22_Ratio-default-nondefault-on-metrics-score

April 30, 2022

[720]:
```
import pandas as pd
import numpy as np
from numpy.random import seed
```

[721]:
```
seed(100)
```

[722]:
```
import warnings
warnings.filterwarnings("ignore")
```

[723]:
```
df = pd.read_excel("./DATA/default of credit card clients.xls", skiprows=1)
df.head()
```

[723]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	1	20000	2	2	1	24	2	2	-1	-1	
1	2	120000	2	2	2	26	-1	2	0	0	
2	3	90000	2	2	2	34	0	0	0	0	
3	4	50000	2	2	1	37	0	0	0	0	
4	5	50000	1	2	1	57	-1	0	-1	0	

	…	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3	\
0	…	0	0	0	0	689	0	
1	…	3272	3455	3261	0	1000	1000	
2	…	14331	14948	15549	1518	1500	1000	
3	…	28314	28959	29547	2000	2019	1200	
4	…	20940	19146	19131	2000	36681	10000	

	PAY_AMT4	PAY_AMT5	PAY_AMT6	default payment next month
0	0	0	0	1
1	1000	0	2000	1
2	1000	1000	5000	0
3	1100	1069	1000	0
4	9000	689	679	0

[5 rows x 25 columns]

[724]:
```
cols = df.columns.tolist()
cols
```

[724]:
```
['ID',
 'LIMIT_BAL',
 'SEX',
 'EDUCATION',
 'MARRIAGE',
 'AGE',
 'PAY_0',
 'PAY_2',
 'PAY_3',
 'PAY_4',
 'PAY_5',
 'PAY_6',
 'BILL_AMT1',
 'BILL_AMT2',
 'BILL_AMT3',
 'BILL_AMT4',
 'BILL_AMT5',
 'BILL_AMT6',
 'PAY_AMT1',
 'PAY_AMT2',
 'PAY_AMT3',
 'PAY_AMT4',
 'PAY_AMT5',
 'PAY_AMT6',
 'default payment next month']
```

[725]:
```
idx1 = df[ df['default payment next month']==0 ].ID.values
idx2 = df[ df['default payment next month']==1 ].ID.values
idx1.shape, idx2.shape
```

[725]:
```
((23364,), (6636,))
```

[726]:
```
n1 = np.random.choice(idx1, 15000)
n2 = np.random.choice(idx2, 5000)
np.shape(n1), np.shape(n2)
```

[726]:
```
((15000,), (5000,))
```

[727]:
```
n11 = np.unique(n1)
n22 = np.unique(n2)
np.shape(n11), np.shape(n22)
```

[727]:
```
((11025,), (3553,))
```

[728]:
```
type(n11), type(n22)
```

[728]:
```
(numpy.ndarray, numpy.ndarray)
```

[729]:
```
def ret_idx(m1, m2):
    idx = list(n11[0:m1]) + list(n22[0:m2])
    return idx
```

[730]:
```
mm = 3000
nn = np.arange(1500,20,-50)
nn
```

[730]:
```
array([1500, 1450, 1400, 1350, 1300, 1250, 1200, 1150, 1100, 1050, 1000,
        950,  900,  850,  800,  750,  700,  650,  600,  550,  500,  450,
        400,  350,  300,  250,  200,  150,  100,   50])
```

[731]:
```
1500*100/3000, 50*100/3000
```

[731]:
```
(50.0, 1.6666666666666667)
```

[732]:
```
idx = ret_idx(950,50)
np.shape(idx)
```

[732]:
```
(1000,)
```

[733]:
```
np.shape(cols)
```

[733]:
```
(25,)
```

[734]:
```
del cols[0]
```

[735]:
```
np.shape(cols)
```

[735]:
```
(24,)
```

[736]:
```
del cols[23]
np.shape(cols)
```

[736]:
```
(23,)
```

[737]:
```
cols
```

[737]:
```
['LIMIT_BAL',
 'SEX',
 'EDUCATION',
 'MARRIAGE',
 'AGE',
 'PAY_0',
 'PAY_2',
 'PAY_3',
 'PAY_4',
```

```
 'PAY_5',
 'PAY_6',
 'BILL_AMT1',
 'BILL_AMT2',
 'BILL_AMT3',
 'BILL_AMT4',
 'BILL_AMT5',
 'BILL_AMT6',
 'PAY_AMT1',
 'PAY_AMT2',
 'PAY_AMT3',
 'PAY_AMT4',
 'PAY_AMT5',
 'PAY_AMT6']
```

[738]:
```
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score

from sklearn import svm
from sklearn.svm import SVC
```

[739]:
```
rr = []
ss = []
```

[740]:
```
for ps in nn:
    ratio = ps/mm
    rr.append(ratio)
    xid = ret_idx(mm, ps)
    #print(np.shape(xid),'\t', ps/mm)
    df1 = df.iloc[xid,:]
    #print(df1.shape)
    y = df1['default payment next month'].values
    data = df1[cols].values
    X = preprocessing.StandardScaler().fit(data).transform(data)
    x_tr, x_t, y_tr, y_t = train_test_split(X, y, test_size=0.36,␣
 ↪random_state=100)
    #print(x_tr.shape, x_t.shape, y_tr.shape, y_t.shape)
    clf = svm.SVC()
    clf.fit(x_tr, y_tr)
    y_p = clf.predict(x_t)
    score = accuracy_score(y_t, y_p)*100
    ss.append(score)
    #print(ratio, '\t', score)
```

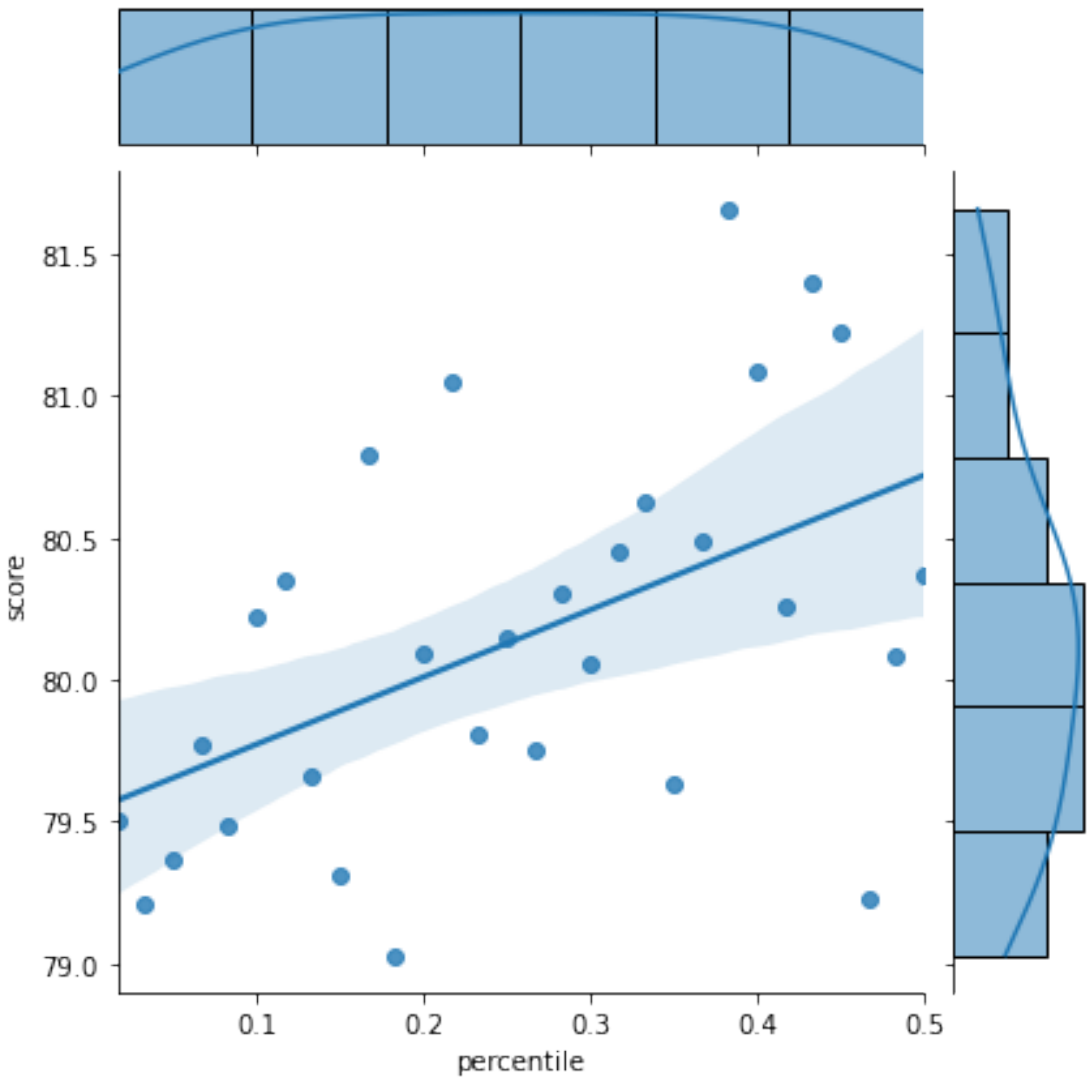
[741]:
```
res = pd.DataFrame(dict(list(zip(['percentile','score'],[rr, ss]))))
res
```

[741]:

	percentile	score
0	0.500000	80.370370
1	0.483333	80.087391
2	0.466667	79.229798
3	0.450000	81.226054
4	0.433333	81.395349
5	0.416667	80.261438
6	0.400000	81.084656
7	0.383333	81.659973
8	0.366667	80.487805
9	0.350000	79.629630
10	0.333333	80.625000
11	0.316667	80.450070
12	0.300000	80.056980
13	0.283333	80.303030
14	0.266667	79.751462
15	0.250000	80.148148
16	0.233333	79.804805
17	0.216667	81.050228
18	0.200000	80.092593
19	0.183333	79.029734
20	0.166667	80.793651
21	0.150000	79.307568
22	0.133333	79.656863
23	0.116667	80.348259
24	0.100000	80.218855
25	0.083333	79.487179
26	0.066667	79.774306
27	0.050000	79.365079
28	0.033333	79.211470
29	0.016667	79.508197

[742]:
```
import seaborn as sns
import matplotlib.pyplot as plt


sns.jointplot(x="percentile", y="score", data=res, kind="reg")
plt.show()
```



[743]:
```
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

[744]:
```
ols_fit = ols('score ~ percentile', res).fit()
ols_fit.summary()
```

[744]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  score   R-squared:                       0.255
Model:                            OLS   Adj. R-squared:                  0.229
Method:                 Least Squares   F-statistic:                     9.594
```

```
Date:                Sat, 30 Apr 2022   Prob (F-statistic):            0.00441
Time:                        20:04:32   Log-Likelihood:                -26.450
No. Observations:                  30   AIC:                             56.90
Df Residuals:                      28   BIC:                             59.70
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     79.5347      0.227    351.146      0.000      79.071      79.999
percentile     2.3711      0.766      3.097      0.004       0.803       3.939
==============================================================================
Omnibus:                        0.105   Durbin-Watson:                   2.095
Prob(Omnibus):                  0.949   Jarque-Bera (JB):                0.023
Skew:                           0.008   Prob(JB):                        0.989
Kurtosis:                       2.866   Cond. No.                         7.40
==============================================================================

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

0.2 => 0.6143 (reproducible 0.6143) 0.22 => 0.2268 (reproducible 0.2268) 0.24 => 1.2323 0.25 => 1.3479 0.26 => 1.6569 0.28 => 2.3537 0.3 => 2.3531 (reproducible 2.3531) 0.32 => 2.7777 0.34 => 2.3691 0.35 => 2.2473 0.36 => 2.3711 0.4 => 1.8541

[ ]:

[ ]:

[ ]:

[ ]: