In [1]:
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
```

In [2]:
```
veri=pd.read_csv("dataset/DogrusalRegresyon.csv")
```

In [3]:
```
veri.head()
```

Out[3]:

	Cmdyet	Yas_Aylik	Bas_cevresi(cm^3)	Boyin_agirligi(gr)
0	1	1	4512	1530
1	1	1	3758	1297
2	1	1	4261	1335
3	1	1	3777	1282
4	1	1	4177	1590

In [4]:
```
X=veri['Bas_cevresi(cm^3)'].values
```

In [5]:
```
y=veri[ 'Boyin_agirligi(gr)' ]
```

In [6]:
```
len(X)
```

Out[6]:
```
237
```

In [7]:
```
X.shape
```

Out[7]:
```
(237, 1)
```

In [8]:
```
X=X.reshape(len(X),1)
```

In [9]:
```
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=42)
```

In [10]:
```
model = LinearRegression()
model.fit(X_train,y_train)
```

Out[10]:
```
LinearRegression()
```

In [11]:
```
y_pred=model.predict(X_test)
```

In [12]:
```
%matplotlib
plt.scatter(X_train, y_train, color='red')
plt.plot(X_train, model.predict(X_train))
```

```
Using matplotlib backend: QtAgg
[<matplotlib.lines.Line2D at 0x29ddb36dfa0>]
```

In [13]:
```
plt.scatter(X_train, y_train, color='red')
plt.plot(X_test, model.predict(X_test))
```

Out[13]:
```
[<matplotlib.lines.Line2D at 0x29ddbb44fd0>]
```

In [14]:
```
print(model.coef_)
print(model.intercept_)
```

```
[0.26481251]
339.83831654867099
```

In [20]:
```
from sklearn.metrics import explained_variance_score, mean_absolute_error,mean_squared_error, median_absolute_error, r2_score
```

In [21]:
```
print(r2_score(y_test, y_pred))
print(mean_absolute_error(y_test, y_pred))
print(mean_squared_error(y_test, y_pred))
print(median_absolute_error(y_test, y_pred))
```

```
0.6919862188599295
55.58499577540606
4617.918994831652
53.39675329725645
```

In [28]:
```
#polinom regresyon
```

In [29]:
```
def func(x):
    return 10*np.sin(x/2) + x/7 +6
```

In [30]:
```
X=np.random.rand(100)*10
```

In [31]:
```
y=func(X) + 2*np.random.randn(*X.shape)
```

In [32]:
```
X=X.reshape(len(X),1)
```

In [33]:
```
plt.scatter(X, y, color='red')
```

Out[33]:
```
<matplotlib.collections.PathCollection at 0x1d8ceab04a30>
```

In [34]:
```
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=42)
```

In [35]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [36]:
```
model_pol=PolynomialFeatures(degree=3)
```

In [37]:
```
X_pol=model_pol.fit_transform(X_train)
```

In [38]:
```
model_pol.fit(X_pol, y_train)
```

Out[38]:
```
PolynomialFeatures(degree=3)
```

In [39]:
```
model2=LinearRegression()
model2.fit(X_pol, y_train)
```

Out[39]:
```
LinearRegression()
```

In [40]:
```
X_grid=np.arange(min(X_train), max(X_train), 0.1)
X_grid=X_grid.reshape(len(X_grid),1)
plt.scatter(X_train, y_train, color='red')
plt.plot(X_grid, model2.predict(model_pol.fit_transform(X_grid)), color='blue')
```

Out[40]:
```
[<matplotlib.lines.Line2D at 0x1d8ceb875fc0>]
```

In [41]:
```
model2.intercept_
model2.coef_
```

Out[41]:
```
array([0.        , 2.15368758, 0.49336386, 0.13277488])
```

In [42]:
```
y_pred=model2.predict(model_pol.fit_transform(X_test))
```

In [43]:
```
r2_score(y_test, y_pred)
```

Out[43]:
```
0.8783786312445749
```

In [44]:
```
"""
Reshape your data either using array.reshape(-1, 1) if your data has a single feature
or array.reshape(1, -1) if it contains a single sample.
"""
```

Out[44]:
```
'\nReshape your data either using array.reshape(-1, 1) if your data has a single feature \nor array.reshape(1, -1) if it contains a single sample.\n'
```

In [45]:
```
#ünlü doğrusal regresyon
```

In [46]:
```
veriseti=pd.read_excel('dataset/ym.xlsx')
```

In [47]:
```
veriseti
```

Out[47]:

	ALT	LAT	SSD	T	GSR	GUC	EKSEN	SONUC
0	50	36.99	7.48	17.7	1.81	1	1	1.716600
1	50	36.99	7.48	17.7	1.81	1	2	2.235164
2	50	36.99	7.48	17.7	1.81	1	3	2.341118
3	50	36.99	7.48	17.7	1.81	1	3	1.150890
4	50	36.99	7.48	17.7	1.81	1	3	6.705319
...	...	...	...	...	...	...	...	...
1615	124	41.45	5.90	12.9	1.52	5	2	9.109464
1616	124	41.45	5.90	12.9	1.52	5	3	9.660183
1617	124	41.45	5.90	12.9	1.52	10	1	14.411507
1618	124	41.45	5.90	12.9	1.52	10	2	18.378940
1619	124	41.45	5.90	12.9	1.52	10	3	19.320388

1620 rows × 8 columns

In [85]:
```
import re
missed_data=[]
non_categorical=[]

for i in veriseti:
    essiz=veriseti[i].unique()
    print(f'{i} özniteliğine ait essiz  veriler {essiz.size}')

    if(True in pd.isnull(essiz)):
        x=f'{i özniteliğine ait kayıp veriler {}'.format(i, pd.isnull(veriseti[i]).sum())
        missed_data.append(x)
    else:
        for j in range(1, np.prod(essiz.shape)):
            if(re.match('nan', str(essiz[j]))):
                break
            if not (re.search('^\d+\.?\d*$|^\d*\.?\d+$', str(essiz[j]))):
                non_categorical.append(i)
                break
```

```
ALT özniteliğine ait essiz  veriler 84
LAT özniteliğine ait essiz  veriler 155
SSD özniteliğine ait essiz  veriler 114
T özniteliğine ait essiz  veriler 96
GSR özniteliğine ait essiz  veriler 4
GUC özniteliğine ait essiz  veriler 10
EKSEN özniteliğine ait essiz  veriler 3
SONUC özniteliğine ait essiz  veriler 1592
```

In [86]:
```
X=veriseti.iloc[:,:-1].values
```

In [87]:
```
y=veriseti.iloc[:,-1].values
```

In [88]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, random_state=42)
```

In [89]:
```
from scipy import stats
```

In [90]:
```
desc=stats.describe(X_train, axis=0)
```

In [94]:
```
#sort istisna normal dağılıma sahip olduğunu test etmek için shownex ve kurtosis
#shownex normal(simetrik), shownex if ten kücük ve kurtosis -3 ise z pozitiflerse normal değilim demir
desc.kurtosis
```

Out[94]:
```
array([-0.66767985, -0.95139949,  0.22268709, -0.88865592, -0.85831744,
       -1.15603994, -1.48750387])
```

In [95]:
```
desc.skewness
```

Out[95]:
```
array([ 0.34099757, -0.11744134, -0.86846921, -0.18834816, -0.87045618,
        0.52798605, -0.45653358])
```

In [96]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
X_train_scaled=scaler.fit_transform(X_train)
print("ayrı-Feature minimum before scaling:\n {}".format(X_train.min(axis=0)))
print("ayrı-Feature maximum before scaling:\n {}".format(X_train.max(axis=0)))
print("ayrı-Feature minimum after scaling:\n {}".format(X_train_scaled.min(axis=0)))
print("ayrı-Feature maximum after scaling:\n {}".format(X_train_scaled.max(axis=0)))

per-feature minimum before scaling:
 [ 0.   33.55  5.83  0.    1.3   1.    1. ]
per-feature maximum before scaling:
 [2.17e+03 4.26e+01 8.48e+00 1.93e+01 1.93e+00 1.00e+01 3.00e+00]
per-feature minimum after scaling:
 [0. 0. 0. 0. 0. 0. 0.]
per-feature maximum after scaling:
 [1. 1. 1. 1. 1. 1. 1.]
```

In [97]:
```
X_test=scaler.transform(X_test)
print("ayrı-Feature minimum after scaling:\n{}".format(X_test.min(axis=0)))
print("ayrı-Feature maximum after scaling:\n{}".format(X_test.max(axis=0)))

per-feature minimum after scaling:
[0. 0. 0. 0. 0. 0. 0.]
per-feature maximum after scaling:
[1. 1. 1. 1. 1. 1. 1.]
```

In [98]:
```
"""
# scale the data using MinMaxScaler
scaler=MinMaxScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
"""
```

Out[98]:
```
'\n# scale the data using MinMaxScaler\nscaler=MinMaxScaler()\nscaler.fit(X_train)\nX_train_scaled = scaler.transform(X_train)\nX_test_scaled = scaler.transform(X_test)\n'
```

In [99]:
```
import statsmodels.formula.api as sm
X=np.append(arr=np.ones((1620,1)).astype(int), values=X, axis=1)
```

In [100]:
```
#veriseti['A']= 1
#veriseti.insert(loc=0, column='A', values=1)
```

In [101]:
```
model=sm.ols(formula='SONUC ~ ALT + LAT + SSD + T + GSR + GUC + EKSEN', data=veriseti).fit()
```

In [102]:
```
model.fit().summary()
```

Out[102]:
```
OLS Regression Results
```

Dep. Variable:	SONUC	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	6600.
Date:	Sun, 19 May 2023	**Prob (F-statistic):**	0.00
Time:	23:55:56	**Log-Likelihood:**	-2579.5
No. Observations:	1620	**AIC:**	5173.
Df Residuals:	1612	**BIC:**	5216.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-17.1192	2.914	-6.072	0.000	-23.234	-11.004
ALT	0.0004	0.000	2.652	0.008	0.000	0.001
LAT	0.1662	0.052	3.190	0.002	0.062	0.270
SSD	-0.1098	0.052	-2.106	0.036	-0.212	-0.007
T	0.0544	0.034	1.595	0.111	-0.013	0.121
GSR	3.0869	0.445	11.453	0.000	4.216	5.958
GUC	1.8728	0.009	211.472	0.000	1.855	1.890
EKSEN	1.2456	0.036	34.335	0.000	1.174	1.317

Omnibus:	10.010	**Durbin-Watson:**	1.522
Prob(Omnibus):	0.007	**Jarque-Bera (JB):**	138.055
Skew:	0.105	**Prob(JB):**	1.05e-30
Kurtosis:	4.415	**Cond. No.**	1.04e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [104]:
```
model=sm.ols(formula='SONUC ~ ALT + LAT + SSD + T + GSR + GUC + EKSEN', data=veriseti).fit()
model.fit().summary()
```

Out[104]:
```
OLS Regression Results
```

Dep. Variable:	SONUC	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	6600.
Date:	Sun, 19 May 2023	**Prob (F-statistic):**	0.00
Time:	23:55:56	**Log-Likelihood:**	-2579.5
No. Observations:	1620	**AIC:**	5173.
Df Residuals:	1612	**BIC:**	5216.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-17.1192	2.914	-6.072	0.000	-23.234	-11.004
ALT	0.0004	0.000	2.652	0.008	0.000	0.001
LAT	0.1662	0.052	3.190	0.002	0.062	0.270
SSD	-0.1098	0.052	-2.106	0.036	-0.212	-0.007
T	0.0544	0.034	1.595	0.111	-0.013	0.121
GSR	3.0869	0.445	11.453	0.000	4.216	5.958
GUC	1.8728	0.009	211.472	0.000	1.855	1.890
EKSEN	1.2456	0.036	34.335	0.000	1.174	1.317

Omnibus:	10.010	**Durbin-Watson:**	1.522
Prob(Omnibus):	0.007	**Jarque-Bera (JB):**	138.055
Skew:	0.105	**Prob(JB):**	1.05e-30
Kurtosis:	4.415	**Cond. No.**	1.04e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [105]:
```
model=sm.ols(formula='SONUC ~ ALT + LAT + SSD + GSR + GUC + EKSEN', data=veriseti).fit()
model.fit().summary()
```

Out[105]:
```
OLS Regression Results
```

Dep. Variable:	SONUC	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	7870.
Date:	2023-05-19 22:47	**BIC:**	5218.2145
No. Observations:	1620	**Log-Likelihood:**	-2579.5
Df Model:	6	**F-statistic:**	6605
Df Residuals:	1613	**Prob (F-statistic)**	0.00
R-squared:	0.966	**Scale:**	1.4313

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-16.7196	1.4568	-6.0130	0.0000	-11.6170	-5.9022
A	-16.7196	1.4568	-6.0130	0.0000	-11.6170	-5.9022
ALT	0.0004	0.0002	2.6523	0.0081	0.0001	0.0008
LAT	0.1662	0.0521	3.1582	0.0018	0.0621	0.2703
SSD	-0.1098	0.0522	-2.1038	0.0355	-0.2122	-0.0074
T	0.0544	0.0341	1.5946	0.1110	-0.0125	0.1214
GSR	3.0869	0.4449	11.4330	0.0000	4.2142	5.9596
GUC	1.8728	0.0089	211.4715	0.0000	1.8553	1.8902
EKSEN	1.2456	0.0363	34.3364	0.0000	1.1745	1.3168

Omnibus:	55.010	**Durbin-Watson:**	1.522
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	138.055
Skew:	0.105	**Prob(JB):**	0.000
Kurtosis:	4.415	**Condition No.:**	1.04e+05

In [106]:
```
veriseti=veriseti.drop(columns="T")
```

In [107]:
```
model=sm.ols(formula='SONUC ~ ALT + LAT + SSD + GSR + GUC + EKSEN', data=veriseti).fit()
model.fit().summary()
```

Out[107]:
```
OLS Regression Results
```

Dep. Variable:	SONUC	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	7870.
Date:	2023-05-19 23:56	**BIC:**	5213.3775
No. Observations:	1620	**Log-Likelihood:**	-2580.6
Df Model:	6	**F-statistic:**	7692.
Df Residuals:	1613	**Prob (F-statistic):**	0.00
R-squared:	0.966	**Scale:**	1.4228

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-14.6569	2.2960	-6.3836	0.0000	-19.1604	-10.1534
ALT	0.0002	0.0001	3.1537	0.0002	0.0001	0.0003
LAT	0.1733	0.0415	2.7316	0.0064	0.0319	0.1947
SSD	-0.0923	0.0511	-1.8076	0.0709	-0.1924	0.0079
GSR	3.2828	0.4451	11.4746	0.0000	4.2097	5.9559
GUC	1.8728	0.0089	211.2721	0.0000	1.8555	1.8902
EKSEN	1.2457	0.0363	34.3193	0.0000	1.1745	1.3168

Omnibus:	54.228	**Durbin-Watson:**	1.521
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	135.940
Skew:	0.098	**Prob(JB):**	0.000
Kurtosis:	4.406	**Condition No.:**	82743

In [108]:
```
veriseti=veriseti.drop(columns="SSD")
```

In [109]:
```
model=sm.ols(formula='SONUC ~ ALT + LAT + GSR + GUC + EKSEN', data=veriseti).fit()
model.fit().summary()
```

Out[109]:
```
OLS Regression Results
```

Dep. Variable:	SONUC	**R-squared:**	0.966
Model:	OLS	**Adj. R-squared:**	0.966
Method:	Least Squares	**F-statistic:**	9217.
Date:	2023-05-19 23:56	**BIC:**	5206.2656
No. Observations:	1620	**Log-Likelihood:**	-2582.5
Df Model:	5	**F-statistic:**	9217
Df Residuals:	1614	**Prob (F-statistic):**	0.00
R-squared:	0.966	**Scale:**	1.4248

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-16.3982	2.0862	-7.8592	0.0000	-20.4879	-12.3085
ALT	0.0002	0.0001	3.6496	0.0001	0.0001	0.0003
LAT	0.1473	0.0370	3.9904	0.0001	0.0750	0.2195
GSR	4.9302	0.4302	11.4591	0.0000	4.0795	5.7809
GUC	1.8728	0.0089	211.2279	0.0000	1.8555	1.8902
EKSEN	1.2458	0.0363	34.3581	0.0000	1.1745	1.3170

Omnibus:	57.253	**Durbin-Watson:**	1.520
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	145.682
Skew:	0.114	**Prob(JB):**	0.000
Kurtosis:	4.431	**Condition No.:**	73187

In [ ]:
```

```