Inconsistency-Induced Learning for Perpetual Learners

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ABSTRACT

One of the long-term research goals in machine learning is how to build never-ending learners. The state-of-the-practice in the field of machine learning thus far is still dominated by the one-time learner paradigm: some learning algorithm is utilized on data sets to produce certain model or target function, and then the learner is put away and the model or function is put to work. Such a learn-once-apply-next (or LOAN) approach may not be adequate in dealing with many real world problems and is in sharp contrast with the human’s lifelong learning process. On the other hand, learning can often be brought on through overcoming some inconsistent circumstances. This paper proposes a framework for perpetual learning agents that are capable of continuously refining or augmenting their knowledge through overcoming inconsistencies encountered during their problem-solving episodes. The never-ending nature of a perpetual learning agent is embodied in the framework as the agent’s continuous inconsistency-induced belief revision process. The framework hinges on the agents recognizing inconsistency in data, information, knowledge, or meta-knowledge, identifying the cause of inconsistency, revising or augmenting beliefs to explain, resolve, or accommodate inconsistency. The authors believe that inconsistency can serve as one of the important learning stimuli toward building perpetual learning agents that incrementally improve their performance over time.

Keywords: Inconsistency, Inconsistency-Induced Learning, LOAN, Machine Learning, Perpetual Learning Agents

1. INTRODUCTION

An important question in the long-term objective of machine learning research is how to build lifelong or never-ending learners (Mitchell, 2006; Thrun & Mitchell, 1995; Thrun, 1995, 1998). The state-of-the-practice in the field of machine learning thus far is largely dominated by the one-time learner paradigm: some learning algorithms are utilized on data sets to produce certain results such as a model or a target function, and then the learner is put away and the results are put to work (Mitchell, 2006). Such a learn-once-apply-next (or LOAN) approach is not adequate for an intelligent agent to deal with many real world problems and is in sharp contrast with human’s lifelong learning process. On the other hand, learning is often brought on through some stimulus. What triggers an agent to be a perpetual learner, always ready to be engaged in the

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next round of learning to incrementally improve its performance, is another dimension of the
desirable lifelong learning behavior for perpetual learning agents.
Inconsistency is ubiquitous in the real world, in human behaviors, and in the computing
systems we build (Brachman & Levesque, 2004; Gotesky, 1968; Zhang, 2009a, 2009b, 2010a,
2010b, 2011a, 2011b; Zhang & Grégoire, 2011). Inconsistency manifests itself in a plethora
of phenomena at different levels in the depth of knowledge, ranging from data, information,
knowledge, meta-knowledge, to expertise. Each time when an inconsistency or a conflicting
circumstance arises during its problem solving episode, an agent recognizes the nature of such
inconsistency, and overcomes the inconsistency through refining or augmenting its knowledge.
Such an agent can be engaged in a continuous and alternating sequence of problem-solving
episodes and inconsistency-induced-learning episodes, with each such iteration resulting in
an incremental performance improvement for the agent. This inconsistency-induced learning
capability can play a pivotal role in developing perpetual learning agents.
In this paper, our focus is on utilizing such inconsistency-induced learning to build per
petual learning agents that incrementally improve their performance over time. We describe a
framework for perpetual learning agents that are capable of continuously revising or augmenting
their knowledge through overcoming inconsistencies encountered during their problem-solving
episodes. In the framework, inconsistencies an agent confronts during its problem-solving episodes
serve as the learning stimuli, and the perpetual learning process is embodied in the continuous
inconsistency-induced belief revisions. The main contributions of our work include: (1) some
fundamental concepts for perpetual learning agents; (2) the role of inconsistency in learning; (3)
inconsistency-induced learning that proves to be a viable and useful approach toward building
perpetual learning agents; and (4) the generality and flexibility of the proposed framework in
accommodating different types of inconsistencies.
The rest of the paper is organized as follows. Section 2 offers a brief review on related work.
Section 3 describes the proposed framework for perpetual learning agents. Section 4 provides a
summary of various types of inconsistencies that can serve for the purpose of learning stimuli.
In Section 5, we discuss the inconsistency-induced learning for a particular type of inconsistency
and use an example to illustrate how such a framework accomplishes the continuous learning
process. Finally, Section 6 concludes the paper with remarks on future work.

2. RELATED WORK

How to build lifelong learners for intelligent agent systems has been an important agenda item in
the field (Mitchell, 2006; Thrun & Mitchell, 1995; Thrun, 1995, 1998). Reports of some initial
research results toward this long-term objective have emerged recently.
The work reported in Carlson, Betteridge, Kisiel, Settles, Hruschka, and Mitchell (2010)
discussed results in developing a never-end language learner called NELL. NELL relies on
semi-supervised learning methods and a collection of knowledge extraction methods to learn
noun phrases from specified semantic categories and with specified semantic relations. With an
initial seed ontology of 123 categories and 55 relations, NELL was able to learn 242,453 new
facts from the web with an estimated precision of 74% during a period of 67 days. NELL has
four component learners: a pattern learner, a semi-structured extractor, a morphological classi-
fier, and a rule learner. Candidate facts produced by component learners have to pass the muster
of the knowledge integrator in order to be promoted to the status of beliefs in the knowledge
base. NELL also accommodates human interaction to approve or reject inference rules learned
by the rule learner component.
Hierarchies of Architectures of Collaborative Computational Intelligence
www.igi-global.com/article/hierarchies-architectures-collaborative-computational-intelligence/2783?camid=4v1a

Computer Systems that Learn
Juan A. Barceló (2009). *Computational Intelligence in Archaeology* (pp. 73-141).
www.igi-global.com/chapter/computer-systems-learn/6821?camid=4v1a