IBM Coursera Capstone Project

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This report contains 6 sections:

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3) Methodology

4) Results,

5) Discussion

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1. Introduction

Before COVID-19 threw all other business strategies or plans into complete disarray, Europe was still getting to grips on how Brexit was going to affect the region.

Now that Britain has chosen to leave the EU, many businesses will relocate their head offices outside of London, the world's former financial center. With this relocation, hundreds of thousands (if not millions) of people will have to uplift their lives and move to another city.

Based on this forbes article, Amsterdam could be the 'new London'. If employees are forced to move from the one city to the other, the big question is: which neighborhoods should these soon-to-be ex-Londoners choose to move to in Amsterdam?

Based on Foursquare data, I aim to cluster Amsterdam and London neighborhoods based on similarity. So if you love your neighborhood in London and want something similar in Amsterdam, this is your go-to guide.

2. Data

I gathered data from three sources: Wikipedia, the Google Maps API and the Foursquare API.

- Wikipedia: I scraped Wikipedia pages for *Borough* and *Neighborhood* data for London and Amsterdam.
- Google Maps: I accessed the google maps API through GeoPy to get *Latitude* and *Longitude* data to correspond with the *Neighborhood* and *Borough* fields, gleaned off Wikipedia.

- Foursquare API: I used the geo-location data from Wikipedia and the Google Maps API to search the Foursquare API using the explore function to get the 10 most common venue categories for each neighborhood in Amsterdam and London respectively.

3. Methodology

As this project relies heavily on API's (Google Maps and Foursquare) and publicly available Wikipedia data, it required a lot of data cleaning and data wrangling. Once the data was in the right format, a *k nearest neighbor's* algorithm was used to cluster the neighborhoods

Broadly, the methodology is as below:

Data Gathering, Exploratory Data Analysis and Visualization

- Gather Wikipedia Neighborhood data for London and Amsterdam
- Use the Google Maps API and GeoPy to get corresponding latitude and longitude values per neighborhood
- Visualizing the Neighborhood breakdown by city
- Use the obtained latitude and longitude values to find the 10 most common venue categories in each neighborhood
- Visualizing the most common venue categories in London and Amsterdam

Clustering Approach

- Explaining why a k nearest neighbor's algorithm was used as well as the selection of k.

Data Gathering

Wikipedia Scraping

To get the London and Amsterdam data I scraped this and that Wikipedia page using pd.read_html to get the neighborhood information.

Figure 1 Initial Wikipedia Data frame for London

	Location	London borough	Post town	Postcode district	Dial code	OS grid ref
0	Abbey Wood	Bexley, Greenwich [7]	LONDON	SE2	020	TQ465785
1	Acton	Ealing, Hammersmith and Fulham[8]	LONDON	W3, W4	020	TQ205805
2	Addington	Croydon[8]	CROYDON	CR0	020	TQ375645
3	Addiscombe	Croydon[8]	CROYDON	CR0	020	TQ345665
4	Albany Park	Bexley	BEXLEY, SIDCUP	DA5, DA14	020	TQ478728

Figure 2 Wikipedia Data frame for Amsterdam

	Borough	Area	Population	Population density	Location (in green)	Neighbourhoods
0	Centrum (Centre)	8.04 km²	86422	13,748/km²	NaN	Binnenstad, Grachtengordel, Haarlemmerbuurt, J...
1	Noord (North)	49.01 km²	94766	2,269/km²	NaN	Banne Buiksloot, Buiksloot, Buikslotermeer, Fl...
2	Nieuw-West(New West)	32.38 km²	151677	4,478/km²	NaN	Geuzenveld, Nieuw Sloten, Oostoever, Osdorp, O...
3	Oost (East)	30.56 km²	135767	7,635/km²	NaN	Uburg, Indische Buurt, Eastern Docklands, Oud...
4	West	9.89 km²	143842	15,252/km²	NaN	Frederik Hendrikbuurt, Houthaven, Spaarndammer...

Both of the above data frames were cleaned, tidied and reshaped so that they were ready to be used to get latitude and longitude values. For those folks who know python, I broadly did the below:

- Drop unnecessary fields: ‘Post Town’, ‘Dial Code’, OS grid ref’, ‘Area’, ‘Population’, ‘Population Density’, ‘location (in green)
- Use regex to remove unnecessary reference brackets, ‘English translations’ of Amsterdam Boroughs and other strings
- Use split and stack on the Amsterdam data frame to parse out the neighborhood field using a comma as the separator

Sourcing Coordinates Using Google Maps API

Next, I had to use the Google Maps API to get the latitude and longitude data given each neighborhood name. Note that Google now charges for its API so I had to enter in my credit card details. The resulting data frame, after joining it back with the original data frame is as below:

Figure 3: Google Maps API Data

	neighborhood	borough	latitude	longitude	city
0	Abbey Wood	Bexley	51.486042	0.120259	london
1	Acton	Ealing	51.512075	-0.267572	london
2	Aldgate	City	51.515987	-0.078379	london
3	Aldwych	Westminster	51.510583	-0.126768	london
4	Anerley	Bromley	51.412571	-0.061397	london

We now have a final geo-location data frame with 368 neighborhoods across both cities with a rough 80/20 split where London has 299 Neighborhoods and Amsterdam only has 69. Given the size of London compared to Amsterdam, it’s no surprise that London has over 3 times as many neighborhoods.

In total, there are 41 unique Boroughs between the two cities. The Borough with the most neighborhoods in Amsterdam is Centrum with 14 Neighborhoods. The Borough with the most neighborhoods in London is Barnet with 26 Neighborhoods.

Based on the neighborhood data, I then used folium to plot the neighborhoods onto each city. You can see that there are far more neighborhoods in London than Amsterdam- which makes sense because London covers a much larger area.

Figure 4: London Neighborhoods

Figure 5: Amsterdam Neighborhoods

Fetching Venue Information from Foursquare

To get our Foursquare Data in a workable format to do our clustering any cleaning and wrangling steps were followed:

- Fetching the JSON file information for every venue within a given radius of our neighborhood coordinates
- Flattening that JSON and parsing out the category for each venue. A category, for example could be a ‘Pub’, ‘Park’, or ‘Soccer Stadium’.
- Finding the number of venues per category within a neighborhood
- Only selecting the top 10 categories by count per neighborhood

The resulting data frame was as below. You can see that the “Venue Category” has been added as the last field.

Figure 6: Data frame with Venue Category

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Abbey Wood	51.486042	0.120259	Greggs	51.490164	0.121305	Bakery
1	Abbey Wood	51.486042	0.120259	Abbey Wood Caravan Club	51.485502	0.120014	Campground
2	Abbey Wood	51.486042	0.120259	Abbey Cafe	51.489754	0.120822	Café
3	Acton	51.512075	-0.267572	Bake Me	51.508452	-0.268543	Creperie
4	Acton	51.512075	-0.267572	The Station House	51.508877	-0.263076	Pub

Now that we have the category for each venue, we need to count the number of venues per category and then only take the top 10 biggest categories per neighborhood. To do this we have to:

- Use ‘onehot’ encoding on our category field.
- Group by Neighborhood, taking the mean of the frequency of occurrence
- Write a function to sort the venues in descending order
- Create a new data frame to display the top venues for each neighborhood

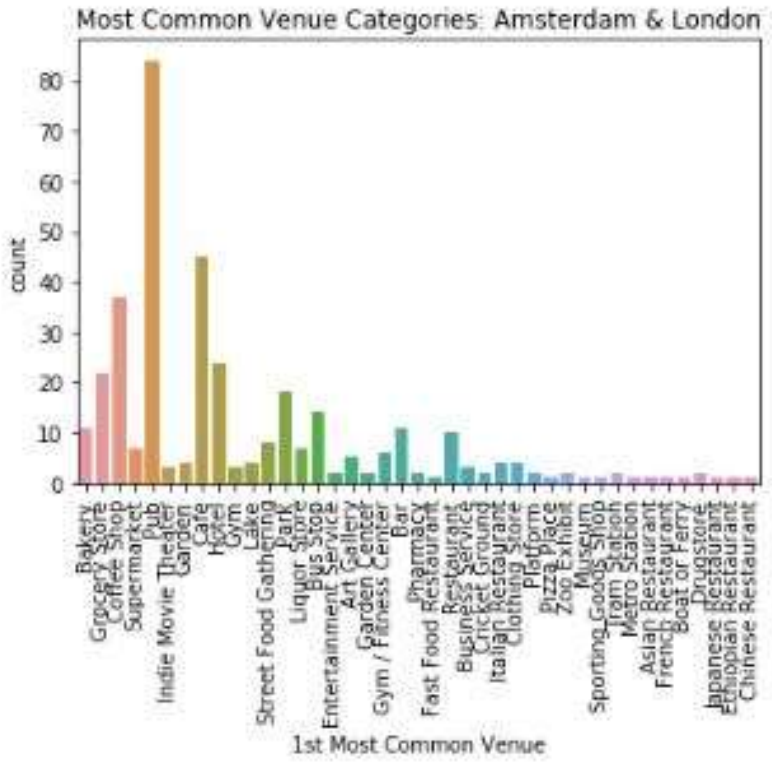
The resulting cleaned data frame is as below:

Figure 7: Top 10 Venue Categories per Neighborhood

	Neighborhood	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	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Bos en Lommer	Tram Station	Bar	Vegetarian / Vegan Restaurant	Bakery	Indonesian Restaurant	Coffee Shop	Gastropub	Snack Place	Thai Restaurant	Grocery Store
1	Buikslotermeer	Supermarket	Bus Stop	Park	Shopping Mall	Turkish Restaurant	Restaurant	Bakery	Fish & Chips Shop	Fish Market	English Restaurant
2	Buikslotermeer	Supermarket	Clothing Store	Drugstore	Convenience Store	Electronics Store	Grocery Store	Bakery	Sandwich Place	Plaza	Restaurant
3	Buitenveldert	Drugstore	Hotel	Gym / Fitness Center	Snack Place	French Restaurant	Bookstore	Furniture / Home Store	Supermarket	Sushi Restaurant	Liquor Store
4	De Baarsjes	Bar	Restaurant	Falafel Restaurant	Greek Restaurant	Supermarket	Italian Restaurant	Pub	Deli / Bodega	Farm	Bistro

Having a look at the most common venues across all neighborhoods we find that people from Amsterdam and London love Pubs, Café’s and Coffee shops. I find it very interesting that there are more than twice as many pubs as there are Coffee Shops

Figure 8: Most Common Venue Categories: Amsterdam and London



Clustering Approach

I chose to use the *'K Nearest Neighbors'* algorithm for clustering due to its ease of use, very simple implementation and given that the classes don't have to be linearly separable.

Based on previous experience, setting the number of clusters to be too high in this kind of analysis can end up making the final clusters hard to make sense of and the clustering hard to interpret. In the same breath if we use too few clusters, then we have homogeneity. Given the above I decided to set the number of clusters used for the analysis to be 5 (not too big and not too small).

4. Results

Once the clustering was complete, we have a final data frame ready for analysis. See below:

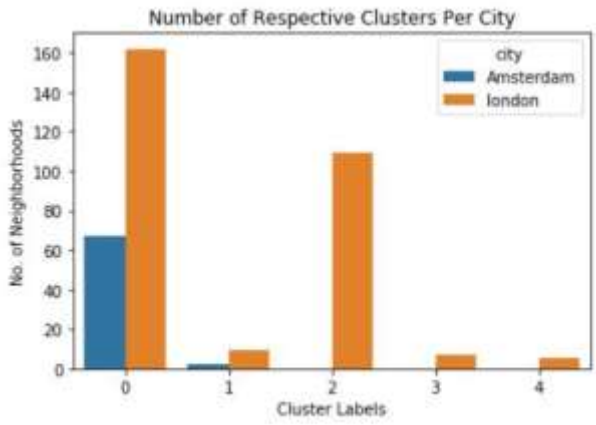
Figure 9: Final Data Frame with Clusters

	Cluster Labels	Neighborhood	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	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	0	Bos en Lommer	Tram Station	Bar	Vegetarian / Vegan Restaurant	Bakery	Indonesian Restaurant	Coffee Shop	Gastropub	Snack Place	Thai Restaurant	Grocery Store
1	0	Bijlmer	Supermarket	Bus Stop	Park	Shopping Mall	Turkish Restaurant	Restaurant	Bakery	Fish & Chips Shop	Fish Market	English Restaurant
2	0	Buikslotermeer	Supermarket	Clothing Store	Drugstore	Convenience Store	Electronics Store	Grocery Store	Bakery	Sandwich Place	Plaza	Restaurant
3	0	Buitenveldert	Drugstore	Hotel	Gym / Fitness Center	Snack Place	French Restaurant	Bookstore	Furniture / Home Store	Supermarket	Sushi Restaurant	Liquor Store
4	0	De Baarsjes	Bar	Restaurant	Falafel Restaurant	Greek Restaurant	Supermarket	Italian Restaurant	Pub	Deli / Bodega	Farm	Bistro

Analyzing the clusters using Figure 10 below, there are a few interesting observations:

- The largest cluster is cluster 0 with over 200 neighborhoods. Cluster 0 has 162 London neighborhoods and 67 Amsterdam Neighborhoods
- The second largest cluster is cluster 2 with 109 Neighborhoods- all from London.
- The third largest cluster is cluster 1 with 11 neighborhoods. 9 London Neighborhoods and 2 Amsterdam Neighborhoods
- Cluster 3 and 4 respectively are the smallest with 7 and 5 neighborhoods respectively- all in London

Figure 10: Number of Clusters per City



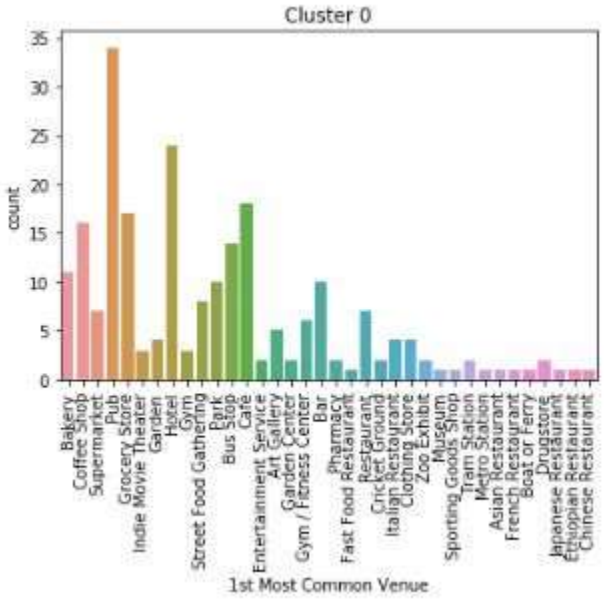
Unfortunately Cluster 2, 3 and 4 don't include any Amsterdam neighborhoods. This could mean that there truly is "no place like home" for Londoners who live in those areas.

Taking a deeper dive into the Clusters, I visualized the top most frequent venue categories. This also helped to get a better naming convention.

Cluster 0: Family Friendly

As you can see below, there are many venue categories in these neighborhoods. There are a high number of Pubs, Hotels, Cafe's, Grocery Stores and Bus Stops. I'd call this neighborhood "Family Friendly".

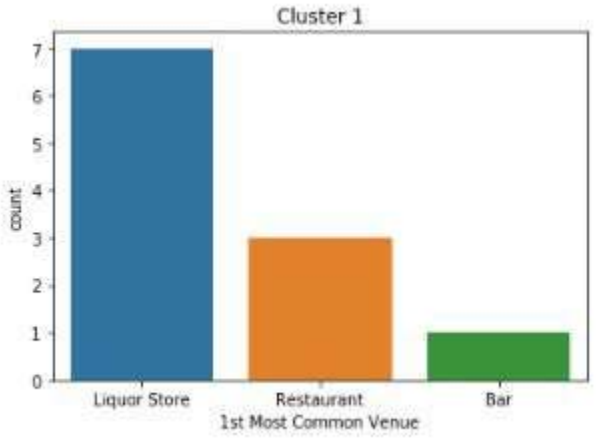
Figure 11: Most Common Venue Categories in Cluster 0



Cluster 1: Party Place

These neighborhoods seem to be pretty homogenous with only 3 categories in the top pick. If you like to party, this could be the place for you as there are many liquor stores, bars and restaurants. I'd call these neighborhoods "Party Place".

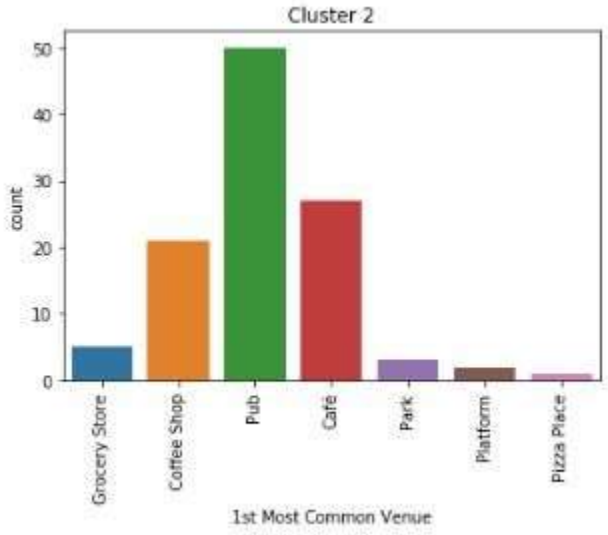
Figure 12: Most Common Venue Categories in Cluster 1



Cluster 2: Coffee Corner

These neighborhoods seem to have more cafe's and coffee shops than other clusters. If you're tired of coffee you could also head over to a pub for a pint. I'd call these neighborhoods "Coffee Corner".

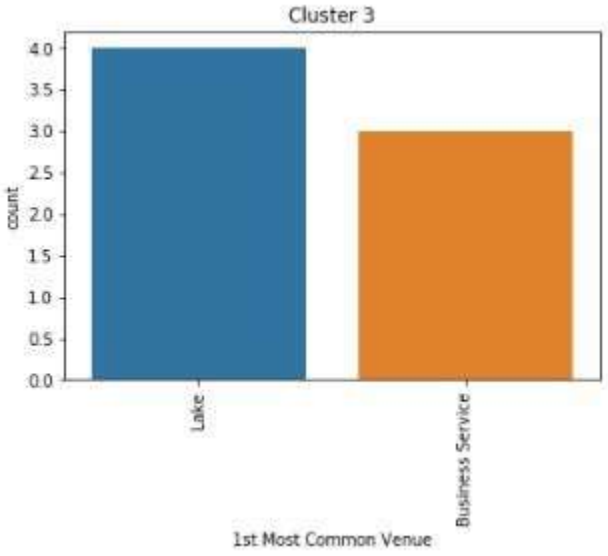
Figure 13: Most Common Venue Categories in Cluster 2



Cluster 3: Lake Views

These neighborhoods have two things that they have in leaps and bounds: lakes and businesses. These could be a “Central Business District” areas with lake-side views. I’d call these neighborhoods “Lake Views”.

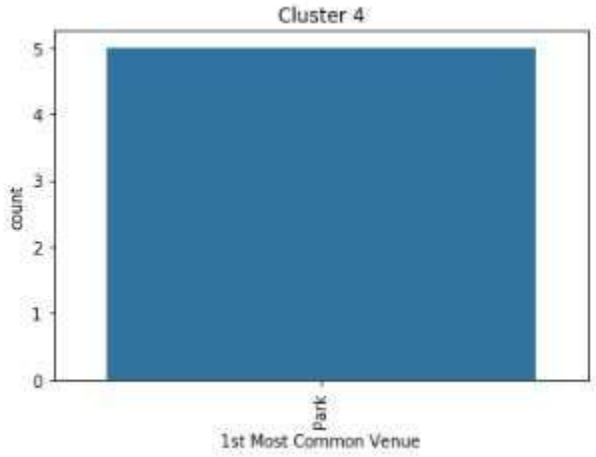
Figure 14: Most Common Venue Categories in Cluster 3



Cluster 4: Park Pozzy

These neighborhoods have one thing in common: parks! I’d call these neighbors “Park Pozzy”

Figure 15: Most Common Venue Categories in Cluster 4



In summary, we have 5 heterogonous clusters:

- Family Friendly (Cluster 0)
- Party Place (Cluster 1)
- Coffee Corner (Cluster 2)
- Lake Views (Cluster 3)
- Park Pozzy" (Custer 4)

Using the below *Figure 11* and *Figure 12* folium maps to visualize the clusters, Londoners can use the below map to find out which cluster they currently live in and which cluster they could move into in Amsterdam.

Figure 16: London Neighborhoods, Colour-coded by Cluster

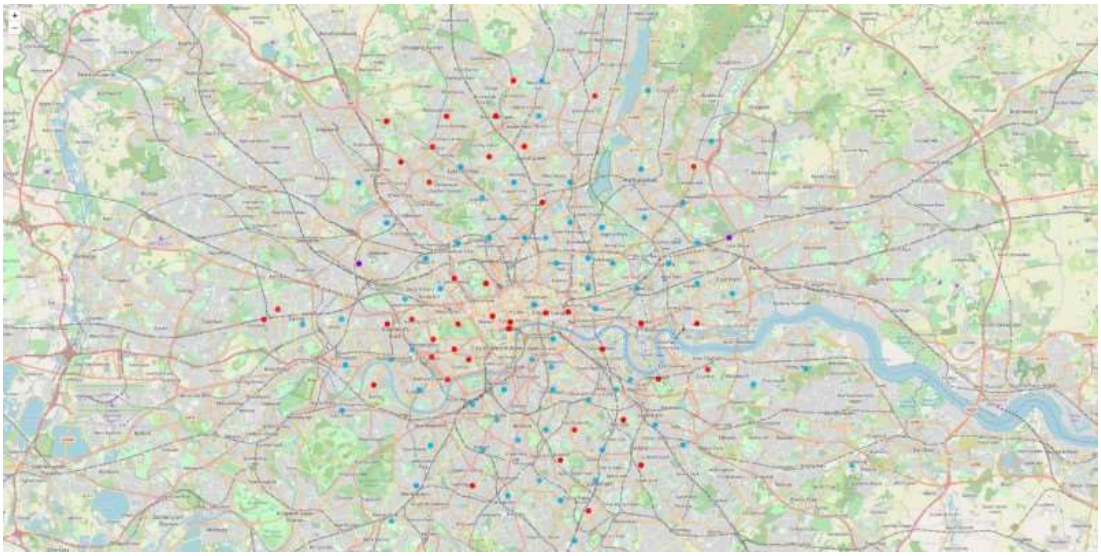
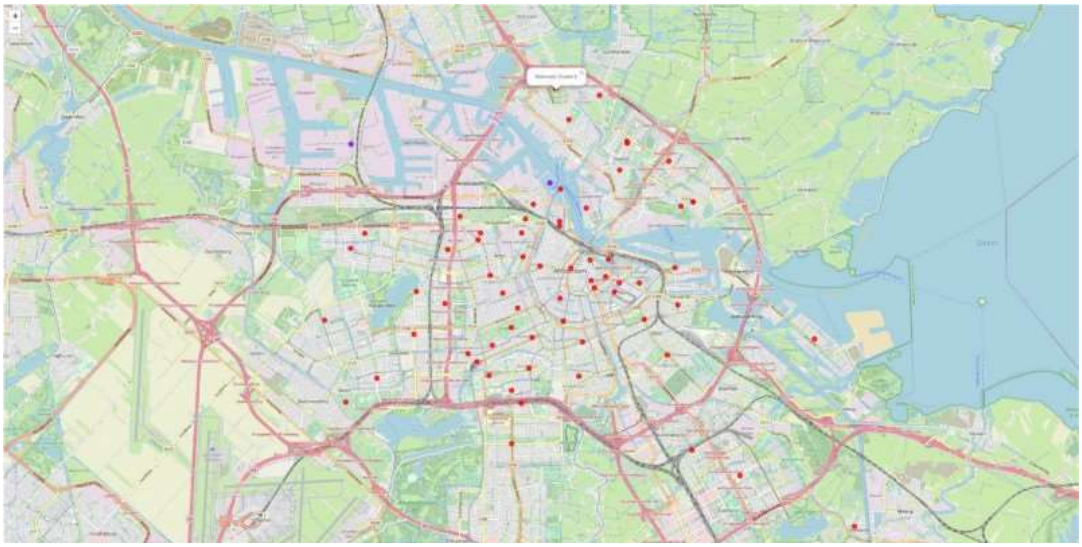


Figure 17: Amsterdam Neighborhoods, Colour-coded by Cluster



5. Discussion

The above tool is a great start although it isn't perfect. Further iterations of this project could be done using different clustering algorithms and numbers of clusters. This could help to solve the issue of not having any Amsterdam neighborhoods in Clusters 2, 3 and 4.

Furthermore, a web-based application would be useful to improve the user experience of this tool. An application where a user can enter in their address in London and then the corresponding Amsterdam neighborhood recommendation pops up, would be preferable to visualize and serve the results.

6. Conclusion

In conclusion, this report presents the steps taken to cluster London and Amsterdam neighborhoods based on similarity of venue category frequency. By using a KNN algorithm 5 neighborhood clusters were presented that were heterogeneous: Family Friendly, Party Place, Coffee Corner, Lake Views and Park Pozzy. As the last 3 clusters only include London neighborhoods, it could be inferred that there truly is "no place like home" for those neighborhoods outside of London.