compute the boundary cases. Furthermore, if the teacher gives contradictory examples, the algorithm requires verification. Since only one element from each equivalence class is used as an example, the number of examples is kept small. Furthermore, previously learned concepts can be used to cover a part of the positive or negative region, thus further reducing the number of examples needed.

**Combining Stochastic Uncertainty and Linguistic Inexactness: Theory and Experimental Evaluation**

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Two major sources of imprecision in human knowledge—linguistic inexactness and stochastic uncertainty—are identified in this work. It is argued that since in most realistic situations these two types exist simultaneously, it is necessary to combine them in a formal framework to yield realistic solutions. This study presents such a framework by combining concepts from probability and fuzzy set theories. In this framework, we have tested four models that try to account for the numeric or linguistic responses in a probability elicitation task. The linguistic models of Kwakernaak, Yager, and Zadeh were found to be relatively effective in predicting subjects' responses (compared to a random choice model). Zadeh's numeric model proved to be insufficient. These results and others tend to suggest that subjects are unable to represent the overall structure of the problem in all its complexity. Instead they adopt a simplified view of the problem by presenting ambiguous linguistic concepts by multiple-crisp representations (the \( \alpha \)-level sets). All of the mental computation is done at these surrogate levels.

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