Bouston_house_Linear_Regression

March 14, 2023

[1]:
```
import pandas as pd
import numpy as np
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
import warnings
warnings.filterwarnings("ignore")
```

[3]:
```
from sklearn.datasets import load_boston
boston = load_boston()
```

[4]:
```
data = pd.DataFrame(boston.data)
```

[5]:
```
data.head()
```

[5]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

[6]:
```
#Adding the feature names to the dataframe
data.columns = boston.feature_names
data.head()
```

[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0

```
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT
0     15.3  396.90   4.98
1     17.8  396.90   9.14
2     17.8  392.83   4.03
3     18.7  394.63   2.94
4     18.7  396.90   5.33
```

[7]:
```
#Adding target variable to dataframe
data['PRICE'] = boston.target
```

[8]:
```
#Check the shape of dataframe
data.shape
```

[8]:
```
(506, 14)
```

[9]:
```
data.columns
```

[9]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'PRICE'],
      dtype='object')
```

[10]:
```
data.dtypes
```

[10]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
PRICE      float64
dtype: object
```

[11]:
```
# Identifying the unique number of values in the dataset
data.nunique()
```

[11]:
```
CRIM       504
ZN          26
INDUS       76
CHAS         2
NOX         81
RM         446
AGE        356
DIS        412
RAD          9
TAX         66
PTRATIO     46
B          357
LSTAT      455
PRICE      229
dtype: int64
```

[12]:
```
# Check for missing values
data.isnull().sum()
```

[12]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
PRICE      0
dtype: int64
```

[13]:
```
# See rows with missing values
data[data.isnull().any(axis=1)]
```

[13]:
```
Empty DataFrame
Columns: [CRIM, ZN, INDUS, CHAS, NOX, RM, AGE, DIS, RAD, TAX, PTRATIO, B, LSTAT,
PRICE]
Index: []
```

[14]:
```
# Viewing the data statistics
data.describe()
```

[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	\
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	

	AGE	DIS	RAD	TAX	PTRATIO	B	\
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	
mean	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	
std	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	
min	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	
25%	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	
50%	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	
75%	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	
max	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	

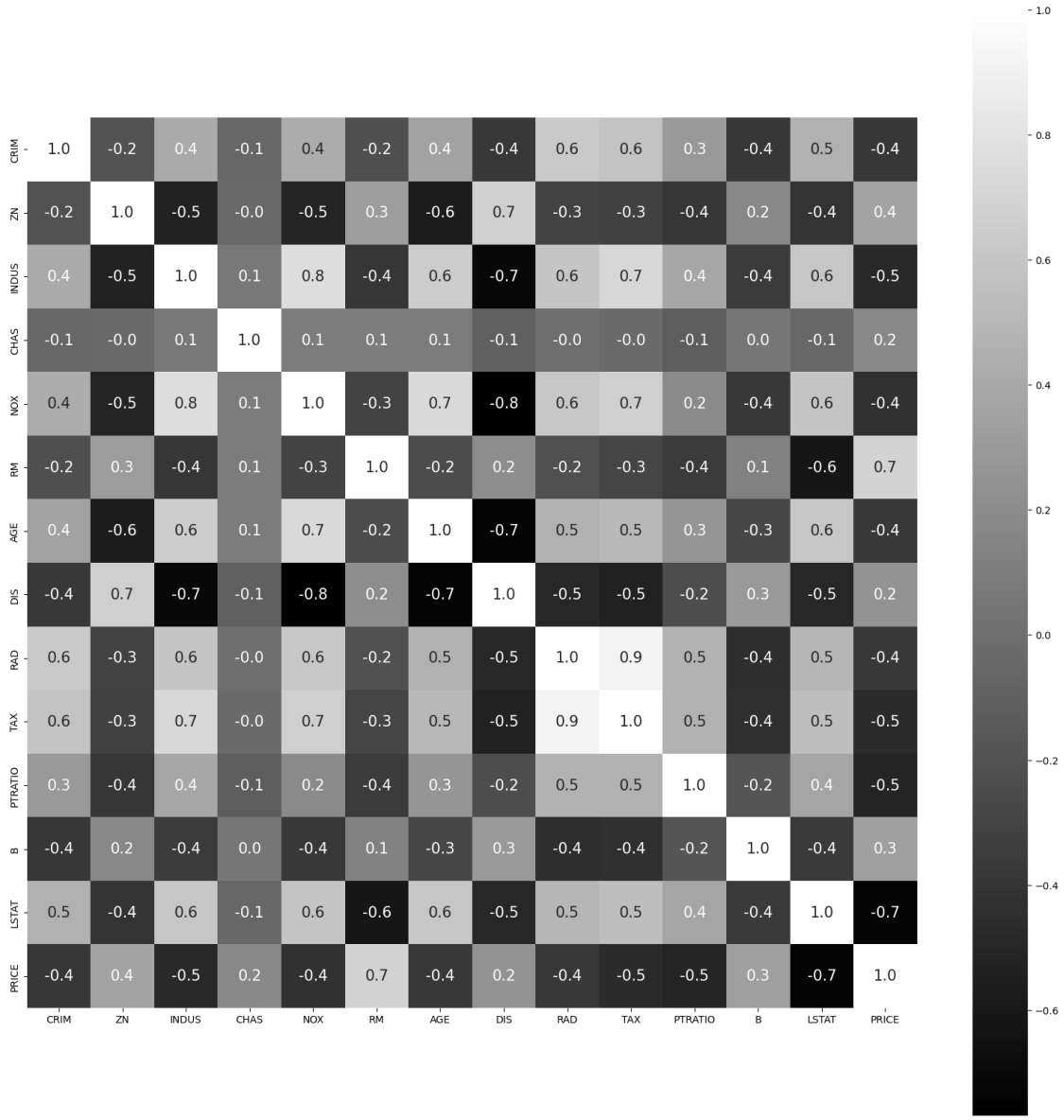
	LSTAT	PRICE
count	506.000000	506.000000
mean	12.653063	22.532806
std	7.141062	9.197104
min	1.730000	5.000000
25%	6.950000	17.025000
50%	11.360000	21.200000
75%	16.955000	25.000000
max	37.970000	50.000000

[15]:
```
# Finding out the correlation between the features
corr = data.corr()
corr.shape
```

[15]: (14, 14)

[16]:
```
# Plotting the heatmap of correlation between features
plt.figure(figsize=(20,20))
sns.heatmap(corr, cbar=True, square= True, fmt='.1f', annot=True,␣
 ↪annot_kws={'size':15}, cmap='gray')
```

[16]: <AxesSubplot:>



[17]:
```
# Spliting target variable and independent variables
X = data.drop(['PRICE'], axis = 1)
y = data['PRICE']
```

[18]:
```
# Splitting to training and testing data

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3,␣
 ↪random_state = 4)
```

[19]:
```
# Import library for Linear Regression
from sklearn.linear_model import LinearRegression
```

[20]:
```
# Create a Linear regressor
lm = LinearRegression()

# Train the model using the training sets
lm.fit(X_train, y_train)
```

[20]:
```
LinearRegression()
```

[21]:
```
# Value of y intercept
lm.intercept_
```

[21]:
```
36.357041376595205
```

[22]:
```
#Converting the coefficient values to a dataframe
coeffcients = pd.DataFrame([X_train.columns,lm.coef_]).T
coeffcients = coeffcients.rename(columns={0: 'Attribute', 1: 'Coefficients'})
coeffcients
```

[22]:

	Attribute	Coefficients
0	CRIM	-0.12257
1	ZN	0.055678
2	INDUS	-0.008834
3	CHAS	4.693448
4	NOX	-14.435783
5	RM	3.28008
6	AGE	-0.003448
7	DIS	-1.552144
8	RAD	0.32625
9	TAX	-0.014067
10	PTRATIO	-0.803275
11	B	0.009354
12	LSTAT	-0.523478

[23]:
```
# Model prediction on train data
y_pred = lm.predict(X_train)
```

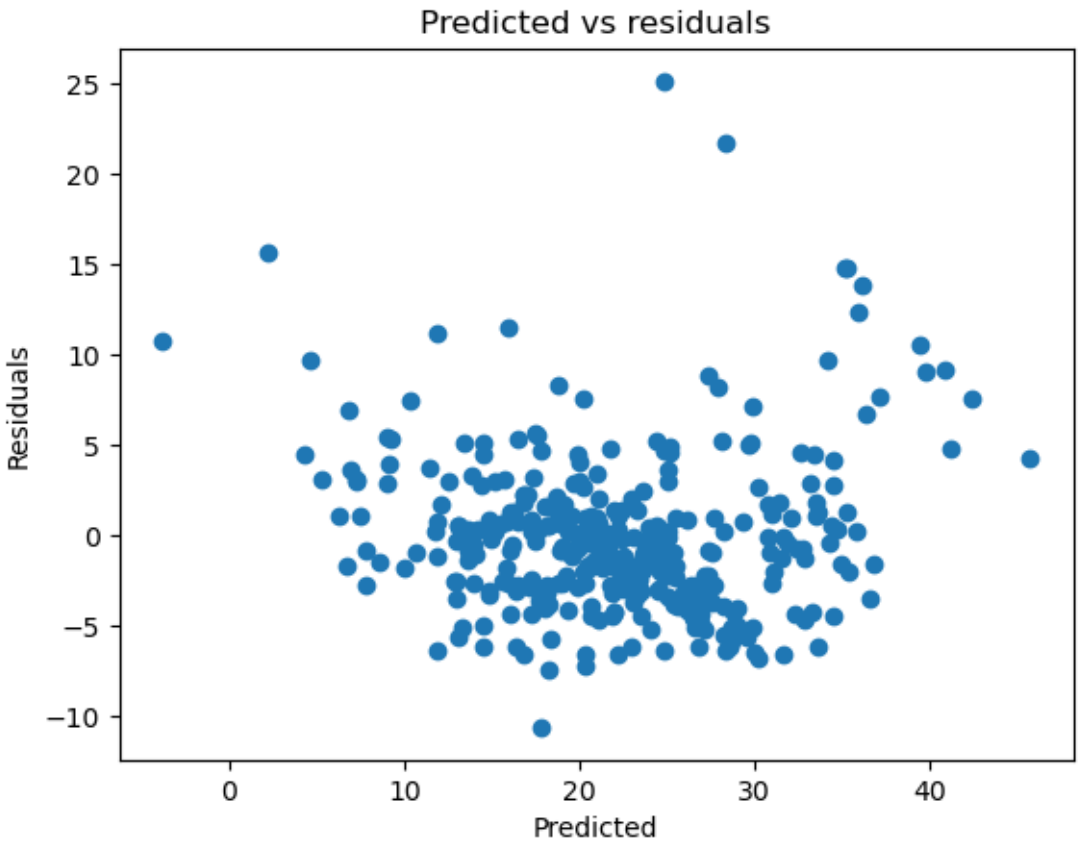
[24]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_train, y_pred))
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_train,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(y_train, y_pred))
print('MSE:',metrics.mean_squared_error(y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_pred)))
```

```
R^2: 0.7465991966746854
```

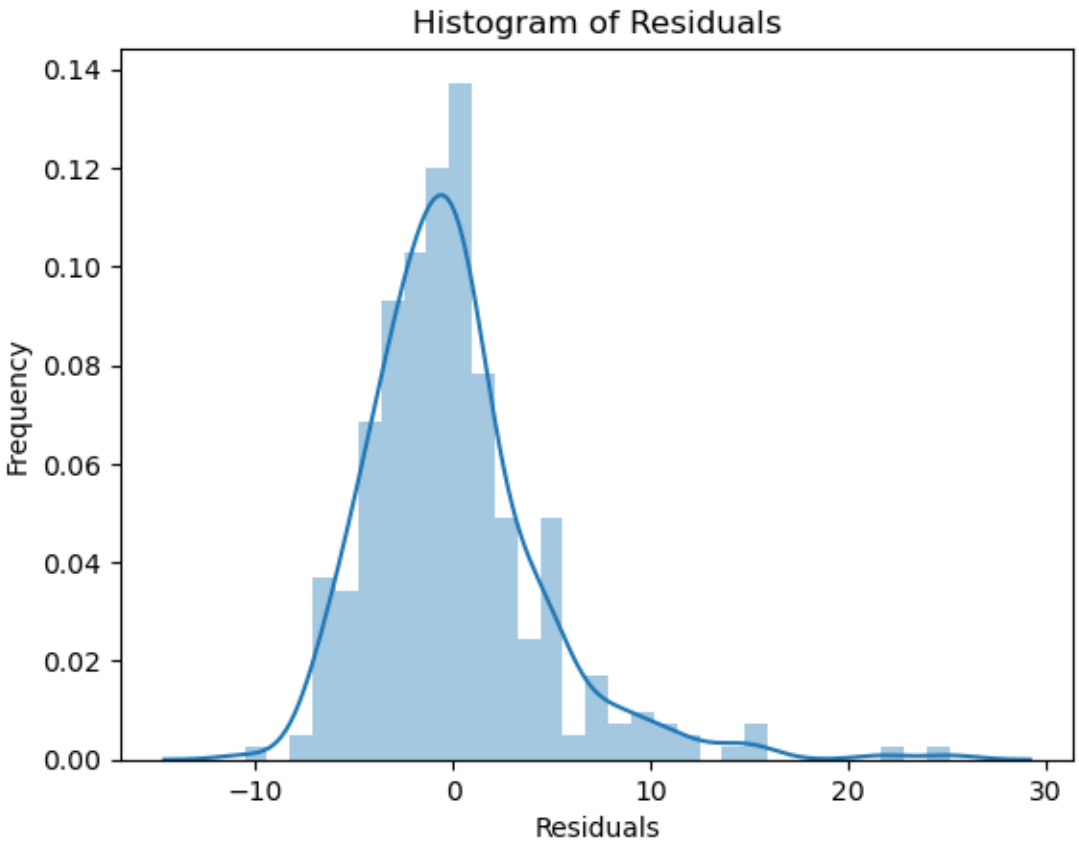
```
Adjusted R^2: 0.736910342429894
MAE: 3.08986109497113
MSE: 19.07368870346903
RMSE: 4.367343437774162
```

[25]:
```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```

[26]:
```
# Checking residuals
plt.scatter(y_pred,y_train-y_pred)
plt.title("Predicted vs residuals")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.show()
```



[27]:
```
# Checking Normality of errors
sns.distplot(y_train-y_pred)
plt.title("Histogram of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.show()
```



[28]:
```
# Predicting Test data with the model
y_test_pred = lm.predict(X_test)
```

[29]:
```
# Model Evaluation
acc_linreg = metrics.r2_score(y_test, y_test_pred)
print('R^2:', acc_linreg)
print('Adjusted R^2:',1 - (1-metrics.r2_score(y_test,␣
 ↪y_test_pred))*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1))
print('MAE:',metrics.mean_absolute_error(y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
```

```
R^2: 0.7121818377409195
Adjusted R^2: 0.6850685326005713
MAE: 3.8590055923707407
MSE: 30.053993307124127
RMSE: 5.482152251362974
```