gta_housing_ml_proj

September 9, 2019

1 The GTA Housing, Machine Learning Project

Currently, the GTA is projected to be the fastest growing region of the province, accounting for over 65 percent of Ontario's net population growth to 2041. In July 2019, the Toronto Real Estate board reported that nearly 8,595 houses were sold which is up 24.3% compared to June 2018. With the massive number of houses being sold, and countless more being listed for sale, data was plentiful regarding the subject.

In this project and analysis, we will attempt to predict the value of a house, given its characteristics using Machine Learning Algorithms. Let's get started!

1.1 Contents

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1.2 Initial Data Analysis

```
In [1]: import pandas as pd
        import os
        import csv

        MY_DIR = "C:\\Users\\Adit Krishnan\\Documents\\Third Year\\gta_ml_proj\\Data Gathering"


        def load_housing_data(my_dir= MY_DIR):
            csv_path = os.path.join(my_dir, "housing_data.csv")
            return pd.read_csv(csv_path,converters={"Price(in CAD)":float})
```

Prior to working with the data, I undertook the task of scraping all the data from the MLS listing site, and formatting it to fit into a CSV file, which we can then work with to analyze the data using pandas. The above code simply loads that data into a pandas data frame, which we can then work with to gain more insight from the data.

```
In [2]: housing = load_housing_data()
        housing.head()
```

```
Out[2]:                                          Address Postal Code   Latitude  \
0            86 Wessenger Dr, Holly, Barrie L4N8N7      L4N8N7  44.328711
1            86 Wessenger Dr, Holly, Barrie L4N8N7      L4N8N7  44.328711
2           118 Ferndale Dr, Ardagh, Barrie L4N6Y6      L4N6Y6  44.359932
3     151 Edgehill Dr H10, 400 North, Barrie L4N1L9      L4N1L9  44.384539
4  126 Bell Farm Rd 311, City Centre, Barrie L4M6J3      L4M6J3  44.410643

   Longitude    City Neighbourhood  Price(in CAD)  # of Bathrooms  \
0 -79.717816  Barrie         Holly         1880.0               2
1 -79.717816  Barrie         Holly         1880.0               2
2 -79.715513  Barrie        Ardagh       149900.0               0
3 -79.712689  Barrie     400 North       234500.0               1
4 -79.676170  Barrie   City Centre       236900.0               1

   # of Bedrooms  Height(in stories)  # of Kitchens  # of Parking Spaces  \
0              3                 2.0            1.0                  3.0
1              3                 2.0            1.0                  3.0
2              0                 NaN            NaN                  NaN
3              2                 NaN            1.0                  NaN
4              1                 NaN            1.0                  NaN

  Lot-Size(in feet)   Total Lot Size(in square ft.) Basement(finished or not)  \
0     14.22 x 35.00                          497.700               No Basement
1     14.22 x 35.00                          497.700               No Basement
2    59.35 x 124.06                         7362.961               No Basement
3               NaN                              NaN               No Basement
4               NaN                              NaN               No Basement

                                         House HTML
0  https://barrie.listing.ca/86-wessenger-dr.S452...
1  https://barrie.listing.ca/86-wessenger-dr.S452...
2  https://barrie.listing.ca/118-ferndale-dr.S450...
3  https://barrie.listing.ca/151-edgehill-dr-h10...
4  https://barrie.listing.ca/126-bell-farm-rd-311...
```

```
In [3]: housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16274 entries, 0 to 16273
Data columns (total 16 columns):
Address                          16274 non-null object
Postal Code                      16268 non-null object
Latitude                         16274 non-null float64
Longitude                        16274 non-null float64
City                             16274 non-null object
Neighbourhood                    16274 non-null object
Price(in CAD)                    16274 non-null float64
# of Bathrooms                   16274 non-null int64
```

```
# of Bedrooms                     16274 non-null int64
Height(in stories)                12184 non-null float64
# of Kitchens                     16002 non-null float64
# of Parking Spaces               10784 non-null float64
Lot-Size(in feet)                 11428 non-null object
 Total Lot Size(in square ft.)    11371 non-null float64
Basement(finished or not)         16274 non-null object
House HTML                        16274 non-null object
dtypes: float64(7), int64(2), object(7)
memory usage: 2.0+ MB
```

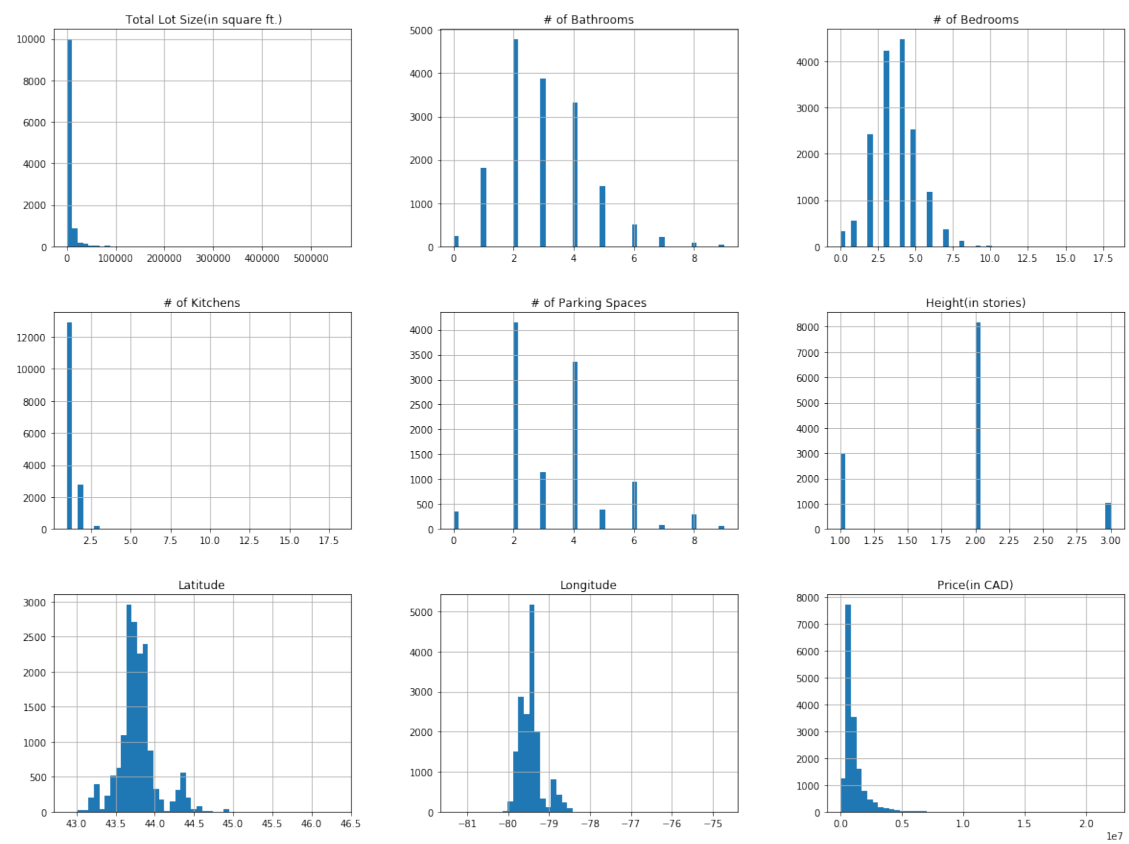
Calling the info() and head() method, we can get a very brief and quick overview of the data. "housing.head()" gives an overview of the top 5 entries in the data and the info method reveals how many of each subcategory is present in the data. Notice that some of the values are missing, which will need to be fixed later on, if we are to use this data for Machine Learning later on.

```
In [4]: housing["# of Parking Spaces"].value_counts()

Out[4]: 2.0    4153
        4.0    3355
        3.0    1139
        6.0     957
        5.0     388
        0.0     345
        8.0     288
        7.0      92
        9.0      60
        1.0       7
        Name: # of Parking Spaces, dtype: int64

In [5]: housing.describe()

Out[5]:            Latitude     Longitude  Price(in CAD)  # of Bathrooms  \
        count  16274.000000  16274.000000   1.627400e+04    16274.000000
        mean      43.781712    -79.444649   1.118783e+06        2.997911
        std        0.252923      0.283367   9.761885e+05        1.454864
        min       42.878706    -81.332785   1.880000e+03        0.000000
        25%       43.656871    -79.649063   5.999000e+05        2.000000
        50%       43.761077    -79.452046   8.299000e+05        3.000000
        75%       43.880001    -79.354488   1.289000e+06        4.000000
        max       46.329364    -74.727106   2.199900e+07        9.000000

               # of Bedrooms  Height(in stories)  # of Kitchens  # of Parking Spaces  \
        count   16274.000000        12184.000000   16002.000000         10784.000000
        mean        3.681639            1.842580       1.220972             3.367953
        std         1.527349            0.550948       0.539928             1.672920
        min         0.000000            1.000000       1.000000             0.000000
        25%         3.000000            2.000000       1.000000             2.000000
```

```
50%          4.000000               2.000000       1.000000              3.000000
75%          5.000000               2.000000       1.000000              4.000000
max         18.000000               3.000000      18.000000              9.000000

        Total Lot Size(in square ft.)
count                   11371.000000
mean                     8191.411673
std                     21214.521967
min                         1.000000
25%                      3201.000000
50%                      4944.511800
75%                      7381.310000
max                    555100.000000
```

Calling housing.describe() we can gain even more valuable information about the data such as the count, mean, standard deviation, etc.

```
In [6]: %matplotlib inline
        import matplotlib.pyplot as plt
        housing.hist(bins=50, figsize=(20, 15))
        plt.show()
```



In [7]:
```
from sklearn.model_selection import StratifiedShuffleSplit, train_test_split
import numpy as np

housing["value_cat"] = np.ceil(housing["Price(in CAD)"] / 100000)
housing["value_cat"].where(housing["value_cat"] < 20, 20.0, inplace=True)

split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing, housing["value_cat"]):
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]
```

Now, we are taking some of the first steps towards preparing our data to be used for Machine Learning processes. We are creating two seperate sets, a training set and a test set which has been split according to an index I created known as the "value_cat" which is based on the prices of the houses. The StratifiedShuffleSplit() method from sklearn ensures that a proportional amount from each price category is chosen to create the train set and test set so that we can avoid any biases in the data. The exact proportions are seen below. Sci-Kit really does make life a little bit easier.

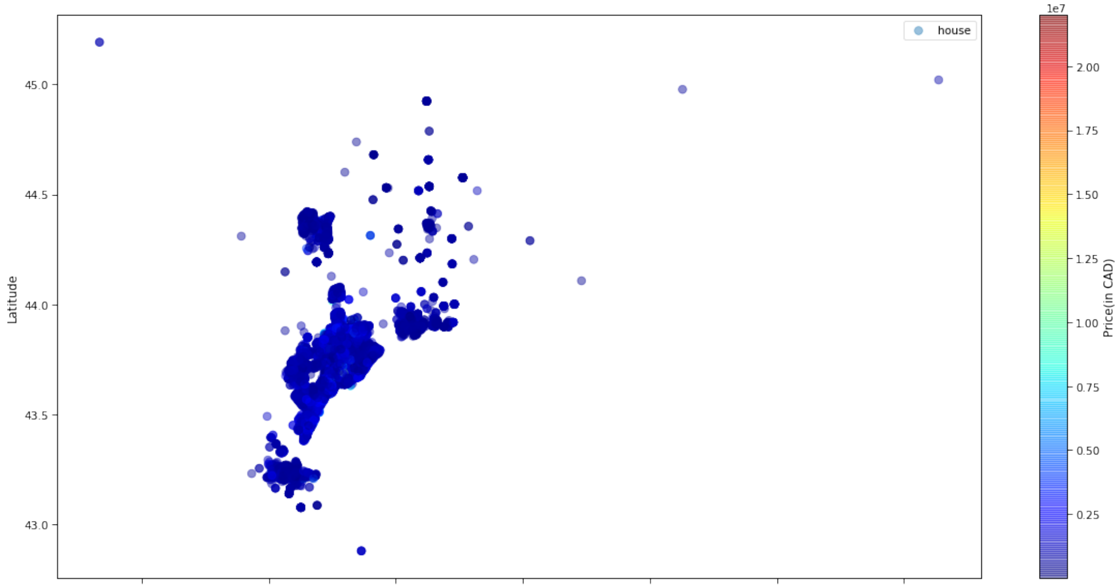
In [8]:
```
housing["value_cat"].value_counts() / len(housing)
```

Out[8]:
```
7.0     0.116075
6.0     0.113863
20.0    0.113617
8.0     0.109008
9.0     0.092725
5.0     0.092233
10.0    0.065933
12.0    0.045041
13.0    0.039327
4.0     0.037790
11.0    0.037237
14.0    0.029372
15.0    0.026361
16.0    0.021384
17.0    0.016960
18.0    0.015546
19.0    0.011859
3.0     0.009156
1.0     0.004240
2.0     0.002274
Name: value_cat, dtype: float64
```

1.3 In-Depth Data Analysis

In [57]:
```
housing = strat_train_set.copy()
# housing.sort_values("Price(in CAD)", ascending=True)
# housing.head()

housing.plot(kind="scatter", x="Longitude", y="Latitude", alpha=0.45,
```

```
                    s=60, label="house", c="Price(in CAD)", cmap=plt.get_cmap("jet"), colorba

plt.legend
plt.rcParams['figure.figsize'] = [20, 10]
plt.rcParams.update({'font.size': 22})
plt.savefig('distribution_of_prices.png', bbox_inches='tight')
```



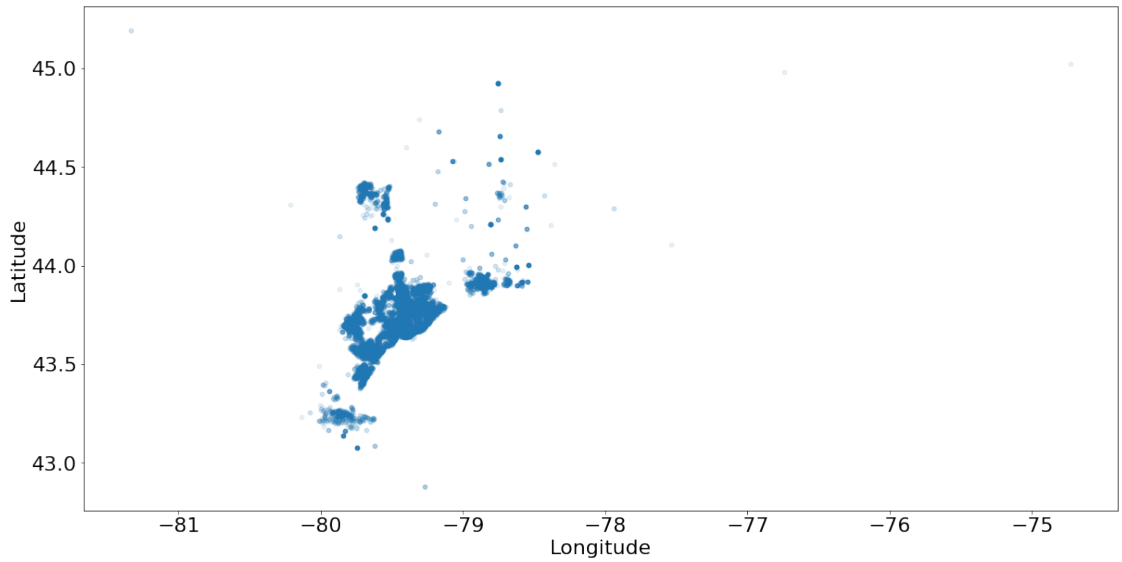
Above, we can see a graph which graphs the distribution of houses in GTA, with as associated color bar on the right which shows their listing price/value. Amazingly, we can kind of see the shape of the shoreline of Lake Ontario on the right side. However, sadly, there is not much insight we can gain from this graph as it just appears to show that most houses are in the $500,000 - $750,000 dollar price range. It is not as effective at communicating the distribution of values of houses in different regions as I expected. Thus, we will have to try using different charts to gain a more better understanding.

```
In [10]: # from ipynb.fs.full.ml_practice_project import test_set_check, split_train_test_by_i
         import hashlib

         def test_set_check(identifier, test_ratio, hash):
             return hash(np.int64(identifier)).digest()[-1] < 256 * test_ratio

         def split_train_test_by_id(data, test_ratio, id_column, hash=hashlib.md5):
             ids = data[id_column]
             in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio, hash))
             return data.loc[~in_test_set], data.loc[in_test_set]
```

```
In [11]: for set in (strat_train_set, strat_test_set):
             set.drop(["value_cat"], axis=1, inplace=True)
```

```
In [12]: housing = strat_train_set.copy()
         housing.plot(kind="scatter", x="Longitude", y="Latitude", alpha=0.1)
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x25fd4744c88>
```



Now, altering the alpha parameter in our graph, makes it a lot easier to visualize where there is a high density of houses. Just by looking at the graph, we can see clearly that the Toronto area has a large density, as well as the surrounding Municipalities near it (Mississauga, Brampton, etc.)

```
In [13]: housing.head()
```

```
Out[13]:                                             Address Postal Code   Latitude  \
         10329  36 Lee Centre Dr Th305, Woburn, Toronto M1H3K2      M1H3K2  43.780730
         8007             291 Poplar St, Donevan, Oshawa L1H6P6      L1H6P6  43.897179
         4119    10 Dunsheath Way 201, Cornell, Markham L6B0A2      L6B0A2  43.891956
         7750             355 Ritson Rd, Central, Oshawa L1H5J4      L1H5J4  43.890936
         1107   29 Saint Eugene St, Bram West, Brampton L6Y0K8      L6Y0K8  43.873265

                Longitude      City Neighbourhood  Price(in CAD)  # of Bathrooms  \
         10329 -79.246955   Toronto        Woburn       539900.0               3
         8007  -78.835035    Oshawa       Donevan       549900.0               2
         4119  -79.276683   Markham       Cornell       485000.0               2
         7750  -78.849669    Oshawa       Central       349000.0               2
         1107  -79.722789  Brampton     Bram West       689900.0               3

                # of Bedrooms  Height(in stories)  # of Kitchens  # of Parking Spaces  \
         10329              2                 2.0            1.0                  NaN
         8007               4                 1.0            2.0                  4.0
         4119               2                 NaN            1.0                  NaN
         7750               3                 1.0            1.0                  5.0
```

```
1107                 4                 2.0            1.0                    2.0

      Lot-Size(in feet)   Total Lot Size(in square ft.)  \
10329               NaN                             NaN
8007     50.00 x 100.00                       5000.0000
4119                NaN                             NaN
7750     33.00 x 100.00                       3300.0000
1107      19.69 x 90.06                       1773.2814

      Basement(finished or not)  \
10329               No Basement
8007                No Basement
4119                No Basement
7750                No Basement
1107                 Unfinished

                                              House HTML
10329  https://toronto.listing.ca/36-lee-centre-dr-th...
8007   https://oshawa.listing.ca/291-poplar-st.E45345...
4119   https://markham.listing.ca/10-dunsheath-way-20...
7750   https://oshawa.listing.ca/355-ritson-rd.E44501...
1107   https://brampton.listing.ca/29-saint-eugene-st...
```

In [14]:
```python
housing["pricing_cat"] = round(housing["Price(in CAD)"], -5)
housing["pricing_cat"]
```

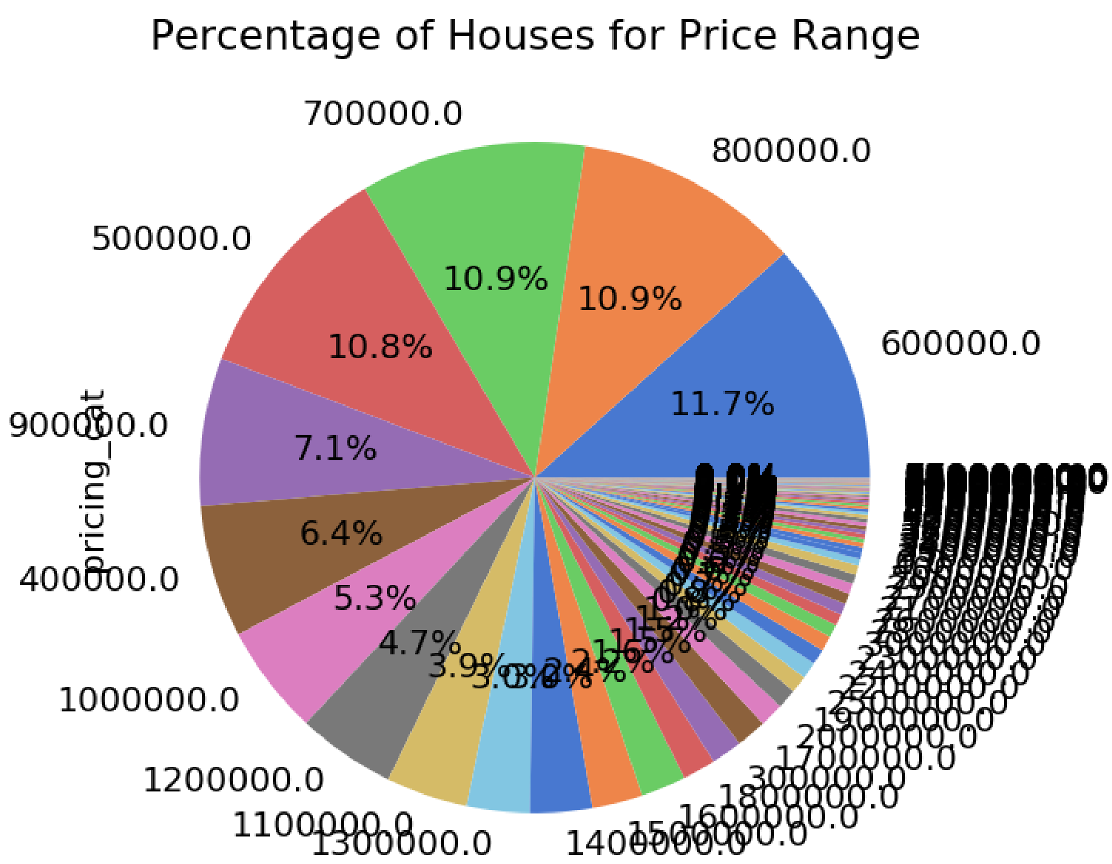
Out[14]:
```
10329     500000.0
8007      500000.0
4119      500000.0
7750      300000.0
1107      700000.0
11337     700000.0
10701     600000.0
12811    1000000.0
7274     1100000.0
14990    7500000.0
9830      400000.0
15346     900000.0
13633    1400000.0
9757      400000.0
387       600000.0
6467     2500000.0
1049      700000.0
4157      500000.0
1507      800000.0
9755      400000.0
14732    3300000.0
11405     700000.0
```

```
5539       700000.0
3874       500000.0
10633      600000.0
10397      600000.0
3337       500000.0
4177       600000.0
4769      1300000.0
9425      4300000.0
            ...
4627      1100000.0
3353       500000.0
386        600000.0
10377      500000.0
2952       700000.0
11270      700000.0
13967     1700000.0
5722       800000.0
13783     1600000.0
9842       400000.0
1511       800000.0
4782      1300000.0
11768      800000.0
15736     1500000.0
11045      700000.0
6977      2700000.0
6468      2500000.0
8431       500000.0
16204      800000.0
10841      600000.0
7707       200000.0
2080       500000.0
10395      500000.0
8822      1100000.0
8593       800000.0
13376     1300000.0
6982       300000.0
7817       400000.0
86         400000.0
948        600000.0
Name: pricing_cat, Length: 13019, dtype: float64
```

Here, we are adding a price category section to our data, so that we can create a pie chart depicting the breakdown of the houses and their respective prices. We can gain a better understanding of exactly what percent of houses fall into a particular price range in the GTA.

```
In [15]: import seaborn as sns
         c = sns.color_palette('muted')
         for i in range(21):
```

```
    c.append(c[i])
ax = housing["pricing_cat"].value_counts().plot(kind='pie', autopct='%1.1f%%', colors=
plt.rcParams.update({'font.size': 12})
```



Ah, so it is just as we hypothesized earlier from the scatter chart. Not the most visually appealing chart, but it confirms that majority of houses in the GTA are in the 600000 to 1000000 dollar price range*

*The price_cat attribute was created by rounding a particular house value down to the nearest 100000 so for example houses in the 600000 price_cat have a price between 600000 to 700000).

```
In [16]: corr_matrix = housing.corr()
         corr_matrix["Price(in CAD)"].sort_values(ascending=False)
```

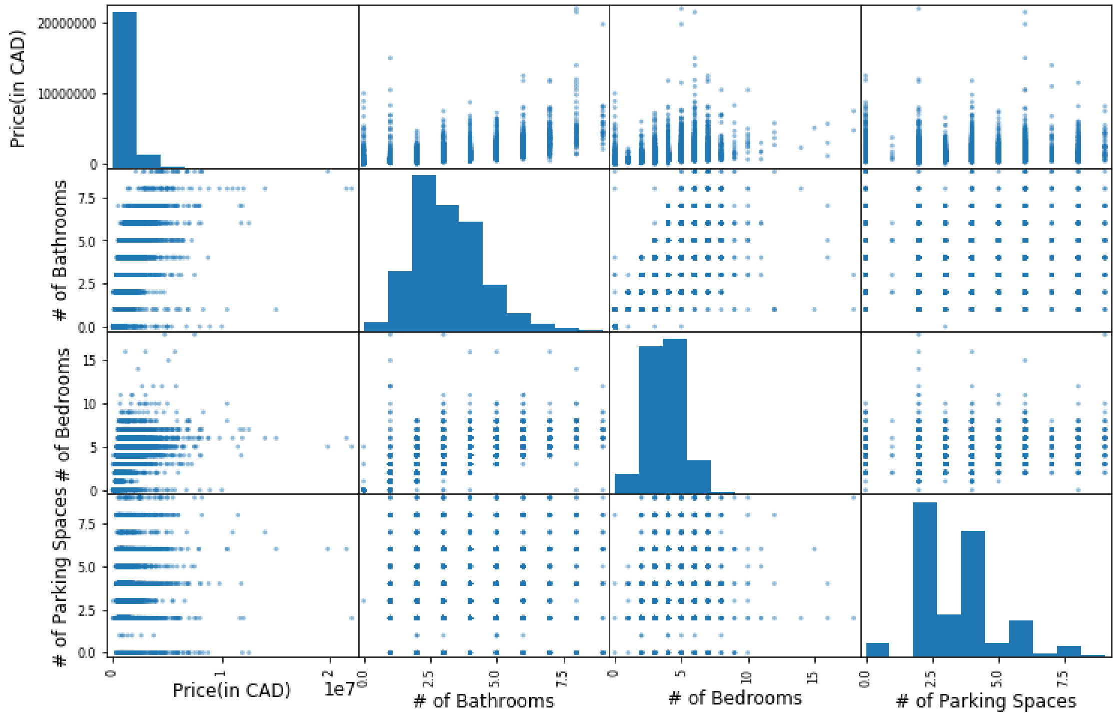
```
Out[16]: Price(in CAD)                     1.000000
         pricing_cat                       0.999603
         # of Bathrooms                    0.568471
         # of Bedrooms                     0.414038
          Total Lot Size(in square ft.)    0.161246
         # of Parking Spaces               0.155015
         # of Kitchens                     0.150059
```

```
Height(in stories)              0.116038
Longitude                      -0.048366
Latitude                       -0.095611
Name: Price(in CAD), dtype: float64
```

By calling the corr method, we can measure the correlation between the variables and see which one correlates the strongest with the price. We can ignore the pricing_cat, and the next strongest variable appears to be the # Of Bathrooms upon first glance. However, I have a feeling this does not tell us the complete picture, and some more work has to be done to gain more insights into the data.

```
In [17]: from pandas.plotting import scatter_matrix

         attributes = ["Price(in CAD)", "# of Bathrooms", "# of Bedrooms",
                       "# of Parking Spaces"]
         scatter_matrix(housing[attributes], figsize=(12, 8))
```

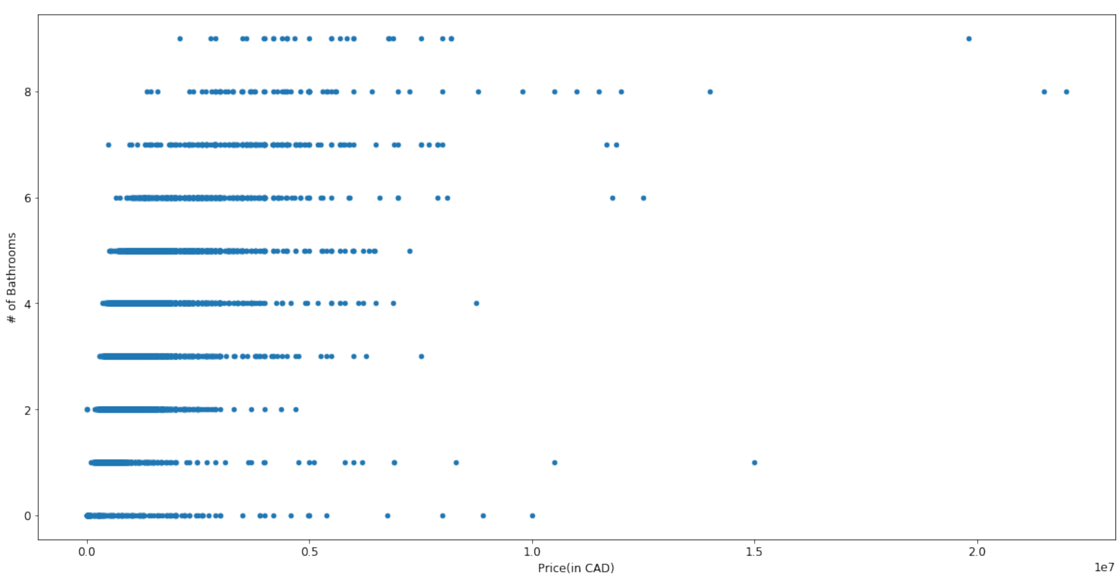
```
Out[17]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD608E4E0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD64E1320>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD650E898>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD8FD7E10>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD90083C8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD9031940>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD9059EB8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD90894A8>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD90894E0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD90D9F60>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD910A518>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD9132A90>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD9166048>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD918B5C0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD91B2B38>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x0000025FD91E30F0>]],
               dtype=object)
```



We can also measure correlation visually using the scatter_matrix method. Recall that # of Bathrooms had a strong correlation so we can take a closer look at that.

```
In [18]: housing.plot(kind="scatter", x="Price(in CAD)", y="# of Bathrooms")
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x25fd50a3b00>
```



We can see now more clearly that the correlation between price and number of bathrooms was not entirely true. Since we are comparing a continous variable with one that has discrete values, these discrepancies can occur. Thus, we see that strictly speaking the characteristics of the house do not have a direct correlation on the value of the house.

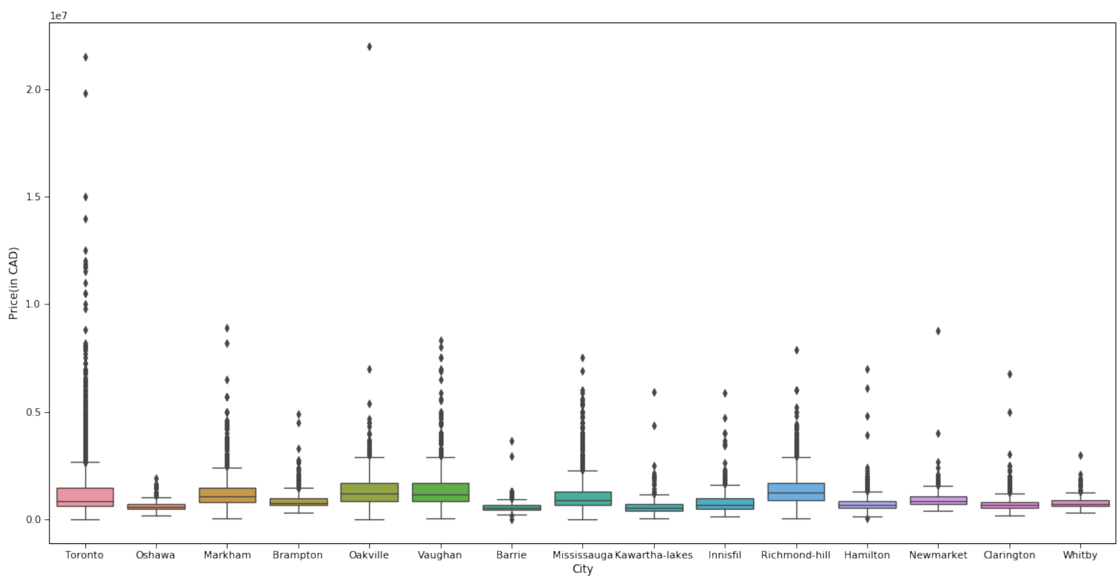
The code below is to implement a stacked bar graph later of the data. This is still a work in progress, and I will be adding more charts and data as I continue to work on this project.

In [19]:
```
import numpy as np
import matplotlib.pyplot as plt

def stacked_bar(data, series_labels, category_labels=None,
                show_values=False, value_format="{}", y_label=None,
                grid=True, reverse=False):
    """Plots a stacked bar chart with the data and labels provided.

    Keyword arguments:
    data            -- 2-dimensional numpy array or nested list
                       containing data for each series in rows
    series_labels   -- list of series labels (these appear in
                       the legend)
    category_labels -- list of category labels (these appear
                       on the x-axis)
    show_values     -- If True then numeric value labels will
                       be shown on each bar
    value_format    -- Format string for numeric value labels
                       (default is "{}")
    y_label         -- Label for y-axis (str)
    grid            -- If True display grid
    reverse         -- If True reverse the order that the
                       series are displayed (left-to-right
                       or right-to-left)
    """
    ny = len(data[0])
    ind = list(range(ny))

    axes = []
    cum_size = np.zeros(ny)

    data = np.array(data)

    if reverse:
        data = np.flip(data, axis=1)
        category_labels = reversed(category_labels)

    for i, row_data in enumerate(data):
        axes.append(plt.bar(ind, row_data, bottom=cum_size,
                            label=series_labels[i]))
        cum_size += row_data
```

```
        if category_labels:
            plt.xticks(ind, category_labels)

        if y_label:
            plt.ylabel(y_label)

        plt.legend()

        if grid:
            plt.grid()
```

```
In [20]: import seaborn as sns
         # import matplotlib.pyplot as plt

         # sns.set_style("darkgrid")
         sns.set_context(context="paper", font_scale=1.2)
         sns.boxplot(x= housing["City"], y= housing["Price(in CAD)"])
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x25fd9394860>
```



Much Better. As opposed to our scatterplot from earlier, I find that this boxplot helps convey a lot more information. Something that surprised me about the data is the fact that the median house value for all of the cities appear to be close. I was expecting cities which I perceived to be "richer", to have much higher median values. However, what we can notice is that these richer cities have a lot more outliers, that are in that higher range. Taking a look at Toronto, Markham, Oakville, Vaughan, and Richmond-Hill, we can see that they have a lot more outliers in that higher price range. Overall, we can gather from the data that all cities in the GTA have a very similar median house value, however, some have a lot more outliers in those higher price ranges than others, namely, the ones we hear as being "rich" neighbourhoods.

However, I still had some questions. Given that a house has all other characteristics equal, would a house be valued more just because it is in another city? This is what I wanted to continue exploring. We can get a quick idea about this calling the median method after grouping by city.

```
In [21]: housing.groupby("City").median()
```

```
Out[21]:                  Latitude  Longitude  Price(in CAD)  # of Bathrooms  \
         City
         Barrie          44.371646 -79.690698       544500.0               3
         Brampton        43.708165 -79.759528       749900.0               3
         Clarington      43.917411 -78.688948       643950.0               3
         Hamilton        43.236815 -79.844465       649900.0               3
         Innisfil        44.306908 -79.548443       674500.0               3
         Kawartha-lakes  44.516657 -78.743576       534900.0               2
         Markham         43.866016 -79.309689      1058000.0               3
         Mississauga     43.575884 -79.647491       889000.0               3
         Newmarket       44.048787 -79.463252       819800.0               3
         Oakville        43.447986 -79.705929      1199000.0               3
         Oshawa          43.911950 -78.859823       561400.0               3
         Richmond-hill   43.881955 -79.439064      1233500.0               4
         Toronto         43.715204 -79.397138       849950.0               2
         Vaughan         43.825952 -79.509967      1150000.0               4
         Whitby          43.907299 -78.947341       700000.0               3

                         # of Bedrooms  Height(in stories)  # of Kitchens  \
         City
         Barrie                      4                 2.0            1.0
         Brampton                    4                 2.0            1.0
         Clarington                  4                 2.0            1.0
         Hamilton                    4                 2.0            1.0
         Innisfil                    3                 2.0            1.0
         Kawartha-lakes              3                 1.0            1.0
         Markham                     4                 2.0            1.0
         Mississauga                 4                 2.0            1.0
         Newmarket                   4                 2.0            1.0
         Oakville                    4                 2.0            1.0
         Oshawa                      4                 2.0            1.0
         Richmond-hill               4                 2.0            1.0
         Toronto                     3                 2.0            1.0
         Vaughan                     4                 2.0            1.0
         Whitby                      4                 2.0            1.0

                         # of Parking Spaces   Total Lot Size(in square ft.)  \
         City
         Barrie                          3.0                      5390.46340
         Brampton                        3.0                      3635.61195
         Clarington                      2.0                      4913.63525
         Hamilton                        3.0                      4490.40890
```

```
Innisfil                          4.0                        8000.00000
Kawartha-lakes                    4.0                       15260.00000
Markham                           3.0                        4689.79480
Mississauga                       4.0                        5722.36210
Newmarket                         4.0                        5122.17200
Oakville                          3.0                        6017.73240
Oshawa                            3.0                        4596.64490
Richmond-hill                     4.0                        5246.00000
Toronto                           3.0                        5040.00000
Vaughan                           3.0                        4311.51050
Whitby                            3.0                        4650.44320

                pricing_cat
City
Barrie             500000.0
Brampton           700000.0
Clarington         600000.0
Hamilton           600000.0
Innisfil           700000.0
Kawartha-lakes     500000.0
Markham           1100000.0
Mississauga        900000.0
Newmarket          800000.0
Oakville          1200000.0
Oshawa             600000.0
Richmond-hill     1200000.0
Toronto            800000.0
Vaughan           1200000.0
Whitby             700000.0
```

So, looking at the table we can notice a number of things. Firstly, the median house values are not as close as what the boxplot is showing. Looking at this table, the differences in median house values are a bit more drastic. Looking at the actual values, the differences in house value are much more evident.

We can see that the median house values are much higher in cities like Richmond-Hill, Oakville, Vaughan, Markham, etc. Also, to answer my question from before, location does appear to be a big factor. For example, the chart shows that that a 3 bathroom and 4 bedroom house in Markham has a median house value that is much less than a house with similar characteristics in Mississauga. In fact, the houses in Mississauga have a cheaper median value, with a larger lot size in comparison with Markham!

I also found it interesting that increase in price, does not necessarily correlate with a larger lot size or even more bedrooms and bathrooms. More rural cities like Innisfil offer larger lot sizes at much cheaper prices.

```
In [22]: housing.groupby("City").mean()
```

```
Out[22]:                  Latitude  Longitude  Price(in CAD)  # of Bathrooms  \
         City
```

Barrie	44.372442	-79.682594	5.742365e+05	2.695364
Brampton	43.712783	-79.759831	8.539067e+05	3.423280
Clarington	43.932429	-78.697343	7.697274e+05	2.751337
Hamilton	43.235404	-79.842744	7.631298e+05	2.737303
Innisfil	44.295131	-79.561133	8.351651e+05	2.664160
Kawartha-lakes	44.478672	-78.737235	6.340200e+05	2.063333
Markham	43.855916	-79.317897	1.300390e+06	3.482366
Mississauga	43.578047	-79.656588	1.171381e+06	3.186574
Newmarket	44.047826	-79.461744	9.658156e+05	3.376900
Oakville	43.447086	-79.707264	1.411635e+06	3.443674
Oshawa	43.911307	-78.863734	5.963383e+05	2.739544
Richmond-hill	43.890603	-79.440855	1.443279e+06	3.611617
Toronto	43.715874	-79.392024	1.256467e+06	2.599777
Vaughan	43.827583	-79.526486	1.450969e+06	3.785803
Whitby	43.915900	-78.945864	8.017837e+05	3.264368

	# of Bedrooms	Height(in stories)	# of Kitchens	\
City				
Barrie	3.644592	1.708333	1.156250	
Brampton	4.203704	1.961612	1.325333	
Clarington	3.462567	1.670588	1.101124	
Hamilton	3.770578	1.702857	1.275676	
Innisfil	3.350877	1.572727	1.094488	
Kawartha-lakes	3.193333	1.294776	1.115108	
Markham	3.980660	2.017192	1.167048	
Mississauga	3.800349	1.881533	1.195013	
Newmarket	4.009119	1.892405	1.226300	
Oakville	3.788562	1.920668	1.071678	
Oshawa	3.669202	1.650307	1.225869	
Richmond-hill	4.116173	1.912088	1.245370	
Toronto	3.332737	1.835043	1.250284	
Vaughan	3.971357	2.075038	1.255051	
Whitby	3.885057	1.850299	1.143678	

	# of Parking Spaces	Total Lot Size(in square ft.)	\
City			
Barrie	3.216667	5664.483476	
Brampton	3.227766	5363.239002	
Clarington	2.738462	15946.609865	
Hamilton	3.325527	11625.353530	
Innisfil	3.655488	20348.946000	
Kawartha-lakes	3.886792	33074.960638	
Markham	3.373134	7288.144178	
Mississauga	3.502525	7995.136732	
Newmarket	3.648936	6703.146041	
Oakville	3.436620	7096.662804	
Oshawa	3.308725	5560.393303	
Richmond-hill	3.616162	7230.602442	

```
Toronto                          3.298597                     5998.385294
Vaughan                          3.307820                     7384.937719
Whitby                           3.319444                     7344.905052

                 pricing_cat
City
Barrie          5.671082e+05
Brampton        8.481481e+05
Clarington      7.620321e+05
Hamilton        7.579685e+05
Innisfil        8.298246e+05
Kawartha-lakes  6.266667e+05
Markham         1.298862e+06
Mississauga     1.168091e+06
Newmarket       9.623100e+05
Oakville        1.407106e+06
Oshawa          5.922053e+05
Richmond-hill   1.443052e+06
Toronto         1.253587e+06
Vaughan         1.449066e+06
Whitby          7.936782e+05
```

```
In [23]: housing = strat_train_set.drop("Price(in CAD)", axis=1)
         housing_labels = strat_train_set["Price(in CAD)"].copy()
```

1.4 Machine Learning/Modelling Stage

Moving onto prepping the data to make it suitable to apply Machine Learning algorithms. Recall that our data had a lot of values missing from it initially. To aid in this, we can use the imputer method, which fills in for these missing values using the median.

```
In [24]: from sklearn.impute import SimpleImputer

         imputer = SimpleImputer(strategy="median")

In [25]: housing_num = housing.drop(['Address', 'Postal Code', 'City', 'Neighbourhood', 'Lot-S
                                    'House HTML'], axis=1)
         imputer.fit(housing_num)

Out[25]: SimpleImputer(copy=True, fill_value=None, missing_values=nan,
                strategy='median', verbose=0)

In [26]: imputer.statistics_

Out[26]: array([ 4.3761637e+01, -7.9450643e+01,  3.0000000e+00,  4.0000000e+00,
                 2.0000000e+00,  1.0000000e+00,  3.0000000e+00,  4.9621000e+03])

In [27]: housing_num.median().values
```

```
Out[27]: array([ 4.3761637e+01, -7.9450643e+01,  3.0000000e+00,  4.0000000e+00,
                 2.0000000e+00,  1.0000000e+00,  3.0000000e+00,  4.9621000e+03])
```

```
In [28]: X = imputer.transform(housing_num)
         print(X)
```

```
[[ 4.37807300e+01 -7.92469550e+01  3.00000000e+00 ...  1.00000000e+00
   3.00000000e+00  4.96210000e+03]
 [ 4.38971790e+01 -7.88350350e+01  2.00000000e+00 ...  2.00000000e+00
   4.00000000e+00  5.00000000e+03]
 [ 4.38919560e+01 -7.92766830e+01  2.00000000e+00 ...  1.00000000e+00
   3.00000000e+00  4.96210000e+03]
 ...
 [ 4.38578245e+01 -7.88497430e+01  2.00000000e+00 ...  1.00000000e+00
   3.00000000e+00  3.03160000e+03]
 [ 4.43940230e+01 -7.97239240e+01  2.00000000e+00 ...  1.00000000e+00
   4.00000000e+00  4.40083380e+03]
 [ 4.36485400e+01 -7.97500900e+01  3.00000000e+00 ...  1.00000000e+00
   2.00000000e+00  2.45629450e+03]]
```

```
In [29]: import pandas as pd
         housing_tr = pd.DataFrame(X, columns=housing_num.columns)
```

```
In [30]: from sklearn.preprocessing import LabelEncoder
         encoder = LabelEncoder()
         housing_cat = housing["Basement(finished or not)"]
         housing_cat_2 = housing["City"]
         housing_cat_encoded = encoder.fit_transform(housing_cat)
         housing_cat_encoded_2 = encoder.fit_transform(housing_cat_2)
         housing_cat_encoded
```

```
Out[30]: array([1, 1, 1, ..., 0, 1, 0])
```

Now, one final step before applying the Machine Learning algorithms is encoding the values. We are using something known as "One Hot Encoding" which transforms non-categorical data into numerical values (either one or zero). This can be easily fed into the algorithm for us to be able to utilize various algorithms. This is not a requirement for all Machine Learning Algorithms, however, it just makes the task a lot easier as we just have to do it once, and apply it to all our ML algorithms afterwards

```
In [31]: from sklearn.preprocessing import OneHotEncoder
         encoder, encoder_2 = OneHotEncoder(), OneHotEncoder()
         housing_cat_1hot = encoder.fit_transform(housing_cat_encoded.reshape(-1, 1))
         housing_cat_1hot_2 = encoder_2.fit_transform(housing_cat_encoded_2.reshape(-1, 1))
         housing_cat_1hot.toarray()
         housing_cat_1hot_2.toarray()
```

```
C:\Users\Adit Krishnan\Anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:371: Futu
If you want the future behaviour and silence this warning, you can specify "categories='auto'"
```

```
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integer
  warnings.warn(msg, FutureWarning)
C:\Users\Adit Krishnan\Anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:371: Futu
If you want the future behaviour and silence this warning, you can specify "categories='auto'"
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integer
  warnings.warn(msg, FutureWarning)
```

```
Out[31]: array([[0., 0., 0., ..., 1., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                ...,
                [0., 0., 0., ..., 0., 0., 0.],
                [1., 0., 0., ..., 0., 0., 0.],
                [0., 1., 0., ..., 0., 0., 0.]])
```

```
In [32]: from sklearn.preprocessing import LabelBinarizer
         encoder = LabelBinarizer()
         housing_cat_1hot = encoder.fit_transform(housing_cat)
```

```
In [33]: from sklearn.pipeline import FeatureUnion, Pipeline
         from sklearn.preprocessing import StandardScaler
         from sklearn.base import BaseEstimator, TransformerMixin
         from sklearn.preprocessing import LabelBinarizer
         from sklearn.impute import SimpleImputer
         from sklearn.base import TransformerMixin

         class MyLabelBinarizer(TransformerMixin):
             def __init__(self, *args, **kwargs):
                 self.encoder = LabelBinarizer(*args, **kwargs)
             def fit(self, x, y=0):
                 self.encoder.fit(x)
                 return self
             def transform(self, x, y=0):
                 return self.encoder.transform(x)

         class DataFrameSelector(BaseEstimator, TransformerMixin):
             def __init__(self, attribute_names):
                 self.attribute_names = attribute_names
             def fit(self, X, y=None):
                 return self
             def transform(self, X):
                 return X[self.attribute_names].values

         num_attribs = list(housing_num)
         cat_attribs = ["Basement(finished or not)"]

         num_pipeline = Pipeline([
```

```
        ('selector', DataFrameSelector(num_attribs)),
        ('imputer', SimpleImputer(strategy="median")),
        ('std_scaler', StandardScaler()),
    ])

    cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        ('label_binarizer', MyLabelBinarizer()),
    ])

    full_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])
```

Just to summarize everything we have done with the dataset thus far, and so that it does not have to be repeated everytime we create a new subset of the housing data, I have utilized sklearn's pipeline method so that we can just call the full_pipeline method to quickly and reliably transform our data whenever it is needed.

```
In [34]: housing_prepared = full_pipeline.fit_transform(housing)
         housing_prepared

Out[34]: array([[-4.87862795e-03,  6.87154679e-01,  6.30111712e-04, ...,
                  0.00000000e+00,  1.00000000e+00,  0.00000000e+00],
                [ 4.57018461e-01,  2.13544511e+00, -6.82988586e-01, ...,
                  0.00000000e+00,  1.00000000e+00,  0.00000000e+00],
                [ 4.36301336e-01,  5.82632495e-01, -6.82988586e-01, ...,
                  0.00000000e+00,  1.00000000e+00,  0.00000000e+00],
                ...,
                [ 3.00918117e-01,  2.08373251e+00, -6.82988586e-01, ...,
                  1.00000000e+00,  0.00000000e+00,  0.00000000e+00],
                [ 2.42775928e+00, -9.89844833e-01, -6.82988586e-01, ...,
                  0.00000000e+00,  1.00000000e+00,  0.00000000e+00],
                [-5.29212682e-01, -1.08184320e+00,  6.30111712e-04, ...,
                  1.00000000e+00,  0.00000000e+00,  0.00000000e+00]])
```

Our data is finally ready to be used for Machine Learning. One of the most common and basic algorithms is Linear Regression. I am just going to test this model to see that everything is working probably thus far.

```
In [35]: from sklearn.linear_model import LinearRegression

         lin_reg = LinearRegression()
         lin_reg.fit(housing_prepared, housing_labels)

Out[35]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
In [36]: some_data = housing.iloc[:5]
         some_labels = housing_labels.iloc[:5]
         some_data_prepared = full_pipeline.transform(some_data)
         print("Predictions:\t", lin_reg.predict(some_data_prepared))
         print("Labels:\t\t", list(some_labels))
```

```
Predictions:         [1138786.2798816   881809.1733219   699133.4982525   928385.21957356
  773111.33271135]
Labels:                 [539900.0, 549900.0, 485000.0, 349000.0, 689900.0]
```

Nice! Atleast everything is working properly. However, as is immediately evident, the regression is working quite poorly, as the predictions it is making is way off. Let's measure the mean squared error to see exactly how bad it is performing.

```
In [37]: from sklearn.metrics import mean_squared_error
         import numpy as np
         housing_predictions = lin_reg.predict(housing_prepared)
         lin_mse = mean_squared_error(housing_labels, housing_predictions)
         lin_rmse = np.sqrt(lin_mse)
         lin_rmse
```

```
Out[37]: 784487.526005666
```

With a mean squared error of nearly $754,862 (indicates that this is the margin of error), this is clearly not the most effective Machine Learning Algorithm. Our best course of action is to move on, and attempt to find a more effective ML algorithm.

```
In [38]: from sklearn.tree import DecisionTreeRegressor

         tree_reg = DecisionTreeRegressor()
         tree_reg.fit(housing_prepared, housing_labels)
```

```
Out[38]: DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=None,
                    max_leaf_nodes=None, min_impurity_decrease=0.0,
                    min_impurity_split=None, min_samples_leaf=1,
                    min_samples_split=2, min_weight_fraction_leaf=0.0,
                    presort=False, random_state=None, splitter='best')
```

Another method we can try is a Decision Tree Regressor, which is a much more advanced algorithm than Linear Regression and will most probably yield much better results.

```
In [39]: some_data = housing.iloc[:5]
         some_labels = housing_labels.iloc[:5]
         some_data_prepared = full_pipeline.transform(some_data)
         print("Predictions:\t", tree_reg.predict(some_data_prepared))
         print("Labels:\t\t", list(some_labels))
```

```
Predictions:         [539900. 549900. 485000. 349000. 689900.]
Labels:                 [539900.0, 549900.0, 485000.0, 349000.0, 689900.0]
```

What! It appears our algorithm is working perfectly! NO, not true. What we are seeing here is an example of something known as "overfitting", as the algorithm is modelling the training set too well and is picking up on the noise. This situation is not ideal, as it indicates that the algorithm fits the training set data too well and thus, does not generalize well to other datasets. We can see this by computing the mean squared error, which I have below.

While it is not perfect, we can definitely see that we are improving and on the right track.

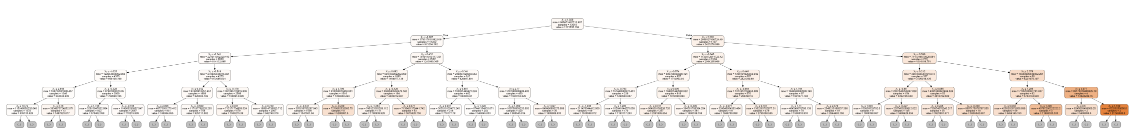
```
In [58]: import numpy as np
         housing_predictions = tree_reg.predict(housing_prepared)
         tree_mse = mean_squared_error(housing_labels, housing_predictions)
         tree_rmse = np.sqrt(tree_mse)
         tree_rmse
```

```
Out[58]: 632964.2559350071
```

Now, we are using a more powerful Machine Learning model known as a Decision Tree Regressor and we can see that the mean squared error has reduced much more drastically, so we are on the right track to picking the most effective model. Let's now working on fine tuning this model.

```
In [41]: from sklearn.externals.six import StringIO
         from IPython.display import Image
         from sklearn.tree import export_graphviz

         dot_data = StringIO()

         export_graphviz(
             tree_reg,
             max_depth = 5,
             out_file="decision_tree.dot",
             filled=True,
             rounded=True,
             special_characters=True
         #     feature_names=housing_labels
         )

         Image("decision_tree.png")
```

Out[41]:



Above, you can see a visualization of how the decision_tree makes decisions (the above image might be a bit hard to see, so I have also uploaded a png of the this same image in the same repository). Without getting too much into the fine details, the decision tree essentially tries to split the training set in such a way that the MSE (Mean Squared Error) is minimized. The value that is predicted at each node is the average of the number of training samples of that particular node. I have not printed the entire tree here as it is quite extensive and my computer simply cannot handle it! However, this process is continued recursively until the algorithm decides that it cannot split any more, in which case that value is returned. This is a gross oversimplification and in reality a lot more goes into how the splits are decided (the CART algorithm, etc.), however, this graphic provides us with a good base level idea of how exactly it works.

Recall, that we had an issue with our decision tree overfitting the data really badly. This is quite a common issue with decision tree regressors, however, we can fix this by tuning and altering the hyperparameters of the model as we are going to do below.

In [42]:
```
from sklearn.model_selection import cross_val_score
import numpy as np
scores = cross_val_score(tree_reg, housing_prepared, housing_labels, scoring="neg_mean
rmse_scores = np.sqrt(-scores)

def display_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard deviation: ", scores.std())

display_scores(rmse_scores)
```

```
Scores:  [678103.41756729 728367.90341763 589514.84471097 699865.43928151
 650274.37477212 647351.0106909  737659.2725168  697438.19237954
 875628.9920093  569584.08231531]
Mean:  687378.7529661366
Standard deviation:  81499.33687433806
```

Above, I have also created a function which will allow us to get a complete picture regarding the accuracy of our algorithms. It will come in handy as we move onto evaluating the effectiveness of our various algorithms.

In [54]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint

param_grid = {'max_depth': sp_randint(1, 100), 'max_features': sp_randint(2, 6),
     'min_samples_split': sp_randint(2, 200), 'min_samples_leaf': sp_randint(1, 50)}


forest_reg = DecisionTreeRegressor()

grid_search = RandomizedSearchCV(forest_reg, param_grid, cv=5, iid=False)

grid_search.fit(housing_prepared, housing_labels)
```

Out[54]:
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=DecisionTreeRegressor(criterion='mse', max_depth=None, max_featur
```

```
                         max_leaf_nodes=None, min_impurity_decrease=0.0,
                         min_impurity_split=None, min_samples_leaf=1,
                         min_samples_split=2, min_weight_fraction_leaf=0.0,
                         presort=False, random_state=None, splitter='best'),
                        fit_params=None, iid=False, n_iter=10, n_jobs=None,
                        param_distributions={'max_depth': <scipy.stats._distn_infrastructure.rv_fro
                        pre_dispatch='2*n_jobs', random_state=None, refit=True,
                        return_train_score='warn', scoring=None, verbose=0)
```

```
In [55]: grid_search.best_estimator_
```

```
Out[55]: DecisionTreeRegressor(criterion='mse', max_depth=80, max_features=4,
                    max_leaf_nodes=None, min_impurity_decrease=0.0,
                    min_impurity_split=None, min_samples_leaf=6,
                    min_samples_split=117, min_weight_fraction_leaf=0.0,
                    presort=False, random_state=None, splitter='best')
```

```
In [56]: from sklearn.tree import DecisionTreeRegressor

         tree_reg = grid_search.best_estimator_
         tree_reg.fit(housing_prepared, housing_labels)
         some_data = housing.iloc[:5]
         some_labels = housing_labels.iloc[:5]
         some_data_prepared = full_pipeline.transform(some_data)
         print("Predictions:\t", tree_reg.predict(some_data_prepared))
         print("Labels:\t\t", list(some_labels))
```

```
Predictions:         [1439646.56989247  674171.84090909  559666.33636364  638928.60526316
  975876.13761468]
Labels:                 [539900.0, 549900.0, 485000.0, 349000.0, 689900.0]
```

```
In [46]: import numpy as np
         housing_predictions = tree_reg.predict(housing_prepared)
         tree_mse = mean_squared_error(housing_labels, housing_predictions)
         tree_rmse = np.sqrt(tree_mse)
         tree_rmse
```

```
Out[46]: 575153.55120528
```

So we can see that by tuning the hyper-parameters, we were able to improve its score slightly. Playing around with the values more, we can probably reduce this mean squared error further. However, I feel that a different algorithm could work more effectively. Since we saw that the decision tree is overfitting our data, another algorithm we can use is the Random Forest Regressor. The best way to think of how a Random Forest Regressor works, is like a collection of decsion tree regressors. The random forest regressor trains on a collection of decision forest regressors, each on a different random subset of the data. Then, to obtain the prediction, looks at the collection and picks the best one. This is obviously an oversimplification, but gives the gist of how it works.

```
In [47]: from sklearn.model_selection import cross_val_score
         import numpy as np

         lin_scores = cross_val_score(lin_reg, housing_prepared, housing_labels, scoring="neg_m
         lin_rmse_scores = np.sqrt(-lin_scores)
         display_scores(lin_rmse_scores)
```

```
Scores:  [905937.1562455  731507.51176736 770690.73385133 793545.65010702
 690684.70468035 759703.93691312 880565.92632985 817647.27194965
 798475.77207244 699380.25203419]
Mean:  784813.8915950817
Standard deviation:  67090.2176049475
```

1.5 Random Forest Regressor

Below is my implementation of the Random Forest Regressor, on the data. The steps to implementing it to our dataset is nearly identical to Decision Trees (fitting, tuning, etc.)

```
In [48]: from sklearn.ensemble import RandomForestRegressor
         import warnings

         with warnings.catch_warnings():
             # ignore all caught warnings
             warnings.filterwarnings("ignore")
             # execute code that will generate warnings
         forest_reg = RandomForestRegressor()
         forest_reg.fit(housing_prepared, housing_labels)
         forest_scores = cross_val_score(forest_reg, housing_prepared, housing_labels, scoring=
         forest_rmse_scores = np.sqrt(-forest_scores)
         display_scores(forest_rmse_scores)
```

```
C:\Users\Adit Krishnan\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:246: FutureWarni
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


Scores:  [606316.68492938 483272.13720027 496643.91825585 532327.9909786
 479926.38911157 503155.72629196 627416.93428443 470838.45888409
 659503.93011619 475411.18723718]
Mean:  533481.3357289518
Standard deviation:  67062.59409870602
```

```
In [49]: from sklearn.model_selection import GridSearchCV

         param_grid = [
             {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
             {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
         ]
```

```
forest_reg = RandomForestRegressor()

grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
scoring='neg_mean_squared_error')

grid_search.fit(housing_prepared, housing_labels)
```

Out[49]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
           oob_score=False, random_state=None, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]}, {'boot
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=0)
```

In [50]:
```
grid_search.best_estimator_
```

Out[50]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=6, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=30, n_jobs=None, oob_score=False,
           random_state=None, verbose=0, warm_start=False)
```

In [51]:
```
cvres = grid_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
654896.993849965 {'max_features': 2, 'n_estimators': 3}
560003.658071006 {'max_features': 2, 'n_estimators': 10}
555666.2297866158 {'max_features': 2, 'n_estimators': 30}
603581.32945781 {'max_features': 4, 'n_estimators': 3}
542203.3442475422 {'max_features': 4, 'n_estimators': 10}
530831.9895079421 {'max_features': 4, 'n_estimators': 30}
598377.2779299777 {'max_features': 6, 'n_estimators': 3}
544215.8819611517 {'max_features': 6, 'n_estimators': 10}
508440.150062489 {'max_features': 6, 'n_estimators': 30}
580314.7250231031 {'max_features': 8, 'n_estimators': 3}
555143.1945704219 {'max_features': 8, 'n_estimators': 10}
509720.4070046275 {'max_features': 8, 'n_estimators': 30}
636541.7602351859 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
561642.2984183421 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
614978.5758393216 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
556090.0606458805 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
```

```
600084.0839064181 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
536357.4548413595 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

Here I was actually displayed some of the parameter values that the graph was testing. We can see that by calling best_estimator_, we are able to get the best result immedieately.

```
In [52]: feature_importances = grid_search.best_estimator_.feature_importances_
         feature_importances
```

```
Out[52]: array([0.14087686, 0.14609311, 0.36529991, 0.07371385, 0.01966259,
                0.0277146 , 0.03116941, 0.18387668, 0.00513103, 0.00436592,
                0.00209605])
```

```
In [53]: final_model = grid_search.best_estimator_

         X_test = strat_test_set.drop("Price(in CAD)", axis=1)
         y_test = strat_test_set["Price(in CAD)"].copy()

         X_test_prepared = full_pipeline.transform(X_test)

         final_predictions = final_model.predict(X_test_prepared)

         final_mse = mean_squared_error(y_test, final_predictions)
         final_rmse = np.sqrt(final_mse)
         print(final_rmse)
```

```
537303.4689205433
```

Overall, we can see that the Random Forest Regressor was able to provide us with the best model for our data-set, by minimizing the mean squared error by the most. However, I am far from done with this project. I will continue to tune my hyper-parameters, as realistically, having MSE of over 500,000 is not good at all. Stay tuned for more updates!