

zad2

December 10, 2019

```
[1]: import pandas as pd
data = pd.read_csv("beauty.csv")
data
```

```
[1]:      tenured  profnumber  minority  age  beautyf2upper  beautyflowerdiv  \
0           0           1           1  36              6              5
1           1           2           0  59              2              4
2           1           3           0  51              5              5
3           1           4           0  40              4              2
4           0           5           0  31              9              7
..          ...          ...          ...  ...          ...          ...
458          0          93           0  32              9              6
459          0          93           0  32              9              6
460          0          94           1  42              7              3
461          0          94           1  42              7              3
462          0          94           1  42              7              3
```

```
      beautyfupperdiv  beautym2upper  beautymlowerdiv  beautymupperdiv  ...  \
0                    7              6              2              4  ...
1                    4              3              2              3  ...
2                    2              3              2              3  ...
3                    5              2              3              3  ...
4                    9              6              7              6  ...
..          ...          ...          ...          ...  ...
458                  6              5              7              8  ...
459                  6              5              7              8  ...
460                  8              4              4              6  ...
461                  8              4              4              6  ...
462                  8              4              4              6  ...
```

```
      nonenglish  onecredit  percentevaluating  profevaluation  students  \
0              0          0          55.81395          4.7          43
1              0          0          85.00000          4.6          20
2              0          0         100.00000          4.1          55
3              0          0          86.95652          4.5          46
4              0          0          87.50000          4.8          48
..          ...          ...          ...          ...          ...
```

| | | | | | |
|-----|---|---|----------|-----|----|
| 458 | 0 | 0 | 42.85714 | 4.1 | 21 |
| 459 | 0 | 0 | 60.46511 | 4.5 | 86 |
| 460 | 1 | 0 | 77.61194 | 4.4 | 67 |
| 461 | 1 | 0 | 81.81818 | 4.4 | 66 |
| 462 | 1 | 1 | 80.00000 | 4.1 | 35 |

| | tenuretrack | blkandwhite | btystdvariance | btystdavepos | btystdaveneg |
|-----|-------------|-------------|----------------|--------------|--------------|
| 0 | 1 | 0 | 2.129806 | 0.201567 | 0.000000 |
| 1 | 1 | 0 | 1.386081 | 0.000000 | -0.826081 |
| 2 | 1 | 0 | 2.537435 | 0.000000 | -0.660333 |
| 3 | 1 | 0 | 1.760577 | 0.000000 | -0.766312 |
| 4 | 1 | 0 | 1.693100 | 1.421450 | 0.000000 |
| .. | ... | ... | ... | ... | ... |
| 458 | 1 | 0 | 3.107088 | 1.143040 | 0.000000 |
| 459 | 1 | 0 | 3.107088 | 1.143040 | 0.000000 |
| 460 | 1 | 0 | 3.018447 | 0.332051 | 0.000000 |
| 461 | 1 | 0 | 3.018447 | 0.332051 | 0.000000 |
| 462 | 1 | 0 | 3.018447 | 0.332051 | 0.000000 |

[463 rows x 64 columns]

```
[2]: #Utwórz regresję przy użyciu piękna (zmienna btystdave), aby przewidzieć oceny
      ↪ kursu (courseevaluation), kontrolując różne
      #inne dane wejściowe.
      import statsmodels.api as sm

      X = data['btystdave']
      Y = data['courseevaluation']
      X = sm.add_constant(X)
      model = sm.OLS(Y, X).fit()
      predictions = model.predict(X)

      model.summary()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\numpy\core\fromnumeric.py:2389:
FutureWarning: Method .ptp is deprecated and will be removed in a future
version. Use numpy.ptp instead.
    return ptp(axis=axis, out=out, **kwargs)
```

```
[2]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:      courseevaluation    R-squared:      0.036
Model:              OLS                Adj. R-squared:  0.034
Method:             Least Squares      F-statistic:    17.08
Date:               Mon, 09 Dec 2019   Prob (F-statistic): 4.25e-05
```

Time: 23:34:56 Log-Likelihood: -375.32
 No. Observations: 463 AIC: 754.6
 Df Residuals: 461 BIC: 762.9
 Df Model: 1
 Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|-----------|--------|---------|---------|-------|--------|--------|
| const | 4.0100 | 0.026 | 157.205 | 0.000 | 3.960 | 4.060 |
| btystdave | 0.1330 | 0.032 | 4.133 | 0.000 | 0.070 | 0.196 |

Omnibus: 15.399 Durbin-Watson: 1.410
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 16.405
 Skew: -0.453 Prob(JB): 0.000274
 Kurtosis: 2.831 Cond. No. 1.29

Warnings:

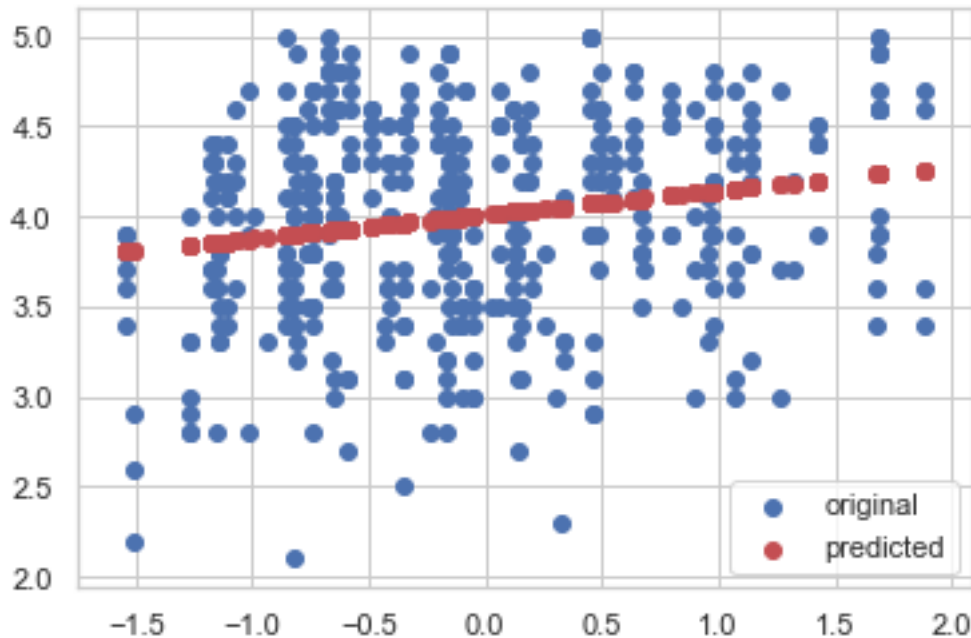
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 ""

```
[7]: # Wyświetl dopasowany model graficznie i objaśnij znaczenie każdego ze
      ↳ współczynników wraz z pozostałym odchyleniem standardowym

import matplotlib.pyplot as plt
import numpy as np

fig, ax = plt.subplots()
scatter=ax.scatter(y=data['courseevaluation'], x=data['btystdave'],c='b',
↳label='original')
scatter=ax.scatter(y=predictions, x=data['btystdave'],c='r', label='predicted')

ax.legend()
plt.show()
```



Coefficients explanation:

Omnibus/Prob(Omnibus) – a test of the skewness and kurtosis of the residual. We hope to see a value close to zero which would indicate normalcy. The Prob (Omnibus) performs a statistical test indicating the probability that the residuals are normally distributed. We hope to see something close to 1 here.

Skew – a measure of data symmetry. We want to see something close to zero, indicating the residual distribution is normal. Note that this value also drives the Omnibus.

Kurtosis – a measure of “peakiness”, or curvature of the data. Higher peaks lead to greater Kurtosis. Greater Kurtosis can be interpreted as a tighter clustering of residuals around zero, implying a better model with few outliers.

Durbin-Watson – tests for homoscedasticity. We hope to have a value between 1 and 2.

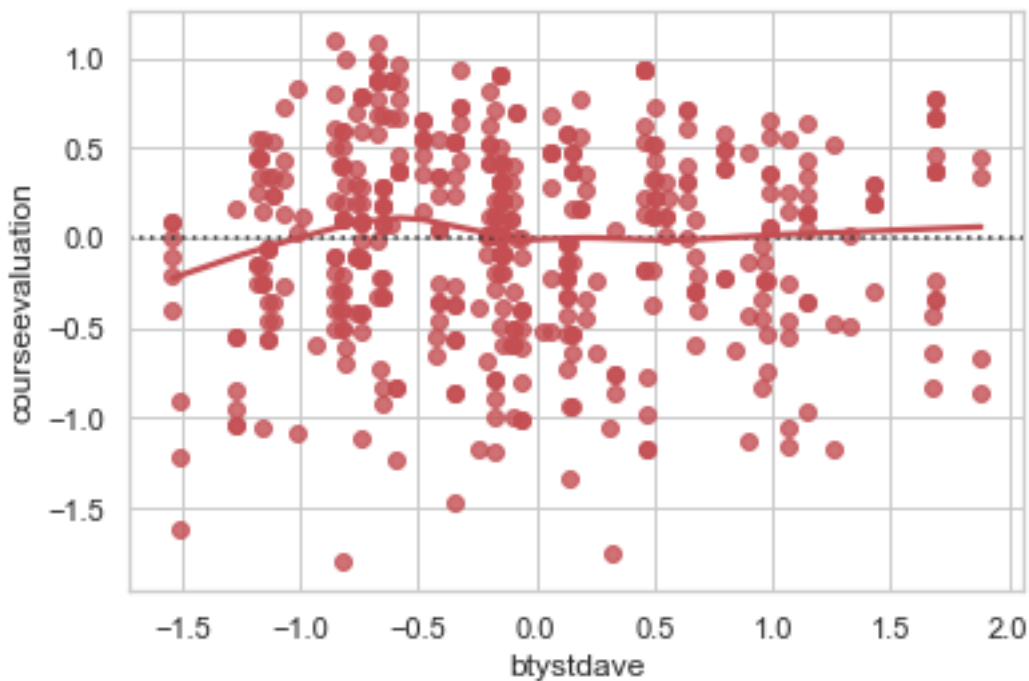
Jarque-Bera (JB)/Prob(JB) – like the Omnibus test in that it tests both skew and kurtosis. We hope to see in this test a confirmation of the Omnibus test.

Condition Number – This test measures the sensitivity of a function’s output as compared to its input. When we have multicollinearity, we can expect much higher fluctuations to small changes in the data, hence, we hope to see a relatively small number, something below 30. source: www.accelerate.com/blog/interpreting-results-from-linear-regression-is-the-data-appropriate

In statistics, the standard deviation (SD, also represented by the lower case Greek letter sigma for the population standard deviation or the Latin letter s for the sample standard deviation) is a measure of the amount of variation or dispersion of a set of values.[1] A low standard deviation indicates that the values tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the values are spread out over a wider range. source:

https://en.wikipedia.org/wiki/Standard_deviation

```
[4]: #Wykreślić residua względem dopasowanych wartości.  
  
#Przypadek jest dwuwymiarowy więc użyję gotowej funkcji:  
#Residua  
  
import seaborn as sns  
  
sns.set(style="whitegrid")  
  
# Plot the residuals after fitting a linear model  
sns.residplot(data['btystdave'], data['courseevaluation'], lowess=True,   
              ↪color="r")  
plt.show()
```



```
[11]: # Dopasuj niektóre inne modele, w tym piękno, a także inne zmienne wejściowe.   
      ↪Dla każdego modelu określ, jakie są predyktory  
      # i jakie są dane wejściowe i wyjaśnij znaczenie każdego z jego współczynników.  
  
#Model 2  
#Predicting course-evaluation from beauty and professor-evaluation. Coeffitients   
      ↪have been explained above.
```

```
X = data[['btystdave', 'profevaluation']]
Y = data['courseevaluation']
X = sm.add_constant(X)
model2 = sm.OLS(Y, X).fit()
predictions2 = model2.predict(X)
model2.summary()
```

```
[11]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:      courseevaluation    R-squared:      0.875
Model:              OLS                Adj. R-squared: 0.874
Method:             Least Squares      F-statistic:    1606.
Date:               Tue, 10 Dec 2019    Prob (F-statistic): 3.22e-208
Time:               00:12:19           Log-Likelihood: 97.136
No. Observations:   463                AIC:           -188.3
Df Residuals:       460                BIC:           -175.9
Df Model:           2
Covariance Type:    nonrobust
=====
==
               coef    std err          t      P>|t|      [0.025
0.975]
-----
--
const          0.0309     0.072     0.427     0.669     -0.111
0.173
btystdave      0.0128     0.012     1.084     0.279     -0.010
0.036
profevaluation 0.9506     0.017    55.504     0.000     0.917
0.984
=====
Omnibus:                 103.892    Durbin-Watson:      1.792
Prob(Omnibus):           0.000    Jarque-Bera (JB):    358.857
Skew:                    -0.996    Prob(JB):            1.19e-78
Kurtosis:                 6.826    Cond. No.            35.1
=====
```

Warnings:

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

```
[12]: from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
import numpy as np
```

```

fig = plt.figure(figsize=(20,20))
ax = fig.add_subplot(111, projection='3d')

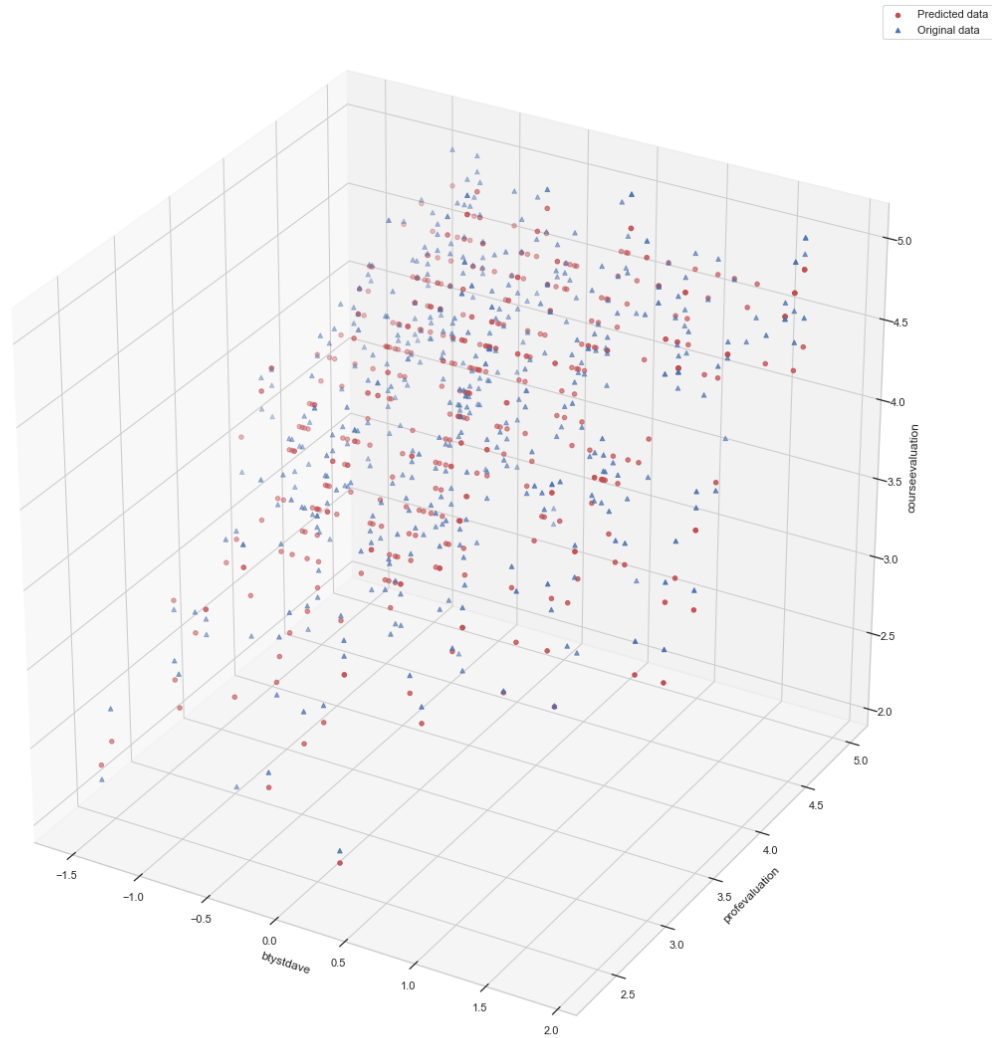
xs = data['btystdave']
ys = data['profevaluation']
zs = predictions2
ax.scatter(xs, ys, zs, c='r', marker='o', label='Predicted data')

xs = data['btystdave']
ys = data['profevaluation']
zs = data['courseevaluation']
ax.scatter(xs, ys, zs, c='b', marker='^', label='Original data')

ax.set_xlabel('btystdave')
ax.set_ylabel('profevaluation')
ax.set_zlabel('courseevaluation')

plt.legend()
plt.show()

```



```
[19]: #Model 3
      #Predicting professor-evaluation from age

      X = data['age']
      Y = data['profevaluation']
      X = sm.add_constant(X)
      model3 = sm.OLS(Y, X).fit()
      predictions3 = model.predict(X)

      model.summary()
```

```
[19]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results


```

=====
Dep. Variable:    courseevaluation    R-squared:                0.036
Model:            OLS                Adj. R-squared:           0.034
Method:          Least Squares       F-statistic:              17.08
Date:            Tue, 10 Dec 2019     Prob (F-statistic):       4.25e-05
Time:            00:23:29            Log-Likelihood:           -375.32
No. Observations: 463                AIC:                     754.6
Df Residuals:    461                BIC:                     762.9
Df Model:        1
Covariance Type: nonrobust
=====

```

```

=====
              coef    std err          t      P>|t|      [0.025    0.975]
-----
const          4.0100     0.026    157.205     0.000     3.960     4.060
btystdave       0.1330     0.032     4.133     0.000     0.070     0.196
=====

```

```

=====
Omnibus:            15.399    Durbin-Watson:           1.410
Prob(Omnibus):      0.000    Jarque-Bera (JB):        16.405
Skew:               -0.453    Prob(JB):                0.000274
Kurtosis:           2.831    Cond. No.                 1.29
=====

```

Warnings:

```

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

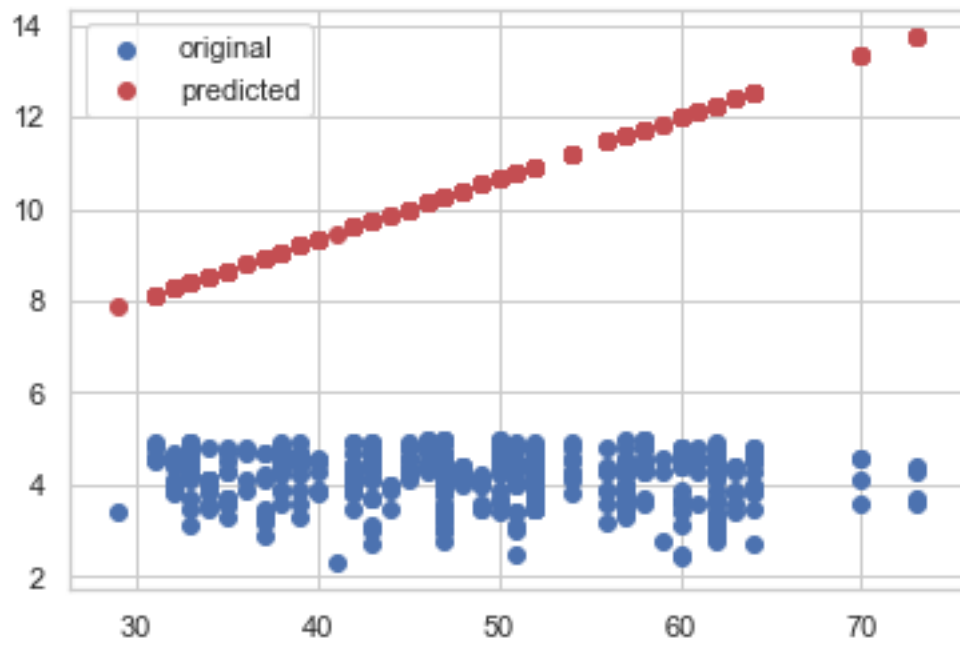
```

```

[20]: fig, ax = plt.subplots()
scatter=ax.scatter(y=data['profevaluation'], x=data['age'],c='b',
↪label='original')
scatter=ax.scatter(y=predictions3, x=data['age'],c='r', label='predicted')

ax.legend()
plt.show()

```



[]: