

Using Soft Computing Techniques to Create a Hybrid Model for Predicting Chapter 11 Return to Shareholders

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Abstract. When Enron and WorldCom filed for bankruptcy the shock was felt worldwide; bankruptcy prediction and bankruptcy recovery prediction have been receiving more attention as people are looking for signs. While there has been extensive research into the area of bankruptcy prediction, there has been little research done on the return to shareholders after companies are released from Chapter 11 bankruptcies in the USA. This study focuses on the creation of a model for predicting the return to shareholders using a hybrid of expert systems and recursive partitioning models. Software used in the creation of the models include; See5, Cubist, and Excel.

Keywords: Bankruptcy, Recursive Partitioning, Decision Tree, Expert System, See5, Cubist, Chapter 11.

1. Introduction

With the fall of firms like, WorldCom, Enron, Consec, and Kmart (\$103 billion, \$63 billion, \$61 billion, and \$14 billion respectively in total assets prior to bankruptcy) [1], many people have been left wondering if there had been signs of bankruptcy prediction.

Economic and environmental changes such as; exchange rates, unemployment rates, sickness of key employees, and new laws, can all be major factors in bankruptcy. Company problems such as, fraud and poor management can also be factors. Even issues like; torts filed against a company or specific issues like; asbestos, environmental, patents, or pension [2], can all be major factors in a company's bankruptcy.

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. The CRSP [3] and Compustat [4] databases accented these selected companies with extended financial data. To be used in the study, companies had to be listed in the NYSE, AMEX or NASDAQ and be available in the CRSP [3] and Compustat [4] databases; which reduced the number of companies used for the study to 170. Financial institutions were also excluded or 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. Of the one hundred and seventy companies used, 125 (74%) of them had no return of value to shareholders and 45 (26%) did have some return.

2.1 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 [5, 6].

Traditionally, one of the pioneers in bankruptcy prediction, Altman [7], 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 reanalysing previous studies, therefore, the number of methods and ratios available is very large [8].

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

Ratios	Source
Cash/Current Liabilities	[6, 9, 10]
Cash/Net Sales	[6, 10]
Cash/Total Assets	[6, 10]
Current Assets/Current Liabilities	[6, 10-13]
Current Assets/Net Sales	[6, 10]
Current Assets/Total Assets	[6, 10, 14]
Current Liabilities/Equity	[6, 9]
Equity/Net Sales	[6, 9, 15]
Inventory/Net Sales	[6, 9]
Long Term Debt/Equity	[6, 14]
Net Sales/Total Assets	[6, 7, 15]
Operating Income/Total Assets	[6, 7, 13]
Retained Earnings/Total Assets	[6, 7, 13]
Working Capital/Net sales	[6, 9, 10]
Working Capital/Equity	[6]
Working Capital/Total Assets	[6, 7, 10-12, 16]
Debt in Current Liabilities/Current Liabilities	
Cash flow / Total Tangible Assets	

3. Previous Bankruptcy Research

“[Bankruptcy would be] like stepping into a tepid bath and slashing your wrists: You might not feel yourself dying, but that’s what would happen [17].”

- Felix G Rohatyn, Chairman, Municipal Assistance Corp

Bankruptcy prediction has been a topic of interest since 1966, when Beaver [12] created a univariate bankruptcy model. In 1968, Altman [7] extended Beaver’s [12] model with the use of multidiscriminant analysis (MDA) to determine if a company was a ‘survivor’ or in ‘financial distress’. Shortly following, models using MDA picked up popularity and were done by various researchers such as Altman, Haldeman, and Narayanan [13] who created a model for USA companies in 1977. While the majority of distress prediction models have been done on US firms, due to the availability of data, in 1994 there were at least three-dozen studies devoted to other countries [18]. MDA analysis continues to be one of the benchmark methods despite heavy criticism [19-22]. 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), only providing 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 [23] and Peel, Peel, Pope [24] in 1980. Multinomial logit was used by Lau [25] and probit by Pacey and Pham [26]. Also during this time, recursive partitioning as used by Marais et al. in 1984 and Frydman et al. in 1985 [27, 28].

Bankruptcy and distress prediction fall into the soft computing category of being a classification problem, as that the final goal is to classify the companies into distress or survival. Some of the general classification problems using soft computing include; survival analysis [29], goal programming [30], multicriteria decision/support methods [31], rough sets methods [30], expert systems [32, 33], neural networks [34], Cox's Proportional Hazards Model [35], and self-organizing maps [36]. In the area of distress prediction for financial institutions, credit union failure prediction models for Australian companies were created [22, 37] as well as ones were created for US banks entering failure [29].

Soft computing methods specifically applied to bankruptcy prediction include probabilistic neural networks [38] and backpropagation neural networks [30, 38]. 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 [39].

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. [40] used macroeconomic factors, as did Platt and Platt [41] 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 [42]; 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 which was created in order to let companies have more time to reorganize their business and finances in order to attempt recovery from bankruptcy or reduce losses. The Chapter 11 process is planned and monitored by a court system through methods like, 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, which then must be approved in the courts. Later the company is released from Chapter 11 and at this time shareholders either lose all value or have some worth. It is important to note that while companies occasionally honor stockholders shares, they are usually limited to stocks bought before a previous date (prior to trouble) and held onto [43].

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. Chapter 11 can however allow a company to get itself into far worse debt and can allow new loans to take higher precedent over previous loans and is therefore not always the best option. 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.

Under Chapter 11 when a loan is re-negotiated 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 to. Due to the risks associated with bankruptcy, many times, crediting companies will close the company down sooner than what would be most beneficial to them (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 [44]. 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 [44].

4. Model Creation

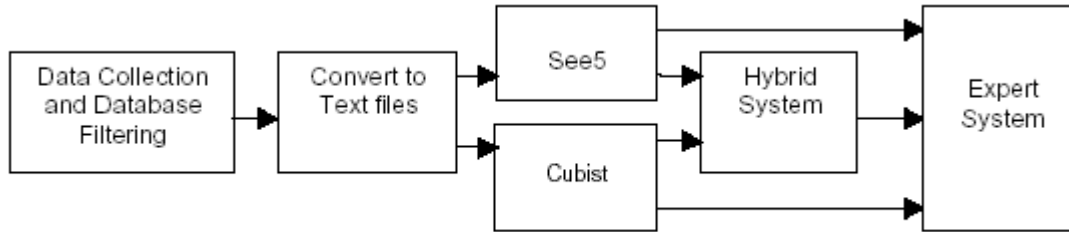


Figure 1

Figure 1 shows an overview of the model that was created. In the first phase, “Data Collection and Database Filtering” data was collected from a variety of sources, compiled into a database, and extensively filtered to meet the criteria. The database was used to create a spreadsheet, which is then converted to the appropriate text files required by See5 and Cubist. The See5 and Cubist software were used to create models and the rules created by them were directly implemented into an Excel spreadsheet. The spreadsheet worked as an expert system and combined the two sets of rules into a final system. The way in which the Hybrid System was created was a simple check if both the See5 and Cubist models made the same prediction, the prediction was used, otherwise there was no prediction made. The final predictions from See5, Cubist, and the Hybrid of them were displayed in the Expert system as well as a scale for support based on how accurately the system made those predictions normally and if the Systems agreed.

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 shareholders 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 shareholders, is classified as having no return.

4.1. See5

The See5 model used 150 cases to create the model and another 20 to test the model. The new See5 model was only rule-based and included 10 rules, which are listed in Table 1.

If none of the rules are valid, the default class is 0. The expert system currently only fires the rule with the highest prediction accuracy value and does not take into account more complex methods of combining rules being fired as See5 does [45].

The See5 model had 28 (of 150) misclassified cases in the training set, 20 Type II errors and 8 Type I errors. See5 also had 7 (of 20) misclassified cases in the testing set, 6 Type II errors and 1 Type I error. The training results are summarized in Table 2 and Table 3 the testing results for See5 are shown. Adding the number of correctly classified fields together and dividing by the total cases determines accuracy as listed.

Table 1: See5 Rulesets

Rule #	If statements:	Then Classify As:
1	Reason for SEC closure of case = 5	-1
2	Reason for SEC closure of case =2	0
3	Earnings per share > -9.2 BAA Corporate Bond Rate (Moody's) <= 7.25	0
4	Reason for SEC closure of case = 1	0
5	Reason for SEC closure of case = 1 BAA Corporate Bond Rate (Moody's) > 7.25 Cash / Current Liabilities > 0.04100772 Current Assets / Net Sales > 0.1635515 Current Assets / Net Sales <= 0.2305321	1
6	Reason for SEC closure of case = 1 Earnings per share <= -9.2	1
7	Current Assets / Net Sales <= 0.2305321 Operating Income / Total Assets > 0.1142438	1
8	Reason for SEC closure of case = 1 BAA Corporate Bond Rate (Moody's) > 7.25 Operating Income / Total Assets <= -0.5581015	1
9	Reason for SEC closure of case = 1 Current Assets / Net Sales <= 0.2305321 Retained Earnings / Total Assets <= -5.033689	1
10	Reason for SEC closure of case = 3	1

Table2: See5 Training

See5 Model Training Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	NoReturn	Return	Unknown
No Return	98	8	0
Return	20	16	0
Unknown	0	0	7
Total	118	24	7
Accuracy	81.2%		

Table3: See5 Testing

See5 Model Testing Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	No Return	Return	Unknown
No Return	9	1	0
Return	6	3	0
Unknown	2	0	0
Total	17	4	0
Accuracy	57.1%		

4.2.Cubist

In the first Cubist model, 181 cases were used in training the Cubist model, which is with fewer cases than used with See5, because of the unknown results for 9 of the datasets, which Cubist was not able to deal with. 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. After review of the model, it was decided that different ratios and set-ups were needed. In following models the results were actually not as good as the first model set. Considering raw data was used instead of ratios, it was assumed that the predictive results would not be as good, however for this software it may be worth while re-visiting the software with information learned from other models and experience and try the original raw data again. The most current model results are available in Table 4 and Table 5. Tweaking the

model to average results when more than one rule fired may also prove useful, at the moment when more than one rule can be fired, the rule with the highest success rate is chosen.

Table 4

Cubist Model Training Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	No Return	Return	Unknown
No Return	87	19	0
Return	17	19	0
Unknown	6	1	0
Total	110	39	0
Accuracy	71.1%		

Table 5

Cubist Model Testing Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	No Return	Return	Unknown
No Return	7	3	0
Return	8	1	0
Unknown	0	0	0
Total	10	9	2
Accuracy	38.1%		

4.3.Hybrid

The test accuracy of See5 alone provided 57.1% accuracy while the Cubist accuracy was 38.1%. While the combination of See5 and Cubist provided a high accuracy in prediction for the training model (89.0% accuracy); however, the test model however was not any more accurate at only 46.7% accuracy. The hybrid results from training are shown in Table 6 and the results from testing are illustrated in Table 7.

Table 6

Combo See5 and Cubist Training Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	No Return	Return	Unknown
No Return	80	1	0
Return	10	9	0
Unknown	0	0	0
Total	90	10	0
Accuracy	89.0%		

Table 7

Combo See5 and Cubist Testing Results	Type I Error: predicted return when none Type II Error: predicted no return when there is		
	PREDICTION		
	No Return	Return	Unknown
No Return	7	1	0
Return	5	0	0
Unknown	2	0	0
Total	14	1	0
Accuracy	46.7%		

The results used to determine the accuracy figure, only included data items, which overlap, in other words the number of correct responses divided by the number of responses that were the same from both models.

6. Conclusion

In summary, the See5 system provided the best prediction method in testing for overall accuracy. The Hybrid system was far more reserved, as expected, only attempting to predict 1 return of value in the test set (although wrongly) and 10 in the training set (only 1 wrongly) when the See5 model predicted 24 in the training set and 4 in the test set (about half the time incorrectly for each). Because of the more reserved nature of the hybrid system it is hard to really say how accurate the model is without more data to test.

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