Computational Models of Human Learning

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Since the inception of the field of machine learning, some researchers have been involved with building computational models of human learning. From the psychologists perspective, there are a variety of reasons to be interested in machine learning:

- Implementing a working computer program that learns forces researchers to precisely specify their theory of human learning. Attempting to implement a computational model can raise new issues that might otherwise have been overlooked. Testing a computational model and comparing its performance to that of human learners can help to identifying shortcomings of existing theories and suggest areas for future research.

- Models of machine learning proposed by either the experimental or theoretical machine learning communities may provide useful insights or starting points for models of human learning.

In my opinion, there are good reasons that every machine learning researcher should also be aware of psychologists findings on human learning:

- Experimental findings on human subjects can call attention to inadequacies of current computational models and suggest areas for possible research. For example, Thau (1992) provides experimental evidence that suggests that human learners, unlike some computational models of unsupervised learning, selectively allocate attention to different dimensions during learning.

- Human learners are the closest approximizations to general purpose learning machines that are available for study. There are many open problems and current research topics in machine learning that are related to learning tasks that people solve every day. Even if one is not interesting in modeling human performance, insights into how people perform these task can provide useful starting points for machine learning. People can acquire new skills without interfering with existing skills. People can learn from incomplete and contradictory information. People can use existing knowledge to aid the learning process, yet can learn in the absence of relevant background knowledge. People can learn from complex, high dimensional visual and auditory data.

This special issue presents a diverse group of papers. Each paper explores a different learning task. A variety of models are proposed to account for human learning behaviors, including neural networks, case-based reasoning, probabilistic models and statistical induction. The paper by Jones and VanLehn investigates a model that accounts for data on how young children learn to add. The paper by Kazman proposes a model of the child acquiring lexical and syntactic knowledge by being exposed to samples of adult's language usage. Martin and Billman investigate how a learner may acquire overlapping concept from unsupervised data. Seifert, Hammond, Johnson, Converse, McDougal and Vanderstoep propose a model of how experiences are stored in memory so that they may be retrieved in appropriate situations. Shultz, Mareschal and Schmidt explore how children learn to predict what will occur when weights are placed on a balance scale.

I have to admit that although the subfield of computational modeling has been around as long as experimental approaches to machine learning and computational learning theory, it hasn't grown as rapidly. One factor that may be responsible for the growth of experimental machine learning is a common set of benchmark problems that researchers can use to compare alternative theories. I believe that much progress has been made due to friendly competition between researchers trying to improve the performance of algorithms on these databases.

It is through comparing and contrasting alternative theories of the same phenomenon that scientific understanding of the phenomenon progresses. Unfortunately, this does not occur often enough in computational modeling of human learning. Notable exceptions include several papers in this issue, and a series of papers on learning the past tense of verbs (Rumelhart & McClelland, 1986; Pinker & Prince, 1988; MacWhinney & Leinbach, 1991; and Ling & Marinov, 1993). I'd like to propose that the UCI Repository of Machine Learning Databases and Domain theories be extended to include databases that have been used to evaluate computational models of human learning.[1] I've stored four databases used in Pazzani (1992) in `ftp.ics.uci.edu:pub/machine-learning-databases/cognitive-modeling` and I encourage others involved in modeling human learning to contact `ml-repository@ics.uci.edu` to archive other databases here. I hope that other researchers will make use of these databases to replicate or improve upon existing models.

I'd like to thank the reviewers of the papers to this special issues, and all authors who submitted

1. By the way, I also believe that much may be gained by studying animal learning, so the archive may also be extended to include such databases.

papers. I have learned much from being involved in this special issue and I look forward to following progress on computational models of human learning.

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