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Towards a True Automatic Archaeology: Integrating Technique and Theory

Abstract: The question of whether it is possible to automate the scientific process is of both great theoretical interest and increasing practical importance because, in many scientific areas, data is being generated much faster than they can be effectively analyzed. I describe here a virtual robotic system which can be physically implemented that applies techniques from artificial intelligence to carry out cycles of scientific experimentation. I am exploring an analogy with the idea of "intelligent" machine, to understand the way we, archaeologists, think. If a computer can be programmed to perform human-like tasks it offers a "model" of the human activity that is less open to argument than the empirical explanations that are normal in philosophy. The purpose is to understand how intelligent behavior in archaeology is possible.

Introduction

Two years ago, at the Computer Applications in Archaeology meeting held in Tomar (Portugal) I asked a very provocative question: Is it possible to build a machine to do archaeology? Very few people at the lecture said "not yet". Most claimed: "fortunately, never!" This paper is the necessary second part for the arguments put on that occasion. Of course, I'm not suggesting that we should substitute human archaeologists by so called "intelligent" machines, but I am exploring an analogy with the idea of artificial intelligence to understand the way we, archaeologists, think. If a computer can be programmed to perform human-like tasks it will offer a "model" of the human activity that is less open to argument than the empirical explanations that are normal in philosophy (Marr 1982; Drennan 2005).

Archaeological Reasoning as Algorithmic Search in a Conceptual Space

The assumption that allows any "intelligent" program to work in our research domain seems to be that incoming patterns are matched against a set of previously memorized templates by means of some explicit rules linking external input and internal explanations (Margolies 1987; Churchland 1989; Simon 1996; Klahr 2000). By making use of some previously stored knowledge, an automated archaeologist would infer from sensory data, what it is that gave rise to that data. If such a model is right, then a specific explanation will be created by searching through a space of possible explanations until the knowledge necessary to generate that explanation is discovered. This requires a great deal of central processing, which is equivalent to a human rational mind (O'Reilly / Munakata 2000; Bechtel / Abrahamsen 2005). The idea is then that an automated archaeologist will first plan how to decompose a given archaeological problem into sub problems for which knowledge already exists, and then it will look for the specific linking of sub-explanations bringing a solution to the preliminary problem. This type of organization can be described as a sequence of THINK (rationally), PERCEIVE-EXPLAIN where the comma indicates that rational thinking, that is, conscious problem decomposition, is done at one step, and data acquisition ("perceiving") is made afterwards, using a-priori background knowledge (Thagard 1989; Simon 1996; Marcus 2001; Wagman 2002; Russell / Norvig 2003).

However, there is a problem. A big one, indeed! It is obvious that we do not understand past social actions by enumerating every possible outcome of every possible social action. A template matching scheme could work provided we had precompiled rules for all events to be explained. To explain social action produced in the past, the automated archaeologist would need a universal knowledge base covering the entire domain of interaction. Unfortunately this is almost impossible to achieve, because it implies the existence of an infinite number of rules which have the ability of recognizing each unique archaeological evidences for what it is and then selecting an appropriate explanation for each possible historical state. An automated archaeologist cannot simply be programmed with predefined bits of knowledge (Franklin 1995; Hendriks-Jansen 1996; Clancey 1997; Arkin 1998; Brooks 1999; Pfeiffer / Scheier 1999).

We should go elsewhere for defining a more convenient analogy for an automated archaeologist. I suggest the use of idea of "reverse engineering" and "inverse problems" for finding the right approach for archaeology automatization.

Archaeological Reasoning as Reverse Engineering

Archaeological problem solving is a fast perfect example of inverse reasoning. That is, the answer is known, but not the question. The problem we want to solve can always be represented in the motto: "Guessing a past event from its vestiges". Here the past event is the question we are looking for, and the vestiges are the answer we can observe. 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 spatio-temporal 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, a reverse engineering approach should be used to adequately interpret archaeological observables as the material consequence of some social actions performed in the past, and probably altered since the moment they were performed.

An inverse problem can be solved by conjecturing unobservable mechanisms that link the input (observation) with the output (explanation). It can be defined as the recognition of observed patterns or the prediction of unobserved outcomes by generalizing from a group of measurements for which the desired outcome is known to a larger set of circumstances. Since Aristotle, generalization has been the paradigmatic form of inductive inference. In our case, the task will be to find the common structure in a given perceptual sequence under the assumption that structure that is common across many individual instances of the same cause-effect relationship must be definitive of that group (Holland et al. 1986; Thagard 1988; Donahue / Palmer 1994; Gillies 1996; Konara 2000).

The presence of communalities implies a high level of regularity in the data, which means that certain characteristics or properties are more probable than others. In agreement with the most habitual definition of probability, we could affirm, then, that a causal event would exhibit some degree of regularity when the more characteristics are "frequent", and the less characteristics are "infrequent" in the known series of observed events. The propensity, inclination or tendency of certain states or events to appear together is then what we need to learn; how unobserved facts can be similar to observed ones.

That is, the automated archaeologist will learn a mapping from the cause to the effect provided some instances of such a mapping are already known or can be provided by direct experience in the world. When subsequently asked to determine whether novel instances belong to the same causal event, those instances that are similar to instances characteristic of a single event of a single class of events will tend to be accepted (Holland et al. 1986; Shrager / Langley 1990; Langley 1996; Wagman 2000).

This way of understanding archaeological problem solving lead us directly to the concepts of Classification and Clustering, because we can always understand the learning task as the partitioning of an observation set according to the similarity criterion and generating class descriptions from these partitions. After all, programming computers to make inference from data is a cross between statistics and computer science, where statisticians provide the mathematical framework to make the inference.

Archaeological Reasoning as a Non-standard Statistical Mechanism

One way of understanding the idea of scientific discovery as relational learning is in "functional" terms: two objects are functionally equivalent (or analogous) if they do the same (or similar) things in the same (or similar) systems in the same (or similar) knowledge domain. The key is the emphasis on the word "do". No other features of the objects are relevant other than the fact that they do the same things under certain conditions - this is to say that it is their potential behavior that is important. Consequently, relational learning can only be carried out in terms of causal interactions. To identify and disentangling the non explicit relationships, we should use available knowledge about the process that generated those effects. And this conjures up an image of a problem solver that is going to use knowledge of possible causal relationships to create knowledge of relationships. Therefore not only communalities are necessary for learning archaeological explanations, but also some kind of contingent relationship between the observed examples, which will determine the type of association learned.

The central problem of inverse engineering is then to specify constraints that will ensure that the predictions drawn by an automated archaeologist will tend to be plausible and relevant to the system's goals. Which inductions should be characterized as plausible can be determined only with reference to the current knowledge of the system. Inverse engineering is thus highly context dependent, being guided by prior knowledge activated in particular situations that confront the automated system as it seeks to achieve its goals.

The trouble with learning based on implicit relationships is that they are not always apparent. To solve this situation we need prior knowledge. There is not any possibility of archaeological explanation based on observations alone. We have to know the solution of the problem if we want to solve it! And to know such a solution implies to have prior knowledge about the social action and how people generated material effects when they did something at some place, sometime. Such knowledge can be integrated in an automated mechanism by means of: the experimental replication, the controlled observation or the simulation of the related factors.

Experimental analysis is the process whereby the antecedents of a phenomenon are manipulated or controlled and their effects are measured. The hypothesized cause is replicated in laboratory conditions in order to generate the material effect as the result of just a single action, all other actions being controlled.

An obvious example is modern use-wear analysis. By replicating lithic tools and using them a determined period of time performing some activity – i.e. cutting fresh wood – we will be able to test the relationship between kinematics, worked material and observed use-wear on the surface of the tool. It is the archaeologist who makes the tool and who performs the activity. In this way the material consequences of cutting fresh wood can be made explicit, and used to discriminate other activity also performed by the archaeologist, for instance, cutting fresh bone.

Regrettably, not all social activities performed in the past can be replicated in the present. What cannot be replicated, on many occasions can be observed or has been observed and someone has witnessed it. Ethnoarchaeology has been defined as the observation in the present of actions that were probably performed in the past. Ethnographic and historically preserved ancient written sources can be used as observational situations in which some causal events took place and were described. The problem with ethnoarchaeological knowledge production is that each description should be considered as a local instance of a more general process. We do not have enough with just one singe known case. To quote the classical example by Binford: Nunamiut description is not enough for understanding Musterian variability. We need a big database of universally distributed hunter-gatherer household descriptions and linked archaeological records if we want to infer some general cause-effect pattern about domestic spaces in such societies.

The implementation of some causal or functional knowledge inside a machine to explain what it "sees", is usually called computer "simulation" of a causal process. The simulation happens when the automated archaeologist executes the knowledge in a controlled way. Such an implementation of knowledge within a computer can be seen as the action of embedding a model of behavior within another model, where the notion of embedding may be envisioned as a logical or causal relation. In some way this approach emulates logical deduction, with the advantage that it is not limited to standard logics.

Archaeological Reasoning as a Probabilistic Framework

Solving an archaeological problem quickly is always uncertain, because some indeterminacy may appear between actions of human work and the visual and structural properties of the material results of such a work. Sometimes a social action happens, but the expected material consequence may not always take place. Other times, the entity we study does not seem to experience any perceptible change which allows us to know if some social action or sequence of social actions were having any causal influence.

The challenge is to derive a consistent mapping from a potentially infinite set of social actions through time to a relatively small number of observable outcomes in the present. What we need are inverse reasoning methods that allow an automated archaeologist to predict a cause even when it is not universally and directly tied with its effect. Rather than assuming that data is generated by a single underlying event, it should be assumed that the archaeological explanation can be modeled as a collection of idiosyncratic "processes", where a process is characterized by a particular probabilistic rule that maps input vectors to output vectors. Therefore, an automated archaeologist can be seen as a kind of heuristic classification machine, a classifier which has the smallest probability of making a mistake.

Accordingly, the solution of archaeological inverse problems should be approached within a probabilistic framework. At one level, the major task of the system may be described as reducing uncertainty about the knowledge domain. In order to accomplish this, the system must learn about the variability characteristic of various properties and relationships, gaining knowledge of what falls inside the range of permissible variation for a category and what falls outside, in the region of the unclassifiable or intrinsically uncertain. In this way, our computational system will be able to learn partially predictive rules even if some irreducible amount of error variance cannot be accounted for.

Conclusions

Artificial Intelligence offers us powerful methods and techniques to bring about this new task. Fuzzy logic, rough sets, genetic algorithms, neural networks and Bayesian networks are among the directions we have to explore to build a truly automated archaeologist. Although statistical reasoning is still giving its support to all these methods, it is not classical statistical inference. Artificial Intelligence paradigms, differ from usual classification and clustering methods in that they are (in comparison at least) robust in the presence of noise, flexible as to the statistical types that can be combined, able to work with feature (attribute) spaces of very high dimensionality, they can be based on non-linear and non monotonic assumptions, they require less training data, and make fewer prior assumptions about data distributions and model parameters.

Bringing artificial intelligence into archaeology introduces new conceptual resources for dealing with the structure and growth of scientific knowledge. The discussion is between what is considered an artificial way of reasoning (computer programs), and a natural way of reasoning (verbal narrative). Critics of computationalism insist that we should not confound scientific statements with predicate logic operations, since discursive practices or argumentations observed in a scientific text are not "formal". By that reason, they are tributary, to a certain extent, from the Natural Language and the narrative structure (literary) of which scientific texts derive. I take the opposite approach: scientific problem solving stems from the acquisition of knowledge from a specific environment, the manipulation of such knowledge, and the intervention in the real world with the manipulated knowledge. The more exhaustive and better structured the knowledge base, the more it emulates a Scientific Theory and the easier will be the solution to the scientific problem, and more adequate the interpretations we get (Barceló 2008).

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