Learning And Predicting Individual Preferences In Multicriteria Decision Making With Neural Networks Vs. Utility Functions

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ABSTRACT

This paper reports an empirical investigation into the performance of neural network technique vs. traditional utility theory-based method in capturing and predicting individual preference in multi-criteria decision making. As a universal function approximator, a neural network can assess individual utility function without imposing strong assumptions on functional form and behavior of the underlying data. Results of this study show that in all cases, the predictive ability of neural network technique was comparable to the multi-attribute utility theory-based models.

Keywords: Decision Analysis; Decision Support Systems; Multi-Criteria Decision Making; Multi-Attribute Utility Theory; Neural Networks; Preference Assessments; Utility Functions

INTRODUCTION

Multi-criteria decision making (MCDM) involves making choices on a set of alternatives, taking into consideration many conflicting qualitative and/or quantitative criteria attributes. To represent and predict individual decision patterns, instead of simply asking a decision maker (DM) to intuitively rank the outcomes, one can assess the DM's cardinal preference with either holistic or decomposition approaches before ranking the alternatives. In the holistic approach, the DM provides his/her overall preference of the outcome associated with each alternative. In the decomposition approach, the DM provides his/her preference for each attribute and its levels. Then, some functional forms are used to aggregate attribute preferences into an outcome preference. Literature suggests various assessment techniques to determine a preference profile. Thus far, the agreement among DM's preferences assessed by using different methods has not been asserted. Assuming that a typical DM is rational, the incompatibility among reported results may stem from the functional form of utility function being used to aggregate attribute preferences.

This paper considers the use of neural networks to address the possible problem of models that inadequately represent incomplete knowledge on a DM's decision pattern, particularly by using an improper utility function. It reports and discusses findings of a comparative study on the performance of utility theory and neural networks in assessing preferences on a multi-criteria decision problem.

MULTI-ATTRIBUTE UTILITY THEORY (MAUT) ASSESSMENT

Among various utility functions that reflect a DM's preference (Luce & Raiffa, 1987; Farquhar, 1977), the most common one is Keeney's MAUT utility function (Keeney, 1974; Keeney & Raiffa, 1976). With assumptions on preferential and utility independences of attributes, a multi-attribute utility function u could be decomposed into many single-attribute functions u_i for the ease of assessment.

Let u, u_i being utility functions scaled from zero to one; k_i being a non-zero scaling constant of the single attribute utility u_i where $0 < k_i < 1$; and $k > -1$ is the solution to

$$1 + k = \prod_{i=1}^{n} [1 + kk_i] \qquad (1)$$

Then, for the number of attributes $n > 3$, the multi-attribute utility function of an individual x is either in additive form,

$$u(x) = \sum_{i=1}^{n} k_i u_i(x_i) \tag{2}$$

or in multiplicative form,

$$1 + ku(x) = \prod_{i=1}^{n} [1 + kk_i u_i(x_i)] \tag{3}$$

The sign of k indicates whether the attributes are complement or substitute for each other. Consequently, Kenney (1974, 1977), Keeney and Raiffa (1976) described a procedure to assess multi-attribute utility function in a decision problem.

Traditional assessment methods have attempted to fit DM's preference into a prescribed utility function using regression or optimization to estimate the function parameters from a sample of decision patterns. Comparative studies have not always shown a strong agreement between results obtained from decomposition and holistic assessments applied to the same DM (Fischer, 1977; Schoemaker & Waid, 1982; Ravinder, 1992). Perhaps the preference profile of a DM may not be captured entirely by Keeney's MAUT function. It appears that one should consider different assessment procedures in order to better represent and model a DM's preference. The mapping of DM's preference requires a more flexible functional form than the one prescribed by the utility theory. Given the existence of a utility function and the individual preference patterns, which is the relationship between decision criteria and decision outcome, Artificial Neural Network (ANN) could approximate a utility function without imposing strong assumptions on the functional form and the behavior of the underlying data.

NEURAL NETWORK ASSESSMENT

The artificial neural network (ANN) technique has enjoyed a rapid expansion and popularity in both academia and industry (Flores, 2011). In theory, an ANN can be considered as a universal approximator of any functional relationship (Funahashi, 1989, Cybenko, 1989; Hornik et al., 1989; Haykin, 2009). In practice, ANN has been used to develop applications for classification, regression, clustering, and association in finance, forecasting, marketing (Turban et al., 2011)

An ANN contains processing/computing units called neurons (or nodes). These nodes are arranged into layers, in which a node in one layer has a weighted connection to each node of the next layer in a particular configuration. A node, as a processing unit, receives inputs from other nodes or from an external stimulus. A weighted sum of these inputs constitutes the argument to an activation or transfer function.

Most applications have used 3-layer networks consisting of one input, one hidden and one output layer. The hidden nodes are needed to introduce nonlinearity into the network. In some cases, more hidden layers are necessary to approximate a higher order function. An input node provides an external signal to the network. An output node produces an output of the network as a whole. A hidden node that is necessary for the computation of complex functions. Node inputs and activations can be discrete, taking on values {0, 1} or {-1, 0, 1}, or be continuous, taking on values in the interval [0,1] or [-1,1]. Each node u_i computes a single numerical node output or activation. Output of a node can be the output of the network as a whole and/or it can be the input to other nodes. Every node, other than input nodes, computes its new activation u_i as a function of the weighted sum of inputs directed to it from other nodes:

$$S_i = \sum_{j=0}^{n} w_{i,j}\, u_j \tag{4}$$

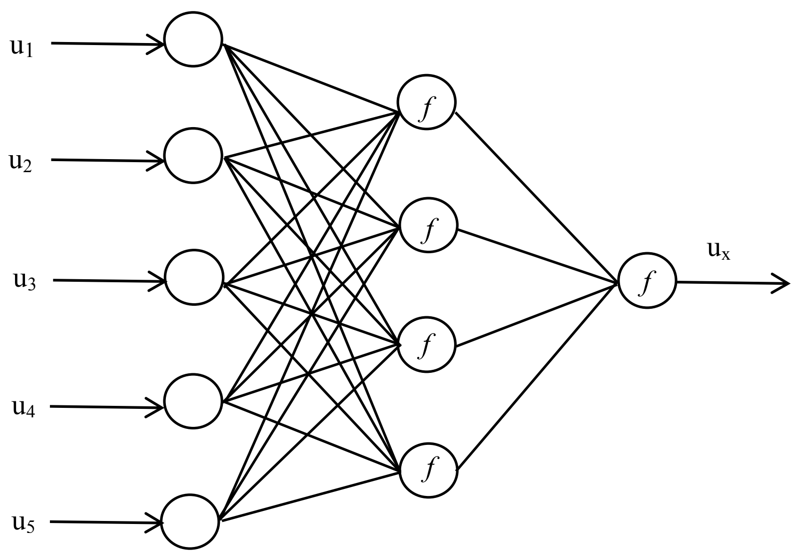
$$u_i = f(S_i) \tag{5}$$

where the activation function, $f(.)$, is usually a nonlinear, bounded and piecewise differentiable function such as the sigmoid function,

$$f(x) = 1/(1 + e^{-x}) \tag{6}$$

A weight represents the strength of association among connected features, concepts, propositions, or events presented to the network. The mechanism of ANN is to use a higher order function, such as a sigmoidal function, to approximate a lower order function. It has been shown that standard multi-layer networks using arbitrary transfer functions in processing units can approximate any Borel measurable function to any desired degree of accuracy (Hassoun, 1995; Steeb, 2005). The construction of a neural network is specific to the problem with a set of input-output patterns, when the pattern changes the network needs to be retrained with new inputs and outputs.

Figure 1. Topology of ANN 5-4-1 to Assess Preference of DM x



The neural network technique has its merit in the flexibility of theory requirement in comparison with mathematical programming and utility-based methods. It does not require assumptions on the probability distributions or objective function structures. Consequently, in an MCDM context, a neural network could predict a DM's preference without specifying his/her utility function, *a priori*. With sufficient data and an appropriate topology, a neural network would generate a better representation of a data set than the utility-based assessment procedure.

A drawback of the ANN technique is that, unlike coefficients in a regression model, the estimated weights of a neural network do not tell us much about the relationship between the independent and dependent variables. Also, the estimation may not be as accurate as the result of a regression determined from a known functional relationship. However, in the regression method has the same difficulty in justifying the use of a high dimensional function for modelling purposes. Then, a result from a traditional nonlinear regression model may violate the prior knowledge about the monotonic relationship (Wang, 1994).

Despite these shortcomings, we believe that the advantages of the neural network technique still merit its use in approximating a DM's utility function and predicting his/her preference.

COMPARATIVE STUDY AND RESULTS

The decision problem in this study involved the project selection and economic appraisal of five proposals to develop, produce and market a new product. DMs were asked to rank the proposals based on five criteria being measured on different scales: some are quantitative, others are qualitative. The problem domain is represented in Table 1.

Table 1. The Problem Domain

NPV of Cash Flow	$[1.0 2.0 3.0 4.0 5.0] millions
Initial Investment	$[2.5 2.0 1.5 1.0 0.5] millions
Market Growth Rate	[fair good very-good]
Capability to Market	[fair good very-good]
Prospect of Technical Success	[fair good very-good]

In this context, comparative results are based on preference assessments of nine DMs. The decomposition and holistic assessments were administered with a standard reference lottery to obtain the necessary parameters of DMs' utility functions (Kenney,1974, 1977). To implement the holistic approach, an orthogonal plan (Addleman, 1962a, 1962b) was used to define a set of 24 possible alternatives / scenarios containing basic patterns for preference assessment to alleviate the burden of cognitive process undergone by DMs.

Table 2. Errors on Assessed Utilities across Methods in Cross-Validation

	Multiplicative MAUT	Additive MAUT	Neural 4	Neural 5	Neural 6
Subject 1					
RMSE Training			0.04145	0.05059	0.05035
RMSE Predicting	0.17467	0.15873	0.20548	0.20643	0.21138
Subject 2					
RMSE Training			0.04275	0.04559	0.04042
RMSE Predicting	0.13633	0.13068	0.05232	0.05078	0.06686
Subject 3					
RMSE Training			0.0470	0.04711	0.04624
RMSE Predicting	0.32026	0.25107	0.20523	0.30968	0.24452
Subject 4					
RMSE Training			0.04895	0.03978	0.04236
RMSE Predicting	0.09855	0.10864	0.07386	0.11247	0.08288
Subject 5					
RMSE Training			0.03768	0.03921	0.03106
RMSE Predicting	0.2235	0.11151	0.05378	0.07680	0.13432
Subject 6					
RMSE Training			0.04819	0.05287	0.05328
RMSE Predicting	0.12103	0.26723	0.07498	0.06081	0.06394
Subject 7					
RMSE Training			0.04364	0.04893	0.04714
RMSE Predicting	0.14099	0.23289	0.12549	0.09102	0.09555
Subject 8					
RMSE Training			0.04733	0.04725	0.04526
RMSE Predicting	0.24877	0.20389	0.10497	0.10796	0.11447
Subject 9					
RMSE Training			0.03548	0.04533	0.04414
RMSE Predicting	0.12682	0.05812	0.08266	0.06906	0.06957

MAUT assessments were conducted with the procedure described in Keeney (1974, 1977). Results assessed from both additive and multiplicative MAUT functions were compared with those from other assessments.

The neural network technique was implemented with a topology of 3-layer network using a backpropagation algorithm. The input layer had 5 nodes, each representing an attribute of the decision problem. The output layer had one output node representing a DM's preference for the alternative being processed. Different network configurations labelled as Neural 4, Neural 5 and Neural 6 with numbers of nodes in the hidden layer varying from four to six, were implemented to obtain the best fit in training and prediction (Figure 1). For each subject, the networks were trained with preference patterns captured in the set of 24 holistic assessments. Performance comparison was conducted with cross-validation on the out-of-sample set of five actual projects of the decision problem. Errors on assessed utilities across methods and subjects are reported in Table 2. The errors in prediction of neural networks are all lower than those of MAUT methods.

Using holistic assessment representing the DM's intuitive preference as the benchmark, the Kendall rank correlation between the ranks by holistic and multiplicative MAUT ranged from -.32 to .95 with a median of .40. Between multiplicative and additive MAUT, the range is -.32 to .80 with a median of .53. Between holistic and Neural 4, the range is .32 to 1 with a median of .84. Between holistic and Neural 5, the range is -.11 to 1 with a median of .74. Between holistic and Neural 6, the range is .11 to .84 with a median of .74. Among these comparisons, Neural 4 had the highest agreement with holistic utility. Therefore, it was used to make further comparisons with other assessments.

Out of nine subjects in this study, between the holistic and MAUT multiplicative assessments, the same best project was identified in 5 cases, the same worst was identified in 4 cases. The same number of similarities was observed between the holistic and MAUT additive assessments. Between the holistic and Neural 4 assessments, the same best project was identified in 7 cases, the same worst was identified in 5 cases. These results indicate that the neural network technique captures decision patterns closely representing intuitive preferences and arrives at more accurate predictions.

On relative performance of neural networks with different configurations, between the holistic and Neural 5 assessments, the same best project was identified in 5 cases, the same worst was identified in 6 cases. Between the holistic and Neural 6 assessments, the same best project was identified in 5 cases, the same worst in 4 cases. This again confirms the prediction capacity of Neural 4 with a simpler configuration. Overall, using any configuration, the performance of the neural network technique in prediction is at least as well as those using the MAUT method.

CONCLUDING REMARKS

Findings of this study demonstrate that a neural network provides two basic advantages over other preference assessment techniques in multi-criteria decision making process. First, it has the ability to discover relationships in the data without making strong assumptions on the data distribution to determine the functional relationship among attributes of the decision problem. Second, a neural network is extremely suitable for detecting nonlinear associations among variables in an incomplete set of decision patterns.

In order to compare with Keeney's MAUT prescribed additive/multiplicative preference functions, this study implemented the same network configuration to represent the same functional relationship among attributes of all subjects. Apparently, the predictive ability of neural networks could be improved with different optimal network topology – function for each DM to approximate and predict his/her preference.

In traditional assessment methods, a quality scale such as "fair", "good" and "very good" assumes an equal distance between each level. This assumption sets a rigid constraint on the value expressions of DMs. Fuzzy Logic would be integrated in neural network training to capture the imprecise linguistic terms in quality judgments and enhance the neural network learning DM's behavior. Also in network building, one has to be involved in a tedious trial and error process to select the appropriate network architecture in terms of numbers of layers and their hidden nodes. To alleviate this task, Genetic Algorithms would be used to search in the space of all possible ANN architectures (Steeb et al., 2005)

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