# Linear versus Nonlinear Models of Expert Decisions in Bankruptcy Prdediction: A Decision Strategy Perspective†

Choong-Nyoung Kim* · Byung-Don Choe**

## ABSTRACT

There have been two dominant paradigms in understanding and modeling an expert's decision-making behavior: output analysis and process-tracing. While the two paradigms are complementary, they have not been used yet in a combined manner. This study extends the previous research work in the two paradigms to inductive modeling research by 1) analyzing individual experts' decision strategies, 2) comparing performance of four popular inductive modeling methods, and 3) matching their performance against the type of decision strategy employed by experts.

## 1. INTRODUCTION

Most descriptive decision research aims at constructing descriptive decision models which emulate, mimic, and replace human judgment. In attempting to understand and model the judgment, two approaches have been dominant: output analysis and process-tracing. The former approach focuses on finding relationships between relevant cues and final decisions of humans, and developing a decision model simulating the relationships. The latter approach focuses on analyzing the actual process of making judgment.

With the introduction of expert system concept, the output-analysis issue has been revisited with a different name, expert-modeling. While the research by computer scientists provides de-

* Department of Business Administration Hallym University
** Department of Business Administration Hallym University

cision researchers with a variety of tools for expert-modeling, valuable methodologies of the process-tracing approach have never been coupled with the expert-modeling research. Without an understanding of the actual process of an expert's decision behavior, it seems to be unlikely to ensure appropriate application of expert-modeling tools and methods.

This paper attempts to combine the behavioral aspect of descriptive decision research with the expert-modeling, by 1) examining an expert's decision behavior through the use of a process-tracing method, 2) building models of human experts with four popular modeling methods, and 3) matching their performance against the type of decision strategy being adopted by individual experts in making decisions.

## 2. Literature Review

This section reviews key literature in behavioral decision research and empirical studies in expert-modeling. A research question is also raised based on the literature review.

### 2.1 Output Analysis

The objective of output analysis research is to develop structural representations of human decision-making processes. To build such representations, statistical methods (e. g., linear regression and discriminant analysis) and inductive learning algorithms (e. g., Learning-By-Examples and the neural network approach) have been mainly applied to various tasks.

#### 2.1.1 Bootstrapping by Linear Models

Bootstrapping is the replacement of a decision maker by the statistical (linear) model of his or her judgment. The statistical methods generate a linear function which represents a decision model with a set of weighted variables. Since the weighted variables are linearly combined to generate a predicted value, they are considered a linear model [17]. Many studies [9, 25, 2] provide evidence on the applicability of bootstrapping, supporting the strength of the linear models.

#### 2.1.2 Expert-modeling by Nonlinear Models

This approach produces decision rules from the example cases an human expert provides [15]. A number of different inductive learning methods have been developed. Among them, ID3 is considered a simple but effective rule-based method for learning by examples (LBE). When it is given a training set of positive and negative examples, ID3 constructs a decision tree for classifying examples into two classes [16].

The inductive learning method is based on the information theory and uses an information-theoretic measure called entropy. Entropy is a measure of the amount of information carried by a message in communication [22]. Based on the entropy concept, information on each cue (independent variable) is processed sequentially and combined logically (conjunctively or disjunctively) along the decision tree [8]. Therefore, a linear combination of input information and other properties of linear models cannot be expected in the method. Rather, the logical information processing in ID3 is very similar to the production rules which follow nonlinear processing. Thus, ID3 is considered a typical nonlinear algorithm.

Recently, the use of neural networks (another inductive learning mechanism) has been addressed by a number of researchers [4, 3, 20, 24, 12]. They reported excellent performance of neural nets, in simulating human decision behavior as well as environmental data. A neural network is a dynamic model consisting of perceptrons (also called nodes), connections between the perceptrons, and layers associated with each perceptron [21]. There are three types of perceptrons: input, output, and hidden layer perceptrons. The input perceptrons receive input values from sources external to the neural network. The output perceptrons produce output of the neural network. The hidden layer perceptrons serve to detect features, regularities, and generalizations in the data. Hidden layers allow neural networks to perform more flexible processing and more powerful classification [14].

Back-propagation (BP) is the most often used paradigm in neural networks [21]. BP learning is actually achieved through a learning rule which changes the connection weights of the network so as to improve the match between the actual and the desired outputs of the system. With the learning rule (also called the delta rule), the goal is to reduce the difference between a network's current output and a desired output by changing the connection weights. Once a network is well trained, it can be used as an excellent decision model.

Since BP generates a decision network in a functional form in which each connection is associated with parameters, compensation among input values may be allowed. However, at the hidden layer, input information is nonlinearly processed and combined to generate input values for the output layer. In this sense, the decision network should be considered a nonlinear model. This does not mean that the decision network cannot deal with linear processing or a linear relationship. The existence of the hidden layer simply makes the network more flexible in information processing.

### 2.2 Process-tracing Research

With the lack of understanding of the actual decision process, previous studies in the output analysis focused on proving superiority of new algorithms to the existing methods. Since the results of the studies were mostly data-dependent, they were difficult to generalize. The results could not explain how or why a certain algorithm performed better than another. Therefore, in order to properly compare the performance of modeling algorithms, the decision-making process should be analyzed. If a better understanding of the decision process could be achieved, performance of each algorithm would be more clearly explained.

Unlike the output analysis approach, the process-tracing approach is concerned with examining the cognitive processes actually used by a decision maker. To examine the processes, various process-tracing techniques have been introduced, such as protocol analysis and other mathematical methods. Since those techniques have been concerned with examining the decision process, they have also contributed to identifying and describing a variety of decision strategies.

The two major types of decision strategies introduced in the decision-making literature are compensatory (or linear) and noncompensatory (or nonlinear) [5, 6, 18]. The compensatory strategy assumes that respective cue (variable) values are combined in an additive manner resulting in an overall value for a given case. This strategy implies that a trade-off between a high value on one cue and a low value on another cue is allowed. A good example of this strategy is the first order linear regression model which graphs a straight line.

On the other hand, the noncompensatory strategy is indicated by the nonlinear or interactive use of cues in which a low value on one cue cannot be compensated for by a high value on another cue [1]. There are four types of nonlinear decision strategies:conjunctive, disjunctive, elimination-by-aspects and lexicographic strategies [23][18]. Conjunctive and disjunctive strategies are directly concerned with classification type decisions.

For example, using the conjunctive strategy, a decision maker sets a minimum requirement for each cue and then rejects decision alternatives which do not meet this minimum standard. On the other hand, the disjunctive strategy requires that an alternative should pass the criterion for at least one cue.

Einhorn [5][6] suggested specific models that approximate the conjunctive and disjunctive strategies. In the conjunctive model, the best response can be achieved when there are equal amounts for every cue without low values on any cues so that this approximation approaches a multiple cutoff procedure. One cannot compensate for the low value on some cues by high values on other cues since the product of all cues is considered important. In the disjunctive model, the best response can be achieved when there is an extremely high value on at least one of the cues so that this approximation approaches the disjunctive model.

These two functions can be fitted to data, after the log transformation is performed, by using multiple linear regression in order to obtain the weighting parameters. If a conjunctive strategy or a disjunctive strategy is being used, Einhorn argues that one of the two models should fit the data better than a linear regression model.

The functional form of a conjunctive strategy is represented as;

$Y = (X_1)^{a1} * (X_2)^{a2} * \cdots * (X_n)^{an}$

With a log transformation, this function becomes

$\log Y = a_1\log(X_1) + a_2\log(X_2) + \cdots + a_n\log(X_n).$

On the other hand, functional form of a disjunctive strategy is represented as

$Y = (1/(b_1-X_1))^{a1} * (1/(b_2-X_2))^{a2} * \cdots * (1/(b_n-X_n)^{an}))$

With a log transformation, this function becomes

$\log Y = -a_1\log(b_1-X_1) - a_2\log(b_2-X_2) - \cdots - a_n\log(b_n-X_n).$

where $a_i$ : coefficient of each variable

$b_i$ : artificial value above the highest of any x

Decision makers may employ a number of decision strategies that are different from each other. Olshavsky [18] argued that multiple decision strategies may be applied in succession in the same decision situation because cognitively, human decision-making consists of a series of subprocesses. This argument implies that it may be very difficult to identify a certain decision strategy from human decision making behavior. What can be found by the process-tracing methods may be the degree of dominance of a decision strategy being used in decision making behavior.

### 2.3 Research Objective

As reviewed in this section, a linkage between the decision strategy and the modeling algorithms in expert-modeling has been missing. One interpretation is that decision strategy has not yet been appropriately considered in modeling human judgment. This finding suggests a need to re-evaluate the previous studies within a new framework which includes decision strategy. Thus, if more reliable decision models or expert systems are to be built, obtaining a more complete understanding of how well a certain strategy is modeled by a certain algorithm is necessary.

Combining the two approaches is also supported by Svenson's argument [23] that "a good theory for human decision making must be based on the data from structural analysis (output analysis) of decision making as well as from process-tracing studies." In summary, this section raises a research question:

"Which strategy of an expert is effectively represented by a certain decision algorithm?"

Consequently, an inference can be made: if there is no significant evidence for the use of nonlinear strategies in expert decision-making behavior, linear models may emulate the expert's decision behavior much better than nonlinear models derived through the use of inductive methods. The counter inference can also be made: if the nonlinear strategy of an expert's judgment is dominant, nonlinear models may capture the nonlinearity much better than linear models. The following section explains how these two inferences are examined.

## 3. Methodology

The experts who participated in this study are experienced loan officers from two commercial banks. Data for two groups of firms, which are categorized by the size of total assets, was used. Group A was composed of 60 firms which have average total assets of approximately $44 million. These 60 cases included 30 failed and 30 nonfailed cases placed in random order. Data for bankrupt firms was chosen from listings in the Wall Street Journal Index for the years 1981-1985. Data for nonbankrupt firms was obtained from the same sources for the same period. These nonbankrupt firms are comparable with the bankrupt firms in terms of asset size and type of business. The financial information about each firm (case) was gathered from publicly available sources such as Moody's OTC Manual.

The second group (Group B) was composed of 59 small business firms. Data for these firms was collected primarily from the real loan cases of a commercial bank in California. The 59 cases included 28 failed and 31 nonfailed cases. To make this group different from Group A, commercial loan cases between $200,000 and $1,000,000 were collected. The total assets of the firms were averaged at $4. 5 million.

For purposes of comparability with the results of the previous studies, this research used about the same number of nonbankrupt (approved) to bankrupt (rejected) cases. To isolate the possible effect of economic conditions from the experiments' treatment effects, this study used data primarily from the period of 1981 through 1985. Similarly, utilities, transportation, and financial companies were excluded because these companies have different financial structures and environments [11].

In this field setting, it was assumed that the size of the total assets reflected the stability and credibility of a firm, and indirectly represented the default risk of a firm. The default risk as a control variable is appropriate for a naturalistic setting such as bankruptcy prediction. However, the primary purpose of using the control variable is to create different risk situations in which different decision strategies could possibly be triggered in decision behavior.

Each expert evaluated cases in the two groups and was required to judge whether a firm would be bankrupt or not within one or two years from the date on which its financial information was prepared. Each expert was provided with financial profiles of real but disguised industrial companies.

The companies were represented by ten commonly used financial ratios computed from the firms' financial statements. The first five ratios were chosen to conform with a factor analysis by Libby [13]; the remaining five ratios are the most commonly cited ratios for bankruptcy prediction in risk analysis literature [11]. The initial selection of the ten ratios as cues was accepted by the experts during the first interview. They agreed that the ratios would provide sufficient quantitative information for bankruptcy prediction and would not cause any information overload. After reviewing all of the sample cases, the experts were asked to weigh each financial ratio that they used during evaluation. Then, since three ratios were not used at all by all three experts, only seven ratios were selected on the basis of the experts' weights and used for model-building (Table 3.1).

**Table 3.1 Selection of Financial Ratios**

(Percentage Weights)

| | Expert 1 | Expert 2 | Expert 3 |
|---|---|---|---|
| N.T. /T.A. | 10 | 30 | 15 |
| C.A. /Sales | 20 | 30 | 15 |
| C.A. /C.L. | 20 | 30 | 20 |
| Cash /T.A. | 0 | 0 | 20 |
| T.D. /T.A. | 25 | 0 | 5 |
| (C.A. /C.L.) /T.A. | 10 | 10 | 5 |
| R.E. /T.A. | 25 | 10 | 20 |

* N.I. : Net Income  T.A. : Total Assets
C.A. : Current Assets  C.L. : Current Liability
T. D. : Total Debt  R.E. : Retained Earnings

This study consisted of three steps: (1) examining the experts' decision strategies, (2) building and evaluating decision models simulating the judgment of the experts, and (3) relating the performance of the decision models to each individual expert's decision strategy determined in the first step.

The ID3 method [19] was used to generate the rule-based models. To generate network-based models, a commercial package applying the Back Propagation Paradigm was used. The network was configured as a 3-layer network and this configuration was applied when constructing all networks. In general, learning was completed after 400,000 iterations in most networks. To generate linear models, SAS, a statistical package that includes logistic regression and discriminant analysis methods was used.

For cross-validation, 50 cases in each group were selected to build decision models, and the remaining cases were used to test the model performance. This process was repeated for every 10 cases of the total 60 (or 59) cases, until all the cases were used as a validation subset. This method achieved a nearly unbiased estimate and maintained a sample size of 60 (or 59) for each validation set.

Three statistical measures were used to examine the predictive validity: percentage accuracy, Chi-square, and Phi-coefficient. Percentage accuracy showed the capability of each model in classifying validation cases correctly, while the other two measures examined how close the decisions made by each model were to the experts' decisions.

# 4. Results

### 4.1 Analysis of Decision Strategy

Table 4.1 summarizes the type of nonlinear strategy using Einhorn's log transformation. In Group A, the decisions of expert 2 were better fitted by a disjunctive transformation. In Group B, the decisions of expert 3 were better fitted by a conjunctive transformation than by a linear regression. The results indicated the dominant existence of nonlinear strategies in the decision behavior of both expert 2 in Group A and expert 3 in Group B.

In Group B, the decisions of expert 1 were better fitted by a linear regression, which indicated the dominant use of linear strategy by expert 1. The decisions in the remaining three experiments were equally fitted by both linear regressions and disjunctive transformations, indicating mixed use of the two strategies. The mixed use can be interpreted as inconsistent behavior or existence of noise.

**Table 4.1 The Results of Einhorn's Log Transformations**

R-Square Values in Group A

| | Expert 1 | Expert 2 | Expert 3 |
|---|---|---|---|
| Linear Reg. | 0.50 ** | 0.35 | 0.45 ** |
| Conjunctive | 0.41 | 0.27 | 0.42 |
| Disjunctive | 0.50 ** | 0.37 * | 0.45 ** |
| Type Determined | Mixed (Linear & Disjunctive) | Disjunctive | Mixed (Linera & Disjunctive) |

R-Square Values in Group B

| | Expert 1 | Expert 2 | Expert 3 |
|---|---|---|---|
| Linear Reg. | 0.70 * | 0.44 ** | 0.51 |
| Conjunctive | 0.69 | 0.42 | 0.52 * |
| Disjunctive | 0.69 | 0.44 ** | 0.51 |
| Type Determined | Linear | Mixed (Linear & Disjunctive) | Conjunctive |

* The fittest model is selected by R-square value.

** If the R-square values of the transformed models (Conjunctive and Disjunctive) would be equal to that of Linear Regression, strategies are considered to be mixed.

### 4.2 Analysis of Model Performance

Table 4.2 gives predictive accuracy (simulation validity) of four algorithms in predicting the decisions of the experts in Group A. Generally, the decisions of the four experts were well-predicted by all algorithms except three experiments: between ID3 and expert 1, between LR and expert 2, and between DA and expert 2. The decisions of expert 1 were very poorly predicted by ID3. Two linear algorithms (LR and DA) did not perform well in simulating the disjunctive strategies of expert 2 which were excellently simulated by ID3.

Table 4.2 also provides chi-square measures, which indicate the existence of structural dependency between the expert and the model decisions. The results show that chi-square statistics exceeded the critical value at the 0.05 significance level except for the three experiments. The Phi-correlation coefficient measures indicate a strong association between the expert and the model decisions. They also have results consistent with those of chi-square measures at the same significance level, and with those of predictive accuracy.

Table 4.3 gives the predictive accuracy of the four algorithms in predicting the decisions of the experts in Group B. Generally, the decisions of the four experts were well-predicted by all algorithms except one case: between ID3 and expert 2 (mixed strategies). The two correlation measures also confirm the poor performance of ID3 in simulating the mixed strategies of expert 2.

**Table 4.2 Model Performance in Group A**

1. Predictive Accuracy (Simulation Validity)

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 66.7% | 58.0% | 76.7% | 81.7% |
| Expert 2 | 65.0% | 85.0% | 66.7% | 75.0% |
| Expert 3 | 68.3% | 69.6% | 70.0% | 77.8% |

2. Chi-square Statistics

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 6.64 | 1.67 * | 17.04 | 24.09 |
| Expert 2 | 1.94 * | 23.80 | 2.55 * | 9.38 |
| Expert 3 | 5.00 | 5.00 | 6.56 | 15.01 |

* If test statistic is less than 3.84, then conclude insignificant correlation at 0.05 significance level.

3. Phi Coefficients (Test Statistics)

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 0.33, (2.58) | 0.16, (1.29) * | 0.53, (4.13) | 0.63, (4.91) |
| Expert 2 | 0.17, (1.39) * | 0.62, (4.88) | 0.20, (1.60) * | 0.39, (3.06) |
| Expert 3 | 0.28, (2.24) | 0.28, (2.24) | 0.33, (2.56) | 0.50. (3.88) |

* If test statistic is less than 1. 645, then conclude insignificant correlation at 0.05 significance level.

**Table 4.2 Model Performance in Group B**

1. Predictive Accuracy (Simulation Validity)

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 93.2% | 76.3% | 89.8% | 88.1% |
| Expert 2 | 67.8% | 54.2% | 76.3% | 83.1% |
| Expert 3 | 67.8% | 71.2% | 71.2% | 71.2% |
| Mean | 77.6% | 69.1% | 80.1% | 80.8% |

2. Chi-square Statistics

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 44.29 | 16.38 | 37.43 | 34.36 |
| Expert 2 | 7.50 | 0.27 * | 15.70 | 25.30 |
| Expert 3 | 7.77 | 11.60 | 9.78 | 9.57 |

* If test statistic is less than 3.84, then conclude insignificant correlation at 0.05 significance level.

3. Phi Coefficients (Test Statistics)

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Expert 1 | 0.86, (6.65) | 0.52, (4.95) | 0.79, (6.12) | 0.76, (5.86) |
| Expert 2 | 0.35, (2.74) | 0.06, (0.52) * | 0.51, (3.96) | 0.65, (5.03) |
| Expert 3 | 0.36, (2.79) | 0.44, (3.41) | 0.40, (3.13) | 0.40, (3.09) |

* If test statistic is less than 1.645, then conclude insignificant correlation at 0.05 significance level.

In both case groups, the performance of neural networks is the best (Mean = 77.8% & 80.8%). Neural networks in this study, defined as nonlinear algorithms, simulated linear or mixed strategies much better than nonlinear strategies. This is attributed to their flexibility in information processing.

For detailed inter-model comparison, the 6 experiments (3 experts time 2 groups) were regrouped into three subgroups, based on the type of strategies (Table 4.4): 2 experiments were in the 'Nonlinear Group', 1 experiment was in the 'Linear Group', and 3 experiments were in the

'Mixed Group'. With this new grouping, Table 4.5 was generated to compare model performance in predicting decisions of three different strategies. As expected, two linear models (LR and DA) predicted the decisions of linear strategies much better than those of nonlinear or mixed strategies. The difference in predictive accuracy was significant as shown in (2) of Table 4.5.

**Table 4.4 Regrouping of Experiments by Decision Strategy**

| Decision strategy | Experiments | Numnber of Cases |
|---|---|---|
| Nonlinear (Conjunctive & Disjunctive) | Strategies of; Expert 2 in Analyzing Group A, Expert 3 in Analyzing Group B | 119 |
| Linear | Strategies of : Expert 1 in Evaluating Group B | 59 |
| Mixed (Linear & Disjunctive) | Strategies of : Exper 1 in Evaluating Group A, Exper 3 in Evaluating Group A, Exper 2 in Evaluating Group B | 1979 |

ID3 as a nonlinear model performed best in predicting the decisions of nonlinear strategies. ID3 also predicted the decisions of linear strategies significantly better than those of mixed strategies. Neural networks performed better in predicting the decisions of linear or mixed strategies rather than those of nonlinear strategies.

**Table 4.5 Comparison of Model Performance**

(1) Mean of Simulation Validity in Different Strategies

| | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Nonlinear strategies | 66.4% | 78.2% | 68.9% | 73.1% |
| Linear strategies | 93.2% | 76.3% | 89.8% | 88.1% |
| Mixed strategies | 69.3% | 59.8% | 73.2% | 80.5% |

(2) Inter-Strategy Comparison of Simulation Validity

(Test Statistics T*)

| comparison | Logistic Regression | ID3 | Discriminant Analysis | Neural Network |
|---|---|---|---|---|
| Nonlinear vs. Linear | 66.4% vs. 93.2% (T=−3.91) * | 78.2% vs. 76.3% (T=3.69)* | 68.9% vs. 89.8% (T=−3.07)* | 73.1% vs. 88.1% (T=−2.28)* |
| Linear vs. Mixed | 93.2& vs. 69.3% (T=3.69)* | 76.3% vs. 59.8% (T=2.29)* | 89.8% vs. 73.2% (T=2.65)* | 80.1% vs. 80.5% (T=1.34)* |
| Nonlinear vs. Mixed | 66.4% vs. 69.3% (T=0.52)* | 78.2% vs. 59.8% (T=3.31)* | 68.9% vs. 73.2% (T=−0.8)* | 73.1% vs. 80.5% (T=−1.49)* |

* If test statistic is greater than 1. 645, conclude that the predictive accuracy is significantly different between two strategies at 0.05 significance level.

Summarizing the analysis of decision strategy, there was strong evidence that two linear models and ID3 could capture or approximate consistent strategies rather than mixed or inconsistent strategies. The two linear algorithms simulated linear strategies significantly better than nonlinear or mixed strategies. ID3 simulated nonlinear strategies significantly better than mixed strategies. However, neural networks simulated linear strategies better than nonlinear strategies.

Table 4.6 shows the results by inter-model comparison in simulating the three different strategies. Test statistics described in part (1) show that two linear models and neural networks simulated linear strategies significantly better than ID3. It follows in part (2) that ID3 simulated nonlinear strategies significantly better than two linear models. The part (3) of this table shows excellent performance of neural networks when mixed strategies were modeled.

To summarize, the Chi-square tests for difference (T*) lead to relationships: 1) between good performance of linear models (LR and DA) and linear strategies, 2) between performance of ID3 and nonlinear strategies, and 3) good performance of BP of neural networks and mixed strategies. Since the mixed strategies mean the existence of multiple different strategies, the result indicated excellent simulation capability of neural networks regardless of the type of decision strategy.

**Table 4.6 Inter-Model Comparison of Simulation Validity**

(1) Between Algorithms in Simulating Linear Strategies

| Comparison | Test Statistics T* |
|---|---|
| Logistic Regression vs. ID3 | 2.56* |
| Logistic Regression vs. Neural Network | 0.95 |
| Logistic Regression vs. Discriminant Analysis | 0.66 |
| Neural Network vs. ID3 | 1.68* |
| Discriminant Analysis vs. ID3 | 1.96* |
| Discriminant Analysis vs. Neural Network | 0.29 |

* If test statistic is greater than 1.645, conclude that the predictive accuracy is significantly different between two strategies at 0.05 significance level.

(2) Between Algorithms in Simulating Nonlinear Strategies

| Comparison | Test Statistics T* |
|---|---|
| ID3 vs. Logistic Regression | 2.03* |
| Neural Network vs. Logistic Regression | 1.13 |
| Discriminant Analysis vs. Logistic Regression | 0.42 |
| ID3 vs. Neural Network | 0.91 |
| ID3 vs. Discriminant Analysis | 1.62* (p=0.053) |
| Neural Network vs. Discriminant Analysis | 0.71 |

(3) Between Algorithms in Simulating Mixed Strategies

| Comparison | Test Statistics T* |
|---|---|
| Logistic Regression vs.ID3 | 1.88* |
| Neural Network vs. Logistic Regression | 2.44* |
| Discriminant Analysis vs. Logistic Regression | 0.82 |
| Neural Network vs. ID3 | 4.27* |
| Discriminant Analysis vs. ID3 | 2.69* (p=0.053) |
| Neural Network vs. Discriminant Analysis | 1.63* (p=0.052) |

* If test statistic is greater than 1.645, conclude that the predictive accuracy is significantly different between two strategies at 0.05 significance level.

### 4.3 Discussion

The major finding of this study was a strong match between modeling algorithms and the type of decision strategies in relation to model performance. For example, linear models performed significantly better in simulating linear strategies than nonlinear strategies. The decision rules of ID3 performed significantly better in simulating nonlinear strategies than linear strategies. When they were compared with two linear models, the superiority of ID3 in simulating nonlinearity was statistically significant.

On the other hand, ID3 did not perform well in the experiments where linear strategies were dominantly employed. Linear models using LR and DA did not perform well in the experiments where nonlinear strategies were dominantly employed. This match, linear strategy and poor performance of ID3 or nonlinear strategy and poor performance of LR and DA, shows limitations of each algorithm in modeling different types of decision strategies.

However, it should be noted that when multiple strategies were employed, the performance of ID3 and two linear models was very poor. This result confirms the limitation of the modeling algorithms in simulating different type of information processing.

In comparing the two linear algorithms, the difference between the two was about the same and statistically insignificant. This result was consistent with the previous comparative study [10].

For the neural network, performance was significantly better in simulating linear strategies than nonlinear strategies. Regardless of strategy type, it generated a relatively accurate decision network even in simulating mixed strategies where it performed significantly better than the other three algorithms. The results reflect the flexible capability of neural networks in information processing (e. g., simulation).

The superior performance of neural networks in this study may not be so surprising for at least two reasons. First, empirical evidence for its superiority to the other algorithms in classification tasks abounds in the literature [4][20]. The results of this study are consistent with these early findings.

Second, the adaptive learning method of the neural network is very similar to the least squared method of the linear regression [3]. One different feature from the linear algorithm is existence of the hidden layer which enables the neural network to handle nonlinear processing. The hidden layer provides additional function to the linear processing feature of the neural network and does not weaken its capability for linear processing.

In summary, the results found here raise some very important issues. The first is that the process-tracing methods can be very useful for selecting a proper expert-modeling approach. The Einhorn's log transformation method could successfully differentiate decision strategies in terms of the type of decision strategy. The use of the mathematical approach may open the way to a much more expanded application of process-tracing approaches into expert-modeling for expert systems.

The second is that decision strategy is proven to be one of the key factors in determining model performance. The results of this study imply a strong need to consider "What type of decision behavior is to be modeled?" as well as "How can the behavior be modeled?".

## 6. Conclusion

The results of this study brought an important concept, decision strategy, to expert-modeling. The inclusion of the new concept, when combined with characteristics of modeling algorithms, helped explain clearly why a certain algorithm performed better than another. The contingent relationship among decision strategy, modeling algorithm, and model performance will be useful for further refinements of future expert-modeling research.

In modeling human experts, there are many factors to be considered. Previous studies using process-tracing approaches identified task characteristics, modeling situations, and individual difference as key factors [7][18][12]. For further research, it may guarantee valuable outcomes to expand the contingent relationship to a framework, which will be able to explain the relationships between model performance and those factors.

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