Computer Science, Artificial Intelligence and Archaeology

Josep Puyol-Gruart

Artificial Intelligence Research Institute (IIIA)
Spanish Scientific Research Council (CSIC)
Campus UAB. 08193 Bellaterra
E-mail: puyol@iiia.csic.es

Abstract

Computer Science and Artificial Intelligence are technologies and research topics, applied to multiple domains. The goal of this paper is to explore which of the new topics, of Artificial Intelligence, can be applied to Archaeology in the future. The aim is not to give solutions to archaeological problems, but to present three new areas that can be useful tothis field: Knowledge Discovery in Databases (KDD), Visual Information Management (VIM), and Multi-agent Systems (MAS).

Introduction

Early in this century, only privileged people—who had the time, the money and the intellectual curiosity—could work in archaeology. We can say that archaeology was for erudite people, everyone being an expert in his own field of study. Excavation diaries provide an example of the method used to gather information, in the past (see Figure 1). They consist of natural language explanations, of the works and circumstances of the excavations, with photographs and drawings of the discovered materials.

Since then, as a result of the development of archaeology, the method of gathering information in excavations began to be performed in a more systematic way. The system used was based on record cards. For every object or structure found, a record card was filled, with some slots or attributes (more or less well defined), and natural language descriptions, photographs and drawings. There are still thousands of manual, records cards.

The development of computers and computer science has produced a change in thinking (as it has in other areas) and has given rise to some new hopes and apprehensions, concerning those new technologies. It is very interesting to consider some of the opinions, about computer science and archaeology, of professor James Doran—one of the pioneers in the application of computer science in archaeology—in the seventies:

> *"[...] It was hard to see how the complex and ill-structured problems facing archaeologists could be tackled, other than by the direct application of their own experience and intelligence"* [Doran70].

We have to remark on some of the words, appearing in the text above: the knowledge domains of archaeology are *complex* and *ill-structured*; archaeologists need their *experience* and *intelligence* to solve these problems.

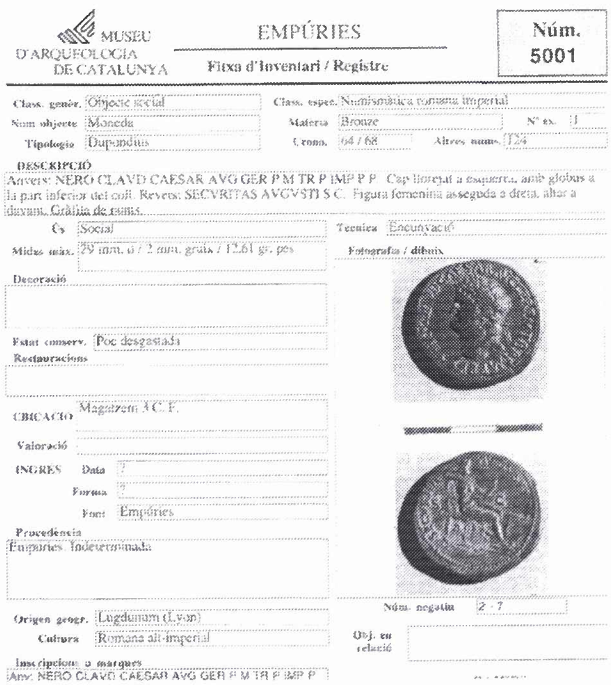
There are many domains of this type, complex and ill-structured, and in general, this includes all the knowledge domains, related to experience: for instance, some parts of medicine, biology, engineering, and moreover, archaeology. Experts in some domains are able to make good deductions from their experience, despite managing imperfect knowledge. Artificial intelligence is one form of attacking this type of problem. One of its goals is the simulation of the reasoning capabilities of experts, when solving problems.

Another interesting fragment, from James Doran, is the following:

> *"[...] Archaeologists collect large quantities of data, and if numerical techniques are to be used at all, then a computer is almost certain to be needed [...]"* [Doran70].

Figure 1. Excavation diary of Empúries by Emili Gandia [MS89]

We should take into account another aspect of archaeology: its practice produces *large quantities of data.* Professor Doran said—of course, in the seventies—that it was "almost certain" that we would have to use computers to apply *numerical techniques.* From the perspective of our current technology, it seems quite ridiculous to talk about the possibility of using computers. Moreover, it seems curious to talk about numerical techniques, forgetting the *symbolic* ones, which are one of the foundations of artificial intelligence.



MUSEU D'ARQUEOLOGIA DE CATALUNYA

EMPÚRIES

Fitxa d'Inventari / Registre

Núm. 5001

Class. genèr. Objecte social — Class. espec. Numismàtica romana imperial

Nom objecte Moneda — Matèria Bronze — Nº ex. 1

Tipologia Dupondius — Crono. 64 / 68 — Altres num. T24

DESCRIPCIÓ

Anvers: NERO CLAVD CAESAR AVG GER P M TR P IMP P P. Cap llorejat a esquerra, amb globus a la part inferior del coll. Revers: SECVRITAS AVGVSTI S C. Figura femenina asseguda a dreta, altar a davant. Gràfila de punts.

Ús Social — Tecnica Encunyació

Mides màx. 29 mm. ø / 2 mm. gruix / 12.61 gr. pes

Fotografia / dibuix

Decoració

Estat conserv. Poc desgastada

Restauracions

UBICACIÓ Magatzem 3 C. F.

Valoració

INGRÉS Data ? Forma ? Font Empúries

Procedència Empúries. Indeterminada

Núm. negatiu 2 · 7

Origen geogr. Lugdunum (Lyon)

Cultura Romana alt-imperial

Obj. en relació

Inscripcions o marques

Anv: NERO CLAVD CAESAR AVG GER P M TR P IMP P

Figure 2. Record card from Empúries Museum.

Computer-based treatment of archaeological problems, in the seventies, was tough, since the numerical management of databases was normally accomplished, using statistical techniques. The interpretation was obviously done manually, using the experience and intelligence of the archaeologist.

What has changed since then? Computer and communication technologies have been spectacularly developed. Now we can talk about the *digital world.* Using the argument, from the best-seller by Nicholas Negroponte (Media-Lab director at MIT), we can consider the transformation of the material world (composed of atoms) to the digital world (composed of bits) [Neg95]. The main advantages of this new digital world are: it facilitates the transportation—at light speed—of the bits, their compression, storage and manipulation.

So far, we have only talked about bits, but we must not forget *pixels.* A pixel—a chain of bits—is the informational unit of digital images. Although photography has been a useful tool for archaeologists for years, it could be even more important in the future. New digital cameras appearing on the market, in the last two or three years, offer easier methods to working with digital images: directly, without intermediate processing—chemical, or atomic processing. Today, archaeologists are using video for archaeological documentation, so, we can say the same things regarding digital video.

Because of this we have to consider multimedia databases. Multimedia information contains a range, from alphanumeric characters to graphics, animation, image, video and audio. Multimedia technology is growing rapidly, thanks to the cheaper and more powerful hardware, needed for the digitalisation and treatment of the information.

The record cards, mentioned above, were made up by atoms (ink for writing on the paper, silver for the photographs) and humans, by using their intelligence, interpreted that information. The digital world causes us to consider the digitalisation of multimedia information and its posterior treatment, using computer science and artificial intelligence techniques. In Figure 2, we can see a computer record of a Roman coin, from the database of the Empúries Museum, containing alphanumeric information and images. Multimedia and hypertext database development allows storing large quantities of the record cards, mentioned above, with digital information.

We should not forget the fast-growing use of telecommunications technology, the Internet network, and multimedia languages, forming the well-known WWW—World Wide Web. Now, we must not only consider local information, but information distributed throughout the world. This has led to a new area of artificial intelligence, based on the idea of *agent.*

How will the future be? Which new research areas, computer science techniques, and artificial intelligence will be able to offer useful tools for archaeology? We will discuss three points in this paper:

1. KDD (Knowledge Discovery in Databases): It is not possible to make manual, knowledge discovery in archaeological databases. It has to be automatised, with the supervision of human experts, for validation and interpretation of newly discovered theories. Besides, we should take into account that the information—by the intrinsic nature of archaeological problems—is imperfect, that is, imprecise, uncertain, vague, and with temporal dependencies.
2. VIM (Visual Information Management): The introduction of multimedia information—especially image and video—to archaeological databases, produces a need to find efficient techniques for the storage, retrieval, and understanding of that kind of information.
3. MAS (Multi-agent Systems): Simulation of primitive societies is a well-known area in archaeology. The current interest in the artificial intelligence research community, on multiagent systems, offers a new opportunity for considering simulation, based on agent ideas.

KDD

Database technology provides easy and efficient methods to store and access large volumes of data. What is the use of a large dataset, stored in a database? The value of the data is determined by the ability to extract information from them—information is data with semantics—useful for decision making and for the understanding of the data sources. Extract information, or knowledge from a database is difficult. The analysis and manual interpretation of data—as with statistical visualisation—are slow, expensive and subjective, and become more difficult as datasets become larger.

Knowledge discovery in databases can be defined as the following:

> *"The nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data"* [FPSS96]

The goal is to identify *patterns* in data. Patterns are expressions, in some language, that allow structuring or grouping the data: for instance, identifying dependencies among them. Models have to be *potentially useful* for something, *understandable* (they have no sense if it is not possible to understand them), *novel* (original, new), and *valid* (clearly applicable to new data).

The KDD process

The KDD process is represented in three steps, as depicted in Figure 3: the *pre-processing* of the data, *data mining* (sometimes referred to as *archaeology of data*) for obtaining patterns, and the interpretation of those patterns. We want to automatize the first and second steps. The last one, the interpretation, has to be done by the human expert, to determine, as mentioned above, whether the discovered patterns are: valid, useful, novel, and understandable.

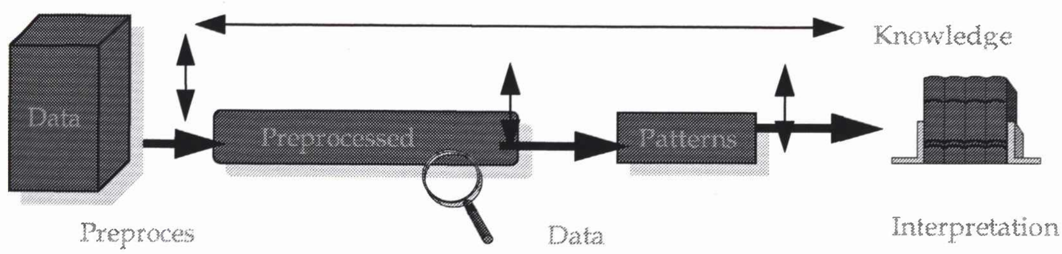


Figure 3. The steps of the KDD process.

The pre-processing of the data is the first step, from raw data to data mining. It consists of the manipulation of the raw data, to make them more tractable, by reducing the noise or the errors, or by selecting only the relevant attributes. In this step, we have to choose which model of database to use: relational, object-oriented, deductive, or hypertext, and the algorithms to make data mining, in accordance with our goals.

Data mining is the step, where we will obtain patterns from the pre-processed data. It is the most interesting step in this paper. The goals of the discovered patterns will be description and prediction. There are two kinds of techniques for the discovery of patterns: statistics (we can say, classical techniques), and Artificial Intelligence techniques (sometimes also using statistics).

Some of the well-known, classical techniques are: *classification* (consisting of identifying, to which of the previously known categories the data belong), *clustering* (from the data, we find a set of categories useful for classifying data), or *dependence modelling* (to discover dependencies among the data).

In this paper, we will talk about Artificial Intelligence techniques to accomplish the data mining. We will use *association rules* and *bayesian networks*, as knowledge representation formalisms. We will discuss the process of knowledge discovery from a database, using these formalisms.

After obtaining the patterns in the previous step, we need the final step of human interpretation is necessary. A set of questions arise in this step. Is this knowledge useful? Can we apply this new knowledge to new data? Are there any conflicts with our previous knowledge? Can we resolve those conflicts?

Discovery of association rules

To work with knowledge, we need to represent it. One of the most-used formalisms for knowledge representation is based on *association rules*. They are the base for most expert systems' language representation. Rules have a very simple syntax; their semantics is easily understandable, and based on logic; they do not imply knowledge about programming or computer science. Here, we have an example of a rule for an archaeological domain:

If pottery(X) and type(X,bf) then chronology(X, 1570)

Using natural language, we can express this rule as: *If X is a pottery and X is of black slip type, then we can assume that the chronology of X is 1570.* Every expression of a rule, the antecedents and the consequent, has a logic value, that is, its either *true* or *false*. For instance, given an object *X*, if this object is a pottery, then the expression *pottery(X)* is true. If all the antecedents of a rule are true, then the consequent will also be true; if any antecedent is false, then the consequent could be either true or false.

Remember, that in general—and in particular, in archaeological domains, knowledge is imperfect, that is, imprecise, uncertain and incomplete. Consider a modification of the previous example of a rule, that introduces the uncertainty idea:

If pottery(X) and type(X,bs) then chronology(X, 1570) in 80% of the cases.

This rule is more realistic, than the one presented before. It is closer to the knowledge of the human expert. This rule is only true in eighty per cent of the cases. That means, that in spite of having an object that is pottery, of a black slip type, it is possible that it does not have the specified chronology. We have introduced a certainty degree to the rule—it is not always true—because we need more antecedents or conditions (that we may have ignored, because we have incomplete knowledge) to reliably conclude the chronology.

Consider using the result of the previous rule's application as the antecedent for another rule:

If chronology(X, 1570) and ...

The logical value of the expression *chronology(X,1570)* is now, not true or false, as before. Its value partains to a certain *confidence degree of being true*, between 0% of confidence—false—and 100%—of course, true. The confidence in the consequent, of a rule of this type, will be a function of the confidence in its antecedents and the confidence in the rule. The computation of the confidence is a task, performed by the expert system program (in this case the human expert has nothing to do with it). This kind of programming is called *declarative*, as opposed to *procedural programming*. Experts declare the knowledge, but they do not specify how to execute it. An expert system would include many rules of this type.

There are two main steps in building an expert system: knowledge acquisition and validation. Knowledge acquisition is the step of programming the human expert's knowledge, using some language, for instance, rules. The validation step consists of verifying that the expert system is useful for solving problems, comparing the expert system results with those of human experts. Validation results should prove a high degree of similarity, between the answers of the expert system and the answers of the human experts.

The human expert encodes—or helps the knowledge engineer to encode—the rules, obtained from his previous experience, in a concrete domain, as in the example above in the classification of pottery. If a rule cannot be applied in all situations, he associates a confidence based on probability—objective or subjective—so that the rule may be applied when its antecedents are true.

The certainty of rules can be based on objective or subjective probability. Subjective probability is given by the human expert, based on his previous experience. Objective probability is based on frequencies. An example of frequency is the relation, between all the cases of pottery, of black slip type, with a chronology of 1570, and the total number of cases of pottery, of black slip type.

At this point, we should return to the main point of this section, the discovery of association rules. Note that a database contains information about frequencies, objective probability. We will be able to benefit from this, in order to extract, automatically, rules from a database. Will these rules be useful, valid, novel, and understandable?

We can think of a knowledge acquisition process, supervised by the human expert, as represented in Figure 4. Consider a database of archaeological objects. Every object has a set of attributes: for instance, the type of material, its colour and its chronology. Consider that we are interested in discovering knowledge from that database about pottery of black slip type.

Using classical techniques, it is easy to obtain from the database the number of occurrences, of objects that are pottery of black slip type. That number represents the *support* of the search. If we decide that this support is enough, we can decide to continue, finding patterns, for determining the chronology of those objects. Now, we can ask the database about the number of objects, that are pottery of black slip type, and with a chronology of 1570. To obtain the *confidence* on the rule above, we should calculate the frequency of pottery, of black slip type, with a chronology of 1570, with respect to the total pottery of black slip type. The truth value, of the newly discovered rule will be that confidence (for instance, eighty percent, as in the example above).

From this example, we can conclude that it is possible to discover rules from a database, though we need the supervision of the human expert, to guide this process. The human expert should also decide whether the new rules are useful, valid, novel and understandable. This is the step of result interpretation. The automatic generation of rules, without restriction, will obtain a large number of rules. Most of those rules will not fulfill the goals of knowledge discovery [AMS+96].

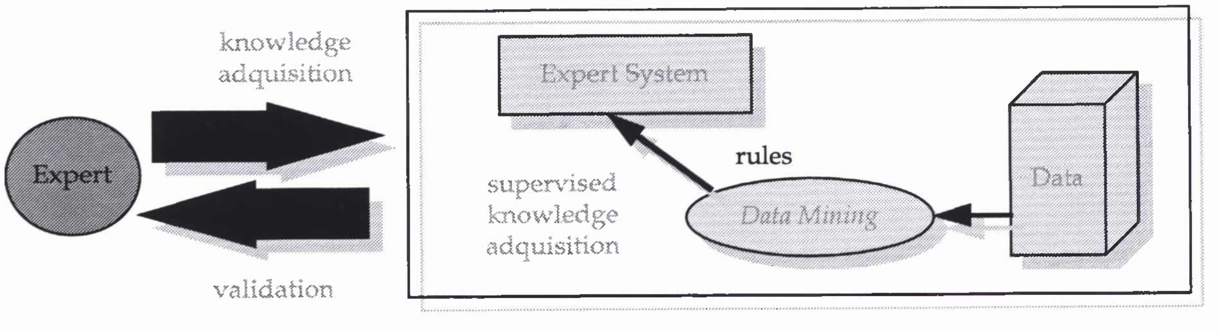


Figure 4. Discovery of association rules.

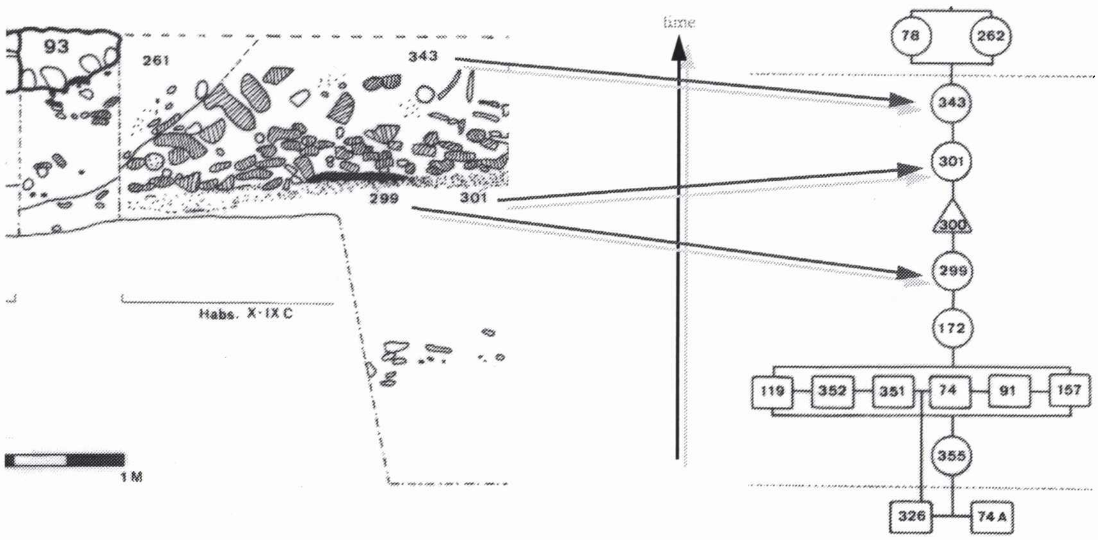


Figure 5. Representation of stratigraphic information.

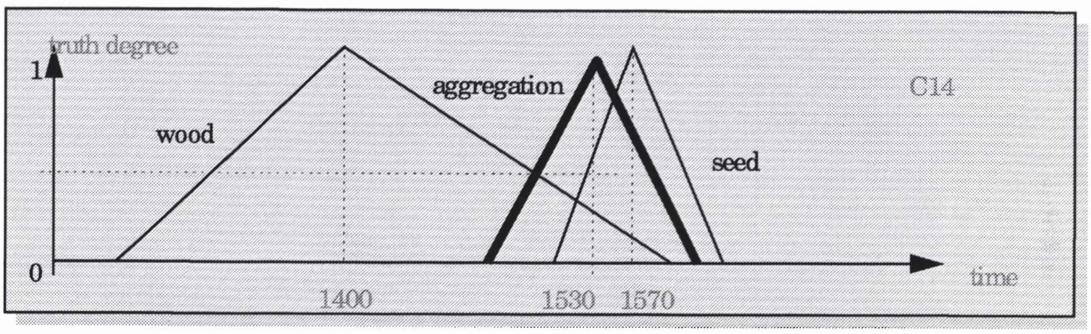


Figure 6. Fuzzy predicates.

Temporal Reasoning

At this point, after viewing a formalism, based on rules to represent knowledge, it is also interesting to talk about the temporal dimension of knowledge. We have said that information can be imprecise, uncertain, moreover incomplete, with temporal dependencies. Temporal reasoning is a topic of Artificial Intelligence, devoted to logic and reasoning regarding time [Vil96].

If we look for applications of temporal reasoning, in archaeology, we will find a lot. For instance, the chronology of archaeological findings, or the stratigraphic study—which determines what comes before or after —talk about time. We can use stratigraphy as an example. In Figure 5, we can see a stratigraphic study of the Vilauba excavation (Camós, Girona, Spain): the left part corresponds to spatial stratigraphy, and the right, to temporal stratigraphy.

It is possible to see how to represent the knowledge, contained in Figure 5. One form of representation uses the same formalism of rules, but temporally qualified. We can add to a predicate, an element, determining *when* that predicate is true. We can consider the predicate used, in the example above, as temporally qualified, "*chronology(X,Y)*", where *Y* refers to time. For instance, we can say that "*chronology(E299,1570)*" is true.

Besides temporally qualified rules, we can use temporal predicates such as "*before(X,Y)*", "*after(Z,T)*", etc. Temporal logic is powerful, because those predicates are related, concerning a concrete temporal semantics. For instance, in a temporal logic, based on time points, if the predicate "*before(a,b)*" is true, then the logic will say that the predicate, "*after(a,b)*", is false. For a temporal logic, based on time intervals, the meaning of those predicates and their relationships would be different, and would deal with other semantics.

Now, it is possible to consider rule programming, using all those predicates; Take, for example, the following rule:

If chronology(E1,X) and chronology(E2,Y) and before(X,Y) and below(E1,E2) ...

where *E1* and *E2* are strata, *X* and *Y* time points, *before* is a temporal predicate and *below* refers to the position of strata. Similar to the previous section, it is possible to consider the possibility to discover these rules from a database. The rules will be associated with confidence and support degrees.

Another interesting aspect to present here is the calculus, with *fuzzy predicates*. Fuzzy logic is another research area of artificial intelligence. We shall introduce it, by means of an example. Imagine that we have found two samples, a piece of wood and a seed, in the strata, E299 (see Figure 6). Charcoal-14 proofs give us a chronology for the wood of about 1400, and for the seed of about 1570. We know that wood is a long life sample, and a seed is a short life sample. So, then, a wood sample is less precise than a seed sample. In this case, we can talk about *vague* or *fuzzy predicates*. We can consider the predicate, *chronology of the seed*, as a function (called characteristic function, as depicted in Figure 6). The truth degree of that predicate is maximum (true) at 1570 and progressively decreases towards false, as the data goes further far from 1570. Similarly, the predicate, *chronology of wood*, is represented as another function, with its maximum at 1400, and which decreases slower than the previous function—because it is a less precise sample. These functions represent *fuzzy sets*.

The difference between classical and fuzzy sets is that the membership of an element, to a fuzzy set, is a degree between true and false, instead of simply true or false. For instance, the membership degree of the seed, to the set of samples of a concrete chronology, is represented by its characteristic function. The seed does not belong to the set of samples from the year 1300. It clearly belongs to the set of samples from 1570, and it has some membership degree to the set of samples from 1530.

We can define the chronology of the strata, by means of a combination of both characteristic functions—those of the wood and the seed. For instance, using aggregation, we can obtain a new characteristic function for the chronology of the strata (see the bold line in Figure 6).

Discovery of bayesian networks

Another formalism for knowledge representation is *bayesian networks*, also called *probabilistic networks* or *causal networks*. Bayesian networks have a probabilistic, semantic. They are used to program probabilistic expert systems. A bayesian network is a graphical representation of uncertain knowledge. We draw a directed, acyclic graph, with arrows representing dependencies among nodes, where the nodes are facts. For instance, in Figure 7, we can see a bayesian network, representing the reasoning process to determine if an excavation area is a *domestic area*.

If we find burned animal bones and charcoal in an excavation, then we can suppose that this site may have been a fireplace. Given this evidence, if we also find storage pits, we can consider this site to have been a domestic area.

After the drawing of dependencies, we must assign probabilities to the nodes and the dependencies, representing measures of uncertainty.

We will use two types of probabilities: *a priori* probabilities and *conditioned* probabilities. Nodes without parents—and then, not conditioned—have *a priori* probabilities. Conditioned probabilities are assigned to nodes with parents.

Consider again the probabilistic network in Figure 7. We have to assign *a priori* probabilities to the following facts without parents: *charcoal, burned animal bones* and *storage pits*. The sense of these probabilities is about the confidence of finding those materials in the excavation area, for instance for charcoal, **P**(C)=80%. Similarly, we can estimate the probabilities of finding burned animal bones or storage pits, **P**(B) and **P**(S), respectively.

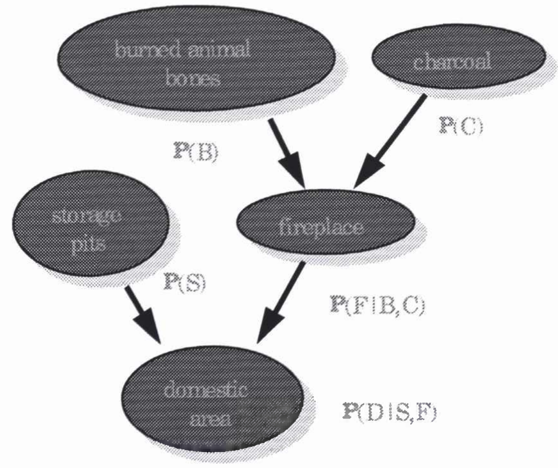


Figure 7. Probabilistic network example.

S	F	P(D I S,F)	
false	false	20%	80%
false	true	75%	25%
true	false	90%	10%
true	true	99%	1%

Table 1. Conditioned probabilities.

Finally, we should consider the conditioned probabilities of the nodes with parents, for instance, the node representing the discovery of a *fireplace*. The fact of finding a fireplace is conditioned by the previous finding of burned animal bones and charcoal. Then, the probabilities of fireplace are probabilities, conditioned by the facts burned animal bones and charcoal (they can be *true* or *false*), expressed as **P**(F I B, C). Similarly, the probabilities of domestic area are conditioned by the facts, fireplace and storage pits, **P**(D I S, F). How can we give values to these probabilities? We should fill in a table, as in Table 1. For instance, if we have found a fireplace (F is *true*) but no storage pits (S is *false*), the probability of finding a domestic area is 75%, and that of not finding it, is 25%. The probability grows to 99%, if we find a fireplace and storage pits (both are *true*). The values of these probabilities can be determined by the knowledge and experience of the archaeologist; in this case, we say that they are subjective.

Bayesian networks are useful to represent causal knowledge. The examples above show that it is a very simple formalism. How can we use a bayesian network, after declaring it? Probabilistic network, reasoning programs allow to calculate other probabilities. For instance, what is the probability of finding a domestic area, without other considerations, **P**(D)?

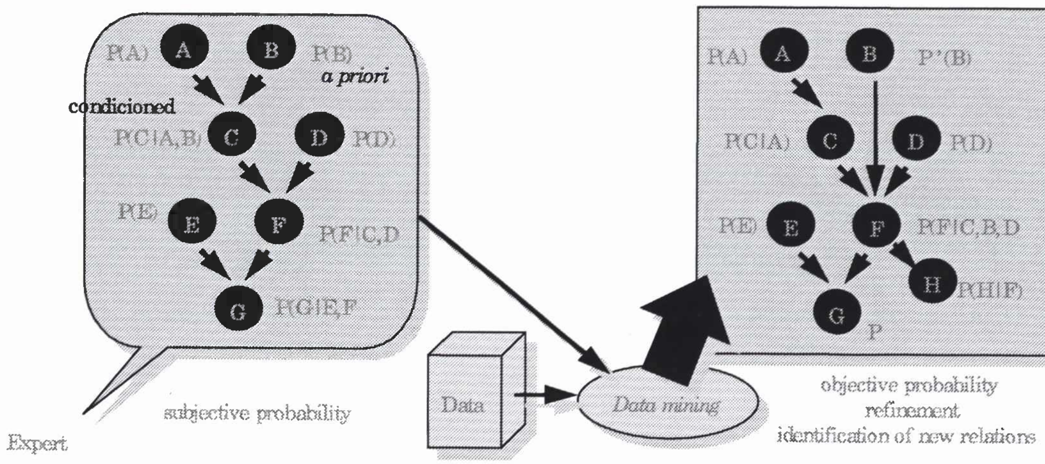


Figure 8. Discovery of probabilistic networks.

Another example: what is the probability of finding a domestic area, given that: we have found charcoal, there are no storage pits, and we ignore the truthfulness—it can be *true* or *false*—of burned animal bones? This probability can be expressed as **P**(D | C=*true*,S=*false*). Another question: what is the probability of finding charcoal, given that we only know that the excavation area is a domestic one, that is, **P**(C | D=*true*)? All these questions can be answered by probabilistic network reasoning programs. They actualise the other probabilities from a given a set of evidence—the set of facts that are *true*.

Similarly, with the discovery of association rules in the previous section, we can consider the discovery of bayesian networks from a database.

The archaeologist can build a bayesian network with subjective probabilities, but the database contains objective probabilities. The knowledge domain of a human expert, represented by means of a bayesian network with subjective probabilities, in addition to the statistical data—objective probabilities—of a database, can be used to refine the initial knowledge of the human expert [Hec96]. The initial knowledge of the human expert can be refined, by changing dependencies or identifying new ones, creating new networks, etc. Figure 8 is a scheme that represents this process: an initial network, given by the expert, is used to guide the process of knowledge discovery. Finally, the expert should supervise the newly obtained bayesian networks, to determine if he can consider them to be actual knowledge discovery.

VIM

The management of visual information has its difficulties, different from those of numeric or symbolic information management. First, we can compare this topic with that of free text information. Retrieval of free text information is based on different techniques: from form statistics to natural language processing. In spite of knowledge, extraction is very difficult; free text has the advantage that every word has a limited number of meanings. This is different with visual information.

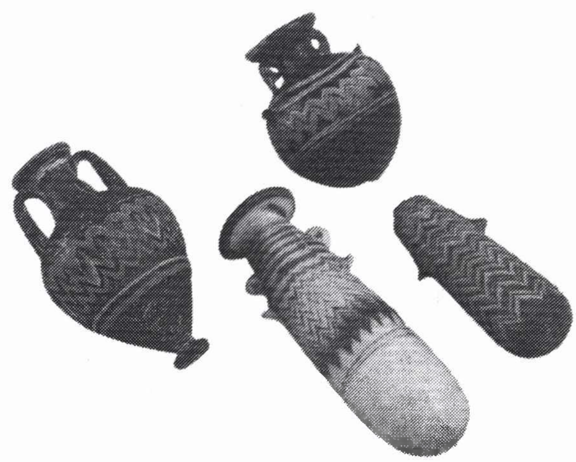


Figure 9. Alabastrons. [MS89]

The kinds of questions, when managing visual information, are similar to those, which arise with textual information. What is the content of the text, the photography, or the video sequence? How can we extract semantic labels from the contents of a picture, to classify the objects we have seen?

Consider Figure 9. To do that, the first problem is to isolate the different objects in the picture (called the segmentation problem). It is much more difficult to deduce that the four objects in the picture can share the same semantic label, alabastron.

Visual information is different from textual, because objects with the same semantic label can have very different appearances, in fact, infinitely different ones. As an example, consider changing the point of view of the observer of an object, the perspective.

When talking about visual information management, we distinguish among four categories of information: features, feature space, feature groups, and image space [GSJ97].

Image analysis algorithms can extract some interesting features from a visual object. Examples of some features are: redness, texture, contrast, etc. Image analysis algorithms transform the original visual object, by means of projections, applying functions and making distance measures among features. Filtering of a hue histogram of an image is an

Figure 10. Roman coin from Empúries.

extract its degree of redness. Distance functions determine degrees of similarity among different objects, by applying that function to a feature of the objects.

Image features always belong to a region in space. For instance, if we consider the texture of an alabastron, in Figure 9, that feature belongs only to the region where the alabastron is located. This is an example of feature space. Typical operations in feature space are: finding boundaries, given an object feature, finding which of the other objects, with the same feature, are its neighbours, making a space partition, etc.

Feature groups are a category of visual information, that group different features to create a more complex one. Image space is the combination of all the previous categories: feature groups belonging to a concrete region in space. We can pose questions, to a database, of the following type: find pieces with circular, geometrical characteristics, of copper colour, with a human face in the middle, and letters around the perimeter. Of course, it is not easy to identify human faces (that is a more complex feature), but it could be a useful description to find coins in the database (see Figure 10). We can consider similar descriptions for Figure 11. Which are the characteristics that, combined, will be useful to identify mosaics, into an image? Given a set of mosaic examples, is it possible to obtain an automatic description of the mosaic object?

People at the California University, in San Diego, have developed a particular software for the retrieval of information, in an image database. The images in the database are represented in three-dimensional space. Each dimension is a feature, chosen by the user. Then, the images are ordered into that space, according to the three features. The process is a cycle of navigating through space, untill an image, similar to the one we are looking for, is found. We select that image, and choose other features of the image found. With these features, the program will represent, again, the database. That cycle is then repeated, approaching the image that we are looking for.

Archaeological databases contain much visual information; the discovery of knowledge, then, has to be associated withvisual management techniques. We can think in discovering knowledge from a visual database. We can obtain rules, managing concepts as features, image space, semantic labels, etc.

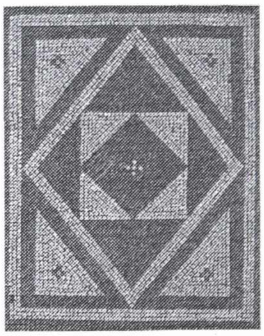


Figure 11. Mosaic [MS89}

MAS

Multiagent systems is a growing interest area, in the community of artificial intelligence. In the previous sections, we have tried to program or simulate the reasoning processes of human experts (archaeologists, in this case). Simulation, in archaeology, is devoted to the simulation of the objects, of archaeological study, the people and their societies, their relationships with the environment and other people, commerce, hunting, etc. Multiagent systems, for simulation of Palaeolithic societies, have already been yet used in the project, EOS [Doran95].

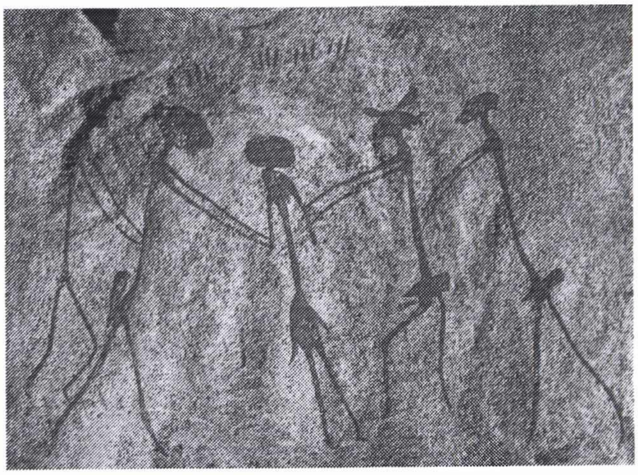


Figure 12. Rock-art from Tanzania

What is an agent, from the point of view of artificial intelligence? Following Wooldridge [WJ,95], we can consider it from two approaches: the weak idea and the strong one. From the weak point of view, an agent is a set of programs that share the following features: *autonomy*—agents evolve without human operation; they have control over their own actions, *sociability*—agents interact and communicate among themselves, *reactivity*—agents have perception of the environment—physical or virtual—and react to the changes in it, *activity*—agents are able to take the initiative; their behaviour is goal-driven. The strong approach considers agents from an anthropomorphic point of view, because it associates mental notions with agents, as knowledge, beliefs, obligations, commitments, intentions and moreover, emotions.

From this perspective, we can see societies of artificial agents as particularly suitable for the simulation of human societies (Figure 12). A multiagent program consists of the programming of agents, with their particularities—roles—in the society, the communication capabilities with other agents, the perception and reaction behaviour to the environment, etc. We can consider defining this behaviour, by means of the rule formalism, explained before.

Conclusions

In the near future, archaeologists will be able to use the results of these new areas, of computer science and artificial intelligence, to improve their research. Digital world, besides the management techniques of visual information and knowledge discovery, in databases, will be useful for understanding information sources. Artificial intelligence is especially useful for experience-based knowledge.

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