

Using Prior Knowledge to Reduce the Cost of Elicitation

Peter Haddawy
Asian Institute of Technology

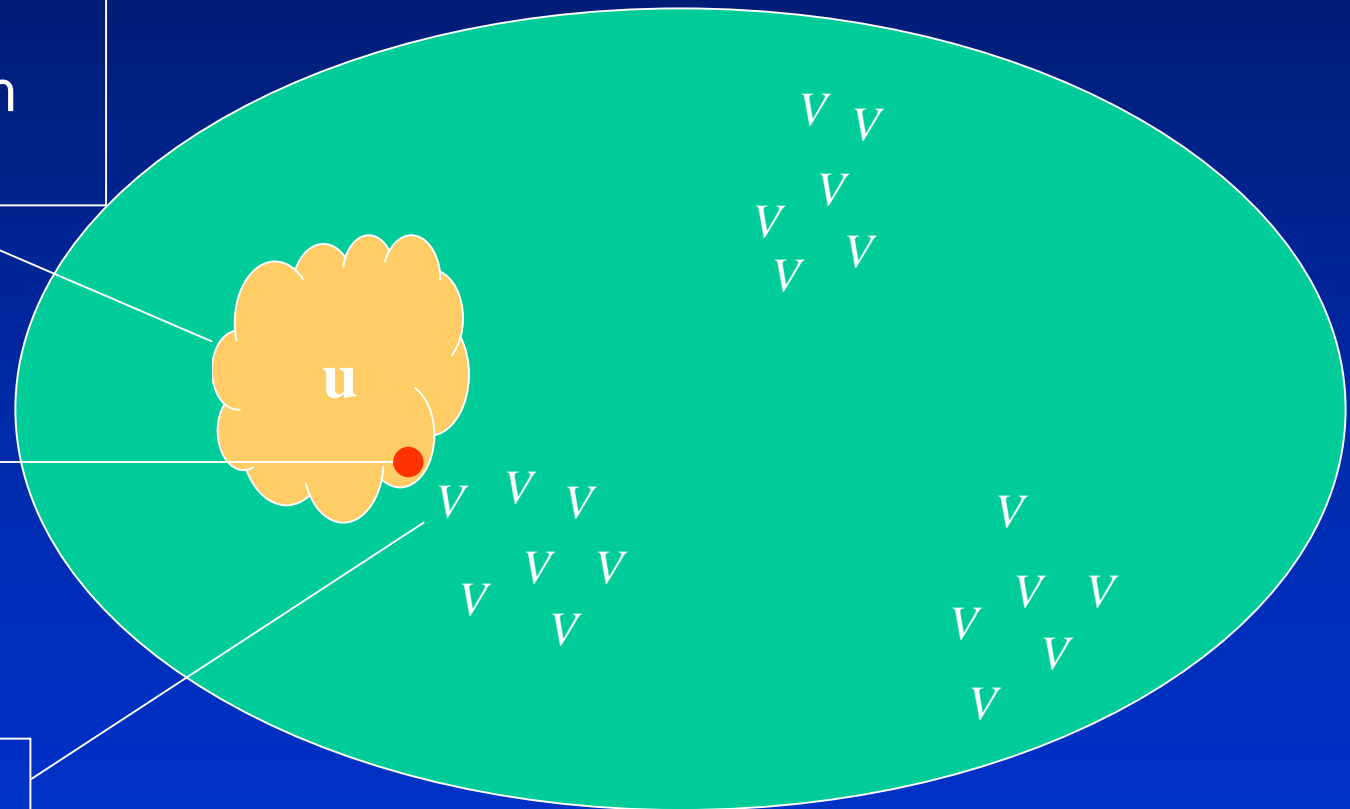
I. Case-Based Preference Elicitation

2. Elicit some preference information from new user

4. Complete the user's preference

3. Find closest user or cluster

1. Case Base of User Preferences



Distance on Preference Orders

- Need a distance measure that
 - ◆ applies to partial preferences under certainty and uncertainty
 - ◆ has nice theoretical properties
 - ◆ is computationally tractable.
- Proposed measure: *probabilistic distance*, defined as *the probability of conflict*.
- On the space of completely specified preference orders, defined as:

$$\delta(\prec_1, \prec_2) = \Pr(\prec_1 \text{ and } \prec_2 \text{ disagree wrt } a, b)$$

(For example, $a \prec_1 b$ and $b \prec_2 a$)

Probabilistic Distance

- The probabilistic distance on complete preference orders is a *metric*.
- Question: How to define it on partial preference orders?
- Observation: a partial order can be viewed as a set of complete orders consistent with it (linear extensions).

Probabilistic Distance

- The probabilistic distance on partial preference orders is defined as:

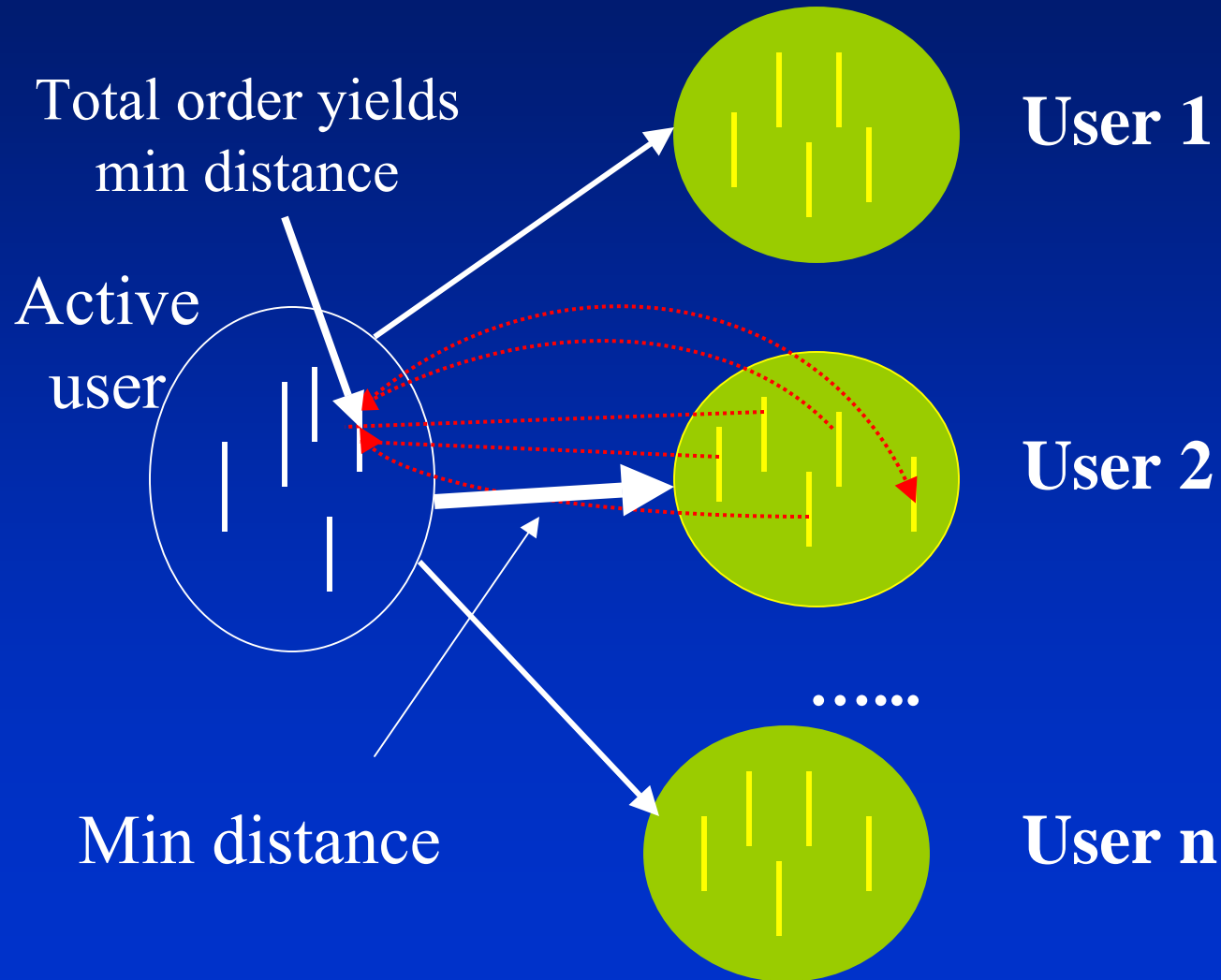
$$\delta(\prec_1, \prec_2) = \Pr(\prec_{v_1} \text{ and } \prec_{v_2} \text{ disagree wrt } a, b)$$

where \prec_{v_1} is consistent with \prec_1

and \prec_{v_2} is consistent with \prec_2

- Computing this distance is not straightforward: the number of extensions can be exponential.
- Use MCMC technique to sample the space of linear extensions
- Can approximate distance in polynomial time

Computing Probabilistic Distance



II. Preference Elicitation via Theory Refinement

- Would like to be able to use assumptions to guide but not constrain the elicitation process
- Theory refinement
 - ◆ Make assumptions that at least approximately apply to a large segment of users
 - Direct flights
 - Faster CPU
 - Better gas mileage
 - ◆ Correct for inaccuracies in assumptions when we encounter an individual to whom they do not apply

KBANN

- Domain theory:
 - ◆ acyclic set of propositional Horn-clauses
- Encoded in a back-propagation neural network.
- Network trained with examples that may not be consistent with the domain theory
- Domain theory supplemented and corrected

Choosing a Flight

- Find a flight from Bangkok to Boston
- Three attributes: time (T), cost(C), and whether or not a layover is involved (L).
- Assume
 - ◆ Attributes are mutually preferentially independent
 - ◆ People prefer shorter flights, cheaper flights, and flights without layovers

Encoding the Assumptions

- Dominance:

$$C_1 < C_2 \ \& \ T_1 \leq T_2 \ \& \ L_1 \leq L_2 \ \Rightarrow \ F_1 \succ F_2$$

$$C_1 \leq C_2 \ \& \ T_1 < T_2 \ \& \ L_1 \leq L_2 \ \Rightarrow \ F_1 \succ F_2$$

$$C_1 \leq C_2 \ \& \ T_1 \leq T_2 \ \& \ L_1 < L_2 \ \Rightarrow \ F_1 \succ F_2$$

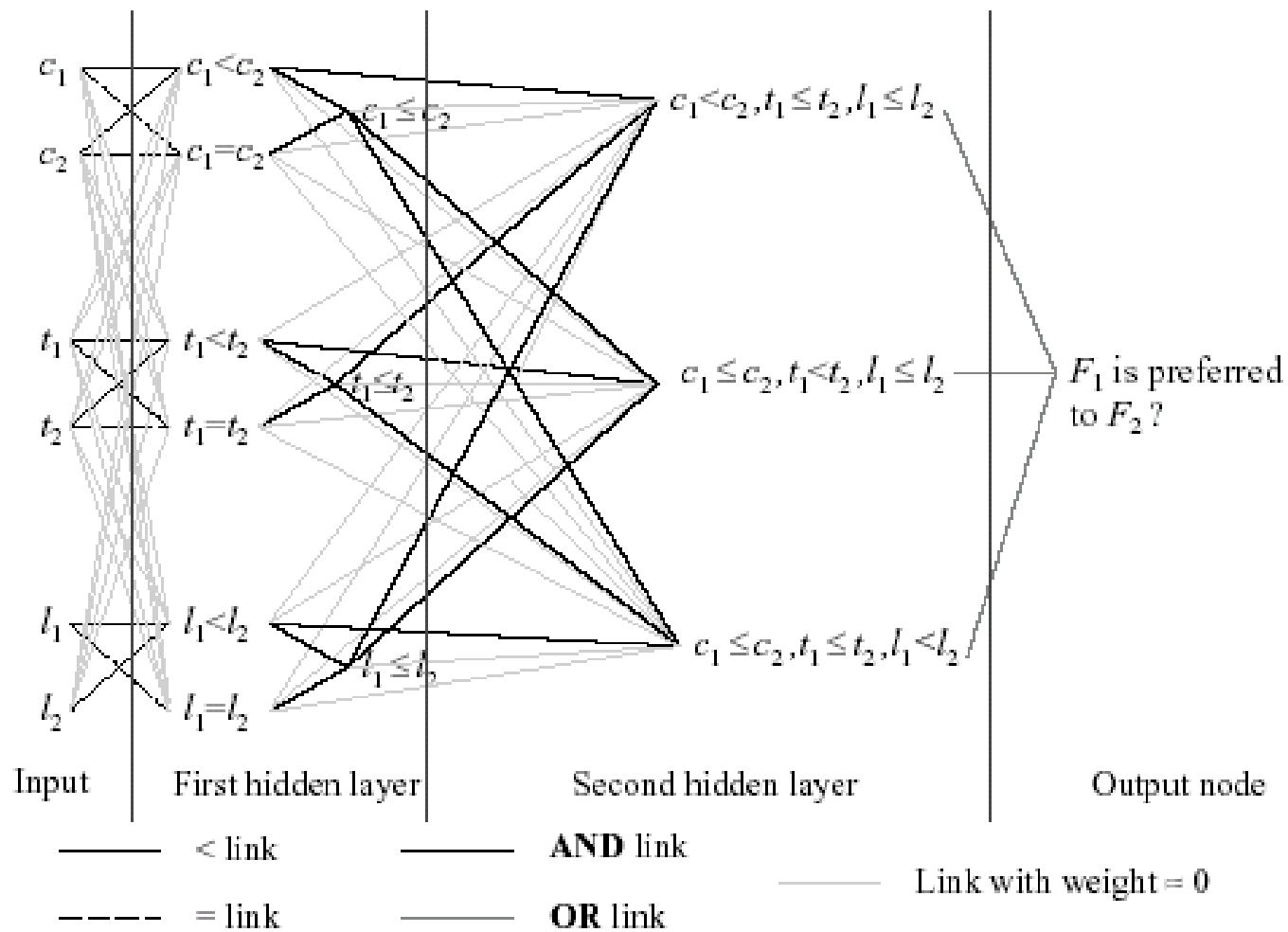
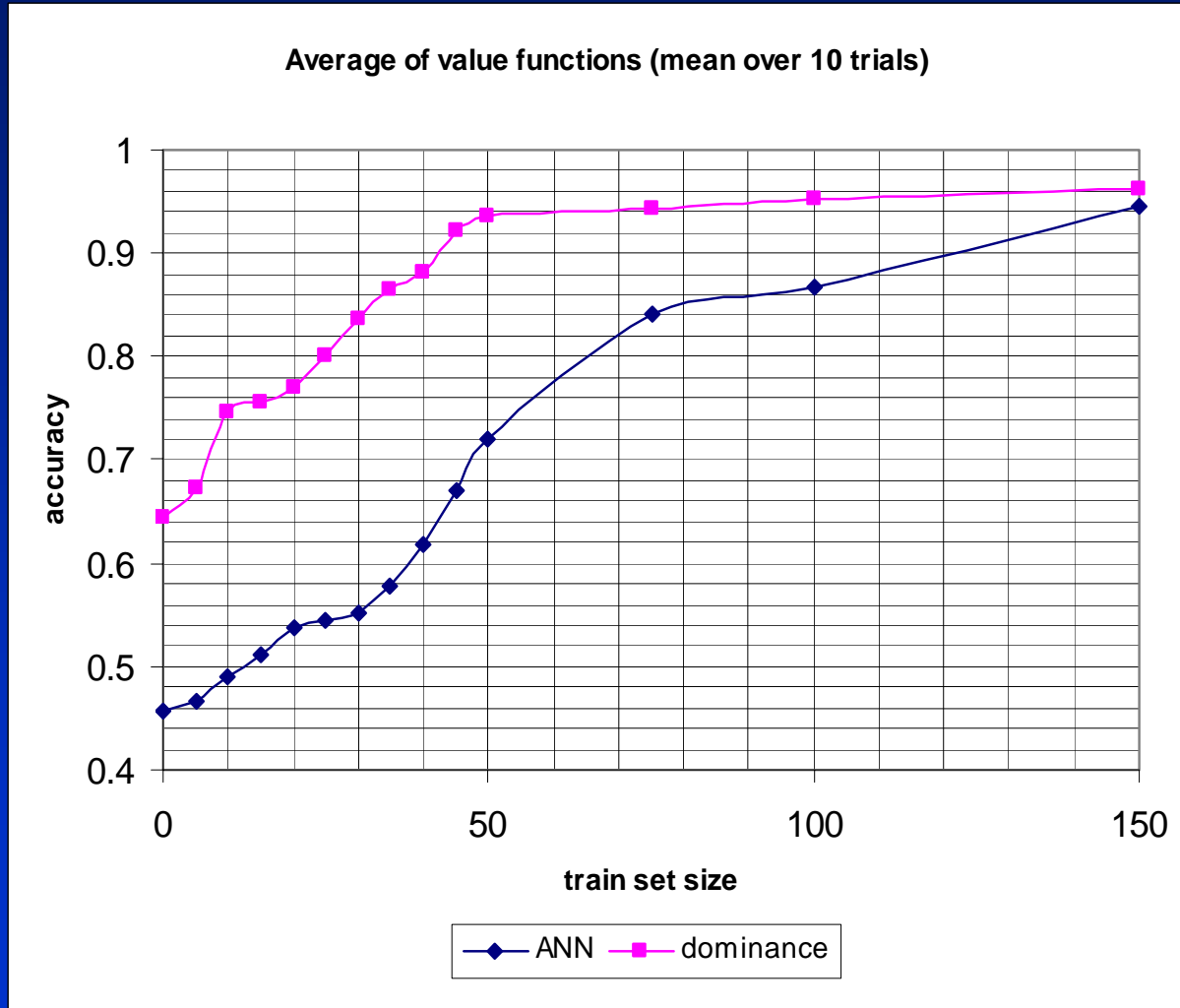


Figure 1. KBANN architecture for modeling user preferences in flights.

Empirical Results

(for preferences consistent with assumptions)

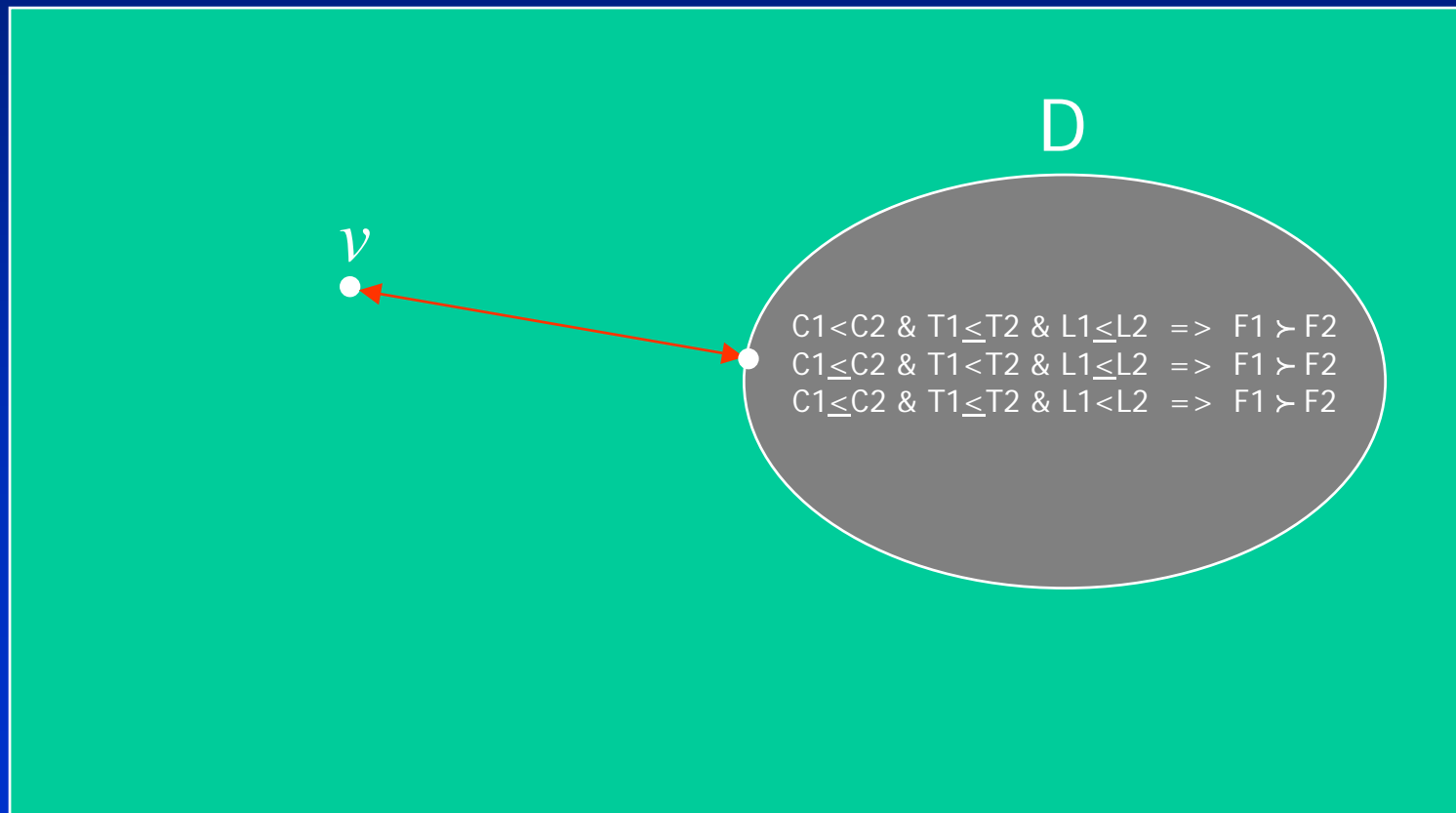


Robustness Analysis

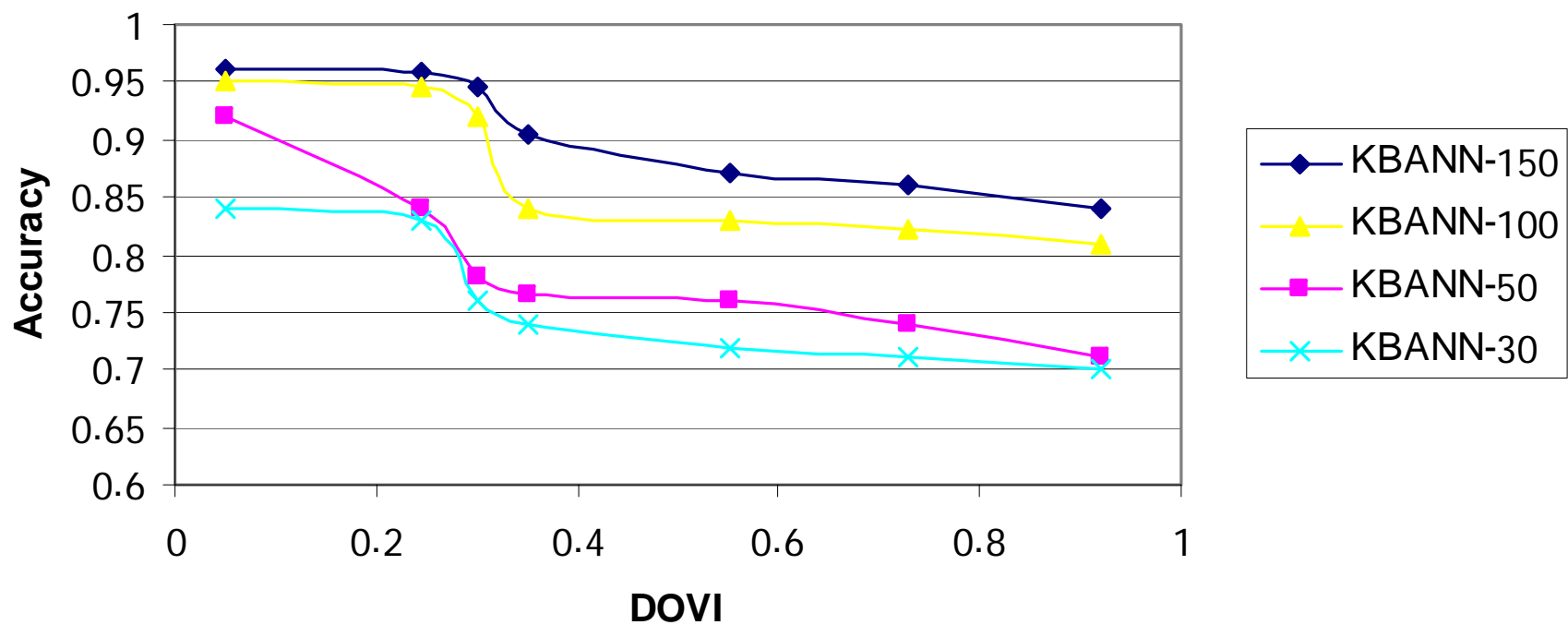
- What about when preferences are not consistent with the assumptions?
- Evaluate by examining the performance of the network for value functions that violate the assumptions to various degrees.
- Need a definition of the degree to which a preference structure (v) violates a domain theory (D).
 - ◆ Use Probabilistic Distance

Degree of Violation

$DOV(v,D)$ = Distance between v and the member of D closest to v .



KBANN PERFORMANCE



Uncertainty

- Network input: standard-gamble questions
- Assumptions
 - ◆ Dominance
 - ◆ Attitude toward risk
- Results similar to those for certainty

Open Questions

- Field in practical applications
- Compare with other theory refinement techniques
- Stronger/weaker theories

- Learning of preferences in the context of negotiation
- Dynamics of preference and the implications for elicitation