## Lecture 8

# Analytical Learning Discussion (4 of 4): Refinement of Approximate Domain Theories by Knowledge-Based Neural Networks

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## Presentation Outline

- Paper
  - "Refinement of Approximate Domain Theories by Knowledge-Based Neural Networks"
  - Authors: Geoffrey G. Towell, Jude W. Shavlik, Michiel O. Noordewier
  - Appears in the Proceedings of the Eighth National Conference on AI
- Overview
  - Use Horn clauses domain theory to create an equivalent artificial neural network(ANN)
    - KBANN algorithm
    - Empirical testing in molecular biology
    - Extension Research of KBANN
- Application to Knowledge Discovery in Database: Issues
  - Combined inductive and analytical learning
  - Key strengths: better than random initial weight? Lead to better generalization accuracy for the final hypothesis?
  - Key weakness: restricted to non-recursive, prepositional domain theories



## KBANN Algorithm

- The KBANN assumes a domain theory can be represented by an ANN
  - Definition of ANN
    - An artificial neural network is composed of a number of nodes, or units, connected by links. Each links has a numeric *weight* associated with it. Learning takes place by updating the *weights*.
  - Given
    - A set of training examples
    - A domain theory consisting of nonrecursive, prepositional Horn clauses
  - Determine
    - An artificial neural network that fits the training examples, biased by the domain theory
  - the knowledge base is translated into ANN

| Knowledge | ANN Correspondences |
|---|---|
| Final Conclusions | Output Units |
| Supporting Facts | Input Units |
| Intermediate Conclusions | Hidden Units |
| Dependencies | Weighted Connections |



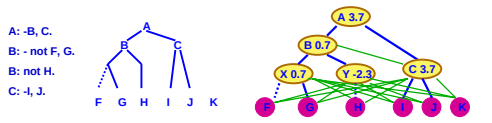
## KBANN Algorithm(continue)

- Translation of rules
  - sets weights on links and biases of units so that units have significant activation only when the corresponding deduction could be made using the domain knowledge
  - Explanations
    - for each mandatory antecedent, assign a weight: w
    - for each prohibitory antecedent, assign a weight: -w
    - bias on the unit: n * w - ∅ for conjunction  w - ∅ for disjunction
- Algorithm specification
  - overview
    - Translate rules to set initial network structure
    - Add units not specified by translation
    - Add links not specified by translation
    - perturb the network by adding near zero random numbers to all link weights and biases



## KBANN Algorithm Examples

- An Illustrative Example (Translation of a Knowledge Base into an ANN)




(a) Domain theory — (b) Hierarchical structure — (c) ANN representation

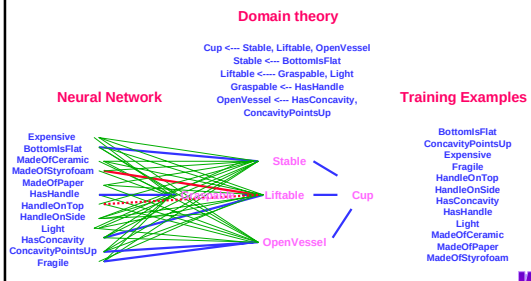
necessary dependence
prohibitory dependence

w = 3
w = -3
refinement links
* units X, Y introduced to handle disjunction



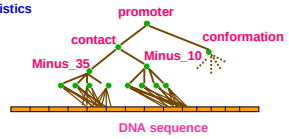
## KBANN Algorithm

- Cup learning task ( from Machine Learning by Tom Mitchell)



## Experimenting with KBANN

- Molecular genetics experiment using KBANN
  - Task
    - learn to recognize DNA segments called promoter regions which influence gene activity
  - Domain theory
    - a promoter involves two subcategories: a contact and a conformation region
    - contact involves two regions
    - rules defining region characteristics
    - example:
      conformation:-@45 “aaxxt”
  - ANN






## Experimenting with KBANN(continue)

- Molecular genetics problem using KBANN(continue)
  - procedure
    - 53 positive and 53 negative training examples
    - N = 106
    - “leave-one-out” method, on each iteration KBANN was trained using 105 of the 106 examples and tested on the remaining example
  - results

| System | Error Rates |
|---|---|
| KBANN | 4/106 |
| Standard Backpropagation | 8/106 |
| O’Neill | 12/106 |
| Nearest Neighbor | 13/106 |
| ID3 | 19/106 |



## Related Work

- Problems specific to Neural Networks
  - Topology determination(restricted to a single layer of hidden units or random setting of link weights)
  - Integration of existing information into the network( how to use background information or improve incorrect domain theories in ANNs )
- KBANN solutions
  - Connect the inputs of network units to the attributes tested by the clause antecedents, assign a weight of w to the unit for each positive antecedent or -w for each negative antecedent
  - initialize the hypothesis to perfectly fit the domain theory, then inductively refine the initial hypothesis as needed to fit the training data



## Summary Points

- Content Critique
  - Key contribution:
    - analytically creates a network equivalent to the given domain theory
    - inductively refines the initial hypothesis to better fit the training data
    - in doing so, it modifies the network weights to overcome the inconsistencies between the domain theory and the observed data.
  - Strengths
    - Generalize more accurately given an approximately correct domain theory
    - Outperform other purely inductive methods when data is scarce
    - Domain theory used in KBANN indicates important features to an example classification
    - Derived features are also specified through deduction, therefore reducing the complexity of an ANN’ final decision



## Summary Points(continue)

- Weaknesses
  - Is restricted to non-recursive, prepositional(i.e.. Variable-free) Horn clauses
  - May be misled given highly inaccurate domain theory
  - Is problematic to extract information from ANNs after learning because some weight settings have no direct Horn clause analog.
  - Blackbox method, which provide good results without explanation
- Presentation Critique
  - Audience: AI (learning, planning), ANN, applied logic researchers
  - Positive and exemplary points
    - Clear example illustrating the translation of knowledge base into an ANN
    - Good experimental results over other inductive learning algorithm
  - Negative points and possible improvements
    - we understand some basic ideas of ANN translation, but still may not be able to do it



## Questions, Comments