22 locations:
Shops Count         57.636364
Shops MFS         5028.117808
Coffee Count        21.772727
Coffee MFS       13272.275323
Food Count          49.136364
Food MFS          1140.840503
Drinks Count        17.454545
Arts Count           5.772727
Sights Count        74.500000
Hipster Count        4.681818
Hipster MFS         30.447658
dtype: float64

# sample locations:
61             Wimbledon
66                Merton
84           Southfields
88     Wandsworth Common
93             West Hill
101        North Dulwich
106           Wandsworth
108               Putney
115             Lewisham
116           Blackheath
Name: Placename, dtype: object
```

**Cluster 4**

This is the beating heart of cultural activity and hipness in London, by our metrics - although it does lose a slight amount on the fact that the hipness has some chain stores. It has a massive number of shops, coffee and food options, with a mix of independent and chain options. Because of the large number of shops however the competition (also rent and business rates) would be very high, making this not a preferred location for our shop opening.

```
### cluster number: 4 has 9 locations:
Shops Count       191.000000
Shops MFS        2995.533499
Coffee Count      190.555556
Coffee MFS       5021.251725
Food Count        249.111111
Food MFS          323.768650
Drinks Count      227.444444
Arts Count        136.777778
Sights Count      226.222222
Hipster Count      19.777778
Hipster MFS         7.589503
dtype: float64

# sample locations:
215                 London
216          Charing Cross
235             Embankment
242          Covent Garden
244                   Soho
246          Oxford Street
248          Oxford Circus
254    Tottenham Court Road
259                Holborn
Name: Placename, dtype: object
```

**Cluster 5**

This cluster is the worst candidate for us to open a shop. It's the least hip, has no activity to draw any kind of footfall. The few existing shops are all chains, although the coffee and food venues are more independent. Looking at the map representation, they are almost entirely outside of central London, so this is not surprising - the shops will more likely than not be grocery stores, and restaurants will be locally owned. This is also the least culturally active location.

```
### cluster number: 5 has 48 locations:
Shops Count          10.187500
Shops MFS         20014.968975
Coffee Count          5.270833
Coffee MFS         8974.225721
Food Count           11.520833
Food MFS            961.352942
Drinks Count          5.104167
Arts Count            2.312500
Sights Count         19.937500
Hipster Count         0.187500
Hipster MFS           0.187500
dtype: float64

# sample locations:
0           Biggin Hill
9            Wallington
11              Belmont
12                Cheam
16          Chessington
17       Malden Rushett
21                 Hook
35     Morden Hall Park
36             Woodside
40        South Norwood
Name: Placename, dtype: object
```

**Cluster 6**

This is one of the better clusters on our metrics count. It has a lot of food and drink options, and the former are quite independent. The coffee options are also significant, although there are quite a lot of chains present. The shops are significant but they are the second worst among all the clusters for independence. If you were looking to open a shop that was not so focused on uniqueness, you would consider this cluster as a viable option.

```
### cluster number: 6 has 47 locations:
Shops Count        126.085106
Shops MFS         8102.034243
Coffee Count       122.510638
Coffee MFS       10992.274526
Food Count         205.191489
Food MFS           730.231981
Drinks Count       138.808511
Arts Count          47.212766
Sights Count       221.319149
Hipster Count       12.659574
Hipster MFS          5.348187
dtype: float64

# sample locations:
179      South Kensington
183              Victoria
188                London
190    Westminster Bridge
194            Marylebone
195           Westminster
196             Southwark
206            South Bank
207             Southwark
209              Waterloo
Name: Placename, dtype: object
```

# 4. Results

Based on our evaluation, Cluster 1 is the most likely candidate for a place to open a shop.

It's worth refining this a bit more to break down where to start our search.

**The "Low Competition" Approach**

One possible way to look at this is to see whether there are other Jewelry shops in the area - look for places with less or no competition but which still have a good amount of other cool shops.

Given that approach, our top 5 options are:

Out[54]:

| | Latitude | Longitude | Placename | Postalcode | Hipster Count | Hipster MFS | Jewel/Shop Density |
|---|---|---|---|---|---|---|---|
| **338** | 51.5480 | -0.0629 | Shacklewell | E8 | 18.0 | 7.111111 | 0.0 |
| **288** | 51.5272 | -0.0611 | Bethnal Green | E2 | 15.0 | 2.066667 | 0.0 |
| **214** | 51.5075 | -0.2050 | Ladbroke Grove | W11 | 13.0 | 4.307692 | 0.0 |
| **173** | 51.4911 | -0.1493 | Belgravia | SW1 | 12.0 | 1.000000 | 0.0 |
| **103** | 51.4548 | -0.1158 | Tulse Hill | SW2 | 11.0 | 1.000000 | 0.0 |

### The "High Footfall" Approach

One other approach might be to worry less about the competition and focus on the total number of venues in the area. This strategy would assume that your goal is footfall, implying that more things to do in the area means more people coming your way.

Given that approach, our top 5 options are:

Out[56]:

| | Latitude | Longitude | Placename | Postalcode | Total Count |
|---|---|---|---|---|---|
| **49** | 51.4126 | -0.2974 | Kingston upon Thames | KT1 | 286.0 |
| **312** | 51.5362 | -0.1030 | Islington | EC1P,EC4P,EC50,N1,N1C,N1P,N7 | 275.0 |
| **210** | 51.5050 | -0.2211 | Western Avenue | W12 | 241.0 |
| **202** | 51.5015 | -0.1619 | Knightsbridge | SW1 | 223.0 |
| **162** | 51.4870 | -0.1910 | West Brompton | SW5 | 219.0 |

### The "Super Hipster" Approach

One final approach might be to just aim for the hippest place you can find, and not worry about anything else. So focus on the number of hip shops and their independence.

Given that approach, our top 5 options are:

Out[57]:

| | Latitude | Longitude | Placename | Postalcode | Hipster Count | Hipster MFS | Jewel/Shop Density |
|---|---|---|---|---|---|---|---|
| **309** | 51.5344 | -0.0694 | Shoreditch | N1 | 18.0 | 1.166667 | 0.072464 |
| **338** | 51.5480 | -0.0629 | Shacklewell | E8 | 18.0 | 7.111111 | 0.000000 |
| **226** | 51.5115 | -0.2059 | Notting Hill | W11 | 16.0 | 3.687500 | 0.027027 |
| **288** | 51.5272 | -0.0611 | Bethnal Green | E2 | 15.0 | 2.066667 | 0.000000 |
| **292** | 51.5279 | -0.1072 | Finsbury | EC1 | 14.0 | 8.857143 | 0.011364 |

# 5. Discussion

This evaluation was done within the constraints of the Foursquare API and the level of free access available. A more complete/mature approach would be to retrieve ratings and price for venues, and to use that to identify the affluence of the specific neighbourhood based on that. We might find that even though an area is moderately populated with shops, these are much more high end. And conversely we may find that an area that has a large number of shops with a high amount of independence is because they are in a poorer area, and therefore less likely to be interested in buying jewellery.

The Foursquare API also had a limited set returned for venues in a particular area, which was not always consistent. Radial searches might return the same number of results even though the radius was increased. There was also a fair amount of overlap on locations, as well as some areas on the map that had limited coverage. More time could be spent on selecting the locations to ensure full map coverage, but also to align with consumer behavior such as focusing on a known set of shopping areas.

We could also retrieve demographic data from a different source such as the UK Census. At the time of this evaluation the most recent data was for 2011 and therefore deemed to be too old to be relevant, but new data will be released within the next 2 years and will be much more up-to-date.

There may also be more useful econographic data that could inform a stronger model. This data often requires a fee, but a student license might be available for the purposes of this study.

Commercial and residential property prices by area would be an incredibly powerful tool, as it would allow for a clear filter of what would be an acceptable price to pay and what a target turnover for a shop would need to be if it opened.

Finally, further exploratory work could be done to build useful features, with the data we have available. A more careful study of the categories available in the given larger groups might mean we exclude categories that are not interesting or useful to the study, or score specific categories higher than others based on their importance.

# 6. Conclusion

We were able to successfully build some metrics of interest to an independent jewelry shop, and use k-means clustering to identify locations in Greater London that are good targets for this kind of business.

Ironically, the original first location for the shop is in 'Shoreditch', which was rated the hippest location in Cluster 1.

So then... Data Science is hip.