project-final

February 2, 2023

[1]:
```python
# import libraries
import pandas as pd
import numpy as np
```

[3]:
```python
# loading data set
df = pd.read_csv("housing.csv")
df.head()
```

[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 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
```

[4]:
```python
# checking data row and coloumns
df.shape
```

[4]:
```
(20640, 10)
```

Independent and dependent var

[5]:
```python
# independedent data
df.columns
```

[5]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity', 'median_house_value'],
      dtype='object')
```

[6]:
```
#dependented data
df["target"]=df.median_house_value
df["target"]
```

[6]:
```
0        452600
1        358500
2        352100
3        341300
4        342200
          …
20635     78100
20636     77100
20637     92300
20638     84700
20639     89400
Name: target, Length: 20640, dtype: int64
```

[7]:
```
#Explore the data for reduce unwantedcolumns in it
# data pre process
```

[8]:
```
df.isnull().sum()
```

[8]:
```
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
target                  0
dtype: int64
```

[9]:
```
df.drop(["longitude","latitude","median_house_value","target"],axis=1)
```

[9]:
```
       housing_median_age  total_rooms  total_bedrooms  population  \
0                      41          880           129.0         322
1                      21         7099          1106.0        2401
2                      52         1467           190.0         496
3                      52         1274           235.0         558
4                      52         1627           280.0         565
…                     …           …              …           …
20635                  25         1665           374.0         845
20636                  18          697           150.0         356
20637                  17         2254           485.0        1007
```

```
20638                   18         1860           409.0         741
20639                   16         2785           616.0        1387

       households  median_income ocean_proximity
0             126         8.3252        NEAR BAY
1            1138         8.3014        NEAR BAY
2             177         7.2574        NEAR BAY
3             219         5.6431        NEAR BAY
4             259         3.8462        NEAR BAY
…           …             …           …
20635         330         1.5603          INLAND
20636         114         2.5568          INLAND
20637         433         1.7000          INLAND
20638         349         1.8672          INLAND
20639         530         2.3886          INLAND

[20640 rows x 7 columns]
```

[10]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  int64
 3   total_rooms         20640 non-null  int64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  int64
 6   households          20640 non-null  int64
 7   median_income       20640 non-null  float64
 8   ocean_proximity     20640 non-null  object
 9   median_house_value  20640 non-null  int64
 10  target              20640 non-null  int64
dtypes: float64(4), int64(6), object(1)
memory usage: 1.7+ MB
```

[11]:
```python
# total_bedrooms      20433  have none value need to replace with frequent␣
 ↪value
df["total_bedrooms"].value_counts()
```

[11]:
```
280.0     55
331.0     51
345.0     50
343.0     49
```

```
393.0     49
          ..
2961.0     1
1915.0     1
1215.0     1
3298.0     1
1052.0     1
Name: total_bedrooms, Length: 1923, dtype: int64
```

[12]:
```python
df["total_bedrooms"].mode()[0]
```

[12]:
```
280.0
```

[13]:
```python
# total_bedrooms  missing value filled with 280
df["total_bedrooms"]=df["total_bedrooms"].fillna(df["total_bedrooms"].mode()[0])
df["total_bedrooms"].unique()
```

[13]:
```
array([ 129., 1106.,  190., …, 3008., 1857., 1052.])
```

[14]:
```python
# Label encoder initialize for preprocess the ocean_proximity
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

[15]:
```python
df["ocean_proximity"]=le.fit_transform(df["ocean_proximity"])
df["ocean_proximity"].unique() # no non value
```

[15]:
```
array([3, 0, 1, 4, 2])
```

[16]:
```python
df.isnull().sum() # data don't have none value now
```

[16]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
ocean_proximity       0
median_house_value    0
target                0
dtype: int64
```

[17]:
```python
# models using  and remove unwanted fields
y=df.iloc[:,-1]
df.
 ↪drop(labels=["target","median_house_value","longitude","latitude"],axis=1,inplace=True)
```

[18]:
```
X=df.iloc[:,:].values
```

[19]:
```
# data split 80:20
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
 ↪2,random_state=42)
```

0.1 Decision tree

[21]:
```
from sklearn.tree import DecisionTreeClassifier
cls=DecisionTreeClassifier()
cls.fit(X_train,y_train)
```

[21]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

[22]:
```
y_pred=cls.predict(X_test)
y_pred
```

[22]:
```
array([ 48700,  73100, 500001, …, 500001,  93000, 201300])
```

[23]:
```
# accuracy of the Decition tree
from sklearn.metrics import r2_score
accuracy = r2_score(y_test,y_pred)*100
accuracy
```

[23]:
```
38.682906859740264
```

[24]:
```
# calc MSE
from sklearn.metrics import mean_squared_error
MSE=mean_squared_error(y_test,y_pred,squared=False)
MSE
```

[24]:
```
89638.42332985885
```

0.2 Checking model with external I/p value

[25]:
```
ip=np.array([52,1467,190.0,496,177,7.2574,3])
ip=ip.reshape((1,-1))
```

[26]:
```
op=cls.predict(ip)
```

```
print(f"what is amount of this mentioned details [52,1467,190.0,496,177,7.
 ↪2574,3] = {op}")
```

```
what is amount of this mentioned details [52,1467,190.0,496,177,7.2574,3] =
[352100]
```

0.3 Random Forest Classifier

```
[27]: from sklearn.ensemble import RandomForestClassifier
      from sklearn.metrics import accuracy_score
```

```
[28]: cls2=RandomForestClassifier()
```

```
[132]: cls2=RandomForestClassifier()
       cls2.fit(X_train,y_train)
       y_pred=cls2.predict(X_test)
       accuracy=accuracy_score(y_pred,y_test)
```

0.4 Linear Regression

```
[30]: from sklearn.linear_model import LinearRegression
      lm=LinearRegression()
```

```
[35]: # original data model coeff and intercept
      lm.fit(X,y)
      print(f"coeff value for original data set {lm.coef_}")

      print(f"intercept_ value for original data set {lm.intercept_}")
```

```
coeff value for original data set [ 1.80597108e+03 -1.84880001e+01
6.79973942e+01 -3.50458680e+01
  1.53518335e+02  4.72832986e+04  4.42114328e+03]
intercept_ value for original data set -47438.1020624511
```

```
[ ]: # trained model coeff and intercept
```

```
[37]: lm.fit(X_train,y_train)
```

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

```
[38]: print(f"coeff value for trained data set {lm.coef_}")
      print(f"intercept_ value for trained data set {lm.intercept_}")
```

```
coeff value for trained data set [ 1.84281689e+03 -2.04801898e+01
1.03232060e+02 -3.39731843e+01
  1.23390221e+02  4.80797245e+04  4.01963337e+03]
intercept_ value for trained data set -51484.087149107596
```

[40]:
```
# y_prediction
```

[41]:
```
lm_pred=lm.predict(X_test)
print(f"model predicted {lm_pred}")
```

```
model predicted [ 74526.3092009  117047.89330818 248509.30160755 …
425935.51243906
 166343.15870535 160335.76187807]
```

Linear Regeression MSE

[50]:
```
from sklearn.metrics import mean_squared_error
import math
print(math.sqrt(mean_squared_error(lm_pred,y_test)))
from sklearn.metrics import r2_score
r_squr = r2_score(y_test,lm_pred)
print(f"accuracy of the models {r_squr}")
print(f"MSE Value ------------------->{mean_squared_error(lm_pred,y_test)}")
print(f"RMSE Value ------------------->{math.
 ↪sqrt(mean_squared_error(lm_pred,y_test))}")
```

```
77029.81628854056
accuracy of the models 0.5471953645027985
MSE Value ------------------->5933592597.446308
RMSE Value ------------------->77029.81628854056
```

[51]:
```
# using state models for improving accuracy
```

[52]:
```
import statsmodels.api as smf
X_train_smf=smf.add_constant(X_train)
lr=smf.OLS(y_train,X_train_smf).fit()
```

[53]:
```
lr.params
```

[53]:
```
const   -51484.087149
x1        1842.816894
x2         -20.480190
x3         103.232060
x4         -33.973184
x5         123.390221
x6       48079.724470
x7        4019.633370
dtype: float64
```

[69]:
```
Model=lr.summary()
```

[69]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 target   R-squared:                       0.572
Model:                            OLS   Adj. R-squared:                  0.572
Method:                 Least Squares   F-statistic:                     3156.
Date:                Thu, 02 Feb 2023   Prob (F-statistic):               0.00
Time:                        20:33:25   Log-Likelihood:            -2.0891e+05
No. Observations:               16512   AIC:                         4.178e+05
Df Residuals:                   16504   BIC:                         4.179e+05
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -5.148e+04   2526.090    -20.381      0.000   -5.64e+04   -4.65e+04
x1          1842.8169     50.691     36.354      0.000    1743.458    1942.176
x2           -20.4802      0.938    -21.835      0.000     -22.319     -18.642
x3           103.2321      8.403     12.285      0.000      86.762     119.702
x4           -33.9732      1.301    -26.122      0.000     -36.522     -31.424
x5           123.3902      9.067     13.608      0.000     105.618     141.163
x6          4.808e+04    381.612    125.991      0.000    4.73e+04    4.88e+04
x7          4019.6334    422.457      9.515      0.000    3191.573    4847.694
==============================================================================
Omnibus:                     3245.984   Durbin-Watson:                   1.965
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            10949.435
Skew:                           0.984   Prob(JB):                         0.00
Kurtosis:                       6.470   Cond. No.                     1.70e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.7e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[59]:
```
X_test_smf=smf.add_constant(X_test)
y_test_predict= lr.predict(X_test_smf)
```

[131]:
```
# mse value
print(f"MSE Value␣
 ↪------------------->{mean_squared_error(y_test_predict,y_test)}")
print(f"RMSE Value ------------------->{math.
 ↪sqrt(mean_squared_error(y_test_predict,y_test))}")
```

```
MSE Value ------------------->5933592597.446303
RMSE Value ------------------->77029.81628854053
```

1 Based on median_income field house value prediction

[111]:
```
# Perform Linear Regression with one independent variable
data = pd.read_csv("housing.csv")
data.head()
```

[111]:
```
   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
```

[112]:
```
y=data.iloc[:,-1].values
X=data.iloc[:,-3].values
data.
↪drop(["longitude","latitude","housing_median_age","total_rooms","total_bedrooms","populatio
```

[112]:
```
       median_income  median_house_value
0             8.3252              452600
1             8.3014              358500
2             7.2574              352100
3             5.6431              341300
4             3.8462              342200
…                …                   …
20635         1.5603               78100
20636         2.5568               77100
20637         1.7000               92300
20638         1.8672               84700
20639         2.3886               89400

[20640 rows x 2 columns]
```

[113]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪2,random_state=42)
```

[114]:
```
from sklearn.linear_model import LinearRegression
lm=LinearRegression()
```

[115]:
```
x_train= X_train.reshape(-1, 1)
x_test = X_test.reshape(-1, 1)
model=lm.fit(x_train,y_train)
model
```

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

[116]:
```
y_pred=lm.predict(x_test)
y_pred
```

[116]:
```
array([114958.91676996, 150606.88213964, 190393.71844449, …,
       431500.77230409, 161245.49973085, 193412.95560084])
```

[117]:
```
r_squr = r2_score(y_test,y_pred)
r_squr
```

[117]: 0.45885918903846656

[118]:
```
# mse value
print(f"MSE Value ------------------->{mean_squared_error(y_pred,y_test)}")
print(f"RMSE Value ------------------->{math.
 ↪sqrt(mean_squared_error(y_pred,y_test))}")
```

```
MSE Value ------------------->7091157771.76555
RMSE Value ------------------->84209.01241414454
```

[119]:
```
x_samp=pd.DataFrame({'median_income':[8.3252]}) # origina value 402600
y_sam_pred1=lm.predict(x_samp)[0]
print(f"median income is 8.3252 and value of the house is  {y_sam_pred1}")
```

```
median income is 8.3252 and value of the house is  393567.41214244824
```

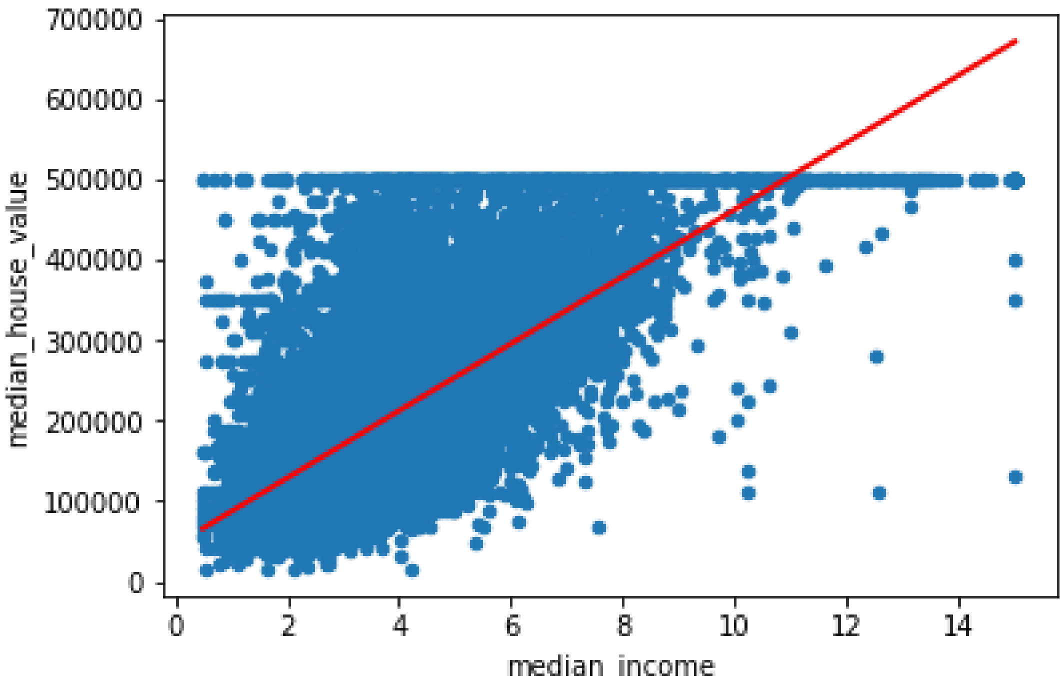
2 minimum and maximum value plot

[85]:
```
import matplotlib.pyplot as plt
x_new=pd.DataFrame({'median_income':[data.median_income.min(),data.
 ↪median_income.max()]})
print(y_pred)
print(x_new)
y_pred=lm.predict(x_new)
data.plot(kind="scatter",x="median_income",y="median_house_value") # relation␣
 ↪ship bw x and y
plt.plot(x_new,y_pred,c='r',linewidth=2)
```

```
[ 65422.46048105 673471.66346121]
   median_income
```

```
0         0.4999
1        15.0001
```

[85]:
```
[<matplotlib.lines.Line2D at 0x7fd08f67fcd0>]
```



Using state model and try to improve accuracy

[89]:
```python
import statsmodels.formula.api as smf
lm1=smf.ols(formula="median_house_value~median_income",data=data).fit()
print(lm1.conf_int())
print(lm1.pvalues)
print(f"r squred value {lm1.rsquared}")
print(f"r squred adj value {lm1.rsquared_adj}")
```

```
                         0             1
Intercept      42492.643908  47678.509499
median_income  41192.485706  42395.212698
Intercept        9.882299e-248
median_income     0.000000e+00
dtype: float64
r squred value 0.47344749180719914
r squred adj value 0.47342197807000586
```

acuracy checking manually

[107]:

```
#value check
#y=mx+c
y=41933.84939381*8.3252        +44459.72916907875
y
```

[107]: 393567.4121424258

[120]:

```
x_samp=pd.DataFrame({'median_income':[8.3252]}) # origina value 402600
y_sam_pred1=lm.predict(x_samp)[0]
print(f"median income is 8.3252 and value of the house is  {y_sam_pred1}")
```

```
median income is 8.3252 and value of the house is  393567.41214244824
```

[ ]:

[ ]: