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Does AI Research Aid Prediction? A Review and Evaluation

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Abstract

Despite the increasing application of Artificial Intelligence (AI) techniques to business over the past decade, there are mixed views regarding their contribution. Assessing the contribution of AI to business has been difficult, in part, due to lack of evaluation criteria. In this study, we identified general criteria for evaluating this body of literature. Within this framework, we examined applications of AI to business forecasting and prediction. For each of the seventy studies located through our search, we evaluated how effectively the proposed technique was compared with alternatives (effectiveness of validation) as well as how well the technique was implemented (effectiveness of implementation). We concluded that by using acceptable practice and providing validated comparisons, 31% (22) of the studies contributed to our knowledge about the applicability of the AI techniques to business. Of these twenty-two studies, twenty supported the potential of AI in forecasting. This small number of studies indicates a need for improved research in this area.

1. INTRODUCTION

Over the past decade, increasing research efforts have been directed at applying Artificial Intelligence (AI) techniques to business situations. More than 250 applications of AI to business problems were indexed in the *Social Science Citation Index* over the period January 1992 to September 1994. Despite this, opinions about the value of these techniques have been mixed. Some consider such approaches effective for unstructured decision making tasks (e.g., Dutta, Shekar and Wong 1994); other researchers have expressed reservations about the potential of AI, suggesting that stronger empirical evidence is necessary (e.g., Chatfield 1993).

The task of consolidating this body of literature is challenging since the area is dynamic and techniques are constantly emerging and improving. Moreover, the diversity of these techniques makes the assessment of their performance difficult unless a general framework is applied. Nonetheless, there is now a substantial body of research examining these techniques, and it would seem useful to develop such a framework and evaluate these studies with the hope of gaining some direction for future research.

The structure of the paper is as follows. First, we explain how studies were selected. Then we describe the criteria that we used to evaluate them. Next, we discuss our findings. Finally, we make some recommendations for improving research.

2. HOW THE STUDIES WERE SELECTED

We were interested in the extent to which studies in AI have contributed to improvements in the accuracy of forecasts and predictions in business. We searched three computer databases (the *Social Science Citation Index*, the *Science Citation Index*, and *ABI Inform)* and the proceedings of the IEEE/INNS Joint International Conferences. Our search yielded a wide range of forecasting and prediction-oriented applications, from weather forecasting to predicting stock prices. For this evaluation we eliminated studies related to weather, biological processes, purely mathematical series, and other non-business applications.

We located thirteen studies that used rule-based (expert) systems, six that used decision trees, and fifty-one that used neural networks for business forecasts and predictions. Although we searched for studies using any AI or machine learning techniques, we encountered none that used evolutionary strategies such as genetic algorithms or approaches like case-based reasoning. Figure 1 illustrates the growth in research efforts in this area over the past decade.

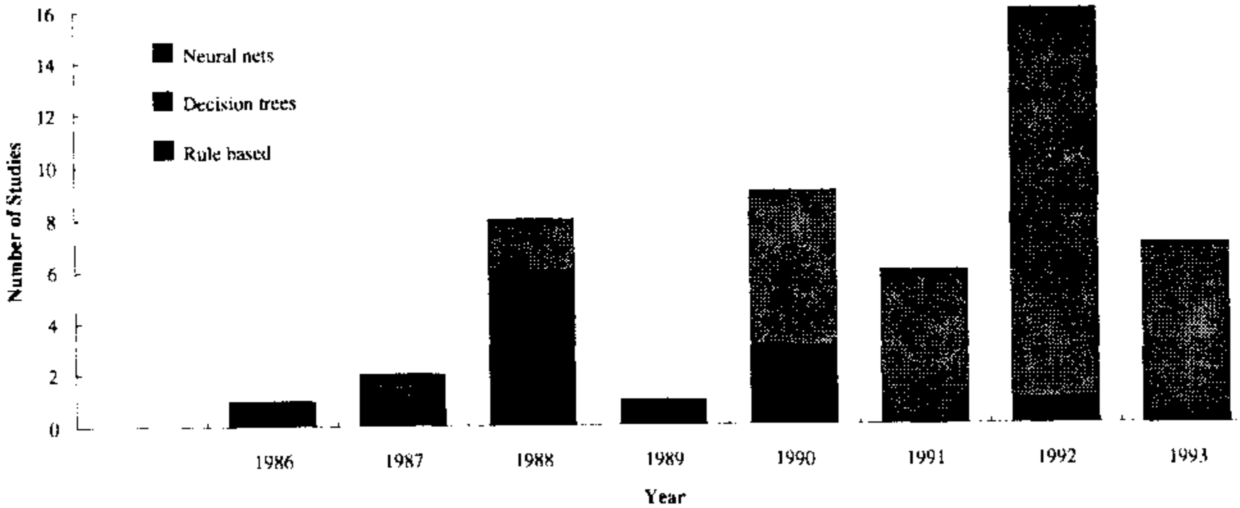

Figure 1. Growth in AI Research Related to Business Forecasting

3. CRITERIA USED TO EVALUATE THE STUDIES

In evaluating studies of AI implementations in forecasting, we were interested in answering two questions. First, did the study appropriately evaluate the predictive capabilities of the proposed technique? There is now a well-established tradition in forecasting research of comparing techniques on the basis of empirical results. If a new approach is to be taken seriously, it must be evaluated in terms of alternatives that are or could be used. If such a comparison was not conducted it is difficult to argue that the study has taught us much about the value of AI for forecasting. In fairness to the AI researchers conducting the studies, it should be noted that this is not always their objective. Sometimes they are using the forecasting or prediction case as a vehicle to explore the dynamics of a particular technique. (An example is Nute, Mann and Brewer [1990] in which a stylized version of the forecast method selection problem is used to explore defeasible logic.) To evaluate the effectiveness of the validation, we used three guidelines described in Collopy, Adya and Armstrong (1994).

Comparisons with well-accepted models: Forecasts from a proposed model should perform at least as well as some well-accepted reference models. For example, if a proposed model does not produce forecasts that are at least as accurate as those from a naive extrapolation, it can not really be argued that the modeling process contributes knowledge which is predictive of trend.

Use of* ex ante *validations: Comparison of forecasts should be based on *ex ante* (out-of-sample) performance. In other words, the sample used to test the predictive capabilities of a model must be different from the samples used to develop and train the model.

Use of a reasonable sample of forecasts: The size of the validation samples should be adequate to allow inferences to be drawn. We considered a forecast sample of over forty to be adequate for comparison.

For studies that have effectively validated the AI technique of interest, we asked a second question: How well was the proposed technique implemented? While a study that suffers from poor validation is not of much use in determining the applicability of the technique to forecasting situations, one that suffers from poor implementation might still be of value. If a method performs comparatively well, even when it has not benefitted from the best possible implementation, there is reason to be encouraged that it will be a contender when it has.

The criteria for assessing effectiveness of implementation varied for the different AI techniques. For each of the techniques, the criteria presented represent our distillation of that literature's best practice. Since best practices change, the fact that a study failed to meet the criteria is not necessarily an indictment of that study. If we wish to use a study to make a case for or against the applicability of a particular AI technique to forecasting or prediction, though, we must be able to determine whether the study represents a good implementation of the technique being used.

In summary then, studies were classified as being of three types. Those that are well implemented and well validated are of interest whatever their outcome. They can be used either to argue that the AI technique in question is useful in forecasting or that it is not, depending upon outcome. These would seem to be the most valuable studies. The second type are studies which have been well validated, even though their implementation might have suffered in some respects. These are important when the technique they propose does well despite the limitations in the

Table 1. Relationship of Validity in Study Outcomes for Rule-Based Studies
Number of Studies

	Successful	Mixed/ Unsuccessful	Not Compared
Problems with Validation	0	0	11
Problems Only with Implementation	1	0	0
No Problems Either Criteria	1	0	0

implementation. They can be used to argue that the technique is applicable and to establish a lower bound on its performance. Finally, there are studies that are of little interest, from the point of view of telling us about the applicability of AI to forecasting and prediction. Some of these have little value because their validation suffers. Others are effectively validated, but they suffer from poor implementation. Since they produce null or negative results it is not possible to determine whether it is because the technique is not applicable or because it has not been well implemented.

4. RULE-BASED STUDIES

Rule-based systems represent the knowledge of experts in the form of rules, typically using an IF <condition> THEN <action> format. The rules for these systems are usually developed through knowledge elicitation techniques such as interviews and protocol analyses or through reviews of empirical literature.

4.1 Effectiveness of Implementation

The effectiveness of rule-based systems is dependent upon the source of the knowledge contained in them and the extent of their calibration. Knowledge acquisition is widely considered a "bottleneck" in the development of expert systems (Barr and Figenbaum 1981; Hayes-Roth, Waterman and Lenat 1982; Duda and Shortliffe 1983). While literature yields rules that are too general to achieve expert performance, reliance only on experts for knowledge may produce rules that are biased and inconsistent. Furthermore, subsequent to knowledge acquisition, calibration of the rule base is important in determining its stability and consistency.

Sources of knowledge: Reviews of knowledge acquisition techniques indicate that researchers have relied primarily upon written materials and verbal interviews with experts for gathering expert judgement (Gammack and Young 1985, Raulefs 1985). Hoffman (1987) and Prereau (1987) have recommended the use of multiple knowledge-elicitation techniques. In evaluating rule-based studies, we considered whether they used multiple sources.

Consideration of alternative rules: In addition to being validated relative to other techniques, it is desirable that a particular set of rules be compared with alternative ones. Experimenting with various rules, performing sensitivity analyses on their parameters, and testing their generalizability by applying them to additional data are examples of the activities that help to insure the development of a robust rule-base.

4.2 Results

Of the thirteen studies that used a rule-based approach, only one met all of the criteria for both effective validation and effective implementation. One other study met all of the criteria for effective validation and produced a positive result. Table 1 summarizes the evaluations of the rule-based studies.

Collopy and Armstrong (1992) used multiple sources for their rules, conducted calibrations using multiple subsets of a data set, and met all three validation criteria. This study used features related both to the structure and the context of the series to determine weights assigned to forecasts from four simple extrapolation methods. Rules for assigning the weights came from protocol sessions with experts in forecasting as well as from the empirical literature on forecasting. Forecasts from the rule-based system were compared with forecasts from the random walk and from an equal-weights combination that had been used in earlier studies. The study identified conditions under which the rules might be expected to perform better than these alternatives and compared their respective performance under the various conditions.

A second of the thirteen studies met the criteria for effective validation, but did not meet both of the implementation criteria. Ho et al. (1990) used multiple sources for rules, but did not evidence calibration effort. It did compare rule-based systems to alternative approaches with favorable results. A summary of the rule-based studies is given in Appendix A.

5. DECISION TREE STUDIES

Six of the studies we located used algorithms that generate decision trees. Among the more widely-used of these algorithms is ID3 (Quinlan 1983). ID3 is a mechanism for discovering a set of classification rules and organizing them in the form of a decision tree. The algorithm takes objects of known classes (*e.g.*, time series that can be best forecast using random walk and those that would benefit from the use of Holt's exponential smoothing) which are described by sets of attribute values, $x_1, \ldots, x_k$ and generates a rule-based system which correctly classifies the objects (Cronan, Glorfeld and Perry 1991). ID3 originated from the Concept Learning System (CLS) developed by Hunt, Marin and Stone (1966). A more recent variation of CLS and ID3 is Analog Concept Learning System (Paterson and Niblett 1982). Studies using CLS and ACLS were encountered in addition to ID3.

5.1 Effectiveness of Implementation

One problem with decision trees is the weak generalizability often associated with them. For instance, ID3 capitalizes on the fact that variables at the lower branches produce a high percentage of correct classifications in the training sample. As a consequence, it produces idiosyncratic decision trees, very closely related to the structure of the sample used in training. The resulting classifications can be poor. Since this is a well-documented problem with decision trees, we expected studies in this domain to attend to it using a three-pronged approach.

Effective use of pruning: Several algorithms and techniques are available that allow decision trees to be terminated before the branches become too sample specific (Quinlan 1987). This is typically done using a stopping rule that restricts the size of the trees and makes them more amenable to interpretation. This also helps to ensure that only significantly discriminating variables are included.

Consideration of alternative rules: As with rule-based systems, examining alternative rules helps to identify problems with sample specific learning.

Assessment of face validity of rules: Since decision tree algorithms are data driven, it is particularly desirable that the meaningfulness of rules be validated by experts.

5.2 Results

Of the six studies, none of the decision tree studies met the criteria for both implementation and validation effectiveness. Four had problems with effectiveness of validation. This was because they relied upon small samples for their validations. Two studies, Carter and Catlett (1987) and Arinze (1994), effectively validated their decision trees and produced positive results despite some problems with effectiveness of implementation.

Carter and Catlett used resampling to produce more than two hundred comparisons. They compared the performance of ID3 and the pruning algorithm C4 and reported that the two were better than existing methods of credit scoring. Performance of the pruning algorithm, C4, was not significantly different from ID3. However, C4 reduced the size and complexity of the decision tree by nearly 70% as compared to ID3. Resampling was also used by Arinze to provide a sample size larger than the 85 time series available for the study. ID3 was trained using thirty randomly selected time series. Its performance was compared with Holt's, time series decomposition, adaptive filtering, exponential smoothing, moving averages, Winter's, and two experts. The classification of ID3 (54.4%) was significantly better than the five forecasting methods other than Holt's (48%). There was also no significant difference between the variance of Holt's and ID3. ID3 also performed better than experts who scored 22.8% and 34.9% in selecting the most accurate method.

The results of the decision tree studies are summarized in Table 2.

Four studies (not included in the six discussed above) compared the performance of decision trees with other AI approaches, specifically with neural networks (Piramuthu, Shaw and Gentry 1994; Hansen, McDonald and Stice 1992; Tam 1991; Tam and Kiang 1992). These are covered in the next section.

6. NEURAL NETWORK STUDIES

An artificial Neural Network (NN) is a computational structure modeled loosely on biological processes. NNs explore many competing hypotheses simultaneously using a massively parallel network composed of non-linear computational elements interconnected by links with variable weights. It is this interconnected set of weights that contains the knowledge generated by the NN. NNs have been successfully used for low-level cognitive tasks such as speech recognition and character recognition. They are being increasingly used for decision support and knowledge induction (Shocken and Ariav 1994; Dutta, Shekar and Wong 1994; Yoon, Guimaraes and Swales 1994).

In general, neural network models are specified by network topology, node characteristics, and training or learning rules. NNs are comprised of a large number of simple processing units, each interacting with others via excitatory or inhibitory connections. Distributed representation over a large number of units, together with local interconnectedness among processing units, provides for fault tolerance. Learning is achieved through a rule that adapts connection weights in response to input patterns. Alterations in the degree of interconnectedness (i.e., the weights associated with the connections) permits adaptability to new situations (Ralston and Reilly 1993). For a discussion of neural networks, see Lippmann (1987).

Table 2. Relationship of Effectiveness to Study Outcomes for Decision Tree Studies
Number of Studies

	Successful	Mixed/ Unsuccessful	Not Compared
Problems with Validation	3	0	1
Problems Only with Implementation	2	0	0
No Problems Either Criteria	0	0	0

6.1 Effectiveness of Implementation

Of the fifty-one neural network papers, forty-four (86%) used error backpropagation as their learning algorithm. It is well established in the literature that this approach suffers from three constraints. First, there is no single configuration that is adequate for all domains or even within a single domain. Their topology must be determined through a process of trial and error. Second, they are vulnerable to problems with local minima (Grossberg 1988). Finally, they are prone to overfitting. These problems can be addressed using well-accepted guidelines.

Testing of alternative configurations: Hornik (1991) provides mathematical proof for the effectiveness of a single hidden layer in almost any classification problem. There is, though, contradictory empirical evidence. Until this inconsistency is resolved, testing of alternative numbers of hidden layers seems desirable. As regards the number of nodes in these hidden layers, several rules-of-thumb, such as average of input and output units, exist. However, use of these rules does not guarantee the effectiveness of the configuration. This makes it important to test a range of layers and nodes.

Manipulation of learning rates and momentum: A proposed solution to the problems of local minima is to allow the network to learn slowly and to reduce this learning rate as training progresses (Pao 1989). This will increase the learning time but will ensure that the network has learned well. Moreover, several initial momentum rates, which conserve the momentum in the rate of change in the network, should be tested.

Adequate sample of Examples: Neural networks are prone to overfitting. That is, the network may learn so specifically from the data used to train it that it does not generalize suitably to unseen data. One solution to the problem is the use of a sample that is adequate in size and representative of the domain. Resampling is an alternative where a large sample is not available.

The conditions identified within this criteria are oriented specifically to backpropagation. This was motivated by the large number of studies we encountered that used this learning algorithm. However, we did find seven studies that used alternative approaches to learning. Of these, two were effective in establishing the predictive validity of their efforts.

6.2 Results

Five of the fifty-one NN studies met the criteria for both implementation and validation effectiveness. Three of these used backpropagation as the learning algorithm. Tang, de Almeida and Fishewick (1991) reported that a NN performed better than Box Jenkins for long-term (12 and 24 month) forecasts, and as well as Box Jenkins for short-term (1 and 6 month) forecasts. DeSilets, et al. (1992) compared the performance of regression models with NNs in the prediction of salinity in Chesapeake bay. Results indicated that neural nets performed effectively as compared to regression models. Gorr, Nagin and Szczypula (1994) compared linear regression, stepwise polynomial regression, and a three layer NN with a linear decision rule used by an admissions committee for predicting student GPAs in a professional school. This was one of the two studies we encountered that satisfied all of the criteria but did not report a positive result for the proposed AI method.

Two of the five successful studies used learning algorithms other than backpropagation. Coats and Fant (1993) used the Cascade Correlation algorithm for predicting financial distress. Comparative assessments were made with discriminant analysis which the neural net outperformed. Hsu, Hsu and Tenorio (1993) used the ClusNet NN for time series forecasting. Results of this learning algorithm were compared with alternative learning algorithms. ClusNet performed only as well as the comparative models. No comparisons were made with traditional approaches.

Of the remaining forty-six studies, twenty-two were effectively validated but had some problems with implementation. Of these, thirteen studies reported that neural networks performed better than comparative models. Wilson and Sharda (1994), Fletcher and Goss (1993), and Tam and Kiang (1992, 1990) developed neural nets for bankruptcy classification. Fletcher and Goss compared their NN with a logit model. The other bankruptcy studies made comparisons with discriminant analysis. Tam and Kiang (1992, 1990) were the only two studies in this domain that compared performances with multiple alternatives: regression, discriminant analysis, logistic, k Nearest Neighbor, and ID3. Wilson and Sharda reported that, although neural nets performed better than the comparative model, the differences were not always significant. Coats and Fant (1992) successfully compared backpropagation neural network with regression in the prediction of financial distress.

Dutta, Shekar and Wong (1994) tested NNs in multiple domains. They used simulated data, corporate bond rating, and product purchase frequency as the test beds for their implementation. Comparisons with multiple regression indicated that, on the simulated data, they did not perform better than neural nets despite a training advantage. In the prediction of bond rating, neural nets consistently outperformed regression, while only one configuration outperformed regression in the purchase frequency domain.

Lee and Jhee (1994) used a neural network for ARMA model identification with ESACF. Using simulated data, it demonstrated superior classification accuracy. The NN was then tested on data from three prior studies where the models were identified using traditional approaches. The authors report that the NN correctly classified US GNP, Consumer Price Index, and caffeine data.

Seven studies compared the performance of alternative models in the prediction of time series. Foster, Collopy and Ungar (1992) compared the performance of linear regression and combining with that of neural networks in the prediction of 181 annual and 203 quarterly time series from the M-Competition (Makridakis, et al. 1982). They used one network to make direct predictions (direct network) and another to combine methods according to features of series (network combining). The authors report that while the direct network performed significantly worse than the comparative methods, network combining significantly outperformed both regression and combining. Interestingly, the networks became more conservative as the forecast horizon increased or as the data became more noisy. This reflects the approach that an expert might take with such data. Connor, Martin and Atlas (1994) and Connor and Atlas (1991) compared the performances of various NN configurations in the prediction of time series. They reported positive performance of the backpropagation net over other alternatives.

Chen, Yu and Moghaddamjo (1992) used neural nets in the domain of electric load forecasting. The network provided better forecasts than ARIMA models. The network also adapted better to changes, indicating robustness. In the same domain, Park et al. (1991) compared the performance of NNs with the approach used by the electric plant. NN outperformed the traditional approach significantly.

Kimoto, et al. (1990) predicted the buying and selling time for stocks in the Tokyo Stock Exchange. Their system, consisting of multiple NNs, was compared to multiple regression. Correlation coefficients with the actual stock movements showed a higher coefficient for neural networks than for regression.

Eighteen (35%) of the fifty-one NN studies, therefore, produced results that are relevant to an evaluation of the applicability of this technique to forecasting and prediction problems. Table 3 summarizes these results.

Four of the studies which met the criteria for effective validation and did not meet those for effective implementation produced negative or mixed results. All of them assumed a fixed learning rate so that there is a possibility that the network had been trapped in a local solution. This could explain their negative results. If the learning rates were permitted to change, it is possible that these NNs would perform well. In addition, three of the studies did not test alternative configurations of the NN. The details of the NN studies are summarized in Appendices C and D.

The neural network studies can be categorized into those that were aimed at classification and prediction and those that attempted to generate future values for time series. Classification studies typically included predicting stock performance, bond rating, bankruptcy classification, and bank failures among others. In all, about twenty-nine of the fifty-one neural network studies were classification studies. Twenty-two studies forecasted time series, eight in the domain of electric load forecasting. Four of these time series studies predicted stock prices and nine performed competitions among various forecasting methods. In the classification literature, three studies met both of our criteria for implementation and validation. The corresponding figure for time series forecasting was two. There was no particular domain that was found to be more successful than the other. Consequently, no significant conclusions could be reached about the performance of NNs by domains.

7. DISCUSSION

Of the seventy studies we evaluated, only six (Gorr, Nagin and Szczypula 1994; Coats and Fant 1993; Hsu, Hsu and Tenorio 1993; Collopy and Armstrong 1992; DeSilets, et al. 1992, Tang, de Almeida and Fishcwick 1991) met all of our criteria for effectiveness of implementation and effectiveness of validation. Of the remaining sixty-four, twenty-seven had no problems with validation but suffered with respect to implementation. However, sixteen of these twenty-seven reported positive results despite implementation problems. These successful studies were of interest to us. Altogether then, of the seventy studies, twenty-two (31%) contributed to our knowledge regarding the applicability of AI to prediction. Twenty of these produced results that were favorable, two produced results that were not.

Table 3. Relationship of Validity to Study Outcomes for Neural Network Studies
Number of Studies

	Successful	Mixed/ Unsuccessful	Not Compared
Problems with Validation	13	4	7
Problems Only with Implementation	13	9	0
No Problems Either Criteria	3	2	0

Table 4. Relationship of Effectiveness to Study Outcomes
Number of Studies

	Successful	Mixed/ Unsuccessful	Not Compared
Problems with Validation	16	4	19
Problems Only with Implementation	16	9	0
No Problems Either Criteria	4	2	0

Two contributions emerged from our evaluation of AI studies in forecasting and prediction. First, we identified criteria for assessing the applications of AI to forecasting and prediction. The criteria are general enough to satisfy many techniques and domains and could serve as an effective framework in evaluating future research in this area. Our second contribution was the conclusion that AI techniques show potential for forecasting and prediction, provided that the techniques are implemented and validated effectively. This is a small step toward a consensus regarding the potential of AI research for the domain. However, this framework also led us to identify a major problem in the AI literature: a large part of the AI research in forecasting and prediction lacks validity. Almost 69% of the research suffered from implementation and/or validation issues. We recommend, therefore, that future research efforts in this direction attend to the validity factors discussed in this study.

Until the impact of AI in forecasting is well established, comparisons must be made between the AI techniques and alternative methods. The methods used for comparison should be simple and well-accepted. The forecasting literature expresses a preference for simpler models unless a strong case has been made for complexity (Collopy, Adya and Armstrong 1994). Moreover, research findings indicate that relatively simple extrapolation models are robust (Armstrong, 1984).

Finally, a large enough sample of forecasts must be generated for fair representation of short and long term forecasts. Successive updating provides a larger sample size for comparing the performance of alternative models. For more details on this approach see Collopy, Adya and Armstrong.

Hybrid approaches might offer promise to realizing the hopes of artificial intelligence in forecasting. With increasing research efforts directed to using machine learning approaches, the focus appears to have shifted away from rule-based systems. However, we feel that in addition to improving research in these two domains, the possibilities of combining rule-based and machine learning approaches is worth exploring.

On a similar note, rather than regarding machine learning approaches as replacements for traditional statistical techniques, they should be considered for use in conjunction with them. An example would be the selection of inputs that contribute most significantly to the prediction or generalization of the problem domain. The more variables that a NN has to search through, the more complex it will be. Moreover, the learning time increases exponentially with the number of input variables. To reduce the complexity of the net, some statistical technique might be used to determine the more significant input variables (see Tam 1991). This smaller set of variables can then be used in the NN for further learning and optimization.

8. CONCLUSIONS

Researchers have been hopeful about the potential for AI techniques in business applications. Empirical evidence though appears to be inconclusive. To get further insights into this inconclusiveness, we evaluated seventy studies that applied AI approaches to business forecasting problems. Our review indicated that problems exist with implementation and validation of research in this domain. Only 31% of the studies that we reviewed could be considered successful both in developing and testing the techniques. First, many of the studies (about 57%) failed to effectively test the newer approaches against established alternatives. Next, some of the studies (about 12%) inadequately addressed problems known to exist in applying the technique of interest and therefore got mixed or negative results. This leaves only a minority of the studies that can be used to draw conclusions about the effectiveness of the approach. Of these studies, most presented successful implementations, in the sense that the method being proposed performed better than the alternatives. This suggests that the application of these approaches to business is promising. There is room, though, to improve the efficiency with which we conduct research toward that end.

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Appendix A. Effectiveness of Rule-Based Studies

Study	Effectiveness of Validation			Effectiveness of Implementation	
	Comparison with Alternatives	*Ex ante* Validation	Adequate Sample	Source of Knowledge	Calibration of Rule Base
Moss, Artis and Ormerod (1994)				∝	
Collopy and Armstrong (1992)	Combining Random Walk	•	•	Protocol analysis Survey of experts Literature	•
Wall et al. (1992)				∝	
Cortes-Rello and Golshani (1990)				Literature	
Ho et al. (1990)	Box Jenkins Operators' decisions	•	•	Interview with operators Literature	
Nute, Mann and Brewer (1990)				Literature	
Szmania and Surgent (1989)				Not indicated	
Kumar and Hsu (1988)				Literature and heuristics	
Kuo (1988)				Module within system	
Kwong and Chen (1988)				Not indicated	
Myers (1988)				∝	
Rahman and Bhatnagar (1988)		•	•	Field data Authors' experience Interview with operators	
Weitz (1986)				Not included	

•Criterion was satisfied
∝Criterion was unclear

Appendix B. Effectiveness of Decision Tree Studies

Study	Algorithm	Effectiveness of Validation			Effectiveness of Implementation		
		Comparison with Alternatives	***Ex ante* Validation**	**Adequate Sample**	**Use of Pruning**	**Alternative Rules**	**Face Validity**
Arinze (1994)	ID3	Holt's Time Series Decomp. Adaptive Filtering Exponential Smoothing Moving Averages Winter's Experts	•	•		•	
Stjepanovic and Jezernik (1991)	ID3		•	•			
Messier and Hansen (1988)	CLS	Discriminant Analysis Individual Judgments Group Decisions	•				
Shaw and Gentry	Not indicated	Logit	•				
Braun and Chandler 1987)	ACLS	Experts Discriminant Analysis	•			•	•
Carter and Catlett (1987)	ID3 CR	Credit scoring	•	•	•	•	

•Criterion was satisfied

Appendix C. Validity of Neural Net Studies

Study	Comparison with Alternative Methods	*Ex Ante* Validation	Adequate Forecast Sample	Tests of Signif.	Effective at Validation
Classification Studies					
Chu and Widjaja (1994)		•	∝		
Dasgupta, Dispensa and Ghose (1994)	Discriminant analysis Logistic regression	•	•	•	•
Dutta, Shekhar and Wong (1994)	Regression models Configurations	•	•		•
Gorr, Nagin and Szczypula (1994)	Multiple and stepwise regression, decision rule	•	•	•	•
Lee and Jhee (1994)	Previously identified models	•	•	•	•
Piramuthu, Shaw and Gentry (1994)	ID3 NEWQ Probit Configurations	•			
Wilson and Sharda (1994)	Discriminant analysis	•	•	•	•
Yoon, Guimaraes and Swales (1994)	Discriminant analysis	•			
Coats and Fant (1993)	Discriminant analysis	•	•	•	•
Fletcher and Goss (1993)	Logit	•	•		•
Kryzanowski, Galler and Wright (1993)		•	•	•	
Refenes, Azema-Barac and Zapranis (1993)	Multiple regression	∝	∝		
Udo (1993)	Multiple regression	•	•		•
Yoon, Swales and Margavio (1993)	Discriminant analysis Configurations	•			
Coats and Fant (1992)	Discriminant analysis	•	•		•
DeSilets et al. (1992)	Regression	•	•		•
Hansen, McDonald and Stice (1992)	5 Qualitative response models Logit Probit ID3	•	•	•	•
Karunanithi and Whitley (1992)	5 Software reliability models	•			
Salchenberger, Cinar and Lash (1992)	Logit	•	•	•	•
Swales and Yoon (1992)	Discriminant analysis Configurations	•			

Study	Comparison with Alternative Methods	*Ex Ante* Validation	Adequate Forecast Sample	Tests of Signif.	Effective at Validation
Tam & Kiang (1992)	Discriminant Regression Logistic k Nearest Neighbor ID3	•	•		•
Tanigawa and Kamijo (1992)	Experts	•	•		•
Hoptroff, Bramson and Hall (1991)	Leading indicators	•			
Lee, Yang and Park (1991)	Results from prior studies	$\propto$			
Tam (1991)	Discriminant Factor-Logistic k Nearest Neighbor ID3	•			
Odom and Sharda (1993)	Discriminant analysis	•			
Surkan and Singleton (1990)	Discriminant analysis Configurations	•			
Tam and Kiang (1990)	Discriminant analysis Factor Logistic k Nearest Neighbor	•	•		•
Dutta and Shekhar (1988)	Regression Configurations	•			
Time Series Forecasting					
Caporaletti et al. (1994)	Traditional estimation approaches	$\propto$	$\propto$		
Connor, Martin and Atlas (1994)	Configurations	•	•		•
Grudnitski and Osburn (1993)		•	•	•	
Hsu, Hsu and Tenorio (1993)	Various NN learning algorithms	•	•		•
Peng, Hubele and Karady (1993)	Box-Jenkins	•	$\propto$	•	
Baba and Kozaki (1992)		•			
Bacha and Meyer (1992)	Configurations	•			
Caire, Hatabian and Muller (1992)	ARIMA	•	•		•
Chakraborty et al. (1992)	Moving Average approach of Tiao and Tsay (1989)	•			
Chen, Yu and Moghaddamjo (1992)	ARIMA	•	•		•
Foster, Collopy and Ungar (1992)	Linear regression Combining A	•	•	•	•

Study	Comparison with Alternative Methods	*Ex Ante* Validation	Adequate Forecast Sample	Tests of Signif.	Effective at Validation
Ho, Hsu and Yang (1992)	Configurations	•	•	•	•
Lee et al. (1992)		∝	∝		
Connor and Atlas (1991)	Configurations	•	•	•	•
de Groot and Wurtz (1991)	3 autoregressive models	•	•	•	•
Tang, de Almeida and Fishewick (1991)	Box-Jenkins	•	•		•
Srinivasan, Liew and Chen (1991)	Exponential smoothing Winter's linear method 2 parameter MA model Multiple regression Simple Reg. & Box Jen.	•			
Kimoto et al. (1990)	Multiple regression	•	•		•
Park et al. (1991)	Approach used by plant	•	•		•
Sharda and Patil (1990)	Box-Jenkins	•	•	•	•
Wolpert and Maill (1990)		•	•		
White (1988)		•	•		

Notation:
•Criterion was satisfied
= Results were mixed
+Results favored NNs
∝Criterion was not clearly identifiable in study
-Results favored alternative to NNs

Appendix D. Implementation of Validated Neural Network Studies

Study	Learning Algorithm	Alternative Configurations	Learning Rate & Momentum	Adequate Examples	Results	Effectiveness of Implementation
Classification Studies						
Gorr, Nagin and Szczypula (1994)	Backpropagation	N	•	•	=	√
DeSilets et al. (1992)	Backpropagation	N	•	•	+	√
Dutta, Shekhar and Wong (1994)	Backpropagation	L&N		•	+	§
Udo (1993)	Backpropagation	L		•	=	
Fletcher and Goss (1993)	Backpropagation	N		•	+	§
Wilson and Sharda (1994)	Backpropagation			•	+	§
Salchenberger, Cinar and Lash (1992)	Backpropagation	L&N		•	=	
Tam and Kiang (1992)	Backpropagation	L&N		•	+	§
Tam and Kiang (1990)	Backpropagation	L&N		•	+	§
Coats and Fant (1992)	Backpropagation			•	+	§
Coats and Fant (19930	Cascade-Correlation	L&N		•	+	√
Hansen, McDonald and Stice (1992)	Backpropagation*			•	-	
Dasgupta, Dispensa and Ghose (1994)	Backpropagation	N		•	=	
Tanigawa and Kamijo (1992)	Backpropagation			•	=	
Lee and Jhee (1994)	Backpropagation	N			+	§
Time Series Forecasting						
de Groot and Wurtz (1991)	Several algorithms	N		•	=	
Tang, de Almeida and Fishcwick (1991)	Backpropagation	L&N	•	•	+	√
Foster, Collopy and Ungar (1992)	Backpropagation	L&N		•	+	§
Connor, Martin and Atlas (1994)	Backpropagation*	L&N		•	+	§
Sharda and Patil (1990)	Backpropagation			•	=	
Connor and Atlas (1991)	William and Zipser (1989) and Backpropagation			•	+	§

Study	Learning Algorithm	Alternative Configurations	Learning Rate & Momentum	Adequate Examples	Results	Effectiveness of Implementation
Hsu, Hsu and Tenorio (1993)	ClusNet			•	=	§
Chen, Yu and Moghaddamjo (1992)	Backpropagation	L&N		•	+	§
Caire, Hatabian and Muller (1992)	Backpropagation	L&N		•	=	
Park, et al. (1991)	Backpropagation	N		•	+	§
Ho et al. (1992)	Backpropagation*		•		=	
Kimoto et al. (1990)	Backpropagation		•	∝	+	§

Notation:
•Criterion was satisfied
= Results were mixed
+Results favored NNs
∝Criterion was not clearly identifiable in study
-Results favored alternative to NNs