Emergent Nature of Cognitive System for Problem–Solving

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***Abstract*— Human problem-solving is enormously flexible. This characteristic cannot easily be explained by the traditional framework base on the computer–metaphor. A series of psychological experiments using an insight problem revealed that multiple constraints operate simultaneously and make continuous interplay with the external environment to generate and modify representations, without central controls. These results indicate that human cognitive system has emergent nature and that a new framework is required to develop flexible intelligent systems.**

I. Introduction

We claim that the human cognitive system for problem-solving has emergent nature. It is generative because it always generates representations by combining fragmentary representations and situational inputs. It is redundant because multiple processes concurrently operate background to support or backup a dominant one. It is open because continuous interplay with the external environment is its basic functioning mode.

This paper examines these characteristics in the filed of insight problem-solving. In the next section, we briefly explain a traditional computer metaphor and point out its limitation. In the remaining sections, we introduce a model of insight problem-solving and show psychological evidence supporting the model. Finally, we discuss model's emergent nature.

II. Beyond Computer Metaphor

To understand the nature of cognition, cognitive science has employed the computer metaphor as a basic research strategy. This metaphor has provided researchers with the rich sources for hypothesis generation, model construction, and model validation. However, irrelevant assumptions have been extrapolated that make it difficult to explain interesting phenomena.

The first assumption is the stability or fixedness of human representations. To have computers solve a problem, programmers prepare a program in advance. In other words, a complete set of procedures must be prestored beforehand. This characteristic leads researchers to presume that human problem-solvers should have a complete set of prestored knowledge implemented in the forms of schemas and mental models. However, it has revealed that schemas must have a very complex structure even to solve a simple problem. This makes it difficult to explain the process of schema acquisition.

The second assumption is that a single set of programs operate during problem-solving. Computers solve a problem by a set of programs relevant to the problem and halt when they are not equipped with these programs. However, people can deal with given situations without a complete set of programs. People combine partially relevant pieces of knowledge, or transfer knowledge in other domains to deal with the situation. In addition, people can react to unexpected information and flexibly switch the mode of problem-solving, whereas computer programs are insensitive to unexpected information and simply neglect it. This suggests that human problem-solving is not characterized as an application of a single set of programs, but as simultaneous activation and interactions of multiple set of programs.

The third assumption is about control. A set of computer programs are controlled by its main routine. However, such classical types of programs are unable to deal with the real world, because the real world is so complex that programmers cannot usually predict whole sequence of events in advance.

The final assumption is about the interaction with the external world. Programs are stored in a self-contained way and usually operate without interacting with the external environment. This requires programs to internally represent all the changes in the environment in advance. This is exactly the notorious "frame problem."

In summary, many researchers implicitly have regarded human problem-solving as the one where a single set of fixed programs operate in a self-contained way without any interactions with the external environment. This framework makes it hard to explore creative and flexible nature of human problem-solving as well as knowledge acquisition, modification, transformation, and reorganization.

However, in 1990's, new approaches were developed and gradually spread over the cognitive science community. They were promoted by situated cognition, evolutionary psychology, neural network modeling, dynamical systems approach, and cognitive neuroscience. Findings from these shed light on the emergent nature of cognition.

III. Insight Problem-Solving

The new trend mentioned above has led many researchers in the field of problem-solving to become aware of the importance of creation. They began to analyze creative problem-solving, such as insight, invention, conceptual combination, scientific discovery, etc [2], [13], [19].

Among various types of creative problem-solving, insight problem-solving has attracted many researchers' attention [14]. Although there are controversies about its definition, insight is traditionally defined as the process by which a problem solver *suddenly* moves from a state of not knowing

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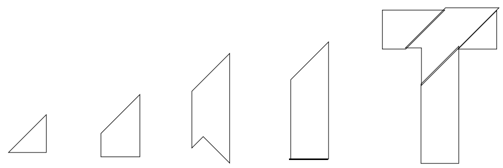

Fig. 1. The T puzzle. Construct the shape of T, using four pieces in the left side. The answer is shown in the rightmost.

how to solve a problem to a state of knowing ho to solve it [9], whereas people gradually and incrementally approach to the solution in standard problem-solving.

Insight has several mysterious properties. First of all, problems used in psychological experiments on insight are far from complex. Many subjects can understand the solution immediately after they are taught. However, it is awfully difficult to find it by themselves. We have used a geometric puzzle, the T puzzle, as a material. Subjects were told to construct the shape of T, using four pieces shown in the left side of Fig.1. It first appears easy to solve it and even young children can understand the solution once it is provided. However, adult subjects usually spend 20–30 minutes to solve it without any experimental manipulations.

Second, people stick to wrong approaches and make same errors again and again. When solving a standard non-insight problem, people usually switch to a different strategy or search another path after noticing failure. But, they do not do so in insight problem-solving. Instead, they repeatedly try wrong strategies that have proved to be unsuccessful. In the case of the T puzzle, subjects typically place the pentagon piece either horizontally or vertically to the baseline and try to fill its notch by other pieces again and again.

Third, there is a kind of readiness for making use of crucial information. In the course of problem-solving, subjects sometimes find crucial information accidentally. But, they do not realize its value, especially when their experience with a given problem is not enough. Kaplan & Simon reported that subjects took more than 10 minutes to solve an insight problem (mutilated checkerboard problem) after they first mentioned about the crucial information [5]. A similar finding was obtained in our experiments using the T puzzle. Even in the initial stage of their problem-solving, subjects occasionally placed the pentagon piece correctly or connected another piece properly. But, they canceled such trials and went back to the wrong approach.

Finally, insight appears to come to problem solvers' mind, suddenly. This means that conscious controls have a weaker power on insight problem-solving than standard ones. In her experiment, Metcalfe asked subjects to rate periodically how close they felt to the solution of either insight or standard problems. She found that subjects' estimation was relatively accurate for the standard problem, but not for the insight problem [10]. In solving the T puzzle, subjects usually experience the same feeling. They reported that they happened to solve it.

These mysterious properties prevent the standard framework from providing a coherent account for insight problem-solving.

IV. DYNAMIC CONSTRAINT RELAXATION

In order to explain these mysteries in a coherent way, we have developed the dynamic constraint relaxation theory of insight [3], [16]. This theory consists of three kinds of constraints (object-level, relational, and goal), and a relaxation mechanism. The main idea is that initial impasses caused by the object-level and relational constraints are detected and evaluated by the goal constrain that gradually changes the operation of constraints. We assume that failure-driven incremental relaxation of the constraints is the basis for insight problem-solving.

A. Constraints

We propose that there should be three types of constraints, object-level, relational, and goal, reflecting basic components of problem representations.

a) Object-level constraint: The object-level constraint reflects people's natural preferences of how given objects are encoded. There are numerous ways of encoding objects. However, people have the strong tendency to encode objects at their basic level. For example, a pen can be encoded to be an object, artifact, stationary goods, writing utensil, black pen, someone's pen, someone's black pen, etc. Among numerous possibilities, people, by default, encode a pen to be a pen. But, people may sometimes encode a pen at a different level of the category hierarchy. This suggests that there are many constraints to encode an object, and these constraints have strength values reflecting the likelihood to be activated. In the previous example, the constraint to encode a pen to be a pen has a higher value than the constraint to encode it as a writing utensil. The distribution of the strength values of specific constraints constitutes the object-level constraint.

In case of geometric puzzles like the T puzzle, the object level constraint represents how a single piece should be placed. Although there are numerous ways to place a piece, people have the strong tendency to place it in a way that its longest side is parallel or perpendicular to the base line (the edge of the desk). When these constraints operate on the pentagon piece, it leads subjects to an impasse. Note that there are many other object-level constraints, as well. Thus, the point here is that the constraints described above has a higher strength value than others.

b) Relational constraint: The relational constraint reflects people's natural preferences of how given objects are related each other. Like encoding an object, there are numerrous ways to relate objects in a given situation. For example, a pen can be related to other objects in ways that it is put on something else, it is rolled by something else, it pokes something else, it is thrown by someone, etc. Among many possible alternatives, it is more likely that the people select the "writing" relation. But, people may sometimes select other relations, depending on the situation. This suggests that there are many constraints to relate objects, and these constraints have different strength values reflecting the likelihood of their activation.

In the geometric puzzle, the relational constraint is concerned with the connection of pieces. Like the object-level constraint, there is an infinite number of ways to connect pieces. However, people prefer to connect them in ways that connected pieces form a simple form. This constraint is not, in itself, wrong. But if it is applied to the pentagon piece, it leads to an impasse. In solving the T puzzle, people try to fill the notch of the pentagon by another piece. It is because they mistakenly suppose that resulting shape cannot be simple if leaving the notch unfilled. However, this notch must not be filled with others, as shown in the Fig.1. It should be noted that, like the object-level constraints, there are a number of constraints with different strength values.

c) Goal constraint: The goal constraint involves the desired state and evaluation function. This constraint evaluates a match between current and desired states, and gives feedback to the object-level and relational constraints responsible for generating the current states.

In the geometric puzzle like the T puzzle, the goal constraint is an image of the shape of "T" and an algorithm computing the degree of mismatch between the current and the goal state.

B. Relaxation

Since the initial strength values of irrelevant constraints are much higher than the relevant ones, people mistakenly encode and relate objects. In other words, the object-level and relational constraints jointly operate to lead problem solvers to an impasse.

When a problem-solving attempt results in failure, feedback provided by the goal constraint dynamically changes the strength values of object-level and relational constraints. Repeated failure sometimes dramatically change the distribution of the constraint strengths. The strength values of initially dominant constraints become lower, while those of less dominant ones become higher. This increases the selection probabilities of less dominant constraints, some of which are crucial for solving the problem. When appropriate constraints are accidentally activated at both object and relational level, an insight comes to mind.

C. Algorithm

Our theory assumes that the object-level, relational, and goal constraints are the distributions of the strength values of more specific constraints. Selection of the specific constraints, c_i^{obj}, c_j^{rel}, c_k^{goal}, follows the softmax algorithm [1]:,

$$P(c_i^{obj}) = \frac{e^{\beta * h_i^t}}{\Sigma_l e^{\beta * h_l^t}},$$

$$P(c_j^{rel}) = \frac{e^{\beta * h_j^t}}{\Sigma_m e^{\beta * h_m^t}},$$

$$P(c_k^{goal}) = \frac{e^{\beta * h_k^t}}{\Sigma_n e^{\beta * h_n^t}},$$

where h^t represents the strength value of the specific constraint at the time t, β is a positive constant. If β approaches 0, every constraint is selected in the equal probability ($1/N$). If β approaches ∞, the selection is carried out in a winner-take-all fashion.

It is important to note that specific constraints are selected probabilistically, which means that constraints with lower strength values can be selected even in the initial stage of problem-solving processes.

A set of specific object-level and relational constraints constitutes one problem-solving trial. Trials are evaluated by the goal constraint. The goal constraint produces $Errors$ by computing the degree of match between the current state and the goal state. Based on the $Error$, feedback is provided to the constraints responsible for that trial. The following algorithm is used for updating the strength value of the constraints:

$$h^{t+1} \longleftarrow h^t + \Delta h^t,$$

$$\Delta h^t = \gamma \frac{e^{\beta * h_i}}{\Sigma_j^N e^{\beta * h_j}} Error,$$

where γ is a parameter representing the learning rate ($0 < \gamma < 1$) and β is the same as the one in the previous equation. This algorithm updates the strength value of the specific constraints being selected and does not change those of unselected constraints. However, this update algorithm dynamically affects the probabilities of unselected constraints, because the sum of $e^{\beta * H_i}/\Sigma_j^N e^{\beta * H_j}$ equals to 1.

By repeated failures, this update algorithm decreases the strength values of initially dominant constraints, which in turn increases the selection probabilities of the relevant constraints.

D. Summary

This model owes much to the findings in many fields of cognitive science. First of all, we do not introduce insight-specific mechanisms to the model. No researchers deny that objects, relations, and goal are fundamental components of problem-solving. The notion of constraint is widely used in various fields of cognitive science, such as object recognition [18], cognitive development [8], analogical reasoning [4], and so on.

We use the softmax as constraint selection algorithm. Although this algorithm is not used quite often in problem-solving literatures, it has two desirable features for modeling human cognition. The first one is its probabilistic nature. By adjusting β, the algorithm naturally represents the probabilistic fluctuation widely observed in many cognitive activities. The second feature is concerned with its statistical normalization. Since the sum of the probabilities of constraints equals to 1, a subtle change in one strength value affects the selection probabilities of all the other constraints.

Although the model is in accord with the general nature of human cognition, it is distinct from other models of insight problem-solving. As mentioned previously, Gestalt psychologists claim that an insight *suddenly* comes to mind. In contrast, our theory proposes incremental relaxation of constraints. We do not deny the sudden nature of insight at the level of "consciousness." However, data obtained at the conscious level are not reliable and tell little about underlying mechanisms [12]. According to our model, subjective reports on suddenness may be concerned with the probabilistic nature of constraint selection.

Most puzzling phenomena concerning insight is that people neglect important information. Some researchers reported it [5], [7], but their models do not provide a coherent account for it. Our model explains it in terms of the multiplicity of constraints. People may sometimes activate a relevant constraint at either object-level or relational level. However, to solve insight problem, *both* constraints must be relaxed. Since the selection probabilities of dominant but irrelevant constraints are quite high, there is little probabilities that relevant constraints are activated at the both level. This is the reason why subjects look over important information accidentally generated.

It is interesting to contrast our theory with a similar view proposed by Knoblich and his colleagues [6]. They have proposed that initial impasses are caused by constraints and its relaxation is crucial for insight. Although both theories admit the key roles of constraint relaxation, there are crucial differences between the two. First of al, constraints in their theory are specific to the task they used and have no possibilities to be applied to other types of tasks. Second, their theory only emphasizes the constraint relaxation, but does not involve any mechanisms of relaxation. Finally, their theory does not assume any interactions with the external environment. Therefore, they cannot explain phenomena involving changes during problem-solving.

V. PSYCHOLOGICAL EVIDENCE

As described above, the theory is based on quite natural assumptions used commonly in many problem-solving studies and a simple relaxation mechanism employed frequently in reinforcement learning. But the theory provides coherent explanations for various kinds of phenomena observed in insight problem-solving. In this section, we show supporting evidence obtained from a series of psychological experiments, using the T puzzle as an experimental material.

A. Constraint

Our theory assumes that the irrelevant object-level and relational constraint jointly operate to lead problem-solvers to impasses. In the case of T puzzle, object-level constraints initially dominant force subjects to place the pentagon piece either horizontally or vertically. Actually, about 70-90% subjects trials fall into this type. If subjects place the pentagon piece in a way to conform to the object-level constraint, a big problem arises to fill the notch of the pentagon in order to make a simple shape. Subjects tried to fill the notch by other pieces to make a simple form like a bar at about 60% of their trials [16].

These results showed that subjects stick to applying inappropriate constraints to the pentagon piece. However, it should be noted that their fixation is not exclusive. The fact that 70-90% (object-level constraint) and 60% of the trials conformed to inappropriate constraints conversely means that subjects selected the appropriate constraints in 10-30% (object-level) and 40% (relational) of their trials. Such deviation can be observed even at the early period of problem-solving processes.

In order to examine whether these constraints actually obstruct problem-solving, we conducted two experiments [11]. In one experiment, we provided one group of subjects with the hint not to place the pentagon piece either horizontally or vertically. This hint prevents the object-level constraint initially dominant from being selected. In another experiment, we provided subjects with the hint not to fill the notch of the pentagon. This hint is expected to prevent subjects from using inappropriate relational constraints. Both manipulations greatly improved subjects' performance. Seven out of 9 subjects in the object-level hint condition and 7 out of 8 subjects in the relation-hint condition could solve the puzzle within 15 minutes, while about 20 % subjects could do so without the hints. Other dependent variables such as the solution time, the number of trials, etc., showed the same patterns. These results strongly support our claim that a set of initially dominant but inappropriate constraints forms obstacles for insight.

B. Relaxation

Although many models of insight problem-solving involve the mechanisms explaining initial impasse, few have proposed detailed mechanisms concerning how and why impasses are overcome [1].

Our theory proposes that initially dominant constraints are gradually relaxed by repeated failure. If it is correct, subjects should use non-standard constraints more frequently in the later phases of their problem-solving. To analyze the time-course differences of the use of non-standard constraints, we divided problem-solving processes into four phases, based on the number of the trials. Tab. I showed the results of the analysis. Although the increase of non-standard constraints was not statistically significant in the relational level [2], the selection of non-standard constraints increased dramatically at the object-level ($F(3, 48)$ =

[1]An exception is MacGregor and his colleagues work [7].

[2]The lack of an increase in the number of the relational constraint violations might be due to the fact that the template sheet relaxed the relational constraint from earlier stages.

TABLE I

THE PERCENTAGES OF SEGMENTS VIOLATING THE OBJECT-LEVEL AND RELATIONAL CONSTRAINTS.

	1/4	2/4	3/4	4/4
Object-level constraint (%)	6	19	13	46
Relational constraint (%)	40	41	47	47

$7.89, p < .001$). Pair-wise comparisons revealed that the violations of object-level constraints in the final phase was more frequent than the others [15].

According to our theory, not only failure but its evaluation by the goal constraint plays a crucial role to get an insight. Trials are evaluated by the goal constraint that computes the degree of failure. If so, insight problem-solving should be facilitated when the goal constraint operates effectively. In one experiment, a group of subjects were given a template sheet printed with an image of a constructed "T," and asked to cover the image by placing the pieces [17]. We expect that this manipulation should facilitate the evaluation of the (mis)match between a current state and the goal. As expected, these subjects solved the puzzle significantly faster than those without the template sheet. More than 70% of the subjects with the template sheet solved the puzzle within 5 minutes, whereas those without the template sheet could not solve it within 15 minutes.

Another experiment examined the function of the goal constraint in a different way. As mentioned above, subjects occasionally place the pentagon piece properly even in the initial phase of their problem-solving. However, these attempts do not directly lead subjects to an insight. Instead, they neglect the important information to be obtained from such placement and get back to the starting point. Why cannot they solve the puzzle immediately after placing the pentagon piece properly? The difficulty may be concerned with matching. Only 20% of the pentagon's sides appear in the outline of the "T" because its longest and second longest sides are placed inside the "T." Thus, even when the pentagon piece is placed properly, it is difficult to realize which part of the "T" it occupies. To increase the ease of matching, we physically transformed each piece. This transformation increased the exposure rates of the pentagon's sides to 23% and 29%. This manipulation greatly facilitated subjects' performance. Five out of 8 subjects in the 23% condition and 6 out of 8 subjects in the 29% condition could solve it within 15 minutes, whereas no subjects in the control condition solve it. Fig.2 shows how the use of non-standard constraints changed during problem-solving. Subjects in the 23% and 29% conditions used non-standard constraints more often even in the initial phase. Its rates increase gradually at the second and/or third phase and become quite high at the final phase. In contrast, the rate is low at the beginning and does not change significantly in the control group.

VI. DISCUSSION

In the first half of the paper, we claim that the human cognitive system has emergent nature. Unlike computer programs, humans construct knowledge online from many pieces of knowledge simultaneously activated, by interacting with the external environment. In the following sections, we introduced a theory of insight problem-solving and showed psychological evidence supporting the theory. In this section, we will consider the theory and its evidence in terms of what is mentioned in the first part of the paper.

The human problem-solving system is not tuned to solve insight problems, in advance. Instead, it uses multiple constraints representing the common sense by default. Although these constraints operate effectively in everyday situations, they work negatively in insight problem-solving. However, people sometimes gain insights. Why is it possible?

The first reason is concerned with multiple and redundant nature of constraints. Humans does not follow a single constraints, even when one constraint appears to be dominant. There are always several constraints, some of which are similar, dissimilar to, and even competing dominant constraints. Since the softmax is used for constraint selection, constraints with lower strength values have chance to be activated.

The second reason why people can solve problems creatively is concerned with interaction between constraints. The strength values of the responsible constraints are always updated by complex interaction between constraints. Initially dominant constraints become weaker by repeated failure they produce. In addition, less dominant constraints occasionally become active, which increases its strength values, at the same time decrease the selection probabilities of dominant ones. These complex interactions between constraints continuously change the strength distribution.

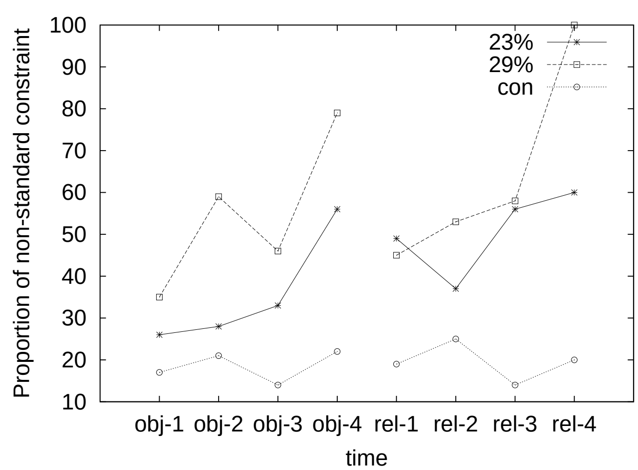

Fig. 2. Time-course differences of the use of non-standard constraint: Obj and rel denote object-level and relational constraint, respectively. The numbers attached to them denote problem-solving phases. For example, obj-1 denotes the proportion of trials that non-standard constraints are used in the first quarter of the problem-solving process.

Important to note, these changes are enabled by the fact that the human problem-solving system interacts with the external environment. As shown in the experiment using the template sheet, people solve the T puzzle more efficiently when the goal constraint is represented externally. Why? A possible reason might be that the externalization matches with the basic mode of functioning of the human problem solving. In human problem-solving, a small fragmentary constraint operates and produces a partial output. Then, another constraints reacts to the output, and produces another partial output, and so on. In addition, the strength values are updated always with reference to the output externally provided. In this sense, human problem-solving is based on continuous interplay with the external environment. In other words, the human problem-solving system is designed to continuously interweave the external information into it. This interplay may be enhanced by externalizing the goal constraint.

In summary, human constraints are always changing during problem-solving, due to the interaction with the external environment. This can be regarded as fluctuation that is important for self-organization. Although dominant constraints constitute an attractor (impasse), fluctuation caused by other constraints and external information help problem-solvers escape from it.

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