Analogy as the Swiss Army Knife of Human-like Learning

Kenneth D. Forbus
Qualitative Reasoning Group, CS Department, Northwestern University
Evanston, IL, 60208 USA
forbus@northwestern.edu

Abstract

There is ample psychological evidence that analogy is ubiquitous in human learning, suggesting that computational models of analogy can play important roles in AI systems that learn in human-like ways. This talk will provide evidence for this, focusing mostly on recent advances in hierarchical analogical learning and working-memory analogical generalizations.

Introduction

In human learning, there is evidence that analogical learning is ubiquitous. This includes visual reasoning (e.g. Matlen et al. 2020), concept learning (e.g. Kotovsky & Gentner 1996), rule learning (Gentner & Medina, 1998) language learning (Gentner & Namy, 2004), theory of mind learning (Hoyos et al., 2020) and conceptual change (Gentner et al. 1997). Inspired by these results, our group has developed computational models of analogical processing that have been used to simulate many of these same phenomena. These models have also been used in deployed, performance-oriented AI systems (e.g. Forbus et al. 2018; Wilson et al. 2019). These models can be thought of as an *analogy stack*, since each builds on the next. Matching, as modeled by SME (Forbus et al. 2016), provides the foundation. Retrieval, as modeled by MAC/FAC (Forbus et al. 1995), uses SME in a second-stage filter after a coarser vector-based filter stage. Generalization, as modeled by SAGE (Kandaswamy & Forbus, 2012), uses MAC/FAC to retrieve items from a *generalization pool* representing the analogical model of a concept, and uses SME to assimilate sufficiently close examples into probabilistic relational generalizations.

These models satisfy several of the desiderata identified by Langley (2022) motivating this symposium. Analogical learning is incremental: Each new example provides new grist for solving future problems, and the analogical models constructed by SAGE can be used at any time. Analogical learning can be used to guide encoding processes, e.g. analogical word sense disambiguation in language (Barbella & Forbus, 2013) and in vision (Chen et al. 2020). Analogical learning is data-efficient, sometimes achieving state of the art performance with orders of magnitude fewer examples than statistical models (Liang & Forbus, 2015). Finally, analogical learning produces *inspectable* representations, relational descriptions that can be communicated to others, as well as potentially debugged within the cognitive architecture itself. These properties help explain why analogy seems so ubiquitous in human cognition, the Swiss Army knife of learning if you will.

Two recent new directions provide additional evidence for the utility of analogy for providing human-like learning for AI systems, be they performance systems or cognitive models (or ideally both!). The first is hierarchical analogical learning, the second is the role of analogical generalization in working memory. We discuss each in turn.

Hierarchical Analogical Learning

Traditional analogical learning using SAGE has shown promise for visual recognition, including in hybrid systems that combine deep learning modules with qualitative visual relations computed by CogSketch (Chen & Forbus, 2021). But most accounts of conceptual knowledge, and some accounts of visual knowledge, involve hierarchical representations. In recognizing sketches, for example, it seems natural to combine evidence from multiple levels of description, such as wheels and handlebars lending credence to the hypothesis that a sketch represents a bicycle. Consequently, we developed a new method, *part-based hierarchical analogical learning* (PHAL; Chen et al. 2023) which exploits the hierarchical visual representations automatically computed via CogSketch. It uses SAGE at each level of representation, but tuned more broadly than usual (e.g. with the FAC output stage of MAC/FAC, used for classification, returning more results), and using the results at coarser levels of representation to filter which finer-grained models are used, then combining them all to perform its final judgement. This method performs at the level of standard non-pretrained deep learning systems on the TU Berlin dataset and establishes a new state of the art for the Coloring Book Object dataset. This latter dataset has only nine examples per concept, a harsh test of data-efficiency. Even the best DL system is barely above chance, easily beaten by SAGE, and PHAL performs even better. The analogical techniques only need to see each example once, versus multiple epochs for DL systems, and do not require GPUs or TPUs. Moreover, the results are inspectable (Figure 1).

Airplane-Level2: SAGEGen1	
(areaTiny PG1)	1.0
(curvedCycle PG1)	0.75
(ellipseShape PG1)	0.75
(above PG1 PG2)	1.0
(above PG1 PG3)	0.5
…	…

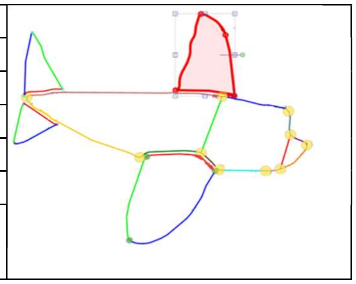

Figure 1. Example of a SAGE part generalization, with a few of the facts and their probabilities shown.

Analogical Generalization in Working Memory

SAGE captures the role of analogical generalization in long-term memory, generalizations that form constituents of our persistent conceptual structure. But there is also evidence that similar processes operate in working memory, potentially explaining the rapid learning occurring during experiments (e.g. Kotovsky & Gentner, 1996; Hoyos et al. in press). To explore these phenomena, we have developed SageWM (Kandaswamy et al. 2014) which uses SME to combine examples in working memory. SageWM differs from SAGE in three important ways: (1) SME is used to across all items in a working memory generalization pool, (2) this is done sequentially, based on recency, and (3) there is a tight upper bound on the number of items in working memory generalization pools. We have used SageWM to model concept learning (Kandaswamy et al. 2014), theory of mind learning (Rabkina et al. 2017), and infant visual learning (Chen et al. 2020).

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