# Data Analysis

July 26, 2020

## 1 Data Analysis

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
```

[5]:
```
# df_1 represents Dataset_C18pop
df_1 = pd.read_csv('Dataset_C18pop_1.csv')
df_1.head()
```

[5]:
```
   Bedrooms  Bathrooms                                            Address  \
0         3        1.0  236 Kaiaraara Bay Road Great Barrier Island, A...
1         1        1.0  14 Te Rangitawhiri Road Great Barrier Island, ...
2         5        3.0  349 Blind Bay Road Great Barrier Island, Auckland
3         2        2.0      8 Omanawa Lane Great Barrier Island, Auckland
4         3        1.0             358 Mangawhai Road Wellsford, Auckland

   Land area      CV   Latitude   Longitude      SA1  0-19 years  20-29 years  \
0       5638  580000 -36.177655  175.359070  7001130          39            9
1       2141  740000 -36.197282  175.416921  7001131          27            6
2       3953  920000 -36.257895  175.436448  7001131          27            6
3       8638  650000 -36.305955  175.492424  7001135          30           21
4      15550  550000 -36.228742  174.545810  7001139          48           30

   30-39 years  40-49 years  50-59 years  60+ years  \
0           18           24           24         42
1            6           18           39         60
2            6           18           39         60
3           21           21           39         69
4           21           21           33         45

                              Suburbs  C18_CURPop  DepIndex
0  Great Barrier Island (Aotea Island)         153         9
```

```
1  Great Barrier Island (Aotea Island)        156          9
2  Great Barrier Island (Aotea Island)        156          9
3  Great Barrier Island (Aotea Island)        201          9
4                               Wellsford        195          5
```

[6]:
```
df_1.dtypes
```

[6]:
```
Bedrooms           int64
Bathrooms        float64
Address           object
Land area          int64
CV                 int64
Latitude         float64
Longitude        float64
SA1                int64
0-19 years         int64
20-29 years        int64
30-39 years        int64
40-49 years        int64
50-59 years        int64
60+ years          int64
Suburbs           object
C18_CURPop         int64
DepIndex           int64
dtype: object
```

[7]:
```
df_1.isnull().values.any()
```

[7]:
```
True
```

[8]:
```
df_1.Bathrooms.isnull().values.any()
```

[8]:
```
True
```

[10]:
```
#clean up NaN values
df_1 = df_1[df_1.Bathrooms.notnull()]
```

[11]:
```
df_1.isnull().values.any()
```

[11]:
```
False
```

[12]:
```
df_1.describe()
```

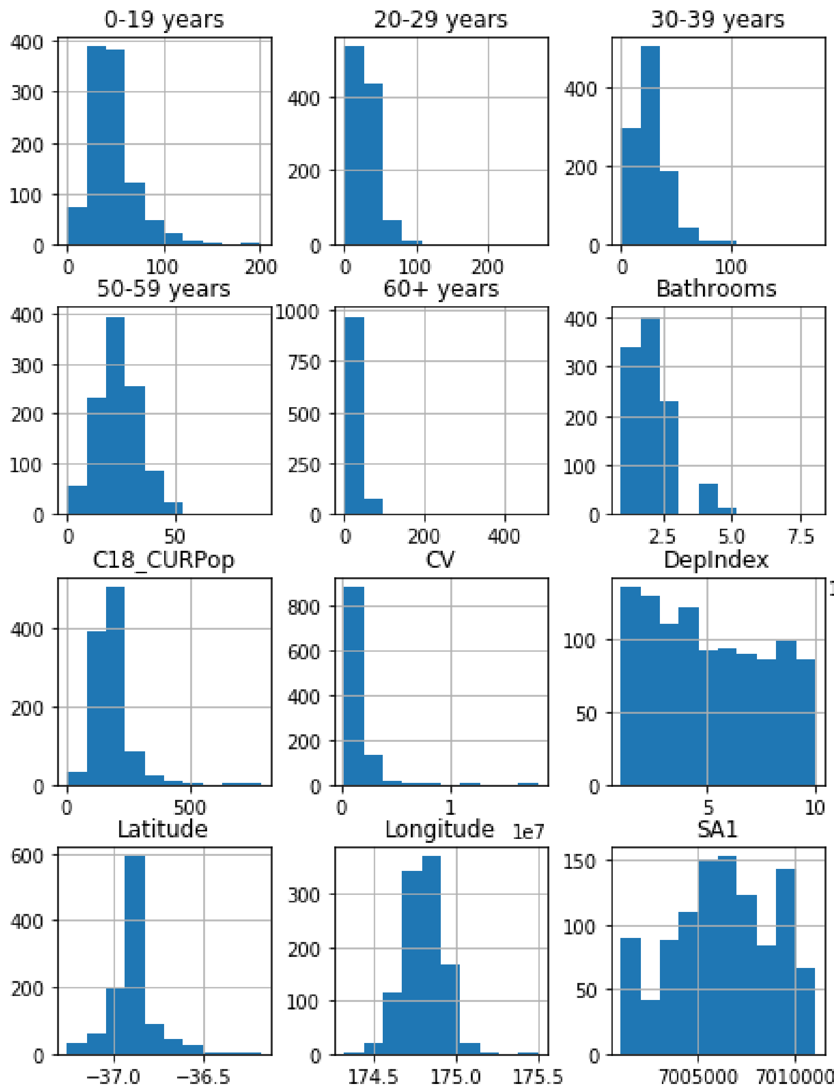
[12]:
```
          Bedrooms    Bathrooms     Land area            CV     Latitude  \
count  1049.000000  1049.000000   1049.000000  1.049000e+03  1049.000000
mean      3.776930     2.073403    858.185891  1.387926e+06   -36.893897
std       1.170487     0.992985   1589.433957  1.184027e+06     0.130158
min       1.000000     1.000000     40.000000  2.700000e+05   -37.265021
25%       3.000000     1.000000    323.000000  7.800000e+05   -36.950722
50%       4.000000     2.000000    572.000000  1.080000e+06   -36.893368
75%       4.000000     3.000000    825.000000  1.600000e+06   -36.856192
max      17.000000     8.000000  22240.000000  1.800000e+07   -36.177655
```

```
        Longitude           SA1   0-19 years   20-29 years   30-39 years  \
count  1049.000000  1.049000e+03  1049.000000  1049.000000  1049.000000
mean    174.799615  7.006327e+06    47.525262    28.893232    26.979981
std       0.119468  2.587674e+03    24.709758    20.995139    17.934747
min     174.317078  7.001130e+06     0.000000     0.000000     0.000000
25%     174.722474  7.004424e+06    33.000000    15.000000    15.000000
50%     174.798648  7.006333e+06    45.000000    24.000000    24.000000
75%     174.880945  7.008385e+06    57.000000    36.000000    33.000000
max     175.492424  7.011028e+06   201.000000   270.000000   177.000000

       40-49 years  50-59 years   60+ years  C18_CURPop     DepIndex
count  1049.000000  1049.000000  1049.000000  1049.000000  1049.000000
mean     24.125834    22.612965    29.382269   179.776930     5.069590
std      10.953205    10.220137    21.820173    71.057174     2.913171
min       0.000000     0.000000     0.000000     3.000000     1.000000
25%      18.000000    15.000000    18.000000   138.000000     2.000000
50%      24.000000    21.000000    27.000000   174.000000     5.000000
75%      30.000000    27.000000    36.000000   207.000000     8.000000
max     114.000000    90.000000   483.000000   789.000000    10.000000
```

[13]:
```
df_1.hist(figsize=(10,10))
```

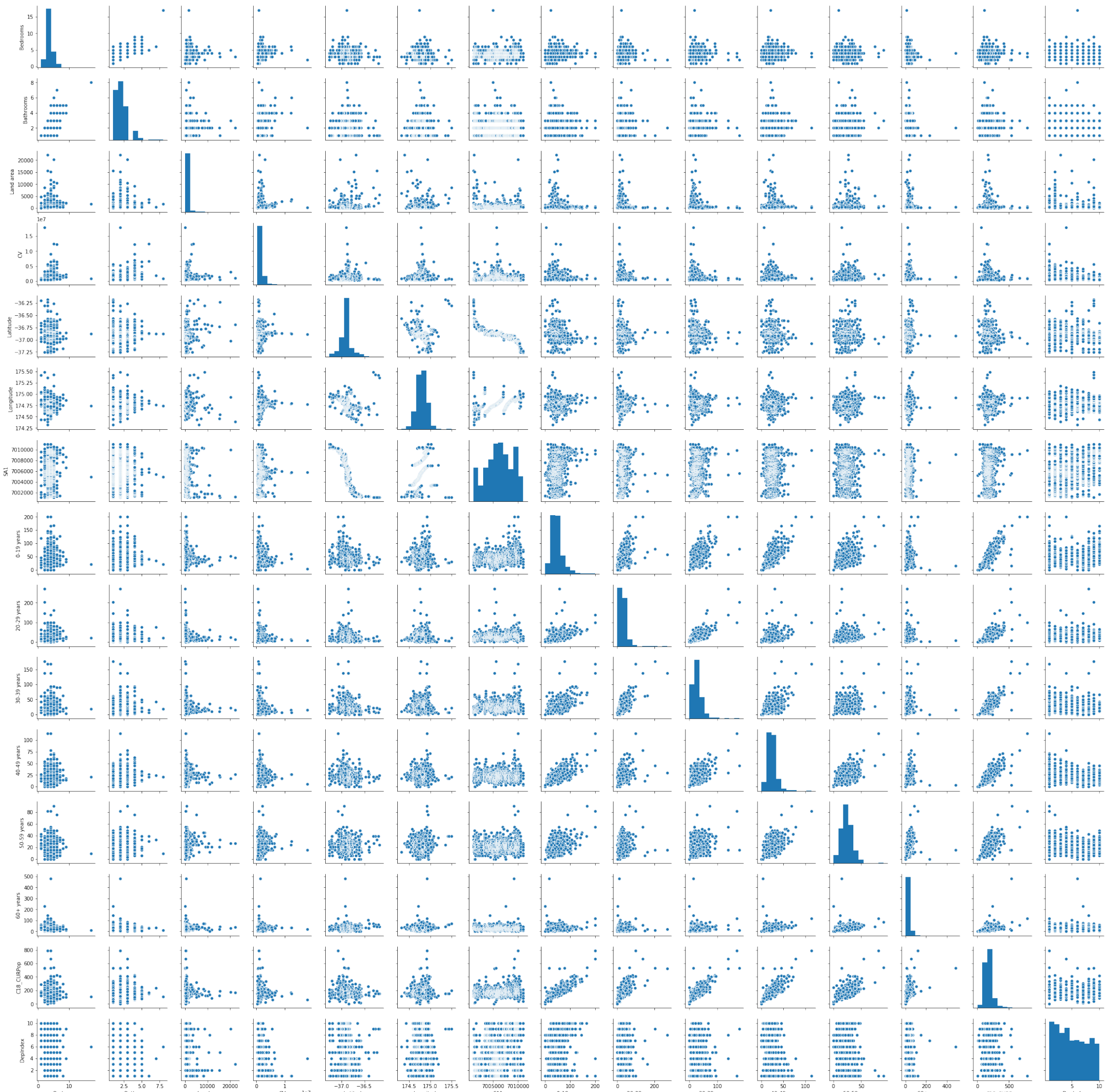
[13]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4fe00b8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4fae438>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4f539b0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4f7cf28>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4f2b4e0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4ed2a58>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4efafd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4eaa5c0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4eaa5f8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4bc10b8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4be6630>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4b8fba8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4bbe160>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4b646d8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4b0dc50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f45d4b3b208>]],
      dtype=object)
```




[14]:
```
sns.pairplot(df_1, size = 2.0)
```

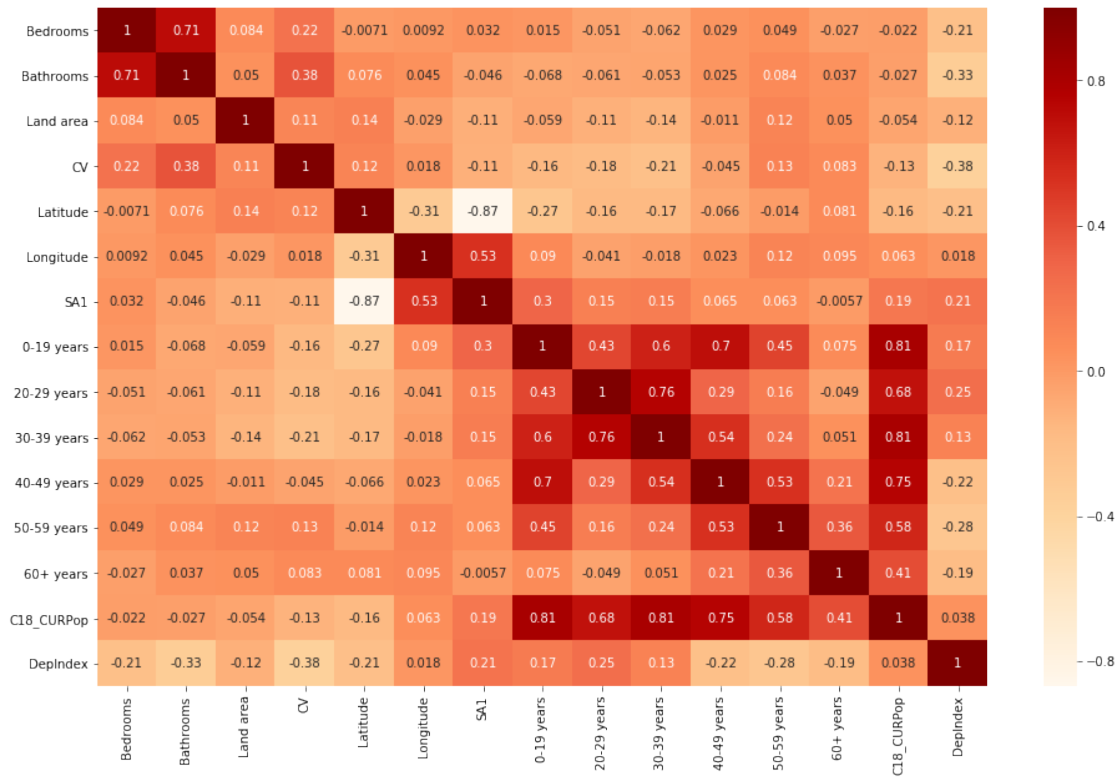
```
/home/nbuser/anaconda3_501/lib/python3.6/site-packages/seaborn/axisgrid.py:2065:
UserWarning: The `size` parameter has been renamed to `height`; pleaes update
your code.
  warnings.warn(msg, UserWarning)
```

[14]:
```
<seaborn.axisgrid.PairGrid at 0x7f45d46f8a20>
```




[15]:
```python
ax, fig = plt.subplots(figsize=(16,10))
correlation_matrix = df_1.corr()
sns.heatmap(correlation_matrix,annot = True, cmap = "OrRd")
```

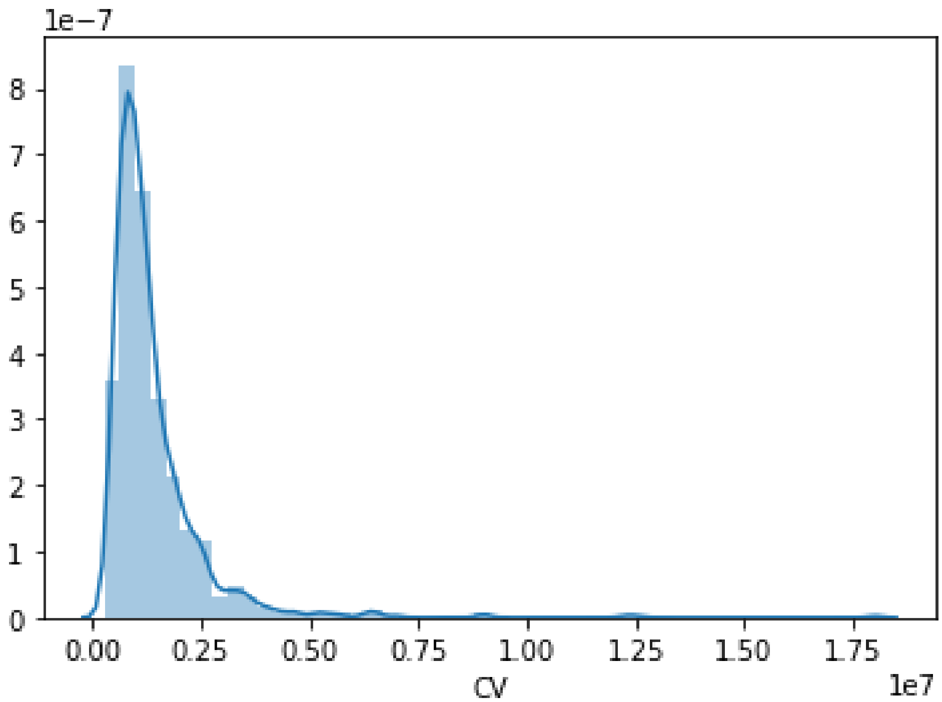
[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f45a9fbe358>
```




[16]:
```
sns.distplot(df_1['CV'])
```

```
/home/nbuser/anaconda3_501/lib/python3.6/site-
packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of
`arr[seq]`. In the future this will be interpreted as an array index,
`arr[np.array(seq)]`, which will result either in an error or a different
result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f45a8bbd470>
```




## 2 Data Processing

From the CV histgraph above we notice some extreme value above 8M, there's part of hours should not be include in our estimation. As it is a single case and cast a extreme values. Similar cases include 15 bedrooms, more than 6 bathrooms, land area more than 16000, and Population more than 600.

[17]:
```
df_1 = df_1.rename({'Land area':'LandArea'},axis=1)
df_1 = df_1[df_1.CV<8000000]
df_1 = df_1[df_1.LandArea<16000]
df_1 = df_1[df_1.Bedrooms<10]
df_1 = df_1[df_1.Bathrooms<= 6]
df_1 = df_1[df_1.C18_CURPop<8000000]
```

The scale of the training data need to be adjust as the CV price is millions based and it exceed the calculation range for float.

[19]:
```
def ScaleAdjust (num):
    return float(num)/1000

df_drop = df_1.drop(['Address','Suburbs'],axis=1)

for column in df_drop.columns:
    df_drop[column] = df_drop[column].apply(ScaleAdjust)
```

[38]:
```
# separate it to train and test by 7:3
x = df_drop.drop(['CV'],axis = 1)
y = df_drop['CV']
train_x, test_x, train_y, test_y = train_test_split(x,y,test_size = 0.3,␣
↪random_state = 22)
```

## 3 Linear Regresssion

Linear Regression isn't the best fit model in the situation. As it can hardly justify the impact of area code, such as "SA1", and how longititue and Latitute contributed to the final output. The location has strong impact on people decision to purchase houses but it can hardly to be linearly quantify.

[39]:
```
linear_model = LinearRegression()
linear_model.fit(train_x,train_y)
```

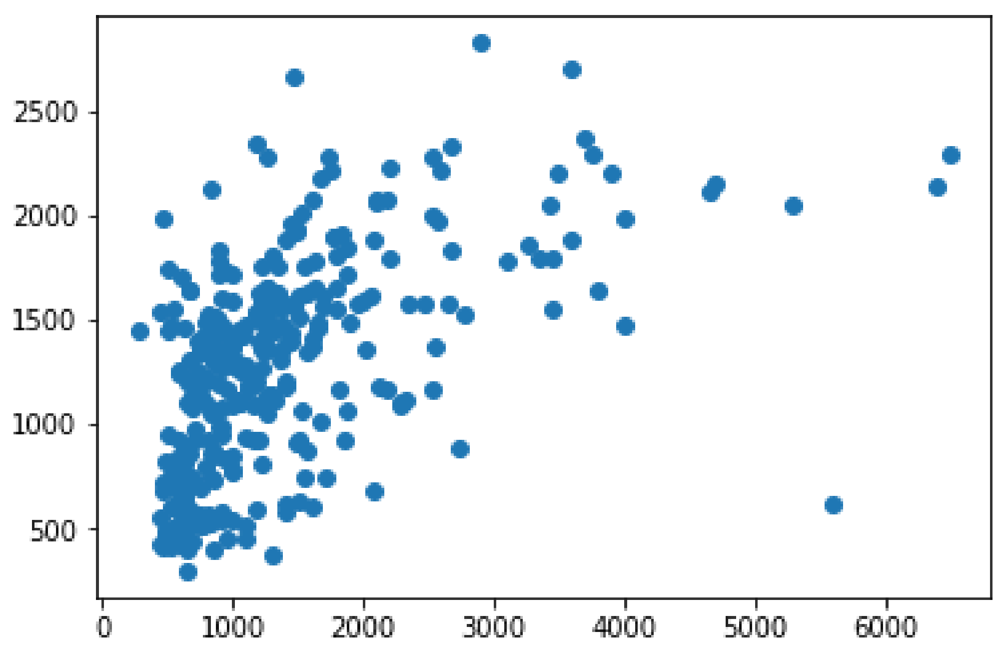
[39]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                 normalize=False)
```

[40]:
```
linear_model.coef_
```

[40]:
```
array([ 1.18475309e+04,  2.80552411e+05, -7.31442092e+00, -5.96570762e+04,
        3.88543570e+05, -3.43679564e+01,  3.12183490e+03,  3.94489978e+03,
       -6.72674231e+03, -6.20698879e+03,  1.30256811e+04,  2.68116981e+03,
       -2.11761880e+03, -9.44175305e+04])
```

[41]:
```
linear_predicted = linear_model.predict(test_x)
plt.scatter (test_y,linear_predicted)
```

[41]:
```
<matplotlib.collections.PathCollection at 0x7f45a7dbc9e8>
```



[42]:
```
linear_model.score(test_x,test_y)
```

[42]:
```
0.28981868462074956
```

## 4 Random Forest Regression

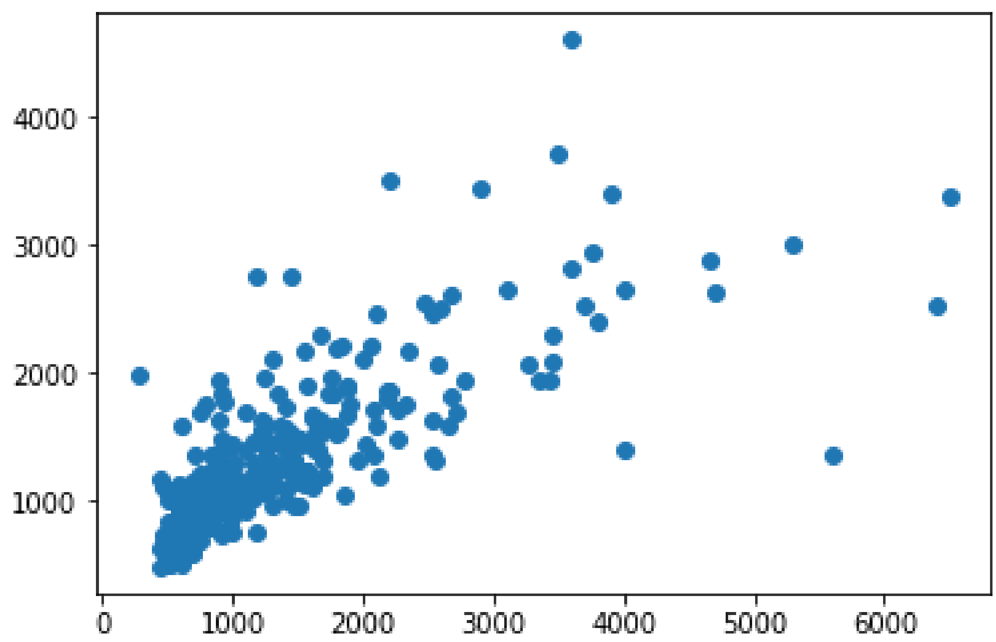
Random Forest Regression will address the problem listing above. Because it has decision trees to help analyse the influence of area code. And the random forest Regression allow a small sample splits, thus, it can better handle extreme training case compare to Linear Regression.

[43]:
```
RFR_model = RandomForestRegressor(n_estimators=100,max_features = 10)
RFR_model.fit(train_x,train_y)
```

[43]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features=10, 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=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[44]:
```
RFR_predicted = RFR_model.predict(test_x)
plt.scatter(test_y,RFR_predicted)
```

[44]:
```
<matplotlib.collections.PathCollection at 0x7f45a7d21f28>
```




[45]:
```
RFR_model.score(test_x,test_y)
```

[45]: 0.5629860202264829