Abductive Networks for Two-Group Classification: A Comparison with Neural Networks

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Abstract

In this study, a new Artificial Intelligence technique for non-linear mapping called Abductive Networks is used for two-group classification of firms. The results are compared with Neural Networks, another AI technique, which has been shown to perform better than the traditional statistical techniques such as multivariate discriminant analysis and logit. In empirical tests, Abductive Networks perform as well or better than Neural Networks on various criteria of measurement such as Type I / Type II accuracy criteria and Distance Between Centroids.

1. Introduction

According to Araiza and Montgomery (1994) and Montgomery (1988), Abductive Reasoning is emerging as a powerful reasoning mechanism in Artificial Intelligence for many diagnostics problems. Abductive Reasoning, in general, is a term used for the thought process for "inference to the best explanation" according to Pierce (1955) and Josephson and Josephson (1994). In other words it is the process of zeroing down on the hypothesis that best explains a situation. Human beings frequently use abductive reasoning in several diagnostic problems. The thought process involves generation of hypotheses and collection of evidence to strengthen or weaken hypotheses until one hypothesis prevails as being the strongest. Doctors, detectives, auditors and troubleshooters, all use abductive reasoning constructs in diagnosis. When applied to numerical problems, abductive reasoning can be used for curve fitting i.e. to zero down on the function that best describes the relationship between the independent and dependent variables. Using abductive reasoning, a network of non-linear polynomial functions can be constructed from example data. The non-linearity and the networking of functions, allow for very complex function building.

In recent past, Neural Networks (NNs) have emerged as a strong non-linear mapping tool. Several researchers including Agarwal, Davis and Ward (1999), Barniv, Agarwal and Leach (1997), Wilson and Sharda (1994), and Kam and Tiang (1992) have studied the performance of NNs for classification problems and found the results to be equal or better than the traditional statistical techniques such as Multiple Discriminant Analysis and Logit. In this study, we empirically compare the performance of abductive networks with NNs on a two-group Bankruptcy Prediction problem using several measurement criteria. The purpose of this research is not to develop a Bankruptcy Prediction

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model, but to establish the effectiveness of a new methodology by comparing its performance to what is now a well established methodology (i.e., NNs) which works better than the traditional statistical methodologies.

We compare the results of Abductive Networks and Neural Networks using three different criteria namely Type I/Type II Accuracy, Cost-Weighted Classification Accuracy and Distance Between Centroids (DBC). Results show that Abductive Networks perform equal or better than Neural Networks on all criteria especially the DBC criteria. Further, Abductive Networks were faster, easier to use and involved fewer design parameters. Given the strong results obtained by abductive networks, they need to be explored further as a viable tool for building two or higher group classification models and perhaps for other curve fitting problems.

The rest of the paper is organized as follows. Section 2 discusses abductive reasoning and abductive networks. Abductive Networks share some similarities with Neural Networks, although they are fundamentally different. Similarities and differences between Abductive Networks and Neural Networks are also discussed in Section 2. In section 3, relevant prior research in classification studies is summarized. Section 4 includes a discussion of measurement criteria used and the experimental setting. This section will also include a description of how the data sets were created and also how Neural Networks were used for classification. Results are tabulated and discussed in section 5. Section 6 provides summary and conclusions and Limitations of the study. Suggestions for further research are discussed in section 7.

2. Abductive Reasoning and Abductive Networks

2.1 Abductive Reasoning

Pierce (1955) and Josephson and Josephson (1994) describe abductive reasoning as the thought process for "Inference to the best explanation." Goel (1989) and Lipton (1991) explain Abductive Reasoning in more detail. Abductive reasoning is used by human beings in many diagnostics problems. In general the thought process involves generating several plausible hypotheses to explain an observed situation, collecting evidence to strengthen or weaken some hypotheses, until one (hopefully the best) hypothesis prevails.

There is nothing new about the basic thought process. However, only recently, due to the advancements in Artificial Intelligence, has the thought process been formalized. See Peng (1986) and Fischer and Goel (1990) for formalisms of Abductive Reasoning. This type of reasoning is used in medical diagnosis, according to Console et.al. (1993), equipment failure diagnosis, according to Montgomery et.al. (1990), criminal investigation, fraud investigation, auditing, speech understanding according to Bonneau et.al. (1992) and Josephson (1990) and Management Fraud, according to Deshmukh and Talluru (1998).

Abduction, according to Josephson and Josephson (1994) follows the following pattern. *D* is a collection of data (facts, observations, givens). *H* explains *D* (would, if true, explain *D*). No other hypothesis can explain *D* as well as *H* does. Therefore, *H* is probably true

Abduction as a form of reasoning process is not as well known as perhaps induction and deduction. As a result, a frequently asked question is how is abduction different from the processes of induction and deduction. The difference lies in the situation in which a particular reasoning process needs to be applied. Peng and Regia (1990) provide a distinction between deduction, induction and abduction as follows. In deduction, a general rule and a specific case are given from which a specific result can be deduced about the specific case.

Given Rule -- All the balls in the box are black
\+ *Case* -- These balls are from the box
Concluded Result -- These balls are black

In Induction, a specific case and a specific result about the case are given, from which a general rule can be hypothesized.

Given Case -- These balls are from the box
\+ *Result* -- These balls are black
Hypothesized Rule -- All balls in the box are black

In contrast to deduction and induction, abductive reasoning consists of a general rule and a specific result from which a specific case can be hypothesized.

Given Rule -- All the balls in the box are black
\+ *Result* -- These balls are black
Hypothesized Case -- These balls are from the box

In Induction, a general rule is being hypothesized. In contrast, in abduction, a specific case is being hypothesized. Moreover, an inductive hypothesis is usually drawn not from a single situation but from a large number of situations that collectively support the plausibility of the hypothesized general rule. In contrast, abductive inference can be and usually is conducted with information about a single situation.

In deduction, if both the general rule and the case are true then the result is also true. In contrast, with abduction, even if both the general rule and the specific result are true, the inferred specific case is only a possibility. In the above example, the observed black balls might actually come from some other place. But absent any other evidence, we can infer that the best explanation is that the balls are from the box. More about abductive reasoning can be learnt from Harman (1965), Pierce (1955), Fann (1970) and Josephson and Josephson (1994).

2.2 Abductive Networks

Abductive networks is a term given to a network of functions, derived using the abductive reasoning process to explain the relationship between the independent and dependent variables. They are basically a curve-fitting tool. What has abductive reasoning got to do with curve fitting? Curve fitting can be thought of as an abductive process. Given a set of observations, many different and plausible functions can be generated (inductively), each explaining the relationship between the independent and the dependent variables. Using an appropriate error function, functions can be compared with other functions, and determined as being better or worse. Using the abductive reasoning process, "inference to the best explanation" i.e. "finding the best function" can be achieved. Of course, the best function is only best amongst those generated and evaluated. There is always a possibility that a better function was never generated for evaluation. To increase the chances of including the best function in the set of generated functions, a network of functions is created. Linear Regression can be considered a special case of curve fitting where the linearity assumption allows one to determine the best linear relationship analytically, without considering many relationships. Since the linearity assumption is an over-simplification for most curve fitting problems, researchers have always tried to use alternative curve fitting methods such as non-linear regression and neural networks.

Because of the inherent uncertainty associated with abduction, analytical derivation of the functions is precluded and empirical methods such as induction must be employed. Subtle relationships that may not be apparent in an analytical analysis may be discovered in the induction process. There are several practical advantages of using inductive methods for discovering relationships. When learning complex relationships, abductive networks evaluate a large number of potential models.

The process of inductively determining the best function for a model is a complex problem. A practical approach to finding the best model is to use a network of functions. Networks simplify induction because only the relationships among small subsets of variables need to be discovered at any given time. The power of abductive networks is derived from the ability to deal with complex problems by subdividing them into smaller, much simpler ones. This is the same concept as an organizational chart in a company, according to Montgomery and Drake (1991). At each layer of a company, information is summarized and passed on to higher levels of management. This allows decisions to be made based on a smaller number of factors at each level, without having to consider all of the details associated with the various options.

2.3 Comparison of Neural Networks and Abductive Networks

We assume the reader has an understanding of Neural Networks. For a basic understanding of Neural Networks, the reader is referred to Lawrence (1994) and Rumelhart and McClelland (1989). Abductive Networks and Neural Networks share many things in common. Firstly, they are both iterative as opposed to analytic processes. They both employ a training phase during which they use training examples to learn the relationship between the independent and dependent variables. A second similarity is that neither technique assumes a statistical distribution within the independent variables. Thirdly, as discussed before, they both generate a non-linear mapping. This non-linearity makes these techniques more versatile in their application. Finally, the mapping between the independent and the dependent variables is built into a network of nodes.

There are differences of course between the two techniques. Most fundamental difference is the nature in which the plausible solutions are generated. While Neural Networks follow a weight adjustment process to generate plausible solutions, according to Peng and Reggia (1990), abductive networks produce plausible functions using the concept of parsimonious covering. Another major difference relates to the design and training parameters of the networks. While NNs have proven to be an effective tool for curve fitting, especially for two-group classification problems, there are many difficulties associated with training a Neural Network. The difficulties arise primarily because of the large number of design and training parameters. Because of the many parameters, it is seldom possible to replicate results even using the same dataset. Amongst the many parameters that need to be controlled are (i) the order in which the dataset is arranged, (ii) the choice of initial weights, (iii) the number of iterations, (iv) the learning rate, (v) the momentum term, (vi) the choice of transfer function, (vii) the training tolerance, (viii) number of hidden layers, (ix) the number of hidden PEs, (x) learning strategy etc. Several experiments need to be performed to obtain good results. Further, convergence, in Neural Networks, can take significant computational time. Abductive Networks differ from Neural Networks in that there aren't as many design or training parameters. Further, abductive networks produced the same results each time, given a dataset, irrespective of the order of arrangement of datasets. Also, the time taken to reach a solution was significantly less compared to Neural Networks without compromising the accuracy of the results.

3. Prior Relevant Research in Bankruptcy Prediction and Classification

Many studies have developed models for Bankruptcy Prediction employing a variety of methodologies including the traditional statistical techniques and the modern Neural Network techniques. Altman (1968), Deakin (1972), Edmister (1972) used Multiple Discriminant Analysis for two-state classification. Ohlson (1980), Zmijewski (1984) and Barniv (1990) used logit for their bankruptcy prediction models. Tam and Kiang (1990,1992), Coats and Fant (1993), Wilson and Sharda (1994) and Boritz et.al. (1995) have used Neural Networks for two-state classification to classify firms as bankrupt or non-bankrupt. In addition, Patuwo et. al. (1993)

and Archer and Wang (1993) have studied two-group classification in general, using Neural Networks. Fanning and Cogger (1994) do a comparative analysis of Neural Networks models for financial distress prediction.

Barniv, Agarwal and Leach (1997) have used Neural Networks for three-state classification and Agarwal, Davis and Ward (1998) have used NNs for four-state classification. It has been sufficiently established that Neural Networks out-perform both Multiple Discriminant Analysis and Logit. Both Wilson and Sharda (1992) and Tam and Kiang (1990,1992) have shown improved Type I and Type II accuracies of Neural Networks over Discriminant Analysis. Agarwal et. al (1988) and Barniv et. al (1987) have shown similar results for multi-state classification. Patuwo et.al. (1993) have studied the effects of sample size and architecture on accuracy of classification. Wilson and Sharda (1994) have studied the effect of composition of training data sets and training tolerance on accuracy of classification. Much more research needs to be done in Neural Networks on improving classification accuracy by varying different parameters.

Not much research has been done in Business Applications of Abductive Networks. Deshmukh and Tulluru (1988) use Model Quest, a Data Mining tool based on Abductive Reasoning to Assess risk of Management Fraud.

4. Measurement Criteria, Data Sets and Experimental Setting

4.1 Measurement Criteria

Three measurement criteria are used to compare the results, namely (i) Type I and Type II Accuracies, (ii) Cost-Weighted Classification Accuracy and (iii) Distance-Between-Centroids. Each of these criteria will now be described. A detailed description of these and other measurement criteria can be found in Agarwal et. al. (1996) and Agarwal et. al. (1998).

Type I and Type II Accuracy: Type I and Type II accuracy is the most commonly used measurement criteria in Bankruptcy Prediction studies. The percentage of bankrupt firms correctly classified gives Type I accuracy, whereas the percentage of healthy firms correctly classified gives Type II accuracy. Conversely, the percentage of bankrupt firms misclassified gives Type I error and the percentage of healthy firms misclassified gives Type II error. A simple mean of Type I and Type II accuracy gives combined accuracy for the model.

Cost-Weighted Classification Accuracy: When Type I and Type II accuracies are combined as a simple mean, we ignore an important fact that Type I error is costlier than Type II error. Differences in cost of misclassification exist because it is costlier to misclassify a bankrupt firm than it is to misclassify a healthy firm. Cost-Weighted Classification Accuracies are therefore used to take into account these differences. The ratio of Cost of Type I error to Cost of Type II error is a matter of judgment. Various estimates, ranging from 10:1 through 100:1, are found in the literature, for example in Barniv (1990). We report our results for selected Misclassification Cost Ratio in the range of 1:1 and 100:1. A 1:1 ratio is equivalent to the simple mean. Cost-Weighted accuracy rewards models with low Type I errors or penalizes models that reduce Type II error at the expense of Type I error.

Distance Between Centroids (DBC) - If we plot the output values of the two classification groups, then two distinct clusters will be observed, one each for the two groups. The distance between the centroids of these two clusters is a measure of how well the groups are segregated. Many decision makers may prefer a better segregation. DBC measure was first used by Agarwal et. al. (1996). A model may produce a high Type I and Type II accuracy yet a lower DBC. Another model may have a low Type I and Type II accuracy yet a high DBC. A high DBC signifies a better discrimination between the groups and vice versa.

4.2 Data Sets and Experimental Setting

Since, the purpose of this study was not to determine the best independent variables (financial ratios) for Bankruptcy Prediction, but to see how well Abductive Networks performed compared to Neural Networks as two-group classifier, variables used in past literature were used without going through a uni-variate analysis or factor analysis. Four financial ratios namely Working Capital/Total Assets, Retained Earnings/Total Assets, Earnings before Interest and Taxes/Total Assets and Market Value of Equity/Total Debt were used. These ratios have been used by Altman (1968), Wilson and Sharda (1994) and Agarwal et. al. (1996). The data was acquired from the Compustat research tapes (for bankrupt firms) and Full-Coverage tapes (for healthy) firms. Firms with first digit SIC code of 3 were used in the model. Restriction of first digit SIC code was considered desirable because normal values of ratios across SIC codes could vary significantly, making the analysis harder. Data for 70 healthy and 70 bankrupt firms was collected. The healthy firms were matched with the bankrupt firms by size (Assets). A training set was created with 40 healthy and 40 bankrupt firms chosen at random. The remaining 60 firms (30 healthy and 30 bankrupt) were used for the holdout sample. Nine more training and holdout sets were created similarly by randomly selecting 40 healthy and 40 bankrupt firms from the original pool of 140 firms. Thus there were ten sets of data to empirically test our models.

4.3 Neural Network Experimental Setting

We built our NNs model using a NN package called Brainmaker™ for Windows, running on Pentium™ 133 PC. Brainmaker™ uses the backpropagation learning algorithm. For details of the backpropagation algorithm see Rumelhart and McClelland (1989) and Lawrence (1995). Our network had four input Processing Elements (PEs), one for each of the independent variables, eight hidden PEs and one output PE. A training tolerance of 0.1 and a momentum of 0.9 was used. A gradually reducing learning rate was used. Learning rate was set at 1.0 initially for the first 1000 runs, and was subsequently reduced to 0.9, 0.75, 0.5, 0.25 and 0.1 for 1000 runs each. One run consisted of showing all 80 observations to the network. These design and learning parameters were found after significant experimentation. Gradually decreasing learning rate produces better results. A training tolerance of 1.0 and momentum of 0.9 also produced strong results. Several values of training tolerance and momentum were used.

4.4 Abductive Networks

AbTech's AIM for Windows, running on Pentium 133, was used to generate Abductive Networks for each of the 10 datasets. AIM for Windows produces a network of functions. It produces a C code of the network of functions. Firms in the testing sample can be run on the C code to determine their classification. There were no design parameters to be set. There is only one way the network will run given the dataset. More information about Abductive Networks can be obtained from AIM User's Manual (1995).

4.5 Multiple Discriminant Analysis

For the sake of comparison and to validate the results of prior Neural Network studies we also ran Multiple Discriminant Analysis (MDA) on our datasets. We used a Statistica® for Windows to run our MDA.

5. Results

Tables 1 through 3 summarize the results of two-group classification using MDA, NNs and Abductive Networks. Table 1 summarizes the results of Type I and Type II accuracy for both the training and holdout sets. Table 2 summarizes the results of Cost-Weighted accuracy for the three models for both training and holdout sets, while Table 3 does the same for the

DBC criteria. Results of both Neural Networks and Abductive Networks were significantly better than those of MDA on all the criteria. Abductive Networks showed very competitive results with Neural Networks in every category. We now discuss the results in detail.

5.1 Type I and Type II Accuracy

Table 1 gives the results for Type I and Type II accuracies for the three models, for both training and holdout sets. The average over 10 sets of the combined Type I and Type II accuracy for the training sets were equal for both Abductive Networks and NNs at 96.38%. These results were clearly superior to the MDA results (80.63%). It may be noted that the increase is purely on account of an increase in Type I accuracy. For the holdout sample, Abductive Networks gave marginally better results (95.16%) than Neural Networks (94.67%). Results of both the non-linear techniques were better than MDA (79.58%). The average Type I accuracy for Abductive Networks was higher than that of Neural Networks for both training and testing sets.

5.2 Cost-Weighted Classification Accuracy

Table 2 summarizes the cost weighted classification accuracy results for cost ratios varying from 1:1 through 100:1, for both the

Table 1
Type I and Type II Classification Accuracies

	Multiple Discriminant Analysis			Neural Networks			Abductive Networks		
	Type-I	Type-II	Overall	Type-I	Type-II	Overall	Type-I	Type-II	Overall
Training Set									
Dataset 1	0.675	0.975	0.825	0.925	1.000	0.963	0.925	1.000	0.963
Dataset 2	0.625	1.000	0.813	0.950	0.975	0.963	0.950	0.975	0.963
Dataset 3	0.625	0.975	0.800	0.925	1.000	0.963	0.950	1.000	0.975
Dataset 4	0.625	0.950	0.788	0.950	0.998	0.963	0.950	0.975	0.963
Dataset 5	0.600	1.000	0.800	0.925	0.975	0.950	0.925	0.925	0.925
Dataset 6	0.675	0.900	0.780	0.900	1.000	0.950	0.950	1.000	0.975
Dataset 7	0.625	0.975	0.800	0.950	1.000	0.975	0.925	1.000	0.963
Dataset 8	0.675	0.950	0.813	0.950	1.000	0.975	0.950	1.000	0.975
Dataset 9	0.650	1.000	0.825	0.950	1.000	0.975	0.950	1.000	0.975
Dataset 10	0.625	1.000	0.813	0.950	0.975	0.963	0.950	0.975	0.963
Average	0.640	0.9725	0.8063	0.937	0.9900	0.9638	0.942	0.9850	0.9638
Holdout Set									
Dataset 1	0.667	0.933	0.800	0.967	0.967	0.967	0.967	0.967	0.967
Dataset 2	0.650	0.950	0.800	0.967	1.000	0.983	0.967	1.000	0.983
Dataset 3	0.617	0.983	0.800	0.933	0.967	0.950	0.967	0.933	0.950
Dataset 4	0.683	1.000	0.842	0.800	0.967	0.883	0.767	1.000	0.883
Dataset 5	0.650	0.933	0.792	0.967	1.000	0.983	0.967	0.933	0.950
Dataset 6	0.650	0.933	0.792	0.900	0.967	0.933	0.933	0.933	0.933
Dataset 7	0.617	0.917	0.767	0.867	0.967	0.917	0.900	1.000	0.950
Dataset 8	0.600	0.950	0.775	0.967	0.933	0.950	1.000	0.967	0.983
Dataset 9	0.683	0.917	0.800	0.967	0.933	0.950	0.967	0.967	0.967
Dataset 10	0.650	0.933	0.792	0.933	0.967	0.950	0.932	0.967	0.944
Average	0.647	0.945	0.796	0.926	0.967	0.947	0.937	0.967	0.952

training and holdout sets. As the cost ratio gets larger, more weight is given to Type I accuracy. Since Abductive Networks had a higher Type I accuracy, the Cost-Weighted Accuracy was higher for Abductive Networks (94.29% at 100:1) compared to Neural Networks (93.8% at 100:1), which in turn was significantly higher than MDA (64.33% at 100:1). Cost-Weighted Accuracy is preferred over Simple Accuracy because it gives appropriate weight to Type I accuracy.

Table 2
Cost-Weighted Classification Accuracy (Average over ten datasets)

Misclassification Cost Ratio	Multiple Discriminant Analysis	Neural Networks	Abductive Networks
Training Sets			
1:1	0.8063	0.9638	0.9638
10:1	0.6702	0.9423	0.9464
25:1	0.6528	0.9395	0.9441
50:1	0.6465	0.9385	0.9433
75:1	0.6444	0.9382	0.9431
100:1	0.6433	0.9380	0.9429
Holdout Sets			
1:1	0.7958	0.9467	0.9516
10:1	0.6738	0.9303	0.9393
25:1	0.6582	0.9282	0.9377
50:1	0.6525	0.9275	0.9372
75:1	0.6506	0.9272	0.9370
100:1	0.6496	0.9270	0.9368

5.3 Distance Between Centroids

The Distance Between Centroids, which, as discussed earlier, is a measure of segregation of the two classified groups is higher for Abductive Networks compared to Neural Networks for every dataset. For a 0-1 dependent variable, the DBC, in the best case will be 1.0. The best case scenario is when 100% of Bankrupt firms produce a 0 output and 100% of healthy firms produce a 1 output. The centroids will then be 0 and 1 respectively for the bankrupt and healthy groups, giving a DBC of 1. A 100% accuracy alone does not guarantee a high DBC. For example, it is possible for 100% of bankrupt firms to produce an output in the range of 0.4 and 0.49 and for 100% of healthy firms to produce an output in the range 0.51 and 0.60. The centroids for each group in this example, will be roughly 0.45 and 0.55 for the two groups, giving a DBC of 0.10. A low DBC implies that the model does not distinguish between the groups very clearly. For our experiments, for the training sample, the DBC for Abductive Networks was 0.87 compared to 0.79 for Neural Networks (Table 3). This is a significant improvement on an already high DBC. For holdout samples as well, the DBC for Abductive Networks is 0.83, compared to 0.78 for Neural Networks.

6. Summary, Conclusions and Limitations

In this paper, a relatively new tool in Artificial Intelligence called Abductive reasoning

Table 3
Distance Between Centroids

	Neural Networks	Abductive Networks
Training Sets		
Dataset 1	0.83	0.88
Dataset 2	0.78	0.84
Dataset 3	0.78	0.88
Dataset 4	0.79	0.89
Dataset 5	0.76	0.81
Dataset 6	0.74	0.89
Dataset 7	0.83	0.87
Dataset 8	0.77	0.90
Dataset 9	0.84	0.89
Dataset 10	0.81	0.85
Average	0.79	0.87
Holdout Sets		
Dataset 1	0.82	0.87
Dataset 2	0.86	0.90
Dataset 3	0.82	0.84
Dataset 4	0.64	0.69
Dataset 5	0.83	0.77
Dataset 6	0.68	0.79
Dataset 7	0.74	0.79
Dataset 8	0.80	0.89
Dataset 9	0.80	0.88
Dataset 10	0.84	0.86
Average	0.78	0.83

networks has been used for two-group classification to classify firms as healthy and bankrupt. The results of Abductive networks are compared with those of Neural Networks and Multiple Discriminant Analysis. Neural Networks have already been proven to give better results than the traditional statistical techniques such as Multiple Discriminant Analysis and Logit. The comparison is done using three criteria namely Type I / Type II Accuracy, Cost-Weighted Classification Accuracy and Distance Between Centroids (DBC). It was found that while both Neural Networks and Abductive Networks perform significantly better than Multiple Discriminant Analysis, Abductive Networks perform equal or marginally better than Neural Networks on Type I and Type II criteria and on Cost-weighted classification criteria. On the DBC criteria, abductive networks performed significantly better than Neural Networks. Further, it was found that Abductive Networks were easier to use, required less computational time and produced consistent results and still gave equal or better results than Neural Networks.

There are certain limitations in this research. A major limitation is that while the Neural Network algorithm and its learning strategies such as backpropagation are widely discussed in the literature, the specific algorithm used by abductive networks is proprietary. Although the general idea of abductive reasoning and abductive networks is discussed in the paper, the specific algorithm remains a black box. Hence the reader cannot duplicate this study by writing his or her own code. Generalizability of research is always a concern in empirical studies like this one. Because Abductive Networks gave good results on our datasets does not imply they will necessarily give better results on other problem sets.

7. Suggestions for Further Research

Given the strong results, Abductive Networks as a tool for binary classification deserve a closer look. Can alternative algorithms produce even better results? Can the misclassification cost ratios be incorporated during the learning phase? How well do they perform on multi-state classification problems, and compare to traditional clustering algorithms. These and other questions need to be explored further.

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