Abstract

The Computational Gauntlet of Human-Like Learning

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Despite impressive advances, machine learning has abandoned many of its early profound insights. The discipline has become overly reliant on statistical analysis of massive data sets and strayed far from its conceptual roots. A promising alternative, common at the field's founding four decades ago, is to develop mechanisms that learn like humans. We can use findings from cognitive psychology to devise a *computational gauntlet* that systems must traverse, giving new criteria for evaluation. Here are six core features of human learning that provide constraints:

- Learning involves the acquisition of **modular cognitive structures**. This does not specify the structures' details; only that expertise consists of discrete mental elements.
- Learned cognitive structures can be **composed during performance**. Relevant elements of expertise are accessed and then combined as needed to produce behavior.
- Expertise is acquired in a **piecemeal manner**, with one element added at a time. Humans learn one cognitive structure, then another, continuing until they achieve broad coverage.
- Learning is an **incremental activity** that processes one experience at a time. This is linked to on-line approaches that interleave learning tightly with performance.
- Learning is **guided by knowledge** that aids interpretation of new experiences. Because acquisition is incremental, it occurs in the context of existing mental structures.
- Cognitive structures are **acquired and refined rapidly**, each from small numbers of training cases. This is enabled by piecemeal, incremental, and knowledge-guided processing.

The literature does contain systems, some older and others more recent, that exhibit these characteristics and thus run the computational gauntlet successfully. These include:

- Cobweb (Fisher, 1987), which constructs probabilistic taxonomies from unsupervised cases;
- Prodigy (Minton, 1990), which acquires control rules from planning traces to guide search;
- SAGE (McClure, 2015), which invokes structural analogy to learn relational concepts; and
- MIL (Muggleton, 2018), which uses meta-interpretive abduction to acquire visual categories.

These artifacts offer positive role models for the research community, but we need more efforts that take seriously the power of human learning and that aim to replicate its main features.

Note: This is an abstract of a published paper: Langley, P. (2022). The computational gauntlet of human-like learning. *Proceedings of the Thirty-Sixth AAAI Conference on Artificial Intelligence* (pp. 12268–12273). Vancouver, BC: AAAI Press. https://doi.org/10.1609/aaai.v36i11.21489

Third International Workshop on Human-Like Computing, September 28–30, 2022, Windsor Great Park, UK
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