Confidence and Support Classification Using Genetically Programmed Neural Logic Networks

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Abstract. Typical learning classifier systems employ conjunctive logic rules for representing domain knowledge. The classifier XCS is an extension of LCS with the ability to learn boolean logic functions for data mining. However, most data mining problems cannot be expressed simply with boolean logic. Neural Logic Network (*Neulonet*) learning is a technique that emulates the complex human reasoning processes through the use of *net rules*. Each *neulonet* is analogous to a learning classifier that is rewarded using support and confidence measures which are often used in association-based classification. Empirical results shows promise in terms of generalization ability and the comprehensibility of rules.

1 *Neulonet* Association Rules as Learning Classifiers

Current research in Neural Logic Network (*Neulonet*) Learning using genetic programming has been shown to be an effective system for data mining [1]. Its novelty lies in its ability to emulate human decision logic through the use of rudimentary neural nets, or *net rules*, that represent the core human logic operations. These richer logic operations can be used to represent common human decision making processes such as a *priority* operation that depicts the notion of assigning varying degrees of bias to different decision factors, or a *majority* operation that involves some strategy of vote-counting. *Net rules* supplement the boolean logic operations of conjunction, disjunction and negation, so as to allow for more elegant expressions of complex logic in any problem domain.

Each *neulonet* represents a condition-action rule in much the same way as a learning classifier in LCS [2] and its corresponding extension to data mining using XCS [3]. The condition part of the classifier in LCS is a string in the alphabet {0,1,#} while inputs to a *neulonet* are ordered pairs $(0,1)$, $(1,0)$, $(0,0)$ representing false, true and unknown. Other than the use of a more expressive set of logic operators, each *neulonet* is evolved using genetic programming [4] based on fitness proportionate selection, as opposed to the use of genetic algorithm in typical LCS. The novelty in this present work lies in using a fitness criterion which accounts for the confidence and support levels that are extensively used in association-based classifiers such as CBA [5] where conjunctive logic rules termed CARs are discovered. The *confidence* of a classifier provides a measure on its accuracy, while *support* gives an indication of the amount of data

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Table 1. Experimental results depicting predictive errors (%) using NARs and CARs. Numbers inside brackets denotes the average number of rules used.

Data Set	CARs	NARs	Data Set	CARs	NARs
anneal	3.6 (34)	**0.3** (18.0)	horse	18.7 (97)	**14.2** (38.4)
auto	27.2 (54)	**16.9** (34.2)	hypo	1.7 (35)	**1.2** (44.3)
breast-w	4.2 (49)	**3.3** (40.7)	iono	8.2 (45)	**6.5** (21.4)
cleve	16.7 (78)	**16.2** (42.1)	iris	7.1 (5)	**4.0** (6.3)
crx	14.1 (142)	**13.3** (82.0)	labor	17.0 (12)	**6.7** (3.1)
diabetes	25.3 (57)	**23.7** (20.8)	lymph	19.6 (36)	**12.0** (21.7)
german	26.5 (172)	**24.8** (63.4)	pima	27.6 (45)	**23.8** (19.9)
glass	27.4 (27)	**21.5** (24.2)	sonar	21.7 (37)	**14.0** (21.6)
heart	18.5 (52)	**14.2** (38.5)	vehicle	31.3 (125)	**29.2** (34.7)
hepati	15.1 (23)	**13.6** (15.1)	wine	8.4 (10)	**1.1** (5.1)

consistent with it. Moreover, generality is achieved by considering parsimony of the *neulonet* structure within the fitness criterion. Such an evolved *neulonet* shall henceforth be termed a *neulonet* association rule (NAR). Another distinct difference from classical LCS, is the two-phase process adopted [5] in ordering the NARs for eventual prediction. Briefly, in the first rule-generation stage, all independent NARs are generated, while the second classifier-building stage provides a methodology to group these NARs to form an accurate predictor.

2 Empirical Study and Discussion

Empirical study is undertaken to compare the predictive ability of systems constructed with NARs as opposed to CARs in CBA. Experiment results based on ten-fold cross validation on twenty data sets from the UCI Machine Learning Repository are presented in table 1. It is evident that *neulonet* classifiers using human logic *net rules* is generally the better choice. The enhanced logic expression in NARs is the primary contributing factor towards the construction of better systems as association-based classifiers using conjunctive logic rules do not have the additional expressiveness and flexibility in handling complex logic inherent in most real-world data. Moreover, the *net rules* represent common human decision processes and therefore amenable towards human comprehension.

References

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