In [1]: H #Null (or Missing) Values Estimation [Please fill the values without highlight in the blank #Data Balance [Only for "classification problem", and please state the original and final a #Feature Selection [Please state the original and final amount of features of each dataset] #After finishing 1) 2) 3), please save your file to .xlsx for this assignment, and save to In [2]: H #conda update scikit-learn In [3]: H #pip install -U imbalanced-learn In [4]: import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.linear\_model import LogisticRegression from sklearn.impute import SimpleImputer from sklearn.model\_selection import train\_test\_split from sklearn.linear\_model import LinearRegression from sklearn.metrics import classification report In [5]: #Load the data data=pd.read csv("bankruptcy.csv") In [6]: H #realize the shape data.shape Out[6]: (6819, 97)

In [7]: ▶

#glace data values #總共有97個col,前兩個分別為編號和是否破產,剩下95個為feature數量 data.head()

# Out[7]:

	Unnamed: 0	Bankrupt?	ROA(C) before interest and depreciation before interest	ROA(A) before interest and % after tax	ROA(B) before interest and depreciation after tax	Operating Gross Margin	Realized Sales Gross Margin	Operating Profit Rate
0	0	1	0.370594	0.424389	0.405750	0.601457	0.601457	0.998969
1	1	1	0.464291	0.538214	0.516730	0.610235	0.610235	0.998946
2	2	1	0.426071	0.499019	0.472295	0.601450	0.601364	0.998857
3	3	1	0.399844	0.451265	0.457733	0.583541	0.583541	0.998700
4	4	1	0.465022	0.538432	0.522298	0.598783	0.598783	0.998973

5 rows × 97 columns

In [8]: ▶

#checking null data
print(data.isnull().sum())

Unnamed: 0	0
Bankrupt?	0
ROA(C) before interest and depreciation before interest	98
ROA(A) before interest and % after tax	100
ROA(B) before interest and depreciation after tax	98
Liability to Equity	100
Degree of Financial Leverage (DFL)	99
Interest Coverage Ratio (Interest expense to EBIT)	99
Net Income Flag	100
Equity to Liability	100
Length: 97, dtype: int64	

```
In [9]: ▶
```

```
#using 最後觀察值推估法(Last Observation Carried Forward(LOCF)) ffill& 下個觀察值推估法(Next O #同時使用兩個方法,以防遺漏
#將處理完的data改名為data_fill
data_fill=data.fillna(method='ffill')
data_fill=data_fill.fillna(method='bfill')
data_fill
```

## Out[9]:

	Unnamed: 0	Bankrupt?	ROA(C) before interest and depreciation before interest	ROA(A) before interest and % after tax	ROA(B) before interest and depreciation after tax	Operating Gross Margin	Realized Sales Gross Margin	Operatir Pro Ra
0	0	1	0.370594	0.424389	0.405750	0.601457	0.601457	0.99896
1	1	1	0.464291	0.538214	0.516730	0.610235	0.610235	0.99894
2	2	1	0.426071	0.499019	0.472295	0.601450	0.601364	0.9988
3	3	1	0.399844	0.451265	0.457733	0.583541	0.583541	0.99870
4	4	1	0.465022	0.538432	0.522298	0.598783	0.598783	0.99897
			•••		•••			
6814	6814	0	0.493687	0.539468	0.543230	0.604455	0.604462	0.99899
6815	6815	0	0.475162	0.538269	0.524172	0.598308	0.598308	0.99899
6816	6816	0	0.472725	0.533744	0.520638	0.610444	0.610213	0.99898
6817	6817	0	0.506264	0.559911	0.554045	0.607850	0.607850	0.99907
6818	6818	0	0.493053	0.570105	0.549548	0.627409	0.627409	0.99808

6819 rows × 97 columns

```
→
```

```
In [10]:
```

```
#check null data
#not null data
print(data_fill.isnull().sum())
```

```
Unnamed: 0
                                                             0
Bankrupt?
                                                             0
 ROA(C) before interest and depreciation before interest
                                                             0
 ROA(A) before interest and % after tax
                                                             0
 ROA(B) before interest and depreciation after tax
                                                             0
 Liability to Equity
                                                             0
Degree of Financial Leverage (DFL)
                                                             0
 Interest Coverage Ratio (Interest expense to EBIT)
                                                             0
Net Income Flag
                                                             0
                                                             0
 Equity to Liability
Length: 97, dtype: int64
```

In [11]:

```
data_fill.columns
```

#### Out[11]:

```
Index(['Unnamed: 0', 'Bankrupt?',
        ' ROA(C) before interest and depreciation before interest',
       ' ROA(A) before interest and % after tax',
       ' ROA(B) before interest and depreciation after tax',
       'Operating Gross Margin', 'Realized Sales Gross Margin',
       ' Operating Profit Rate', ' Pre-tax net Interest Rate',
       ' After-tax net Interest Rate',
       ' Non-industry income and expenditure/revenue',
       'Continuous interest rate (after tax)', 'Operating Expense Rat
е',
       ' Research and development expense rate', ' Cash flow rate',
       ' Interest-bearing debt interest rate', ' Tax rate (A)',
       ' Net Value Per Share (B)', ' Net Value Per Share (A)',
       ' Net Value Per Share (C)', ' Persistent EPS in the Last Four Seas
ons',
       ' Cash Flow Per Share', ' Revenue Per Share (Yuan ¥)',
       ' Operating Profit Per Share (Yuan ¥)',
       ' Per Share Net profit before tax (Yuan ¥)',
       ' Realized Sales Gross Profit Growth Rate',
       ' Operating Profit Growth Rate', ' After-tax Net Profit Growth Rat
       ' Regular Net Profit Growth Rate', ' Continuous Net Profit Growth
Rate',
       ' Total Asset Growth Rate', ' Net Value Growth Rate',
       ' Total Asset Return Growth Rate Ratio', ' Cash Reinvestment %',
       ' Current Ratio', ' Quick Ratio', ' Interest Expense Ratio',
       ' Total debt/Total net worth', ' Debt ratio %', ' Net worth/Asset
s',
       'Long-term fund suitability ratio (A)', 'Borrowing dependency',
       ' Contingent liabilities/Net worth',
       ' Operating profit/Paid-in capital',
       ' Net profit before tax/Paid-in capital',
       ' Inventory and accounts receivable/Net value', ' Total Asset Turn
over',
       ' Accounts Receivable Turnover', ' Average Collection Days',
       ' Inventory Turnover Rate (times)', ' Fixed Assets Turnover Freque
ncy',
       ' Net Worth Turnover Rate (times)', ' Revenue per person',
       'Operating profit per person', 'Allocation rate per person',
       ' Working Capital to Total Assets', ' Quick Assets/Total Assets',
       ' Current Assets/Total Assets', ' Cash/Total Assets',
       ' Quick Assets/Current Liability', ' Cash/Current Liability', ' Current Liability to Assets', ' Operating Funds to Liability',
       ' Inventory/Working Capital', ' Inventory/Current Liability',
       ' Current Liabilities/Liability', ' Working Capital/Equity', ' Current Liabilities/Equity', ' Long-term Liability to Current As
sets',
       ' Retained Earnings to Total Assets', ' Total income/Total expens
e',
       ' Total expense/Assets', ' Current Asset Turnover Rate',
         Quick Asset Turnover Rate', ' Working capitcal Turnover Rate',
       ' Cash Turnover Rate', ' Cash Flow to Sales', ' Fixed Assets to As
```

```
bankruptcy-hw3 new select - Jupyter Notebook
2022/6/1 晚上11:25
  sets',
         ' Current Liability to Liability', ' Current Liability to Equity',
         ' Equity to Long-term Liability', ' Cash Flow to Total Assets',
         ' Cash Flow to Liability', ' CFO to Assets', ' Cash Flow to Equit
         ' Current Liability to Current Assets', ' Liability-Assets Flag',
         ' Net Income to Total Assets', ' Total assets to GNP price',
         ' No-credit Interval', ' Gross Profit to Sales',
         ' Net Income to Stockholder's Equity', ' Liability to Equity',
         ' Degree of Financial Leverage (DFL)',
         ' Interest Coverage Ratio (Interest expense to EBIT)',
         ' Net Income Flag', ' Equity to Liability'],
        dtvpe='object')
  In [12]:
                                                                                              M
  #區分出預測值和feature
 y=data_fill["Bankrupt?"]
  x=data_fill.drop(["Unnamed: 0","Bankrupt?"],axis=1)
  In [13]:
 y.value_counts()
  #0 6599
  #1 220
  Out[13]:
```

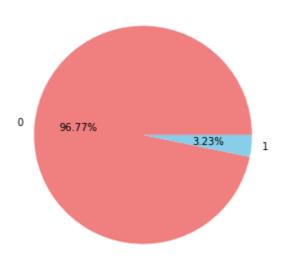
6599 1 220

Name: Bankrupt?, dtype: int64

In [14]: ▶

```
#觀察資料佔比差異,建議使用過採樣處理
plt.figure( figsize=(10,5) )
y.value_counts().plot( kind='pie', colors=['lightcoral','skyblue'], autopct='%1.2f%%' )
plt.title( 'Bankrupt' ) # 圖標題
plt.ylabel( '' )
plt.show()
```

# Bankrupt



# In [15]:

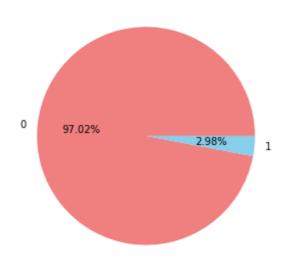
```
#將資料區分為訓練集和測試集
```

x\_train, x\_test, y\_train, y\_test = train\_test\_split(x, y, test\_size=0.3,random\_state=42)

In [16]:

```
#確定取樣後的訓練集為均勻的
plt.figure( figsize=(10,5) )
y_train.value_counts().plot( kind='pie', colors=['lightcoral','skyblue'], autopct='%1.2f%%'
plt.title( 'Bankrupt' ) # 圖標題
plt.ylabel( '' )
plt.show()
```

### Bankrupt



In [17]: ▶

y\_train.shape

### Out[17]:

(4773,)

```
In [18]:
                                                                                                              H
x_train
Out[18]:
            ROA(C)
                      ROA(A)
                                   ROA(B)
            before
                                                        Realized
                                                                              Pre-tax
                                                                                       After-tax
                       before
                                    before
                                            Operating
                                                                 Operating
                                                                                                       Non-
        interest and
                                                          Sales
                                                                                  net
                                                                                            net
                      interest
                               interest and
                                                Gross
                                                                     Profit
                                                                                                         inc
                                                          Gross
       depreciation
                                                                             Interest
                                                                                        Interest
                       and %
                               depreciation
                                               Margin
                                                                      Rate
                                                                                                 expenditure
            before
                                                         Margin
                                                                                Rate
                                                                                          Rate
                     after tax
                                  after tax
            interest
 5632
          0.500951
                    0.584169
                                  0.553777
                                             0.600614
                                                       0.600549
                                                                  0.999025
                                                                            0.797528
                                                                                      0.809438
  903
          0.479647
                    0.588748
                                  0.530007
                                             0.609666
                                                       0.609666
                                                                  0.998971
                                                                            0.797330
                                                                                      0.809240
 2666
          0.516502
                    0.580953
                                  0.568714
                                             0.610682
                                                       0.610682
                                                                  0.999128
                                                                            0.797571
                                                                                      0.809469
  109
          0.446302
                    0.531509
                                  0.499545
                                                       0.595771
                                             0.595771
                                                                  0.998895
                                                                            0.797324
                                                                                      0.809286
 5316
          0.575245
                    0.560565
                                  0.547781
                                             0.600001
                                                       0.600001
                                                                  0.999034
                                                                            0.797440
                                                                                      0.809349
In [19]:
y_train
Out[19]:
5632
         0
903
         0
2666
         0
109
         0
5316
         0
3772
         0
5191
         0
5226
         0
5390
         0
860
Name: Bankrupt?, Length: 4773, dtype: int64
In [20]:
                                                                                                              H
#進行過採樣處理
from imblearn.over_sampling import SMOTE
```

x\_train, y\_train = SMOTE().fit\_resample(x\_train, y\_train)

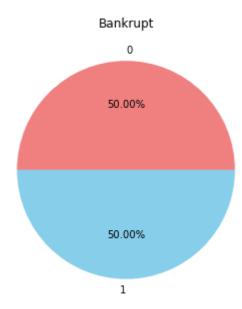
```
In [21]:
y_train.shape
```

```
Out[21]:
```

(9262,)

In [22]:

```
#觀察新的資料佔比差異
plt.figure( figsize=(10,5) )
y_train.value_counts().plot( kind='pie', colors=['lightcoral','skyblue'], autopct='%1.2f%%'
plt.title( 'Bankrupt' ) # 圖標題
plt.ylabel( '' )
plt.show()
```



In [23]:

```
#合成新的資料
```

data\_balance=pd.concat([x\_train,y\_train],axis=1)
data\_balance

### Out[23]:

	ROA(C) before interest and depreciation before interest	ROA(A) before interest and % after tax	ROA(B) before interest and depreciation after tax	Operating Gross Margin	Realized Sales Gross Margin	Operating Profit Rate	Pre-tax net Interest Rate	After-tax net Interest Rate	Non- inc expenditure
0	0.500951	0.584169	0.553777	0.600614	0.600549	0.999025	0.797528	0.809438	
1	0.479647	0.588748	0.530007	0.609666	0.609666	0.998971	0.797330	0.809240	
2	0.516502	0.580953	0.568714	0.610682	0.610682	0.999128	0.797571	0.809469	
3	0.446302	0.531509	0.499545	0.595771	0.595771	0.998895	0.797324	0.809286	
4	0.575245	0.560565	0.547781	0.600001	0.600001	0.999034	0.797440	0.809349	
		•••							•
1	0.407000	0.400744	0 500704	0.505504	^ 50000	^ ^^^^	^ 700045	000007	<b>&gt;</b>

In [24]: ▶

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.datasets import make_classification
clf = AdaBoostClassifier(n_estimators=120, random_state=0)

# clf = tree.DecisionTreeClassifier()
# clf = clf.fit(X, Y)
model = clf
#先觀察都沒做feature selection前的mode準確度
#由於是分類問題,適用LogisticRegression
# model = LogisticRegression(max_iter=1000)
model.fit(x_train,y_train)
```

#### Out[24]:

AdaBoostClassifier(n\_estimators=120, random\_state=0)

### In [25]:

```
#觀察迴歸模型的準確度
print(classification_report(y_train, model.predict(x_train)))
print(classification_report(y_test, model.predict(x_test)))
```

	precision	recall	f1-score	support
0	0.99	0.97	0.98	4631
1	0.97	0.99	0.98	4631
accuracy			0.98	9262
macro avg	0.98	0.98	0.98	9262
weighted avg	0.98	0.98	0.98	9262
	precision	recall	f1-score	support
0	precision 0.98	recall 0.96	f1-score 0.97	support 1968
0				
1	0.98	0.96	0.97 0.43	1968 78
accuracy	0.98 0.36	0.96 0.54	0.97 0.43 0.95	1968 78 2046
1	0.98	0.96	0.97 0.43	1968 78

```
In [26]: ▶
```

```
#feature selection
#使用filter法中的皮爾森相關係數方法作為篩選
#設在相關係數前n大的數字

def feature_selection_n(n):
    featuresCorr = data_balance.corr()
    targetCorr=abs(featuresCorr["Bankrupt?"])
    targetCorr = targetCorr.drop("Bankrupt?")
    result =pd.Series.argsort(-targetCorr)
    targetCorr=targetCorr[result]
    selectedFeatures=targetCorr[0:n]
    #print(f"Number of selected features: {len(selectedFeatures)} \n\nHighly relative featureturn selectedFeatures)
```

```
In [27]:
```

```
selectedFeatures=feature_selection_n(4)
selectedFeatures
```

#### Out[27]:

```
Net worth/Assets 0.598710
Debt ratio % 0.595721
Per Share Net profit before tax (Yuan ¥) 0.570813
ROA(C) before interest and depreciation before interest 0.569048
Name: Bankrupt?, dtype: float64
```

In [28]: ▶

x\_train=data\_balance[selectedFeatures.index]
x\_train

# Out[28]:

	Net worth/Assets	Debt ratio %	Per Share Net profit before tax (Yuan ¥)	ROA(C) before interest and depreciation before interest
0	0.888200	0.111800	0.184454	0.500951
1	0.847689	0.152311	0.166755	0.479647
2	0.966895	0.033105	0.181969	0.516502
3	0.906310	0.093690	0.167960	0.446302
4	0.882396	0.117604	0.179935	0.575245
9257	0.824272	0.175728	0.161288	0.467220
9258	0.786659	0.213341	0.174660	0.494583
9259	0.806011	0.193989	0.193313	0.494676
9260	0.872011	0.127989	0.155082	0.417124
9261	0.837775	0.162225	0.166181	0.463788

9262 rows × 4 columns

```
In [29]:
```

```
y_train = data_balance["Bankrupt?"]
data_new=pd.concat([y_train,x_train],axis=1)
data_new
```

#### Out[29]:

	Bankrupt?	Net worth/Assets	Debt ratio %	Per Share Net profit before tax (Yuan ¥)	ROA(C) before interest and depreciation before interest
0	0	0.888200	0.111800	0.184454	0.500951
1	0	0.847689	0.152311	0.166755	0.479647
2	0	0.966895	0.033105	0.181969	0.516502
3	0	0.906310	0.093690	0.167960	0.446302
4	0	0.882396	0.117604	0.179935	0.575245
9257	1	0.824272	0.175728	0.161288	0.467220
9258	1	0.786659	0.213341	0.174660	0.494583
9259	1	0.806011	0.193989	0.193313	0.494676
9260	1	0.872011	0.127989	0.155082	0.417124
9261	1	0.837775	0.162225	0.166181	0.463788

9262 rows × 5 columns

```
In [30]:
```

```
data_new.to_csv('bankruptcy_HW1_train.csv')
```

```
In [31]:
```

```
#觀察select後的準確度
```

```
In [32]:
```

```
clf = AdaBoostClassifier(n_estimators=120, random_state=0)

# clf = tree.DecisionTreeClassifier()
# clf = clf.fit(X, Y)
model = clf
#先觀察都沒做feature selection前的mode準確度
#由於是分類問題,適用LogisticRegression
# model = LogisticRegression(max_iter=1000)
model.fit(x_train,y_train)
```

#### Out[32]:

AdaBoostClassifier(n\_estimators=120, random\_state=0)

In [33]: ▶

x\_test\_selection=x\_test[selectedFeatures.index]

x\_test\_selection

# Out[33]:

	Net worth/Assets	Debt ratio %	Per Share Net profit before tax (Yuan ¥)	ROA(C) before interest and depreciation before interest
239	0.956193	0.043807	0.156963	0.434456
2850	0.870000	0.130000	0.188522	0.542534
2687	0.921365	0.078635	0.202305	0.584897
6500	0.772682	0.227318	0.151842	0.436942
2684	0.817305	0.182695	0.182345	0.506898
4315	0.904979	0.095021	0.176546	0.487739
2228	0.873265	0.126735	0.188747	0.517720
1083	0.905463	0.094537	0.184982	0.524204
3355	0.902984	0.097016	0.201928	0.576074
861	0.839859	0.160141	0.198539	0.516453

2046 rows × 4 columns

```
In [34]: ▶
```

```
data_test=pd.concat([y_test,x_test_selection],axis=1)
data_test
```

### Out[34]:

	Bankrupt?	Net worth/Assets	Debt ratio %	Per Share Net profit before tax (Yuan ¥)	ROA(C) before interest and depreciation before interest
239	0	0.956193	0.043807	0.156963	0.434456
2850	0	0.870000	0.130000	0.188522	0.542534
2687	0	0.921365	0.078635	0.202305	0.584897
6500	1	0.772682	0.227318	0.151842	0.436942
2684	0	0.817305	0.182695	0.182345	0.506898
4315	0	0.904979	0.095021	0.176546	0.487739
2228	0	0.873265	0.126735	0.188747	0.517720
1083	0	0.905463	0.094537	0.184982	0.524204
3355	0	0.902984	0.097016	0.201928	0.576074
861	0	0.839859	0.160141	0.198539	0.516453

2046 rows × 5 columns

In [36]:

```
data_test.to_csv('bankruptcy_HW1_test.csv')
```

```
In [37]:
```

```
print(classification_report(y_train, model.predict(x_train)))
print(classification_report(y_test, model.predict(x_test_selection)))
```

	precision	recall	†1-score	support
0	0.91	0.85	0.88	4631
1	0.86	0.92	0.89	4631
accuracy			0.88	9262
macro avg	0.89	0.88	0.88	9262
weighted avg	0.89	0.88	0.88	9262
	precision	recall	f1-score	support
0	precision 0.99	recall 0.84	f1-score 0.91	support 1968
0 1				
_	0.99	0.84	0.91	1968
1	0.99	0.84	0.91 0.29	1968 78