Lab1

March 21, 2023

[ ]:
```
import matplotlib.pyplot as plt
import matplotlib as matplotlib
import seaborn as sns

# unused but required import for doing 3d projections with matplotlib < 3.2
import mpl_toolkits.mplot3d  # noqa: F401
import numpy
import pandas as pd
from sklearn import datasets
from sklearn.decomposition import PCA
from scipy import stats as st
from scipy.io import arff
```

[ ]:
```
attr_names = ['net profit / total assets', 'total liabilities / total assets',␣
↪'working capital / total assets'
              , 'current assets / short-term liabilities'
              , '[(cash + short-term securities + receivables - short-term␣
↪liabilities) / (operating expenses - depreciation)] * 365'
              , 'retained earnings / total assets', 'EBIT / total assets',␣
↪'book value of equity / total liabilities'
              , 'sales / total assets', 'equity / total assets', '(gross profit␣
↪+ extraordinary items + financial expenses) / total assets'
              , 'gross profit / short-term liabilities', '(gross profit +␣
↪depreciation) / sales', '(gross profit + interest) / total assets'
              , '(total liabilities * 365) / (gross profit + depreciation)',␣
↪'(gross profit + depreciation) / total liabilities'
              , 'total assets / total liabilities', 'gross profit / total␣
↪assets', 'gross profit / sales', '(inventory * 365) / sales'
              , 'sales (n) / sales (n-1)', 'profit on operating activities /␣
↪total assets', 'net profit / sales', 'gross profit (in 3 years) / total␣
↪assets'
              , '(equity - share capital) / total assets', '(net profit +␣
↪depreciation) / total liabilities', 'profit on operating activities /␣
↪financial expenses'
              , 'working capital / fixed assets', 'logarithm of total assets',␣
↪'(total liabilities - cash) / sales', '(gross profit + interest) / sales'
```

```
              , '(current liabilities * 365) / cost of products sold',␣
↪'operating expenses / short-term liabilities', 'operating expenses / total␣
↪liabilities'
              , 'profit on sales / total assets', 'total sales / total assets',␣
↪'(current assets - inventories) / long-term liabilities'
              , 'constant capital / total assets', 'profit on sales / sales',␣
↪'(current assets - inventory - receivables) / short-term liabilities'
              , 'total liabilities / ((profit on operating activities +␣
↪depreciation) * (12/365))', 'profit on operating activities / sales'
              , 'rotation receivables + inventory turnover in days',␣
↪'(receivables * 365) / sales', 'net profit / inventory'
              , '(current assets - inventory) / short-term liabilities',␣
↪'(inventory * 365) / cost of products sold'
              , 'EBITDA (profit on operating activities - depreciation) / total␣
↪assets', 'EBITDA (profit on operating activities - depreciation) / sales'
              , 'current assets / total liabilities', 'short-term liabilities /␣
↪total assets', '(short-term liabilities * 365) / cost of products sold)'
              , 'equity / fixed assets', 'constant capital / fixed assets',␣
↪'working capital', '(sales - cost of products sold) / sales'
              , '(current assets - inventory - short-term liabilities) / (sales␣
↪- gross profit - depreciation)', 'total costs /total sales'
              , 'long-term liabilities / equity', 'sales / inventory', 'sales /␣
↪receivables', '(short-term liabilities *365) / sales'
              , 'sales / short-term liabilities', 'sales / fixed assets']

attr_dict = {}

for i in range (1, len(attr_names) + 1):
    attr_dict['Attr' + str(i)] = attr_names[i-1]

attr_dict_inverse = dict((v, k) for k,v in attr_dict.items())
```

[ ]:
```
data1 = arff.loadarff('1year.arff')
data2 = arff.loadarff('2year.arff')
data3 = arff.loadarff('3year.arff')
data4 = arff.loadarff('4year.arff')
data5 = arff.loadarff('5year.arff')
df_data = pd.DataFrame(data1[0])
df_data = pd.DataFrame(df_data.append(pd.DataFrame(data2[0]), ignore_index =␣
↪True))
df_data = pd.DataFrame(df_data.append(pd.DataFrame(data3[0]), ignore_index =␣
↪True))
df_data = pd.DataFrame(df_data.append(pd.DataFrame(data4[0]), ignore_index =␣
↪True))
df_data = pd.DataFrame(df_data.append(pd.DataFrame(data5[0]), ignore_index =␣
↪True))
```

```
df_data.loc[df_data['class'] == b'1','class'] = 'bankrupt'
df_data.loc[df_data['class'] == b'0','class'] = 'not bankrupt'
```

```
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\28503489.py:7: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a
future version. Use pandas.concat instead.
  df_data = pd.DataFrame(df_data.append(pd.DataFrame(data2[0]), ignore_index =
True))
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\28503489.py:8: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a
future version. Use pandas.concat instead.
  df_data = pd.DataFrame(df_data.append(pd.DataFrame(data3[0]), ignore_index =
True))
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\28503489.py:9: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a
future version. Use pandas.concat instead.
  df_data = pd.DataFrame(df_data.append(pd.DataFrame(data4[0]), ignore_index =
True))
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\28503489.py:10:
FutureWarning: The frame.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  df_data = pd.DataFrame(df_data.append(pd.DataFrame(data5[0]), ignore_index =
True))
```

[ ]:
```
print(df_data)
```

```
          Attr1    Attr2     Attr3    Attr4     Attr5    Attr6     Attr7  \
0      0.200550  0.37951  0.396410  2.04720   32.3510  0.38825  0.249760
1      0.209120  0.49988  0.472250  1.94470   14.7860  0.00000  0.258340
2      0.248660  0.69592  0.267130  1.55480   -1.1523  0.00000  0.309060
3      0.081483  0.30734  0.458790  2.49280   51.9520  0.14988  0.092704
4      0.187320  0.61323  0.229600  1.40630   -7.3128  0.18732  0.187320
…           …        …        …        …        …        …        …
43400  0.012898  0.70621  0.038857  1.17220  -18.9070  0.00000  0.013981
43401 -0.578050  0.96702 -0.800850  0.16576  -67.3650 -0.57805 -0.578050
43402 -0.179050  1.25530 -0.275990  0.74554 -120.4400 -0.17905 -0.154930
43403 -0.108860  0.74394  0.015449  1.08780  -17.0030 -0.10886 -0.109180
43404 -0.105370  0.53629 -0.045578  0.91478  -56.0680 -0.10537 -0.109940

         Attr8    Attr9    Attr10  …    Attr56    Attr57   Attr58    Attr59  \
0      1.33050  1.13890  0.504940  …  0.121960  0.397180  0.87804  0.001924
1      0.99601  1.69960  0.497880  …  0.121300  0.420020  0.85300  0.000000
2      0.43695  1.30900  0.304080  …  0.241140  0.817740  0.76599  0.694840
3      1.86610  1.05710  0.573530  …  0.054015  0.142070  0.94598  0.000000
4      0.63070  1.15590  0.386770  …  0.134850  0.484310  0.86515  0.124440
…          …        …         …  …       …         …        …
43400  0.41600  1.67680  0.293790  …  0.020169  0.043904  1.01220  1.259400
```

```
43401 -0.40334  0.93979 -0.390040  … -0.064073  1.482000  1.06410 -0.018084
43402 -0.26018  1.17490 -0.326590  …  0.148880  0.548240  0.85112 -0.522430
43403  0.12531  0.84516  0.093224  … -0.183200 -1.167700  1.18320  6.092400
43404  0.86460  0.95040  0.463670  … -0.052186 -0.227250  1.05220  0.003196

         Attr60   Attr61   Attr62  Attr63    Attr64         class
0        8.4160   5.1372   82.658  4.4158   7.42770  not bankrupt
1        4.1486   3.2732  107.350  3.4000  60.98700  not bankrupt
2        4.9909   3.9510  134.270  2.7185   5.20780  not bankrupt
3        4.5746   3.6147   86.435  4.2228   5.54970  not bankrupt
4        6.3985   4.3158  127.210  2.8692   7.89800  not bankrupt
…           …        …        …       …         …           …
43400   13.4720  12.4320   49.117  7.4313   2.27990      bankrupt
43401  110.7200  44.7590   81.220  4.4940   5.13050      bankrupt
43402    9.8526   3.4892  207.870  1.7559   9.95270      bankrupt
43403   13.8860   6.0769   83.122  4.3911   0.95575      bankrupt
43404    7.7332   4.7174  136.850  2.6672   2.79270      bankrupt

[43405 rows x 65 columns]
```

[ ]:
```
df_data.describe()
```

[ ]:
```
              Attr1         Attr2         Attr3         Attr4         Attr5  \
count  43397.000000  43397.000000  43397.000000  43271.000000  4.331600e+04
mean       0.035160      0.590212      0.114431      6.314702 -3.853466e+02
std        2.994109      5.842748      5.439429    295.434425  6.124303e+04
min     -463.890000   -430.870000   -479.960000     -0.403110 -1.190300e+07
25%        0.003429      0.268980      0.021521      1.049500 -4.908000e+01
50%        0.049660      0.471900      0.196610      1.569800 -1.034500e+00
75%        0.129580      0.688320      0.403390      2.787450  5.063425e+01
max       94.280000    480.960000     28.336000  53433.000000  1.250100e+06

              Attr6         Attr7         Attr8         Attr9        Attr10  \
count  43397.000000  43397.000000  43311.000000  43396.000000  43397.000000
mean      -0.056107      0.093478     12.640779      2.652166      0.626868
std        7.201326      5.713075    505.894281     62.932732     14.670597
min     -508.410000   -517.480000   -141.410000     -3.496000   -479.910000
25%        0.000000      0.005776      0.430275      1.018500      0.295470
50%        0.000000      0.059634      1.070400      1.195350      0.505970
75%        0.089446      0.150880      2.615700      2.062500      0.709100
max      543.250000    649.230000  53432.000000   9742.300000   1099.500000

       …        Attr55        Attr56        Attr57        Attr58  \
count  …  4.340400e+04  4.327800e+04  43398.000000  4.332100e+04
mean   …  7.672188e+03 -2.621959e+01     -0.010510  3.002644e+01
std    …  7.005310e+04  5.327862e+03     13.674072  5.334454e+03
min    … -1.805200e+06 -1.108300e+06  -1667.300000 -1.986900e+02
```

```
25%    …  2.755425e+01  9.348500e-03      0.014649  8.753200e-01
50%    …  1.088350e+03  5.294300e-02      0.119670  9.509600e-01
75%    …  4.993325e+03  1.290975e-01      0.284605  9.926400e-01
max    …  6.123700e+06  2.931500e+02    552.640000  1.108300e+06

             Attr59        Attr60         Attr61        Attr62        Attr63  \
count  43398.000000  4.125300e+04   43303.000000  4.327800e+04  43271.000000
mean       1.333288  4.480858e+02      17.033202  1.502328e+03      9.343074
std      122.104445  3.234560e+04     553.049406  1.392667e+05    124.177354
min     -327.970000 -1.244000e+01     -12.656000 -2.336500e+06     -1.543200
25%        0.000000  5.545500e+00       4.510150  4.214400e+01      3.097650
50%        0.006366  9.791700e+00       6.636300  7.132600e+01      5.087600
75%        0.236052  2.018100e+01      10.394500  1.172200e+02      8.598850
max    23853.000000  4.818700e+06  108000.000000  2.501600e+07  23454.000000

              Attr64
count   42593.000000
mean       72.788592
std      2369.339482
min    -10677.000000
25%         2.176800
50%         4.282500
75%         9.776200
max    294770.000000

[8 rows x 64 columns]
```

[ ]:
```python
analysis =pd.concat((df_data.var().to_frame(), df_data.std().to_frame(),
 df_data.mean().to_frame()), axis = 1)
analysis.columns = ['var', 'std', 'mean']

analysis.transpose()
```

```
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\2505699666.py:1:
FutureWarning: The default value of numeric_only in DataFrame.var is deprecated.
In a future version, it will default to False. In addition, specifying
'numeric_only=None' is deprecated. Select only valid columns or specify the
value of numeric_only to silence this warning.
  analysis =pd.concat((df_data.var().to_frame(), df_data.std().to_frame(),
df_data.mean().to_frame()), axis = 1)
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\2505699666.py:1:
FutureWarning: The default value of numeric_only in DataFrame.std is deprecated.
In a future version, it will default to False. In addition, specifying
'numeric_only=None' is deprecated. Select only valid columns or specify the
value of numeric_only to silence this warning.
  analysis =pd.concat((df_data.var().to_frame(), df_data.std().to_frame(),
df_data.mean().to_frame()), axis = 1)
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\2505699666.py:1:
```

```
FutureWarning: The default value of numeric_only in DataFrame.mean is
deprecated. In a future version, it will default to False. In addition,
specifying 'numeric_only=None' is deprecated. Select only valid columns or
specify the value of numeric_only to silence this warning.
  analysis =pd.concat((df_data.var().to_frame(), df_data.std().to_frame(),
df_data.mean().to_frame()), axis = 1)
```

[ ]:

```
         Attr1      Attr2      Attr3         Attr4         Attr5      Attr6  \
var   8.964688  34.137703  29.587386  87281.499653  3.750708e+09  51.859101
std   2.994109   5.842748   5.439429    295.434425  6.124303e+04   7.201326
mean  0.035160   0.590212   0.114431      6.314702 -3.853466e+02  -0.056107

          Attr7          Attr8        Attr9      Attr10  …        Attr55  \
var   32.639222  255929.023208  3960.528710  215.226425  …  4.907436e+09
std    5.713075     505.894281    62.932732   14.670597  …  7.005310e+04
mean   0.093478      12.640779     2.652166    0.626868  …  7.672188e+03

            Attr56      Attr57        Attr58        Attr59        Attr60  \
var   2.838612e+07  186.980234  2.845639e+07  14909.495529  1.046238e+09
std   5.327862e+03   13.674072  5.334454e+03    122.104445  3.234560e+04
mean -2.621959e+01   -0.010510  3.002644e+01      1.333288  4.480858e+02

             Attr61        Attr62        Attr63        Attr64
var   305863.645244  1.939521e+10  15420.015228  5.613770e+06
std      553.049406  1.392667e+05    124.177354  2.369339e+03
mean      17.033202  1.502328e+03      9.343074  7.278859e+01

[3 rows x 64 columns]
```

[ ]:

```python
df_data.apply(lambda column : column.isna().sum()).to_frame().transpose()
```

[ ]:

```
   Attr1  Attr2  Attr3  Attr4  Attr5  Attr6  Attr7  Attr8  Attr9  Attr10  …  \
0      8      8      8    134     89      8      8     94      9       8  …

   Attr56  Attr57  Attr58  Attr59  Attr60  Attr61  Attr62  Attr63  Attr64  \
0     127       7      84       7    2152     102     127     134     812

   class
0      0

[1 rows x 65 columns]
```

[ ]:

```python
attr_dict['Attr60']
```

[ ]: 'sales / inventory'

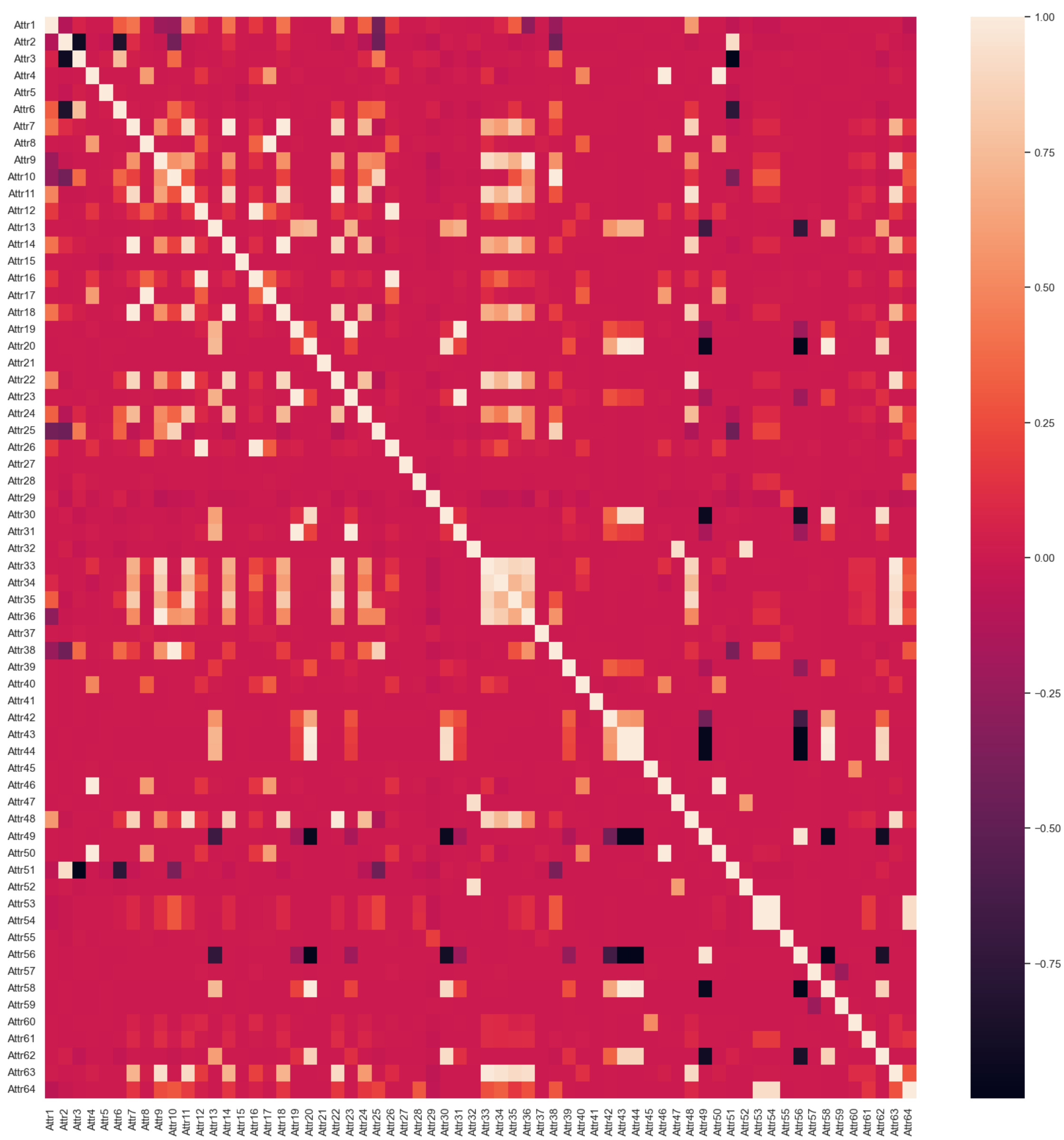
[ ]:

```python
import seaborn as sns
```

```
corDataFr = df_data.corr()
corDataFrSortId = corDataFr.index
corDataFrSorted = corDataFr.loc[:, corDataFrSortId]
sns.set(rc={'figure.figsize':(20,20)})
sns.heatmap(corDataFrSorted)
```

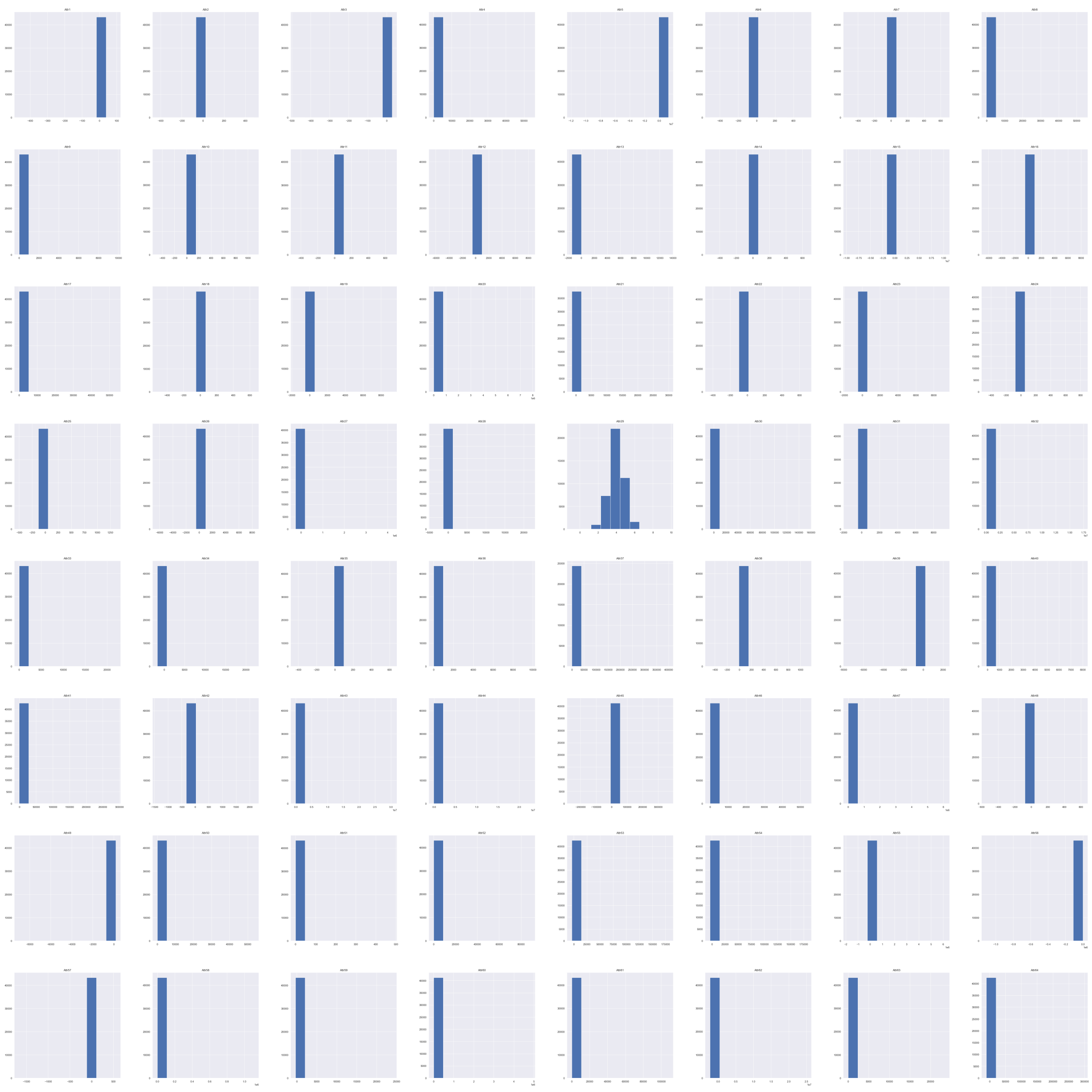
```
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\3977857954.py:3:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  corDataFr = df_data.corr()
```

[ ]: <Axes: >



[ ]:

```python
_ = df_data.hist(figsize = (80, 80))
plt.savefig("histograms.png")
```



[ ]:

```python
df_data_bankr = df_data[df_data['class'] == 'bankrupt']
df_data_nobankr = df_data[df_data['class'] == 'not bankrupt']

for column in df_data_bankr.iloc[:, :-1]:
    df_data_bankr = df_data_bankr.fillna(df_data_bankr[column].fillna(df_data_bankr[column].mean()).to_frame())
```

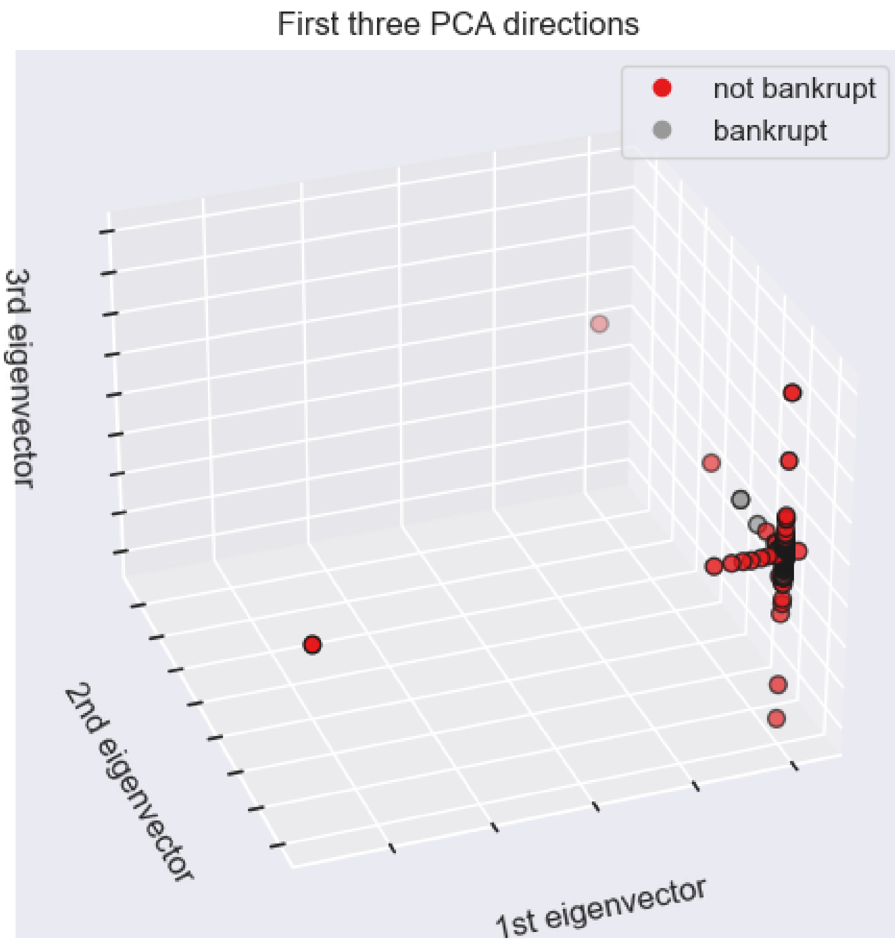
```
for column in df_data_nobankr.iloc[:, :-1]:
    df_data_nobankr = df_data_nobankr.fillna(df_data_nobankr[column].
 ↪fillna(df_data_nobankr[column].mean()).to_frame())

df_data_mean = df_data.fillna(df_data_bankr).fillna(df_data_nobankr)
```

```
[ ]: df_data_bankr = df_data[df_data['class'] == 'bankrupt']
df_data_nobankr = df_data[df_data['class'] == 'not bankrupt']

for column in df_data_bankr.iloc[:, :-1]:
    df_data_bankr = df_data_bankr.fillna(df_data_bankr[column].
 ↪fillna(df_data_bankr[column].median()).to_frame())

for column in df_data_nobankr.iloc[:, :-1]:
    df_data_nobankr = df_data_nobankr.fillna(df_data_nobankr[column].
 ↪fillna(df_data_nobankr[column].median()).to_frame())

df_data.fillna(df_data_bankr)
df_data = df_data.fillna(df_data_bankr).fillna(df_data_nobankr)
```

Wizualizacja PCA i t-SNE

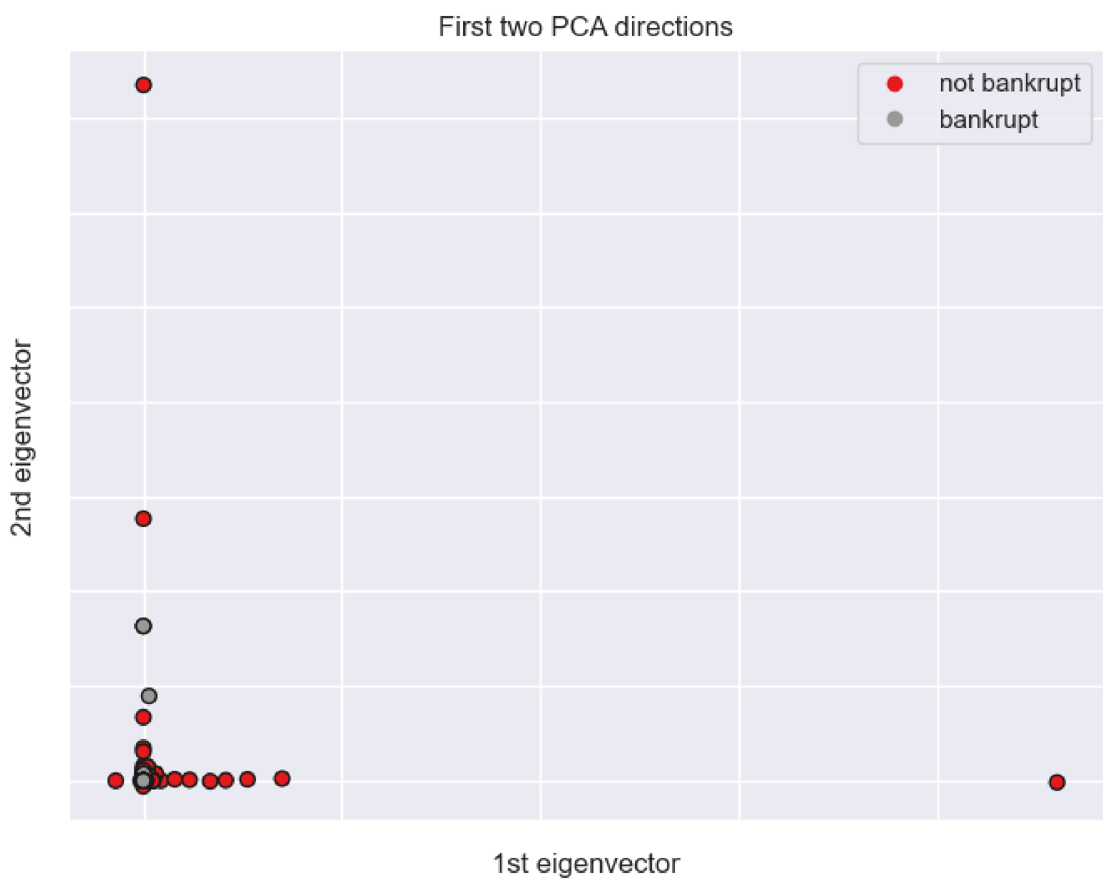
```
[ ]: # To getter a better understanding of interaction of the dimensions
# plot the first three PCA dimensions
fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot(111, projection="3d", elev=-150, azim=110)

X_reduced = PCA(n_components=3).fit_transform(df_data.iloc[:, :-1])
scatter = ax.scatter(
    X_reduced[:, 0],
    X_reduced[:, 1],
    X_reduced[:, 2],
    c=[1 if x == 'bankrupt' else 0 for x in df_data['class']],
    cmap=plt.cm.Set1,
    edgecolor="k",
    s=40,
)
ax.set_title("First three PCA directions")
ax.set_xlabel("1st eigenvector")
ax.xaxis.set_ticklabels([])
ax.set_ylabel("2nd eigenvector")
ax.yaxis.set_ticklabels([])
ax.set_zlabel("3rd eigenvector")
ax.zaxis.set_ticklabels([])

labels = df_data['class'].unique()
handles = [plt.Line2D([],[],marker="o", ls="",
```

```
                          color=scatter.cmap(scatter.norm(yi))) for yi in [1 if x␣
 ↪== 'bankrupt' else 0 for x in df_data['class'].unique()]]
plt.legend(handles, labels)

plt.show()
```



[ ]:
```
# To getter a better understanding of interaction of the dimensions
# plot the first three PCA dimensions
fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot()

X_reduced = PCA(n_components=2).fit_transform(df_data.iloc[:, :-1])
scatter = ax.scatter(
    X_reduced[:, 0],
    X_reduced[:, 1],
    c=[1 if x == 'bankrupt' else 0 for x in df_data['class']],
    cmap=plt.cm.Set1,
```

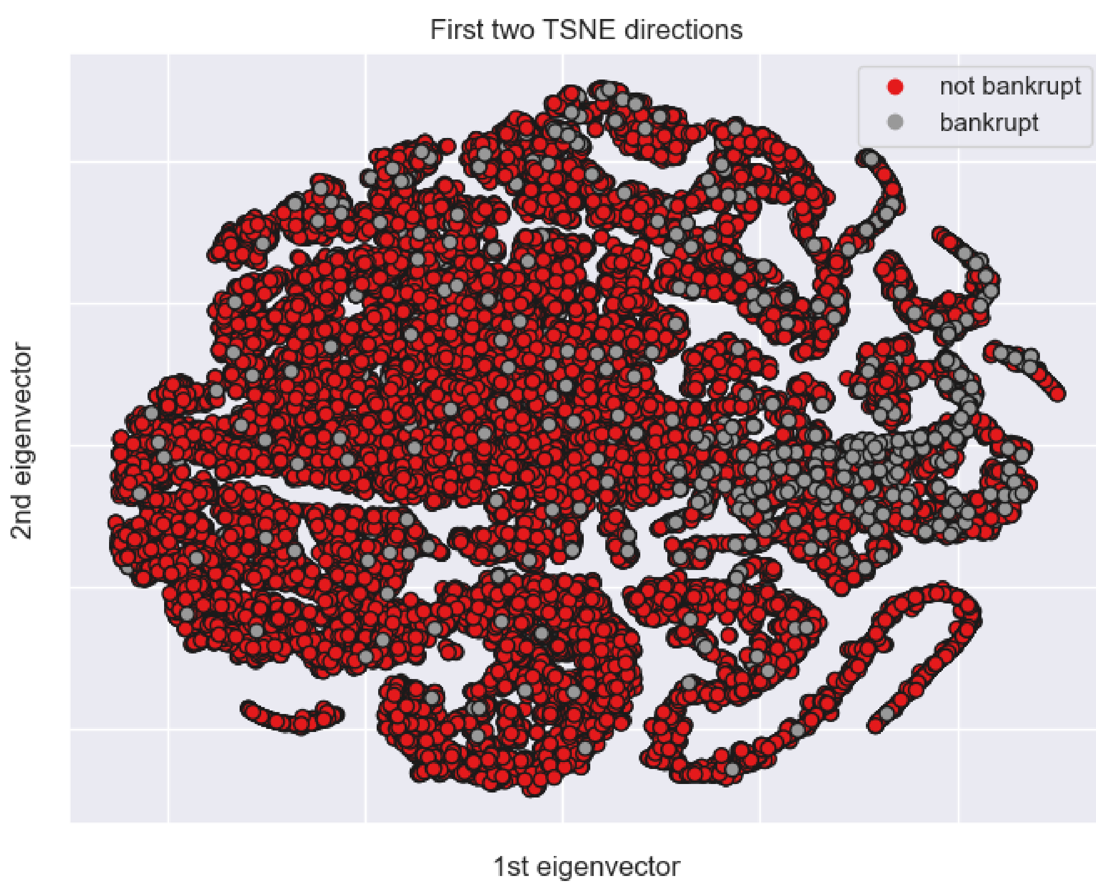
```
    edgecolor="k",
    s=40,
)

ax.set_title("First two PCA directions")
ax.set_xlabel("1st eigenvector")
ax.xaxis.set_ticklabels([])
ax.set_ylabel("2nd eigenvector")
ax.yaxis.set_ticklabels([])

labels = df_data['class'].unique()
handles = [plt.Line2D([],[],marker="o", ls="",
                      color=scatter.cmap(scatter.norm(yi))) for yi in [1 if x␣
 ↪== 'bankrupt' else 0 for x in df_data['class'].unique()]]
plt.legend(handles, labels)

plt.show()
```



[ ]:
```python
# from sklearn.manifold import TSNE

# fig = plt.figure(1, figsize=(8, 6))
# ax = fig.add_subplot(111, projection="3d", elev=-150, azim=110)

# X_reduced = TSNE(n_components=3).fit_transform(df_data.iloc[:, :-1])
# scatter = ax.scatter(
#     X_reduced[:, 0],
#     X_reduced[:, 1],
#     X_reduced[:, 2],
#     c=[1 if x == 'bankrupt' else 0 for x in df_data['class']],
#     cmap=plt.cm.Set1,
#     edgecolor="k",
#     s=40,
# )

# #ax.scatter(X_reduced[y == 0, 1], X_reduced[y == 0, 0], color='blue',␣
 ↪edgecolor="k", label='Iris Setosa')
# #ax.scatter(X_reduced[y == 1, 1], X_reduced[y == 1, 0], color='red',␣
 ↪edgecolor="k", label='Iris Versicolour')
# #ax.scatter(X_reduced[y == 2, 1], X_reduced[y == 2, 0], color='yellow',␣
 ↪edgecolor="k", label='Iris Virginica')

# ax.set_title("First three TSNE directions")
# ax.set_xlabel("1st eigenvector")
# ax.xaxis.set_ticklabels([])
# ax.set_ylabel("2nd eigenvector")
# ax.yaxis.set_ticklabels([])
# ax.set_zlabel("3rd eigenvector")
# ax.zaxis.set_ticklabels([])

# labels = df_data['class'].unique()
# handles = [plt.Line2D([],[],marker="o", ls="",
#                        color=scatter.cmap(scatter.norm(yi))) for yi in [1 if x␣
 ↪== 'bankrupt' else 0 for x in df_data['class'].unique()]]
# plt.legend(handles, labels)

# plt.show()
```

[ ]:
```python
from sklearn.manifold import TSNE

fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot()

X_reduced = TSNE(n_components=2).fit_transform(df_data.iloc[:, :-1])
scatter = ax.scatter(
    X_reduced[:, 0],
```

```python
    X_reduced[:, 1],
    c=[1 if x == 'bankrupt' else 0 for x in df_data['class']],
    cmap=plt.cm.Set1,
    edgecolor="k",
    s=40,
)

ax.set_title("First two TSNE directions")
ax.set_xlabel("1st eigenvector")
ax.xaxis.set_ticklabels([])
ax.set_ylabel("2nd eigenvector")
ax.yaxis.set_ticklabels([])

labels = df_data['class'].unique()
handles = [plt.Line2D([],[],marker="o", ls="",
                      color=scatter.cmap(scatter.norm(yi))) for yi in [1 if x␣
 ↪== 'bankrupt' else 0 for x in df_data['class'].unique()]]
plt.legend(handles, labels)

plt.show()
```



Dalsze czyszczenie danych

[ ]:
```
df_data
Q1 = df_data.quantile(0.25)
Q3 = df_data.quantile(0.75)

IQR = Q3 - Q1
IQR

upper=Q3+1.5*IQR
lower=Q1-1.5*IQR

df_data2 = df_data[~((df_data > upper) | (df_data < lower)).any(axis=1)]
# df_data2 = df_data[((df_data > upper) | (df_data < lower))]

df_data2
```

```
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\134953181.py:2:
FutureWarning: The default value of numeric_only in DataFrame.quantile is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  Q1 = df_data.quantile(0.25)
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\134953181.py:3:
FutureWarning: The default value of numeric_only in DataFrame.quantile is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  Q3 = df_data.quantile(0.75)
C:\Users\Daniel\AppData\Local\Temp\ipykernel_16992\134953181.py:11:
FutureWarning: Automatic reindexing on DataFrame vs Series comparisons is
deprecated and will raise ValueError in a future version. Do `left, right =
left.align(right, axis=1, copy=False)` before e.g. `left == right`
  df_data2 = df_data[~((df_data > upper) | (df_data < lower)).any(axis=1)]
```

[ ]:

	Attr1	Attr2	Attr3	Attr4	Attr5	Attr6	Attr7 \
8	0.009020	0.63202	0.053735	1.12630	-37.842	0.000000	0.014434
33	0.001222	0.53108	0.201300	1.54310	-44.797	0.042436	0.002745
62	0.018510	0.75869	-0.119860	0.83860	-67.711	-0.090519	0.031603
78	0.011123	0.18941	0.369170	2.94910	47.755	0.011123	0.016622
81	0.030232	0.41512	0.094882	1.31720	-120.450	0.084006	0.044036
…	…	…	…	…	…	…	…
43296	0.034999	0.72977	-0.036695	0.94191	-60.260	0.000000	0.034433
43297	-0.002445	0.56949	0.038483	1.09750	-72.746	0.000000	-0.002445
43308	0.075638	0.40351	0.006306	1.03140	-28.666	0.000000	0.086580
43327	0.119110	0.50490	0.197170	1.39050	-76.361	0.000000	0.142030
43332	0.046136	0.58764	0.061231	1.12780	-40.801	0.046136	0.060462

```
        Attr8    Attr9   Attr10  …    Attr56    Attr57   Attr58   Attr59  \
8      0.58223  1.33320  0.36798  …  0.180110  0.024512  0.84165  0.34094
33     0.87355  0.99091  0.46393  … -0.009171  0.002635  1.00920  0.34583
62     0.31836  1.83970  0.24153  …  0.038160  0.076636  0.98291  0.00000
78     3.32560  1.00520  0.62991  …  0.005168  0.017658  0.99483  0.00000
81     1.40890  1.05210  0.58488  …  0.049558  0.051690  0.95044  0.19832
…        …        …      …  …        …         …       …
43296  0.37029  1.58960  0.27023  …  0.045307  0.129520  0.95280  0.24317
43297  0.75583  1.11890  0.43044  …  0.013238 -0.005679  0.96577  0.39267
43308  1.47820  1.07420  0.59649  …  0.106620  0.126810  0.91940  0.33945
43327  0.98057  1.77980  0.49509  …  0.092460  0.240580  0.93291  0.00000
43332  0.45953  1.05900  0.27004  …  0.055699  0.170850  0.94430  0.40194

       Attr60   Attr61   Attr62   Attr63  Attr64         class
8       9.9665   4.2382  116.500   3.1330  2.5603  not bankrupt
33      4.0888  10.3480   89.081   4.0974  3.5477  not bankrupt
62      8.9659   4.5812  147.340   2.4772  4.8773  not bankrupt
78     30.8770   7.8559   30.578  11.9370  5.1221  not bankrupt
81      5.1896   6.6222  118.830   3.0716  1.5162  not bankrupt
…         …        …      …        …       …        …
43296   6.9657  11.5040  145.040   2.5166  3.9245      bankrupt
43297   4.7241   6.1986  128.740   2.8351  1.9741      bankrupt
43308  15.0070   9.3041   68.309   5.3434  1.3552      bankrupt
43327   3.3242  11.0560  103.550   3.5250  5.9740      bankrupt
43332   6.5538   3.5131  146.200   2.4966  2.6022      bankrupt

[3850 rows x 65 columns]
```

[ ]:
```
df_data2.describe()
```

[ ]:
```
            Attr1        Attr2        Attr3        Attr4        Attr5  \
count 3850.000000  3850.000000  3850.000000  3850.000000  3850.000000
mean     0.050727     0.470124     0.151639     1.602069   -17.004994
std      0.050716     0.156929     0.168054     0.758787    44.189034
min     -0.156460     0.000000    -0.415910     0.267830  -192.800000
25%      0.015637     0.357210     0.030896     1.072950   -43.991250
50%      0.041946     0.471035     0.135360     1.384300   -16.315000
75%      0.077536     0.583653     0.259737     1.899825     9.199225
max      0.298820     1.086800     0.764960     5.209500   191.950000

            Attr6        Attr7        Attr8        Attr9       Attr10  …  \
count 3850.000000  3850.000000  3850.000000  3850.000000  3850.000000  …
mean     0.038896     0.061654     1.382940     1.480301     0.507645  …
std      0.070942     0.058265     1.020990     0.633999     0.153887  …
min     -0.133970    -0.156460    -0.079862     0.402210    -0.086794  …
25%      0.000000     0.021305     0.680665     1.027600     0.397970  …
50%      0.000000     0.050645     1.066450     1.133450     0.500075  …
```

```
75%        0.079857     0.093150     1.729250     1.826150     0.621333  …
max        0.223200     0.320140     5.832800     3.628000     1.000000  …

              Attr55        Attr56        Attr57        Attr58        Attr59  \
count    3850.000000   3850.000000   3850.000000   3850.000000   3850.000000
mean     2131.528118      0.050664      0.110925      0.952738      0.177526
std      3211.549513      0.059568      0.118544      0.054131      0.177111
min     -7414.000000     -0.165210     -0.389490      0.707260      0.000000
25%       198.400000      0.015572      0.031200      0.932138      0.000000
50%      1223.950000      0.039603      0.085301      0.964330      0.146950
75%      3536.575000      0.075192      0.166785      0.985620      0.302840
max     12431.000000      0.297530      0.688410      1.165200      0.589640

             Attr60        Attr61        Attr62        Attr63        Attr64
count   3850.000000   3850.000000   3850.000000   3850.000000   3850.000000
mean      11.022922      7.798744     84.194217      5.214771      4.608622
std        7.542564      3.513926     35.876740      2.390961      3.464187
min        2.691200      2.458200      0.000000      1.646300      0.469200
25%        5.659325      5.178500     56.772000      3.482450      2.196000
50%        8.465250      7.015850     79.254000      4.605400      3.568650
75%       14.038500      9.721050    104.810000      6.413225      5.871175
max       39.347000     19.127000    221.710000     15.755000     20.569000

[8 rows x 64 columns]
```

[ ]:
```
z_threshold = 3
df_data_z_score=((df_data.iloc[:, :-1]-df_data.iloc[:, :-1].mean())/df_data.
 ↪iloc[:, :-1].std()).abs()
outliers = (df_data_z_score > z_threshold)

df_data2 = df_data[~outliers.any(axis=1)]
df_data2
```

[ ]:
```
          Attr1    Attr2     Attr3    Attr4     Attr5    Attr6     Attr7  \
1      0.209120  0.49988  0.472250  1.94470   14.7860  0.00000  0.258340
2      0.248660  0.69592  0.267130  1.55480   -1.1523  0.00000  0.309060
3      0.081483  0.30734  0.458790  2.49280   51.9520  0.14988  0.092704
4      0.187320  0.61323  0.229600  1.40630   -7.3128  0.18732  0.187320
5      0.228220  0.49794  0.359690  1.75020  -47.7170  0.00000  0.281390
…           …        …         …        …         …        …
43400  0.012898  0.70621  0.038857  1.17220  -18.9070  0.00000  0.013981
43401 -0.578050  0.96702 -0.800850  0.16576  -67.3650 -0.57805 -0.578050
43402 -0.179050  1.25530 -0.275990  0.74554 -120.4400 -0.17905 -0.154930
43403 -0.108860  0.74394  0.015449  1.08780  -17.0030 -0.10886 -0.109180
43404 -0.105370  0.53629 -0.045578  0.91478  -56.0680 -0.10537 -0.109940

         Attr8    Attr9    Attr10  …    Attr56    Attr57   Attr58    Attr59  \
```

```
1       0.99601  1.69960  0.497880  …  0.121300  0.420020  0.85300  0.000000
2       0.43695  1.30900  0.304080  …  0.241140  0.817740  0.76599  0.694840
3       1.86610  1.05710  0.573530  …  0.054015  0.142070  0.94598  0.000000
4       0.63070  1.15590  0.386770  …  0.134850  0.484310  0.86515  0.124440
5       1.00830  1.97860  0.502060  …  0.139320  0.454570  0.85891  0.023002
…           …        …         …  …       …          …         …        …
43400   0.41600  1.67680  0.293790  …  0.020169  0.043904  1.01220  1.259400
43401  -0.40334  0.93979 -0.390040  … -0.064073  1.482000  1.06410 -0.018084
43402  -0.26018  1.17490 -0.326590  …  0.148880  0.548240  0.85112 -0.522430
43403   0.12531  0.84516  0.093224  … -0.183200 -1.167700  1.18320  6.092400
43404   0.86460  0.95040  0.463670  … -0.052186 -0.227250  1.05220  0.003196

         Attr60   Attr61   Attr62  Attr63    Attr64         class
1        4.1486   3.2732  107.350  3.4000  60.98700  not bankrupt
2        4.9909   3.9510  134.270  2.7185   5.20780  not bankrupt
3        4.5746   3.6147   86.435  4.2228   5.54970  not bankrupt
4        6.3985   4.3158  127.210  2.8692   7.89800  not bankrupt
5        3.4028   8.9949   88.444  4.1269  12.29900  not bankrupt
…           …        …        …       …         …           …
43400   13.4720  12.4320   49.117  7.4313   2.27990      bankrupt
43401  110.7200  44.7590   81.220  4.4940   5.13050      bankrupt
43402    9.8526   3.4892  207.870  1.7559   9.95270      bankrupt
43403   13.8860   6.0769   83.122  4.3911   0.95575      bankrupt
43404    7.7332   4.7174  136.850  2.6672   2.79270      bankrupt

[42264 rows x 65 columns]
```

[ ]:
```
df_data2.describe()
```

[ ]:
```
              Attr1         Attr2         Attr3         Attr4          Attr5  \
count  42264.000000  42264.000000  42264.000000  42264.000000   42264.00000
mean       0.061693      0.523181      0.187992      3.038638      -2.02163
std        0.206044      0.476727      0.427600      8.612294    2994.21849
min       -6.453500      0.000000    -14.989000     -0.403110 -139260.00000
25%        0.003930      0.271918      0.022899      1.052300     -48.63500
50%        0.050091      0.472715      0.196200      1.567900      -1.21015
75%        0.129632      0.686782      0.400520      2.759125      49.44200
max        4.075300     16.643000     11.927000    841.760000  155870.00000

              Attr6         Attr7         Attr8         Attr9        Attr10  \
count  42264.000000  42264.000000  42264.000000  42264.000000  42264.000000
mean       0.004258      0.075850      3.213418      1.724685      0.459671
std        0.520487      0.218366     15.696948      1.427685      0.486513
min      -21.330000     -6.453500     -2.003200     -1.215700    -15.643000
25%        0.000000      0.006349      0.434103      1.019600      0.296868
50%        0.000000      0.060099      1.070150      1.199850      0.505210
75%        0.089241      0.150633      2.580000      2.063475      0.706233
```

```
max       17.113000      4.075300   1424.300000     49.092000     12.602000

       …          Attr55         Attr56         Attr57         Attr58  \
count  …   42264.000000   42264.000000   42264.000000   42264.000000
mean   …    5237.298240      -0.278831       0.139531       1.951722
std    …   21109.787974      49.903194       1.505998      81.818560
min    … -198780.000000   -8534.600000     -40.399000      -4.549700
25%    …      35.330500       0.009703       0.015656       0.875800
50%    …    1106.300000       0.053085       0.120400       0.950890
75%    …    4928.200000       0.128543       0.284687       0.992320
max    …  217780.000000       2.763300      39.003000    8603.500000

             Attr59         Attr60         Attr61          Attr62         Attr63  \
count  42264.000000   42264.000000   42264.000000    42264.000000   42264.000000
mean       0.314469      71.994748      11.788502      161.327786       7.853389
std        5.397831     984.219088      36.657924     2213.899858      12.189176
min     -256.990000     -12.440000     -12.656000     -236.530000      -1.543200
25%        0.000000       5.708825       4.539000       42.379500       3.123075
50%        0.008054       9.848750       6.651150       71.203500       5.107850
75%        0.240265      19.230500      10.386000      116.432500       8.560400
max      308.150000   90260.000000    1632.100000   205000.000000     342.000000

             Attr64
count  42264.000000
mean      20.884361
std      118.103995
min       -3.726500
25%        2.218175
50%        4.283650
75%        9.558225
max     5825.400000

[8 rows x 64 columns]
```

[ ]:
```
df_data_std=((df_data2.iloc[:, :-1]-df_data2.iloc[:, :-1].mean())/df_data2.
 ↪iloc[:, :-1].std())
df_data_std = df_data_std.join(df_data2.iloc[:, -1])
df_data_std
```

[ ]:
```
          Attr1     Attr2     Attr3     Attr4     Attr5     Attr6     Attr7  \
1      0.715513 -0.048877  0.664776 -0.127021  0.005613 -0.008182  0.835709
2      0.907414  0.362343  0.185075 -0.172293  0.000290 -0.008182  1.067980
3      0.096049 -0.452756  0.633298 -0.063379  0.018026  0.279780  0.077183
4      0.609711  0.188890  0.097306 -0.189536 -0.001767  0.351712  0.510475
5      0.808212 -0.052946  0.401539 -0.149605 -0.015261 -0.008182  0.941266
…           …         …         …         …         …         …         …
43400 -0.236817  0.383928 -0.348772 -0.216718 -0.005639 -0.008182 -0.283327
```

```
43401 -3.104882  0.931012 -2.312540 -0.333579 -0.021823 -1.118777 -2.994520
43402 -1.168403  1.535719 -1.085084 -0.266259 -0.039549 -0.352187 -1.056851
43403 -0.827748  0.463072 -0.403515 -0.226518 -0.005003 -0.217332 -0.847340
43404 -0.810810  0.027498 -0.546235 -0.246608 -0.018050 -0.210627 -0.850821

         Attr8     Attr9    Attr10  …    Attr56    Attr57    Attr58  \
1     -0.141264 -0.017570  0.078537  …  0.008018  0.186248 -0.013429
2     -0.176879 -0.291160 -0.319808  …  0.010420  0.450338 -0.014492
3     -0.085833 -0.467600  0.234031  …  0.006670  0.001686 -0.012292
4     -0.164536 -0.398397 -0.149844  …  0.008290  0.228937 -0.013280
5     -0.140481  0.177851  0.087128  …  0.008379  0.209189 -0.013357
…           …         …         …  …         …         …         …
43400 -0.178214 -0.033540 -0.340959  …  0.005992 -0.063498 -0.011483
43401 -0.230412 -0.549768 -1.746532  …  0.004303  0.891415 -0.010849
43402 -0.221291 -0.385088 -1.616114  …  0.008571  0.271387 -0.013452
43403 -0.196733 -0.616050 -0.753210  …  0.001916 -0.868016 -0.009393
43404 -0.149635 -0.542336  0.008220  …  0.004542 -0.243547 -0.010994

        Attr59    Attr60    Attr61    Attr62    Attr63    Attr64  \
1     -0.058258 -0.068934 -0.232291 -0.024381 -0.365356  0.339554
2      0.070467 -0.068078 -0.213801 -0.012222 -0.421266 -0.132735
3     -0.058258 -0.068501 -0.222975 -0.033828 -0.297854 -0.129840
4     -0.035205 -0.066648 -0.203850 -0.015411 -0.408903 -0.109957
5     -0.053997 -0.069692 -0.076207 -0.032921 -0.305721 -0.072693
…           …         …         …         …         …         …
43400  0.175058 -0.059461  0.017554 -0.050685 -0.034628 -0.157526
43401 -0.061609  0.039346  0.899410 -0.036184 -0.275604 -0.133390
43402 -0.155044 -0.063139 -0.226399  0.021023 -0.500238 -0.092560
43403  1.070417 -0.059040 -0.155808 -0.035325 -0.284046 -0.168738
43404 -0.057666 -0.065292 -0.192894 -0.011056 -0.425475 -0.153184

              class
1      not bankrupt
2      not bankrupt
3      not bankrupt
4      not bankrupt
5      not bankrupt
…               …
43400      bankrupt
43401      bankrupt
43402      bankrupt
43403      bankrupt
43404      bankrupt

[42264 rows x 65 columns]
```

[ ]:
```
df_data_norm=df_data2.iloc[:, :-1].copy()
for column in df_data_norm.columns:
    df_data_norm[column] = df_data_norm[column]  / df_data_norm[column].abs().
 ↪max()

df_data_norm = df_data_norm.join(df_data2.iloc[:, -1])
df_data_norm
```

[ ]:
```
          Attr1     Attr2     Attr3     Attr4     Attr5     Attr6     Attr7  \
1      0.032404  0.030035  0.031506  0.002310  0.000095  0.000000  0.040031
2      0.038531  0.041815  0.017822  0.001847 -0.000007  0.000000  0.047890
3      0.012626  0.018467  0.030608  0.002961  0.000333  0.007027  0.014365
4      0.029026  0.036846  0.015318  0.001671 -0.000047  0.008782  0.029026
5      0.035364  0.029919  0.023997  0.002079 -0.000306  0.000000  0.043603
…           …        …        …         …        …        …        …
43400  0.001999  0.042433  0.002592  0.001393 -0.000121  0.000000  0.002166
43401 -0.089572  0.058104 -0.053429  0.000197 -0.000432 -0.027100 -0.089572
43402 -0.027745  0.075425 -0.018413  0.000886 -0.000773 -0.008394 -0.024007
43403 -0.016868  0.044700  0.001031  0.001292 -0.000109 -0.005104 -0.016918
43404 -0.016328  0.032223 -0.003041  0.001087 -0.000360 -0.004940 -0.017036

          Attr8     Attr9    Attr10  …    Attr56    Attr57    Attr58  \
1      0.000699  0.034621  0.031828  …  0.000014  0.010397  0.000099
2      0.000307  0.026664  0.019439  …  0.000028  0.020242  0.000089
3      0.001310  0.021533  0.036664  …  0.000006  0.003517  0.000110
4      0.000443  0.023546  0.024725  …  0.000016  0.011988  0.000101
5      0.000708  0.040304  0.032095  …  0.000016  0.011252  0.000100
…           …        …        …   …   …         …        …
43400  0.000292  0.034156  0.018781  …  0.000002  0.001087  0.000118
43401 -0.000283  0.019143 -0.024934  … -0.000008  0.036684  0.000124
43402 -0.000183  0.023933 -0.020878  …  0.000017  0.013571  0.000099
43403  0.000088  0.017216  0.005959  … -0.000021 -0.028904  0.000138
43404  0.000607  0.019360  0.029641  … -0.000006 -0.005625  0.000122

         Attr59    Attr60    Attr61    Attr62    Attr63    Attr64  \
1      0.000000  0.000046  0.002006  0.000524  0.009942  0.010469
2      0.002255  0.000055  0.002421  0.000655  0.007949  0.000894
3      0.000000  0.000051  0.002215  0.000422  0.012347  0.000953
4      0.000404  0.000071  0.002644  0.000621  0.008389  0.001356
5      0.000075  0.000038  0.005511  0.000431  0.012067  0.002111
…           …        …        …         …        …        …
43400  0.004087  0.000149  0.007617  0.000240  0.021729  0.000391
43401 -0.000059  0.001227  0.027424  0.000396  0.013140  0.000881
43402 -0.001695  0.000109  0.002138  0.001014  0.005134  0.001709
43403  0.019771  0.000154  0.003723  0.000405  0.012839  0.000164
43404  0.000010  0.000086  0.002890  0.000668  0.007799  0.000479
```

```
              class
1       not bankrupt
2       not bankrupt
3       not bankrupt
4       not bankrupt
5       not bankrupt
…                …
43400       bankrupt
43401       bankrupt
43402       bankrupt
43403       bankrupt
43404       bankrupt

[42264 rows x 65 columns]
```

[ ]:
```
from sklearn import linear_model
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

print('Dane standartyzowane')
reg = linear_model.LinearRegression()

X_train, X_test, y_train, y_test = train_test_split( df_data_std.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_std.iloc[:, -1]]
    , test_size=0.33, random_state=42)

reg.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in reg.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane normalizowane')
reg = linear_model.LinearRegression()

X_train, X_test, y_train, y_test = train_test_split( df_data_norm.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_norm.iloc[:, -1]]
    , test_size=0.33, random_state=42)

reg.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in reg.predict(X_test)]
real_data = y_test
```

```
print(classification_report(real_data, prediction, target_names=['not␣
↪bankrupt', 'bankrupt']))
```

```
Dane standartyzowane
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.98     13274
    bankrupt       0.00      0.00      0.00       674

    accuracy                           0.95     13948
   macro avg       0.48      0.50      0.49     13948
weighted avg       0.91      0.95      0.93     13948

Dane normalizowane
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.98     13274
    bankrupt       0.00      0.00      0.00       674

    accuracy                           0.95     13948
   macro avg       0.48      0.50      0.49     13948
weighted avg       0.91      0.95      0.93     13948
```

[ ]:
```
print('Dane bez outliers')
reg = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split( df_data2.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data2.iloc[:, -1]]
    , test_size=0.33, random_state=42)

reg.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in reg.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
↪bankrupt', 'bankrupt']))

print('Dane z outliers')
reg = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split( df_data.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data.iloc[:, -1]]
    , test_size=0.33, random_state=42)

reg.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in reg.predict(X_test)]
```

```
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane z outliers (na = mean)')
reg = linear_model.LinearRegression()
X_train, X_test, y_train, y_test = train_test_split( df_data_mean.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_mean.iloc[:, -1]]
    , test_size=0.33, random_state=42)

reg.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in reg.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))
```

```
Dane bez outliers
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.98     13274
    bankrupt       0.00      0.00      0.00       674

    accuracy                           0.95     13948
   macro avg       0.48      0.50      0.49     13948
weighted avg       0.91      0.95      0.93     13948

Dane z outliers
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.97     13603
    bankrupt       0.15      0.00      0.01       721

    accuracy                           0.95     14324
   macro avg       0.55      0.50      0.49     14324
weighted avg       0.91      0.95      0.93     14324

Dane z outliers (na = mean)
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.97     13603
    bankrupt       0.14      0.00      0.01       721

    accuracy                           0.95     14324
   macro avg       0.55      0.50      0.49     14324
weighted avg       0.91      0.95      0.93     14324
```

[ ]:

```python
from sklearn.neural_network import MLPClassifier

print('Dane standartyzowane')
clf = MLPClassifier(random_state=1, max_iter=300)

X_train, X_test, y_train, y_test = train_test_split( df_data_std.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_std.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane normalizowane')
clf = MLPClassifier(random_state=1, max_iter=300)

X_train, X_test, y_train, y_test = train_test_split( df_data_norm.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_norm.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))
```

```
Dane standartyzowane

c:\Users\Daniel\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:684:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  warnings.warn(

              precision    recall  f1-score   support

not bankrupt       0.97      0.99      0.98     13274
    bankrupt       0.65      0.30      0.41       674

    accuracy                           0.96     13948
   macro avg       0.81      0.64      0.69     13948
```

```
weighted avg       0.95      0.96      0.95     13948

Dane normalizowane
              precision    recall  f1-score   support

not bankrupt       0.95      1.00      0.97     13274
    bankrupt       0.42      0.04      0.07       674

    accuracy                           0.95     13948
   macro avg       0.68      0.52      0.52     13948
weighted avg       0.93      0.95      0.93     13948

c:\Users\Daniel\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:684:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[ ]:

```
print('Dane bez outliers')
clf = MLPClassifier(random_state=1, max_iter=300)
X_train, X_test, y_train, y_test = train_test_split( df_data2.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data2.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane z outliers')
clf = MLPClassifier(random_state=1, max_iter=300)
X_train, X_test, y_train, y_test = train_test_split( df_data.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane z outliers (na = mean)')
```

```
clf = MLPClassifier(random_state=1, max_iter=300)
X_train, X_test, y_train, y_test = train_test_split( df_data_mean.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_mean.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test


print(classification_report(real_data, prediction, target_names=['not␣
↪bankrupt', 'bankrupt']))
```

```
Dane bez outliers
              precision    recall  f1-score   support

not bankrupt       0.96      0.96      0.96     13274
    bankrupt       0.18      0.16      0.17       674

    accuracy                           0.92     13948
   macro avg       0.57      0.56      0.56     13948
weighted avg       0.92      0.92      0.92     13948

Dane z outliers
              precision    recall  f1-score   support

not bankrupt       0.95      0.99      0.97     13603
    bankrupt       0.27      0.06      0.10       721

    accuracy                           0.94     14324
   macro avg       0.61      0.53      0.54     14324
weighted avg       0.92      0.94      0.93     14324

Dane z outliers (na = mean)
              precision    recall  f1-score   support

not bankrupt       0.96      0.91      0.94     13603
    bankrupt       0.15      0.30      0.20       721

    accuracy                           0.88     14324
   macro avg       0.56      0.61      0.57     14324
weighted avg       0.92      0.88      0.90     14324
```

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
```

```python
print('Dane standartyzowane')
clf = DecisionTreeClassifier(random_state=0)

X_train, X_test, y_train, y_test = train_test_split( df_data_std.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_std.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane normalizowane')
clf = DecisionTreeClassifier(random_state=0)

X_train, X_test, y_train, y_test = train_test_split( df_data_norm.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_norm.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))
```

```
Dane standartyzowane
              precision    recall  f1-score   support

not bankrupt       0.99      0.99      0.99     13274
    bankrupt       0.73      0.73      0.73       674

    accuracy                           0.97     13948
   macro avg       0.86      0.86      0.86     13948
weighted avg       0.97      0.97      0.97     13948

Dane normalizowane
              precision    recall  f1-score   support

not bankrupt       0.99      0.98      0.98     13274
    bankrupt       0.69      0.71      0.70       674

    accuracy                           0.97     13948
   macro avg       0.84      0.85      0.84     13948
```

```
weighted avg       0.97      0.97      0.97     13948
```

[ ]:
```
print('Dane bez outliers')
clf = DecisionTreeClassifier(random_state=0)
X_train, X_test, y_train, y_test = train_test_split( df_data2.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data2.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane z outliers')
clf = DecisionTreeClassifier(random_state=0)
X_train, X_test, y_train, y_test = train_test_split( df_data.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))

print('Dane z outliers (na = mean)')
clf = DecisionTreeClassifier(random_state=0)
X_train, X_test, y_train, y_test = train_test_split( df_data_mean.iloc[:, :-1]
    , [ 1 if x == 'bankrupt' else 0 for x in df_data_mean.iloc[:, -1]]
    , test_size=0.33, random_state=42)

clf.fit(X_train, y_train)

prediction = [1 if x > 0.5 else 0 for x in clf.predict(X_test)]
real_data = y_test

print(classification_report(real_data, prediction, target_names=['not␣
 ↪bankrupt', 'bankrupt']))
```

```
Dane bez outliers
              precision    recall  f1-score   support
```

```
not bankrupt       0.99      0.99      0.99     13274
    bankrupt       0.74      0.73      0.74       674

    accuracy                           0.97     13948
   macro avg       0.87      0.86      0.86     13948
weighted avg       0.97      0.97      0.97     13948

Dane z outliers
              precision    recall  f1-score   support

not bankrupt       0.99      0.98      0.99     13603
    bankrupt       0.71      0.79      0.75       721

    accuracy                           0.97     14324
   macro avg       0.85      0.89      0.87     14324
weighted avg       0.98      0.97      0.97     14324

Dane z outliers (na = mean)
              precision    recall  f1-score   support

not bankrupt       0.99      0.99      0.99     13603
    bankrupt       0.80      0.82      0.81       721

    accuracy                           0.98     14324
   macro avg       0.90      0.90      0.90     14324
weighted avg       0.98      0.98      0.98     14324
```

Wyniki: Standartyzacja ogólnie daje lepsze wyniki niż normalizacja, ale każda metoda jest lepsza niż jej brak (wyjątek drzewo decyzyjne).

Wartości odstające są niejednoznaczne, w niektórych przypadkach ich usunięcie polepsza klasyfikacje, w innych robi gorzej.

Były porównane dwie strategii uzupełnienia danych, używanie mediany i średniej wartości atrybutu dla klasy. W przypadku drzewa decyzyjnego używanie średniej daje lepsze rezultaty niż mediana, dla pozostałych wybranych metod lepiej działa strategia mediany.