California House Pricing Project

August 29, 2020

[224]:
```
#import required libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[225]:
```
#loading the housing data
house_data = pd.read_excel('housing_data.xlsx')
```

[226]:
```
#Printing the first few lines
house_data.head()
```

[226]:

	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

[227]:
```
#Extract input (X) and output (Y) data from the dataset.
x_feature = house_data.iloc[:, 0:-1]
y_target = house_data.loc[:, ['median_house_value']]
```

[228]:
```
#feature everything except median_house_value
x_feature.head()
```

[228]:

	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        NEAR BAY
1        2401        1138         8.3014        NEAR BAY
2         496         177         7.2574        NEAR BAY
3         558         219         5.6431        NEAR BAY
4         565         259         3.8462        NEAR BAY
```

[229]:
```
#Target is median_house_value
y_target.head()
```

[229]:
```
   median_house_value
0              452600
1              358500
2              352100
3              341300
4              342200
```

[230]:
```
#Fill the missing values with the mean of the respective column
#We see that total_bedrooms has null value
x_feature.isnull().any()
```

[230]:
```
longitude             False
latitude              False
housing_median_age    False
total_rooms           False
total_bedrooms         True
population            False
households            False
median_income         False
ocean_proximity       False
dtype: bool
```

[231]:
```
#CHecking how many null values
x_feature.isnull().sum()
```

[231]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
ocean_proximity         0
dtype: int64
```

[232]:
```
x_feature.iloc[290:293, :]
```

[232]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity
290	-122.16	37.77	47	1256	NaN	570	218	4.3750	NEAR BAY
291	-122.16	37.77	48	977	194.0	446	180	4.7708	NEAR BAY
292	-122.16	37.77	45	2324	397.0	968	384	3.5739	NEAR BAY

[233]:
```
x_feature.total_bedrooms.mean()
```

[233]:
```
537.8705525375618
```

[234]:
```
#Filling total_bedrooms with the mean of total_bedrooms
x_feature.total_bedrooms.fillna(x_feature.total_bedrooms.mean(), inplace = True)
```

[235]:
```
x_feature.dtypes
```

[235]:
```
longitude             float64
latitude              float64
housing_median_age      int64
total_rooms             int64
total_bedrooms        float64
population              int64
households              int64
median_income         float64
ocean_proximity        object
dtype: object
```

[236]:
```
#Convert categorical column in the dataset to numerical data.
#We see ocean_proximity is categorical data
x_feature.iloc[290:293, :]
```

[236]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity
290	-122.16	37.77	47	1256	537.870553	570	218	4.3750	NEAR BAY
291	-122.16	37.77	48	977	194.000000	446	180	4.7708	NEAR BAY
292	-122.16	37.77	45	2324	397.000000	968	384	3.5739	NEAR BAY

[237]:
```
#So to convert ocean_proximity, we will Pandas dummy variable then we will␣
↪concat this data with the other features
x_feature.groupby('ocean_proximity').size()
```

[237]:
```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
ISLAND           5
NEAR BAY      2290
NEAR OCEAN    2658
dtype: int64
```

[238]:
```
x = x_feature['ocean_proximity'].str.get_dummies()
x_features = pd.concat([x_feature.drop(['ocean_proximity'], axis =1), x], axis␣
↪= 1)
```

[239]:
```
x_features.head()
```

[239]:

	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	<1H OCEAN	INLAND	ISLAND	NEAR BAY	\
0	322	126	8.3252	0	0	0	1	
1	2401	1138	8.3014	0	0	0	1	
2	496	177	7.2574	0	0	0	1	
3	558	219	5.6431	0	0	0	1	
4	565	259	3.8462	0	0	0	1	

	NEAR OCEAN
0	0
1	0
2	0
3	0
4	0

[240]:
```
#Checking the data types of x_features.
x_features.dtypes
```

[240]:
```
longitude             float64
latitude              float64
housing_median_age      int64
total_rooms             int64
total_bedrooms        float64
```

```
population              int64
households              int64
median_income         float64
<1H OCEAN               int64
INLAND                  int64
ISLAND                  int64
NEAR BAY                int64
NEAR OCEAN              int64
dtype: object
```

[241]:
```
x_features.loc[290:293, 'total_bedrooms']
```

[241]:
```
290    537.870553
291    194.000000
292    397.000000
293    349.000000
Name: total_bedrooms, dtype: float64
```

[242]:
```
x_features.total_bedrooms.mean()
```

[242]:
```
537.8705525375639
```

[243]:
```
#longitude and latitude will not help our model so we will drop them
x_features = x_features.drop(['longitude','latitude'], axis = 'columns')
```

[244]:
```
x_features.iloc[290:293, :]
```

[244]:

	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	<1H OCEAN	INLAND	ISLAND	NEAR BAY	NEAR OCEAN
290	47	1256	537.870553	570	218	4.3750	0	0	0	1	0
291	48	977	194.000000	446	180	4.7708	0	0	0	1	0
292	45	2324	397.000000	968	384	3.5739	0	0	0	1	0

[245]:
```
x_features.shape
```

[245]:
```
(20640, 11)
```

[246]:
```
y_target.shape
```

[246]:
```
(20640, 1)
```

[247]:
```
#Split the data into 80% training dataset and 20% test dataset.
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x_features, y_target,␣
↪test_size = 0.2, random_state = 1)
```

[248]:
```
x_train.shape
```

[248]:
```
(16512, 11)
```

[249]:
```
y_train.shape
```

[249]:
```
(16512, 1)
```

[264]:
```
#Standardize training and test datasets.
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

[268]:
```
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
y_train = scaler.fit_transform(y_train)
y_test = scaler.transform(y_test)
```

[281]:
```
#Perform Linear Regression on training data.
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train, y_train)
```

[281]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[282]:
```
#Predict output for test dataset using the fitted model.
predict = model.predict(x_test)
print(predict)
```

```
[[ 0.31120225]
 [-0.98278118]
 [ 0.30847265]
 …
 [ 0.59224681]
 [ 0.58981548]
 [-0.6432792 ]]
```

[284]:
```
#Print root mean squared error (RMSE) from Linear Regression.
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, predict)
print('Root Mean Squared Error(RMSE) is %.2f' %mse)
#Since our RMSE value is .37, We can sat that our model can predict the data␣
↪accurately
```

```
Root Mean Squared Error(RMSE) is 0.37
```

[294]:
```
x_train.view
```

[294]:
```
<function ndarray.view>
```

[302]:
```
#Perform Linear Regression with one independent variable:
#Extract just the median_income column from the independent variables (from␣
 ↪X_train and X_test).
x_train_median_income = x_train[:,[5]]
x_test_median_income = x_test[:,[5]]
```

[311]:
```
#Perform Linear Regression to predict housing values based on median_income.
median_income_model = LinearRegression()
median_income_model.fit(x_train_median_income, y_train)
```

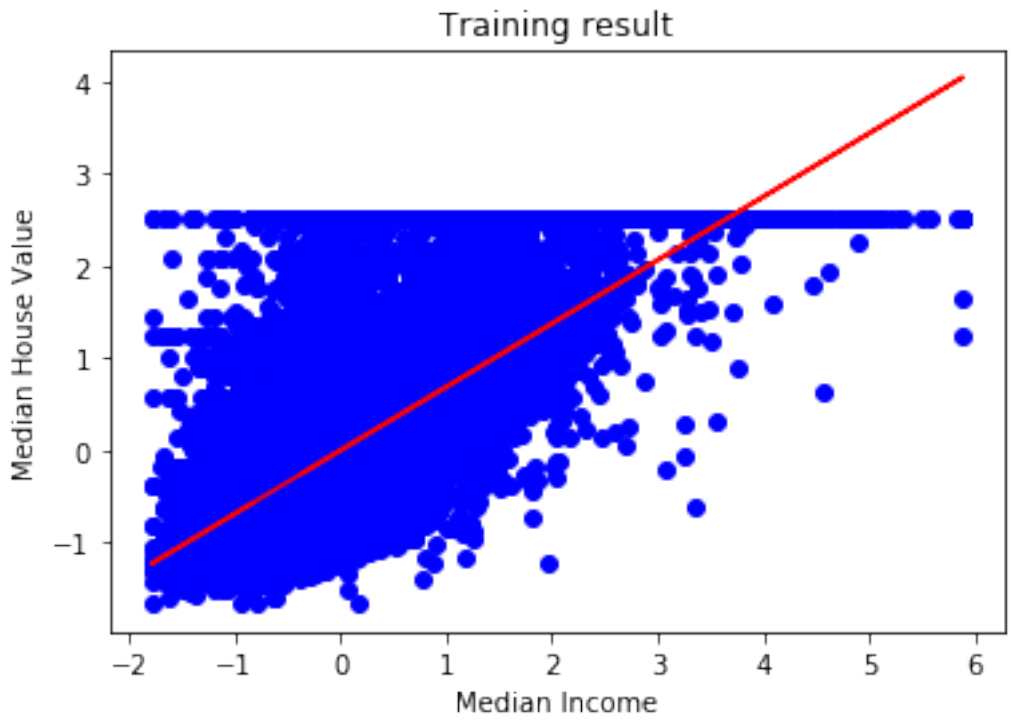
[311]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[313]:
```
#Predict output for test dataset using the fitted model.
predict_with_median_income = median_income_model.predict(x_test_median_income)
print(predict_with_median_income)
```

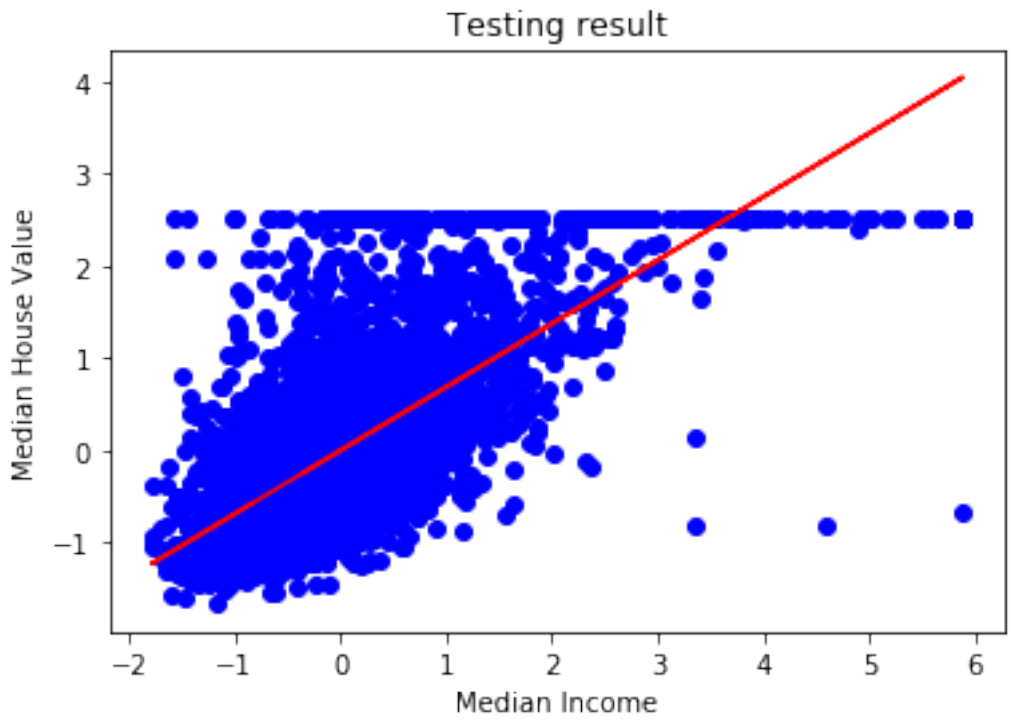
```
[[-0.22781174]
 [-0.69045767]
 [ 0.04986313]
 …
 [ 0.42635417]
 [ 0.36341163]
 [-0.42595343]]
```

[317]:
```
#Plot the fitted model for training data as well as for test data to check if
#the fitted model satisfies the test data.
import matplotlib.pyplot as plt
%matplotlib inline
```

[321]:
```
plt.scatter(x_train_median_income, y_train, color = 'blue')
plt.plot (x_train_median_income, median_income_model.
 ↪predict(x_train_median_income), color = 'red')
plt.title ('Training result')
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.show()
```



[323]:
```
plt.scatter(x_test_median_income, y_test, color = 'blue')
plt.plot (x_train_median_income, median_income_model.
 ↪predict(x_train_median_income), color = 'red')
plt.title ('Testing result')
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.show()
```


Testing result
Median House Value
Median Income
4
3
2
1
0
−1
−2
−1
0
1
2
3
4
5
6

[ ]: