Capstone Project - Business' Advisor in Toronto

Applied Data Science Capstone

IBM/Coursera

Description of the Problem

I would like to analyze where to open a restaurant in Toronto. Continuing with the studies we have done so far on the previous courses, in this capstone I will expand them ir order to determine the most appropiate neighborhood for a restaurant.

Description of the Data

The dataset was provided by the previous course and the foursquare API will be used to get the venues' locations.

- This dataset has three columns: PostalCode, Borough, and Neighborhood
- Boroughs with a **Not assigned** will be ignored.
- More than one neighborhood can exist in one postal code area. Those rows will be combined into one row with the neighborhoods separated with a comma.
- If a cell has a borough but a Not assigned neighborhood, then the neighborhood will be the same as the borough.

	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

How will the data be used to solve the problem?

To get the latitude/longitude for each postal code I will use the following data set [Link (https://cocl.us/Geospatial_data)](https://cocl.us/Geospatial_data).
After mergin both dataset I will get something like this:

	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

Then, everything will be ready to use FourSquare API to retrieve venues for earch neighborhood.
To visualize the data I will use maps and plots.

Methodology

Modules

In [191]:

```
#!conda install -c conda-forge geopy --yes # uncomment this line if you haven't completed the Foursquare
 API lab
#!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you haven't completed the Four
square API lab

#import pixiedust # Debugging
import numpy as np
import pandas as pd
import json
import matplotlib.cm as cm
import matplotlib.colors as colors
import requests
import folium # map rendering library
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import DBSCAN

from geopy.geocoders import Nominatim
from pandas.io.json import json_normalize
from sklearn.cluster import KMeans

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.filterwarnings("ignore")
pd.options.mode.chained_assignment = None

%matplotlib inline
```

In [2]:
```
# Using read_html from pandas module
# Picking the first element as it is the table we need
df = pd.read_html('https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M')[0]
df.head()
```

Out[2]:

	Postcode	Borough	Neighbourhood
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

Renaming columns

In [3]:
```
# Renaming columns
df.columns = ['PostalCode', 'Borough', 'Neighborhood']
df.head()
```

Out[3]:

	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

Only process the cells that have an assigned borough. Ignore cells with a borough that is **Not assigned**.

In [4]:
```
# Dropping cells with a borough that is Not assigned.
df.replace("Not assigned", np.nan, inplace=True)
df.dropna(axis=0, subset=['Borough'], inplace=True)
```

More than one neighborhood can exist in one postal code area. Those rows will be combined into one row with the neighborhoods separated with a comma.

In [5]:
```
# Defining a lamnda function to process each row.
def f(x):
    return pd.Series(dict(A = x.loc[:,'PostalCode'].values[0],
                          B = x.loc[:,'Borough'].values[0],
                          C = x.loc[:,'Borough'].values[0] if (x['Neighborhood'].values[0] is np.nan) else
('%s' % ', '.join(x['Neighborhood']))))

df_grouped = df.groupby('PostalCode').apply(f)
```

In [6]:
```
# Reindexing
df_grouped.index = range(0, len(df_grouped))
df_grouped.columns = ['PostalCode', 'Borough', 'Neighborhood']
df_grouped.head()
```

Out[6]:

	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

Adding coordinates

In [7]:
```
coords = pd.read_csv("Geospatial_Coordinates.csv")
latitudes = []
longitudes = []

for index, row in df_grouped.iterrows():
    latitudes.append(coords[coords['Postal Code'] == row['PostalCode']].values[0][1])
    longitudes.append(coords[coords['Postal Code'] == row['PostalCode']].values[0][2])

df_grouped = df_grouped.assign(latitude = latitudes, longitude = longitudes)
df_grouped.head()
```

Out[7]:

	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 [8]:
```
# Working only with Toronto's Boroughs
df_toronto = df_grouped[df_grouped['Borough'].str.contains(r'Toronto')]
df_toronto.head()
```

Out[8]:

	PostalCode	Borough	Neighborhood	latitude	longitude
37	M4E	East Toronto	The Beaches	43.676357	-79.293031
41	M4K	East Toronto	The Danforth West, Riverdale	43.679557	-79.352188
42	M4L	East Toronto	The Beaches West, India Bazaar	43.668999	-79.315572
43	M4M	East Toronto	Studio District	43.659526	-79.340923
44	M4N	Central Toronto	Lawrence Park	43.728020	-79.388790

In [9]:
```
df_toronto.columns = map(lambda s: s.capitalize(), df_toronto.columns)
```

Adding Venues

In [213]:
```
CLIENT_ID = '***' # your Foursquare ID
CLIENT_SECRET = '***' # your Foursquare Secret
VERSION = '20180605' # Foursquare API version
LIMIT = 100
radius = 500
```

In [11]:
```python
# Defining a function to get the venues nearby
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_secret={}&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 venue_list])
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

Getting toronto venues for each neighborhood

In [12]:
```
toronto_venues = getNearbyVenues(names=df_toronto['Neighborhood'],
                                   latitudes=df_toronto['Latitude'],
                                   longitudes=df_toronto['Longitude']
                                  )
```

The Beaches
The Danforth West, Riverdale
The Beaches West, India Bazaar
Studio District
Lawrence Park
Davisville North
North Toronto West
Davisville
Moore Park, Summerhill East
Deer Park, Forest Hill SE, Rathnelly, South Hill, Summerhill West
Rosedale
Cabbagetown, St. James Town
Church and Wellesley
Harbourfront, Regent Park
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
Roselawn
Forest Hill North, Forest Hill West
The Annex, North Midtown, Yorkville
Harbord, University of Toronto
Chinatown, Grange Park, Kensington Market
CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadina, Railway Lands, South Niagara
Stn A PO Boxes 25 The Esplanade
First Canadian Place, Underground city
Christie
Dovercourt Village, Dufferin
Little Portugal, Trinity
Brockton, Exhibition Place, Parkdale Village
High Park, The Junction South
Parkdale, Roncesvalles
Runnymede, Swansea
Business Reply Mail Processing Centre 969 Eastern

In [215]:
```
toronto_venues.head()
```

Out[215]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster	Cluster Color
0	The Beaches	43.676357	-79.293031	Glen Manor Ravine	43.676821	-79.293942	Trail	0	#6826fe
1	The Beaches	43.676357	-79.293031	The Big Carrot Natural Food Market	43.678879	-79.297734	Health Food Store	0	#6826fe
2	The Beaches	43.676357	-79.293031	Grover Pub and Grub	43.679181	-79.297215	Pub	0	#6826fe
3	The Beaches	43.676357	-79.293031	Upper Beaches	43.680563	-79.292869	Neighborhood	0	#6826fe
4	The Danforth West, Riverdale	43.679557	-79.352188	Pantheon	43.677621	-79.351434	Greek Restaurant	1	#504afc

Checking whether the dataframe has null values or not

In [14]:
```
toronto_venues.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1711 entries, 0 to 1710
Data columns (total 7 columns):
Neighborhood              1711 non-null object
Neighborhood Latitude     1711 non-null float64
Neighborhood Longitude    1711 non-null float64
Venue                     1711 non-null object
Venue Latitude            1711 non-null float64
Venue Longitude           1711 non-null float64
Venue Category            1711 non-null object
dtypes: float64(4), object(3)
memory usage: 93.6+ KB
```

Number of Unique Venues

In [15]:
```
len(toronto_venues['Venue Category'].unique())
```

Out[15]: 235

Unique Venues in Toronto

In [27]:
```
toronto_venues['Venue Category'].unique()
```

```
Out[27]: array(['Trail', 'Health Food Store', 'Pub', 'Neighborhood',
       'Greek Restaurant', 'Ice Cream Shop', 'Cosmetics Shop',
       'Italian Restaurant', 'Brewery', 'Yoga Studio', 'Restaurant',
       'Fruit & Vegetable Store', 'Dessert Shop', 'Pizza Place',
       'Juice Bar', 'Bookstore', 'Indian Restaurant',
       'Furniture / Home Store', 'Grocery Store', 'Spa', 'Diner',
       'Bubble Tea Shop', 'Coffee Shop', 'Caribbean Restaurant', 'Bakery',
       'Sports Bar', 'Café', 'American Restaurant', 'Sushi Restaurant',
       'Liquor Store', 'Gym', 'Burger Joint', 'Fish & Chips Shop', 'Park',
       'Pet Store', 'Burrito Place', 'Steakhouse', 'Movie Theater',
       'Fast Food Restaurant', 'Sandwich Place', 'Food & Drink Shop',
       'Fish Market', 'Gay Bar', 'Cheese Shop', 'Chinese Restaurant',
       'Middle Eastern Restaurant', 'Thai Restaurant',
       'Comfort Food Restaurant', 'Stationery Store',
       'Seafood Restaurant', 'Coworking Space', 'Gastropub',
       'Latin American Restaurant', 'Bar', 'Convenience Store', 'Bank',
       'Clothing Store', 'Gym / Fitness Center', 'Dim Sum Restaurant',
       'Swim School', 'Bus Line', 'Breakfast Spot', 'Hotel', 'Dog Run',
       'Sporting Goods Shop', 'Mexican Restaurant', 'Salon / Barbershop',
       'Metro Station', 'Bagel Shop', 'Toy / Game Store', 'Gourmet Shop',
       'Farmers Market', 'Pharmacy', 'Flower Shop', 'Discount Store',
       'Fried Chicken Joint', 'Dance Studio', 'Playground', 'Supermarket',
       'Vietnamese Restaurant', 'Light Rail Station', 'Building',
       'Japanese Restaurant', 'Jewelry Store', 'Butcher',
       'General Entertainment', 'Taiwanese Restaurant', 'Deli / Bodega',
       'Gift Shop', 'Market', 'Beer Store', 'Snack Place',
       'Theme Restaurant', 'Ramen Restaurant', 'Tea Room', 'Hobby Shop',
       'Creperie', 'Ethiopian Restaurant', "Men's Store",
       'Arts & Crafts Store', 'Smoke Shop', 'Wings Joint',
       'Polish Restaurant', 'Sake Bar', 'Persian Restaurant', 'Theater',
       'Nightclub', 'Video Game Store', 'Mediterranean Restaurant',
       'Afghan Restaurant', 'Health & Beauty Service', 'Strip Club',
       'Sculpture Garden', 'Plaza', 'Shoe Store', 'Cafeteria',
       'Historic Site', 'Chocolate Shop', 'Performing Arts Venue',
       'French Restaurant', 'Event Space', 'Art Gallery',
       'Electronics Store', 'Antique Shop', 'Comic Shop', 'Music Venue',
       'Taco Place', 'Vegetarian / Vegan Restaurant', 'Beer Bar',
       'Shopping Mall', 'Miscellaneous Shop', 'Tanning Salon',
       'College Rec Center', 'Modern European Restaurant',
       'Department Store', 'Lounge', 'Wine Bar', 'Hookah Bar', 'Lake',
       'Lingerie Store', 'Poutine Place', 'Other Great Outdoors',
```

```
 'Office', 'Food Truck', 'BBQ Joint', 'Church', 'Poke Place',
 'Hostel', 'New American Restaurant', 'Smoothie Shop', 'Jazz Club',
 'Cocktail Bar', 'Camera Store', 'Fountain', 'Tailor Shop',
 'Eastern European Restaurant', 'Concert Hall', 'Museum',
 'Basketball Stadium', 'Bistro', 'Belgian Restaurant', 'Beach',
 'Irish Pub', 'Portuguese Restaurant', 'Art Museum',
 'Falafel Restaurant', 'Donut Shop', 'Salad Place',
 'Korean Restaurant', 'Asian Restaurant', 'Speakeasy', 'Food Court',
 'Noodle House', 'Monument / Landmark', 'Colombian Restaurant',
 'General Travel', 'Record Shop', 'Brazilian Restaurant',
 'Gluten-free Restaurant', 'Skating Rink', 'Roof Deck', 'Aquarium',
 'Train Station', 'History Museum', 'Scenic Lookout',
 'Baseball Stadium', 'Festival', 'Hotel Bar', 'Soup Place',
 'Cupcake Shop', 'Garden', 'Jewish Restaurant', 'College Gym',
 'College Arts Building', 'Organic Grocery', 'Gaming Cafe',
 'Dumpling Restaurant', 'Martial Arts Dojo', 'Hotpot Restaurant',
 'Doner Restaurant', 'Filipino Restaurant', 'Hospital',
 'Bed & Breakfast', 'Airport', 'Airport Lounge', 'Harbor / Marina',
 'Airport Food Court', 'Airport Gate', 'Boutique',
 'Airport Terminal', 'Airport Service', 'Boat or Ferry',
 'Molecular Gastronomy Restaurant', 'Optical Shop', 'Opera House',
 'Baby Store', 'Athletics & Sports', 'Cuban Restaurant',
 'Mac & Cheese Joint', 'Malay Restaurant', 'Tapas Restaurant',
 'Southern / Soul Food Restaurant', 'Climbing Gym', 'Stadium',
 'Intersection', 'Flea Market', 'Cajun / Creole Restaurant',
 'Bus Stop', 'Food', 'Indie Movie Theater', 'Post Office',
 'Skate Park', 'Garden Center', 'Auto Workshop', 'Recording Studio'],
dtype=object)
```

Plot

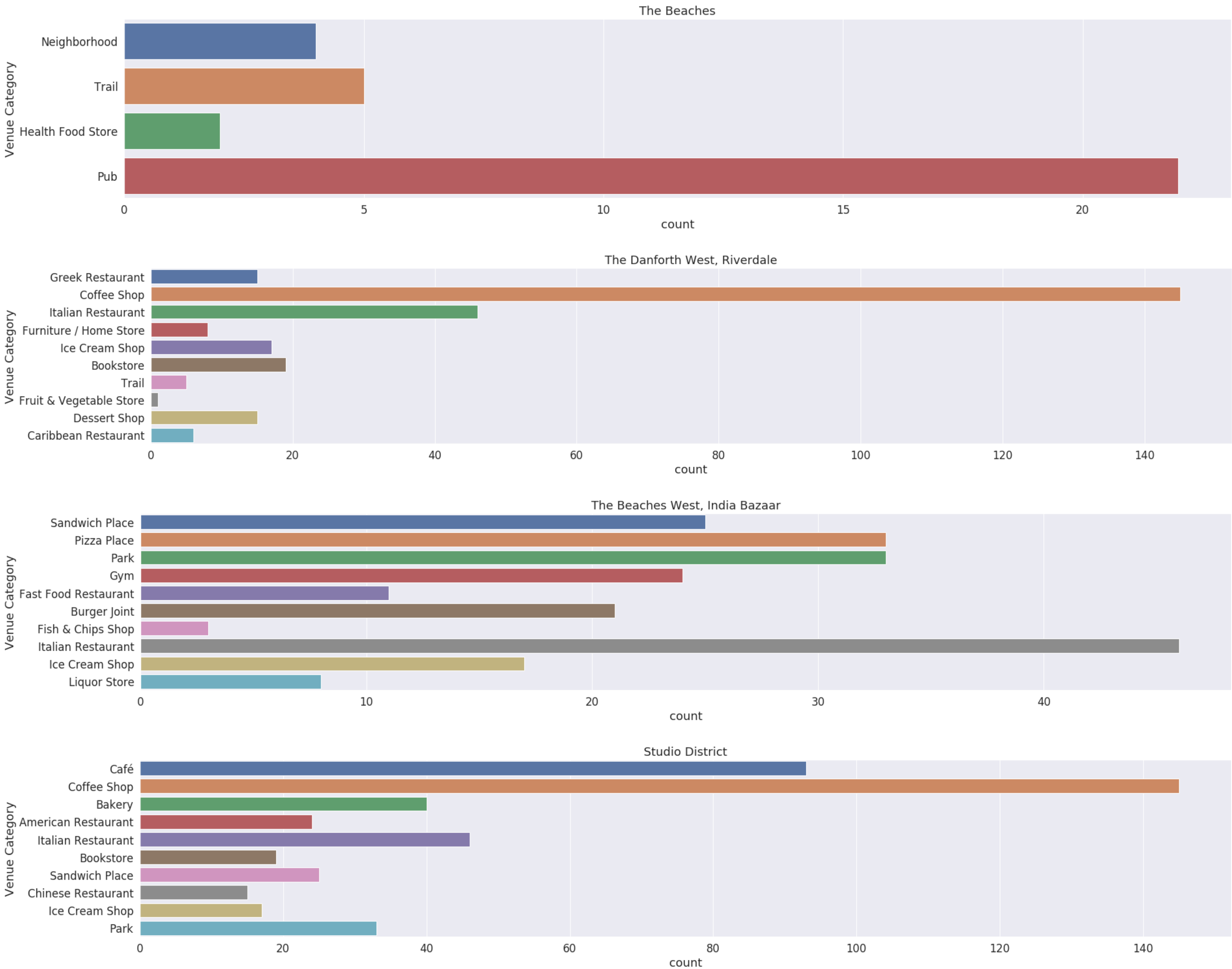
Plotting quantity of venues per neighborhood

As we can see in the previous list, there are 235 categories on Toronto. How many per neighborhood?

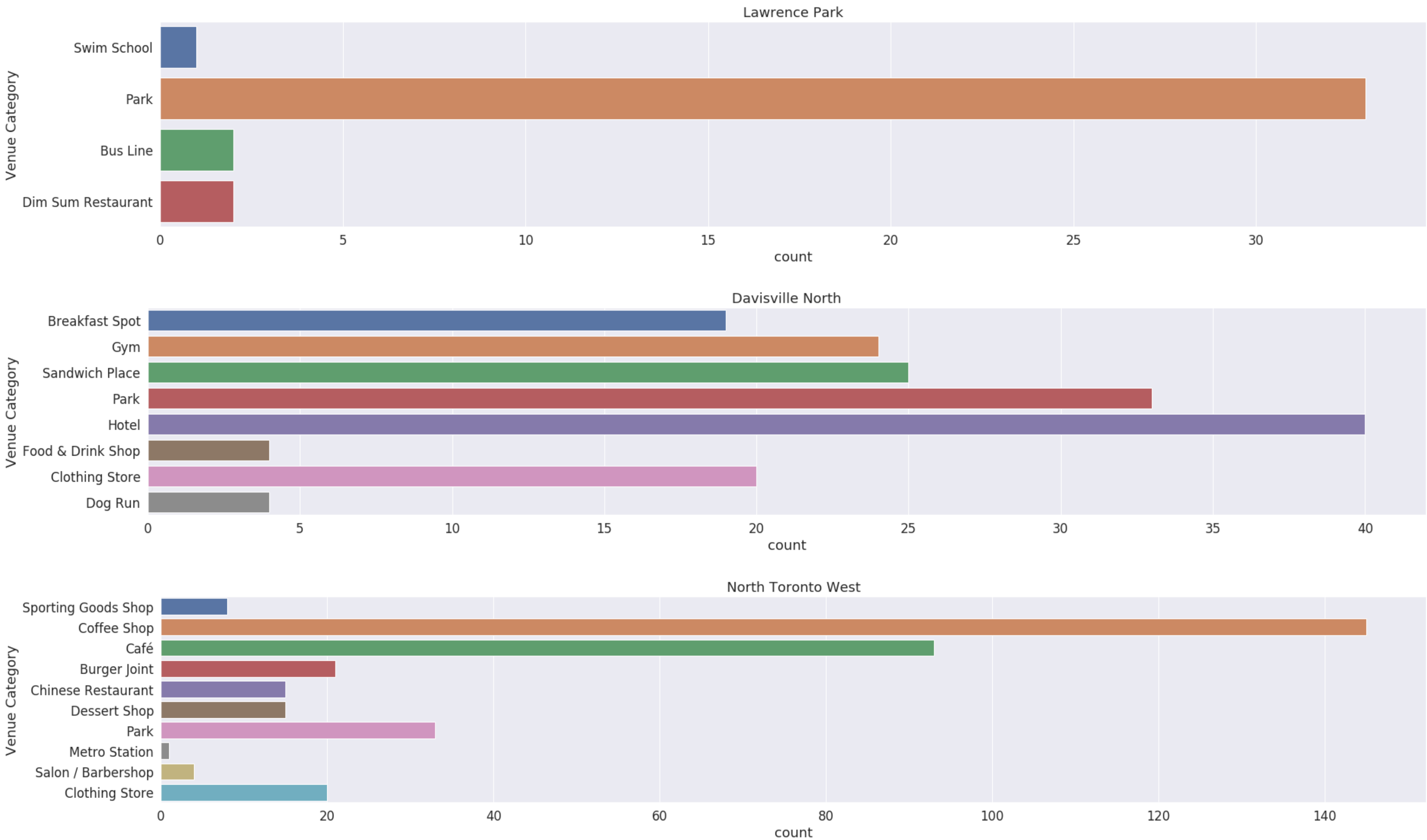
In [214]:
```
def plot_venues(df, column):
    values = [neighborhood for neighborhood in toronto_venues[column].unique()]
    for value in values:
        plt.figure(figsize=(30,5))
        sns.set(font_scale=1.5)
        plt.title(value)
        sns.countplot(y='Venue Category', data = toronto_venues, order = toronto_venues[toronto_venues[co
lumn] == value]['Venue Category'].value_counts().iloc[:10].index)
        #plt.savefig(value+".png")
```

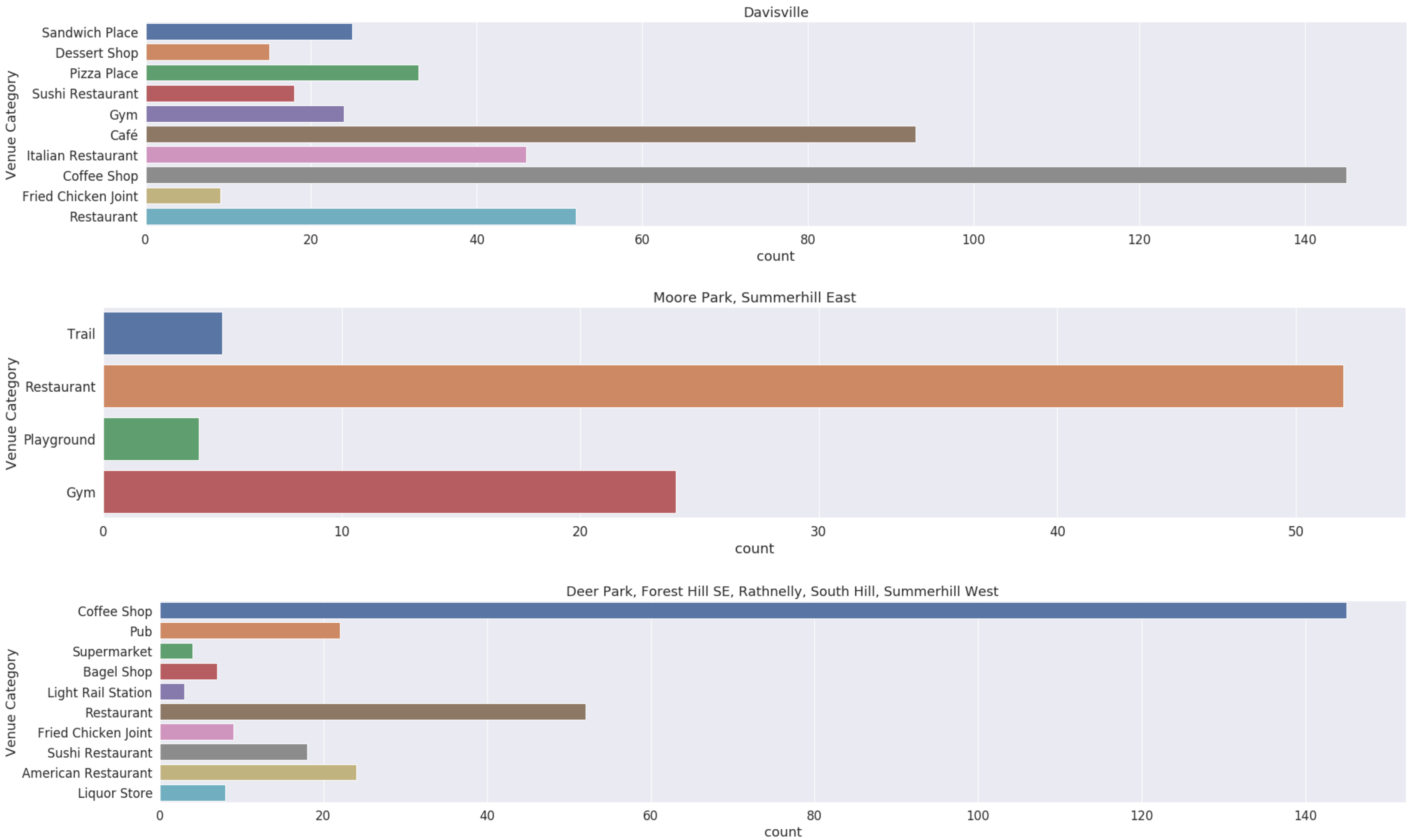
In [192]:

```
plot_venues(toronto_venues, "Neighborhood")
```

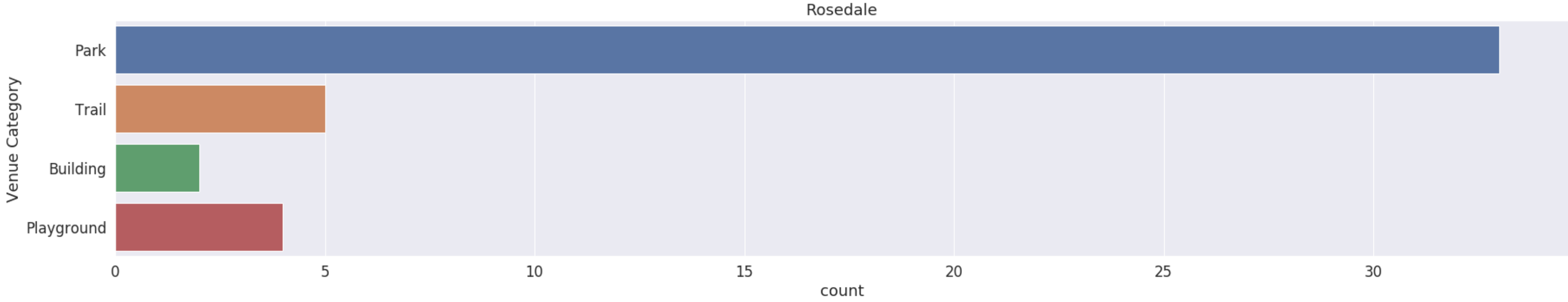


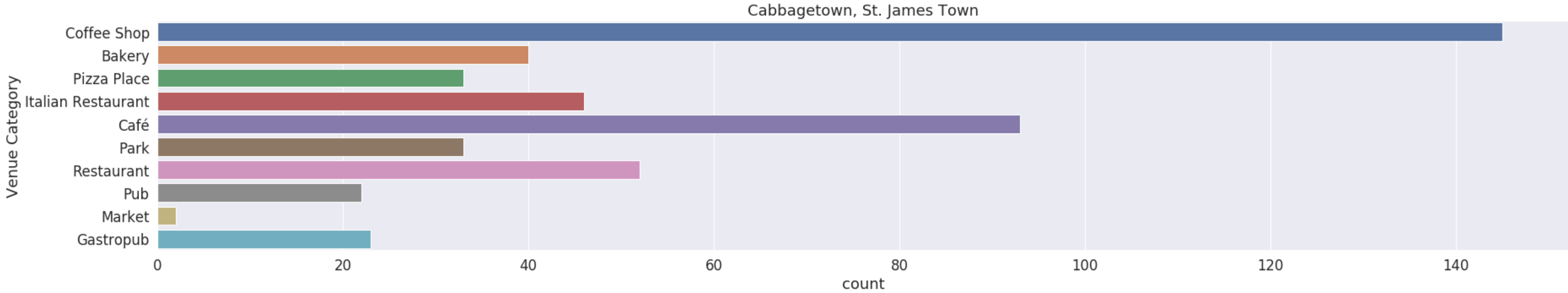
The Beaches
Neighborhood
Trail
Health Food Store
Pub
Venue Category
0
5
10
15
20
count
The Danforth West, Riverdale
Greek Restaurant
Coffee Shop
Italian Restaurant
Furniture / Home Store
Ice Cream Shop
Bookstore
Trail
Fruit & Vegetable Store
Dessert Shop
Caribbean Restaurant
Venue Category
0
20
40
60
80
100
120
140
count
The Beaches West, India Bazaar
Sandwich Place
Pizza Place
Park
Gym
Fast Food Restaurant
Burger Joint
Fish & Chips Shop
Italian Restaurant
Ice Cream Shop
Liquor Store
Venue Category
0
10
20
30
40
count
Studio District
Café
Coffee Shop
Bakery
American Restaurant
Italian Restaurant
Bookstore
Sandwich Place
Chinese Restaurant
Ice Cream Shop
Park
Venue Category
0
20
40
60
80
100
120
140
count

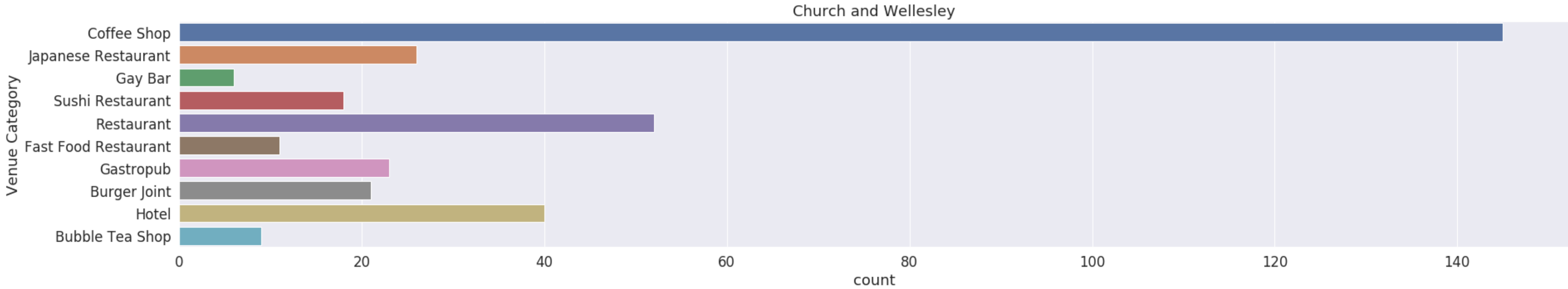

Lawrence Park
Venue Category
Swim School
Park
Bus Line
Dim Sum Restaurant
0
5
10
15
20
25
30
count
Davisville North
Venue Category
Breakfast Spot
Gym
Sandwich Place
Park
Hotel
Food & Drink Shop
Clothing Store
Dog Run
0
5
10
15
20
25
30
35
40
count
North Toronto West
Venue Category
Sporting Goods Shop
Coffee Shop
Café
Burger Joint
Chinese Restaurant
Dessert Shop
Park
Metro Station
Salon / Barbershop
Clothing Store
0
20
40
60
80
100
120
140
count



Davisville
Sandwich Place
Dessert Shop
Pizza Place
Sushi Restaurant
Gym
Café
Italian Restaurant
Coffee Shop
Fried Chicken Joint
Restaurant
Venue Category
0
20
40
60
80
100
120
140
count
Moore Park, Summerhill East
Trail
Restaurant
Playground
Gym
Venue Category
0
10
20
30
40
50
count
Deer Park, Forest Hill SE, Rathnelly, South Hill, Summerhill West
Coffee Shop
Pub
Supermarket
Bagel Shop
Light Rail Station
Restaurant
Fried Chicken Joint
Sushi Restaurant
American Restaurant
Liquor Store
Venue Category
0
20
40
60
80
100
120
140
count

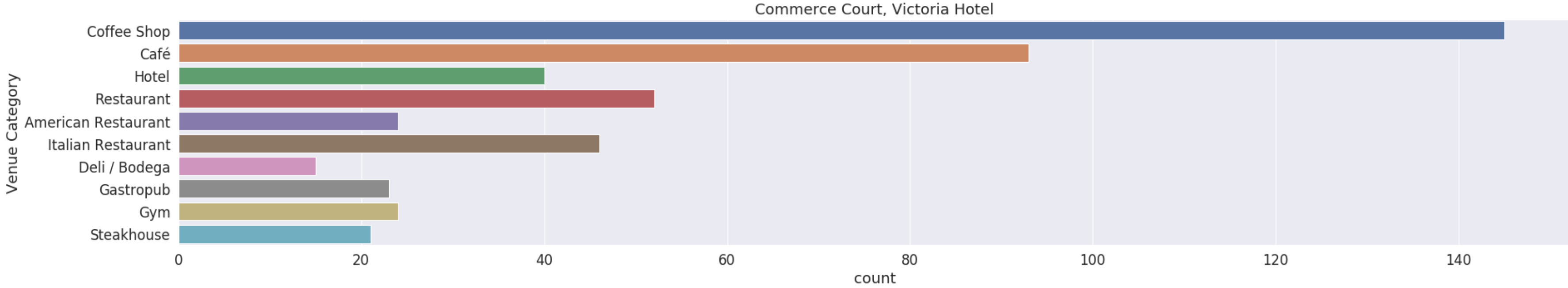

Rosedale
Venue Category
Park
Trail
Building
Playground
0
5
10
15
20
25
30
count

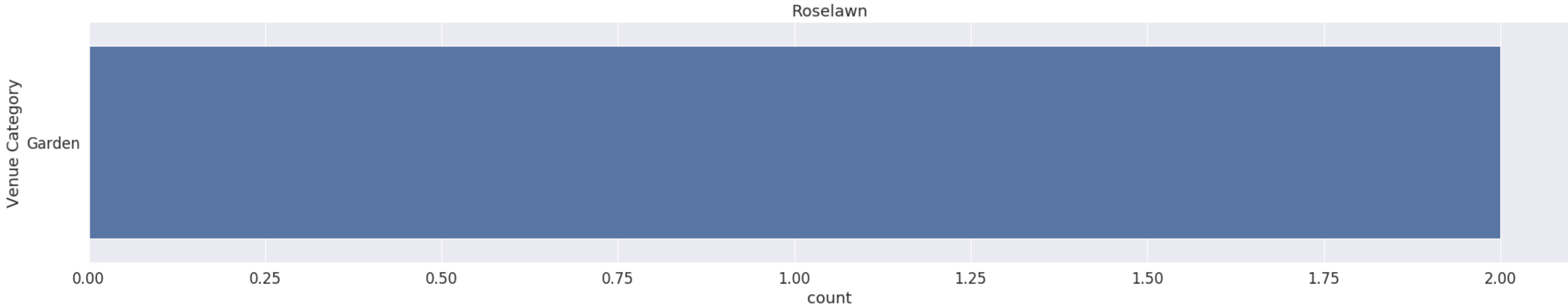

Cabbagetown, St. James Town
Venue Category
Coffee Shop
Bakery
Pizza Place
Italian Restaurant
Café
Park
Restaurant
Pub
Market
Gastropub
0
20
40
60
80
100
120
140
count

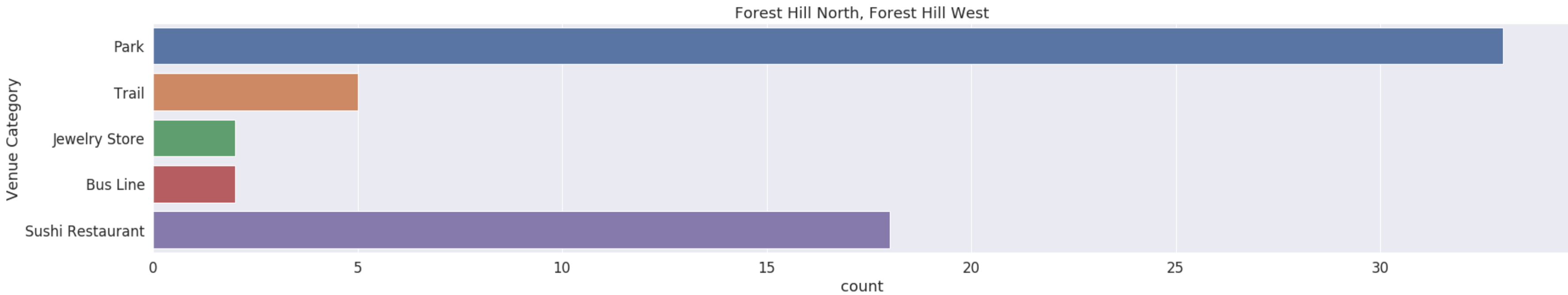

Church and Wellesley
Venue Category
Coffee Shop
Japanese Restaurant
Gay Bar
Sushi Restaurant
Restaurant
Fast Food Restaurant
Gastropub
Burger Joint
Hotel
Bubble Tea Shop
0
20
40
60
80
100
120
140
count

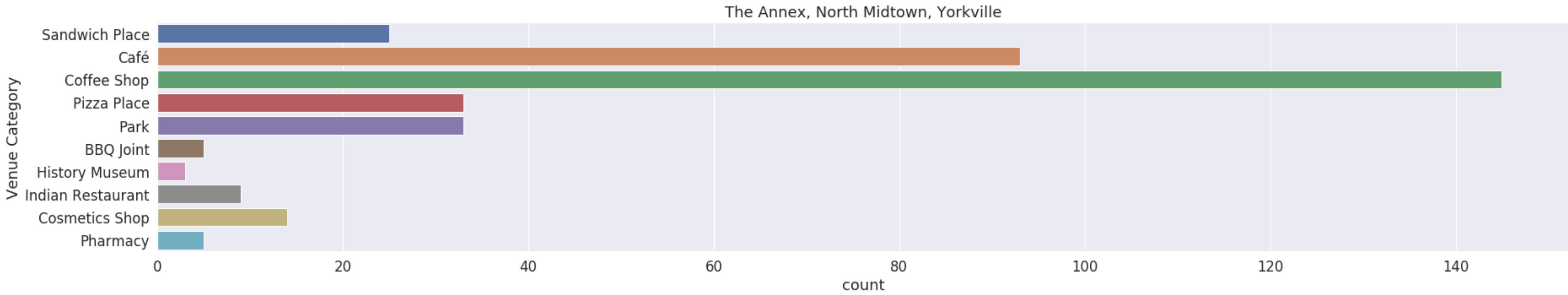

Harbourfront, Regent Park
Venue Category
Coffee Shop
Park
Bakery
Pub
Café
Gym / Fitness Center
Mexican Restaurant
Breakfast Spot
Restaurant
Theater
0 20 40 60 80 100 120 140
count
Ryerson, Garden District
Venue Category
Clothing Store
Coffee Shop
Café
Middle Eastern Restaurant
Cosmetics Shop
Fast Food Restaurant
Restaurant
Pizza Place
Bookstore
Japanese Restaurant
0 20 40 60 80 100 120 140
count
St. James Town
Venue Category
Coffee Shop
Café
Restaurant
Hotel
Italian Restaurant
Cocktail Bar
Clothing Store
Beer Bar
Cosmetics Shop
Bakery
0 20 40 60 80 100 120 140
count
Berczy Park
Venue Category
Coffee Shop
Cocktail Bar
Farmers Market
Beer Bar
Bakery
Italian Restaurant
Café
Steakhouse
Cheese Shop
Seafood Restaurant
0 20 40 60 80 100 120 140
count

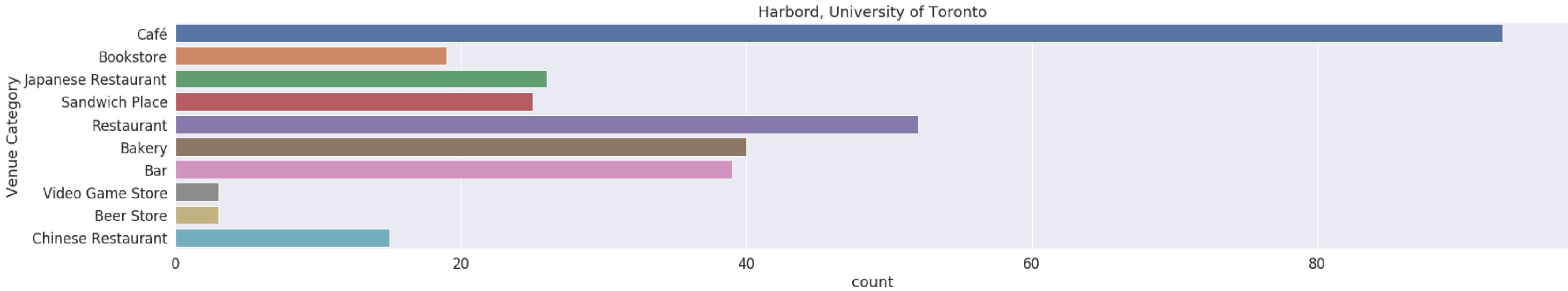

Central Bay Street
Venue Category
Coffee Shop
Italian Restaurant
Café
Burger Joint
Sandwich Place
Ice Cream Shop
Middle Eastern Restaurant
Bubble Tea Shop
Japanese Restaurant
Spa
0
20
40
60
80
100
120
140
count
Adelaide, King, Richmond
Venue Category
Coffee Shop
Café
Bar
Steakhouse
Cosmetics Shop
Burger Joint
Hotel
Thai Restaurant
American Restaurant
Restaurant
0
20
40
60
80
100
120
140
count
Harbourfront East, Toronto Islands, Union Station
Venue Category
Coffee Shop
Hotel
Aquarium
Café
Brewery
Fried Chicken Joint
Scenic Lookout
Park
Music Venue
Plaza
0
20
40
60
80
100
120
140
count
Design Exchange, Toronto Dominion Centre
Venue Category
Coffee Shop
Café
Hotel
Restaurant
American Restaurant
Bakery
Gastropub
Italian Restaurant
Deli / Bodega
Bar
0
20
40
60
80
100
120
140
count

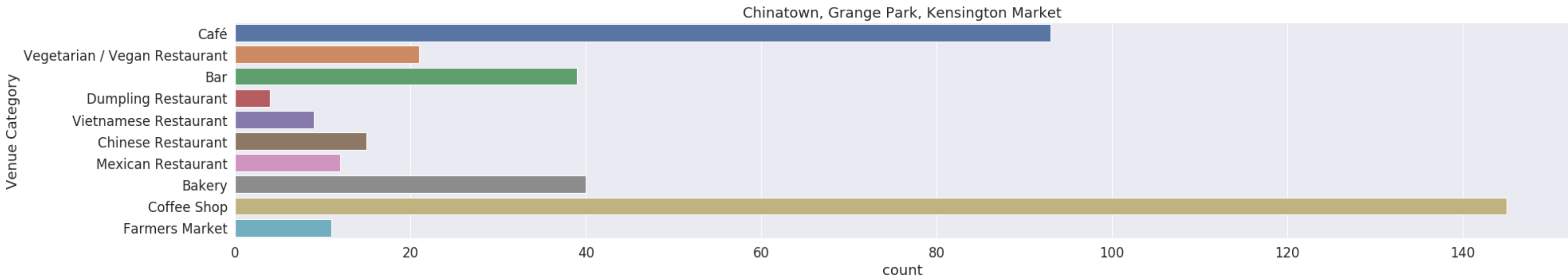

Commerce Court, Victoria Hotel
Venue Category
Coffee Shop
Café
Hotel
Restaurant
American Restaurant
Italian Restaurant
Deli / Bodega
Gastropub
Gym
Steakhouse
0
20
40
60
80
100
120
140
count

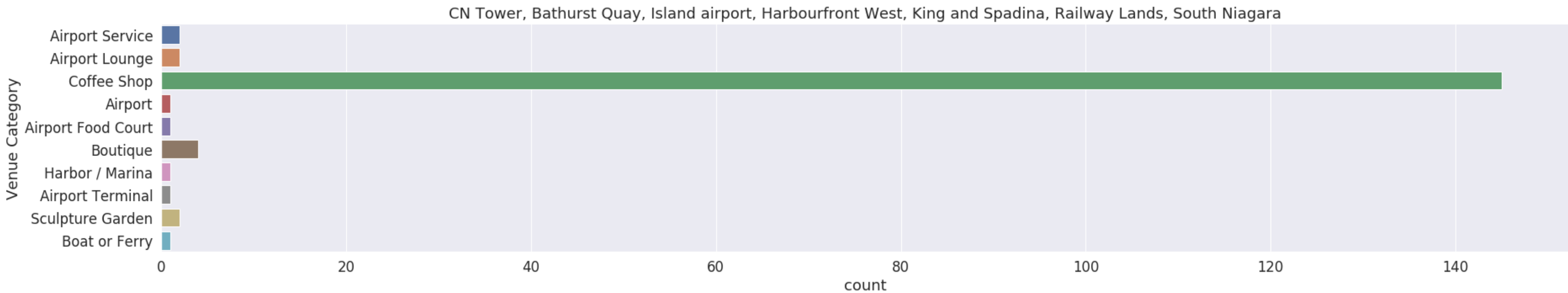

Roselawn
Venue Category
Garden
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
count

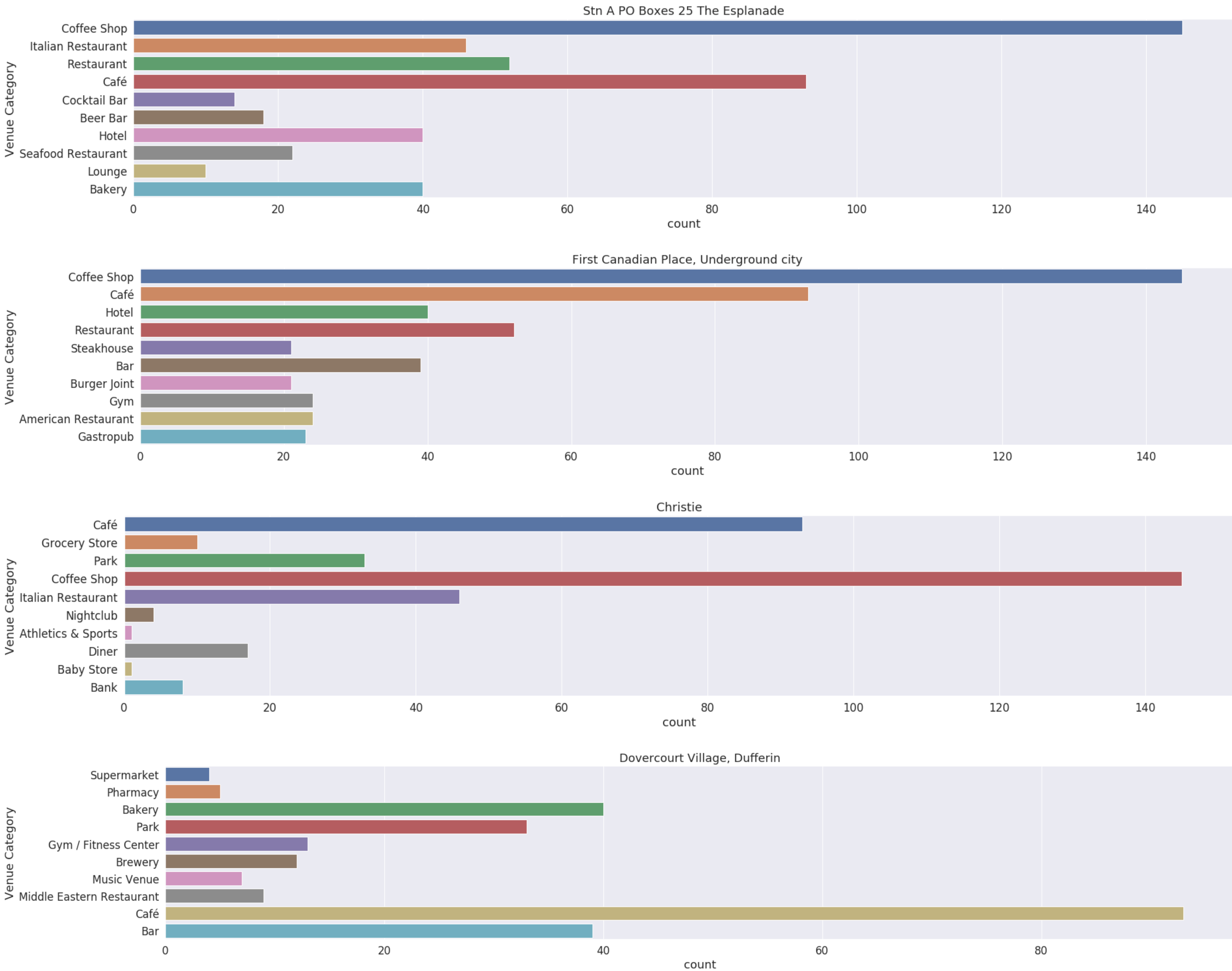

Forest Hill North, Forest Hill West
Venue Category
Park
Trail
Jewelry Store
Bus Line
Sushi Restaurant
0
5
10
15
20
25
30
count

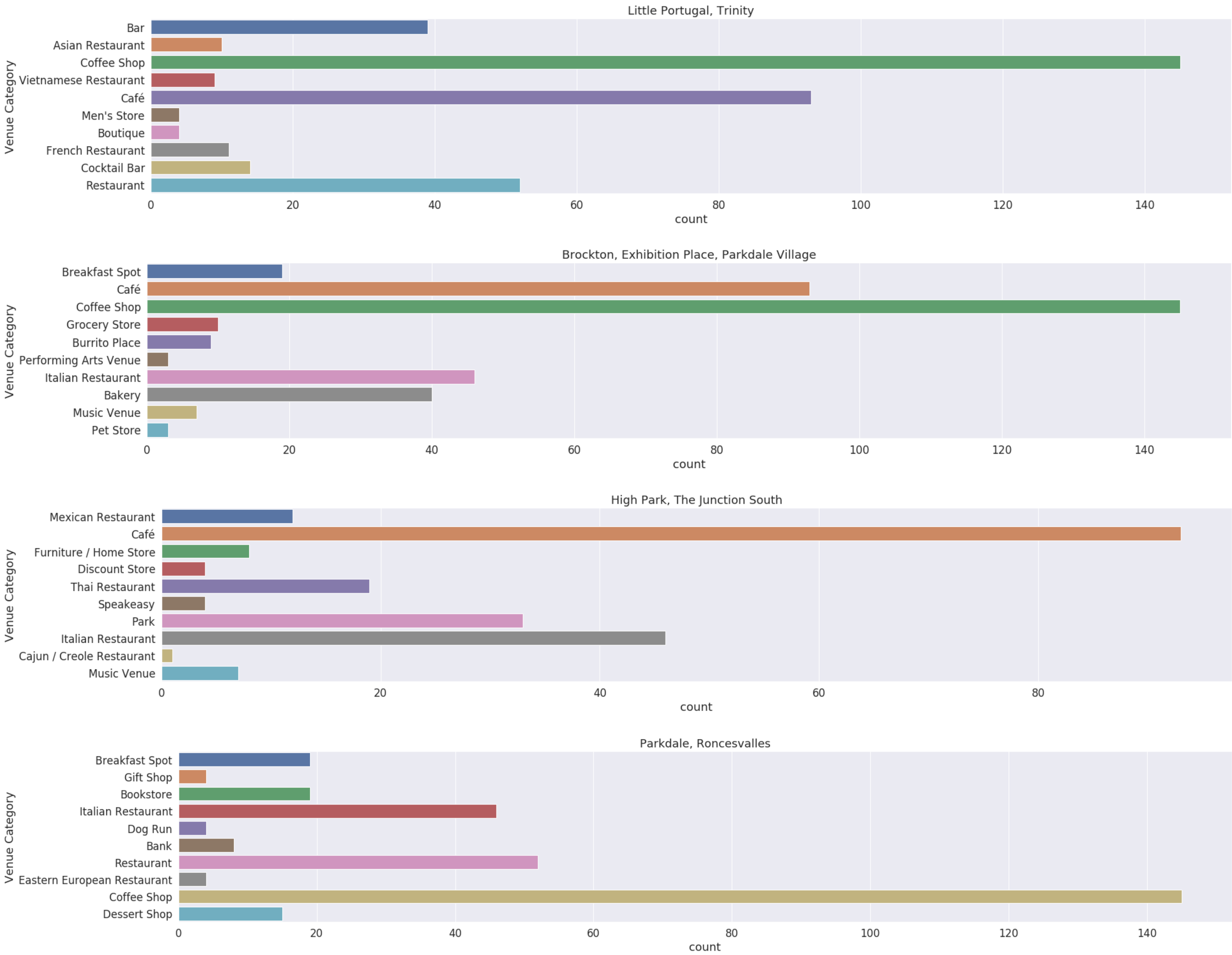

The Annex, North Midtown, Yorkville
Venue Category
Sandwich Place
Café
Coffee Shop
Pizza Place
Park
BBQ Joint
History Museum
Indian Restaurant
Cosmetics Shop
Pharmacy
0
20
40
60
80
100
120
140
count

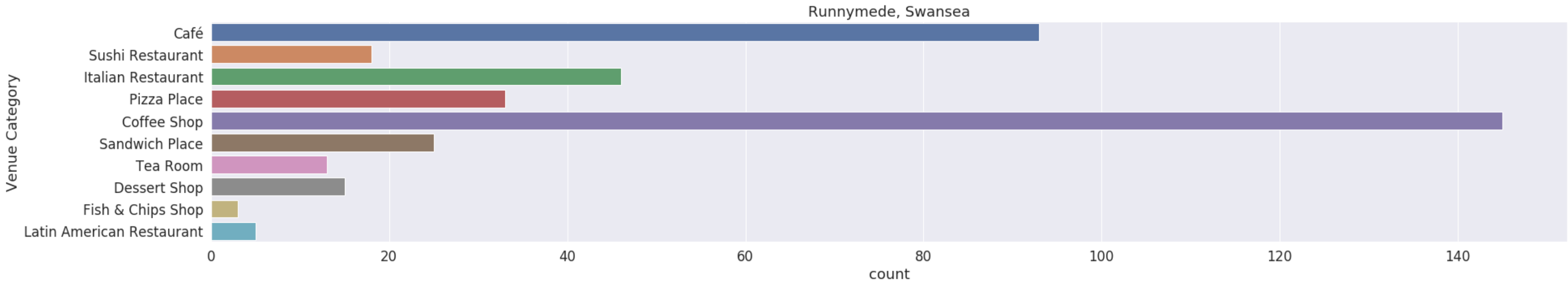

Harbord, University of Toronto
Venue Category
Café
Bookstore
Japanese Restaurant
Sandwich Place
Restaurant
Bakery
Bar
Video Game Store
Beer Store
Chinese Restaurant
0
20
40
60
80
count

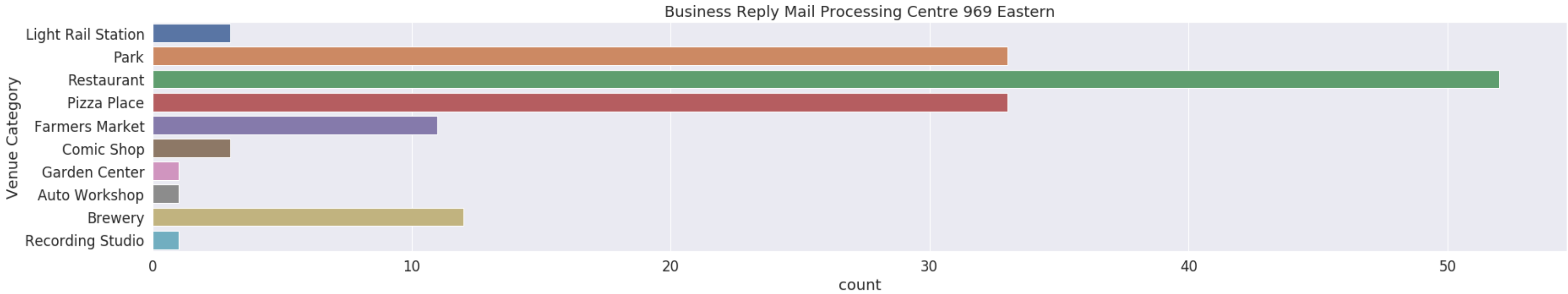

Chinatown, Grange Park, Kensington Market
Venue Category
Café
Vegetarian / Vegan Restaurant
Bar
Dumpling Restaurant
Vietnamese Restaurant
Chinese Restaurant
Mexican Restaurant
Bakery
Coffee Shop
Farmers Market
0
20
40
60
80
100
120
140
count


CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadina, Railway Lands, South Niagara
Venue Category
Airport Service
Airport Lounge
Coffee Shop
Airport
Airport Food Court
Boutique
Harbor / Marina
Airport Terminal
Sculpture Garden
Boat or Ferry
0
20
40
60
80
100
120
140
count


Stn A PO Boxes 25 The Esplanade
Venue Category
Coffee Shop
Italian Restaurant
Restaurant
Café
Cocktail Bar
Beer Bar
Hotel
Seafood Restaurant
Lounge
Bakery
0
20
40
60
80
100
120
140
count
First Canadian Place, Underground city
Venue Category
Coffee Shop
Café
Hotel
Restaurant
Steakhouse
Bar
Burger Joint
Gym
American Restaurant
Gastropub
0
20
40
60
80
100
120
140
count
Christie
Venue Category
Café
Grocery Store
Park
Coffee Shop
Italian Restaurant
Nightclub
Athletics & Sports
Diner
Baby Store
Bank
0
20
40
60
80
100
120
140
count
Dovercourt Village, Dufferin
Venue Category
Supermarket
Pharmacy
Bakery
Park
Gym / Fitness Center
Brewery
Music Venue
Middle Eastern Restaurant
Café
Bar
0
20
40
60
80
count

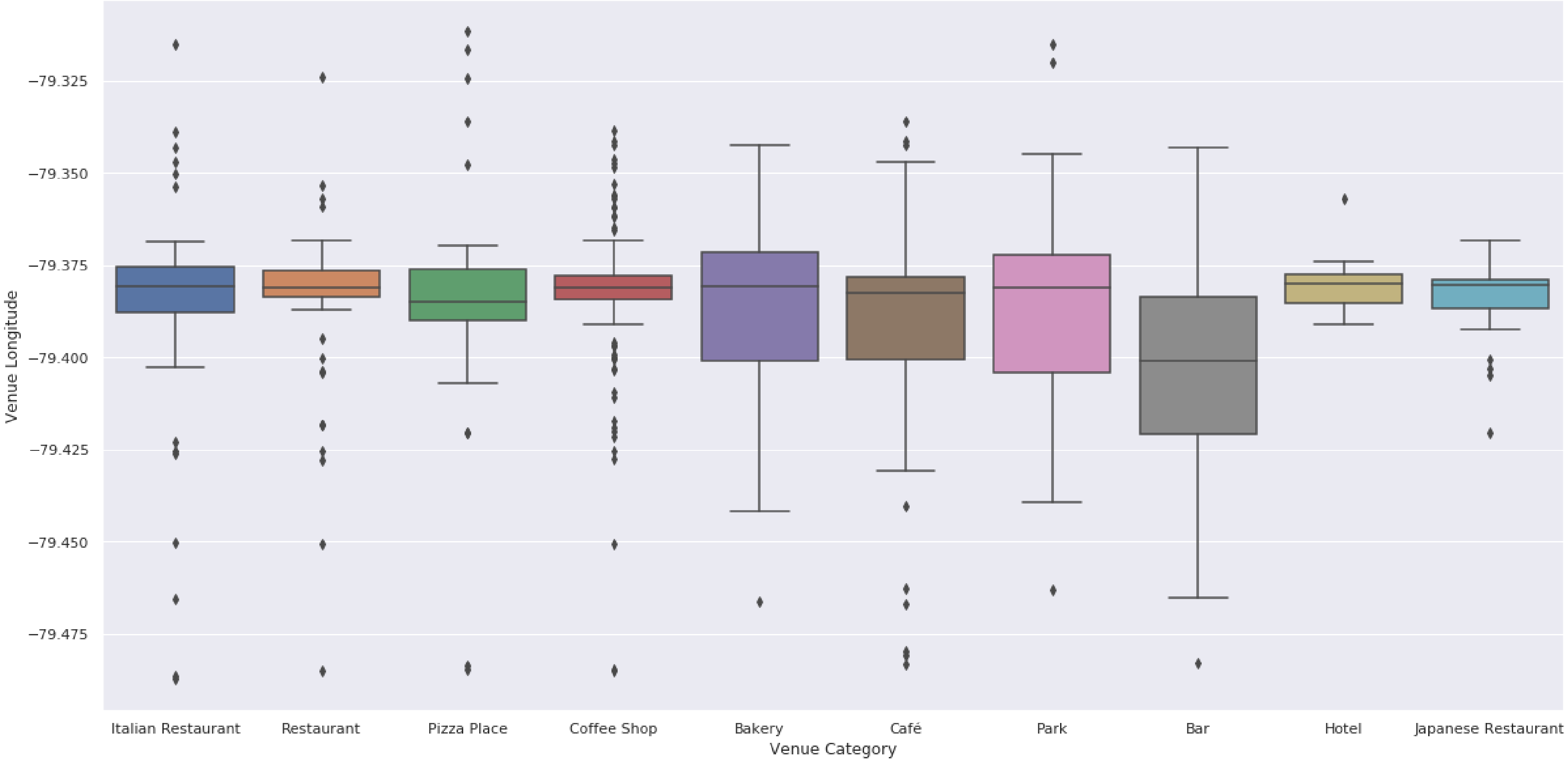

Little Portugal, Trinity
Venue Category
Bar
Asian Restaurant
Coffee Shop
Vietnamese Restaurant
Café
Men's Store
Boutique
French Restaurant
Cocktail Bar
Restaurant
0
20
40
60
80
100
120
140
count
Brockton, Exhibition Place, Parkdale Village
Venue Category
Breakfast Spot
Café
Coffee Shop
Grocery Store
Burrito Place
Performing Arts Venue
Italian Restaurant
Bakery
Music Venue
Pet Store
0
20
40
60
80
100
120
140
count
High Park, The Junction South
Venue Category
Mexican Restaurant
Café
Furniture / Home Store
Discount Store
Thai Restaurant
Speakeasy
Park
Italian Restaurant
Cajun / Creole Restaurant
Music Venue
0
20
40
60
80
count
Parkdale, Roncesvalles
Venue Category
Breakfast Spot
Gift Shop
Bookstore
Italian Restaurant
Dog Run
Bank
Restaurant
Eastern European Restaurant
Coffee Shop
Dessert Shop
0
20
40
60
80
100
120
140
count





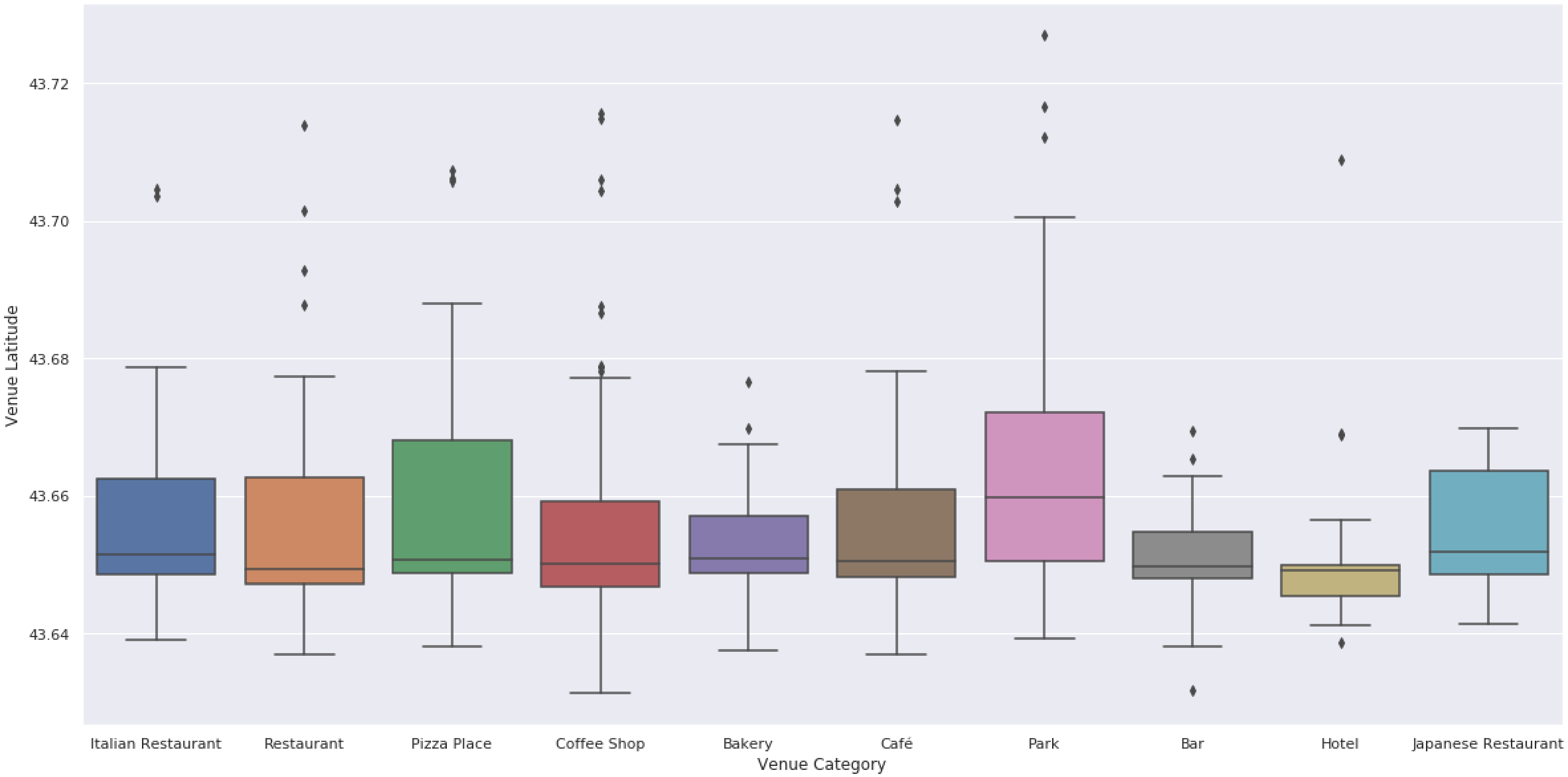
Plotting Venue Category vs Venu Longitude

In [69]:
```
plt.figure(figsize=(20,10))
sns.set(font_scale=1)
indexes = toronto_venues['Venue Category'].value_counts()[:10].index
toronto_venues[toronto_venues['Venue Category'].isin(indexes)]
sns.boxplot(x='Venue Category',y='Venue Longitude',data=toronto_venues[toronto_venues['Venue Category'].i
sin(indexes)])
plt.savefig('category_longitude.png')
```



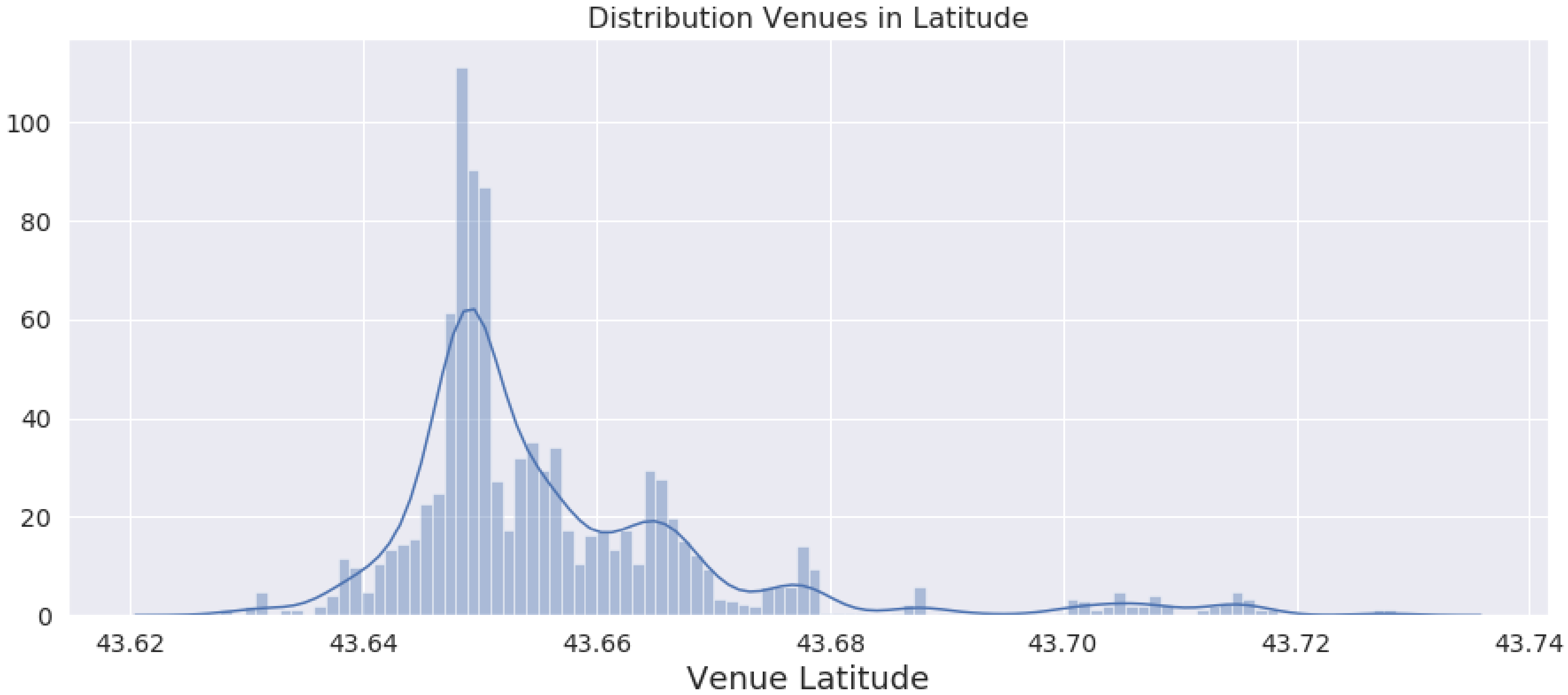
Plotting Venue Category vs Venu Latitude

In [174]:
```
plt.figure(figsize=(20,10))
sns.set(font_scale=1)
indexes = toronto_venues['Venue Category'].value_counts()[:10].index
toronto_venues[toronto_venues['Venue Category'].isin(indexes)]
sns.boxplot(x='Venue Category',y='Venue Latitude',data=toronto_venues[toronto_venues['Venue Category'].is
in(indexes)])
plt.savefig("category_latitude.png")
```



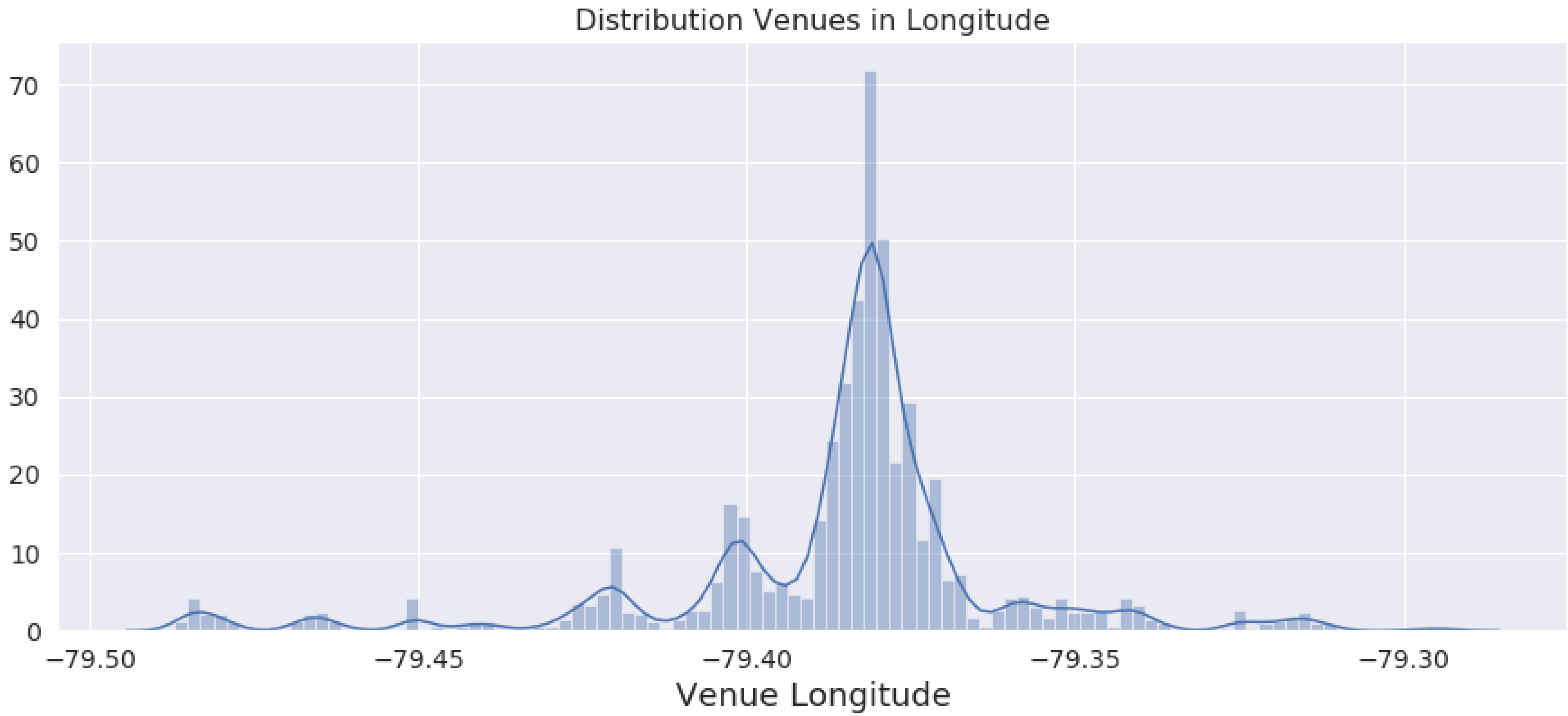
Plotting Distribution Venues in Latitude

In [193]:
```
plt.figure(figsize=(15,6))
plt.title('Distribution Venues in Latitude', fontsize=16)
plt.tick_params(labelsize=14)
sns.distplot(toronto_venues['Venue Latitude'], bins=100);
```



Plotting Distribution Venues in Longitude

In [194]:
```
plt.figure(figsize=(15,6))
plt.title('Distribution Venues in Longitude', fontsize=16)
plt.tick_params(labelsize=14)
sns.distplot(toronto_venues['Venue Longitude'], bins=100);
```



Let's plot on a map the first 10 venues with more presence at Toronto

In [20]:
```
indexes = toronto_venues['Venue Category'].value_counts()[:10].index
indexes

toronto_top10_venues = toronto_venues[toronto_venues['Venue Category'].isin(indexes)]

colors_array = cm.rainbow(np.linspace(0, 1, len(toronto_top10_venues['Venue Category'].unique())))
```

In [21]:
```python
rainbow = [colors.rgb2hex(i) for i in colors_array]
```

In [22]:
```python
categories = toronto_top10_venues['Venue Category'].unique()
color_df = pd.DataFrame(categories)
color_df['color'] = rainbow
color_df.columns = ['Category', 'Color']
color_df.head()
```

Out[22]:

	Category	Color
0	Italian Restaurant	#8000ff
1	Restaurant	#4856fb
2	Pizza Place	#10a2f0
3	Coffee Shop	#2adddd
4	Bakery	#62fbc4

In [186]:
```python
toronto_top10_venues['Color'] = toronto_top10_venues['Venue Category'].map(lambda category: color_df[colo
r_df['Category'] == category]['Color'].values[0])
toronto_top10_venues.head()
```

Out[186]:

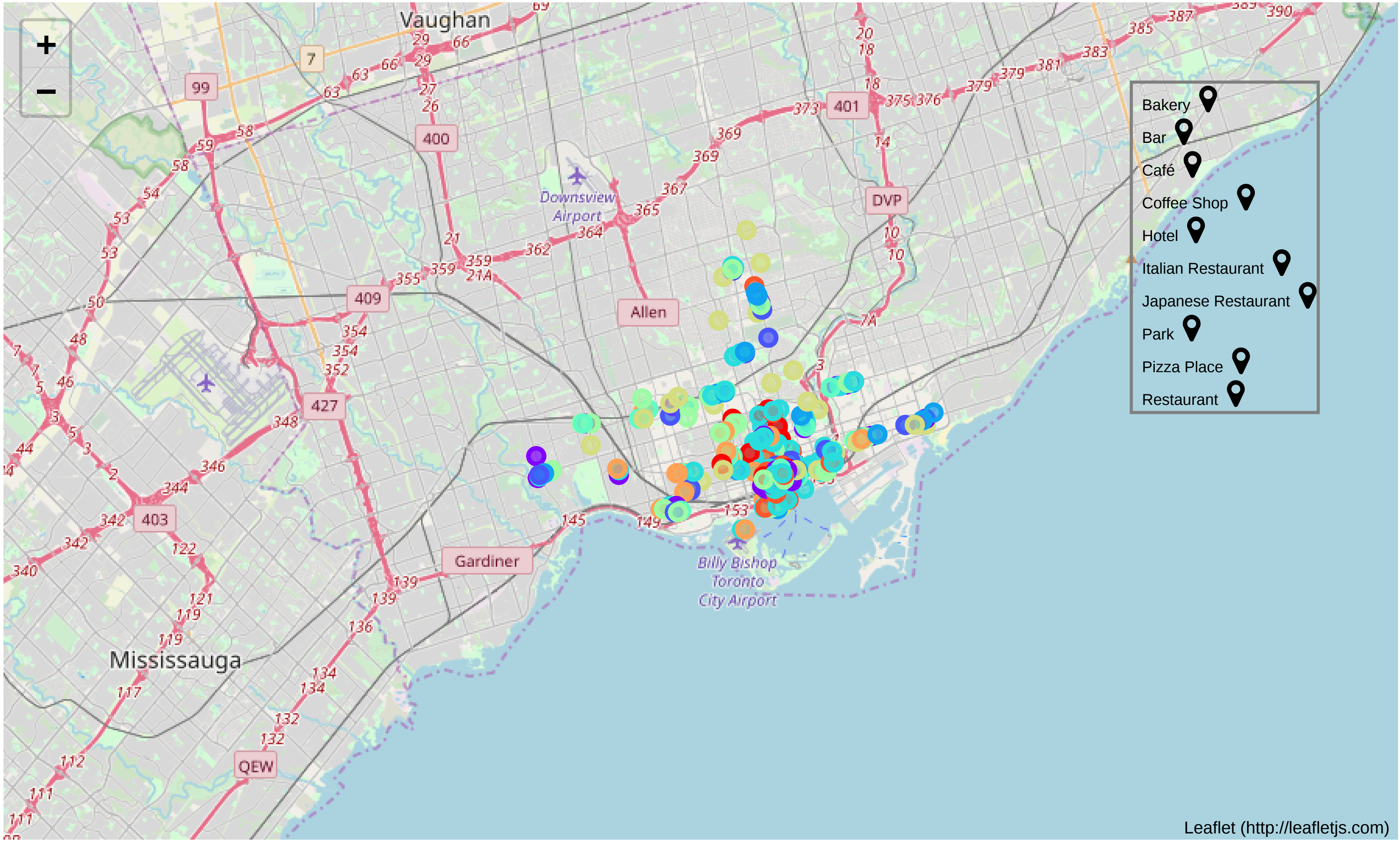
	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Color
9	The Danforth West, Riverdale	43.679557	-79.352188	Cafe Fiorentina	43.677743	-79.350115	Italian Restaurant	#8000ff
14	The Danforth West, Riverdale	43.679557	-79.352188	7 Numbers	43.677062	-79.353934	Italian Restaurant	#8000ff
16	The Danforth West, Riverdale	43.679557	-79.352188	Rikkochez	43.677267	-79.353274	Restaurant	#4856fb
19	The Danforth West, Riverdale	43.679557	-79.352188	Pizzeria Libretto	43.678489	-79.347576	Pizza Place	#10a2f0
34	The Danforth West, Riverdale	43.679557	-79.352188	Marvel Coffee Co.	43.678630	-79.347460	Coffee Shop	#2adddd

In [24]:
```
toronto_top10_venues.shape
```
Out[24]:
```
(547, 8)
```
In [25]:
```
address = 'Toronto'

geolocator = Nominatim(user_agent="ny_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geographical coordinate of Toronto are {}, {}.'.format(latitude, longitude))
```
```
The geographical coordinate of Toronto are 43.653963, -79.387207.
```

In [195]:

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

# add markers to the map
markers_colors = []
for lat, lon, color, category in zip(toronto_top10_venues['Venue Latitude'], toronto_top10_venues['Venue
 Longitude'], toronto_top10_venues['Color'], toronto_top10_venues['Venue Category']):

    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=category,
        color=color,
        fill=True,
        fill_color=color,
        fill_opacity=0.7).add_to(map_clusters)

legend_html = '<div style="position: fixed;top: 50px; right: 50px; width: auto; border:2px solid grey; z-
index:9999; font-size:10px;background-color:#ffffff">'

for group in toronto_top10_venues.groupby(['Venue Category', 'Color']).groups.keys():
    legend_html += '  ' + group[0] + '  <i class="fa fa-map-marker fa-2x" style="color:' + grou
p[1] +  '"></i><br>'

legend_html += '</div>'

map_clusters.get_root().html.add_child(folium.Element(legend_html))

map_clusters
```

Out[195]:



Density-Based Clustering

In [196]:
```
df_latlng = toronto_venues[['Venue Latitude', 'Venue Longitude']]
df_latlng.head()
```

Out[196]:

	Venue Latitude	Venue Longitude
0	43.676821	-79.293942
1	43.678879	-79.297734
2	43.679181	-79.297215
3	43.680563	-79.292869
4	43.677621	-79.351434

StandardScaler is used to keep relative distances between venues.

In [74]:
```
latlng = StandardScaler().fit_transform(np.nan_to_num(df_latlng))
latlng[:5]
```

Out[74]:
```
array([[1.3537186 , 3.45764199],
       [1.49142489, 3.31535502],
       [1.51166107, 3.33481641],
       [1.60411693, 3.49791304],
       [1.40726741, 1.30033056]])
```

In [75]:
```
dbscan = DBSCAN(eps=0.2, min_samples=3)
dbscan.fit(latlng)

print('labels:', np.unique(dbscan.labels_))
```

```
labels: [-1  0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20]
```

In [114]:
```
toronto_venues['Cluster'] = dbscan.labels_
toronto_venues.head()
```

Out[114]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster
0	The Beaches	43.676357	-79.293031	Glen Manor Ravine	43.676821	-79.293942	Trail	0
1	The Beaches	43.676357	-79.293031	The Big Carrot Natural Food Market	43.678879	-79.297734	Health Food Store	0
2	The Beaches	43.676357	-79.293031	Grover Pub and Grub	43.679181	-79.297215	Pub	0
3	The Beaches	43.676357	-79.293031	Upper Beaches	43.680563	-79.292869	Neighborhood	0
4	The Danforth West, Riverdale	43.679557	-79.352188	Pantheon	43.677621	-79.351434	Greek Restaurant	1

Next is to create an array of colors to plot each venue on the map based on the cluster this time

In [116]:
```
colors_array_cluster = cm.rainbow(np.linspace(0, 1, len(toronto_venues['Cluster'].unique())))
rainbow_cluster = [colors.rgb2hex(i) for i in colors_array_cluster]
```

In [117]:
```
d = {'Color':rainbow_cluster,'Cluster':list(np.unique(dbscan.labels_))}
df_cluster_color = pd.DataFrame(d)
df_cluster_color.head()
```

Out[117]:

	Color	Cluster
0	#8000ff	-1
1	#6826fe	0
2	#504afc	1
3	#386df9	2
4	#208ef4	3

In [131]:
```
toronto_venues['Cluster Color'] = toronto_venues['Cluster'].map(lambda c: df_cluster_color[df_cluster_col
or['Cluster'] == c]['Color'].values[0])
toronto_venues.head()
```

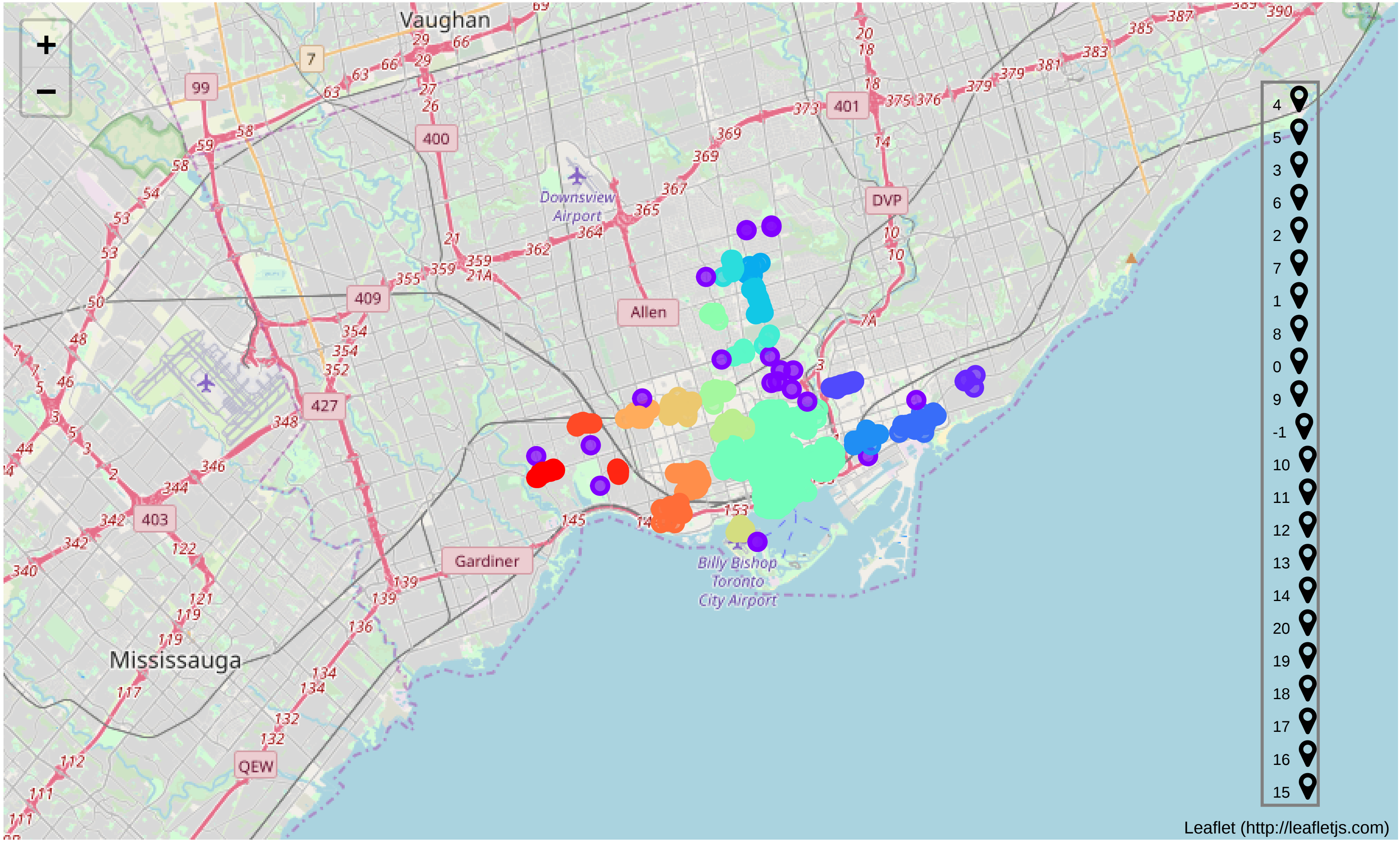
Out[131]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster	Cluster Color
0	The Beaches	43.676357	-79.293031	Glen Manor Ravine	43.676821	-79.293942	Trail	0	#6826fe
1	The Beaches	43.676357	-79.293031	The Big Carrot Natural Food Market	43.678879	-79.297734	Health Food Store	0	#6826fe
2	The Beaches	43.676357	-79.293031	Grover Pub and Grub	43.679181	-79.297215	Pub	0	#6826fe
3	The Beaches	43.676357	-79.293031	Upper Beaches	43.680563	-79.292869	Neighborhood	0	#6826fe
4	The Danforth West, Riverdale	43.679557	-79.352188	Pantheon	43.677621	-79.351434	Greek Restaurant	1	#504afc

In [198]:

```
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to the map
markers_colors = []
for lat, lon, color, cluster in zip(toronto_venues['Venue Latitude'], toronto_venues['Venue Longitude'], toronto_venues['Cluster Color'], toronto_venues['Cluster']):

    folium.CircleMarker(
        [lat, lon],
        radius=5,
        color=color,
        fill=True,
        fill_color=color,
        fill_opacity=0.7).add_to(map_clusters)

legend_html = '<div style="position: fixed;top: 50px; right: 50px; width: auto; border:2px solid grey; z-index:9999; font-size:10px;background-color:#ffffff">'

for group in toronto_venues.groupby(['Cluster Color', 'Cluster']).groups.keys():
    legend_html += '  ' + str(group[1]) + '  <i class="fa fa-map-marker fa-2x" style="color:' + str(group[0]) +  '"></i><br>'

legend_html += '</div>'

map_clusters.get_root().html.add_child(folium.Element(legend_html))

map_clusters
```

Out[198]:



Cluster Analysis

Let's check which clusters are the most densely populated.

In [149]:
```
toronto_venues['Cluster'].value_counts()
```

Out[149]:
```
 9     1228
 16      64
 1       44
 3       38
 5       38
 2       37
 20      35
 12      31
 11      23
 17      22
 18      22
-1       21
 6       20
 14      17
 8       14
 19      14
 15      13
 13      12
 4        6
 10       5
 0        4
 7        3
Name: Cluster, dtype: int64
```

As we can see in the following list, cluster 9 is overcrowded compared with others. Lets analyze this cluster again with DBSCAN.

In [199]:
```python
toronto_venues_c9 = toronto_venues[toronto_venues['Cluster'] == 9]
toronto_venues_c9.drop(['Cluster', 'Cluster Color'], axis=1, inplace=True) ## Dropping the previous analy
sis made
toronto_venues_c9.head()
```

Out[199]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
199	Cabbagetown, St. James Town	43.667967	-79.367675	Cranberries	43.667843	-79.369407	Diner
200	Cabbagetown, St. James Town	43.667967	-79.367675	F'Amelia	43.667536	-79.368613	Italian Restaurant
201	Cabbagetown, St. James Town	43.667967	-79.367675	Butter Chicken Factory	43.667072	-79.369184	Indian Restaurant
202	Cabbagetown, St. James Town	43.667967	-79.367675	Kingyo Toronto	43.665895	-79.368415	Japanese Restaurant
203	Cabbagetown, St. James Town	43.667967	-79.367675	Murgatroid	43.667381	-79.369311	Restaurant

In [200]:
```python
df_latlng = toronto_venues_c9[['Venue Latitude', 'Venue Longitude']]
df_latlng.head()
```

Out[200]:

	Venue Latitude	Venue Longitude
199	43.667843	-79.369407
200	43.667536	-79.368613
201	43.667072	-79.369184
202	43.665895	-79.368415
203	43.667381	-79.369311

In [201]:
```
latlng = StandardScaler().fit_transform(np.nan_to_num(df_latlng))
latlng[:5]
```

Out[201]:
```
array([[2.38125294, 1.33275947],
       [2.33528933, 1.42433016],
       [2.26587349, 1.35845134],
       [2.08949989, 1.44719023],
       [2.31216006, 1.34378935]])
```

In [202]:
```
dbscan = DBSCAN(eps=0.2, min_samples=3)
dbscan.fit(latlng)

print('labels:', np.unique(dbscan.labels_))
```

```
labels: [-1  0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16]
```

In [203]:
```
toronto_venues_c9['Cluster'] = dbscan.labels_
toronto_venues_c9.head()
```

Out[203]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster
199	Cabbagetown, St. James Town	43.667967	-79.367675	Cranberries	43.667843	-79.369407	Diner	0
200	Cabbagetown, St. James Town	43.667967	-79.367675	F'Amelia	43.667536	-79.368613	Italian Restaurant	0
201	Cabbagetown, St. James Town	43.667967	-79.367675	Butter Chicken Factory	43.667072	-79.369184	Indian Restaurant	0
202	Cabbagetown, St. James Town	43.667967	-79.367675	Kingyo Toronto	43.665895	-79.368415	Japanese Restaurant	0
203	Cabbagetown, St. James Town	43.667967	-79.367675	Murgatroid	43.667381	-79.369311	Restaurant	0

In [204]:

```
colors_array_cluster = cm.rainbow(np.linspace(0, 1, len(toronto_venues_c9['Cluster'].unique())))
rainbow_cluster = [colors.rgb2hex(i) for i in colors_array_cluster]

d = {'Color':rainbow_cluster,'Cluster':list(np.unique(dbscan.labels_))}
df_cluster_color = pd.DataFrame(d)
df_cluster_color.head()

toronto_venues_c9['Cluster Color'] = toronto_venues_c9['Cluster'].map(lambda c: df_cluster_color[df_clust
er_color['Cluster'] == c]['Color'].values[0])
toronto_venues_c9.head()
```

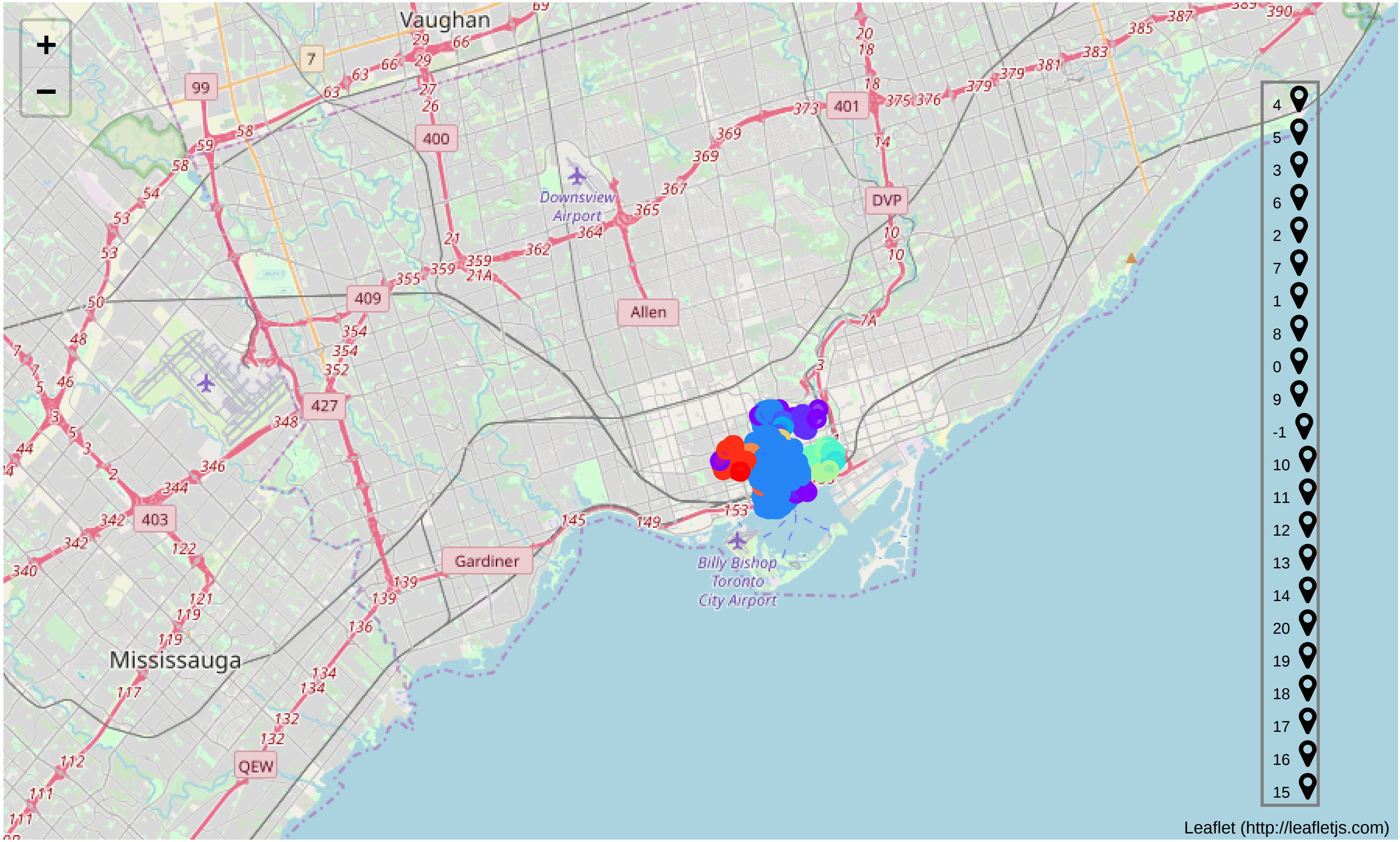
Out[204]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Cluster	Cluster Color
199	Cabbagetown, St. James Town	43.667967	-79.367675	Cranberries	43.667843	-79.369407	Diner	0	#622ffe
200	Cabbagetown, St. James Town	43.667967	-79.367675	F'Amelia	43.667536	-79.368613	Italian Restaurant	0	#622ffe
201	Cabbagetown, St. James Town	43.667967	-79.367675	Butter Chicken Factory	43.667072	-79.369184	Indian Restaurant	0	#622ffe
202	Cabbagetown, St. James Town	43.667967	-79.367675	Kingyo Toronto	43.665895	-79.368415	Japanese Restaurant	0	#622ffe
203	Cabbagetown, St. James Town	43.667967	-79.367675	Murgatroid	43.667381	-79.369311	Restaurant	0	#622ffe

In [206]:

```python
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# add markers to the map
markers_colors = []
for lat, lon, color, cluster in zip(toronto_venues_c9['Venue Latitude'], toronto_venues_c9['Venue Longitude'], toronto_venues_c9['Cluster Color'], toronto_venues_c9['Cluster']):

    folium.CircleMarker(
        [lat, lon],
        radius=5,
        color=color,
        fill=True,
        fill_color=color,
        fill_opacity=0.7).add_to(map_clusters)

legend_html = '<div style="position: fixed;top: 50px; right: 50px; width: auto; border:2px solid grey; z-index:9999; font-size:10px;background-color:#ffffff">'

for group in toronto_venues.groupby(['Cluster Color', 'Cluster']).groups.keys():
    legend_html += '  ' + str(group[1]) + '  <i class="fa fa-map-marker fa-2x" style="color:' + str(group[0]) +  '"></i><br>'

legend_html += '</div>'

map_clusters.get_root().html.add_child(folium.Element(legend_html))

map_clusters
```

Out[206]:



Now we have the same pattern as before. One cluster (number 2) is overcrowded compared with others.

In [207]:
```
toronto_venues_c9['Cluster'].value_counts()
```

Out[207]:
```
 2     964
 15     94
 0      38
 1      36
 9      21
-1      14
 13     12
 16      7
 6       7
 5       6
 4       5
 8       5
 7       4
 11      3
 10      3
 12      3
 3       3
 14      3
Name: Cluster, dtype: int64
```

In [210]:
```
toronto_venues_c9['Venue Category'].value_counts().iloc[:20]
```

Out[210]:
```
Coffee Shop                        119
Café                                64
Hotel                               39
Restaurant                          38
Italian Restaurant                  30
Bakery                              30
Japanese Restaurant                 23
Bar                                 22
Steakhouse                          20
Gastropub                           20
Seafood Restaurant                  20
American Restaurant                 19
Vegetarian / Vegan Restaurant       18
Burger Joint                        18
Pizza Place                         18
Clothing Store                      17
Beer Bar                            17
Park                                16
Gym                                 16
Thai Restaurant                     16
Name: Venue Category, dtype: int64
```

In [209]:
```
toronto_venues_c16 = toronto_venues[toronto_venues['Cluster'] == 16]
toronto_venues_c16['Venue Category'].value_counts().iloc[:20]
```

Out[209]:
```
Bar                                8
Asian Restaurant                   3
Coffee Shop                        3
Vietnamese Restaurant              2
Café                               2
Men's Store                        2
Boutique                           2
French Restaurant                  2
Cocktail Bar                       2
Restaurant                         2
Pizza Place                        2
Yoga Studio                        1
Southern / Soul Food Restaurant    1
Mac & Cheese Joint                 1
Cupcake Shop                       1
Playground                         1
Record Shop                        1
Juice Bar                          1
Art Gallery                        1
Deli / Bodega                      1
Name: Venue Category, dtype: int64
```

Results & Discussion

- I analyzed venues from Toronto neighborhoods group by postalcode. One part of it was done on the previous course but I wanted to expand that analysis further. By having venues I could plot the ammount of the them per neighborhood and see what was each one of this composed by.
- A boxplot was used to analyze the top 10 of the most frequent categories for latitude and logitude.
- I plotted distribution of venues bases on their locations. One for latitude and the other for longitude. It seems there is a bigger density between latitudes(43,64 | 43,66) and longitudes (-79,40 |-79,35). It means, most of the venues are here.
- I plotted the top 10 categories on a map confirming the hypotesis of the previous point.
- DBSCAN was used two times, once for the entire dataset and the second one for the most overcrowed cluster. The analysis on these clusters are in the following section.

Conclusion

We can see that cluster 9 is by far the most crowded cluster calculated with many **Coffe Shops** in it. Most of the **Venue Category** found in this cluster can be grouped as **FOOD** except for the **Hotel**. It makes sense since, for example, travelers want to enjoy the gastronomic options around city and still have a place where to rest nearby. It seems to be a good option for business related with food. As the density increases the cost of terrain does too, so a next step for the analysis might be including terrain cost.

On the other side, the second most crowded cluster is **16** and it has options related with **FOOD** as the previous cluster had, but it has other options related with **shopping** that might be interesting for turists as well.

For investors this analysis can be found very useful to know where to open the next store in the city. It was out of scope the prices of the terrains or the availability of them. This could be for future steps.