msa_phase_1

July 26, 2020

1 Auckland House Prices Analysis

1.1 Executive Summary:

It is of interest to build a predictive model for the Capital value of Auckland properties. The original dataset given consists of typical housing attributes and the SA1 area unit classification, along with the number of people from different ages groups within the SA1 area. To improve this dataset, two variables were added:

- The 2018 recorded population at the addresses in our dataset, based on the 2018 census and Koordinate.
- The 2018 Deprivation index which is an indicator of the socio-economic status for a SA1 area.

After the data cleaning stage, the final dataset consisted of 1050 observations (an outlier was removed) and 14 explanatory variables.

Different models and transformations were applied, and the resulting model used was a random forest model with a prediction score of 53.3%.

1.2 1. Data collection - API calling and Webscraping

[269]:
```
import sys
import json
import pandas as pd
import requests
import time
import re
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

[91]:
```
"""
# defined a function to get the C18_CURPop
# Inputs:
# - lat = latitude
# - lon = logitude
# Outputs:
```

```
# - C18_CURPop
"""

def get_C18_CURPop(lat,lon):
    url = 'https://koordinates.com/services/query/v1/vector.json'
    params = {
        'key': '39747fad883a4b3786e25fc80942264d',
        'layer': '104612',
        'x':lon,
        'y':lat
    }
    response = requests.get(url,params=params)

    if response.status_code !=200:
        return pd.Series({'C18_CURPop':response.status_code})

    C18_CURPop = response.
 ↪json()['vectorQuery']['layers']['104612']['features'][0]['properties']['C18_CURPop']
    return pd.Series({'C18_CURPop':C18_CURPop})
```

Test if function is working correctly:

[65]:
```
get_C18_CURPop(-37.0129205,174.90406940000003)
```

[65]:
```
C18_CURPop    174
dtype: int64
```

Read in the assignment csv

[32]:
```
df = pd.read_csv('Dataset for Assignment.csv')
```

Append the column to the assignment dataset. Code is commented to prevent running again as it takes awhile. The combined file was saved and loaded when required instead of running this step.

[33]:
```
#df['C18_CURPop'] = df.apply(lambda x:␣
 ↪get_C18_CURPop(x['Latitude'],x['Longitude']),axis=1)
#df.to_csv('data_with_census.csv')
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-33-b5b1ea5764b0> in <module>
----> 1 df['C18_CURPop'] = df.apply(lambda x:␣
↪get_C18_CURPop(x['Latitude'],x['Longitude']),axis=1)


~/anaconda3_501/lib/python3.6/site-packages/pandas/core/frame.py in␣
↪apply(self, func, axis, broadcast, raw, reduce, result_type, args, **kwds)
```

```
      6012                          args=args,
      6013                          kwds=kwds)
   -> 6014         return op.get_result()
      6015
      6016     def applymap(self, func):


      ~/anaconda3_501/lib/python3.6/site-packages/pandas/core/apply.py in␣
↪get_result(self)
      140             return self.apply_raw()
      141
   --> 142         return self.apply_standard()
      143
      144     def apply_empty_result(self):


      ~/anaconda3_501/lib/python3.6/site-packages/pandas/core/apply.py in␣
↪apply_standard(self)
      246
      247         # compute the result using the series generator
   --> 248         self.apply_series_generator()
      249
      250         # wrap results


      ~/anaconda3_501/lib/python3.6/site-packages/pandas/core/apply.py in␣
↪apply_series_generator(self)
      275             try:
      276                 for i, v in enumerate(series_gen):
   --> 277                     results[i] = self.f(v)
      278                     keys.append(v.name)
      279             except Exception as e:


      <ipython-input-33-b5b1ea5764b0> in <lambda>(x)
   ----> 1 df['C18_CURPop'] = df.apply(lambda x:␣
↪get_C18_CURPop(x['Latitude'],x['Longitude']),axis=1)


      NameError: ("name 'get_C18_CURPop' is not defined", 'occurred at index 0')
```

Loading dataset with the C18_CURPop column

[271]:
```
df= pd.read_csv('data_with_census.csv')
```

[272]:
```
df.head()
```

[272]:
```
   Unnamed: 0  Bedrooms  Bathrooms                                  Address  \
0           0         5        3.0  106 Lawrence Crescent Hill Park, Auckland
1           1         5        3.0             8 Corsica Way Karaka, Auckland
2           2         6        4.0    243 Harbourside Drive Karaka, Auckland
3           3         2        1.0  2/30 Hardington Street Onehunga, Auckland
4           4         3        1.0    59 Israel Avenue Clover Park, Auckland

  Land area       CV   Latitude   Longitude      SA1  0-19 years  20-29 years  \
0       714   960000 -37.012920  174.904069  7009770          48           27
1       564  1250000 -37.063672  174.922912  7009991          42           18
2       626  1250000 -37.063580  174.924044  7009991          42           18
3        65   740000 -36.912996  174.787425  7007871          42            6
4       601   630000 -36.979037  174.892612  7008902          93           27

   30-39 years  40-49 years  50-59 years  60+ years      Suburbs  C18_CURPop
0           24           21           24         21     Manurewa         174
1           12           21           15         30       Karaka         129
2           12           21           15         30       Karaka         129
3           21           21           12         15     Onehunga         120
4           33           30           21         33  Clover Park         231
```

Download file to get the Deprivation Index

[36]:
```
!curl https://www.otago.ac.nz/wellington/otago730418.txt -O
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 1192k  100 1192k    0     0   153k      0  0:00:07  0:00:07 --:--:--  200k
```

Read in the dataset (delimiter is tabs).

[293]:
```
sa_df = pd.read_csv('otago730418.txt',sep = "\t")
```

[294]:
```
sa_df.head()
```

[294]:
```
   SA12018_code  NZDep2018  NZDep2018_Score  URPopnSA1_2018  SA22018_code  \
0       7000000       10.0           1245.0             141        100100
1       7000001       10.0           1245.0             114        100100
2       7000002        NaN              NaN               0        100300
3       7000003       10.0           1207.0             225        100100
4       7000004        9.0           1093.0             138        100100

                SA22018_name
0                North Cape
1                North Cape
2  Inlets Far North District
3                North Cape
4                North Cape
```

Drop columns that are not need. Only keep the column required for merging and the NZ Deprivation Index

[295]:
```
sa_df = sa_df.
↪drop(['NZDep2018_Score','URPopnSA1_2018','SA22018_code','SA22018_name'],axis=1)
```

Create a new temporary dataframe to complete the merge

[296]:
```
temp_df = df
```

[297]:
```
joined_df = pd.merge(temp_df,sa_df, how = 'left',left_on = 'SA1',right_on =␣
↪'SA12018_code')
```

[298]:
```
joined_df.head()
```

[298]:

	Unnamed: 0	Bedrooms	Bathrooms	Address	Land area	CV	Latitude	Longitude	SA1	0-19 years	20-29 years	30-39 years	40-49 years	50-59 years	60+ years	Suburbs	C18_CURPop	SA12018_code	NZDep2018
0	0	5	3.0	106 Lawrence Crescent Hill Park, Auckland	714	960000	-37.012920	174.904069	7009770	48	27	24	21	24	21	Manurewa	174	7009770	6.0
1	1	5	3.0	8 Corsica Way Karaka, Auckland	564	1250000	-37.063672	174.922912	7009991	42	18	12	21	15	30	Karaka	129	7009991	1.0
2	2	6	4.0	243 Harbourside Drive Karaka, Auckland	626	1250000	-37.063580	174.924044	7009991	42	18	12	21	15	30	Karaka	129	7009991	1.0
3	3	2	1.0	2/30 Hardington Street Onehunga, Auckland	65	740000	-36.912996	174.787425	7007871	42	6	21	21	12	15	Onehunga	120	7007871	2.0
4	4	3	1.0	59 Israel Avenue Clover Park, Auckland	601	630000	-36.979037	174.892612	7008902	93	27	33	30	21	33	Clover Park	231	7008902	9.0

Removed the unnecessary columns from the dataset

[299]:
```
joined_df = joined_df.drop(['Unnamed: 0','SA12018_code'], axis = 1)
```

[300]:
```
joined_df.to_csv('combined_data.csv')
```

2 2. Data Analysis and Model building

2.1 2.1. Data Cleaning

[301]:
```
joined_df= pd.read_csv('combined_data.csv')
```

[302]:
```
joined_df.dtypes
```

[302]:
```
Unnamed: 0       int64
Bedrooms         int64
Bathrooms      float64
Address         object
Land area       object
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
NZDep2018      float64
dtype: object
```

Drop extra columns

[303]:
```
joined_df = joined_df.drop(['Unnamed: 0'], axis = 1)
```

Clean the land area column, as some values contained " m^2". We only want numeric values.

[305]:
```
joined_df['Land area'] = joined_df['Land area'].str.extract('(\d+)').
↪astype(float)
```

[306]:
```
joined_df.dtypes
```

[306]:
```
Bedrooms         int64
Bathrooms      float64
Address         object
Land area      float64
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
NZDep2018      float64
dtype: object
```

[307]:
```
joined_df.describe()
```

[307]:
```
          Bedrooms    Bathrooms     Land area            CV     Latitude  \
count  1051.000000  1049.000000   1051.000000  1.051000e+03  1051.000000
mean      3.777355     2.073403    856.989534  1.387521e+06   -36.893715
std       1.169412     0.992985   1588.156219  1.182939e+06     0.130100
min       1.000000     1.000000     40.000000  2.700000e+05   -37.265021
25%       3.000000     1.000000    321.000000  7.800000e+05   -36.950565
50%       4.000000     2.000000    571.000000  1.080000e+06   -36.893132
75%       4.000000     3.000000    825.000000  1.600000e+06   -36.855789
max      17.000000     8.000000  22240.000000  1.800000e+07   -36.177655

         Longitude           SA1   0-19 years  20-29 years  30-39 years  \
count  1051.000000  1.051000e+03  1051.000000  1051.000000  1051.000000
mean    174.799325  7.006319e+06    47.549001    28.963844    27.042816
std       0.119538  2.591262e+03    24.692205    21.037441    17.975408
min     174.317078  7.001130e+06     0.000000     0.000000     0.000000
25%     174.720779  7.004416e+06    33.000000    15.000000    15.000000
50%     174.798575  7.006325e+06    45.000000    24.000000    24.000000
75%     174.880944  7.008384e+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    NZDep2018
count  1051.000000  1051.000000  1051.000000  1051.000000  1051.000000
mean     24.125595    22.615604    29.360609   179.914367     5.063749
std      10.942770    10.210578    21.805031    71.059280     2.913471
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   210.000000     8.000000
max     114.000000    90.000000   483.000000   789.000000    10.000000
```

Check if there is any null values in dataset

[67]:
```
joined_df.isnull().values.any()
```

[67]:
```
True
```

Check which columns contained nulls

[50]:
```
joined_df.isnull().sum()
```

[50]:
```
Bedrooms        0
Bathrooms       2
Address         0
Land area       0
```

```
CV              0
Latitude        0
Longitude       0
SA1             0
0-19 years      0
20-29 years     0
30-39 years     0
40-49 years     0
50-59 years     0
60+ years       0
Suburbs         1
C18_CURPop      0
SA12018_code    0
NZDep2018       0
dtype: int64
```

Take a look at the rows with nulls

[309]:
```
null_rows = joined_df[joined_df.isnull().any(axis=1)]
null_rows
```

[309]:
```
     Bedrooms  Bathrooms                                          Address  \
309         4        NaN                  14 Hea Road Hobsonville, Auckland
311         4        NaN                  16 Hea Road Hobsonville, Auckland
568         1        1.0  14 Te Rangitawhiri Road Great Barrier Island, ...

     Land area       CV   Latitude   Longitude      SA1  0-19 years  \
309      214.0  1250000 -36.798371  174.647430  7002267          60
311      245.0  1100000 -36.798371  174.647430  7002267          60
568     2141.0   740000 -36.197282  175.416921  7001131          27

     20-29 years  30-39 years  40-49 years  50-59 years  60+ years  \
309           66           60           24           24         18
311           66           60           24           24         18
568            6            6           18           39         60

         Suburbs  C18_CURPop  NZDep2018
309  Hobsonville         252        2.0
311  Hobsonville         252        2.0
568          NaN         156        9.0
```

The SA1 is related to the suburb and we can look for rows with the same SA1, and use their suburb value for the missing value.

[310]:
```
joined_df.loc[joined_df['SA1'] == 7001131]
```

[310]:
```
     Bedrooms  Bathrooms                                          Address  \
568         1        1.0  14 Te Rangitawhiri Road Great Barrier Island, ...
569         5        3.0  349 Blind Bay Road Great Barrier Island, Auckland

     Land area      CV   Latitude   Longitude      SA1  0-19 years  \
```

```
568     2141.0  740000 -36.197282  175.416921  7001131          27
569     3953.0  920000 -36.257895  175.436448  7001131          27

     20-29 years  30-39 years  40-49 years  50-59 years  60+ years  \
568            6            6           18           39         60
569            6            6           18           39         60

                                Suburbs  C18_CURPop  NZDep2018
568                                 NaN         156        9.0
569  Great Barrier Island (Aotea Island)         156        9.0
```

[311]:
```
joined_df.at[568,'Suburbs'] = joined_df.iloc[569]['Suburbs']
```

[312]:
```
joined_df.loc[joined_df['SA1'] == 7001131]
```

[312]:
```
     Bedrooms  Bathrooms                                              Address  \
568         1        1.0  14 Te Rangitawhiri Road Great Barrier Island, ...
569         5        3.0  349 Blind Bay Road Great Barrier Island, Auckland

     Land area      CV   Latitude   Longitude      SA1  0-19 years  \
568     2141.0  740000 -36.197282  175.416921  7001131          27
569     3953.0  920000 -36.257895  175.436448  7001131          27

     20-29 years  30-39 years  40-49 years  50-59 years  60+ years  \
568            6            6           18           39         60
569            6            6           18           39         60

                                Suburbs  C18_CURPop  NZDep2018
568  Great Barrier Island (Aotea Island)         156        9.0
569  Great Barrier Island (Aotea Island)         156        9.0
```

To impute the missing bathroom values, the average bathroom for houses with 4 bedrooms was used.

[313]:
```
impute_val = round(joined_df.loc[joined_df['Bedrooms'] == 4]['Bathrooms'].
↪mean(),0)
```

[314]:
```
rep_ind = [309,311]

for i in range(len(rep_ind)):
    joined_df.at[rep_ind[i],'Bathrooms'] = impute_val
```

Check if there are any more missing values

[26]:
```
joined_df.isnull().values.any()
```

[26]:
```
False
```

2.2 2.2. Exploratory Analysis

Take a quick look at the mean, min, max and quartiles. Initially, there were 1051 observations in the dataset.

[316]:
```
joined_df.describe()
```

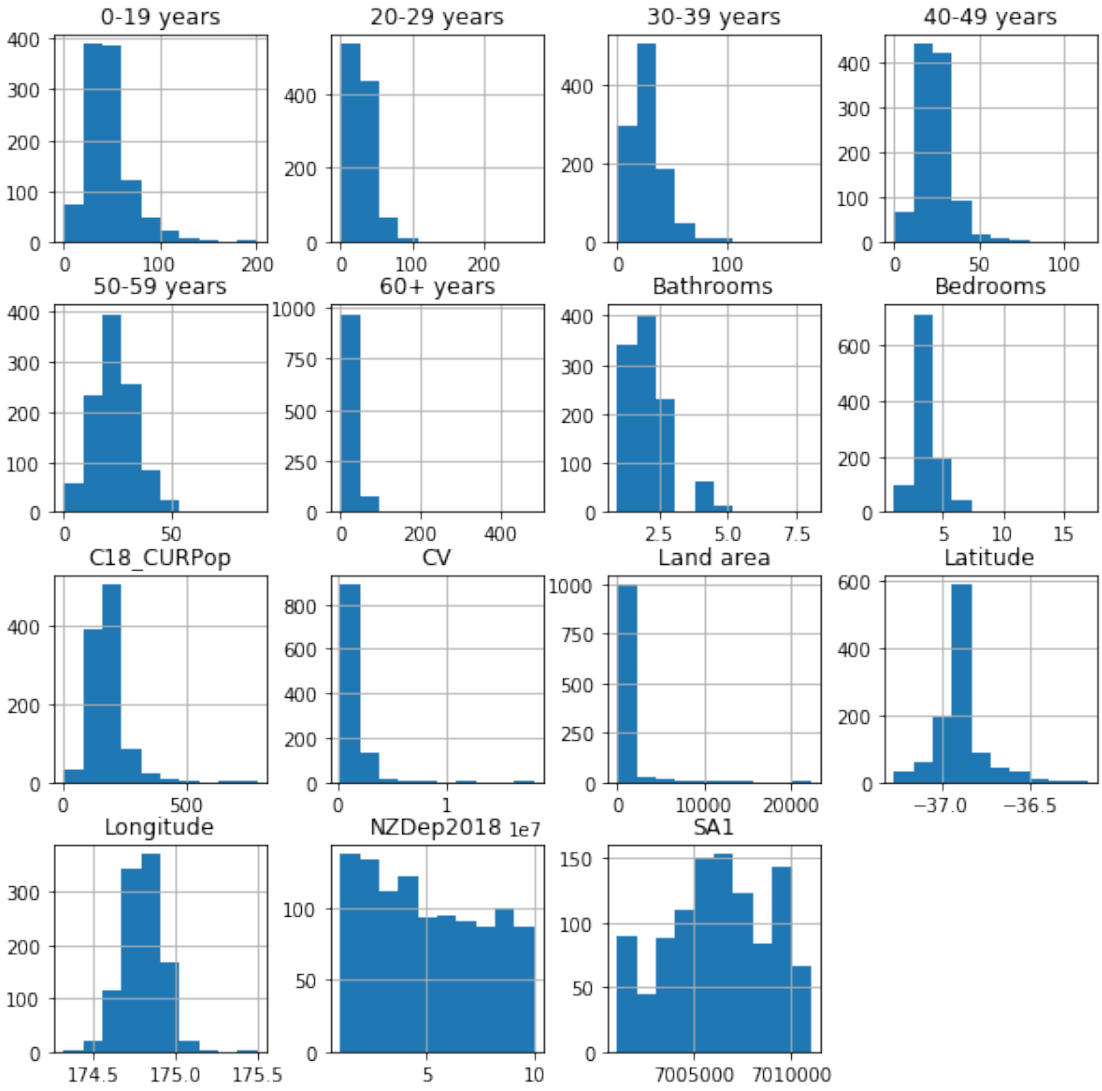
[316]:
```
          Bedrooms    Bathrooms     Land area            CV     Latitude  \
count  1051.000000  1051.000000   1051.000000  1.051000e+03  1051.000000
mean      3.777355     2.073264    856.989534  1.387521e+06   -36.893715
std       1.169412     0.992044   1588.156219  1.182939e+06     0.130100
min       1.000000     1.000000     40.000000  2.700000e+05   -37.265021
25%       3.000000     1.000000    321.000000  7.800000e+05   -36.950565
50%       4.000000     2.000000    571.000000  1.080000e+06   -36.893132
75%       4.000000     3.000000    825.000000  1.600000e+06   -36.855789
max      17.000000     8.000000  22240.000000  1.800000e+07   -36.177655

         Longitude           SA1   0-19 years  20-29 years  30-39 years  \
count  1051.000000  1.051000e+03  1051.000000  1051.000000  1051.000000
mean    174.799325  7.006319e+06    47.549001    28.963844    27.042816
std       0.119538  2.591262e+03    24.692205    21.037441    17.975408
min     174.317078  7.001130e+06     0.000000     0.000000     0.000000
25%     174.720779  7.004416e+06    33.000000    15.000000    15.000000
50%     174.798575  7.006325e+06    45.000000    24.000000    24.000000
75%     174.880944  7.008384e+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    NZDep2018
count  1051.000000  1051.000000  1051.000000  1051.000000  1051.000000
mean     24.125595    22.615604    29.360609   179.914367     5.063749
std      10.942770    10.210578    21.805031    71.059280     2.913471
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   210.000000     8.000000
max     114.000000    90.000000   483.000000   789.000000    10.000000
```

Take a look at the distribution of the numeric variables

[317]:
```
joined_df.hist(figsize=(10,10))
```

[317]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8afc080>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8a4aef0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8a76470>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad87dd9e8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8785f60>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad87ab1d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8752748>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad877acf8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fdad877ad30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad86d57f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad86f9d68>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad86ab320>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8651898>,
```

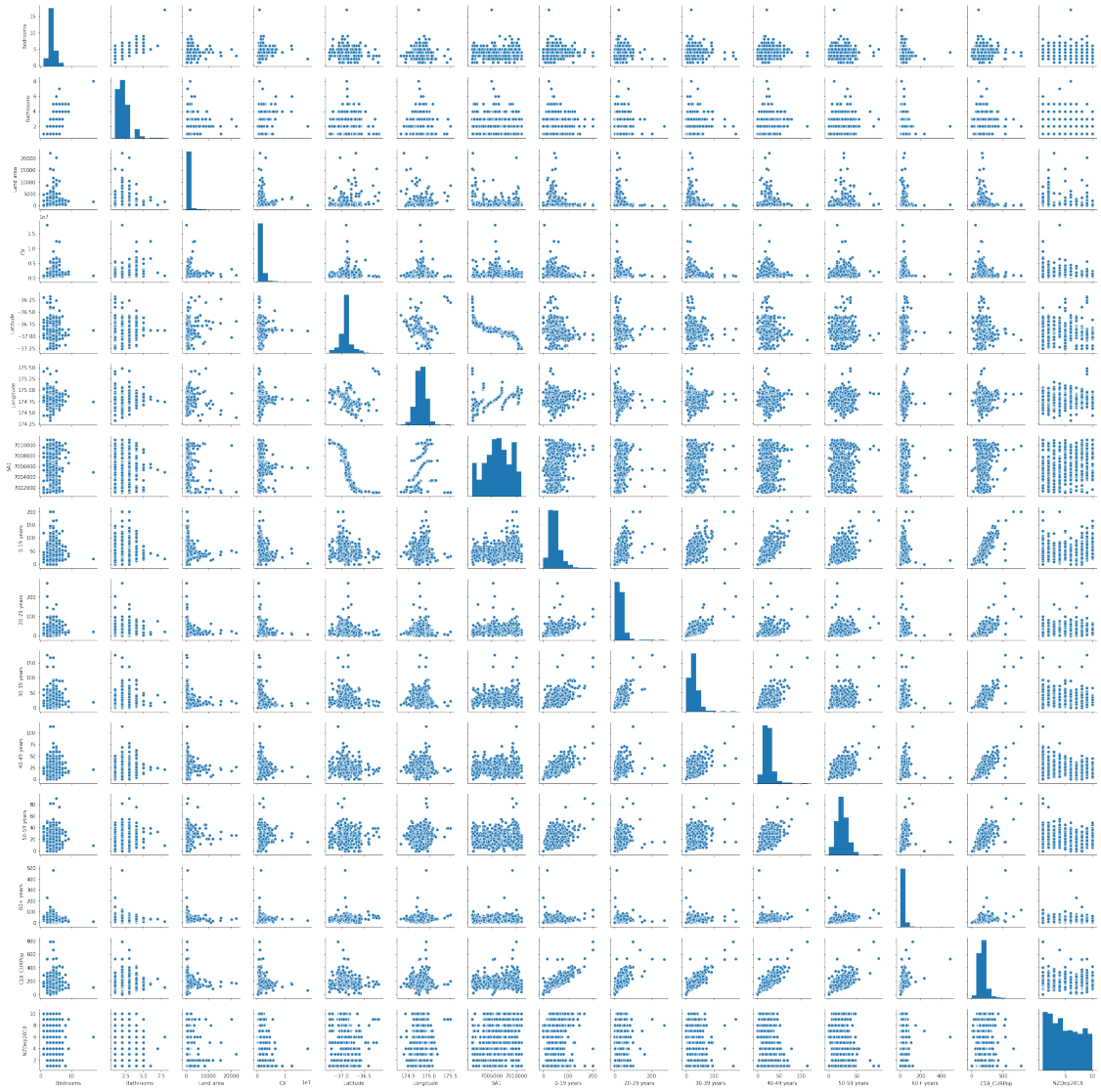
```
   <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad8679e10>,
   <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad83e93c8>,
   <matplotlib.axes._subplots.AxesSubplot object at 0x7fdad838f940>]],
dtype=object)
```



I noticed that many of the variables seem to be right skewed. This suggest that a log transform may be required in the model.

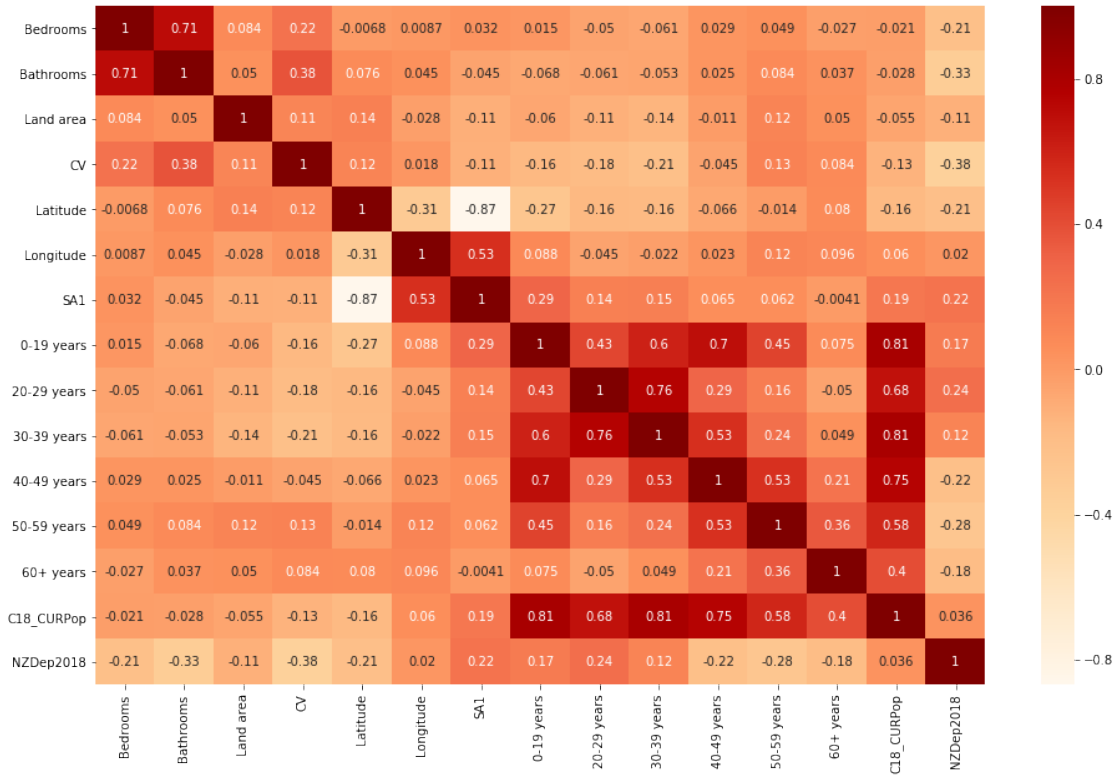
[319]:
```
sns.pairplot(joined_df, height = 2.0)
```

[319]:
```
<seaborn.axisgrid.PairGrid at 0x7fdad7e99f60>
```



From the pairs plot we notice that there may be an outlier in the bedrooms variables. Some variables are discrete. There doesn't seem to be any obvious relationships.

[320]:
```
ax, fig = plt.subplots(figsize=(16,10))
correlation_matrix = joined_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="OrRd")
plt.show()
```

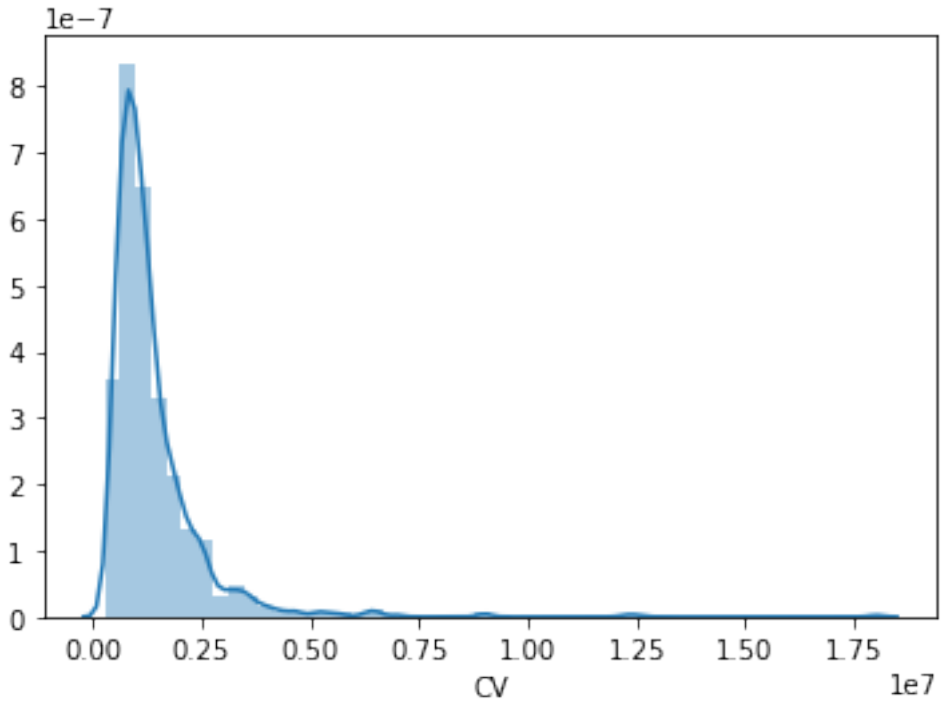


Looking at the CV row, there is not any significant correlations. Looking at the age group factors there is correlation between these factors, such as between 0-19 years and 40-49 years, this makes sense as they would be part of families.

[321]:
```
sns.distplot(joined_df['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
```

[321]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdb250bebe0>
```



Upon closer inspection of the capital value we notice that it is right skewed. Again, suggesting a log transformation is required.

2.3 2.3. Extra data cleaning

Remove the outlier for the bedrooms variables

[323]:
```
room_outlier = joined_df.index[joined_df['Bedrooms']==joined_df['Bedrooms'].
↪max()][0]
```

[324]:
```
joined_df = joined_df.drop([room_outlier])
```

[325]:
```
joined_df.describe()
```

[325]:
```
          Bedrooms    Bathrooms     Land area            CV     Latitude  \
count  1050.000000  1050.000000   1050.000000  1.050000e+03  1050.000000
mean      3.764762     2.067619    856.285714  1.388118e+06   -36.893724
std       1.096357     0.975486   1588.749029  1.183344e+06     0.130162
min       1.000000     1.000000     40.000000  2.700000e+05   -37.265021
25%       3.000000     1.000000    320.000000  7.800000e+05   -36.950644
50%       4.000000     2.000000    570.500000  1.080000e+06   -36.893250
75%       4.000000     3.000000    825.000000  1.600000e+06   -36.855781
max       9.000000     7.000000  22240.000000  1.800000e+07   -36.177655

         Longitude           SA1   0-19 years  20-29 years  30-39 years  \
count  1050.000000  1.050000e+03  1050.000000  1050.000000  1050.000000
mean    174.799383  7.006320e+06    47.574286    28.971429    27.051429
```

```
std       0.119581  2.592167e+03    24.690355    21.046028    17.981805
min     174.317078  7.001130e+06     0.000000     0.000000     0.000000
25%     174.720427  7.004415e+06    33.000000    15.000000    15.000000
50%     174.798612  7.006329e+06    45.000000    24.000000    24.000000
75%     174.880945  7.008384e+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    NZDep2018
count  1050.000000  1050.000000  1050.000000  1050.000000  1050.000000
mean     24.128571    22.628571    29.377143   179.980000     5.062857
std      10.947559    10.206782    21.808829    71.061263     2.914716
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   210.000000     8.000000
max     114.000000    90.000000   483.000000   789.000000    10.000000
```

[326]:
```
joined_df.head()
```

[326]:
```
   Bedrooms  Bathrooms                                    Address  Land area  \
0         5        3.0  106 Lawrence Crescent Hill Park, Auckland      714.0
1         5        3.0            8 Corsica Way Karaka, Auckland      564.0
2         6        4.0    243 Harbourside Drive Karaka, Auckland      626.0
3         2        1.0  2/30 Hardington Street Onehunga, Auckland       65.0
4         3        1.0    59 Israel Avenue Clover Park, Auckland      601.0

        CV   Latitude   Longitude      SA1  0-19 years  20-29 years  \
0   960000 -37.012920  174.904069  7009770          48           27
1  1250000 -37.063672  174.922912  7009991          42           18
2  1250000 -37.063580  174.924044  7009991          42           18
3   740000 -36.912996  174.787425  7007871          42            6
4   630000 -36.979037  174.892612  7008902          93           27

   30-39 years  40-49 years  50-59 years  60+ years      Suburbs  C18_CURPop  \
0           24           21           24         21     Manurewa         174
1           12           21           15         30       Karaka         129
2           12           21           15         30       Karaka         129
3           21           21           12         15     Onehunga         120
4           33           30           21         33  Clover Park         231

   NZDep2018
0        6.0
1        1.0
2        1.0
3        2.0
4        9.0
```

2.4 2.4. Modelling

[328]:
```
from sklearn.model_selection import train_test_split
```

Drop variables that are not numeric

[329]:
```
model_df = joined_df.drop(['Address','Suburbs'],axis=1)
```

[330]:
```
model_df.head()
```

[330]:
```
   Bedrooms  Bathrooms  Land area       CV   Latitude   Longitude      SA1  \
0         5        3.0      714.0   960000 -37.012920  174.904069  7009770
1         5        3.0      564.0  1250000 -37.063672  174.922912  7009991
2         6        4.0      626.0  1250000 -37.063580  174.924044  7009991
3         2        1.0       65.0   740000 -36.912996  174.787425  7007871
4         3        1.0      601.0   630000 -36.979037  174.892612  7008902

   0-19 years  20-29 years  30-39 years  40-49 years  50-59 years  60+ years  \
0          48           27           24           21           24         21
1          42           18           12           21           15         30
2          42           18           12           21           15         30
3          42            6           21           21           12         15
4          93           27           33           30           21         33

   C18_CURPop  NZDep2018
0         174        6.0
1         129        1.0
2         129        1.0
3         120        2.0
4         231        9.0
```

Create the model matrix (x) and response variable (y)

[331]:
```
x = model_df.drop(['CV'],axis=1)
```

[332]:
```
x.head()
```

[332]:
```
   Bedrooms  Bathrooms  Land area   Latitude   Longitude      SA1  0-19 years  \
0         5        3.0      714.0 -37.012920  174.904069  7009770          48
1         5        3.0      564.0 -37.063672  174.922912  7009991          42
2         6        4.0      626.0 -37.063580  174.924044  7009991          42
3         2        1.0       65.0 -36.912996  174.787425  7007871          42
4         3        1.0      601.0 -36.979037  174.892612  7008902          93

   20-29 years  30-39 years  40-49 years  50-59 years  60+ years  C18_CURPop  \
0           27           24           21           24         21         174
1           18           12           21           15         30         129
2           18           12           21           15         30         129
3            6           21           21           12         15         120
4           27           33           30           21         33         231

   NZDep2018
```

```
0        6.0
1        1.0
2        1.0
3        2.0
4        9.0
```

[335]:
```
y = model_df['CV']
```

Create the train and test datasets for linear regression

[336]:
```
train_x, test_x, train_y, test_y = train_test_split(x,y,test_size=0.
↪25,random_state=1)
```

[337]:
```
from sklearn.linear_model import LinearRegression
```

[338]:
```
model = LinearRegression()
```

[339]:
```
model.fit(train_x,train_y)
```

[339]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[340]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

[340]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

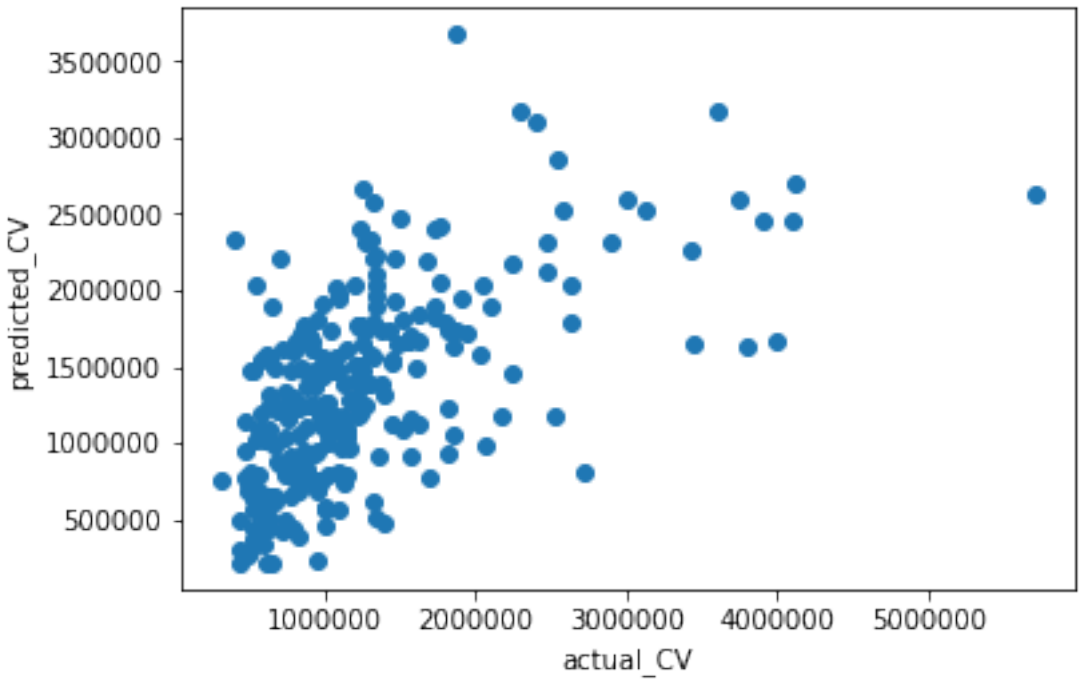
[341]:
```
model.coef_
```

[341]:
```
array([-9.24900774e+04,  4.52379335e+05,  4.98279516e+01, -9.54371954e+04,
        1.18917964e+05, -2.41761425e+01,  1.46021816e+04,  1.62194394e+04,
        1.19905572e+03,  2.96027501e+03,  2.32407690e+04,  1.34166052e+04,
       -1.32893585e+04, -1.06503249e+05])
```

[342]:
```
predicted = model.predict(test_x)
```

[343]:
```
plt.scatter(test_y,predicted)
plt.xlabel('actual_CV')
plt.ylabel('predicted_CV')
```

[343]:
```
Text(0, 0.5, 'predicted_CV')
```



[344]:
```
model.score(test_x,test_y)
```

[344]:
```
0.27805893870473297
```

The first model fitted is a simple linear regression. The resulting R^2 value was 27.8%. To improve the model, log transformations were used.

[345]:
```
log_y = np.log(y)
```

[346]:
```
train_x, test_x, train_y, test_y = train_test_split(x,log_y,test_size=0.
↪25,random_state=1)
```

[347]:
```
log_y_model = LinearRegression()
```

[348]:
```
log_y_model.fit(train_x,train_y)
```

[348]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[349]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

[349]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

[361]:
```
log_y_model.coef_
```

[361]:
```
array([ 4.57366277e-02,  1.48132049e-01,  2.26222618e-05,  2.93794834e-02,
       -9.58765294e-03, -1.38372420e-05,  1.11110704e-03,  4.11827656e-03,
       -2.67708592e-03,  2.45229959e-03,  8.10319281e-03,  3.31407162e-03,
       -2.70245068e-03, -7.05692788e-02])
```

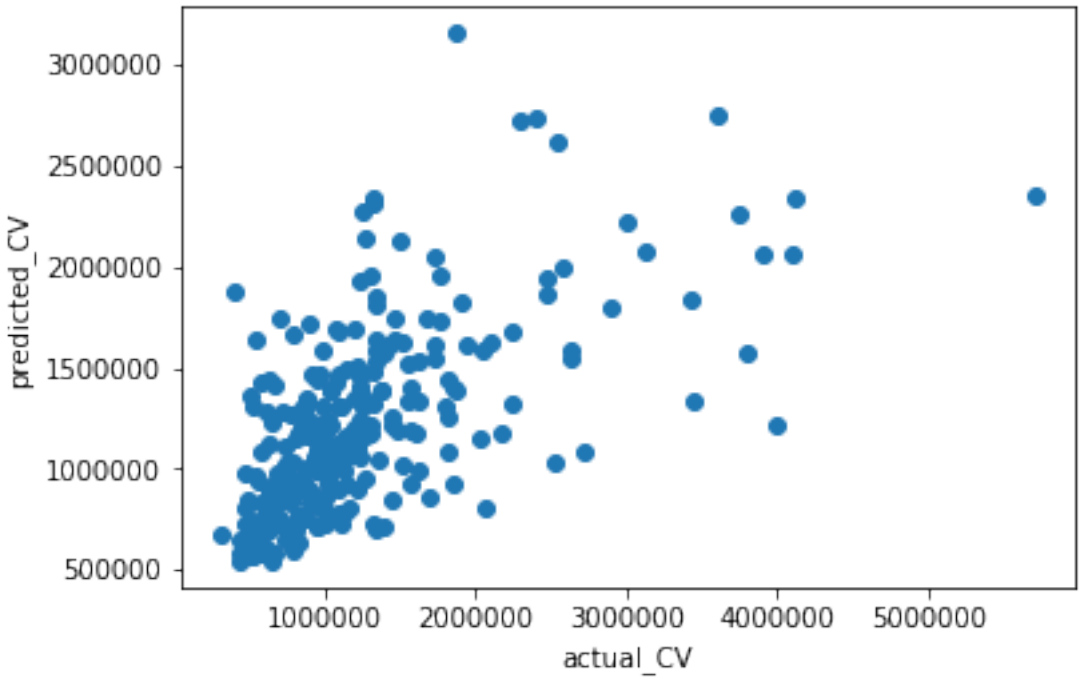
[350]:
```
log_y_model.score(test_x,test_y)
```

[350]:
```
0.4217693034562491
```

[351]:
```
predicted = log_y_model.predict(test_x)
```

[352]:
```
plt.scatter(np.exp(test_y),np.exp(predicted))
plt.xlabel('actual_CV')
plt.ylabel('predicted_CV')
```

[352]:
```
Text(0, 0.5, 'predicted_CV')
```



The second model fitted is a simple linear regression, with the response variable log transformed. The resulting R^2 value was 42.2%. To improve this model, the design matrix could also have been logged, however it may not make sense to log some of these variables so this was not attempted.

Instead of using simple linear regression, a random forest was used to improve the results.

[356]:
```
from sklearn.ensemble import RandomForestRegressor

regressor = RandomForestRegressor()
regressor.fit(train_x, train_y)
pred_y = regressor.predict(test_x)
```

```
/home/nbuser/anaconda3_501/lib/python3.6/site-
packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of
n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

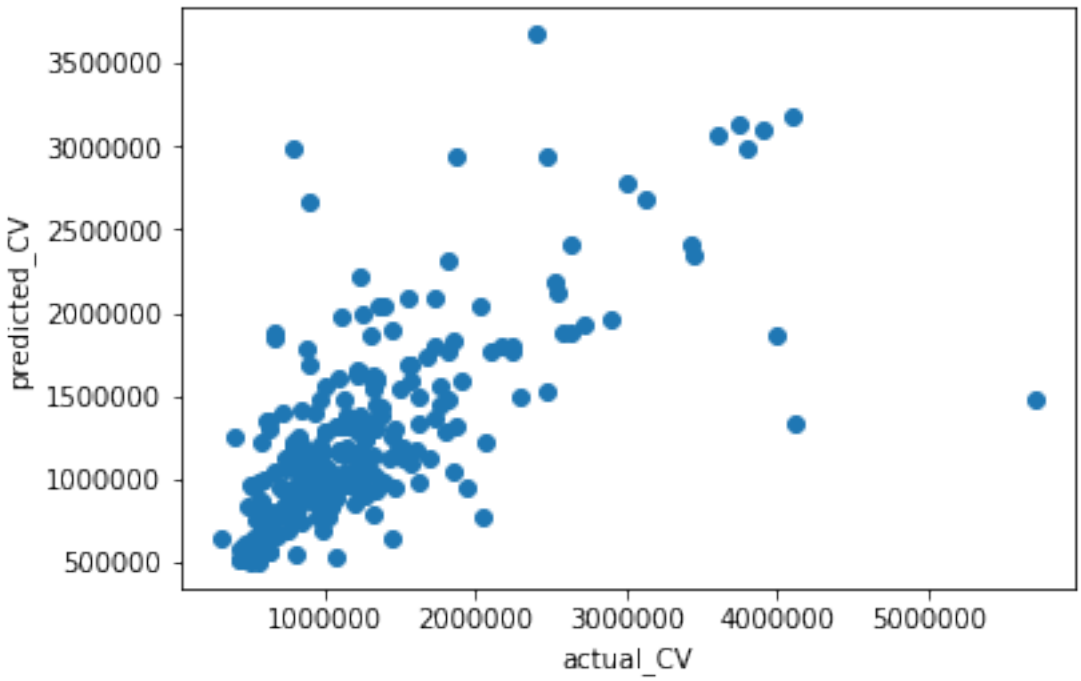
[357]:
```
regressor.score(test_x,test_y)
```

[357]:
```
0.5333180780790467
```

[358]:
```
predicted = regressor.predict(test_x)
```

[359]:
```
plt.scatter(np.exp(test_y),np.exp(predicted))
plt.xlabel('actual_CV')
plt.ylabel('predicted_CV')
```

[359]:
```
Text(0, 0.5, 'predicted_CV')
```



The random forest improved the prediction score to 53.3%. Other methods such as boosting could have been used.

2.5 2.5. Conclusion

- The best model achieve was a random forest model with a logged response variable. The prediction score was 53.3%.
- Improvements to the model:
- Further analysis into the individual varaibles would have improved the model. Such as taking log transformations or performing other types of transformations
- Using other regression methods such as regular trees, boosting or neural networks.
- Incorporate the non-numeric values into the model using methods such as encoding.
- Since the dataset is not too large, cross-validation could be used to help improve the accuracy of the train and test.