Week 5 Capstone Report - Segmenting and Clustering Neighbourhoods in Fredericton-Github Submit

1 Segmenting and Clustering Neighborhoods in Fredericton, NB

1.1 Applied Data Science Capstone Week 5 Peer-Graded Project Report

1.2 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.

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

```
[73]: &lt;IPython.core.display.Image object&gt;
```

1.3 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/
2. Fredericton Neighbourhoods: 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
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
5. Fredericton locations of interest: https://github.com/JasonLUrquhart/Applied-Data-Science-Capstone/blob/master/Fredericton%20Locations.xlsx
6. Foursquare Developers Access to venue data: 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.

2 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. 6. Determine if an area, such as the Knowledge Park needs a coffee shop.

2.0.1 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.

2.0.2 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.

2.0.3 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.

2.1 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.

5. 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.

6. 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.

7. 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.

8. We were able to determine the top 10 most common venues by location of interest.

9. Statisically, we determined there are no coffee shops within the Knowledge Park clusters.

2.2 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.

2.3 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.

3 APPENDIX: Analysis

3.0.1 Load Libraries

[74]:
```
import numpy as np # library to handle data in a vectorized manner

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

import json # library to handle JSON files

!conda install -c conda-forge geopy --yes # uncomment this line if you␣
 ↪haven't completed the Foursquare API lab
```

```
from geopy.geocoders import Nominatim # convert an address into latitude␣
 ↪and longitude values

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

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

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

# for webscraping import Beautiful Soup
from bs4 import BeautifulSoup

import xml

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

print('Libraries imported.')
```

```
Solving environment: done

# All requested packages already installed.

Solving environment: done

# All requested packages already installed.

Libraries imported.
```

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

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

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

[77]:

```
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 'properties': {'FID': 1,
```

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```

[78]:
```
g = requests.get('https://opendata.arcgis.com/datasets/
↪6179d35eacb144a5b5fdcc869f86dfb5_0.geojson')
demog_geo = g.json()
```

[79]:
```
demog_data = demog_geo['features']
demog_data[0]
```

[79]:
```
{'type': 'Feature',
 'properties': {'FID': 1,
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  'DBUID': '1310024304',
  'DAUID': '13100243',
  'CDUID': '1310',
  'CTUID': '3200002.00',
  'CTNAME': '0002.00',
  'DBuid_1': '1310024304',
  'DBpop2011': 60,
  'DBtdwell20': 25,
  'DBurdwell2': 22,
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  'Shape_Area': 2.81310751889e-06,
  'CTIDLINK': 3200002,
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    [-66.634784212921, 45.9519239912381]]]}}
```

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

[80]:
```
['Capstone Project Course.ipynb',
 'Fredericton_Census_Tract_Demographics.csv',
 '.DS_Store',
 'Fredericton_Census_Tract_Demographics.xlsx',
```

```
 'Crime_by_neighbourhood_2017.xlsx',
 'Capstone Fredericton Crime and Police Station Location.ipynb',
 'Boston_Neighborhoods (1).geojson',
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Github submit.ipynb',
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 ↪Toronto_Part
2_files']
```

[81]:

```
opencrime = 'Crime_by_neighbourhood_2017.xlsx'
```

[82]:

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

```
['Crime_by_neighbourhood_2017']
```

[83]:

```
crime_df = workbook.parse('Crime_by_neighbourhood_2017')
crime_df.head()
```

[83]:

```
        Neighbourhood                 From_Date                   To_Date ␣
 ↪\
0  Fredericton South  2017-01-05T00:00:00.000Z  2017-01-26T00:00:00.000Z
1  Fredericton South  2017-03-04T00:00:00.000Z  2017-03-06T00:00:00.000Z
```

```
2  Fredericton South  2017-05-07T00:00:00.000Z                       NaN
3  Fredericton South  2017-06-20T00:00:00.000Z  2017-06-21T00:00:00.000Z
4  Fredericton South  2017-07-09T00:00:00.000Z  2017-07-10T00:00:00.000Z

   Crime_Code        Crime_Type  Ward         City  FID
0        2120  B&E NON-RESIDNCE     7  Fredericton    1
1        2120  B&E NON-RESIDNCE     7  Fredericton    2
2        2120  B&E NON-RESIDNCE    12  Fredericton    3
3        2120  B&E NON-RESIDNCE    12  Fredericton    4
4        2120  B&E NON-RESIDNCE     7  Fredericton    5
```

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

3.1 What is the crime count by neighbourhood?

[128]:
```python
crime_data = crime_df.groupby(['Neighbourhood']).size().
 ↪to_frame(name='Count').reset_index()
crime_data
```

[128]:
```
                     Neighbourhood  Count
0                    Barkers Point     47
1                        Brookside     54
2                Brookside Estates      9
3          Brookside Mini Home Park      5
4                     College Hill     41
5                 Colonial heights      9
6                Cotton Mill Creek      4
7                   Diamond Street      1
8                        Doak Road      1
9                          Douglas      3
10                        Downtown    127
11                  Dun's Crossing     18
12                     Forest Hill     12
13               Fredericton South     85
14                 Fulton Heights      36
15                    Garden Creek     13
16                    Garden Place      4
17                Gilridge Estates      3
18                       Golf Club      7
19                   Grasse Circle      1
20          Greenwood Minihome Park      2
21                   Hanwell North      8
22                   Heron Springs      3
```

23	Highpoint Ridge	5
24	Kelly's Court Minihome Park	1
25	Knob Hill	4
26	Knowledge Park	1
27	Lian / Valcore	7
28	Lincoln	13
29	Lincoln Heights	14
30	Main Street	78
31	Marysville	39
32	McKnight	4
33	McLeod Hill	3
34	Monteith / Talisman	12
35	Montogomery / Prospect East	16
36	Nashwaaksis	25
37	Nethervue Minihome Park	1
38	North Devon	113
39	Northbrook Heights	10
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

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

[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

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

[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
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
```

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

[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
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
```

[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:
DeprecationWarning: Using Nominatim with the default "geopy/1.18.1"␣
↪`user_agent`
is strongly discouraged, as it violates Nominatim's ToS
https://operations.osmfoundation.org/policies/nominatim/ and may possibly␣
↪cause
403 and 429 HTTP errors. Please specify a custom `user_agent` with
`Nominatim(user_agent="my-application")` or by overriding the default
`user_agent`: `geopy.geocoders.options.default_user_agent =␣
↪"my-application"`.
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.

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

fredericton_1_map = folium.Map(location=[45.97, -66.65], width=1000,␣
↪height=750,zoom_start=12)

fredericton_1_map
```

[89]: <folium.folium.Map at 0x1a1f6b9278>

[90]:
```
fredericton_geo = r.json()

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

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

fredericton_1_map
```

[90]: <folium.folium.Map at 0x1a1f6b9278>

3.2 Examine Crime Types

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

[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
```

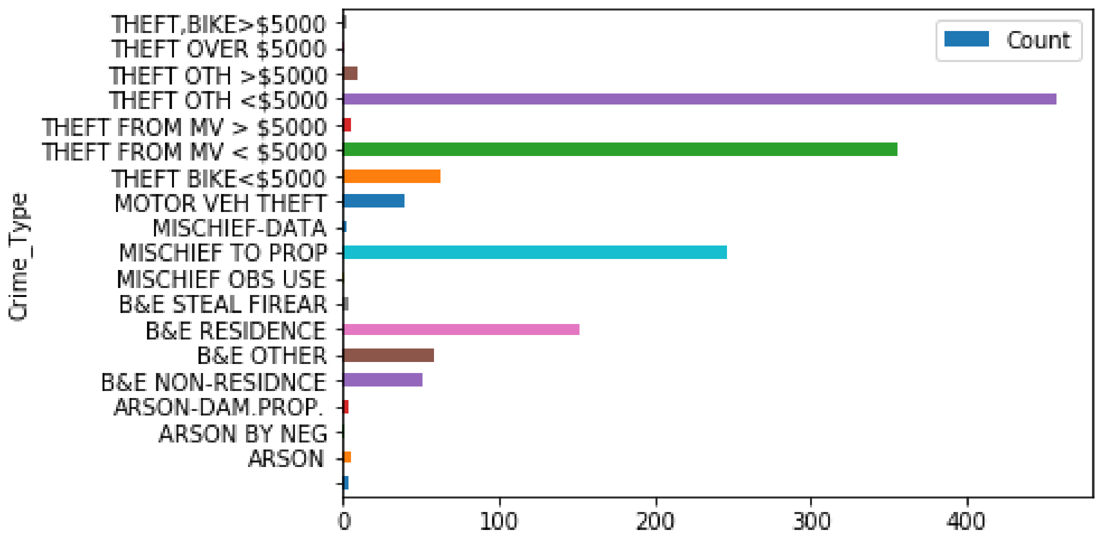
[154]:
```
crimetype_data.describe()
```

[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
```

[140]:
```
crimepivot = crime_df.pivot_table(index='Neighbourhood',␣
 ↪columns='Crime_Type', aggfunc=pd.Series.count, fill_value=0)
crimepivot
```

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

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




```
[ ]:
```

3.3 Let's examine theft from vehicles

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

```
[93]:            Neighbourhood  Crime_Code             Crime_Type ␣
      ↪Ward  \
18          Fredericton South        2142  THEFT FROM MV < $5000     7
19          Fredericton South        2142  THEFT FROM MV < $5000     7
20          Fredericton South        2142  THEFT FROM MV < $5000     7
21          Fredericton South        2142  THEFT FROM MV < $5000    12
22          Fredericton South        2142  THEFT FROM MV < $5000    12
23          Fredericton South        2142  THEFT FROM MV < $5000     7
24          Fredericton South        2142  THEFT FROM MV < $5000     7
25          Fredericton South        2142  THEFT FROM MV < $5000     7
26          Fredericton South        2142  THEFT FROM MV < $5000    11
27          Fredericton South        2142  THEFT FROM MV < $5000    11
28          Fredericton South        2142  THEFT FROM MV < $5000    12
29          Fredericton South        2142  THEFT FROM MV < $5000    12
30          Fredericton South        2142  THEFT FROM MV < $5000     7
51              Barkers Point        2142  THEFT FROM MV < $5000     6
52              Barkers Point        2142  THEFT FROM MV < $5000     6
53              Barkers Point        2142  THEFT FROM MV < $5000     6
```

54	Barkers Point	2142	THEFT FROM MV < $5000	6
55	Barkers Point	2142	THEFT FROM MV < $5000	6
56	Barkers Point	2142	THEFT FROM MV < $5000	6
57	Barkers Point	2142	THEFT FROM MV < $5000	6
58	Barkers Point	2142	THEFT FROM MV < $5000	6
100	Sandyville	2142	THEFT FROM MV < $5000	5
107	South Devon	2142	THEFT FROM MV < $5000	4
108	South Devon	2142	THEFT FROM MV < $5000	4
109	South Devon	2142	THEFT FROM MV < $5000	4
110	South Devon	2142	THEFT FROM MV < $5000	4
111	South Devon	2142	THEFT FROM MV < $5000	4
112	South Devon	2142	THEFT FROM MV < $5000	4
113	South Devon	2142	THEFT FROM MV < $5000	4
114	South Devon	2142	THEFT FROM MV < $5000	4
115	South Devon	2142	THEFT FROM MV < $5000	4
116	South Devon	2142	THEFT FROM MV < $5000	4
117	South Devon	2142	THEFT FROM MV < $5000	4
118	South Devon	2142	THEFT FROM MV < $5000	4
119	South Devon	2142	THEFT FROM MV < $5000	4
120	South Devon	2142	THEFT FROM MV < $5000	4
121	South Devon	2142	THEFT FROM MV < $5000	4
122	South Devon	2142	THEFT FROM MV < $5000	4
123	South Devon	2142	THEFT FROM MV < $5000	4
124	South Devon	2142	THEFT FROM MV < $5000	4
125	South Devon	2142	THEFT FROM MV < $5000	4
126	South Devon	2142	THEFT FROM MV < $5000	4
127	South Devon	2142	THEFT FROM MV < $5000	4
128	South Devon	2142	THEFT FROM MV < $5000	4
151	Sandyville	2142	THEFT FROM MV < $5000	5
156	Knob Hill	2142	THEFT FROM MV < $5000	5
165	Youngs Crossing	2142	THEFT FROM MV < $5000	4
166	Youngs Crossing	2142	THEFT FROM MV < $5000	4
167	Youngs Crossing	2142	THEFT FROM MV < $5000	4
168	Youngs Crossing	2142	THEFT FROM MV < $5000	4
169	Youngs Crossing	2142	THEFT FROM MV < $5000	4
170	Youngs Crossing	2142	THEFT FROM MV < $5000	4
201	Marysville	2142	THEFT FROM MV < $5000	5
252	Marysville	2142	THEFT FROM MV < $5000	5
278	Douglas	2142	THEFT FROM MV < $5000	1
280	McLeod Hill	2142	THEFT FROM MV < $5000	2
281	McLeod Hill	2142	THEFT FROM MV < $5000	2
301	Marysville	2142	THEFT FROM MV < $5000	0
302	Marysville	2142	THEFT FROM MV < $5000	5
303	Marysville	2142	THEFT FROM MV < $5000	5

304	Marysville	2142	THEFT FROM MV < $5000	5
305	Marysville	2142	THEFT FROM MV < $5000	5
306	Marysville	2142	THEFT FROM MV < $5000	5
307	Marysville	2142	THEFT FROM MV < $5000	5
308	Marysville	2142	THEFT FROM MV < $5000	5
330	Saint Mary's First Nation	2142	THEFT FROM MV < $5000	3
349	Sandyville	2142	THEFT FROM MV < $5000	5
354	Nashwaaksis	2142	THEFT FROM MV < $5000	1
355	Nashwaaksis	2142	THEFT FROM MV < $5000	1
356	Nashwaaksis	2142	THEFT FROM MV < $5000	1
357	Nashwaaksis	2142	THEFT FROM MV < $5000	1
358	Nashwaaksis	2142	THEFT FROM MV < $5000	1
359	Nashwaaksis	2142	THEFT FROM MV < $5000	1
360	Nashwaaksis	2142	THEFT FROM MV < $5000	1
361	Nashwaaksis	2142	THEFT FROM MV < $5000	1
362	Nashwaaksis	2142	THEFT FROM MV < $5000	1
377	Northbrook Heights	2142	THEFT FROM MV < $5000	2
378	Northbrook Heights	2142	THEFT FROM MV < $5000	2
379	Northbrook Heights	2142	THEFT FROM MV < $5000	1
380	Northbrook Heights	2142	THEFT FROM MV < $5000	2
381	Northbrook Heights	2142	THEFT FROM MV < $5000	2
388	Heron Springs	2142	THEFT FROM MV < $5000	2
389	Heron Springs	2142	THEFT FROM MV < $5000	2
400	Downtown	2142	THEFT FROM MV < $5000	10
401	Downtown	2142	THEFT FROM MV < $5000	11
402	Downtown	2142	THEFT FROM MV < $5000	11
403	Downtown	2142	THEFT FROM MV < $5000	10
404	Downtown	2142	THEFT FROM MV < $5000	10
405	Downtown	2142	THEFT FROM MV < $5000	10
408	Downtown	2142	THEFT FROM MV < $5000	10
410	Downtown	2142	THEFT FROM MV < $5000	10
411	Downtown	2142	THEFT FROM MV < $5000	10
412	Downtown	2142	THEFT FROM MV < $5000	10
413	Downtown	2142	THEFT FROM MV < $5000	10
414	Downtown	2142	THEFT FROM MV < $5000	10
415	Downtown	2142	THEFT FROM MV < $5000	10
416	Downtown	2142	THEFT FROM MV < $5000	10
417	Downtown	2142	THEFT FROM MV < $5000	10
418	Downtown	2142	THEFT FROM MV < $5000	10
419	Downtown	2142	THEFT FROM MV < $5000	10
420	Downtown	2142	THEFT FROM MV < $5000	10
421	Downtown	2142	THEFT FROM MV < $5000	10
422	Downtown	2142	THEFT FROM MV < $5000	10
506	Downtown	2142	THEFT FROM MV < $5000	10

520	Fulton Heights	2142	THEFT FROM MV < $5000	3
521	Fulton Heights	2142	THEFT FROM MV < $5000	3
522	Fulton Heights	2142	THEFT FROM MV < $5000	3
523	Fulton Heights	2142	THEFT FROM MV < $5000	3
524	Fulton Heights	2142	THEFT FROM MV < $5000	2
525	Fulton Heights	2142	THEFT FROM MV < $5000	3
526	Fulton Heights	2142	THEFT FROM MV < $5000	3
527	Fulton Heights	2142	THEFT FROM MV < $5000	3
528	Fulton Heights	2142	THEFT FROM MV < $5000	3
529	Fulton Heights	2142	THEFT FROM MV < $5000	2
530	Fulton Heights	2142	THEFT FROM MV < $5000	3
531	Fulton Heights	2142	THEFT FROM MV < $5000	3
569	Main Street	2142	THEFT FROM MV < $5000	2
570	Main Street	2142	THEFT FROM MV < $5000	3
571	Main Street	2142	THEFT FROM MV < $5000	2
572	Main Street	2142	THEFT FROM MV < $5000	2
573	Main Street	2142	THEFT FROM MV < $5000	3
574	Main Street	2142	THEFT FROM MV < $5000	2
575	Main Street	2142	THEFT FROM MV < $5000	2
576	Main Street	2142	THEFT FROM MV < $5000	2
577	Main Street	2142	THEFT FROM MV < $5000	2
578	Main Street	2142	THEFT FROM MV < $5000	2
604	Golf Club	2142	THEFT FROM MV < $5000	12
614	Gilridge Estates	2142	THEFT FROM MV < $5000	1
622	Nethervue Minihome Park	2142	THEFT FROM MV < $5000	12
625	Monteith / Talisman	2142	THEFT FROM MV < $5000	12
626	Monteith / Talisman	2142	THEFT FROM MV < $5000	12
631	Garden Creek	2142	THEFT FROM MV < $5000	12
640	Highpoint Ridge	2142	THEFT FROM MV < $5000	12
641	Highpoint Ridge	2142	THEFT FROM MV < $5000	12
642	Highpoint Ridge	2142	THEFT FROM MV < $5000	12
643	Highpoint Ridge	2142	THEFT FROM MV < $5000	12
650	Golf Club	2142	THEFT FROM MV < $5000	12
651	Golf Club	2142	THEFT FROM MV < $5000	12
653	Golf Club	2142	THEFT FROM MV < $5000	12
752	Golf Club	2142	THEFT FROM MV < $5000	12
764	Woodstock Road	2142	THEFT FROM MV < $5000	12
765	Woodstock Road	2142	THEFT FROM MV < $5000	12
766	Woodstock Road	2142	THEFT FROM MV < $5000	12
767	Woodstock Road	2142	THEFT FROM MV < $5000	12
768	Woodstock Road	2142	THEFT FROM MV < $5000	12
769	Woodstock Road	2142	THEFT FROM MV < $5000	12
770	Woodstock Road	2142	THEFT FROM MV < $5000	12
771	Woodstock Road	2142	THEFT FROM MV < $5000	12

772	Woodstock Road	2142	THEFT FROM MV < $5000	12
773	Woodstock Road	2142	THEFT FROM MV < $5000	12
774	Woodstock Road	2142	THEFT FROM MV < $5000	12
775	Woodstock Road	2142	THEFT FROM MV < $5000	12
776	Woodstock Road	2142	THEFT FROM MV < $5000	0
777	Woodstock Road	2142	THEFT FROM MV < $5000	12
778	Woodstock Road	2142	THEFT FROM MV < $5000	12
779	Woodstock Road	2142	THEFT FROM MV < $5000	12
780	Woodstock Road	2142	THEFT FROM MV < $5000	12
781	Woodstock Road	2142	THEFT FROM MV < $5000	12
787	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
788	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
789	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
790	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
791	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
792	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
793	Sunshine Gardens	2142	THEFT FROM MV < $5000	10
809	Plat	2142	THEFT FROM MV < $5000	0
810	Plat	2142	THEFT FROM MV < $5000	11
811	Plat	2142	THEFT FROM MV < $5000	11
812	Plat	2142	THEFT FROM MV < $5000	10
813	Plat	2142	THEFT FROM MV < $5000	11
814	Plat	2142	THEFT FROM MV < $5000	10
815	Plat	2142	THEFT FROM MV < $5000	10
816	Plat	2142	THEFT FROM MV < $5000	10
817	Plat	2142	THEFT FROM MV < $5000	10
818	Plat	2142	THEFT FROM MV < $5000	10
819	Plat	2142	THEFT FROM MV < $5000	11
820	Plat	2142	THEFT FROM MV < $5000	10
821	Plat	2142	THEFT FROM MV < $5000	10
822	Plat	2142	THEFT FROM MV < $5000	10
823	Plat	2142	THEFT FROM MV < $5000	10
824	Plat	2142	THEFT FROM MV < $5000	10
825	Plat	2142	THEFT FROM MV < $5000	0
826	Plat	2142	THEFT FROM MV < $5000	11
827	Plat	2142	THEFT FROM MV < $5000	10
828	Plat	2142	THEFT FROM MV < $5000	10
829	Plat	2142	THEFT FROM MV < $5000	10
830	Plat	2142	THEFT FROM MV < $5000	11
831	Plat	2142	THEFT FROM MV < $5000	11
832	Plat	2142	THEFT FROM MV < $5000	10
833	Plat	2142	THEFT FROM MV < $5000	11
835	Plat	2142	THEFT FROM MV < $5000	10
836	Plat	2142	THEFT FROM MV < $5000	11

837	Plat	2142	THEFT FROM MV < $5000	10
838	Plat	2142	THEFT FROM MV < $5000	10
839	Plat	2142	THEFT FROM MV < $5000	11
840	Plat	2142	THEFT FROM MV < $5000	10
841	Plat	2142	THEFT FROM MV < $5000	10
842	Plat	2142	THEFT FROM MV < $5000	10
843	Plat	2142	THEFT FROM MV < $5000	10
844	Plat	2142	THEFT FROM MV < $5000	10
845	Plat	2142	THEFT FROM MV < $5000	11
846	Plat	2142	THEFT FROM MV < $5000	10
847	Plat	2142	THEFT FROM MV < $5000	10
848	Plat	2142	THEFT FROM MV < $5000	11
849	Plat	2142	THEFT FROM MV < $5000	10
855	Southwood Park	2142	THEFT FROM MV < $5000	7
856	Southwood Park	2142	THEFT FROM MV < $5000	7
857	Southwood Park	2142	THEFT FROM MV < $5000	7
865	Lincoln Heights	2142	THEFT FROM MV < $5000	7
866	Lincoln Heights	2142	THEFT FROM MV < $5000	7
867	Lincoln Heights	2142	THEFT FROM MV < $5000	7
868	Lincoln Heights	2142	THEFT FROM MV < $5000	7
869	Lincoln Heights	2142	THEFT FROM MV < $5000	7
871	Lincoln Heights	2142	THEFT FROM MV < $5000	7
875	Lincoln Heights	2142	THEFT FROM MV < $5000	7
880	Skyline Acrea	2142	THEFT FROM MV < $5000	8
881	Lincoln Heights	2142	THEFT FROM MV < $5000	7
886	Skyline Acrea	2142	THEFT FROM MV < $5000	8
887	Lincoln Heights	2142	THEFT FROM MV < $5000	7
892	Skyline Acrea	2142	THEFT FROM MV < $5000	8
893	Lincoln Heights	2142	THEFT FROM MV < $5000	7
898	Skyline Acrea	2142	THEFT FROM MV < $5000	8
899	Skyline Acrea	2142	THEFT FROM MV < $5000	8
900	Skyline Acrea	2142	THEFT FROM MV < $5000	8
901	Skyline Acrea	2142	THEFT FROM MV < $5000	8
902	Skyline Acrea	2142	THEFT FROM MV < $5000	8
903	Skyline Acrea	2142	THEFT FROM MV < $5000	8
904	Skyline Acrea	2142	THEFT FROM MV < $5000	8
905	Skyline Acrea	2142	THEFT FROM MV < $5000	8
906	Skyline Acrea	2142	THEFT FROM MV < $5000	8
907	Skyline Acrea	2142	THEFT FROM MV < $5000	8
913	Poet's Hill	2142	THEFT FROM MV < $5000	8
914	Poet's Hill	2142	THEFT FROM MV < $5000	8
922	Dun's Crossing	2142	THEFT FROM MV < $5000	8
923	Dun's Crossing	2142	THEFT FROM MV < $5000	8
924	Dun's Crossing	2142	THEFT FROM MV < $5000	8

925	Dun's Crossing	2142	THEFT FROM MV < $5000	8
926	Dun's Crossing	2142	THEFT FROM MV < $5000	8
927	Dun's Crossing	2142	THEFT FROM MV < $5000	8
928	Dun's Crossing	2142	THEFT FROM MV < $5000	8
929	Dun's Crossing	2142	THEFT FROM MV < $5000	8
930	Dun's Crossing	2142	THEFT FROM MV < $5000	8
938	Southwood Park	2142	THEFT FROM MV < $5000	7
939	Southwood Park	2142	THEFT FROM MV < $5000	7
940	Southwood Park	2142	THEFT FROM MV < $5000	7
941	Southwood Park	2142	THEFT FROM MV < $5000	7
946	The Hill	2142	THEFT FROM MV < $5000	9
947	The Hill	2142	THEFT FROM MV < $5000	9
948	The Hill	2142	THEFT FROM MV < $5000	9
949	The Hill	2142	THEFT FROM MV < $5000	10
950	The Hill	2142	THEFT FROM MV < $5000	10
951	The Hill	2142	THEFT FROM MV < $5000	11
952	The Hill	2142	THEFT FROM MV < $5000	9
954	The Hill	2142	THEFT FROM MV < $5000	10
955	The Hill	2142	THEFT FROM MV < $5000	10
956	The Hill	2142	THEFT FROM MV < $5000	9
957	The Hill	2142	THEFT FROM MV < $5000	9
969	Forest Hill	2142	THEFT FROM MV < $5000	8
970	Forest Hill	2142	THEFT FROM MV < $5000	8
971	Forest Hill	2142	THEFT FROM MV < $5000	8
972	Forest Hill	2142	THEFT FROM MV < $5000	8
973	Forest Hill	2142	THEFT FROM MV < $5000	8
974	Forest Hill	2142	THEFT FROM MV < $5000	8
975	Forest Hill	2142	THEFT FROM MV < $5000	8
976	Forest Hill	2142	THEFT FROM MV < $5000	8
989	Lincoln Heights	2142	THEFT FROM MV < $5000	7
996	Diamond Street	2142	THEFT FROM MV < $5000	1
1027	College Hill	2142	THEFT FROM MV < $5000	11
1028	College Hill	2142	THEFT FROM MV < $5000	11
1029	College Hill	2142	THEFT FROM MV < $5000	11
1030	College Hill	2142	THEFT FROM MV < $5000	11
1031	College Hill	2142	THEFT FROM MV < $5000	11
1032	College Hill	2142	THEFT FROM MV < $5000	11
1033	College Hill	2142	THEFT FROM MV < $5000	11
1034	College Hill	2142	THEFT FROM MV < $5000	11
1035	College Hill	2142	THEFT FROM MV < $5000	11
1036	College Hill	2142	THEFT FROM MV < $5000	11
1060	Brookside Estates	2142	THEFT FROM MV < $5000	2
1061	Brookside Estates	2142	THEFT FROM MV < $5000	2
1062	Brookside Estates	2142	THEFT FROM MV < $5000	2

1116	Lincoln	2142	THEFT FROM MV < $5000	7
1124	Colonial heights	2142	THEFT FROM MV < $5000	12
1125	Colonial heights	2142	THEFT FROM MV < $5000	12
1126	Colonial heights	2142	THEFT FROM MV < $5000	12
1127	Colonial heights	2142	THEFT FROM MV < $5000	12
1128	Colonial heights	2142	THEFT FROM MV < $5000	11
1129	Colonial heights	2142	THEFT FROM MV < $5000	11
1131	Garden Place	2142	THEFT FROM MV < $5000	12
1132	Garden Place	2142	THEFT FROM MV < $5000	12
1133	Garden Place	2142	THEFT FROM MV < $5000	12
1144	Waterloo Row	2142	THEFT FROM MV < $5000	11
1145	Waterloo Row	2142	THEFT FROM MV < $5000	11
1146	Waterloo Row	2142	THEFT FROM MV < $5000	11
1151	University Of New Brunswick	2142	THEFT FROM MV < $5000	11
1152	University Of New Brunswick	2142	THEFT FROM MV < $5000	11
1153	University Of New Brunswick	2142	THEFT FROM MV < $5000	11
1154	University Of New Brunswick	2142	THEFT FROM MV < $5000	11
1163	Saint Thomas University	2142	THEFT FROM MV < $5000	11
1173	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1174	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1175	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1176	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1177	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1178	Williams / Hawkins Area	2142	THEFT FROM MV < $5000	2
1181	McKnight	2142	THEFT FROM MV < $5000	2
1187	Shadowood Estates	2142	THEFT FROM MV < $5000	2
1188	Shadowood Estates	2142	THEFT FROM MV < $5000	2
1240	Lian / Valcore	2142	THEFT FROM MV < $5000	12
1284	North Devon	2142	THEFT FROM MV < $5000	4
1285	North Devon	2142	THEFT FROM MV < $5000	4
1286	North Devon	2142	THEFT FROM MV < $5000	4
1287	North Devon	2142	THEFT FROM MV < $5000	4
1288	North Devon	2142	THEFT FROM MV < $5000	4
1289	North Devon	2142	THEFT FROM MV < $5000	4
1290	North Devon	2142	THEFT FROM MV < $5000	4
1302	Rail Side	2142	THEFT FROM MV < $5000	12
1306	Rail Side	2142	THEFT FROM MV < $5000	12
1316	Silverwood	2142	THEFT FROM MV < $5000	12
1317	Silverwood	2142	THEFT FROM MV < $5000	12
1339	Prospect	2142	THEFT FROM MV < $5000	9
1340	Prospect	2142	THEFT FROM MV < $5000	9
1341	Prospect	2142	THEFT FROM MV < $5000	9
1342	Prospect	2142	THEFT FROM MV < $5000	9
1343	Prospect	2142	THEFT FROM MV < $5000	9

1344	Prospect	2142	THEFT FROM MV < $5000	9
1345	Prospect	2142	THEFT FROM MV < $5000	11
1346	Prospect	2142	THEFT FROM MV < $5000	9
1347	Prospect	2142	THEFT FROM MV < $5000	9
1348	Prospect	2142	THEFT FROM MV < $5000	9
1349	Prospect	2142	THEFT FROM MV < $5000	9
1369	North Devon	2142	THEFT FROM MV < $5000	3
1370	North Devon	2142	THEFT FROM MV < $5000	3
1371	North Devon	2142	THEFT FROM MV < $5000	3
1372	North Devon	2142	THEFT FROM MV < $5000	3
1377	North Devon	2142	THEFT FROM MV < $5000	3
1380	Hanwell North	2142	THEFT FROM MV < $5000	12
1381	Hanwell North	2142	THEFT FROM MV < $5000	12
1382	Hanwell North	2142	THEFT FROM MV < $5000	12
1387	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	11
1388	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	11
1389	Montogomery / Prospect East	2142	THEFT FROM MV < $5000	9
1403	Fredericton South	2142	THEFT FROM MV < $5000	7
1408	Fredericton South	2142	THEFT FROM MV < $5000	12
1409	Fredericton South	2142	THEFT FROM MV < $5000	12
1410	Fredericton South	2142	THEFT FROM MV < $5000	12
1411	Fredericton South	2142	THEFT FROM MV < $5000	12
1412	Fredericton South	2142	THEFT FROM MV < $5000	12
1413	Fredericton South	2142	THEFT FROM MV < $5000	12
1420	Woodstock Road	2142	THEFT FROM MV < $5000	12
1421	Woodstock Road	2142	THEFT FROM MV < $5000	10
1437	North Devon	2142	THEFT FROM MV < $5000	3
1438	North Devon	2142	THEFT FROM MV < $5000	3
1439	North Devon	2142	THEFT FROM MV < $5000	3
1440	North Devon	2142	THEFT FROM MV < $5000	3
1441	North Devon	2142	THEFT FROM MV < $5000	3
1459	Monteith / Talisman	2142	THEFT FROM MV < $5000	12

	City	FID
18	Fredericton	19
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622	Fredericton	623
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631	Fredericton	632
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819	Fredericton	820
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865	Fredericton	866
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868	Fredericton	869
869	Fredericton	870
871	Fredericton	872
875	Fredericton	876
880	Fredericton	881
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886	Fredericton	887
887	Fredericton	888
892	Fredericton	893
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898	Fredericton	899
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1062	Fredericton	1063
1116	Fredericton	1117
1124	Fredericton	1125
1125	Fredericton	1126
1126	Fredericton	1127
1127	Fredericton	1128
1128	Fredericton	1129
1129	Fredericton	1130
1131	Fredericton	1132
1132	Fredericton	1133
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1176	Fredericton	1177
1177	Fredericton	1178
1178	Fredericton	1179
1181	Fredricton	1182
1187	Fredericton	1188
1188	Fredericton	1189
1240	Fredericton	1241
1284	Fredericton	1285
1285	Fredericton	1286
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1288	Fredericton	1289
1289	Fredericton	1290
1290	Fredericton	1291
1302	Fredericton	1303
1306	Fredericton	1307
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1317  Fredericton  1318
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1412  Fredericton  1413
1413  Fredericton  1414
1420  Fredericton  1421
1421  Fredericton  1422
1437  Fredericton  1438
1438  Fredericton  1439
1439  Fredericton  1440
1440  Fredericton  1441
1441  Fredericton  1442
1459  Fredericton  1460
```

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

[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
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
```

[155]:
```
mvcrime_data.describe()
```

[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
```

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

[95]:
```
                     Neighbourh  MVCrime_Count
0                 Barkers Point              8
1             Brookside Estates              3
2                  College Hill             10
3              Colonial heights              6
4                Diamond Street              1
5                       Douglas              1
6                      Downtown             21
7                Dun's Crossing              9
8                   Forest Hill              8
9             Fredericton South             20
10               Fulton Heights             12
11                 Garden Creek              1
12                 Garden Place              3
13             Gilridge Estates              1
14                    Golf Club              5
15                Hanwell North              3
16               Heron Springs               2
```

```
17                  Highpoint Ridge           4
18                        Knob Hill           1
19                   Lian / Valcore           1
20                          Lincoln           1
21                  Lincoln Heights          11
22                      Main Street          10
23                      Marysville           10
24                        McKnight            1
25                      McLeod Hill           2
26              Monteith / Talisman           3
27   Montogomery / Prospect East              3
28                      Nashwaaksis           9
29          Nethervue Minihome Park           1
30                      North Devon          17
31               Northbrook Heights           5
32                             Plat          40
33                      Poet's Hill           2
34                         Prospect          11
35                        Rail Side           2
36         Saint Mary's First Nation          1
37          Saint Thomas University           1
38                       Sandyville           3
39                Shadowood Estates           2
40                       Silverwood           2
41                    Skyline Acrea          13
42                      South Devon          22
43                   Southwood Park           7
44                 Sunshine Gardens           7
45                         The Hill          11
46   University Of New Brunswick              4
47                     Waterloo Row           3
48          Williams / Hawkins Area           6
49                    Woodstock Road         20
50                  Youngs Crossing           6
```

[96]:

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

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

fredericton_c_map
```

[96]: <folium.folium.Map at 0x1a21f745f8>

```
[97]: ## Motor Vehicle Crime <$5000 Count
fredericton_geo = r.json()
threshold_scale = np.linspace(mvcrime_data['MVCrime_Count'].min(),␣
 ↪mvcrime_data['MVCrime_Count'].max(),6,dtype=int)
threshold_scale = threshold_scale.tolist()
threshold_scale[-1] = threshold_scale[-1]+1

fredericton_c_map.
 ↪choropleth(geo_data=fredericton_geo,data=mvcrime_data,columns=['Neighbourh',␣
 ↪'MVCrime_Count'],key_on='feature.properties.Neighbourh',
    threshold_scale=threshold_scale, fill_color='YlOrRd',fill_opacity=0.
 ↪7,line_opacity=0.1,legend_name='Fredericton Neighbourhoods')
fredericton_c_map
```

```
[97]: <folium.folium.Map at 0x1a21f745f8>
```

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

```
[98]: opendemog = 'Fredericton_Census_Tract_Demographics.xlsx'

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

```
['Fredericton_Census_Tract_Demogr']
```

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

```
[99]:    FID  OBJECTID       DBUID     DAUID  CDUID    CTUID  CTNAME      ␣
 ↪DBuid_1  \
0    1       501  1310024304  13100243   1310  3200002       2  1310024304
1    2       502  1310032004  13100320   1310  3200010      10  1310032004
2    3       503  1310017103  13100171   1310  3200014      14  1310017103
3    4       504  1310018301  13100183   1310  3200012      12  1310018301
4    5       505  1310022905  13100229   1310  3200007       7  1310022905

   DBpop2011  DBtdwell20  DBurdwell2  Shape_Leng  Shape_Area  CTIDLINK  \
0         60          25          22    0.007462    0.000003   3200002
1         15           3           3    0.009008    0.000003   3200010
2          0           0           0    0.010602    0.000007   3200014
3        108          60          50    0.039599    0.000068   3200012
4        129          47          44    0.011833    0.000005   3200007
```

```
   Shape__Area  Shape__Length
0     0.000003       0.007462
1     0.000003       0.009008
2     0.000007       0.010602
3     0.000068       0.039599
4     0.000005       0.011834
```

[ ]:

```

```

[ ]:

```

```

[100]:

```
# Population Density
world_geo = r'world_countries.json' # geojson file
fredericton_d_map = folium.Map(location=[45.94, -66.63], width=1200,␣
 ↪height=750,zoom_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='
 ↪properties.OBJECTID',
    threshold_scale=threshold_scale,fill_color='PuBuGn',fill_opacity=0.7,␣
 ↪line_opacity=0.1,legend_name='Fredericton Population Density')
fredericton_d_map
```

[100]: <folium.folium.Map at 0x1a22023588>

3.5 Let's look at specific locations in Fredericton

[101]:

```
pointbook = 'Fredericton Locations.xlsx'

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

```
['Sheet1']
```

[102]:

```
location_df = workbook_2.parse('Sheet1')
location_df
```

```
[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
```

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

```
[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
```

3.5.1 Add location markers to map

```
[104]: for lat, lng, point in zip(location_df['Latitude'],␣
        ↪location_df['Longitude'], location_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
```

```
[104]: &lt;folium.folium.Map at 0x1a21f745f8&gt;
```

```
[ ]:
```

3.6 Explore Fredericton Neighbourhoods

Define Foursquare Credentials and Version

[2]:
```
CLIENT_ID = 'Nope' # your Foursquare ID
CLIENT_SECRET = 'Secret' # your Foursquare Secret
VERSION = '20181201' # Foursquare API version

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

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

3.7 Let's take a look at nearby venues

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

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

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?
↪&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.
↪format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).
↪json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
```

```
            v['venue']['name'],
            v['venue']['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 venue_list])
    nearby_venues.columns = ['Location',
                  'Location Latitude',
                  'Location Longitude',
                  'Venue',
                  'Venue id',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category'
                   ]

    return(nearby_venues)
```

[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
```

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

```
(166, 8)
```

[108]:
```
                       Location  Location Latitude  Location Longitude  \
0                Knowledge Park          45.931143          -66.652700
1                Knowledge Park          45.931143          -66.652700
```

2	Knowledge Park	45.931143	-66.652700
3	Knowledge Park	45.931143	-66.652700
4	Knowledge Park	45.931143	-66.652700
5	Knowledge Park	45.931143	-66.652700
6	Knowledge Park	45.931143	-66.652700
7	Knowledge Park	45.931143	-66.652700
8	Knowledge Park	45.931143	-66.652700
9	Knowledge Park	45.931143	-66.652700
10	Knowledge Park	45.931143	-66.652700
11	Knowledge Park	45.931143	-66.652700
12	Knowledge Park	45.931143	-66.652700
13	Knowledge Park	45.931143	-66.652700
14	Knowledge Park	45.931143	-66.652700
15	Knowledge Park	45.931143	-66.652700
16	Knowledge Park	45.931143	-66.652700
17	Knowledge Park	45.931143	-66.652700
18	Knowledge Park	45.931143	-66.652700
19	Knowledge Park	45.931143	-66.652700
20	Knowledge Park	45.931143	-66.652700
21	Knowledge Park	45.931143	-66.652700
22	Knowledge Park	45.931143	-66.652700
23	Knowledge Park	45.931143	-66.652700
24	Knowledge Park	45.931143	-66.652700
25	Knowledge Park	45.931143	-66.652700
26	Knowledge Park	45.931143	-66.652700
27	Knowledge Park	45.931143	-66.652700
28	Knowledge Park	45.931143	-66.652700
29	Knowledge Park	45.931143	-66.652700
30	Knowledge Park	45.931143	-66.652700
31	Fredericton Hill	45.948512	-66.656045
32	Fredericton Hill	45.948512	-66.656045
33	Fredericton Hill	45.948512	-66.656045
34	Fredericton Hill	45.948512	-66.656045
35	Fredericton Hill	45.948512	-66.656045
36	Fredericton Hill	45.948512	-66.656045
37	Fredericton Hill	45.948512	-66.656045
38	Fredericton Hill	45.948512	-66.656045
39	Fredericton Hill	45.948512	-66.656045
40	Fredericton Hill	45.948512	-66.656045
41	Fredericton Hill	45.948512	-66.656045
42	Fredericton Hill	45.948512	-66.656045
43	Fredericton Hill	45.948512	-66.656045
44	Fredericton Hill	45.948512	-66.656045
45	Fredericton Hill	45.948512	-66.656045

46	Fredericton Hill	45.948512	-66.656045
47	Fredericton Hill	45.948512	-66.656045
48	Nashwaaksis	45.983382	-66.644856
49	Nashwaaksis	45.983382	-66.644856
50	Nashwaaksis	45.983382	-66.644856
51	Nashwaaksis	45.983382	-66.644856
52	Nashwaaksis	45.983382	-66.644856
53	Nashwaaksis	45.983382	-66.644856
54	Nashwaaksis	45.983382	-66.644856
55	Nashwaaksis	45.983382	-66.644856
56	Nashwaaksis	45.983382	-66.644856
57	Nashwaaksis	45.983382	-66.644856
58	Nashwaaksis	45.983382	-66.644856
59	Nashwaaksis	45.983382	-66.644856
60	Nashwaaksis	45.983382	-66.644856
61	Nashwaaksis	45.983382	-66.644856
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
67	University of New Brunswick	45.948121	-66.641406
68	University of New Brunswick	45.948121	-66.641406
69	University of New Brunswick	45.948121	-66.641406
70	University of New Brunswick	45.948121	-66.641406
71	University of New Brunswick	45.948121	-66.641406
72	University of New Brunswick	45.948121	-66.641406
73	University of New Brunswick	45.948121	-66.641406
74	University of New Brunswick	45.948121	-66.641406
75	University of New Brunswick	45.948121	-66.641406
76	University of New Brunswick	45.948121	-66.641406
77	Devon	45.968802	-66.622738
78	Devon	45.968802	-66.622738
79	Devon	45.968802	-66.622738
80	Devon	45.968802	-66.622738
81	Devon	45.968802	-66.622738
82	Devon	45.968802	-66.622738
83	Devon	45.968802	-66.622738
84	Devon	45.968802	-66.622738
85	Devon	45.968802	-66.622738
86	Devon	45.968802	-66.622738
87	Devon	45.968802	-66.622738
88	Devon	45.968802	-66.622738
89	New Maryland	45.892795	-66.683673

90	New Maryland	45.892795	-66.683673
91	New Maryland	45.892795	-66.683673
92	New Maryland	45.892795	-66.683673
93	Marysville	45.978913	-66.589491
94	Marysville	45.978913	-66.589491
95	Marysville	45.978913	-66.589491
96	Marysville	45.978913	-66.589491
97	Marysville	45.978913	-66.589491
98	Skyline Acres	45.931827	-66.640339
99	Skyline Acres	45.931827	-66.640339
100	Skyline Acres	45.931827	-66.640339
101	Skyline Acres	45.931827	-66.640339
102	Hanwell	45.902315	-66.755113
103	Hanwell	45.902315	-66.755113
104	Downtown	45.958327	-66.647211
105	Downtown	45.958327	-66.647211
106	Downtown	45.958327	-66.647211
107	Downtown	45.958327	-66.647211
108	Downtown	45.958327	-66.647211
109	Downtown	45.958327	-66.647211
110	Downtown	45.958327	-66.647211
111	Downtown	45.958327	-66.647211
112	Downtown	45.958327	-66.647211
113	Downtown	45.958327	-66.647211
114	Downtown	45.958327	-66.647211
115	Downtown	45.958327	-66.647211
116	Downtown	45.958327	-66.647211
117	Downtown	45.958327	-66.647211
118	Downtown	45.958327	-66.647211
119	Downtown	45.958327	-66.647211
120	Downtown	45.958327	-66.647211
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
148                    Downtown          45.958327          -66.647211
149                    Downtown          45.958327          -66.647211
150                    Downtown          45.958327          -66.647211
151                    Downtown          45.958327          -66.647211
152                    Downtown          45.958327          -66.647211
153                    Downtown          45.958327          -66.647211
154                    Downtown          45.958327          -66.647211
155                    Downtown          45.958327          -66.647211
156                    Downtown          45.958327          -66.647211
157                    Downtown          45.958327          -66.647211
158                    Downtown          45.958327          -66.647211
159                    Downtown          45.958327          -66.647211
160                    Downtown          45.958327          -66.647211
161                    Downtown          45.958327          -66.647211
162                    Downtown          45.958327          -66.647211
163                    Downtown          45.958327          -66.647211
164                    Downtown          45.958327          -66.647211
165                    Downtown          45.958327          -66.647211

                                         Venue  \
0                            Costco Wholesale
1                                    PetSmart
2                                  Montana's
3                                Boston Pizza
4                                    Michaels
5                           Alcool NB Liquor
6                                    Best Buy
7                                    Wal-Mart
8                               Booster Juice
9                                 Dairy Queen
```

10	H&M
11	Dairy Queen (Treat)
12	Winners
13	East Side Mario's
14	McDonald's
15	Home Sense
16	The Shoe company
17	Avalon Spa Uptown
18	Wicker Emporium
19	Dollarama
20	Bed Bath & Beyond
21	GAP Factory Store
22	carter's | OshKosh B'gosh
23	Deluxe Fish & Chips
24	Hallmark
25	NB Liquor
26	Corbett Center
27	Costco Food Court
28	Sleep Country
29	Sport Chek Regent Mall
30	Rôtisserie St-Hubert
31	YMCA Fredericton
32	20 Twenty Club
33	Shoppers Drug Mart
34	Subway
35	Canadian Tire
36	Tim Hortons
37	The Aitken University Centre - UNB
38	Queen Square Park
39	Great Canadian Bagel
40	Monkey Cakes
41	Papa John's Pizza
42	Greco
43	Dick's Grocery Store
44	Tingley's Ice Cream
45	Domino's Pizza
46	Jumbo Video
47	Goody Shop
48	Peters Meat, Seafood & Lobster Market
49	Tim Hortons
50	The Northside Market
51	Shoppers Drug Mart
52	Subway
53	Subway

54	Kentucky Fried Chicken
55	Nashwaaksis Field House
56	KFC
57	Tim Hortons
58	Thai spice
59	Mike's Old Fashioned Bakery
60	Cox Electronics
61	A Pile Of Scrap!
62	Jim Gilberts Wheels And Deals
63	Trailway Brewery
64	The North Side Market
65	Avalon SalonSpa
66	Tony Pepperoni
67	The Richard J. CURRIE Center - UNB
68	Charlotte Street Arts Centre
69	Sobeys
70	YMCA Fredericton
71	20 Twenty Club
72	The Cellar Pub & Grill - UNB
73	Harvey's
74	Tim Hortons
75	Tim Hortons
76	College Hill Social Club
77	New England Pizza
78	Wolastoq Wharf
79	Dairy Queen
80	Pharmacie Jean Coutu
81	Tim Hortons
82	Henry Park
83	Giant Tiger
84	york arena
85	St. Mary's Supermarket
86	Dixie Lee
87	St Marys Smoke Shop
88	Carleton Park
89	New York Fries
90	Centre De Danse Roca Dance Center
91	Baseball, Basketball, Tennis and Hockey In One…
92	Circle K
93	Tim Hortons
94	Royals Field
95	Northside Pharmacy
96	Marysville Place
97	Circle K

98	Grant Harvey Centre
99	Kimble Field
100	Mandarin Palace
101	Oriental Pearl
102	Advanced Fabrics
103	Country Style
104	Cafe Loka & Bistro
105	Boyce Farmers Market
106	Second Cup
107	Lunar Rogue
108	Jonnie Java Roasters
109	Picaroon's Brewtique
110	Sobeys
111	Luna Pizza
112	Palate Restaurant & Cafe
113	Alcool NB Liquor
114	coffee and friends
115	Chess Piece Pâtisserie & Cafe
116	Victory Meat Market
117	Exhibition Grounds
118	The Abbey Café & Gallery
119	Charlotte Street Arts Centre
120	Isaac's Way
121	YMCA Fredericton
122	Read's News Stand
123	King Street Ale House
124	540 Kitchen and Bar
125	Dimitri's Souvlaki
126	Smoke's Poutinerie
127	Snooty Fox
128	Officer's Square
129	Fredericton Playhouse
130	Willie O'Ree Place
131	The Joyce
132	Cora's Breakfast & Lunch
133	Strange Adventures
134	Naru Japanese Cuisine
135	Mexicali Rosas
136	Brewbakers
137	Dolan's Pub
138	Beaverbrook Art Gallery
139	McGinnis Landing
140	Atlantic Superstore
141	20 Twenty Club

142	Geek Chic
143	Wilser's Room
144	Tim Hortons
145	TD Canada Trust
146	Fit4Less
147	Harvey's
148	Shoppers Drug Mart
149	Shan
150	bulgogi
151	William's Seafood
152	Subway
153	Capital Complex
154	boom! Nightclub
155	Tim Hortons
156	King's Place Mall
157	Running Room
158	The Happy Baker
159	Owl's Nest Bookstore
160	Tingley's Ice Cream
161	Jumbo Video
162	Enterprise Rent-A-Car
163	Domino's Pizza
164	Papa John's Pizza
165	Queen Square Park

	Venue id	Venue Latitude	Venue Longitude	\
0	4e18ab92183880768f43bff6	45.927034	-66.663447	
1	4bbca501a0a0c9b6078f1a0f	45.929768	-66.659939	
2	4e50406e62844166699b0780	45.931511	-66.662507	
3	4b64944af964a52041bf2ae3	45.938123	-66.660037	
4	4c489858417b20a13b82e1a9	45.929965	-66.659548	
5	4b77335df964a5202c872ee3	45.930680	-66.664180	
6	5520124a498e0467bb6e81c8	45.937673	-66.660380	
7	4bad313ff964a5208c373be3	45.934081	-66.663539	
8	4c42414e520fa59334f9caac	45.935198	-66.663602	
9	4b86f05bf964a52009a731e3	45.938004	-66.659442	
10	509c3265498efdffc5739a0f	45.935196	-66.663290	
11	4cc6123cbde8f04d9ce0b44b	45.934520	-66.663988	
12	4caa46a744a8224b96e42640	45.930427	-66.659758	
13	4b55d89bf964a520a2f227e3	45.931376	-66.663417	
14	4c6e9ef665eda09377e951d0	45.934575	-66.663319	
15	54024f60498ee424eedb7bf9	45.930528	-66.660103	
16	4bd76dfa5cf276b0fb469b00	45.929636	-66.660449	
17	4cd99e0f51fc8cfa4369f05d	45.930774	-66.660927	

18	4e6baff588772457c4fd1968	45.930897	-66.661338
19	4ba3dd18f964a520d86738e3	45.930897	-66.661714
20	5083f283e4b0bf87c15e9ea1	45.930097	-66.662166
21	50a8f005e4b0e4f42e033a2a	45.930211	-66.662416
22	50a51363e4b0a3e2f7db76bf	45.929978	-66.662966
23	4e5d0b99fa76a4cf148d9a15	45.931722	-66.663131
24	4cd96cf651fc8cfa522eef5d	45.930646	-66.663745
25	5985f08b6cf01a7e38b85fba	45.930228	-66.664395
26	57854d05498e301b3b5a4448	45.929733	-66.664601
27	53693053498ef3e4ea63560f	45.927383	-66.663544
28	555b5660498eae864c440e77	45.929074	-66.664605
29	4ca4ecae8a65bfb717422b22	45.935211	-66.663525
30	57164569498e9bb9e88d52b0	45.929838	-66.664749
31	4e93476b8231bf0d17ba3e24	45.953217	-66.649478
32	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112
33	4fb699dc7bebbeb2a6c7ba88	45.942627	-66.655523
34	4bae3571f964a52076923be3	45.940931	-66.657445
35	4bb52ba72ea19521201caa2f	45.944409	-66.666820
36	4dc29f89d4c07da169fbf84b	45.943720	-66.646907
37	4b6458eff964a52052ac2ae3	45.941644	-66.663667
38	4b7acb0ef964a520113d2fe3	45.950961	-66.648245
39	4b784edbf964a52013c42ee3	45.941040	-66.657545
40	4ec147368231b62f43026067	45.940938	-66.657346
41	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285
42	4cfc0660c51fa1cdd3d7e92b	45.954055	-66.647290
43	4c545e5db426ef3b11cc7e8a	45.941957	-66.663877
44	4c13c001b7b9c9284e12aa37	45.957087	-66.655855
45	50f9bbc75d24acebc259244d	45.957177	-66.656638
46	4bc0d29a920eb71307a2192c	45.957286	-66.656312
47	4b8580edf964a5201d6231e3	45.951172	-66.644000
48	4c4e04ecfb742d7fe7bba62d	45.976652	-66.649765
49	4b742f31f964a520b7cb2de3	45.975294	-66.646977
50	50270b2ae4b042eaf816ee61	45.977779	-66.635003
51	4c745e08db52b1f781f775dc	45.976515	-66.648534
52	4bc5db23693695213a9a8488	45.976886	-66.648661
53	4c87f3b4bf40a1cd09fd08b4	45.989114	-66.652061
54	4eefb90ba69ddc7bcb336081	45.975903	-66.646846
55	4b73436cf964a52016a52de3	45.984849	-66.643635
56	4c9267139199bfb7786c14df	45.975907	-66.646870
57	4c0104cf360a9c74bb11d9a0	45.989221	-66.652208
58	503658e5e4b00b386cc5d972	45.975890	-66.647424
59	4d67fde7709bb60c5eacb014	45.976560	-66.650030
60	4d07eab6611ff04d4f4718fb	45.976112	-66.649222
61	4e9f0e9b93ad5d11f3d36ba1	45.984398	-66.633329

62	4b9a7ef5f964a520b6ba35e3	45.980784	-66.633311
63	574a1b86cd10af189e38500e	45.975442	-66.649496
64	501c19f7e4b01c57ff1b1212	45.977837	-66.635168
65	4bc31784920eb71312ec1c2c	45.974591	-66.644756
66	4c88f56dbbec6dcbe9f2d758	45.991888	-66.648599
67	4dbae5806e815ab0de5d2637	45.946698	-66.637891
68	4b7f0318f964a5203d1030e3	45.955620	-66.639324
69	4b6727daf964a520493e2be3	45.954891	-66.645920
70	4e93476b8231bf0d17ba3e24	45.953217	-66.649478
71	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112
72	4b7ac93ef964a520b53c2fe3	45.945434	-66.641626
73	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021
74	4c865c1774d7b60c3f41a3d8	45.945185	-66.641545
75	4dc29f89d4c07da169fbf84b	45.943720	-66.646907
76	4b7aca23f964a520df3c2fe3	45.945162	-66.641472
77	4c09984e7e3fc928b64bf282	45.967675	-66.629905
78	4fbaafb0e4b0c7f68a419500	45.969975	-66.632568
79	4c5cab2894fd0f473c69c945	45.969077	-66.632059
80	4eb9523077c8972738ac89b2	45.967766	-66.630551
81	4b5b0812f964a520d8df28e3	45.969381	-66.632730
82	4c8e283dad01199c7923726d	45.963992	-66.620283
83	4c95354f58d4b60c80443029	45.967715	-66.630410
84	4b6c4f10f964a520792f2ce3	45.964888	-66.617110
85	4b9fa6adf964a520c93137e3	45.971945	-66.631248
86	4c5cacc5d25320a103fdc37a	45.962257	-66.624952
87	4ebddf8a4690d233887bf4a6	45.972270	-66.631348
88	4bce2eeb29d4b7138521a8dc	45.961182	-66.626310
89	4d8771fc651041bd194d9b30	45.890420	-66.683580
90	55fdfc2b498ed76a0f7aa3f6	45.890978	-66.692237
91	4e48415862e148603b8b3fc2	45.890726	-66.692814
92	4b9e633ef964a5202fdf36e3	45.885412	-66.688995
93	4baa1b40f964a520174b3ae3	45.978193	-66.593041
94	4c573f916201e21edff8736e	45.980267	-66.588412
95	4c8bee978018a1cdd1f2e7d2	45.980194	-66.588628
96	4ce6d19be1eeb60c512d99ae	45.980243	-66.588277
97	4bb88fe853649c74431847fb	45.979250	-66.593232
98	4f915a7ee4b01406ebc873ae	45.925002	-66.641004
99	4fdaa8c2e4b08f3358b1b3d1	45.930535	-66.631233
100	4b786998f964a5204ecc2ee3	45.935440	-66.631007
101	4ec68431775bf65c02417199	45.930085	-66.629518
102	53c133a4498e933c415c6118	45.905297	-66.750944
103	56356c83498e17f8ed69a380	45.905937	-66.751084
104	4e70d116152073dd03c2c50e	45.957570	-66.647978
105	4b5163b4f964a5204d4c27e3	45.958354	-66.639654

106	4b7067c6f964a5205a182de3	45.961385	-66.642372
107	4b8c53e7f964a520d4ca32e3	45.959998	-66.639116
108	4bc47e80920eb71369c71e2c	45.962226	-66.643852
109	4ced5cfe7b943704ea782653	45.962701	-66.642731
110	4b6727daf964a520493e2be3	45.954891	-66.645920
111	4be47e9b2468c92811dbfe42	45.962246	-66.643788
112	4c2e0e6ae760c9b69bdf4549	45.962338	-66.641776
113	4d9a52120d5f224bc5f7a34e	45.956140	-66.647558
114	4b533f74f964a520009427e3	45.961842	-66.643479
115	53c00bcc498e1f34dc3687ae	45.963354	-66.644017
116	4bd1ffd341b9ef3bcb19fde5	45.962661	-66.645820
117	4c76d45d07818cfafe94d2e3	45.960078	-66.655522
118	57178722498e4222f7d5b298	45.961301	-66.640188
119	4b7f0318f964a5203d1030e3	45.955620	-66.639324
120	51c8a824498ef33c708ac9e9	45.960944	-66.637796
121	4e93476b8231bf0d17ba3e24	45.953217	-66.649478
122	4b4b6bf2f964a5200a9b26e3	45.961859	-66.643464
123	5283fd1c498e138a8297590c	45.960460	-66.641012
124	53ab370e498e91a454f49e67	45.961657	-66.640152
125	4bacf7e8f964a520571f3be3	45.963093	-66.644479
126	51756ac6498ece19b79a31f6	45.962032	-66.644021
127	4b4ca053f964a52006b826e3	45.960794	-66.638927
128	4c83b0df2f1c236a4bc54443	45.961754	-66.639084
129	4b516b64f964a520df4c27e3	45.960101	-66.636969
130	4b76879ef964a520a5502ee3	45.963017	-66.646100
131	4b624863f964a5203b402ae3	45.960309	-66.636806
132	4b8130c7f964a520e99930e3	45.962282	-66.641607
133	4babdcbdf964a5200cd03ae3	45.962733	-66.643315
134	50461342e4b0c55b9639accc	45.961721	-66.640125
135	4c65dd9a19f3c9b697769eff	45.962811	-66.646079
136	4b6754faf964a5208d482be3	45.960703	-66.640935
137	4b516ddbf964a520144d27e3	45.962886	-66.644615
138	4c13a7f7b7b9c92865dea937	45.959878	-66.635858
139	4b6df601f964a5203d9f2ce3	45.963013	-66.646536
140	4b5b0a91f964a5205fe028e3	45.958260	-66.658048
141	4c5388b0f5f3d13ac74ba5f8	45.951042	-66.648112
142	4b516f03f964a520324d27e3	45.960573	-66.639225
143	4ba01983f964a520f15937e3	45.963192	-66.644089
144	4b6455b0f964a52067ab2ae3	45.959873	-66.639259
145	4b6d8261f964a52022792ce3	45.963891	-66.645782
146	4c9381ab94a0236a70ac8312	45.958634	-66.657319
147	4bbdff85f57ba59320bdaeb9	45.953544	-66.645021
148	4db07df34df03036e8bbb640	45.961351	-66.644493
149	4dfb6fc31f6eeef806aacc25	45.961818	-66.643706

150	4b605f0ff964a5203de229e3	45.961522	-66.642742
151	4b7c26f5f964a52061802fe3	45.959296	-66.655663
152	4b6b883df964a5205a0e2ce3	45.962580	-66.645032
153	4b6faa7cf964a52073f92ce3	45.963245	-66.644123
154	4ba240eef964a52050e737e3	45.962315	-66.641645
155	4ba8bdb3f964a5204ceb39e3	45.959933	-66.655493
156	4bc61ba4d35d9c74292de23a	45.961679	-66.643267
157	4c6d4adb23c1a1cdffc81bcf	45.961812	-66.643510
158	4b703d21f964a5204c0d2de3	45.960536	-66.641465
159	4d6ea0c98df1548152778123	45.963051	-66.643872
160	4c13c001b7b9c9284e12aa37	45.957087	-66.655855
161	4bc0d29a920eb71307a2192c	45.957286	-66.656312
162	4d3ae3edbf6d5481b26fd1e1	45.957743	-66.656527
163	50f9bbc75d24acebc259244d	45.957177	-66.656638
164	4ecc29f59adfd1f5b5c7bbb1	45.956655	-66.657285
165	4b7acb0ef964a520113d2fe3	45.950961	-66.648245

	Venue Category
0	Warehouse Store
1	Pet Store
2	Restaurant
3	Sports Bar
4	Arts & Crafts Store
5	Liquor Store
6	Electronics Store
7	Big Box Store
8	Smoothie Shop
9	Fast Food Restaurant
10	Clothing Store
11	Fast Food Restaurant
12	Clothing Store
13	Italian Restaurant
14	Fast Food Restaurant
15	Department Store
16	Shoe Store
17	Spa
18	Furniture / Home Store
19	Discount Store
20	Furniture / Home Store
21	Clothing Store
22	Kids Store
23	Seafood Restaurant
24	Gift Shop
25	Liquor Store

26	Shopping Plaza
27	Fast Food Restaurant
28	Mattress Store
29	Sporting Goods Shop
30	Restaurant
31	Gym
32	Bar
33	Pharmacy
34	Sandwich Place
35	Hardware Store
36	Coffee Shop
37	Hockey Arena
38	Park
39	Bakery
40	Bakery
41	Pizza Place
42	Pizza Place
43	Smoke Shop
44	Ice Cream Shop
45	Pizza Place
46	Video Store
47	Bakery
48	Grocery Store
49	Coffee Shop
50	Farmers Market
51	Pharmacy
52	Sandwich Place
53	Sandwich Place
54	Fast Food Restaurant
55	Gym
56	Fast Food Restaurant
57	Coffee Shop
58	Thai Restaurant
59	Bakery
60	Electronics Store
61	Arts & Crafts Store
62	Auto Dealership
63	Beer Store
64	Farmers Market
65	Spa
66	Pizza Place
67	Basketball Court
68	Art Gallery
69	Grocery Store

70	Gym
71	Bar
72	Pub
73	Burger Joint
74	Coffee Shop
75	Coffee Shop
76	Bar
77	Pizza Place
78	Seafood Restaurant
79	Fast Food Restaurant
80	Pharmacy
81	Coffee Shop
82	Baseball Field
83	Department Store
84	Skating Rink
85	Grocery Store
86	Fast Food Restaurant
87	Smoke Shop
88	Park
89	Fast Food Restaurant
90	Dance Studio
91	Baseball Field
92	Gas Station
93	Coffee Shop
94	Baseball Stadium
95	Pharmacy
96	Park
97	Gas Station
98	Hockey Arena
99	Baseball Field
100	Chinese Restaurant
101	Chinese Restaurant
102	Rental Service
103	Coffee Shop
104	Café
105	Farmers Market
106	Coffee Shop
107	Pub
108	Coffee Shop
109	Brewery
110	Grocery Store
111	Italian Restaurant
112	Restaurant
113	Liquor Store

114	Coffee Shop
115	Café
116	Grocery Store
117	Racetrack
118	Café
119	Art Gallery
120	Restaurant
121	Gym
122	Coffee Shop
123	Pub
124	Gastropub
125	Greek Restaurant
126	Fast Food Restaurant
127	Pub
128	Park
129	Performing Arts Venue
130	Hockey Arena
131	Pub
132	Breakfast Spot
133	Hobby Shop
134	Sushi Restaurant
135	Mexican Restaurant
136	Restaurant
137	Pub
138	Art Museum
139	Steakhouse
140	Supermarket
141	Bar
142	Toy / Game Store
143	Bar
144	Coffee Shop
145	Bank
146	Gym / Fitness Center
147	Burger Joint
148	Pharmacy
149	Chinese Restaurant
150	Korean Restaurant
151	Seafood Restaurant
152	Sandwich Place
153	Bar
154	Nightclub
155	Coffee Shop
156	Shopping Mall
157	Sporting Goods Shop

```
158                   Bakery
159                Bookstore
160           Ice Cream Shop
161              Video Store
162      Rental Car Location
163              Pizza Place
164              Pizza Place
165                     Park
```

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

```
There are 73 unique venue categories.
```

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

```
There are 153 unique venues.
```

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

[111]:
```
                             Location  Location Latitude  Location␣
 ↪Longitude  \
Location
Devon                               1                  1              ␣
 ↪ 1
Downtown                            1                  1              ␣
 ↪ 1
Fredericton Hill                    1                  1              ␣
 ↪ 1
Hanwell                             1                  1              ␣
 ↪ 1
Knowledge Park                      1                  1              ␣
 ↪ 1
Marysville                          1                  1              ␣
 ↪ 1
Nashwaaksis                         1                  1              ␣
 ↪ 1
New Maryland                        1                  1              ␣
 ↪ 1
Skyline Acres                       1                  1              ␣
 ↪ 1
```

```
University of New Brunswick         1                  1                  ␣
↪ 1

                             Venue  Venue id  Venue Latitude  Venue␣
↪Longitude  \
Location
Devon                           12        12              12            ␣
↪ 12
Downtown                        61        62              62            ␣
↪ 62
Fredericton Hill                17        17              17            ␣
↪ 17
Hanwell                          2         2               2            ␣
↪  2
Knowledge Park                  31        31              31            ␣
↪ 31
Marysville                       5         5               5            ␣
↪  5
Nashwaaksis                     17        19              19            ␣
↪ 19
New Maryland                     4         4               4            ␣
↪  4
Skyline Acres                    4         4               4            ␣
↪  4
University of New Brunswick      9        10              10            ␣
↪ 10

                             Venue Category
Location
Devon                                    11
Downtown                                 44
Fredericton Hill                         13
Hanwell                                   2
Knowledge Park                           23
Marysville                                5
Nashwaaksis                              15
New Maryland                              4
Skyline Acres                             3
University of New Brunswick               8
```

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

[112]:

```
                          Location  Location Latitude  Location Longitude  \
Venue Category
Art Gallery                      2                  2                   2
Art Museum                       1                  1                   1
Arts & Crafts Store              2                  2                   2
Auto Dealership                  1                  1                   1
Bakery                           3                  3                   3
Bank                             1                  1                   1
Bar                              3                  3                   3
Baseball Field                   3                  3                   3
Baseball Stadium                 1                  1                   1
Basketball Court                 1                  1                   1
Beer Store                       1                  1                   1
Big Box Store                    1                  1                   1
Bookstore                        1                  1                   1
Breakfast Spot                   1                  1                   1
Brewery                          1                  1                   1
Burger Joint                     2                  2                   2
Café                             1                  1                   1
Chinese Restaurant               2                  2                   2
Clothing Store                   1                  1                   1
Coffee Shop                      7                  7                   7
Dance Studio                     1                  1                   1
Department Store                 2                  2                   2
Discount Store                   1                  1                   1
Electronics Store                2                  2                   2
Farmers Market                   2                  2                   2
Fast Food Restaurant             5                  5                   5
Furniture / Home Store           1                  1                   1
Gas Station                      2                  2                   2
Gastropub                        1                  1                   1
Gift Shop                        1                  1                   1
Greek Restaurant                 1                  1                   1
Grocery Store                    4                  4                   4
Gym                              4                  4                   4
Gym / Fitness Center             1                  1                   1
Hardware Store                   1                  1                   1
Hobby Shop                       1                  1                   1
Hockey Arena                     3                  3                   3
Ice Cream Shop                   2                  2                   2
Italian Restaurant               2                  2                   2
Kids Store                       1                  1                   1
Korean Restaurant                1                  1                   1
Liquor Store                     2                  2                   2
```

```
Mattress Store                1                  1                    1
Mexican Restaurant            1                  1                    1
Nightclub                     1                  1                    1
Park                          4                  4                    4
Performing Arts Venue         1                  1                    1
Pet Store                     1                  1                    1
Pharmacy                      5                  5                    5
Pizza Place                   4                  4                    4
Pub                           2                  2                    2
Racetrack                     1                  1                    1
Rental Car Location           1                  1                    1
Rental Service                1                  1                    1
Restaurant                    2                  2                    2
Sandwich Place                3                  3                    3
Seafood Restaurant            3                  3                    3
Shoe Store                    1                  1                    1
Shopping Mall                 1                  1                    1
Shopping Plaza                1                  1                    1
Skating Rink                  1                  1                    1
Smoke Shop                    2                  2                    2
Smoothie Shop                 1                  1                    1
Spa                           2                  2                    2
Sporting Goods Shop           2                  2                    2
Sports Bar                    1                  1                    1
Steakhouse                    1                  1                    1
Supermarket                   1                  1                    1
Sushi Restaurant              1                  1                    1
Thai Restaurant               1                  1                    1
Toy / Game Store              1                  1                    1
Video Store                   2                  2                    2
Warehouse Store               1                  1                    1

                        Venue  Venue id  Venue Latitude  Venue Longitude ␣
 ↪\
Venue Category
Art Gallery                 1         1               1                1
Art Museum                  1         1               1                1
Arts & Crafts Store         2         2               2                2
Auto Dealership             1         1               1                1
Bakery                      5         5               5                5
Bank                        1         1               1                1
Bar                         4         4               4                4
Baseball Field              3         3               3                3
Baseball Stadium            1         1               1                1
```

Basketball Court	1	1	1	1
Beer Store	1	1	1	1
Big Box Store	1	1	1	1
Bookstore	1	1	1	1
Breakfast Spot	1	1	1	1
Brewery	1	1	1	1
Burger Joint	1	1	1	1
Café	3	3	3	3
Chinese Restaurant	3	3	3	3
Clothing Store	3	3	3	3
Coffee Shop	6	13	13	13
Dance Studio	1	1	1	1
Department Store	2	2	2	2
Discount Store	1	1	1	1
Electronics Store	2	2	2	2
Farmers Market	3	3	3	3
Fast Food Restaurant	9	10	10	10
Furniture / Home Store	2	2	2	2
Gas Station	1	2	2	2
Gastropub	1	1	1	1
Gift Shop	1	1	1	1
Greek Restaurant	1	1	1	1
Grocery Store	4	4	4	4
Gym	2	2	2	2
Gym / Fitness Center	1	1	1	1
Hardware Store	1	1	1	1
Hobby Shop	1	1	1	1
Hockey Arena	3	3	3	3
Ice Cream Shop	1	1	1	1
Italian Restaurant	2	2	2	2
Kids Store	1	1	1	1
Korean Restaurant	1	1	1	1
Liquor Store	2	3	3	3
Mattress Store	1	1	1	1
Mexican Restaurant	1	1	1	1
Nightclub	1	1	1	1
Park	4	4	4	4
Performing Arts Venue	1	1	1	1
Pet Store	1	1	1	1
Pharmacy	3	5	5	5
Pizza Place	5	5	5	5
Pub	6	6	6	6
Racetrack	1	1	1	1
Rental Car Location	1	1	1	1

Rental Service	1	1	1	1
Restaurant	5	5	5	5
Sandwich Place	1	4	4	4
Seafood Restaurant	3	3	3	3
Shoe Store	1	1	1	1
Shopping Mall	1	1	1	1
Shopping Plaza	1	1	1	1
Skating Rink	1	1	1	1
Smoke Shop	2	2	2	2
Smoothie Shop	1	1	1	1
Spa	2	2	2	2
Sporting Goods Shop	2	2	2	2
Sports Bar	1	1	1	1
Steakhouse	1	1	1	1
Supermarket	1	1	1	1
Sushi Restaurant	1	1	1	1
Thai Restaurant	1	1	1	1
Toy / Game Store	1	1	1	1
Video Store	1	1	1	1
Warehouse Store	1	1	1	1

	Venue Category
Venue Category	
Art Gallery	1
Art Museum	1
Arts & Crafts Store	1
Auto Dealership	1
Bakery	1
Bank	1
Bar	1
Baseball Field	1
Baseball Stadium	1
Basketball Court	1
Beer Store	1
Big Box Store	1
Bookstore	1
Breakfast Spot	1
Brewery	1
Burger Joint	1
Café	1
Chinese Restaurant	1
Clothing Store	1
Coffee Shop	1
Dance Studio	1

Department Store	1
Discount Store	1
Electronics Store	1
Farmers Market	1
Fast Food Restaurant	1
Furniture / Home Store	1
Gas Station	1
Gastropub	1
Gift Shop	1
Greek Restaurant	1
Grocery Store	1
Gym	1
Gym / Fitness Center	1
Hardware Store	1
Hobby Shop	1
Hockey Arena	1
Ice Cream Shop	1
Italian Restaurant	1
Kids Store	1
Korean Restaurant	1
Liquor Store	1
Mattress Store	1
Mexican Restaurant	1
Nightclub	1
Park	1
Performing Arts Venue	1
Pet Store	1
Pharmacy	1
Pizza Place	1
Pub	1
Racetrack	1
Rental Car Location	1
Rental Service	1
Restaurant	1
Sandwich Place	1
Seafood Restaurant	1
Shoe Store	1
Shopping Mall	1
Shopping Plaza	1
Skating Rink	1
Smoke Shop	1
Smoothie Shop	1
Spa	1
Sporting Goods Shop	1

```
Sports Bar                           1
Steakhouse                           1
Supermarket                          1
Sushi Restaurant                     1
Thai Restaurant                      1
Toy / Game Store                     1
Video Store                          1
Warehouse Store                      1
```

[ ]:

3.8 Analyze each Location

[113]:

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

# add neighbourhood column back to dataframe
freddy_onehot['Location'] = fredericton_data_venues['Location']

# move neighbourhood column to the first column
fixed_columns = [freddy_onehot.columns[-1]] + list(freddy_onehot.columns[:
↪-1])
freddy_onehot = freddy_onehot[fixed_columns]

freddy_onehot.head()
```

[113]:

```
         Location  Art Gallery  Art Museum  Arts & Crafts Store  \
0  Knowledge Park            0           0                    0
1  Knowledge Park            0           0                    0
2  Knowledge Park            0           0                    0
3  Knowledge Park            0           0                    0
4  Knowledge Park            0           0                    1

   Auto Dealership  Bakery  Bank  Bar  Baseball Field  Baseball Stadium  \
0                0       0     0    0               0                 0
1                0       0     0    0               0                 0
2                0       0     0    0               0                 0
3                0       0     0    0               0                 0
4                0       0     0    0               0                 0

   Basketball Court  Beer Store  Big Box Store  Bookstore  Breakfast Spot␣
↪ \
```

```
0                  0            0              0          0                0
1                  0            0              0          0                0
2                  0            0              0          0                0
3                  0            0              0          0                0
4                  0            0              0          0                0

   Brewery  Burger Joint  Café  Chinese Restaurant  Clothing Store  \
0        0             0     0                   0               0
1        0             0     0                   0               0
2        0             0     0                   0               0
3        0             0     0                   0               0
4        0             0     0                   0               0

   Coffee Shop  Dance Studio  Department Store  Discount Store  \
0            0             0                 0               0
1            0             0                 0               0
2            0             0                 0               0
3            0             0                 0               0
4            0             0                 0               0

   Electronics Store  Farmers Market  Fast Food Restaurant  \
0                  0               0                     0
1                  0               0                     0
2                  0               0                     0
3                  0               0                     0
4                  0               0                     0

   Furniture / Home Store  Gas Station  Gastropub  Gift Shop  \
0                       0            0          0          0
1                       0            0          0          0
2                       0            0          0          0
3                       0            0          0          0
4                       0            0          0          0

   Greek Restaurant  Grocery Store  Gym  Gym / Fitness Center  Hardware␣
↪Store  \
0                 0              0    0                     0            ␣
↪   0
1                 0              0    0                     0            ␣
↪   0
2                 0              0    0                     0            ␣
↪   0
3                 0              0    0                     0            ␣
↪   0
```

```
4                   0               0    0                     0
↪   0

   Hobby Shop  Hockey Arena  Ice Cream Shop  Italian Restaurant  Kids
↪Store  \
0           0             0               0                   0
↪0
1           0             0               0                   0
↪0
2           0             0               0                   0
↪0
3           0             0               0                   0
↪0
4           0             0               0                   0
↪0

   Korean Restaurant  Liquor Store  Mattress Store  Mexican Restaurant  \
0                  0             0               0                   0
1                  0             0               0                   0
2                  0             0               0                   0
3                  0             0               0                   0
4                  0             0               0                   0

   Nightclub  Park  Performing Arts Venue  Pet Store  Pharmacy  Pizza
↪Place  \
0          0     0                      0          0         0
↪0
1          0     0                      0          1         0
↪0
2          0     0                      0          0         0
↪0
3          0     0                      0          0         0
↪0
4          0     0                      0          0         0
↪0

   Pub  Racetrack  Rental Car Location  Rental Service  Restaurant  \
0    0          0                    0               0           0
1    0          0                    0               0           0
2    0          0                    0               0           1
3    0          0                    0               0           0
4    0          0                    0               0           0
```

```
   Sandwich Place  Seafood Restaurant  Shoe Store  Shopping Mall  \
0               0                   0           0              0
1               0                   0           0              0
2               0                   0           0              0
3               0                   0           0              0
4               0                   0           0              0

   Shopping Plaza  Skating Rink  Smoke Shop  Smoothie Shop  Spa  \
0               0             0           0              0    0
1               0             0           0              0    0
2               0             0           0              0    0
3               0             0           0              0    0
4               0             0           0              0    0

   Sporting Goods Shop  Sports Bar  Steakhouse  Supermarket  Sushi␣
↪Restaurant  \
0                    0           0           0            0            ␣
↪   0
1                    0           0           0            0            ␣
↪   0
2                    0           0           0            0            ␣
↪   0
3                    0           1           0            0            ␣
↪   0
4                    0           0           0            0            ␣
↪   0

   Thai Restaurant  Toy / Game Store  Video Store  Warehouse Store
0                0                 0            0                1
1                0                 0            0                0
2                0                 0            0                0
3                0                 0            0                0
4                0                 0            0                0
```

[114]:
```
freddy_onehot.shape
```

[114]: (166, 74)

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

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

[115]:
```
                      Location  Art Gallery  Art Museum  Arts & Crafts␣
↪Store  \
0                        Devon     0.000000    0.000000               0.
↪000000
1                     Downtown     0.016129    0.016129               0.
↪000000
2              Fredericton Hill    0.000000    0.000000               0.
↪000000
3                      Hanwell     0.000000    0.000000               0.
↪000000
4               Knowledge Park     0.000000    0.000000               0.
↪032258
5                  Marysville      0.000000    0.000000               0.
↪000000
6                  Nashwaaksis     0.000000    0.000000               0.
↪052632
7                 New Maryland     0.000000    0.000000               0.
↪000000
8                Skyline Acres     0.000000    0.000000               0.
↪000000
9  University of New Brunswick     0.100000    0.000000               0.
↪000000

   Auto Dealership    Bakery      Bank       Bar  Baseball Field  \
0         0.000000  0.000000  0.000000  0.000000        0.083333
1         0.000000  0.016129  0.016129  0.048387        0.000000
2         0.000000  0.176471  0.000000  0.058824        0.000000
3         0.000000  0.000000  0.000000  0.000000        0.000000
4         0.000000  0.000000  0.000000  0.000000        0.000000
5         0.000000  0.000000  0.000000  0.000000        0.000000
6         0.052632  0.052632  0.000000  0.000000        0.000000
7         0.000000  0.000000  0.000000  0.000000        0.250000
8         0.000000  0.000000  0.000000  0.000000        0.250000
9         0.000000  0.000000  0.000000  0.200000        0.000000

   Baseball Stadium  Basketball Court  Beer Store  Big Box Store ␣
↪Bookstore  \
```

```
0              0.0               0.0    0.000000        0.000000    0.
 ↪000000
1              0.0               0.0    0.000000        0.000000    0.
 ↪016129
2              0.0               0.0    0.000000        0.000000    0.
 ↪000000
3              0.0               0.0    0.000000        0.000000    0.
 ↪000000
4              0.0               0.0    0.000000        0.032258    0.
 ↪000000
5              0.2               0.0    0.000000        0.000000    0.
 ↪000000
6              0.0               0.0    0.052632        0.000000    0.
 ↪000000
7              0.0               0.0    0.000000        0.000000    0.
 ↪000000
8              0.0               0.0    0.000000        0.000000    0.
 ↪000000
9              0.0               0.1    0.000000        0.000000    0.
 ↪000000

   Breakfast Spot   Brewery  Burger Joint      Café  Chinese Restaurant  \
0        0.000000  0.000000      0.000000  0.000000            0.000000
1        0.016129  0.016129      0.016129  0.048387            0.016129
2        0.000000  0.000000      0.000000  0.000000            0.000000
3        0.000000  0.000000      0.000000  0.000000            0.000000
4        0.000000  0.000000      0.000000  0.000000            0.000000
5        0.000000  0.000000      0.000000  0.000000            0.000000
6        0.000000  0.000000      0.000000  0.000000            0.000000
7        0.000000  0.000000      0.000000  0.000000            0.000000
8        0.000000  0.000000      0.000000  0.000000            0.500000
9        0.000000  0.000000      0.100000  0.000000            0.000000

   Clothing Store  Coffee Shop  Dance Studio  Department Store  \
0        0.000000     0.083333          0.00          0.083333
1        0.000000     0.096774          0.00          0.000000
2        0.000000     0.058824          0.00          0.000000
3        0.000000     0.500000          0.00          0.000000
4        0.096774     0.000000          0.00          0.032258
5        0.000000     0.200000          0.00          0.000000
6        0.000000     0.105263          0.00          0.000000
7        0.000000     0.000000          0.25          0.000000
8        0.000000     0.000000          0.00          0.000000
```

9	0.000000	0.200000	0.00	0.000000

	Discount Store	Electronics Store	Farmers Market	Fast Food Restaurant
0	0.000000	0.000000	0.000000	0.166667
1	0.000000	0.000000	0.016129	0.016129
2	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.032258	0.032258	0.000000	0.129032
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.052632	0.105263	0.105263
7	0.000000	0.000000	0.000000	0.250000
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000

	Furniture / Home Store	Gas Station	Gastropub	Gift Shop
0	0.000000	0.00	0.000000	0.000000
1	0.000000	0.00	0.016129	0.000000
2	0.000000	0.00	0.000000	0.000000
3	0.000000	0.00	0.000000	0.000000
4	0.064516	0.00	0.000000	0.032258
5	0.000000	0.20	0.000000	0.000000
6	0.000000	0.00	0.000000	0.000000
7	0.000000	0.25	0.000000	0.000000
8	0.000000	0.00	0.000000	0.000000
9	0.000000	0.00	0.000000	0.000000

	Greek Restaurant	Grocery Store	Gym	Gym / Fitness Center
0	0.000000	0.083333	0.000000	0.000000
1	0.016129	0.032258	0.016129	0.016129
2	0.000000	0.000000	0.058824	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.052632	0.052632	0.000000
7	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.100000	0.100000	0.000000

	Hardware Store	Hobby Shop	Hockey Arena	Ice Cream Shop
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.016129	0.016129	0.016129
2	0.058824	0.000000	0.058824	0.058824
3	0.000000	0.000000	0.000000	0.000000

4	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.000000	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.250000	0.000000
9	0.000000	0.000000	0.000000	0.000000

	Italian Restaurant	Kids Store	Korean Restaurant	Liquor Store \
0	0.000000	0.000000	0.000000	0.000000
1	0.016129	0.000000	0.016129	0.016129
2	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.032258	0.032258	0.000000	0.064516
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.000000	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000

	Mattress Store	Mexican Restaurant	Nightclub	Park \
0	0.000000	0.000000	0.000000	0.083333
1	0.000000	0.016129	0.016129	0.032258
2	0.000000	0.000000	0.000000	0.058824
3	0.000000	0.000000	0.000000	0.000000
4	0.032258	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.200000
6	0.000000	0.000000	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000

	Performing Arts Venue	Pet Store	Pharmacy	Pizza Place	Pub \
0	0.000000	0.000000	0.083333	0.083333	0.000000
1	0.016129	0.000000	0.016129	0.032258	0.080645
2	0.000000	0.000000	0.058824	0.176471	0.000000
3	0.000000	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.032258	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.200000	0.000000	0.000000
6	0.000000	0.000000	0.052632	0.052632	0.000000
7	0.000000	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000	0.100000

```
   Racetrack  Rental Car Location  Rental Service  Restaurant  Sandwich␣
 ↪Place  \
0   0.000000             0.000000             0.0    0.000000        0.
 ↪000000
1   0.016129             0.016129             0.0    0.048387        0.
 ↪016129
2   0.000000             0.000000             0.0    0.000000        0.
 ↪058824
3   0.000000             0.000000             0.5    0.000000        0.
 ↪000000
4   0.000000             0.000000             0.0    0.064516        0.
 ↪000000
5   0.000000             0.000000             0.0    0.000000        0.
 ↪000000
6   0.000000             0.000000             0.0    0.000000        0.
 ↪105263
7   0.000000             0.000000             0.0    0.000000        0.
 ↪000000
8   0.000000             0.000000             0.0    0.000000        0.
 ↪000000
9   0.000000             0.000000             0.0    0.000000        0.
 ↪000000

   Seafood Restaurant  Shoe Store  Shopping Mall  Shopping Plaza  \
0            0.083333    0.000000       0.000000        0.000000
1            0.016129    0.000000       0.016129        0.000000
2            0.000000    0.000000       0.000000        0.000000
3            0.000000    0.000000       0.000000        0.000000
4            0.032258    0.032258       0.000000        0.032258
5            0.000000    0.000000       0.000000        0.000000
6            0.000000    0.000000       0.000000        0.000000
7            0.000000    0.000000       0.000000        0.000000
8            0.000000    0.000000       0.000000        0.000000
9            0.000000    0.000000       0.000000        0.000000

   Skating Rink  Smoke Shop  Smoothie Shop       Spa  Sporting Goods Shop␣
 ↪ \
0      0.083333    0.083333       0.000000  0.000000             0.000000
1      0.000000    0.000000       0.000000  0.000000             0.016129
2      0.000000    0.058824       0.000000  0.000000             0.000000
3      0.000000    0.000000       0.000000  0.000000             0.000000
4      0.000000    0.000000       0.032258  0.032258             0.032258
5      0.000000    0.000000       0.000000  0.000000             0.000000
```

```
6      0.000000    0.000000        0.000000  0.052632                0.000000
7      0.000000    0.000000        0.000000  0.000000                0.000000
8      0.000000    0.000000        0.000000  0.000000                0.000000
9      0.000000    0.000000        0.000000  0.000000                0.000000

   Sports Bar  Steakhouse  Supermarket  Sushi Restaurant  Thai Restaurant␣
 ↪ \
0    0.000000    0.000000     0.000000          0.000000         0.000000
1    0.000000    0.016129     0.016129          0.016129         0.000000
2    0.000000    0.000000     0.000000          0.000000         0.000000
3    0.000000    0.000000     0.000000          0.000000         0.000000
4    0.032258    0.000000     0.000000          0.000000         0.000000
5    0.000000    0.000000     0.000000          0.000000         0.000000
6    0.000000    0.000000     0.000000          0.000000         0.052632
7    0.000000    0.000000     0.000000          0.000000         0.000000
8    0.000000    0.000000     0.000000          0.000000         0.000000
9    0.000000    0.000000     0.000000          0.000000         0.000000

   Toy / Game Store  Video Store  Warehouse Store
0          0.000000     0.000000         0.000000
1          0.016129     0.016129         0.000000
2          0.000000     0.058824         0.000000
3          0.000000     0.000000         0.000000
4          0.000000     0.000000         0.032258
5          0.000000     0.000000         0.000000
6          0.000000     0.000000         0.000000
7          0.000000     0.000000         0.000000
8          0.000000     0.000000         0.000000
9          0.000000     0.000000         0.000000
```

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

[116]: (10, 74)

3.8.2 Print each Location with the top 5 most common venues

[117]:
```
num_top_venues = 5

for hood in freddy_grouped['Location']:
    print("----"+hood+"----")
    temp = freddy_grouped[freddy_grouped['Location'] == hood].T.
 ↪reset_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
```

```
    temp['freq'] = temp['freq'].astype(float)
    temp = temp.round({'freq': 2})
    print(temp.sort_values('freq', ascending=False).
↪reset_index(drop=True).head(num_top_venues))
    print('\n')
```

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


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


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


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


----Knowledge Park----
                    venue  freq
```

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


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


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


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


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


----University of New Brunswick----
              venue  freq
```

```
0       Coffee Shop   0.2
1               Bar   0.2
2   Basketball Court   0.1
3               Gym   0.1
4     Grocery Store   0.1
```

3.8.3 Now into a pandas dataframe

[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]
```

[119]:
```
num_top_venues = 10

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

# create columns according to number of top venues
columns = ['Location']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1,␣
 ↪indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
location_venues_sorted = pd.DataFrame(columns=columns)
location_venues_sorted['Location'] = freddy_grouped['Location']

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

location_venues_sorted
```

[119]:
```
                   Location 1st Most Common Venue 2nd Most Common␣
 ↪Venue  \
0                     Devon  Fast Food Restaurant          Grocery Store
1                  Downtown           Coffee Shop                    Pub
2            Fredericton Hill                Bakery            Pizza Place
```

```
3                  Hanwell       Rental Service           Coffee Shop
4           Knowledge Park  Fast Food Restaurant       Clothing Store
5              Marysville      Baseball Stadium           Gas Station
6              Nashwaaksis           Coffee Shop       Sandwich Place
7             New Maryland           Gas Station         Dance Studio
8            Skyline Acres   Chinese Restaurant       Baseball Field
9 University of New Brunswick                  Bar           Coffee Shop

  3rd Most Common Venue 4th Most Common Venue   5th Most Common Venue  \
0            Smoke Shop              Pharmacy             Coffee Shop
1                   Bar                  Café              Restaurant
2          Hockey Arena            Smoke Shop          Hardware Store
3       Warehouse Store          Dance Studio        Department Store
4 Furniture / Home Store         Liquor Store              Restaurant
5              Pharmacy                  Park             Coffee Shop
6        Farmers Market  Fast Food Restaurant                     Gym
7  Fast Food Restaurant        Baseball Field  Furniture / Home Store
8          Hockey Arena   Arts & Crafts Store             Coffee Shop
9           Art Gallery                   Pub            Burger Joint

 6th Most Common Venue 7th Most Common Venue 8th Most Common Venue  \
0   Seafood Restaurant                  Park      Department Store
1                 Park           Pizza Place        Grocery Store
2          Video Store        Ice Cream Shop                  Park
3       Discount Store     Electronics Store       Farmers Market
4      Warehouse Store            Shoe Store            Pet Store
5            Gift Shop             Gastropub      Greek Restaurant
6                  Spa     Electronics Store           Beer Store
7     Department Store        Discount Store     Electronics Store
8 Gym / Fitness Center                   Gym        Grocery Store
9     Basketball Court         Grocery Store                   Gym

  9th Most Common Venue  10th Most Common Venue
0          Skating Rink             Pizza Place
1          Hockey Arena        Greek Restaurant
2              Pharmacy             Coffee Shop
3  Fast Food Restaurant  Furniture / Home Store
4        Mattress Store               Gift Shop
5 Furniture / Home Store         Clothing Store
6           Pizza Place                Pharmacy
7        Farmers Market         Warehouse Store
8      Greek Restaurant               Gift Shop
9             Gift Shop        Greek Restaurant
```

3.9 Cluster Fredericton Locations

3.9.1 Run k-means to cluster Locations into 5 clusters

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

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

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

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

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

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

[121]:
```
freddy_merged = location_df

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

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

freddy_merged# check the last columns!
```

[121]:
```
                    Location   Latitude  Longitude  Cluster Labels  \
0             Knowledge Park  45.931143 -66.652700               1
1           Fredericton Hill  45.948512 -66.656045               1
2                Nashwaaksis  45.983382 -66.644856               1
3  University of New Brunswick  45.948121 -66.641406               0
4                      Devon  45.968802 -66.622738               1
5               New Maryland  45.892795 -66.683673               4
6                 Marysville  45.978913 -66.589491               1
7              Skyline Acres  45.931827 -66.640339               3
8                    Hanwell  45.902315 -66.755113               2
9                   Downtown  45.958327 -66.647211               1
```

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue \
0	Fast Food Restaurant	Clothing Store	Furniture / Home Store
1	Bakery	Pizza Place	Hockey Arena
2	Coffee Shop	Sandwich Place	Farmers Market
3	Bar	Coffee Shop	Art Gallery
4	Fast Food Restaurant	Grocery Store	Smoke Shop
5	Gas Station	Dance Studio	Fast Food Restaurant
6	Baseball Stadium	Gas Station	Pharmacy
7	Chinese Restaurant	Baseball Field	Hockey Arena
8	Rental Service	Coffee Shop	Warehouse Store
9	Coffee Shop	Pub	Bar

	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue \
0	Liquor Store	Restaurant	Warehouse Store
1	Smoke Shop	Hardware Store	Video Store
2	Fast Food Restaurant	Gym	Spa
3	Pub	Burger Joint	Basketball Court
4	Pharmacy	Coffee Shop	Seafood Restaurant
5	Baseball Field	Furniture / Home Store	Department Store
6	Park	Coffee Shop	Gift Shop
7	Arts & Crafts Store	Coffee Shop	Gym / Fitness Center
8	Dance Studio	Department Store	Discount Store
9	Café	Restaurant	Park

	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue \
0	Shoe Store	Pet Store	Mattress Store
1	Ice Cream Shop	Park	Pharmacy
2	Electronics Store	Beer Store	Pizza Place
3	Grocery Store	Gym	Gift Shop
4	Park	Department Store	Skating Rink
5	Discount Store	Electronics Store	Farmers Market
6	Gastropub	Greek Restaurant	Furniture / Home Store
7	Gym	Grocery Store	Greek Restaurant
8	Electronics Store	Farmers Market	Fast Food Restaurant
9	Pizza Place	Grocery Store	Hockey Arena

	10th Most Common Venue
0	Gift Shop
1	Coffee Shop
2	Pharmacy
3	Greek Restaurant
4	Pizza Place
5	Warehouse Store
6	Clothing Store

```
7               Gift Shop
8  Furniture / Home Store
9        Greek Restaurant
```

[122]:

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

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

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(freddy_merged['Latitude'],␣
 ↪freddy_merged['Longitude'], 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],fill=True,fill_color=rainbow[cluster-1]
        fill_opacity=0.7).add_to(map_clusters)
map_clusters
```

[122]:

```
<folium.folium.Map at 0x1a21ffa390>
```