HW2_RA_LAB2_ITDSIU21095

October 14, 2022

[1]:
```
import pandas as pd, numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

[22]:
```
df = pd.read_csv('CH01PR22.txt', sep = '\s+', header = None, names = ['the␣
 ↪hardness of the plastic','the elapsed time'])
df.head()
```

[22]:

	the hardness of the plastic	the elapsed time
0	199.0	16.0
1	205.0	16.0
2	196.0	16.0
3	200.0	16.0
4	218.0	24.0

0.1 a

[23]:
```
X = df['the elapsed time']
Y = df['the hardness of the plastic']
X_bar = np.mean(X)
Y_bar = np.mean(Y)
X_err = X - X_bar
Y_err = Y - Y_bar
print(X_bar, Y_bar)
X_err.head()
```

```
28.0 225.5625
```

[23]:
```
0   -12.0
1   -12.0
2   -12.0
3   -12.0
4    -4.0
Name: the elapsed time, dtype: float64
```

[24]:
```
A = np.sum(X_err*Y_err)
B = np.sum(X_err**2)
print(A,'\n',B)
```

```
2604.0
 1280.0
```

[25]:
```
b1 = A / B
b0 = Y_bar - b1*X_bar
print(b1, b0)
```

```
2.034375 168.60000000000002
```

[26]:
```
n= len(X)
Y_hat = b0 + b1 * X
resid = Y - Y_hat
```

[27]:
```
SSE = np.sum((Y - Y_hat)**2)
MSE = SSE / (n-2)
print(MSE, SSE)
```

```
10.458928571428588 146.42500000000024
```

[28]:
```
SSR = np.sum((Y_hat - Y_bar)**2)
MSR = SSR/1
SSR
```

[28]:
```
5297.512499999998
```

[29]:
```
SSTO = SSE + SSR
SSTO
```

[29]:
```
5443.937499999998
```

[30]:
```
model = smf.ols('Y ~ X', data=df)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.973
Model:                            OLS   Adj. R-squared:                  0.971
Method:                 Least Squares   F-statistic:                     506.5
Date:                Fri, 14 Oct 2022   Prob (F-statistic):           2.16e-12
Time:                        19:14:19   Log-Likelihood:                -40.414
No. Observations:                  16   AIC:                             84.83
Df Residuals:                      14   BIC:                             86.37
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    168.6000      2.657     63.454      0.000     162.901     174.299
X              2.0344      0.090     22.506      0.000       1.840       2.228
==============================================================================
Omnibus:                        0.955   Durbin-Watson:                   2.466
Prob(Omnibus):                  0.620   Jarque-Bera (JB):                0.711
Skew:                           0.068   Prob(JB):                        0.701
Kurtosis:                       1.976   Cond. No.                         96.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
C:\Users\PC\anaconda3\lib\site-packages\scipy\stats\stats.py:1541: UserWarning:
kurtosistest only valid for n>=20 … continuing anyway, n=16
  warnings.warn("kurtosistest only valid for n>=20 … continuing "
```

[31]:
```
anova_result = sm.stats.anova_lm(results, typ=2)
print(anova_result)
```

```
              sum_sq    df           F        PR(>F)
X         5297.5125   1.0  506.506232  2.158814e-12
Residual   146.4250  14.0         NaN           NaN
```

MODEL Y = 168.6 + 2.03X

0.2 b

The alternative conclusions are:

H0 : 1 == 0

Ha : 1 != 0

[32]:
```
alpha = 0.01
f = stats.f.ppf(q = 1 - alpha, dfn = 1, dfd = n-2)
f
```

[32]:
```
8.861592665176424
```

The decision rule is:

If F* <= 8.86, conclude H0

If F* >= 8.86, conclude Ha

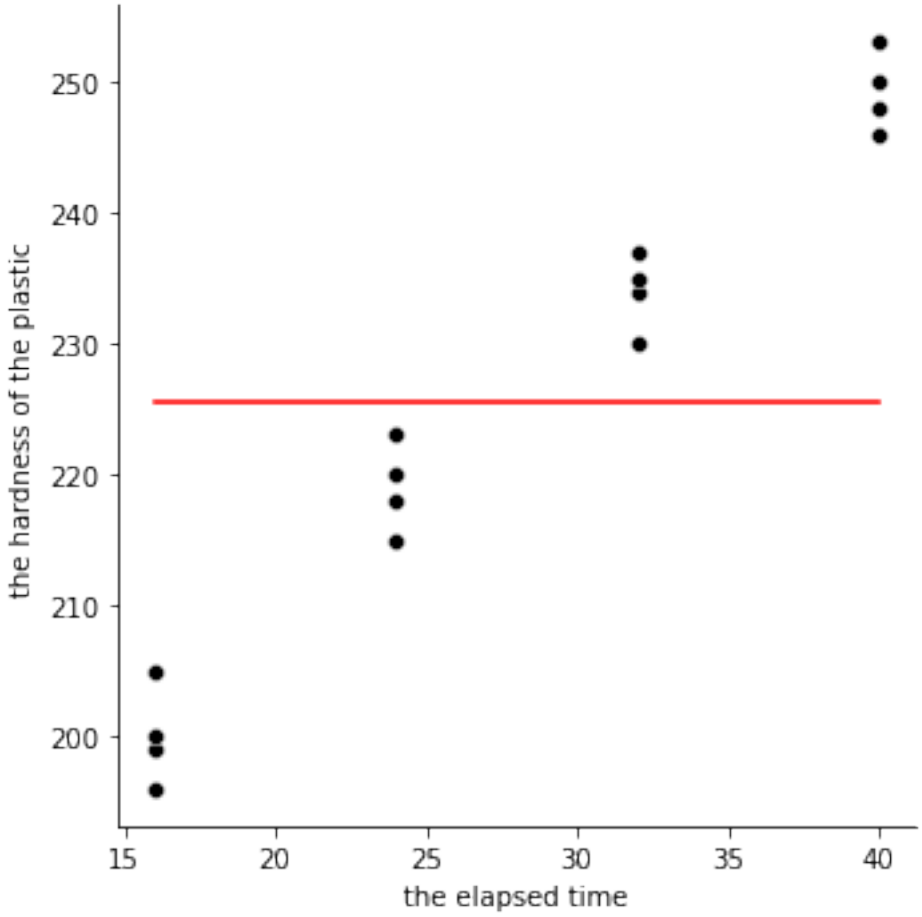
[33]:
```
# F star is:
f_star = MSR /MSE
f_star
```

[33]: 506.50623185931266

Since F* = 506.5 > F = 8.86, we conclude Ha, that B1 != 0, or that there is a linear assiciation between X and Y.

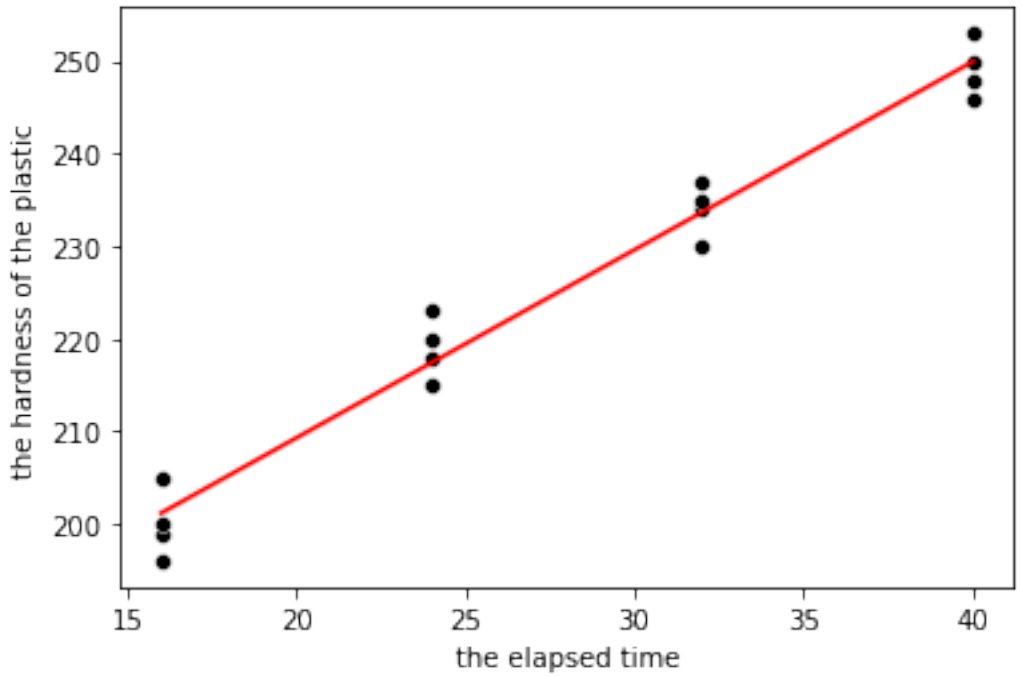
0.3 c

[57]:
```
#Plot the deviations   -  _hat against
sns.relplot(x ='the elapsed time', y ='the hardness of the plastic',data=df,␣
 ↪color ='black')
x =np.linspace(20,120,20);
sns.scatterplot(x='the elapsed time', y='the hardness of the plastic', data=df,␣
 ↪color = 'black')
sns.lineplot(x ='the elapsed time', y= Y_bar, data=df,color = 'red')
plt.show()
```



[54]:
```
#Plot the deviations Y_hat -  _bar against
```

```
sns.scatterplot(x='the elapsed time', y='the hardness of the plastic', data=df,␣
 ↪color = 'black')
sns.lineplot(x='the elapsed time', y= Y_hat, data=df, color = 'red')
plt.show()
```



On the graphs, it is apparent that the residuals Yi − Yi_hat much smaller than the deviations Yi_hat − Y_bar of the predictors from the mean. Thus the SSR should be much larger than the SSE, and we expect R^2 = SSR /SSTO to be close to 1.

0.4 d

[16]:
```
# Coefficient of determination:
R2 = SSR/SSTO
r = np.sqrt(R2)
print(R2,r)
```

```
0.9731031078148857 0.9864598865716161
```

R^2 = 0.973 and r = 0.986