USING A NEUROFUZZY EXPERT SYSTEM TO ADDRESS AMBIGUITY PROBLEMS IN DEBT/EQUITY ISSUES OF CLOSELY HELD CORPORATIONS

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ABSTRACT

With a new round of tax laws being introduced almost every year, complexity has increased for the tax professional. In addition, the tax professional is also facing increased competition, constantly advancing technology and a more litigious environment. Tax planning is becoming more complex and the aid that was promised from the development of expert systems has not materialized. The purpose of this paper is to illustrate how a tax planner might develop decision rules for determining the capital structure of a closely held corporation by the use of fuzzy logic and neural networks. If these decision rules are based upon the judgment of "experts" as they relate to the determination of whether an interest deduction by a closely-held corporation is reasonable in specific situations, less experienced tax planners can benefit from the know-how of the these experts.

INTRODUCTION

Accounting firms have developed several applications of expert systems in accounting and tax. Specific applications include ExperTAX developed by Coopers and Lybrand, FSA developed by Arthur Andersen and ASQ developed by Arthur Young. However expert systems are not being developed and used in accounting as extensively as they were earlier projected. Many problems have slowed their growth. One such problem was the need to use precise variables generally combined with a linear model. It was soon recognized that experts simply don't use precise variables and linear models. Another problem was that for an expert system to be refined with all of its variables and decision rules, the system had to be known and this was not always true. Two current developments are currently being integrated in the area of expert systems that may help solve these problems. Fuzzy logic is replacing Boolean logic in many new systems. And neural networks are being used to help learn complex systems that are not fully understood.

Fuzzy logic was developed to aid computers in solving problems in a manner more characteristic of human expert problem solving. Zadeh (1965) introduced the fuzzy set theory as a branch of classical set theory. It allows for systems with human interaction to tolerate vagueness and ambiguity that is natural in personal judgments. This vagueness and ambiguity should not be confused with the uncertainty that is created by randomness, which is best dealt with using probability. Rather vagueness and ambiguity deal with the imprecise nature of human language.

Neural networks are an attempt to mimic the way the human brain learns. Neural nets use a number of simple computational neurons that attempt to behave as a human brain cell would behave. Each neuron receives inputs and processes outputs to other neurons until an output signal is generated. The computer system can perform numerous iterations at high speed that should allow the learning process to be more efficient and possibly give us insights that may have taken human experts years to discover.

The purpose of this paper is to illustrate how fuzzy logic and neural networks can be used to develop an expert system to aid tax planners in assisting their clients in ambiguous tax planning situations such as determining debt/equity issues of a closely held corporation. If these decision rules are based upon the judgment of "experts" as they relate to the determination of what level of debt is reasonable in specific situations, less experienced tax planners can benefit from the know-how of the these experts. These experts could include the judges of tax decisions if we are trying to predict the outcome of a potential case. Internal Revenue Agents would be used if we were trying to predict the possibility of an audit. Experienced tax planners could be used if we trying to evaluate the best method of structuring a complex tax transaction. The use of fuzzy logic allows for any ambiguities that may occur among the experts in their determinations of the variable that go into the decision and the output. Neural networks can help in the development of a complex system that may not even be completely understood by the experts that make these decisions on a regular basis. Together fuzzy logic and neural networks may be able to overcome many of the problems that have slowed the growth of expert systems in the tax field.

Under Internal Revenue Code (IRC) §385(a) the Secretary is authorized to prescribe regulations that would determine if an equity interest in a corporation is to be treated for income tax purposes as stock or indebtedness. While there has been a myriad of factors that have been set forward in the IRC, the regulations and rulings, the numerous court cases, these factors are subjective and ambiguous. There has been no guidance as to what weight these factors carry and no factor has been deemed determinative.

Because of these new complexities in what was already a complex area, tax planners need assistance. With a large number of factors that can impact the determination of the debt, a set of rules that can be applied to current situations would be helpful. However, the traditional statistical techniques used to predict reasonable compensation have not been helpful to the tax practitioner.

The purpose of this project is to begin the development of a decision model that can be used to help the owner of a closely-held corporation determine a reasonable capital structure of their firm that minimizes their tax cost within the constraint of the tax law. The results of this study may be used to develop an expert system that could be used by tax professionals in advising their clients in ambiguous planning situations. Incorporating it in a neural network model may also refine the model. The purpose of this study is to develop a framework to assist professionals to appropriately classify financial instruments. The remainder of this paper is composed of five sections. First, background is provided regarding the evolution of characterization under the tax law. Second, a discussion is provided of the development of decision aids for ambiguous areas of the tax law. Third, the development of experts systems for tax planning models is analyzed. Fourth, the system design and a model development is set forth.

BACKGROUND

A significant, yet long-standing, problem confronted by tax professionals concerns how to determine whether a corporate financial instrument should be classified as debt or equity. The ambiguous nature by which such classification has historically been made reflects the difficulty encountered in making this determination. This ambiguity can be attributed to the myriad of factors set forth by Congress, the Service and the Courts as relevant to making this determination, and to the frequent raising of capital through utilization of instruments possessing characteristics associated with both debt and equity (hybrid securities). No guidance has been provided as to what weight these factors carry and no particular factor has been deemed determinative. Exacerbating the uncertainty faced in resolving classification is the lack of relevant regulations and the Service's refusal to issue advance rulings concerning how a financial instrument will be classified for tax purposes. Whether an instrument is considered debt or equity have important financial ramifications. For example, classification affects the rating to be given the entity, the determination of whether the entity satisfies certain regulatory requirements and the computation of earnings per share. In addition, whether an instrument is considered debt and equity have the following vital tax implications:

1)	The payment of interest on debt is deductible whereas the payment of dividends on equity is not.
2)	Worthless debt may qualify for an ordinary deduction whereas worthless equity will give rise to a capital loss.
3)	Equity is more amenable for use in accomplishing nonrecognition transactions, e.g., Section 351 transactions and reorganizations, than is debt.
4)	Section 1244 and ordinary loss treatment may be available with respect to equity but not with respect to losses on debt.
5)	The discharge of debt may give rise to application of I.R.C. section 108, end rules regarding discharges of indebtedness.
6)	Should debt be characterized as a second class of stock, it will affect the ability of the organization to qualify as an S Corporation.
7)	Where a corporation holds equity it may enable receipt of a dividends-received deduction.

Operationalization of Section 385

As pointed out by the Second Circuit in the landmark case of O.P.P. Holding Corp., "the shareholder is an adventurer in the corporate business, he takes the risk, and profits from success. The creditor, in compensation, for not sharing the profits, is to be paid independently of the risk of success, and gets to dip into the capital when the payment due arrives."

Transforming this expression of into a workable standard for distinguishing debt and equity has proven problematic. Congress has long recognized this problem. The issue arose in the process of devising the 1954 Code. In the course of the promulgating definitions of certain terms relevant to corporate transactions and reorganizations the 1954 Senate Finance Committee noted:

" Your committee believes that any attempt to write into the statute precise definitions which will classify for tax purposes the many types of corporate stocks and securities will be frustrated by the numerous characteristics of an interchangeable nature which can be given to these instruments."

It was not until 1969 that Congress enacted a Code section intended to provide clarification. That section was I.R.C. Section 385. I.R.C. Section 385 lists five factors as relevant for distinguishing debt from equity. These factors were:

1)	Whether there is a written unconditional promise to pay on demand or on a specified date, a fixed amount of money in return for an adequate consideration and to pay a fixed rate of interest.
2)	Whether there is subordination to, or convertibility over, other debt.
3)	The ratio of debt to equity.
4)	Whether there is convertibility of debt into stock.
5)	The relationship between stockholdings and the holdings of the interest in question.

These factors largely mirror factors set forth in case law. Still Congress authorized the Treasury to establish regulations defining the application of these factors in an effort to distinguish debt from equity. Over the years the Service has made several attempts to issue proposed and final regulations concerning application of these factors. Consistently the effective date of the issuance of these regulations was delayed until finally in 1983 the attempts at regulations were withdrawn.

Today I.R.C. §385 continues as part of the Internal Revenue Code, without the clarification of regulations. Nevertheless, the Section and reliance on case law provides some insight into factors relevant to distinguishing debt from equity. That Congress has not forsaken its concern with the area is evident in its 1992 enactment of I.R.C. §385(c) that provides that the initial characterization accorded an instrument by a corporation binds the issuer and all holders other than the Internal Revenue Service.

The Service has maintained a hard line to the classification of an instrument as debt. Although regulations concerning the debt/equity distinction are lacking, the Service's position on factors relevant to classifying a corporate instrument can be gleaned from examination of IRS pronouncements. Most recently a recitation of factors considered by the Service was set forth in Rev. Rul. 94-47 and 94-48. In these rulings the Service indicated that it was particularly interested in instruments containing long maturity periods or an ability to repay principal with stock. The Service also noted that characterization of an instrument would be determined based upon examination of the terms of the instrument and the surrounding facts and circumstances, in light of a litany of factors with no particular factor being determination. Factors mentioned in the rulings as relevant to resolving characterization include:

1)	Whether there is an unconditional promise on the part of the issuer to pay a sum certain on demand or at a fixed maturity date that is in the reasonably foreseeable future.

2)	Whether holders of the instruments possess the right to enforce the payment of interest and principal.
3)	Whether the rights of the holders of the instruments are subordinate to the rights of general creditors.
4)	Whether the instruments give holders the right to participate in management of the issuer.
5)	Whether the issuer is thinly capitalized.
6)	Whether there is identity between holders of the instruments and stockholders of the issuer.
7)	The label placed upon the instruments by the parties.
8)	Whether the instruments are intended to be treated as debt or equity for non-tax purposes, including regulatory, rating or financial accounting purposes.

These factors are consistent with both those factors mentioned in I.R.C. Section 385 and prescribed by case law. Of some interest and uncertainty is the role and weight to be accorded the ability of the issuer to repay principal with stock and the duration until maturity.

DEVELOPING DECISION AIDS FOR AMBIGUOUS AREAS OF THE TAX LAW

Subjective Decision Aids

Stare decisis is a doctrine or policy of following rules or principles established in previous judicial decisions unless they contravene the ordinary principles of justice. Because of this doctrine, developing decision aids for ambiguous areas of the tax law is critical. Stare decisis compels tax professionals to determine the factors that must be considered when analyzing areas of the law that require subjective determinations, and to weigh these factors in some method so that proper and consistent advice can be given to their clients which is congruous with the judicial history.

When tax professionals render advice for an ambiguous scenario, the relevant law for that area is reviewed and a subjective determination of the impact of prior law on their client's current situation is made. There are several problems with this type of a decision model, including biased observations, nonreplicable results, and limited ability to generalize results. Researchers have recognized that tax professionals need objective methods to help them reach conclusions when dealing with ambiguity. The quantitative approaches that have been used are summarized in the next section.

Development of a Predictive Model

The Brunswick Lens Model (Brunswick, 1952) depicts the decision maker as utilizing a set of cues to predict the environment, or the "true fact." Jensen and Horwitz (1979) used the Brunswick Lens Model to develop a theoretical framework for quantifying judicial decisions. This was done by characterizing the judges as the decision-makers, the true events of the case as the environment, and the facts of the case as the cue set. Kilpatrick (1984) extended this framework to depict the taxpayer/advisor as the decision-maker, the court's decisions as the environment, and the variables used by the judges as the cue set to predict the judges' decision. This theoretical framework has been the basis of studies that attempt to predict the outcome of judicial decisions with the use of the general linear model.

The development of mathematical models in tax cases can be divided into two main areas. The first area deals with the identification and significance of factors applied by the courts in their decisions for specific tax issues (e.g., Boyd, 1977; Englebrecht & Rolfe, 1982; Burns & Groomer, 1983). The second area is concerned with developing a model that accurately predicts a court's decision for a given issue, so that tax professionals can use these models when dealing with similar tax issues (e.g., Stewart, 1982; Kilpatrick, 1984; Judd, 1985). Most of these studies have relied on multiple discriminate analysis, multivariate probit analysis, or logit analysis to develop prediction models.

Problems with Predictive Models

Several limitations have been noted to the general linear model analysis of court decisions (e.g., Kramer, 1982). First, any model developed for the purpose of prediction using data from court decisions will be limited because of the dynamic nature of the tax law. Second, an inherent problem with using case analysis is that the sample only includes those cases that are litigated. Many cases are settled before they are litigated and are not included. Third, the data are based on published court opinions. The variables cited in the case opinion may be selected to substantiate the judge's opinion while other important variables may be left out of the opinion. Asking a panel of tax experts (i.e., judges, CPA's, attorneys, etc.) to rate the factors that they would use when resolving specific ambiguous tax questions could mitigate the latter two problems. Fourth, the general linear model requires a digitization of subjective human opinions. This digitization implies an exactness that does not exist. Rough set theory will assist professionals in making better decisions.

DEVELOPMENT OF EXPERT SYSTEMS FOR TAX PLANNING MODELS

Expert systems in tax planning have been with us for over twenty years. For the complex environment of taxation, expert systems seem an ideal tool to aid the practitioner in making tax planning a more accurate, consistent, and efficient process. In 1977, McCarty introduced TAXMAN I. This expert system helped analyze the tax consequences of certain corporate reorganizations. This was one of the first uses of an expert system for tax planning. In 1979, TAXMAN II was developed to analyze and develop the cognitive patterns used by lawyers and judges in tax cases (McCarty et al., 1979). TAXADVISOR was a system designed to assist in individual income and transfer tax planning (Michaelsen, 1982). Other expert systems that incorporated tax planning include INVESTOR (Michaelsen, 1987), FINANCIAL ADVISOR (Bailey, 1985), and ExperTAX (Shpilberg et al., 1986). Michaelsen and Messier (1987) cited several potential roles and problems for expert systems in taxation. Those roles include assisting in tax compliance, tax planning, education, and academic tax research. The problems cited include determining the appropriate path to the solution of a problem, the uncertainty and the stability of the tax rules, semantic ambiguity of the issues, and the integration of broad judicial concepts, such as "substance over form," with specific rules.

The Fuzzy Expert System

One of the great expectations of the modern computer age has been the development of Artificial Intelligence (AI). A subset of AI that has seen some limited success is expert systems. Generally, expert systems are computer programs that use the specific knowledge of experts to guide a novice through a complex maze of information to make a decision that would be the same as a decision made by an expert. A fuzzy expert system is simply an expert system that uses fuzzy logic instead of the traditional Boolean logic. The use of fuzzy logic does create several significant differences. In the traditional expert system, a question would be answered with a Yes\No type of response. If yes was answered, the system would take the user to a specific set of follow-up questions and eventually a decision. However if no was the response, a different set of follow-up questions and a different decision would evolve. For example, does the owner\employee have a high level of qualifications for the job being performed? If the employee has a high level of qualifications then the response is yes, if not the response is no. Under a fuzzy expert system, the answers would be given in a response that reflects a membership function. For example, in the case of the same question, "does the written instrument favor a classification as debt?" The response could be any one of the following:

♦	The written instrument has a very favorable level as debt since there is a complete formal document.
♦	The written instrument has a favorable level as debt since there is a fairly complete document.
♦	The written instrument has a moderate level as debt since there is a document with some characteristics.
♦	The written instrument has an unfavorable level as debt since there is a document with few characteristics.
♦	The written instrument has a very unfavorable level as debt since there is no formal document.

Another difference is the use of probability in the traditional expert system. In developing a much more complex model, the traditional expert system could utilize the five levels of response that were shown above through the use of probability. For example, the probability of written instrument being classified at different levels of a formal debt instrument could be illustrated as follows:

A very favorable level as debt since there is a complete formal document.	5%
A favorable level as debt since there is a fairly complete document.	75%
A moderate level as debt since there is a document with some characteristics.	15%
An unfavorable level as debt since there is a document with few characteristics.	5%
A very unfavorable level as debt since there is no formal document.	0%
	100%

This represents that the instrument in a given situation has a 75% probability of being classified as a fairly complete document or a 15% probability of being classified as a document with some characteristics. However, these two classifications are mutually exclusive and the level of qualifications must be one or the other (with a 90% probability) but cannot be both. Whereas, the membership function of a fuzzy expert system measures a specific situation to its fit in a given level. Two highly qualified experts may look at a specific fact pattern of this variable. The first one comes to a conclusion that the written instrument has a favorable level as debt since there is a fairly complete document while the other expert determines the written instrument has a moderate level as debt since there is a document with some proper characteristics. While this appears inconsistent, fuzzy logic allows for this type of ambiguity. The membership function of each level is measured on a 0 to 1 scale. The measure of membership function might look like the following:

A very favorable level as debt since there is a complete formal document.	.1
A favorable level as debt since there is a fairly complete document.	.8
A moderate level as debt since there is a document with some characteristics.	.4
An unfavorable level as debt since there is a document with few characteristics.	.2
A very unfavorable level as debt since there is no formal document.	.0

The key difference between the two is that all probability functions must equal 100%, whereas membership functions do not necessarily equal 1.0. The difference is in the meaning of the numbers. When there is a 75% probability that the written instrument has a favorable level as debt, there must be a 25% probability that the written instrument does not have a favorable level of qualifications. However when there is a .8 membership function that the written instrument has a favorable level as debt it merely means that the debt instrument's level of qualifications could be viewed by one expert as favorable and another expert as moderate. But the experts feel it may be more favorable (.8) than moderate (.4). Another difference in the traditional and fuzzy expert systems is in the output. Like the input variables in a fuzzy system, the output variable can be multiple levels with certain decision rules and possible decision rules. The traditional expert system generally outputs a single decision based on the inputs. While this has a real appeal, the problem is that the answers to many complex questions are not always so simple.

SYSTEM DESIGN

The purpose of a fuzzy expert system is to develop a group of decision rules to determine a specific membership function. These decision rules will then make up the rule base. Once the variables that affect the output have been determined, the structure that represents the information flow of the system is designed. The inference process is used to establish the rule base by taking the actual values of the input variables through the system design and determining the level of the output variable. The system design is a three-step procedure that includes definition of the linguistic variables, determination of the type of membership function, and the creation of a rule base.

Definition of the Linguistic Variables

The first step in the system design is to determine the specific linguistic values of the input variables. The linguistic values of the input variables are those fuzzy variables that the expert uses to make a judgment. For example, one of the factors used to determine the debt/equity level of a closely held corporation has been the creditors participation in the management of the business. This would be the linguistic variable and could be measured on various levels. These levels represent the linguistic interpretation of a technical measure such as the three levels: high, medium and low. If however it is determined that five levels may be more helpful very high and very low could be added. An odd number of levels is generally used in fuzzy logic systems which allows there to be a middle level between the extremes. Since short-term human memory can only process up to 7 symbols at a time, there are generally 3, 5, or 7 levels. At any time during the system design or the later optimization of the system linguistic variables and levels can be added or deleted.

Determination of the Type of Membership Function

The next step is to determine the degree for which the chosen level satisfies the linguistic variable. This degree of support that the value of a technical figure has for the linguistic variable represents its' membership function. As was illustrated above for the variable of the debt instrument, the membership functions of a fuzzy expert system for the debt instrument might look like the following:

A very favorable level as debt since there is a complete formal document.	.1
A favorable level as debt since there is a fairly complete document.	.8
A moderate level as debt since there is a document with some characteristics.	.4
An unfavorable level as debt since there is a document with few characteristics.	.2
A very unfavorable level as debt since there is no formal document.	.0

Creation of a Rule Base

All of the fuzzy subsets are assigned to each output variable and are combined to form a single subset for each output variable. From this output, a rule base can be created. Two types of rules will be developed certain rules and possible rules. Certain rules would be those rules were observations of membership function always have resulted in the same output. For example, if the debt instrument variable was favorable or very favorable and the debt/equity variable was favorable, the interest deduction was allowed in every observation no matter what the other variables were. Possible rules are when a given combination of variables has resulted in more than one outcome. Possible rules are the consequence of two or more expert determinations finding a different result for input with the same membership function, such as the Second Circuit and the Sixth Circuit coming to different judgments on the same fact pattern. Once the rule base is constructed, an inexperienced tax planner could easily follow any certain rule with full confidence. But, a possible rule would indicate that the inexperienced tax planner should seek the help of a more experienced planner.

Use Of Neural Networks To Train Fuzzy Logic Expert Systems

Traditional expert systems have tended to focus on developing decision rules for well-defined problems that the factors have been clearly defined. Neural networks have addressed the development of solutions to less clearly defined inputs. While most expert systems have used a deductive reasoning process to establish its' rule base, whereas neural networks depend on inductive reasoning to learn. The neural network approach to problem solving simulates the human brain. The program uses experience to solve problems that it may have not been exposed to before. Neural networks also have the ability to change as the environment changes.

Fuzzy logic appears to be the perfect compliment to neural networks. A major benefit of fuzzy logic has been its adaptability to simple if-then solutions. This has reduced design time for many engineers in developing very efficient systems that have been clearly defined. But in the case of systems where problems exist and there is no clear solution, the neural network has the ability to train itself from the existing data sets. With all of the court cases and the various rulings by the Internal Revenue Service, a large amount of data exists. Identifying the variables in the cases and rulings and entering them into the neural network could develop a model developed without using an expert to interpret all of those cases and rulings.

THE NEUROFUZZY EXPERT SYSTEM FOR DETERMINING DEBT STRUCTURE

This section explains how the problem of determining the debt/equity structure of a closely held corporation could be modeled using Inform Software's fuzzyTECH and NeuroFuzzy programs designed for business applications.

Definition of the Linguistic Variables

The first step in the system design is to define the linguistic variables. For purposes of this paper, in order to ease illustration, only five independent variables will be used to determine the one dependent variable. The dependent variable is the reasonableness of the debt\equity structure of a closely held corporation. The five independent variables the courts have used in determining the debt\equity structure of a closely held corporation that will be used in this discussion include:

- Unconditional promise to pay
- Right to enforce payment
- Subordinated rights
- Management participation
- Thin capitalization.

Determination of the Type of Membership Function

For the dependent variable and each of the five independent variables, the levels of the membership functions need to be established. The dependent variable, the debt/equity structure, three levels will be used. The first level, reasonable, will represent a set of facts were the debt\equity structure used by the taxpayer is accepted by the court. The third level, unreasonable, would represent a decision by the court the debt\equity structure used by the taxpayer was not reasonable the court used the amount of debt deemed reasonable by the Internal Revenue Service. The middle level, questionable, would represent those findings were the court compromised between the taxpayer and the IRS's positions. If this level is later determined to be to broad, two additional levels could be added. Somewhat questionable could represent those compromise cases that are much closer the taxpayer's position and very questionable could represent those cases closer to the IRS's positions.

For the independent variables, three levels could be used to represent their membership function. Favorable would indicate that the variable supported the taxpayer's position. For example, in the court opinion the debt/equity ratio is determined to be inline with the debt/equity ratios of other companies in similar businesses and the same industry or the creditor has complete ability to enforce the payment of interest and principal, these variables would be favorable to the taxpayer. Unfavorable would indicate that the variable did not support the deductibility of the interest by the business. For instance, no debt instrument exists and there is merely an understanding the debt will be paid sometime in the future. The middle level will be labeled neutral and would generally indicate no mention of the variable in the court's opinion or an opinion of the court that the variable had little or no effect. Once again, if additional variable were deemed necessary they could be added later.

Creation of a Rule Base

Once the model has been created and the database for the court decision has been entered into model, the NeuroFuzzy system will learn the model and should create a set of rules that could then be used by practitioners in helping their clients plan. As mentioned above these rules will come in two classes, certain and possible. If the cases inputted into the model with identical membership function levels all have the same determination then the rule will be certain. For example, if six cases had the following membership functions:

Unconditional promise to pay	neutral
Right to enforce payment	favorable
Subordinated rights	neutral
Management participation	favorable
Thin capitalization	unfavorable

And all six cases were determined to be reasonable, this rule would be certain. However, if four of the cases were determined to be reasonable and two were questionable, this would be classified as a possible rule.

With five variables and three levels of membership function, there are 243 possible combinations. Many of these combinations will collapse into a smaller number of rules. For example, if every combination of membership functions where unconditional promise to pay and thin capitalization was favorable and the court determined that the debt/equity structure was reasonable no matter what the other three membership functions were, one decision rule would cover 27 of the possible combinations.

CONCLUSION

This paper has illustrated one approach the tax planner has available to address the problem of applying the ambiguous tax law to their client's particular situations. By using the prior decisions of the courts, the tax planner could develop a set of decision rules that would aid them in making a determination of debt/equity structure for closely held corporations in future planning situations. It should be stressed that the learning of rules is dependent upon the relevance of the value of the selected attribute to the conclusion in the cases provided. Over time, more evaluations can be added to the model. As long as the attributes are relevant and the determinations are consistent the decision rules will become more reliable.

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