Segmenting and Clustering Neighborhoods in Fredericton, NB

Applied Data Science Capstone Week 5 Peer-Graded Project Report

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/fredericton.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-neighbourhood2017--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-tractdemographics--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-dusecteur-de-recensement)
5. Fredericton locations of interest: https://github.com/JasonLUrquhart/Applied-Data-Science-Capstone/blob/master/Fredericton%20Locations.xlsx (https://github.com/JasonLUrquhart/Applied-Data-ScienceCapstone/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 # library to handle data in a vectorized manner

import pandas as pd # library for data analysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files

!conda install -c conda-forge geopy --yes # uncomment this lineif you haven't comp
leted the Foursquare API lab
from geopy.geocoders import Nominatim # convert an address into latitude and longit
ude values

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

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

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

# for webscraping import Beautiful Soup
from bs4 import BeautifulSoup

import xml

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

print('Libraries imported.')
```

```
Solving environment: done


# All requested packages already installed.


Solving environment: done
```

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

```
# All requested packages already installed.
```

```
Libraries imported.
```

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

Out[3]:
```
'/Users/jasonkristaurquhart/Documents/GitHub/Coursera-IBM-Applied-Data-Science-Capstone-Project'
```

In [75]:
```
r = requests.get('https://opendata.arcgis.com/datasets/823d86e17a6d47808c6e4f1c2dd97928_0.geojson')
fredericton_geo = r.json()
```

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

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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    [-66.5998465063764, 45.8962889533894],
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    [-66.6805601346545, 45.9456570693391],
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    [-66.690998558256, 45.9498794400526],
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```

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[-66.6521284559121, 45.9301264722544],
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[-66.6531166027247, 45.9293392062996],
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[-66.6550120479742, 45.9291455121693]],
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[-66.6328775593735, 45.8879357750148],
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[-66.6362462416889, 45.8890987927924],
[-66.6370098096804, 45.8896365239624],
[-66.6381596532441, 45.8909183040123],
[-66.6385818614276, 45.8918186586532],
[-66.6387435581788, 45.8925689430378],
[-66.6385908445805, 45.8940757335582],
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```
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    [-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',
 'Boston_Neighborhoods.geojson',
 '.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	FredeSrioctuotnh 7	05T00:002:0001.70-0001Z- Fredericton	26T00:002:0001.70-0001Z- 1	2120	RBE&SEI		DNNOCNE-	
1	FredeSrioctuotnh 7	04T00:002:0001.70-0003Z- Fredericton	06T00:002:0001.70-0003Z- 2	2120	RBE&SEI		DNNOCNE-	
2	FredeSrioctuotnh Fredericton	07T00:002:0001.70-0005Z- 3	NaN	2120	RBE&SEI DNNOCNE-	12		
3	FredeSrioctuotnh 12	20T00:002:0001.70-0006Z- Fredericton	21T00:002:0001.70-0006Z- 4	2120	RBE&SEI		DNNOCNE-	
4	FredeSrioctuotnh 7	09T00:002:0001.70-0007Z- Fredericton	10T00:002:0001.70-0007Z- 5	2120	RBE&SEI		DNNOCNE-	

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

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

What is the crime count by neighbourhood?

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
39	Northbrook Heights	10

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

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

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

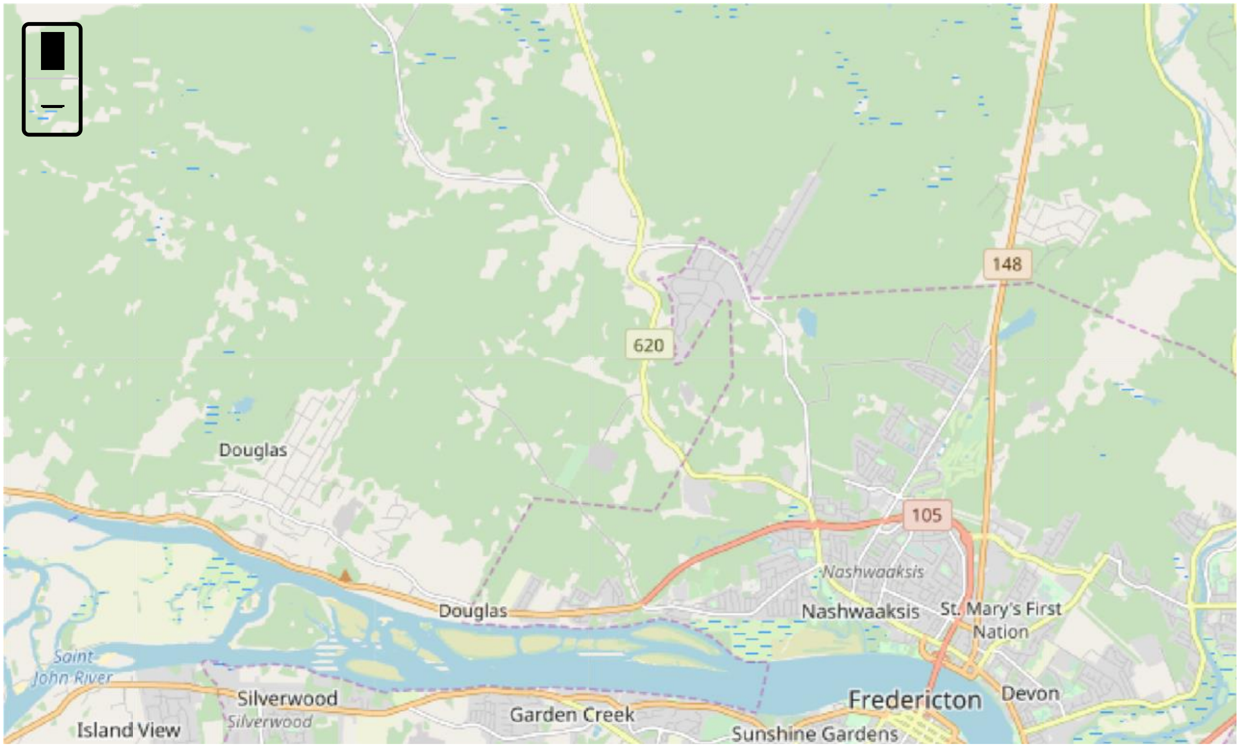
In [88]:

```
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.
```

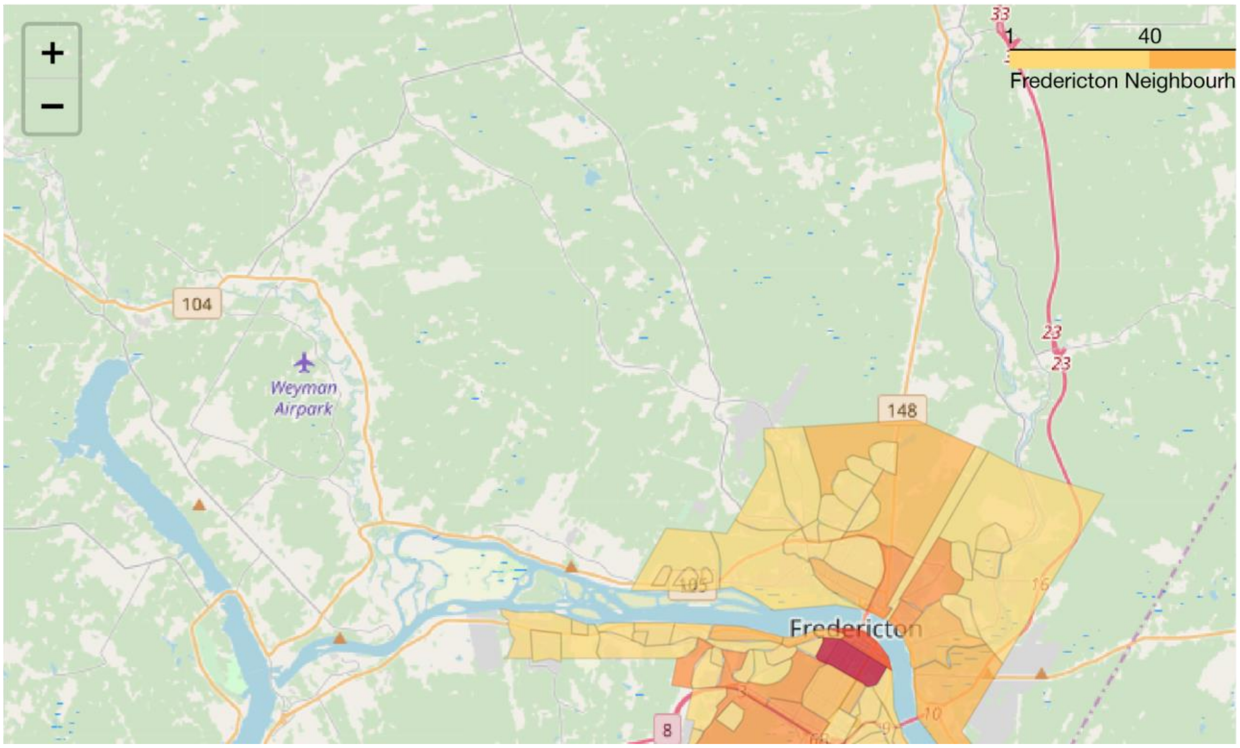
In [89]:
```
world_geo = r'world_countries.json' # geojson file

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_Count'].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=['Neighbourh', 'Crime_Count'],
    key_on='feature.properties.Neighbourh', threshold_scale=threshold_scale,fill_color='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]:

Crime_Type / Neighbourhood	City ARSON	ARSON BY NEG	B&E ARSON DAM.PROP.	B&E NON RESIDNCE	B&E OTHER	B&E RESIDENCE	STEAL FIREAR	MISCHIEF OBS USE	MISCHIE TO PRO
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	0	0	0	0	0	0	3	0	0 **heights**
Cotton Mill	0	0	0	0	0	0	0	0	0 **Creek**
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 Minihome Park	0	0	0	0	0	1	0	0	0
Hanwell North	0	0	0	0	0	1	2	0	0
Heron Springs	0	0	0	0	0	0	1	0	0
Highpoint	0	0	0	0	0	0	0	0	0 **Ridge**
Kelly's Court Minihome Park	0	0	0	0	0	0	0	0	0
Knob Hill	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

ARSON B&E

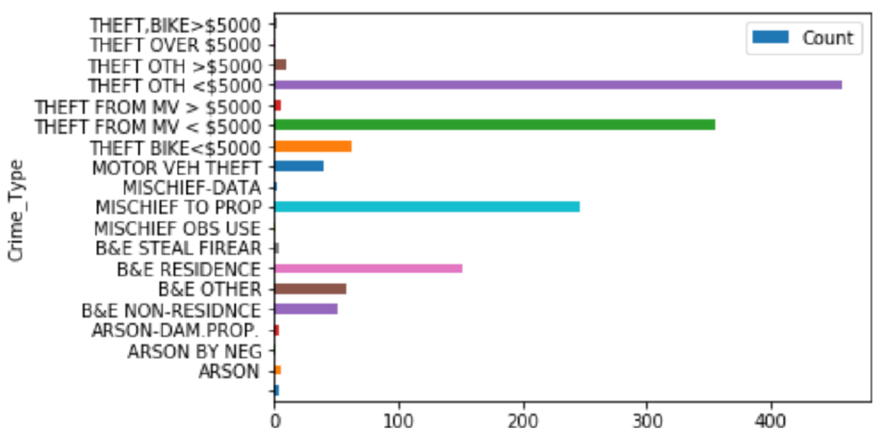
Crime_Type / Neighbourhood	ARSON	ARSON BY NEG	ARSON DAM.PROP.	B&E NON RESIDNCE	B&E OTHER	B&E RESIDENCE	STEAL FIREAR	MISCHIEF OBS USE	MISCHIE TO PRO
Lincoln Heights	0	0	0	0	0	1	1	0	0
Main Street	0	0	0	1	2	4	8	0	1
Marysville	0	1	0	0	1	2	5	0	0
McKnight	0	0	0	0	0	0	0	0	0
McLeod Hill	0	0	0	0	0	0	0	0	0
Monteith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

Crime_Type	ARSON	ARSON BY NEG	ARSON DAM.PROP.	B&E NON RESIDNCE	B&E OTHER	B&E RESIDENCE	STEAL FIREAR	MISCHIEF OBS USE	MISCHIE TO PRO

Neighbourhood									
The Hugh John Flemming Forestry Center	0	0	0	0	1	2	0	0	0
University Of New Brunswick	0	0	0	0	0	0	1	0	0
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	FID
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

<

<

<

<

2142 THEFT FROM MV < $5000 2 Fredericton

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FID
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					379

	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FID

2142
THEFT
FROM MV <
$5000
Fredericto
n 2142
THEFT
FROM MV <
$5000
Fredericto
n 2142
THEFT
FROM MV <
$5000
Fredericto
n 2142
THEFT
FROM MV <
$5000
Fredericto
n

9	2142	THEFT FROM MV < $5000	2	Fredericton	0

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

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531 Fulton Heights 3 532

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56 Main Street 57 **Neighbourhood** **Crime_Code** **Crime_Type** **Ward** **City**

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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

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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 12 776

776 Woodstock Road 0 777

777 Woodstock Road 12 778

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77 Woodstock Road 1 78

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	Neighbourhood	Crime_Code	Crime_Type	Ward	City	FID

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

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39	2142	THEFT FROM MV < $5000	Fredericton	0

THEFT FROM MV < $5000 10 Fredericton 833 **833** Plat 2142 THEFT FROM MV < $5000 11 Fredericton 834

835 Plat 10 836 **836** Plat 11 837 **837** Plat 10 838

838 Plat 10 839

8	Plat	11	84 **Neighbourhood**	**Crime_Code**	**Crime_Type**	**Ward**	**City**
	FID						

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

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3 2142 THEFT FROM MV < $5000 Fredericton

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 8 907 **907** Skyline Acrea 8 908

913 Poet's Hill 8 914 **914** Poet's Hill 8 915

922 Dun's Crossing 8 923 **Neighbourhood Crime_Code Crime_Type Ward City**

FID

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

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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 11 1029 **1029** College Hill 11 1030 **1030** College Hill 11 1031 **1031** College Hill 11 1032

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Neighbourhood Crime_Code Crime_Type Ward City FID

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 FID**

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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

14 7 North Devon 2142 THEFT FROM MV $5000 3 Fredericton 1438 **Neighbourhood** **Crime_Code** **Crime_Type** **Ward** **City** **FID**

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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
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

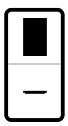
In [96]:

```
world_geo = r'world_countries.json' # geojson file

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

fredericton_c_map
```

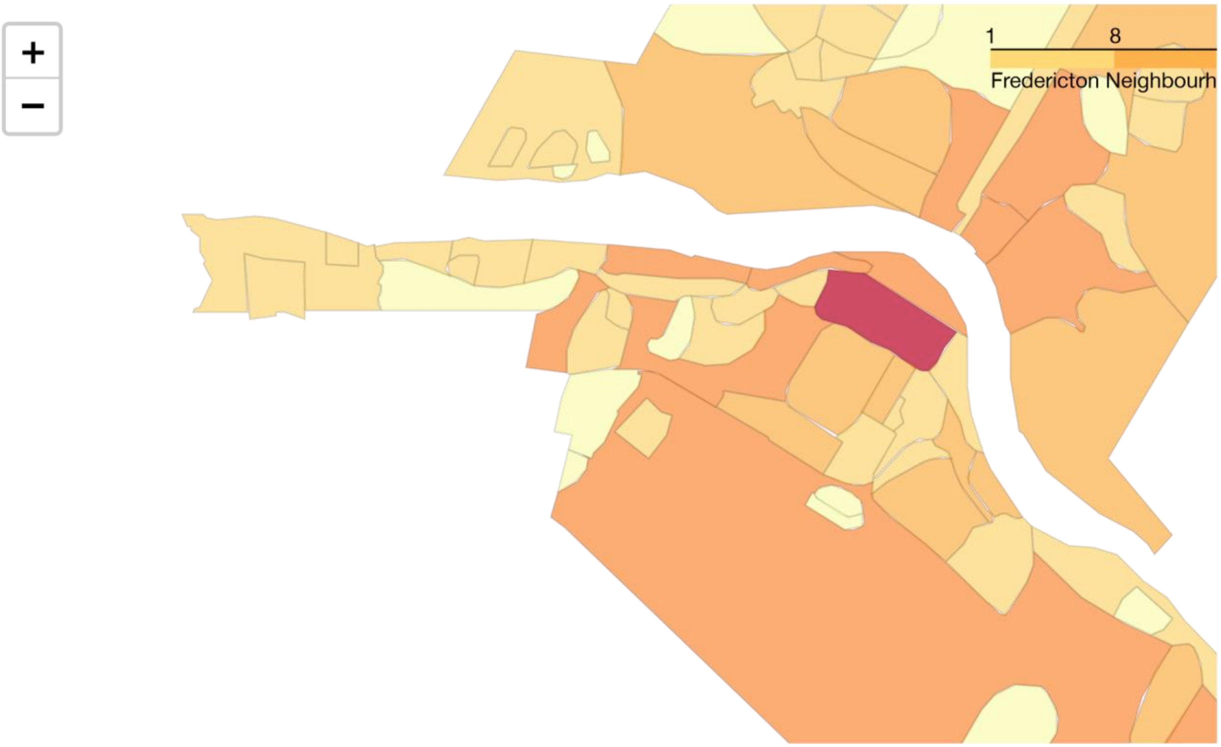
Out[96]:



In [97]:
```
## Motor Vehicle Crime <$5000 Count
fredericton_geo = r.json()
threshold_scale = np.linspace(mvcrime_data['MVCrime_Count'].min(), mvcrime_data['MVCrime_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=['Neighbourh', 'MVCrime_Count'],key_on='feature.properties.Neighbourh',
    threshold_scale=threshold_scale, fill_color='YlOrRd',fill_opacity=0.7,line_opacity=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	DB
0	1	501	1310024304	131002431310	3200002	2	1310024304	60	25	**1**	2
		502	1310032004	131003201310	3200010	10	1310032004	15	3		
2	3	503	1310017103	131001711310	3200014	14	1310017103	0	0		

3	4	504	1310018301	131001831310		3200012	12	1310018301	108	60
4	5	505	1310022905	13100229	1310	3200007	7	1310022905	129	47

In [ ]:

```

```

In [ ]:

```

```

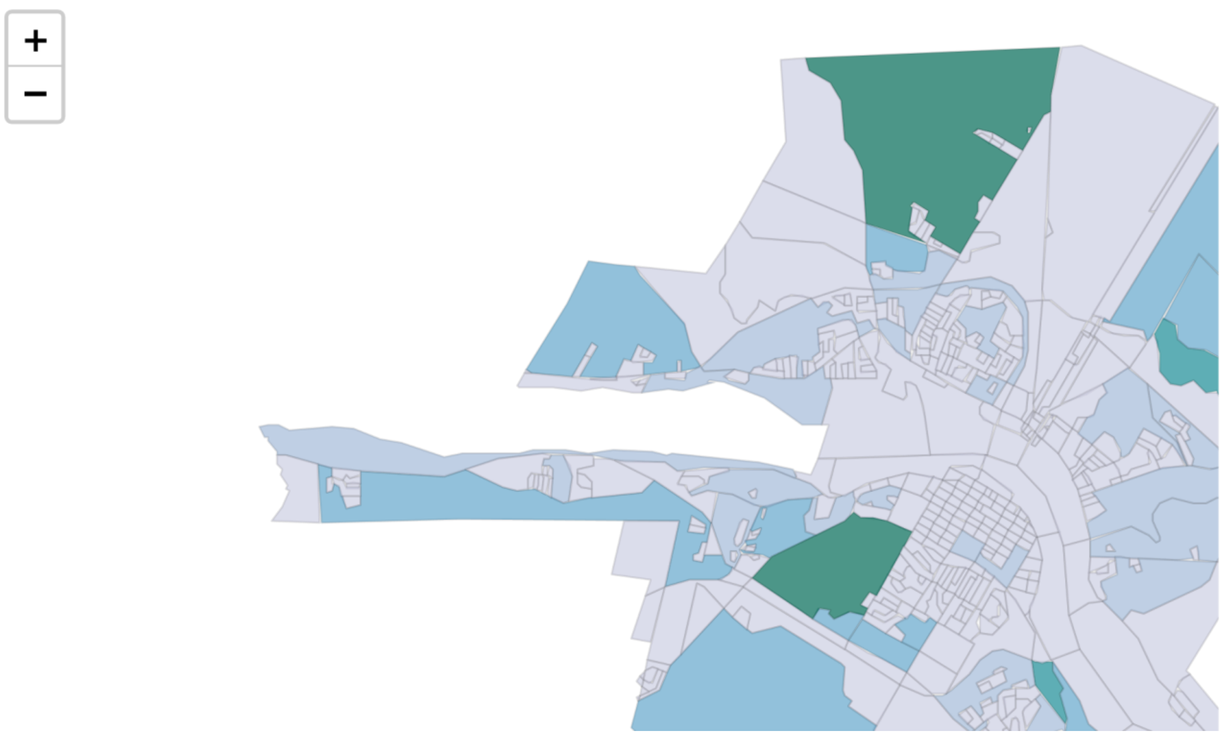
In [100]:

```
# Population Density
world_geo = r'world_countries.json' # geojson file
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	-66.652710
1	Fredericton Hill	NaN	45.948523	-66.656045
2	Nashwaaksis	NaN	45.984382	-66.654867
3	University of New Brunswick	NaN	45.948121	-66.641406
4	Devon	NaN	45.968802	-66.622839
5	New Maryland	NaN	45.8102795	-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
```

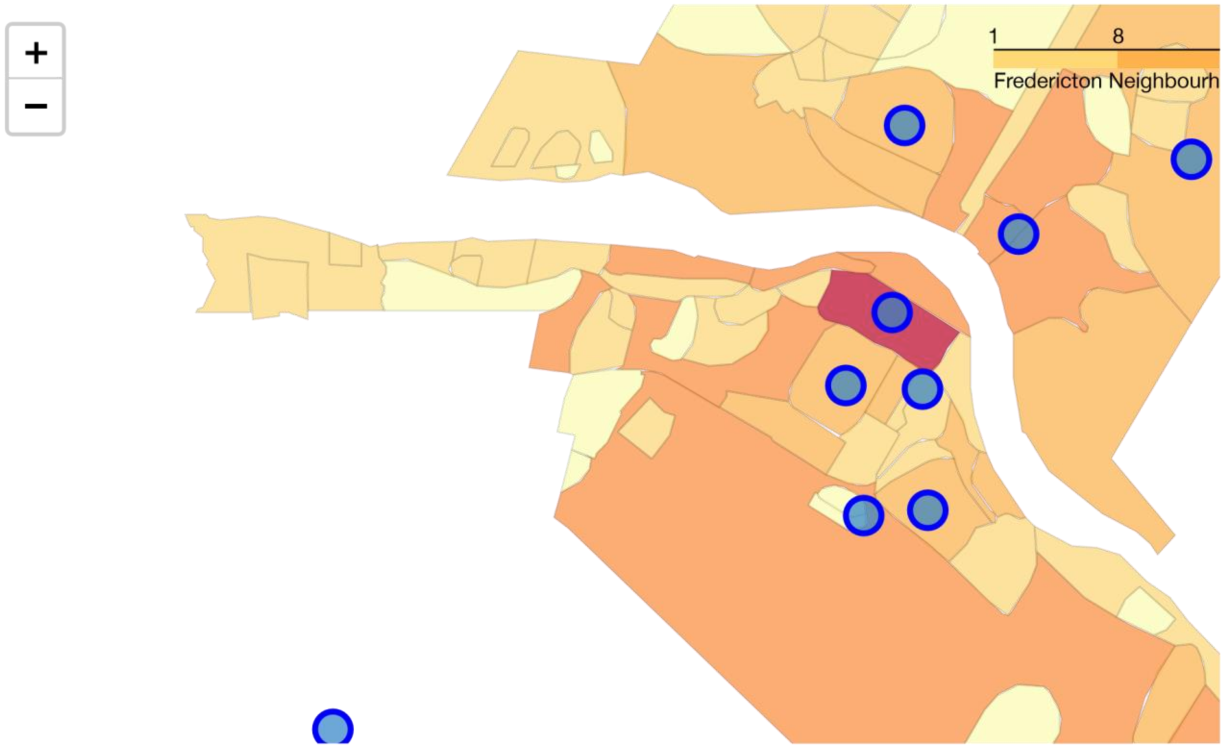
Out[103]:

	Location	Latitude	Longitude
1	Knowledge Park	45.931143	-66.652700
2	Fredericton Hill	45.948512	-66.656045
3	Nashwaaksis	45.983382	-66.644856
4	University of New Brunswick	45.948121	-66.641406
5	Devon	45.968802	-66.622738
6	New Maryland	45.892795	-66.683673
7	Marysville	45.978913	-66.589491
8	Skyline Acres	45.931827	-66.640339
9	Hanwell	45.902315	-66.755113
10	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' # your Foursquare ID
CLIENT_SECRET = 'Secret' # your Foursquare Secret
VERSION = '20181201' # Foursquare API version

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)
```

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

```
        # create the API request URL
        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)

        # make the GET request
        results =
requests.get(url).json()["response"]['groups'][0]['items']
        # return only relevant information for each nearby venue
venues_list.append([(             name,              lat,
lng,                          v['venue']['name'],
v['venue']['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
```

```
(166, 8)
```

Out[108]:

Location Latitude	Location Longitude	Location	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
	Park						

0	Knowledge Park	45.931143	-66.652700	Costco Wholesale	4e18ab92183880768f43bff6	45.927034	-66.663447	Ware
1	Knowledge Park	45.931143	-66.652700	PetSmart	4bbca501a0a0c9b6078f1a0f	45.929768	-66.659939	Pe
2	Knowledge Park	45.931143	-66.652700	Montana's	4e50406e62844166699b0780	45.931511	-66.662507	Rest
3	Knowledge Park	45.931143	-66.652700	Boston Pizza	4b64944af964a52041bf2ae3	45.938123	-66.660037	Spo
4	Knowledge Park	45.931143	-66.652700	Michaels	4c489858417b20a13b82e1a9	45.929965	-66.659548	Arts &
5	Knowledge Park	45.931143	-66.652700	Alcool NB Liquor	4b77335df964a5202c872ee3	45.930680	-66.664180	Liquo
6	Knowledge Park	45.931143	-66.652700	Best Buy	5520124a498e0467bb6e81c8	45.937673	-66.660380	Elec
7	Knowledge Park	45.931143	-66.652700	Wal-Mart	4bad313ff964a5208c373be3	45.934081	-66.663539	B
8	Knowledge Park	45.931143	-66.652700	Booster Juice	4c42414e520fa59334f9caac	45.935198	-66.663602	Sm
9	Knowledge Park	45.931143	-66.652700	Dairy Queen	4b86f05bf964a52009a731e3	45.938004	-66.659442	Fas Rest
10	Knowledge Park	45.931143	-66.652700	H&M	509c3265498efdffc5739a0f	45.935196	-66.663290	C
11	Knowledge Park	45.931143	-66.652700	Dairy Queen (Treat)	4cc6123cbde8f04d9ce0b44b	45.934520	-66.663988	Fas Rest
12	Knowledge Park	45.931143	-66.652700	Winners	4caa46a744a8224b96e42640	45.930427	-66.659758	C
13	Knowledge Park	45.931143	-66.652700	East Side Mario's	4b55d89bf964a520a2f227e3	45.931376	-66.663417	Rest
14	Knowledge Park	45.931143	-66.652700	McDonald's	4c6e9ef665eda09377e951d0	45.934575	-66.663319	Fas Rest
15	Knowledge Park	45.931143	-66.652700	Home Sense	54024f60498ee424eedb7bf9	45.930528	-66.660103	Depa
16	Knowledge Park	45.931143	-66.652700	The Shoe company	4bd76dfa5cf276b0fb469b00	45.929636	-66.660449	Shoe
17	Knowledge Park	45.931143	-66.652700	Avalon Spa Uptown	4cd99e0f51fc8cfa4369f05d	45.930774	-66.660927	
18	Knowledge Park	45.931143	-66.652700	Wicker Emporium	4e6baff588772457c4fd1968	45.930897	-66.661338	Fur Home
19	Knowledge Park	45.931143	-66.652700	Dollarama	4ba3dd18f964a520d86738e3	45.930897	-66.661714	Di
20	Knowledge Park	45.931143	-66.652700	Bed Bath & Beyond	5083f283e4b0bf87c15e9ea1	45.930097	-66.662166	Fur Home
21	Knowledge Park	45.931143	-66.652700	GAP Factory Store	50a8f005e4b0e4f42e033a2a	45.930211	-66.662416	C
22	Knowledge Park	45.931143	-66.652700	carter's | OshKosh B'gosh	50a51363e4b0a3e2f7db76bf	45.929978	-66.662966	Kids
23	Knowledge Park	45.931143	-66.652700	Deluxe Fish & Chips	4e5d0b99fa76a4cf148d9a15	45.931722	-66.663131	S Rest
24	Knowledge	45.931143	-66.652700	Hallmark	4cd96cf651fc8cfa522eef5d	45.930646	-66.663745	Gif

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
25	Park	45.931143	-66.652700	NB Liquor	5985f08b6cf01a7e38b85fba	45.930228	-66.664395	Liquo
26	Knowledge Park	45.931143	-66.652700	Corbett Center	57854d05498e301b3b5a4448	45.929733	-66.664601	Sh
	Knowledge							

27	Knowledge Park	45.931143	-66.652700	Costco Food Court	53693053498ef3e4ea63560f	45.927383	-66.663544	Fas Rest
28	Knowledge Park	45.931143	-66.652700	Sleep Country	555b5660498eae864c440e77	45.929074	-66.664605	M
29	Knowledge Park	45.931143	-66.652700	Sport Chek Regent Mall	4ca4ecae8a65bfb717422b22	45.935211	-66.663525	Sp Goods
30	Knowledge Park	45.931143	-66.652700	Rôtisserie St-Hubert	57164569498e9bb9e88d52b0	45.929838	-66.664749	Rest
31	Fredericton Hill	45.948512	-66.656045	YMCA Fredericton	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
32	Fredericton Hill	45.948512	-66.656045	20 Twenty Club	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112	
33	Fredericton Hill	45.948512	-66.656045	Shoppers Drug Mart	4fb699dc7bebbeb2a6c7ba88	45.942627	-66.655523	Pha
34	Fredericton Hill	45.948512	-66.656045	Subway	4bae3571f964a52076923be3	45.940931	-66.657445	San
35	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	Coffee
37	Fredericton Hill	45.948512	-66.656045	The Aitken University Centre - UNB	4b6458eff964a52052ac2ae3	45.941644	-66.663667	H
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	
41	Fredericton Hill	45.948512	-66.656045	Papa John's Pizza	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285	Pizza
42	Fredericton Hill	45.948512	-66.656045	Greco	4cfc0660c51fa1cdd3d7e92b	45.954055	-66.647290	Pizza
43	Fredericton Hill	45.948512	-66.656045	Dick's Grocery Store	4c545e5db426ef3b11cc7e8a	45.941957	-66.663877	Smoke
44	Fredericton Hill	45.948512	-66.656045	Tingley's Ice Cream	4c13c001b7b9c9284e12aa37	45.957087	-66.655855	Ice
45	Fredericton Hill	45.948512	-66.656045	Domino's Pizza	50f9bbc75d24acebc259244d	45.957177	-66.656638	Pizza
46	Fredericton Hill	45.948512	-66.656045	Jumbo Video	4bc0d29a920eb71307a2192c	45.957286	-66.656312	Video
47	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 Location Venue Venue id Venue Venue Latitude

					Longitude Latitude Longitude Ca			
49	Nashwaaksis	45.983382	-66.644856	Tim Hortons	4b742f31f964a520b7cb2de3	45.975294	-66.646977	Coffee
50	Nashwaaksis	45.983382	-66.644856	The Northside Market	50270b2ae4b042eaf816ee61	45.977779	-66.635003	F
51	Nashwaaksis	45.983382	-66.644856	Shoppers Drug Mart	4c745e08db52b1f781f775dc	45.976515	-66.648534	Pha
52	Nashwaaksis	45.983382	-66.644856	Subway	4bc5db23693695213a9a8488	45.976886	-66.648661	San
53	Nashwaaksis	45.983382	-66.644856	Subway	4c87f3b4bf40a1cd09fd08b4	45.989114	-66.652061	San
54	Nashwaaksis	45.983382	-66.644856	Kentucky Fried Chicken	4eefb90ba69ddc7bcb336081	45.975903	-66.646846	Fas Rest
55	Nashwaaksis	45.983382	-66.644856	Nashwaaksis Field House	4b73436cf964a52016a52de3	45.984849	-66.643635	
56	Nashwaaksis	45.983382	-66.644856	KFC	4c9267139199bfb7786c14df	45.975907	-66.646870	Fas Rest
57	Nashwaaksis	45.983382	-66.644856	Tim Hortons	4c0104cf360a9c74bb11d9a0	45.989221	-66.652208	Coffee
58	Nashwaaksis	45.983382	-66.644856	Thai spice	503658e5e4b00b386cc5d972	45.975890	-66.647424	Rest
59	Nashwaaksis	45.983382	-66.644856	Mike's Old Fashioned Bakery	4d67fde7709bb60c5eacb014	45.976560	-66.650030	
60	Nashwaaksis	45.983382	-66.644856	Cox Electronics	4d07eab6611ff04d4f4718fb	45.976112	-66.649222	Elec
61	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
65	Nashwaaksis	45.983382	-66.644856	Avalon SalonSpa	4bc31784920eb71312ec1c2c	45.974591	-66.644756	
66	Nashwaaksis	45.983382	-66.644856	Tony Pepperoni	4c88f56dbbec6dcbe9f2d758	45.991888	-66.648599	Pizza
67	University of New Brunswick	45.948121	-66.641406	The Richard J. CURRIE Center - UNB	4dbae5806e815ab0de5d2637	45.946698	-66.637891	Bas -
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
	University of							

70	New Brunswick	45.948121	-66.641406	FredeYrMictCoAn	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
71	University of New Brunswick	45.948121	-66.641406	20 TwCelnutby	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112	

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
72	New Brunswick	45.948121	-66.641406	Pub & Grill - UNB	4b7ac93ef964a520b53c2fe3	45.945434	-66.641626	
73	University of New Brunswick	45.948121	-66.641406	Harvey's	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021	Burge
74	University of New Brunswick	45.948121	-66.641406	Tim Hortons	4c865c1774d7b60c3f41a3d8	45.945185	-66.641545	Coffee
75	University of New Brunswick	45.948121	-66.641406	Tim Hortons	4dc29f89d4c07da169fbf84b	45.943720	-66.646907	Coffee
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	Pizza
78	Devon	45.968802	-66.622738	Wolastoq Wharf	4fbaafb0e4b0c7f68a419500	45.969975	-66.632568	S Rest
79	Devon	45.968802	-66.622738	Dairy Queen	4c5cab2894fd0f473c69c945	45.969077	-66.632059	Fas Rest
80	Devon	45.968802	-66.622738	Pharmacie Jean Coutu	4eb9523077c8972738ac89b2	45.967766	-66.630551	Pha
81	Devon	45.968802	-66.622738	Tim Hortons	4b5b0812f964a520d8df28e3	45.969381	-66.632730	Coffee
82	Devon	45.968802	-66.622738	Henry Park	4c8e283dad01199c7923726d	45.963992	-66.620283	Ba
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
85	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 Rest
87	Devon	45.968802	-66.622738	St Marys Smoke Shop	4ebddf8a4690d233887bf4a6	45.972270	-66.631348	Smoke
88	Devon	45.968802	-66.622738	Carleton Park	4bce2eeb29d4b7138521a8dc	45.961182	-66.626310	
89	New Maryland	45.892795	-66.683673	New York Fries	4d8771fc651041bd194d9b30	45.890420	-66.683580	Fas Rest
90	New Maryland	45.892795	-66.683673	Centre De Danse Roca Dance Center	55fdfc2b498ed76a0f7aa3f6	45.890978	-66.692237	
	University of	The Cellar						

	Location	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
S								
91	New Maryland	45.892795	-66.683673	Baseball, Basketball, Tennis and Hockey In One...	4e48415862e148603b8b3fc2	45.890726	-66.692814	Ba
92	New Maryland	45.892795	-66.683673	Circle K	4b9e633ef964a5202fdf36e3	45.885412	-66.688995	Gas S
93	Marysville	45.978913	-66.589491	Tim Hortons	4baa1b40f964a520174b3ae3	45.978193	-66.593041	Coffee
94	Marysville	45.978913	-66.589491	Royals Field	4c573f916201e21edff8736e	45.980267	-66.588412	Ba
95	Marysville	45.978913	-66.589491	Pharmacy	4c8bee978018a1cdd1f2e7d2	45.980194	-66.588628	Pha
96	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 S
98	Skyline Acres	45.931827	-66.640339	Grant Harvey Centre	4f915a7ee4b01406ebc873ae	45.925002	-66.641004	H
99	Skyline Acres	45.931827	-66.640339	Kimble Field	4fdaa8c2e4b08f3358b1b3d1	45.930535	-66.631233	Ba
100	Skyline Acres	45.931827	-66.640339	Mandarin Palace	4b786998f964a5204ecc2ee3	45.935440	-66.631007	C Rest
101	Skyline Acres	45.931827	-66.640339	Oriental Pearl	4ec68431775bf65c02417199	45.930085	-66.629518	C Rest
102	Hanwell	45.902315	-66.755113	Advanced Fabrics	53c133a4498e933c415c6118	45.905297	-66.750944	S
103	Hanwell	45.902315	-66.755113	Country Style	56356c83498e17f8ed69a380	45.905937	-66.751084	Coffee
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	Coffee
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	Coffee
109	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	Rest
112	Downtown	45.958327	-66.647211	Palate Restaurant & Cafe	4c2e0e6ae760c9b69bdf4549	45.962338	-66.641776	Rest
113	Downtown	45.958327	-66.647211	Alcool NB Liquor	4d9a52120d5f224bc5f7a34e	45.956140	-66.647558	Liquo
114	Downtown	45.958327	-66.647211	coffee and friends	4b533f74f964a520009427e3	45.961842	-66.643479	Coffee
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	Rac
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	Rest
				Northside				

		Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Ca
121	Downtown	45.958327	-66.647211	Fredericton	4e93476b8231bf0d17ba3e24	45.953217	-66.649478	
122	Downtown	45.958327	-66.647211	Read's News Stand	4b4b6bf2f964a5200a9b26e3	45.961859	-66.643464	Coffee
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	
126	Downtown	45.958327	-66.647211	Smoke's Poutinerie	51756ac6498ece19b79a31f6	45.962032	-66.644021	Rest Fas Rest
127	Downtown	45.958327	-66.647211	Snooty Fox	4b4ca053f964a52006b826e3	45.960794	-66.638927	
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	H
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	Bre
133	Downtown	45.958327	-66.647211	Strange Adventures	4babdcbdf964a5200cd03ae3	45.962733	-66.643315	Hobby
134	Downtown	45.958327	-66.647211	Naru Japanese Cuisine	50461342e4b0c55b9639accc	45.961721	-66.640125	
135	Downtown	45.958327	-66.647211	Mexicali Rosas	4c65dd9a19f3c9b697769eff	45.962811	-66.646079	Rest M Rest
136	Downtown	45.958327	-66.647211	Brewbakers	4b6754faf964a5208d482be3	45.960703	-66.640935	Rest
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	Steak
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	Coffee
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	F

YMCA

147	Downtown	45.958327	-66.647211	Harvey's	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021	Burge
	Location	**Location Latitude**	**Location Longitude**	**Venue**	**Venue id**	**Venue Latitude**	**Venue Longitude**	**Ca**
148	Downtown	45.958327	-66.647211	Drug Mart	4db07df34df03036e8bbb640	45.961351	-66.644493	Pha
149	Downtown	45.958327	-66.647211	Shan	4dfb6fc31f6eeef806aacc25	45.961818	-66.643706	C Rest
150	Downtown	45.958327	-66.647211	bulgogi	4b605f0ff964a5203de229e3	45.961522	-66.642742	K Rest
151	Downtown	45.958327	-66.647211	William's Seafood	4b7c26f5f964a52061802fe3	45.959296	-66.655663	S Rest
152	Downtown	45.958327	-66.647211	Subway	4b6b883df964a5205a0e2ce3	45.962580	-66.645032	San
153	Downtown	45.958327	-66.647211	Capital Complex	4b6faa7cf964a52073f92ce3	45.963245	-66.644123	
154	Downtown	45.958327	-66.647211	boom! Nightclub	4ba240eef964a52050e737e3	45.962315	-66.641645	Nig
155	Downtown	45.958327	-66.647211	Tim Hortons	4ba8bdb3f964a5204ceb39e3	45.959933	-66.655493	Coffee
156	Downtown	45.958327	-66.647211	King's Place Mall	4bc61ba4d35d9c74292de23a	45.961679	-66.643267	Sh
157	Downtown	45.958327	-66.647211	Running Room	4c6d4adb23c1a1cdffc81bcf	45.961812	-66.643510	Sp Goods
158	Downtown	45.958327	-66.647211	The Happy Baker	4b703d21f964a5204c0d2de3	45.960536	-66.641465	
159	Downtown	45.958327	-66.647211	Owl's Nest Bookstore	4d6ea0c98df1548152778123	45.963051	-66.643872	Boo
160	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	Video
162	Downtown	45.958327	-66.647211	Enterprise Rent-A-Car	4d3ae3edbf6d5481b26fd1e1	45.957743	-66.656527	Ren Lo
163	Downtown	45.958327	-66.647211	Domino's Pizza	50f9bbc75d24acebc259244d	45.957177	-66.656638	Pizza
164	Downtown	45.958327	-66.647211	Papa John's	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285	Pizza

Shoppers

							Pizza
165	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['Venue 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	Location Latitude	Location Longitude	Venue	Venue id	Venue Latitude	Venue Longitude	Venue Category
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 Center	1	1	1	1	1	1	1	1

Location Location Latitude Location Longitude Venue Venue id Venue Latitude Venue Longitude Venue Category

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	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 Location Venue Venue Venue Venue Venue Latitude Longitude id Latitude Longitude 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]:

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

# add neighbourhood column back to dataframe
freddy_onehot['Location'] = fredericton_data_venues['Location']
# move neighbourhood column to the first column
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	KnowlePdagrek	0	0	0	0	0	0	0	0	0	0	0
1	KnowlePdagrek	0	0	0	0	0	0	0	0	0	0	0
2	KnowlePdagrek	0	0	0	0	0	0	0	0	0	0	0
3	KnowlePdagrek	0	0	0	0	0	0	0	0	0	0	0
4	KnowlePdagrek	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 Stadium	Ba

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]:

```python
num_top_venues = 10

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

# create columns according to number of top venues
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))

# create a new dataframe
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]:

1st Most	2nd	3rd Most	4th Most	5th Most	6th Most	7th Most	8th Most	9

	Location	Common	Common Venue	Most Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common Venue	Common C 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 Re
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	Re
9	University of New Brunswick	Bar	Coffee Shop	Art Gallery	Pub	Burger Joint	Basketball Court	Grocery Store	Gym	G

Cluster Fredericton Locations

Run k-means to cluster Locations into 5 clusters

In [120]:
```
# set number of clusters
kclusters = 5

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

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

# check cluster labels generated for each row in the dataframe
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

# add clustering labels
freddy_merged['Cluster Labels'] = kmeans.labels_

# merge fredericton_grouped with location df to add latitude/longitude for each loc
ation
freddy_merged = freddy_merged.join(location_venues_sorted.set_index('Location'), on
='Location')

freddy_merged# check the last columns!
```

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 M Com Ve

Shop

0	Knowledge Park	45.931143	-66.652700	1	Fast Food Restaurant	Clothing Store	Furniture / Home Store	Liquor Store	Restaurant	Wareh S
1	Fredericton Hill	45.948512	-66.656045	1	Bakery	Pizza Place	Hockey Arena	Smoke Shop	Hardware Store	Video S
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	Baske C
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 S
6	Marysville	45.978913	-66.589491	1	Baseball Stadium	Gas Station	Pharmacy	Park	Coffee Shop	Gift S
7	Skyline Acres	45.931827	-66.640339	3	Chinese Restaurant	Baseball Field	Hockey Arena	Arts & Crafts Store	Coffee Shop	G Fit C
8	Hanwell	45.902315	-66.755113	2	Rental Service	Coffee Shop	Warehouse Store	Dance Studio	Department Store	Disc S
9	Downtown	45.958327	-66.647211	1	Coffee	Pub	Bar	Café	Restaurant	

In [122]:

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

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

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(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 [ ]:
```