Chapter III
Computer Systems that Learn

INVERSE REASONING

Inverse problems are among the most challenging in computational and applied science and have been studied extensively (Bunge, 2006; Hensel, 1991; Kaipio & Somersalo, 2004; Kirsch, 1996; Pizlo, 2001; Sabatier, 2000; Tarantola, 2005; Woodbury, 2002). Although there is no precise definition, the term refers to a wide range of problems that are generally described by saying that their answer is known, but not the question. An obvious example would be "Guessing the intentions of a person from her/his behavior." In our case: "Guessing a past event from its vestiges." In archaeology, the main source for inverse problems lies in the fact that archaeologists generally do not know why archaeological observables have the shape, size, texture, composition, and spatiotemporal location they have. Instead, we have sparse and noisy observations or measurements of perceptual properties, and an incomplete knowledge of relational contexts and possible causal processes. From this information, an inverse engineering approach should be used to interpret adequately archaeological observables as the material consequence of some social actions.

A naïve solution would be to list all possible consequences of the same cause. This universal knowledge base would contain all the knowledge needed to "guess" in a rational way the most probable cause of newly observed effects. This way of solving inverse problems implies a kind of instance-based learning, which represents knowledge in terms of specific cases or experiences and relies on flexible matching methods to retrieve these cases and apply them to new situations. This way of learning, usually called *case-based learning*, is claimed to be a paradigm of the human way of solving complex diagnostic problems in domains like archaeology. To act as a human expert, a computer system needs to make decisions based on its accumulated experience contained in successfully solved cases. Descriptions of past experiences, represented as cases, are stored in a knowledge base for later retrieval. When the computer sensor perceives a new case with similar parameters, the system searches for stored cases with problem characteristics similar to the new one, finds the closest fit, and applies the solutions of the old case to the new case. Successful solutions are tagged to the new case and both are stored together with the other cases in the knowledge base. Unsuccessful solutions also are appended to the case base along with explanations as to why the solutions did not work.

The suggestion that the intelligent machine should define causal events in terms of the observation of a repeated series of similar events typically relies on a kind of regularity assumption demanding that 'similar problems have similar solutions' (Hüllermeier, 2007; Kolodner, 1993). In other words, a learning machine can be broadly defined as any device whose actions are influenced by past experiences, so that learning procedures changes within an agent that over time enable it to perform more effectively within its environment (Arkin, 1998). The idea is that once a system has a rule that fits past data, if the future is similar to the past, the system will make correct predictions for novel instances (Alpaydin, 2004). This mechanism implies the search for maximal explanatory similarity between the situation being explained and some previously explained scenario (Falkenheimer, 1990).

The trouble is that in most real cases, there are infinite observations that can be linked to a single social action, making them impossible to list by extension. Even the most systematic and long-term record keeping is unlikely to recover all the possible combinations of values that can arise in nature. Thus, the learning task becomes one of finding some solution that identifies essential patterns in the samples that are not overly specific to the sample data. Added complications arise because any inferential task is often fraught with uncertainty. From an analytical perspective, this means that it is quite possible that two similar or even identical samples of prior cases will fall into different classes because there may be ambiguity within the learning sample. If many of our samples are ambiguous for a given set of features, we must conclude that these features have poor explanatory power, and no good solution to the problem may be possible with them alone.

Although we cannot follow the case-based approach in a real research situation, it suggests that an inverse problem can only be solved if there is some prior information about the necessary cause-effect mapping. In other words, the automated archaeologist needs a record of past experiences linking the observed material effects with their cause. It should learn a rule for grouping observable archaeological features in virtue of which they belong to sets of material effects of the same social action. Obviously, the intelligent machine has not enough with rules linking properties observed to co-occur in the instances. We should not forget that, in archaeology we deal with events and not with objects. Consequently, what our automated archaeologist should learn is not a category of similar objects, but the description of a *causal event*. The task is to find perceptual properties that are coherent across different realizations of the causal process.

Robots can potentially learn how to behave either by modifying existing behaviors (adaptation) or by learning new ones. This type of learning can be related to Piaget's theory of cognitive development, in which *assimilation* refers to the modification or reorganization of the existing set of available behaviors, and *accommodation* is the process involved with the acquisition of new behaviors. Robots can also learn how to sense correctly by either learning where to look or determining what to look for.

For instance, the machine will understand what a house, a castle, a burial, a tool are when it learns how a prototypical house, a prototypical castle, a prototypical burial, a prototypical tool have been made, under which social and economic conditions they have existed. Through learning, the automated archaeologist will build a model predicting features that can be perceived in the archaeological record. The automated archaeologist may not be able to identify the causal process completely, but it can construct a good and useful approximation. That approximation may not explain everything, but may still be able to account for some part of the data. Although identifying the complete process may not be possible, an intelligent machine can still detect certain patterns or regularities.

This is exactly what philosophers of science have called *induction* (Bunge, 2006; Genesareth & Nilsson, 1987; Gibbins, 1990; Gillies, 1996; Holland et al., 1986, Langley & Zytkow, 1989; Williamson, 2004; Tawfik, 2004). It can be defined as the way of connecting two predicates

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