Abstract

Architectures that implement the Common Model of Cognition - Soar, ACT-R, and Sigma - have a prominent place in research on cognitive modeling as well as on designing complex intelligent agents. In this paper, we explore how computational models of analogical processing can be brought into these architectures to enable concept acquisition from examples obtained interactively. We propose a new analogical concept memory for Soar that augments its current system of declarative long-term memories. We frame the problem of concept learning as embedded within the larger context of interactive task learning (ITL) and embodied language processing (ELP). We demonstrate that the analogical learning methods implemented in the proposed memory can quickly learn a diverse types of novel concepts that are useful not only in recognition of a concept in the environment but also in action selection. Our approach has been instantiated in an implemented cognitive system Aileen and evaluated on a simulated robotic domain.

Keywords: cognitive architectures, common model of cognition, intelligent agents, concept representation and acquisition, interactive learning, analogical reasoning and generalization, interactive task learning

1. Introduction

The recent proposal for the common model of cognition (CMC; Laird et al. 2017) identifies the central themes in the past 30 years of research in three cognitive architectures - Soar (Laird, 2012), ACT-R (Anderson, 2009), and Sigma (Rosenbloom et al., 2016). These architectures have been prominent not only in cognitive modeling but also in designing complex intelligent agents. CMC architectures aim to implement a set of domain-general computational processes which operate over domain-specific knowledge to produce effective task behavior. Early research in CMC architectures studied procedural knowledge - the knowledge of how to perform tasks, often expressed as if-else rules. It explored the computational underpinnings of a general purpose decision making process that can apply hand-engineered procedural knowledge to perform a wide-range of tasks. Later research studied various ways in which procedural knowledge can be learned and optimized.

While CMC architectures have been applied widely, Hinrichs and Forbus (2017) note that reasoning in them focuses exclusively on problem solving, decision making, and behavior. Further, they argue that a distinctive and arguably signature feature of human intelligence is being able to build complex conceptual structures of the world. In the CMC terminology, the knowledge of concepts is declarative knowledge - the knowledge of what. An example of declarative knowledge is the final goal state of the tower-of-hanoi puzzle. In contrast, procedural knowledge in tower-of-hanoi are the set of rules that guide action selection in service of achieving the goal state. CMC architectures agree that conceptual structures are useful for intelligent behavior. To solve tower-of-hanoi, understanding the goal state is critical. However, there is limited understanding of how declarative knowledge about the world is acquired in CMC architectures. In this paper, we study the questions of declarative concept representation, acquisition, and usage in task performance in a prominent CMC architecture - Soar. As it is similar to ACT-R and Sigma in the organization of computation and information, our findings can be generalized to those architectures as well.

1.1. Declarative long-Term memories in Soar

In the past two decades, algorithmic research in Soar has augmented the architecture with decalartive long-term memories (dLTMs). Soar has two - semantic (Derbinsky et al., 2010) and episodic (Derbinsky and Laird, 2009) - that serve distinct cognitive functions following the hypotheses about organization of memory in humans (Tulving and Craik, 2005). Semantic memory enables enriching what is currently observed in the world with what is known generally about it. For example, if a dog is observed in the environment, for certain types of tasks it may be useful to elaborate that it is a type of a mammal. Episodic memory gives an agent a personal history which can later be recalled to establish reference to shared experience with a collaborator, to aid in decision-making by predicting the outcome of possible courses of action, to aid in reasoning by creating an internal model of the environment, and by keeping track of progress on long-term goals. The history is also useful in deliberate reflection about past events to improve behavior through other types of learning such as reinforcement learning or explanation-based learning. Us-
ing dLTM s in Soar agents has enable reasoning complexity that wasn’t possible earlier [Xu and Laird, 2010, Mohan and Laird, 2014] [Kirk and Laird, 2014; Mininger and Laird, 2018].

However, a crucial question remains unanswered - how is general world knowledge in semantic memory acquired? We posit that this knowledge is acquired in two distinctive ways. [Kirk and Laird, 2014, 2019] explore the view that semantic knowledge is acquired through interactive instruction when natural language describes relevant declarative knowledge. An example concept is the goal of tower-of-hanoi a small block is on a medium block and a large block is below the medium block. Here, the trainer provides the definition of the concept declaratively which is later operationalized so that it can be applied to recognize the existence of a tower and in applying actions while solving tower-of-hanoi. In this paper, we explore an alternative view that this knowledge is acquired through examples demonstrated as a part of instruction. We augment Soar dLTM s with a new concept memory that aims at acquiring general knowledge about the world by collecting and analyzing similar experiences, functionally bridging episodic and semantic memories.

1.2. Algorithms for analogical processing

To design the concept memory, we leverage the computational processes that underlie analogical reasoning and generalization in the Companions cognitive architecture - the Structure Mapping Engine (SME; Forbus et al., 2017) and the Sequential Analogical Generalization Engine (SAGE; McLure et al., 2015). Analogical matching, retrieval, and generalization is the foundation of the Companions Cognitive architecture. In Why we are so smart?, Gentner claims that what makes human cognition superior to other animals is “First, relational concepts are critical to higher-order cognition, but relational concepts are both non-obvious in initial learning and elusive in memory retrieval. Second, analogy is the mechanism by which relational knowledge is revealed. Third, language serves both to invite learning relational concepts and to provide cognitive stability once they are learned” (Gentner, 2003). Gentner’s observations provide a compelling case for exploring analogical processing as a basis for concept learning. Our approach builds on the analogical concept learning work done in Companions (Hinrichs and Forbus, 2017). Previous analogical learning work includes spatial prepositions Lockwood (2009), spatial concepts (McLure et al., 2015), physical reasoning problems (Kienz et al., 2011), and activity recognition (Chen et al., 2019). This diversity of reasoning tasks motivates our use of analogical processing to develop an architectural concept memory. Adding to this line of research, our work shows that you can learn a variety of conceptual knowledge within a single system. Furthermore, that such a system can be applied to not only learn how to recognize the concepts but also acting on them in the environment within an interactive task learning session.

1.3. Concept formation and its interaction with complex cognitive phenomenon

Our design exploration of an architectural concept memory is motivated by the interactive task learning problem (ITL; Gluck and Laird, 2019) in embodied agents. ITL agents rely on natural interaction modalities such as embodied dialog to learn new tasks. Conceptual knowledge, language, and task performance are inextricably tied - language is a medium through which conceptual knowledge about the world is communicated and learned. Task performance is aided by the conceptual knowledge about the world. Consequently, embodied language processing (ELP) for ITL provides a set of functional requirements that an architectural concept memory must address. Embedding concept learning within the ITL and ELP contexts is a significant step forward from previous explorations in concept formation. Prior approaches have studied concept formation independently of how they will be used in a complex cognitive system, often focusing on the problems of recognizing the existence of a concept in input data and organizing concepts into a similarity-based hierarchy. We study concept formation within the context of higher-order cognitive phenomenon. We posit that concepts are learned through interactions with an interactive trainer who structures a learner’s experience. The input from the trainer help group concrete experiences together and a generalization process distills common elements to form a concept definition.

1.4. Theoretical Commitments, Claims, and Contributions

Our work is implemented in Soar and consequently, brings to bear the theoretical postulates the architecture implements. More specifically, we build upon the following theoretical commitments:

1. Diverse representation of knowledge: In the past decade, the CMC architectures have adopted the view that architectures for general intelligence implement diverse methods for knowledge representation and reasoning. This view has been very productive in not only studying an increasing variety of problems but also in integrating advances in AI algorithmic research in the CMC framework. We contribute to this view by exploring how algorithms for analogical processing can be integrated into a CMC architecture.

2. Deliberate access of conceptual knowledge: Following CMC architectures, we assume that declarative, conceptual knowledge is accessed through deliberation over when and how to use that knowledge. The architectures incorporates well-defined interfaces i.e. buffers in working memory that contain information as well as an operation the declarative memory must execute on the information. Upon reasoning, information may be stored, accessed, or projected (described in further detail in Section 4).
3. Impasse-driven processing and learning: Our approach leverages impasse in Soar, a meta-cognitive signal that can variably indicate uncertainty or failure in reasoning. Our approach uses impasses (and the corresponding state stack) to identify and pursue opportunities to learn.

4. A benevolent interactive trainer: We assume existence of an intelligent trainer that adopts a collaborative goal with the learning system that it learns correct definitions of concepts. Upon being prompted, the trainer provides correct information to the learner to base its concept learning upon.

Based on these theoretical commitments, our paper contributes an integrative account of a complex cognitive phenomenon - interactive concept learning. Specifically, this paper:

1. defines the concept formation problem within larger cognitive phenomenon of ELP and ITL;
2. identifies a desiderata for an architectural concept memory;
3. implements a concept memory for Soar agents using the models of analogical processing;
4. introduces a novel process - curriculum of guided participation - for interactive concept learning;
5. introduces a novel framework for evaluating interactive concept formation.

Our implementation is a functional (and not an architectural) integration of analogical processing in Soar’s declarative long-term memory systems. It characterizes how an analogical concept memory can be interfaced with the current mechanisms. Through experiments and system demonstration, we show that an analogical concept memory leads to competent behavior in ITL. It supports learning of diverse types of concepts useful in ITL. Learned concept representations support recognition during ELP as well as action based on those concepts during task performance. The concepts are from few examples provided interactively.

2. Preliminaries - The AILEEN Cognitive System

AILEEN is a cognitive system that learns new concepts through interactive experiences (linguistic and situational) with a trainer in a simulated world. A system diagram is shown in Figure 1. AILEEN lives in a simulated robotic world built in Webots. The world contains a table-top on which various simple objects can be placed. A simulated camera above the table captures top-down visual information. AILEEN is engaged in a continuous perceive-decide-act loop with the world. A trainer can set up a scene in the simulated world by placing simple objects on the scene and providing instructions to the agent. AILEEN is designed in Soar which has been integrated with a deep learning-based vision module and an analogical concept memory. It is related to Rosie, a cognitive system that has demonstrated interactive, flexible learning on a variety of tasks (Mohan et al. 2012, 2014; Mohan and Laird 2014, Kirk and Laird 2014, Mininger and Laird 2018), and implements a similar organization of knowledge.

Visual Module. The visual module processes the image taken from the simulated camera. It produces output in two channels: object detections as bounding boxes whose centroids are localized on the table-top and two perceptual symbols or percepts corresponding to the object’s shape and color each. The module is built using a deep learning framework - You Only Look Once (YOLO: Redmon et al. 2016). YOLO is pre-trained with supervision from the ground truth in the simulator (12,000 images). It is detects four shapes (error rate < 0.1%) - box (percept - CVBox), cone (CVCone), ball (CVSphere), and cylinder (CVCylinder).

For colors, each detected region containing an object is cropped from the image, and a K-means clustering is applied all color pixel values within the crop. Next, two weighted heuristics are applied that selects the cluster that likely comprises the detected shape among any background pixels and/or neighboring objects. The first heuristic selects the cluster with the maximum number of pixels. The second heuristic selects the cluster with the centroid that is closest to the image center of the cropped region. The relative weighted importance of each of these heuristics is then trained using a simple grid search over $w_1$ and $w_2$: $Score = w_1R_s + w_2(1-C_s)$, $s \in D$, where $w_1 + w_2 = 1$, $D$ is the set clusters, $R_s$ denotes the ratio between the number of pixels in each cluster and the the number of pixels in the image crop, and $C_s$ is the Euclidean distance between the centroid of the cluster and the image center normalized by the cropped image width. The average RGB value for all pixels included in the cluster with the highest score is calculated and compared with the preset list of color values. The color label associated with the color value that has the smallest Euclidean distance to the average RGB value is selected. The module can recognize 5 colors (error rate < 0.1%): CVGreen, CVBlue, CVRed, CVYellow, and CVPurple. Note that the percepts are named so to be readable for system designers - the agent does not rely on the percept symbol strings for any reasoning.

Spatial Processing Module. The spatial processing module uses QSRLIB (Gatsoulis et al. 2016) to process the bounding boxes and centroids generated by the visual module to generate a qualitative description of the spatial configuration of objects. For every pair of objects, the module extracts qualitative descriptions using two spatial calculi.

https://www.cyberbotics.com/
Figure 1: System diagram for Advanced cognItive LEarning for Embodied compreheNsion (AILLEN)

(qsrs): cardinal direction (CDC) and region connection (RCC8). Additionally, the spatial processing module can also convert a set of calculi into regions and sample points from them. This enables Aileen to identify locations in continuous space that satisfy qualitative spatial constraints when planning actions.

World representation, Intrinsic & Extrinsic Behaviors. The outputs of the visual module and the spatial module are collected into an object-oriented relational representation of the current state of the world. Each detected object is asserted and represented with attributes that indicated its color and shape visual properties and is assigned a unique identifier. Qualitative relationships extracted by the spatial processing module are represented as as binary relation between relevant objects. The set of objects that exist on the scene and qualitative relationships between them capture the current state of the world and are written to Soar’s working memory graph.

Interactive and learning behaviors in Aileen are driven by its procedural knowledge encoded as rules in Soar and similarly to Rosie (Mohan et al., 2012) consists of knowledge for:

1. Interaction: As in Rosie (Mohan et al., 2012) Aileen implements collaborative discourse theory (Rich et al., 2001) to manage its interactive behavior. It captures the state of task-oriented interaction and is integrated with comprehension, task execution, and learning.

2. Comprehension: Aileen implements the Indexical Model of comprehension (Mohan et al., 2014) to process language by grounding it in the world and domain knowledge. This model formulates language understanding as a search process. It interprets linguistic symbols and their associated semantics as cues to search the current environment as well as domain knowledge. Formulating language comprehension in this fashion integrates naturally with interaction and learning where ambiguities and failures in the search process drive interaction and learning.

3. External task execution: Aileen has been programmed with primitive actions that enable it to manipulate its environment: point(o), pick-up(o), and place([x, y, z]). Following Mohan and Laird (2014), each primitive action has a proposal rule that encodes its pre-conditions, a model that captures state changes expected to occur when the action is applied, and an application rule. Additionally, given a task goal, Aileen can use iterative-deepening search to plan a sequence of primitive actions to achieve the goal and execute the task in the world.

4. Learning: Learning in Aileen is the focus of this paper and is significantly different from Rosie. Rosie uses an interactive variation of explanation-based learning (Mohan and Laird, 2014) to learn representation and execution of tasks. Aileen uses analogical reasoning and generalization to learn diverse concepts including those relevant to task performance (Sections 3 and 4). A crucial distinction is that EBL requires a complete domain theory to correctly generalize observed examples while analogical reasoning and generalization can operate with partial domain theory by leveraging statistical information in observed examples.

The ongoing ITL research in Soar demonstrates the strength of this organization of knowledge in hybrid cog-
nitive systems. Our conjecture is that an ideal concept memory in an architecture must support complex, integrated, intelligent behavior such as ELP and ITL.

Using Conceptual Knowledge in Aileen. Consider the world in Figure 1 and the corresponding working memory graph in Figure 2. Semantic memory stores concept definitions corresponding to various words used to interact with Aileen. Maps (M1, M2, M3, M4, M5, M6) - in semantic memory (shown in Figure 2) - associate words (cylinder) to their conceptual definition (percept CVCylinder). Maps provide bi-directional access to the association between words and concept definitions. The semantic memory can be queried with a word to retrieve its concept definition. The semantic memory can also we queried with a concept definition to access the word that describes it. Phrases (1) blue cone left of red cylinder and (2) move blue cone right of red cylinder can be understood via indexical comprehension (details by as follows:

1. Parse the linguistic input into semantic components. Both (1) and (2) have two references to objects: {or1: obj-ref{property:blue, property:cylinder}} and {or2: obj-ref{property:red, property:cone}}. Additionally, (1) has a reference to a spatial relationship: {rel1: {rel-name: left of, argument1: or1, argument2: or2}}. (2) has a reference to an action: {act1: {act-name: move, argument1: or1, argument2: or2, relation: left of}}. For this paper, we assume that the knowledge for this step is pre-encoded.

2. Create a goal for grounding each reference. The goal of processing an object reference is to find a set of objects that satisfy the properties specified. It starts with first resolving properties. The process queries semantic memory for a percept that corresponds to various properties in the parse. If the knowledge in Figure 2 is assumed, property blue resolves to percept CVBlue, cone to CVCon, red to CVRed, and cylinder to CVCylinder. Using these percepts, Aileen queries its scene to resolve object references. For or1, it finds an object that has both CVBlue and CVCon in its description. Let or1 resolve to o1 and or2 to o2 where o1 and o2 are identifiers of objects visible on the scene. The goal of processing a relation reference is to find a set of spatial calculi that correspond to the name specified. If knowledge in Figure 2 is assumed, rel1 in (1) is resolved to a conjunction of qrs w(a1,a2)∧dc(a1,a2) i.e., object mapping to a1 should be east (in CDC) of a2 and they should be disconnected. Similarly, act1 in (2) resolves to a task goal which is a conjunction of qrs w(a1,a2)∧dc(a1,a2)

3. Compose all references: Use semantic constraints to resolve the full input. For (1) and (2) a1 is matched to ar1 and consequently to o1. Similarly, a2 is resolved to o2 via ar2.

Tasks are represented in Aileen as goals that it must achieve in its environment. Upon being asked to execute a task, move blue cone right of red cylinder, indexical comprehension determines the desired goal state as w(a1,a2)∧dc(a1,a2). Now, Aileen must execute a sequence of actions to achieve this desired goal state in its environment. Leveraging standard pre-conditions and effects of actions, Aileen can simulate the results of applying plausible actions in any state. Through an iterative deepening search conducted over actions, Aileen can generate and execute a plan that will achieve a desired goal state in the environment.

3. The Interactive Concept Learning Problem

With an understanding of how indexical comprehension connects language with perceptions and actions and how tasks are executed, we can begin to define the concept learning problem. Our main question is this - where does the conceptual knowledge in semantic memory (in Figure 2) come from? We study how this knowledge is
acquired through interactions with an intelligent trainer who demonstrates relevant concepts by structuring the learner’s environment. In Soar, episodic memory stores contextual experiences while the semantic memory stores general, context-independent facts. Our approach uses supervision from an intelligent trainer to group contextual experiences together. An analogical generalization process distills the common elements in grouped contextual experience. This process can be seen as mediating knowledge in Soar’s episodic and semantic memories.

To develop our ideas further, we focus on learning three kinds of concepts. These concepts are crucial for ELP and ITL. Visual concepts correspond to perceptual attributes of objects and include colors and shapes. They provide meaning to nouns and adjectives in the linguistic input. Spatial concepts correspond to configuration of objects and provide grounding to prepositional phrases in the linguistic input. Action concepts correspond to temporal changes in object configurations and provide grounding to verb phrases.

3.1. A Curriculum of Guided Participation

We introduce a novel interactive process for training AILEEN to recognize and use novel concepts - guided participation. Guided participation sequences and presents lessons - conjoint stimuli (world and language) - to AILEEN. A lesson consists of a scenario setup in AILEEN’s world and an interaction with AILEEN. A scenario can be a static scene when training visual and spatial concepts or a sequence of scenes when training an action concept. An interaction has a linguistic component (content) and a non-linguistic component (signal). The signal component of instruction guides reasoning in AILEEN and determines how it processes and responds to the content. Currently, AILEEN can interpret and process the following types of signals:

1. inform: AILEEN performs active learning. It uses all its available knowledge to process the content through indexical comprehension (Section 3). If failures occur, AILEEN creates a learning goal for itself. In this goal, it uses the current scenario to generate a concrete example of the concept described in the content. This example is sent to its concept memory. If no failure occurs, AILEEN does not learn from the example. AILEEN learning is deliberate; it evaluates the applicability of its current knowledge in processing the linguistic content. It learns only when the current knowledge isn’t applicable, and consequently, AILEEN accumulates the minimum number of examples necessary to correctly comprehend the content.

2. verify: AILEEN analyzes the content through indexical comprehension and determines if the content refers to specific objects, spatial relationships, or actions in the accompanying scenario. If AILEEN lacks knowledge to complete verification, AILEEN indicates a failure to the instructor.

3. react: This signal is defined only when the linguistic content contains a reference to an action. AILEEN uses its knowledge to produce an action instantiation. Upon instantiation, AILEEN determines a goal state in the environment and then plans, a sequence of actions to achieve the goal state. This sequence of actions is executed in the environment.

Incorporating these variations in how AILEEN responds to the linguistic content in a lesson enables flexible interactive learning. A trainer can evaluate the current state of knowledge in AILEEN by assigning it verify and react lessons. While the verify lesson tests if AILEEN can recognize a concept in the world, the react lesson tests if AILEEN can use a known concept to guide its own behavior in the environment. Observations of failures helps the trainer in structuring inform lessons that guide AILEEN’s learning. In an inform lesson, AILEEN evaluates its own learning and only adds examples when necessary. Such learning strategy distributes the onus of learning between both participants. Lessons can be structured in a flexible, reactive way in real human-robot training scenarios.

3.2. Desiderata for a Concept Memory

We extend the concept memory desiderata originally proposed by [Langley, 1987] to enable embedding it within larger reasoning tasks, in this case ELP and ITL:

D0 Is (a) architecturally integrated and (b) uses relational representations.

D1 Can represent and learn a diverse types of concepts. In particular, for AILEEN, the concept memory must be able to learn visual concepts, spatial concepts, and action concepts.

D2 Learn from exemplars acquired through experience in the environment. AILEEN is taught through lessons that have two stimuli - a scenario and linguistic content that describes it.

D3 Enable incremental accumulation of knowledge. Interactive learning is a distinctive learning approach in which behavior is intertwined with learning. It has been previously argued that interleaving behavior and learning splits the onus of learning between the instructor and the learner such that the instructor can observe the learner’s behavior and provide more examples/instruction if necessary.

D4 Learn from little supervision as realistically humans cannot provide a lot of examples.

D5 Facilitate diverse reasoning over definitions of concepts.

(a) Evaluate existence of a concept in the current environment, including its typicality. This enables recognizing a concept in the environment.
enrichment cannot be provided through a demonstration which is automatically encoded in Soar’s episodic memory. An episodic trace are provided through a demonstration which is automated by SME (Forbus et al., 2017) and SAGE (McLure et al., 2015) and can learn visual, spatial, and action concepts (desiderata [Di]). Below we describe each function of concept memory is built with these models. The current implementation of the memory represents knowledge as predicate calculus statements or facts, we have implemented methods that automatically converts Soar’s object-oriented graph description to a list of facts when needed. Example translations from Soar’s working memory graph to predicate calculus statements are shown in Table 1. Visual and spatial learning requires generating facts from the current scene. Examples for action learning are provided through a demonstration which is automatically encoded in Soar’s episodic memory. An episodic trace of facts is extracted from the episodic memory (shown in Table 1). We will rely on examples in Table 1 for illustrating the operation of the concept memory in the remainder of this section. We have summarized various terms and parameters used in analogical processing in Table 2.

4.1. Creation and Storage

When Aileen identifies a new concept in linguistic content (word red), it creates a new symbol RRed. This new symbol is incorporated in a map in Soar’s semantic memory and is passed on to the concept memory for creation of a new concept via the create command. The concept memory creates a new reasoning symbol as well as a new generalization context (shown in Figure 3). A generalization context is an accumulation of concrete experiences with a concept. Each generalization context is a set of individual examples and generalizations. After creating a new concept, Soar stores an example in the concept memory. The command \{store: [(isa o2 CVRed) (isa o2 CVCylinder) (isa o2 RRed)], concept: RRed\} stores that the object o2 in the world is an example of the concept RRed. This example A is stored in the RRed generalization context as is - as a set of facts. Assume that at a later time, Soar sends another example B of RRed concept through the command \{store: [(isa o3 CVRed) (isa o3 CVCube) (isa o3 RRed)], concept: RRed\}. The concept memory adds the new example to the RRed generalization context by these two computational steps:

1. SME performs an analogical match between the two examples. The result of analogical matching has two components: a correspondence set and a similarity score. A correspondence set contains alignment of each fact in one example with at most one fact from other. The similarity score indicates the degree of overlap between the two representations. In the two examples A and B, there are two corresponding facts: (isa o2 CVRed) aligns with (isa o3 CVRed) and (isa o2 RRed) aligns with (isa o3 RRed). If the similarity score exceeds an assimilation threshold (Table 2), SAGE continues to the next step to create a generalization.

2. SAGE assimilates the two examples A and B into a generalization (e.g. Figure 3). It:
Table 2: Terms used in analogical processing, their definitions, and values in Aileen’s concept memory

| Term               | Definition                                                                 | Value |
|--------------------|----------------------------------------------------------------------------|-------|
| Similarity         | The score representing the quality of an analogical match, degree of overlap |       |
| Correspondence     | A one-to-one alignment between the compared representations                |       |
| Candidate Inference| Inferences resulting from the correspondences of the analogy               |       |
| Assimilation       | Score required to include a new example into a generalization instead of storing it as an example | 0.01  |
| Probability        | Only facts exceeding this value are considered part of the concept.         | 0.6   |
| Match              | Score required to consider that an inference is applicable in a given scene | 0.75  |

(a) Uses the correspondence to create abstract entities. In the two examples provided, (isa o2 RRed) aligns with (isa o3 RRed) and (isa o2 CVRed) with (isa o3 CVRed). Therefore, identifiers o2 and o3 can be replaced with an abstract entity (GenEntFn 0 RRedMt).

(b) Maintains a probability that a fact belongs in the generalization. Because (isa (GenEntFn 0 RRedMt) RRed) and (isa (GenEntFn 0 RRedMt) CVRed) are common in both examples, they are assigned a probability of 1. Other facts are not in the correspondences and appear in 1 of the 2 examples in the generalization resulting in a probability of 0.5. Each time a new example is added to this generalization, the probabilities will be updated to reflect the number of examples for which the facts were aligned with each other.

Upon storage in a generalization context, a generalization becomes available for matching and possible assimilation with future examples enabling incremental (D3), example-driven (D2) learning.

4.2. Query

During indexical comprehension, Aileen evaluates if a known concept exists in the current world through the query command. Assume that in an example scene with two objects, indexical comprehension attempts to find the one that is referred to by red through (query: {scene: [(isa o4 CVRed) (isa o4 CVBox) (isa o5 CVGreen) (isa o2 CVCylinder)], pattern: (isa ?o RRed)}).

In response to this command, the concept memory evaluates if it has enough evidence in the generalization context for RRed to infer (isa o2 RRed). The concept memory performs this inference through the following computations.

1. SME generates a set of candidate inferences. It matches the scene with the generalization in Figure 3 (right). This match results in a correspondence between the facts (isa o4 CVRed) (in scene) and (isa (GenEntFn 0 RRedMt) CVRed), which aligns o4 with (GenEntFn 0 RRedMt). Other facts that have arguments that align, but are not in the correspondences, are added to the set of candidate inferences. In our example, a candidate inference would be (isa o4 RRed).

2. Aileen filters the candidate inferences based on the pattern in the query command. It removes all inferences that do not fit the pattern. If the list has an element, further support is calculated.

3. Aileen evaluates the support for inference by comparing the similarity score of the match to the match threshold. That is, the more facts in the generalization that participate in the analogical match then it is more likely that the inference is valid.

Through queries to the concept memory and resultant analogical inferences, the working memory graph (of the world in Figure 4) is enhanced. This enhanced working memory graph supports indexical comprehension in Section 3.

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Figure 3: (left) SAGE maintains a generalization context for each concept. For each example (circle) of a concept, it is either added to a generalization (rounded rectangle) or maintained as an independent example for the concept. (right) Facts and their probabilities in generalization context for RRed.

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| Facts                                           | P  |
|-------------------------------------------------|----|
| (isa (GenEntFn 0 RRedMt) RRed)                  | 1.0|
| (isa (GenEntFn 0 RRedMt) CVRed)                 | 1.0|
| (isa (GenEntFn 0 RRedMt) CVCube)                | 0.5|
| (isa (GenEntFn 0 RRedMt) CVCylinder)            | 0.5|
Note that the internal concept symbols in blue (such as RBlue) are generalization contexts in the concept memory that accumulate examples from training. Consequently, the ‘meaning’ of the world blue will evolve as more examples are accumulated.

4.3. Projection

In ITL, simply recognizing that an action has been demonstrated is insufficient, the agent must also be able to perform the action if directed (desiderata D5). One of the advantages of analogical generalization is that the same mechanism is used for recognition and projection. Consider the example scene Figure 5 in which the trainer asks Aileen to move the blue cone to the right of the red cylinder using the react signal. Assume that Aileen has previously seen some other examples of this action that are stored in concept memory as episodic traces (an example is shown in Figure 1).

During indexical comprehension, Aileen performs queries to identify the blue cone, O1, and red cylinder, O2. Similarly, it maps the verb and the related preposition to RMove and RRightOf. To act, Aileen uses its concept memory to project the action through the command {project: (trace: [(H T0 (dc o1 o2)) (H T0 (e o1 o2)) (isa AileenStartTime T0) ...]), concept: RMove}. A summary is shown in Figure 5 starting at T0. In response, the concept memory performs the following computations:

1. SME generates a set of candidate inferences. SME to matches the current scene expressed as a trace against the generalization context of the action RMove. SME generates all the candidate inferences that symbolically describe the next states of the action concept.

2. Aileen filters the candidate inferences to determine which apply in the immediate next state (shown in Figure 5). For example, the trace in the project command contains episode T0 as the AileenStartTime. The filter computation will select facts that are expected to be held in (t) and that the (after (t) T0) holds.

This retrieval is accepted by Aileen to be next desired state it must try to achieve in the environment.

5. Evaluation

In this section, we evaluate how the proposed concept memory address the desiderata outlined in section 4.2. As per desiderata D0, the concept memory can be integrated into a CMC architecture through its interfaces (defined in section 4) and SME & SAGE support inference and learning over relational representations (in Table 1). For the remaining desiderata, we conducted a set of empirical experiments and demonstrations.

H1 As per D1 can the concept memory learn a diverse types of concepts? Our hypothesis is that because SME & SAGE operate over relational, structured representations, the concept memory designed with these algorithms can learn a variety of concepts. We designed our experiments to study how Aileen learns visual, spatial, and action concepts.

H2 As per D2, D3, & D4, can the concepts be learned incrementally through limited, situated experience? Aileen can learn from a curriculum of guided participation that incrementally introduces a variety of concepts through a conjoint stimuli of scene information with language. We designed our learning experiments to reflect how a human-like teaching (Ramaraj et al. 2021) would unfold and report our observations about the memory's performance especially focusing on the number of examples needed to learn from.

H3 As per D5, does the concept memory support diverse reasoning? The representations acquired by the concept memory not only support recognition of a concept on the scene, it also guides action selection as well as identifying opportunities to learn.

Method. We performed separate learning experiments for visual, spatial, and action concepts (D1). We leverage the lessons of guided participation in the design of our experimental trials. Each trial is a sequence of inform lessons. In an inform lesson, a concept is randomly selected from a pre-determined set and shown to Aileen accompanied with linguistic content describing the concept (D2). The lesson is simplified, i.e, there are no distractor objects (examples are shown in Figures 6, 7, & 8). The lesson is presented to Aileen and we record the number of store requests it makes to the concept memory. Recall that Aileen learns actively; i.e, it deliberately evaluates if it can understand the linguistic content with its current knowledge and stores examples only when necessary. The number of store requests made highlight the impact of such active learning.

Additionally, to measure generality and correctness, we test Aileen knowledge after every inform lesson through two exams: generality and specificity (examples are shown in Figures 6, 7, & 8). Both exams are made up of 5 verify lessons that are randomly selected at the beginning of the trial. As Aileen learns, the scores on these test demonstrate how well Aileen can apply what it has learned until now. In the generality lessons, Aileen is asked to verify if the concept in the linguistic input exists on the scene. If Aileen returns with a success status, it is given a score of 1 and 0 otherwise. In the specificity exam, Aileen is asked to verify the existence of a concept, however, the scenario does not contain the concept that is referred to in the linguistic content. If Aileen returns with a failed status, it is given a score of 1 and 0 otherwise. Both types of exam lessons have 0 – 3 distractor objects introduced.
on the scene to evaluate if existence of noise impacts the application of conceptual knowledge.

**Results.** Figure 6 illustrates visual concept learning. AILEEN begins without any knowledge of any concept. As two concepts (green and cone) are introduced in the first lesson, it provides several store commands to its concept memory (shown in blue bars). The number of commands reduces as the training progresses demonstrating that the learning is active and opportunistic (D5c). As is expected, the score on the generality exam starts at 5, this is to be expected as well. This is because if a concept is unknown, AILEEN cannot recognize it on the scene. However, this score grows very quickly with training eventually reaching perfect performance at lesson 15. The score on the specificity exam starts at 5, this is to be expected as well. This is because if a concept is unknown, AILEEN cannot recognize it on the scene. However, as the trial progress we see that this score doesn’t drop. This indicates that conceptual knowledge of one concept doesn’t bleed into others. Note that the exams have distractor objects while learning occurred without any distractors - good scores on these exams demonstrate the strength of relational representations implemented in AILEEN. Finally, AILEEN learns from very few examples indicated that such learning systems can learn online with human trainers (D3 D4).

Figure 7 illustrates spatial concept learning (commenced after all visual concepts are already known). Spatial relationships are defined between two objects very low in the beginning because AILEEN doesn’t know any concepts. However, this score grows very quickly with training eventually reaching perfect performance at lesson 15. The score on the specificity exam starts at 5, this is to be expected as well. This is because if a concept is unknown, AILEEN cannot recognize it on the scene. However, as the trial progress we see that this score doesn’t drop. This indicates that conceptual knowledge of one concept doesn’t bleed into others. Note that the exams have distractor objects while learning occurred without any distractors - good scores on these exams demonstrate the strength of relational representations implemented in AILEEN. Finally, AILEEN learns from very few examples indicated that such learning systems can learn online with human trainers (D3 D4).

Figure 8 illustrates action learning (commenced after all visual and spatial concepts have been learned). Actions are generated through the template move object reference 1 relation object reference 2. Similarly to spatial concepts, the learning space is very large and complex. When AILEEN asks, it is provided a demonstration of action performance as shown in Figure 8 (T0, T1, T2). AILEEN stores the demonstration trace in its episodic memory. For storing an example in the concept memory, information in Soar’s episodic memory is translated into an episodic trace as shown Table 1. Similarly to visual and spatial learning, inform lessons with simplified scene are used to teach a concept. Exams made up of positive and negative verify lessons are used to evaluate learning. As we see in Figure 9 AILEEN can quickly learn action concepts. Errors towards the later part of the experimental trial occur for the same reason we identified in spatial learning.

**Task Demonstration.** After visual, spatial, and action concepts were taught, we used a react lesson to see if AILEEN could perform the actions when asked. Consider the time T0 in Figure 9 when AILEEN is asked to move the blue cone right of the red cylinder. It can successfully use methods of analogical processing to guide action planning through the concept memory interface. First, it uses

\[
(\text{H} (:\text{skolem (GenEntFn 0 0 rMoveMt)) (held O1))}
\]

\[
(\text{after (:\text{skolem (GenEntFn 0 0 rMoveMt)) T0})
\]

**Figure 5:** Candidate inferences indicate that the next state of the move action is to hold object 05. Skolem terms are generated by SME to indicate that the candidate inference refers to an entity from the concept for which there is no correspondence in the scene. In this case, the skolem represents the next temporal state of the action as denoted by the after relation.
Figure 6: (left) Learning curve for visual concepts averaged from 10 trials. A trial includes lessons from 5 colors and 4 and shapes = 20 unique objects. Lessons include reference only to shape and color and shape. (right) Examples of an inform lesson (I) and generality (G) and specificity (S) exam lessons. The blue bars show the average number of create or store commands executed in the concept memory. The pink and green lines show average score on the generality and specificity exams respectively.

Figure 7: (left) Learning curve for spatial concepts averaged from 10 trials. A trial includes lessons about 4 types of binary relations defined over 20 unique objects. (right) Examples of an inform lesson (I) and generality (G) and specificity (S) exam lessons. The blue bars show the average number of create or store commands executed in the concept memory. The pink link shows average score on the generality exam and the green bar at the top shows the average score on the specificity exam.

Figure 8: (left) Learning curve for action concepts averaged from 5 trials. A trial includes lessons about 1 verb move with 4 different relations and two objects chosen from 20 unique objects. The blue bars show the average number of create or store commands executed in the concept memory. The pink link shows average score on the generality exam and the green bar at the top shows the average score on the specificity exam. (right) A demonstration.
its visual concepts during indexical comprehension to resolve blue cone to (O1) and the red cylinder to (O2). It maps the verb move to a known action trace indexed by RMove. Then, it projects this action in the future. As described in Section 4.3, the concept memory returns with a set of predicates that have to be true in the next state (\texttt{holds}(O1)). AILEEN plans using its pre-encoded actions models and iterative deepening search. The search results in \texttt{pick-up}(O1) where O1. After executing a \texttt{pick-up} action, AILEEN invokes projection again to determine if \texttt{RMove} requires more steps. In this case, it does, and the candidate inferences specify that O1 should be located to the w of O2 and they should be topologically disjoint. Further, these candidate inferences indicate that this is the last step in the action, and therefore AILEEN marks the action as completed after executing it.

The symbolic actions generated through planning are incrementally transformed into concrete information required to actuate the robot. \texttt{pick-up} executed on a specific object can be directly executed using an inverse kinematics solver. \texttt{place} action is accompanied with qualitative constraints. For example, to place o1 to right of o2, it must be place in a location that is to the west and such that their bounding boxes are disconnected. AILEEN uses QSRLIB to sample a point that satisfies the constraint. Once a point is identified, the inverse kinematics solver can actuate the robot to achieve the specified configuration. The successive projection and their interaction with action planning is shown in Figure 9.

6. Related Work

Diverse disciplines in AI have proposed approaches for concept learning from examples however, not all approaches can be integrated in a CMC architecture. We use the desiderata defined in Section 3.2 to evaluate the utility of various concept learning approaches. The vast majority study the problem in isolation and consider only flat representations violating the desiderata \texttt{D1}. ML-based classification approaches are designed for limited types of concepts (such as object properties), violating desiderata \texttt{D1} and require a large number of examples, violating desiderata \texttt{D4} which are added in batch-mode, violating desiderata \texttt{D5}. On the other hand, while EBL and Inductive logic programming [Muggleton and De Raedt, 1994] can learn from few datapoints, they require fully-specified domain theory violating desiderata \texttt{D2}. Bayesian concept learning [Tenenbaum, 1999] uses propositional representations, violating \texttt{D0} and each demonstration has focused on a single type of concept, violating \texttt{D1}.

There are a few cognitive systems’ approaches to the concept learning problem that aim toward the desiderata that we delineated in Section 3. In the late 1980s - early 1990s, there was a concerted effort to align machine learning and cognitive science around concept formation (Fisher, 1987). For example, Labyrinth (Thompson and Langley, 1991) creates clusters of examples, summary descriptions, and a hierarchical organization of concepts using a sequence of structure examples. COBWEB3 (Fisher, 1987) incorporates numeric attributes and provides a prob-

![Figure 9: A simplified view of how AILEEN plans a sequence of actions using its concept memory. The process starts at the current state in T0 that is used to generate a project command to the concept memory. The memory returns the predicates to be achieved in the next state. An iterative deepening search determines the action that will achieve it. This successive projection and planning continues until the terminal state.]
abilistic definition differences between concepts. Building off these ideas, TRESTLE (MacLellan et al. 2015) learns concepts that include structural, relational, and numerical information. Our work can be seen as a significant step in advancing these research efforts. First, the proposed concept memory leverages the computational models of analogical processing that have been shown to emulate analogical reasoning in humans. Second, we place the concept learning problem within the larger problems of ELP and ITL in a cognitive architecture context. We demonstrate not only concept formation but also how learned concepts are applied for recognition, scene understanding, and action reasoning. By integrating with vision techniques, we demonstrate one way in which concept formation is tied to sensing.

Another thread of work in the cognitive system’s community that we build upon is that of analogical learning and problem-solving. Early analogical problem-solving systems include Cascade (VanLehn et al. 1991), Prodigy (Veloso et al. 1995), and Eureka (Jones and Langley 2005). They typically used analogy in two ways: (1) as analogical search control knowledge where previous examples were used to guide the selection of which problem-solving operator to apply at any time, and (2) for the application of example-specific operators in new situations. AILEEN differs in two important ways: (1) it relaxes the need for explicit goals further in its use of projection to specify the next subgoal of an action, and (2) it uses analogical generalization on top of analogical learning to remove extraneous knowledge from the concept.

7. Discussion, Conclusions, and Future Work

In this paper, we explored the design and evaluation of a novel concept memory for Soar (and other CMC cognitive architectures). The computations in the memory use models of analogical processing - SAGE and SME. This memory can be used to acquire new situated, concepts in interactive settings. The concepts learned are not only useful in ELP and recognition but also in task execution. While the results presented here are encouraging, the work described in this paper is only a small first step towards an architectural concept memory. We have only explored a functional integration of analogical processing in Soar. The memory has not been integrated into the architecture but is a separate module that Soar interacts with. There are significant differences between representations that Soar employs and those in the memory. For an efficient integration and a reactive performance that Soar has historically committed to, several engineering enhancements have to be made.

There are several avenues for extending this work. We are looking at three broad classes of research: disjunctive concepts, composable concepts, and expanded mixed-initiative learning. Disjunctive concepts arise from homographs (e.g., bow in musical instrument versus bow the part of a ship) as well as when the spatial calculi does not align with the concept or the functional aspects of the objects must be taken into account (e.g., a cup is under a teapot when it is under the spigot, while a saucer is under a cup when it is directly underneath). One of the promises of relational declarative representations of the form learned here is that they are composable. This isn’t fully exploited for learning actions with spatial relations in them. Our approach ends up with different concepts for move-left and move-above. A better solution would be to have these in the same generalization such that AILEEN would be able to respond to the command to move cube below cylinder assuming it been taught a move action previously along with the concepts for below, cube, and cylinder. Another avenue is contextual application of concepts. For example, bigger box requires comparison between existing objects. Finally a cognitive system should learn not only from a structured curriculum designed by an instructor but also in a semi-supervised fashion while performing tasks. In our context this means adding additional examples to concepts when they were used as part of a successful execution. This also means, when there are false positives that lead to incorrect execution, revising the learned concepts based on this knowledge. One approach from analogical generalization focuses on exploiting these near-misses with SAGE (McLure et al. 2015).

Inducing general conceptual knowledge from observations is a crucial capability of generally intelligent agents. The capability supports a variety of intelligent behavior such as operation in partially observable scenarios (where conceptual knowledge elaborates what is not seen), in language understanding (including ELP), in commonsense reasoning, as well in task execution. Analogical processing enables robust incremental induction from few examples and has been demonstrated as a key cognitive capability in humans. This paper explores how analogical processing can be integrated into the Soar cognitive architecture which is capable of flexible and contextual decision making and has been widely used to design complex intelligent agents. This paper paves way for an exciting exploration of new kinds of intelligent behavior enabled by analogical processing.

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