

zad2

December 11, 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:

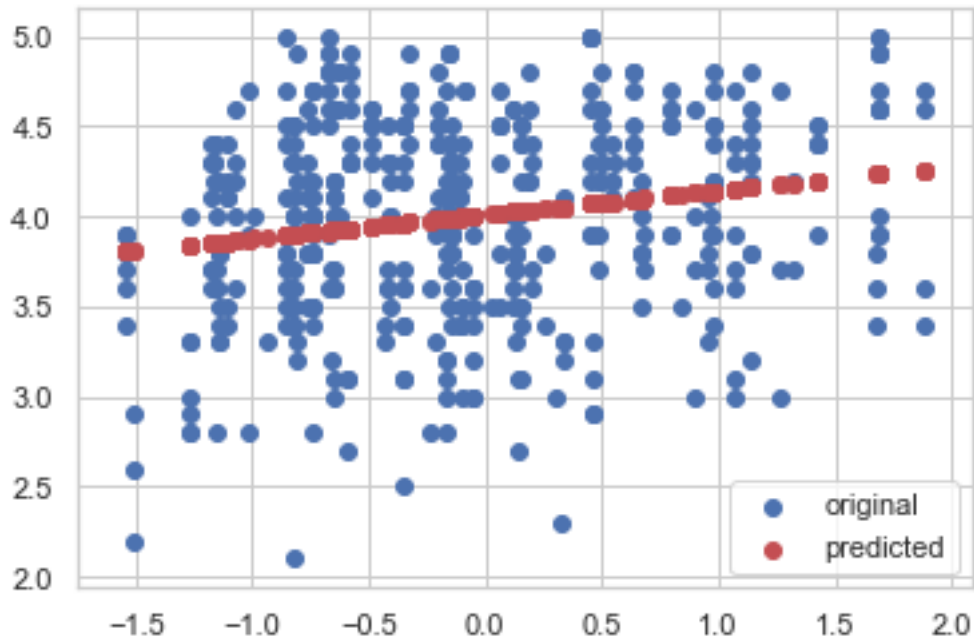
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 ""

```
[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:

[0.025 - 0.975] - Confidence interval - is a type of interval estimate, computed from the statistics of the observed data, that might contain the true value of an unknown population parameter. The interval has an associated confidence level, or coverage that, loosely speaking, quantifies the level of confidence that the deterministic parameter is captured by the interval. More strictly speaking, the confidence level represents the frequency (i.e. the proportion) of possible confidence intervals that contain the true value of the unknown population parameter.

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.

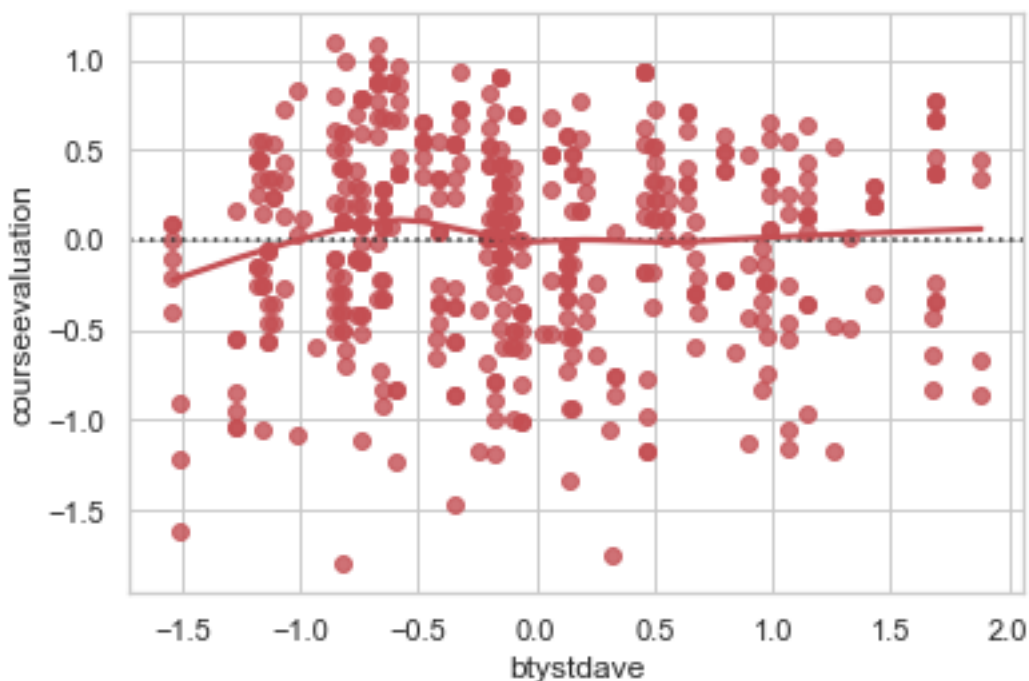
Durbin-Watson – tests for homoscedasticity. We hope to have a value between 1 and 2.

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.

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
www.accelebrate.com/blog/interpreting-results-from-linear-regression-is-the-data-appropriate
https://en.wikipedia.org/wiki/Confidence_interval

```
[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. Coefficients
      ↪ 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

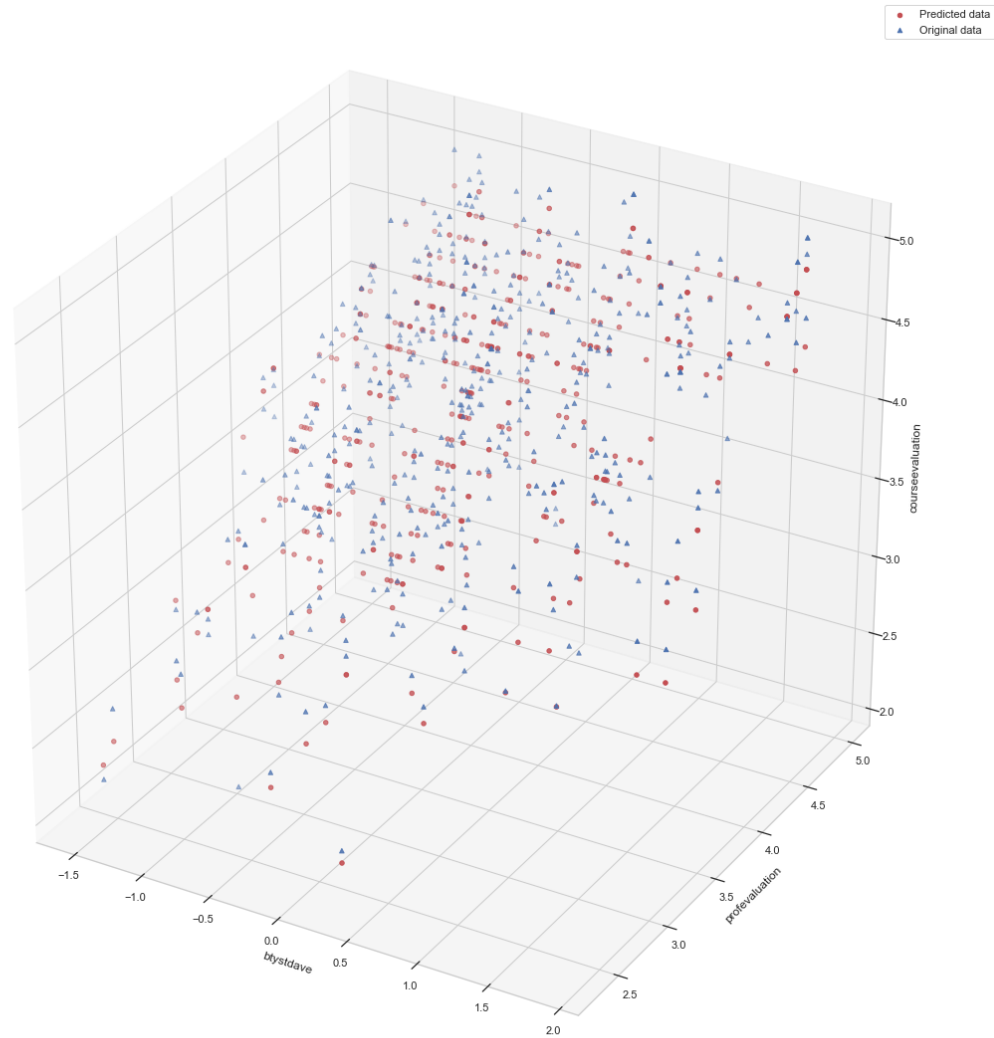
fig = plt.figure(figsize=(20,20))
ax = fig.add_subplot(111, projection='3d')

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]
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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.
"""

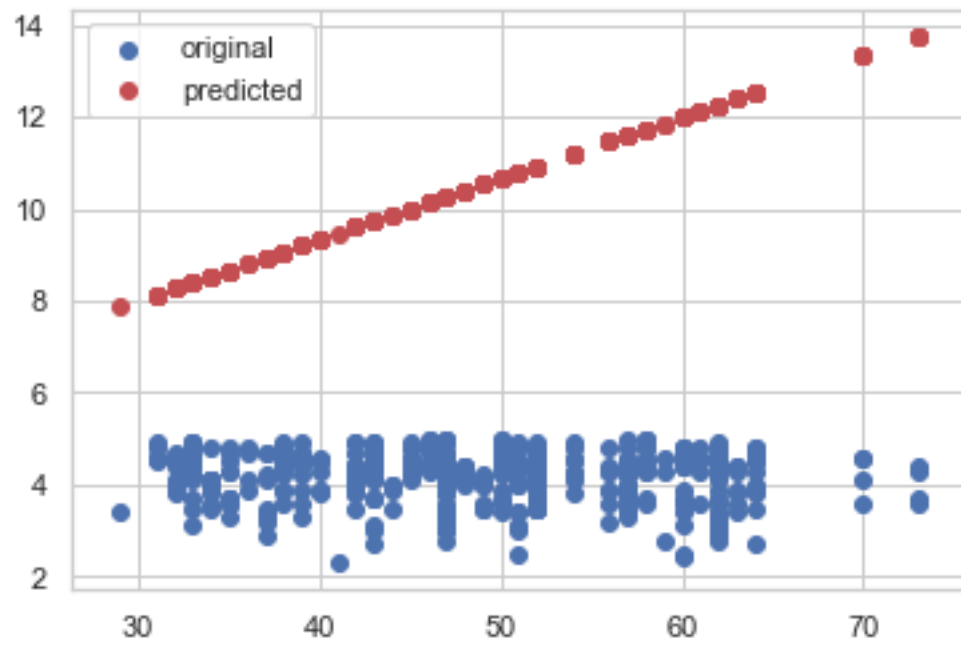
```

```

[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()

```



[]: