

Chapter I

“Automatic” Archaeology: A Useless Endeavour, an Impossible Dream, or Reality?

AUTOMATA: THE AWFUL TRUTH ABOUT HUMANS AND MACHINES

Let us begin with a trivial example. Imagine a machine with artificial sensors, a brain, and some communication device. Suppose that such a machine is able to “see” prehistoric artifacts made of flint. The purpose of this automated archaeologist should be to “explain” the function of archaeological material. It decides consequently to measure, for instance, three properties: shape, texture, and size. The shape sensor will output a 1 if the prehistoric tool is approximately round and a -1 if it is more elliptical. The texture sensor will output a 1 if the surface of the artifact is smooth and a -1 if it is rough. The size sensor will output a 1 if the artifact is greater than 20 cm, and a -1 if it is less than 20 cm. The three sensor outputs will then be fed as input to the thinking core of the robot, whose purpose is to execute a function deciding which kind of tool has been discovered buried at this precise location. An input pattern is determined to belong to class *Knife* if there is a function, which relates incoming inputs with an already defined concept “knife,” or otherwise a “scraper.” As each observed element passes through the sensors, it can be represented by a

three dimensional vector. The first element of the vector will represent shape, the second element will represent texture, and the third element will represent size.

$$P = \begin{pmatrix} Shape \\ Texture \\ Size \end{pmatrix}$$

Therefore, a prototype knife would be represented by

$$P_1 = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}$$

and a prototype scraper would be represented by

$$P_2 = \begin{pmatrix} 1 \\ -1 \\ 1 \end{pmatrix}$$

The task of this automated archaeologist will be to assign to any artifact, represented by some features, visual or not, some meaning or explanatory concept. In other words, the performance of

such an automated archaeologist is a three-stage process: Feature extraction, recognition, and explanation by which an input (description of the archaeological record) is transformed into an explanatory concept, in this case, the *function* of an archaeologically perceived entity (Figure 1). In order for the system to make a decision as to whether the object is a knife or a scraper, input information should be recognized, that is “categorized,” in such a way that once “activated” the selected categories will guide the selection of a response.

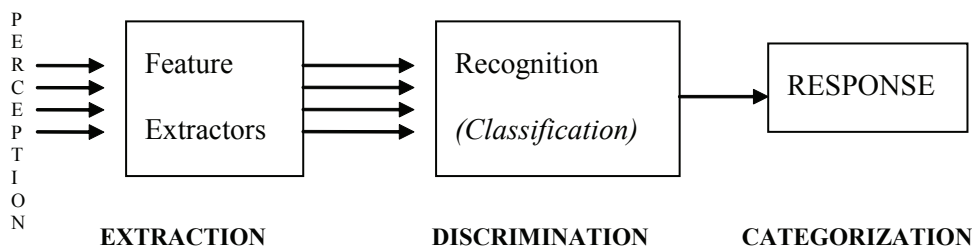
Let us move to a more interesting example. Imagine a specialized mobile robot equipped with video cameras, 3D scanners, remote sensors, excavator arms, suction heads and tubes, manipulation hands for taking samples exploring in the search of evidence for archaeological sites, excavating the site by itself, describing the discovered evidence, and analyzing samples and materials (Barceló, 2007). Or even better, imagine a team of robots doing different kinds of archaeological tasks, those tasks that, up to now, have been a matter of human performance. The idea is to develop an exploration system that allows a robot to explore and extract relevant features from the world around it, expressing them in some specific way. This unit should use visual and non-visual information to make decisions about how to find archaeological evidence. This specialized robot will use stereoscopic CCD cameras, laser rangars, sonar, infrared sensors, georadar, magnetometers, and construct a multidimensional representation

of geometric space. From this representation, it will recognize locations, plan trajectories, and distinguish objects by shape, color, and location. The robot should acquire a sense of general spatial awareness, and to be able to do it, it probably needs an especially fine representation of the volume around it to precisely locate archaeological objects and structures and visually monitor performance. In other words, the first member of our team has to learn how to find an archaeological site, based on the perceived properties of the observed archaeological elements.

The second member of the team emulates *what most archaeologists think is the definition of their job: the excavation of an archaeological site*. Archaeological robots should do much more than just explore and visualize what is observable. They should take samples from the ground, and they should dig and unearth material evidence. When evaluating the differences between visual and non-visual information, the robot takes the decision of removing what prevents the visualization of the archaeological evidence: earth. The explorer becomes an excavator.

It is easy to see that this team of robots also needs some specialized *understanding* component. *This component is concerned with a specific mechanism able to identify archaeological evidence, and to solve specific goals linked to this distinction*. The automated archaeologist should correlate evidence and explanation adequately in order to *generate* a solution to an archaeological problem. *In the same way, our intelligent machine*

Figure 1.1. The performance of an automated archaeologist as a three-stage process



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