An atypical method for prognosis and analysis of financial insolvency

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ABSTRACT

In recent years, bankruptcy prediction has been a hot topic among the myriad of data analysts traversing across the globe so in this research paper I have presented a general framework regarding various methodologies for the prediction of bankruptcy by taking a skewed dataset and comparing it against the conventional methods. Also by taking into account various financial ratios of an enterprise and following a multi-variant approach of discriminant analysis, predicting the solvency of enterprise and thereby bankruptcy. In parallel to others, evolution in computing technology has given rise to an era in which Artificial Intelligence (AI) and machine learning form the foundation of bankruptcy prediction models. This paper aims at developing a framework of prediction using the ANN (Artificial Neural Network). The dataset will be used for analysis and the outcome of the study of conventional models will be viewed as a reference for comparison with the results of the current forecast model. Thus a breakthrough can be achieved in this sparsely trodden arena of finance which in the amalgamation of data science will alleviate the situations of banks and enterprises.

Keywords: Bankruptcy, Neural Network, ANN, Prediction.

INTRODUCTION

In recent years, the issue of corporate bankruptcy has drawn the attention of many finance industry investors, such as company investors, market analysts, banking, policymakers, and shareholders. Predicting financial disaster is not only critical for decision-making in banking firms but also, to some degree, decides the country's financial distress, as incorrect decision-making in banking firms can have a disastrous impact on a national or often global scale. While it is recognized that the neural network is among the best ways to predict bankruptcy, there are a few issues that need to be discussed for optimal neural performance. First, the learning algorithm used to train the neural network plays a crucial role in evaluating the efficiency of the neural network. Secondly, what is the perfect classification rate, so that the framework can be used by financial firms? Almost all of the related research focuses on finding the best framework for the financial decision-making problem. The suggested framework not only discusses the probability of predicting bankruptcy utilizing different financial ratios but also analyzes the best training algorithm. The best training algorithm will be delayed mostly on basis of the highest classification pace.

The dataset is all about the prediction of the bankruptcy of Polish companies. The data was collected from the Emerging Markets Info Service (EMIS), a database includes details on growing markets around the world. The bankrupt firms were evaluated in the period from 2000-2012, while the remaining operating companies were assessed between 2007 to 2013. Our prediction method is generally based on the analysis of the financial rates for the third year of the forecasting period and the respective class label indicating bankruptcy position after three years. The data includes 10503 (financial reports), of which 495 are bankrupt firms and 10008 are bankrupt companies.

Within this paper, we prove that Neural Networks are able to accurately predict whether a business will go bankrupt with high accuracy. We also show that the information obtained from training a dataset model could be used when training frameworks on future datasets for faster learning.

RELATED WORK

Bankruptcy prediction is an important and intensively researched subject in the field of data analytics. In short, there are two basic approaches conceptually available to predict bankruptcy: STRUCTURAL and EMPIRICAL. The former is primarily based on data collected on the financial statements and explains how these financial ratios have deteriorated as long as firms face bankruptcy. Comparison to prior empiric methods, neural networks do not need assumptions about the distribution of data and allow for nonlinear relationships alongside a linear model. This consideration is extremely crucial for bankruptcy predictions because the relationship between the probability of default and the explanatory variables does not have to be linear.

LITERATURE SURVEY

In [1]Naidu, G.P. et al; demonstrated that in the current long periods of financial disturbance, it is not astonishing that the bankruptcy prediction issue survives from extraordinary enthusiasm to analysts just as lenders, investors, and examiners. Firm bankruptcy is an issue all through the industrialized nations of the world.

In [2]Son, H., et al; has presented that financial ratios of variety are usually used. In a multivariate approach to discriminating analysis, in an effort for prediction of firm bankruptcies. Discriminant analysis is the technique used to build classification schemes in order to assign prior unlabeled predictions to the appropriate group.

In [3]Jia, Z., et al; mentioned that investors have a strong interest in this issue of decision. They want to recognize the negative developments of their lenders. Shareholders have common monetary worries. The auditors, as a standard obligation, must evaluate the financial status of the company in order to decide whether or not the operating capacity of the business is at risk.

In [4]Kliestik, T. et al; has shown that discriminant analysis is the technique used to divide objects into separate groups as per the characteristics observed by the object. Essentially, a linear function is developed that calculates the "score" for an object. This method is a weighted linear combo of the observed values of the object based on the distinguishing characteristics. In fact, these weights determine the maximum importance and impact of the different characteristics. An object is then classified according to its discriminatory score. Computer software programs often calculate the probability of group identity as per this process.

Hosaka, T.[5], implemented that multi-layer, feed-forward neural networks have been found to be of use to a variety of problem domains in and outside the business sector. For example, neural networks at large have been trained to evaluate whether loan applications must be approved.

García, V.[6], et al; proposed that the prevention and detection of fraud is another area for neural network applications in business. Credit risk analysis, a difficult and costly issue faced by banks, was dealt with by the National Bank of New York through neural networks. These models have proved to be even more productive than traditional regression analysis. In addition, neural networks have been successfully used to validate bank signatures.

Naidu G.P.[7], et al; suggested that neural networks have greater comprehension and distinction between two ideas (bankrupt firms and non-bankrupt firms) whenever an equal number of examples of each concept is used in the learning process. This finding is not significantly different from one's assumptions and previous results in a biased analysis.

PROPOSED SYSTEM APPROACH

An ANN (Artificial Neural Network) is a mathematical model that is inspired by the ability of our brain to process information. It consists of several interconnected nodes (neurons) that use interconnectedness to solve particular issues. The special advantage of this model is that it is capable of taking into account previous experience and thus making a more informed decision over a span of years.

The simplest neural networks are divided into three layers of components: input layers, hidden layers, and output layers. The input layer is responsible for providing raw data to the hidden layers. Each neuron connection throughout the hidden layer is connected with a weight (numeric value), and during several incarnations in the Learning phase, the weights in the hidden layer are modified to obtain an appropriate output when providing a specific input. Finally, the neurons in the output layer generate output based on input activities and hidden layers. The representative model for Artificial neural network is given below:

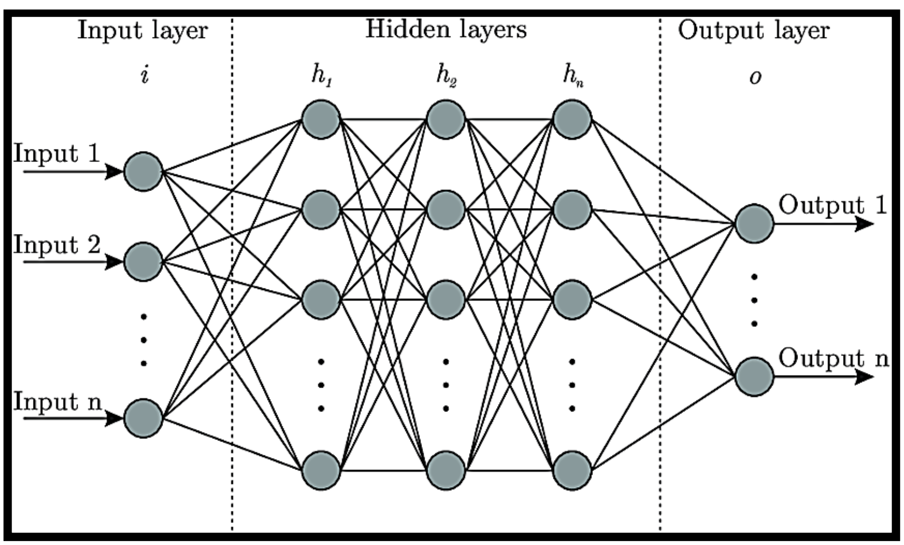


Figure 1 : Schematic representation of ANN

We use the sigmoid function as the activation function given below.

$$\boxed{\emptyset(\mathbf{z}) = \frac{\mathbf{1}}{\mathbf{1} + \mathbf{e}^{-\mathbf{z}}}}$$

Equation 1 : Sigmoid function

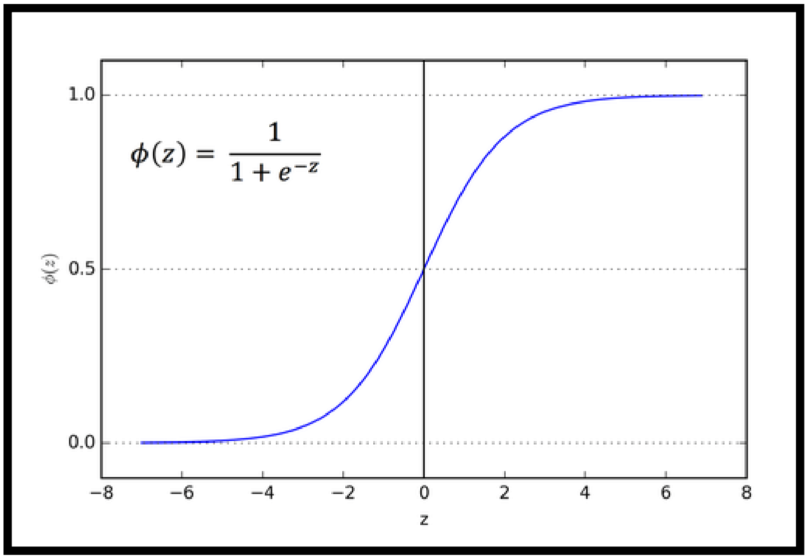


Figure 2 : Range of Sigmoidal function.

All these concepts are used in the training process for further predictions. Like in every prediction test, the inputs (arc weights) of the neural network model need to be calculated just before the model can be used for prediction purposes. The method for deciding these weights is called preparation. The training process is a vital part of the use of neural networks.

During the preparation procedure, examples or models are introduced to the I/P layer of a system. The enactment estimations of the information hubs are weighted and aggregated at every hub in the concealed layer. The weighted aggregate is moved by a fitting exchange work into the hub's actuation esteem. It at that point turns into a contribution to the hubs in the yield layer. At long last output is gotten to coordinate the ideal worth. The point of preparing is to limit the contrasts between the Artificial Neural Network O/P and the realized objective qualities for all preparation designs.

Also, we will compare a technique called bootstrap aggregating or bragging to train our model.

$$\boxed{\begin{aligned}\boldsymbol{X_j} &= [\boldsymbol{X_1} + \boldsymbol{X_2} + \boldsymbol{X_3} + \boldsymbol{X_4} + \cdots + \boldsymbol{X_p}] \\ \boldsymbol{Y_j} &= [\boldsymbol{Y_1} + \boldsymbol{Y_2} + \boldsymbol{Y_3} + \boldsymbol{Y_4} + \cdots + \boldsymbol{Y_p}]\end{aligned}}$$

Equation 2 : Training subsets in term of X and Y

Here the training set is $\boldsymbol{X_j}$ whereas the set of responses is $\boldsymbol{Y_j}$. The training was divided into n random subsets. The model then constructs the decision tree for each partition. This is executed to handle the issue suffered by the traditional decision tree, i.e. the problem of rising variance with increasing tree depth. When the training is completed, the final estimation for new X_p can be made by averaging all the predictions from the different n tree generated by the divided dataset i.e.

$$Y_n = \frac{1}{n} \sum_{i=1}^{n} f_n\,(X_p)$$

Equation 3 : Sample mean for the function

The data set used in this specific case has a total of 65 attributes. However, not all the attributes may be required to measure bankruptcy. Detailed analysis of previous works on bankruptcy prediction discovered 3 major factors to bankruptcy, listed below:

1. Liquidity:

In layman's terms, Liquidity is defined as the capacity of a company to meet its financial responsibilities as they arise. Let's claim the Company X has some short-term loans. In this case, the ability of X to pay off its loan and the efficiency with which X does so is called the 'liquidity ratio.' The liquidity ratio as a whole consists of the three most popular estimations and the average figure is the most popular and progressive of them, so much so that it is almost compatible with the liquidity ratio.

$$\text{Liquidity ratio} = \frac{\textbf{Present assets}}{\textbf{Present liabilities}}$$

Equation 4 : Equation to calculate Liquidity

Liquidity means how fast you can get your hands on your cash. Liquidity also plays a significant role as it helps you to take advantage of opportunities. If you have cash and quick access to the bank, and there's a lot going on, so it's harder for you to avoid the chance. Money, savings account, checkable account are liquid assets as they can quickly be turned into money as and when necessary.

2. EBIT:

Earnings before interest and taxes (EBIT) is an indicator of the profitability of a company. EBIT can be calculated as profits minus expenditure with exception of interest and taxes. EBIT is also known as net revenue, gross expenses, and income before debt and taxes. It can be calculated as:

$$EBIT = Taxes + Net\ Income + Interest$$

Equation 5 : Equation to calculate EBIT

3. Solvency:

In simple words, Solvency is the ability of a firm to meet its financial liabilities in the long term. Allow the organization to have 'X' debt obligations. Now, in order for the company to continue to be sustainable, the overall value of its properties must be higher than 'X.' Mathematically the solvency ratio can be expressed as:

$$\text{Solvency ratio} = \frac{\textbf{Depreciation+Net Profit}}{\textbf{Total liabilities}}$$

Equation 6 : Equation to calculate the ratio of Solvency

These three important attributes are formulated, this is of the highest concern that all attributes are independent, i.e. not all traits must be correlated. It is therefore crucial to set the above by using the Pearson coefficient.

RESULTS

We got the results as we were done with the calculations on our dataset:

Now, let us find out if there is some correlation among the missing features.

Using the heatmap function from missing no library, let us plot the heat maps for all the dataframes.

Input:

```
In [41]: # generate the heatmap for all the dataframes
         def generate_heatmap(dfs):
             for i in range(5):
                 missing_df_i = dfs[i].columns[dfs[i].isnull().any()].tolist()
                 msno.heatmap(dfs[i][missing_df_i], figsize=(20,20))

         generate_heatmap(dataframes)
```

Figure 3 : Input for generating heat maps

Output:

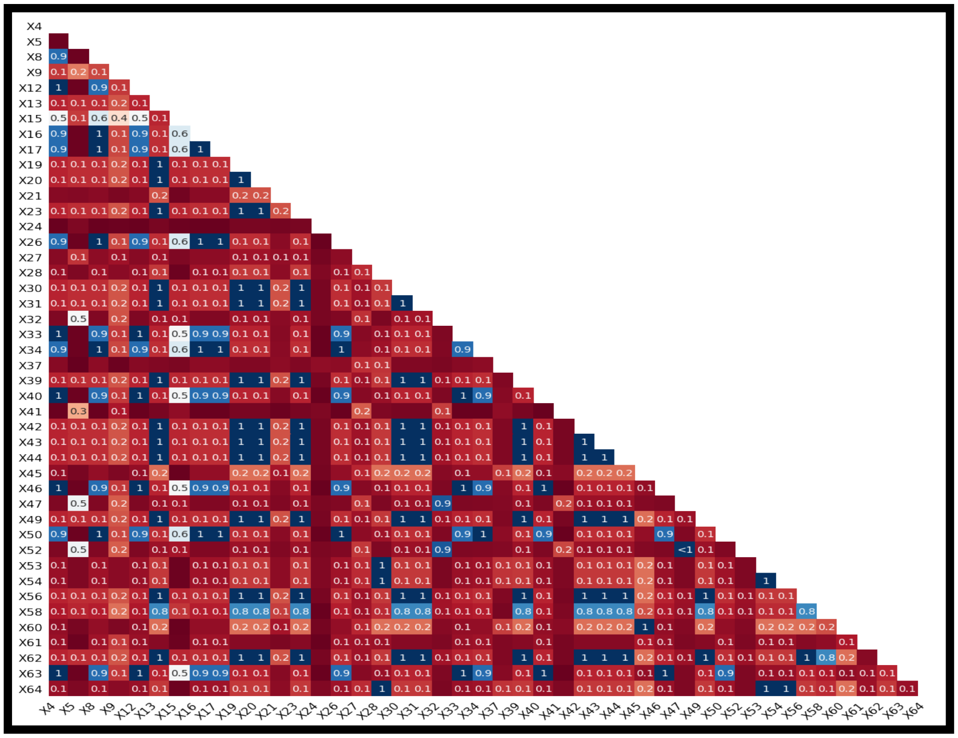
:

Figure 4 : Output : Heat Maps

The heat maps above, for all the 5 dataframes, describe the degree of nullity relationship between different features.

The scope of this nullity relationship is from - 1 to 1 (- 1 ≤ R ≤ 1).

Highlights with no missing worth are barred in the heat map.

In the event that the nullity relationship is extremely near zero (- 0.05 < R < 0.05), no worth will be shown.

An ideal positive nullity relationship (R=1) demonstrates when the principal includes and the second element both have comparing missing qualities.

An ideal negative nullity relationship (R=-1) implies that one of the highlights is missing and the second isn't absent.

The takeaway is that, in each dataframe, there are some features that are heavily correlated (R = 1 or -1) and also there are features that are not essentially correlated.

- **Calculations:**

Attribute	Mean	Standard deviation
Liquidity Ratio	8.679	521.012

Attribute	Mean	Standard deviation
Solvency	2.523	109.236
EBIT	0.068	0.659

Table 1 : For the specific attributes we calculated Mean and Standard deviation

Attribute	Corresponding Subscript Notation
Liquidity Ratio	1
Solvency	2
EBIT	3

Table 2 : References for a particular attribute

The Pearson correlation coefficient is a proportion of the correlation between two factors X and Y. It has an incentive somewhere in the range of +1 and −1, where 1 is all out sure direct correlation, 0 is no straight correlation, and −1 is complete negative direct correlation.

$$\boxed{\mathbf{r} = \mathbf{r}_{\mathbf{x}\,\mathbf{y}} = \frac{\mathbf{Cov}\ (\mathbf{x}, \mathbf{y})}{\mathbf{S}_{\mathbf{x}}\ \mathbf{x}\mathbf{S}_{\mathbf{y}}}}$$

Equation 7 : Pearson correlation coefficient

Where, Random event = X and Y

Standard deviation of event X and Y are SX and SY.

Co-variance X and Y = Cov(x,y).

If $-1 < r_{xy} < 1$

Then Event Y is independent of Event X.

Attributes Concerned	*Pearson Correlation Coefficient*	*Pearson Correlation Coefficient Value*
1 & 2	R12	0.121709442195
2 & 3	R23	0.503565500850

Attributes Concerned	*Pearson Correlation Coefficient*	*Pearson Correlation Coefficient Value*
3 & 1	R31	0.001677816273

Table 3 : Values of correlation coefficients

As a result, the neural network unmistakably outflanked the analysis investigation in expectation exactness of both bankrupt and non-bankrupt firms under changing preparing and testing conditions. Furthermore, it was demonstrated that neural networks offer a huge improvement in the forecast over the unadulterated possibility and that their utilization in expectation can decrease blunders in this issue space by as much as 93% over the possibility.

Neural Networks, thusly, speak to an arrangement strategy that is a strong and promising methodology in the expectation of firm solidness. While this examination is exploratory and has a few constraints as noted, it has demonstrated the guarantee of neural networks using a lot of strong measurable investigations that ought to be used as exploration proceeds here.

CONCLUSION AND FUTURE WORK

In this paper, we came to know that neural networks can be used to predict the financial status of firms with large accuracy. The three components considered for estimation are independent of each other and therefore the use of these factors to evaluate bankruptcy is more or less acceptable. Using a neural network with a sigmoidal activation function, an error of 4.4349 percent occurs after 150 epochs. Nevertheless, the outcome of the Random Forest Classification was poor relative to the previous approach, with a higher error rate, precisely 5.1954 percent. We have also found that a neural network is more effective in forecasting a company's bankruptcy.

For future work, we propose to reach this dilemma as a problem of outlier detection where firms with a safe operation are not an anomaly. This framework will be able to address the issue of skew class. We do believe like this question may be a red flag for some other financial concern and not just potential bankruptcy.

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