Week 3 - Evaluating Toronto Neighborhoods

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Initial download of Toronto data from Wikipedia

Use Pandas to scrape the web page and create a panda dataframe

In [2]:
```
# import required libraries
import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import numpy as np
```

In [3]:
```
# Use Pandas to scrape HTML table from Wikipedia; create a dataframe from results
data = pd.read_html('http://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:
df = data[0]
print(df.shape)
df.head()
```

```
(180, 3)
```

Out[3]:

	Postal Code	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	Regent Park, Harbourfront

In [4]:
```
# Remove rows where the Borough has not been assigned
df=df[df['Borough']!='Not assigned']
df.shape
```

Out[4]:
```
(103, 3)
```

For next portion, collect the latitude and longitude of each Postal Code

Combine this data with the data from the initial data frame to form one dataframe with all information

In [5]:
```
# Need to find latitude and longitude of each neighborhood
# Per the instructions, the geocoder package is unreliable.  I was unable to make
# Using the provided CSV file to create a dataframe of postal codes with latitude
geodata = pd.read_csv(r'C:\Users\garyn\OneDrive\Documents\Coursera_Labs\Week_3_la
geodata.head()
```

Out[5]:

	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

In [6]:
```
# Using merge to combine original dataframe with latitude and longitude dataframe
df = pd.merge(df, geodata, on='Postal Code', how='outer')
df.head()
```

Out[6]:

	Postal Code	Borough	Neighborhood	Latitude	Longitude
0	M3A	North York	Parkwoods	43.753259	-79.329656
1	M4A	North York	Victoria Village	43.725882	-79.315572
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494

Download the appropriate libraries to use the Foursquare API to explore

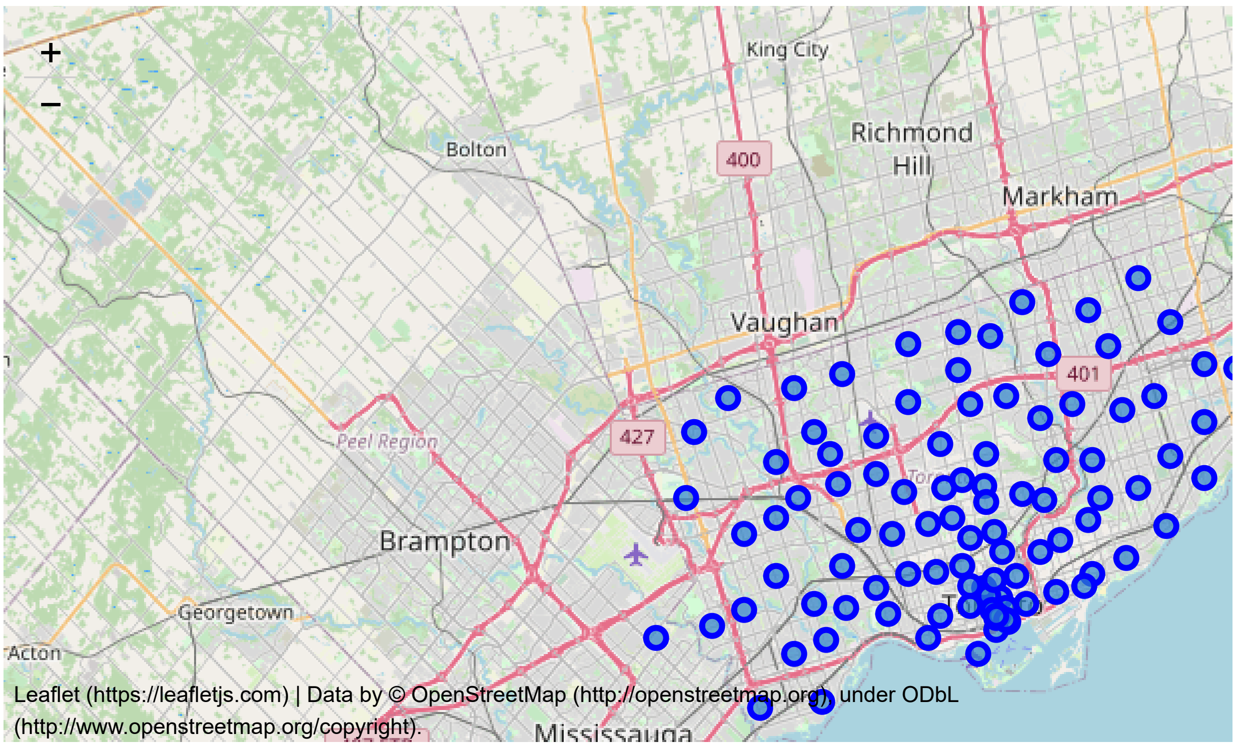
Use Venues similar to the New York lab earlier in the course

In [26]:
```
import json # library to handle JSON files

#!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # convert an address into latitude and long

import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas data

# 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.')
```

```
Libraries imported.
```

In [8]:
```
# create map of Toronto using latitude and longitude values
map_toronto = folium.Map(location=[43.657952, -79.387383], zoom_start=10)

# add markers to map
for lat, lng, borough, neighborhood in zip(df['Latitude'], df['Longitude'], df['E
    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)

map_toronto
```

Out[8]:



In [9]:
```
# Setup the Foursquare API information

CLIENT_ID = 'BRBDGCKR00L1JCYN5RD3ZDJ2BNOJ5YOVAN3F2KZNVVUVB3VW' # your Foursquare
CLIENT_SECRET = '5N1FQNDEEVF0LSK4A1SFM41P4KFSGECE1T23QNK20K1SD4PR' # your Foursqu
VERSION = '20180605' # Foursquare API version

print('Your credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: BRBDGCKR00L1JCYN5RD3ZDJ2BNOJ5YOVAN3F2KZNVVUVB3VW
CLIENT_SECRET:5N1FQNDEEVF0LSK4A1SFM41P4KFSGECE1T23QNK20K1SD4PR
```

In [10]:
```
LIMIT = 100 # limit of number of venues returned by Foursquare API
radius = 500 # define radius
```

In [11]:
```
# Create function to collect venue information from all neighborhoods in Toronto
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_
            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
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

In [12]:
```
# Collect the information from Foursquare for Toronta neighborhoods
toronto_venues = getNearbyVenues(df['Neighborhood'],
                                   df['Latitude'],
                                   df['Longitude']
                                  )
```

```
Parkwoods
Victoria Village
Regent Park, Harbourfront
Lawrence Manor, Lawrence Heights
Queen's Park, Ontario Provincial Government
Islington Avenue, Humber Valley Village
Malvern, Rouge
Don Mills
Parkview Hill, Woodbine Gardens
Garden District, Ryerson
Glencairn
West Deane Park, Princess Gardens, Martin Grove, Islington, Cloverdale
Rouge Hill, Port Union, Highland Creek
Don Mills
Woodbine Heights
St. James Town
Humewood-Cedarvale
Eringate, Bloordale Gardens, Old Burnhamthorpe, Markland Wood
Guildwood, Morningside, West Hill
The Beaches
Berczy Park
Caledonia-Fairbanks
Woburn
Leaside
Central Bay Street
Christie
Cedarbrae
Hillcrest Village
Bathurst Manor, Wilson Heights, Downsview North
Thorncliffe Park
Richmond, Adelaide, King
Dufferin, Dovercourt Village
Scarborough Village
Fairview, Henry Farm, Oriole
Northwood Park, York University
East Toronto, Broadview North (Old East York)
Harbourfront East, Union Station, Toronto Islands
Little Portugal, Trinity
Kennedy Park, Ionview, East Birchmount Park
Bayview Village
Downsview
The Danforth West, Riverdale
Toronto Dominion Centre, Design Exchange
Brockton, Parkdale Village, Exhibition Place
Golden Mile, Clairlea, Oakridge
York Mills, Silver Hills
Downsview
India Bazaar, The Beaches West
Commerce Court, Victoria Hotel
North Park, Maple Leaf Park, Upwood Park
Humber Summit
```

```
Cliffside, Cliffcrest, Scarborough Village West
Willowdale, Newtonbrook
Downsview
Studio District
Bedford Park, Lawrence Manor East
Del Ray, Mount Dennis, Keelsdale and Silverthorn
Humberlea, Emery
Birch Cliff, Cliffside West
Willowdale, Willowdale East
Downsview
Lawrence Park
Roselawn
Runnymede, The Junction North
Weston
Dorset Park, Wexford Heights, Scarborough Town Centre
York Mills West
Davisville North
Forest Hill North & West, Forest Hill Road Park
High Park, The Junction South
Westmount
Wexford, Maryvale
Willowdale, Willowdale West
North Toronto West, Lawrence Park
The Annex, North Midtown, Yorkville
Parkdale, Roncesvalles
Canada Post Gateway Processing Centre
Kingsview Village, St. Phillips, Martin Grove Gardens, Richview Gardens
Agincourt
Davisville
University of Toronto, Harbord
Runnymede, Swansea
Clarks Corners, Tam O'Shanter, Sullivan
Moore Park, Summerhill East
Kensington Market, Chinatown, Grange Park
Milliken, Agincourt North, Steeles East, L'Amoreaux East
Summerhill West, Rathnelly, South Hill, Forest Hill SE, Deer Park
CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Quay, So
uth Niagara, Island airport
New Toronto, Mimico South, Humber Bay Shores
South Steeles, Silverstone, Humbergate, Jamestown, Mount Olive, Beaumond Height
s, Thistletown, Albion Gardens
Steeles West, L'Amoreaux West
Rosedale
Stn A PO Boxes
Alderwood, Long Branch
Northwest, West Humber - Clairville
Upper Rouge
St. James Town, Cabbagetown
First Canadian Place, Underground city
The Kingsway, Montgomery Road, Old Mill North
Church and Wellesley
Business reply mail Processing Centre, South Central Letter Processing Plant To
ronto
Old Mill South, King's Mill Park, Sunnylea, Humber Bay, Mimico NE, The Queenswa
y East, Royal York South East, Kingsway Park South East
Mimico NW, The Queensway West, South of Bloor, Kingsway Park South West, Royal
York South West
```

Explore the venue information that downloaded from Foursquare

In [13]:
```
# Get shape and head() of dataframe
print(toronto_venues.shape)
toronto_venues.head()
```

```
(2129, 7)
```

Out[13]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Parkwoods	43.753259	-79.329656	Brookbanks Park	43.751976	-79.332140	Park
1	Parkwoods	43.753259	-79.329656	Variety Store	43.751974	-79.333114	Food & Drink Shop
2	Victoria Village	43.725882	-79.315572	Victoria Village Arena	43.723481	-79.315635	Hockey Arena
3	Victoria Village	43.725882	-79.315572	Portugril	43.725819	-79.312785	Portuguese Restaurant
4	Victoria Village	43.725882	-79.315572	Tim Hortons	43.725517	-79.313103	Coffee Shop

In [14]:
```
# Number of venues returned for each neighborhood
toronto_venues.groupby('Neighborhood').count()
```

Out[14]:

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Neighborhood						
Agincourt	5	5	5	5	5	5
Alderwood, Long Branch	8	8	8	8	8	8
Bathurst Manor, Wilson Heights, Downsview North	20	20	20	20	20	20
Bayview Village	4	4	4	4	4	4
Bedford Park, Lawrence Manor East	24	24	24	24	24	24
Berczy Park	58	58	58	58	58	58
Birch Cliff, Cliffside West	4	4	4	4	4	4
Brockton, Parkdale Village, Exhibition Place	22	22	22	22	22	22

Summarize unique categories from returned venues

In [15]:
```
print('There are {} uniques categories.'.format(len(toronto_venues['Venue Categor
```

```
There are 268 uniques categories.
```

Analyze Each Neighborhood in Toronto

In [16]:
```
# one hot encoding
toronto_onehot = pd.get_dummies(toronto_venues[['Venue Category']], prefix="", pr

# add neighborhood column back to dataframe
toronto_onehot['Neighborhood'] = toronto_venues['Neighborhood']

# move neighborhood column 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()
```

```
(2129, 268)
```

Out[16]:

	Yoga Studio	Accessories Store	Afghan Restaurant	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antiqu Sho
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

Similar to the New Yort lab, group rows by neighborhood by taking the mean

of the frequency of occurrence of each category

In [17]:
```
toronto_grouped = toronto_onehot.groupby('Neighborhood').mean().reset_index()
print(toronto_grouped.shape)
toronto_grouped.head()
```

```
(93, 268)
```

Out[17]:

	Neighborhood	Yoga Studio	Accessories Store	Afghan Restaurant	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	A Re
0	Agincourt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
1	Alderwood, Long Branch	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
2	Bathurst Manor, Wilson Heights, Downsview North	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
3	Bayview Village	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
4	Bedford Park, Lawrence Manor East	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(

Print each neighborhood with top 5 most common venues

Then, add that to a pandas dataframe

In [18]:

```
num_top_venues = 5

for hood in toronto_grouped['Neighborhood']:
    print("----"+hood+"----")
    temp = toronto_grouped[toronto_grouped['Neighborhood'] == 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(r
    print('\n')
```

```
----Agincourt----
                      venue  freq
0             Clothing Store   0.2
1             Breakfast Spot   0.2
2                     Lounge   0.2
3  Latin American Restaurant   0.2
4               Skating Rink   0.2


----Alderwood, Long Branch----
            venue  freq
0     Pizza Place  0.25
1  Sandwich Place  0.12
2             Gym  0.12
3            Pool  0.12
4    Dance Studio  0.12


----Bathurst Manor, Wilson Heights, Downsview North----
```

In [19]:

```
# Insert the most common venues data into a pandas dataframe
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]
```

In [20]:
```
# The following code creates a new dataframe that will display the top 10 venues
num_top_venues = 10

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

# create columns according to number of top venues
columns = ['Neighborhood']
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['Neighborhood'] = toronto_grouped['Neighborhood']

for ind in np.arange(toronto_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(toronto

neighborhoods_venues_sorted.head()
```

Out[20]:

	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	(
0	Agincourt	Lounge	Latin American Restaurant	Breakfast Spot	Skating Rink	Clothing Store	Drugstore	Discount Store	Di
1	Alderwood, Long Branch	Pizza Place	Dance Studio	Pub	Gym	Coffee Shop	Sandwich Place	Pool	
2	Bathurst Manor, Wilson Heights, Downsview North	Coffee Shop	Bank	Frozen Yogurt Shop	Shopping Mall	Bridal Shop	Sandwich Place	Diner	R
3	Bayview Village	Café	Bank	Chinese Restaurant	Japanese Restaurant	Women's Store	Discount Store	Distribution Center	
4	Bedford Park, Lawrence Manor East	Coffee Shop	Restaurant	Sandwich Place	Italian Restaurant	Thai Restaurant	Pharmacy	Pizza Place	

Now to cluster the neighborhoods into 5 clusters

Picking the number 5 semi-randomly ("semi-randomly" as it was used in the New York lab)

In [21]:
```
# set number of clusters
kclusters = 5

toronto_grouped_clustering = toronto_grouped.drop('Neighborhood', 1)

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

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

Out[21]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [28]:
```
# add clustering labels for new dataframe to include the cluster and its top 10 v
neighborhoods_venues_sorted.insert(0, df[list("ABCD")] = df[list("ABCD")].fillna(

toronto_merged = df

# merge toronto_grouped with toronto_data to add latitude/longitude for each neig
toronto_merged = toronto_merged.join(neighborhoods_venues_sorted.set_index('Neigh

toronto_merged.head()
```

Out[28]:

	Postal Code	Borough	Neighborhood	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd M Comm Ve
0	M3A	North York	Parkwoods	43.753259	-79.329656	1.0	Food & Drink Shop	Park	Wom S
1	M4A	North York	Victoria Village	43.725882	-79.315572	2.0	Portuguese Restaurant	Coffee Shop	Fre Restau
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636	2.0	Coffee Shop	Park	
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763	2.0	Clothing Store	Accessories Store	Furnit H S
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494	2.0	Coffee Shop	Diner	S Restau

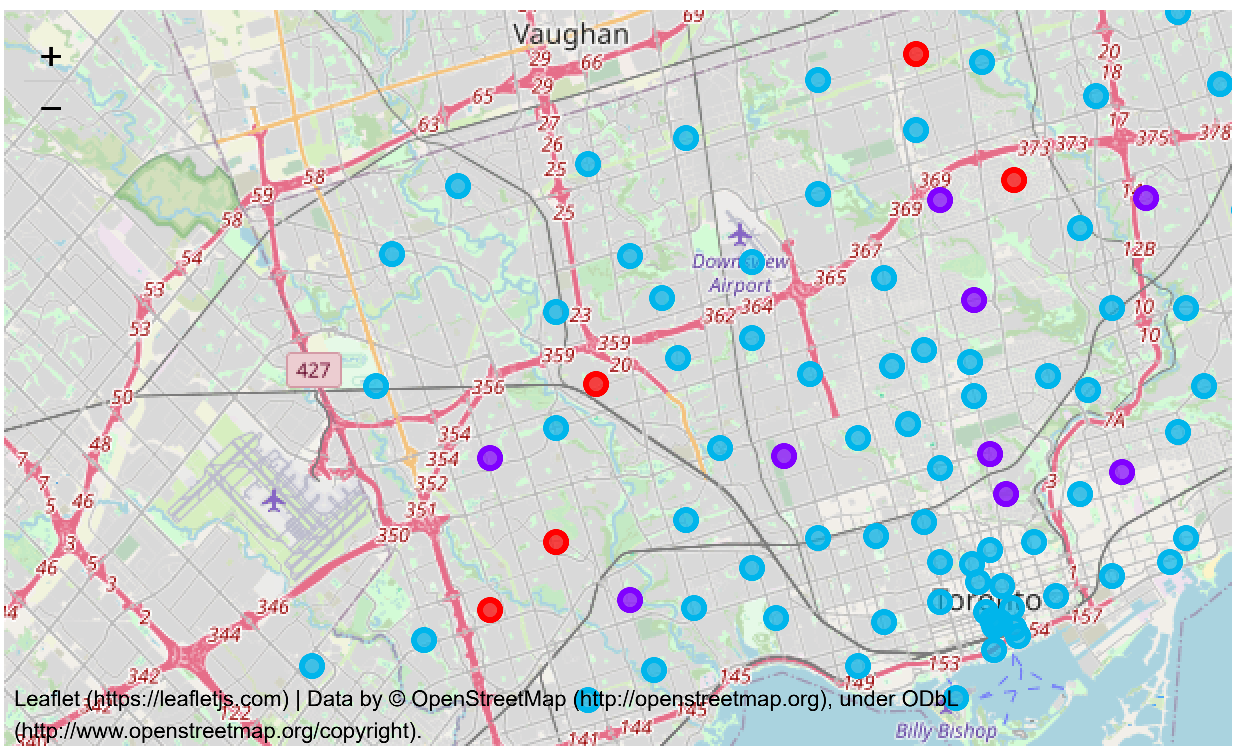
Visualize the clusters

In [35]:
```
# Adminstrative information needed to map

toronto_merged['Cluster Labels'] = toronto_merged['Cluster Labels'].fillna(0.0).a

address = 'Toronto, CA'

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

```
The geograpical coordinate of Toronto are 43.6534817, -79.3839347.
```

In [36]:
```python
# create map
import folium



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(toronto_merged['Latitude'], toronto_merged['Lon
    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[36]:



Finally, examine the clusters

In [37]:
```
# CLUSTER #1
toronto_merged.loc[toronto_merged['Cluster Labels'] == 0, toronto_merged.columns[
```

Out[37]:

	Borough	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 M Comm Ve
5	Etobicoke	0	NaN	NaN	NaN	NaN	NaN	NaN	
11	Etobicoke	0	NaN	NaN	NaN	NaN	NaN	NaN	
32	Scarborough	0	Playground	Women's Store	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Distribu Ce
45	North York	0	NaN	NaN	NaN	NaN	NaN	NaN	
52	North York	0	NaN	NaN	NaN	NaN	NaN	NaN	
64	York	0	NaN	NaN	NaN	NaN	NaN	NaN	
85	Scarborough	0	Park	Playground	Sculpture Garden	Dog Run	Dessert Shop	Dim Sum Restaurant	D
95	Scarborough	0	NaN	NaN	NaN	NaN	NaN	NaN	

In [38]:
```
# CLUSTER #2
toronto_merged.loc[toronto_merged['Cluster Labels'] == 1, toronto_merged.columns[
```

Out[38]:

	Borough	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	7t C
0	North York	1	Food & Drink Shop	Park	Women's Store	Diner	Discount Store	Distribution Center	D
21	York	1	Park	Pool	Women's Store	Greek Restaurant	Gourmet Shop	Ethiopian Restaurant	Ele
35	East York	1	Park	Metro Station	Convenience Store	Women's Store	Doner Restaurant	Diner	D
61	Central Toronto	1	Park	Bus Line	Swim School	Dog Run	Dim Sum Restaurant	Diner	D
66	North York	1	Park	Convenience Store	Women's Store	Donut Shop	Diner	Discount Store	Dis
77	Etobicoke	1	Park	Sandwich Place	Department Store	Event Space	Ethiopian Restaurant	Electronics Store	Eu Res
83	Central Toronto	1	Park	Women's Store	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Dis
91	Downtown Toronto	1	Park	Trail	Playground	Dim Sum Restaurant	Diner	Discount Store	Dis
98	Etobicoke	1	Park	River	Smoke Shop	Dog Run	Dessert Shop	Dim Sum Restaurant	

In [39]:
```
# CLUSTER #3
toronto_merged.loc[toronto_merged['Cluster Labels'] == 2, toronto_merged.columns|
```

Out[39]:

	Borough	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
1	North York	2	Portuguese Restaurant	Coffee Shop	French Restaurant	Hockey Arena	Intersection
2	Downtown Toronto	2	Coffee Shop	Park	Pub	Bakery	Theater
3	North York	2	Clothing Store	Accessories Store	Furniture / Home Store	Boutique	Vietnamese Restaurant
4	Downtown Toronto	2	Coffee Shop	Diner	Sushi Restaurant	Yoga Studio	College Auditorium
7	North York	2	Gym	Asian Restaurant	Beer Store	Japanese Restaurant	Coffee Shop
8	East York	2	Pizza Place	Gym / Fitness Center	Gastropub	Fast Food Restaurant	Intersection

In [40]:
```
# CLUSTER #4
toronto_merged.loc[toronto_merged['Cluster Labels'] == 3, toronto_merged.columns|
```

Out[40]:

	Borough	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
12	Scarborough	3	Bar	Women's Store	Donut Shop	Diner	Discount Store	Distribution Center	Dog Run

In [41]:
```
# CLUSTER #5
toronto_merged.loc[toronto_merged['Cluster Labels'] == 4, toronto_merged.columns|
```

Out[41]:

	Borough	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 Mos Commor Venue
6	Scarborough	4	Fast Food Restaurant	Dessert Shop	Farmers Market	Falafel Restaurant	Event Space	Ethiopian Restaurant	Electronics Store

In [ ]: