California Housig Price Prediction

July 15, 2020

0.1 California Housing Price Prediction Project

0.1.1 Part A: Predict housing prices using all feature variables

1. Import Necessary libraries to use

[1]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection  import train_test_split
```

2. Read housing data from Excel file and inspect the data and datatypes

[2]:
```
df_California_housing_data = pd.read_excel("California_housing_data.xlsx")
df_California_housing_data.head()
```

[2]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income ocean_proximity  median_house_value
0         322         126         8.3252        NEAR BAY              452600
1        2401        1138         8.3014        NEAR BAY              358500
2         496         177         7.2574        NEAR BAY              352100
3         558         219         5.6431        NEAR BAY              341300
4         565         259         3.8462        NEAR BAY              342200
```

[3]:
```
df_California_housing_data.dtypes
```

[3]:
```
longitude             float64
latitude              float64
housing_median_age      int64
total_rooms             int64
total_bedrooms        float64
population              int64
```

```
households              int64
median_income         float64
ocean_proximity        object
median_house_value      int64
dtype: object
```

3. From above we got to know that only ocean_proximity is non-numeric column, lets replace it with numeric values in step 6.

4. Standardize the target and fill missing values with mean of respective columns.

[4]:
```
df_California_housing_data["median_house_value"] = np.
↪log(df_California_housing_data["median_house_value"])
```

[5]:
```
#Check for ROWS with MISSING VALUES
df_California_housing_data[df_California_housing_data.isnull().any(axis=1)]
```

[5]:
```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
290      -122.16     37.77                  47         1256             NaN
341      -122.17     37.75                  38          992             NaN
538      -122.28     37.78                  29         5154             NaN
563      -122.24     37.75                  45          891             NaN
696      -122.10     37.69                  41          746             NaN
…            …         …                   …           …               …
20267    -119.19     34.20                  18         3620             NaN
20268    -119.18     34.19                  19         2393             NaN
20372    -118.88     34.17                  15         4260             NaN
20460    -118.75     34.29                  17         5512             NaN
20484    -118.72     34.28                  17         3051             NaN

       population  households  median_income ocean_proximity  \
290           570         218         4.3750        NEAR BAY
341           732         259         1.6196        NEAR BAY
538          3741        1273         2.5762        NEAR BAY
563           384         146         4.9489        NEAR BAY
696           387         161         3.9063        NEAR BAY
…             …           …             …              …
20267        3171         779         3.3409      NEAR OCEAN
20268        1938         762         1.6953      NEAR OCEAN
20372        1701         669         5.1033       <1H OCEAN
20460        2734         814         6.6073       <1H OCEAN
20484        1705         495         5.7376       <1H OCEAN

       median_house_value
290             11.994734
341             11.351582
```

```
538             12.063356
563             12.417548
696             12.091783
…                   …
20267           12.303653
20268           12.028141
20372           12.925618
20460           12.461102
20484           12.294999

[207 rows x 10 columns]
```

[6]:
```
#From above observation total_bedrooms column has missing values so replace it␣
↪with mean of total_bedrooms.
df_California_housing_data["total_bedrooms"] =␣
↪df_California_housing_data["total_bedrooms"].replace(np.
↪nan,df_California_housing_data["total_bedrooms"].mean())
```

[7]:
```
#Checking again if any missing values exists for other columns other than␣
↪total_bedrooms
df_California_housing_data[df_California_housing_data.isnull().any(axis=1)]
```

[7]:
```
Empty DataFrame
Columns: [longitude, latitude, housing_median_age, total_rooms, total_bedrooms,
population, households, median_income, ocean_proximity, median_house_value]
Index: []
```

5. Check the total categories available for non-numeric categorical column, "ocean_proximity".

[8]:
```
df_California_housing_data.groupby('ocean_proximity').describe()
```

[8]:
```
                longitude                                                   \
                    count        mean       std     min     25%      50%
ocean_proximity
<1H OCEAN          9136.0 -118.847766  1.588888 -124.14 -118.50 -118.275
INLAND             6551.0 -119.732990  1.900950 -123.73 -121.35 -120.000
ISLAND                5.0 -118.354000  0.070569 -118.48 -118.33 -118.320
NEAR BAY           2290.0 -122.260694  0.147004 -122.59 -122.41 -122.250
NEAR OCEAN         2658.0 -119.332555  2.327307 -124.35 -122.02 -118.260

                                  latitude             … median_income  \
                     75%     max     count       mean  …           75%
ocean_proximity                                        …
<1H OCEAN       -118.0000 -116.62   9136.0  34.560577  …      5.180500
INLAND          -117.8400 -114.31   6551.0  36.731829  …      3.961500
ISLAND          -118.3200 -118.32      5.0  33.358000  …      2.833300
```

```
NEAR BAY        -122.1400 -122.01    2290.0  37.801057  …       5.054425
NEAR OCEAN      -117.1825 -116.97    2658.0  34.738439  …       4.837400

                         median_house_value                                  \
                    max               count        mean        std         min
ocean_proximity
<1H OCEAN         15.0001            9136.0   12.296695   0.429593    9.769956
INLAND            15.0001            6551.0   11.610977   0.482824    9.615739
ISLAND             3.3906               5.0   12.829966   0.221861   12.568978
NEAR BAY          15.0001            2290.0   12.345131   0.507030   10.021271
NEAR OCEAN        15.0001            2658.0   12.299245   0.521518   10.021271


                      25%         50%         75%         max
ocean_proximity
<1H OCEAN         12.008231   12.277695   12.574528   13.122365
INLAND            11.258033   11.594505   11.911366   13.122365
ISLAND            12.611538   12.935311   13.017003   13.017003
NEAR BAY          11.998433   12.362221   12.753327   13.122365
NEAR OCEAN        11.918391   12.343440   12.684633   13.122365

[5 rows x 72 columns]
```

6. There is one categorical column called ocean_proximity with 5 categories. Replace categorical column with integer values and view the modified dataframe.

[9]:
```python
cleanup_cats  = {"ocean_proximity":     {"<1H OCEAN": 1, "INLAND": 2, "ISLAND":
 ↪3,"NEAR BAY":4, "NEAR OCEAN":5 }}
df_California_housing_data.replace(cleanup_cats, inplace=True)
df_California_housing_data.head()
```

[9]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income  ocean_proximity  median_house_value
0         322         126         8.3252                4           13.022764
1        2401        1138         8.3014                4           12.789684
2         496         177         7.2574                4           12.771671
3         558         219         5.6431                4           12.740517
4         565         259         3.8462                4           12.743151
```

7. Split features and target variables in to X_features and Y_target

[10]:
```
X_features = df_California_housing_data.iloc[:,:-1]
Y_target = df_California_housing_data.iloc[:,-1:]
```

8. View Features dataset and shape of the dataframe

[11]:
```
X_features.head()
```

[11]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880           129.0
1    -122.22     37.86                  21         7099          1106.0
2    -122.24     37.85                  52         1467           190.0
3    -122.25     37.85                  52         1274           235.0
4    -122.25     37.85                  52         1627           280.0

   population  households  median_income  ocean_proximity
0         322         126         8.3252                4
1        2401        1138         8.3014                4
2         496         177         7.2574                4
3         558         219         5.6431                4
4         565         259         3.8462                4
```

[12]:
```
X_features.shape
```

[12]: (20640, 9)

9. View Target dataset

[13]:
```
Y_target.head()
```

[13]:
```
   median_house_value
0           13.022764
1           12.789684
2           12.771671
3           12.740517
4           12.743151
```

[14]:
```
Y_target.shape
```

[14]: (20640, 1)

10. Split the original dataset in to training and test datasets with 80% training and 20% test dataset

[15]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X_features,␣
↪Y_target,test_size=0.2, random_state = 1)
```

11. view the shape of splitted train and test datasets

```
[16]: X_train.shape,X_test.shape, Y_train.shape, Y_test.shape
```

```
[16]: ((16512, 9), (4128, 9), (16512, 1), (4128, 1))
```

12: Create a model to predict the housing prices outcome

```
[17]: linreg = LinearRegression()
      linreg.fit(X_train, Y_train)
```

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

```
[18]: #Print the intercept and coefficients
      linreg.coef_, linreg.intercept_
```

```
[18]: (array([[-2.83742511e-01, -2.85020462e-01,  3.30446057e-03,
               -2.55046046e-05,  3.82669160e-04, -1.75730920e-04,
                3.29035909e-04,  1.76792041e-01, -1.14211075e-02]]),
       array([-12.49089022]))
```

13. Predict the House Price from our trained model

```
[19]: #Predict the outcome for the testing dataset
      Y_pred = linreg.predict(X_test)
      Y_pred
```

```
[19]: array([[12.27225661],
             [11.52356751],
             [12.28176997],
             …,
             [12.4349876 ],
             [12.30948071],
             [11.77940924]])
```

14: Calculate the Mean Square Error (MSE)

```
[20]: #Import required libraries for calculating root MSE (mean square error)
      from sklearn import metrics
```

```
[21]: #root mean squared error calculation:
      rmse = np.sqrt(metrics.mean_squared_error(Y_test,Y_pred))
      rmse
```

```
[21]: 0.34835878102223805
```

[22]:
```
#taking exponent to get correct values as we normalized the prices using log
print(np.exp(Y_test.values[0]),np.exp(Y_pred[0]))
print(np.exp(Y_test.values[10]),np.exp(Y_pred[10]))
print(np.exp(Y_test.values[4101]),np.exp(Y_pred[4101]))
```

```
[355000.] [213684.64980857]
[293800.] [201067.31760443]
[324700.] [335781.23144686]
```

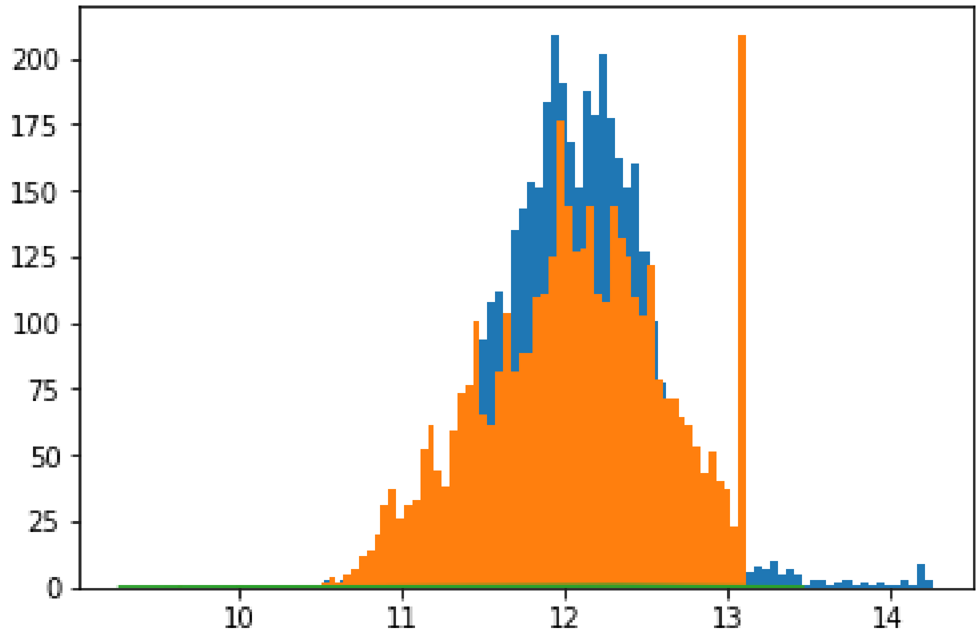
[23]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

[24]:
```
X_test['median_income']
```

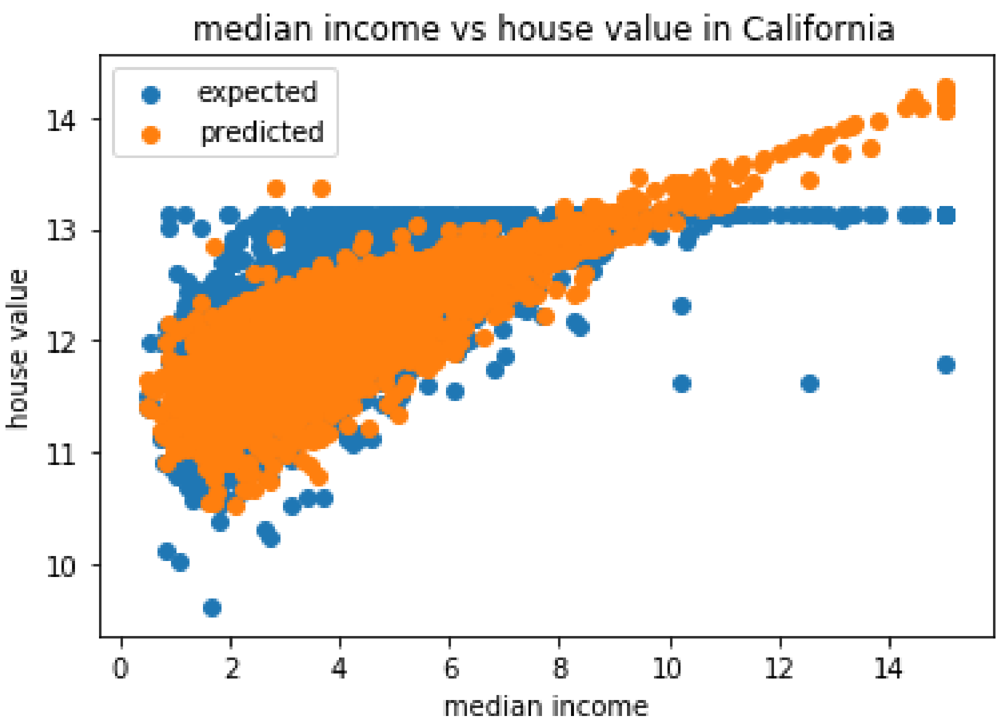
[24]:
```
4712     3.2500
2151     1.9784
15927    4.0132
82       1.5208
8161     5.1795
          …
2319     2.3173
5341     2.1875
16888    5.0480
6823     4.8750
11878    2.7054
Name: median_income, Length: 4128, dtype: float64
```

[25]:
```
plt.hist(np.array(Y_pred), bins=75,label = "expected")
plt.hist(np.array(Y_test['median_house_value']), bins=75,label = "predicted")
sns.distplot(np.array(Y_test['median_house_value']))
```

[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb02afc6bd0>
```



[26]:
```
plt.scatter(np.array(X_test['median_income']),np.
 ↪array(Y_test['median_house_value']),label = "expected")
plt.scatter(np.array(X_test['median_income']),np.array(Y_pred), label =␣
 ↪"predicted")
plt.title('median income vs house value in California')
plt.xlabel('median income')
plt.ylabel('house value')
plt.legend()
plt.show()
```



0.1.2 Part B: Predict housing prices using median income feature

[27]:
```
# lets use median_income as feature column and nuild our model. We already␣
↪cleaned the data and amputed missing values with mean in section A and␣
↪converted categorical column to numeric.
X_features_B = df_California_housing_data["median_income"]
Y_target_B = df_California_housing_data.iloc[:,-1:]
```

[28]:
```
#take a look at our data
X_features_B, Y_target_B
```

[28]:
```
(0        8.3252
 1        8.3014
 2        7.2574
 3        5.6431
 4        3.8462
            …
 20635    1.5603
 20636    2.5568
 20637    1.7000
 20638    1.8672
 20639    2.3886
```

```
Name: median_income, Length: 20640, dtype: float64,
       median_house_value
0               13.022764
1               12.789684
2               12.771671
3               12.740517
4               12.743151
…                   …
20635           11.265745
20636           11.252859
20637           11.432799
20638           11.346871
20639           11.400876

[20640 rows x 1 columns])
```

[29]:
```
#Split the training and test data and look at their shape
X_train_B, X_test_B, Y_train_B, Y_test_B = train_test_split(X_features_B,␣
↪Y_target_B,test_size=0.2, random_state = 1)
X_train_B.shape,X_test_B.shape, Y_train_B.shape, Y_test_B.shape
```

[29]:
```
((16512,), (4128,), (16512, 1), (4128, 1))
```

[30]:
```
#create linear regression model using scikit learn
linreg_B = LinearRegression()
linreg_B.fit(X_train_B.values.reshape(-1,1), Y_train_B)
```

[30]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[31]:
```
#Print the intercept and coefficients
linreg_B.coef_, linreg_B.intercept_
```

[31]:
```
(array([[0.19809328]]), array([11.32193123]))
```

[32]:
```
#Predict the outcome for the testing dataset
Y_pred_B = linreg_B.predict(X_test_B.values.reshape(-1,1))
np.exp(Y_pred_B)
```

[32]:
```
array([[157272.3666001 ],
       [122251.90391769],
       [182941.04003019],
       …,
       [224561.7769342 ],
       [216996.38772007],
       [141188.73186901]])
```

[33]:
```
#lets plot a graph of predicted and expected values
plt.scatter(X_test_B,Y_test_B,label = "expected")
plt.scatter(X_test_B,Y_pred_B, label = "predicted")
plt.title('median income vs house value in California')
plt.xlabel('median income')
plt.ylabel('house value')
plt.legend()
plt.show()
```