# Capstone Project: The Battle of Neighbourhoods – Toronto

## 1. Introduction / Business Problem

*Identify the business problem*:

Toronto is the largest city in Canada with an estimated population of more than 6 million, so it is a good place for entrepreneurs eager to open new businesses that become profitable and drive a great number of customers.

The goal of this project is to use the Foursquare API to provide the location data and clustering of venues information to find out what would be the best neighbourhoods in the area of the Centre of Toronto to open a new gym venue.

Everybody knows that regular physical activity improves your health and well-being. It has benefits for all ages and abilities including reducing your risk of developing many chronic diseases, increasing your energy, your self-esteem and improving your sleep. So, nowadays, people are going to gyms more frequently due to the increasing interest in a healthy lifestyle.

*Target audience:*

This project is aimed to entrepreneurs or business owners who want to open a new gym in the Centre of Toronto or grow their current business in a profitable location where little or no gyms exist today.

## 2. Data

For the purpose of this project, we will need to have the list of Neighbourhoods of Toronto city, as well as the geographical location of the Toronto's Neighbourhoods and the venue data of gyms through Foursquare API.

Here are the details:

* Wikipedia page with the Neighbourhoods and postal codes of Toronto city ( https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M )

# List of postal codes of Canada: M

From Wikipedia, the free encyclopedia

This is a list of postal codes in Canada where the first letter is M. Postal codes beginning with M are located within the city of Toronto in the province of Ontario. Only the first three characters
Sortation Area.

Canada Post provides a free postal code look-up tool on its website,[1] via its applications for such smartphones as the iPhone and BlackBerry,[2] and sells hard-copy directories and CD-ROM
which allow customers to properly match addresses and postal codes. Hard-copy directories can also be consulted in all post offices, and some libraries.

## Toronto - 103 FSAs [ edit ]

Note: There are no rural FSAs in Toronto, hence no postal codes should start with M0. However, the postal code M0R 8T0 is assigned to an Amazon warehouse in Mississauga, suggesting th
FSA for high volume addresses.

| Postal Code | Borough | Neighbourhood |
|---|---|---|
| M1A | Not assigned | Not assigned |
| M2A | Not assigned | Not assigned |
| M3A | North York | Parkwoods |
| M4A | North York | Victoria Village |
| M5A | Downtown Toronto | Regent Park, Harbourfront |
| M6A | North York | Lawrence Manor, Lawrence Heights |
| M7A | Downtown Toronto | Queen's Park, Ontario Provincial Government |
| M8A | Not assigned | Not assigned |
| M9A | Etobicoke | Islington Avenue, Humber Valley Village |
| M1B | Scarborough | Malvern, Rouge |
| M2B | Not assigned | Not assigned |
| M3B | North York | Don Mills |
| M4B | East York | Parkview Hill, Woodbine Gardens |
| M5B | Downtown Toronto | Garden District, Ryerson |
| M6B | North York | Glencairn |
| M7B | Not assigned | Not assigned |
| M8B | Not assigned | Not assigned |
| M9B | Etobicoke | West Deane Park, Princess Gardens, Martin Grove, Islington, Cloverdale |

The Wikipedia site provide the following information: postal code, borough and the name of the neighbourhoods existing in Toronto.
We need to scrape the data from the Wikipedia table into a data frame as below:

| | PostalCode | Borough | Neighborhood |
|---|---|---|---|
| **0** | M3A | North York | Parkwoods |
| **1** | M4A | North York | Victoria Village |
| **2** | M5A | Downtown Toronto | Regent Park, Harbourfront |
| **3** | M6A | North York | Lawrence Manor, Lawrence Heights |
| **4** | M7A | Downtown Toronto | Queen's Park, Ontario Provincial Government |

* the geographical coordinates of each postal code through reading the CSV file (https://cocl.us/Geospatial_data) and transforming it into a Pandas data frame.

| Postal Coc | Latitude | Longitude |
|---|---|---|
| M1B | 43.80669 | -79.1944 |
| M1C | 43.78454 | -79.1605 |
| M1E | 43.76357 | -79.1887 |
| M1G | 43.77099 | -79.2169 |
| M1H | 43.77314 | -79.2395 |
| M1J | 43.74473 | -79.2395 |
| [illegible] | [illegible] | [illegible] |

| | Postal Code | Latitude | Longitude |
|---|---|---|---|
| **0** | M1B | 43.806686 | -79.194353 |
| **1** | M1C | 43.784535 | -79.160497 |
| **2** | M1E | 43.763573 | -79.188711 |
| **3** | M1G | 43.770992 | -79.216917 |
| **4** | M1H | 43.773136 | -79.239476 |

* explore and get the venues data using Foursquare API:

For retrieving the name, location and category of venues in Toronto, we need to create an account within Foursquare API and use the Client_ID and Client_Secret to pull the necessary data.

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| **0** | The Beaches | 43.676357 | -79.293031 | Glen Manor Ravine | 43.676821 | -79.293942 | Trail |
| **1** | The Beaches | 43.676357 | -79.293031 | The Big Carrot Natural Food Market | 43.678879 | -79.297734 | Health Food Store |
| **2** | The Beaches | 43.676357 | -79.293031 | Grover Pub and Grub | 43.679181 | -79.297215 | Pub |
| **3** | The Beaches | 43.676357 | -79.293031 | Upper Beaches | 43.680563 | -79.292869 | Neighborhood |
| **4** | The Danforth West, Riverdale | 43.679557 | -79.352188 | Pantheon | 43.677621 | -79.351434 | Greek Restaurant |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| [illegible] | Business reply mail Processing Centre, South | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

## 3. Methodology

### *3.1 Exploratory Data Analysis*

When getting the data from Wikipedia source, we need to make the following transformations:

- Ignore data where a Borough is ‘not assigned’.
- If a cell has a Borough but a ‘not assigned’ Neighbourhood, then the Neighbourhood will be the same as the Borough.
- Group the data by PostalCode and Borough

| | PostalCode | Borough | Neighborhood |
|---|---|---|---|
| 0 | M1B | Scarborough | Malvern, Rouge |
| 1 | M1C | Scarborough | Rouge Hill, Port Union, Highland Creek |
| 2 | M1E | Scarborough | Guildwood, Morningside, West Hill |
| 3 | M1G | Scarborough | Woburn |
| 4 | M1H | Scarborough | Cedarbrae |

Then we combine this dataframe (df) with the geographical data that includes latitude and longitude information (geo_df) based on PostalCode, obtaining the toronto.df dataframe:

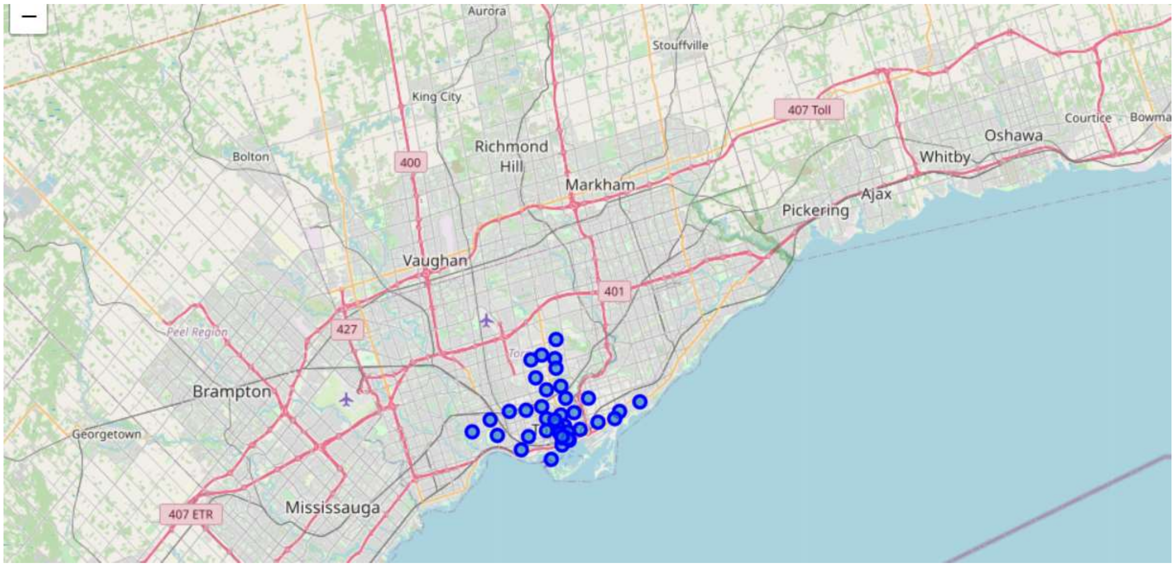
```
# Merge both dataframes on PostalCode
toronto = pd.merge(df, geo_df, on='PostalCode')
toronto.head()
```

| | PostalCode | Borough | Neighborhood | Latitude | Longitude |
|---|---|---|---|---|---|
| 0 | M1B | Scarborough | Malvern, Rouge | 43.806686 | -79.194353 |
| 1 | M1C | Scarborough | Rouge Hill, Port Union, Highland Creek | 43.784535 | -79.160497 |
| 2 | M1E | Scarborough | Guildwood, Morningside, West Hill | 43.763573 | -79.188711 |
| 3 | M1G | Scarborough | Woburn | 43.770992 | -79.216917 |
| 4 | M1H | Scarborough | Cedarbrae | 43.773136 | -79.239476 |

Afterwards, we filter out the data to Boroughs containing the word "Toronto" in their names, which represents the area of the Centre of Toronto.

We create a folium map to have a visual representation:

```
# Create a map of Toronto to plot the Boroughs with "Toronto" in its name
latitude = 43.651070
longitude = -79.347015

map_toronto = folium.Map(location=[latitude, longitude], zoom_start=10)

for lat, lng, borough, neighborhood in zip(toronto_central['Latitude'], toronto_central['Longitude'], toronto_central['Borough'],
                                           toronto_central['Neighborhood']):
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_toronto)
```




Now using Foursquare API we explore the Neighbourhoods and get the nearby venues within a 500-meters radius

```
print(toronto_central_venues.shape)
print('There are {} uniques categories.'.format(len(toronto_central_venues['Venue Category'].unique())))
toronto_central_venues
```

```
(1624, 7)
There are 235 uniques categories.
```

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| **0** | The Beaches | 43.676357 | -79.293031 | Glen Manor Ravine | 43.676821 | -79.293942 | Trail |
| **1** | The Beaches | 43.676357 | -79.293031 | The Big Carrot Natural Food Market | 43.678879 | -79.297734 | Health Food Store |
| **2** | The Beaches | 43.676357 | -79.293031 | Grover Pub and Grub | 43.679181 | -79.297215 | Pub |
| **3** | The Beaches | 43.676357 | -79.293031 | Upper Beaches | 43.680563 | -79.292869 | Neighborhood |
| **4** | The Danforth West, Riverdale | 43.679557 | -79.352188 | Pantheon | 43.677621 | -79.351434 | Greek Restaurant |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **1619** | Business reply mail Processing Centre, South C... | 43.662744 | -79.321558 | TTC Russell Division | 43.664908 | -79.322560 | Light Rail Station |
| **1620** | Business reply mail Processing Centre, South C... | 43.662744 | -79.321558 | Jonathan Ashbridge Park | 43.664702 | -79.319898 | Park |
| **1621** | Business reply mail Processing Centre, South C... | 43.662744 | -79.321558 | Olliffe On Queen | 43.664503 | -79.324768 | Butcher |
| | Business reply mail Processing Centre, South | | | | | | |

Then we group the venues by Neighbourhood:

| Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|
| Berczy Park | 55 | 55 | 55 | 55 | 55 | 55 |
| Brockton, Parkdale Village, Exhibition Place | 23 | 23 | 23 | 23 | 23 | 23 |
| Business reply mail Processing Centre, South Central Letter Processing Plant Toronto | 16 | 16 | 16 | 16 | 16 | 16 |
| CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Quay, South Niagara, Island airport | 16 | 16 | 16 | 16 | 16 | 16 |
| Central Bay Street | 68 | 68 | 68 | 68 | 68 | 68 |
| Christie | 16 | 16 | 16 | 16 | 16 | 16 |
| Church and Wellesley | 75 | 75 | 75 | 75 | 75 | 75 |
| Commerce Court, Victoria Hotel | 100 | 100 | 100 | 100 | 100 | 100 |
| Davisville | 33 | 33 | 33 | 33 | 33 | 33 |
| Davisville North | 9 | 9 | 9 | 9 | 9 | 9 |
| Dufferin, Dovercourt Village | 13 | 13 | 13 | 13 | 13 | 13 |
| First Canadian Place, Underground city | 100 | 100 | 100 | 100 | 100 | 100 |
| Forest Hill North & West, Forest Hill Road Park | 4 | 4 | 4 | 4 | 4 | 4 |
| Garden District, Ryerson | 100 | 100 | 100 | 100 | 100 | 100 |

Then we start to analyse each Neighbourhood, firstly using one-hot encoding format and secondly grouping the data by Neighbourhood and by the mean of the frequency of occurrence of each category:

### Analyze each Neighborhood

```
# one hot encoding
toronto_onehot = pd.get_dummies(toronto_central_venues[['Venue Category']], prefix="", prefix_sep="")

# add Borough column to the dataframe
toronto_onehot['Neighborhoods'] = toronto_central_venues['Neighborhood']

# move Neighborhood to the first column
fixed_columns = [toronto_onehot.columns[-1]] + list(toronto_onehot.columns[:-1])
toronto_onehot = toronto_onehot[fixed_columns]

print(toronto_onehot.shape)
toronto_onehot.head()
```

```
(1624, 236)
```

| | Neighborhoods | Afghan Restaurant | Airport | Airport Food Court | Airport Gate | Airport Lounge | Airport Service | Airport Terminal | American Restaurant | Antique Shop | ... | Theater | Theme Restaurant | Toy / Game Store | Trail | Train Station | Vegetarian / Vegan Restaurant | Video Game Store | Vietnamese Restaurant | Win Ba |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 1 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | The Danforth West, Riverdale | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |

```
# Let's group data by Neighborhood and by the mean of the frequency of ocurrence of each category

toronto_grouped = toronto_onehot.groupby(['Neighborhoods']).mean().reset_index()

print(toronto_grouped.shape)
toronto_grouped.head()
```

(39, 236)

| | Neighborhoods | Afghan Restaurant | Airport | Airport Food Court | Airport Gate | Airport Lounge | Airport Service | Airport Terminal | American Restaurant | Antique Shop | ... | Theater | Theme Restaurant | Toy / Game Store | Trail | Train Station | Vegetarian / Vegan Restaurant | Video Game Store | Vietnamese Restaurant |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Berczy Park | 0.0 | 0.0000 | 0.0000 | 0.0000 | 0.000 | 0.000 | 0.0000 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.018182 | 0.0 | 0.0 |
| 1 | Brockton, Parkdale Village, Exhibition Place | 0.0 | 0.0000 | 0.0000 | 0.0000 | 0.000 | 0.000 | 0.0000 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| 2 | Business reply mail Processing Centre, South C... | 0.0 | 0.0000 | 0.0000 | 0.0000 | 0.000 | 0.000 | 0.0000 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| 3 | CN Tower, King and Spadina, Railway Lands, Har... | 0.0 | 0.0625 | 0.0625 | 0.0625 | 0.125 | 0.125 | 0.0625 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 |
| 4 | Central Bay Street | 0.0 | 0.0000 | 0.0000 | 0.0000 | 0.000 | 0.000 | 0.0000 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.014706 | 0.0 | 0.0 |

Finally, we get the average of gyms by Neighbourhood. Remember that the goal of this project is to find out the best Neighbourhood to open a new gym in the area of Centre of Toronto:

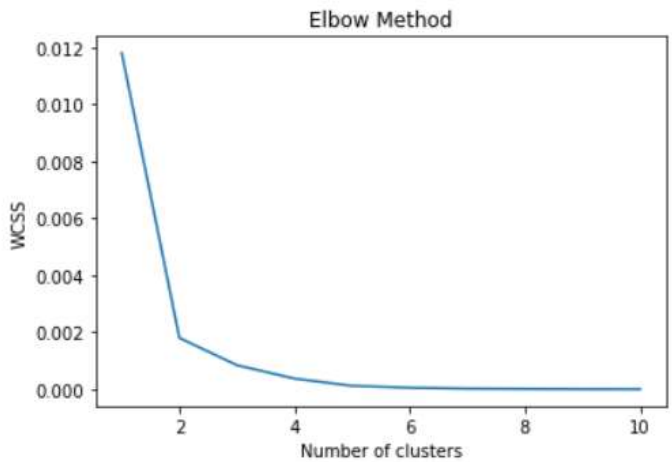
```
gym_data = toronto_grouped[['Neighborhoods', 'Gym']]
gym_data.head()
```

| | Neighborhoods | Gym |
|---|---|---|
| 0 | Berczy Park | 0.000000 |
| 1 | Brockton, Parkdale Village, Exhibition Place | 0.043478 |
| 2 | Business reply mail Processing Centre, South C... | 0.000000 |
| 3 | CN Tower, King and Spadina, Railway Lands, Har... | 0.000000 |
| 4 | Central Bay Street | 0.000000 |

### *3.2 Clustering Model*

We want to cluster the Neighbourhoods based on the criteria of having a similar number of gyms in them. To do so we use the K-Means method. But how to know which is the optimal number of clusters? Using the Elbow method, which consists of training multiple models using different number of clusters and storing the value of inertia_property (wcss) every time.

```
wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=100, n_init=10, random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```




We can conclude that the optimum K value is 5, so we will have 5 clusters.

So we run K-Means clustering with this value and create a new data frame including the clusters:

```
### Create a new dataframe that includes the clusters
toronto_merged = gym_data.copy()

toronto_merged['Cluster Labels'] = kmeans.labels_
```

```
toronto_merged.head()
```

| | Neighborhoods | Gym | Cluster Labels |
|---|---|---|---|
| 0 | Berczy Park | 0.000000 | 0 |
| 1 | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 |
| 2 | Business reply mail Processing Centre, South C... | 0.000000 | 0 |
| 3 | CN Tower, King and Spadina, Railway Lands, Har... | 0.000000 | 0 |
| 4 | Central Bay Street | 0.000000 | 0 |

Next, we merge this data frame with the one containing the venues (toronto_central_venues):

```
### Merge toronto_merged with toronto_venues
toronto_merged = toronto_merged.join(toronto_central_venues.set_index('Neighborhood'), on='Neighborhoods')

print(toronto_merged.shape)
toronto_merged.head()
```

```
(1624, 9)
```

| | Neighborhoods | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Berczy Park | 0.0 | 0 | 43.644771 | -79.373306 | The Keg Steakhouse + Bar - Esplanade | 43.646712 | -79.374768 | Restaurant |
| 0 | Berczy Park | 0.0 | 0 | 43.644771 | -79.373306 | LCBO | 43.642944 | -79.372440 | Liquor Store |
| 0 | Berczy Park | 0.0 | 0 | 43.644771 | -79.373306 | Fresh On Front | 43.647815 | -79.374453 | Vegetarian / Vegan Restaurant |
| 0 | Berczy Park | 0.0 | 0 | 43.644771 | -79.373306 | Goose Island Brewhouse | 43.647329 | -79.373541 | Beer Bar |
| 0 | Berczy Park | 0.0 | 0 | 43.644771 | -79.373306 | Hockey Hall Of Fame (Hockey Hall of Fame) | 43.646974 | -79.377323 | Museum |

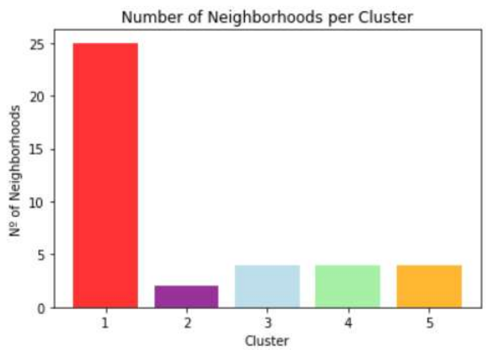
We create a folium map to plot the clusters and Neighbourhoods:

```
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=10)

x = np.arange(kclusters)
ys = [i+x+(i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

markers_colors = []
for lat, lng, poi, cluster in zip(toronto_merged['Neighborhood Latitude'], toronto_merged['Neighborhood Longitude'],
                                  toronto_merged['Neighborhood'], toronto_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```


## 4. Results and Discussion

We have a total of five clusters (0, 1, 2, 3, 4) and we get how many neighbourhoods there are in each cluster.

```
objects = (1, 2, 3, 4, 5)
y_pos = np.arange(len(objects))
performance = gym_data['Cluster Labels'].value_counts().to_frame().sort_index(ascending=True)
perf = performance['Cluster Labels'].tolist()
plt.bar(y_pos, perf, align='center', alpha=0.8, color=['red', 'purple', 'lightblue', 'lightgreen', 'orange'])
plt.xticks(y_pos, objects)
plt.ylabel('Nº of Neighborhoods')
plt.xlabel('Cluster')
plt.title('Number of Neighborhoods per Cluster')

plt.show()
```




Then we analyse each cluster.

*Cluster1 – colour red*

This cluster encompasses the Boroughs of East and Downtown Toronto, where the main Neighbourhoods are The Beaches, Kensington Market, Chinatown, Grange Park, Regent Park and Harbourfront. The total number of Neighbourhoods within this cluster are 25.

In this cluster, there was no gym venues.

```
cluster1_df.sort_values(['Gym'], ascending=False)
```

| | Borough | Neighborhood | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | East Toronto | The Beaches | 0.0 | 0 | 43.676357 | -79.293031 | Grover Pub and Grub | 43.679181 | -79.297215 | Pub |
| **421** | Downtown Toronto | Kensington Market, Chinatown, Grange Park | 0.0 | 0 | 43.653206 | -79.400049 | Global Cheese | 43.654623 | -79.400606 | Cheese Shop |
| **414** | Downtown Toronto | Kensington Market, Chinatown, Grange Park | 0.0 | 0 | 43.653206 | -79.400049 | Little Pebbles | 43.654883 | -79.400264 | Coffee Shop |
| **415** | Downtown Toronto | Kensington Market, Chinatown, Grange Park | 0.0 | 0 | 43.653206 | -79.400049 | El Rey | 43.652764 | -79.400048 | Cocktail Bar |
| **416** | Downtown Toronto | Kensington Market, Chinatown, Grange Park | 0.0 | 0 | 43.653206 | -79.400049 | Millie Creperie | 43.654994 | -79.399829 | Dessert Shop |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **209** | Downtown Toronto | Regent Park, Harbourfront | 0.0 | 0 | 43.654260 | -79.360636 | Tandem Coffee | 43.653559 | -79.361809 | Coffee Shop |
| **210** | Downtown Toronto | Regent Park, Harbourfront | 0.0 | 0 | 43.654260 | -79.360636 | Cooper Koo Family YMCA | 43.653249 | -79.358008 | Distribution Center |
| **211** | Downtown Toronto | Regent Park, Harbourfront | 0.0 | 0 | 43.654260 | -79.360636 | Impact Kitchen | 43.656369 | -79.356980 | Restaurant |
| **212** | Downtown Toronto | Regent Park, Harbourfront | 0.0 | 0 | 43.654260 | -79.360636 | Soulpepper Theatre | 43.650780 | -79.357615 | Theater |
| **626** | East Toronto | Business reply mail Processing Centre, South C... | 0.0 | 0 | 43.662744 | -79.321558 | Ashbridges Bay Skatepark | 43.662548 | -79.315631 | Skate Park |

*Cluster2 – colour purple*

This cluster includes Central Toronto and East Toronto as Boroughs and there are two Neighbourhoods in it. The average of gym venues is 0.06 and the total number of these venues is 3.

```
cluster2_df.sort_values(['Gym'], ascending=False)
```

| | Borough | Neighborhood | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|---|
| 26 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Marcheleo's Gourmet Marketplace | 43.708041 | -79.392195 | Gourmet Shop |
| 39 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Viva Napoli | 43.705752 | -79.389125 | Pizza Place |
| 29 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Thobors Boulangerie Patisserie Café | 43.704514 | -79.388616 | Café |
| 30 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Marigold Indian Bistro | 43.702881 | -79.388008 | Indian Restaurant |
| 31 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Zee Grill | 43.704985 | -79.388476 | Seafood Restaurant |
| 32 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | Starbucks | 43.705923 | -79.389548 | Coffee Shop |
| 33 | Central Toronto | Davisville | 0.060606 | 1 | 43.704324 | -79.388790 | June Rowlands Park | 43.700517 | -79.389189 | Park |
| | Central | | | | | | | | | |

*Cluster3 – colour lightblue*

In this cluster there are 4 Neighbourhoods and a total of 6 gym venues in it.

```
cluster3_df.sort_values(['Gym'], ascending=False)
```

| | Borough | Neighborhood | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|---|
| 246 | Downtown Toronto | Queen's Park, Ontario Provincial Government | 0.030303 | 2 | 43.662301 | -79.389494 | Queen's Park | 43.663946 | -79.392180 | Park |
| 196 | West Toronto | Runnymede, Swansea | 0.030303 | 2 | 43.651571 | -79.484450 | Awai | 43.650412 | -79.478477 | Vegetarian / Vegan Restaurant |
| 211 | West Toronto | Runnymede, Swansea | 0.030303 | 2 | 43.651571 | -79.484450 | The Coffee Bouquets | 43.648785 | -79.485940 | Coffee Shop |
| 210 | West Toronto | Runnymede, Swansea | 0.030303 | 2 | 43.651571 | -79.484450 | (The New) Moksha Yoga Bloor West | 43.648658 | -79.485242 | Yoga Studio |
| 208 | West Toronto | Runnymede, Swansea | 0.030303 | 2 | 43.651571 | -79.484450 | Supper Solved | 43.648781 | -79.485233 | Restaurant |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 139 | Downtown Toronto | Stn A PO Boxes | 0.020833 | 2 | 43.646435 | -79.374846 | NAMI | 43.650853 | -79.375887 | Japanese Restaurant |
| 140 | Downtown Toronto | Stn A PO Boxes | 0.020833 | 2 | 43.646435 | -79.374846 | The Old Spaghetti Factory | 43.646964 | -79.374403 | Italian Restaurant |
| | Downtown | | | | | | | | | |

*Cluster4 – colour lightgreen*

This cluster is about Downtown Toronto Borough and has 4 Neighbourhoods as well as cluster3. The highest average of gyms in this cluster is 0.013 and there is a total of 4 gyms.

```
cluster4_df.sort_values(['Gym'], ascending=False)
```

| | Borough | Neighborhood | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Downtown Toronto | Church and Wellesley | 0.013333 | 3 | 43.665860 | -79.383160 | Rolltation | 43.669388 | -79.386566 | Sushi Restaurant |
| **48** | Downtown Toronto | Church and Wellesley | 0.013333 | 3 | 43.665860 | -79.383160 | The Blake House | 43.664468 | -79.377471 | American Restaurant |
| **55** | Downtown Toronto | Church and Wellesley | 0.013333 | 3 | 43.665860 | -79.383160 | Cawthra Square Dog Park | 43.666583 | -79.380040 | Dog Run |
| **54** | Downtown Toronto | Church and Wellesley | 0.013333 | 3 | 43.665860 | -79.383160 | Woody's and Sailor | 43.664390 | -79.380361 | Gay Bar |
| **53** | Downtown Toronto | Church and Wellesley | 0.013333 | 3 | 43.665860 | -79.383160 | Wish | 43.668759 | -79.385694 | Restaurant |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **173** | Downtown Toronto | Garden District, Ryerson | 0.010000 | 3 | 43.657162 | -79.378937 | The Black Canary Espresso Bar | 43.657029 | -79.381385 | Café |

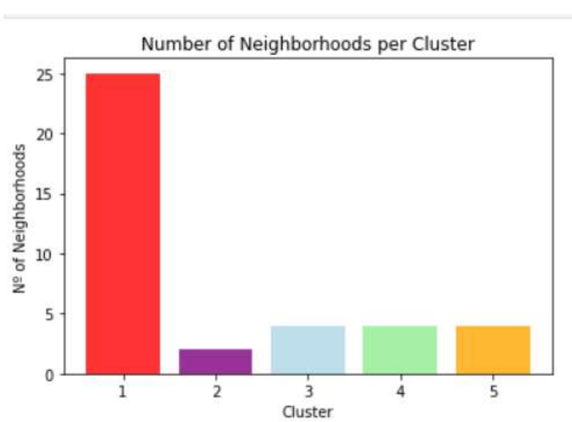
*Cluster5 – colour orange*

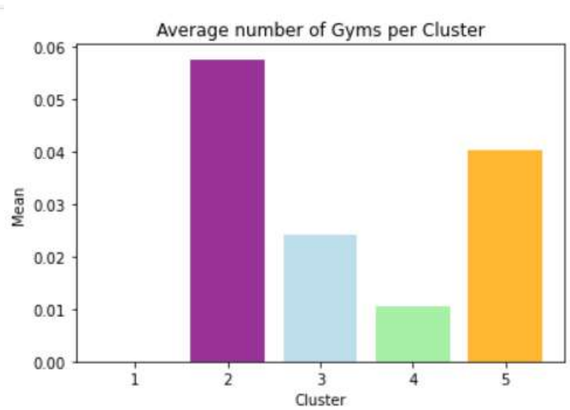
In this cluster there are also 4 Neighbourhoods in Borough like West Toronto and Downtown Toronto. The highest average of gyms in this cluster is 0.043 and there are 13 gyms in total.

```
cluster5_df.sort_values(['Gym'], ascending=False)
```

| | Borough | Neighborhood | Gym | Cluster Labels | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|---|---|---|
| **322** | West Toronto | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 | 43.636847 | -79.428191 | Lamport Stadium | 43.638778 | -79.423534 | Stadium |
| **311** | West Toronto | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 | 43.636847 | -79.428191 | Gardiner Expy & Dufferin St | 43.633800 | -79.425460 | Intersection |
| **300** | West Toronto | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 | 43.636847 | -79.428191 | Dunn Milk Variety | 43.633667 | -79.431549 | Convenience Store |
| **301** | West Toronto | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 | 43.636847 | -79.428191 | Joe Rockhead's Climbing Gym | 43.636342 | -79.423582 | Climbing Gym |
| **302** | West Toronto | Brockton, Parkdale Village, Exhibition Place | 0.043478 | 4 | 43.636847 | -79.428191 | RED Nightclub | 43.637794 | -79.423759 | Nightclub |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **106** | Downtown Toronto | Commerce Court, Victoria Hotel | 0.040000 | 4 | 43.648198 | -79.379817 | Prairie Girl Bakery | 43.648332 | -79.382305 | Cupcake Shop |
| **105** | Downtown Toronto | Commerce Court, Victoria Hotel | 0.040000 | 4 | 43.648198 | -79.379817 | Metropolitan Resto Bar | 43.650062 | -79.377181 | Italian Restaurant |
| [illegible] | Downtown | [illegible] | [illegible] | 4 | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

## 5. Conclusion



In this project, we manage to cluster the Centre of Toronto city using demographic data by Neighbourhoods, which help us identify which were the most suitable for opening a new gym.

Most of the gym venues in the Centre of Toronto city are in cluster2 represented by the purple colour. The Neighbourhoods located in Central Toronto that have the highest average of gyms are Davisville, India Bazaar and The Beaches West.

Even though cluster1 has the larger number of Neighbourhoods (25), there is no gym within it, so this is a great opportunity to open a new one, with no competition. So Neighbourhoods like The Beaches, Kensington Market, Chinatown, Grange Park, Regent Park, Harbourfront would be the ideal location for the opening of a gym.

We must also point out that there is at least one drawback in this analysis and it is the fact of only using the data that come from Foursqare API, without looking for richer information like population of different Neighbourhoods to have one more element to make the decision.