zad1

December 11, 2019

```
[1]: import pandas as pd
    exercise = pd.read_csv("exercise.csv")
[2]: exercise.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 60 entries, 0 to 59
    Data columns (total 3 columns):
          40 non-null float64
    У
          60 non-null float64
    x1
    x2
          60 non-null float64
    dtypes: float64(3)
    memory usage: 1.5 KB
[3]: # let's see what's inside
    exercise
[3]:
                 x1
                        x2
            У
        15.68 6.87
                     14.09
               4.40
    1
         6.18
                      4.35
    2
        18.10 0.43 18.09
    3
         9.07 2.73
                      8.65
        17.97 3.25
    4
                    17.68
    5
        10.04 5.30
                      8.53
        20.74 7.08
    6
                    19.50
    7
         9.76 9.73
                      0.72
         8.23 4.51
                      6.88
    8
         6.52 6.40
    9
                      1.26
    10
        15.69 5.72 14.62
        15.51 6.28 14.18
    11
    12
        20.61 6.14 19.68
    13
        19.58 8.26 17.75
         9.72 9.41
    14
                      2.44
    15
        16.36 2.88 16.10
    16
        18.30 5.74 17.37
    17
        13.26 0.45 13.25
    18
        12.10 3.74 11.51
```

```
18.15 5.03 17.44
     19
     20
         16.80
                 9.67
                       13.74
     21
         16.55
                 3.62
                       16.15
         18.79
                 2.54
     22
                       18.62
     23
         15.68
                 9.15
                       12.74
          4.08
                 0.69
                         4.02
     24
     25
         15.45
                 7.97
                       13.24
         13.44
                 2.49
                       13.21
     26
     27
         20.86
                 9.81
                        18.41
     28
         16.05
                 7.56
                        14.16
     29
          6.00
                 0.98
                         5.92
     30
          3.29
                 0.65
                         3.22
     31
          9.41
                 9.00
                         2.74
         10.76
                7.83
     32
                         7.39
          5.98
                 0.26
                         5.97
     33
     34
         19.23
                 3.64
                       18.89
         15.67
                 9.28
     35
                        12.63
     36
          7.04
                 5.66
                         4.18
         21.63
                 9.71
     37
                       19.32
         17.84
     38
                 9.36
                       15.19
     39
          7.49
                 0.88
                         7.43
     40
           NaN
                 9.87
                       10.43
     41
           {\tt NaN}
                 9.99
                       15.72
     42
           NaN
                 8.39
                         0.35
     43
           {\tt NaN}
                 0.80
                       10.91
           NaN
                 9.58
                       15.82
           NaN
                 4.82
                       11.90
     45
     46
           {\tt NaN}
                 2.97
                         2.46
     47
                 8.80
                         4.09
           NaN
     48
           {\tt NaN}
                 6.07
                         1.80
     49
           NaN
                 0.19
                       13.54
     50
           {\tt NaN}
                 4.19
                       19.13
                 5.39
     51
           NaN
                       14.84
     52
                 6.58
           NaN
                         5.28
                 2.36
     53
           NaN
                       15.42
     54
           {\tt NaN}
                 2.37
                         4.12
     55
           NaN
                 1.52
                         6.54
     56
           {\tt NaN}
                 2.07
                         2.67
                 6.70 12.85
     57
           NaN
     58
            NaN
                 2.02
                         8.36
     59
           NaN
                 9.63
                       12.16
[7]: # Wczytać plik do dataframe'a
     df = pd.DataFrame(exercise,columns=['y','x1','x2'])
     #separate known info data from rest
```

```
available_info = df[:40]
    # Create array with data provided for prediction
    for_prediction = df[40:60]
    df.describe()
[7]:
                                      x2
                           x1
    count 40.000000
                     60.000000 60.000000
                     5.323500 10.994167
    mean
          13.590250
    std
           5.279126
                     3.188782 5.904045
           3.290000 0.190000 0.350000
    min
    25%
           9.325000 2.527500 5.760000
    50%
          15.590000 5.525000 12.685000
    75%
          18.002500 8.292500 15.745000
           21.630000 9.990000 19.680000
    max
[5]: # dopasować model regresji liniowej przewidujący y z x1, x2, używającu
     →pierwszych 40 punktów danych w pliku.
    import statsmodels.api as sm
    X = available_info[['x1','x2']]
    Y = available_info['y']
    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)
[5]: <class 'statsmodels.iolib.summary.Summary'>
                              OLS Regression Results
    ______
    Dep. Variable:
                                                                         0.972
                                         R-squared:
    Model:
                                    OLS Adj. R-squared:
                                                                        0.971
    Method:
                          Least Squares F-statistic:
                                                                         652.4
    Date:
                        Tue, 10 Dec 2019 Prob (F-statistic):
                                                                     1.41e-29
    Time:
                               13:27:43 Log-Likelihood:
                                                                      -50.985
    No. Observations:
                                     40 ATC:
                                                                        108.0
                                         BTC:
    Df Residuals:
                                     37
                                                                         113.0
    Df Model:
                                      2
```

nonrobust

Covariance Type:

x1 0.5148 0.046 11.216 0.000 0.422 0.608 x2 0.8069 0.024 33.148 0.000 0.758 0.856 Omnibus: 14.478 Durbin-Watson: 2.508 Prob(Omnibus): 0.001 Jarque-Bera (JB): 15.393 Skew: 1.341 Prob(JB): 0.000454		coef	std err	t	P> t	[0.025	0.975]
Prob(Omnibus): 0.001 Jarque-Bera (JB): 15.393 Skew: 1.341 Prob(JB): 0.000454	x1	0.5148	0.046	11.216	0.000	0.422	2.101 0.608 0.856
	Prob(Omnibu Skew:	======= s):	C 1	.001 Jaro	que-Bera (JB o(JB):):	2.509 15.393 0.000454 38.7

Warnings:

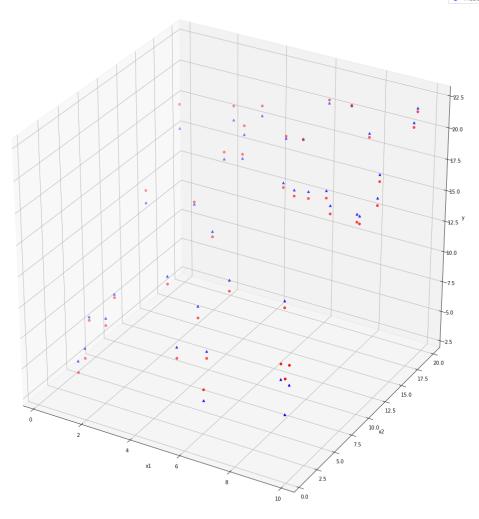
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

11 11 11

```
[10]: # Podsumować wnioski i sprawdźić dopasowanie modelu. - sprawdzam graficznie
      →wykorzystując wykres
      # Wyświetl oszacowany model graficznie
      # Wnioski: współczynnik przy zmiennej x2 jest większy niż przy zmiennej x1, u
      →więc można powiedzieć,
      # że jej znaczenie w regresji jest większe. Niska wartość składowej stałej.
      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 = available_info['x1']
      ys = available info['x2']
      zs = available_info['y']
      ax.scatter(xs, ys, zs, c='r', marker='o', label='Original data')
      xs = available_info['x1']
      ys = available_info['x2']
      zs = predictions
      ax.scatter(xs, ys, zs, c='b', marker='^', label='Predicted data')
      ax.set_xlabel('x1')
      ax.set_ylabel('x2')
      ax.set_zlabel('y')
```

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

Original data
 Predicted data



```
[7]: # Wykonaj wykres residuów dla tego modelu. Czy wydaje się, że założenia zostały⊔
⇒ spełnione?

# Odp.: Residua są małe, można powiedzieć że założenia zostały spełnione.

residuals = available_info['y'] - predictions
print(residuals)

fig = plt.figure(figsize=(20,20))
```

```
ax = fig.add_subplot(111, projection='3d')

xs = available_info['x1']
ys = available_info['x2']
zs = residuals
ax.scatter(xs, ys, zs, c='r', marker='o', label='Residuals')

ax.set_xlabel('x1')
ax.set_ylabel('x2')
ax.set_zlabel('residuals')

plt.legend()
plt.show()
0 -0.541378
```

```
1
    -0.910400
2
     1.966323
3
    -0.630421
4
     0.715394
5
    -0.886653
6
     0.045077
7
    2.854778
8
    -0.958536
9
     0.893360
10
    -0.367014
11
    -0.480263
12
     0.253753
    -0.310290
13
14
     1.591616
15
     0.570807
16
     0.013661
17
     1.021517
18
    -0.428169
19
     0.172692
20
    -0.580425
21
     0.339501
22
     1.142405
23
    -0.625805
24
    -0.834170
25
    -0.651788
26
    0.183580
27
    -0.360813
28
    -0.583082
29
    -0.596613
30
    -0.958042
31
     1.250612
```

32

-0.549235

```
33 -0.286295

34 0.798246

35 -0.613969

36 -0.561885

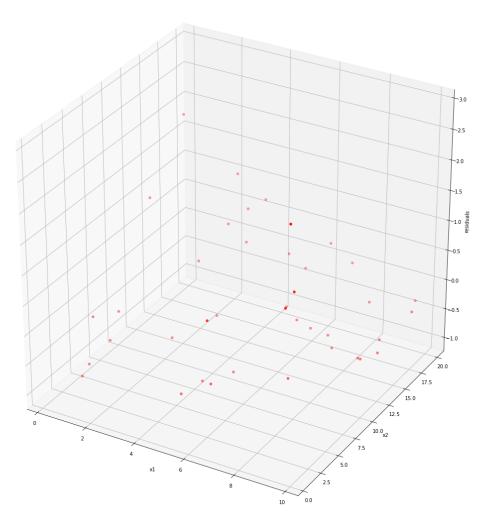
37 -0.273629

38 -0.550868

39 -0.273580

dtype: float64
```

• Residuals



[8]: # Wykonaj prognozy dla pozostałych 20 punktów danych w pliku. Oceń pewność co⊔
→do prognozach?

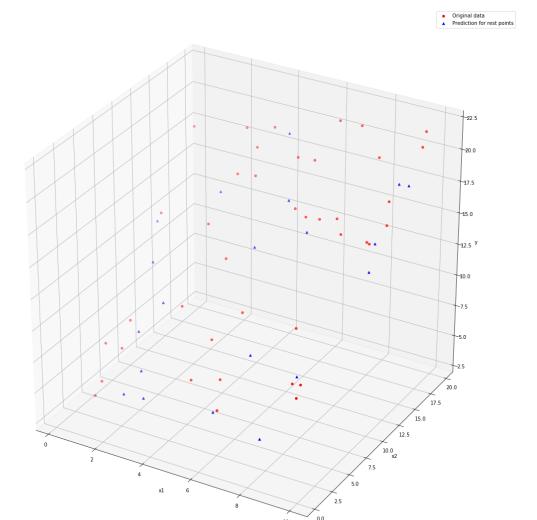
Na podstawie poprzednich wyników szacuję że prognozy mają dosyć dużą pewność, ⊔

Na podstawie poprzednich wyników szacuję że prognozy mają dosyć dużą pewność,⊔ ⇔ponieważ residua były małe,

predykcje ładnie odpowiadały oryginalnycm wartościom.

```
# Prediction for rest 20 points
     X = for_prediction[['x1','x2']]
     X = sm.add_constant(X)
     predictions2 = model.predict(X)
     print(predictions2)
    40
          14.812484
    41
          19.142865
    42
          5.916816
    43
          10.530475
    44
          19.012485
    45
          13.398863
    46
         4.829144
    47
           9.145767
    48
           5.892489
    49
          12.338639
    50
          18.908561
    51
          16.064649
    52
          8.963122
    53
         14.972786
    54
          5.859744
    55
          7.374900
          4.535267
    56
    57
          15.133280
    58
           9.100899
    59
          16.084900
    dtype: float64
    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)
[9]: #Predictions has been made above, but additionaly I will make a plot of them.
     fig = plt.figure(figsize=(20,20))
     ax = fig.add_subplot(111, projection='3d')
     xs = available_info['x1']
     ys = available_info['x2']
     zs = available_info['y']
     ax.scatter(xs, ys, zs, c='r', marker='o', label='Original data')
     xs = for_prediction['x1']
     ys = for_prediction['x2']
     zs = predictions2
```

```
ax.scatter(xs, ys, zs, c='b', marker='^', label='Prediction for rest points')
ax.set_xlabel('x1')
ax.set_ylabel('x2')
ax.set_zlabel('y')
plt.legend()
plt.show()
```



[]: