Finding Insight with Abductive Inference

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1 Introduction

Insight problems are a common topics among both problem solving buffs and artificial intelligence researchers. Problem solvers enjoy these problems not for the intense frustration they induce nor for the seemingly impossible level of difficulty they offer but for the moment of insight that one experiences when a solution is discovered. Researchers, on the other hand, are interested in the mental processes these problem solvers use when arriving at a solution. The primary questions are: what causes impasses [26] in problem solving, and how are humans able to overcome these impasses via insight? One of the primary tools psychologists have used to understand the processes of the mind is introspection, the self-reporting of inner thoughts [25]. The issue with applying this tool to insight problems lies in the impenetrability of the subconscious mind, which many believe is crucial to the insight process [23, 7, 4]. Unable to observe the insight process, many contradictory theories have arisen, each telling believable stories about what is actually taking place within the mind when insight is achieved. In previous work, computational models derived from these theories have been used to successfully predict behavior of humans on various insight problems [24, 3, 9, 22, 17, 12, 11, 16] but none of these models provides a complete solution. Additionally, none of these models have been implemented in a computational system, an important step in insuring that the model is consistant and complete. This paper proposes a computational model for insight phenomena which utilizes abductive inference to restructure the problem and iterative sampling to increase performance. This model is consistent with the heuristic search hypotheses [25] and uses means-ends analysis [18] to generate domain independent search heuristics. This paper also proposes the implementation of this model via an extension to the ICARUS cognitive architecture that will allow the model to be experimentally tested.

2 Background

The model presented in this paper utilizes abductive inference and iterative sampling as the primary mechanisms to solve insight problems. Therefore, insight problems, abductive inference, and iterative sampling are briefly explained. Additionally, means-ends heuristics and ICARUS are mentioned throughout the paper, so each will be quickly covered. Once these underlying concepts are explained, previous work will be covered, and then the new model will be presented.

2.1 Insight problems

Insight problems are commonly defined as problems which are nearly impossible to solve without some crucial insight or reformulation of the problem. This insight most often takes the form of additional domain operators that were not considered, awareness of constraints that are improperly self imposed, or incorrect default assumptions that are corrected. A well-known insight problem is the nine dots problem in figure 1. The challenge is to connect all nine dots by drawing four consecutive straight lines without lifting the pen from the paper and never retracing a line. This problem is surprisingly difficult to solve and has reported

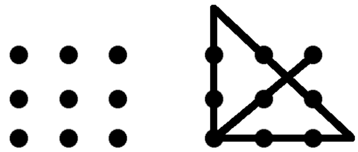

Figure 1: The classical nine dots problem and its solution.

experimental success rates of 0% in timed trials among those who have never seen the problem before [17]. If one attempts to solve this problem without going outside the box, a solution is impossible. Knowledge of this requirement is what would be considered insight. This insight leads one to release assumed constraints. Insight enables one to find solutions to problems that appear trivial but are actually quite difficult to find. Insight problems often evoke a type of "Aha!" or "Eureka" reaction in the problem solver when they realize they have discovered a solution.

2.2 Abductive Inference

Abductive inference [15], often called plausible reasoning, can be used to make inferences that seem reasonable even though they may not be logically valid. For example, when using deductive inference on the facts, A and $A \rightarrow B$ we can deduce B. With abductive inference we could use the facts, B and $A \rightarrow B$ to say that A is plausibly true. The abductive inference used in this paper, an approach discussed by Langley and Bridewell, is a computational account of everyday inference in the abductive framework [2]. This approach uses a coherence metric to generate numerous inferences which all fit together and are plausibly true. This approach finds something similar to a deductive closure; however, instead of halting when all inferences have been made, inference halts when any further inferences will lower the coherence of the knowledge base. In this paper it is proposed that abduction can be used as a mechanism to reformulate the problem which changes the landscape of the heuristic search and, further, facilitates an insightful solution.

2.3 Iterative Sampling

Iterative sampling [13] is a nonsystematic search technique similar to depth-first search. Where depth-first search backtracks when it gets stuck, iterative sampling restarts the search from the root node. This is useful in problem solving because if a child node is incorrectly expanded early in the search, then depth-first search will continue to explore the unfruitful area of the search space until it backtracks to where the mistake was made. Iterative sampling on the other hand will have the opportunity to select a completely different node at each level of the search tree on each iteration. Langley has shown that it performs better then depth-first search in situations where there are multiple solutions and the branching factor is high [13].

2.4 Means-ends heuristics

The heuristic search hypothesis [19], now believed by many to be fact, states that intelligent systems search with heuristic estimates because they have limited resources and cannot evaluate all states in the search space. This hypothesis has a corollary that the type of search intelligent agents perform is non-optimal, but experimental results show that it is near-optimal and can tractably be performed with limited resources [8].

Means-ends analysis is a search control technique first introduced by Allen Newell and Herbert Simon[18]. This technique works by comparing the difference between the current state and the goal state, then taking actions (or planning to take actions) that minimize the difference between these two states. This minimization of difference ensures that one is always moving closer to the goal state. This type of heuristic is domain independent and works well as long as there are no places in the search where no action minimizes the difference between the current and goal states.

2.5 ICARUS

ICARUS [14] is a cognitive architecture which uses hierarchical concepts and skills to represent the world. The system contains inference, execution, and problem solving modules to reason about the world. When given a goal or task, the system currently uses the inference engine and execution engine to attempt a solution to the problem. When no solution can be found, the problem solving engine activates, which is capable of finding novel solutions to problems by using means-ends analysis. When a novel problem is solved a new skill is learned so that the problem can be handled in the future without having to redo the expensive problem solving search.

3 Previous Work in Insight

The topic of insight has a rich history and has been discussed by scientists across many fields. There are countless stories of great scientists experiencing scientific insight when making some of the most influential discoveries. One commonly-cited example is when Archimedes discovered the principle of displacement [4]. He was tasked with determining if the king's crown was pure gold, an answer requiring him to calculate the volume of the crown without melting it down. Having spent some time working on the problem without having success, he slipped into a bathtub to relax; upon noticing the rise in the water level, he realized he could find the density of the crown by measuring the displacement of the water.

Because insight problems are so pervasive throughout science, many researchers have attempted to construct theories explaining these phenomena. What follows are some dominant theories that have taken hold in the past century: Hadamard's theory of scientific insight, Ohlsson's restructuring theory, Simon's theory of selective forgetting, Langley and Jones's theory of spreading activation, and MacGregor and Omerod's theory of heuristic progress.

3.1 Hadamard's theory of insight

Hadamard outlines the four phases of scientific insight that appear to occur in all known instances of scientific insight [7]. These four phases are: preparation, incubation, illumination, and verification. Each stage is distinct, and any theory of insight should explain what takes place in each phase of the process.

The preparation phase is when one becomes aware of the problem and does the leg work to acquire all relevant knowledge on the problem. During this phase intense effort is exhibited to solve the problem but the solver is unsuccessful. At this point the solver gives up and enters the incubation phase. In the incubation phase one focuses their conscious attention on other things. This phase can last anywhere from a few seconds to a few months but eventually concludes in the illumination phase. In the illumination phase, one experiences an "Aha" moment and sees the solution to the problem. This leads to the final phase, verification, where the solver ensures the solution that they discovered is valid.

Hadamard presents an explanation for these four steps by separating the mind into three distinct regions: the unconscious, the fringe conscious, and the conscious. The unconscious is the workings of the mind which take place hidden from the conscious mind. The fringe conscious is the area of the mind separating the unconscious from the conscious which is only partly hidden from the conscious. Lastly, the conscious mind is where conscious thought takes place.

His theory consists of an explanation of what takes place during each of the four stages of the insight process. During the first phase he believes that the conscious mind collects information and stores it in memory. Then unconscious mind takes over during the incubation phase and attempts to piece together all of the information accumulated during the preparation phase. When a possible solution is discovered, it is placed into the fringe consciousness where it is eventually discovered by the conscious mind, triggering the illumination phase. At this point the verification phase takes place in the conscious mind ensuring that the solution is correct.

Modern work by Eliza Segal [24] claims that this is most likely not taking place. The experimental evidence she presented shows that shorter periods of distracting activity (incubation) between the initial problem attempt (preparation) and the second problem attempt (possible illumination) resulted in more success than longer periods of distraction. This hints that the unconscious mind is most likely not working and performing calculations, which would benefit from longer periods of rest and incubation.

3.2 Ohlsson's restructuring theory

Ohlsson's restructuring theory [21, 20] draws from the work of the gestalt psychologists who believed that the mind uses structures to represent every situation and that there are forces that unbalance these structures. In this framework an unsolved problem is characterized by a imbalance between the current structure and the goal structure. If there is enough of an imbalance then the problem is restructured.

With this in mind, Ohlsson's restructuring theory states that restructuring takes place is the problem description space. Thus when a problem solver is unsuccessful at solving a problem they search for a new description of the problem in the problem description space. When a new description is found this constitutes reformulation and gives the problem solver a new perspective of the problem which may be solvable. Ohlsson also presents the idea of look-ahead which is combined with the resturcturing results in flashes of insight when one gets close to a solution. This work has been affirmed experimentally with human subjects by recording eye movement, timing data, and solution rates [12].

3.3 Simon's theory of selective forgetting

Simon's theory of selective forgetting [25] presents an account of the the insight process that is very different from the theory of autonomous unconscious thought put forth by Hadamard. Simon believes humans perform problem solving via heuristic search [18] guided by sturctures in short and long term memory. When one first attempts to solve an insight problem, having no background knowledge, the solver's search is lead down an unfruitful path which results in an impasse– a deadend in the search. It is important to point out that during the search, one constructs short term memory concepts from the problem statement and long term memory which are used, in this case, to misguide search. When the search is being conducted, patterns are recognized and learned in the form of long-term memory structures which are stored away. After one gets frustrated and gives up, one begins to forget the misguiding structures that exist in short-term memory. When again presented with the problem the solver has to re-perform the search. This time, however, they have the structures in long-term memory from the previous search which leads to the construction of very different guiding structures in short-term memory. These new structures successfully guide the solver to a solution. This theory, while more feasible than that presented by Hadamard, does not explain how the strutures in memory are formed and used during search.

3.4 Langley and Jones's theory of spreading activation

It was commonly believed that analogy plays a crucial role in the insight process [4, 5] but the process through which analogy is used to give insight was only indirectly explained by Gentner's model of similarity-based retrieval [6]. Langley and Jones took this concept and created a theory of spreading activation which explained the insight process. When faced with an insight problem, the solver creates structures and indexes them in memory for later retrieval. These structures also strengthen their connections with similar connected structures as the solver attempts to solve the problem. At some point, the problem solver gives up, unable to find a solution. At a later point, some external cue stimulates the activation of a structure in memory that– through the previously strengthened connections– causes an analogy to be formed. This analogy results in a mapping of the solution to the externally-activated structure which provides an analogical solution to the insight problem. Lastly, the problem solver verifies that the analogy works for the given problem. This theory can believably account for stories such as that of Archimedes and Poincarè but is a weaker explanation for insight problems that appear to be solved without any kind of analogical mapping.

3.5 MacGregor and Omerod's theory of heuristic progress

A more recent theory of the insight process is presented by MacGregor and Omerod [17] which explains the insight process as a result of heuristic depth-first search. In this theory, the solver attempts to solve the insight problem using heuristic search through the problem space. The search performed is a depth-first search where the heuristic estimates how much closer an action will move the solver towards the goal. When depth-first search is performed, promising states are saved for later use while the best states are expanded. Because heuristic depth-first search is performed, the solver can get stuck resulting in an impasse. When attempting to solve the problem again, the solver this time evaluates one of the other promising states. Eventually one of these promising states leads the solver to a solution.

This theory paints a lower-level picture about what is taking place in insight problems and is backed up by experimental evidence from subjects solving the nine-dots problem [17, 22, 3]. The problem with this theory lies in the fact that it does not account for how search is conducted once an impasse is reached. It explaints that the promising states are explored but offers no explanation for how one promising state is selected over another.

3.6 Commentary

These five theories offer a diverse array of explanations as to what could be taking place within the mind when one solves an insight problem. Each one of the theories presented above has certain shortcomings that should be addressed. Hadamard does not explain how the unconscious mind finds solutions. Ohlsson presents the idea of restructuring but does not present a framework for how problems can be restructured or what the problem description space looks like. Langley and Jones use analogy but do not explain how analogy is used to solve problems that do not appear to have any analogical mapping. Lastly, Macgregor and Omerod present heuristic search as the cause of impasses but do not adequately explain how one overcomes these impasses.

This paper attempts to provide an explaination for the insight phenomenon which addresses these issues. Additionally, it proposes that the model presented be implemented in the ICARUS cognitive architecture and tested on the nine-dots problem.

4 Proposed Explaination of Insight

The proposed theory of insight assumes that the problem solver has all the operators necessary to solve the insight problem but that the necessary operators are simply not being considered during problem solving. Under this assumption, the proposed theory tells a story about what is happening during the insight process. When faced with a problem, the solver constructs an initial representation of the problem (initial and goal states) and performs heuristically guided search to solve the problem, as MacGregor and Omerod propose. Since the search is guided by a means-ends heuristic, those operators which do not have high estimates of progress towards the goal are not considered. This theory posits that the operator necessary to solve the problem fall under this category. After failing to solve the problem, the solver uses inference (in this case, abduction over the goal state) and generalized failures to restructure the problem, similar to the theory presented by Ohlsson. This restructuring of the problem changes the means-ends heuristic estimates for all of the operators. Insight then occurs when the heuristic landscape changes such that the required operator is now considered, leading to a solution.

As an example, this theory should enable a solver to solve the nine-dots problem. During the initial formulation of the problem, the goal is described as no more then four lines having been drawn and all nine dots having been crossed. The assumption in this model is that the solver can only draw lines that begin and end on a dot. To enable a solution, there is an additional operator to create extra dots outside the box to which one can draw lines. To perform the abductive inference, the solver would need a concept for collinearity which can be used to determine if a set of points is, in fact, collinear. When the problem solver first attempts to solve the problem, it will fail because the heuristics will rate the operator for creating a dot as not moving you any closer to your goal, resulting in it never being considered in the search. When abductive inference is performed on the goal state, the concept for collinearity can be chained off of to create a new goal for a dot existing outside of the original nine. Since the points near the corners are collinear in two different ways, instead of just one, coherence leads them to be added to the goal statement; both points necessary for a solution will be included in this set of new goals. Now when the search is performed, the solver will have the goal of having dots outside the original nine, which leads the solver to use this operator to create these dots. Once these dots are created, there is now a viable solution available in the space.

5 Proposed ICARUS extensions

To verify that the proposed model performs appropriately on insight problems, an extension to the ICARUS cognitive architecture is proposed that would follow this model. Each of the components of the theory will be codified into the appropriate ICARUS modules.

5.1 Restructuring Mechanisms

5.2 Abductive Inference

ICARUS already has a module which performs abductive inference [15, 2], but it is currently not utilized in problem solving. Thus, the proposed modification would be to use the inference module during problem solving to further enumerate the goal state. This enumeration and reformulation of the goal state will affect the means-ends search heuristic, changing the landscape of the search. This change in the search space is akin to Ohlsson's restructuring theory and explains how one reformulates the problem when an impasse is reached. The hope would be that the new search space possess a heuristic landscape that is conducive to reaching the solution by heuristic search. One important issue is that other inference mechanisms aside from abduction could possibly be included in the restructuring, such as analogy or induction.

5.3 Performance Mechanisms

5.3.1 Iterative Sampling

After each restruction of the problem, it will be beneficial to start the search from the beginning with the new information. This makes iterative sampling an ideal search mechanism. Additionally, iterative sampling should greatly benefit from the generalized failure contexts produced by ICARUS's failed search attempts, making it an even better choice.

This modification should be relatively easy to add to ICARUS by having the search restart from the root node at each failure instead of backtracking. Additionally, iterative sampling uses a non-deterministic child selection technique [13] which will need to be biased by the search heuristics. To facilitate this, a simple probability distribution based on the heuristics will be used. As an illustrative example, if state P has children states C_1, C_2, and C_3 and the heuristic for each child state evaluates to the following:

$$\begin{aligned} h(C_1) &= 2 \\ h(C_2) &= 3 \\ h(C_3) &= 1 \end{aligned}$$

Then each child state will have the following probabilty of being selected:

$$\begin{aligned} p_{C_1} &= \frac{2}{2+3+1} \\ &= \frac{1}{3} \\ p_{C_2} &= \frac{3}{2+3+1} \end{aligned}$$

$$
\begin{aligned}
&= \frac{1}{2} \\
p_{C_3} &= \frac{1}{2+3+1} \\
&= \frac{1}{6}
\end{aligned}
$$

This probability distribution enables different paths to be explored during problem solving but favors those branches with higher heuristic estimates. This modification biases the search based on the heuristics and should increase the performance of the search.

The only downside of the iterative sampling modification is that the agent will act in the real world instead completing the plan in memory before acting [14]. Thus, when search is restarted the root problem will be different than it was when the problem solver last attempted search from the root problem.

It is unclear as to whether or not this will have an effect on solving insight problems. If it does, ICARUS will have to be modified to include the ability to virtually simulate plans in memory instead of carrying out the search in the external world. This modification should be doable but may be unnecessary for the sake of the proposed extension.

6 Plans for evaluation

To evaluate the proposed theory and extension to ICARUS, the nine-dots problem will be codified into an ICARUS problem and ICARUS will be tasked with trying to find a solution. The problem will be defined with an initial state of nine dots and their adjacency relations. The goal state will be one in which all the dots have a line through them and four lines have been drawn. There will be three primitive skills: one that enables the agent to draw lines between dots that are collinear, another that places the pen (for starting location), and a final action for creating new dots. There will be various concepts used to make inferences about the current situation, for example: collinear, adjacent, or crossed. Defined in this fashion, there is a solution available in the search space, and the solution is not explicitly coded.

6.1 Experimental design

The proposed experiment will be modeled after the lesion studies [1] used to understand regions of the brain. In these studies, subjects with various brain lesions were asked to perform certain tasks that healthy humans could perform. The inability for the subject to solve a problem signified that the damaged area of the brain is necessary to perform the requested task. In this case, the version with the proposed extensions (analogous to a healthy human) will be tasked with solving the nine-dots problem. The system will be a time limit to solve the problem and is expected to succeed. Next, the version of ICARUS without the proposed extensions (analogous to a patient with the lesion) will be given the nine-dots problem and the same time limit to find a solution. Since both trials have the same three primitive actions, this experiment is intended to show that restructuring of the problem enables the problem solver to consider the create dot action, which is necessary for a solution. The original version of ICARUS's inability to solve the problem will support that these mechanisms are necessary to solve insight problems.

6.2 Claims and hypotheses

There are two primary hypothesis for this experiment. First that the version of ICARUS with the proposed extensions will not find a solution immediately and will be forced to reformulate the problem using inference. Once the problem is reformulated the heuristic will be more conducive to quickly finding a solution. Secondly, it is hypothesized that the version of ICARUS without the extensions will be unable to solve the problem. It will most likely make a number of incorrect choices in higher branches of the search tree and explore an unfruitful branch of the seach space.

7 Concluding remarks

Previous work has pointed out how difficult it can be to pinpoint a single specific feature of insight problems that explains why they are challenging [10]. For this reason, it is highly-unlikely that the proposed model, which only addresses insight problems with unconsidered operators, will generalize to all insight problems. If this experiment is successful, it will present another possible explanation for the insight problem solving phenomenon in problems with unconsidered operators. This model also presents a method by which Ohlsson's problem restructuring could be taking place, namely via abductive inference.

While abductive inference may lead a solver to discovering the insight necessary to solve a given problem, it may also provide false insight and lead to overconstrained problem spaces without a solution. Coincidentally, while this model offers abduction as a solution for how one can overcome impasses, one must be wary that it may also lead to the formation of new impasses. For this reason, abduction shows great promise as an explaination for the formation and removal of impasses. How exactly abduction plays a role in this process needs to be further explored. To discover the specifics of the role that this mechanism plays in insight, further experimentation such as those proposed are necessary.

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