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Beyond classification: the use of artificial intelligence techniques for the interpretation of archaeological data

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31.1 Introduction

Archaeology, despite its relatively short history, is already faced with the problem of a large accumulation of data. This will inevitably become more pressing in the future. As a means of dealing with the problem, archaeologists have naturally turned to the use of computers. The more traditional uses include the recording of archaeological data, statistical analysis of the data, electronic publishing of the results and graphical display of sites and artifacts (e.g., Richards & Ryan 1985; Rahtz 1988).

More recently, advances in Artificial Intelligence (AI), in particular Expert Systems, have encouraged archaeologists and others to experiment with this new technology (Baker 1986; Doran 1988) as a means of automating higher level classificatory and interpretational tasks. We have identified four main uses to which AI technology has been put in archaeology: (1) assistance in the use of specific analytic techniques (e.g., Vitali & Lagrange 1988); (2) classification of artifacts (e.g., Bishop & Thomas 1984, Ennals & Brough 1982); (3) interpretation of archaeological data (e.g., Doran 1977); (4) modeling of archaeological reasoning (e.g., Gardin *et al.* 1987; Lagrange & Renaud 1985, Gallay 1989).

Our aim in this paper is to discuss: (1) the results of an experiment in designing and implementing an archaeological interpreter; and, (2) to point out certain inadequacies in this system and suggest possible future extensions.

The rest of this paper has the following format. In section two, we describe a model of interpretation and draw out the basic features necessary for automating the task of interpretation. The model is subsequently used for building an expert system, KIVA, for interpreting archaeological data. The system itself is presented in section three. In section four, we discuss the shortcomings of KIVA-like systems and present a new architecture for expert systems for interpreting archaeological data which will, we believe, answer to the needs of archaeologists.

31.2 Model of archaeological interpretation

Our model of interpretative reasoning is based on the work of J-C Gardin (Gardin 1980, Gardin *et al.* 1987) in which he puts forward what he calls a logicist analysis of archaeological reasoning. This approach takes archaeological reasoning to be a process of applying transformations to initial propositions (Po) to arrive at terminal

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propositions (Pn) or interpretations via a series of intermediary propositions (Pi). This is illustrated in Fig. 31.1.

In brief, according to this model, archaeological interpretation has the following components:

- Classification of features and finds. The term features encompasses the various aspects of archaeological sites both man-made and natural such as pits, ditches, walls etc. Finds are mobile features which are either man-made (artifacts) or natural (ecofacts) such as bone fragments. The process of classification involves a transformation from raw facts to finds and features.
- The reconstruction of past human activities in terms of activity areas and their associated activity. An activity area is a significant area of a site at which identifiable human activities (e.g., cooking or hide-working) were carried out.
- Cultural interpretation. That is, the creation of an interpretation or cultural profile for the site as a whole which includes a determination of the technology, subsistence, social organization and religious or other beliefs of the occupants of the site.

As this model shows, classification can be subsumed within archaeological interpretation. However, we deal mainly with the results of classification, whether this is provided by the excavator's description and/or statistical analyses. Thus, we are concerned with the latter two components of the model given above.

While many of the expert systems which have been designed in terms of the above model have been forward chainer¹, archaeological interpretation contains a top-down² as well as a bottom-up³ component. Gardin (1980) discusses the top-down component in terms of the validation of interpretations. We want to draw attention to another (related) aspect of the top-down reasoning in archaeological interpretation: archaeologists go onto a site with a certain expectation of what they will find. This expectation is used to interpret both individual artifacts and their relationships to other finds and features. Expectation is incorporated in the model of archaeological interpretation illustrated in Fig. 31.2. The double headed arrows indicate the bi-directional nature of archaeological reasoning.

Another feature of archaeological interpretation that makes its implementation difficult is that it is inherently uncertain. As in everyday reasoning, the inferences that are made are usually plausible rather than certain. This is because there is inevitably a gap between the material evidence and the interpretations placed upon it. While there have been attempts to produce law-like generalizations in archaeology (e.g., Schiffer 1976), these have mostly been confined to the lower levels of interpretation and there is some doubt about their applicability even at this level. However, archaeological reasoning is uncertain in another way. Since there is a limited supply of data available and this may be destroyed in the process of excavation which precedes interpretation, the evidence upon which the archaeologist bases an interpretation will always be incomplete. This incompleteness in the data will result in uncertain inferences.

In summary, the model seems intuitively to capture the actual practice of archaeologists. For example, when an archaeologist interprets a site he/she has a model of the kind of site which determines what he/she expects to find. This model can

¹That is, they move from the initial data to the final interpretation by the iterative firing of rules whose conditions are satisfied.

²By top-down we mean the move from possible interpretations to attempts to confirm these in terms of data.

³By bottom-up we mean the move from data to interpretations. This is most naturally implemented by a forward chaining control technique.

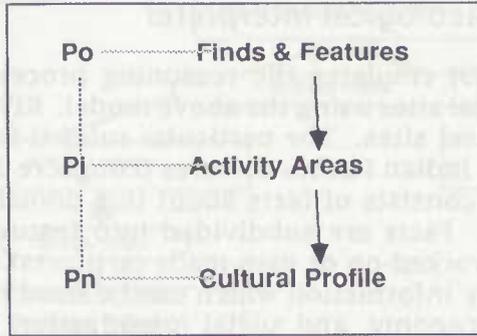


Figure 31.1: Model of Interpretation

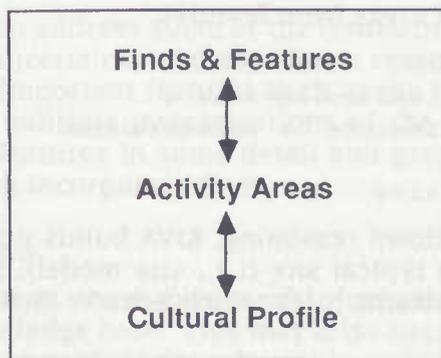


Figure 31.2: Interpretation in Archaeology

be used in designing an archaeological interpreter. The expectations of what may be found at a site could be represented as a site model, which can be used to reason top-down. The expectation-based approach also provides us with a means of dealing with the multiplicity of contending interpretations which arise as a result of the uncertain nature of archaeological reasoning. This is done by comparing the possible interpretations against the model and eliminating those which are impossible.

31.3 KIVA—the archaeological interpreter

KIVA⁴ (Patel & Stutt 1989) emulates the reasoning processes of archaeologists in interpreting archaeological sites using the above model. KIVA is designed to interpret hypothetical archaeological sites. The particular rules it incorporates are based on the findings of American Indian Pueblo cultures (Longacre 1970, Schiffer 1976). The knowledge base of KIVA consists of facts about this domain and heuristic rules for interpreting those facts. Facts are subdivided into features and finds. We define finds as either objects, worked-on or man-made (artifacts) and unworked or natural (ecofacts). Artifacts carry information which can be used in making interpretations about the technology, economy, and social organization. Ecofacts are important indicators of, for example, environmental conditions and the temporal sequence of the site. Features refer to the physical characteristics of the site. These include cut features (e.g., pit), accumulation (e.g., debris), enclosing features (e.g., ring of stones, palisades, area demarcations), and mound. Features provide important information regarding the spatial layout of an archaeological site. For example, the number of rooms in the site, burial places, fire places, etc. At the cultural-profile level, they provide information on the social organization of the occupants of the site. The activity areas are derived from the features by the rules of interpretation.

Fig. 31.3 shows KIVA's processing in schematic form. The initial propositions (Po) are finds and features and the terminal proposition (Pn) is the cultural profile. The rectangular boxes between the Po and Pn propositions are the intermediary propositions (Pi). The rounded boxes represent the transformations (i.e., rules) for reasoning about propositions. The expectations about the pueblo site are represented in the site model.⁵

KIVA rules do both bottom-up and top-down reasoning. The bottom-up reasoning produces possible solutions. This can be exemplified by the following rule for inferring the existence of kivas from features.

```
IF
    the feature is an enclosing-area &
    the placement of feature is subterranean
THEN
    the feature is a kiva
```

In order to perform top-down reasoning, KIVA builds up all possible solutions and, from its knowledge of a typical site (i.e., site model), picks out the best solution (or solutions). The constraint rules which achieve this can be exemplified by the following:

```
IF possible activity of area is butchery &
    area is indoors
THEN
    mark as false
```

⁴In this paper, 'KIVA' refers to the program and 'kiva' to an activity area in which various ritual activities were conducted.

⁵Note that the site model is shown in the figure for clarity. In the actual implementation, the model is embedded in the constraint and site rules.

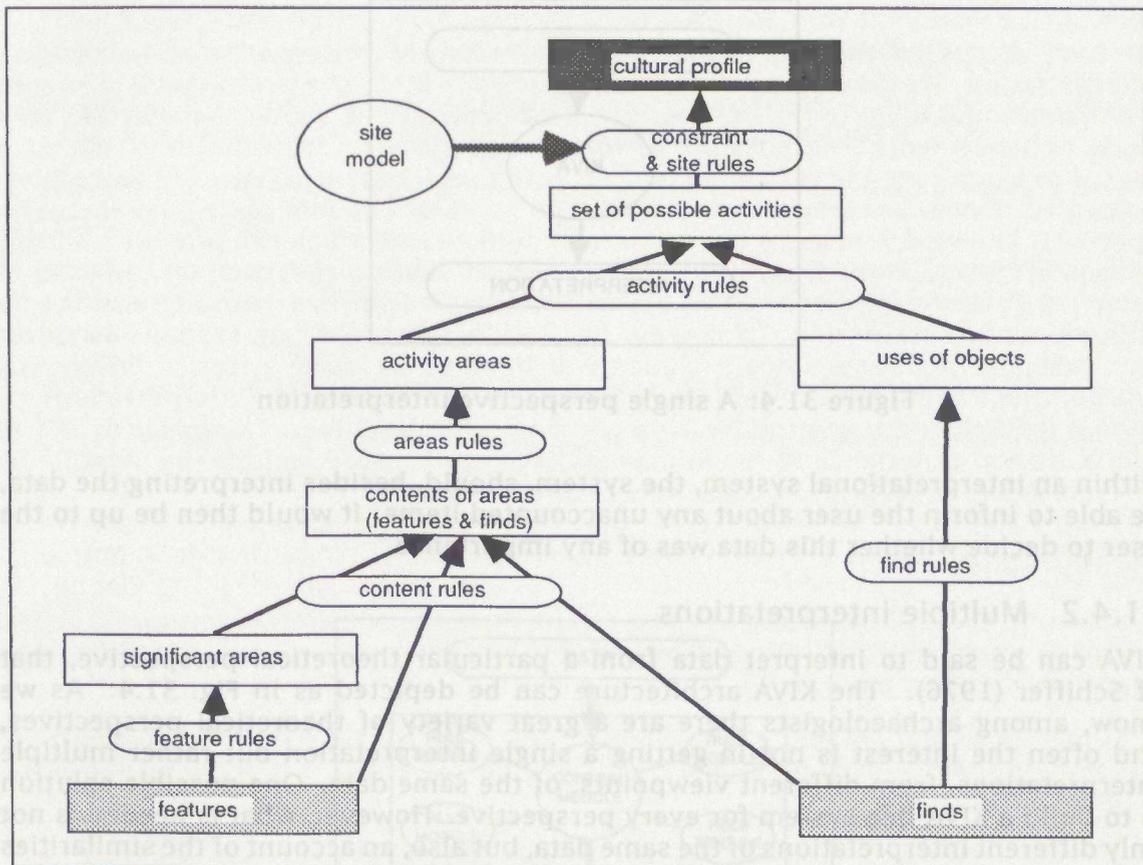


Figure 31.3: Reasoning in KIVA

31.4 Looking ahead

In KIVA, we have attempted to address some of the issues in archaeological interpretation, i.e., how to handle uncertainty and top-down reasoning. However, we find that the system lacks some important features such as the handling of unaccounted data and the possibility of multiple interpretations of the same data. In this section, we look at these new features in some detail and propose an architecture for interpretation systems which incorporate them.

31.4.1 Unaccounted data

We define unaccounted data as those pieces of information for which no rule is available in the current knowledge base. This may arise because the knowledge base is inadequately constructed or because the relevant knowledge is not yet available to the archaeological expert. The former is really a problem for knowledge engineering and could be dealt with by the further use of knowledge acquisition techniques in an attempt to make the knowledge base complete. The latter, which we refer to as anomalous data, plays an important role in archaeological interpretation. As well as being interested in the types of data they expect to find on a particular site, archaeologists are also interested in data that are anomalous since these serve to generate new knowledge. As an easy solution to the problem of dealing with anomalous data

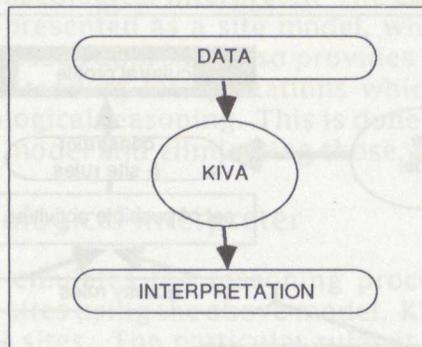


Figure 31.4: A single perspective interpretation

within an interpretational system, the system, should, besides interpreting the data, be able to inform the user about any unaccounted items. It would then be up to the user to decide whether this data was of any importance.

31.4.2 Multiple interpretations

KIVA can be said to interpret data from a particular theoretical perspective, that of Schiffer (1976). The KIVA architecture can be depicted as in Fig. 31.4. As we know, among archaeologists there are a great variety of theoretical perspectives, and often the interest is not in getting a single interpretation but rather multiple interpretations, from different viewpoints, of the same data. One possible solution is to build a KIVA-like system for every perspective. However, what is needed is not only different interpretations of the same data, but also, an account of the similarities and differences between them.

31.4.3 A new architecture for archaeological interpreters

A better solution to the multiple interpretation problem is to include within a single system a number of KIVA-like modules which could be accessed by a control mechanism, as illustrated in Fig. 31.5. The system then has a rule module for every theoretical perspective (e.g., structuralist, marxist). The control module would contain a simple inference mechanism for comparing interpretations.

The proposed architecture has a number of advantages over the KIVA system for interpretation.

1. It can provide different interpretations for the same data. Each rule module would be equal to a KIVA system and would contain heuristics for interpreting data from a theoretical perspective.
2. It would be able to compare the various interpretations and report the differences and similarities.
3. It would be able to say which data are left unaccounted for by each of the rule modules.

Note that the tools for creating such an architecture already exist. The creation of rule modules can be facilitated by the ASKE system (Patel 1988) for knowledge acquisition. The control module's function of coordinating the various rule modules, has much in common with ASParch (Stutt 1989), a tool for interacting with interpretations via stylized argument exchanges.

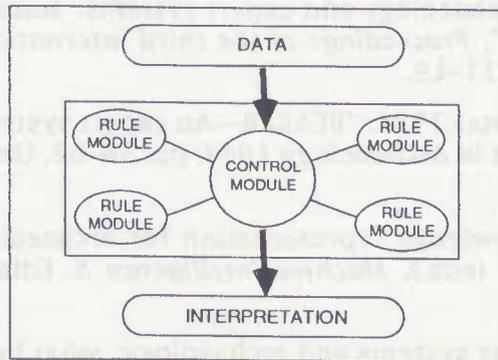


Figure 31.5: A multiple perspective interpretation

31.5 Conclusion

We have discussed the design and implementation of systems for archaeological interpretation. We drew attention to inadequacies in KIVA, our prototype interpreter, and made some suggestions for possible future enhancements. We believe that with these enhancements it is possible to construct a system which not only acts as a means of examining the reasoning of archaeologists (the fourth use of AI techniques discussed above) but which also can take on some of the role of an assistant with specialist knowledge of some domain or sub-domain and which can provide multiple alternative suggestions from within alternative theoretical perspectives. Instead of referring to an outside specialist, the excavation director can consult the friendly computational interpreter. Of course, he/she does not abdicate responsibility for the final interpretation since a choice will have to be made between competing possibilities. The system described above can prune unlikely interpretations, it cannot (and should not) produce only one final interpretation. This must be left to the skills and experience of the human archaeologist whose feel for the most likely interpretation is beyond the capacities of any machine.

Bibliography

- BAKER, K. G. 1986. "Archaeology and expert systems: some problems encountered during practical work", *Proceedings of the third international expert systems conference, London*, pp. 211-19.
- BISHOP, M. C. & J. THOMAS 1984. "BEAKER—An expert system for the BBC Micro". *in Computer Applications in Archaeology 1984*, pp. 56-62. University of Birmingham, Birmingham.
- DORAN, J. 1977. "Knowledge representation for archaeological inference". *in* Elcock, E. & Michie, D., (eds.), *Machine Intelligence 8*. Edinburgh University Press, Edinburgh.
- DORAN, J. 1988. "Expert systems and archaeology: what lies ahead?". *In* Ruggles & Rahtz 1988, pp. 237-241.
- ENNALS, R. & D. R. BROUGH 1982. "Representing the knowledge of the expert archaeologist", *Computer Applications in Archaeology*, pp. 133-44.
- GALLAY, A. 1989. "Logicism: a French view of archaeological theory founded in computational perspective", *Antiquity*, 63: 27-39.
- GARDIN, J.-C. 1980. *Archaeological constructs*. Cambridge University Press, Cambridge.
- GARDIN, J.-C., O. GUILLAUME, Q. HERMAN, A. HESNARD, M-S. LAGRANGE, M. RENAUD, & E. ZADORA-RIO 1987. *Systèmes experts et sciences humaines: Le cas de l'archéologie*. Eyrolles, Paris.
- LAGRANGE, M. & M. RENAUD 1985. "Intelligent knowledge-based systems in archaeology: a computerised simulation of reasoning by means of an expert system", *Computers and the Humanities*, 19: 37-52.
- LONGACRE, W. A. 1970. *Reconstructing Prehistoric Pueblo Societies*. University of New Mexico Press, Albuquerque.
- PATEL, J. 1988. "ASKE: towards an automated knowledge acquisition system", Technical Report 36, HCRL, The Open University, Milton Keynes.

PATEL, J. & A STUTT 1989. "Reducing uncertainty in archaeological interpretation using expectation-based reasoning". in Kelly & Rector, (eds.), *Research and Development in Expert Systems V*. Cambridge University Press, Cambridge.

RAHTZ, S. P. Q., (ed.) 1988. *Computer and Quantitative Methods in Archaeology 1988*, International Series 446, Oxford. British Archaeological Reports.

RICHARDS, J. & N. RYAN 1985. *Data Processing in Archaeology*. Cambridge University Press, Cambridge.

RUGGLES, C. L. N. & S. P. Q. RAHTZ, (eds.) 1988. *Computer and Quantitative Methods in Archaeology 1987*, International Series 393, Oxford. British Archaeological Reports.

SCHIFFER, M. B. 1976. *Behavioral Archaeology*. Academic Press, New York.

STUTT, A. 1989. *Argument in the humanities: a knowledge-based approach*. PhD thesis, The Open University, Milton Keynes.

VITALI, V. & M-S. LAGRANGE 1988. "An expert system for the provenance determination of archaeological ceramics based on INAA data". In Ruggles & Rahtz 1988.

3.2. Shape recognition

In creating shape information from two-dimensional or three-dimensional objects an increasing difficulty is achieved as the size and complexity of the objects increase. This is due to the fact that the number of features that can be used to describe the objects increases. The number of features that can be used to describe the objects increases as the size and complexity of the objects increase. The number of features that can be used to describe the objects increases as the size and complexity of the objects increase.

The central problem in shape recognition is the fact that the number of features that can be used to describe the objects increases as the size and complexity of the objects increase. The number of features that can be used to describe the objects increases as the size and complexity of the objects increase.

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