Financial Ratio’s to predict Company’s Financial Failure or Bankruptcy

Multiple research has been done on financial stability or financial failure of an organization since 1930[1]. Different research have been in place since late 1960’s to use financial ratio’s for predicting Bankruptcy. Bankruptcy is used to signify a company that has no operational source of money to operate the business and is in no position to repay the debts it owes to its creditors. It is a difficult situation to be in as the company comes down to a stand-still state and leaves the employees and suppliers/customers in a high & financial instability state. Increased competitors and uncertainty in the global economy these days can be a cause to drive large organizations towards bankruptcy. The recent example being that of the British travel company, Thomas Cook which suddenly declared bankruptcy and left 21,000 people out of work and million dollars of investor money down the drains. Thus, it is impossible to overstate the damage caused in terms of the financial loss.[6]

Financial ratios are one of the most important tools for assessing and analyzing the performance of firms. They help to compare and analyze a firm’s overall health based on various parameters. Investors can use financial ratios to get an insight to the firm’s profitability and its investment prospects. Thus, by using historical data from financial statements, financial ratios help in forecast a firm’s future health. Additionally, they also help to compare and contrast financial performance of firms among their competitors. In spite of the long standing research in this area, several attempt towards exploring this relationship has led to limited success owing largely to the existence of variability in every stock markets. The variance in volatility of these markets makes it difficult to obtain a uniform measure[5]. Bankruptcy prediction is a very important task for many related financial institutions. In general, the aim is to predict the likelihood that a firm may go bankrupt. Financial institutions are in need of effective prediction models in order to make appropriate lending decisions [2], stock price prediction and more.

Related Work:

Features that are selected such as financial ratio’s and statistical or machine learning techniques used will be important factors that strongly affect the prediction performance. While many related works have proposed novel prediction techniques, very few have analyzed the discriminatory power of the features related to bankruptcy prediction. In addition to financial ratios (FRs), corporate governance indicators (CGIs) have been found to be another important type of input variable[2]. Complete prediction performance by combining Corporate Governance Indicators and Financial Ratio’s

However, the prediction performance obtained by combining CGIs and FRs has not been fully examined. Only some selected CGIs and FRs have been used in related studies and the chosen features differed from study to study. In this study explore all the Financial Ratio’s and Corporate Governance Indicators **through Deep Learning methods**.

Author assessed the prediction performance obtained by combining seven different categories of Financial Ratio’s and five different categories of corporate governance indicators. The experimental results, based on a real-world dataset from Taiwan, show that the FR categories of solvency and profitability and the CGI categories of board structure and ownership structure are the most important features in bankruptcy prediction. Some of the Algorithms and techniques that were compared are Support Vector Machines (SVM), k-nearest neighbor (KNN), Naïve Bayes Classifier (NB), Classification and Regression Trees(CART) and MLP(Multi-Layer Perceptron). Features for the machine learning models are stepwise discriminant analysis (SDA) (Fisher, 1936), stepwise logistic regression (SLR) (Fisher & Yates, 1963), and t-testing (Zimmerman, 1997)3 and the wrapper based methods of the genetic algorithm (GA) (Holland, 1975) and recursive feature elimination (RFE) (Guyon, Weston, Barnhill, & Vapnik, 2002).

Data:

In this Article we will use various predictive models to see how accurate they are in detecting whether we can appropriately predict which companies will face bankrptcy in the future. This Taiwanese Bankruptcy Prediction Data Set is taken from UCI Machine Learning Repository. As described in the data section, the dataset contains:

* 95 features (X1-X95, business regulations of Taiwan Stock Exchange)
* 1 Vector of labels

Our aim in this project is to use these features to understand their impact/role on the selected models and how they can help us recognizing the companies that are close to bankrupcty. All the variables that are part of this dataset are numeric and complete in nature.This is the same data set that was used by Liang D and Co[2] for research and donated to UCI community.

|  |  |
| --- | --- |
| X1 Cost of Interest-bearing Debt | X49 Fixed Assets Per Employee |
| X2 Cash Reinvestment Ratio | X50 total assets to GNP price |
| X3 Current Ratio | X51 Return On Total Assets(C) |
| X4 Acid Test | X52 Return On Total Assets(A) |
| X5 Interest Expenses/Total Revenue | X53 Return On Total Assets(B) |
| X6 Total Liability/Equity Ratio | X54 Gross Profit /Net Sales |
| X7 Liability/Total Assets | X55 Realized Gross Profit/Net Sales |
| X8 Interest-bearing Debt/Equity | X56 Operating Income /Net Sales |
| X9 Contingent Liability/Equity | X57 Pre-Tax Income/Net Sales |
| X10 Operating Income/Capital | X58 Net Income/Net Sales |
| X11 Pretax Income/Capital | X59 Net Non-operating Income Ratio |
| X12 Working Capital to Total Assets | X60 Net Income-Exclude Disposal Gain or Loss/Net Sales |
| X13 Quick Assets/Total assets | X61 EPS-Net Income |
| X14 Current Assets/Total Assets | X62 Pretax Income Per Share |
| X15 Cash/Total Assets | X63 Retained Earnings to Total Assets |
| X16 Quick Assets/Current Liability | X64 Total Income to Total Expenses |
| X17 Cash/Current Liability | X65 Total Expenses to Assets |
| X18 Current Liability to Assets | X66 Net Income to Total Assets |
| X19 Operating Funds to Liability | X67 Gross Profit to Sales |
| X20 Inventory/Working Capital | X68 Net Income to Stockholder's Equity |
| X21 Inventory/Current Liability | X69 One if Net Income is Negative for the Last Two Years; Zero Otherwise |
| X22 Current Liabilities/Liability | X70 (Inventory +Accounts Receivables) /Equity |
| X23 Working Capital/Equity | X71 Total Asset Turnover |
| X24 Current Liabilities/Equity | X72 Accounts Receivable Turnover |
| X25 Long-term Liability to Current Assets | X73 Days Receivable Outstanding |
| X26 Current Liability to Current Assets | X74 Inventory Turnover |
| X27 One if Total Liability exceeds Total Assets; | X75 Fixed Asset Turnover |
| X28 Equity to Liability | X76 Equity Turnover |
| X29 Equity/Total Assets | X77 Current Assets to Sales |
| X30 (Long-term Liability+Equity)/Fixed Assets | X78 Quick Assets to Sales |
| X31 Fixed Assets to Assets | X79 Working Capital to Sales |
| X32 Current Liability to Liability | X80 Cash to Sales |
| X33 Current Liability to Equity | X81 Cash Flow to Sales |
| X34 Equity to Long-term Liability | X82 No-credit Interval |
| X35 Liability to Equity | X83 Cash Flow from Operating/Current Liabilities |
| X36 Degree of Financial Leverage | X84 Cash Flow to Total Assets |
| X37 Interest Coverage Ratio | X85 Cash Flow to Liability |
| X38 Operating Expenses/Net Sales | X86 CFO to Assets |
| X39 (Research and Development Expenses)/Net Sales | X87 Cash Flow to Equity |
| X40 Effective Tax Rate | X88 Realized Gross Profit Growth Rate |
| X41 Book Value Per Share(B) | X89 Operating Income Growth |
| X42 Book Value Per Share(A) | X90 Net Income Growth |
| X43 Book Value Per Share(C) | X91 Continuing Operating Income after Tax Growth |
| X44 Cash Flow Per Share | X92 Net Income-Excluding Disposal Gain or Loss Growth |
| X45 Sales Per Share | X93 Total Asset Growth |
| X46 Operating Income Per Share | X94 Total Equity Growth |
| X47 Sales Per Employee | X95 Return on Total Asset Growth |
| X48 Operation Income Per Employee |  |

Implementation:

Comparing to all the feature selection methods Step wise Linear Regression was giving good percentage [2].

SMOTE:

The challenge of working with imbalanced datasets is that most machine learning techniques will ignore, and in turn have poor performance on, the minority class, although typically it is performance on the minority class that is most important.

One approach to addressing imbalanced datasets is to oversample the minority class. The simplest approach involves duplicating examples in the minority class, although these examples don’t add any new information to the model. Instead, new examples can be synthesized from the existing examples. This is a type of [data augmentation](https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/) for the minority class and is referred to as the **Synthetic Minority Oversampling Technique**, or **SMOTE** for short.

This procedure can be used to create as many synthetic examples for the minority class as are required.

LOGISTIC REGRESSION

It is the go-to method for binary classification problems (problems with two class values).

Logistic regression is named for the function used at the core of the method, the logistic function.

The [logistic function](https://en.wikipedia.org/wiki/Logistic_function), also called the sigmoid function was developed by statisticians to describe properties of population growth in ecology, rising quickly and maxing out at the carrying capacity of the environment. It’s an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits.

1 / (1 + e^-value)

Where e is the [base of the natural logarithms](https://en.wikipedia.org/wiki/E_(mathematical_constant)) (Euler’s number or the EXP() function in your spreadsheet) and value is the actual numerical value that you want to transform.

The coefficients (Beta values b) of the logistic regression algorithm must be estimated from your training data. This is done using maximum-likelihood estimation.

[Maximum-likelihood estimation](https://en.wikipedia.org/wiki/Maximum_likelihood) is a common learning algorithm used by a variety of machine learning algorithms, although it does make assumptions about the distribution of your data (more on this when we talk about preparing your data).

The best coefficients would result in a model that would predict a value very close to 1 (e.g. male) for the default class and a value very close to 0 (e.g. female) for the other class. The intuition for maximum-likelihood for logistic regression is that a search procedure seeks values for the coefficients (Beta values) that minimize the error in the probabilities predicted by the model to those in the data (e.g. probability of 1 if the data is the primary class).

We are not going to go into the math of maximum likelihood. It is enough to say that a minimization algorithm is used to optimize the best values for the coefficients for your training data. This is often implemented in practice using efficient numerical optimization algorithm

RANDOM FOREST CLASSIFIER

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of **ensemble learning,** which is a process of *combining multiple classifiers to solve a complex problem and to improve the performance of the model.*

As the name suggests, ***"Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset."*** Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

**The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.**

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier:

There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.

The predictions from each tree must have very low correlations.

**XGBOOST**

XGBoost is an [ensemble learning](https://courses.analyticsvidhya.com/courses/ensemble-learning-and-ensemble-learning-techniques?utm_source=blog&utm_medium=an-end-to-end-guide-to-understand-the-math-behind-xgboost) method. Sometimes, it may not be sufficient to rely upon the results of just one machine learning model. Ensemble learning offers a systematic solution to combine the predictive power of multiple learners. The resultant is a single model which gives the aggregated output from several models.

**CATBOOST**

CatBoost is a recently open-sourced machine learning algorithm from Yandex. It can easily integrate with deep learning frameworks like Google’s TensorFlow and Apple’s Core ML. It can work with diverse data types to help solve a wide range of problems that businesses face today. To top it up, it provides best-in-class accuracy.

It is especially powerful in two ways:

* It yields state-of-the-art results without extensive data training typically required by other machine learning methods, and
* Provides powerful out-of-the-box support for the more descriptive data formats that accompany many business problems.

“CatBoost” name comes from two words “**Cat**egory” and “**Boost**ing”.

As discussed, the library works well with multiple **Cat**egories of data, such as audio, text, image including historical data.

“**Boost**” comes from gradient boosting machine learning algorithm as this library is based on gradient boosting library. Gradient boosting is a powerful machine learning algorithm that is widely applied to multiple types of business challenges like fraud detection, recommendation items, forecasting and it performs well also. It can also return very good result with relatively less data, unlike DL models that need to learn from a massive amount of data.

Conclusion:

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# 3) USE OF FINANCIAL RATIOS TO MEASURE THE QUALITY OF EARNINGS

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