EA, neural networks & fuzzy systems

Michael J. Watts

http://mike.watts.net.nz

Lecture Outline

- Advantages of fuzzy systems
- Problems with fuzzy systems
- Applying EA to fuzzy systems
- Problems with ANN
- Applying EA to neural networks

Advantages of Fuzzy Systems

- Comprehensibility
- Parsimony
- Modularity
- Explainability
- Uncertainty
- Parallelism
- Robust

Disadvantages of Fuzzy Systems

- Defining the rules
  - where do the rules come from?
  - major problem with rule-based systems
  - need to get enough rules to be accurate
  - rules need to be expressive
    - comprehensibility
  - rules need to be accurate
  - mustn't use too many rules

Disadvantages of Fuzzy Systems

- Optimisation
  - a change in the MF can require a change in the rules
  - a change in the rules can require a change in the MF
  - each parameter / choice effects the others
  - multi-parameter optimisation problem

Applying EA to Fuzzy Systems

- Many of the problems with fuzzy systems are combinatorial in nature
  - MF parameters
  - MF / rule interdependencies
- EA are well suited to solving combinatorial problems

Applying EA to Fuzzy Systems

- There are three main ways in which evolutionary algorithms have been applied to fuzzy systems
  - optimising MF
  - optimising rules
  - optimising the entire system

Optimisation of MF

- Selection of MF parameters
- Use a fixed number of MF
- Fixed number of rules
- EA selects e.g. centre and width of MF

Optimisation of MF

- Optimisation of existing MF
- Evolve deltas for the centres / widths of the MF
- Fixed number of MF
- Initial parameters determined *a priori*

Optimisation of MF

- Problems with this approach
- Fixed number of MF
- Optimising MF without optimising rules
- Must have the optimal number of rules beforehand
  - how do you know this if the MF aren't optimised?

Optimisation of Rules

- Fixed number of MF
- Fixed number of rules
- EA selects which MF is active for each input and output for each rule
- May vary number of antecedents
  - null entries for MF

Optimisation of Rules

- Problems with this approach
- Fixed number of MF
- Fixed parameters of MF
  - are the MF optimal?
- Fixed number of rules
  - are there enough?
  - are there too many?

Optimisation of Fuzzy Systems

- Evolve both MF and rules simultaneously
- Obviates problems with interdependency of MF and rules
- Many methods in use

Optimisation of Fuzzy Systems

- One rule for each combination of input MF
- EA evolves
  - parameters of input MF
  - output MF to activate
- Evolving a rule matrix
- Still problems with fixed number of rules / MF

Optimisation of Fuzzy Systems

- Use a messy GA
- Evolve the number of rules
- Evolution will retain only the necessary rules
- Rules will be minimal length
- Rule encoding consists of a list of MF parameters

Problems with ANN

- Choosing the number of hidden layers
  - how many are enough?
- Choosing the number of hidden nodes
  - how many are enough?
- As number of connections approaches the number of training examples, generalisation decreases

Problems with ANN

- Initialisation of weights
- Random initialisation can cause problems with training
  - start in a bad spot

EA and ANNs

- Many aspects of using ANNs can be approached by EA
- Topology selection
  - number of hidden layers
  - number of nodes in hidden layers

EA and ANNs

- Connection weights
  - initial weight values for backpropagation training
  - EA based training

ANN Topology Selection by EA

- Hidden layers
- Arena, 1993. Treats each chromosome as a 2D matrix
- Each cell of the matrix indicates the presence or absence of a neuron

ANN Topology Selection by EA

- Schiffman, Joost and Werner, 1993
- Chromosome determines number of nodes present
- Also indicate connectivity of the nodes
- Problems
  - initialisation of the weights

Initial Weight Selection

- Performance of backprop influenced by initial weights of network
  - Belew, McInerney and Schraudolph, 1991
- Used a GA to select the initial values of the network
- Fitness determined by how quickly the network trains and how well it solves the problem

Selecting Control Parameters

- Choi and Bluff, 1995
- Used a GA to select for an MLP
  - number of hidden nodes
  - learning rate
  - momentum
  - training epochs

Selecting Control Parameters

- Watts, Major and Tate, 2002
- Used a GA to select for an MLP
  - input features
  - hidden neurons
  - learning rate
  - momentum
  - Epochs

EA Training

- EA used to select values of connection weights
- Fitness determined as the inverse of the error over the training set
  - EA will seek to minimise error
- Initial weights of network encoded into an individual in the initial EA population

EA Training

- GA can be used
  - permutation problem
- EP has proven to be useful for this
  - Blondie 24
- ES is not commonly used to train ANN

Other Applications

- Hugo de Garis' fully self connected networks
- Each neuron in the network is connected to every other neuron, as well as itself
- Can only be trained by GA

Other Applications

- Learning algorithms can also be evolved
  - rather than using an existing learning rule, the EA evolved one
- Not widely used

Summary

- EA are capable of optimising several aspects of fuzzy systems
- Best to use an EA to evolve the entire system
  - optimisation of components ignores problems with interdependencies between these components
- Many of the problems associated with ANN can be addressed with EA
- Topology selection, parameter selection and training are the most common

References

- P. Arena, R. Caponetto L. Fortuna and M.G. Xibilia. M.L.P. Optimal Topology via Genetic Algorithms. In: *Artificial Neural Nets and Genetic Algorithms* pg670-674
- B. Choi and K. Bluff . Genetic Optimisation of Control Parameters of a Neural Network, In: *Proceedings of ANNES'95* pg174-177, 1995
- R.K. Belew, J. McInerney and N.N. Schraudolph. Evolving Networks: Using the Genetic Algorithm with Connectionist Learning. In: *Artificial Life III* pg511-547
- W. Schiffmann M. Joost and R.Werner Application of Genetic Algorithms to the Construction of Topologies for Multilayer Perceptrons. In: *Artificial Neural Nets and Genetic Algorithms* pg 675-682