# **CAPSTONE PROJECT**

Battle of the neighborhoods 2021



2021-08-09

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## Introduction

This section contains the description of the background of the focus of this project, the business problem, as well as a description of who might be interested in the results of this project.

### Background

As the world is becoming more connected and industries become integrated, more and more people relocate from one country to another in pursuit of new career opportunities. These relocations cause a disruption in the lives of these people and their families as they are required to familiarise themselves with a new country, new people, new culture, new language (perhaps) and new environment.

One of the biggest struggles of newly relocating families is finding a neighborhood and a place to live in that is compatible to their needs, and perhaps even similar to what they are used to.

#### **Problem**

A man and his wife, like many other couples and families, will be relocating to Amsterdam, Netherlands. They are relocating from Toronto, Canada and want to find neighborhoods that are similar to what they are used to. They are, unfortunately, not familiar with the Amsterdam's neighborhoods and need some help. They currently live in Willowdale, Toronto, Canada.

### Solution approach

The approach that will be followed in pursuit of solving this problem will be to first cluster the Toronto neighborhoods according to the venues found within a 500m radius of a neighborhood's centroid. Then, using this built cluster model, classify the Amsterdam neighborhoods into the same clusters to find similar neighborhoods to the ones in Toronto. The data required for this will be discussed in the next section.

#### Interest

This is of interest to anyone relocating from one city to another, regardless of country, and require more information on their new city's neighborhoods, especially the similarity of these neighborhoods with their current city's neighborhoods.

## **Data**

This section contains a description of the data to be used in this analysis, as well as an explanation of the data cleaning and preparation tasks that are required for the proposed analytical model.

## Data required and sources

The data components required for the proposed analytical model are listed in the table below, as well as their respective sources.

Data component	Data source	Data fields
List of Toronto	Wikipedia page:	- Neighborhood name
neighborhoods	https://en.wikipedia.org/w/index.php?titl	- Neighborhood postal code
	e=List of postal codes of Canada: M&	
	oldid=945633050.	
List of Amsterdam	Wikipedia page:	- Neighborhood name
neighborhoods	https://en.wikipedia.org/wiki/Template:N	- Neighborhood district
	eighborhoods of Amsterdam	
Geolocations of all	Bing Maps API	- Neighborhood latitude
neighborhoods		- Neighborhood longitude
Venue information per	Foursquare API (Explore)	- Venue name
neighborhood		- Venue latitude
		- Venue longitude
		- Venue category

## Data cleaning and preparation

The following data cleaning tasks were done per data component:

Data component	Data cleaning tasks		
List of Toronto	1. Create Soup from website, extract relevant data points		
neighborhoods	2. Remove Postal codes with unassigned neighborhoods		
List of Amsterdam	1. Create Soup from website, extract relevant data points		
neighborhoods			
Geolocations of all	1. Create a function that uses Bing Maps API to geocode an address		
neighborhoods	2. Loop through neighborhoods using the function to geocode addresses		
	3. Function retries geocoding when first attempts fail		
Venue information per	1. Create a function that uses Foursquare API to retrieve venue data per		
neighborhood	neighborhood, extract relevant data points per venue		
	2. Loop through neighborhoods and extract data through API using function		

The following data preparation tasks were done to prepare the data for the analytical model:

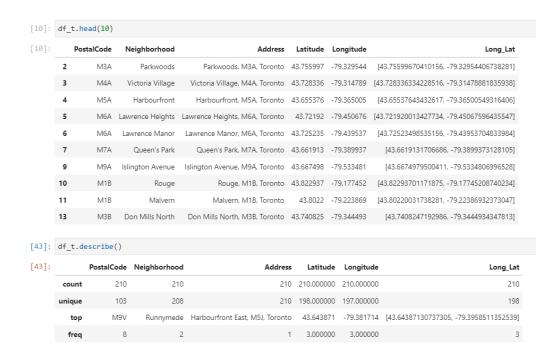
Data preparation	Data preparation tasks
Determine frequency of	1. Combine venue datasets into one dataframe (to ensure all categories are
occurrence of venues by	included for features in clustering model)
category per	2. One hot encode each venue according to the venue category
neighborhood (used by	3. Summarise the neighborhoods by calculating the mean of the frequency of
clustering model)	occurrence of venues by venue category for each neighborhood
Identify the top 10 venue categories per neighborhood (used to view resulting clusters'	Create a function that will sort venue categories per neighborhood by frequency of occurrence Use function to sort venue categories and identify top 10 venue categories per neighborhood
neighborhoods)	3. Create a dataframe containing the 1 <sup>st</sup> most common venue category, up to 10 <sup>th</sup> most common venue category, per neighborhood.

## Exploratory data analysis

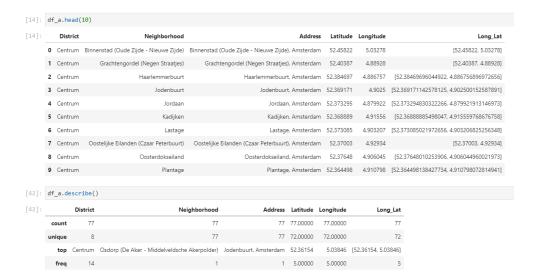
This sub-section contains descriptions of the exploratory data analysis tasks that were done to gain a better understanding of the data that is required for this analytical model.

#### Neighborhoods data

There are 210 neighborhoods in Toronto, which have all been geocoded to obtain their latitudinal and longitudinal coordinates.



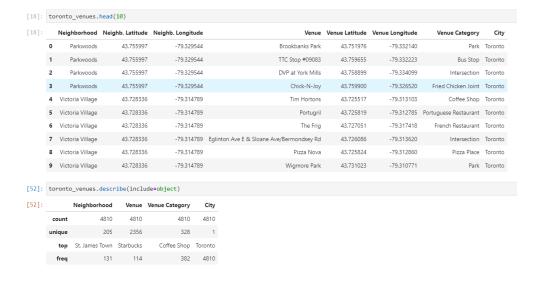
There are 77 neighborhoods in Amsterdam, which have all been geocoded to obtain their latitudinal and longitudinal coordinates.



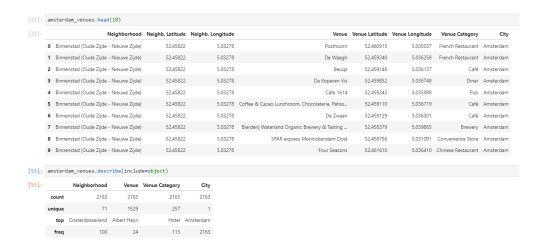
**Key observation**: the number of Amsterdam neighborhoods is less than half of the number of Toronto neighborhoods. Luckily, Toronto's neighborhoods will be used to create and train the clustering model, so it is advantageous to have more data for this.

#### Venues data

There are 4810 different venues across Toronto's neighborhoods, that are categorised into 328 different venue categories.



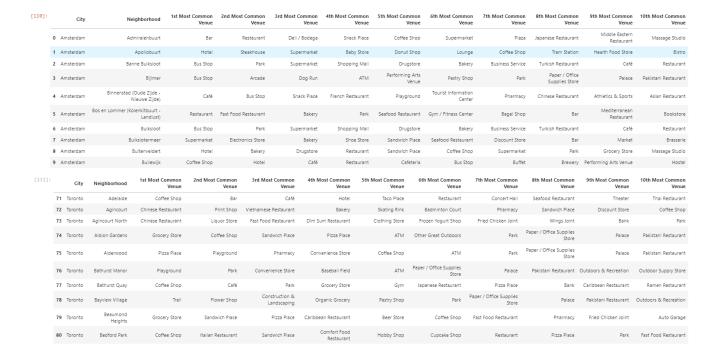
There are 2163 different venues across Amsterdam's neighborhoods, that are categorised into 257 different venue categories.



**Key observation**: to be able to use the same clustering model to classify Amsterdam's neighborhoods, one has to use all the venue categories found across Toronto and Amsterdam's neighborhoods when training the clustering model.

#### Top venues per neighborhood

The venues can be sorted according to frequency of occurrence of the venue category, per neighborhood. The top occurring venue categories can then be viewed. These datasets are used to view clusters' underlying neighborhoods once clustered.



## Final dataset (model ready):

An excerpt from the final dataset containing the frequency of occurrence of venue categories in a format that is ready for model can be seen below. This dataset consists of 276 rows (Toronto and Amsterdam neighborhoods combined) and 387 columns (387 unique venue categories across Toronto and Amsterdam neighborhoods)

[81]:		City	Neighborhood	ATM	Accessories Store	Afghan Restaurant	African Restaurant	Airport	Airport Food Court		Airport Service	Airport Terminal	American Restaurant
	0	Amsterdam	Admiralenbuurt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	1	Amsterdam	Apollobuurt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	2	Amsterdam	Banne Buiksloot	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	3	Amsterdam	Bijlmer	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	4	Amsterdam	Binnenstad (Oude Zijde - Nieuwe Zijde)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	4												
[112]:	]: all_grouped.shape												
[112]:	(2	76, 387)											

# **Methodology & Results**

This section contains an explanation of the analytical approach that was followed in the pursuit of solving the problem as stated in the Introduction section.

### **Approach**

Clustering is done on the Toronto neighborhoods to create clusters of similar neighborhoods based on the venues found in those neighborhoods. The model built from the clustering is then used to classify the Amsterdam neighborhoods into the same clusters, to find similar neighborhoods to the ones in Toronto.

K-means Clustering was found to be the most suitable for this problem because of its simplicity and strength, which is advantageous considering the number of features in the dataset. Also, there is no need for a hierarchy of clusters, so hierarchical clustering was not considered. The k parameter is specified as 10 (i.e. 10 clusters). 10 is chosen for k because of the meaningful split that results in the neighborhoods, compared to other, lower values for k.

K-means Clustering is applied using the KMeans package from the sklearn.cluster module. This package allows you to create a KMeans object which makes use of machine learning to build the clustering model, given certain parameters and training data. The training dataset consists of the frequency of occurrence of the venue categories (as features) per neighborhood. Clustering is done on the Toronto neighborhoods using the *fit()* function of the KMeans object.

A model is created and stored in the KMeans object, based on the clustering of the Toronto neighborhoods. This created model is then used to predict the cluster of each Amsterdam neighborhood, given the frequency of occurrence of the different venue categories in each neighborhood. Basically, the created clustering model stored in the KMeans object is used to classify the Amsterdam neighborhoods using the *predict()* function of the object.

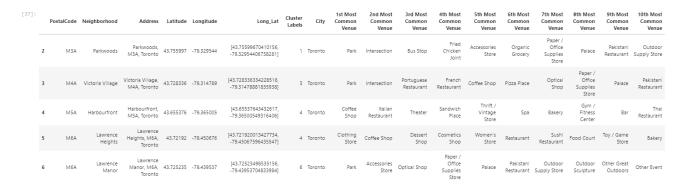
The resulting cluster labels given to Toronto and Amsterdam neighborhoods are presented and analysed by plotting the neighborhoods on a geographical map and using colored markers (a different color for each cluster). This is done using the *folium* package. These maps can be used to browse through neighborhoods that are similar to the neighborhoods of Toronto.

## **Results, Discussion & Conclusion**

This section contains the results from the built model, using the data prepared earlier in the process. The results are analysed and discussed in the last part of this section.

### Results

The resulting cluster labels are combined with the dataset containing the neighborhood names, along with their top 10 occurring venue categories. Below figure shows an excerpt from this dataframe containing the Toronto neighborhoods.



And below is an excerpt from the Amsterdam dataframe.



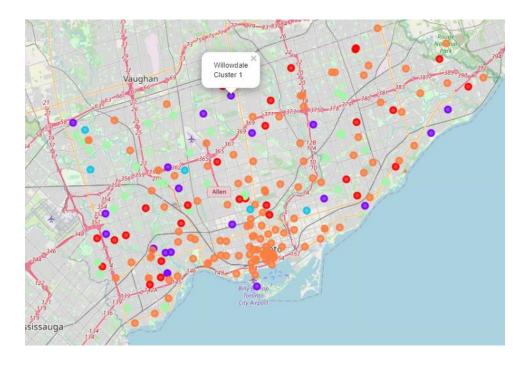
The count for Toronto neighborhoods per cluster can be seen below.

[38]:		Neighborhood
	Cluster Labels	
	0	8
	1	20
	2	5
	3	31
	4	123
	5	2
	6	9
	7	5
	8	3
	9	1

And below is the count for Amsterdam neighborhoods per the same clusters.

[41]:		Neighborhood
	Cluster Labels	
	0	5
	1	4
	2	1
	4	61

The clustered neighborhoods were plotted on a geographical map using a different color marker for a different cluster. Shown below is the resulting map for the Toronto neighborhoods. This map is interactive — when you click on a marker, a popup will appear showing the name of the neighborhood and its cluster.



Shown below is the resulting map for the Amsterdam neighborhoods.



When analysing the clusters, a count of the top 10 occurring venue categories gives one a good idea of the profile of the cluster. In the table below is shown the 20 venue categories that are found the most in the top 10 venue categories of the number 9 labeled cluster for Toronto.

```
[145]: Coffee Shop
   Café
                                     63
   Restaurant
   Park
                                     46
   Sandwich Place
                                     40
                                     34
   Grocery Store
   Italian Restaurant
                                     31
   Pizza Place
                                     28
   Bakery
   Fast Food Restaurant
   Pharmacy
                                     25
   Bar
                                     25
                                     23
   Gym
   Hotel
                                     20
   Bank
   Japanese Restaurant
                                     19
   Paper / Office Supplies Store
                                     18
   Palace
                                     17
   MTA
                                     16
   Sushi Restaurant
   dtype: int64
```

And here are the counts for the 20 venue categories for Amsterdam.

```
[146]: Restaurant
   Bar
   Coffee Shop
                                    28
   Café
                                    28
   Park
                                    25
   Hotel
                                    24
   Bus Stop
                                    18
   Paper / Office Supplies Store
   Bakery
   Supermarket
                                    15
   ATM
                                    14
   Palace
   Snack Place
                                    13
   Italian Restaurant
                                    12
   Pakistani Restaurant
   Plaza
   Pizza Place
   French Restaurant
                                     9
   Cocktail Bar
   dtype: int64
```

### Discussion

When the number of neighborhoods per cluster is counted, it is clear that some clusters are more prevalent than others, indicating that there are more of these similar type neighborhoods in the city. The cluster that is predominant is labeled '4'. From the venue categories counts found in this cluster's top 10 venue categories, it is evident that these cluster 4 neighborhoods are dominated by restaurants, bars, coffee shops, cafés, parks, hotels, and so on.

Below follows a brief profile of each cluster, listing the 5 venue categories that are most prevalent in each of these cluster's neighborhoods' top 10 occurring venue categories.

Clusterlabel	Toronto: 5 most prevalent top 10 venue categories (occurences)	Amsterdam: 5 most prevalent venue categories
0	Restaurant (8)	Restaurant (5)
	Palace (6)	Hotel (3)
	Park (6)	Sandwich Place (2)
	Paper / Office Supplies Store (4)	Coffee Shop (2)
	Pakistani Restaurant (4)	Convenience Store (2)
1	Park (20)	Park (4)
	Palace (19)	Café (3)
	Pakistani Restaurant (19)	Bus Stop (3)
	Paper / Office Supplies Store (18)	Palace (2)
	Outdoor Supply Store (16)	Bakery (2)
2	Palace (5)	Pakistani Restaurant (1)
	Paper / Office Supplies Store (5)	Park (1)
	Coffee Shop (5)	Accessories Store (1)
	Park (5)	Organic Grocery (1)
	Pastry Shop (4)	Palace (1)
3	Pizza Place (25)	N/A
	Paper / Office Supplies Store (21)	

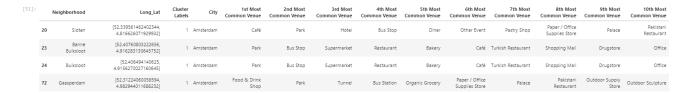
	Palace (20)		
	Coffee Shop (15)		
	Pakistani Restaurant (15)		
4	Coffee Shop (90)	Restaurant (30)	
	Café (59)	Coffee Shop (29)	
	Restaurant (45)	Café (28)	
	Park (40)	Bar (26)	
	Bakery (34)	Hotel (22)	
5	Pakistani Restaurant (2)	N/A	
	Park (2)		
	Pharmacy (2)		
	Accessories Store (2)		
	Palace (2)		
6	Other Great Outdoors (9)	N/A	
	Outdoor Sculpture (9)		
	Palace (9)		
	Pakistani Restaurant 9)		
	Outdoor Supply Store (9)		
7	Trail (5)	N/A	
	Pakistani Restaurant (5)		
	Outdoor Sculpture (5)		
	Palace (5)		
	Outdoor Supply Store (5)		
8	Pakistani Restaurant (3)	N/A	
	Park (3)		
	Other Great Outdoors (3)		
	Accessories Store (3)		
	Palace (3)		
9	Seafood Restaurant (1)	N/A	
	Pakistani Restaurant (1)		
	Other Great Outdoors (1)		
	Accessories Store (1)		
	Palace (1)		

In the end, the Toronto clusters weren't as transferrable to the Amsterdam neighborhoods, considering only four of the nine clusters were actually 'found' in the Amsterdam neighborhoods. This could be due to data limitations or accuracy.

### Conclusion

The problem was solved using the proposed analytical approach. It is possible to classify neighborhoods of one city, using a clustering model based on another city's neighborhoods. Using this model, one can identify neighborhoods that are similar to the one's found in the training data, which could assist people relocating from one city to another in finding a suitable neighborhood to look for accommodation.

In the case of the couple moving from Willowdale, Toronto: Willowdale is clustered into the cluster labeled '1'. The Amsterdam neighborhoods that are classified as similar to Willowdale's cluster is shown below.



The profile of this cluster can be viewed in the Discussion section.

There is, however, room for improvement in this model. The following is a list of proposed possible improvements that can be explored for this model:

- 1. Use a larger (or smaller) value for the radius around a neighborhood's centroid from which to retrieve venue information.
- 2. Test and compare the DBSCAN clustering algorithm's performance and accuracy.
- 3. Include other neighborhood data that could improve the profiling of neighborhoods, not just venues.
- 4. Do clustering on all neighborhoods (both cities).