Chapter 11 Return Prediction Models and Software Reviews

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Abstract. After the failure of many high profile firms such as Enron, WorldCom, Kmart, and Conseco; bankruptcy prediction and bankruptcy recovery prediction has become high interest. While there has been extensive research into the area of bankruptcy prediction, there has been little research done on the return to stockholders after companies are released from Chapter 11 bankruptcies in the USA. A history of bankruptcy prediction is provided, as well as a discussion on fraud detection, general bankruptcy information, and a brief background overview for bankruptcy prediction ratios used. This study focuses on the software used in the application of various prediction models to predict the return of investment in companies filling for Chapter 11 bankruptcy. Models were created using the software packages; See5, Cubist, and PolyAnalyst. These packages were used to create various models using decision trees, rules, a decision forest, and a linear regression model. The data mining models created use statistics and other soft computing methods to provide insight on limited use of the models for predicting the return to stockholders with the methods tried, variables used, and only the information at the time of Chapter 11 bankruptcy filing. While the results were not as solid as hoped for in blind testing with a 40% error rate (which may have be due to curve fitting, as the best model has only a 2.4% error rate in training), they do point out various pitfalls and future directions which are both clear and are predicted to provide better results with the addition of historical data, more cases, and general economic factors. A large section of this study focuses on the benefits and drawbacks found from the use of the software packages. Benefits such as, their general acceptance and use and drawbacks like; their black-box approach, lack of tweak-ability, and user knowledge requirements for and correct application.

Keywords. Data Mining, Case-based reasoning, Applications, Machine Learning

1 INTRODUCTION

In the wake of the failure of firms like, Enron ($63 billion, in total assets prior to bankruptcy), WorldCom ($103 billion), Kmart ($14 billion), and Conseco ($61 billion)[1], many people have been left wondering if there had been telltale signs for each so that they might have been able to sell stocks, recall loans, or even fix the problems.

Economy changes such as exchange rates, fraud, torts filed against a company, or problems with specific issues like; asbestos (Eagle-Picher Industries Inc, Federal-Mogul Corporation, and Kaiser Aluminum Corp.), environmental (Gulf USA Corp. and The Jesup Group Inc.), patents (Paragon Trade Brands, Inc. and Smith International Inc.), or pension (CF & I Steel Corp., Geneva Steel Holdings Corp., and Kaiser Steel Corp)[2], can all be major factors in a company's bankruptcy.

Fraud may cause a company to go into bankruptcy or be used by a company to hide that it is going into bankruptcy. Detecting fraud can be done with methods such as; cash flow analysis[3], chaos theory, and using Benford's Law[4].

2 DATA AND CHOICE OF VARIABLES

Data was collected from the SEC (Securities and Exchange Commission) on companies who filed for chapter 11 and had cases closed between 1994 and 1999 for the purposes of SEC monitoring, which resulted in 200 companies collected from this source. This data was used to create the models for this study. Initial review of the data indicated that the small number of companies might be a problem in creating an accurate model [5] and, therefore, for bankruptcy prediction, companies were also collected from the webBRD database[2]. The webBRD database includes all of the companies with $100 million plus in assets (measured in 1980 dollars according to the last 10-K that was filed with the SEC), are considered public from SEC filings for at least three years prior to bankruptcy, and who did not file to go private more than one year prior to bankruptcy, and companies who went through bankruptcy courts for the purpose of administration. The number of cases between 1 October 1980 and 30 June 2002 [2] totaled 569. The CRSP [6] and Compustat [7] databases also provided most of the financial data listed of the companies used in the study.

2.1 **Data Requirements**

To be used in the study, companies had to be listed in the NYSE, AMEX or NASDAQ and be available in the CRSP [6] and Compustat [7] databases. Financial institutions were excluded. For the chapter 11 cases; share prices had to be available 1 day or up to 6 months before filing and a reason for closure of the case by the SEC had to be available.

2.2 Ratios

In order to create a bankruptcy prediction model, or use soft computing methods, it is important to determine which indicators are most important in bankruptcy prediction. Many times soft computing methods have been used to select which factors would be best for models[8, 9].

Traditionally, one of the pioneers in bankruptcy prediction, Altman [10], suggested the following parameters:

- Working capital/total assets
- Retained earnings/total assets
- Earnings before interest and taxes/total assets
- Market capitalization’s/total debt
- Sales/total assets

These ratios were chosen because of the following reasons, by using total assets, we are providing an indication of firm size and this many times is used as a normalizing factor. Working capital provides an indication of ability of the firm to pay short-term obligations. Earnings are important because they show how competitive a company is and if it drops too low may be an indicator for the loss of competitive edge.

Many other ratio variations have been used and tried though the years without being revisited, therefore, providing no ideal set of ratios to use in bankruptcy prediction models. Researchers tend to be interested in getting a new set of parameters, ratios, etc and reanalyzing previous studies, therefore, the number of methods and ratios available is very large. [3]

The following table provides a list of ratios used in this study for bankruptcy prediction, and other studies that have used them.

Table 1. Ratios Used in Model Creation

Ratio	Source
Cash/Current Liabilities	[9, 11, 12]
Cash/Net Sales	[9, 12]
Cash/Total Assets	[9, 12]
Current Assets/Current Liabilities	[9, 12-15]
Current Assets/Net Sales	[9, 12]
Current Assets/Total Assets	[9, 12, 16]
Current Liabilities/Equity	[9, 11]
Equity/Fixed Assets	[9, 17]
Equity/Net Sales	[9, 11, 18]
Inventory/Net Sales	[9, 11]
Long Term Debt/Equity	[9, 16]
Net Sales/Total Assets	[9, 10, 18]
Operating Income/Total Assets	[9, 10, 15]
Retained Earnings/Total Assets	[9, 10, 15]
Working Capital/Net sales	[9, 11, 12]
Working Capital/Equity	[9]
Working Capital/Total Assets	[9, 10, 12-14, 19]
Op income/ net sales	[20]
Long term debt reduction / long term debt	New

Debt in Current Liabilities/Current Liabilities	New
Debt - Due in One Year / Long term debt	New
Debt - Due in 2 Year / Long term debt	New
Debt - Due in 3 Year / Long term debt	New
Debt - Due in 4 Year / Long term debt	New
Debt - Due in 5 Year / Long term debt	New
Research and Development Expense/ Assets – Total	New

The ratios with debt due in various years were not used in any of the other readings, most likely, because they were not as easily available. While they seem like they may provide some insight on the financial situation of a company, because if the company were taking on more debt in recent years to balance losses in income, it did not seem to provide much information in the final models, to date.

3 PREVIOUS BANKRUPTCY RESEARCH

Beaver [14] is often referred to as one the founders of bankruptcy research, for his univariate bankruptcy model. Later Altman [10] extended Beaver's [14] model with the use of multidiscriminant analysis (MDA) to create a model which was meant to determine if a company was a 'survivor' or in 'financial distress'. Models using MDA picked up popularity and were done by various researchers; Altman, Haldeman, and Narayanan [15] created a model for USA companies. The majority of distress prediction models have been done on US firms due to the availability of data; however in 1994 there were at least three dozen studies devoted to other countries [21]. MDA analysis continues to be one of the benchmark methods despite heavy criticism [22-25]. Most of the arguments against discriminant analysis were based on the requirements imposed by the statistical method, such as; a multivariate normal distribution (often violated by using dummy variables for example) only provided an ordinal ranking and the difficulty in determining the significance level of variables in the overall score. Because of MDA criticism, logit was used by Ohlson [26] and Peel, Peel, Pope [27]. Multinomial logit was used by Lau [28] and probit by Pacey and Pham [29]. Also during this time recursive partitioning was used [30, 31].

Bankruptcy and distress prediction fall into the soft computing category by being a classification problem, such that the final goal is to classify the companies into distress or survival. Some of the general classification problems using soft computing included; survival analysis[32], goal programming [33], multicriteria decision/support methods [34], rough sets methods [33], expert systems [35, 36], neural networks [37], Cox's Proportional Hazards Model [38], and self-organizing maps [39]. In the area of distress prediction for financial institutions, credit union failure prediction models for Australian companies were created [25, 40] as well as ones were created for US banks entering failure [32].

Soft computing methods specifically applied to bankruptcy prediction include probabilistic neural networks [41] and backpropagation neural networks [33, 41]. These soft computing models were specifically important because they offer qualitative methods that traditional quantitative tools in statistics and economics cannot quantify because of the complexity in translating the systems into precise functions [42].

Various methods used in prediction have been studied as well as the use of different ratios and factors incorporated into models for predicting distress; such as, environmental factors, interest rates, employment rates, and factors that point to competition in the industry. Rose et al. [43] used macroeconomic factors, as did Platt and Platt [44] who also incorporated business running costs, such as how much it would cost for a new business to form. One recent advance in bankruptcy prediction included receiver operating characteristics curves [45]; in which firm specific and economy wide data were used, and it was determined that there was little difference, whenever overall economic data was used in the model or not.

3.1 Bankruptcy in the USA

Chapter 11 is a form of bankruptcy in the USA. Chapter 11 was created in order to let companies have more time to either attempt to recover from bankruptcy or allow companies to attempt to reduce losses through planned methods (such as: giving managers a break from collectors for a time; loan renegotiation; allow time for liquidation--in order to get better value from sales; or allow companies to reorganize the company structure). For a company to file for chapter 11 they must submit a plan detailing what they are aiming for and how they expect to get there. In the filing process courts must first approve the plan submitted. Then the company is released from Chapter 11. When a company is released from Chapter 11 bankruptcy, shareholders either loose all value or have some worth.

Another form of bankruptcy is Chapter 7. Chapter 7 is chosen less often, since creditors usually get back less than they do under chapter 11. However, Chapter 11 allows companies to get themselves into worse debt and allows new loans to take higher precedent over previous loans. Various research projects have been devoted to determining which type of bankruptcy, creditors should push for, in order to get the most value for their specific situation. When a loan is re-negotiated, under chapter 11, to a lower amount, even if the company is able to pay the creditor back later, the full amount of the original loan, it is not required. Due to the risks associated with bankruptcy, many times, crediting companies will close the company down sooner than it should have (getting less of their debt repaid than what might have been possible with more time), this leads to races among the collectors, since whoever collects first, gets the most; the others may get nothing. In many situations, if both creditors had waited, there may have been better and fairer payments possible for both parties [46]. Because of this, not only would it be beneficial to know if a company is going into bankruptcy before other entities know, it would also be beneficial to judge if the company would be able to recover or provide shareholders with any return value [46].

4 MODEL CREATION

Models were created using the software packages; See5, Cubist, and PolyAnalyst. These packages were used to create decision trees, rules, a decision forest, and a linear regression model. PolyAnalyst was by far the most robust software package and is able to design the following types of models; decision forest, summary statistics, linear regression, cluster analysis, decision trees, nearest neighbor, and a polynet predictor (also known as a neural network). See5 was able to create decision trees and rules. Cubist was able to create rules and basic statistics. In general, decision trees are used to quickly and graphically view data and can be converted to rulesets easily as well. In PolyAnalyst, "The Decision Tree exploration engine helps solve the task of classifying cases into multiple categories. Decision Tree is PolyAnalyst's fastest algorithm when dealing with large amounts of records. Decision Tree report provides an easily interpreted decision tree diagram and a predicted versus real table [47]."

The models were evaluated based on their overall prediction of the number of errors as well as the type of misclassification. Type I errors represent the false prediction that stockholders will receive some value from their investment, when in fact they receive no value. Type II errors represent the false prediction that a company that does have return to stockholders, is classified as having no return.

The model created provides insight on how the return to stockholders could not be predicted with the methods tried, variables used, and using only the information at the time of Chapter 11 bankruptcy filing.

4.1 See 5

In the See5 model, 190 cases were used for training and 10 for testing. After boosting was applied, 8 were misclassified in the initial model creation giving a result of 4.2% (1 Type I and 6 Type II) and of the 10 used for testing, 4 were misclassified providing a result of 40% misclassification error (1 Type I and 3 Type II). See5 was simple to use, yet in testing it was not a very accurate model. Much of this may be due to a lack of data to create the model, as well as lack of inputs. In distress prediction models, it is shown that various values were good for prediction for which the data was not available in these models. With increased inputs and increased data it is suspected that a more accurate model could be created. According to the See5 software help files, one of the reasons to use See5 is that, "…classifiers are expressed as decision trees or sets of if-then rules, forms that are generally easier to understand than neural networks [48]."

See5 has an option to use boosting (used here) which is based on research done by Freund and Schapire. Boosting will generate multiple classifiers and combine them into one; which is meant to improve accuracy [48]. With training sets, which have a lot of noise, boosting can actually reduce the accuracy [48]. It may be that the noise in the dataset actually reduced the accuracy of the model and farther studies would prove it to be more accurate without the use of boosting.

4.2 Decision Trees

In this study, the PolyAnalyst decision tree produced an error rate of 27.50%, but only removed the 9 unknowns by simply branching on the 'date in which the company was dismissed from bankruptcy' (in other terms; if the company had not been dismissed it predicted that it would be unknown, this method also misclassifying 2 of the known values as unknown), which was far worse than the See5 error rate of 4.2% created with the training data. When the See5 model was tested, it proved far worse than the PolyAnalyst's Decision tree model, with 50% being misclassified. So, it is only predicting something that could easily have been removed based on simple logic without much data exploration and does not shed light on the fact that if the unknowns are removed and all else are classified as no return, you would only get a 27.50% error rate.

4.3 Cubist

181 cases were used in training the Cubist model. This is fewer cases than were used with See5 because of the unknown results for 9 of the datasets which were removed (because of the previous misclassifications with See5 and Cubist not accepting unknown fields). In the training set, the average error was about 16.78%, however, the relative error was 40%, and the correlation coefficient was 0.86. The test set provided an average error of only 15.64%, however, the relative error was 50% and there was no correlation coefficient.

4.4 Decision Forest

The decision forest provided an error of 31.5% however accomplished this by classifying all of the companies as having no final stock price value. And, therefore, works as a sort of benchmark for the maximum error rate. Therefore, if Type I errors mattered most to get rid of, this model would give what seems like acceptable answers, while, actually performing no prediction.

4.5 Linear Regression

The linear regression model using PolyAnalyst produced a standard error of 0.8999, and when the formula was applied to the data, 64 were wrongly classified: none were type I errors, however there were 64 type II errors. This method had more type II errors than any other method.

5 RESULTS

Table 2. Results from Training the Models

Program	# wrong	Errors %	Type I	Type II	Unknown
See5 Tree boost	8	4.2	1	6	9
See5 Rules Boost	8	4.2	1	6	9
PolyAnalyst Decision Forest	63	31.50	0	63	0
PolyAnalyst Linear Regression	64	31.80	0	64	0
PolyAnalyst Decision Tree	55	27.50	0	53	11
Cubist		40.0			

Table 3. Results from Testing the Models

Program	Number wrong	Errors %	Type I	Type II	Unknown
See5 Tree boost	4	40.0	1	3	
See5 Rules Boost	4	40.0	1	3	
Cubist		50.0			

5 CONCLUSION

The benefits of using the analysis packages (See5, PolyAnalyst, and Cubist) are in their use and testing over time. The drawbacks of the packages, used, are that many times they have a black-box approach. They don't tell what was done to get the final results. This is especially true for many of the features of PolyAnalyst, which also, did not allow for as much tweaking. None of the packages here were designed specifically for bankruptcy or distress prediction, only general data analysis, which meant they required user knowledge and correct application. This was illustrated by the initial results from the See5 study, where using the data without ratios, provided much lower prediction results. The packages also provided output, in the form of classification groups, rather than a numeric scale.

When reviewing the decision forest results, it can be seen that by *only* classifying *all* the companies as having no return to stockholders after Chapter 11 bankruptcy, there is an error rate of 68.50%. This then only points out that without doing any prediction 68.5% of the time, this data will show no value. Implying any error rate above 31.50% is of little value. When this is compared to the model created in See5 (with an error rate of 12.6% on trial 0 and 5 and a boost result of 2.4%) the training proves promising, however when the trial is run, the boost showed a 40% error rate (with 4 of 10 being miss-classified) far above the minimum of 31.50%. The high error rate with See5 may be due to curve fitting, which with added pruning may provide better results however more data would need to be collected and separated into blind and testing groups in order to avoid creation bias. Cubist proved no better with a relative error of 40% in training and 50% in testing. The linear regression provided by PolyAnalyst proved to be even worse, with a standard error of 89%. If proving that none of the results were beneficial was not disheartening enough, the results from the decision tree created in PolyAnalyst had an error rate of only 27.50% this, when it simply split the data into 3 sections based on the date the company was released from bankruptcy, which in retrospect, should have been left out anyway.

While PolyAnalyst provided much flash and splash, and many types of models, the best model created here, used See5. With more data it may prove to be much more powerful as it did attempt to keep tree sizes and other factors down to a much lower level (15-17 levels verses 1 level).

Future research goals include: running various other tools and re-running many of the tools used here with other inputs like economic factors. Other goals include adding more data with time-series analysis. This would include data before Chapter 11 bankruptcy was filed.

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