Segmenting and Clustering Neighborhoods in Fredericton, NB

Applied Data Science Capstone Week 5 Peer-Graded Project Report

By Ashna Kumar

Introduction to the opportunity

Fredericton is the Capital City of the only Canadian fully-bilingual Province of New Brunswick and is beautifully located on the banks of the Saint John River. While one of the least populated provincial capital cities with a population base of less than 60 thousand residents, it offers a wide spectrum of venues and is a governement, university and cultural hub.

As the city grows and develops, it becomes increasingly important to examine and understand it quantitiatively. The City of Fredericton provides open data for everyone and encourages entrepreneurial use to develop services for the benefit of its ciitzens.

Developers, investors, policy makers and/or city planners have an interest in answering the following questions as the need for additional services and citizen protection:

1. What neighbourhoods have the highest crime?
2. Is population density correlated to crime level?
3. Using Foursquare data, what venues are most common in different locations within the city?
4. Does the Knowledge Park really need a coffee shop?

Does the Open Data project have specific enough or thick enough data to empower decisions to be made or is it too aggregate to provide value in its current detail? Let's find out.

In [73]:
```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "http://www.tourismfredericton.ca/sites/default/files/field/image/freder
icton.jpg")
```

Out[73]:

Data

To understand and explore we will need the following City of Fredericton Open Data:

1. Open Data Site: http://data-fredericton.opendata.arcgis.com/ (http://data-fredericton.opendata.arcgis.com/)
2. Fredericton Neighbourhoods: http://data-fredericton.opendata.arcgis.com/datasets/neighbourhoods--quartiers (http://data-fredericton.opendata.arcgis.com/datasets/neighbourhoods--quartiers)
3. Fredericton Crime by Neighbourhood: http://data-fredericton.opendata.arcgis.com/datasets/crime-by-neighbourhood- 2017--crime-par-quartier-2017 (http://data-fredericton.opendata.arcgis.com/datasets/crime-by-neighbourhood-2017-- crime-par-quartier-2017)
4. Fredericton Census Tract Demographics: http://data-fredericton.opendata.arcgis.com/datasets/census-tract- demographics--donn%C3%A9es-d%C3%A9mographiques-du-secteur-de-recensement (http://data- fredericton.opendata.arcgis.com/datasets/census-tract-demographics--donn%C3%A9es-d%C3%A9mographiques-du- secteur-de-recensement)
5. Fredericton locations of interest: https://github.com/ashnakumar/Coursera_Capstone/blob/master/Fredericton%20Locations.xlsx
6. Foursquare Developers Access to venue data: https://foursquare.com/ (https://foursquare.com/)

Using this data will allow exploration and examination to answer the questions. The neighbourhood data will enable us to properly group crime by neighbourhood. The Census data will enable us to then compare the population density to examine if areas of highest crime are also most densely populated. Fredericton locations of interest will then allow us to cluster and quantitatively understand the venues most common to that location.

Methodology

All steps are referenced beleow in the Appendix: Analysis section. The methodology will include:

1. Loading each data set
2. Examine the crime frequency by neighbourhood
3. Study the crime types and then pivot analysis of crime type frequency by neighbourhood
4. Understand correlation between crimes and population density
5. Perform k-means statisical analysis on venues by locations of interest based on findings from crimes and neighbourhood
6. Determine which venues are most common statistically in the region of greatest crime count then in all other locations of interest.
7. Determine if an area, such as the Knowledge Park needs a coffee shop.

Loading the data

After loading the applicable libraries, the referenced geojson neighbourhood data was loaded from the City of Fredericton Open Data site. This dataset uses block polygon shape coordinates which are better for visualization and comparison. The City also uses Ward data but the Neighbourhood location data is more accurate and includes more details. The same type of dataset was then loaded for the population density from the Stats Canada Census tracts.

The third dataset, an excel file, "Crime by Neighbourhood 2017" downloaded from the City of Fredericton Open Data site is found under the Public Safety domain. This dataset was then uploaded for the analysis. It's interesting to note the details of this dataset are aggregated by neighbourhood. It is not an exhaustive set by not including all crimes (violent offenses) nor specific location data of the crime but is referenced by neighbourhood.

This means we can gain an understanding of the crime volume by type by area but not specific enough to understand the distribution properties. Valuable questions such as, "are these crimes occuring more often in a specific area and at a certain time by a specific demographic of people?" cannot be answered nor explored due to what is reasonably assumed to be personal and private information with associated legal risks.

There is value to the city to explore the detailed crime data using data science to predict frequency, location, timing and conditions to best allocated resources for the benefit of its citizens and it's police force. However, human behaviour is complex requiring thick profile data by individual and the conditions surrounding the event(s). To be sufficient for reliable future prediction it would need to demonstrate validity, currency, reliability and sufficiency.

Exploring the data

Exploring the count of crimes by neighbourhood gives us the first glimpse into the distribution.

One note is the possibility neighbourhoods names could change at different times. The crime dataset did not mention which specific neighbourhood naming dataset it was using but we assumed the neighbourhood data provided aligned with the neighbourhoods used in the crime data. It may be beneficial for the City to note and timestamp neighbourhood naming in the future or simply reference with neighbourhood naming file it used for the crime dataset.

An example of data errors: There was an error found in the naming of the neighbourhood "Platt". The neighbourhood data stated "Plat" while the crime data stated "Platt". Given the crime dataset was most simple to manipulate it was modified to "Plat". The true name of the neighbourhood is "Platt".

First Visualization of Crime

Once the data was prepared, a choropleth map was created to view the crime count by neighbourhood. As expected the region of greatest crime count was found in the downtown and Platt neighbourhoods.

Examining the crime types enables us to learn the most frequent occuring crimes which we then plot as a bar chart to see most frequenty type.

Theft from motor vehicles is most prevalent in the same area as the most frequent crimes. It's interesting to note this area is mostly residential and most do not have garages. It would be interesting to further examine if surveillance is a deterant for motor vehicle crimes in the downtown core compared to low surveillance in the Platt neighbourhood.

Examining 2nd most common crime given it is specific: theft from vehicles

After exploring the pivot table showing Crime_Type by Neighbourhood, we drill into a specific type of crime, theft from vehicles and plot the choropleth map to see which area has the greatest frequency.

Again, the Platt neighbourhood appears as the most frequent. Is this

due to population density?

Introducing the Census data to explore the correlation between crime frequency and population density.

Visualising the population density enables us to determine that the Platt neighbourhood has lower correlation to crime frequency than I would have expected.

It would be interesting to further study the Census data and if this captures the population that is renting or more temporary/transient poplution, given the City is a University hub.

Look at specific locations to understand the connection to venues using Foursquare data

Loading the "Fredericton Locations" data enables us to perform a statistical analysis on the most common venues by location.

We might wonder if the prevalence of bars and clubs in the downtown region has something to do with the higher crime rate in the near Platt region.

Plotting the latitude and longitude coordinates of the locations of interest onto the crime choropleth map enables us to now study the most common venues by using the Foursquare data.

Analysing each Location

Grouping rows by location and the mean of the frequency of occurance of each category we venue categories we study the top five most common venues.

Putting this data into a pandas dataframe we can then determine the most common venues by location and plot onto a map.

Results

The analysis enabled us to discover and describe visually and quantitatively:

1. Neighbourhoods in Fredericton
2. Crime freqency by neighbourhood
3. Crime type frequency and statistics. The mean crime count in the City of Fredericton is 22.
4. Crime type count by neighbourhood.
   Theft from motor vehicles is most prevalent in the same area as the most frequent crimes. It's interesting to note this area is mostly residential and most do not have garages. It would be interesting to further examine if surveillance is a deterant for motor vehicle crimes in the downtown core compared to low surveillance in the Platt neighbourhood.

1. Motor Vehicle crimes less than $5000 analysis by neighbourhood and resulting statistics.
   The most common crime is **Other Theft less than 5k** followed by **Motor Vehicle Theft less than 5k**. There is a mean of 6 motor vehicle thefts less than 5k by neighbourhood in the City.
2. That population density and resulting visual correlation is not strongly correlated to crime frequency. Causation for crime is not able to be determined given lack of open data specificity by individual and environment.
3. Using k-menas, we were able to determine the top 10 most common venues within a 1 km radius of the centroid of the highest crime neighbourhood. **The most common venues in the highest crime neighbourhood are coffee shops followed by Pubs and Bars**.

While, it is not valid, consistent, reliable or sufficient to assume a higher concentration of the combination of coffee shops, bars and clubs predicts the amount of crime occurance in the City of Fredericton, this may be a part of the model needed to be able to in the future.

1. We were able to determine the top 10 most common venues by location of interest.
2. Statisically, we determined there are no coffee shops within the Knowledge Park clusters.

Discussion and Recommendations

The City of Fredericton Open Data enables us to gain an understanding of the crime volume by type by area but not specific enough to understand the distribution properties. Valuable questions such as, "are these crimes occuring more often in a specific area and at a certain time by a specific demographic of people?" cannot be answered nor explored due to what is reasonably assumed to be personal and private information with associated legal risks.

There is value to the city to explore the detailed crime data using data science to predict frequency, location, timing and conditions to best allocated resources for the benefit of its citizens and it's police force. However, human behaviour is complex requiring thick profile data by individual and the conditions surrounding the event(s). To be sufficient for reliable future prediction it would need to demonstrate validity, currency, reliability and sufficiency.

A note of caution is the possibility neighbourhoods names could change. The crime dataset did not mention which specific neighbourhood naming dataset it was using but we assumed the neighbourhood data provided aligned with the neighbourhoods used in the crime data. It may be beneficial for the City to note and timestamp neighbourhood naming in the future or simply reference with neighbourhood naming file it used for the crime dataset.

Errors exist in the current open data. An error was found in the naming of the neighbourhood "Platt". The neighbourhood data stated "Plat" while the crime data stated "Platt". Given the crime dataset was most simple to manipulate it was modified to "Plat". The true name of the neighbourhood is "Platt".

Theft from motor vehicles is most prevalent in the same area as the most frequent crimes. It is interesting to note this area is mostly residential and most do not have garages. It would be interesting to further examine if surveillance is a deterant for motor vehicle crimes in the downtown core compared to low surveillance in the Platt neighbourhood.

It would be interesting to further study the Census data and if this captures the population that is renting or more temporary/transient poplution, given the City is a University hub.

Given the findings of the top 10 most frequent venues by locations of interest, the Knowledge Park does not have Coffee Shops in the top 10 most common venues as determined from the Foursquare dataset. Given this area has the greatest concentration of stores and shops as venues, it would be safe to assume a coffee shop would be beneficial to the business community and the citizens of Fredericton.

Conclusion

Using a combination of datasets from the City of Fredericton Open Data project and Foursquare venue data we were able to analyse, discover and describe neighbhourhoods, crime, population density and statistically describe quantitatively venues by locations of interest.

While overall, the City of Fredericton Open Data is interesting, it misses the details required for true valued quantitiatve analysis and predictive analytics which would be most valued by investors and developers to make appropriate investments and to minimize risk.

The Open Data project is a great start and empowers the need for a "Citizens Like Me" model to be developed where citizens of digital Fredericton are able to share their data as they wish for detailed analysis that enables the creation of valued services.

APPENDIX: Analysis

Load Libraries

In [74]:
```
import numpy as np

import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json

!conda install -c conda-forge geopy --yes # uncomment this line if you haven't comp
leted the Foursquare API lab
from geopy.geocoders import Nominatim


import requests
from pandas.io.json import json_normalize



import matplotlib.cm as cm
import matplotlib.colors as colors


from sklearn.cluster import KMeans


from bs4 import BeautifulSoup

import xml

!conda install -c conda-forge folium=0.5.0 --yes
import folium

print('Libraries imported.')
```

```
Solving environment: done

# All requested packages already installed.

Solving environment: done

# All requested packages already installed.

Libraries imported.
```

In [3]:
```
pwd
```

Out[3]:
```
'/Users/ashnakristaurquhart/Documents/GitHub/Coursera-IBM-Applied-Data-Science-Cap
stone-Project'
```

In [75]:
```
r = requests.get('https://opendata.arcgis.com/datasets/823d86e17a6d47808c6e4f1c2dd9
7928_0.geojson')
fredericton_geo = r.json()
```

In [76]:
```
neighborhoods_data = fredericton_geo['features']
```

In [77]:
```
neighborhoods_data[0]
```

```
Out[77]: {'type': 'Feature',
          'properties': {'FID': 1,
           'OBJECTID': 1,
           'Neighbourh': 'Fredericton South',
           'Shape_Leng': 40412.2767429,
           'Shape_Area': 32431889.0002},
          'geometry': {'type': 'Polygon',
           'coordinates': [[[-66.6193489311946, 45.8688925859664],
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```

[-66.7051919397451, 45.9388543785676],
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[-66.6524428662616, 45.9296016295261],
[-66.6531166027247, 45.9293392062996],
[-66.6540508506202, 45.9291580085852],
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[[-66.6318085641854, 45.8878357293373],
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```
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    [-66.617345688111, 45.8989772091164],
    [-66.6203819937714, 45.8954199312614],
    [-66.6263468072579, 45.8892363524244],
    [-66.6281254715205, 45.8883672199348],
    [-66.6291315846387, 45.8880795903605],
    [-66.6304521081064, 45.8878732464875],
    [-66.6318085641854, 45.8878357293373]]]}}
```


In [78]:

```
g = requests.get('https://opendata.arcgis.com/datasets/6179d35eacb144a5b5fdcc869f86dfb5_0.geojson')
demog_geo = g.json()
```

In [79]:

```
demog_data = demog_geo['features']
demog_data[0]
```

Out[79]:


```
{'type': 'Feature',
 'properties': {'FID': 1,
  'OBJECTID': 501,
  'DBUID': '1310024304',
  'DAUID': '13100243',
  'CDUID': '1310',
  'CTUID': '3200002.00',
  'CTNAME': '0002.00',
  'DBuid_1': '1310024304',
  'DBpop2011': 60,
  'DBtdwell20': 25,
  'DBurdwell2': 22,
  'Shape_Leng': 0.00746165241824,
  'Shape_Area': 2.81310751889e-06,
  'CTIDLINK': 3200002,
  'Shape_Area': 2.81310897700361e-06,
  'Shape_Length': 0.00746165464503067},
 'geometry': {'type': 'Polygon',
  'coordinates': [[[-66.634784212921, 45.9519239912381],
    [-66.6351046935752, 45.9507605156138],
    [-66.6378263667982, 45.9510868696778],
    [-66.636944377136, 45.9521037018384],
    [-66.634784212921, 45.9519239912381]]]}}
```


In [ ]:

In [80]:
```
import os
os.listdir('.')
```

Out[80]:
```
['Capstone Project Course.ipynb',
 'Fredericton_Census_Tract_Demographics.csv',
 '.DS_Store',
 'Fredericton_Census_Tract_Demographics.xlsx',
 'Crime_by_neighbourhood_2017.xlsx',
 'Capstone Fredericton Crime and Police Station Location.ipynb',
 'Boston_Neighborhoods (1).geojson',
 'Fredericton Locations.xlsx',
 'Week 3 Capstone - Segmenting and Clustering Neighbourhoods in Toronto_Part 2.ipy
nb',
 'Fredericton.jpg',
 'Week 3 Capstone - Segmenting and Clustering Neighbourhoods in Toronto_Part 2.pd
f',
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 '.ipynb_checkpoints',
 '.git',
 'Week 3 Capstone - Segmenting and Clustering Neighbourhoods in Toronto.ipynb',
 'Week 4 Capstone - Segmenting and Clustering Neighbourhoods in Boston.ipynb',
 'Week 3 Capstone - Segmenting and Clustering Neighbourhoods in Toronto_Part 2.ht
m',
 'Week 4 Capstone - Segmenting and Clustering Neighbourhoods in Fredericton.ipyn
b',
 'Week 4 Capstone - Segmenting and Clustering Neighbourhoods in Fredericton - Gith
ub submit.ipynb',
 'Week 3 Capstone - Segmenting and Clustering Neighbourhoods in Toronto_Part 2_fil
es']
```

In [81]:
```
opencrime = 'Crime_by_neighbourhood_2017.xlsx'
```

In [82]:
```
workbook = pd.ExcelFile(opencrime)
print(workbook.sheet_names)
```

```
['Crime_by_neighbourhood_2017']
```

In [83]:
```
crime_df =workbook.parse('Crime_by_neighbourhood_2017')
crime_df.head()
```

Out[83]:

	Neighbourhood	From_Date	To_Date	Crime_Code	Crime_Type	Ward	City	FID
0	Fredericton South	2017-01-05T00:00:00.000Z	2017-01-26T00:00:00.000Z	2120	B&E NON-RESIDNCE	7	Fredericton	1
1	Fredericton South	2017-03-04T00:00:00.000Z	2017-03-06T00:00:00.000Z	2120	B&E NON-RESIDNCE	7	Fredericton	2
2	Fredericton South	2017-05-07T00:00:00.000Z	NaN	2120	B&E NON-RESIDNCE	12	Fredericton	3
3	Fredericton South	2017-06-20T00:00:00.000Z	2017-06-21T00:00:00.000Z	2120	B&E NON-RESIDNCE	12	Fredericton	4
4	Fredericton South	2017-07-09T00:00:00.000Z	2017-07-10T00:00:00.000Z	2120	B&E NON-RESIDNCE	7	Fredericton	5

In [84]:
```
crime_df.drop(['From_Date', 'To_Date'], axis=1,inplace=True)
```

What is the crime count by neighbourhood?

In [128]:
```
crime_data = crime_df.groupby(['Neighbourhood']).size().to_frame(name='Count').rese
t_index()
crime_data
```

Out[128]:

	Neighbourhood	Count
0	Barkers Point	47
1	Brookside	54
2	Brookside Estates	9
3	Brookside Mini Home Park	5
4	College Hill	41
5	Colonial heights	9
6	Cotton Mill Creek	4
7	Diamond Street	1
8	Doak Road	1
9	Douglas	3
10	Downtown	127
11	Dun's Crossing	18
12	Forest Hill	12
13	Fredericton South	85
14	Fulton Heights	36
15	Garden Creek	13
16	Garden Place	4
17	Gilridge Estates	3
18	Golf Club	7
19	Grasse Circle	1
20	Greenwood Minihome Park	2
21	Hanwell North	8
22	Heron Springs	3
23	Highpoint Ridge	5
24	Kelly's Court Minihome Park	1
25	Knob Hill	4
26	Knowledge Park	1
27	Lian / Valcore	7
28	Lincoln	13
29	Lincoln Heights	14
30	Main Street	78
31	Marysville	39
32	McKnight	4
33	McLeod Hill	3
34	Monteith / Talisman	12
35	Montogomery / Prospect East	16
36	Nashwaaksis	25
37	Nethervue Minihome Park	1
38	North Devon	113

	Neighbourhood	Count
39	Northbrook Heights	10
40	Plat	198
41	Poet's Hill	4
42	Prospect	81
43	Rail Side	3
44	Regiment Creek	1
45	Royal Road	7
46	Saint Mary's First Nation	25
47	Saint Thomas University	1
48	Sandyville	9
49	Serenity Lane	2
50	Shadowood Estates	5
51	Silverwood	12
52	Skyline Acrea	27
53	South Devon	68
54	Southwood Park	16
55	Springhill	1
56	Sunshine Gardens	10
57	The Hill	44
58	The Hugh John Flemming Forestry Center	3
59	University Of New Brunswick	15
60	Waterloo Row	9
61	Wesbett / Case	1
62	West Hills	5
63	Williams / Hawkins Area	17
64	Woodstock Road	41
65	Youngs Crossing	16

In [153]:
```
crime_data.describe()
```

Out[153]:

	Count
count	66.000000
mean	22.121212
std	34.879359
min	1.000000
25%	3.000000
50%	9.000000
75%	23.250000
max	198.000000

In [86]:
```
crime_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'Crime_C
ount'}, inplace=True)
crime_data
```

Out[86]:

	Neighbourh	Crime_Count
0	Barkers Point	47
1	Brookside	54
2	Brookside Estates	9
3	Brookside Mini Home Park	5
4	College Hill	41
5	Colonial heights	9
6	Cotton Mill Creek	4
7	Diamond Street	1
8	Doak Road	1
9	Douglas	3
10	Downtown	127
11	Dun's Crossing	18
12	Forest Hill	12
13	Fredericton South	85
14	Fulton Heights	36
15	Garden Creek	13
16	Garden Place	4
17	Gilridge Estates	3
18	Golf Club	7
19	Grasse Circle	1
20	Greenwood Minihome Park	2
21	Hanwell North	8
22	Heron Springs	3
23	Highpoint Ridge	5
24	Kelly's Court Minihome Park	1
25	Knob Hill	4
26	Knowledge Park	1
27	Lian / Valcore	7
28	Lincoln	13
29	Lincoln Heights	14
30	Main Street	78
31	Marysville	39
32	McKnight	4
33	McLeod Hill	3
34	Monteith / Talisman	12
35	Montogomery / Prospect East	16
36	Nashwaaksis	25
37	Nethervue Minihome Park	1
38	North Devon	113

	Neighbourh	Crime_Count
39	Northbrook Heights	10
40	Plat	198
41	Poet's Hill	4
42	Prospect	81
43	Rail Side	3
44	Regiment Creek	1
45	Royal Road	7
46	Saint Mary's First Nation	25
47	Saint Thomas University	1
48	Sandyville	9
49	Serenity Lane	2
50	Shadowood Estates	5
51	Silverwood	12
52	Skyline Acrea	27
53	South Devon	68
54	Southwood Park	16
55	Springhill	1
56	Sunshine Gardens	10
57	The Hill	44
58	The Hugh John Flemming Forestry Center	3
59	University Of New Brunswick	15
60	Waterloo Row	9
61	Wesbett / Case	1
62	West Hills	5
63	Williams / Hawkins Area	17
64	Woodstock Road	41
65	Youngs Crossing	16

In [87]:
```
crime_data.rename({'Platt': 'Plat'},inplace=True)
crime_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'Crime_C
ount'}, inplace=True)
crime_data
```

Out[87]:

	Neighbourh	Crime_Count
0	Barkers Point	47
1	Brookside	54
2	Brookside Estates	9
3	Brookside Mini Home Park	5
4	College Hill	41
5	Colonial heights	9
6	Cotton Mill Creek	4
7	Diamond Street	1
8	Doak Road	1
9	Douglas	3
10	Downtown	127
11	Dun's Crossing	18
12	Forest Hill	12
13	Fredericton South	85
14	Fulton Heights	36
15	Garden Creek	13
16	Garden Place	4
17	Gilridge Estates	3
18	Golf Club	7
19	Grasse Circle	1
20	Greenwood Minihome Park	2
21	Hanwell North	8
22	Heron Springs	3
23	Highpoint Ridge	5
24	Kelly's Court Minihome Park	1
25	Knob Hill	4
26	Knowledge Park	1
27	Lian / Valcore	7
28	Lincoln	13
29	Lincoln Heights	14
30	Main Street	78
31	Marysville	39
32	McKnight	4
33	McLeod Hill	3
34	Monteith / Talisman	12
35	Montogomery / Prospect East	16
36	Nashwaaksis	25
37	Nethervue Minihome Park	1
38	North Devon	113

	Neighbourh	Crime_Count
39	Northbrook Heights	10
40	Plat	198
41	Poet's Hill	4
42	Prospect	81
43	Rail Side	3
44	Regiment Creek	1
45	Royal Road	7
46	Saint Mary's First Nation	25
47	Saint Thomas University	1
48	Sandyville	9
49	Serenity Lane	2
50	Shadowood Estates	5
51	Silverwood	12
52	Skyline Acrea	27
53	South Devon	68
54	Southwood Park	16
55	Springhill	1
56	Sunshine Gardens	10
57	The Hill	44
58	The Hugh John Flemming Forestry Center	3
59	University Of New Brunswick	15
60	Waterloo Row	9
61	Wesbett / Case	1
62	West Hills	5
63	Williams / Hawkins Area	17
64	Woodstock Road	41
65	Youngs Crossing	16

In [88]:
```
address = 'Fredericton, Canada'

geolocator = Nominatim()
location =geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Fredericton, New Brunswick is {}, {}.'.format(
latitude, longitude))
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3: DeprecationWarnin
g: Using Nominatim with the default "geopy/1.18.1" `user_agent` is strongly discou
raged, as it violates Nominatim's ToS https://operations.osmfoundation.org/policie
s/nominatim/ and may possibly cause 403 and 429 HTTP errors. Please specify a cust
om `user_agent` with `Nominatim(user_agent="my-application")` or by overriding the
default `user_agent`: `geopy.geocoders.options.default_user_agent = "my-applicatio
n"`. In geopy 2.0 this will become an exception.
  This is separate from the ipykernel package so we can avoid doing imports until

The geograpical coordinate of Fredericton, New Brunswick is 45.966425, -66.645813.
```

In [89]:
```
world_geo = r'world_countries.json'

fredericton_1_map = folium.Map(location=[45.97, -66.65], width=1000, height=750,zoo
m_start=12)

fredericton_1_map
```

Out[89]:

In [90]:

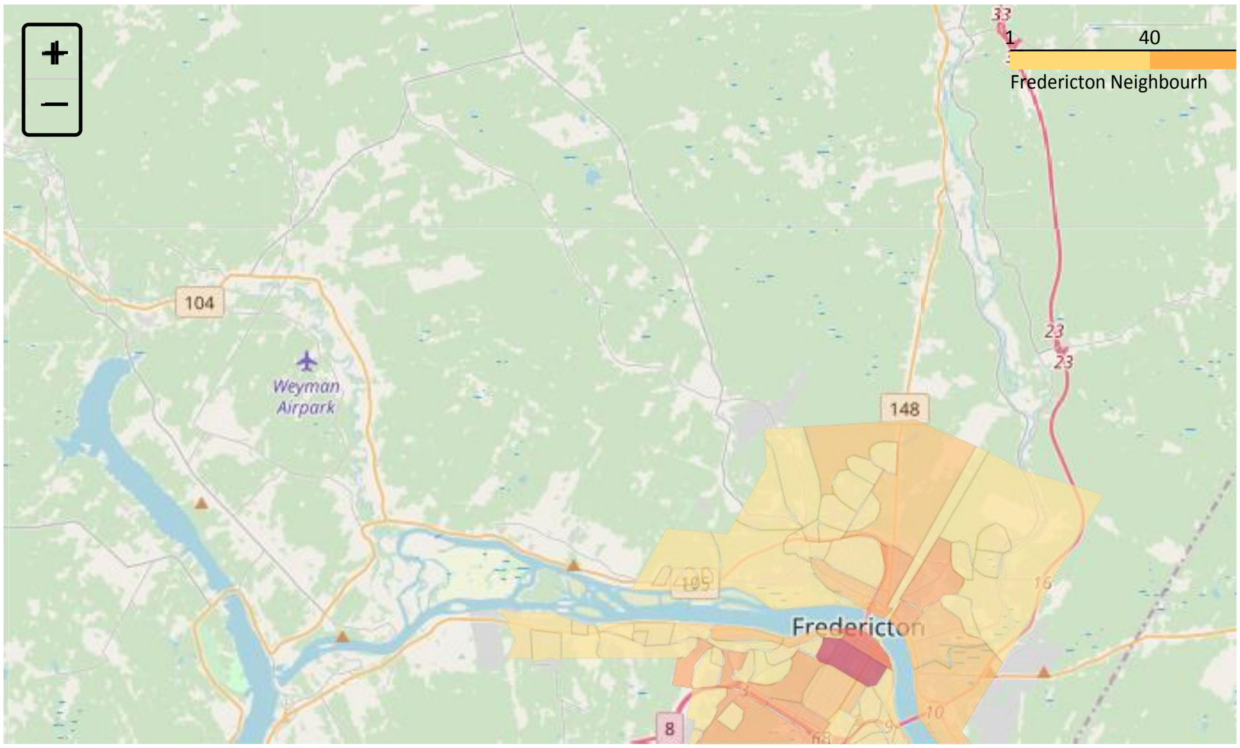
```
fredericton_geo = r.json()

threshold_scale = np.linspace(crime_data['Crime_Count'].min(),crime_data['Crime_Cou
nt'].max(), 6,dtype=int)
threshold_scale = threshold_scale.tolist()
threshold_scale[-1] = threshold_scale[-1]+1

fredericton_1_map.choropleth(geo_data=fredericton_geo, data=crime_data,columns=['Ne
ighbourh', 'Crime_Count'],
    key_on='feature.properties.Neighbourh', threshold_scale=threshold_scale,fill_co
lor='YlOrRd', fill_opacity=0.7,
    line_opacity=0.1, legend_name='Fredericton Neighbourhoods')

fredericton_1_map
```

Out[90]:



Examine Crime Types

In [131]:
```
crimetype_data = crime_df.groupby(['Crime_Type']).size().to_frame(name='Count').reset_index()
crimetype_data
```

Out[131]:

	Crime_Type	Count
0		4
1	ARSON	5
2	ARSON BY NEG	1
3	ARSON-DAM.PROP.	4
4	B&E NON-RESIDNCE	51
5	B&E OTHER	58
6	B&E RESIDENCE	151
7	B&E STEAL FIREAR	3
8	MISCHIEF OBS USE	1
9	MISCHIEF TO PROP	246
10	MISCHIEF-DATA	2
11	MOTOR VEH THEFT	40
12	THEFT BIKE<$5000	63
13	THEFT FROM MV < $5000	356
14	THEFT FROM MV > $5000	5
15	THEFT OTH <$5000	458
16	THEFT OTH >$5000	9
17	THEFT OVER $5000	1
18	THEFT,BIKE>$5000	2

In [154]:
```
crimetype_data.describe()
```

Out[154]:

	Count
count	19.000000
mean	76.842105
std	133.196706
min	1.000000
25%	2.500000
50%	5.000000
75%	60.500000
max	458.000000

In [140]:
```
crimepivot = crime_df.pivot_table(index='Neighbourhood', columns='Crime_Type', aggf
unc=pd.Series.count, fill_value=0)
crimepivot
```

Out[140]:

City									
Crime_Type	**ARSON**	**ARSON BY NEG**	**ARSON-DAM.PROP.**	**B&E NON-RESIDNCE**	**B&E OTHER**	**B&E RESIDENCE**	**B&E STEAL FIREAR**	**MISCHIEF OBS USE**	**MISCHI TO PRO**
Neighbourhood									
Barkers Point	0	0	0	0	2	7	7	1	0
Brookside	0	0	0	0	2	0	0	0	0
Brookside Estates	0	0	0	0	1	1	0	0	0
Brookside Mini Home Park	0	0	0	0	0	0	0	1	0
College Hill	0	2	0	0	0	2	13	0	0
Colonial heights	0	0	0	0	0	0	3	0	0
Cotton Mill Creek	0	0	0	0	0	0	0	0	0
Diamond Street	0	0	0	0	0	0	0	0	0
Doak Road	0	0	0	0	0	0	0	0	0
Douglas	0	0	0	0	0	0	0	0	0
Downtown	0	1	0	1	7	0	3	0	0
Dun's Crossing	0	0	0	0	0	0	1	0	0
Forest Hill	0	0	0	0	1	0	0	0	0
Fredericton South	1	0	0	0	6	1	1	0	0
Fulton Heights	0	0	0	0	1	0	6	0	0
Garden Creek	0	0	0	0	2	1	1	0	0
Garden Place	0	0	0	0	0	0	0	0	0
Gilridge Estates	0	0	0	0	0	0	0	0	0
Golf Club	0	0	0	0	0	0	1	0	0
Grasse Circle	1	0	0	0	0	0	0	0	0
Greenwood	0	0	0	0	0	1	0	0	0
Hanwell North Minihome Park	0	0	0	0	0	1	2	0	0
Heron Springs	0	0	0	0	0	0	1	0	0
Highpoint Ridge	0	0	0	0	0	0	0	0	0
Kelly's Court	0	0	0	0	0	0	0	0	0
Knob Hill Minihome Park	0	0	0	0	0	0	1	0	0
Knowledge Park	1	0	0	0	0	0	0	0	0
Lian / Valcore	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	2	2	2	0	0

City

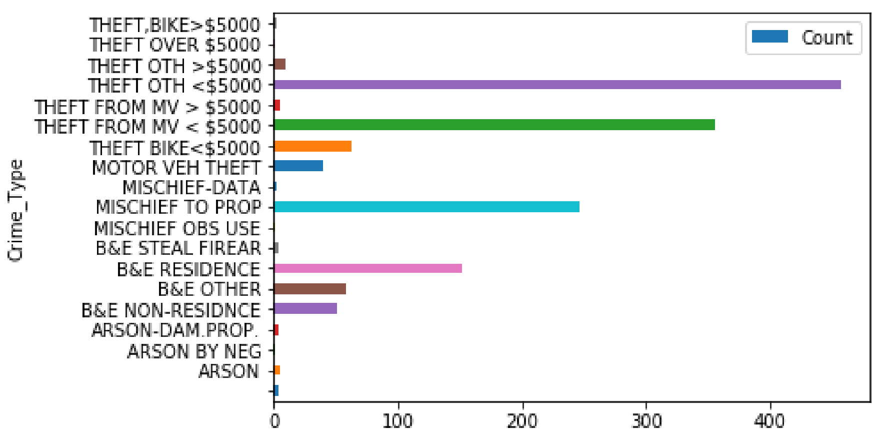
Crime_Type / Neighbourhood	ARSON	ARSON BY NEG	ARSON DAM.PROP.	B&E NON-RESIDNCE	B&E OTHER	B&E RESIDENCE	B&E STEAL FIREAR	MISCHIEF OBS USE	MISCHI TO PRO
Lincoln	0	0	0	0	0	1	1	0	0
Main Street Heights	0	0	0	1	2	4	8	0	1
Marysville	0	1	0	0	1	2	5	0	0
McKnight	0	0	0	0	0	0	0	0	0
McLeod Hill	0	0	0	0	0	0	0	0	0
Monteith /	0	0	0	0	2	2	4	0	0
Montogomery / Talisman	0	0	0	0	0	0	0	0	0
Nashwaaksis	0	0	0	1	2	0	3	0	0
Prospect East Nethervue	0	0	0	0	0	0	0	0	0
North Devon	0	0	0	0	5	4	11	0	0
Minihome Park Northbrook	0	0	0	0	0	0	2	0	0
Plat	0	0	0	0	4	10	18	0	0
Heights Poet's Hill	0	0	0	0	0	0	1	0	0
Prospect	0	0	0	0	1	0	2	0	0
Rail Side	0	0	0	0	0	0	0	0	0
Regiment	0	0	0	0	0	0	0	0	0
Royal Road	0	0	0	0	3	2	2	0	0
Saint Mary's Creek	0	0	0	0	0	0	1	0	0
Saint Thomas	0	0	0	0	0	0	0	0	0
First Nation Sandyville	0	0	0	0	0	2	2	0	0
Serenity Lane University	0	0	0	0	1	1	0	0	0
Shadowood	0	0	0	0	0	0	0	0	0
Silverwood	0	0	0	0	0	0	3	0	0
Skyline Acrea Estates	0	1	0	0	1	1	2	0	0
South Devon	0	0	1	0	0	6	16	0	0
Southwood	0	0	0	0	0	0	2	0	0
Springhill	0	0	0	0	0	0	1	0	0
Sunshine Park	0	0	0	0	0	1	0	0	0
The Hill	0	0	0	0	2	1	12	1	0

Gardens **City**

City									
Crime_Type	**ARSON**	**ARSON BY NEG**	**ARSON-DAM.PROP.**	**B&E NON-RESIDNCE**	**B&E OTHER**	**B&E RESIDENCE**	**B&E STEAL FIREAR**	**MISCHIEF OBS USE**	**MISCHI TO PRO**
Neighbourhood									
The Hugh John	0	0	0	0	1	2	0	0	0
Flemming Forestry Center	0	0	0	0	0	0	1	0	0
University Of New Brunswick									
Waterloo Row	0	0	0	0	0	1	2	0	0
Wesbett / Case	1	0	0	0	0	0	0	0	0
West Hills	0	0	0	0	0	1	1	0	0
Williams / Hawkins Area	0	0	0	0	0	1	2	0	0
Woodstock Road	0	0	0	0	2	0	5	0	0
Youngs Crossing	0	0	0	1	0	0	2	0	0

In [92]:
```
crimetype_data.plot(x='Crime_Type', y='Count', kind='barh')
```

Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0x11682a860>



In [ ]:

Let's examine theft from vehicles

In [93]:
```
mvcrime_df = crime_df.loc[crime_df['Crime_Type'] == 'THEFT FROM MV < $5000']
mvcrime_df
```

Out[93]:

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FID
18	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	19
19	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	20
20	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	21
21	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	22
22	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	23
23	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	24
24	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	25
25	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	26
26	Fredericton South	2142	THEFT FROM MV < $5000	11	Fredericton	27
27	Fredericton South	2142	THEFT FROM MV < $5000	11	Fredericton	28
28	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	29
29	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	30
30	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	31
51	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	52
52	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	53
53	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	54
54	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	55
55	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	56
56	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	57
57	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	58
58	Barkers Point	2142	THEFT FROM MV < $5000	6	Fredericton	59
100	Sandyville	2142	THEFT FROM MV < $5000	5	Fredericton	101
107	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	108
108	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	109
109	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	110
110	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	111
111	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	112
112	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	113
113	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	114
114	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	115
115	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	116
116	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	117
117	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	118
118	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	119
119	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	120
120	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	121
121	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	122
122	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	123
123	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	124

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
124	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	125
125	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	126
126	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	127
127	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	128
128	South Devon	2142	THEFT FROM MV < $5000	4	Fredericton	129
151	Sandyville	2142	THEFT FROM MV < $5000	5	Fredericton	152
156	Knob Hill	2142	THEFT FROM MV < $5000	5	Fredericton	157
165	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	166
166	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	167
167	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	168
168	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	169
169	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	170
170	Youngs Crossing	2142	THEFT FROM MV < $5000	4	Fredericton	171
201	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	202
252	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	253
278	Douglas	2142	THEFT FROM MV < $5000	1	Fredericton	279
280	McLeod Hill	2142	THEFT FROM MV < $5000	2	Fredericton	281
281	McLeod Hill	2142	THEFT FROM MV < $5000	2	Fredericton	282
301	Marysville	2142	THEFT FROM MV < $5000	0	Fredericton	302
302	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	303
303	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	304
304	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	305
305	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	306
306	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	307
307	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	308
308	Marysville	2142	THEFT FROM MV < $5000	5	Fredericton	309
330	Saint Mary's First Nation	2142	THEFT FROM MV < $5000	3	Fredericton	331
349	Sandyville	2142	THEFT FROM MV < $5000	5	Fredericton	350
354	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	355
355	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	356
356	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	357
357	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	358
358	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	359
359	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	360
360	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	361
361	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	362
362	Nashwaaksis	2142	THEFT FROM MV < $5000	1	Fredericton	363
377	Northbrook Heights	2142	THEFT FROM MV < $5000	2	Fredericton	378
378	Northbrook Heights	2142	THEFT FROM MV < $5000	2	Fredericton	379

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
379	Northbrook Heights	2142	THEFT FROM MV < $5000	1	Fredericton	380
380	Northbrook Heights	2142	THEFT FROM MV < $5000	2	Fredericton	381
381	Northbrook Heights	2142	THEFT FROM MV < $5000	2	Fredericton	382
388	Heron Springs	2142	THEFT FROM MV < $5000	2	Fredericton	389
389	Heron Springs	2142	THEFT FROM MV < $5000	2	Fredericton	390
400	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	401
401	Downtown	2142	THEFT FROM MV < $5000	11	Fredericton	402
402	Downtown	2142	THEFT FROM MV < $5000	11	Fredericton	403
403	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	404
404	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	405
405	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	406
408	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	409
410	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	411
411	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	412
412	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	413
413	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	414
414	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	415
415	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	416
416	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	417
417	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	418
418	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	419
419	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	420
420	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	421
421	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	422
422	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	423
506	Downtown	2142	THEFT FROM MV < $5000	10	Fredericton	507
520	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	521
521	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	522
522	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	523
523	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	524
524	Fulton Heights	2142	THEFT FROM MV < $5000	2	Fredericton	525
525	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	526
526	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	527
527	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	528
528	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	529
529	Fulton Heights	2142	THEFT FROM MV < $5000	2	Fredericton	530
530	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	531
531	Fulton Heights	2142	THEFT FROM MV < $5000	3	Fredericton	532
569	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	570

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
570	Main Street	2142	THEFT FROM MV < $5000	3	Fredericton	571
571	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	572
572	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	573
573	Main Street	2142	THEFT FROM MV < $5000	3	Fredericton	574
574	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	575
575	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	576
576	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	577
577	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	578
578	Main Street	2142	THEFT FROM MV < $5000	2	Fredericton	579
604	Golf Club	2142	THEFT FROM MV < $5000	12	Fredericton	605
614	Gilridge Estates	2142	THEFT FROM MV < $5000	1	Fredericton	615
622	Nethervue Minihome Park	2142	THEFT FROM MV < $5000	12	Fredericton	623
625	Monteith / Talisman	2142	THEFT FROM MV < $5000	12	Fredericton	626
626	Monteith / Talisman	2142	THEFT FROM MV < $5000	12	Fredericton	627
631	Garden Creek	2142	THEFT FROM MV < $5000	12	Fredericton	632
640	Highpoint Ridge	2142	THEFT FROM MV < $5000	12	Fredericton	641
641	Highpoint Ridge	2142	THEFT FROM MV < $5000	12	Fredericton	642
642	Highpoint Ridge	2142	THEFT FROM MV < $5000	12	Fredericton	643
643	Highpoint Ridge	2142	THEFT FROM MV < $5000	12	Fredericton	644
650	Golf Club	2142	THEFT FROM MV < $5000	12	Fredericton	651
651	Golf Club	2142	THEFT FROM MV < $5000	12	Fredericton	652
653	Golf Club	2142	THEFT FROM MV < $5000	12	Fredericton	654
752	Golf Club	2142	THEFT FROM MV < $5000	12	Fredericton	753
764	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	765
765	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	766
766	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	767
767	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	768
768	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	769
769	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	770
770	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	771
771	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	772
772	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	773
773	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	774
774	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	775
775	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	776
776	Woodstock Road	2142	THEFT FROM MV < $5000	0	Fredericton	777
777	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	778
778	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	779
779	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	780

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
780	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	781
781	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	782
787	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	788
788	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	789
789	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	790
790	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	791
791	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	792
792	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	793
793	Sunshine Gardens	2142	THEFT FROM MV < $5000	10	Fredericton	794
809	Plat	2142	THEFT FROM MV < $5000	0	Fredericton	810
810	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	811
811	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	812
812	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	813
813	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	814
814	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	815
815	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	816
816	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	817
817	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	818
818	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	819
819	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	820
820	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	821
821	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	822
822	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	823
823	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	824
824	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	825
825	Plat	2142	THEFT FROM MV < $5000	0	Fredericton	826
826	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	827
827	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	828
828	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	829
829	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	830
830	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	831
831	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	832
832	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	833
833	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	834
835	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	836
836	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	837
837	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	838
838	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	839
839	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	840

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
840	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	841
841	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	842
842	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	843
843	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	844
844	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	845
845	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	846
846	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	847
847	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	848
848	Plat	2142	THEFT FROM MV < $5000	11	Fredericton	849
849	Plat	2142	THEFT FROM MV < $5000	10	Fredericton	850
855	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	856
856	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	857
857	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	858
865	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	866
866	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	867
867	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	868
868	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	869
869	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	870
871	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	872
875	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	876
880	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	881
881	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	882
886	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	887
887	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	888
892	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	893
893	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	894
898	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	899
899	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	900
900	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	901
901	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	902
902	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	903
903	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	904
904	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	905
905	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	906
906	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	907
907	Skyline Acrea	2142	THEFT FROM MV < $5000	8	Fredericton	908
913	Poet's Hill	2142	THEFT FROM MV < $5000	8	Fredericton	914
914	Poet's Hill	2142	THEFT FROM MV < $5000	8	Fredericton	915
922	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	923

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
923	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	924
924	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	925
925	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	926
926	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	927
927	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	928
928	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	929
929	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	930
930	Dun's Crossing	2142	THEFT FROM MV < $5000	8	Fredericton	931
938	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	939
939	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	940
940	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	941
941	Southwood Park	2142	THEFT FROM MV < $5000	7	Fredericton	942
946	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	947
947	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	948
948	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	949
949	The Hill	2142	THEFT FROM MV < $5000	10	Fredericton	950
950	The Hill	2142	THEFT FROM MV < $5000	10	Fredericton	951
951	The Hill	2142	THEFT FROM MV < $5000	11	Fredericton	952
952	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	953
954	The Hill	2142	THEFT FROM MV < $5000	10	Fredericton	955
955	The Hill	2142	THEFT FROM MV < $5000	10	Fredericton	956
956	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	957
957	The Hill	2142	THEFT FROM MV < $5000	9	Fredericton	958
969	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	970
970	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	971
971	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	972
972	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	973
973	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	974
974	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	975
975	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	976
976	Forest Hill	2142	THEFT FROM MV < $5000	8	Fredericton	977
989	Lincoln Heights	2142	THEFT FROM MV < $5000	7	Fredericton	990
996	Diamond Street	2142	THEFT FROM MV < $5000	1	Fredericton	997
1027	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1028
1028	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1029
1029	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1030
1030	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1031
1031	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1032
1032	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1033

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FI
1033	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1034
1034	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1035
1035	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1036
1036	College Hill	2142	THEFT FROM MV < $5000	11	Fredericton	1037
1060	Brookside Estates	2142	THEFT FROM MV < $5000	2	Fredericton	1061
1061	Brookside Estates	2142	THEFT FROM MV < $5000	2	Fredericton	1062
1062	Brookside Estates	2142	THEFT FROM MV < $5000	2	Fredericton	1063
1116	Lincoln	2142	THEFT FROM MV < $5000	7	Fredericton	1117
1124	Colonial heights	2142	THEFT FROM MV < $5000	12	Fredericton	1125
1125	Colonial heights	2142	THEFT FROM MV < $5000	12	Fredericton	1126
1126	Colonial heights	2142	THEFT FROM MV < $5000	12	Fredericton	1127
1127	Colonial heights	2142	THEFT FROM MV < $5000	12	Fredericton	1128
1128	Colonial heights	2142	THEFT FROM MV < $5000	11	Fredericton	1129
1129	Colonial heights	2142	THEFT FROM MV < $5000	11	Fredericton	1130
1131	Garden Place	2142	THEFT FROM MV < $5000	12	Fredericton	1132
1132	Garden Place	2142	THEFT FROM MV < $5000	12	Fredericton	1133
1133	Garden Place	2142	THEFT FROM MV < $5000	12	Fredericton	1134
1144	Waterloo Row	2142	THEFT FROM MV < $5000	11	Fredericton	1145
1145	Waterloo Row	2142	THEFT FROM MV < $5000	11	Fredericton	1146
1146	Waterloo Row	2142	THEFT FROM MV < $5000	11	Fredericton	1147
1151	University Of New Brunswick	2142	THEFT FROM MV < $5000	11	Fredericton	1152
1152	University Of New Brunswick	2142	THEFT FROM MV < $5000	11	Fredericton	1153
1153	University Of New Brunswick	2142	THEFT FROM MV < $5000	11	Fredericton	1154
1154	University Of New Brunswick	2142	THEFT FROM MV < $5000	11	Fredericton	1155
1163	Saint Thomas University	2142	THEFT FROM MV < $5000	11	Fredericton	1164
1173	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1174
1174	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1175
1175	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1176
1176	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1177
1177	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1178
1178	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2	Fredericton	1179
1181	McKnight	2142	THEFT FROM MV < $5000	2	Fredricton	1182
1187	Shadowood Estates	2142	THEFT FROM MV < $5000	2	Fredericton	1188
1188	Shadowood Estates	2142	THEFT FROM MV < $5000	2	Fredericton	1189
1240	Lian / Valcore	2142	THEFT FROM MV < $5000	12	Fredericton	1241
1284	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1285
1285	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1286
1286	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1287
1287	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1288

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	
1288	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1289
1289	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1290
1290	North Devon	2142	THEFT FROM MV < $5000	4	Fredericton	1291
1302	Rail Side	2142	THEFT FROM MV < $5000	12	Fredericton	1303
1306	Rail Side	2142	THEFT FROM MV < $5000	12	Fredericton	1307
1316	Silverwood	2142	THEFT FROM MV < $5000	12	Fredericton	1317
1317	Silverwood	2142	THEFT FROM MV < $5000	12	Fredericton	1318
1339	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1340
1340	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1341
1341	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1342
1342	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1343
1343	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1344
1344	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1345
1345	Prospect	2142	THEFT FROM MV < $5000	11	Fredericton	1346
1346	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1347
1347	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1348
1348	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1349
1349	Prospect	2142	THEFT FROM MV < $5000	9	Fredericton	1350
1369	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1370
1370	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1371
1371	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1372
1372	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1373
1377	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1378
1380	Hanwell North	2142	THEFT FROM MV < $5000	12	Fredericton	1381
1381	Hanwell North	2142	THEFT FROM MV < $5000	12	Fredericton	1382
1382	Hanwell North	2142	THEFT FROM MV < $5000	12	Fredericton	1383
1387	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	11	Fredericton	1388
1388	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	11	Fredericton	1389
1389	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	9	Fredericton	1390
1403	Fredericton South	2142	THEFT FROM MV < $5000	7	Fredericton	1404
1408	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1409
1409	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1410
1410	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1411
1411	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1412
1412	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1413
1413	Fredericton South	2142	THEFT FROM MV < $5000	12	Fredericton	1414
1420	Woodstock Road	2142	THEFT FROM MV < $5000	12	Fredericton	1421
1421	Woodstock Road	2142	THEFT FROM MV < $5000	10	Fredericton	1422
1437	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1438

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FID
1438	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1439
1439	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1440
1440	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1441
1441	North Devon	2142	THEFT FROM MV < $5000	3	Fredericton	1442
1459	Monteith / Talisman	2142	THEFT FROM MV < $5000	12	Fredericton	1460

In [94]:
```
mvcrime_data = mvcrime_df.groupby(['Neighbourhood']).size().to_frame(name='Count').
reset_index()
mvcrime_data
```

Out[94]:

	Neighbourhood	Count
0	Barkers Point	8
1	Brookside Estates	3
2	College Hill	10
3	Colonial heights	6
4	Diamond Street	1
5	Douglas	1
6	Downtown	21
7	Dun's Crossing	9
8	Forest Hill	8
9	Fredericton South	20
10	Fulton Heights	12
11	Garden Creek	1
12	Garden Place	3
13	Gilridge Estates	1
14	Golf Club	5
15	Hanwell North	3
16	Heron Springs	2
17	Highpoint Ridge	4
18	Knob Hill	1
19	Lian / Valcore	1
20	Lincoln	1
21	Lincoln Heights	11
22	Main Street	10
23	Marysville	10
24	McKnight	1
25	McLeod Hill	2
26	Monteith / Talisman	3
27	Montogomery / Prospect East	3
28	Nashwaaksis	9
29	Nethervue Minihome Park	1
30	North Devon	17
31	Northbrook Heights	5
32	Plat	40
33	Poet's Hill	2
34	Prospect	11
35	Rail Side	2
36	Saint Mary's First Nation	1
37	Saint Thomas University	1
38	Sandyville	3

	Neighbourhood	Count
39	Shadowood Estates	2
40	Silverwood	2
41	Skyline Acrea	13
42	South Devon	22
43	Southwood Park	7
44	Sunshine Gardens	7
45	The Hill	11
46	University Of New Brunswick	4
47	Waterloo Row	3
48	Williams / Hawkins Area	6
49	Woodstock Road	20
50	Youngs Crossing	6

In [155]:

```
mvcrime_data.describe()
```

Out[155]:

	MVCrime_Count
count	51.000000
mean	6.980392
std	7.457855
min	1.000000
25%	2.000000
50%	4.000000
75%	10.000000
max	40.000000

In [95]:
```
mvcrime_data.rename({'Platt': 'Plat'},inplace=True)
mvcrime_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'MVCri
me_Count'}, inplace=True)
mvcrime_data
```

Out[95]:

	Neighbourh	MVCrime_Count
0	Barkers Point	8
1	Brookside Estates	3
2	College Hill	10
3	Colonial heights	6
4	Diamond Street	1
5	Douglas	1
6	Downtown	21
7	Dun's Crossing	9
8	Forest Hill	8
9	Fredericton South	20
10	Fulton Heights	12
11	Garden Creek	1
12	Garden Place	3
13	Gilridge Estates	1
14	Golf Club	5
15	Hanwell North	3
16	Heron Springs	2
17	Highpoint Ridge	4
18	Knob Hill	1
19	Lian / Valcore	1
20	Lincoln	1
21	Lincoln Heights	11
22	Main Street	10
23	Marysville	10
24	McKnight	1
25	McLeod Hill	2
26	Monteith / Talisman	3
27	Montogomery / Prospect East	3
28	Nashwaaksis	9
29	Nethervue Minihome Park	1
30	North Devon	17
31	Northbrook Heights	5
32	Plat	40
33	Poet's Hill	2
34	Prospect	11
35	Rail Side	2
36	Saint Mary's First Nation	1
37	Saint Thomas University	1
38	Sandyville	3

	Neighbourh	MVCrime_Count
39	Shadowood Estates	2
40	Silverwood	2
41	Skyline Acrea	13
42	South Devon	22
43	Southwood Park	7
44	Sunshine Gardens	7
45	The Hill	11
46	University Of New Brunswick	4
47	Waterloo Row	3
48	Williams / Hawkins Area	6
49	Woodstock Road	20
50	Youngs Crossing	6

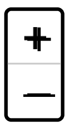
In [96]:

```
world_geo = r'world_countries.json'

fredericton_c_map = folium.Map(location=[45.91, -66.65], width=1000, height=750,zoom_start=12)

fredericton_c_map
```

Out[96]:

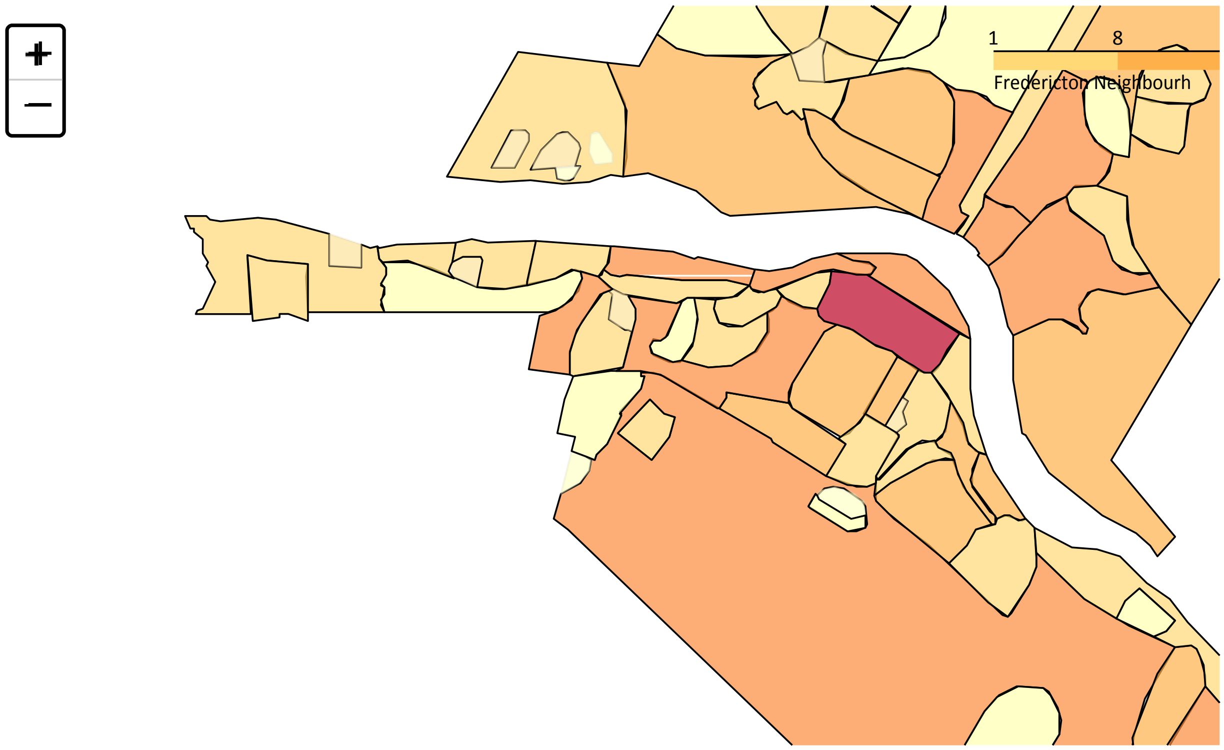


In [97]:

```
fredericton_geo = r.json()
threshold_scale = np.linspace(mvcrime_data['MVCrime_Count'].min(), mvcrime_data['MV
Crime_Count'].max(),6,dtype=int)
threshold_scale = threshold_scale.tolist()
threshold_scale[-1] = threshold_scale[-1]+1

fredericton_c_map.choropleth(geo_data=fredericton_geo,data=mvcrime_data,columns=['N
eighbourh', 'MVCrime_Count'],key_on='feature.properties.Neighbourh',
    threshold_scale=threshold_scale, fill_color='YlOrRd',fill_opacity=0.7,line_opac
ity=0.1,legend_name='Fredericton Neighbourhoods')
fredericton_c_map
```

Out[97]:



Is it possible the higher rate of crime in the downtown area is due to population density?

In [98]:

```
opendemog = 'Fredericton_Census_Tract_Demographics.xlsx'

workbook = pd.ExcelFile(opendemog)
print(workbook.sheet_names)
```

```
['Fredericton_Census_Tract_Demogr']
```

In [99]:
```
demog_df =workbook.parse('Fredericton_Census_Tract_Demogr')
demog_df.head()
```

Out[99]:

	FID	OBJECTID	DBUID	DAUID	CDUID	CTUID	CTNAME	DBuid_1	DBpop2011	DBtdwell20 D
0	1	501	1310024304	13100243	1310	3200002	2	1310024304	60	25
1	2	502	1310032004	13100320	1310	3200010	10	1310032004	15	3
2	3	503	1310017103	13100171	1310	3200014	14	1310017103	0	0
3	4	504	1310018301	13100183	1310	3200012	12	1310018301	108	60
4	5	505	1310022905	13100229	1310	3200007	7	1310022905	129	47

In [ ]:

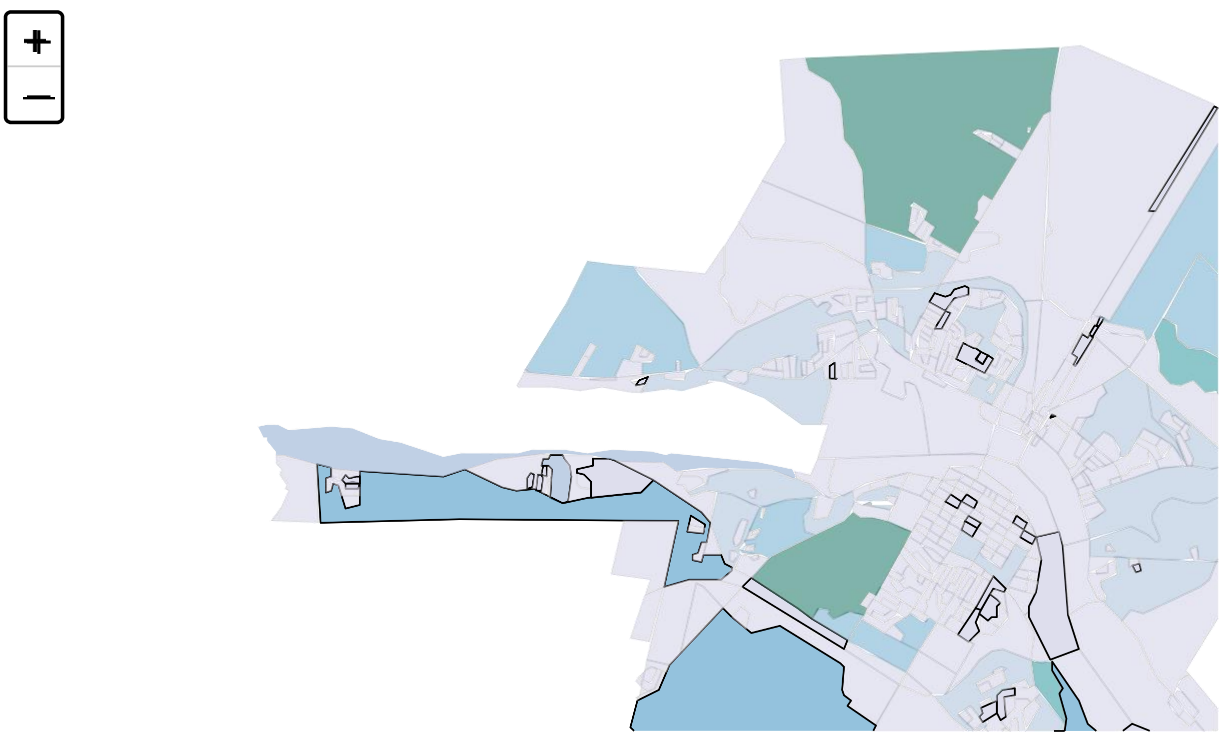
In [ ]:

In [100]:
```
world_geo = r'world_countries.json'
fredericton_d_map = folium.Map(location=[45.94, -66.63], width=1200, height=750,zoo
m_start=12)
fredericton_d_map

threshold_scale = np.linspace(demog_df['DBpop2011'].min(),demog_df['DBpop2011'].max
(),6,dtype=int)
threshold_scale = threshold_scale.tolist()
threshold_scale[-1] = threshold_scale[-1]+1

fredericton_d_map.choropleth(geo_data=demog_geo,data=demog_df,columns=['OBJECTID',
'DBpop2011'],key_on='feature.properties.OBJECTID',
    threshold_scale=threshold_scale,fill_color='PuBuGn',fill_opacity=0.7, line_opac
ity=0.1,legend_name='Fredericton Population Density')
fredericton_d_map
```

Out[100]:



Let's look at specific locations in Fredericton

In [101]:
```
pointbook = 'Fredericton Locations.xlsx'

workbook_2 = pd.ExcelFile(pointbook)
print(workbook_2.sheet_names)
```

```
['Sheet1']
```

In [102]:
```
location_df = workbook_2.parse('Sheet1')
location_df
```

Out[102]:

	Location	Neighbourh	Latitude	Longitude
0	Knowledge Park	NaN	45.931143	-66.652700
1	Fredericton Hill	NaN	45.948512	-66.656045
2	Nashwaaksis	NaN	45.983382	-66.644856
3	University of New Brunswick	NaN	45.948121	-66.641406
4	Devon	NaN	45.968802	-66.622738
5	New Maryland	NaN	45.892795	-66.683673
6	Marysville	NaN	45.978913	-66.589491
7	Skyline Acres	NaN	45.931827	-66.640339
8	Hanwell	NaN	45.902315	-66.755113
9	Downtown	NaN	45.958327	-66.647211

In [103]:
```
location_df.drop(['Neighbourh'], axis=1,inplace=True)
location_df
```

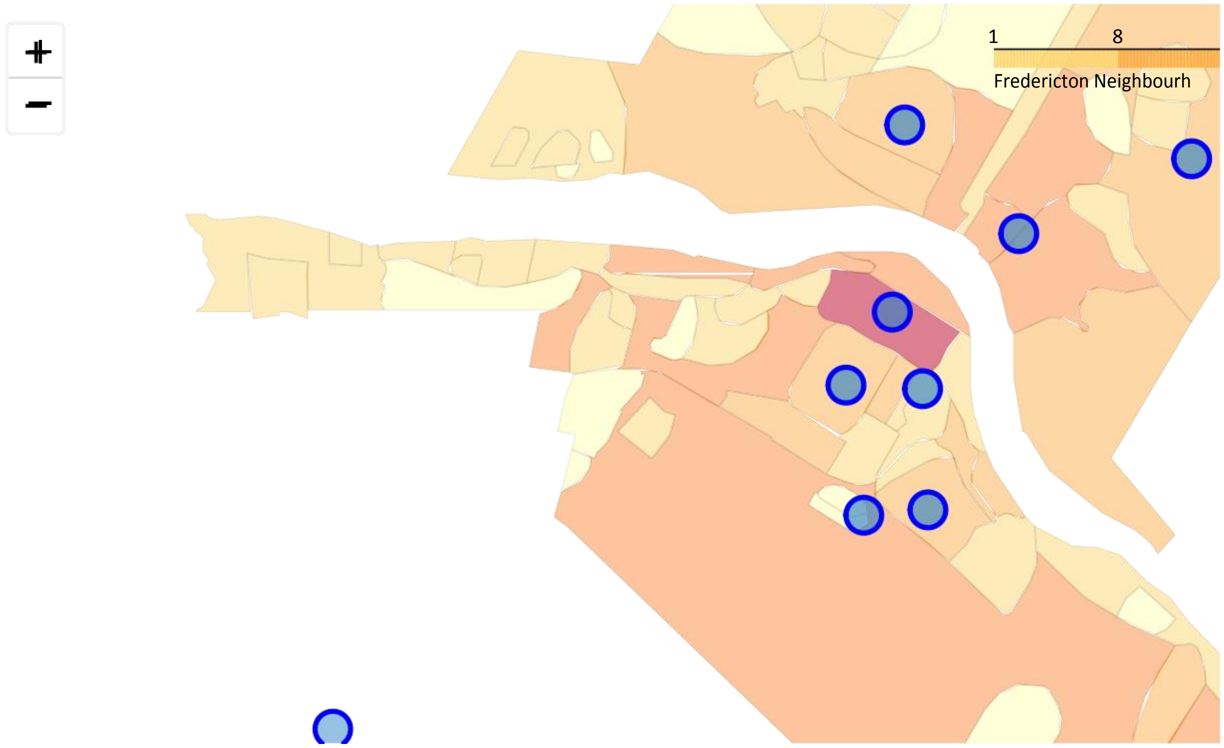
Out[103]:

	Location	Latitude	Longitude
0	Knowledge Park	45.931143	-66.652700
1	Fredericton Hill	45.948512	-66.656045
2	Nashwaaksis	45.983382	-66.644856
3	University of New Brunswick	45.948121	-66.641406
4	Devon	45.968802	-66.622738
5	New Maryland	45.892795	-66.683673
6	Marysville	45.978913	-66.589491
7	Skyline Acres	45.931827	-66.640339
8	Hanwell	45.902315	-66.755113
9	Downtown	45.958327	-66.647211

Add location markers to map

In [104]:
```
for lat, lng, point in zip(location_df['Latitude'], location_df['Longitude'], locat
ion_df['Location']):
    label = '{}'.format(point)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker([lat, lng],radius=1,popup=label,color='blue',fill=True,fill
_color='#3186cc',fill_opacity=0.7,
        parse_html=False).add_to(fredericton_c_map)
fredericton_c_map
```

Out[104]:



In [ ]:

Explore Fredericton Neighbourhoods

Define Foursquare Credentials and Version

In [2]:
```
CLIENT_ID = 'Nope'
CLIENT_SECRET = 'Secret'
VERSION = '20181201'

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

```
Your credentails:
CLIENT_ID: Nope
CLIENT_SECRET:Secret
```

Let's take a look at nearby venues

In [106]:
```
def getNearbyVenues(names, latitudes, longitudes, radius=1000, LIMIT=100):

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


        url ='https://api.foursquare.com/v2/venues/explore?&client_id={}&client_se
cret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)


        results = requests.get(url).json()["response"]['groups'][0]['items']


        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['id'],
            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 ve
nue_list])
    nearby_venues.columns = ['Location',
                  'Location Latitude',
                  'Location Longitude',
                  'Venue',
                  'Venue id',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category'
                   ]

    return(nearby_venues)
```

In [107]:
```
fredericton_data_venues = getNearbyVenues(names=location_df['Location'],
                                   latitudes=location_df['Latitude'],
                                   longitudes=location_df['Longitude']
                                  )
```

```
Knowledge Park
Fredericton Hill
Nashwaaksis
University of New Brunswick
Devon
New Maryland
Marysville
Skyline Acres
Hanwell
Downtown
```

In [108]:
```
print(fredericton_data_venues.shape)
fredericton_data_venues
```

```
(166, 8)
```

Out[108]:

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
0	Knowledge Park	45.931143	-66.652700	Costco Wholesale	4e18ab92183880768f43bff6	45.927034	-66.663447	War
	Park	45.931143	-66.652700	Best Buy	5520124a498e0467bb6e81c8	45.937673	-66.660380	
1	Knowledge Park	45.931143	-66.652700	PetSmart	4bbca501a0a0c9b6078f1a0f	45.929768	-66.659939	Pe
	Park	45.931143	-66.652700	Wal-Mart	4bad313ff964a5208c373be3	45.934081	-66.663539	
2	Knowledge Park	45.931143	-66.652700	Montana's	4e50406e62844166699b0780	45.931511	-66.662507	Res
	Park	45.931143	-66.652700	Booster Juice	4c42414e520fa59334f9caac	45.935198	-66.663602	
3	Knowledge Park	45.931143	-66.652700	Michaels	4c489858417b20a13b82e1a9	45.929965	-66.659548	Arts &
4	Knowledge Park	45.931143	-66.652700	Boston Pizza	[illegible]	[illegible]	-66.660037	Spo
	Park	45.931143	-66.652700	Dairy Queen	4b86f05bf964a52009a731e3	45.938004	-66.659442	
5	Knowledge	45.931143	-66.652700	Alcool NB	4b77335df964a5202c872ee3	45.930680	-66.664180	Liquo
	Park	45.931143	-66.652700	H&M	509c3265498efdffc5739a0f	45.935196	-66.663290	Elec
6	Knowledge Park	45.931143	-66.652700	Dairy Queen (Treat)	4cc6123cbde8f04d9ce0b44b	45.934520	-66.663988	B Sm
7	Knowledge Park	45.931143	-66.652700	Winners	4caa46a744a8224b96e42640	45.930427	-66.659758	Fas Res
8	Knowledge Park	45.931143	-66.652700	East Side Mario's	4b55d89bf964a520a2f227e3	45.931376	-66.663417	C Fas Res
9	Knowledge Park	45.931143	-66.652700	McDonald's	4c6e9ef665eda09377e951d0	45.934575	-66.663319	C
1	Knowledge Park	45.931143	-66.652700	Home Sense	54024f60498ee424eedb7bf9	45.930528	-66.660103	Res Fas Res
1	Knowledge Park	45.931143	-66.652700	The Shoe company	4bd76dfa5cf276b0fb469b00	45.929636	-66.660449	Depa Sho
1	Knowledge Park	45.931143	-66.652700	Avalon Spa	4cd99e0f51fc8cfa4369f05d	45.930774	-66.660927	
1	Knowledge Park	45.931143	-66.652700	Uptown Wicker Emporium	4e6baff588772457c4fd1968	45.930897	-66.661338	Fur Hom
1	Knowledge Park							
1	Knowledge Park							
1	Knowledge Park							
1	Knowledge Park							
1	Knowledge Park							
1	Knowledge Park	45.931143	-66.652700	Dollarama	4ba3dd18f964a520d86738e3	45.930897	-66.661714	Di
2	Knowledge Park	45.931143	-66.652700	Bed Bath & Beyond	5083f283e4b0bf87c15e9ea1	45.930097	-66.662166	Fur Hom
2	Knowledge Park	45.931143	-66.652700	GAP Factory Store	50a8f005e4b0e4f42e033a2a	45.930211	-66.662416	C
2	Knowledge Park	45.931143	-66.652700	carter's | OshKosh B'gosh	50a51363e4b0a3e2f7db76bf	45.929978	-66.662966	Kid
2	Knowledge Park	45.931143	-66.652700	Deluxe Fish & Chips	4e5d0b99fa76a4cf148d9a15	45.931722	-66.663131	S Res
2	Knowledge Park	45.931143	-66.652700	Hallmark	4cd96cf651fc8cfa522eef5d	45.930646	-66.663745	Gif

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
2	Knowledge Park	45.931143	-66.652700	NB Liquor	5985f08b6cf01a7e38b85fba	45.930228	-66.664395	Liquo
2	Knowledge Park	45.931143	-66.652700	Corbett Center	57854d05498e301b3b5a4448	45.929733	-66.664601	Sh
2	Knowledge Park	45.931143	-66.652700	Costco Food Court	53693053498ef3e4ea63560f	45.927383	-66.663544	Fas Res
2	Knowledge Park	45.931143	-66.652700	Sleep Country	555b5660498eae864c440e77	45.929074	-66.664605	M
2	Knowledge Park	45.931143	-66.652700	Sport Chek Regent Mall	4ca4ecae8a65bfb717422b22	45.935211	-66.663525	S Good
30	Knowledge Park	45.931143	-66.652700	Rôtisserie St-Hubert	57164569498e9bb9e88d52b0	45.929838	-66.664749	Res
3	Fredericton Hill	45.948512	-66.656045	YMCA	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
3	Fredericton Hill	45.948512	-66.656045	Fredericton 20 Twenty Club	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112	
3	Fredericton Hill	45.948512	-66.656045	Shoppers Drug Mart	4fb699dc7bebbeb2a6c7ba88	45.942627	-66.655523	Ph
34	Fredericton Hill	45.948512	-66.656045	Subway	4bae3571f964a52076923be3	45.940931	-66.657445	Sa
3	Fredericton Hill	45.948512	-66.656045	Canadian Tire	4bb52ba72ea19521201caa2f	45.944409	-66.666820	Ha
36	Fredericton Hill	45.948512	-66.656045	Tim Hortons	4dc29f89d4c07da169fbf84b	45.943720	-66.646907	Coffe
3	Fredericton Hill	45.948512	-66.656045	The Aitken University Centre - UNB	4b6458eff964a52052ac2ae3	45.941644	-66.663667	
38	Fredericton Hill	45.948512	-66.656045	Queen Square Park	4b7acb0ef964a520113d2fe3	45.950961	-66.648245	
39	Fredericton Hill	45.948512	-66.656045	Great Canadian Bagel	4b784edbf964a52013c42ee3	45.941040	-66.657545	
40	Fredericton Hill	45.948512	-66.656045	Monkey Cakes	4ec147368231b62f43026067	45.940938	-66.657346	
4	Fredericton Hill	45.948512	-66.656045	Papa John's Pizza	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285	Pizz
42	Fredericton Hill	45.948512	-66.656045	Greco	4cfc0660c51fa1cdd3d7e92b	45.954055	-66.647290	Pizz
4	Fredericton Hill	45.948512	-66.656045	Dick's Grocery Store	4c545e5db426ef3b11cc7e8a	45.941957	-66.663877	Smok
44	Fredericton Hill	45.948512	-66.656045	Tingley's Ice Cream	4c13c001b7b9c9284e12aa37	45.957087	-66.655855	Ice
4	Fredericton Hill	45.948512	-66.656045	Domino's Pizza	50f9bbc75d24acebc259244d	45.957177	-66.656638	Pizz
46	Fredericton Hill	45.948512	-66.656045	Jumbo Video	4bc0d29a920eb71307a2192c	45.957286	-66.656312	Vide
4	Fredericton Hill	45.948512	-66.656045	Goody Shop	4b8580edf964a5201d6231e3	45.951172	-66.644000	
48	Nashwaaksis	45.983382	-66.644856	Peters Meat, Seafood & Lobster Market	4c4e04ecfb742d7fe7bba62d	45.976652	-66.649765	G

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
49	Nashwaaksis	45.983382	-66.644856	Tim Hortons	4b742f31f964a520b7cb2de3	45.975294	-66.646977	Coffe
50	Nashwaaksis	45.983382	-66.644856	The Northside Market	50270b2ae4b042eaf816ee61	45.977779	-66.635003	F
5	Nashwaaksis	45.983382	-66.644856	Shoppers Drug Mart	4c745e08db52b1f781f775dc	45.976515	-66.648534	Ph
52	Nashwaaksis	45.983382	-66.644856	Subway	4bc5db23693695213a9a8488	45.976886	-66.648661	Sa
53	Nashwaaksis	45.983382	-66.644856	Subway	4c87f3b4bf40a1cd09fd08b4	45.989114	-66.652061	Sa
54	Nashwaaksis	45.983382	-66.644856	Kentucky Fried Chicken	4eefb90ba69ddc7bcb336081	45.975903	-66.646846	Fas Res
5	Nashwaaksis	45.983382	-66.644856	Nashwaaksis Field House	4b73436cf964a52016a52de3	45.984849	-66.643635	
5	Nashwaaksis	45.983382	-66.644856	KFC	4c9267139199bfb7786c14df	45.975907	-66.646870	Fas Res
57	Nashwaaksis	45.983382	-66.644856	Tim Hortons	4c0104cf360a9c74bb11d9a0	45.989221	-66.652208	Coffe
58	Nashwaaksis	45.983382	-66.644856	Thai spice	503658e5e4b00b386cc5d972	45.975890	-66.647424	Res
59	Nashwaaksis	45.983382	-66.644856	Mike's Old Fashioned Bakery	4d67fde7709bb60c5eacb014	45.976560	-66.650030	
6	Nashwaaksis	45.983382	-66.644856	Cox Electronics	4d07eab6611ff04d4f4718fb	45.976112	-66.649222	Elec
6	Nashwaaksis	45.983382	-66.644856	A Pile Of Scrap!	4e9f0e9b93ad5d11f3d36ba1	45.984398	-66.633329	Arts &
62	Nashwaaksis	45.983382	-66.644856	Jim Gilberts Wheels And Deals	4b9a7ef5f964a520b6ba35e3	45.980784	-66.633311	Dea
63	Nashwaaksis	45.983382	-66.644856	Trailway Brewery	574a1b86cd10af189e38500e	45.975442	-66.649496	Bee
64	Nashwaaksis	45.983382	-66.644856	The North Side Market	501c19f7e4b01c57ff1b1212	45.977837	-66.635168	F
				Avalon SalonSpa	4bc31784920eb71312ec1c2c	45.974591	-66.644756	
65	Nashwaaksis	45.983382	-66.644856	Tony Pepperoni	4dbae5806e815ab0de5d2637	45.946698	-66.637891	Bas
66	Nashwaaksis	45.983382	-66.644856	The Richard J. CURRIE Center - UNB	4c88f56dbbec6dcbe9f2d758	45.991888	-66.648599	Pizz
67	University of Brunswick	45.948121	-66.641406					
68	University of New Brunswick	45.948121	-66.641406	Charlotte Street Arts Centre	4b7f0318f964a5203d1030e3	45.955620	-66.639324	Art
69	University of New Brunswick	45.948121	-66.641406	Sobeys	4b6727daf964a520493e2be3	45.954891	-66.645920	G
70	University of New Brunswick	45.948121	-66.641406	YMCA Fredericton	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
71	University of New Brunswick	45.948121	-66.641406	20 Twenty Club	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112	

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
72	University of New Brunswick	45.948121	-66.641406	The Cellar Pub & Grill - UNB	4b7ac93ef964a520b53c2fe3	45.945434	-66.641626	
73	University of New Brunswick	45.948121	-66.641406	Harvey's	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021	Burg
74	University of New Brunswick	45.948121	-66.641406	Tim Hortons	4c865c1774d7b60c3f41a3d8	45.945185	-66.641545	Coffe
		45.948121	-66.641406	Tim Hortons	4dc29f89d4c07da169fbf84b	45.943720	-66.646907	Coffe
75	University of New Brunswick							
76	University of New Brunswick	45.948121	-66.641406	College Hill Social Club	4b7aca23f964a520df3c2fe3	45.945162	-66.641472	
77	Devon	45.968802	-66.622738	New England Pizza	4c09984e7e3fc928b64bf282	45.967675	-66.629905	Pizz
7	Devon	45.968802	-66.622738	Wolastoq Wharf	4fbaafb0e4b0c7f68a419500	45.969975	-66.632568	S Res
79	Devon	45.968802	-66.622738	Dairy Queen	4c5cab2894fd0f473c69c945	45.969077	-66.632059	Fas Res
8	Devon	45.968802	-66.622738	Pharmacie Jean Coutu	4eb9523077c8972738ac89b2	45.967766	-66.630551	Ph
81	Devon	45.968802	-66.622738	Tim Hortons	4b5b0812f964a520d8df28e3	45.969381	-66.632730	Coffe
82	Devon	45.968802	-66.622738	Henry Park	4c8e283dad01199c7923726d	45.963992	-66.620283	B
83	Devon	45.968802	-66.622738	Giant Tiger	4c95354f58d4b60c80443029	45.967715	-66.630410	Depa
84	Devon	45.968802	-66.622738	york arena	4b6c4f10f964a520792f2ce3	45.964888	-66.617110	Skatin
8	Devon	45.968802	-66.622738	St. Mary's Supermarket	4b9fa6adf964a520c93137e3	45.971945	-66.631248	G
86	Devon	45.968802	-66.622738	Dixie Lee	4c5cacc5d25320a103fdc37a	45.962257	-66.624952	Fas Res
87	Devon	45.968802	-66.622738	St Marys Smoke Shop	4ebddf8a4690d233887bf4a6	45.972270	-66.631348	Smok
88	Devon	45.968802	-66.622738	Carleton	4bce2eeb29d4b7138521a8dc	45.961182	-66.626310	Park
8	New Maryland	45.892795	-66.683673	New York Fries	4d8771fc651041bd194d9b30	45.890420	-66.683580	Fas Res
9	New Maryland	45.892795	-66.683673	Centre De Danse Roca Dance Center	55fdfc2b498ed76a0f7aa3f6	45.890978	-66.692237	
91	New Maryland	45.892795	-66.683673	Baseball, Basketball, Tennis and Hockey In One...	4e48415862e148603b8b3fc2	45.890726	-66.692814	B
9	New Maryland	45.892795	-66.683673	Circle K	4b9e633ef964a5202fdf36e3	45.885412	-66.688995	Gas
93	Marysville	45.978913	-66.589491	Tim Hortons	4baa1b40f964a520174b3ae3	45.978193	-66.593041	Coffe
94	Marysville	45.978913	-66.589491	Royals Field	4c573f916201e21edff8736e	45.980267	-66.588412	B S

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
9	Marysville	45.978913	-66.589491	Northside Pharmacy	4c8bee978018a1cdd1f2e7d2	45.980194	-66.588628	Ph
9	Marysville	45.978913	-66.589491	Marysville Place	4ce6d19be1eeb60c512d99ae	45.980243	-66.588277	
97	Marysville	45.978913	-66.589491	Circle K	4bb88fe853649c74431847fb	45.979250	-66.593232	Gas
9	Skyline Acres	45.931827	-66.640339	Grant Harvey Centre	4f915a7ee4b01406ebc873ae	45.925002	-66.641004	
9	Skyline Acres	45.931827	-66.640339	Kimble Field	4fdaa8c2e4b08f3358b1b3d1	45.930535	-66.631233	B
10	Skyline Acres	45.931827	-66.640339	Mandarin Palace	4b786998f964a5204ecc2ee3	45.935440	-66.631007	C Res
10	Skyline Acres	45.931827	-66.640339	Oriental Pearl	4ec68431775bf65c02417199	45.930085	-66.629518	C Res
102	Hanwell	45.902315	-66.755113	Advanced Fabrics	53c133a4498e933c415c6118	45.905297	-66.750944	
103	Hanwell	45.902315	-66.755113	Country Style	56356c83498e17f8ed69a380	45.905937	-66.751084	Coffe
104	Downtown	45.958327	-66.647211	Cafe Loka & Bistro	4e70d116152073dd03c2c50e	45.957570	-66.647978	
105	Downtown	45.958327	-66.647211	Boyce Farmers Market	4b5163b4f964a5204d4c27e3	45.958354	-66.639654	F
106	Downtown	45.958327	-66.647211	Second Cup	4b7067c6f964a5205a182de3	45.961385	-66.642372	Coffe
107	Downtown	45.958327	-66.647211	Lunar Rogue	4b8c53e7f964a520d4ca32e3	45.959998	-66.639116	
108	Downtown	45.958327	-66.647211	Jonnie Java Roasters	4bc47e80920eb71369c71e2c	45.962226	-66.643852	Coffe
10	Downtown	45.958327	-66.647211	Picaroon's Brewtique	4ced5cfe7b943704ea782653	45.962701	-66.642731	B
110	Downtown	45.958327	-66.647211	Sobeys	4b6727daf964a520493e2be3	45.954891	-66.645920	G
111	Downtown	45.958327	-66.647211	Luna Pizza	4be47e9b2468c92811dbfe42	45.962246	-66.643788	Res
112	Downtown	45.958327	-66.647211	Palate Restaurant & Cafe	4c2e0e6ae760c9b69bdf4549	45.962338	-66.641776	Res
113	Downtown	45.958327	-66.647211	Alcool NB Liquor	4d9a52120d5f224bc5f7a34e	45.956140	-66.647558	Liquo
11	Downtown	45.958327	-66.647211	coffee and friends	4b533f74f964a520009427e3	45.961842	-66.643479	Coffe
115	Downtown	45.958327	-66.647211	Chess Piece Pâtisserie & Cafe	53c00bcc498e1f34dc3687ae	45.963354	-66.644017	
116	Downtown	45.958327	-66.647211	Victory Meat Market	4bd1ffd341b9ef3bcb19fde5	45.962661	-66.645820	G
117	Downtown	45.958327	-66.647211	Exhibition Grounds	4c76d45d07818cfafe94d2e3	45.960078	-66.655522	Ra
118	Downtown	45.958327	-66.647211	The Abbey Café & Gallery	57178722498e4222f7d5b298	45.961301	-66.640188	
119	Downtown	45.958327	-66.647211	Charlotte Street Arts Centre	4b7f0318f964a5203d1030e3	45.955620	-66.639324	Art
120	Downtown	45.958327	-66.647211	Isaac's Way	51c8a824498ef33c708ac9e9	45.960944	-66.637796	Res

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
121	Downtown	45.958327	-66.647211	YMCA Fredericton	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
122	Downtown	45.958327	-66.647211	Read's News Stand	4b4b6bf2f964a5200a9b26e3	45.961859	-66.643464	Coffe
123	Downtown	45.958327	-66.647211	King Street Ale House	5283fd1c498e138a8297590c	45.960460	-66.641012	
124	Downtown	45.958327	-66.647211	540 Kitchen and Bar	53ab370e498e91a454f49e67	45.961657	-66.640152	Gas
125	Downtown	45.958327	-66.647211	Dimitri's Souvlaki	4bacf7e8f964a520571f3be3	45.963093	-66.644479	Res
126	Downtown	45.958327	-66.647211	Smoke's Poutinerie	51756ac6498ece19b79a31f6	45.962032	-66.644021	Fas
127	Downtown	45.958327	-66.647211	Snooty Fox	4b4ca053f964a52006b826e3	45.960794	-66.638927	Res
128	Downtown	45.958327	-66.647211	Officer's Square	4c83b0df2f1c236a4bc54443	45.961754	-66.639084	
129	Downtown	45.958327	-66.647211	Fredericton Playhouse	4b516b64f964a520df4c27e3	45.960101	-66.636969	Perf Arts
130	Downtown	45.958327	-66.647211	Willie O'Ree Place	4b76879ef964a520a5502ee3	45.963017	-66.646100	
131	Downtown	45.958327	-66.647211	The Joyce	4b624863f964a5203b402ae3	45.960309	-66.636806	
132	Downtown	45.958327	-66.647211	Cora's Breakfast & Lunch	4b8130c7f964a520e99930e3	45.962282	-66.641607	Br
133	Downtown	45.958327	-66.647211	Strange Adventures	50461342e4b0c55b9639accc	45.961721	-66.640125	Res
134	Downtown	45.958327	-66.647211	Naru Japanese Cuisine	4c65dd9a19f3c9b697769eff	45.962811	-66.646079	M
135	Downtown	45.958327	-66.647211	Mexicali Rosas	4babdcbdf964a5200cd03ae3	45.962733	-66.643315	Hobb Res
136	Downtown	45.958327	-66.647211	Brewbakers	4b6754faf964a5208d482be3	45.960703	-66.640935	Res
137	Downtown	45.958327	-66.647211	Dolan's Pub	4b516ddbf964a520144d27e3	45.962886	-66.644615	
138	Downtown	45.958327	-66.647211	Beaverbrook Art Gallery	4c13a7f7b7b9c92865dea937	45.959878	-66.635858	Art M
139	Downtown	45.958327	-66.647211	McGinnis Landing	4b6df601f964a5203d9f2ce3	45.963013	-66.646536	Stea
140	Downtown	45.958327	-66.647211	Atlantic Superstore	4b5b0a91f964a5205fe028e3	45.958260	-66.658048	Super
141	Downtown	45.958327	-66.647211	20 Twenty Club	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112	
142	Downtown	45.958327	-66.647211	Geek Chic	4b516f03f964a520324d27e3	45.960573	-66.639225	Toy /
143	Downtown	45.958327	-66.647211	Wilser's Room	4ba01983f964a520f15937e3	45.963192	-66.644089	
144	Downtown	45.958327	-66.647211	Tim Hortons	4b6455b0f964a52067ab2ae3	45.959873	-66.639259	Coffe
145	Downtown	45.958327	-66.647211	TD Canada Trust	4b6d8261f964a52022792ce3	45.963891	-66.645782	
146	Downtown	45.958327	-66.647211	Fit4Less	4c9381ab94a0236a70ac8312	45.958634	-66.657319	
147	Downtown	45.958327	-66.647211	Harvey's	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021	Burg

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
14	Downtown	45.958327	-66.647211	Shoppers Drug Mart	4db07df34df03036e8bbb640	45.961351	-66.644493	Ph
14	Downtown	45.958327	-66.647211	Shan	4dfb6fc31f6eeef806aacc25	45.961818	-66.643706	C Res
150	Downtown	45.958327	-66.647211	bulgogi	4b605f0ff964a5203de229e3	45.961522	-66.642742	Res
15	Downtown	45.958327	-66.647211	William's Seafood	4b7c26f5f964a52061802fe3	45.959296	-66.655663	S Res
152	Downtown	45.958327	-66.647211	Subway	4b6b883df964a5205a0e2ce3	45.962580	-66.645032	Sa
15	Downtown	45.958327	-66.647211	Capital Complex	4b6faa7cf964a52073f92ce3	45.963245	-66.644123	
15	Downtown	45.958327	-66.647211	boom! Nightclub	4ba240eef964a52050e737e3	45.962315	-66.641645	Ni
155	Downtown	45.958327	-66.647211	Tim Hortons	4ba8bdb3f964a5204ceb39e3	45.959933	-66.655493	Coffe
15	Downtown	45.958327	-66.647211	King's Place Mall	4bc61ba4d35d9c74292de23a	45.961679	-66.643267	Sh
15	Downtown	45.958327	-66.647211	Running Room	4c6d4adb23c1a1cdffc81bcf	45.961812	-66.643510	S Good
15	Downtown	45.958327	-66.647211	The Happy Baker	4b703d21f964a5204c0d2de3	45.960536	-66.641465	
15	Downtown	45.958327	-66.647211	Owl's Nest Bookstore	4d6ea0c98df1548152778123	45.963051	-66.643872	Bo
16	Downtown	45.958327	-66.647211	Tingley's Ice Cream	4c13c001b7b9c9284e12aa37	45.957087	-66.655855	Ice
161	Downtown	45.958327	-66.647211	Jumbo Video	4bc0d29a920eb71307a2192c	45.957286	-66.656312	Vide
16	Downtown	45.958327	-66.647211	Enterprise Rent-A-Car	4d3ae3edbf6d5481b26fd1e1	45.957743	-66.656527	Ren L
16	Downtown	45.958327	-66.647211	Domino's Pizza	50f9bbc75d24acebc259244d	45.957177	-66.656638	Pizz
16	Downtown	45.958327	-66.647211	Papa John's Pizza	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285	Pizz
16	Downtown	45.958327	-66.647211	Queen Square Park	4b7acb0ef964a520113d2fe3	45.950961	-66.648245	

In [109]:
```
print('There are {} unique venue categories.'.format(len(fredericton_data_venues['V
enue Category'].unique())))
```

There are 73 unique venue categories.

In [110]:
```
print('There are {} unique venues.'.format(len(fredericton_data_venues['Venue id'].
unique())))
```

There are 153 unique venues.

In [111]:
```
univen = fredericton_data_venues.groupby('Location').nunique('Venue Category')
univen
```

Out[111]:

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Venue Category
Location								
Devon	1	1	1	12	12	12	12	11
Downtown	1	1	1	61	62	62	62	44
Fredericton Hill	1	1	1	17	17	17	17	13
Hanwell	1	1	1	2	2	2	2	2
Knowledge Park	1	1	1	31	31	31	31	23
Marysville	1	1	1	5	5	5	5	5
Nashwaaksis	1	1	1	17	19	19	19	15
New Maryland	1	1	1	4	4	4	4	4
Skyline Acres	1	1	1	4	4	4	4	3
University of New Brunswick	1	1	1	9	10	10	10	8

In [112]:
```
fredericton_data_venues.groupby('Venue Category').nunique()
```

Out[112]:

Venue Category	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Venue Category
Art Gallery	2	2	2	1	1	1	1	1
Art Museum	1	1	1	1	1	1	1	1
Arts & Crafts Store	2	2	2	2	2	2	2	1
Auto Dealership	1	1	1	1	1	1	1	1
Bakery	3	3	3	5	5	5	5	1
Bank	1	1	1	1	1	1	1	1
Bar	3	3	3	4	4	4	4	1
Baseball Field	3	3	3	3	3	3	3	1
Baseball Stadium	1	1	1	1	1	1	1	1
Basketball Court	1	1	1	1	1	1	1	1
Beer Store	1	1	1	1	1	1	1	1
Big Box Store	1	1	1	1	1	1	1	1
Bookstore	1	1	1	1	1	1	1	1
Breakfast Spot	1	1	1	1	1	1	1	1
Brewery	1	1	1	1	1	1	1	1
Burger Joint	2	2	2	1	1	1	1	1
Café	1	1	1	3	3	3	3	1
Chinese Restaurant	2	2	2	3	3	3	3	1
Clothing Store	1	1	1	3	3	3	3	1
Coffee Shop	7	7	7	6	13	13	13	1
Dance Studio	1	1	1	1	1	1	1	1
Department Store	2	2	2	2	2	2	2	1
Discount Store	1	1	1	1	1	1	1	1
Electronics Store	2	2	2	2	2	2	2	1
Farmers Market	2	2	2	3	3	3	3	1
Fast Food Restaurant	5	5	5	9	10	10	10	1
Furniture / Home Store	1	1	1	2	2	2	2	1
Gas Station	2	2	2	1	2	2	2	1
Gastropub	1	1	1	1	1	1	1	1
Gift Shop	1	1	1	1	1	1	1	1
Greek Restaurant	1	1	1	1	1	1	1	1
Grocery Store	4	4	4	4	4	4	4	1
Gym	4	4	4	2	2	2	2	1
Gym / Fitness	1	1	1	1	1	1	1	1

Center

Venue Category	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Venue Category
Hardware Store	1	1	1	1	1	1	1	1
Hobby Shop	1	1	1	1	1	1	1	1
Hockey Arena	3	3	3	3	3	3	3	1
Ice Cream Shop	2	2	2	1	1	1	1	1
Italian Restaurant	2	2	2	2	2	2	2	1
Kids Store	1	1	1	1	1	1	1	1
Korean Restaurant	1	1	1	1	1	1	1	1
Liquor Store	2	2	2	2	3	3	3	1
Mattress Store	1	1	1	1	1	1	1	1
Mexican Restaurant	1	1	1	1	1	1	1	1
Nightclub	1	1	1	1	1	1	1	1
Park	4	4	4	4	4	4	4	1
Performing Arts Venue	1	1	1	1	1	1	1	1
Pet Store	1	1	1	1	1	1	1	1
Pharmacy	5	5	5	3	5	5	5	1
Pizza Place	4	4	4	5	5	5	5	1
Pub	2	2	2	6	6	6	6	1
Racetrack	1	1	1	1	1	1	1	1
Rental Car Location	1	1	1	1	1	1	1	1
Rental Service	1	1	1	1	1	1	1	1
Restaurant	2	2	2	5	5	5	5	1
Sandwich Place	3	3	3	1	4	4	4	1
Seafood Restaurant	3	3	3	3	3	3	3	1
Shoe Store	1	1	1	1	1	1	1	1
Shopping Mall	1	1	1	1	1	1	1	1
Shopping Plaza	1	1	1	1	1	1	1	1
Skating Rink	1	1	1	1	1	1	1	1
Smoke Shop	2	2	2	2	2	2	2	1
Smoothie Shop	1	1	1	1	1	1	1	1
Spa	2	2	2	2	2	2	2	1
Sporting Goods Shop	2	2	2	2	2	2	2	1
Sports Bar	1	1	1	1	1	1	1	1
Steakhouse	1	1	1	1	1	1	1	1
Supermarket	1	1	1	1	1	1	1	1

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Venue Category
Venue Category								
Sushi Restaurant	1	1	1	1	1	1	1	1
Thai Restaurant	1	1	1	1	1	1	1	1
Toy / Game Store	1	1	1	1	1	1	1	1
Video Store	2	2	2	1	1	1	1	1
Warehouse Store	1	1	1	1	1	1	1	1

In [ ]:

Analyze each Location

In [113]:

```
freddy_onehot = pd.get_dummies(fredericton_data_venues[['Venue Category']], prefix=
"", prefix_sep="")


freddy_onehot['Location'] = fredericton_data_venues['Location']


fixed_columns = [freddy_onehot.columns[-1]] + list(freddy_onehot.columns[:-1])
freddy_onehot = freddy_onehot[fixed_columns]

freddy_onehot.head()
```

Out[113]:

	Location	Art Gallery	Art Museum	Arts & Crafts Store	Auto Dealership	Bakery	Bank	Bar	Baseball Field	Baseball Stadium	Basketball Court	Beer Store
0	Knowledge Park	0	0	0	0	0	0	0	0	0	0	0
1	Knowledge Park	0	0	0	0	0	0	0	0	0	0	0
2	Knowledge Park	0	0	0	0	0	0	0	0	0	0	0
3	Knowledge Park	0	0	0	0	0	0	0	0	0	0	0
4	Knowledge Park	0	0	1	0	0	0	0	0	0	0	0

In [114]:

```
freddy_onehot.shape
```

Out[114]: (166, 74)

Group rows by location and by the mean of the frequency of occurrence of each category

In [115]:
```
freddy_grouped = freddy_onehot.groupby('Location').mean().reset_index()
freddy_grouped
```

Out[115]:

	Location	Art Gallery	Art Museum	Arts & Crafts Store	Auto Dealership	Bakery	Bank	Bar	Baseball Field	Baseball Ba Stadium
0	Devon	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.083333	0.0
1	Downtown	0.016129	0.016129	0.000000	0.000000	0.016129	0.016129	0.048387	0.000000	0.0
2	Fredericton Hill	0.000000	0.000000	0.000000	0.000000	0.176471	0.000000	0.058824	0.000000	0.0
3	Hanwell	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
4	Knowledge Park	0.000000	0.000000	0.032258	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
5	Marysville	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.2
6	Nashwaaksis	0.000000	0.000000	0.052632	0.052632	0.052632	0.000000	0.000000	0.000000	0.0
7	New Maryland	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.250000	0.0
8	Skyline Acres	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.250000	0.0
9	University of New Brunswick	0.100000	0.000000	0.000000	0.000000	0.000000	0.000000	0.200000	0.000000	0.0

In [116]:
```
freddy_grouped.shape
```

Out[116]: (10, 74)

Print each Location with the top 5 most common venues

In [117]:
```
num_top_venues = 5

for hood in freddy_grouped['Location']:
    print("----"+hood+"----")
    temp = freddy_grouped[freddy_grouped['Location'] == 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(num
_top_venues))
    print('\n')
```

```
----Devon----
                  venue  freq
0  Fast Food Restaurant  0.17
1           Coffee Shop  0.08
2         Grocery Store  0.08
3    Seafood Restaurant  0.08
4          Skating Rink  0.08


----Downtown----
         venue  freq
0  Coffee Shop  0.10
1          Pub  0.08
2         Café  0.05
3   Restaurant  0.05
4   Bar    0.05


----Fredericton Hill----
            venue  freq
0          Bakery  0.18
1     Pizza Place  0.18
2    Hockey Arena  0.06
3      Smoke Shop  0.06
4  Ice Cream Shop  0.06


----Hanwell----
                 venue  freq
0          Coffee Shop   0.5
1       Rental Service   0.5
2          Art Gallery   0.0
3  Rental Car Location   0.0
4            Racetrack   0.0


----Knowledge Park----
                    venue  freq
0    Fast Food Restaurant  0.13
1          Clothing Store  0.10
2            Liquor Store  0.06
3              Restaurant  0.06
4  Furniture / Home Store  0.06


----Marysville----
              venue  freq
0       Coffee Shop   0.2
1          Pharmacy   0.2
2              Park   0.2
3  Baseball Stadium   0.2
4       Gas Station   0.2


----Nashwaaksis----
                  venue  freq
0        Farmers Market  0.11
1        Sandwich Place  0.11
2           Coffee Shop  0.11
3  Fast Food Restaurant  0.11
4            Beer Store  0.05


----New Maryland----
```

```
                  venue  freq
0  Fast Food Restaurant  0.25
1        Baseball Field  0.25
2           Gas Station  0.25
3          Dance Studio  0.25
4           Art Gallery  0.00


----Skyline Acres----
                venue  freq
0  Chinese Restaurant  0.50
1        Hockey Arena  0.25
2      Baseball Field  0.25
3           Pet Store  0.00
4      Rental Service  0.00


----University of New Brunswick----
              venue  freq
0       Coffee Shop   0.2
1               Bar   0.2
2  Basketball Court   0.1
3  Gym            0.1
4     Grocery Store   0.1
```

Now into a pandas dataframe

In [118]:
```python
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 [119]:
```
num_top_venues = 10

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


columns = ['Location']
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))


location_venues_sorted = pd.DataFrame(columns=columns)
location_venues_sorted['Location'] =freddy_grouped['Location']

for ind in np.arange(freddy_grouped.shape[0]):
    location_venues_sorted.iloc[ind, 1:] =return_most_common_venues(freddy_grouped
.iloc[ind, :], num_top_venues)

location_venues_sorted
```

Out[119]:

	Location	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	Devon	Fast Food Restaurant	Grocery Store	Smoke Shop	Pharmacy	Coffee Shop	Seafood Restaurant	Park	Department Store	
1	Downtown	Coffee Shop	Pub	Bar	Café	Restaurant	Park	Pizza Place	Grocery Store	
2	Fredericton Hill	Bakery	Pizza Place	Hockey Arena	Smoke Shop	Hardware Store	Video Store	Ice Cream Shop	Park	P
3	Hanwell	Rental Service	Coffee Shop	Warehouse Store	Dance Studio	Department Store	Discount Store	Electronics Store	Farmers Market	F R
4	Knowledge Park	Fast Food Restaurant	Clothing Store	Furniture / Home Store	Liquor Store	Restaurant	Warehouse Store	Shoe Store	Pet Store	
5	Marysville	Baseball Stadium	Gas Station	Pharmacy	Park	Coffee Shop	Gift Shop	Gastropub	Greek Restaurant	F
6	Nashwaaksis	Coffee Shop	Sandwich Place	Farmers Market	Fast Food Restaurant	Gym	Spa	Electronics Store	Beer Store	
7	New Maryland	Gas Station	Dance Studio	Fast Food Restaurant	Baseball Field	Furniture / Home Store	Department Store	Discount Store	Electronics Store	
8	Skyline Acres	Chinese Restaurant	Baseball Field	Hockey Arena	Arts & Crafts Store	Coffee Shop	Gym / Fitness Center	Gym	Grocery Store	R
9	University of New Brunswick	Bar	Coffee Shop	Art Gallery	Pub	Burger Joint	Basketball Court	Grocery Store	Gym	

Cluster Fredericton Locations

Run k-means to cluster Locations into 5 clusters

In [120]:

```
kclusters = 5

freddy_grouped_clustering = freddy_grouped.drop('Location', 1)


kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(freddy_grouped_clustering
)


kmeans.labels_[0:10]
```

Out[120]:

```
array([1, 1, 1, 0, 1, 4, 1, 3, 2, 1], dtype=int32)
```

Now creating a new dataframe including the cluster as well as the top 10 venues for each Location

In [121]:
```
freddy_merged = location_df

freddy_merged['Cluster Labels'] = kmeans.labels_


freddy_merged = freddy_merged.join(location_venues_sorted.set_index('Location'), on
='Location')

freddy_merged
```

Out[121]:

	Location	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Com V
0	Knowledge Park	45.931143	-66.652700	1	Fast Food Restaurant	Clothing Store	Furniture / Home Store	Liquor Store	Restaurant	Wareh
1	Fredericton Hill	45.948512	-66.656045	1	Bakery	Pizza Place	Hockey Arena	Smoke Shop	Hardware Store	Video
2	Nashwaaksis	45.983382	-66.644856	1	Coffee Shop	Sandwich Place	Farmers Market	Fast Food Restaurant	Gym	
3	University of New Brunswick	45.948121	-66.641406	0	Bar	Coffee Shop	Art Gallery	Pub	Burger Joint	Bask
4	Devon	45.968802	-66.622738	1	Fast Food Restaurant	Grocery Store	Smoke Shop	Pharmacy	Coffee Shop	Sea Resta
5	New Maryland	45.892795	-66.683673	4	Gas Station	Dance Studio	Fast Food Restaurant	Baseball Field	Furniture / Home Store	Depart
6	Marysville	45.978913	-66.589491	1	Baseball Stadium	Gas Station	Pharmacy	Park	Coffee Shop	Gift
7	Skyline Acres	45.931827	-66.640339	3	Chinese Restaurant	Baseball Field	Hockey Arena	Arts & Crafts Store	Coffee Shop	G Fi C
8	Hanwell	45.902315	-66.755113	2	Rental Service	Coffee Shop	Warehouse Store	Dance Studio	Department Store	Disc
9	Downtown	45.958327	-66.647211	1	Coffee Shop	Pub	Bar	Café	Restaurant	

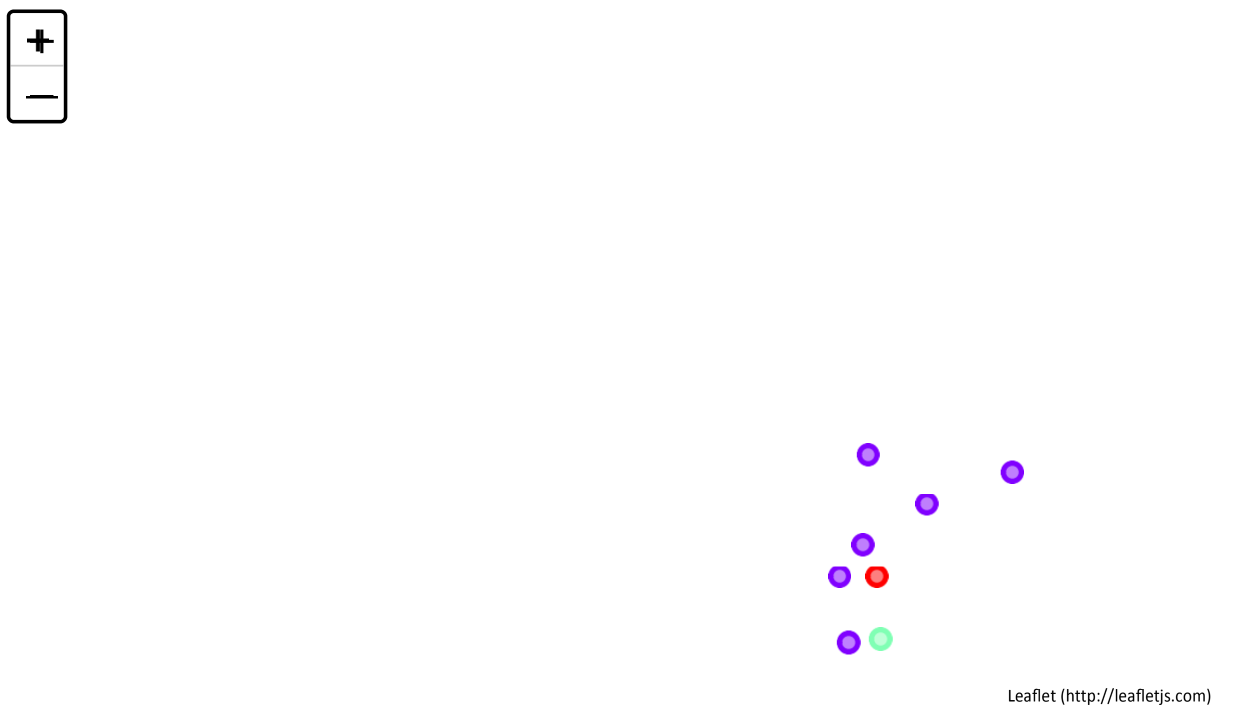
In [122]:

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


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


markers_colors = []
for lat, lon, poi, cluster in zip(freddy_merged['Latitude'], freddy_merged['Longitu
de'], freddy_merged['Location'], freddy_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],f
ill=True,fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)
map_clusters
```

Out[122]:



In [ ]: