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Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System

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Abstract. The economic consequence of corporate failure is enormous, especially for the stakeholders of public-held companies. Prior to a corporate failure, the firm's financial status is frequently in distress. Consequently, finding a method to identify corporate financial distress as early as possible is clearly a matter of considerable interest to investors, creditors, auditors and other stakeholders. This paper uses a composite rule induction system (CRIS; Liang 1992) to derive rules for predicting corporate financial distress in Taiwan. In addition, this paper compares the prediction performance of cris, neural computing and the logit model. The empirical results indicate that both CRIS and neural computing outperform the logit model in predicting financial distress. Although both CRIS and neural computing perform rather well, CRIS has the advantage that the derived rules are easier to understand and interpret.

Keywords: *corporate financial distress, machine learning, neural computing, composite rule induction system.*

1. INTRODUCTION

The economic consequence of corporate failure is enormous, especially for the stakeholders of public-held companies. Prior to a corporate failure, the firm's financial status is frequently in distress. Consequently, finding a method to identify corporate financial distress as early as possible is clearly a matter of considerable interest to investors, creditors, auditors and other stakeholders. The significance of this issue has stimulated a lot of research concerning the prediction of corporate bankruptcy or financial distress. These studies often used the statistical approach or iterative learning approach[1] to develop prediction models.

The statistical approach includes discriminant analysis, regression analysis, logit analysis or probit analysis and usually requires that the data follow certain distributional assumptions to generate robust results (Beaver 1966, Altman 1968, Beaver 1968, Deakin 1972, Aharony et al. 1980, Ohlson 1980, Zmijewski 1983, Platt & Platt 1990, Hill et al. 1996, Clark et al. 1997, Mossman et al. 1998). Although financial data and ratios rarely have a normal distribution, rank transformation of data has been shown to be useful to make the models less sensitive to non-normal distributions. Kane et al. (1998) apply rank transformation to financial ratios and the results indicate an improvement in predicting corporate failure. Iterative learning models, on the other hand, are free from distribution constraints because they are based on criteria other than sample mean and variance (Frydman et al. 1985, Messier & Hansen 1988, Odom & Sharda 1990, Liang 1992, Tam & Kiang 1992, Hansen et al. 1993, Wilson & Sharda 1994, Lee et al. 1996).

Iterative learning models refer to the process of training computers to derive rules or to develop algorithms from existing cases. Several iterative learning methods have been developed, including neural computing and inductive learning systems. Neural computing uses artificial neural networks (ANN) to emulate a human's biological neural network and to develop algorithms from the given samples (cases), whereas an inductive learning system derives rules. Prior research indicates that neural computing outperforms statistical models in predicting business failure (Odom & Sharda 1990, Tam & Kiang 1992).

ID3 (Quinlan 1979) is an inductive learning system and is more effective than discriminant analysis in predicting bankruptcy and loan default (Messier & Hansen 1988). However, ID3 did not outperform statistical models in other studies (Tam & Kiang 1992, Liang et al. 1992, Hansen et al. 1993). The rule induction mechanisms of ID3 process nominal and non-nominal variables in the same way without considering their different characteristics. In addition, the probability

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[1] Some researchers also used statistical models along with iterative models for performance comparison purposes.

assessments for the rules are typically based on the frequency of occurrence in the training data set. Consequently, Liang (1992) proposed a composite rule induction system (CRIS) to overcome these drawbacks.

This study uses CRIS to derive rules for predicting corporate financial distress in Taiwan. In addition, the study compares the prediction performance of CRIS, neural computing and the logit model. The remainder of the paper is organized as follows. The next section discusses prior research dealing with the prediction of corporate financial distress, which suggests the methods used in the present study. The methodology section defines the operational terms and explains data collection, models and model validation. The ensuing section presents the empirical results and data analyses. Finally, conclusions and limitations of the study are presented.

2. PREDICTION OF CORPORATE FINANCIAL DISTRESS

Statistical models

Numerous research projects have been conducted to identify early warning indicators of corporate financial distress. In the 60's, researchers used statistical models to identify financial ratios that could classify companies into failure or non-failure groups. The statistical approach includes univariate and multivariate models. In his pioneering work, Beaver (1966) used a dichotomous classification test to identify financial ratios for corporate failure prediction. He used 30 financial ratios and 79 pairs of companies (failure/non-failure). The best discriminant factor was the working capital/debt ratio, which correctly identified 90 percent of the firms one year prior to failure. The second best discriminant factor was the net income/total assets ratio, which had 88 percent accuracy. Subsequently, there have been relatively few studies using the univariate model for bankruptcy prediction, and researchers overwhelmingly used multivariate models instead.

Altman (1968) was the first researcher to develop a multivariate statistical model to discriminate failure from non-failure firms. He used multivariate discriminant analysis (MDA), and the initial sample was composed of 66 firms with 33 firms in each of the two (failure/non-failure) groups. The five financial ratios used in his MDA model were working capital/total assets, retained earnings/total assets, earning before interest and tax/total assets, market value of equity/book value of total liabilities, and sales/total assets. The model was extremely accurate in classifying 95% of the total sample correctly one year prior to failure (-1 year), but misclassification of failed firms increased significantly as the prediction time increased (28% at –2 years, 52% at –3 years, 71% at –4 years).

Martin (1977) used the logit model for bank failure prediction. Subsequently, Ohlson (1980) also used the logit model to predict business failure with a sample of 105 bankrupt firms and 2,058 non-failing firms. The nine financial ratios included in the model were the firm size (log of a price-level deflated measure of total assets), total liabilities/total assets, working capital/total assets, current liabilities/current assets, a dummy variable indicating whether total assets were greater or less than total liabilities, net income/total assets, funds from operation/total liabilities, another dummy variable indicating whether net income was negative for the last two years and change of net income. Ohlson used a relatively unbiased sampling procedure because the failure/non-failure ratio in his study was more realistic. However, the model did not perform as well as MDA, which suggested that previous researchers might have overstated the discriminatory power of their models (Morris 1997).

Zmijewski (1984) examined the “choice-base” sample bias and “sample selection” bias typically faced by financial distress researchers. Contrary to the common 1:1 failure/non-failure matching, he used the probit model on six sets of data where the ratio of failure/non-failure varied from 1:1 to 1:20. The results indicated that the choice-based sample bias decreased as the failure/non-failure ratio approached the population probability. In addition, with regard to the sample selection bias, the results indicated a significant bias existed in the majority of the tests conducted. However, for both issues, the results did not indicate significant changes in overall classification and prediction rates.

Neural computing

Neural computing has generated considerable research interest and has been applied in various areas, including the prediction of corporate bankruptcy or financial distress. Neural computing is a computer system that consists of a network of interconnected units called artificial neurons (AN). AN are organized in layers inside the network. The first layer is the input layer, and the last is the output layer. Hidden layers exist between the input and output layers, and there can be several hidden layers for complex applications. Computer programs process the training sample to identify the relationships between input and output data. Neural computing is more adaptive to the real world situation because it is not subject to distribution constraints. This advantage makes neural computing an appealing tool for developing prediction models because the variance-covariance matrices of failed/non-failed firms are often not equal, and financial data seldom follow the multivariate normal distribution, each of which is a violation of the MDA assumptions.

Odom and Sharda (1990) used the same financial ratios employed by Altman (1968) and applied ANN to a sample of 65 failed and 64 non-failed firms. The training sample comprised 38 failed and 36 non-failed firms. A three-layer neural network was created with five hidden nodes. Their model correctly identified all failed and non-failed firms in the training sample, compared to 86.8% accuracy by MDA. Regarding the performance with holdout samples, ANN had an accuracy rate of 77% or higher, whereas MDA could hit the target only between 59% and 70%. Subsequently, several studies also revealed that ANN outperformed other prediction models (Hansen & Messier 1991, Salchenberger et al. 1992, Tam & Kiang 1992, Coats & Fant 1993, Hansen et al. 1993, Altman et al. 1994, Wilson & Sharda 1994).

Inductive learning systems

ID3 is a relatively simple mechanism for discovering a classification rule from a collection of objects belonging to two classes (Quinlan 1979). Each object must be described in terms of a fixed set of attributes, each of which has its own set of possible values. An object is classified by starting at the root of the decision tree, finding the value of the tested attribute in the given object, taking the branch appropriate to that value, and continuing the process until a leaf is reached. ID3 uses entropy to measure the values of each attribute and then derives rules through a repetitive decomposition process that minimizes the overall entropy. Messier and Hansen (1988) used ID3 to derive prediction rules from loan default and corporate bankruptcy cases. The loan default training sample contained 32 firms with 16 in each group (default or non-default). In the corporate bankruptcy case, the training sample contained 8 bankrupt and 15 non-bankrupt firms. For the holdout samples, the rules derived by ID3 correctly classified the bankrupt/non-bankrupt firms with perfect accuracy and 87.5% accuracy for the loan default.

The recursive partitioning algorithm (RPA) is a non-parametric classification technique. The method starts with the sample data, their financial characteristics, the actual group classification, the prior probabilities, and the misclassification costs. A binary tree is built where a rule is derived for each node. The rule is based on a single variable, which can easily explain the failure of a firm (Cronan et al. 1991). Frydman et al. (1985) used a sample of 58 failed firms along with 142 non-failed firms to derive prediction rules. The empirical results of their study indicated the RPA model outperformed MDA. The goal of their study was to minimize the expected cost of misclassification, whereas the objective of Messier and Hansen's (1988) study was to minimize the number of misclassifications. However, RPA has two disadvantages (Zopounidis & Dimitras 1998). First, it is a forward selection method and the same variable can be used again in the classification rule at a later stage with a different cut-off value. Second, continuation of partitioning processes can result in a tree where every single firm is correctly classified by one terminal node and may have the problem of overfitting.[2]

[2] Overfitting refers to a model that fits exceptionally well on to the data from which it is derived, but far less well on to other data from a holdout sample (Morris 1997).

Although prior research indicated that inductive learning systems outperformed statistical models, Liang (1992) pointed out that the algorithms had several limitations. The limitations included lower accuracy for real number data, lower efficiency for larger samples, difficulty in assessing the probability associated with rules, and a single algorithm for both nominal and non-nominal attributes. Consequently, Liang proposed a composite rule induction system (CRIS) to overcome these drawbacks and applied CRIS to a bankruptcy data set containing 50 cases. Each case included four nominal and five non-nominal attributes. Twelve experiments were conducted and the data set was randomly divided into a training sample and a holdout sample. The results indicated that CRIS had the highest accuracy (80.8%) followed by ANN (78.3%) in bankruptcy prediction. Both CRIS and ANN outperformed MDA (75.8%).

This paper applies CRIS to derive rules for predicting corporate financial distress in Taiwan. In addition, it performs an empirical comparison of predictive capability among CRIS, neural computing and the logit model.

3. METHODOLOGY

Financially distressed companies

Although numerous (especially small) business firms in Taiwan went bankrupt or had financial distress, their financial data are often unavailable. Consequently, we use the data from the Taiwan Stock Exchange (TSE). The Trading Code #46 of TSE specifies the conditions of a financially distressed company, which include bankruptcy, reorganization and default. The financial statements of financially distressed companies per TSE Trading Code are listed in a special database, which can be easily identified.

Classification accuracy

Table 1 explains the determination of classification accuracy in this paper. P_{11} denotes the probability of a normal company being correctly classified, whereas P_{22} denotes the probability of a financially distressed company being correctly classified. On the other hand, (classification) Type I error refers to the probability that a financially distressed company is mistakenly classified as normal ($1 - P_{22}$) and Type II error represents the probability that a normal company is mistakenly classified as financially distressed ($1 - P_{11}$). The overall classification accuracy (P) is the probability that companies are correctly classified as either normal or financially distressed. To our knowledge, there has been no research dealing with the misclassification cost of Type I and Type II errors in Taiwan. Consequently, similar to previous studies (Messier & Hansen 1988, Liang 1992), the objective of this paper is to minimize the number of misclassifications.

	Classified as normal company	Classified as financially distressed company
Actual normal company	P_{11}	$1 - P_{11}$ (Type II error)
Actual financially distressed company	$1 - P_{22}$ (Type I error)	P_{22}

Table 1. Classification accuracy table

Data collection

There have been only a few financially distressed companies on TSE after 1985. Most financially distressed companies on TSE had financial problems during the period between 1981 and 1985. Twenty-eight companies were in financial distress during the above period but complete financial data are available for only 19 firms. To control the unwanted bias, a distressed firm was matched with a normal one according to industry and firm size. In addition to the 1:1 matched sample (38 firms), this study also attempted to create a 1:2 matched sample. Due to the high concentration in some industries, four distressed firms were not matched with the second normal firms of similar size. Therefore, 53 firms were included in the second training sample (19:34).

Financial ratios

The usefulness of financial ratios and cash flow data for bankruptcy prediction is substantial in comparison with the use of market return data (Mossman et al. 1998). Furthermore, the model using financial ratios from the year immediately preceding bankruptcy has the best results. Consequently, this paper uses financial data of one year prior to financial distress to induce rules. Prior researchers have identified financial ratios (of corporate America) for bankruptcy prediction or financial distress prediction. However, due to the possible differences of firm characteristics between corporate America and TSE firms, this paper uses fourteen financial ratios commonly included in the financial filing with TSE. This paper then examines the explanatory capability of these financial ratios using step-wise regression and selects five variables for the final model. These five variables are total liabilities/total assets, quick assets/current liabilities, sales/fixed assets, margin/sales and cash dividend per share.

Models

The rule induction mechanism of CRIS is composed of three major components: 1) a hypothesis generator that determines hurdle values and the proper relationship between dependent and independent attributes, 2) a probability calculator that determines the probability associated with each rule, and 3) a rule scheduler that determines how candidate rules should be organized to form a structure. The construction process includes the following steps:

1. The training data containing non-nominal independent variables and nominal dependent variables are entered.
2. Different algorithms are used for hypothesis generation based on different properties of nominal and non-nominal attributes.
3. The hypotheses are converted to candidate rules by assessing their probabilities and making necessary modifications.
4. The resulting candidate rules are evaluated and selected to form a decision structure that can interpret the existing cases and facilitate future prediction.

This paper also uses PCNeuron to construct ANN. The input layer has five process units and the output layer has two process units. Although the optimal number of process units for the hidden layer is determined by trial and error, a general rule of thumb is the average number of the input and output process units. Therefore, in the present study, there are three process units in the hidden layer.

Model validation

If the training sample is not a fair representation of the problem domain, the resulting classification error rate can be misleading (Hansen et al. 1993). Some studies used the same training data for model validation after the models were constructed. As a consequence, the misclassification rate would be very low and there may exist the problem of overfitting. One solution to this problem is to construct the model from the training sample and use a holdout sample for validation. Furthermore, the researcher can use the holdout sample from a latter period to test how robust discriminatory power is over time (Joy & Tollefson 1975). Unfortunately, a post holdout sample is not available in Taiwan due to the fact that TSE has only a few financially distressed firms after 1985.

The validation is performed in three steps. First, all data are used for both model construction and model validation (i.e., no holdout sample). The results facilitate examining the possibility of overfitting. Second, similar to prior research (Liang 1992), this study repeats the experiment 20 times and the average accuracy percentage is computed. In each experiment, thirteen financially distressed firms are randomly selected into the training sample and the remaining six firms are treated as the holdout sample. Accordingly, the matched normal firms are assigned into the training and holdout samples, respectively. Finally, the jackknife method (Lachenbruch 1967) is also used for model validation. The following hypotheses are tested.

H_1: There is no significant difference in classification accuracy between CRIS and the logit model.
H_2: There is no significant difference in classification accuracy between ANN and the logit model.
H_3: There is no significant difference in classification accuracy between CRIS and ANN.

4. EMPIRICAL RESULTS

Classification accuracy

The comparison of classification accuracy across models of various studies may not be meaningful if the financial ratios and data are different. Table 2 presents classification accuracy among CRIS, neural computing and the logit model when all data are used in the training sample (i.e., no holdout sample). All three models perform well with accuracy of at least 89%. The overall accuracy consistently improves for all three models when the sample size is increased from 38 firms (19:19) to 53 firms (19:34). The logit model has the best performance (94.34%) with 53 firms in the training sample. Nonetheless, this might be the overfitting as a result of using the same data for model validation.

Matched sample (distressed firms: normal firms) = 19:19			
Model	Financially distressed	Normal companies	Overall
CRIS	89.47%	94.74%	92.11%
ANN	89.47%	89.47%	89.47%
Logit model	89.47%	89.47%	89.47%
Matched sample (distressed firms: normal firms) = 19:34			
Model	Financially distressed	Normal companies	Overall
CRIS	89.47%	94.12%	92.45%
ANN	89.47%	94.12%	92.45%
Logit model	94.74%	94.12%	94.34%

Table 2. Classification accuracy with no holdout sample

Table 3 indicates that both CRIS and neural computing outperform the logit model when holdout samples are used. Again, all three models consistently improve their overall accuracy when the sample size is increased. The increase of sample size significantly improves the accuracy of classifying normal firms. It appears that CRIS is the only model whose Type I error probability is consistently lower than that of Type II error.

Matched sample (distressed firms: normal firms) = 19:19			
Model	Financially distressed	Normal companies	Overall
CRIS	95.83%	83.33%	89.58%
ANN	86.67%	89.17%	87.92%
Logit model	79.19%	86.67%	82.92%
Matched sample (distressed firms: normal firms) = 19:34			
Model	Financially distressed	Normal companies	Overall
CRIS	94.17%	94.12%	94.13%
ANN	95.00%	94.57%	94.72%
Logit model	83.33%	93.21%	89.74%

Table 3. Classification accuracy with 20 experiments

Table 4 presents the results using the jackknife method. Again, both CRIS and neural computing outperform the logit model. Although the logit model has the highest accuracy in predicting corporate financial distress, it also has the highest Type II error. The results also indicate a positive effect on the overall classification accuracy as the sample sizes increased.

Matched sample (distressed firms: normal firms) = 19:19			
Model	Financially distressed companies	Normal companies	All companies
CRIS	89.47%	84.21%	86.84%
ANN	84.21%	89.47%	86.84%
Logit model	78.95%	84.21%	81.58%
Matched sample (distressed firms: normal firms) = 19:34			
Model	Financially distressed companies	Normal companies	All companies
CRIS	89.47%	94.12%	92.45%
ANN	89.47%	94.12%	92.45%
Logit model	94.74%	88.24%	88.68%

Table 4. Classification accuracy using the jackknife method

Comparison among models

The Wilcoxon rank test is performed to examine any significant difference between the models. The results (Tables 5, 6 and 7) indicate that CRIS outperforms the logit model in both cases (34-firms sample and 53-firms sample), while neural computing outperforms the logit model only with the 53-firms sample size. It appears that there is no significant performance difference between CRIS and neural computing.

	Distressed firms: normal firms = 19:19	Distressed firms: normal firms = 19:34
ΣR_i	-84	-46
ΣR_i^2	1430.5	343
$T = \Sigma R_i/\mathrm{SQRT}(\Sigma R_i^2)$	-2.22 Pr = 0.0132 *	-2.48 Pr = 0.0066 *

Table 5. Comparison of CRIS and the logit model. *CRIS significantly outperforms the logit model.

	Distressed firms: normal firms = 19:19	Distressed firms: normal firms = 19:34
ΣR_i	-38	-55
ΣR_i^2	1695.5	343
$T = \Sigma R_i/\mathrm{SQRT}(\Sigma R_i^2)$	-0.92 Pr = 0.1788	-2.97 Pr = 0.0015 *

Table 6. Comparison of ANN and the logit model. *ANN significantly outperforms the logit model

	Distressed firms: normal firms = 19:19	Distressed firms: normal firms = 19:34
ΣR_i	-14	3
ΣR_i^2	267	4.5
$T = \Sigma R_i/\mathrm{SQRT}(\Sigma R_i^2)$	-0.86 Pr = 0.1949	1.42 Pr = 0.9222

Table 7. Comparison of CRIS and ANN

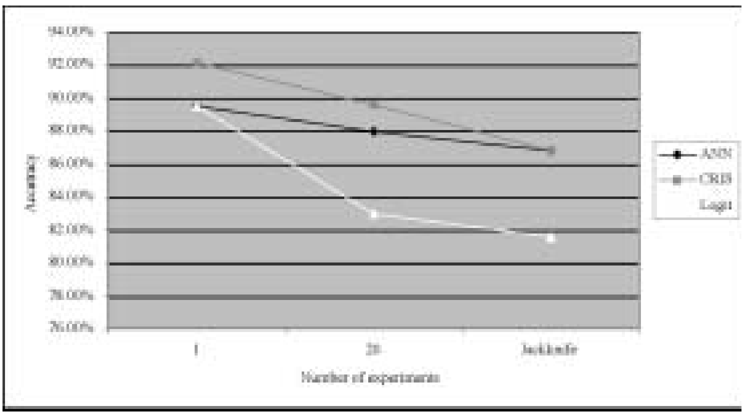

Figure 1.Comparison of accuracy among models. Sample Size: 38 Firms

Overall, both CRIS and neural computing outperform the logit model (Figure 1 and Figure 2). Although there is no significant performance difference between CRIS and neural computing, it is easier to follow the (decision) rules derived by CRIS. The hidden layer of ANN is difficult, to interpret. In addition, larger training samples can achieve a better result in predicting corporate financial distress (Figure 3).

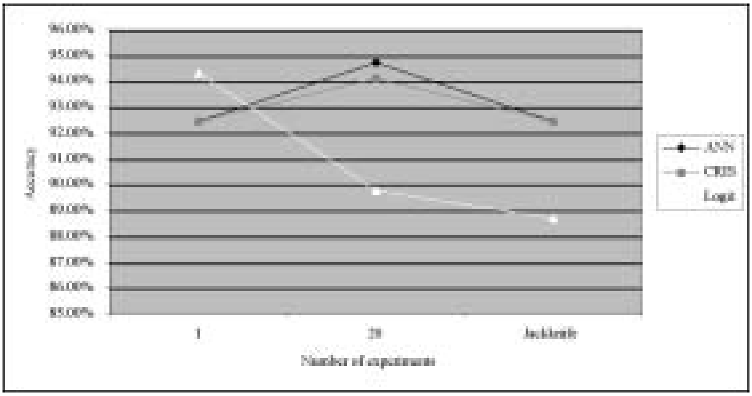

Figure 2. Comparison of accuracy among models. Sample Size: 54 Firms

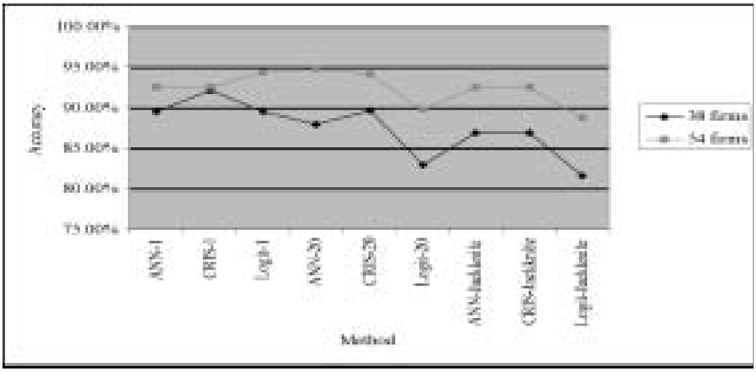

Figure 3. Comparison of accuracy with different sample sizes

5. CONCLUSIONS

It is important to understand the early warning indicators and implications of corporate financial distress. If the stakeholder can predict a company is on its way to a financial distress, he/she can take a necessary action in time. Similarly, it is vitally important for an auditor to be able to assess whether or not a company is a going concern in preparing the audit report (Morris 1997). The significant consequence of corporate financial distress has generated a lot of research interest and numerous methods have been applied to develop prediction models.

This paper used CRIS to derive rules for the prediction of corporate financial distress in Taiwan. Using step-wise regression, this study identified five financial ratios-total liabilities/total assets, quick assets/current liabilities, sales/fixed assets, margin/sales and cash dividend per share—that could effectively predict a financial distress. Then, it applied CRIS and ANN to develop the financial distress prediction model using these five financial ratios. The empirical results indicate that both CRIS and ANN outperform the logit model. Although both CRIS and ANN perform rather well, CRIS has the advantage that the derived rules are easier for humans to learn (the rules derived by CRIS are shown in the Appendix).

Due to the limitations of TSE data, this paper used only 19 financially distressed firms. Accordingly, the results may be qualified as a consequence of the small sample size (Liang et al. 1992, Bhattacharyya & Pendharkar 1998). Furthermore, since the best prediction model of machine learning is identified through iterative cycles, the results reported in this paper do not provide any conclusive statements regarding the performance of CRIS and ANN. As explained earlier, the comparison of classification accuracy across models may not be meaningful if the financial ratios and data are different. The purpose of this paper is not to identify "the" model. Instead, this paper attempts to apply an effective tool to assist stakeholders in predicting corporate financial distress in Taiwan. More studies are needed to continue this learning process. In many cases, the prediction accuracy can be improved by inventing a more appropriate set of features to describe the available data (Mitchell 1999).

We do have reason to search for machine learning programs that will avoid the inefficiencies of human learning (Simon 1983). Indeed, humans do not outperform machine learning when adequate historical data are available (Kattan et al. 1993). The process of knowledge acquisition using interviews or protocol analysis can be time-consuming and ineffective. An effective rule induction system can assist knowledge engineers in identifying knowledge by collecting previous cases solved by experts and identifying attributes that are relevant for decision-making. Advances in machine learning have made it possible to apply effective tools to a variety of business problems in order to extract extra information from existing data. Researchers can apply an effective inductive system such as CRIS to solve other business problems. Subsequent studies can also incorporate the prior probability of financial distress and misclassification costs to improve the generalization of the research results.

APPENDIX: RULES DERIVED BY CRIS

FROM 1:1 MATCHING

If Gross Margin/Sales >= 31.8818
Then BANKRUPTCY = YES with probability = 0.86
If Liability Ratio >= 69.3450
Then BANKRUPTCY = YES with probability = 0.84

..
If FA Turnover >= 3.2517
Then BANKRUPTCY = NO with probability = 0.76
..
If Gross Margin/Sales >= 27.5881
Then BANKRUPTCY = YES with probability = 0.70
..
If Liability Ratio < 61.0398
Then BANKRUPTCY = NO with probability = 0.88
..
If Liability Ratio < 67.0905
Then BANKRUPTCY = NO with probability = 0.82
..
If Liability Ratio >= 67.0905
Then BANKRUPTCY = YES with probability = 0.82
..
The structure misclassifies the following in 38 input cases: #6 17 36

FROM 1:2 MATCHING

If Liability Ratio < 64.7217
Then BANKRUPTCY = NO with probability = 0.85
..
If Per Cash dividend >= 0.2549
Then BANKRUPTCY = NO with probability = 0.88
..
If Current Ratio < 18.4393
Then BANKRUPTCY = YES with probability = 0.61
..
If Gross Margin/Sales < 0.1514
Then BANKRUPTCY = YES with probability = 0.65
..
If Liability Ratio >= 71.3438
Then BANKRUPTCY = YES with probability = 0.88
..
If Liability Ratio < 66.4588
Then BANKRUPTCY = NO with probability = 0.83
..
If Liability Ratio >= 66.4588
Then BANKRUPTCY = YES with probability = 0.83
..
The structure misclassifies the following in 53 input cases: #10 11 37 51

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