

# Configuration Manual

MSc Research Project  
FinTech

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# Configuration Manual

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## 1 Environment Setup

The studies were conducted in a Google Colab environment (Bisong and Bisong (2019)) utilizing a Jupyter Notebook (Kluyver et al. (2016)) and the Python programming language(Sanner et al. (1999)). Table 2 shows the various tools used with their purpose.

Sl. No.	Tools and Technologies	Purpose
1	Microsoft Excel	<i>For the purpose of storing and retrieving Taiwanese bankruptcy data in CSV format</i>
2	Google Colaboratory	<i>Free, cloud-based Jupyter notebook for collaborative Python programming and experimentation</i>
3	Jupyter Notebook	<i>To implement Python Codes</i>
4	Python	<i>For carrying out a high-level coding task for machine learning</i>

Table 1: Various Tools and Technologies, and Purpose

Following Python Packages were used

Name	Description
Pandas	<i>Data processing</i>
Numpy	<i>Linear algebra with features</i>
Seaborn, Pyplot and Matplotlib	<i>Data Visualization</i>
Sci-kit learn	<i>For Data pre-processing and model implementation</i>
Imbalanced learn	<i>For Data resampling and ensemble model implementation</i>

Table 2: Various Tools and Technologies, and Purpose

# 2 Data Analysis

## 2.1 Data Upload

The data was collected in CSV format as shown below

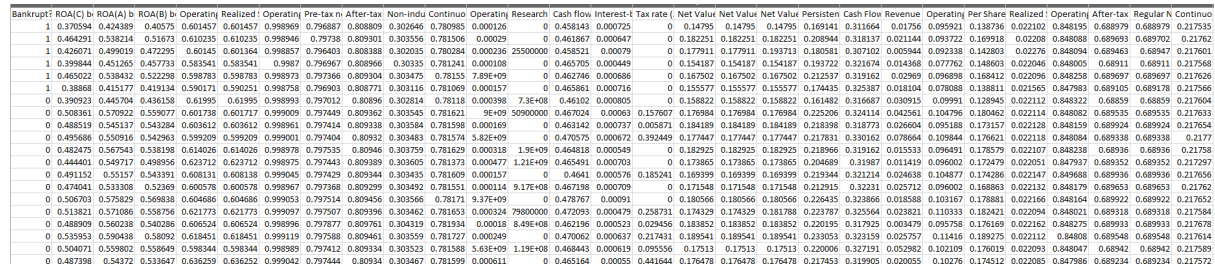


Figure 1: Data in Excel

## 2.2 Checking for null values and duplicates

It's crucial to check if there are any missing values in the dataset as this can degrade the model quality. Also, checking for duplicates is an important phase. The steps include

Step 1: `df.info()` gives the null value information Step 2: `df.duplicated()` gives number of duplicates values.

## 2.3 Feature Selection

The features were chosen using Pearson's correlation co-efficients as shown below. This create a set of features by dropping highly correlated independent variables. Based on the literature, it is found that  $> |0.7|$  is assumed to be strong correlation (Dormann et al. (2013)).

## 2.4 Data Normalization

All the variables were scaled using min-max scaler and standard scaler as shown below.

## 2.5 Dimensionality Reduction

Principal Component Analysis (PCA) is a widely used technique for reducing the dimensionality of high-dimensional data while preserving as much variance as possible (Abdi and Williams (2010)). It entails converting the initial variables into a new collection of uncorrelated variables (principal components) that account for the majority of the variability in the data. In this study, the top 8 principal components accounted for 99% of the variation in the dataset.

## 2.6 Train and Test Split

Splitting data into training and test set are important as they will be used to train and evaluate the models. The 70% of the data were used to train the model while 30% to test the model using stratified sampling strategy.

Net Income to Total Assets	-0.2343	0.9244	0.9916	0.9326	0.5054	0.5034	0.7979	0.9066
Total assets to GNP price	-0.0551	-0.0068	0.0104	0.0030	-0.2580	-0.2581	0.0156	0.0624
No-credit interval	-0.1117	0.1893	0.2126	0.1807	0.0974	0.0965	0.1567	0.1925
Gross Profit to Sales	-0.1476	0.5062	0.4965	0.5157	1.0000	0.9991	0.6856	0.5870
Net Income to Stockholder's Equity	-0.2191	0.8989	0.9694	0.9060	0.4505	0.4483	0.7655	0.8575
Liability to Equity	-0.2007	-0.2409	-0.2357	-0.2456	-0.3816	-0.3822	-0.2377	-0.3301
Degree of Financial Leverage (DFL)	-0.1471	0.2199	0.2355	0.2282	0.0416	0.0415	0.2304	0.2430
Interest Coverage Ratio (Interest expense to EBIT)	-0.1275	0.1836	0.1910	0.1930	0.0159	0.0151	0.1979	0.1913
Equity to Liability	-0.2172	0.2475	0.2425	0.2523	0.3858	0.3864	0.2434	0.3365
	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

Figure 2: Correlation Between a Few Variables

Transform data using min-max scaler and standard scaler

As we can see, there are many outliers in the dataset, we can perform min-max scaling.

A **Min-Max Scaling** is typically done via the following equation:

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

$X_i$  is the  $i^{th}$  sample of dataset.

We will also do experiment with standardized or Z-score normalized data. The features will be rescaled as a result of standardization (or Z-Score normalization), and they will then possess the characteristics of a conventional normal distribution with:

$$\mu = 0$$

And

$$\sigma = 1$$

Where  $\mu$  is the mean (average) and  $\sigma$  is the standard deviation from the mean; standard scores (also called **Z** scores) of the samples are calculated as follows:

$$z = \frac{x - \mu}{\sigma}$$

Reference: [https://colab.research.google.com/github/JL1829/turbo-funicular/blob/master/\\_notebooks/2020-09-19-About%20Feature%20Scaling%20and%20Normalization.ipynb#scrollTo=TetPOB43NPye](https://colab.research.google.com/github/JL1829/turbo-funicular/blob/master/_notebooks/2020-09-19-About%20Feature%20Scaling%20and%20Normalization.ipynb#scrollTo=TetPOB43NPye)

```
[ ] min_max = MinMaxScaler()
std_scl = StandardScaler()

X_min_max = min_max.fit_transform(X_non_corr)
X_std_scl = std_scl.fit_transform(X_non_corr)
```

Figure 3: Scaling

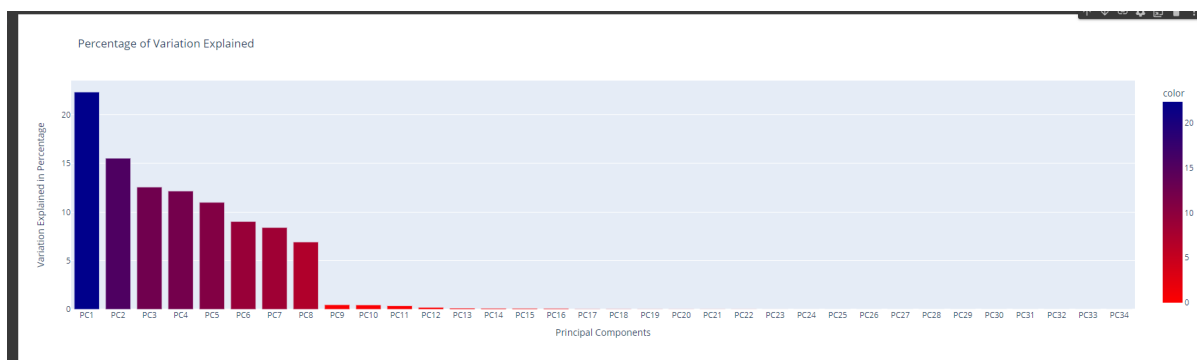


Figure 4: PCA

## 2.7 Resampling

As the data is biased towards non-bankrupt events, the resampling strategies including Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al. (2002); Smiti and Soui (2020)), Random Oversampling (ROS) (Mohammed et al. (2020)), and Random Undersampling (RUS) (Wang and Liu (2021); Liu et al. (2008)) have been implemented. The SMOTE and Over-sampling created new data points for minority class, i.e., class with bankruptcy events.

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