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Experimental Analysis of Bankruptcy Prediction with SHAP framework on Polish Companies

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Abstract

With the fast development of artificial intelligence day by day, users are demanding explanations about the results of algorithms and want to know what parameters influence the results. In this paper, we propose a model for bankruptcy prediction with interpretability using the SHAP framework. SHAP (SHAPley Additive exPlanations) is framework that gives a visualized result that can be used for explanation and interpretation of machine learning models. As a result, we can describe which features are important for the result of our deep learning model. SHAP framework Force plot result gives us top features which are mainly reflecting overall model score. Even though Fully Connected Neural Networks are a "black box" model, Shapley values help us to alleviate the "black box" problem. FCNNs perform well with complex dataset with more than 60 financial ratios. Combined with SHAP framework, we create an effective model with understandable interpretation. Bankruptcy is a rare event, then we avoid imbalanced dataset problem with the help of SMOTE. SMOTE is one of the oversampling technique that resulting synthetic samples are generated for the minority class. It uses K-nearest neighbors algorithm for line connecting method in order to producing examples. We expect our model results assist financial analysts who are interested in forecasting bankruptcy prediction of companies in detail.

Keywords: *Shapley value, Explainability, Bankruptcy prediction, Model interpretability, Transparency*

1. Introduction

In recent years, artificial intelligence-based financial analysis applications have become widely used in decision making. Among those financial analysis applications, bankruptcy prediction is a notably widely studied field. The purpose of bankruptcy prediction is to forecast whether the borrower will default or go bankrupt in the future due to specific reasons. Also, it can prevent human stakeholders from economic losses and allows them to understand which financial indicators will lead a company to bankruptcy.

Although those AI based applications have shown effective results, the decision needs to be convincing to human because users are demanding a detailed explanation of the results. According to this requirement, the

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governments of some countries have passed laws and regulations. For example, the European Union introduced a new law called “right of explanation”, while the United States submitted a bill called “Algorithmic Accountability Act” to the Senate in February 2022.[1]

One of widely used explainable AI (XAI) models is Shapley Additive Explanations (SHAP) framework, devised by Lundberg and Lee in 2016 [2]. Shapley value is a very successful concept in cooperative game theory, American mathematician Lloyd Shapley invented this idea in 1953 and he was also awarded the Nobel prize for economics in 2012 [3]. SHAP helps human to determine which of the given financial indicators have a major impact on bankruptcy and has been proved to be an effective tool to implement machine learning model with interpretation.

Considering these backgrounds, it will be meaningful research to implement explainable AI models for bankruptcy prediction task. In this study, we use fully connected neural networks [4] (FCNNs) with three hidden layers to construct bankruptcy prediction model. Although FCNNs are considered as “black box” model, SHAP framework implementation gives a model transparency. Furthermore, SHAP will provide reasonable explanation about contributions of features.

This paper consists of five sections. Section 2 is about background, while Section 3 describes the algorithm we used and data and hyperparameter tuning. Moreover, Section 4 is a part for experiment and results, then finally Section 5 is for conclusion.

2. Background

The motivation behind the XAI is lacking transparency of the black-box approaches. Machine Learning Model needs to explain its result to the end users, otherwise system will not meet the requirement of customers nowadays. Many leading Artificial Intelligence (AI) research organizations and universities such as UC Berkeley, Carnegie Mellon University and Institute for Human and Machine Cognition (IHMC) are participating in DARPA’s (Defense Advanced Research Projects Agency) XAI program [1] which has $2 billion dollars for funding. Their toolkit library is still under development phase and can be used for commercial purposes not only for military application.

The first definition for interpretability is “The degree to which a human can understand the cause of a decision in a model” given by O. Biran and C. Cotton [5] in 2017. Therefore, interpretability can be measured between low and high, but no such measurement has been used yet.

As for bankruptcy prediction research, the first publicly known bankruptcy prediction was published in 1930's, using ratio analysis [6]. As AI becomes more advanced, commercial banks and investment companies are interested in bankruptcy predictive models with advanced machine learning techniques. For instance, deep learning method is widely used for classification tasks like bankruptcy prediction.

In 2012, Evangelos Sfakianakis published paper called Bankruptcy prediction model for Greek companies implementing multivariate discriminant analysis [7]. After three years, “Variable selection and corporate bankruptcy forecasts” [8] paper utilized the state-of-the-art LASSO variable selection method for the bankruptcy data from the companies in the United States of America. New idea for bankruptcy prediction that supports relational data is presented in [9] in 2017. According to the result of this research [9], relational data and financial data together gave increased forecasting ability.

SHAP framework can be used with almost any machine learning algorithms including FCNNs. Therefore, we can give proper explanations in detail by FCNNs implementation to end user. Then financial analysts can use these results for decision to lend or not to lend, also they can use the results for their own further research or analysis as well. Thanks to SHAP framework, it is possible to know contribution of each feature for the final results. Consequently, explainability from the framework can give feedback to developers to verify if the model is working as expected.

3. Methodology

3.1 Algorithms

As for the algorithms and models for our study, we use Fully connected neural networks (FCNNs), shown in Figure 1. FCNNs (or sometimes called "densely connected neural network") is one type of artificial neural network and widely used due to its structure agnostic characteristic [10]. It is called fully connected because of the architecture, each neuron in a layer is connected to every neuron of the next layer [11].

Main drawback of FCNNs is that they consist of too many weights to train than needed, and thus sometimes training time is much longer than those of other algorithms. Considering this drawback, we choose to use FCNNs with three hidden layers which consists of 33 neurons for each layer. In our experiment, ReLU was used as activation function for hidden layers and, Sigmoid was used for final output layer.

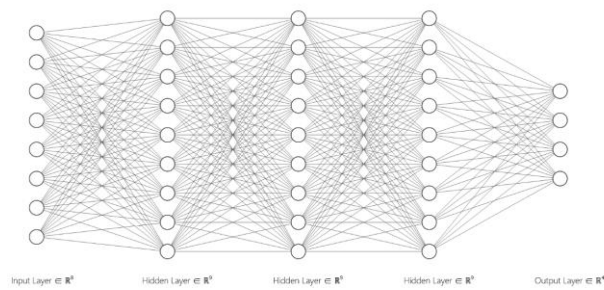

Figure 1. Fully Connected Neural Network

Theoretically, the Shapley value is the average marginal contribution of each attribute value across all possible values in the attribute space. We can use these values to determine every attribute contribution in coalition game [12]. For better understanding, assume that friends share only one cab to go to different places they want, then each passenger's payment can be calculated using Shapley values [3]. In basic concept of this game theory, Shapley value meets requirements for fairness properties such as efficiency, symmetry, null player and group additivity [13].

When we implement SHAP python library to Machine learning models, we should keep in mind that adding more features will cause geometric growth for computation time. In other words, this is called the curse of dimensionality because SHAP generates all possible combinations of features during calculation process. So, in our experiment, we used the data containing less than 70 features to avoid this exponential dimensionality problem.

3.2 Data

The dataset we used is bankruptcy prediction of Polish companies which were analyzed in the year 2012. The data source is from Emerging Markets Information Service (EMIS), which is an open database containing information on emerging markets globally. Data containing 5,438 instances (financial statements), 419 of them are bankrupted. The data has 64 financial ratios as features and we use all features for improved SHAP implementation.

We used 70% of the data for training the models and kept 30% of the data as a holdout set to test the model. Among the scikit-learn packages, *model_selection* has function called *train_test_split* in order to divide arrays or matrices into training and test data randomly. This function has specific parameter named "*stratify*" which stands for keep chosen column's data distribution into train and test data proportionally during splitting process. We split data with *stratify=y* option that helped us so that 419 bankrupted instances were equally divided for training (70%) and test (30%). We tuned our hyperparameter, as the number of epochs is equal to 50 and batch size is 512. We used Sigmoid activation function for output layer, therefore output values are real numbers between 0 and 1. In order to make binary classification, we set threshold value as 0.5 which means if value is less than 0.5 we interpret as 0 or "bankrupted".

4. Experiment and Results

Our stratified data contains 5,438 records, out of which 419 of the total records are bankrupted giving us a dataset with 8% of target samples which is moderately imbalanced. Therefore, we used SMOTE [14] to resampling for training in order to avoid imbalanced data problem. We implemented our experiment using the Python-based Keras[1] and SHAP[2] library.

In addition, we used Tensorflow for the Artificial Neural Network. We ran the experiment on a PC with 32GB of RAM and a core i7 processor, shown in the Table 1.

Table 1. Performance metrics

	Precision	Recall	F1-score	Support	Accuracy
All				1,629	0.65
0	0.94	0.67	0.78	1,506	
1	0.10	0.46	0.17	123	
Macro avg	0.52	0.56	0.47	1,629	
Weighted avg	0.87	0.65	0.74	1,629	

As is shown in the Table 1, model accuracy is 0.65. In every three hidden layers, we set Dropout value as 0.2 and set loss function as Binary Cross entropy. Recall scores quite similar because of SMOTE resampling. Precision and F1 score of bankrupted instances are significantly low compared to not-bankrupted instances. *Support* indicates number of actual occurrences of the class in the dataset. Summation from each class support numbers is equal to total number of the instances.

The Force plot of SHAP framework for our experiment is as follows (in Figure 2):

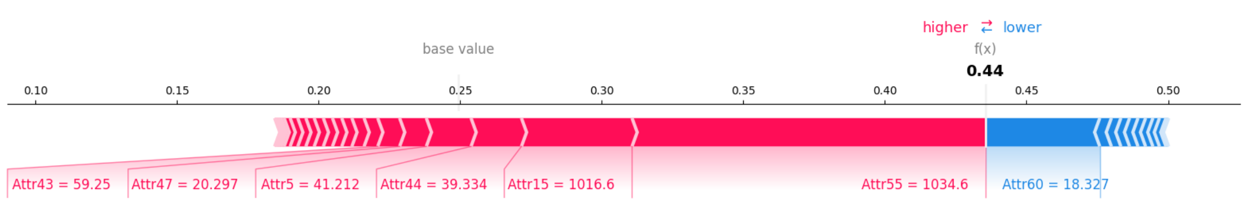

Figure 2. SHAP Force plot

We will explain attributes in the Figure 2 in the Table 2:

[1] Keras official website. https://keras.io/

[2] SHAP website. https://shap.readthedocs.io/en/latest/

Table 2. Feature details

Name	Explanation	Shapley value	Force
Attr55	working capital	1,034.6	Higher
Attr15	(total liabilities * 365) / (gross profit + depreciation)	1,016.6	Higher
Attr44	(receivables * 365) / sales	39.3	Higher
Attr05	[(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365	41.2	Higher
Attr47	(inventory * 365) / cost of products sold	20.2	Higher
Attr43	rotation receivables + inventory turnover in days	59.2	Higher
Attr60	sales / inventory	18.3	Lower

As is shown in the Figure 2 and the Table 2, derived from our bankruptcy prediction model, the red items in the left, such as *working capital* and *(total liabilities * 365) / (gross profit + depreciation)* ratio pushed model score higher while the blue item in the right, *sales / inventory* ratio has decreasing effect that pull down overall model score lower. Values on the axis are top features of the dataset. Model output value is 0.44. *Working capital* is the first top feature and its calculated Shapley value is 1,034.6 then followed by features Attr15, Attr44 and Attr05. These Shapley values are calculated by getting the average of differences from every possible generated subsets. This means the Shapley value is the mean value of marginal contributions from those generated subsets.

5. Conclusion

SHAP framework allows us to explain FCNNs approach for bankruptcy prediction in detail. There are other frameworks like QII framework for model interpretation based on Shapley value similar to SHAP framework. QII framework estimation method is sampling-based. Quantitative Input Influence (QII) is also has interventional nature which is aimed at changing a process or situation while SHAP framework approach is conditional. For this reason, SHAP framework is suitable for our experiment.

In this paper, we propose a model for bankruptcy prediction with interpretability using the SHAP framework. As a result, we can describe which features are important for the result of our deep learning model. Even though Fully Connected Neural Networks are a “black box” model, Shapley values help us to alleviate the “black box” problem. Therefore, FCNNs perform well with complex dataset like more than 60 financial ratios. Combined with SHAP framework, we created an effective model with understandable interpretation.

We expect our model results assist financial analysts who want to forecast bankruptcy prediction of companies in detail.

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