Project

June 14, 2018

1 California Housing Price Prediction

```
In [1]: #Imports
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import StandardScaler
        from sklearn.linear_model import LinearRegression
        from sklearn.metrics import mean_squared_error
        from sklearn.tree import DecisionTreeRegressor
        from sklearn.ensemble import RandomForestRegressor
        from math import sqrt
```

1.1 Loading the data and Exploratory data analysis - EDA

```
In [2]: data = pd.read_csv(r'C:\Users\Admin\Desktop\Projects\Projects for submission\Californi
        data.head()
```

Out[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

```
In [3]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
```

```
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null int64
total_rooms           20640 non-null int64
total_bedrooms        20433 non-null float64
population            20640 non-null int64
households            20640 non-null int64
median_income         20640 non-null float64
ocean_proximity       20640 non-null object
median_house_value    20640 non-null int64
dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
```

```
In [4]: data.describe(include='all')
```

Out[4]:

	longitude	latitude	housing_median_age	total_rooms	\
count	20640.000000	20640.000000	20640.000000	20640.000000	
unique	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	
mean	-119.569704	35.631861	28.639486	2635.763081	
std	2.003532	2.135952	12.585558	2181.615252	
min	-124.350000	32.540000	1.000000	2.000000	
25%	-121.800000	33.930000	18.000000	1447.750000	
50%	-118.490000	34.260000	29.000000	2127.000000	
75%	-118.010000	37.710000	37.000000	3148.000000	
max	-114.310000	41.950000	52.000000	39320.000000	

	total_bedrooms	population	households	median_income	\
count	20433.000000	20640.000000	20640.000000	20640.000000	
unique	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	
mean	537.870553	1425.476744	499.539680	3.870671	
std	421.385070	1132.462122	382.329753	1.899822	
min	1.000000	3.000000	1.000000	0.499900	
25%	296.000000	787.000000	280.000000	2.563400	
50%	435.000000	1166.000000	409.000000	3.534800	
75%	647.000000	1725.000000	605.000000	4.743250	
max	6445.000000	35682.000000	6082.000000	15.000100	

	ocean_proximity	median_house_value
count	20640	20640.000000
unique	5	NaN
top	<1H OCEAN	NaN
freq	9136	NaN

```
mean                NaN       206855.816909
std                 NaN       115395.615874
min                 NaN        14999.000000
25%                 NaN       119600.000000
50%                 NaN       179700.000000
75%                 NaN       264725.000000
max                 NaN       500001.000000
```

1.2 Handling missing values

```
In [5]: data.isna().any()
```

```
Out[5]: longitude             False
        latitude              False
        housing_median_age    False
        total_rooms           False
        total_bedrooms         True
        population            False
        households            False
        median_income         False
        ocean_proximity       False
        median_house_value    False
        dtype: bool
```

```
In [6]: data = data.fillna(data.mean())
```

```
In [7]: data.isna().any()
```

```
Out[7]: longitude             False
        latitude              False
        housing_median_age    False
        total_rooms           False
        total_bedrooms        False
        population            False
        households            False
        median_income         False
        ocean_proximity       False
        median_house_value    False
        dtype: bool
```

1.3 Encoding categorical data

```
In [8]: df_with_dummies = pd.get_dummies( data, columns = ['ocean_proximity'] )
```

1.4 Splitting the dataset into training and testing datasets

```
In [9]: train, test = train_test_split(df_with_dummies, test_size=0.3)
        columnKey = train.columns.get_loc('median_house_value')
        median_income_columnKey = train.columns.get_loc('median_income')
```

1.5 Standardizing the data

```
In [10]: scaler = StandardScaler()
         scaler.fit(train)
         train = scaler.transform(train)
         scaler.fit(test)
         test = scaler.transform(test)
```

```
In [11]: y_train=train[:, columnKey]
         y_test=test[:, columnKey]
         X_train = np.delete(train,columnKey,axis = 1)
         X_test = np.delete(test,columnKey,axis = 1)
```

1.6 Performing Linear Regression

1.6.1 Performing Linear Regression on training data

```
In [12]: lm = LinearRegression()
         lm.fit(X_train, y_train)
         print("Intercept on y axis:")
         print(lm.intercept_)
         print("Coefficient of x:")
         print(lm.coef_)
```

```
Intercept on y axis:
-1.365622234911372e-15
Coefficient of x:
[-0.44697882 -0.45387679  0.12093245 -0.1192087   0.29452887 -0.38009237
  0.24656919  0.64015584  0.0519497  -0.10956535  0.02044369  0.02398617
  0.05191279]
```

1.6.2 Predicting output for test dataset using the fitted model

```
In [13]: y_pred = lm.predict(X_test)
         print("Predicted values:")
         y_pred
```

```
Predicted values:
```

```
Out[13]: array([ 0.45389318, -0.47586357, -0.20330861, ..., -0.10129702,
                 0.09179008,  0.52083557])
```

1.6.3 Printing root mean squared error (RMSE) from Linear Regression

```
In [14]: print("Root mean square error value:")
         sqrt(mean_squared_error(y_test, y_pred))
```

```
Root mean square error value:
```

```
Out[14]: 0.5819542853164533
```

1.7 Performing Decision Tree Regression

1.7.1 Performing Decision Tree Regression on training data

```
In [15]: decisiontree = DecisionTreeRegressor(random_state=0)
         DT_model = decisiontree.fit(X_train, y_train)
```

1.7.2 Predicting output for test dataset using the fitted model

```
In [16]: y_DT_pred=DT_model.predict(X_test)
         print("Predicted values:")
         y_DT_pred
```

```
Predicted values:


Out[16]: array([-0.43287975, -1.1511054 , -0.81576057, ..., -0.40608674,
                 0.40116087,  0.62155502])
```

1.7.3 Printing root mean squared error (RMSE) from Decision Tree Regressionű

```
In [17]: print("Root mean square error value:")
         sqrt(mean_squared_error(y_test, y_DT_pred))
```

```
Root mean square error value:


Out[17]: 0.6376532036247837
```

1.8 Performing Random Forest Regression

1.8.1 Performing Random Forest Regression on training data

```
In [18]: randomforest = RandomForestRegressor(random_state=0, n_jobs=-1)
         RF_model = randomforest.fit(X_train, y_train)
```

1.8.2 Predicting output for test dataset using the fitted model

```
In [19]: y_RF_Pred=RF_model.predict(X_test)
         print("Predicted values:")
         y_RF_Pred
```

```
Predicted values:


Out[19]: array([-0.24982296, -1.11359518, -0.67030043, ..., -0.13625515,
                 0.39217225,  0.79484533])
```

1.8.3 Printing root mean squared error (RMSE) from Random Forest Regression

```
In [20]: print("Root mean square error value:")
         sqrt(mean_squared_error(y_test, y_RF_Pred))
```

```
Root mean square error value:
```

```
Out[20]: 0.4668745300517969
```

1.9 Performing Linear Regression with one independent variable (Bonus exercise)

1.9.1 Extracting just the median_income column from the independent variables (from X_train and X_test)

```
In [21]: X_train_median_income=train[:, median_income_columnKey]
         X_test_median_income=test[:, median_income_columnKey]
```

1.9.2 Performing Linear Regression to predict housing values based on median_income

```
In [22]: lm_one_variable = LinearRegression()
         X_train_median_income = X_train_median_income.reshape(-1, 1)
         y_train = y_train.reshape(-1, 1)
         lm_one_variable.fit(X_train_median_income, y_train)
         print("Intercept on y axis:")
         print(lm_one_variable.intercept_)
         print("Coefficient of x:")
         print(lm_one_variable.coef_)
```

```
Intercept on y axis:
[2.13617573e-16]
Coefficient of x:
[[0.68194285]]
```

1.9.3 Predicting output for test dataset using the fitted model

```
In [23]: X_test_median_income = X_test_median_income.reshape(-1, 1)
         y_pred_one_variable = lm_one_variable.predict(X_test_median_income)
         print("Predicted values:")
         y_pred_one_variable
```

```
Predicted values:
```

```
Out[23]: array([[ 0.21996341],
                [-0.18348094],
                [-0.44156509],
                ...,
                [ 0.60959461],
                [-0.23901985],
                [ 0.14588768]])
```

```
In [24]: y_test =y_test.reshape(-1, 1)
         print("Root mean square error value:")
         sqrt(mean_squared_error(y_test, y_pred_one_variable))
```

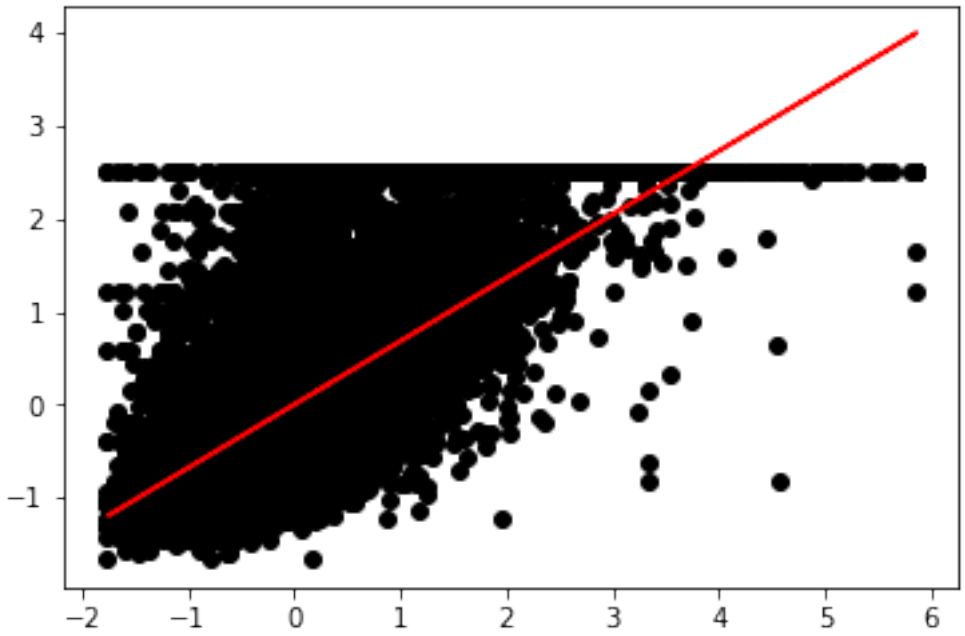
```
Root mean square error value:
```

```
Out[24]: 0.7121860437662826
```

1.9.4 Plotting the fitted model against training data

```
In [25]: plt.scatter(X_train_median_income.ravel(), y_train.ravel(), color='black')
         plt.plot(X_test_median_income.ravel(), y_pred_one_variable.ravel(), color='red')
```

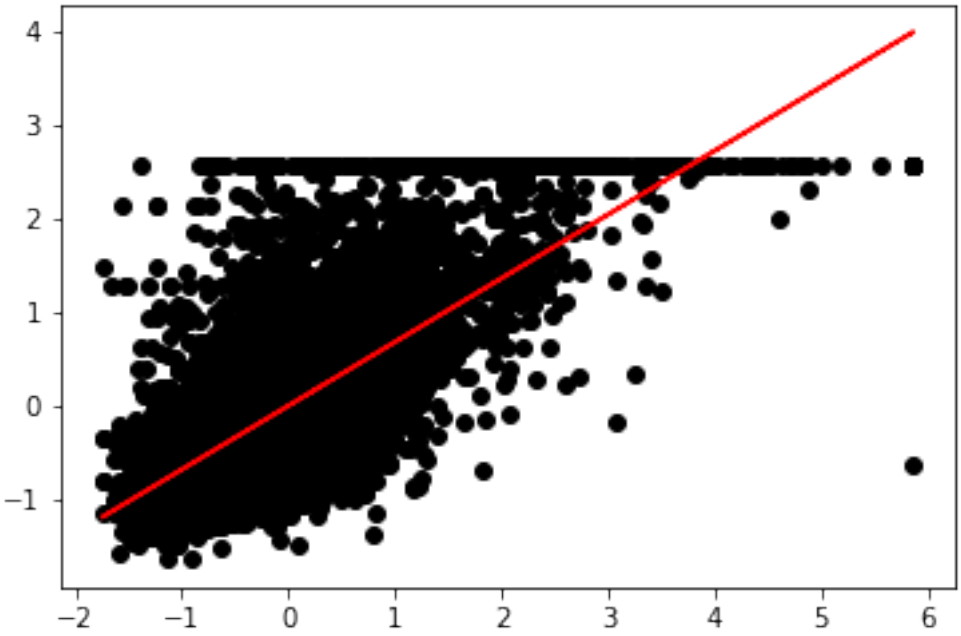
```
Out[25]: [<matplotlib.lines.Line2D at 0x32646afc50>]
```



1.9.5 Plotting the fitted model against testing data

```
In [26]: plt.scatter(X_test_median_income.ravel(), y_test.ravel(), color='black')
         plt.plot(X_test_median_income.ravel(), y_pred_one_variable.ravel(), color='red')
```

```
Out[26]: [<matplotlib.lines.Line2D at 0x32646af470>]
```


4
3
2
1
0
−1
−2
−1
0
1
2
3
4
5
6