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In [6]: # -*- coding: utf-8 -*-
        """
        Created on Sun Oct 7 15:47:50 2018

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        """

        import numpy as np
        import pandas as pd
        import scipy.stats as stats
        import matplotlib.pyplot as plt
        import sklearn
        from sklearn.datasets import load_boston
        from sklearn.metrics import r2_score

        boston = load_boston()
        bos = pd.DataFrame(boston.data)

        X = bos.iloc[:, [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 11]].values
        Y = bos.iloc[:, 12].values

        from sklearn.cross_validation import train_test_split
        X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.1, random_state = 0)

        from sklearn.linear_model import LinearRegression
        regressor = LinearRegression()
        regressor.fit(X_train, Y_train)

        Y_pred = regressor.predict(X_test)
        print("Rsquare %f.10f\n"%(r2_score(Y_test,Y_pred)))

        df2 = pd.DataFrame(np.random.randint(low = 0, high = 10, size=(51,2)), columns = ["Test", "Predicted"])
        df2 ["Test"] = Y_test
        df2["Predicted"] = Y_pred
        print(df2)

        X = bos.iloc[:, :-1].values
        Y = bos.iloc[:, 12].values

        # Building the optimal model using Backward Elimination
        import statsmodels.formula.api as sm
        X = np.append(arr = np.ones((506, 1)).astype(int), values = X, axis = 1)
        #X_opt = X[:, [0, 1, 2, 3, 4, 5]]
        X_opt = X[:, :-1]
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regressor_OLS = sm.OLS(endog = Y, exog = X_opt).fit()
print(regressor_OLS.summary())

#X_opt = X[:, [0, 1, 2, 3, 4, 5]]
X_opt = X[:, [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 11]]
regressor_OLS = sm.OLS(endog = Y, exog = X_opt).fit()
print(regressor_OLS.summary())
```

Rsquare 0.472757.10f

	Test	Predicted
0	7.34	5.959792
1	9.53	17.564101
2	10.50	13.449262
3	19.77	22.878492
4	12.34	10.563367
5	8.47	12.495776
6	11.45	14.111716
7	9.29	11.820954
8	12.64	15.424514
9	10.63	15.498500
10	20.62	29.524109
11	21.22	19.341722
12	17.79	17.263366
13	28.28	26.457282
14	1.92	7.920136
15	4.74	3.029344
16	10.74	13.489045
17	4.08	3.684551
18	5.33	6.436183
19	8.77	10.668035
20	7.20	9.154575
21	12.03	17.664826
22	14.09	13.462900
23	7.19	7.192765
24	10.21	10.760460
25	13.33	31.480650
26	13.83	14.887065
27	15.79	20.151852
28	4.21	2.779322
29	17.09	14.759709
30	18.03	17.447196
31	14.70	16.623954
32	10.15	13.219908
33	12.40	12.096116
34	9.04	11.633471
35	14.64	18.278034
36	26.77	20.272443
37	8.88	18.080766
38	17.64	18.439250
39	24.10	17.902636
40	8.58	7.918184
41	14.15	10.229469

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42  9.09   8.371196
43 18.14  20.857925
44   8.65   8.754513
45   9.14  11.427659
46 15.84  13.246092
47 15.12  16.976412
48 29.29  22.516690
49   9.42  10.177163
50 15.02  18.243472

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OLS Regression Results

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Dep. Variable:          y      R-squared:          0.651
Model:                  OLS    Adj. R-squared:      0.643
Method:                 Least Squares  F-statistic:      83.78
Date:                   Sat, 13 Oct 2018  Prob (F-statistic):  2.00e-105
Time:                   18:12:17  Log-Likelihood:    -1445.9
No. Observations:      506      AIC:              2916.
Df Residuals:          494      BIC:              2966.
Df Model:               11
Covariance Type:       nonrobust
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	coef	std err	t	P> t	[0.025	0.975]
const	26.1867	4.227	6.194	0.000	17.881	34.493
x1	0.1099	0.029	3.815	0.000	0.053	0.166
x2	0.0144	0.012	1.169	0.243	-0.010	0.039
x3	0.1008	0.055	1.831	0.068	-0.007	0.209
x4	-1.1829	0.772	-1.533	0.126	-2.699	0.333
x5	6.2343	3.413	1.827	0.068	-0.471	12.939
x6	-4.3814	0.317	-13.806	0.000	-5.005	-3.758
x7	0.0885	0.011	7.927	0.000	0.067	0.110
x8	0.1671	0.179	0.933	0.351	-0.185	0.519
x9	0.0652	0.059	1.098	0.273	-0.051	0.182
x10	-0.0009	0.003	-0.254	0.800	-0.007	0.006
x11	0.1068	0.117	0.909	0.364	-0.124	0.337

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Omnibus:                49.986  Durbin-Watson:          1.185
Prob(Omnibus):          0.000  Jarque-Bera (JB):        295.703
Skew:                   0.016  Prob(JB):                 6.15e-65
Kurtosis:               6.745  Cond. No.                 1.16e+04
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Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.16e+04. This might indicate that there are strong multicollinearity or other numerical problems.

OLS Regression Results

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=====
Dep. Variable:          y      R-squared:          0.651
Model:                  OLS    Adj. R-squared:       0.644
Method:                 Least Squares  F-statistic:      92.33
Date:                   Sat, 13 Oct 2018  Prob (F-statistic): 2.09e-106
Time:                   18:12:17  Log-Likelihood:   -1445.9
No. Observations:      506      AIC:              2914.
Df Residuals:          495      BIC:              2960.
Df Model:               10
Covariance Type:        nonrobust
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	coef	std err	t	P> t	[0.025	0.975]
const	26.0718	4.199	6.209	0.000	17.821	34.322
x1	0.1100	0.029	3.821	0.000	0.053	0.166
x2	0.0137	0.012	1.142	0.254	-0.010	0.037
x3	0.0947	0.049	1.917	0.056	-0.002	0.192
x4	-1.1590	0.765	-1.515	0.130	-2.662	0.344
x5	6.1684	3.400	1.814	0.070	-0.511	12.848
x6	-4.3751	0.316	-13.841	0.000	-4.996	-3.754
x7	0.0884	0.011	7.930	0.000	0.066	0.110
x8	0.1662	0.179	0.929	0.353	-0.185	0.518
x9	0.0533	0.036	1.474	0.141	-0.018	0.124
x10	0.1046	0.117	0.894	0.372	-0.125	0.334

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Omnibus:                50.069  Durbin-Watson:          1.185
Prob(Omnibus):           0.000  Jarque-Bera (JB):        296.678
Skew:                    0.020  Prob(JB):                 3.78e-65
Kurtosis:                 6.751  Cond. No.                  2.02e+03
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Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.02e+03. This might indicate that there are strong multicollinearity or other numerical problems.