**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/freder](http://www.tourismfredericton.ca/sites/default/files/field/image/freder) icton.jpg")

Out[73]:

# Data

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

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

1. 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.
2. Using k-menas, we were able to determine the top 10 most common venues within a 1 km radius of the centroid of the highest crime neighbourhood. **The most common venues in the highest crime neighbourhood are coﬀee shops followed by Pubs and Bars**.

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

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

# Discussion and Recommendations

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

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

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

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

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

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

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

# Conclusion

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

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

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

**APPENDIX: Analysis**

## Load Libraries

In [74]:

**import numpy as np**

**import pandas as pd** pd.set\_option('display.max\_columns', **None**) pd.set\_option('display.max\_rows', **None**)

**import json**

!conda install -c conda-forge geopy --yes # uncomment this line **if** you haven't comp leted the Foursquare API lab

**from geopy.geocoders import** Nominatim

**import requests**

**from pandas.io.json import** json\_normalize

**import matplotlib.cm as cm**

**import matplotlib.colors as colors**

**from sklearn.cluster import** KMeans

**from bs4 import** BeautifulSoup

**import xml**

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

**import folium**

print('Libraries imported.')

Solving environment: done

# All requested packages already installed.

Solving environment: done

# All requested packages already installed. Libraries imported.

In [3]:

pwd

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

In [75]:

r = requests.get('https://opendata.arcgis.com/datasets/823d86e17a6d47808c6e4f1c2dd9 7928\_0.geojson')

fredericton\_geo = r.json()

In [76]:

neighborhoods\_data = fredericton\_geo['features']

In [77]:

neighborhoods\_data[0]

Out[77]: {'type': 'Feature',

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In [78]:

g = requests.get('https://opendata.arcgis.com/datasets/6179d35eacb144a5b5fdcc869f86 dfb5\_0.geojson')

demog\_geo = g.json()

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In [79]:

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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',

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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]:

Fredericton

South

2017-05-

07T00:00:00.000Z

**Crime\_Type**

B&E NON- RESIDNCE

|  |  |  |
| --- | --- | --- |
| **Ward** | **City** | **FID** |
| 7 | Fredericton | 1 |
| 7 | Fredericton | 2 |
| 12 | Fredericton | 3 |
| 12 | Fredericton | 4 |
| 7 | Fredericton | 5 |

|  |  |  |
| --- | --- | --- |
| **Neighbourhood** | **From\_Date** | **To\_Date Crime\_Code** |
| **0** Fredericton | 2017-01- | 2017-01- 2120 |
| South | 05T00:00:00.000Z | 26T00:00:00.000Z |
| **1** Fredericton | 2017-03- | 2017-03- 2120 |
| South | 04T00:00:00.000Z | 06T00:00:00.000Z |

B&E NON- RESIDNCE

NaN 2120 B&E NON- RESIDNCE

Fredericton

**2**

**3**

South

Fredericton

**4**

South

2017-06-

20T00:00:00.000Z

2017-07-

09T00:00:00.000Z

2017-06-

21T00:00:00.000Z

2017-07-

10T00:00:00.000Z

2120 B&E NON- RESIDNCE

2120 B&E NON- RESIDNCE

In [84]:

crime\_df.drop(['From\_Date', 'To\_Date'], axis=1,inplace=**True**)

# What is the crime count by neighbourhood?

In [128]:

crime\_data = crime\_df.groupby(['Neighbourhood']).size().to\_frame(name='Count').rese t\_index()

crime\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[128]: |  | | |
|  |  | **Neighbourhood** | **Count** |
|  | **0** | Barkers Point | 47 |
|  | **1** | Brookside | 54 |
|  | **2** | Brookside Estates | 9 |
|  | **3** | Brookside Mini Home Park | 5 |
|  | **4** | College Hill | 41 |
|  | **5** | Colonial heights | 9 |
|  | **6** | Cotton Mill Creek | 4 |
|  | **7** | Diamond Street | 1 |
|  | **8** | Doak Road | 1 |
|  | **9** | Douglas | 3 |
|  | **10** | Downtown | 127 |
|  | **11** | Dun's Crossing | 18 |
|  | **12** | Forest Hill | 12 |
|  | **13** | Fredericton South | 85 |
|  | **14** | Fulton Heights | 36 |
|  | **15** | Garden Creek | 13 |
|  | **16** | Garden Place | 4 |
|  | **17** | Gilridge Estates | 3 |
|  | **18** | Golf Club | 7 |
|  | **19** | Grasse Circle | 1 |
|  | **20** | Greenwood Minihome Park | 2 |
|  | **21** | Hanwell North | 8 |
|  | **22** | Heron Springs | 3 |
|  | **23** | Highpoint Ridge | 5 |
|  | **24** | Kelly's Court Minihome Park | 1 |
|  | **25** | Knob Hill | 4 |
|  | **26** | Knowledge Park | 1 |
|  | **27** | Lian / Valcore | 7 |
|  | **28** | Lincoln | 13 |
|  | **29** | Lincoln Heights | 14 |
|  | **30** | Main Street | 78 |
|  | **31** | Marysville | 39 |
|  | **32** | McKnight | 4 |
|  | **33** | McLeod Hill | 3 |
|  | **34** | Monteith / Talisman | 12 |
|  | **35** | Montogomery / Prospect East | 16 |
|  | **36** | Nashwaaksis | 25 |
|  | **37** | Nethervue Minihome Park | 1 |
|  | **38** | North Devon | 113 |

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

In [153]:

crime\_data.describe()

Out[153]:

**Count count** 66.000000

**mean** 22.121212

**std** 34.879359

**min** 1.000000

**25%** 3.000000

**50%** 9.000000

**75%** 23.250000

**max** 198.000000

In [86]:

crime\_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'Crime\_C ount'}, inplace=**True**)

crime\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[86]: |  | | |
|  |  | **Neighbourh** | **Crime\_Count** |
|  | **0** | Barkers Point | 47 |
|  | **1** | Brookside | 54 |
|  | **2** | Brookside Estates | 9 |
|  | **3** | Brookside Mini Home Park | 5 |
|  | **4** | College Hill | 41 |
|  | **5** | Colonial heights | 9 |
|  | **6** | Cotton Mill Creek | 4 |
|  | **7** | Diamond Street | 1 |
|  | **8** | Doak Road | 1 |
|  | **9** | Douglas | 3 |
|  | **10** | Downtown | 127 |
|  | **11** | Dun's Crossing | 18 |
|  | **12** | Forest Hill | 12 |
|  | **13** | Fredericton South | 85 |
|  | **14** | Fulton Heights | 36 |
|  | **15** | Garden Creek | 13 |
|  | **16** | Garden Place | 4 |
|  | **17** | Gilridge Estates | 3 |
|  | **18** | Golf Club | 7 |
|  | **19** | Grasse Circle | 1 |
|  | **20** | Greenwood Minihome Park | 2 |
|  | **21** | Hanwell North | 8 |
|  | **22** | Heron Springs | 3 |
|  | **23** | Highpoint Ridge | 5 |
|  | **24** | Kelly's Court Minihome Park | 1 |
|  | **25** | Knob Hill | 4 |
|  | **26** | Knowledge Park | 1 |
|  | **27** | Lian / Valcore | 7 |
|  | **28** | Lincoln | 13 |
|  | **29** | Lincoln Heights | 14 |
|  | **30** | Main Street | 78 |
|  | **31** | Marysville | 39 |
|  | **32** | McKnight | 4 |
|  | **33** | McLeod Hill | 3 |
|  | **34** | Monteith / Talisman | 12 |
|  | **35** | Montogomery / Prospect East | 16 |
|  | **36** | Nashwaaksis | 25 |
|  | **37** | Nethervue Minihome Park | 1 |
|  | **38** | North Devon | 113 |

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

In [87]:

crime\_data.rename({'Platt': 'Plat'},inplace=**True**)

crime\_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'Crime\_C ount'}, inplace=**True**)

crime\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[87]: |  | | |
|  |  | **Neighbourh** | **Crime\_Count** |
|  | **0** | Barkers Point | 47 |
|  | **1** | Brookside | 54 |
|  | **2** | Brookside Estates | 9 |
|  | **3** | Brookside Mini Home Park | 5 |
|  | **4** | College Hill | 41 |
|  | **5** | Colonial heights | 9 |
|  | **6** | Cotton Mill Creek | 4 |
|  | **7** | Diamond Street | 1 |
|  | **8** | Doak Road | 1 |
|  | **9** | Douglas | 3 |
|  | **10** | Downtown | 127 |
|  | **11** | Dun's Crossing | 18 |
|  | **12** | Forest Hill | 12 |
|  | **13** | Fredericton South | 85 |
|  | **14** | Fulton Heights | 36 |
|  | **15** | Garden Creek | 13 |
|  | **16** | Garden Place | 4 |
|  | **17** | Gilridge Estates | 3 |
|  | **18** | Golf Club | 7 |
|  | **19** | Grasse Circle | 1 |
|  | **20** | Greenwood Minihome Park | 2 |
|  | **21** | Hanwell North | 8 |
|  | **22** | Heron Springs | 3 |
|  | **23** | Highpoint Ridge | 5 |
|  | **24** | Kelly's Court Minihome Park | 1 |
|  | **25** | Knob Hill | 4 |
|  | **26** | Knowledge Park | 1 |
|  | **27** | Lian / Valcore | 7 |
|  | **28** | Lincoln | 13 |
|  | **29** | Lincoln Heights | 14 |
|  | **30** | Main Street | 78 |
|  | **31** | Marysville | 39 |
|  | **32** | McKnight | 4 |
|  | **33** | McLeod Hill | 3 |
|  | **34** | Monteith / Talisman | 12 |
|  | **35** | Montogomery / Prospect East | 16 |
|  | **36** | Nashwaaksis | 25 |
|  | **37** | Nethervue Minihome Park | 1 |
|  | **38** | North Devon | 113 |

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

In [88]:

address = 'Fredericton, Canada'

geolocator = Nominatim()

location = geolocator.geocode(address) latitude = location.latitude longitude = location.longitude

print('The geograpical coordinate of Fredericton, New Brunswick is **{}**, **{}**.'.format( latitude, longitude))

/anaconda3/lib/python3.7/site-packages/ipykernel\_launcher.py:3: DeprecationWarnin g: Using Nominatim with the default "geopy/1.18.1" `user\_agent` is strongly discou raged, as it violates Nominatim's ToS https://operations.osmfoundation.org/policie s/nominatim/ and may possibly cause 403 and 429 HTTP errors. Please specify a cust om `user\_agent` with `Nominatim(user\_agent="my-application")` or by overriding the default `user\_agent`: `geopy.geocoders.options.default\_user\_agent = "my-applicatio n"`. In geopy 2.0 this will become an exception.

This is separate from the ipykernel package so we can avoid doing imports until The geograpical coordinate of Fredericton, New Brunswick is 45.966425, -66.645813.

In [89]:



+

~~−~~

world\_geo = r'world\_countries.json'

fredericton\_1\_map = folium.Map(location=[45.97, -66.65], width=1000, height=750,zoo m\_start=12)

fredericton\_1\_map

Out[89]:

In [90]:

fredericton\_geo = r.json()

threshold\_scale = np.linspace(crime\_data['Crime\_Count'].min(),crime\_data['Crime\_Cou nt'].max(), 6,dtype=int)

threshold\_scale = threshold\_scale.tolist() threshold\_scale[-1] = threshold\_scale[-1]+1

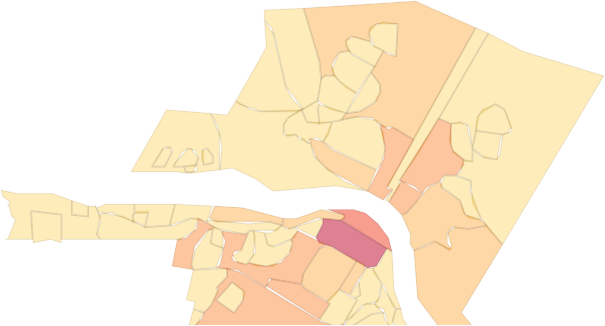
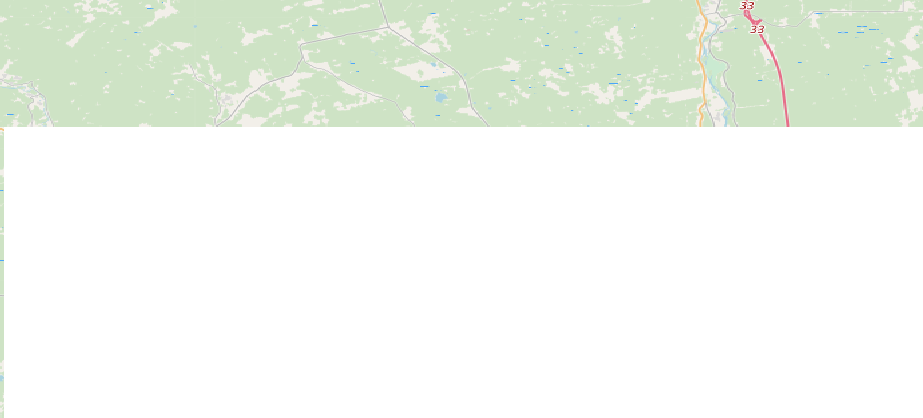
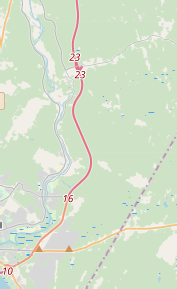
fredericton\_1\_map.choropleth(geo\_data=fredericton\_geo, data=crime\_data,columns=['Ne ighbourh', 'Crime\_Count'],

key\_on='feature.properties.Neighbourh', threshold\_scale=threshold\_scale,fill\_co lor='YlOrRd', fill\_opacity=0.7,

line\_opacity=0.1, legend\_name='Fredericton Neighbourhoods')

fredericton\_1\_map

Out[90]:



+

~~−~~

1

40

Fredericton Neighbourh

# Examine Crime Types

In [131]:

crimetype\_data = crime\_df.groupby(['Crime\_Type']).size().to\_frame(name='Count').res et\_index()

crimetype\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[131]: |  | | |
|  |  | **Crime\_Type** | **Count** |
|  | **0** |  | 4 |
|  | **1** | ARSON | 5 |
|  | **2** | ARSON BY NEG | 1 |
|  | **3** | ARSON-DAM.PROP. | 4 |
|  | **4** | B&E NON-RESIDNCE | 51 |
|  | **5** | B&E OTHER | 58 |
|  | **6** | B&E RESIDENCE | 151 |
|  | **7** | B&E STEAL FIREAR | 3 |
|  | **8** | MISCHIEF OBS USE | 1 |
|  | **9** | MISCHIEF TO PROP | 246 |
|  | **10** | MISCHIEF-DATA | 2 |
|  | **11** | MOTOR VEH THEFT | 40 |
|  | **12** | THEFT BIKE<$5000 | 63 |
|  | **13** | THEFT FROM MV < $5000 | 356 |
|  | **14** | THEFT FROM MV > $5000 | 5 |
|  | **15** | THEFT OTH <$5000 | 458 |
|  | **16** | THEFT OTH >$5000 | 9 |
|  | **17** | THEFT OVER $5000 | 1 |
|  | **18** | THEFT,BIKE>$5000 | 2 |

In [154]:

crimetype\_data.describe()

Out[154]:

**Count count** 19.000000

**mean** 76.842105

**std** 133.196706

**min** 1.000000

**25%** 2.500000

**50%** 5.000000

**75%** 60.500000

**max** 458.000000

In [140]:

crimepivot = crime\_df.pivot\_table(index='Neighbourhood', columns='Crime\_Type', aggf unc=pd.Series.count, fill\_value=0)

crimepivot

Out[140]:

**City**

**Crime\_Type ARSON**

**ARSON BY NEG**

**B&E STEAL FIREAR**

|  |  |  |  |
| --- | --- | --- | --- |
| **ARSON-** | **B&E NON-** | **B&E** | **B&E** |
| **DAM.PROP.** | **RESIDNCE** | **OTHER** | **RESIDENCE** |

**MISCHIEF OBS USE**

**MISCHI TO PRO**

**Neighbourhood**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Barkers Point** 0 | 0 | 0 | 0 | 2 | 7 | 7 | 1 | 0 |
| **Brookside** 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 |
| **Brookside** 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| **Brookside Mini** 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 |
| **Cotton Mill** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Diamond** 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** 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** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Golf Club** 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **Grasse Circle** 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Greenwood** 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **Hanwell North** 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 |
| **Kelly's Court** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Knob Hill** 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **Knowledge** 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 |

**Estates**

**Home Park**

**heights**

**Creek**

**Street**

**South**

**Estates**

**Minihome Park**

**Ridge**

**Minihome Park**

**Park**

**ARSON NEG**

**ARSON-**

**B&E NON-**

**B&E**

**B&E**

**B&E FIREAR**

**MISCHIEF**

**MISCHI**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Crime\_Type ARSON BY DAM.PROP.** | | | | **RESIDNCE** | **OTHER** | **RESIDENCE STEAL OBS USE TO PRO** | | |
| **Neighbourhood** | | | |  |  |  | | |
| **Lincoln** 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 |
| **Montogomery /** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Nashwaaksis** 0 | 0 | 0 | 1 | 2 | 0 | 3 | 0 | 0 |
| **Nethervue** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **North Devon** 0 | 0 | 0 | 0 | 5 | 4 | 11 | 0 | 0 |
| **Northbrook** 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** 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Royal Road** 0 | 0 | 0 | 0 | 3 | 2 | 2 | 0 | 0 |
| **Saint Mary's** 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **Saint Thomas** 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** 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** 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 |
| **Springhill** 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **Sunshine** 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **The Hill** 0 | 0 | 0 | 0 | 2 | 1 | 12 | 1 | 0 |

**Heights**

**Talisman**

**Prospect East**

**Minihome Park**

**Heights**

**Creek**

**First Nation**

**University**

**Estates**

**Park**

**Gardens**

**Crime\_Type ARSON**

**ARSON BY NEG**

**ARSON- DAM.PROP.**

**B&E NON- RESIDNCE**

**B&E OTHER**

**B&E RESIDENCE**

**B&E STEAL FIREAR**

**MISCHIEF OBS USE**

**MISCHI TO PRO**

**Neighbourhood**

**The Hugh John**

**Flemming Forestry Center**

**University Of**

**New Brunswick**

0 0 0 0 1 2 0 0 0

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 /** 0 0 0 0 0 1 2 0 0

**Hawkins Area**

**Woodstock** 0 0 0 0 2 0 5 0 0

**Road**

**Youngs**



**Crossing**

0

0

0

1

0

0

2

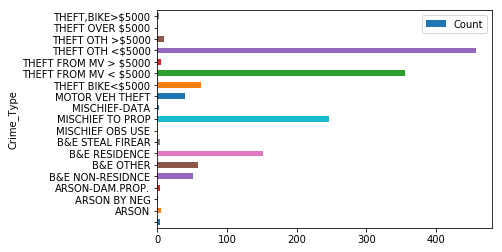
0

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 |

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

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

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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 Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 772 |
| **772** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 773 |
| **773** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 774 |
| **774** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 775 |
| **775** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 776 |
| **776** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 0 | Fredericton | 777 |
| **777** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 778 |
| **778** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 779 |
| **779** | Woodstock Road | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 780 |

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

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

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

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **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 |

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

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Neighbourhood** | **Crime\_Code** | **Crime\_Type** | **Ward** | **City** | **FID** |
| **1438** | North Devon | 2142 | THEFT FROM MV < $5000 | 3 | Fredericton | 1439 |
| **1439** | North Devon | 2142 | THEFT FROM MV < $5000 | 3 | Fredericton | 1440 |
| **1440** | North Devon | 2142 | THEFT FROM MV < $5000 | 3 | Fredericton | 1441 |
| **1441** | North Devon | 2142 | THEFT FROM MV < $5000 | 3 | Fredericton | 1442 |
| **1459** | Monteith / Talisman | 2142 | THEFT FROM MV < $5000 | 12 | Fredericton | 1460 |

In [94]:

mvcrime\_data = mvcrime\_df.groupby(['Neighbourhood']).size().to\_frame(name='Count'). reset\_index()

mvcrime\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[94]: |  | | |
|  |  | **Neighbourhood** | **Count** |
|  | **0** | Barkers Point | 8 |
|  | **1** | Brookside Estates | 3 |
|  | **2** | College Hill | 10 |
|  | **3** | Colonial heights | 6 |
|  | **4** | Diamond Street | 1 |
|  | **5** | Douglas | 1 |
|  | **6** | Downtown | 21 |
|  | **7** | Dun's Crossing | 9 |
|  | **8** | Forest Hill | 8 |
|  | **9** | Fredericton South | 20 |
|  | **10** | Fulton Heights | 12 |
|  | **11** | Garden Creek | 1 |
|  | **12** | Garden Place | 3 |
|  | **13** | Gilridge Estates | 1 |
|  | **14** | Golf Club | 5 |
|  | **15** | Hanwell North | 3 |
|  | **16** | Heron Springs | 2 |
|  | **17** | Highpoint Ridge | 4 |
|  | **18** | Knob Hill | 1 |
|  | **19** | Lian / Valcore | 1 |
|  | **20** | Lincoln | 1 |
|  | **21** | Lincoln Heights | 11 |
|  | **22** | Main Street | 10 |
|  | **23** | Marysville | 10 |
|  | **24** | McKnight | 1 |
|  | **25** | McLeod Hill | 2 |
|  | **26** | Monteith / Talisman | 3 |
|  | **27** | Montogomery / Prospect East | 3 |
|  | **28** | Nashwaaksis | 9 |
|  | **29** | Nethervue Minihome Park | 1 |
|  | **30** | North Devon | 17 |
|  | **31** | Northbrook Heights | 5 |
|  | **32** | Plat | 40 |
|  | **33** | Poet's Hill | 2 |
|  | **34** | Prospect | 11 |
|  | **35** | Rail Side | 2 |
|  | **36** | Saint Mary's First Nation | 1 |
|  | **37** | Saint Thomas University | 1 |
|  | **38** | Sandyville | 3 |

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

In [155]:

mvcrime\_data.describe()

Out[155]:

**MVCrime\_Count**

**count** 51.000000

**mean** 6.980392

**std** 7.457855

**min** 1.000000

**25%** 2.000000

**50%** 4.000000

**75%** 10.000000

**max** 40.000000

In [95]:

mvcrime\_data.rename({'Platt': 'Plat'},inplace=**True**)

mvcrime\_data.rename(index=str, columns={'Neighbourhood':'Neighbourh','Count':'MVCri me\_Count'}, inplace=**True**)

mvcrime\_data

|  |  |  |  |
| --- | --- | --- | --- |
| Out[95]: |  | | |
|  |  | **Neighbourh** | **MVCrime\_Count** |
|  | **0** | Barkers Point | 8 |
|  | **1** | Brookside Estates | 3 |
|  | **2** | College Hill | 10 |
|  | **3** | Colonial heights | 6 |
|  | **4** | Diamond Street | 1 |
|  | **5** | Douglas | 1 |
|  | **6** | Downtown | 21 |
|  | **7** | Dun's Crossing | 9 |
|  | **8** | Forest Hill | 8 |
|  | **9** | Fredericton South | 20 |
|  | **10** | Fulton Heights | 12 |
|  | **11** | Garden Creek | 1 |
|  | **12** | Garden Place | 3 |
|  | **13** | Gilridge Estates | 1 |
|  | **14** | Golf Club | 5 |
|  | **15** | Hanwell North | 3 |
|  | **16** | Heron Springs | 2 |
|  | **17** | Highpoint Ridge | 4 |
|  | **18** | Knob Hill | 1 |
|  | **19** | Lian / Valcore | 1 |
|  | **20** | Lincoln | 1 |
|  | **21** | Lincoln Heights | 11 |
|  | **22** | Main Street | 10 |
|  | **23** | Marysville | 10 |
|  | **24** | McKnight | 1 |
|  | **25** | McLeod Hill | 2 |
|  | **26** | Monteith / Talisman | 3 |
|  | **27** | Montogomery / Prospect East | 3 |
|  | **28** | Nashwaaksis | 9 |
|  | **29** | Nethervue Minihome Park | 1 |
|  | **30** | North Devon | 17 |
|  | **31** | Northbrook Heights | 5 |
|  | **32** | Plat | 40 |
|  | **33** | Poet's Hill | 2 |
|  | **34** | Prospect | 11 |
|  | **35** | Rail Side | 2 |
|  | **36** | Saint Mary's First Nation | 1 |
|  | **37** | Saint Thomas University | 1 |
|  | **38** | Sandyville | 3 |

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

In [96]:

world\_geo = r'world\_countries.json'

fredericton\_c\_map = folium.Map(location=[45.91, -66.65], width=1000, height=750,zoo m\_start=12)

fredericton\_c\_map

Out[96]:



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In [97]:



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Fredericton Neighbourh

fredericton\_geo = r.json()

threshold\_scale = np.linspace(mvcrime\_data['MVCrime\_Count'].min(), mvcrime\_data['MV Crime\_Count'].max(),6,dtype=int)

threshold\_scale = threshold\_scale.tolist() threshold\_scale[-1] = threshold\_scale[-1]+1

fredericton\_c\_map.choropleth(geo\_data=fredericton\_geo,data=mvcrime\_data,columns=['N eighbourh', 'MVCrime\_Count'],key\_on='feature.properties.Neighbourh',

threshold\_scale=threshold\_scale, fill\_color='YlOrRd',fill\_opacity=0.7,line\_opac ity=0.1,legend\_name='Fredericton Neighbourhoods')

fredericton\_c\_map

Out[97]:

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

In [98]:

opendemog = 'Fredericton\_Census\_Tract\_Demographics.xlsx'

workbook = pd.ExcelFile(opendemog) print(workbook.sheet\_names)

['Fredericton\_Census\_Tract\_Demogr']



In [99]:

demog\_df = workbook.parse('Fredericton\_Census\_Tract\_Demogr') demog\_df.head()

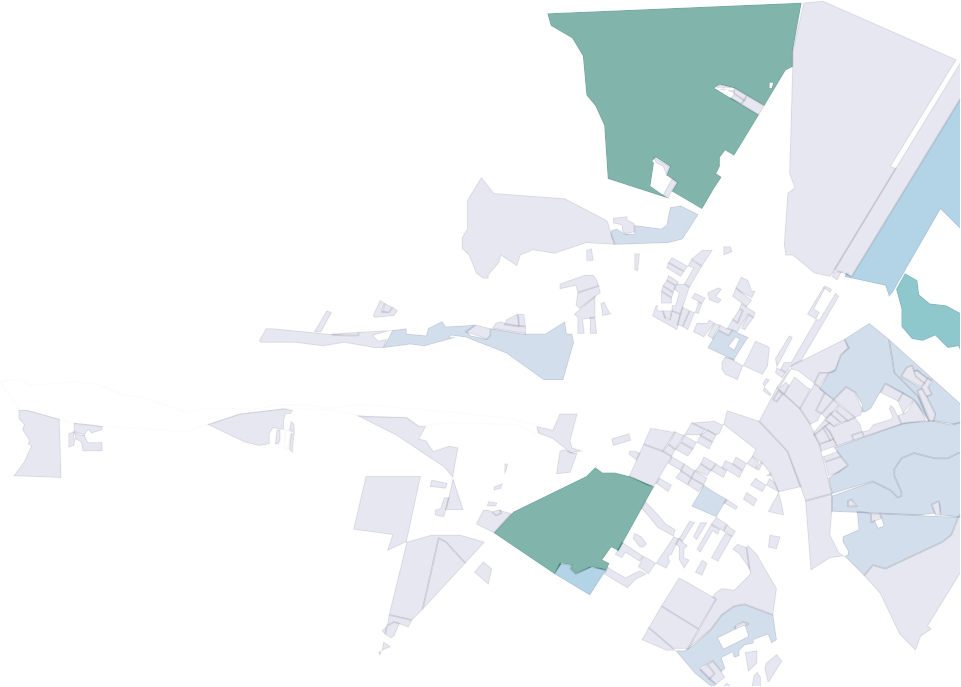
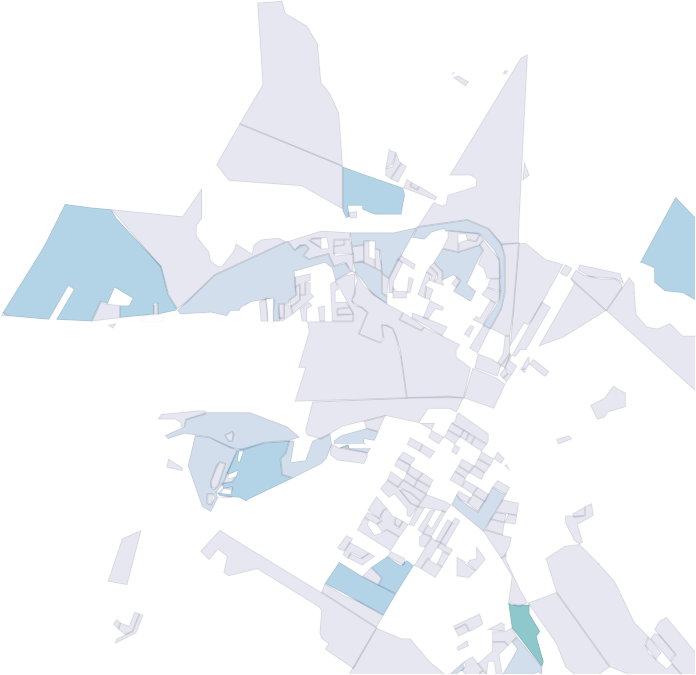
|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Out[99]: |  | | | | | | | | | | |
|  |  | **FID** | **OBJECTID** | **DBUID** | **DAUID** | **CDUID** | **CTUID** | **CTNAME** | **DBuid\_1** | **DBpop2011** | **DBtdwell20 D** |
|  | **0** | 1 | 501 | 1310024304 | 13100243 | 1310 | 3200002 | 2 | 1310024304 | 60 | 25 |
|  | **1** | 2 | 502 | 1310032004 | 13100320 | 1310 | 3200010 | 10 | 1310032004 | 15 | 3 |
|  | **2** | 3 | 503 | 1310017103 | 13100171 | 1310 | 3200014 | 14 | 1310017103 | 0 | 0 |
|  | **3** | 4 | 504 | 1310018301 | 13100183 | 1310 | 3200012 | 12 | 1310018301 | 108 | 60 |
|  | **4** | 5 | 505 | 1310022905 | 13100229 | 1310 | 3200007 | 7 | 1310022905 | 129 | 47 |
| In [ ]: |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| In [ ]: |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| In [100]: |  |  |  |  |  |  |  |  |  |  |  |
|  | world\_geo = r'world\_countries.json'  fredericton\_d\_map = folium.Map(location=[45.94, -66.63], width=1200, height=750,zoo m\_start=12)  fredericton\_d\_map  threshold\_scale = np.linspace(demog\_df['DBpop2011'].min(),demog\_df['DBpop2011'].max (),6,dtype=int)  threshold\_scale = threshold\_scale.tolist() threshold\_scale[-1] = threshold\_scale[-1]+1  fredericton\_d\_map.choropleth(geo\_data=demog\_geo,data=demog\_df,columns=['OBJECTID', 'DBpop2011'],key\_on='feature.properties.OBJECTID',  threshold\_scale=threshold\_scale,fill\_color='PuBuGn',fill\_opacity=0.7, line\_opac ity=0.1,legend\_name='Fredericton Population Density')  fredericton\_d\_map | | | | | | | | | | |

Out[100]:



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# Let's look at speciﬁc locations in Fredericton

In [101]:

pointbook = 'Fredericton Locations.xlsx'

workbook\_2 = pd.ExcelFile(pointbook) print(workbook\_2.sheet\_names)

['Sheet1']

In [102]:

location\_df = workbook\_2.parse('Sheet1') location\_df

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Out[102]: |  | | | | |
|  |  | **Location** | **Neighbourh** | **Latitude** | **Longitude** |
|  | **0** | Knowledge Park | NaN | 45.931143 | -66.652700 |
|  | **1** | Fredericton Hill | NaN | 45.948512 | -66.656045 |
|  | **2** | Nashwaaksis | NaN | 45.983382 | -66.644856 |
|  | **3** | University of New Brunswick | NaN | 45.948121 | -66.641406 |
|  | **4** | Devon | NaN | 45.968802 | -66.622738 |
|  | **5** | New Maryland | NaN | 45.892795 | -66.683673 |
|  | **6** | Marysville | NaN | 45.978913 | -66.589491 |
|  | **7** | Skyline Acres | NaN | 45.931827 | -66.640339 |
|  | **8** | Hanwell | NaN | 45.902315 | -66.755113 |
|  | **9** | Downtown | NaN | 45.958327 | -66.647211 |

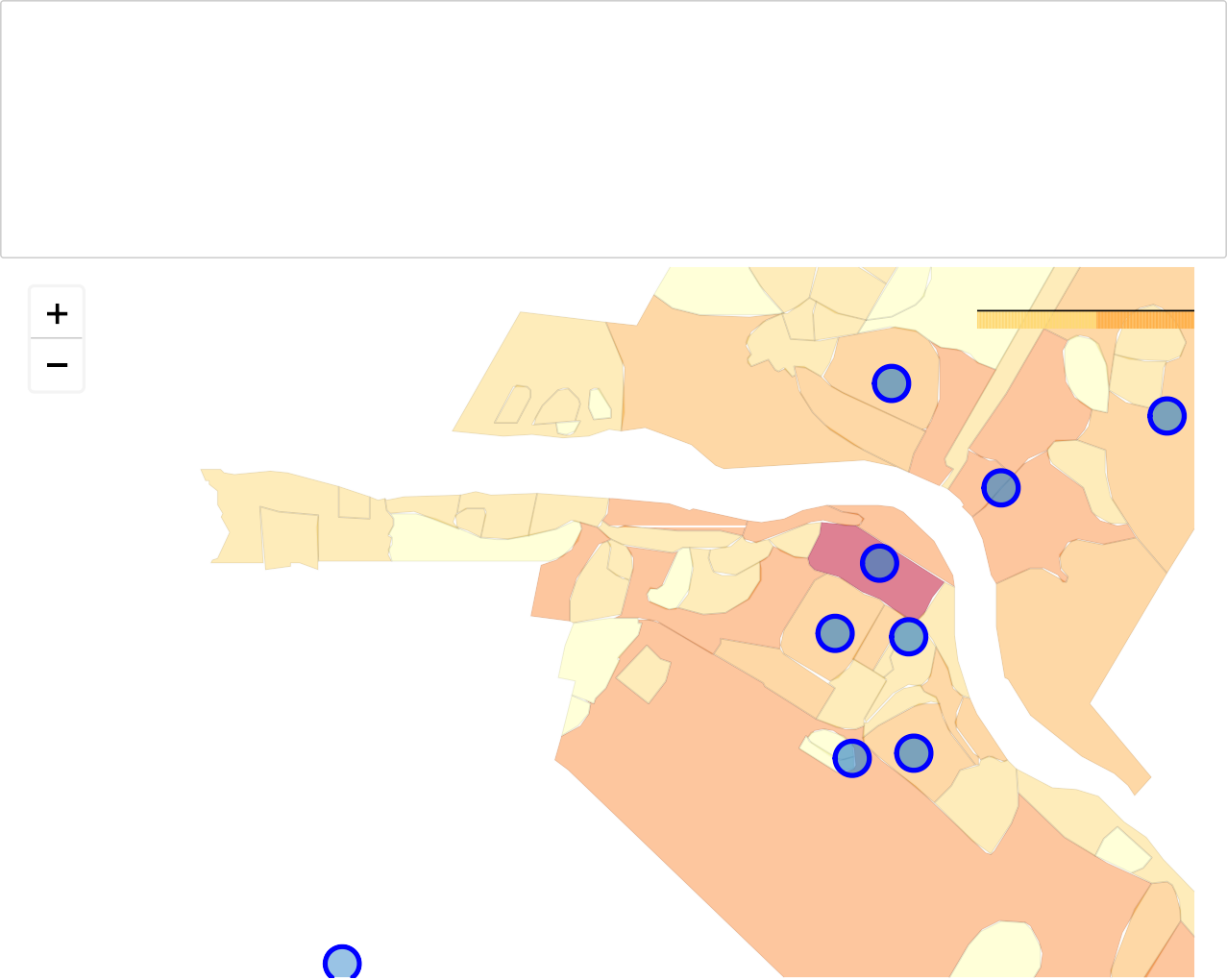
In [103]:

location\_df.drop(['Neighbourh'], axis=1,inplace=**True**) location\_df

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Out[103]: |  | | | |
|  |  | **Location** | **Latitude** | **Longitude** |
|  | **0** | Knowledge Park | 45.931143 | -66.652700 |
|  | **1** | Fredericton Hill | 45.948512 | -66.656045 |
|  | **2** | Nashwaaksis | 45.983382 | -66.644856 |
|  | **3** | University of New Brunswick | 45.948121 | -66.641406 |
|  | **4** | Devon | 45.968802 | -66.622738 |
|  | **5** | New Maryland | 45.892795 | -66.683673 |
|  | **6** | Marysville | 45.978913 | -66.589491 |
|  | **7** | Skyline Acres | 45.931827 | -66.640339 |
|  | **8** | Hanwell | 45.902315 | -66.755113 |
|  | **9** | Downtown | 45.958327 | -66.647211 |

## Add location markers to map

In [104]:



**for** lat, lng, point **in** zip(location\_df['Latitude'], location\_df['Longitude'], locat ion\_df['Location']):

label = '**{}**'.format(point)

label = folium.Popup(label, parse\_html=**True**)

folium.CircleMarker([lat, lng],radium=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

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Fredericton Neighbourh

Out[104]:

In [ ]:

# Explore Fredericton Neighbourhoods

### Deﬁne Foursquare Credentials and Version

In [2]:

CLIENT\_ID = 'Nope' CLIENT\_SECRET = 'Secret' VERSION = '20181201'

print('Your credentails:') print('CLIENT\_ID: ' + CLIENT\_ID) print('CLIENT\_SECRET:' + CLIENT\_SECRET)

Your credentails: CLIENT\_ID: Nope CLIENT\_SECRET:Secret

# Let's take a look at nearby venues

In [106]:

**def** getNearbyVenues(names, latitudes, longitudes, radius=1000, LIMIT=100):

venues\_list=[]

**for** name, lat, lng **in** zip(names, latitudes, longitudes): print(name)

url = 'https://api.foursquare.com/v2/venues/explore?&client\_id=**{}**&client\_se cret=**{}**&v=**{}**&ll=**{}**,**{}**&radius=**{}**&limit=**{}**'.format(

CLIENT\_ID, CLIENT\_SECRET, VERSION,

lat, lng, radius, LIMIT)

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

venues\_list.append([( name,

lat, lng,

v['venue']['name'],

v['venue']['id'], v['venue']['location']['lat'],

v['venue']['location']['lng'],

v['venue']['categories'][0]['name']) **for** v **in** results])

nearby\_venues = pd.DataFrame([item **for** venue\_list **in** venues\_list **for** item **in** ve nue\_list])

nearby\_venues.columns = ['Location',

'Location Latitude', 'Location Longitude', 'Venue',

'Venue id', 'Venue Latitude',

'Venue Longitude', 'Venue Category'

]

**return**(nearby\_venues)

In [107]:

fredericton\_data\_venues = getNearbyVenues(names=location\_df['Location'],

latitudes=location\_df['Latitude'], longitudes=location\_df['Longitude']

)

Knowledge Park Fredericton Hill Nashwaaksis

University of New Brunswick Devon

New Maryland Marysville Skyline Acres Hanwell Downtown

In [108]:

print(fredericton\_data\_venues.shape) fredericton\_data\_venues

(166, 8)

Out[108]:

**Location Location**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Latitude** | **Longitude** | **Latitude** | | | **Longitude** | **Ca** |
| **0** Knowledge 45.931143 -66.652700 Costco 4e18ab92183880768f43bﬀ6 45.927034 -66.663447 War | | | | | | |
| Park |  | Wholesale |  |  |  |  |
| **1** Knowledge 45.931143 | -66.652700 | PetSmart | 4bbca501a0a0c9b6078f1a0f | 45.929768 | -66.659939 | Pe |
| **2** Knowledge 45.931143 | -66.652700 | Montana's | 4e50406e62844166699b0780 | 45.931511 | -66.662507 | Res |
| **3** Knowledge 45.931143 | -66.652700 | Boston Pizza | 4b64944af964a52041bf2ae3 | 45.938123 | -66.660037 | Spo |

**Location**

**Venue Venue id Venue**

**Venue**

Park Park

Park

Knowledge

**4**

Park

45.931143 -66.652700 Michaels 4c489858417b20a13b82e1a9 45.929965 -66.659548 Arts &

Knowledge

**5**

Park

Knowledge

**6**

Park

Knowledge

**7**

Park

Knowledge

**8**

Park

Knowledge

**9**

Park

Knowledge

**10**

Park

Knowledge

**11**

Park

Knowledge

**12**

Park

Knowledge

**13**

Park

Knowledge

**14**

Park

Knowledge

**15**

Park

Knowledge

**16**

Park

Knowledge

**17**

Park

Knowledge

**18**

Park

45.931143 -66.652700 Alcool NB

45.931143 -66.652700 The Shoe

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | | Liquor |  | | |
| 45.931143 | -66.652700 | Best Buy | 5520124a498e0467bb6e81c8 | 45.937673 | -66.660380 |
| 45.931143 | -66.652700 | Wal-Mart | 4bad313ﬀ964a5208c373be3 | 45.934081 | -66.663539 |
| 45.931143 | -66.652700 | Booster Juice | 4c42414e520fa59334f9caac | 45.935198 | -66.663602 |
| 45.931143 | -66.652700 | Dairy Queen | 4b86f05bf964a52009a731e3 | 45.938004 | -66.659442 |
| 45.931143 | -66.652700 | H&M | 509c3265498efdﬀc5739a0f | 45.935196 | -66.663290 |
| 45.931143 | -66.652700 | Dairy Queen  (Treat) | 4cc6123cbde8f04d9ce0b44b | 45.934520 | -66.663988 |
| 45.931143 | -66.652700 | Winners | 4caa46a744a8224b96e42640 | 45.930427 | -66.659758 |
| 45.931143 | -66.652700 | East Side Mario's | 4b55d89bf964a520a2f227e3 | 45.931376 | -66.663417 |
| 45.931143 | -66.652700 | McDonald's | 4c6e9ef665eda09377e951d0 | 45.934575 | -66.663319 |
| 45.931143 | -66.652700 | Home Sense | 54024f60498ee424eedb7bf9 | 45.930528 | -66.660103 |

company

45.931143 -66.652700 Avalon Spa

Uptown

45.931143 -66.652700 Wicker

Emporium

4b77335df964a5202c872ee3 45.930680 -66.664180 Liquo

Elec

B

Sm

Fas Res

C

Fas Res

C

Res

Fas Res

Depa

4bd76dfa5cf276b0fb469b00 45.929636 -66.660449 Sho

4cd99e0f51fc8cfa4369f05d 45.930774 -66.660927

4e6baﬀ588772457c4fd1968 45.930897 -66.661338 Fur

Hom

Knowledge

**19**

Park

45.931143 -66.652700 Dollarama 4ba3dd18f964a520d86738e3 45.930897 -66.661714 Di

Knowledge

**20**

Park

Knowledge

**21**

Park

Knowledge

**22**

Park

Knowledge

**23**

Park

Knowledge

**24**

Park

45.931143 -66.652700 Bed Bath &

Beyond

5083f283e4b0bf87c15e9ea1 45.930097 -66.662166 Fur

Hom

C

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 45.931143 -66.652700 GAP Factory 50a8f005e4b0e4f42e033a2a  Store | | | | 45.930211 | -66.662416 |  |
| carter's |  45.931143 -66.652700 OshKosh 50a51363e4b0a3e2f7db76bf | | | | 45.929978 | -66.662966 | Kid |
| B'gosh  45.931143 -66.652700 Deluxe Fish 4e5d0b99fa76a4cf148d9a15 | | | | 45.931722 | -66.663131 | S |
|  |  | & Chips |  |  |  | Res |
| 45.931143 | -66.652700 | Hallmark | 4cd96cf651fc8cfa522eef5d | 45.930646 | -66.663745 | Gif |

**Location Location**

**Latitude**

**Location Longitude**

**Venue Venue id Venue Latitude**

**Venue Longitude Ca**

Knowledge 45.931143 -66.652700 NB Liquor 5985f08b6cf01a7e38b85fba 45.930228 -66.664395 Liquo Park

**25**

Knowledge

**26**

Park

Knowledge

**27**

Park

Knowledge

**28**

Park

Knowledge

**29**

Park

**30** Knowledge

45.931143 -66.652700 Corbett

Center

45.931143 -66.652700 Costco Food

Court

45.931143 -66.652700 Sleep

Country

45.931143 -66.652700 Sport Chek

Regent Mall

Rôtisserie

57854d05498e301b3b5a4448 45.929733 -66.664601 Sh

53693053498ef3e4ea63560f 45.927383 -66.663544 Fas

Res

555b5660498eae864c440e77 45.929074 -66.664605 M

4ca4ecae8a65bfb717422b22 45.935211 -66.663525 S

Good

Park 45.931143 -66.652700

Fredericton 45.948512 -66.656045 Hill

**31**

Fredericton 45.948512 -66.656045 Hill

**32**

Fredericton 45.948512 -66.656045 Hill

**33**

**34** Fredericton

St-Hubert 57164569498e9bb9e88d52b0 45.929838 -66.664749 Res

YMCA 4e93476b8231bf0d17ba3e24 45.953217 -66.649478

Fredericton

20 Twenty 4c5388b0f5f3d13ac74ba5f8 45.951042 -66.648112

Club

Shoppers 4fb699dc7bebbeb2a6c7ba88 45.942627 -66.655523 Ph Drug Mart

Sa

Hill 45.948512 -66.656045 Subway 4bae3571f964a52076923be3 45.940931 -66.657445

Fredericton 45.948512 -66.656045 Hill

**35**

**36** Fredericton

Canadian 4bb52ba72ea19521201caa2f 45.944409 -66.666820 Ha Tire

Hill 45.948512 -66.656045 Tim Hortons 4dc29f89d4c07da169fbf84b 45.943720 -66.646907 Coﬀe

The Aitken

Fredericton 45.948512 -66.656045 Hill

**37**

1. Fredericton

University Centre -

UNB

Queen

4b6458eﬀ964a52052ac2ae3 45.941644 -66.663667

Hill 45.948512 -66.656045

1. Fredericton

Square Park 4b7acb0ef964a520113d2fe3 45.950961 -66.648245

Great

Hill 45.948512 -66.656045

1. Fredericton

Canadian

Bagel

Monkey

4b784edbf964a52013c42ee3 45.941040 -66.657545

Hill 45.948512 -66.656045

Fredericton 45.948512 -66.656045 Hill

**41**

**42** Fredericton

Cakes 4ec147368231b62f43026067 45.940938 -66.657346

Papa John's 4ecc29f59adfd1f5b5c7bbb1 45.956655 -66.657285 Pizz Pizza

Hill 45.948512 -66.656045 Greco 4cfc0660c51fa1cdd3d7e92b 45.954055 -66.647290 Pizz

Fredericton 45.948512 -66.656045 Hill

**43**

**44** Fredericton

Dick's Grocery Store

Tingley's Ice

4c545e5db426ef3b11cc7e8a 45.941957 -66.663877 Smok

Ice

Hill 45.948512 -66.656045

Fredericton 45.948512 -66.656045 Hill

**45**

**46** Fredericton

Cream 4c13c001b7b9c9284e12aa37 45.957087 -66.655855

Domino's 50f9bbc75d24acebc259244d 45.957177 -66.656638 Pizz Pizza

Hill 45.948512 -66.656045 Jumbo Video 4bc0d29a920eb71307a2192c 45.957286 -66.656312 Vide

Fredericton 45.948512 -66.656045 Goody Shop 4b8580edf964a5201d6231e3 45.951172 -66.644000

**47**

Hill

Peters Meat,

**48** Nashwaaksis 45.983382 -66.644856

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 | Coﬀe |

**50** Nashwaaksis 45.983382 -66.644856

The Northside Market

50270b2ae4b042eaf816ee61 45.977779 -66.635003 F

Nashwaaksis 45.983382 -66.644856 Shoppers

**51**

Drug Mart

4c745e08db52b1f781f775dc 45.976515 -66.648534 Ph

**52** Nashwaaksis 45.983382 -66.644856 Subway 4bc5db23693695213a9a8488 45.976886 -66.648661 Sa

**53** Nashwaaksis 45.983382 -66.644856 Subway 4c87f3b4bf40a1cd09fd08b4 45.989114 -66.652061 Sa

**54** Nashwaaksis 45.983382 -66.644856

Kentucky

Fried Chicken

4eefb90ba69ddc7bcb336081 45.975903 -66.646846

Fas Res

Nashwaaksis 45.983382 -66.644856 Nashwaaksis

**55**

Field House

4b73436cf964a52016a52de3 45.984849 -66.643635

Nashwaaksis 45.983382 -66.644856 KFC 4c9267139199bfb7786c14df 45.975907 -66.646870 Fas

**56**

Res

**57** Nashwaaksis 45.983382 -66.644856 Tim Hortons 4c0104cf360a9c74bb11d9a0 45.989221 -66.652208 Coﬀe

**58** Nashwaaksis 45.983382 -66.644856 Thai spice 503658e5e4b00b386cc5d972 45.975890 -66.647424 Res

Mike's Old

**59** Nashwaaksis 45.983382 -66.644856

Fashioned

Bakery

4d67fde7709bb60c5eacb014 45.976560 -66.650030

Nashwaaksis 45.983382 -66.644856 Cox Electronics

**60**

Nashwaaksis 45.983382 -66.644856 A Pile Of

**61**

Scrap!

Jim Gilberts

4d07eab6611ﬀ04d4f4718fb 45.976112 -66.649222 Elec

4e9f0e9b93ad5d11f3d36ba1 45.984398 -66.633329 Arts &

**62** Nashwaaksis 45.983382 -66.644856

|  |  |  |
| --- | --- | --- |
| **63** Nashwaaksis | 45.983382 | -66.644856 |
| **64** Nashwaaksis | 45.983382 | -66.644856 |
| **65** Nashwaaksis | 45.983382 | -66.644856 |
| **66** Nashwaaksis | 45.983382 | -66.644856 |
| University of  **67** New | 45.948121 | -66.641406 |

Brunswick University of

Wheels And

Deals

Trailway Brewery

The North Side Market

Avalon SalonSpa

Tony Pepperoni

The Richard

J. CURRIE Center -

UNB

Charlotte

4b9a7ef5f964a520b6ba35e3 45.980784 -66.633311 Dea

574a1b86cd10af189e38500e 45.975442 -66.649496 Bee

F

|  |  |  |  |
| --- | --- | --- | --- |
| 501c19f7e4b01c57ﬀ1b1212 | 45.977837 | -66.635168 |  |
| 4bc31784920eb71312ec1c2c | 45.974591 | -66.644756 |  |
| 4c88f56dbbec6dcbe9f2d758 | 45.991888 | -66.648599 | Pizz |

4dbae5806e815ab0de5d2637 45.946698 -66.637891 Bas

1. New

Brunswick

45.948121 -66.641406

Street Arts

Centre

4b7f0318f964a5203d1030e3 45.955620 -66.639324 Art

University of

1. New

Brunswick

|  |  |  |
| --- | --- | --- |
| University of  **70** | 45.948121 | -66.641406 |
| Brunswick |  |  |
| University of  **71** | 45.948121 | -66.641406 |
| Brunswick |  |  |

New

New

45.948121 -66.641406 Sobeys 4b6727daf964a520493e2be3 45.954891 -66.645920 G

YMCA

|  |  |  |
| --- | --- | --- |
| 4e93476b8231bf0d17ba3e24 | 45.953217 | -66.649478 |
| 4c5388b0f5f3d13ac74ba5f8 | 45.951042 | -66.648112 |

Fredericton

20 Twenty

Club

**Location Location**

**Latitude**

University of

**Location Longitude**

**Venue Venue id Venue Latitude**

The Cellar

**Venue Longitude Ca**

1. New

Brunswick

University of

45.948121 -66.641406

Pub & Grill -

UNB

4b7ac93ef964a520b53c2fe3 45.945434 -66.641626

1. New

Brunswick

University of

1. New

Brunswick

University of

1. New

Brunswick

University of

45.948121 -66.641406 Harvey's 4bbdﬀ85f57ba59320bdaeb9 45.953544 -66.645021 Burg

45.948121 -66.641406 Tim Hortons 4c865c1774d7b60c3f41a3d8 45.945185 -66.641545 Coﬀe

45.948121 -66.641406 Tim Hortons 4dc29f89d4c07da169fbf84b 45.943720 -66.646907 Coﬀe

1. New

Brunswick

45.948121 -66.641406 College Hill

Social Club

New

4b7aca23f964a520df3c2fe3 45.945162 -66.641472

**77** Devon 45.968802 -66.622738

England

Pizza

4c09984e7e3fc928b64bf282 45.967675 -66.629905 Pizz

Devon 45.968802 -66.622738 Wolastoq

**78**

Wharf

4fbaafb0e4b0c7f68a419500 45.969975 -66.632568 S

Res

Fas

**79** Devon 45.968802 -66.622738 Dairy Queen 4c5cab2894fd0f473c69c945 45.969077 -66.632059

Res

Devon 45.968802 -66.622738 Pharmacie

**80**

Jean Coutu

4eb9523077c8972738ac89b2 45.967766 -66.630551 Ph

**81** Devon 45.968802 -66.622738 Tim Hortons 4b5b0812f964a520d8df28e3 45.969381 -66.632730 Coﬀe

**82** Devon 45.968802 -66.622738 Henry Park 4c8e283dad01199c7923726d 45.963992 -66.620283 B

**83** Devon 45.968802 -66.622738 Giant Tiger 4c95354f58d4b60c80443029 45.967715 -66.630410 Depa

**84** Devon 45.968802 -66.622738 york arena 4b6c4f10f964a520792f2ce3 45.964888 -66.617110 Skatin

Devon 45.968802 -66.622738 St. Mary's

**85**

Supermarket

4b9fa6adf964a520c93137e3 45.971945 -66.631248 G

Devon 45.968802 -66.622738 Dixie Lee 4c5cacc5d25320a103fdc37a 45.962257 -66.624952 Fas

**86**

Res

Devon 45.968802 -66.622738 St Marys

**87**

Smoke Shop

Carleton

4ebddf8a4690d233887bf4a6 45.972270 -66.631348 Smok

**88** Devon 45.968802 -66.622738

Park 4bce2eeb29d4b7138521a8dc 45.961182 -66.626310

New Maryland

**89**

45.892795 -66.683673 New York

Fries

Centre De

4d8771fc651041bd194d9b30 45.890420 -66.683580 Fas

Res

New Maryland

**90**

**91** New

45.892795 -66.683673

Danse Roca

Dance Center

Baseball, Basketball,

55fdfc2b498ed76a0f7aa3f6 45.890978 -66.692237

B

Maryland 45.892795 -66.683673

Tennis and Hockey In

One...

4e48415862e148603b8b3fc2 45.890726 -66.692814

New Maryland

**92**

45.892795 -66.683673 Circle K 4b9e633ef964a5202fdf36e3 45.885412 -66.688995 Gas

**93** Marysville 45.978913 -66.589491 Tim Hortons 4baa1b40f964a520174b3ae3 45.978193 -66.593041 Coﬀe

**94** Marysville 45.978913 -66.589491 Royals Field 4c573f916201e21edﬀ8736e 45.980267 -66.588412 B

S

Pharmacy

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Location Location** | | | **Location Venue Venue id Venue Venue** | | | | | |
| **Latitude** | | | **Longitude** | **Latitude** | | | **Longitude** | **Ca** |
| **95** Marysville 45.978913 -66.589491 Northside 4c8bee978018a1cdd1f2e7d2 | | | | | | 45.980194 | -66.588628 | Ph |
| **96** Marysville 45.978913 | | | -66.589491 | Marysville 4ce6d19be1eeb60c512d99ae | | 45.980243 | -66.588277 |  |
|  |  |  |  | Place |  |  |  |  |
| **97** | Marysville | 45.978913 | -66.589491 | Circle K | 4bb88fe853649c74431847fb | 45.979250 | -66.593232 | Gas |
| **98** | Skyline | 45.931827 | -66.640339 | Grant Harvey | 4f915a7ee4b01406ebc873ae | 45.925002 | -66.641004 |  |
| Acres | | |  | Centre |  |  |  | |
| **99** Skyline 45.931827 | | | -66.640339 | Kimble Field | 4fdaa8c2e4b08f3358b1b3d1 | 45.930535 | -66.631233 B | |
| **100** | Skyline | 45.931827 | -66.640339 | Mandarin | 4b786998f964a5204ecc2ee3 | 45.935440 | -66.631007 | C |
| Acres | | Palace | | | Res | | | |
| **101** | Skyline | 45.931827 | -66.640339 | Oriental | 4ec68431775bf65c02417199 | 45.930085 | -66.629518 | C |
| Acres Pearl | | | | | |  |  | Res |
| **102** Hanwell 45.902315 -66.755113 Advanced 53c133a4498e933c415c6118 | | | | | | 45.905297 | -66.750944 |  |
| **103** Hanwell 45.902315 -66.755113 Country 56356c83498e17f8ed69a380 | | | | | | 45.905937 | -66.751084 | Coﬀe |
| **104** Downtown 45.958327 -66.647211 Cafe Loka & 4e70d116152073dd03c2c50e | | | | | | 45.957570 | -66.647978 |  |

Acres

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | Fabrics | | | | | |
| Style | | | | | |
| Bistro | | | | | |
| **105** | Downtown | 45.958327 | -66.647211 | Boyce Farmers | 4b5163b4f964a5204d4c27e3 | 45.958354 | -66.639654 | F |
|  |  |  |  | Market |  |  |  |  |
| **106** | Downtown | 45.958327 | -66.647211 | Second Cup | 4b7067c6f964a5205a182de3 | 45.961385 | -66.642372 | Coﬀe |
| **107** | Downtown | 45.958327 | -66.647211 | Lunar Rogue | 4b8c53e7f964a520d4ca32e3 | 45.959998 | -66.639116 |  |
| **108** Downtown 45.958327 -66.647211 Jonnie Java 4bc47e80920eb71369c71e2c | | | | | | 45.962226 | -66.643852 | Coﬀe |
| **109** | Downtown | 45.958327 | -66.647211 | Picaroon's | 4ced5cfe7b943704ea782653 | 45.962701 | -66.642731 | B |
|  |  |  |  | Brewtique |  |  |  | |
| **110** | Downtown | 45.958327 | -66.647211 | Sobeys | 4b6727daf964a520493e2be3 | 45.954891 | -66.645920 G | |
| **111** | Downtown | 45.958327 | -66.647211 | Luna Pizza | 4be47e9b2468c92811dbfe42 | 45.962246 | -66.643788 Res | |
|  |  |  |  | Palate |  |  |  | |
| **112** | Downtown | 45.958327 | -66.647211 | Restaurant & | 4c2e0e6ae760c9b69bdf4549 | 45.962338 | -66.641776 Res | |
|  |  |  |  | Cafe |  |  |  | |
| **113** Downtown 45.958327 -66.647211 Alcool NB 4d9a52120d5f224bc5f7a34e | | | | | | 45.956140 | -66.647558 | Liquo |

Roasters

Liquor

Downtown 45.958327 -66.647211 coﬀee and

**114**

friends

Chess Piece

4b533f74f964a520009427e3 45.961842 -66.643479 Coﬀe

**115** Downtown 45.958327 -66.647211

Pâtisserie &

Cafe

53c00bcc498e1f34dc3687ae 45.963354 -66.644017

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **116**  **117** | Downtown  Downtown | 45.958327  45.958327 | -66.647211 Victory Meat 4bd1ﬀd341b9ef3bcb19fde5 45.962661 -66.645820 G  Market  -66.647211 Exhibition 4c76d45d07818cfafe94d2e3 45.960078 -66.655522 Ra | | | | | |
|  |  |  |  | Grounds |  |  |  |  |
|  |  |  |  | The Abbey |  |  |  |  |
| **118** | Downtown | 45.958327 | -66.647211 | Café & | 57178722498e4222f7d5b298 | 45.961301 | -66.640188 |  |
|  |  |  |  | Gallery |  |  |  |  |
|  |  |  |  | Charlotte |  |  |  |  |
| **119** | Downtown | 45.958327 | -66.647211 | Street Arts | 4b7f0318f964a5203d1030e3 | 45.955620 | -66.639324 | Art |
|  |  |  |  | Centre |  |  |  |  |
| **120** | Downtown | 45.958327 | -66.647211 | Isaac's Way | 51c8a824498ef33c708ac9e9 | 45.960944 | -66.637796 | Res |

**Location Location**

**Location**

**Venue Venue id Venue Latitude**

**Venue Longitude Ca**

YMCA

Fredericton

Read's News Stand

King Street Ale House

540 Kitchen

and Bar

Dimitri's Souvlaki

Smoke's Poutinerie

4e93476b8231bf0d17ba3e24 45.953217 -66.649478

4b4b6bf2f964a5200a9b26e3 45.961859 -66.643464 Coﬀe

5283fd1c498e138a8297590c 45.960460 -66.641012

53ab370e498e91a454f49e67 45.961657 -66.640152 Gas

4bacf7e8f964a520571f3be3 45.963093 -66.644479 Res

51756ac6498ece19b79a31f6 45.962032 -66.644021 Fas

Res

Snooty Fox 4b4ca053f964a52006b826e3 45.960794 -66.638927

|  |  |  |  |
| --- | --- | --- | --- |
|  | | **Latitude** | **Longitude** |
| **121** | Downtown | 45.958327 | -66.647211 |
| **122** | Downtown | 45.958327 | -66.647211 |
| **123** | Downtown | 45.958327 | -66.647211 |
| **124** | Downtown | 45.958327 | -66.647211 |
| **125** | Downtown | 45.958327 | -66.647211 |
| **126** | Downtown | 45.958327 | -66.647211 |
| **127** | Downtown | 45.958327 | -66.647211 |
| **128** | Downtown | 45.958327 | -66.647211 |
| **129** | Downtown | 45.958327 | -66.647211 |
| **130** | Downtown | 45.958327 | -66.647211 |
| **131** | Downtown | 45.958327 | -66.647211 |
| **132** | Downtown | 45.958327 | -66.647211 |
| **133** | Downtown | 45.958327 | -66.647211 |
| **134** | Downtown | 45.958327 | -66.647211 |
| **135** | Downtown | 45.958327 | -66.647211 |
| **136** | Downtown | 45.958327 | -66.647211 |
| **137** | Downtown | 45.958327 | -66.647211 |
| **138** | Downtown | 45.958327 | -66.647211 |
| **139** | Downtown | 45.958327 | -66.647211 |
| **140** | Downtown | 45.958327 | -66.647211 |
| **141** | Downtown | 45.958327 | -66.647211 |
| **142** | Downtown | 45.958327 | -66.647211 |
| **143** | Downtown | 45.958327 | -66.647211 |
| **144** | Downtown | 45.958327 | -66.647211 |
| **145** | Downtown | 45.958327 | -66.647211 |
| **146** | Downtown | 45.958327 | -66.647211 |
| **147** | Downtown | 45.958327 | -66.647211 |

Oﬃcer's Square

Fredericton Playhouse

Willie O'Ree

Place The Joyce

Cora's Breakfast &

Lunch

Strange Adventures

Naru Japanese Cuisine

Mexicali Rosas

Brewbakers Dolan's Pub

Beaverbrook Art Gallery

McGinnis Landing

Atlantic Superstore

20 Twenty

Club Geek Chic

Wilser's Room

Tim Hortons TD Canada

Trust

Fit4Less Harvey's

4c83b0df2f1c236a4bc54443 45.961754 -66.639084

4b516b64f964a520df4c27e3 45.960101 -66.636969 Perf

|  |  |  |  |
| --- | --- | --- | --- |
|  | | | Arts |
| 4b76879ef964a520a5502ee3 | 45.963017 | -66.646100 |  |
| 4b624863f964a5203b402ae3 | 45.960309 | -66.636806 |  |
| 4b8130c7f964a520e99930e3 | 45.962282 | -66.641607 | Br |
| 4babdcbdf964a5200cd03ae3 | 45.962733 | -66.643315 | Hobb |

50461342e4b0c55b9639accc 45.961721 -66.640125 Res

4c65dd9a19f3c9b697769eﬀ 45.962811 -66.646079 M

|  |  |  |  |
| --- | --- | --- | --- |
|  | | | Res |
| 4b6754faf964a5208d482be3 | 45.960703 | -66.640935 | Res |
| 4b516ddbf964a520144d27e3 | 45.962886 | -66.644615 |  |
| 4c13a7f7b7b9c92865dea937 | 45.959878 | -66.635858 | Art M |
| 4b6df601f964a5203d9f2ce3 | 45.963013 | -66.646536 | Stea |
| 4b5b0a91f964a5205fe028e3 | 45.958260 | -66.658048 | Super |
| 4c5388b0f5f3d13ac74ba5f8 | 45.951042 | -66.648112 |  |
| 4b516f03f964a520324d27e3 | 45.960573 | -66.639225 | Toy / |
| 4ba01983f964a520f15937e3 | 45.963192 | -66.644089 |  |
| 4b6455b0f964a52067ab2ae3 | 45.959873 | -66.639259 | Coﬀe |
| 4b6d8261f964a52022792ce3 | 45.963891 | -66.645782 |  |
| 4c9381ab94a0236a70ac8312 | 45.958634 | -66.657319 |  |
| 4bbdﬀ85f57ba59320bdaeb9 | 45.953544 | -66.645021 | Burg |

**Location Location**

**Latitude**

**Location Longitude**

**Venue Venue id Venue Latitude**

**Venue Longitude Ca**

Downtown 45.958327 -66.647211 Shoppers

**148**

Drug Mart

4db07df34df03036e8bbb640 45.961351 -66.644493 Ph

Downtown 45.958327 -66.647211 Shan 4dfb6fc31f6eeef806aacc25 45.961818 -66.643706 C

**149**

Res

**150** Downtown 45.958327 -66.647211 bulgogi 4b605f0ﬀ964a5203de229e3 45.961522 -66.642742 Res

Downtown 45.958327 -66.647211 William's

**151**

Seafood

**152** Downtown 45.958327 -66.647211 Subway

Downtown 45.958327 -66.647211 Capital

**153**

Complex

Downtown 45.958327 -66.647211 boom!

**154**

Nightclub

**155** Downtown 45.958327 -66.647211 Tim Hortons

Downtown 45.958327 -66.647211 King's Place

**156**

Mall

Downtown 45.958327 -66.647211 Running

**157**

Room

Downtown 45.958327 -66.647211 The Happy

**158**

Baker

Downtown 45.958327 -66.647211 Owl's Nest

**159**

Bookstore

Downtown 45.958327 -66.647211 Tingley's Ice

**160**

Cream

**161** Downtown 45.958327 -66.647211 Jumbo Video

Downtown 45.958327 -66.647211 Enterprise

**162**

Rent-A-Car

Downtown 45.958327 -66.647211 Domino's

**163**

Pizza

Downtown 45.958327 -66.647211 Papa John's

**164**

Pizza

Downtown 45.958327 -66.647211 Queen

**165**

Square Park

4b7c26f5f964a52061802fe3 45.959296 -66.655663 S

Res

Sa

|  |  |  |  |
| --- | --- | --- | --- |
| 4b6b883df964a5205a0e2ce3 | 45.962580 | -66.645032 |  |
| 4b6faa7cf964a52073f92ce3 | 45.963245 | -66.644123 |
| 4ba240eef964a52050e737e3 | 45.962315 | -66.641645 | Ni |
| 4ba8bdb3f964a5204ceb39e3 | 45.959933 | -66.655493 | Coﬀe |
| 4bc61ba4d35d9c74292de23a  4c6d4adb23c1a1cdﬀc81bcf | 45.961679  45.961812 | -66.643267  -66.643510 | Sh  S  Good |
| 4b703d21f964a5204c0d2de3 | 45.960536 | -66.641465 |  |
| 4d6ea0c98df1548152778123 | 45.963051 | -66.643872 | Bo |
| 4c13c001b7b9c9284e12aa37 | 45.957087 | -66.655855 | Ice |
| 4bc0d29a920eb71307a2192c | 45.957286 | -66.656312 | Vide |
| 4d3ae3edbf6d5481b26fd1e1 | 45.957743 | -66.656527 | Ren L |
| 50f9bbc75d24acebc259244d | 45.957177 | -66.656638 | Pizz |
| 4ecc29f59adfd1f5b5c7bbb1 | 45.956655 | -66.657285 | Pizz |
| 4b7acb0ef964a520113d2fe3 | 45.950961 | -66.648245 |  |

In [109]:

print('There are **{}** unique venue categories.'.format(len(fredericton\_data\_venues['V enue Category'].unique())))

There are 73 unique venue categories.

In [110]:

print('There are **{}** unique venues.'.format(len(fredericton\_data\_venues['Venue id']. unique())))

There are 153 unique venues.

In [111]:

univen = fredericton\_data\_venues.groupby('Location').nunique('Venue Category') univen

Out[111]:

**Location Location**

**Latitude**

**Location Longitude**

**Venue Venue**

**id**

**Venue Latitude**

**Venue Longitude**

**Venue Category**

**Brunswick**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Location** |  | | | | | | | |
| **Devon** | 1 | 1 | 1 | 12 | 12 | 12 | 12 | 11 |
| **Downtown** | 1 | 1 | 1 | 61 | 62 | 62 | 62 | 44 |
| **Fredericton Hill** | 1 | 1 | 1 | 17 | 17 | 17 | 17 | 13 |
| **Hanwell** | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 |
| **Knowledge Park** | 1 | 1 | 1 | 31 | 31 | 31 | 31 | 23 |
| **Marysville** | 1 | 1 | 1 | 5 | 5 | 5 | 5 | 5 |
| **Nashwaaksis** | 1 | 1 | 1 | 17 | 19 | 19 | 19 | 15 |
| **New Maryland** | 1 | 1 | 1 | 4 | 4 | 4 | 4 | 4 |
| **Skyline Acres** | 1 | 1 | 1 | 4 | 4 | 4 | 4 | 3 |
| **University of New** 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**

**Store**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Art Gallery** 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| **Art Museum** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Arts & Crafts** 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** 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** 5 | 5 | 5 | 9 | 10 | 10 | 10 | 1 |
| **Furniture / Home** 1 | 1 | 1 | 2 | 2 | 2 | 2 | 1 |
| **Gas Station** 2 | 2 | 2 | 1 | 2 | 2 | 2 | 1 |
| **Gastropub** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Gift Shop** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Greek Restaurant** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Grocery Store** 4 | 4 | 4 | 4 | 4 | 4 | 4 | 1 |
| **Gym** 4 | 4 | 4 | 2 | 2 | 2 | 2 | 1 |
| **Gym / Fitness** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Restaurant**

**Restaurant**

**Store**

**Center**

**Venue Category**

**Location Location**

**Latitude**

**Location Longitude**

**Venue Venue**

**id**

**Venue Latitude**

**Venue Longitude**

**Venue Category**

**Restaurant**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Hardware Store** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Hobby Shop** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Hockey Arena** 3 | 3 | 3 | 3 | 3 | 3 | 3 | 1 |
| **Ice Cream Shop** 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| **Italian Restaurant** 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 |
| **Kids Store** 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Korean** 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** 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** 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** 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** 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** 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 |

**Restaurant**

**Venue**

**Location**

**Restaurant**

**Shop**

**Location Location**

**Latitude**

**Location Longitude**

**Venue Venue**

**id**

**Venue Latitude**

**Venue Longitude**

**Venue Category**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Venue Category** |  | | | | | | | |
| **Sushi Restaurant** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Thai Restaurant** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Toy / Game Store** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Video Store** | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| **Warehouse Store** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| In [ ]: |  |  |  |  |  |  |  |  |  |

# Analyze each Location

In [113]:

freddy\_onehot = pd.get\_dummies(fredericton\_data\_venues[['Venue Category']], prefix= "", prefix\_sep="")

freddy\_onehot['Location'] = fredericton\_data\_venues['Location']

fixed\_columns = [freddy\_onehot.columns[-1]] + list(freddy\_onehot.columns[:-1]) freddy\_onehot = freddy\_onehot[fixed\_columns]

freddy\_onehot.head()

Out[113]:

**Location**

Knowledge

**Art Gallery**

**Art Museum**

**Arts & Crafts Store**

**Auto Bakery Bank Bar**

**Dealership**

**Baseball**

**Field**

**Baseball Stadium**

**Basketball**

**Court**

**Beer Store**

**0** Park 0 0 0 0 0 0 0 0 0 0 0

Knowledge 0 0 0 0 0 0 0 0 0 0 0

**1**

Park

Knowledge 0 0 0 0 0 0 0 0 0 0 0

**2**

Park

Knowledge 0 0 0 0 0 0 0 0 0 0 0

**3**

Park

Knowledge 0 0 1 0 0 0 0 0 0 0 0

**4**

Park

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 Bakery Bank Bar**

**Dealership**

**Baseball**

**Field**

**Baseball Ba Stadium**

**0** Devon 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.083333 0.0

**1** Downtown 0.016129 0.016129 0.000000 0.000000 0.016129 0.016129 0.048387 0.000000 0.0

Fredericton

**2** 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

Knowledge

**4** 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

New

**7** Maryland 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.250000 0.0

Skyline 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.250000 0.0

**8**

Acres

University of

**9** 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----

|  |  |  |  |
| --- | --- | --- | --- |
| 0 | Fast | venue  Food Restaurant | freq  0.17 |
| 1 |  | Coffee Shop | 0.08 |
| 2 |  | Grocery Store | 0.08 |

* 1. Seafood Restaurant 0.08
  2. 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

1. Bakery 0.18
2. Pizza Place 0.18
3. Hockey Arena 0.06
4. Smoke Shop 0.06
5. Ice Cream Shop 0.06

----Hanwell----

venue freq

1. Coffee Shop 0.5
2. Rental Service 0.5
3. Art Gallery 0.0
4. Rental Car Location 0.0
5. Racetrack 0.0

----Knowledge Park----

venue freq

1. Fast Food Restaurant 0.13
2. Clothing Store 0.10
3. Liquor Store 0.06
4. Restaurant 0.06
5. Furniture / Home Store 0.06

----Marysville----

venue freq

1. Coffee Shop 0.2
2. Pharmacy 0.2
3. Park 0.2
4. Baseball Stadium 0.2
5. Gas Station 0.2

----Nashwaaksis----

venue freq

1. Farmers Market 0.11
2. Sandwich Place 0.11
3. Coffee Shop 0.11
4. Fast Food Restaurant 0.11
5. Beer Store 0.05

----New Maryland----

venue freq

1. Fast Food Restaurant 0.25
2. Baseball Field 0.25
3. Gas Station 0.25
4. Dance Studio 0.25
5. Art Gallery 0.00

----Skyline Acres----

venue freq

1. Chinese Restaurant 0.50
2. Hockey Arena 0.25
3. Baseball Field 0.25
4. Pet Store 0.00
5. 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]:

**def** return\_most\_common\_venues(row, num\_top\_venues): row\_categories = row.iloc[1:]

row\_categories\_sorted = row\_categories.sort\_values(ascending=**False**)

**return** row\_categories\_sorted.index.values[0:num\_top\_venues]

In [119]:

num\_top\_venues = 10

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

columns = ['Location']

**for** ind **in** np.arange(num\_top\_venues):

**try**:

columns.append('**{}{}** Most Common Venue'.format(ind+1, indicators[ind]))

**except**:

columns.append('**{}**th Most Common Venue'.format(ind+1))

location\_venues\_sorted = pd.DataFrame(columns=columns) location\_venues\_sorted['Location'] = freddy\_grouped['Location']

**for** ind **in** np.arange(freddy\_grouped.shape[0]):

location\_venues\_sorted.iloc[ind, 1:] = return\_most\_common\_venues(freddy\_grouped

.iloc[ind, :], num\_top\_venues)

location\_venues\_sorted

Out[119]:

**Location**

**1st Most Common**

**Venue**

**2nd Most Common**

**Venue**

**3rd Most Common**

**Venue**

**4th Most Common**

**Venue**

**5th Most Common**

**Venue**

**6th Most Common**

**Venue**

**7th Most Common**

**Venue**

**8th Most Common**

**Venue**

Devon Fast Food

**0**

Restaurant

Grocery Store

Smoke Shop

Pharmacy Coﬀee Shop

Seafood Restaurant

Park Department

Store

Downtown Coﬀee Shop

**1**

Pub Bar Café Restaurant Park Pizza

Place

Grocery Store

Fredericton

**2**

Hill

**3** Hanwell

Bakery Pizza

Hockey

Smoke

Hardware

Video Store Ice Cream

Park P

Knowledge

**4**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Place | Arena | Shop | Store |  | Shop |  | |
| Rental | Coﬀee | Warehouse | Dance | Department | Discount | Electronics | Farmers | F |
| Service | Shop | Store | Studio | Store | Store | Store | Market | R |

Park

**5**

Fast Food Restaurant

Baseball

Clothing

Store

Gas

Furniture /

Home Store

Liquor Restaurant Store

Coﬀee

Warehouse Shoe Store Pet Store Store

Greek F

Marysville

Stadium

Station Pharmacy Park

Shop Gift Shop Gastropub

Restaurant

Nashwaaksis Coﬀee Shop

**6**

Sandwich

Place

Farmers Market

Fast Food Restaurant

Gym Spa Electronics Store

Beer Store

New Maryland

**7**

Skyline Acres

**8**

University of

**9**

Gas Station

Chinese Restaurant

Dance Studio

Baseball

Field

Coﬀee

Fast Food Restaurant

Hockey Arena

Baseball

Field

Arts & Crafts Store

Furniture /

Home Store

Coﬀee Shop

Burger

Department

Store

Gym / Fitness Center

Basketball

Discount

Store

Gym

Grocery

Electronics

Store

Grocery

Store R

New Brunswick

Bar

Shop Art Gallery Pub

Joint

Court

Store Gym

# Cluster Fredericton Locations

## Run k-means to cluster Locations into 5 clusters

In [120]:

kclusters = 5

freddy\_grouped\_clustering = freddy\_grouped.drop('Location', 1)

kmeans = KMeans(n\_clusters=kclusters, random\_state=0).fit(freddy\_grouped\_clustering

)

kmeans.labels\_[0:10]

Out[120]: array([1, 1, 1, 0, 1, 4, 1, 3, 2, 1], dtype=int32)

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

In [121]:

freddy\_merged = location\_df

freddy\_merged['Cluster Labels'] = kmeans.labels\_

freddy\_merged = freddy\_merged.join(location\_venues\_sorted.set\_index('Location'), on

='Location')

freddy\_merged

Out[121]:

**Location Latitude Longitude Cluster**

**Labels**

**0** Knowledge

**1st Most Common**

**Venue**

Fast Food

**2nd Most Common**

**Venue**

Clothing

**3rd Most Common**

**Venue**

Furniture /

**4th Most Common**

**Venue**

Liquor

**5th Most Common**

**Venue**

**6th Com**

**V**

Wareh

Park 45.931143 -66.652700 1

Restaurant

Store

Home Store

Store Restaurant

Fredericton

**1**

Hill

45.948512 -66.656045 1 Bakery Pizza

Place

Hockey Arena

Smoke Shop

Hardware

Store

Video

Nashwaaksis 45.983382 -66.644856 1 Coﬀee

**2**

Shop

University of

**3**

Sandwich

Place

Coﬀee

Farmers Market

Fast Food Restaurant

Gym

Burger

Bask

New Brunswick

45.948121 -66.641406 0 Bar

Shop Art Gallery Pub

Joint

Devon 45.968802 -66.622738 1 Fast Food

**4**

Restaurant

Grocery Store

Smoke Shop

Pharmacy Coﬀee Shop

Sea Resta

New 45.892795 -66.683673 4

**5**

Maryland

Gas Station

Dance Studio

Fast Food Restaurant

Baseball

Field

Furniture /

Home Store

Depart

Marysville 45.978913 -66.589491 1 Baseball

**6**

Stadium

Gas Station

Pharmacy Park Coﬀee Shop

Gift

**7** Skyline

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Acres |  | | |
| **8** | Hanwell | 45.902315 | -66.755113 | 2 |
| **9** | Downtown | 45.958327 | -66.647211 | 1 |

45.931827 -66.640339 3

Chinese Restaurant

Rental Service

Baseball

Field

Coﬀee Shop

Hockey Arena

Warehouse

Store

Arts & Crafts Store

Dance Studio

Coﬀee Shop

Department

Store

G

Fi C

Disc

Coﬀee Shop

Pub Bar Café Restaurant

In [122]:

map\_clusters = folium.Map(location=[latitude, longitude], zoom\_start=11)

x = np.arange(kclusters)

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

markers\_colors = []

**for** lat, lon, poi, cluster **in** zip(freddy\_merged['Latitude'], freddy\_merged['Longitu de'], freddy\_merged['Location'], freddy\_merged['Cluster Labels']):

label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse\_html=**True**) folium.CircleMarker([lat, lon], radius=5,popup=label,color=rainbow[cluster-1],f

ill=**True**,fill\_color=rainbow[cluster-1], fill\_opacity=0.7).add\_to(map\_clusters)

map\_clusters

Out[122]:



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[Leaﬂet (http://leaﬂetjs.com)](http://leafletjs.com/)

In [ ]: