# Battle of the Neighborhoods in Toronto

## Introduction

This capstone project utilizes the Foursquare data to study the market for restaurants and service oriented small businesses in the Downtown Toronto area. For the analyses of this study, K-means clustering is used classify the neighborhoods and venues into clusters. The study explores the neighborhoods that currently have a higher concentration of restaurant businesses, and areas where there are opportunities for opening service oriented businesses.

## Problem Description and Background

An important aspect of determining the potential for new businesses in an area before investing into the place is to do market research. Market research helps businesses determine the potential strengths, opportunities, potential competition, and the likelihood of success when opening a new business when entering a new market. Until now most market research was conducted through data collected from questionaires and surveys. These data were then analyzed. However the emergence of data science and information technology, and the ability to access platforms such as foursquare that make such data available for research has helped in evolving this process of exploring a new market or area, a more scientific endeavor.

In week 3 we learned in this class, how to use and access Foursquare data. As part of the week 3 assignment, we also segmented and clustered Toronto neighborhoods. So, it was determined that applying the foursquare data to compare the potential strengths, opportunities, and competition for opening new restaurants or small service oriented businesses in Toronto will be an interesing study. Therefore, I decided to pursue my analysis to examine the potential for opening restaurants and service oriented businesses by comparing different Toronto neighborhoods.

## Data Description

### The data for this study was obtained from two different sources:

- Postal codes and neighborhood information for Toronto was obtained from the following wikipedia page (https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M (https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M)). The data for Toronto was then scraped and cleaned as described below and a data frame include postal code, neighborhood and borough information was then constructed.
- Information on services and amenities in different locations were obtained from the Foursquare. As suggested in week 3, a free developer account was first setup with foursquare.com. Client Id, client secret information were obtained. Then using a version number the data for downtown Toronto was then extracted and merged with the table created above. These processes are explained below.

**First the tools needed for these analysis were imported and installed as shown below:**

In [3]:
```
import numpy as np # library to handle data as arrays and vectors

import pandas as pd # Tools for handling data structures
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files

!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # Conversion of an address to latitudes and l
ongitudes

import requests # library to handle requests
from pandas.io.json import json_normalize # transforming JSON to a pandas dataframe


# Importing Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.cluster import KMeans

!conda install -c conda-forge folium=0.5.0 --yes
import folium # map rendering library

print('Libraries imported.')
```

```
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - geopy


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    certifi-2019.11.28         |           py36_0         149 KB  conda-forge
    geographiclib-1.50         |             py_0          34 KB  conda-forge
    openssl-1.1.1d             |       h516909a_0         2.1 MB  conda-forge
    ca-certificates-2019.11.28 |       hecc5488_0         145 KB  conda-forge
    geopy-1.20.0               |             py_0          57 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         2.5 MB

The following NEW packages will be INSTALLED:

    geographiclib:   1.50-py_0         conda-forge
    geopy:           1.20.0-py_0       conda-forge

The following packages will be UPDATED:

    ca-certificates: 2019.11.27-0                 --> 2019.11.28-hecc5488_0 con
da-forge
    certifi:         2019.11.28-py36_0            --> 2019.11.28-py36_0     con
da-forge

The following packages will be DOWNGRADED:

    openssl:         1.1.1d-h7b6447c_3            --> 1.1.1d-h516909a_0     con
da-forge


Downloading and Extracting Packages
certifi-2019.11.28   | 149 KB    | ##################################### | 100%
geographiclib-1.50   | 34 KB     | ##################################### | 100%
openssl-1.1.1d       | 2.1 MB    | ##################################### | 100%
ca-certificates-2019 | 145 KB    | ##################################### | 100%
geopy-1.20.0         | 57 KB     | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - folium=0.5.0


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    branca-0.3.1               |             py_0          25 KB  conda-forge
```

In [ ]:

## Web scraping the table with postal codes from the Wikipedia page

In [4]:
```
from bs4 import BeautifulSoup # NextBeautifulSoup is imported for scraping the tabl
e off the wikipedia page
```

In [5]:
```
# getting data from internet
link='https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M'
link_page= requests.get(link).text

# using beautiful soup to parse the HTML/XML codes.
soup = BeautifulSoup(link_page,'lxml')
```

In [6]:
```
table = soup.find('table', {'class': 'wikitable sortable'}).tbody #Source info on t
he wikipedia page reveals that the table is classified as wiki sortable
```

In [7]:
```
rows = table.find_all('tr') # Page source also reveals that tr indicates tags for r
ows and th represents tags for columns

# taking out the sapces in between
columns = ['PostalCode', 'Borough', 'Neighborhood']
# [v.text.replace('\n','') for v in rows[0].find_all('th')]
print(columns)
```

```
['PostalCode', 'Borough', 'Neighborhood']
```

## Assigning columns to the data frames

In [8]:
```
df = pd.DataFrame(columns=columns)
df
```

Out[8]:

| PostalCode | Borough | Neighborhood |
|---|---|---|

## Preparing the table in csv format

In [9]:
```
from pandas import DataFrame

for i in range(1, len(rows)):
    tds = rows[i].find_all('td')

    if len(tds) == 3:
        values = [tds[0].text, tds[1].text, tds[2].text.replace('\n','')]
    else:
        values = [td.text.replace('\n','') for td in tds]

    # populating the dataframe with the data that we just extarcted from the HTML t
able
    df = df.append(pd.Series(values, index=columns), ignore_index=True)

export_csv= df.to_csv(r'C:\Users\fhce\Desktop\export_dataframe.csv', index = None,
header=True)
```

In [10]:
```
print(df)
```

| | PostalCode | Borough | \ |
|---|---|---|---|
| 0 | M1A | Not assigned | |
| 1 | M2A | Not assigned | |
| 2 | M3A | North York | |
| 3 | M4A | North York | |
| 4 | M5A | Downtown Toronto | |
| 5 | M6A | North York | |
| 6 | M6A | North York | |
| 7 | M7A | Downtown Toronto | |
| 8 | M8A | Not assigned | |
| 9 | M9A | Queen's Park | |
| 10 | M1B | Scarborough | |
| 11 | M1B | Scarborough | |
| 12 | M2B | Not assigned | |
| 13 | M3B | North York | |
| 14 | M4B | East York | |
| 15 | M4B | East York | |
| 16 | M5B | Downtown Toronto | |
| 17 | M5B | Downtown Toronto | |
| 18 | M6B | North York | |
| 19 | M7B | Not assigned | |
| 20 | M8B | Not assigned | |
| 21 | M9B | Etobicoke | |
| 22 | M9B | Etobicoke | |
| 23 | M9B | Etobicoke | |
| 24 | M9B | Etobicoke | |
| 25 | M9B | Etobicoke | |
| 26 | M1C | Scarborough | |
| 27 | M1C | Scarborough | |
| 28 | M1C | Scarborough | |
| 29 | M2C | Not assigned | |
| 30 | M3C | North York | |
| 31 | M3C | North York | |
| 32 | M4C | East York | |
| 33 | M5C | Downtown Toronto | |
| 34 | M6C | York | |
| 35 | M7C | Not assigned | |
| 36 | M8C | Not assigned | |
| 37 | M9C | Etobicoke | |
| 38 | M9C | Etobicoke | |
| 39 | M9C | Etobicoke | |
| 40 | M9C | Etobicoke | |
| 41 | M1E | Scarborough | |
| 42 | M1E | Scarborough | |
| 43 | M1E | Scarborough | |
| 44 | M2E | Not assigned | |
| 45 | M3E | Not assigned | |
| 46 | M4E | East Toronto | |
| 47 | M5E | Downtown Toronto | |
| 48 | M6E | York | |
| 49 | M7E | Not assigned | |
| 50 | M8E | Not assigned | |
| 51 | M9E | Not assigned | |
| 52 | M1G | Scarborough | |
| 53 | M2G | Not assigned | |
| 54 | M3G | Not assigned | |
| 55 | M4G | East York | |
| 56 | M5G | Downtown Toronto | |
| 57 | M6G | Downtown Toronto | |
| 58 | M7G | Not assigned | |
| 59 | M8G | Not assigned | |
| 60 | M9G | Not assigned | |
| 61 | M1H | Scarborough | |
| 62 | M2H | North York | |

## Next the not assigned cells are removed

In [11]:
```
df.head()
```

Out[11]:

| | PostalCode | Borough | Neighborhood |
|---|---|---|---|
| 0 | M1A | Not assigned | Not assigned |
| 1 | M2A | Not assigned | Not assigned |
| 2 | M3A | North York | Parkwoods |
| 3 | M4A | North York | Victoria Village |
| 4 | M5A | Downtown Toronto | Harbourfront |

In [12]:
```
data = df[df.Borough != 'Not assigned'] # Removing the not assigned rows
data.head()
```

Out[12]:

| | PostalCode | Borough | Neighborhood |
|---|---|---|---|
| 2 | M3A | North York | Parkwoods |
| 3 | M4A | North York | Victoria Village |
| 4 | M5A | Downtown Toronto | Harbourfront |
| 5 | M6A | North York | Lawrence Heights |
| 6 | M6A | North York | Lawrence Manor |

## Integrating the Neighborhoods with duplicate postal codes

In [13]:
```
data = data.groupby(['PostalCode','Borough'])['Neighborhood'].apply(lambda x: ', '.
join(x)).reset_index()
data.head()
```

Out[13]:

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

## Number of rows in the cleaned table

In [14]:
```
data.shape[0]
```

Out[14]: 103

## Obtaining the Latitudes and Longitudes

In [15]:
```
geocoder = pd.read_csv("https://cocl.us/Geospatial_data")

# Both tables should have the same column name for postal codes before the two tables are merged

geocoder.rename(columns={'Postal Code':'PostalCode'}, inplace=True)
```

In [47]:
```
geocoder.head()
```

Out[47]:

| | PostalCode | 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 |

In [16]:
```
geo = pd.merge(data, geocoder, on='PostalCode') #Merging the two tables by postal code
```

In [17]:
```
geo.head()
```

Out[17]:

| | PostalCode | Borough | Neighborhood | Latitude | Longitude |
|---|---|---|---|---|---|
| **0** | M1B | Scarborough | Rouge, Malvern | 43.806686 | -79.194353 |
| **1** | M1C | Scarborough | Highland Creek, Rouge Hill, Port Union | 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 |

In [18]:
```
geo.tail()
```

Out[18]:

| | PostalCode | Borough | Neighborhood | Latitude | Longitude |
|---|---|---|---|---|---|
| **98** | M9N | York | Weston | 43.706876 | -79.518188 |
| **99** | M9P | Etobicoke | Westmount | 43.696319 | -79.532242 |
| **100** | M9R | Etobicoke | Kingsview Village, Martin Grove Gardens, Richv... | 43.688905 | -79.554724 |
| **101** | M9V | Etobicoke | Albion Gardens, Beaumond Heights, Humbergate, ... | 43.739416 | -79.588437 |
| **102** | M9W | Etobicoke | Northwest | 43.706748 | -79.594054 |

# Getting latitudes and longitudes for Toronto

In [19]:
```
address = 'Toronto, ON'

geolocator = Nominatim(user_agent="to_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinates of Toronto are {}, {}.'.format(latitude, longitude))
```

```
The geograpical coordinates of Toronto are 43.653963, -79.387207.
```

## Next a map of the different neighborhoods of Toronto are generated

In [1]:
```
map_to = folium.Map(location=[latitude, longitude], zoom_start=10)

# add the map markers
for lat, lng, borough, neighborhood in zip(geo['Latitude'], geo['Longitude'], geo['Borough'], geo['Neighborhood']):
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html = True)
    folium.CircleMarker(
        [lat, lng],
        radius = 5,
        popup = label,
        color = 'green',
        fill = True,
        fill_color = '#3186cc',
        fill_opacity = 0.7,
        parse_html = False).add_to(map_to)

map_to
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-659288336e0b> in <module>
----> 1 map_to = folium.Map(location=[latitude, longitude], zoom_start=10)
      2
      3 # add the map markers
      4 for lat, lng, borough, neighborhood in zip(geo['Latitude'], geo['Longitude'], geo['Borough'], geo['Neighborhood']):
      5     label = '{}, {}'.format(neighborhood, borough)

NameError: name 'folium' is not defined
```

In [53]:
```
tn_data = geo[geo['Borough'] == 'Downtown Toronto'].reset_index(drop=True)
tn_data
```

Out[53]:

| | PostalCode | Borough | Neighborhood | Latitude | Longitude |
|---|---|---|---|---|---|
| 0 | M4W | Downtown Toronto | Rosedale | 43.679563 | -79.377529 |
| 1 | M4X | Downtown Toronto | Cabbagetown, St. James Town | 43.667967 | -79.367675 |
| 2 | M4Y | Downtown Toronto | Church and Wellesley | 43.665860 | -79.383160 |
| 3 | M5A | Downtown Toronto | Harbourfront | 43.654260 | -79.360636 |
| 4 | M5B | Downtown Toronto | Ryerson, Garden District | 43.657162 | -79.378937 |
| 5 | M5C | Downtown Toronto | St. James Town | 43.651494 | -79.375418 |
| 6 | M5E | Downtown Toronto | Berczy Park | 43.644771 | -79.373306 |
| 7 | M5G | Downtown Toronto | Central Bay Street | 43.657952 | -79.387383 |
| 8 | M5H | Downtown Toronto | Adelaide, King, Richmond | 43.650571 | -79.384568 |
| 9 | M5J | Downtown Toronto | Harbourfront East, Toronto Islands, Union Station | 43.640816 | -79.381752 |
| 10 | M5K | Downtown Toronto | Design Exchange, Toronto Dominion Centre | 43.647177 | -79.381576 |
| 11 | M5L | Downtown Toronto | Commerce Court, Victoria Hotel | 43.648198 | -79.379817 |
| 12 | M5S | Downtown Toronto | Harbord, University of Toronto | 43.662696 | -79.400049 |
| 13 | M5T | Downtown Toronto | Chinatown, Grange Park, Kensington Market | 43.653206 | -79.400049 |
| 14 | M5V | Downtown Toronto | CN Tower, Bathurst Quay, Island airport, Harbo... | 43.628947 | -79.394420 |
| 15 | M5W | Downtown Toronto | Stn A PO Boxes 25 The Esplanade | 43.646435 | -79.374846 |
| 16 | M5X | Downtown Toronto | First Canadian Place, Underground city | 43.648429 | -79.382280 |
| 17 | M6G | Downtown Toronto | Christie | 43.669542 | -79.422564 |
| 18 | M7A | Downtown Toronto | Queen's Park | 43.662301 | -79.389494 |

# Exploration of Toronto using Foursquare API

## The first glimpse of the venues

In [90]:
```
address = 'Downtown Toronto, ON'

geolocator = Nominatim(user_agent="dt_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Downtown Toronto are {}, {}.'.format(latitude,
longitude))
```

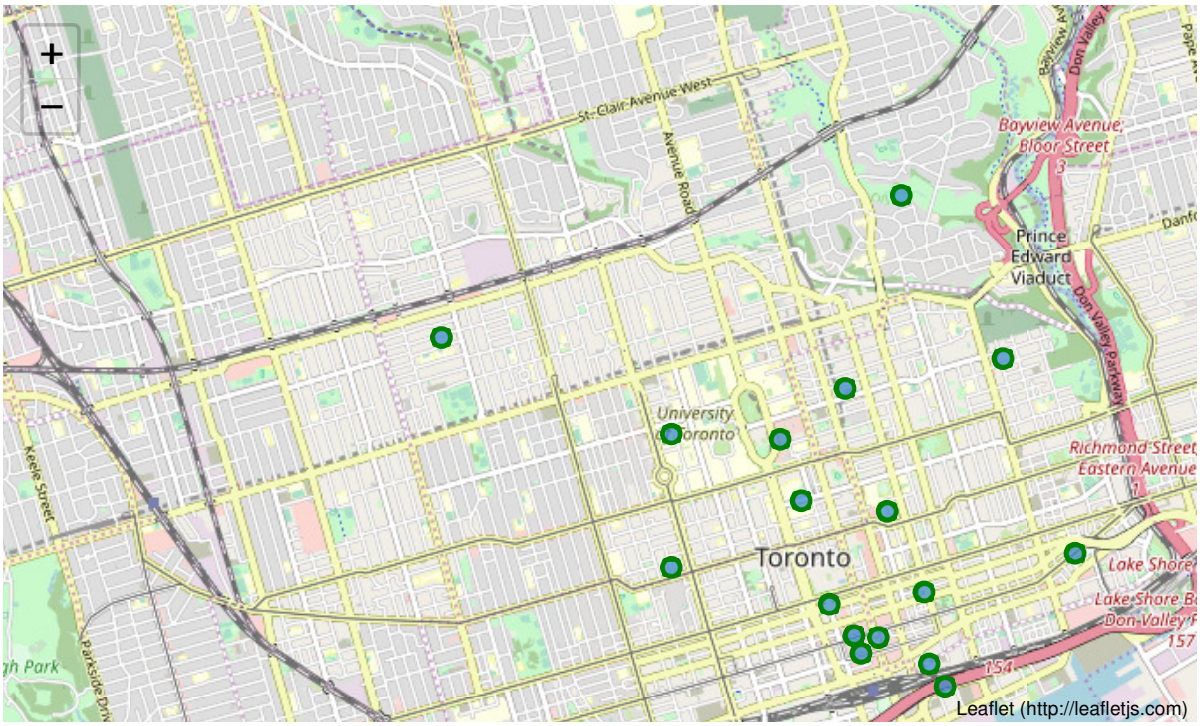
```
The geograpical coordinate of Downtown Toronto are 43.6563221, -79.3809161.
```

In [92]:
```
# create map of Downtown Toronto using latitude and longitude values
map_dt = folium.Map(location=[latitude, longitude], zoom_start=13)

# add markers to map
for lat, lng, label in zip(dt_data['Latitude'], dt_data['Longitude'], dt_data['Neighborhood']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius = 5,
        popup = label,
        color = 'green',
        fill = True,
        fill_color = '#3186cc',
        fill_opacity = 0.7,
        parse_html = False).add_to(map_dt)

map_dt
```

Out[92]:




In [93]:
```
CLIENT_ID = 'TKWB5N0HKVWA3JDXVKKZED0VKRX4AHU2UEVGZ0BHRMDET0HF' # your Foursquare ID
CLIENT_SECRET = 'VQE04FETG0HFOFVM2PYLUFLMPQZFHH314RZHEN0FFNVIEKBL' # your Foursquare Secret
VERSION = '20191231' # Foursquare API version
```

## The Chinatown, Grange Park, Kensington Market neighborhood of Toronto was next explored

In [94]:
```
dt_data.loc[13, 'Neighborhood']
```

Out[94]:
```
'Chinatown, Grange Park, Kensington Market'
```

In [95]:
```
to_geo_latitude = dt_data.loc[13, 'Latitude'] # neighborhood latitude value
to_geo_longitude = dt_data.loc[13, 'Longitude'] # neighborhood longitude value

to_geo_name = dt_data.loc[13, 'Neighborhood'] # neighborhood name

print('Latitude and longitude values of {} are {}, {}.'.format(to_geo_name,
                                                               to_geo_latitude,
                                                               to_geo_longitude))
```

```
Latitude and longitude values of Chinatown, Grange Park, Kensington Market are 4
3.6532057, -79.4000493.
```

In [116]:
```
LIMIT = 100 # limit of number of venues returned by Foursquare API
radius = 500 # define radius

url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}
&v={}&ll={},{}&radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    to_geo_latitude,
    to_geo_longitude,
    radius,
    LIMIT)
url
```

Out[116]:
```
'https://api.foursquare.com/v2/venues/explore?&client_id=TKWB5N0HKVWA3JDXVKKZED0
VKRX4AHU2UEVGZ0BHRMDET0HF&client_secret=VQE04FETG0HFOFVM2PYLUFLMPQZFHH314RZHEN0F
FNVIEKBL&v=20191231&ll=43.6532057,-79.4000493&radius=500&limit=100'
```

In [117]:
```
results = requests.get(url).json()
```

In [118]:
```
# function that extracts the category of the venue
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
```

venues = results['response']['groups'][0]['items']

nearby_venues = json_normalize(venues) # flatten JSON

# filter columns

filtered_columns = ['venue.name', 'venue.categories', 'venue.location.lat', 'venue.location.lng'] nearby_venues =nearby_venues.loc[:, filtered_columns]

# filter the category for each row

nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type, axis=1)

# clean columns

nearby_venues.columns = [col.split(".")[-1] for col in nearby_venues.columns]

nearby_venues.head()

In [120]:
```
print('{} venues were returned by Foursquare.'.format(nearby_venues.shape[0]))
```

```
92 venues were returned by Foursquare.
```

## Other neighborhoods in the downtown Toronto are were next explored:

In [121]:
```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_s
ecret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in v
enue_list])
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

In [122]:
```
dt_venues = getNearbyVenues(names = dt_data['Neighborhood'],
                            latitudes = dt_data['Latitude'],
                            longitudes = dt_data['Longitude']
                           )
```

```
Rosedale
Cabbagetown, St. James Town
Church and Wellesley
Harbourfront
Ryerson, Garden District
St. James Town
Berczy Park
Central Bay Street
Adelaide, King, Richmond
Harbourfront East, Toronto Islands, Union Station
Design Exchange, Toronto Dominion Centre
Commerce Court, Victoria Hotel
Harbord, University of Toronto
Chinatown, Grange Park, Kensington Market
CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadina, Ra
ilway Lands, South Niagara
Stn A PO Boxes 25 The Esplanade
First Canadian Place, Underground city
Christie
Queen's Park
```

## Data Exploration of number of venues in the Downtown Toronto area:

In [123]:
```
print(dt_venues.shape)
dt_venues.head()
```

```
(1314, 7)
```

Out[123]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| 0 | Rosedale | 43.679563 | -79.377529 | Rosedale Park | 43.682328 | -79.378934 | Playground |
| 1 | Rosedale | 43.679563 | -79.377529 | Whitney Park | 43.682036 | -79.373788 | Park |
| 2 | Rosedale | 43.679563 | -79.377529 | Alex Murray Parkette | 43.678300 | -79.382773 | Park |
| 3 | Rosedale | 43.679563 | -79.377529 | Milkman's Lane | 43.676352 | -79.373842 | Trail |
| 4 | Cabbagetown, St. James Town | 43.667967 | -79.367675 | Cranberries | 43.667843 | -79.369407 | Diner |

### Number of venues in each area

In [124]:
```
dt_venues.groupby('Neighborhood').count()
```

Out[124]:

| Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|
| Adelaide, King, Richmond | 100 | 100 | 100 | 100 | 100 | 100 |
| Berczy Park | 57 | 57 | 57 | 57 | 57 | 57 |
| CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadina, Railway Lands, South Niagara | 12 | 12 | 12 | 12 | 12 | 12 |
| Cabbagetown, St. James Town | 43 | 43 | 43 | 43 | 43 | 43 |
| Central Bay Street | 82 | 82 | 82 | 82 | 82 | 82 |
| Chinatown, Grange Park, Kensington Market | 92 | 92 | 92 | 92 | 92 | 92 |
| Christie | 17 | 17 | 17 | 17 | 17 | 17 |
| Church and Wellesley | 85 | 85 | 85 | 85 | 85 | 85 |
| Commerce Court, Victoria Hotel | 100 | 100 | 100 | 100 | 100 | 100 |
| Design Exchange, Toronto Dominion Centre | 100 | 100 | 100 | 100 | 100 | 100 |
| First Canadian Place, Underground city | 100 | 100 | 100 | 100 | 100 | 100 |
| Harbord, University of Toronto | 36 | 36 | 36 | 36 | 36 | 36 |
| Harbourfront | 48 | 48 | 48 | 48 | 48 | 48 |
| Harbourfront East, Toronto Islands, Union Station | 100 | 100 | 100 | 100 | 100 | 100 |
| Queen's Park | 41 | 41 | 41 | 41 | 41 | 41 |
| Rosedale | 4 | 4 | 4 | 4 | 4 | 4 |
| Ryerson, Garden District | 100 | 100 | 100 | 100 | 100 | 100 |
| St. James Town | 100 | 100 | 100 | 100 | 100 | 100 |
| Stn A PO Boxes 25 The Esplanade | 97 | 97 | 97 | 97 | 97 | 97 |

In [125]:
```
print('There are {} uniques categories.'.format(len(dt_venues['Venue Category'].unique())))
```

```
There are 211 uniques categories.
```

## Next 'one hot encoding' is applied to obtain the different venue categories:

In [126]:
```
# one hot encoding
dt_onehot = pd.get_dummies(dt_venues[['Venue Category']], prefix="", prefix_se
p="")

# add neighborhood column back to dataframe
dt_onehot['Neighborhoods'] = dt_venues['Neighborhood']
# using 'Neighborhoods' instead of 'Neighborhood' to avoid confusions with the ori
ginal neighborhood column in the dataframe

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

dt_onehot.head()
```

Out[126]:

| | Neighborhoods | Airport | Airport Food Court | Airport Lounge | Airport Service | Airport Terminal | American Restaurant | Antique Shop | Aquarium | Art Gallery | Arts & Crafts Store |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Rosedale | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | Rosedale | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | Rosedale | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | Rosedale | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **4** | Cabbagetown, St. James Town | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

In [127]:
```
dt_onehot.shape
```

Out[127]: (1314, 212)

The data is explored further to examine the frequencies within each category when grouped by neighborhoods:

In [128]:
```
dt_grouped = dt_onehot.groupby('Neighborhoods').mean().reset_index()
dt_grouped
```

Out[128]:

| | Neighborhoods | Airport | Airport Food Court | Airport Lounge | Airport Service | Airport Terminal | American Restaurant | Antique Shop | Aquarium | A Galle |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Adelaide, King, Richmond | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.020000 | 0.000000 | 0.00 | 0.0100( |
| 1 | Berczy Park | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0175 |
| 2 | CN Tower, Bathurst Quay, Island airport, Harbo... | 0.083333 | 0.083333 | 0.166667 | 0.166667 | 0.083333 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 3 | Cabbagetown, St. James Town | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 4 | Central Bay Street | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.012195 | 0.000000 | 0.00 | 0.0000( |
| 5 | Chinatown, Grange Park, Kensington Market | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 6 | Christie | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 7 | Church and Wellesley | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.011765 | 0.000000 | 0.00 | 0.0000( |
| 8 | Commerce Court, Victoria Hotel | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.030000 | 0.000000 | 0.00 | 0.0100( |
| 9 | Design Exchange, Toronto Dominion Centre | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.030000 | 0.000000 | 0.00 | 0.0100( |
| 10 | First Canadian Place, Underground city | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.020000 | 0.000000 | 0.00 | 0.0100( |
| 11 | Harbord, University of Toronto | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 12 | Harbourfront | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.020833 | 0.00 | 0.0208 |
| 13 | Harbourfront East, Toronto Islands, Union Station | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.05 | 0.0100( |
| 14 | Queen's Park | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 15 | Rosedale | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.00 | 0.0000( |
| 16 | Ryerson, Garden District | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010000 | 0.000000 | 0.00 | 0.0100( |
| 17 | St. James Town | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010000 | 0.000000 | 0.00 | 0.0100( |
| 18 | Stn A PO Boxes 25 The Esplanade | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.010309 | 0.010309 | 0.00 | 0.0206 |

In [129]:
```
dt_grouped.shape
```

Out[129]: (19, 212)

### The 5 most common venues for each neighborhood are identified

In [130]:
```
num_top_venues = 5

for hood in dt_grouped['Neighborhoods']:
    print("----"+hood+"----")
    temp = dt_grouped[dt_grouped['Neighborhoods'] == hood].T.reset_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).reset_index(drop=True).head(nu
m_top_venues))
    print('\n')
```

```
----Adelaide, King, Richmond----
              venue  freq
0       Coffee Shop  0.08
1              Café  0.05
2               Bar  0.04
3        Steakhouse  0.04
4  Sushi Restaurant  0.03


----Berczy Park----
            venue  freq
0     Coffee Shop  0.09
1    Cocktail Bar  0.05
2          Bakery  0.04
3  Farmers Market  0.04
4        Beer Bar  0.04


----CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadin
a, Railway Lands, South Niagara----
              venue  freq
0    Airport Lounge  0.17
1   Airport Service  0.17
2           Airport  0.08
3     Boat or Ferry  0.08
4  Sculpture Garden  0.08


----Cabbagetown, St. James Town----
                venue  freq
0               Café  0.07
1         Coffee Shop  0.07
2  Italian Restaurant  0.05
3             Bakery  0.05
4                Pub  0.05


----Central Bay Street----
                venue  freq
0         Coffee Shop  0.17
1                Café  0.05
2  Italian Restaurant  0.05
3        Burger Joint  0.04
4      Sandwich Place  0.04


----Chinatown, Grange Park, Kensington Market----
                           venue  freq
0                           Café  0.07
1          Vietnamese Restaurant  0.05
2  Vegetarian / Vegan Restaurant  0.05
3             Chinese Restaurant  0.04
4                    Coffee Shop  0.04


----Christie----
                venue  freq
0               Café  0.18
1       Grocery Store  0.18
2               Park  0.12
3   Convenience Store  0.06
4  Athletics & Sports  0.06
```

## A data frame is constructed to include the above information

The venues are sorted in descending order:

In [131]:
```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

    return row_categories_sorted.index.values[0:num_top_venues]
```

## Similarly a top 10 list of common venues for each are is then constructed:

In [132]:
```
num_top_venues = 10

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Neighborhoods']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhoods'] = dt_grouped['Neighborhoods']

for ind in np.arange(dt_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(dt_group
ed.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[132]:

| | Neighborhoods | 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 | |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Adelaide, King, Richmond | Coffee Shop | Café | Steakhouse | Bar | Restaurant | Burger Joint | Sushi Restaurant | Asian Restaurant | F |
| 1 | Berczy Park | Coffee Shop | Cocktail Bar | Farmers Market | Seafood Restaurant | Steakhouse | Bakery | Beer Bar | Cheese Shop | |
| 2 | CN Tower, Bathurst Quay, Island airport, Harbo... | Airport Lounge | Airport Service | Harbor / Marina | Sculpture Garden | Airport Food Court | Airport Terminal | Boat or Ferry | Boutique | F |
| 3 | Cabbagetown, St. James Town | Café | Coffee Shop | Pizza Place | Restaurant | Pub | Bakery | Italian Restaurant | Liquor Store | |
| 4 | Central Bay Street | Coffee Shop | Café | Italian Restaurant | Burger Joint | Sandwich Place | Ice Cream Shop | Chinese Restaurant | Japanese Restaurant | |

## K-Mean Clustering is then run to sort the neighborhoods into 5 clusters

In [133]:
```
# set number of clusters
kclusters = 5

dt_grouped_clustering = dt_grouped.drop('Neighborhoods', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(dt_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

Out[133]:
```
array([0, 0, 2, 0, 3, 0, 4, 0, 0, 0], dtype=int32)
```

A new dataframe is then constructed comprising of the clusters and the top 10 venues for each neighborhood:

In [134]:
```
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

dt_merged = dt_data

# merge toronto_grouped with toronto_data to add latitude/longitude for each neigh
borhood
dt_merged = dt_merged.join(neighborhoods_venues_sorted.set_index('Neighborhoods'),
on='Neighborhood')

#neighborhoods_venues_sorted = neighborhoods_venues_sorted.drop(columns = ['Cluste
r Labels'])

#neighborhoods_venues_sorted.head()

dt_merged.head()
```

Out[134]:

| | PostalCode | Borough | Neighborhood | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4t Co |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | M4W | Downtown Toronto | Rosedale | 43.679563 | -79.377529 | 1 | Park | Playground | Trail | I |
| **1** | M4X | Downtown Toronto | Cabbagetown, St. James Town | 43.667967 | -79.367675 | 0 | Café | Coffee Shop | Pizza Place | Res |
| **2** | M4Y | Downtown Toronto | Church and Wellesley | 43.665860 | -79.383160 | 0 | Coffee Shop | Japanese Restaurant | Sushi Restaurant | C |
| **3** | M5A | Downtown Toronto | Harbourfront | 43.654260 | -79.360636 | 3 | Coffee Shop | Park | Bakery | |
| **4** | M5B | Downtown Toronto | Ryerson, Garden District | 43.657162 | -79.378937 | 0 | Coffee Shop | Clothing Store | Café | Cos |

## Visualization of the Clustered Analysis

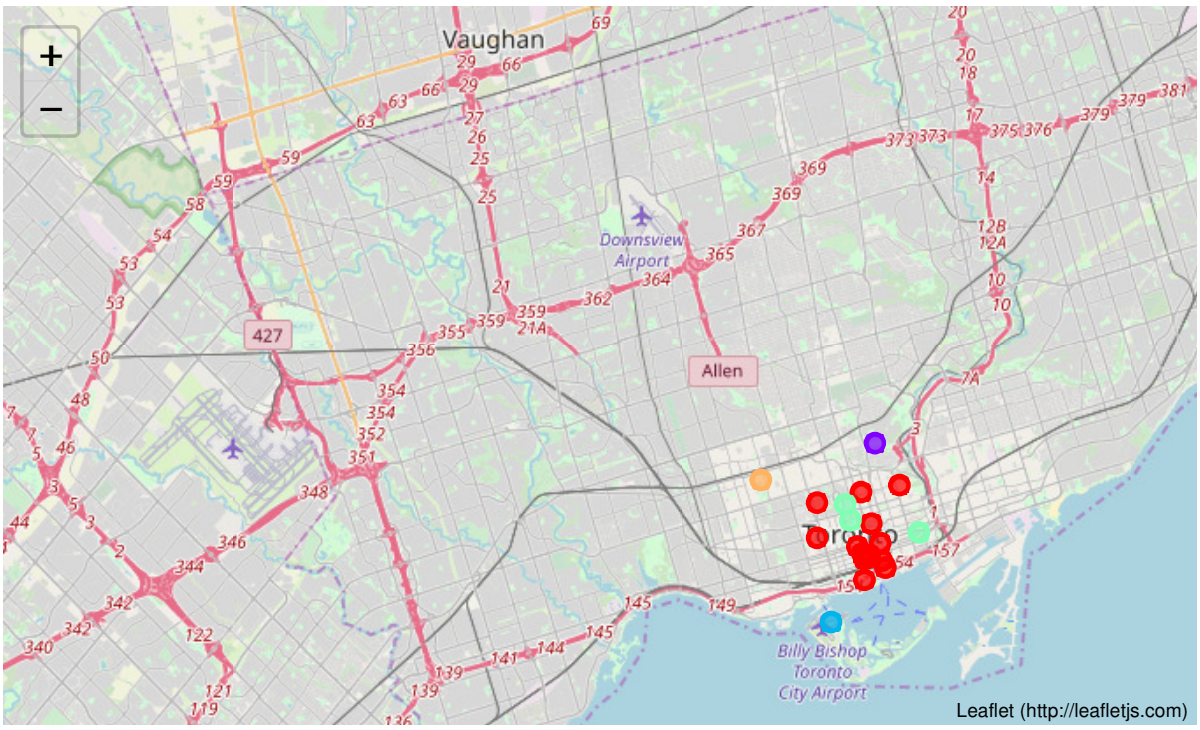
In [138]:
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
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]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(dt_merged['Latitude'], dt_merged['Longitude'], d
t_merged['Neighborhood'], dt_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[138]:




## Exploration of Cluster 1

In [139]:
```
dt_merged.loc[dt_merged['Cluster Labels'] == 0, dt_merged.columns[[2] + list(range
(5, dt_merged.shape[1]))]]
```

Out[139]:

| | Neighborhood | Cluster Labels | 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 |
|---|---|---|---|---|---|---|---|---|---|
| **1** | Cabbagetown, St. James Town | 0 | Café | Coffee Shop | Pizza Place | Restaurant | Pub | Bakery | Italian Restaurant |
| **2** | Church and Wellesley | 0 | Coffee Shop | Japanese Restaurant | Sushi Restaurant | Gay Bar | Restaurant | Burger Joint | Gym |
| **4** | Ryerson, Garden District | 0 | Coffee Shop | Clothing Store | Café | Cosmetics Shop | Bakery | Middle Eastern Restaurant | Theater |
| **5** | St. James Town | 0 | Café | Coffee Shop | Restaurant | Hotel | Clothing Store | Cosmetics Shop | Beer Bar |
| **6** | Berczy Park | 0 | Coffee Shop | Cocktail Bar | Farmers Market | Seafood Restaurant | Steakhouse | Bakery | Beer Bar |
| **8** | Adelaide, King, Richmond | 0 | Coffee Shop | Café | Steakhouse | Bar | Restaurant | Burger Joint | Sushi Restaurant |
| **9** | Harbourfront East, Toronto Islands, Union Station | 0 | Coffee Shop | Aquarium | Italian Restaurant | Hotel | Café | Scenic Lookout | Restaurant |
| **10** | Design Exchange, Toronto Dominion Centre | 0 | Coffee Shop | Hotel | Café | Restaurant | Bar | American Restaurant | Seafood Restaurant |
| **11** | Commerce Court, Victoria Hotel | 0 | Coffee Shop | Café | Restaurant | Hotel | American Restaurant | Seafood Restaurant | Gym |
| **12** | Harbord, University of Toronto | 0 | Café | Restaurant | Bakery | Sandwich Place | Bookstore | Japanese Restaurant | Italian Restaurant |
| **13** | Chinatown, Grange Park, Kensington Market | 0 | Café | Vietnamese Restaurant | Vegetarian / Vegan Restaurant | Bar | Dumpling Restaurant | Coffee Shop | Chinese Restaurant |
| **15** | Stn A PO Boxes 25 The Esplanade | 0 | Coffee Shop | Café | Restaurant | Japanese Restaurant | Cocktail Bar | Hotel | Seafood Restaurant |
| **16** | First Canadian Place, Underground city | 0 | Coffee Shop | Café | Gym | Hotel | Restaurant | Steakhouse | Asian Restaurant |

***Cluster 1 appears to have a lot of coffee shops and restaurants***

# Exploration of Cluster 2:

In [140]:
```
dt_merged.loc[dt_merged['Cluster Labels'] == 1, dt_merged.columns[[2] + list(range
(5, dt_merged.shape[1]))]]
```

Out[140]:

| | Neighborhood | Cluster Labels | 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 M Comr Ve |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Rosedale | 1 | Park | Playground | Trail | Dessert Shop | Ethiopian Restaurant | Empanada Restaurant | Electronics Store | Eas Europ Restau |

## Exploration of Cluster 3

In [141]:
```
dt_merged.loc[dt_merged['Cluster Labels'] == 2, dt_merged.columns[[2] + list(range
(5, dt_merged.shape[1]))]]
```

Out[141]:

| | Neighborhood | Cluster Labels | 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 |
|---|---|---|---|---|---|---|---|---|---|---|
| **14** | CN Tower, Bathurst Quay, Island airport, Harbo... | 2 | Airport Lounge | Airport Service | Harbor / Marina | Sculpture Garden | Airport Food Court | Airport Terminal | Boat or Ferry | Boutique |

## Exploration of Cluster 4

In [142]:
```
dt_merged.loc[dt_merged['Cluster Labels'] == 3, dt_merged.columns[[2] + list(range
(5, dt_merged.shape[1]))]]
```

Out[142]:

| | Neighborhood | Cluster Labels | 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 M Com Ve |
|---|---|---|---|---|---|---|---|---|---|---|
| **3** | Harbourfront | 3 | Coffee Shop | Park | Bakery | Pub | Café | Mexican Restaurant | Breakfast Spot | Restau |
| **7** | Central Bay Street | 3 | Coffee Shop | Café | Italian Restaurant | Burger Joint | Sandwich Place | Ice Cream Shop | Chinese Restaurant | Japa Restau |
| **18** | Queen's Park | 3 | Coffee Shop | Gym | Park | College Auditorium | Smoothie Shop | Sandwich Place | Burger Joint | Bu F |

***Cluster 4 also has a number of restaurants and coffee shops***

## Exploration of Cluster 5

In [143]:
```
dt_merged.loc[dt_merged['Cluster Labels'] == 4, dt_merged.columns[[2] + list(range
(5, dt_merged.shape[1]))]]
```

Out[143]:

| | Neighborhood | Cluster Labels | 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 |
|---|---|---|---|---|---|---|---|---|---|---|
| **17** | Christie | 4 | Grocery Store | Café | Park | Candy Store | Diner | Italian Restaurant | Baby Store | Athletics & Sports |

***Cluster 5 appears to be more of a residential area with service businesses***

# Results

The results of this study are shown above. The results indicate that when we use the K-means clustering for the Toronto downtown area, if arranges the venues across 5 different clusters. Cluster 1 has a heavier concentration of restaurants and coffee shops. Clusters 2 and 5 appear more residential with a higher concentration of grocery stores, parks, playgrounds candy stores, baby stores etc. Cluster 3 is the area around the airport. Finally, cluster 4 also has a high concentration of restaurants, coffee shops and other food places. Cluster 4 appears to be an area that caters to students and young adults.

# Discussion and Conclusion

The results from this study indicate that while Clusters 1 and 4 present the biggest market for opening restaurants, there is also a lot of competitions given the heavy concentration food businesses in these areas. Perhaps opening a restaurant in the Cluster 2 or Cluster 5 will have higher risk but also the potential for greater opportunities. Cluster 3, which is the airport area is also another possibility, since Toronto has a large international airport and many tourists and travelers pass by this area everyday.

For small service oriented businesses such as laundry, day care, plumbing, electrical, financial services etc. the residential clusters 2 and 5 have the most opportunity. Additionally, Cluster 3 that has educational institutions nearby, also provides the opportunity for opening of some of these businesses as well.

Overall, the capstone case was beneficial exercise, which helped me pull all of the learning from the previous courses and integrating the tools in analyzing this case study. I felt like I learned a lot about geospatial analysis, and obtaining Restful API from a service like Foursquare.

In [ ]: