Introducing SB-CoRLA, a Schema-Based Constructivist Robot Learning Architecture

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Abstract

We introduce the SB-CoRLA architecture that we have developed by extending our previously developed centralized ASyMTRe architecture (CA) to enable constructivist learning for multi-robot team tasks. We believe that the schema-based approach used in ASyMTRe is a useful abstraction for enabling constructivist learning. The CA algorithm only finds complete solutions for the entire team and is not well-suited for identifying useful schema chunks that can be used to find future task solution. Thus, we explore an Evolutionary Learning (EL) technique for the offline learning of schema chunks. We compare the solutions discovered by the EL algorithm with those that are found using CA, as well as with a third algorithm that randomizes the CA algorithm, called RA. Four different applications in simulation are used to evaluate the techniques. Our results show that the EL approach finds solutions of comparable quality to the CA technique, while also providing the added benefit of learning highly fit schema chunks.

1. Introduction

In prior work, F. Tang and Parker [8], [11] developed the ASyMTRe approach to automatically generate robot team task solutions for coalitions performing multi-robot tasks (taxonomized as ST-MR-IA, per [7]). The ASyMTRe approach is inspired by the theory of information invariants [5] and schema theory [1], and finds team task solutions by configuring the schema building blocks on each robot such that the resulting configuration achieves the specified task with the lowest cost possible. Because the challenge of locating a low-cost configuration of schemas across multiple robot team members is an NP-hard search problem [12] (which is also true for other task allocation problems), the ASyMTRe search algorithm that finds potential coalitions is based loosely on the findings of Shehory [10], who showed that for non-super-additive domains, better solutions consist of smaller coalition sizes. These concepts are implemented in ASyMTRe through heuristics that direct the search toward smaller team solutions first. Parker and F. Tang showed, through empirical evaluations, that the heuristic-based centralized ASyMTRe search algorithm generates very good solutions quite quickly for several types of applications. (F. Tang and Parker also implemented a distributed version of ASyMTRe [8], [13]; for clarity, we focus on the centralized version in this paper.) A major benefit of this approach is that it enables robots to easily share sensory, computational, and effector capabilities in solving challenging multi-robot tasks.

In continuing work, our objective is to extend the ASyMTRe architecture to enable constructivist learning in the multi-robot team. Constructivist learning is a method for learning new knowledge and skills based upon past experience; this type of learning is recognized to be a common method used by humans from infancy to adulthood for lifelong learning [2]. Because much of human learning seems to be based on schema building blocks, our intent is to build upon our schema-based abstraction of ASyMTRe to enable constructivist robot learning. We believe that collections of schemas, called "chunks", analogous to the *Sensory Computational Systems (SCSs)* of Donald's information invariants theory [5], could be learned. Most of the chunks present intermediate solutions to the search problem. (In this paper, "schema chunk", "SCS", "intermediate solution", and "partial solution" are used as synonyms). Ultimately, our objective is to enable robot teams to learn and build up chunks constructively, in order to store knowledge from previous search processes, and to improve the efficiency for future searches.

However, the current solution search strategy of ASyMTRe does not construct chunks that would be amenable to this constructivist learning process. Thus, the goal of our current research is to determine if an alternative search strategy can have the benefit of facilitating constructivist learning in multi-robot teams, and if so, how its solution quality compares to other possible search techniques. The long term goal of our research is to develop a Schema-Based, Constructivist Robot Learning Architecture, which we call "SB-CoRLA", that can combine online solution searching and offline learning, in order to find a better solution more efficiently for the same task, and to find new solutions for future tasks using schemas chunks.

A search technique that we believe would be appropriate for offline learning of schema chunks is an evolutionary search technique. An evolutionary search technique could make use of a genetic algorithm to search the solution space by repeatedly combining highly-fit intermediate solutions to generate lower-cost complete solutions. We have developed such an evolutionary search technique called “EL” (Evolutionary Learning). EL is of particular interest to our constructivist learning objective, since we believe that the highly-fit intermediate solutions found in the evolutionary search can be beneficial as higher-level building blocks for constructivist learning.

To explore alternative search techniques, we compare the centralized version of the previously implemented ASyMTRe search algorithm (CA) with a Randomized ASyMTRe search algorithm (RA). RA makes use of the same fundamental search algorithm of ASyMTRe, but rather than making a greedy heuristic search of the potential multi-robot team task solutions, it randomly selects possible solutions.

Because the partial solutions generated by EL will ultimately be used as higher-level building blocks by online search algorithms, we compare the cost of the partial solutions with the cost of the solutions generated by CA and RA. The cost of a solution is the sum of the costs of the active schemas used in the solution. If a robot is not assigned a task in a partial solution, no schema is activated for that robot, hence the cost for an unassigned robot is zero. Only if the solution cost of EL is comparable to (or lower than) CA or RA for the coalition formation problem does it make sense to us to use this technique as a foundation for constructivist learning in multi-robot coalitions.

The remainder of this paper is organized as follows. Section 2 describes related work. Section 3 lays out the SB-CoRLA architecture. Section 4 presents the three search algorithms: the centralized ASyMTRe search algorithm (CA), the Randomized ASyMTRe search algorithm (RA), and the Evolutionary Learning search algorithm (EL). Section 5 describes the simulated applications and the settings used to study the alternative algorithms, followed by a discussion of the results in Section 6. Section 7 concludes with some summary remarks.

2. Related Work

The schema-based building block approach, upon which all three of our search algorithms are based, is derived from the work of Arbib [1] and others. Arbib gives an overview of the theoretical aspects of schemas and explores schema theory from the neurological perspective. The definition of perceptual schema and motor schema originated from Arbib. Schemas are recursive in the sense that they can be divided into sub-schemas. Our research in constructivist learning is aimed at recursively building higher-level schemas based on existing schemas. We present more details about our search algorithms in [14].

Other constructivist learning approaches include Drescher [6] and Chaput [3], [4]. They both developed schema-based constructivist learning models to emulate an infant exploring the environment using very basic perceptual schemas and motor schemas. Their work concentrated on the biological verification of the constructivist point of view using very basic level schemas that reflect the inherent abilities of an infant. Unlike their approach, our emphasis

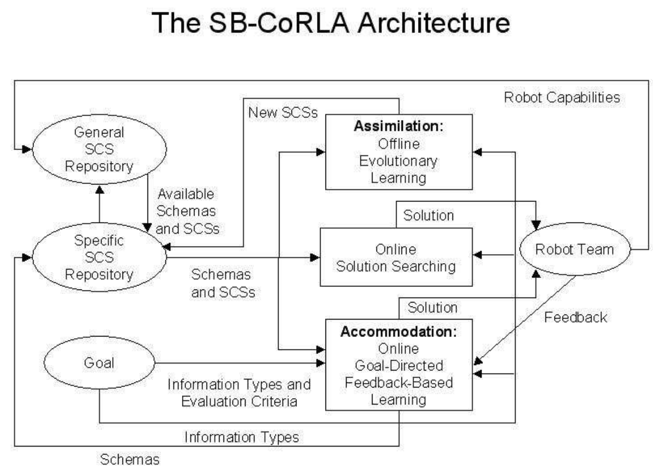

Fig. 1. SB-CoRLA Architectural Overview.

lies in automatically generating robot behaviors. We employ higher-level schemas, aiming for less computational complexity.

Our overall ideas for combining the offline search process for schema chunks together with the online use of these chunks to solve current tasks, in a constructivist learning model, originated from Piaget [9]. According to Piaget, the basic process of constructive intelligence development consists of two parts: assimilation and accommodation. *Assimilation* refers to reflecting novelties in the environment by assembling existing knowledge; *accommodation* refers to modifying existing knowledge to adjust to the environment. This paper proposes offline learning to accomplish assimilation. This offline learning process makes use of our EL search algorithm to generate chunks of schemas (SCSs). These chunks can then be used to generate new task solutions, with chunks treated in a similar manner as fundamental schemas. That is, chunks become more abstract schemas, which can then be treated the same as low-level schemas in the task solution generation process. The process iterates, with the objective of demonstrating constructivist learning over time.

3. The SB-CoRLA Architecture

Figure 1 shows the high level architecture of SB-CoRLA, which consists of three major processes: 1) assimilation, which is offline evolutionary learning; 2) online solution searching; and, 3) accommodation, which is online goal-directed feedback-based learning. The general SCS repository is the knowledge base of the system that stores the original schemas and the more complex, learned SCSs (schema chunks). The specific SCS repository is a subset of the general SCS repository and is created based on each specific robot team’s configurations and available capabilities of the current robots. The existing online ASyMTRe search technique, which we call CA (for Centralized ASyMTRe), will still be the main algorithm for finding online coalition solutions. However, a new offline learning process will be used to explore the schema base and identify chunks that

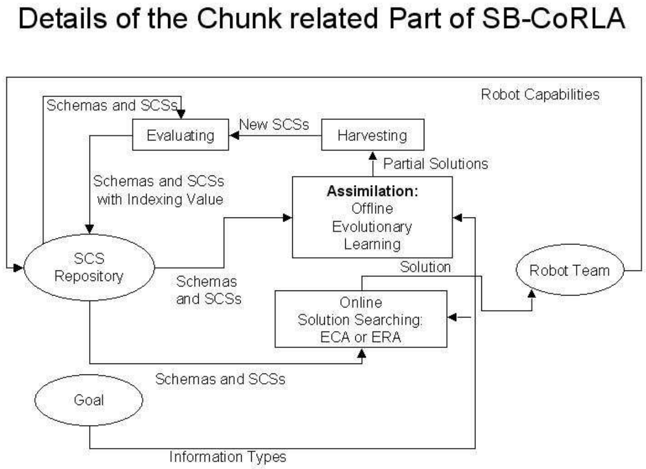

Fig. 2. Details of processes in the SB-CoRLA architecture that are related to chunks.

can be used in later online search processes to speed up the search for complex solutions. When the robots are not busy performing tasks, the assimilation process searches for partial solutions and learns new chunks for future use. When the robot team has an immediate task to perform, the online search generates task solutions for the robot team based on the goal definition and the existing SCS repository. The robot team then carries out the task solution with the lowest cost. Accommodation modifies existing schemas to generate new schemas. This aspect of the approach is the subject of future research.

Figure 2 shows more details about the processes of generating, learning, and utilizing chunks. The assimilation process searches for highly-fit partial solutions based on the existing SCS repository. A harvesting process generates new chunks (SCSs) based on the partial solutions. An evaluating process assigns index values to the new SCSs, as well as to the existing schemas and SCSs from the SCS repository. We are currently working on finding good criteria to measure the distance from the chunk to the final goal. This evaluation process evaluates schemas and chunks. It is different from the evaluation process in EL, which evaluates individual solutions in each population. The indexed basic schemas and SCSs are used in the online solution search process to generate task solutions. The existing CA and RA algorithms need to be extended, in order to include SCSs in the search process. In ongoing work, we are extending CA and RA to create the ECA and ERA algorithms for this purpose.

4. The Algorithms

The CA, RA, and EL algorithms use the schema-based abstraction implemented in ASyMTRe [8], in which the search space consists of basic *schemas* [1], each of which requires and produces certain input(s) and output(s) called *information types*. The schemas represent basic robot capabilities and are categorized into perceptual schemas, motor schemas, and communication schemas. The inputs and outputs of schemas can be interconnected if their information types match. The ASyMTRe process of automatically connecting the schemas through matching information types defines the information flow through the multi-robot system, thus generating the behavior control for the robot coalition.

The solutions for all three search algorithms consist of combinations and interconnections of active schemas on each robot in the robot team that allow the team to accomplish the task. This section describes the approaches used by each of the three search algorithms to find these solutions. Please refer to our publication [14] for more details.

4.1. Centralized ASyMTRe Search Algorithm (CA)

The Centralized ASyMTRe algorithm (CA) is a two-step, anytime algorithm for searching for the proper connections of schemas to accomplish the goal task. The first step is to find all potential schema connections ("potential solutions") that can provide the required information types for a goal in an individual robot. The second step is to instantiate a specific solution on each robot, by sequentially searching through permutation sequences of individual robots until a simultaneous solution for all robot team members is found. For n robots on the team, there are $n!$ permutation sequences that must be analyzed, hence the problem is NP-hard. The CA algorithm attempts to find reasonable cost solutions quickly by using a heuristic to guide its search that finds solutions for the less capable robots (i.e., robots that must be part of the solution, but which have fewer schema resources to work with) first, in order to avoid resource shortages. The CA cost function defines the solution cost as the cumulative sum of the individual schema costs. Each schema cost is a weighted sum of its estimated energy cost and its success probability.

The CA algorithm is designed to be an anytime algorithm, so that as soon as a valid solution is discovered, it is made available to the robot team. Thus, the CA approach is a greedy search approach that *theoretically* searches, in an anytime fashion, all $n!$ permutations of robots, selecting the best solution found. Although F. Tang and Parker showed two applications for which the CA algorithm computes the first solution very quickly (i.e., in a matter of seconds) and within a small multiple of the optimal solution (where it could be computed), it is unclear whether the solutions found are good approximations to the optimal solutions in general.

4.2. Randomized ASyMTRe Search Algorithm (RA)

The Randomized ASyMTRe algorithm (RA) uses the same two-step, anytime search algorithm used by CA. The RA approach first generates potential solutions for each of the robots and then performs a sequential search through each permutation arrangement of robots to assign solutions to individual robots. However, in contrast with the CA approach, the RA approach does not perform a greedy search when assigning solutions to robots. Instead, RA selects viable solutions randomly from among all possible solutions for each robot.

4.3. Evolutionary Learning Search Algorithm (EL)

The Evolutionary Learning (EL) approach makes use of a genetic algorithm that maintains a population of p individuals, each of which represents a configuration of schemas that may be a possible solution to the robot team coalition task or subtask. A solution is called a "complete solution" if it enables all of the robot team members to finish their tasks. A "partial solution" provides solutions for some team members to finish their tasks. Table I shows the various parameters that must be defined for EL, and their default values.

In the EL approach, an initial population is created that consists of individuals having random connections of schemas, with the following restrictions: first, schemas can only be connected if they have matching information types; and second, connections across different robots (which we call *inter-robot* connections) can only occur between communications schemas. As the initial population is built, the number of interconnections between schemas on different robots and between schemas on the same robot (which we call *intra-robot* connections) are governed by two connection rates specified by the user: the inter-robot connection rate, ρ, and the intra-robot connection rate, κ. Note that these individuals do not necessarily represent complete solutions, since they may not fully (or even partially) solve the task given to the robots. This maintenance of partial solutions during the search process is one of the principal ways in which the EL algorithm differs from the CA and RA algorithms. These partial solutions represent chunks of schemas that solve important subtasks.

As with any genetic algorithm, the fitness value of each individual, F, is determined after each new generation is created through either initialization or evolution. In our definition, F depends not only on the aggregated cost of the active schemas, c, (which is the criterion also used in CA and RA to calculate the cost of the solution), but also on the complexity of the solution, x, and the degree of goal achievement, q and u. The value of x is measured by the total number of schema connections for that solution, and is normalized to the range $[0, 1]$. The degree of goal achievement is measured in two ways: 1) by the percentage of information types that are required by the goal and that are fulfilled (q/q_{max}), and 2) by the percentage of robots that can fulfill their individual goals (u/n). F is calculated as a weighted sum of the normalized values of c, x, q, and u. The weight for each factor is domain-specific and determined by the user.

In our approach, the evolutionary process consists of fitness proportionate selection, single point crossover operations, and single point mutations.

For n robots, m different kinds of schemas, and p individual solutions in each population, there are up to mn available schemas in the search space, and up to $(mn)^2$ possible ways of connecting the schemas. If we have a maximum of g generations, then the EL computational complexity for initializing a population, performing genetic operations, and pruning and evaluating the generated solutions is $O((mn)^2pg)$.

TABLE I

EL PARAMETERS AND THEIR DEFAULT VALUES.

Name	Description	Default Value
p	population size	500
ξ	number of individuals selected for reproduction	50
γ	probability for crossover	90%
δ	probability for mutation	5%
κ	intra-robot connection rate	50%
ρ	inter-robot connection rate	50%
w_c	weight for the aggregated cost of active schemas; used to calculate fitness	0.2
w_x	weight for the complexity; used to calculate fitness	0.1
w_q	weight for the percentage of information types required by the goal that are fulfilled; used to calculate fitness	0.1
w_u	weight for the percentage of robots that can achieve their goals; used to calculate fitness	0.6

5. Simulations

Four applications were implemented in simulation to compare the three algorithms: (A_1) multi-robot transportation, (A_2) box pushing, (A_3) robot formation, and (A_4) limited resource. In these applications, based on the available sensors, each robot possesses different combinations of perceptual schemas. The goal of each search algorithm is to determine which combination of sensors, distributed across which robots, constitutes the lowest cost solution that accomplishes the task.

Application A_1 requires robots to help each other (through sharing sensory information) in reaching their goal position. Various methods of sensor sharing are possible in this application, as implemented by F. Tang [11] on both physical and simulated robots. For example, if a robot has GPS and/or a laser, it can apply a perceptual schema to localize itself. If a robot has a laser and/or a camera, it can apply another perceptual schema to calculate the relative position of another robot within its sensing range.

Application A_2 requires robots to help each other push a box to a goal location. Again, various methods of sensor sharing are possible in this application, as implemented by F. Tang [11] on both physical and simulated robots. In this application, if a robot has a laser, it can apply a perceptual schema to measure the box's position relative to itself, or activate another perceptual schema to confirm contact with the box. If a robot has a camera, it can detect the goal location and use a third perceptual schema to calculate its push direction. With sonar, a robot can apply a fourth perceptual schema to detect the position of the box.

F. Tang's implementations of both applications A_1 and A_2 [11] made use of the CA algorithm. Her results showed

TABLE II

TIME (IN WALL CLOCK SECONDS) NEEDED FOR CA AND RA TO GENERATE THEIR FIRST SOLUTIONS FOR APPLICATIONS A_1, A_2, AND A_3, FOR A TEAM OF 25 ROBOTS. THE VALUES ARE AVERAGED OVER 10 RUNS.

	A_1	A_2	A_3
CA	0.077	0.151	0.033
RA	0.047	0.158	0.033

that CA is capable of solving those two problems with highly satisfactory results.

Applications A_3 and A_4 are designed to test the limitations of CA. They are designed only as abstract applications, and are not implemented on physical robots. Application A_3 models n robots following each other in a long chain. The first robot is the leader of the formation and does not need any information from the other robots. The i^{th} robot needs a unique information type from the $(i-1)^{th}$ robot, indicating the $(i-1)^{th}$ robot's position, so that the i^{th} robot can maintain the formation.

Application A_4 consists of n robots. In this application, except for the last q robots (robots n, n-1, n-2, ..., n-q+1), all robots can accomplish their goals without help from other robots, i.e., without information communicated by other robots. However, if they can receive external help from other robots, then the cost of the solution can be lowered. The last q robots must receive external help in order to achieve their goals. Only the first h robots (robots 1, 2, ..., h), can offer this external help; hence the name "limited resource."

The three search strategies were tested using heterogeneous robot teams whose size varied from 5 to 25 robots. A robot can have three different sensors for application A_1 (GPS, laser, and camera), and three different sensors for application A_2 (laser, camera, and sonar). Applications A_3 and A_4 are theoretical tests with only abstract sensors. We compose heterogeneous robot teams by randomly choosing different available sensors and consequently different schemas for each robot. For the EL algorithm in these experiments, the default parameter values shown in Table I were used unless indicated otherwise.

6. Results and Discussion

Using the simulation results, we compare the time CA and RA require to generate solutions, the solution quality of CA and RA, the solution improvement over time of EL, and the solution quality of CA, RA, and EL.

Since RA is developed as an alternative online solution search technique to CA, we first compare the times required by CA and RA to generate the first solutions. Table II shows the average time needed for CA and RA to generate their first solutions for a team of 25 robots. These results show that CA and RA are effectively equivalent in the amount of time required to generate a first solution for the applications A_1, A_2, and A_3.

The simulations show that the CA solutions always have a cost less than or equal to the solutions generated by RA, *if a solution can be found by CA* [14]. However, application A_4 poses a challenge for CA. Because of the nature of the limited resource requirements, a greedy search can only find the solution for specific sequences of robots. Because the heuristics of CA are designed to search all small solutions first, and because the number of possible solutions is exponential in the number of robots, CA is not able to find a solution for a team of 15 robots even after 50 hours of continuous running time (on a typical present-day Linux PC). However, the RA approach is able to find a solution after 30 minutes.

The EL algorithm is developed for offline constructivist learning. We examine its ability to improve its results over time. We also compare its result with CA via the cost of active schemas in the solution. EL generates both intermediate solutions (i.e., a partial solution in which only some of the robots can achieve the goal) as well as complete solutions. If EL generates good intermediate solutions in the beginning, then as the generations evolve and the fitness of the solution improves, more and more robots can accomplish the task, and eventually a complete solution can be found. However, sometimes, especially as the number of robots and schemas increases, EL does not guarantee a complete solution. (Presumably, a different set of EL parameter settings might overcome this problem, although in general, evolutionary techniques cannot guarantee convergence.) Figure 3 shows EL's simulation results for application A_1 with 25 robots ($\kappa = 0.3$, $\rho = 0.2$). This figure shows that the solution fitness increases over time. This solution quality improvement can be credited to the evolving connections among *chunks* of schemas. Hence, EL provides a structural basis to further explore the search space, finding patterns of schema connections that cause the solution fitness to improve. We further compare the solution quality of CA and EL for application A_1. (Because CA's result is superior to RA for application A_1, we only compare EL with CA and omit the comparison between EL and RA.) Figure 4 shows the cost for each robot in the solutions generated by CA and EL. This simulation uses a team of 25 robots. EL generates a partial solution that enables 16 robots to achieve their individual goals. From these 16 robots, 11 robots have solutions comparable to CA.

In summary, the simulations show that CA is usually very effective in finding solutions with low cost quickly. RA finds solutions in the same timely manner as CA, albeit with higher cost. However, CA cannot always find solutions in the time permitted, as discussed earlier for application A_4 that we developed to challenge the concept of CA. In contrast, RA was able to find solutions in this case. In RA, the cost of the discovered solution decreases throughout the search process.

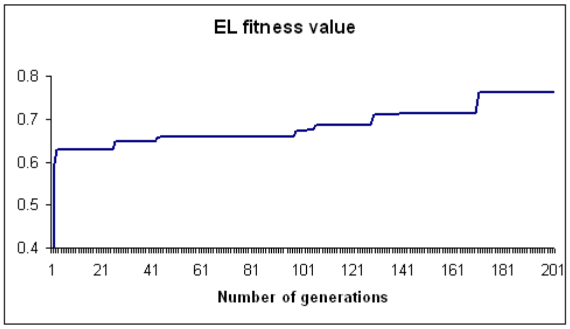

Fig. 3. The graph shows, during the search, the change of the fitness value over time.

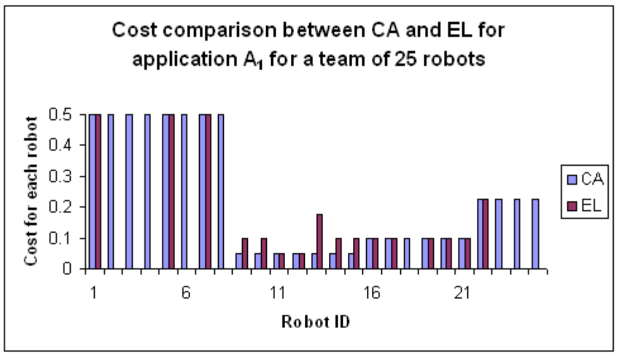

Fig. 4. Comparison of solution cost for each robot in a team of 25 robots performing application A_1.

7. Conclusions and Future Work

In this paper, we have introduced the SB-CoRLA architecture, especially the chunks related part of the architecture, and explored three different schema-based search strategies for generating robot coalitions to solve multi-robot team tasks — Centralized ASyMTRe (CA), Randomized ASyMTRe (RA), and Evolutionary Learning (EL). We compared these search strategies using four different simulated applications. The objective of these studies was to validate that our evolutionary learning technique can serve as the basis for constructivist learning without sacrificing solution quality.

RA is developed as alternative online solution search technique to CA. Our simulation results showed that neither the CA nor the RA approach is always superior. For example, the heuristic CA approach can often find good solutions much more quickly than the other approaches. However, on one simulated application, CA was unable to find a solution in the allotted time whereas RA was able to find multiple solutions.

EL is developed for the purpose of offline constructivist learning. Our studies showed that the EL approach is comparable to the CA and RA approaches, and thus can serve as a valid foundation for continual robot learning. The main characteristic that EL has for this purpose is the ability to generate partial solutions, or chunks of schemas, that can be used to generate more complete solutions. This ability to generate partial solutions is especially important for constructivist learning, since we need a means to record and apply knowledge from previous searches to future problems. These partial solutions can be recorded as chunks of schemas, consisting of active schemas, connections among these schemas, and information types that the chunk, as a whole, requires and provides. A chunk of schemas can then be recorded in a schema repository and utilized for later search. For future studies of constructivist learning, we will apply the EL algorithm to develop a schema repository to hold learned chunks of connected schemas, and apply the chunks in subsequent search processes to solve new problems.

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