HousingProj

September 12, 2021

[1]:
```
#%pylab inline
import pandas as pd
import numpy as np

df = pd.read_csv('Housing Project/housingproj.csv')
#print(df.head(5))
print(df.shape)




#FILL the missing Values
df.isnull().sum()
```

```
(20640, 10)
```

[1]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
median_house_value      0
dtype: int64
```

Data Dictionary:

Features:'longitude', 'latitude', 'housing_median_age', 'total_rooms', 'total_bedrooms', 'population', 'households', 'median_income', 'ocean_proximity'

Label: median_house_value

There are 20640 rows and 10 features. Since the resonse variable is continuous, it can be considered as linear regression problem.

[2]:

```
#df.describe().transpose()
#impute missing values with mean
#df['total_bedrooms'].head()
df.total_bedrooms.fillna(df.total_bedrooms.mean(),inplace=True)
df.total_bedrooms.head()
#print(tbdr_mean)
```

[2]:

```
0     129.0
1    1106.0
2     190.0
3     235.0
4     280.0
Name: total_bedrooms, dtype: float64
```

[3]:

```
from sklearn.preprocessing import LabelEncoder

# Scikit Learn
lb_temp = LabelEncoder()

df['ocean_Dist'] = lb_temp.fit_transform(df.ocean_proximity)

#print(df['ocean_Dist'])
# Coding the labels. Converting the categories into the numbers.
print(df.head(10))
df1=df.drop(columns=['ocean_proximity'])
print(df1.head())
```

```
   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
5    -122.25     37.85                  52          919           213.0
6    -122.25     37.84                  52         2535           489.0
7    -122.25     37.84                  52         3104           687.0
8    -122.26     37.84                  42         2555           665.0
9    -122.25     37.84                  52         3549           707.0

   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
5         413         193         4.0368        NEAR BAY              269700
6        1094         514         3.6591        NEAR BAY              299200
```

```
7        1157         647      3.1200       NEAR BAY              241400
8        1206         595      2.0804       NEAR BAY              226700
9        1551         714      3.6912       NEAR BAY              261100

   ocean_Dist
0           3
1           3
2           3
3           3
4           3
5           3
6           3
7           3
8           3
9           3
   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  median_house_value  ocean_Dist
0         322         126         8.3252              452600           3
1        2401        1138         8.3014              358500           3
2         496         177         7.2574              352100           3
3         558         219         5.6431              341300           3
4         565         259         3.8462              342200           3
```

```
[4]: #create dummy for Ocean_Dist

     #dummy = pd.get_dummies(df1['ocean_Dist'],prefix='ocean_dist',drop_first=True)

     #display(dummy)

     df1 = df1.join(pd.
      ↪get_dummies(df1['ocean_Dist'],prefix='ocean_dist',drop_first=True))
     display(df1)
     df1.shape
```

```
       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
...          ...       ...                 ...          ...             ...
20635    -121.09     39.48                  25         1665           374.0
```

```
20636    -121.21     39.49                  18         697           150.0
20637    -121.22     39.43                  17        2254           485.0
20638    -121.32     39.43                  18        1860           409.0
20639    -121.24     39.37                  16        2785           616.0

       population  households  median_income  median_house_value  ocean_Dist  \
0             322         126         8.3252              452600           3
1            2401        1138         8.3014              358500           3
2             496         177         7.2574              352100           3
3             558         219         5.6431              341300           3
4             565         259         3.8462              342200           3
...           ...         ...            ...                 ...         ...
20635         845         330         1.5603               78100           1
20636         356         114         2.5568               77100           1
20637        1007         433         1.7000               92300           1
20638         741         349         1.8672               84700           1
20639        1387         530         2.3886               89400           1

       ocean_dist_1  ocean_dist_2  ocean_dist_3  ocean_dist_4
0                 0             0             1             0
1                 0             0             1             0
2                 0             0             1             0
3                 0             0             1             0
4                 0             0             1             0
...             ...           ...           ...           ...
20635             1             0             0             0
20636             1             0             0             0
20637             1             0             0             0
20638             1             0             0             0
20639             1             0             0             0

[20640 rows x 14 columns]
```

```
[4]: (20640, 14)
```

```
[5]: #splitting to X and Y
X = df1.drop(columns = ['median_house_value',])
Y = df1[['median_house_value']]
print(Y.head())
print(X.head())
list(X.columns)
list(Y.columns)
```

```
   median_house_value
0              452600
1              358500
2              352100
```

```
3             341300
4             342200
   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_Dist  ocean_dist_1  \
0         322         126         8.3252           3             0
1        2401        1138         8.3014           3             0
2         496         177         7.2574           3             0
3         558         219         5.6431           3             0
4         565         259         3.8462           3             0

   ocean_dist_2  ocean_dist_3  ocean_dist_4
0             0             1             0
1             0             1             0
2             0             1             0
3             0             1             0
4             0             1             0
```

[5]:
```
['median_house_value']
```

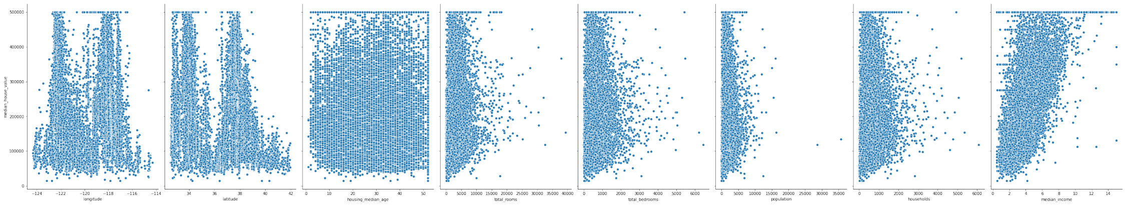
[7]:
```

```

[6]:
```
import seaborn as sns

#allow plot to appear inline
%matplotlib inline

sns.pairplot(df1, x_vars =␣
↪['longitude','latitude','housing_median_age','total_rooms','total_bedrooms',
                                'population','households','median_income'],
              y_vars='median_house_value', height=7,aspect =0.7, kind='scatter');
```



[7]:

```
#Model Building
#print(X.shape)
#print(Y.shape)

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
X_train,X_test, Y_train,Y_test = train_test_split(X,Y, test_size=0.3,␣
 ↪random_state=42)

#X_standard = ss.
 ↪fit_transform(X_train[['longitude','latitude','housing_median_age','total_rooms','total_bed
     #                                      ␣
 ↪'population','households','median_income','ocean_dist_1','ocean_dist_2','ocean_dist_3','oce
#display(X_standard[:10])
```

[8]:

```
#display (X_standard[:10])
#print ()
display (X_test[:100])
print ()
display (Y_train[:10])
print ()
display (Y_test[:10])
```

```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
20046    -119.01     36.06                  25         1505      537.870553
3024     -119.46     35.14                  30         2943      537.870553
15663    -122.44     37.80                  52         3830      537.870553
20484    -118.72     34.28                  17         3051      537.870553
9814     -121.93     36.62                  34         2351      537.870553
...          ...       ...                 ...          ...             ...
6052     -117.76     34.04                  34         1914      537.870553
15975    -122.45     37.77                  52         2602      537.870553
14331    -117.15     32.72                  51         1321      537.870553
1606     -122.08     37.88                  26         2947      537.870553
10915    -117.87     33.73                  45         2264      537.870553

       population  households  median_income  ocean_Dist  ocean_dist_1  \
20046        1392         359         1.6812           1             1
3024         1565         584         2.5313           1             1
15663        1310         963         3.4801           3             0
20484        1705         495         5.7376           0             0
9814         1063         428         3.7250           4             0
...           ...         ...            ...         ...           ...
6052         1564         328         2.8347           1             1
15975        1330         647         3.5435           3             0
14331         781         499         1.3071           4             0
```

```
1606          825         626          2.9330           3              0
10915        1970         499          3.4193           0              0

       ocean_dist_2  ocean_dist_3  ocean_dist_4
20046             0             0             0
3024              0             0             0
15663             0             1             0
20484             0             0             0
9814              0             0             1
...             ...           ...           ...
6052              0             0             0
15975             0             1             0
14331             0             0             1
1606              0             1             0
10915             0             0             0

[100 rows x 13 columns]
```

```
       median_house_value
7061               193800
14689              169700
17323              259800
10056              136100
15750              500001
15283              281300
18551              216100
7555               117400
15700              500001
12364              104200
```

```
       median_house_value
20046               47700
3024                45800
15663              500001
20484              218600
9814               278000
13311              158700
7113               198200
7668               157500
18246              340000
5723               446600
```

[9]:

```
# split is 70% for training and 30% for testing
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)
```

```
(14448, 13)
(14448, 1)
(6192, 13)
(6192, 1)
```

[5]:

```

```

```
   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
5    -122.25     37.85                  52          919           213.0
6    -122.25     37.84                  52         2535           489.0
7    -122.25     37.84                  52         3104           687.0
8    -122.26     37.84                  42         2555           665.0
9    -122.25     37.84                  52         3549           707.0

   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
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5         413         193         4.0368        NEAR BAY              269700
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7        1157         647         3.1200        NEAR BAY              241400
8        1206         595         2.0804        NEAR BAY              226700
9        1551         714         3.6912        NEAR BAY              261100

   ocean_Dist
0           3
1           3
2           3
3           3
4           3
5           3
6           3
7           3
8           3
9           3
```

```
   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  median_house_value  ocean_Dist
0         322         126         8.3252              452600           3
1        2401        1138         8.3014              358500           3
2         496         177         7.2574              352100           3
3         558         219         5.6431              341300           3
4         565         259         3.8462              342200           3
```

[36]:

```
# import model
from sklearn.linear_model import LinearRegression

# instantiate
linreg = LinearRegression()

# fit the model to the training data
linreg.fit(X_train, Y_train)

#print the intercept and the coeff
print (linreg.intercept_)
print (linreg.coef_)
```

```
[-2253987.60135963]
[[-2.65022024e+04 -2.49155605e+04  1.10597481e+03 -5.87232467e+00
   1.05721352e+02 -3.73269694e+01  4.23132106e+01  3.92696824e+04
   7.26435303e+03 -4.83404123e+04  1.21359840e+05 -2.78591058e+04
  -2.58843992e+04]]
```

[11]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

#display (X_train[:5])
#print ()

X_train.total_bedrooms = scaler.fit_transform(X_train[['total_bedrooms']])
X_train.total_rooms = scaler.fit_transform(X_train[['total_rooms']]) # x is␣
 ↪column then (x- mean(x))/sd(x)
#display (X_train[:5])
X_train.population = scaler.fit_transform(X_train[['population']])
X_train.households = scaler.fit_transform(X_train[['households']])
X_train.longitude = scaler.fit_transform(X_train[['longitude']])
X_train.latitude = scaler.fit_transform(X_train[['latitude']])
X_train.housing_median_age=  scaler.
 ↪fit_transform(X_train[['housing_median_age']])
X_train.median_income=  scaler.fit_transform(X_train[['median_income']])


X_test.total_bedrooms = scaler.fit_transform(X_test[['total_bedrooms']])
X_test.total_rooms = scaler.fit_transform(X_test[['total_rooms']]) # x is␣
 ↪column then (x- mean(x))/sd(x)
#display (X_train[:5])
X_test.population = scaler.fit_transform(X_test[['population']])
X_test.households = scaler.fit_transform(X_test[['households']])
X_test.longitude = scaler.fit_transform(X_test[['longitude']])
X_test.latitude = scaler.fit_transform(X_test[['latitude']])
X_test.housing_median_age=  scaler.fit_transform(X_test[['housing_median_age']])
X_test.median_income=  scaler.fit_transform(X_test[['median_income']])


Y_train.median_house_value=scaler.fit_transform(Y_train[['median_house_value']])
Y_test.median_house_value=scaler.fit_transform(Y_test[['median_house_value']])

display (X_train[:5])
display (Y_train[:5])
```

```
/usr/local/lib/python3.7/site-packages/pandas/core/generic.py:5303:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
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SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
7061    0.780934 -0.805682            0.509357    -0.113242       -0.337870
14689   1.245270 -1.339473           -0.679873    -0.213566       -0.013884
17323  -0.277552 -0.496645           -0.362745    -0.482639       -0.614210
10056  -0.706938  1.690024           -1.155565    -0.848339       -0.926284
15750  -1.430902  0.992350            1.857152     0.251071        0.400626

       population  households  median_income  ocean_Dist  ocean_dist_1  \
7061    -0.184117   -0.243508       0.133506           0             0
14689   -0.376191   -0.013267      -0.532218           4             0
17323   -0.611240   -0.565322       0.170990           4             0
10056   -0.987495   -0.949929      -0.402916           1             1
15750    0.086015    0.426285      -0.299285           3             0

       ocean_dist_2  ocean_dist_3  ocean_dist_4
7061              0             0             0
14689             0             0             1
17323             0             0             1
10056             0             0             0
15750             0             1             0


       median_house_value
7061            -0.113387
```

```
14689          -0.321603
17323           0.456831
10056          -0.611895
15750           2.532087
```

[11]:

```
display (X_train[:5])
display (Y_train[:5])
```

```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
7061    0.780934 -0.805682            0.509357    -0.113242       -0.337870
14689   1.245270 -1.339473           -0.679873    -0.213566       -0.013884
17323  -0.277552 -0.496645           -0.362745    -0.482639       -0.614210
10056  -0.706938  1.690024           -1.155565    -0.848339       -0.926284
15750  -1.430902  0.992350            1.857152     0.251071        0.400626

       population  households  median_income  ocean_Dist  ocean_dist_1  \
7061    -0.184117   -0.243508       0.133506           0             0
14689   -0.376191   -0.013267      -0.532218           4             0
17323   -0.611240   -0.565322       0.170990           4             0
10056   -0.987495   -0.949929      -0.402916           1             1
15750    0.086015    0.426285      -0.299285           3             0

       ocean_dist_2  ocean_dist_3  ocean_dist_4
7061              0             0             0
14689             0             0             1
17323             0             0             1
10056             0             0             0
15750             0             1             0
```

```
       median_house_value
7061            -0.113387
14689           -0.321603
17323            0.456831
10056           -0.611895
15750            2.532087
```

[12]:

```
display (X_test[:5])
display (Y_test[:5])
```

```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
20046   0.262460  0.221006           -0.302678    -0.498771        0.010928
3024    0.037969 -0.209747            0.096730     0.147762        0.010928
15663  -1.448662  1.035689            1.854125     0.546562        0.010928
20484   0.407132 -0.612406           -0.941731     0.196319        0.010928
9814   -1.194239  0.483203            0.416256    -0.118405        0.010928
```

```
       population  households  median_income  ocean_Dist  ocean_dist_1  \
20046   -0.024915   -0.358030      -1.152099           1             1
3024     0.130364    0.230115      -0.701791           1             1
15663   -0.098516    1.220811      -0.199201           3             0
20484    0.256024   -0.002529       0.996622           0             0
9814    -0.320216   -0.177665      -0.069475           4             0

       ocean_dist_2  ocean_dist_3  ocean_dist_4
20046             0             0             0
3024              0             0             0
15663             0             1             0
20484             0             0             0
9814              0             0             1


       median_house_value
20046           -1.387817
3024            -1.404401
15663            2.560130
20484            0.103898
9814             0.622376
```

[12]:

```
# import model
from sklearn.linear_model import LinearRegression

# instantiate
linreg = LinearRegression()

# fit the model to the training data
linreg.fit(X_train, Y_train)

#print the intercept and the coeff
print (linreg.intercept_)
print (linreg.coef_)
```

```
[0.11545353]
[[-0.45859533 -0.4597284   0.12052227 -0.10973858  0.38341869 -0.36770133
   0.13972452  0.64626901  0.06276157 -0.41764494  1.04850829 -0.24069332
  -0.22363252]]
```

[16]:

```
# predictions on the testing data
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
Y_pred = linreg.predict(X_test)

print ("Rsqd = ", r2_score(Y_pred, Y_test))
```

```
#print("RMSE = ", np.sqrt(mean_squared_error(Y_pred, Y_test)))


#from sklearn.metrics import r2_score
#print ("Rsqd = ", r2_score(y_pred, y_test))

from sklearn.metrics import mean_squared_error
import numpy as np
print("RMSE = ", np.sqrt(mean_squared_error(Y_pred, Y_test)))
```

```
Rsqd =  0.44601645334137796
RMSE =  0.6003199071326119
```

[18]:

```
print(Y_pred)
```

```
[[-1.22438041]
 [-0.63011131]
 [ 0.49699754]
 …
 [ 0.65545862]
 [-0.8198401 ]
 [ 0.09491845]]
```

[ ]:

```
```