Group Coursework Submission Form

Specialist Masters Programme

Please list all names of group members: (Surname, first name) 1. Chen, Christina 2. Luo, Jianshan 3. Hao, Ming	4. Gogia, Nipun 5. Tsatsis, Spyridon **GROUP NUMBER:** **4**
MSc in: Actuarial Management (1.2.4); Financial Mathematics (5.); Actuarial Science with Business Analytics(3.)	
Module Code: SMM284	
Module Title: Applied Machine Learning	
Lecturer: Michael Dowling	**Submission Date: 18/07/2022**

Declaration:

By submitting this work, we declare that this work is entirely our own except those parts duly identified and referenced in my submission. It complies with any specified word limits and the requirements and regulations detailed in the coursework instructions and any other relevant programme and module documentation. In submitting this work we acknowledge that we have read and understood the regulations and code regarding academic misconduct, including that relating to plagiarism, as specified in the Programme Handbook. We also acknowledge that this work will be subject to a variety of checks for academic misconduct.

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Marker's Comments (if not being marked on-line):

Deduction for Late Submission of assignment:

For Students:
Once marked please refer to Moodle for your final coursework grade, including your Peer Assessment grade.

Introduction

This coursework uses a gold medal dataset called Company Bankruptcy Prediction from Kaggle.com with the usability score equal to 10. The Taiwan Economic Journal gathered these data from 1999 to 2009. Also, the Taiwan Stock Exchange is involved to define company bankruptcy.

The dataset contains 6819 entries. Each entry has 96 attributes, which are conventional accounting ratios to demostrate a company's financial stability.

In this coursework, we are going to explore the characteristics of bankruptcy company, and use applied machine learning to predict companies bankruptcy. We are going to analyse the dataset in the following steps:

Firstly, we will clean the dataset and go through Basic analysis to have a basic knowledge of the dataset.

Secondly, we will use 7 differences machine learning classifiers to predict the company bankruptcy. And then try to find a good model.

Finally, to improve the predictiotion, we will use 3 Deep learning models to predict the company bankruptcy. And then try to find a best model among our results.

In below, there is a table of content which maps the material from each class to the analysis provided in our report.

In [ ]:
```
data = [['Class 1',' Data clean including 1) handling missing data 2) text to
 sparse process 3) oversampling the minority class 4) data standardization'],
        ['Class 1', 'Basic Analysis including 1) Boxplot 2) Correlation Coeffi
cient analysis'],
        ['Class 2 & 3 ','Basic Classifier : 1) Basic Logistic Classifier 2) De
cision Tree 3)Random Forest '],
        ['Class 2 & 3 ','Adance Classifier : 1) Support Vector Machine 2) Grad
ient Boosting 3)XG Boosting 4) Ensemble Modelling'],
        ['Class 4','Not included as there is not textual data in our dataset'
],
        ['Class 5','Deep learning : 1) Simple Deep Learning Network 2) Weighte
d/Cost sensitive Deep Learning Network 3) Hyper-parametrization']]

print(data[0],'\n',
data[1],'\n',
data[2],'\n',
data[3],'\n',
data[4],'\n',
data[5],'\n',)
```

```
['Class 1', ' Data clean including 1) handling missing data 2) text to sparse
process 3) oversampling the minority class 4) data standardization']
 ['Class 1', 'Basic Analysis including 1) Boxplot 2) Correlation Coefficient
analysis']
 ['Class 2 & 3 ', 'Basic Classifier : 1) Basic Logistic Classifier 2) Decisio
n Tree 3)Random Forest ']
 ['Class 2 & 3 ', 'Adance Classifier : 1) Support Vector Machine 2) Gradient
Boosting 3)XG Boosting 4) Ensemble Modelling']
 ['Class 4', 'Not included as there is not textual data in our dataset']
 ['Class 5', 'Deep learning : 1) Simple Deep Learning Network 2) Weighted/Cos
t sensitive Deep Learning Network 3) Hyper-parametrization']
```

Part 1 Data clean and basic analysis

In this section, we focus on basic analysis on dataset by boxplots and correlation coeffient to understand our dataset first. Also, we clean the dataset which includes:1) handling the missing data 2) convert the textual data into numerical data 3) handling the imbalance dataset 4) data standardization

In [ ]:
```python
# load Libraries
# core quantitative analysis packages
import numpy as np
import pandas as pd

# visualisation
import matplotlib.pyplot as plt # default package
%matplotlib inline

# machine learning

# models ordered in order of usage in the worksheet
# Standardize features
from sklearn.preprocessing import StandardScaler
# machine learning packages
from sklearn.model_selection import train_test_split
# finding features packages
from sklearn.feature_selection import SelectKBest, f_classif
```

In [ ]:
```python
# import dataset
df = pd.read_csv('/content/data.csv')
```

In [ ]:
```python
# briefly view the dataset
df.head(2)
```

Out[ ]:

	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	Af I
0	1	0.370594	0.424389	0.40575	0.601457	0.601457	0.998969	0.796887	0.:
1	1	0.464291	0.538214	0.51673	0.610235	0.610235	0.998946	0.797380	0.:

2 rows × 96 columns

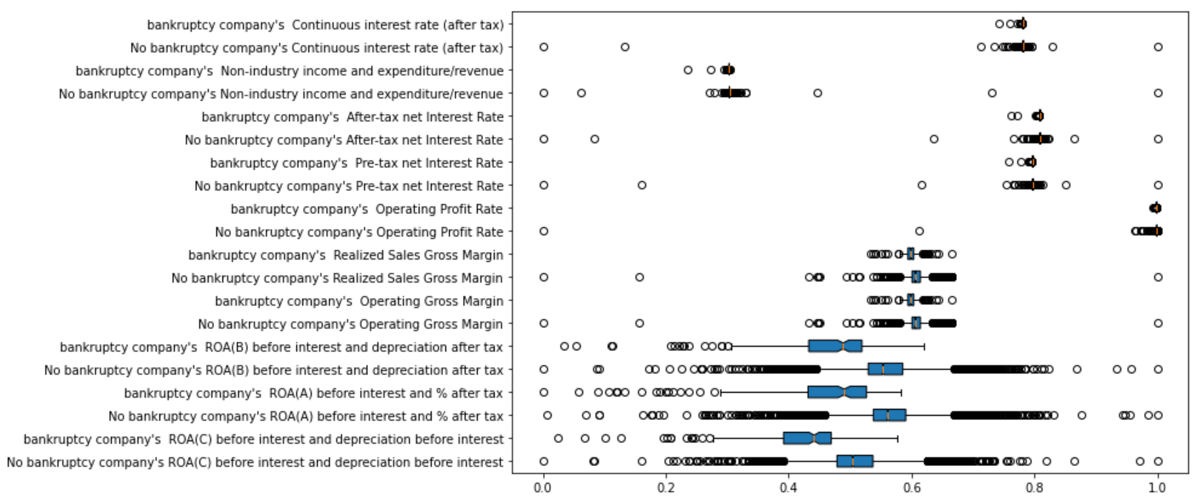
Boxplots

In [ ]:
```python
# seperate the dataset into bankruptcy companies(0) and no bankruptcy companie
s(1)
grouped = df.groupby(df['Bankrupt?'])

df_not_bankrupt = grouped.get_group(0)

df_bankrupt = grouped.get_group(1)
```

In [ ]:

```python
# boxplot to have an overview of the differences between the ratios of bankrup
tcy companies and the ratios of not bankruptcy companies
data,data_names = [],[]

for i in df.columns :
    if i != 'Bankrupt?':
        data.append(df_not_bankrupt[i])
        data.append(df_bankrupt[i])
        data_names.append("No bankruptcy company's" + i)
        data_names.append("bankruptcy company's " + i)

# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[:20], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[:20])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```

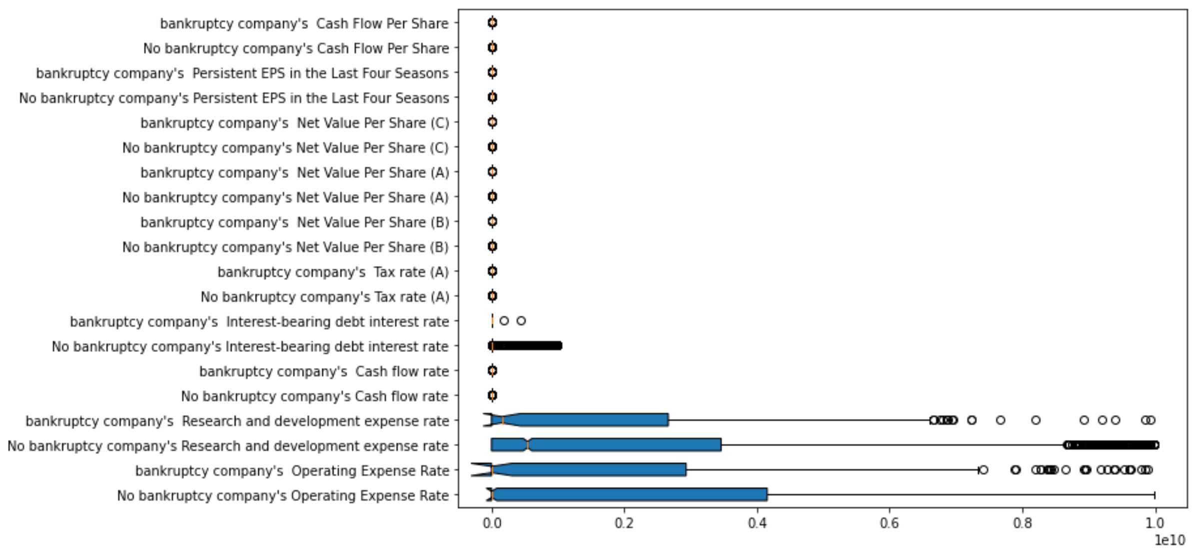


This boxplot has suggestes that ROA(A), ROA(B), and ROA(C) may be helpful to disguinish the bankruptcy company. Because the companies are not bankrupt have higher mediam, right skewed and smaller spread of IQR than the companies are bankrupt, they have higher and stable return on their assets than the companies are bankrupt. So, a company can use the return on asset to pay its annual debts.

This can be found in Operating Gross Margin too. Higher the Operating Gross Margin indicates the higher earning relatively to net expense. So, the companies are not bankrupt have shown higher profitabiltiy than the companies are bankrupt

In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[20:40], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[20:40])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```

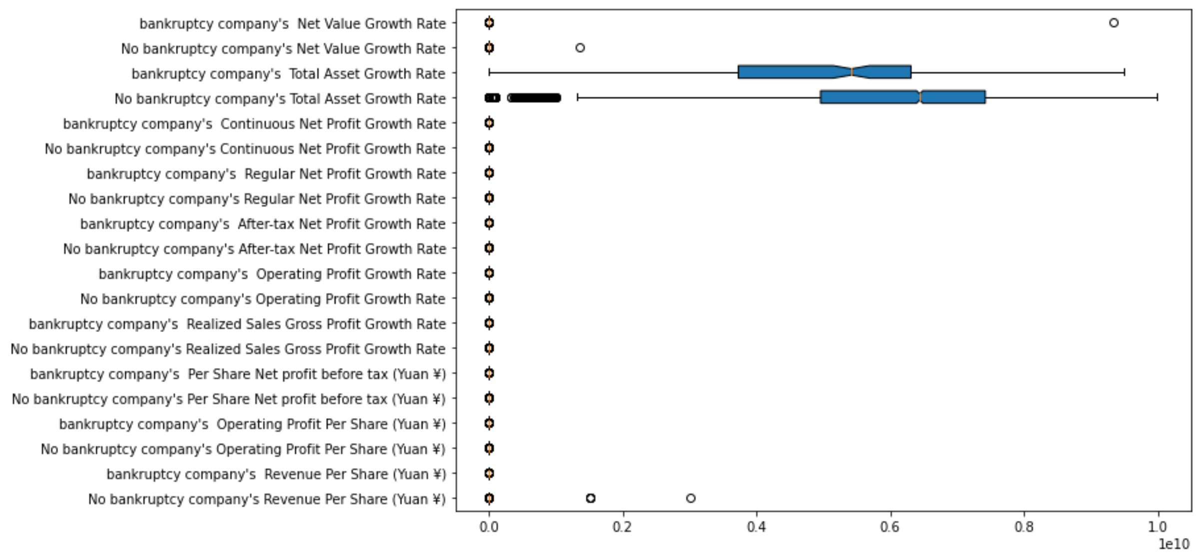


This boxplot has shown the companies are not bankrupt have spend more on developement and research than the companies are bankrupt, as they have higher mediam, right skewed and larger IQR than the companies are bankrupt. The company will survive longer if it spends extra money on future development.

Operating expense rate indicate how much does company spend on operation. This may not be helpful, as no bankrupt companies spense more on operation than the companies are bankrupt.

In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[40:60], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[40:60])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```

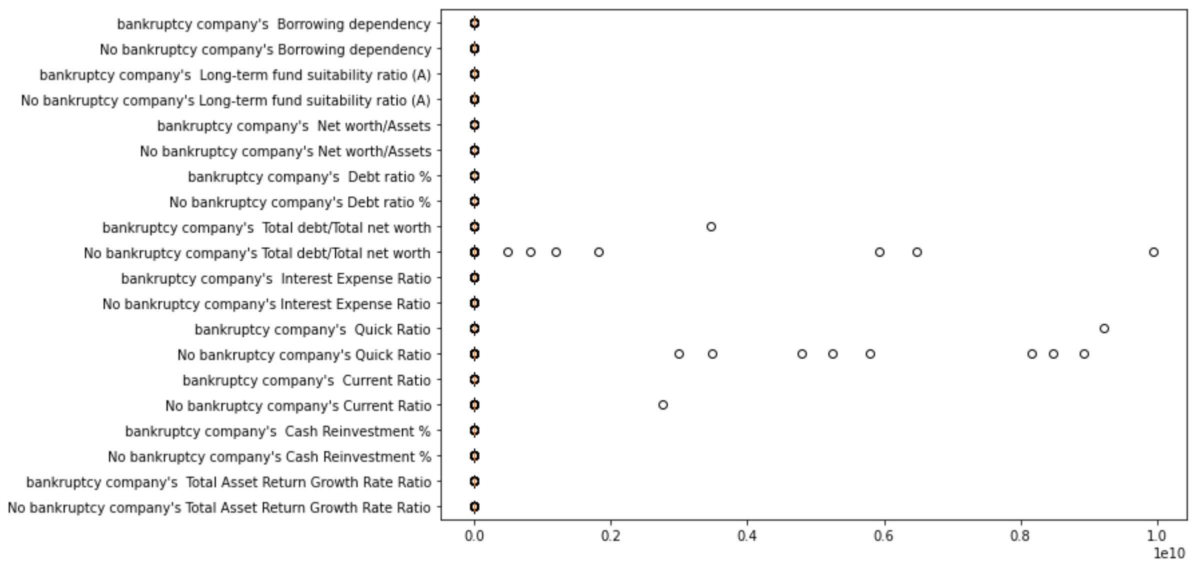


This boxplot shown that has shown the companies are not bankrupt have higer asset growth than the companies are bankrupt, as they have higher mediam, right skewed and larger IQR than the companies are bankrupt. The higher the asset growth rate indicates higher future stock return, which can prevent the company goes bankruptcy by selling its shares to buy the debts.

In [ ]:

```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[60:80], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[60:80])

plt.show()
```

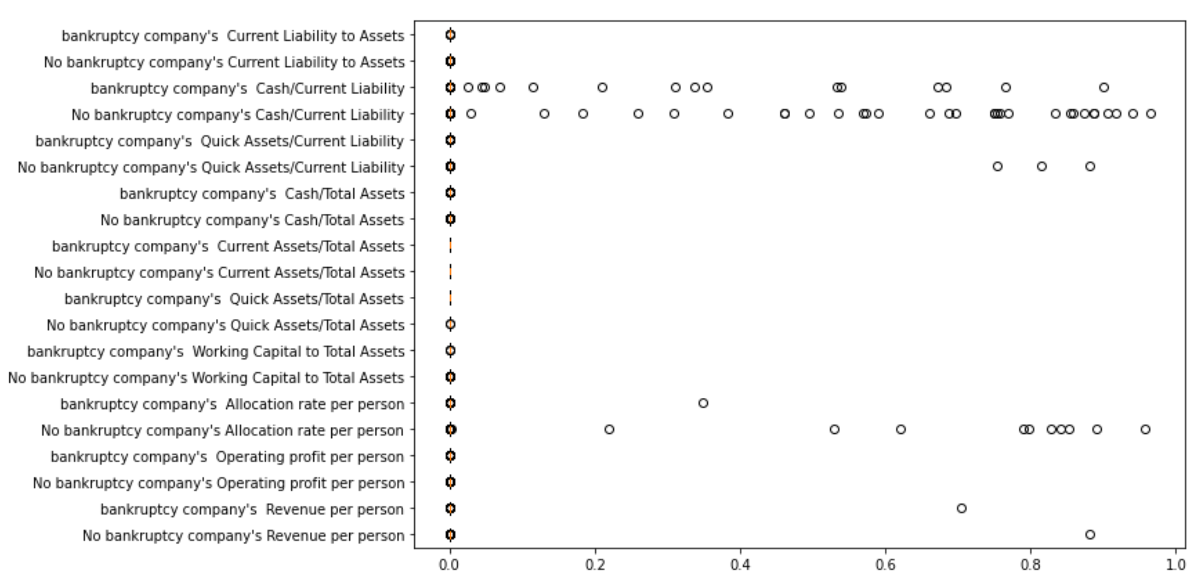
```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



In [ ]:

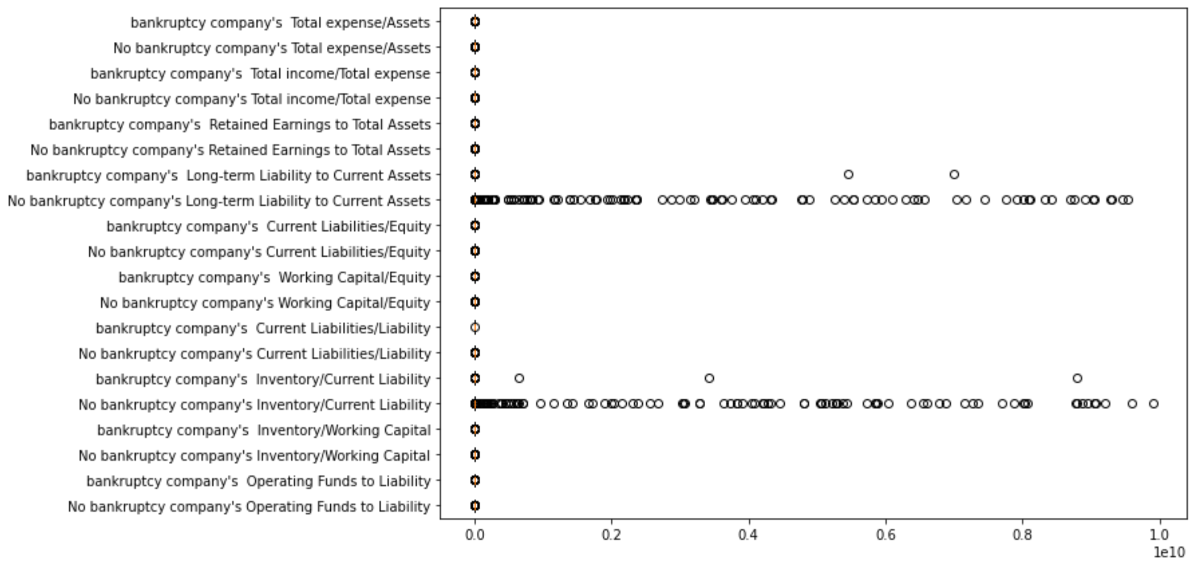
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[100:120], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[100:120])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



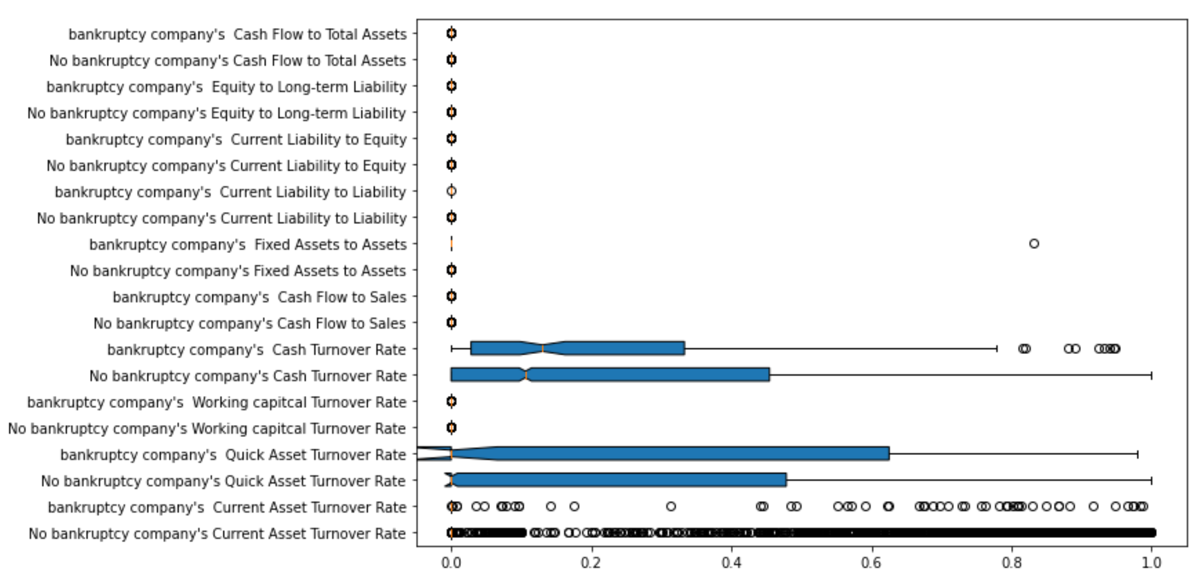
In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[120:140], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[120:140])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[140:160], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[140:160])

plt.show()
```

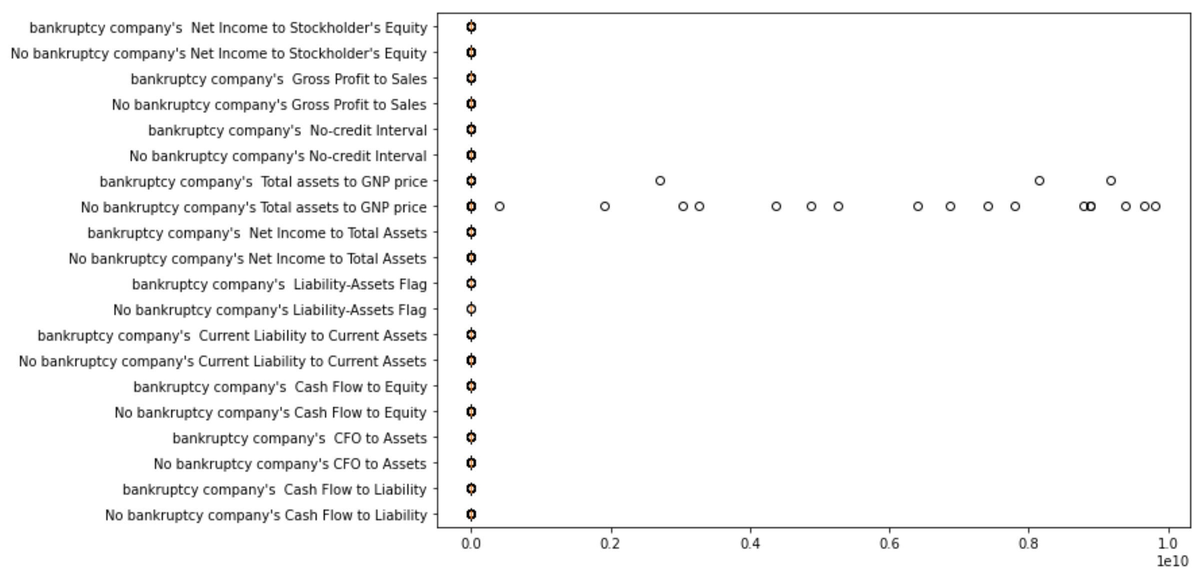
```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



This boxplot shown that has shown the companies are not bankrupt have higer cash turnover rate than the companies are bankrupt, as they have higher mediam, right skewed and larger IQR than the companies are bankrupt. The higher the cash turnover rate indicates the company can more quickly replenish its cash using its sales revenue to pay the debts, which can prevent the company goes bankruptcy.

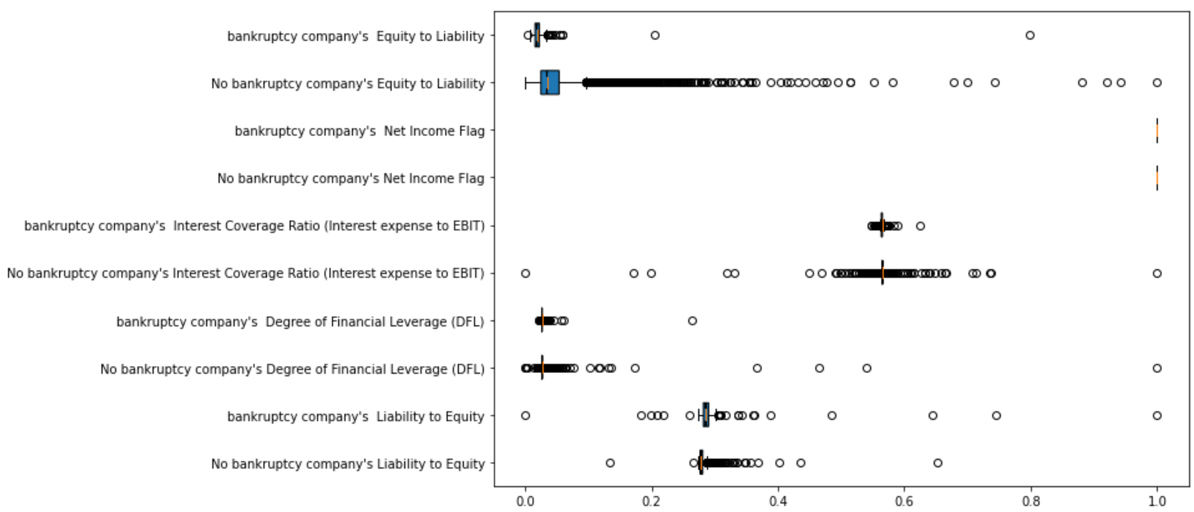
In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[160:180], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[160:180])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



In [ ]:
```
# setup the figure of boxplot
fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)

# Creating axes instance
bp = ax.boxplot(data[180:190], patch_artist = True,notch ='True', vert = 0)

# x-axis labels
ax.set_yticklabels(data_names[180:190])

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/__init__.py:1376: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths o
r shapes) is deprecated. If you meant to do this, you must specify 'dtype=obj
ect' when creating the ndarray.
  X = np.atleast_1d(X.T if isinstance(X, np.ndarray) else np.asarray(X))
```



This boxplot shown that has shown the companies are not bankrupt have higer equity to liability than the companies are bankrupt, as they have higher mediam, right skewed and larger IQR than the companies are bankrupt. The higher the equity to liability indicates the company has smaller proportion of loans than equity, which can prevent the company goes bankruptcy.

correlation coefficient check

In [ ]:
```
corr_matrix = df.corr()
corr_matrix['Bankrupt?'].sort_values(ascending=False).head(10)

corr_dict = {
  "accounting ratio": corr_matrix.columns,
  "correlations": corr_matrix['Bankrupt?'].values,
  "absolute correlation" : map(abs,corr_matrix['Bankrupt?'].values),
}

df_corr = pd.DataFrame(data=corr_dict)
df_corr.sort_values(by='absolute correlation', ascending=False).head(10)
```

Out[ ]:

	accounting ratio	correlations	absolute correlation
0	Bankrupt?	1.000000	1.000000
86	Net Income to Total Assets	-0.315457	0.315457
2	ROA(A) before interest and % after tax	-0.282941	0.282941
3	ROA(B) before interest and depreciation after...	-0.273051	0.273051
1	ROA(C) before interest and depreciation befor...	-0.260807	0.260807
38	Net worth/Assets	-0.250161	0.250161
37	Debt ratio %	0.250161	0.250161
19	Persistent EPS in the Last Four Seasons	-0.219560	0.219560
68	Retained Earnings to Total Assets	-0.217779	0.217779
43	Net profit before tax/Paid-in capital	-0.207857	0.207857

The table above has shown the top 10 accounting ratios which are significantly correlated to 'bankrupt? '

Debt ratio has positive correlations coefficient value, which means that it has positive relatinship to Bankrupt as Bankruptcy is denoted as 1.Converstly, other raitos have negative correlation coefficent relatinship to the bankrupt.

Higher the debt ratio, indicate companies are bankrupt have to pay higher level of debt payments than the companies are not bankrupt.

ROA(A), ROA(B), and ROA(C) has been further proven that help to examine whether a company is not bankrupt.

Net income to total assets, Net profit before tax/Paid-in capitalis, and Per Share Net profit before tax are the profitability ratio. the higher the ratio, indicates the company has greater ability in generating its revenue over a year.

Net worth/ assets is used to shown margin of assets and liabilitiy as net worth is total assets minus total liabilities. higher the Net worth / assets indicate the company is solvent as it has relatively lower liabilties than its asset.

higher Persistent EPS in the Last Four Seasons is the profibility ratio. a higher EPS would suggest that a company is more valuable. If investors are comfortable paying a higher price for shares, then that could reflect strong profits or expectations of high profits.

Retained Earnings to Total Assets indicates total retained earnings that the company generates compare to the total assets of the company at the end of the specific accounting period. So, it illustrate how much does company use retained earning to reinvest rather than pay dividend. This may help the company grow and survive longer. However, for the mature companies may have smaller retained earning as they use their profit to pay their shareholders, such as natural resource industries.

Data clean

In [ ]:
```
# briefly check dataset values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6819 entries, 0 to 6818
Data columns (total 96 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Bankrupt?                                                 6819 non-null
int64
 1    ROA(C) before interest and depreciation before interest  6819 non-null
float64
 2    ROA(A) before interest and % after tax                   6819 non-null
float64
 3    ROA(B) before interest and depreciation after tax        6819 non-null
float64
 4    Operating Gross Margin                                   6819 non-null
float64
 5    Realized Sales Gross Margin                              6819 non-null
float64
 6    Operating Profit Rate                                    6819 non-null
float64
 7    Pre-tax net Interest Rate                                6819 non-null
float64
 8    After-tax net Interest Rate                              6819 non-null
float64
 9    Non-industry income and expenditure/revenue              6819 non-null
float64
 10   Continuous interest rate (after tax)                     6819 non-null
float64
 11   Operating Expense Rate                                   6819 non-null
float64
 12   Research and development expense rate                    6819 non-null
float64
 13   Cash flow rate                                           6819 non-null
float64
 14   Interest-bearing debt interest rate                      6819 non-null
float64
 15   Tax rate (A)                                             6819 non-null
float64
 16   Net Value Per Share (B)                                  6819 non-null
float64
 17   Net Value Per Share (A)                                  6819 non-null
float64
 18   Net Value Per Share (C)                                  6819 non-null
float64
 19   Persistent EPS in the Last Four Seasons                  6819 non-null
float64
 20   Cash Flow Per Share                                      6819 non-null
float64
 21   Revenue Per Share (Yuan ¥)                               6819 non-null
float64
 22   Operating Profit Per Share (Yuan ¥)                      6819 non-null
float64
 23   Per Share Net profit before tax (Yuan ¥)                 6819 non-null
float64
 24   Realized Sales Gross Profit Growth Rate                  6819 non-null
float64
 25   Operating Profit Growth Rate                             6819 non-null
float64
 26   After-tax Net Profit Growth Rate                         6819 non-null
float64
 27   Regular Net Profit Growth Rate                           6819 non-null
float64
 28   Continuous Net Profit Growth Rate                        6819 non-null
float64
 29   Total Asset Growth Rate                                  6819 non-null
float64
 30   Net Value Growth Rate                                    6819 non-null
float64
 31   Total Asset Return Growth Rate Ratio                     6819 non-null
float64
 32   Cash Reinvestment %                                      6819 non-null
float64
 33   Current Ratio                                            6819 non-null
```

```
float64
 34   Quick Ratio                                           6819 non-null
float64
 35   Interest Expense Ratio                                6819 non-null
float64
 36   Total debt/Total net worth                            6819 non-null
float64
 37   Debt ratio %                                          6819 non-null
float64
 38   Net worth/Assets                                      6819 non-null
float64
 39   Long-term fund suitability ratio (A)                  6819 non-null
float64
 40   Borrowing dependency                                  6819 non-null
float64
 41   Contingent liabilities/Net worth                      6819 non-null
float64
 42   Operating profit/Paid-in capital                      6819 non-null
float64
 43   Net profit before tax/Paid-in capital                 6819 non-null
float64
 44   Inventory and accounts receivable/Net value           6819 non-null
float64
 45   Total Asset Turnover                                  6819 non-null
float64
 46   Accounts Receivable Turnover                          6819 non-null
float64
 47   Average Collection Days                               6819 non-null
float64
 48   Inventory Turnover Rate (times)                       6819 non-null
float64
 49   Fixed Assets Turnover Frequency                       6819 non-null
float64
 50   Net Worth Turnover Rate (times)                       6819 non-null
float64
 51   Revenue per person                                    6819 non-null
float64
 52   Operating profit per person                           6819 non-null
float64
 53   Allocation rate per person                            6819 non-null
float64
 54   Working Capital to Total Assets                       6819 non-null
float64
 55   Quick Assets/Total Assets                             6819 non-null
float64
 56   Current Assets/Total Assets                           6819 non-null
float64
 57   Cash/Total Assets                                     6819 non-null
float64
 58   Quick Assets/Current Liability                        6819 non-null
float64
 59   Cash/Current Liability                                6819 non-null
float64
 60   Current Liability to Assets                           6819 non-null
float64
 61   Operating Funds to Liability                          6819 non-null
float64
 62   Inventory/Working Capital                             6819 non-null
float64
 63   Inventory/Current Liability                           6819 non-null
float64
 64   Current Liabilities/Liability                         6819 non-null
float64
 65   Working Capital/Equity                                6819 non-null
float64
 66   Current Liabilities/Equity                            6819 non-null
float64
 67   Long-term Liability to Current Assets                 6819 non-null
float64
 68   Retained Earnings to Total Assets                     6819 non-null
float64
 69   Total income/Total expense                            6819 non-null
float64
 70   Total expense/Assets                                  6819 non-null
```

```
float64
 71   Current Asset Turnover Rate                             6819 non-null
float64
 72   Quick Asset Turnover Rate                               6819 non-null
float64
 73   Working capitcal Turnover Rate                          6819 non-null
float64
 74   Cash Turnover Rate                                      6819 non-null
float64
 75   Cash Flow to Sales                                      6819 non-null
float64
 76   Fixed Assets to Assets                                  6819 non-null
float64
 77   Current Liability to Liability                          6819 non-null
float64
 78   Current Liability to Equity                             6819 non-null
float64
 79   Equity to Long-term Liability                           6819 non-null
float64
 80   Cash Flow to Total Assets                               6819 non-null
float64
 81   Cash Flow to Liability                                  6819 non-null
float64
 82   CFO to Assets                                           6819 non-null
float64
 83   Cash Flow to Equity                                     6819 non-null
float64
 84   Current Liability to Current Assets                     6819 non-null
float64
 85   Liability-Assets Flag                                   6819 non-null
int64
 86   Net Income to Total Assets                              6819 non-null
float64
 87   Total assets to GNP price                               6819 non-null
float64
 88   No-credit Interval                                      6819 non-null
float64
 89   Gross Profit to Sales                                   6819 non-null
float64
 90   Net Income to Stockholder's Equity                      6819 non-null
float64
 91   Liability to Equity                                     6819 non-null
float64
 92   Degree of Financial Leverage (DFL)                      6819 non-null
float64
 93   Interest Coverage Ratio (Interest expense to EBIT)      6819 non-null
float64
 94   Net Income Flag                                         6819 non-null
int64
 95   Equity to Liability                                     6819 non-null
float64
dtypes: float64(93), int64(3)
memory usage: 5.0 MB
```

This section of code has shown that there have no missing data as each attribute has 6819 entries and do not need word-to-sparse process as data are numerical.

Oversample the minority data (bankruptcy companies)

In [ ]:
```
df['Bankrupt?'].value_counts()
```

Out[ ]:
```
0    6599
1     220
Name: Bankrupt?, dtype: int64
```

This has shown that the dataset is highly imbalanced. As a result, there will be bias throughout the model's training process, with classes with more samples being favoured over classes with minori class. So, we need to oversample the bankruptcy companies' data to overcome this issue in our case. In the following, we have used Borderline-SMOTE to oversample our dataset. The the advantage of using this method is enable us to select the samples of data that belongs to the minority class. Also, this method can produce new synthetic samples and inherit the characteristerist of bankruptcy companies, because it extracts the feature of the minority class to produce the new samples.

In [ ]:
```
# using Synthetic Minority Over-Sampling Technique or SMOTE to balance out our dataset
from imblearn.over_sampling import BorderlineSMOTE
```

In [ ]:
```
# install imblearn
#import sys
#!{sys.executable} -m pip install imblearn
```

In [ ]:
```
# define dataset
X = df.drop(columns = ['Bankrupt?']).to_numpy() # continuous data
y = df['Bankrupt?'].to_numpy() # binary data

#SMOTE With Selective Synthetic Sample Generation
# borderline-SMOTE for imbalanced dataset
oversample = BorderlineSMOTE()
# transform the dataset
X, y = oversample.fit_resample(X, y)
```

In [ ]:
```
# convert from array to panda.dataframe
df_oversampled = pd.DataFrame(X, columns = [name for name in df.columns if name != 'Bankrupt?']  )
df_oversampled.insert(0, 'Bankrupt?', y)
```

In [ ]:
```
df_oversampled['Bankrupt?'].value_counts()
```

Out[ ]:
```
1    6599
0    6599
Name: Bankrupt?, dtype: int64
```

On above, it shown that we have generated a balanced dataset.

In [ ]:
```
grouped_2 = df_oversampled.groupby(df_oversampled['Bankrupt?'])
df_not_bankrupt_2 = grouped_2.get_group(0)
df_bankrupt_2 = grouped_2.get_group(1)
```

In [ ]:
```
df_bankrupt_2.describe()
```

Out[ ]:

	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	Operatin Profit Rat
count	6599.0	6599.000000	6599.000000	6599.000000	6599.000000	6599.000000	6599.00000
mean	1.0	0.419856	0.461287	0.462507	0.597579	0.597611	0.99868
std	0.0	0.061657	0.081747	0.071162	0.012007	0.012012	0.00079
min	1.0	0.024277	0.000000	0.033514	0.532906	0.532906	0.99188
25%	1.0	0.390606	0.429011	0.433893	0.594298	0.594326	0.99874
50%	1.0	0.435985	0.484452	0.482358	0.598650	0.598768	0.99887
75%	1.0	0.463529	0.516856	0.510825	0.602886	0.602922	0.99894
max	1.0	0.576951	0.582861	0.619091	0.665151	0.665151	0.99925

8 rows × 96 columns

In [ ]:
```
df_bankrupt.describe()
```

Out[ ]:

	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	P
count	220.0	220.000000	220.000000	220.000000	220.000000	220.000000	220.000000	2:
mean	1.0	0.418503	0.456947	0.461483	0.598670	0.598717	0.998739	
std	0.0	0.081068	0.107674	0.091825	0.014595	0.014583	0.000709	
min	1.0	0.024277	0.000000	0.033514	0.532906	0.532906	0.991888	
25%	1.0	0.391703	0.431531	0.432665	0.593924	0.593915	0.998748	
50%	1.0	0.441330	0.490215	0.488597	0.598802	0.598899	0.998899	
75%	1.0	0.469276	0.526630	0.519153	0.603500	0.603493	0.998976	
max	1.0	0.576951	0.582861	0.619091	0.665151	0.665151	0.999254	

8 rows × 96 columns

In comparison, we can see after oversampling the banrkupts companies data has increase to 6599, meanwhile the characteristics of the banrkupts companies data does not change significantly.

data standardization

We see the mean not equal 0 and std smaller than 1 from the table on above. So, we need to standardize our dataset, data standardization is making sure the consistency when we comparing the each attributes in regression models.

In [ ]:
```
# we can use the sklearn standardscale fot this
scale = StandardScaler()

df_scale = scale.fit_transform(df_oversampled) # all the numerical data are st
andardised

df_sc = pd.DataFrame(df_scale, columns=df_oversampled.columns, index=df_oversa
mpled.index)# transforms matrix back to a dataframe

df_sc.describe().round(2) # check it works .describe()

display(df_sc.describe())

# useful BEFORE MEASURING VARIABLE IMPORTANCE IN REGRESSION MODELS
```

	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
count	13198.000000	1.319800e+04	1.319800e+04	1.319800e+04	1.319800e+04	1.319800e+04
mean	0.000000	-2.067347e-16	-1.033673e-15	-2.411904e-16	-5.719659e-15	2.067347e-16
std	1.000038	1.000038e+00	1.000038e+00	1.000038e+00	1.000038e+00	1.000038e+00
min	-1.000000	-6.250420e+00	-5.819008e+00	-6.359039e+00	-3.862165e+01	-3.866216e+01
25%	-1.000000	-4.808295e-01	-4.312993e-01	-4.409344e-01	-3.829384e-01	-3.819499e-01
50%	0.000000	6.700062e-02	1.746400e-01	1.118323e-01	-6.738051e-02	-6.810546e-02
75%	1.000000	5.475528e-01	5.734998e-01	5.615086e-01	3.783524e-01	3.787187e-01
max	1.000000	7.221400e+00	5.553993e+00	6.119860e+00	2.543624e+01	2.546230e+01

8 rows × 96 columns

Finding the feature by machine learning

split the dataset into Training set, validation test, and Test set

In [ ]:
```
y = df_sc['Bankrupt?']
X = df_sc.drop(columns=['Bankrupt?'])
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, tes
t_size=0.2) # split data into 80% training set and 20% test set
X_test, X_valid, y_test, y_valid = train_test_split(X_test, y_test, random_sta
te=84, test_size=0.5) # further split the test set into 10% validation set and
10% test set
```

We have split the dataset into 80% training set which allow the model have sufficient source to learn, and then improve its prediction performance.

Furthermore, we have split the test set into 10% validation set and 10% test set. The validation set will use to fit-tune the model, and the test set will be used to see whether we have overfitting the model.

```
In [ ]: feature_selection=SelectKBest(f_classif,k=10).fit(X_train,y_train)      # k nu
        mber of specified features
        selected_features=X_train.columns[feature_selection.get_support()]
        selected_features
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/feature_selection/_univariate_
selection.py:112: UserWarning: Features [93] are constant.
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarn
ing)
/usr/local/lib/python3.7/dist-packages/sklearn/feature_selection/_univariate_
selection.py:113: RuntimeWarning: invalid value encountered in true_divide
  f = msb / msw
```

```
Out[ ]: Index([' ROA(C) before interest and depreciation before interest',
               ' ROA(A) before interest and % after tax',
               ' ROA(B) before interest and depreciation after tax',
               ' Persistent EPS in the Last Four Seasons',
               ' Per Share Net profit before tax (Yuan ¥)', ' Debt ratio %',
               ' Net worth/Assets', ' Net profit before tax/Paid-in capital',
               ' Working Capital to Total Assets', ' Net Income to Total Assets'],
              dtype='object')
```

The SelectKBest technique chooses features based on the top k scores(further exlanation in part 3).

We can see the results are the same as our correlation coeffient analysis. Therefore,we think it is reasonable to use the these 10 features for our later research.

Save the 10 selected features dataset

```
In [ ]: # save the data set with 10 selected features for regression
        #df = df_sc.copy()
        #df_sc_10features= df.drop(columns=[column for column in df_sc.columns if colu
        mn not in selected_features and column != 'Bankrupt?'])
        #df_sc_10features.to_csv('data_oversampled_standardized_10features.csv',index
         = False)
```

Part 2 Basic Logistic Classifier and More Advanced Classifier models

We now use the oversampled and standardized data with the ten selected features to do classifier machine learning.

Firstly, we leverage several models to learn and train. Secondly, we use our models to predict by the validation data, and we adjust models' parameters to let the each model be best-fit. Then, we focus on the accuracy for prediction and blend all models with accuracy higher than 90% by using ensemble learning. In this report, voting model is used. Finally, we verify our aggregate model with test data and inspect our final accuracy.

In [ ]:
```
#machine learning
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifie
r
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from xgboost import XGBRegressor
from sklearn.ensemble import VotingClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from xgboost import XGBClassifier
from numpy import mean,std
from matplotlib import pyplot
```

In [ ]:
```
df = pd.read_csv('/content/data_oversampled_standardized_10features.csv')
y = df['Bankrupt?']
X = df.drop(columns=['Bankrupt?'])
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, tes
t_size=0.2) # split data into 80% training set and 20% test set
X_test, X_valid, y_test, y_valid = train_test_split(X_test, y_test, random_sta
te=84, test_size=0.5) # further split the test set into 10% validation set and
10% test set
```

In [ ]:
```
y_train=np.where(y_train<=0,0,1) # change the  y_train from -1 and 1 into  0 a
nd 1
y_valid=np.where(y_valid<=0,0,1) # change the  y_valid from -1 and 1 into  0 a
nd 1
y_test=np.where(y_test<=0,0,1) # change the  y_test from -1 and 1 into  0 and
 1
```

Basic Logistic Classifier

In [ ]:
```
#basic logistic regression model
lr = LogisticRegression()
lr.fit(X_train, y_train)

# using our model to predict
y_predlr = lr.predict(X_valid)

# Making the Confusion Matrix
cmlr = confusion_matrix(y_valid, y_predlr)
print(cmlr)

# Number of wrong classifier: number of predictions which differ from the vali
dation data
print('# of wrong classifiers: %d' % (y_predlr != y_valid).sum()) # out of 132
0


# Accuracy
print("Linear Classifier's Accuracy is ", accuracy_score(y_valid,y_predlr)*100
)

# intercept and betas
lr.intercept_, lr.coef_
```

```
[[569  66]
 [ 58 627]]
# of wrong classifiers: 124
Linear Classifier's Accuracy is  90.6060606060606
```

Out[ ]:
```
(array([0.23717021]),
 array([[-1.1259338 ,  4.0678692 ,  0.26632712, -3.38568221,  0.55694416,
          0.90058616, -0.90058616,  0.28274188, -0.17114521, -4.37568657]]))
```

There are 124 wrong classifiers out of 1320 and the accuracy score is 90.606%, indicating that the logistic regression model is a good model for prediction for this data.

In [ ]:
```
# improving estimation with gridsearch

param_grid = {"fit_intercept": [True, False]
             }

grid_search = GridSearchCV(lr, param_grid, cv=10,
                           scoring="accuracy", return_train_score=True)

grid_search.fit(X_train, y_train)

grid_search.best_params_
```

Out[ ]:
```
{'fit_intercept': True}
```

The result tells us that the Logistic model is better to include the intercept.

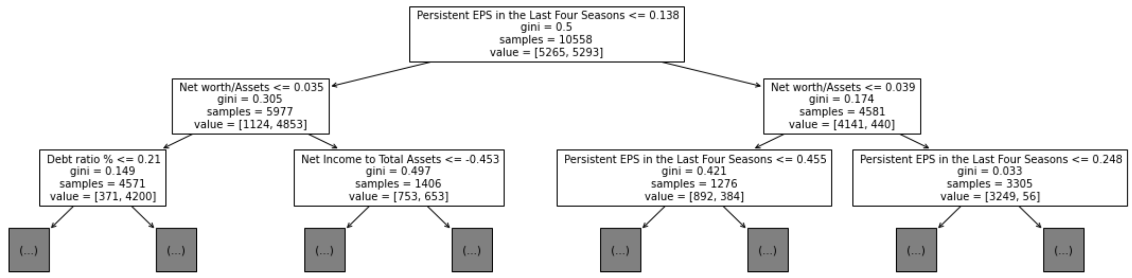
Decison Tree

In [ ]:
```
# Decision Tree

# Note how the code structure is almost the same as logistic regression. This
 simplicity is why Python is so popular

dt = DecisionTreeClassifier(max_depth=30,random_state=1)
dt.fit(X_train, y_train)

# using our model to predict for validation set
y_preddt = dt.predict(X_valid)

# Making the Confusion Matrix
cmdt = confusion_matrix(y_valid, y_preddt)
print(cmdt)

# Number of wrong classifier: number of predictions which differ from the vali
dation data
print('# of wrong classifiers: %d' % (y_preddt != y_valid).sum())

#Acccuracy
print("Decision Tree's Accuracy is ", accuracy_score(y_valid,y_preddt)*100)
```

```
[[581  54]
 [ 51 634]]
# of wrong classifiers: 105
Decision Tree's Accuracy is  92.04545454545455
```

The number of wrong classifiers is 105 out of 1320 and the accuracy score is 92.045%, indicating a slightly better prediction out of the Decision Tree model compared to the Logistic Regression model. However, an issue with decision tree is that it is very sensitive to the validation data so may be an overfitted model.

```python
# See the decision tree
plt.figure(figsize=(20,5))
plot_tree(dt, max_depth=2, fontsize=10, feature_names=X_train.columns)
plt.show()
```



The decision tree shows the process of predicting whether a company is going to go bankruptcy step by step using the 10 selected features.

Random Forest

```python
# Random Forests

rf = RandomForestClassifier(n_estimators = 50,random_state=42)

rf.fit(X_train, y_train)

y_predrf = rf.predict(X_valid)

# Making the Confusion Matrix
cmrf = confusion_matrix(y_valid, y_predrf)
print(cmrf)

# Accuracy
print("Accuracy is ", accuracy_score(y_valid,y_predrf)*100)
```

```
[[592  43]
 [ 16 669]]
Accuracy is  95.53030303030303
```

We can see that the accuracy of a Random Forest model to prediction is even better. This may be becasue that Random Forests model can better identify features' importance through assessing its performance on subsets of data.

```python
# fine-tune the Random Forest model using GridSearch

param_grid = [
    {'n_estimators': [10, 30, 50], 'max_features': ['auto', 4, 6, 8],'random_state':[42]},
    {'bootstrap': [False], 'n_estimators': [10, 30, 50], 'max_features': ['auto', 4, 6, 8],'random_state':[42]}
]

grid_forest = GridSearchCV(rf, param_grid, cv=5,
                          scoring='accuracy',
                          return_train_score=True)

grid_forest.fit(X_train, y_train)

grid_forest.best_params_
```

```
{'bootstrap': False,
 'max_features': 'auto',
 'n_estimators': 50,
 'random_state': 42}
```

In [ ]:
```
# check all the GridSearch results

cvres = grid_forest.cv_results_

for gridsearch_accuracy_score, params in zip(cvres['mean_test_score'], cvres[
'params']):
    print(gridsearch_accuracy_score, params)
```

```
0.9435497950849088 {'max_features': 'auto', 'n_estimators': 10, 'random_stat
e': 42}
0.9491378583322568 {'max_features': 'auto', 'n_estimators': 30, 'random_stat
e': 42}
0.9486641940484907 {'max_features': 'auto', 'n_estimators': 50, 'random_stat
e': 42}
0.9444027855533067 {'max_features': 4, 'n_estimators': 10, 'random_state': 4
2}
0.9486645529190533 {'max_features': 4, 'n_estimators': 30, 'random_state': 4
2}
0.9489483298164018 {'max_features': 4, 'n_estimators': 50, 'random_state': 4
2}
0.9442131224609908 {'max_features': 6, 'n_estimators': 10, 'random_state': 4
2}
0.9474334923129926 {'max_features': 6, 'n_estimators': 30, 'random_state': 4
2}
0.9477173140691615 {'max_features': 6, 'n_estimators': 50, 'random_state': 4
2}
0.9443076848542269 {'max_features': 8, 'n_estimators': 10, 'random_state': 4
2}
0.9468652656359904 {'max_features': 8, 'n_estimators': 30, 'random_state': 4
2}
0.9474332680188908 {'max_features': 8, 'n_estimators': 50, 'random_state': 4
2}
0.9476225722406442 {'bootstrap': False, 'max_features': 'auto', 'n_estimator
s': 10, 'random_state': 42}
0.9497067130327433 {'bootstrap': False, 'max_features': 'auto', 'n_estimator
s': 30, 'random_state': 42}
0.9505590754776568 {'bootstrap': False, 'max_features': 'auto', 'n_estimator
s': 50, 'random_state': 42}
0.9447810799850711 {'bootstrap': False, 'max_features': 4, 'n_estimators': 1
0, 'random_state': 42}
0.9485699008081765 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3
0, 'random_state': 42}
0.9493277008598537 {'bootstrap': False, 'max_features': 4, 'n_estimators': 5
0, 'random_state': 42}
0.9444976170994647 {'bootstrap': False, 'max_features': 6, 'n_estimators': 1
0, 'random_state': 42}
0.9465809055739776 {'bootstrap': False, 'max_features': 6, 'n_estimators': 3
0, 'random_state': 42}
0.9463915564934039 {'bootstrap': False, 'max_features': 6, 'n_estimators': 5
0, 'random_state': 42}
0.9363508964586653 {'bootstrap': False, 'max_features': 8, 'n_estimators': 1
0, 'random_state': 42}
0.9391931064553637 {'bootstrap': False, 'max_features': 8, 'n_estimators': 3
0, 'random_state': 42}
0.9391931064553637 {'bootstrap': False, 'max_features': 8, 'n_estimators': 5
0, 'random_state': 42}
```

Checked that when parameters 'bootstrap'= False, 'max_features'= 'auto', 'n_estimators'= 50 and 'random_state'= 42, the model has the largest accuracy score(95.056%)

In [ ]:
```python
# check what particularly works in the 'best model'

feature_importances = grid_forest.best_estimator_.feature_importances_

# attach names to each of the features
attributes = X_train.columns
sorted(zip(feature_importances, attributes), reverse=True)
```

Out[ ]:
```
[(0.17111685272115257, ' Persistent EPS in the Last Four Seasons'),
 (0.15902234512654478, ' Net Income to Total Assets'),
 (0.1272057268056115, ' Retained Earnings to Total Assets'),
 (0.11041869070063609, ' ROA(B) before interest and depreciation after tax'),
 (0.10276763722523657, ' Net worth/Assets'),
 (0.0903144698815091, ' Debt ratio %'),
 (0.08673031804199668, ' Net profit before tax/Paid-in capital'),
 (0.0683508180644228, ' Per Share Net profit before tax (Yuan ¥)'),
 (0.04437303791327464, ' ROA(A) before interest and % after tax'),
 (0.039700103519615254,
  ' ROA(C) before interest and depreciation before interest')]
```

With this extra bit of code we can see that the most important features that used for prediction in the best model.

In [ ]:
```python
# Now we use the test dataset to check for overfitting
final_model = grid_forest.best_estimator_

final_predictions = final_model.predict(X_test)

#Acccuracy
print("Accuracy is ", accuracy_score(y_test,final_predictions)*100)
```

```
Accuracy is  95.3030303030303
```

The high accuracy score indicates that there is no overfitting in the model as the model still predicts well for the test data.

In [ ]:
```python
from sklearn.metrics import f1_score
f1_score(y_test, final_predictions, average='weighted')
```

Out[ ]:
```
0.9530706573210668
```

F1 score is used to measure model performance by calculating the harmonic mean of precision and recall for the minority positive class. A higher F1 score is, the better model is.

More Advanced Classifier Models

Support Vector Machine

In [ ]:
```
# SVM Regression

svc = SVC(kernel = 'linear', C = 2.0, random_state=1)

svc.fit(X_train, y_train)
# using our model to predict
y_predsvc = svc.predict(X_valid)

# Making the Confusion Matrix
cmsvc = confusion_matrix(y_valid, y_predsvc)
print(cmsvc)

# Number of wrong classfier
print('# of wrong classfiers: %d' % (y_predsvc != y_valid).sum())

# Accuracy
print("Accuracy is ", accuracy_score(y_valid,y_predsvc)*100)
```

```
[[567  68]
 [ 50 635]]
# of wrong classfiers: 118
Accuracy is  91.06060606060606
```

Gradient Boosting

In [ ]:
```
# Gradient Boosting
gb = GradientBoostingClassifier(n_estimators=100, random_state=42)

gb.fit(X_train, y_train)

# using our model to predict
y_predgb = gb.predict(X_valid)

# Making the Confusion Matrix
cmgb = confusion_matrix(y_valid, y_predgb)
print(cmgb)

# Number of wrong classfier
print('# of wrong classfiers: %d' % (y_predgb != y_valid).sum())

# Accuracy
print("Accuracy is ", accuracy_score(y_valid,y_predgb)*100)
```

```
[[568  67]
 [ 35 650]]
# of wrong classfiers: 102
Accuracy is  92.27272727272727
```

XG Boosting

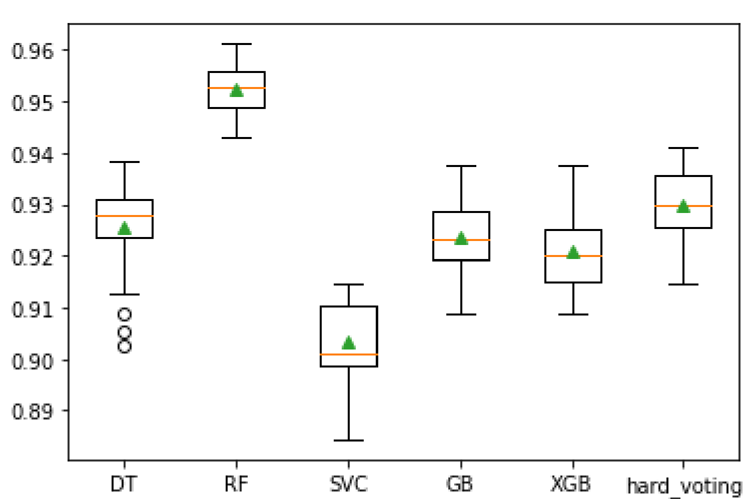
In [ ]:
```
# XG Boosting
xg = XGBClassifier(n_estimators=100, random_state=42)

xg.fit(X_train, y_train)

# using our model to predict
y_predxg = xg.predict(X_valid)
# Making the Confusion Matrix
cmxg = confusion_matrix(y_valid, y_predxg)
print(cmxg)

# Number of wrong classfier
print('# of wrong classfiers: %d' % (y_predxg != y_valid).sum())

# Accuracy
print("Accuracy is ", accuracy_score(y_valid,y_predxg)*100)
```

```
[[562  73]
 [ 30 655]]
# of wrong classfiers: 103
Accuracy is  92.1969696969697
```

Ensemble Modelling

```
In [ ]: def get_voting():
    # define base models
    models = list()
    models.append(('DT',DecisionTreeClassifier(max_depth=30,random_state=1)))
    models.append(('RF',RandomForestClassifier(bootstrap = False, max_features
= 4, n_estimators = 50, random_state=42)))
    models.append(('SVC',SVC(kernel = 'linear', C = 2.0, random_state=1)))
    models.append(('GB',GradientBoostingClassifier(n_estimators=100, random_st
ate=42)))
    models.append(('XGB',XGBClassifier(n_estimators=100, random_state=42)))

    enemble = VotingClassifier(estimators=models,voting='hard')  # use hard vo
ting

    return enemble


def get_model():
    # get all models
    models = dict()
    models['DT'] = DecisionTreeClassifier(max_depth=30,random_state=1)
    models['RF'] = RandomForestClassifier(bootstrap = False, max_features = 4,
n_estimators = 50, random_state=42)
    models['SVC'] = SVC(kernel = 'linear', C = 2.0, random_state=1)
    models['GB'] = GradientBoostingClassifier(n_estimators=100, random_state=4
2)
    models['XGB'] =XGBClassifier(n_estimators=100, random_state=42)
    models['hard_voting'] = get_voting()

    return models


def evaluate_model(model, X, y):
    # evaluate models
    cv = RepeatedStratifiedKFold(n_splits=10,n_repeats=3,random_state=1)
    score = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1,
error_score='raise')
    return score

models = get_model()
results, names = list(), list()
for name,model in models.items():
    scores = evaluate_model(model, X_train, y_train)
    results.append(scores)
    names.append(name)
    print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))
pyplot.boxplot(results, labels=names, showmeans=True)
pyplot.show()
```

```
>DT 0.926 (0.009)
>RF 0.952 (0.005)
>SVC 0.903 (0.008)
>GB 0.924 (0.008)
>XGB 0.921 (0.007)
>hard_voting 0.930 (0.007)
```



Cross Validation Scores is used to determine whether the given models are optimal. We noticed that hard_voting model is above the average level of all models, only inferior to the Random Forest model. Finally, test our final voting model with the test data.

Hard Voting

A voting classifier is a machine learning model that learns from an ensemble of several models and forecasts an output (class) based on the highest probability by all given classifiers' predictions.

In [ ]:
```
# hard_voting model
models=get_model()
hv = models['hard_voting']
hv.fit(X_test,y_test)

# using hard_voting model to predict
y_predhv = hv.predict(X_test)

# Making the Confusion Matrix
cmhv = confusion_matrix(y_test, y_predhv)
print(cmhv)

# Number of wrong classfier
print('# of wrong classfiers: %d' % (y_predhv != y_test).sum())

# Accuracy
print("Accuracy is ", accuracy_score(y_test,y_predhv)*100)
```

```
[[664  35]
 [  6 615]]
# of wrong classfiers: 41
Accuracy is  96.8939393939394
```

The accuracy of predicting for the test data is 96.81%, which is the highest among all the models we fit, indicating that the hard_voting model is the best model for prediction.

In [ ]:
```
f1_score(y_test, y_predhv, average='weighted')
```

Out[ ]:
```
0.9689647601155884
```

Part 3 Deep Learning

Pre-Processing

Regarding the analysis of the Deep Learning architecture, the most important feature of the dataset that must be taken into great consideration is the imbalanced set of bankruptcies. As the event of a bankruptcy is pretty “rare” the dataset should incorporate some method of over/under-sampling or both, knowing that given the balanced focus on misclassification errors, most standard neural network algorithms are not well suited to datasets with a severely skewed class distribution.

The structure of the DL architecture that was implemented is displayed along with commentary about the reasoning and choices that were made.

In [ ]:
```
%reset
```

```
Once deleted, variables cannot be recovered. Proceed (y/[n])? y
```

In [ ]:
```
# standard quantitative packages
import numpy as np
import pandas as pd

# machine learning packages
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# visualisation
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
%matplotlib inline

# tensorflow and keras for deep learning
import tensorflow as tf
from tensorflow import keras
```

In [ ]:
```
df = pd.read_csv('data.csv')
df.head(2)
```

Out[ ]:

	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	Af I
0	1	0.370594	0.424389	0.40575	0.601457	0.601457	0.998969	0.796887	0.8
1	1	0.464291	0.538214	0.51673	0.610235	0.610235	0.998946	0.797380	0.8

2 rows × 96 columns

In [ ]:
```
df.describe()
```

Out[ ]:

	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	Operat Profit R
count	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000000	6819.000
mean	0.032263	0.505180	0.558625	0.553589	0.607948	0.607929	0.9987
std	0.176710	0.060686	0.065620	0.061595	0.016934	0.016916	0.0130
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	0.000000	0.476527	0.535543	0.527277	0.600445	0.600434	0.9989
50%	0.000000	0.502706	0.559802	0.552278	0.605997	0.605976	0.9990
75%	0.000000	0.535563	0.589157	0.584105	0.613914	0.613842	0.9990
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0000

8 rows × 96 columns

From the descriptive statistics we notice that our dataset is regularized with each column obtaining values between min:0 and max:1 . The dataset is rich in terms of features spanning through 95 different metrics for determining the bankruptcy of a company.

The next step is to split the data into the training and test sets.

Note: We could also (optionaly) introduce the “random_state” input in the “train_test_split” command to have reproductivity of the results. (set seed for the “random” splits)

```
In [ ]: y = df['Bankrupt?']
        X = df.drop(columns=['Bankrupt?'])
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
        X_test, X_valid, y_test, y_valid = train_test_split(X_test, y_test, test_size=
        0.5)
```

```
In [ ]: import seaborn as sns
        import matplotlib.pyplot as plt
        from tensorflow import keras
```

A popular library in the Scikit-learn module to select the “best” features of a given dataset is SelectKbest . The SelectKBest method selects the features according to the K highest score. By changing the 'score_func' parameter we can apply the method for both classification and regression data. Selecting the most important features is a critical process when we prepare a large dataset for training.

```
In [ ]: from sklearn.feature_selection import SelectKBest, f_classif
        from sklearn.model_selection import train_test_split
```

Import additional packages/module The choice of 20 most important features was our target, as a consensus view, enough to predict the bankruptcies observed.

```
In [ ]: feature_selection=SelectKBest(f_classif,k=20).fit(X_train,y_train) # k number
         of specified features
        selected_features=X_train.columns[feature_selection.get_support()]

        /usr/local/lib/python3.7/dist-packages/sklearn/feature_selection/_univariate_
        selection.py:112: UserWarning: Features [93] are constant.
          warnings.warn("Features %s are constant." % constant_features_idx, UserWarn
        ing)
        /usr/local/lib/python3.7/dist-packages/sklearn/feature_selection/_univariate_
        selection.py:113: RuntimeWarning: invalid value encountered in true_divide
          f = msb / msw
```

```
In [ ]: selected_features

Out[ ]: Index([' ROA(C) before interest and depreciation before interest',
               ' ROA(A) before interest and % after tax',
               ' ROA(B) before interest and depreciation after tax',
               ' Net Value Per Share (B)', ' Net Value Per Share (A)',
               ' Net Value Per Share (C)', ' Persistent EPS in the Last Four Season
        s',
               ' Operating Profit Per Share (Yuan ¥)',
               ' Per Share Net profit before tax (Yuan ¥)', ' Debt ratio %',
               ' Net worth/Assets', ' Borrowing dependency',
               ' Operating profit/Paid-in capital',
               ' Net profit before tax/Paid-in capital',
               ' Working Capital to Total Assets', ' Current Liability to Assets',
               ' Retained Earnings to Total Assets',
               ' Current Liability to Current Assets', ' Net Income to Total Assets',
               ' Net Income to Stockholder's Equity'],
              dtype='object')
```

The selected features have been also used in the analysis part (1).However, the result is slightly different as we use the standardized dataset in part 1)

Simple Deep Learning Network

For our first approach, a simple DL network will be presented without taking any account of the imbalanced set to set the basis and see how a simple Sequential model will behave.

The DL network model will be a Sequential model with 2 dense layers, both with activation functions ‘ReLu’ (Rectify Linear) and an output layer with the sigmoid activation function to ensure predictions are probabilities in the range [0,1]. Stochastic gradiend decent will be used as the fitting optimizer and the loss function will be “binary crossentropy” as the best choice for the classification problem.

In [ ]:
```
model = keras.models.Sequential([
    keras.layers.Input(shape=(20,)),
    keras.layers.Dense(33, activation='relu'),
    keras.layers.Dense(11, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])
```

In [ ]:
```
model.compile(loss='binary_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])
```

In [ ]:
```
X_train = X_train[selected_features]
```

In [ ]:
```
X_valid = X_valid[selected_features]
```

In [ ]:
```
X_test = X_test[selected_features]
```

In [ ]:
```
history = model.fit(X_train, y_train, epochs=30, validation_data=(X_valid, y_v
alid))
```

```
Epoch 1/30
171/171 [==============================] - 1s 3ms/step - loss: 0.3849 - accur
acy: 0.9148 - val_loss: 0.1797 - val_accuracy: 0.9692
Epoch 2/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1534 - accur
acy: 0.9672 - val_loss: 0.1356 - val_accuracy: 0.9692
Epoch 3/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1394 - accur
acy: 0.9672 - val_loss: 0.1323 - val_accuracy: 0.9692
Epoch 4/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1383 - accur
acy: 0.9672 - val_loss: 0.1319 - val_accuracy: 0.9692
Epoch 5/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1381 - accur
acy: 0.9672 - val_loss: 0.1318 - val_accuracy: 0.9692
Epoch 6/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1380 - accur
acy: 0.9672 - val_loss: 0.1317 - val_accuracy: 0.9692
Epoch 7/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1378 - accur
acy: 0.9672 - val_loss: 0.1316 - val_accuracy: 0.9692
Epoch 8/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1378 - accur
acy: 0.9672 - val_loss: 0.1315 - val_accuracy: 0.9692
Epoch 9/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1376 - accur
acy: 0.9672 - val_loss: 0.1314 - val_accuracy: 0.9692
Epoch 10/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1375 - accur
acy: 0.9672 - val_loss: 0.1313 - val_accuracy: 0.9692
Epoch 11/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1374 - accur
acy: 0.9672 - val_loss: 0.1312 - val_accuracy: 0.9692
Epoch 12/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1372 - accur
acy: 0.9672 - val_loss: 0.1311 - val_accuracy: 0.9692
Epoch 13/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1371 - accur
acy: 0.9672 - val_loss: 0.1310 - val_accuracy: 0.9692
Epoch 14/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1370 - accur
acy: 0.9672 - val_loss: 0.1309 - val_accuracy: 0.9692
Epoch 15/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1368 - accur
acy: 0.9672 - val_loss: 0.1308 - val_accuracy: 0.9692
Epoch 16/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1367 - accur
acy: 0.9672 - val_loss: 0.1307 - val_accuracy: 0.9692
Epoch 17/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1366 - accur
acy: 0.9672 - val_loss: 0.1306 - val_accuracy: 0.9692
Epoch 18/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1364 - accur
acy: 0.9672 - val_loss: 0.1304 - val_accuracy: 0.9692
Epoch 19/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1363 - accur
acy: 0.9672 - val_loss: 0.1304 - val_accuracy: 0.9692
Epoch 20/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1362 - accur
acy: 0.9672 - val_loss: 0.1302 - val_accuracy: 0.9692
Epoch 21/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1360 - accur
acy: 0.9672 - val_loss: 0.1301 - val_accuracy: 0.9692
Epoch 22/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1359 - accur
acy: 0.9672 - val_loss: 0.1300 - val_accuracy: 0.9692
Epoch 23/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1357 - accur
acy: 0.9672 - val_loss: 0.1299 - val_accuracy: 0.9692
Epoch 24/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1356 - accur
acy: 0.9672 - val_loss: 0.1298 - val_accuracy: 0.9692
Epoch 25/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1354 - accur
```

```
acy: 0.9672 - val_loss: 0.1296 - val_accuracy: 0.9692
Epoch 26/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1353 - accur
acy: 0.9672 - val_loss: 0.1296 - val_accuracy: 0.9692
Epoch 27/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1351 - accur
acy: 0.9672 - val_loss: 0.1294 - val_accuracy: 0.9692
Epoch 28/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1350 - accur
acy: 0.9672 - val_loss: 0.1293 - val_accuracy: 0.9692
Epoch 29/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1348 - accur
acy: 0.9672 - val_loss: 0.1292 - val_accuracy: 0.9692
Epoch 30/30
171/171 [==============================] - 0s 2ms/step - loss: 0.1347 - accur
acy: 0.9672 - val_loss: 0.1291 - val_accuracy: 0.9692
```

In [ ]:
```
score = model.evaluate(X_test ,y_test, batch_size = 128)
```

```
6/6 [==============================] - 0s 3ms/step - loss: 0.1239 - accuracy:
0.9707
```

The validation accuracy achieved is around 97.07%.

The accuracy of the network is evaluated on the test dataset at a value of 96.92%.

Weighted/Cost sensitive Deep Learning Network

The backpropagation method that neural networks use in their training process, poses a limitation of this method, as examples from each class are treated with the same weights, which for imbalanced datasets means that the model is adapted a lot more for one class than another. The backpropagation algorithm can be modified based on misclassification errors in proportion to the importance of the class, referred to as weighted neural networks or cost-sensitive neural networks. This has the effect of allowing the model to account with greater impact on cases from the minority class than the majority class in datasets which are severely skewed.

The implemented method for our DL architecture was based on the example found here: (https://machinelearningmastery.com/cost-sensitive-neural-network-for-imbalanced-classification/ (https://machinelearningmastery.com/cost-sensitive-neural-network-for-imbalanced-classification/))

Assign weights for each class on a scale from 1 to 100.

The class distribution of the test dataset is a 1:100 ratio for the minority class to the majority class. The reduction of the error from the majority class is dramatically scaled down to very small numbers that may have limited or only a very minor effect on model weights.

In [ ]:
```
class_weight = {0: 1.,
                1: 100.}
```

As before, the architecture of the network will be the same.

In [ ]:
```
model = keras.models.Sequential([
    keras.layers.Input(shape=(20,)),
    keras.layers.Dense(33, activation='relu'),
    keras.layers.Dense(11, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])
```

In [ ]:
```
model.compile(loss='binary_crossentropy',
             optimizer='sgd',
             metrics=['accuracy'])
```

The train and validation sets will be reduced to the appropriate sizes based on the most important features selected by the “SelectKbest” method presented before. The number of epochs chosen is 30.

In [ ]:
```
X_train = X_train[selected_features]
```

In [ ]:
```
X_valid = X_valid[selected_features]
```

In [ ]:
```
X_test = X_test[selected_features]
```

This time in the fitting command we will introduce the class weights as discussed above.

In [ ]:
```
history = model.fit(X_train, y_train, epochs=30, class_weight=class_weight, va
lidation_data=(X_valid, y_valid))
```

```
Epoch 1/30
171/171 [==============================] - 1s 3ms/step - loss: 2.3792 - accur
acy: 0.0328 - val_loss: 1.3304 - val_accuracy: 0.0308
Epoch 2/30
171/171 [==============================] - 0s 2ms/step - loss: 2.2806 - accur
acy: 0.0328 - val_loss: 1.4622 - val_accuracy: 0.0308
Epoch 3/30
171/171 [==============================] - 0s 2ms/step - loss: 2.2535 - accur
acy: 0.0328 - val_loss: 1.5371 - val_accuracy: 0.0308
Epoch 4/30
171/171 [==============================] - 0s 2ms/step - loss: 2.1841 - accur
acy: 0.0328 - val_loss: 1.3902 - val_accuracy: 0.0308
Epoch 5/30
171/171 [==============================] - 0s 2ms/step - loss: 2.0801 - accur
acy: 0.0328 - val_loss: 1.0931 - val_accuracy: 0.0308
Epoch 6/30
171/171 [==============================] - 0s 2ms/step - loss: 1.9537 - accur
acy: 0.0328 - val_loss: 1.0665 - val_accuracy: 0.0308
Epoch 7/30
171/171 [==============================] - 0s 2ms/step - loss: 1.7743 - accur
acy: 0.1652 - val_loss: 0.9466 - val_accuracy: 0.3035
Epoch 8/30
171/171 [==============================] - 0s 2ms/step - loss: 1.7233 - accur
acy: 0.3505 - val_loss: 1.0884 - val_accuracy: 0.2742
Epoch 9/30
171/171 [==============================] - 0s 2ms/step - loss: 1.5780 - accur
acy: 0.4504 - val_loss: 0.4769 - val_accuracy: 0.8358
Epoch 10/30
171/171 [==============================] - 0s 2ms/step - loss: 1.6230 - accur
acy: 0.4849 - val_loss: 0.3925 - val_accuracy: 0.8871
Epoch 11/30
171/171 [==============================] - 0s 2ms/step - loss: 1.6482 - accur
acy: 0.4829 - val_loss: 0.6214 - val_accuracy: 0.6935
Epoch 12/30
171/171 [==============================] - 0s 3ms/step - loss: 1.4686 - accur
acy: 0.5573 - val_loss: 1.3124 - val_accuracy: 0.3152
Epoch 13/30
171/171 [==============================] - 1s 3ms/step - loss: 1.4489 - accur
acy: 0.5529 - val_loss: 0.4168 - val_accuracy: 0.8372
Epoch 14/30
171/171 [==============================] - 1s 7ms/step - loss: 1.4782 - accur
acy: 0.5611 - val_loss: 0.6869 - val_accuracy: 0.6569
Epoch 15/30
171/171 [==============================] - 1s 6ms/step - loss: 1.5001 - accur
acy: 0.5732 - val_loss: 0.9313 - val_accuracy: 0.5235
Epoch 16/30
171/171 [==============================] - 1s 6ms/step - loss: 1.4530 - accur
acy: 0.5727 - val_loss: 0.4901 - val_accuracy: 0.8035
Epoch 17/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4474 - accur
acy: 0.5844 - val_loss: 0.6159 - val_accuracy: 0.6950
Epoch 18/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4925 - accur
acy: 0.5764 - val_loss: 2.8264 - val_accuracy: 0.0499
Epoch 19/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4376 - accur
acy: 0.5600 - val_loss: 1.1163 - val_accuracy: 0.3886
Epoch 20/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3510 - accur
acy: 0.5998 - val_loss: 3.2774 - val_accuracy: 0.0587
Epoch 21/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4020 - accur
acy: 0.5826 - val_loss: 3.5032 - val_accuracy: 0.0499
Epoch 22/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4091 - accur
acy: 0.5872 - val_loss: 0.6299 - val_accuracy: 0.6979
Epoch 23/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4414 - accur
acy: 0.5995 - val_loss: 2.3859 - val_accuracy: 0.0894
Epoch 24/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3598 - accur
acy: 0.5877 - val_loss: 1.1468 - val_accuracy: 0.4223
Epoch 25/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3768 - accur
```

```
acy: 0.5982 - val_loss: 0.7982 - val_accuracy: 0.5968
Epoch 26/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3531 - accur
acy: 0.6007 - val_loss: 2.7436 - val_accuracy: 0.0880
Epoch 27/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3708 - accur
acy: 0.6077 - val_loss: 2.4102 - val_accuracy: 0.1393
Epoch 28/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3290 - accur
acy: 0.6090 - val_loss: 0.4616 - val_accuracy: 0.8138
Epoch 29/30
171/171 [==============================] - 0s 2ms/step - loss: 1.3413 - accur
acy: 0.6286 - val_loss: 0.6902 - val_accuracy: 0.6760
Epoch 30/30
171/171 [==============================] - 0s 2ms/step - loss: 1.4498 - accur
acy: 0.5764 - val_loss: 0.5920 - val_accuracy: 0.7155
```

In [ ]:
```
score = model.evaluate(X_test ,y_test, batch_size = 128)
```

```
6/6 [==============================] - 0s 2ms/step - loss: 0.5682 - accuracy:
0.7214
```

The validation accuracy achieved is around 71.55%.

The accuracy of the network is evaluated on the test dataset at a value of 65.2%.

The accuracy of this cost sensitive neural network is given by the ROC-AUC (Receiver Operating Characteristic Curve - Area Under Curve) score which is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve.

In [ ]:
```
yhat = model.predict(X_test)
```

In [ ]:
```
from sklearn.metrics import roc_auc_score
score = roc_auc_score(y_test, yhat)
```

In [ ]:
```
print('ROC AUC: %.3f' % score)
```

```
ROC AUC: 0.927
```

Hyper-Parametrization

As a final part we will also present a useful Keras library that would provide another approach to our classification problem. The Keras Tuner is a library that helps pick the optimal set of hyperparameters for TensorFlow. The process of selecting the right set of hyperparameters for the machine learning architecture is called “hyper parameter tuning”. The model build is a sequential model with 2 hidden layers with similar activation functions.

In [ ]:
```
import keras_tuner as kt
```

In [ ]:
```
# install keras_tuner
#import sys
#!{sys.executable} -m pip install keras_tuner
```

```
In [ ]: def build_model(hp):
            model = keras.Sequential()
            model.add(keras.layers.Dense(units=hp.Int('units',
                                         min_value=25,
                                         max_value=125,
                                         step=25),
                             activation='relu'))
            model.add(keras.layers.Dense(
                hp.Choice('units', [4, 8, 12, 16]),
                activation='relu'))
            model.add(keras.layers.Dense(1, activation='sigmoid'))
            model.compile(loss='binary_crossentropy',
                      optimizer='sgd',
                      metrics=['accuracy'])
            return model
```

The RandomSearch tuner will be used to manage the hyperparameter search process, including model creation, training, and evaluation.

Note: The directory path should be changed into a new folder directory before runtime.

```
In [ ]: tuner = kt.RandomSearch(
            build_model,
            objective='val_accuracy',
            directory='/Users/spyrostsatsis/Desktop/untitled_project',
        )
```

Using the following commands, we will extract again the “best” features for our dataset and train the model through the scope of the hyper parameterization.

```
In [ ]: tuner.search(X_train, y_train, epochs=5, validation_data=(X_valid, y_valid))
        best_hp=tuner.get_best_hyperparameters(num_trials=1)[0]

        Trial 4 Complete [00h 00m 05s]
        val_accuracy: 0.9692082405090332

        Best val_accuracy So Far: 0.9692082405090332
        Total elapsed time: 00h 00m 23s
        INFO:tensorflow:Oracle triggered exit
```

```
In [ ]: best_hp.get('units')

Out[ ]: 75
```

```
In [ ]: nnModel = tuner.hypermodel.build(best_hp)
```

By introducing the test set to evaluate our model we will also perform an accuracy score to assess the results.

```
In [ ]: y_pred = nnModel.predict(X_test)
```

```
In [ ]: type(y_test)

Out[ ]: pandas.core.series.Series
```

```
In [ ]: y_test_arr = y_test.to_numpy()
```

```
In [ ]: y_pred = y_pred.astype(int)
```

```
In [ ]: from sklearn.metrics import accuracy_score
```

In [ ]:
```
accuracy_score(y_test_arr, y_pred)
```
Out[ ]: 0.9706744868035191

The achieved accuracy score is about 97.4%.

In [ ]:
```
from sklearn.metrics import f1_score
f1_score(y_test_arr, y_pred, average='weighted')
```
Out[ ]: 0.9562299259879905

Summary

In this coursework, we have used correlation coefficient and SelectedKbest machine learning model to find most significant features to used in company bankruptcy prediction.

Secondly, We have mananged to use different classifiers to find a good model in company bankruptcy prediction. We have found that Random Forest model provides F1 score 0.9531 and Hard voting model provides F1 score 0.9690. This suggest that Hard Voting model is better at predicting company bankruptcy.

Finally, we have combined hyper-parametrization and learning model to predict the company bankruptcy, which provides F1 score 0.9562.

Therefore, we can say that Hard voting model is a good model for company bankruptcy predictions. However, we believe that if increase the number of hidden layers in the deep learning will give us a higher result.