AucklandHousePrices

July 26, 2020

1 Auckland House Prices Analysis

Executive Summary The dataset is based in Auckland the objective to create a linear regression to prdict house price base on features in the data, which was provided in the MSA phase 1 data-science pathway. It contains all a variety of information regarding houses in Auckland along with price evaluation and land and bedroom information as well as longitude and latitude information. However, some information related to the population for housing was missing. So API call to a 2018 census dataset was conducted using longitude, latitude through a vector query and SA1 from the initial dataset for each house and a new column was inserted into the dataset. Additionally, the depression index was also added to the primary dataset using Otago researched-based dataset on house depression in Auckland.Finally, some data clean was completed; Nan values were replaced with estimates. Some of the data in the housing data set contained categorical data which required transformations for plotting visualisations. These were suburbs and address.

The analysis is based on 981 observations for each of the 17 variables. A correlation matrix was used initially to see if any of the 17 variables were related price CV (estimate of the house price) if they had a strong relationship.Before this, descriptive statistics was used initially to determine the spread of each variable. Additionally, outliers were removed with an interquartile range metric using land Area. Three correlated values were found; these were Bedrooms, Bathrooms, NZDep2018.Finally, a linear regression model was then fitted to predict CV base on these inputs.

[309]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import json
import sys
import pandas as pd
import requests
import time
%matplotlib inline
```

[311]:
```
#different suburbs effect prices bedrrom size of house land etc  givin a price␣
↪,surburbs, rooms predict the price
# using regression good anaylsis techiques using to determine
house_prices = pd.read_csv('DatasetforAssignment.csv')
#remove data types i.e  object to float
house_prices.head()
```

[311]:
```
   Bedrooms  Bathrooms                                    Address Land area  \
0         5        3.0  106 Lawrence Crescent Hill Park, Auckland       714
1         5        3.0              8 Corsica Way Karaka, Auckland       564
2         6        4.0      243 Harbourside Drive Karaka, Auckland       626
3         2        1.0  2/30 Hardington Street Onehunga, Auckland        65
4         3        1.0      59 Israel Avenue Clover Park, Auckland       601

        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
0           24           21           24         21     Manurewa
1           12           21           15         30       Karaka
2           12           21           15         30       Karaka
3           21           21           12         15     Onehunga
4           33           30           21         33  Clover Park
```

[313]:
```python
#remove convert colcumn to float and remove chars in text
house_prices['Land area'] = house_prices['Land area'].str.extract('(\d+)').
 ↪astype(float)
```

[315]:
```python
#load in the depresisation scores
dep_indexs = pd.read_excel('otago730395.xlsx')
dep_indexs.head()
```

[315]:
```
   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
```

[317]:
```python
#now we need to get make the requests from the API for population at Latitude␣
 ↪and Longitude
def get_pop_at_lat_long(long,lat):
    url = 'https://koordinates.com/services/query/v1/vector.json'
    #from nz cenius data
    layer_id = 104612
```

```
    params = {
        'key':'772a6ce37abd44a7a65fb8af6ad6ac28',
        'layer' : layer_id,
        'x':long,
        'y':lat,
        'format':'json'
    }
    response = requests.get(url,params = params)
    if(response.status_code != 200):
        return response.status_code
    return response.json()

# handles the reponse from the function above extracts relvatant information
def parse_response(input_json_response,sa1):
    layer_id = '104612'
    cencius_data =␣
↪input_json_response['vectorQuery']['layers'][layer_id]['features']
    for item in cencius_data:
        res_SA1 = item['properties']['SA12018_V1_00']
        if (int(res_SA1) == int(sa1) ):
            C18_CURPop = item['properties']['C18_CURPop']
            return {"SA12018_V1_00":int(sa1),"C18_CURPop":int(C18_CURPop)}
    return {"SA12018_V1_00":int(sa1),"C18_CURPop":None}

# used to get population value
def extract_population(long,lat,sa1):
    api_data_response = get_pop_at_lat_long(long,lat)
    population_value =  parse_response(api_data_response,sa1)
    return population_value["C18_CURPop"]

#extract the dep index from one dataframe ouput it SA1
def extract_depreciation(df_dep,sa1):
    # get row where sa1 has the same value
    row = df_dep.loc[df_dep['SA12018_code'] == sa1]
    return float(row['NZDep2018'])
```

[319]:
```
sample_house_prices['C18_CURPop'] = sample_house_prices.apply(lambda row :␣
↪extract_population(row['Longitude'],row['Latitude'],row['SA1']),axis = 1)
sample_house_prices.head()
```

[319]:
```
   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
```

[321]:
```python
#adding the depreciation  colcumn
sample_house_prices['NZDep2018'] = sample_house_prices.apply(lambda row :␣
 ↪extract_depreciation(dep_indexes,row['SA1']),axis = 1)
sample_house_prices.head()
```

[321]:
```
   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
```

Adding the two extra columns for houses price dataset

[323]:
```
house_prices['C18_CURPop'] = house_prices.apply(lambda row :␣
↪extract_population(row['Longitude'],row['Latitude'],row['SA1']),axis = 1)
```

[339]:
```
house_prices['NZDep2018'] = house_prices.apply(lambda row :␣
↪extract_depreciation(dep_indexes,row['SA1']),axis = 1)
```

[327]:
```
house_prices.head()
```

[327]:
```
   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
```

The above data frame imported contains a variety of information for houses in Auckland. An investigation is being conducted to determine if we can estimate houses prices based on information related house features. To determine the relevant features, we are going to perform some visualisations with the data frame to look for patterns.

[328]:
```
# check if any row has null value NEED to check for outliers
pd.isnull(house_prices[:]).any(axis=1)
nan_stuff = house_prices[house_prices.isnull().any(axis=1)]
```

```python
print(nan_stuff)
```

```
     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
```

[329]:
```python
#from this we found NaN values in the dataset two bathroom entrys and Suburb␣
↪entry
subs = house_prices[house_prices['Suburbs'] == 'Hobsonville']
print(subs)
```

```
     Bedrooms  Bathrooms                                Address  Land area  \
223         4        2.0  10 Eyton Kay Road Hobsonville, Auckland      161.0
309         4        NaN        14 Hea Road Hobsonville, Auckland      214.0
310         4        2.0        12 Hea Road Hobsonville, Auckland      191.0
311         4        NaN        16 Hea Road Hobsonville, Auckland      245.0
449         5        4.0     10 Mantis Lane Hobsonville, Auckland      336.0
460         4        2.0   12 Williams Road Hobsonville, Auckland      450.0
666         3        2.0     17 Kanuka Road Hobsonville, Auckland      259.0

          CV   Latitude   Longitude      SA1  0-19 years  20-29 years  \
223   860000 -36.795951  174.655930  7002301          51           36
309  1250000 -36.798371  174.647430  7002267          60           66
310   530000 -36.798371  174.647430  7002267          60           66
311  1100000 -36.798371  174.647430  7002267          60           66
449   545000 -36.801329  174.666149  7002304          33           30
460  1125000 -36.800550  174.645182  7002271          12           12
666   920000 -36.793782  174.660944  7002295          45           24

     30-39 years  40-49 years  50-59 years  60+ years      Suburbs  \
223           57           18            6         12  Hobsonville
```

```
309           60           24           24          18  Hobsonville
310           60           24           24          18  Hobsonville
311           60           24           24          18  Hobsonville
449           24           15           12          18  Hobsonville
460            9            6            9          75  Hobsonville
666           48           15            6          12  Hobsonville

     C18_CURPop  NZDep2018
223         174        1.0
309         252        2.0
310         252        2.0
311         252        2.0
449         135        4.0
460         129        7.0
666         147        2.0
```

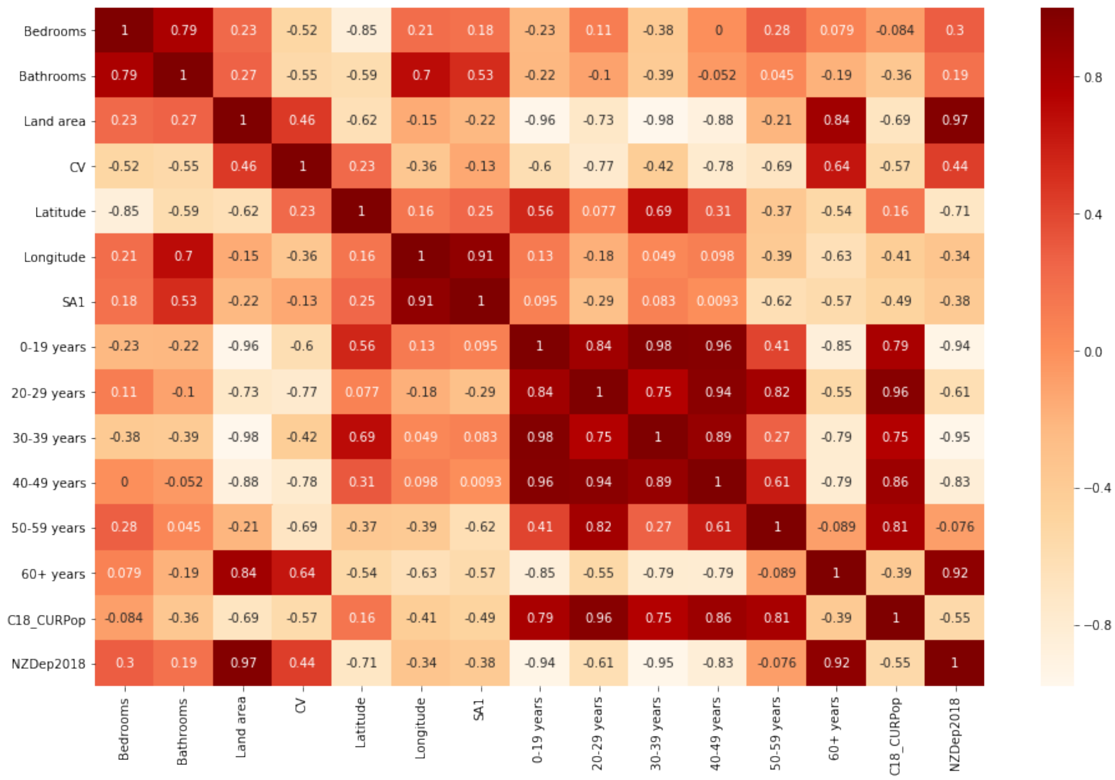
[330]:
```python
print(house_prices.dtypes)
```

```
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
```

[331]:
```python
speard_attributes = house_prices.describe()
```

[340]:
```python
subs_unclean = house_prices[house_prices['Suburbs'] == 'Hobsonville']
subs = subs_unclean.dropna()
```

[333]:
```python
#using the subs we will try to predict the nan value for bathrooms based on␣
 ↪similar houses in the suburbs  consider values of 0.5 and higher
ax, fig = plt.subplots(figsize= (16,10))
correlation_matrix = subs.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="OrRd")
plt.show()
```



From the correlation matrix above, we found some features related to CV they now used later for predicting them. These are a houses Bedrooms, Bathrooms and house depression index.

[334]:
```
#creating a linear regression model for Bathrooms
feature_names = ['Bedrooms','SA1','CV','Latitude','Longitude']
#contains the rows we need to predict to fill in.
input_for_predicting = subs_unclean[subs_unclean['Bathrooms'].isna()]
input_for_predicting
```

[334]:
```
     Bedrooms  Bathrooms                            Address  Land area  \
309         4        NaN  14 Hea Road Hobsonville, Auckland      214.0
311         4        NaN  16 Hea Road Hobsonville, Auckland      245.0

          CV   Latitude  Longitude      SA1  0-19 years  20-29 years  \
309  1250000 -36.798371  174.64743  7002267          60           66
311  1100000 -36.798371  174.64743  7002267          60           66

     30-39 years  40-49 years  50-59 years  60+ years      Suburbs  \
309           60           24           24         18  Hobsonville
311           60           24           24         18  Hobsonville

     C18_CURPop  NZDep2018
309         252        2.0
311         252        2.0
```

[335]:
```
#Machine learning model
#split into trainning set and test set for after trainning

from sklearn.model_selection import train_test_split
y = subs[['Bathrooms']]
x = subs[feature_names]
print(x)
print(y)
```

```
     Bedrooms      SA1       CV   Latitude   Longitude
223         4  7002301   860000 -36.795951  174.655930
310         4  7002267   530000 -36.798371  174.647430
449         5  7002304   545000 -36.801329  174.666149
460         4  7002271  1125000 -36.800550  174.645182
666         3  7002295   920000 -36.793782  174.660944
     Bathrooms
223        2.0
310        2.0
449        4.0
460        2.0
666        2.0
```

[336]:
```
# we have the input and output data ready now we can go about finding linear␣
↪regression model to predict bathroom subur
#import linear regression model for cont data
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

[337]:
```
model.fit(x,y)
```

[337]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[338]:
```
#determine model coefficents
model.coef_
```

[338]:
```
array([[ 8.06711279e-01, -3.49804349e-02,  5.87961799e-07,
        -3.46078799e+01,  1.26950090e+02]])
```

[341]:
```
# from nan row
x_input = input_for_predicting[feature_names]
predicted_bathrooms = model.predict(x_input)
```

[342]:
```
predicted_bathrooms = np.round(predicted_bathrooms) # round the float value
```

[343]:
```
house_prices.loc[house_prices['Bathrooms'].isnull(),'Bathrooms'] =␣
↪predicted_bathrooms
house_prices[house_prices['Suburbs'] == 'Hobsonville']
```

[343]:
```
     Bedrooms  Bathrooms                                  Address  Land area  \
223         4        2.0  10 Eyton Kay Road Hobsonville, Auckland      161.0
309         4        2.0        14 Hea Road Hobsonville, Auckland      214.0
310         4        2.0        12 Hea Road Hobsonville, Auckland      191.0
311         4        2.0        16 Hea Road Hobsonville, Auckland      245.0
449         5        4.0     10 Mantis Lane Hobsonville, Auckland      336.0
460         4        2.0   12 Williams Road Hobsonville, Auckland      450.0
666         3        2.0     17 Kanuka Road Hobsonville, Auckland      259.0

          CV   Latitude   Longitude      SA1  0-19 years  20-29 years  \
223   860000 -36.795951  174.655930  7002301          51           36
309  1250000 -36.798371  174.647430  7002267          60           66
310   530000 -36.798371  174.647430  7002267          60           66
311  1100000 -36.798371  174.647430  7002267          60           66
449   545000 -36.801329  174.666149  7002304          33           30
460  1125000 -36.800550  174.645182  7002271          12           12
666   920000 -36.793782  174.660944  7002295          45           24

     30-39 years  40-49 years  50-59 years  60+ years      Suburbs  \
223           57           18            6         12  Hobsonville
309           60           24           24         18  Hobsonville
310           60           24           24         18  Hobsonville
311           60           24           24         18  Hobsonville
449           24           15           12         18  Hobsonville
460            9            6            9         75  Hobsonville
666           48           15            6         12  Hobsonville

     C18_CURPop  NZDep2018
223         174        1.0
309         252        2.0
310         252        2.0
311         252        2.0
449         135        4.0
460         129        7.0
666         147        2.0
```

Once again we check if null value exists

[344]:
```
last_nan = house_prices[house_prices.isnull().any(axis=1)]
last_nan
```

[344]:
```
     Bedrooms  Bathrooms                                          Address  \
568         1        1.0  14 Te Rangitawhiri Road Great Barrier Island, ...

     Land area      CV   Latitude   Longitude      SA1  0-19 years  \
568     2141.0  740000 -36.197282  175.416921  7001131          27

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

```
     C18_CURPop  NZDep2018
568         156        9.0
```

it's only one entry so just check google maps and checked if in the subset of Surburbs

[345]:
```
# Great Barrier Island is the column so we just need to replace that entry.Used␣
↪a google search because it was only one entry and was catgolical
house_prices.loc[house_prices['Suburbs'].isnull(),'Suburbs'] = 'Great Barrier␣
↪Island (Aotea Island)'
```

[346]:
```
#complete with the nan completely clean from the dataset
house_prices.isnull().values.any()
```

[346]:
```
False
```

Now I will going to look at the spread of each column

[347]:
```
def Outlier_range(q1,q3):
    IQR = q3 - q1
    lower = q1 - 1.5 * IQR
    upper = q3 + 1.5 * IQR
    return [lower,upper]
```

[348]:
```
#encoding the suburbs as dictonary so that visulation libary's can plot the␣
↪surburbs column
labels = house_prices['Suburbs'].astype('category').cat.categories.tolist()
replace_map_comp = {'Suburbs' : {k: v for k,v in␣
↪zip(labels,list(range(1,len(labels)+1)))}}
replace_map_comp
```

[348]:
```
{'Suburbs': {'Albany Heights': 1,
  'Alfriston': 2,
  'Army Bay': 3,
  'Auckland Central': 4,
  'Avondale': 5,
  'Beach Haven': 6,
  'Beachlands': 7,
  'Belmont': 8,
  'Birkdale': 9,
  'Birkenhead': 10,
  'Blockhouse Bay': 11,
  'Bombay': 12,
  'Botany Downs': 13,
  'Browns Bay': 14,
  'Buckland': 15,
  'Bucklands Beach': 16,
  'Burswood': 17,
  'Campbells Bay': 18,
  'Chatswood': 19,
  'Clarks Beach': 20,
```

```
'Clendon Park': 21,
'Clover Park': 22,
'Cockle Bay': 23,
'Conifer Grove': 24,
'Dairy Flat': 25,
'Dannemora': 26,
'Drury': 27,
'East Tamaki': 28,
'East Tamaki Heights': 29,
'Eastern Beach': 30,
'Eden Terrace': 31,
'Ellerslie': 32,
'Epsom': 33,
'Farm Cove': 34,
'Favona': 35,
'Flat Bush': 36,
'Forrest Hill': 37,
'Freemans Bay': 38,
'Glen Eden': 39,
'Glen Innes': 40,
'Glendene': 41,
'Glendowie': 42,
'Glenfield': 43,
'Golflands': 44,
'Goodwood Heights': 45,
'Great Barrier Island (Aotea Island)': 46,
'Green Bay': 47,
'Greenlane': 48,
'Grey Lynn': 49,
'Gulf Harbour': 50,
'Half Moon Bay': 51,
'Hatfields Beach': 52,
'Helensville': 53,
'Henderson': 54,
'Herne Bay': 55,
'Highland Park': 56,
'Hillcrest': 57,
'Hillsborough': 58,
'Hobsonville': 59,
'Howick': 60,
'Huapai': 61,
'Huia': 62,
'Hunua': 63,
'Kaipara Flats': 64,
'Karaka': 65,
'Kawakawa Bay': 66,
'Kelston': 67,
```

```
'Kingsland': 68,
'Kohimarama': 69,
'Kumeu': 70,
'Laingholm': 71,
'Leigh': 72,
'Long Bay': 73,
'Lynfield': 74,
'Mangere': 75,
'Mangere Bridge': 76,
'Mangere East': 77,
'Manukau': 78,
'Manurewa': 79,
'Manurewa East': 80,
'Maraetai': 81,
'Massey': 82,
'Matakatia': 83,
'Mauku': 84,
'Meadowbank': 85,
'Mellons Bay': 86,
'Milford': 87,
'Mission Bay': 88,
'Morningside': 89,
'Mount Albert': 90,
'Mount Eden': 91,
'Mount Roskill': 92,
'Mount Wellington': 93,
'Murrays Bay': 94,
'Narrow Neck': 95,
'New Lynn': 96,
'New Windsor': 97,
'Northcote': 98,
'Okura': 99,
'Omiha': 100,
'One Tree Hill': 101,
'Onehunga': 102,
'Oneroa': 103,
'Onetangi': 104,
'Opaheke': 105,
'Orakei': 106,
'Orewa': 107,
'Ostend': 108,
'Otahuhu': 109,
'Otara': 110,
'Oteha': 111,
'Paerata': 112,
'Pahurehure': 113,
'Pakuranga': 114,
```

```
'Pakuranga Heights': 115,
'Palm Beach': 116,
'Panmure': 117,
'Papakura': 118,
'Papatoetoe': 119,
'Parakai': 120,
'Paremoremo': 121,
'Parnell': 122,
'Patumahoe': 123,
'Penrose': 124,
'Pinehill': 125,
'Pohuehue': 126,
'Point Chevalier': 127,
'Point England': 128,
'Pokeno': 129,
'Ponsonby': 130,
'Pukekohe': 131,
'Rakino Island': 132,
'Ramarama': 133,
'Randwick Park': 134,
'Ranui': 135,
'Red Beach': 136,
'Red Hill': 137,
'Redvale': 138,
'Remuera': 139,
'Rosehill': 140,
'Rothesay Bay': 141,
'Royal Oak': 142,
'Saint Johns': 143,
'Saint Marys Bay': 144,
'Sandringham': 145,
'Schnapper Rock': 146,
'Silverdale': 147,
'Snells Beach': 148,
'Somerville': 149,
'South Head': 150,
'St Heliers': 151,
'Stanmore Bay': 152,
'Stonefields': 153,
'Sunnyhills': 154,
'Sunnyvale': 155,
'Surfdale': 156,
'Swanson': 157,
'Takanini': 158,
'Te Atatu Peninsula': 159,
'Te Atatu South': 160,
'The Gardens': 161,
```

```
 'Three Kings': 162,
 'Tindalls Beach': 163,
 'Titirangi': 164,
 'Torbay': 165,
 'Totara Heights': 166,
 'Totara Park': 167,
 'Totara Vale': 168,
 'Tuakau': 169,
 'Unsworth Heights': 170,
 'Wade Heads': 171,
 'Wai O Taiki Bay': 172,
 'Waiheke Island': 173,
 'Waimauku': 174,
 'Wainui': 175,
 'Waitakere': 176,
 'Waitoki': 177,
 'Waiuku': 178,
 'Warkworth': 179,
 'Waterview': 180,
 'Wattle Downs': 181,
 'Wellsford': 182,
 'Wesley': 183,
 'West Harbour': 184,
 'Westmere': 185,
 'Weymouth': 186,
 'Whenuapai': 187,
 'Windsor Park': 188,
 'Wiri': 189}}
```

[349]:
```
#making a copy to modify the suburbs data directly
house_prices_replace = house_prices.copy()
```

[350]:
```
#replace the numeric values in dataframe for suburbs
house_prices_replace.replace(replace_map_comp, inplace=True)
```

[351]:
```
house_prices_replace.dtypes
```

[351]:
```
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          int64
C18_CURPop       int64
NZDep2018      float64
dtype: object
```

[352]:
```
#droping the address column because suburbs can act as more generic input for
 ↪our model
house_prices_replace.drop(['Address'],axis=1).head()
```

[352]:
```
   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

   Suburbs  C18_CURPop  NZDep2018
0       79         174        6.0
1       65         129        1.0
2       65         129        1.0
3      102         120        2.0
4       22         231        9.0
```

[353]:
```
stats_house_prices_replace= house_prices_replace.describe()
stats_house_prices_replace
house_prices_replace.shape
house_prices_replace.describe()
```

[353]:
```
          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      Suburbs   C18_CURPop  \
count  1051.000000  1051.000000  1051.000000  1051.000000  1051.000000
mean     24.125595    22.615604    29.360609    94.834443   179.914367
std      10.942770    10.210578    21.805031    50.446475    71.059280
min       0.000000     0.000000     0.000000     1.000000     3.000000
25%      18.000000    15.000000    18.000000    54.000000   138.000000
50%      24.000000    21.000000    27.000000    93.000000   174.000000
75%      30.000000    27.000000    36.000000   139.000000   210.000000
max     114.000000    90.000000   483.000000   189.000000   789.000000

         NZDep2018
count  1051.000000
mean      5.063749
std       2.913471
min       1.000000
25%       2.000000
50%       5.000000
75%       8.000000
max      10.000000
```

Initial Data Exploration The initial exploration of the data began with the collecting of current population value through an API then merging the existing data frame and combining with depreciation index of houses. Then NAN values in the dataset were replaced with estimates. Finally along with converting a suburbs column into category variable. The descriptive statistics summary was used to calculate outliers. This then reduced the number of rows to 1051—shown bellow with an interquartile estimate.

[354]:
```
#removing outliers from Land Area CV these should also remove the houses rows␣
 ↪larger amounts bedrooms
q1 = stats_house_prices_replace['Land area'].loc['25%']
q3 = stats_house_prices_replace['Land area'].loc['75%']
outrang = Outlier_range(q1,q3)
print(outrang)
house_prices_replace = house_prices_replace[house_prices_replace['Land area'] < ␣
 ↪outrang[1]] # check if outside the outer range
```

```
[-435.0, 1581.0]
```

[355]:
```
house_prices_replace.describe()
```

[355]:

```
          Bedrooms   Bathrooms    Land area            CV    Latitude  \
count   981.000000  981.000000   981.000000  9.810000e+02  981.000000
mean      3.733945    2.047910   560.669725  1.326148e+06  -36.896886
std       1.053449    0.955515   334.873663  1.003560e+06    0.120351
min       1.000000    1.000000    40.000000  2.700000e+05  -37.265021
25%       3.000000    1.000000   304.000000  7.700000e+05  -36.949429
50%       4.000000    2.000000   536.000000  1.050000e+06  -36.894835
75%       4.000000    3.000000   763.000000  1.550000e+06  -36.857091
max       8.000000    7.000000  1573.000000  1.800000e+07  -36.298627

         Longitude           SA1  0-19 years  20-29 years  30-39 years  \
count   981.000000  9.810000e+02  981.000000   981.000000   981.000000
mean    174.797593  7.006361e+06   47.828746    29.483180    27.623853
std       0.107924  2.538859e+03   25.147103    21.451249    18.260256
min     174.433162  7.001158e+06    0.000000     0.000000     0.000000
25%     174.723850  7.004537e+06   33.000000    18.000000    15.000000
50%     174.797892  7.006334e+06   45.000000    27.000000    24.000000
75%     174.879070  7.008379e+06   57.000000    36.000000    36.000000
max     175.187565  7.011028e+06  201.000000   270.000000   177.000000

        40-49 years  50-59 years  60+ years     Suburbs  C18_CURPop  \
count    981.000000   981.000000  981.000000  981.000000  981.000000
mean      24.024465    22.244648   28.993884   94.107034  180.458716
std       11.017677    10.016175   22.196662   50.093645   72.527219
min        0.000000     0.000000    0.000000    3.000000    3.000000
25%       18.000000    15.000000   18.000000   54.000000  138.000000
50%       24.000000    21.000000   27.000000   92.000000  174.000000
75%       30.000000    27.000000   36.000000  139.000000  210.000000
max      114.000000    90.000000  483.000000  189.000000  789.000000

         NZDep2018
count   981.000000
mean      5.160041
std       2.897549
min       1.000000
25%       3.000000
50%       5.000000
75%       8.000000
max      10.000000
```

[356]:

```python
house_prices_replace.shape
# removed some of rows which outliers
```

[356]: (981, 17)

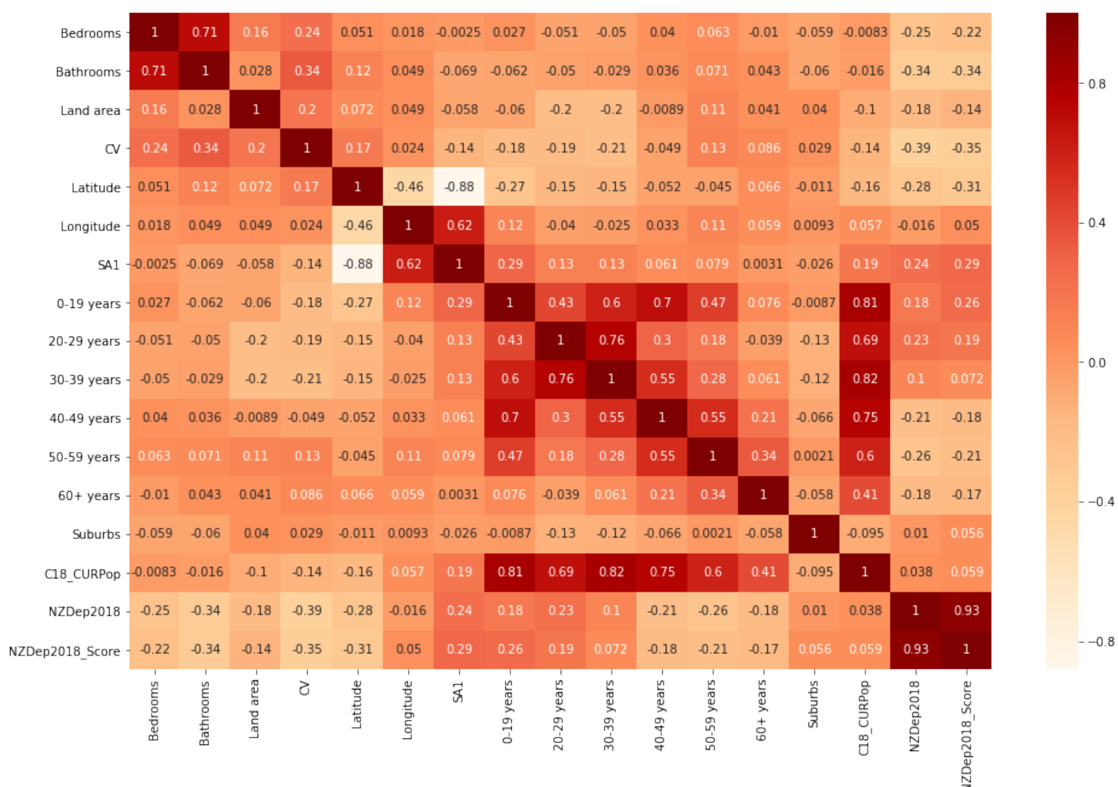
Their exists a continuous version of NZDEP index otago datatset so adding it to house_prices datatset see if releationship could be found.

[358]:
```python
def continuous_extract_depreciation(df_dep,sa1):
    # get row where sa1 has the same value
    row = df_dep.loc[df_dep['SA12018_code'] == sa1]
    return float(row['NZDep2018_Score'])
```

[359]:
```python
house_prices_replace['NZDep2018_Score'] = house_prices_replace.apply(lambda row :
↪ continuous_extract_depreciation(dep_indexs,row['SA1']),axis = 1)
```

Correlation and Relationships Numeric Relationships The correlation between the numeric columns was calculated and observed in the below correlation plot. (The right colour bar indicated the correlation values. For example, the dark red means correlation value is 1, and pale yellow means correlation value is negative 1.) The graph shows that Bedrooms, Bathrooms and NZDep2018 correlate with CV.

[360]:
```python
# check the collrection matrix now  added the continous depression
ax, fig = plt.subplots(figsize= (16,10))
correlation_matrix = house_prices_replace.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="OrRd")
plt.show()
```

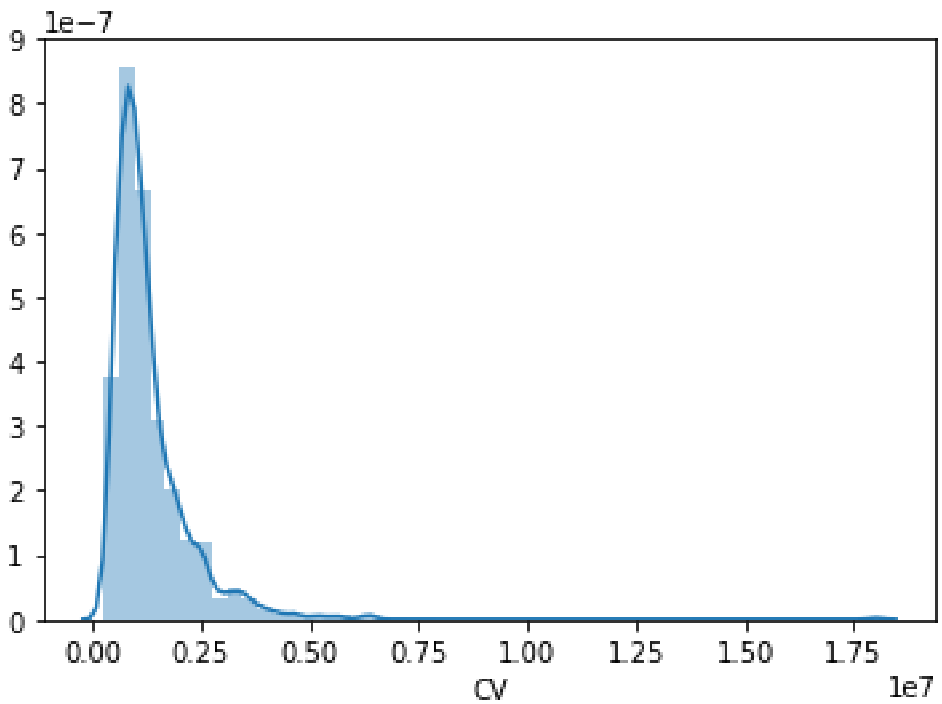


Bellow using the correlation matrix for CV visulations for, releated variables were created and analyzed.

[361]:
```python
sns.distplot(house_prices_replace['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
```

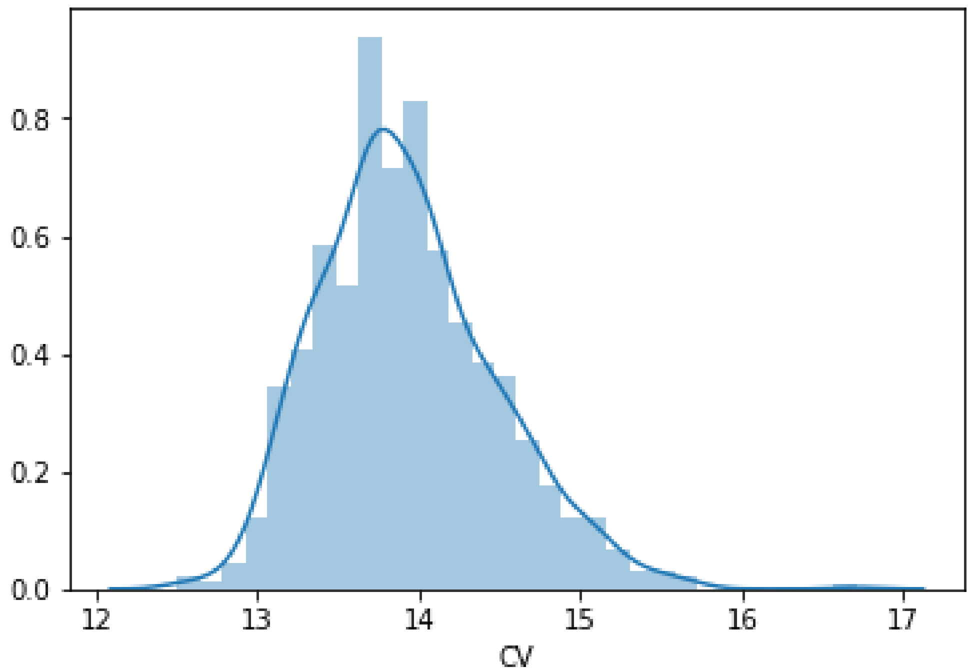
[361]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3c7e3037b8>
```



Price of the house is right-skewed, so log transformation was applied resulting in more normally distributed data

[362]:
```
sns.distplot(np.log(house_prices_replace['CV']))
```

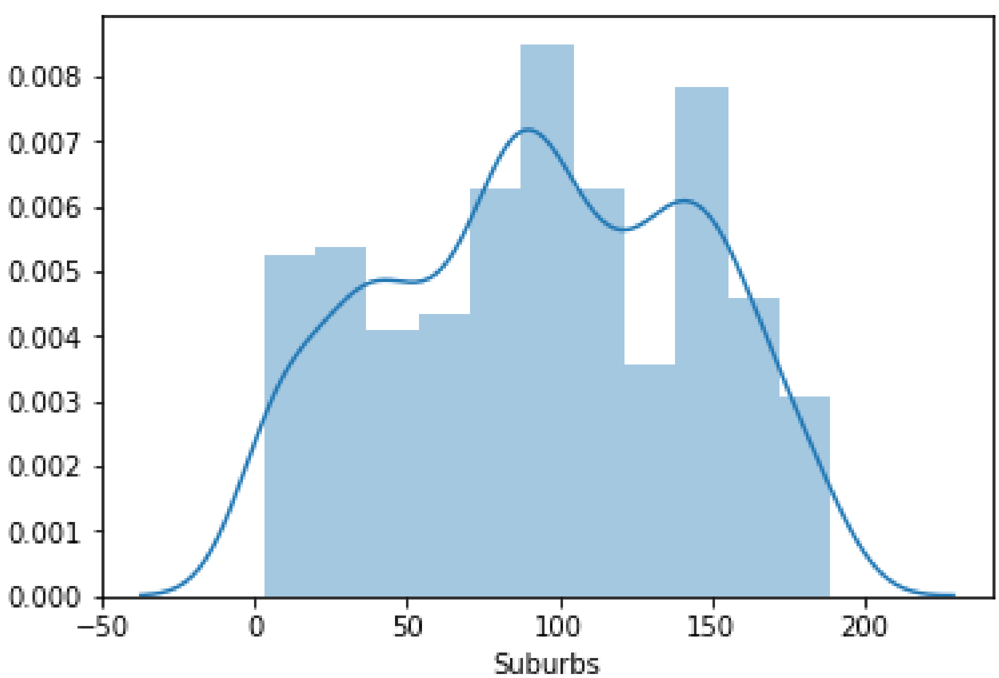
[362]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3c7eb02470>
```



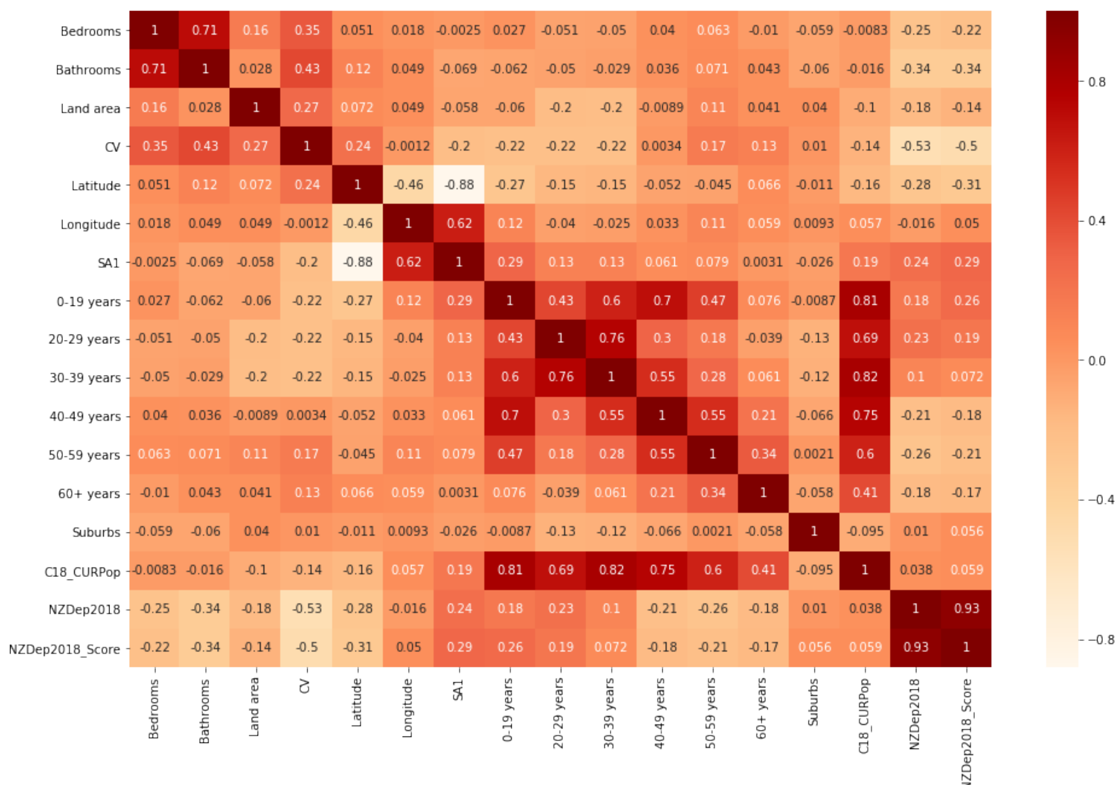
[363]:
```
# now the price is in log form
house_prices_replace['CV'] = house_prices_replace['CV'].apply(np.log)
```

[364]:
```
sns.distplot(house_prices_replace['Suburbs'])
```

[364]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3c7cbae400>
```



[365]:
```
# check the collrection matrix now  added the continous depression
ax, fig = plt.subplots(figsize= (16,10))
correlation_matrix = house_prices_replace.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="OrRd")
plt.show()
```



The above correlation matrix indicates CV is related negatively with NZDep index value and positively associated with Bathroom area, hinting at the higher number of bathrooms in the house, the higher it estimated cost. So we will now develop the linear regression model for CV based on NZDep index bedrooms, Bathrooms. Note that the output of CV is log form, so when using the linear model for predications, it required to exp the output to get house price.

Analysis

In this analysis, Linear regression was tested. These algorithms were trained with 40% of the data. Testing the model with the remaining 60% of the data yielded the following results:

[366]:
```
#define the inputs x contains NZDep2018 data along with Bathroom data
#define y out data being log of CV
x =  house_prices_replace[['Bedrooms','Bathrooms','NZDep2018']]
y =  house_prices_replace['CV']
#dealing with 981 data points per column
len(x)
```

[366]: 981

[367]:
```
#splicting the data into training and predicting batchs
train_x , test_x, train_y, test_y = train_test_split(x,y,test_size = 0.4,␣
↪random_state=42)
```

[368]:
```
#define a new regression linear model
model_CV = LinearRegression()
```

[369]:
```
model_CV.fit(train_x,train_y)
```

[369]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

[370]:
```
#determine model coeffcents
model_CV.coef_
```

[370]:
```
array([ 0.02176466,  0.15031556, -0.08151677])
```

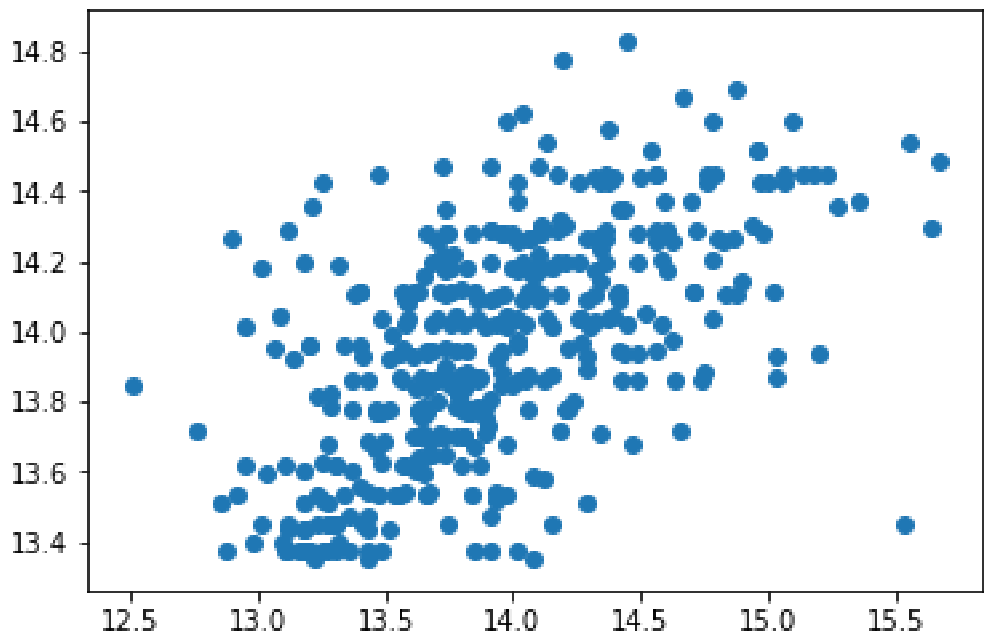
[372]:
```
predicted = model_CV.predict(test_x)
```

Analysis The decision for the model chosen, process and results

Conclusion This analysis has shown that the (house price) in log scale prediction can not be confidently predicted from it's a number of Bedrooms, Bathrooms and property depreciation index. The accuracy rate is 33% which bellow 50 % and scatter plot has revealed house price doesn't follow a linear trend there might need to be some additional work need with cleaning the input into the model or transformations need on the inputs.

[373]:
```
plt.scatter(test_y,predicted)
```

[373]:
```
<matplotlib.collections.PathCollection at 0x7f3c6abc6898>
```



[374]:
```
model_CV.score(test_x,test_y)
```

[374]: 0.33913597501995824

The model above give a score of 0.34. which similar to corrlated values in correlation matrix.However from looking at the scatter plot it looks like data is very sparce it indicates it more cleaning would need to be done with input into the model.