

Chapter II

Problem Solving in the Brain and by the Machine

LOOKING FOR SOLUTIONS

What does an “intelligent” human being when she tries to solve a problem? In general, she uses the word “problem” to mean different things:

- As a question to be answered,
- As a series of circumstances that hinder the attainment of an objective,
- As a proposition directed to verify the way some results are known.

Research in cognitive sciences suggests “Problem solving is any goal-directed sequence of cognitive operations” (Anderson, 1980, p. 257). According to Sloman (1987) “to *have* a goal” is to use a symbolic structure represented in some formalism to describe a state of affairs to be produced, preserved or prevented. Then, any rational agent, be artificial or natural, has a “problem” when an intention or goal cannot be achieved directly. Jackson (1983) summarizes this type of approach as:

PROBLEM= GOAL+OBSTACLE

When a specific goal is blocked, we have a problem. When we know ways round the block

or how to remove it, we have less a problem. In our case, the automated archaeologist *wants* to know the cause of the observed material outcomes of social action. What blocks this goal is a lack of knowledge: it does not know the particular mechanism that caused in the past what it sees in the present. To remove this obstacle it must learn some specific knowledge: *how* a causal process or processes generated the specific measurable properties determining the observed evidence. To the automated archaeologist, problem solving has the task of devising some causal mechanism that may mediate between the observation and its cause or causes. Consequently, explanatory mechanisms taken in pursuit of that goal can be regarded as problem solving. In other words, explanation is a kind of problem solving where the facts to be explained are treated as goals to be reached, and hypotheses can be generated to provide the desired explanations (Thagard, 1988).

Problem solving has been defined as the successive addition of knowledge until the obstacle, which prevented goal achievement, is surmounted (Newell & Simon, 1972). A cognitive machine will solve a problem just by adding knowledge to a situation where it identifies some lack of knowledge. Therefore, a foundation prescriptive rule, one that is so obvious that we always forget

it in real life: if you want to solve problems effectively in a given complex domain, you should have as much knowledge or information as you can about that domain.

We cannot use any bit of knowledge we wish, because there is only a finite set of right answers to a problem. Looking for the needed knowledge constitutes part of the procedure. The less knowledge available, the more “problematic,” and troublesome is the solution and the more difficult will be to produce a result. In this sense “problematic” means “poor in knowledge.” This is true for archaeology as for any other scientific discipline. It is true for both humans and for robots!

When there is insufficient knowledge, a problem cannot be solved. The robot needs specific knowledge for specifying what it knows and what it wants to do (goal). Acquiring this knowledge implies solving a previous problem (sub-goal). Each of the new sub-goals defines a problem that can be attacked independently. Problem decomposition constitutes, at the same time, a problem. Finding a solution to each sub-goal will require fewer steps than solving the overall compound goal. The idea is:

TO DECOMPOSE THE PROBLEM

If you want to reach the objective *G*,
and it is not fulfilled using the
previous condition *C*,

then, look for sub-goal *C*.

Once *C* has been attained, then proceed until
G.

When the solution of each sub-goal depends in a major way of the solution of other sub-goals, and the best solution requires trade-offs between competing constraints, it is most efficient to solve all the goals incrementally in parallel. This allows information about the results to accrue in each sub-problem and to affect the emerging decisions about the remaining sub-problems. This procedure illustrates several important points about problem

solving. First, it should be explicitly guided by knowledge of what to do. Second, an initial goal can lead to subsequent sub-goals that effectively decompose the problem into smaller parts. Third, methods can be applied *recursively*.

Problem solving always begins with the identification of the difficulty or obstacle that prevent goal achievement. Once identified, we appeal to available information—previous knowledge—and we decide the starting point of the procedure. As we have already seen, in archaeology, this obstacle is a lack of knowledge on the social cause of some perceived features. Therefore, we need external information (expertise, already solved problems, known cases, scientific knowledge, etc.) so that we can make inferences and possibly choose what to do next. Any information missing from the problem statement has to be inferred from somewhere. All these sources of information together constitute the “space” in which problem solving takes place (Robertson, 2001; Wagman, 2002).

We need a full and exhaustive problem space. We can think of such a problem space as the equivalent of a problem solver’s memory: a large encyclopedia or library, the information stored by topics (nodes), liberally cross-referenced (associational links), and with an elaborate index (recognition capability) that gives direct access through multiple entries to the topics (Simon, 1996, p. 88). The idea seems to be that solutions to a problem exist before the problem at some location in this problem space.

In archaeology, the problem space is constituted by those valid scientific facts, possible interpretations, and work hypothesis related to a specific subject. When considering historical problem solving through the looking glass of problem spaces, it appears that the temporality of social action is a sizable structure. It consists of:

1. A space of alternative social actions that could have been occurred,

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