Analogy and Episodic Memory to Support Domain Learning in a Cognitive Architecture: An Exploration

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Introduction

Organisms learn from experience in many ways. One component of learning from experience is recording what has happened in the world when actions are taken, a form of episodic memory, and distilling such experience over time to learn models of phenomena for generating expectations. As further actions are taken, the accuracy of such models can be monitored, to detect surprises and to help identify and prioritize learning goals. This publication-based talk will describe some recent results in exploring the use of analogical generalization over episodic memories in the Companion cognitive architecture to formulate models of the effects of actions in a complex dynamic world. Measures of novelty, surprise and for prioritization of learning goals will be discussed.

Episodic Memory and Analogy

How human episodic memory is organized is still an open question. Given the centrality of analogy in human cognition (e.g. Gentner, 2003), it seems reasonable that a common way of structuring episodic memories could be as cases, so that they can be accessed via analogical retrieval (e.g. MAC/FAC, Forbus et al. 1995) with more transferable knowledge constructed incrementally via generalization (e.g. SAGE, McLure et al. 2015). The Companion cognitive architecture (Forbus et al. 2009; Forbus 2016; Forbus & Hinrichs, in press) incorporates these analogical processing models, along with SME (Forbus et al 2016), which MAC/FAC and SAGE are built upon. The Companion architecture also includes facilities for language understanding, sketch understanding (Forbus et al. 2011), and integration with simulators. For example, Companions can interact with Freeciv[1], an open-source version of Civilization 2, which is a popular strategy game. The attraction of such games to players is their complexity, e.g. building civilizations and transportation networks, exploration, technology research, military operations, over hundreds of turns. Such complexity makes Freeciv useful for exploring learning about complex dynamics (McFate et al. 2014; Hinrichs & Forbus, 2016). For example, by storing cases of both positive outcomes and negative outcomes generated by experimentation, a Companion has learned to perform city management (Hinrichs & Forbus, 2007).

This talk goes beyond that work by focusing on how a Companion can distill models of actions via analogical generalization while observing human players. For each action the person takes, the Companion records information about the state of the world before and after the action, and uses some general-purpose heuristics to attempt to explain immediate events in terms of the action. For each occurrence of each action, a case consisting of this information is stored. Storage occurs via a SAGE generalization pool for each command (e.g., doMove, doIrrigate). The generalization pool for a command can be thought of as an analogy-derived model for what happens when that command is used. By letting the system watch replays from six different games, it builds up over 4,200 cases across 34 different commands.

Inspecting these generalization pools leads to some interesting insights. First, the number of generalizations and outliers in a pool provides an indication of how well the action is understood. If there are many cases all forming a single generalization, then that command has straightforward local consequences (e.g. doIrrigate). When there are multiple generalizations, comparing their structures can be illuminating: For example, in doResearch, the generalizations differ only in the number of requirements and opportunities, making them artifacts of the encoding strategy, which could be eliminated via re-representation. Thus properties of the generalization pools provide a signal about how encoding strategies might be improved.

Analogical generalization also provides a means of detecting and quantifying novelty and surprise. Novelty can be detected in two ways: Failure to retrieve a similar experience, and by analysis of candidate inferences indicating differences. When little is known, all is novel – surprise, I argue, occurs when a novel situation is experienced for a type of situation that was considered to already be well understood. The degree of surprise can be estimated based on the number of cases in the pool and frequency information for relationships within them that are computed for the generalizations: When there are many cases and highly certain outcomes, a new outcome can be more surprising. doMove provides an excellent example: It occurs frequently, so a dominant analogical model is quickly built up. But when a unit moves into a hut, there are five different things that might happen, leading initially to surprises.

[1] http://www.freeciv.org/

In addition to summarizing the results of these experiments, I will describe work in progress on making adaptable encoding strategies guided by the system's own analysis of its experience.

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References

Forbus, K. (2016). Software Social Organisms: Implications for Measuring AI Progress. *AI Magazine*. 37(1):85-90.

Forbus, K., Ferguson, R., Lovett, A., & Gentner, D. (2016). Extending SME to handle large-scale cognitive modeling. *Cognitive Science*, DOI:10.1111/cogs.12377, pp. 1-50.

Forbus, K., Gentner, D. & Law, K. (1995). MAC/FAC: A model of similarity-based retrieval. *Cognitive Science*, 19:141-205.

Forbus, K. & Hinrichs, T., (in press). Analogy and Qualitative Representations in the Companion Cognitive Architecture. *AI Magazine*.

Forbus, K., Klenk, M., & Hinrichs, T. (2009). Companion Cognitive Systems: Design Goals and Lessons Learned So Far. *IEEE Intelligent Systems*, 24(4):36-46

Forbus, K., Usher, J., Lovett, A., Lockwood, K., & Wetzel, J. (2011). CogSketch: Sketch understanding for Cognitive Science Research and for Education. *Topics in Cognitive Science*, 3(4):648-666.

Gentner, D. (2003) Why we're so smart. In D. Gentner & S. Goldin-Meadow (Eds.), *Language in mind: Advances in the study of language and thought.* MIT Press

Hinrichs, T., & Forbus, K. (2007). Analogical Learning in a Turn-based Strategy Game. *Proceedings of IJCAI-2007*.

Hinrichs, T. and Forbus, K. (2016). Qualitative Models for Strategic Planning. In *Advances in Cognitive Systems*, Volume 4, 2016, pages 75-92.

McFate, C., Forbus, K., & Hinrichs, T. (2014). Using Narrative Function to Extract Qualitative Information from Natural Language Texts. *Proceedings of AAAI-2014*.

McLure, M.D., Friedman S.E. and Forbus, K.D. (2015). Extending Analogical Generalization with Near-Misses. *Proceedings of AAAI-2015*.

Tomai, E. and Forbus, K. (2009). EA NLU: Practical Language Understanding for Cognitive Modeling. *Proceedings of the 22nd International Florida Artificial Intelligence Research Society Conference*. Sanibel Island, Florida.