Computer Science, Artificial Intelligence and Archaeology

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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 in the future to Archaeology. The aim is not to give solutions to archaeological problems, but to present three new areas that can be useful to it: 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 be working in archaeology. We can say that archaeology was for erudite people, everyone being an expert on his knowledge area. Excavation diaries are an example of information gathering used then (see Figure 1). They consisted of natural language explanations of the works and circumstances of the excavation, besides photographs and drawings of the discovered materials.

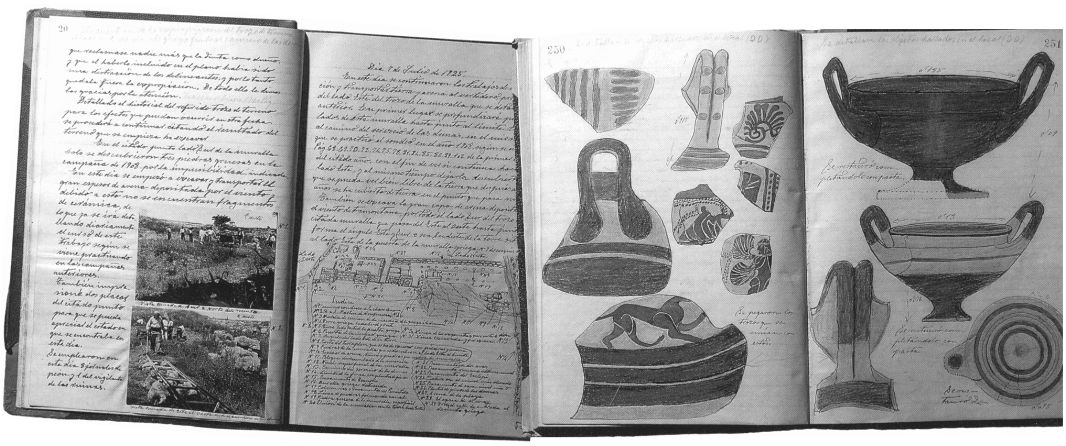

Figure 1. Excavation diary of Empúries by Emili Gandia [MS89]

After that, as a result of the development of archaeology, information gathering in the excavations was 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 produced a change of thought—in the same way as in other areas—and put some hopes and apprehensions concerning those news 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 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. In general all the knowledge domains related with experience: for instance, some parts of medicine, biology, engineering, moreover archaeology. Experts in some domain are able to make good deductions from their experience, despite managing imperfect knowledge. Artificial intelligence is one form of attacking this type of problems. One of its goals is the simulation of the reasoning capabilities of experts when solving problems.

Another interesting fragment of 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]

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 we would have to use computers (*almost certain*) to apply *numerical techniques*. With the perspective of our current technology, it could seem quite ridiculous to talk about the possibility of using computers. Moreover it could seem curious talking about numerical techniques forgetting the *symbolic* ones, one of the foundations of artificial intelligence.

Computer-based treatment of archaeological problems in the seventies was tough as the numerical managing of databases, normally using statistical techniques. The interpretation was obviously manual, by means of the experience and intelligence of the archaeologist.

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 núms. 124

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
Tècnica 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
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Figure 2. Record card from Empúries Museum.

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

So far we have only talked about bits, but we have not to 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 more important in the future. The new digital cameras appearing in the market in the last two or three years offer easier methods to work with digital images: directly, without intermediate processing—chemical processing, of course, atomic processing. Today archaeologists are using video as archaeological documentation, then we can say the same things for digital video.

Because of that we have to consider multimedia databases. Multimedia information contains 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.

Record cards mentioned above was made by atoms (ink for the writing on paper, silver for the photographs) and humans, by means of their intelligence was interpreting that information. Digital world drives us to think on the digitalisation of multimedia information and the 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 to store large quantities of record cards mentioned above, but with digital information.

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

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

1. KDD (Knowledge Discovery in Databases): It is not possible to make manual knowledge discovery in archaeological databases. We have to automatise it with the supervision of human experts for validating and interpreting the new discovered theories. Besides we should take into account that 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—specially image and video—to the archaeological databases produce a need to find efficient techniques to store, retrieve and understand 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 utility of a large dataset stored in a database? The value of data is given by the ability to extract information from them—information is data with semantics—useful for decision making and for the understanding of the source of data. Extract information or knowledge from a database is difficult. The analysis and manual interpretation of data—as the statistical visualisation—is slow, expensive and subjective, and it becomes 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* from data. Patterns are expressions in some language that allow structuring or grouping 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 on new data.

The KDD process

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

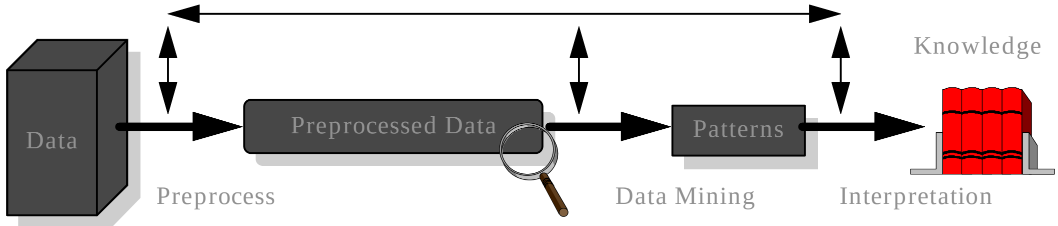

Figure 3. The steps of the KDD process.

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

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

Some of the well-known classical techniques are: *classification*, consisting in identifying to which of the previously known categories belongs data; *clustering*, from data we find a set of categories useful to classify data; or *dependence modelling*, to discover dependencies among data.

In this paper we will talk about Artificial Intelligence techniques to make 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.

From the patterns obtained in the previous step, we need the final step of human interpretation. A set of questions will appear in this step. Is it useful this knowledge? Can we apply this new knowledge to new data? Do we have conflicts with our previous knowledge? Can we solve those conflicts?

Discovery of association rules

To work with knowledge, we need to represent it. One of the most used formalism for knowledge representation is based on *association rules*. They are the base of most of expert systems language representation. Rules have a very simple syntax; its semantics is easily understandable, based on logic; it does not imply knowledge about programming or computer science. Here we have an example of rule of 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 type black slip, then we can assure that the chronology of X is 1570*. Every expression of a rule, the antecedents and the consequent, has a logic value, that is, they are *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 will be the consequent; if any antecedent is false, then the consequent could be 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 rule that introduces the uncertainty idea:

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

This rule is more realistic that the explained before. It is closer to the knowledge of the human expert. This rule is only true in the eighty per cent of cases. That means that in spite of having an object that is a pottery of type black slip, it would be possible that they do not have that chronology. We have introduced a certainty degree to the rule—it is not always true—because we would need more antecedents or conditions—that we ignore them because we have incomplete knowledge—to conclude the chronology surely.

Consider to use the result of the application of the previous rule as antecedent of another one:

If chronology(X, 1570) and ...

The logical value of the expression *chronology(X,1570)* now it is not true or false as before. Its value belongs to a certain *confidence degree of being true*, between 0% of confidence—false—and 100%—of course, true. The confidence of the consequent of a rule of this type will be a function of the confidences of its antecedents and the confidence of the rule. The computation of the confidences 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 programming*, as opposed to *procedural* one. Experts declare the knowledge, but they do not specify how to execute it. An expert system would have many rules of this type.

There are two main steps to build an expert system: knowledge acquisition and validation. Knowledge acquisition is the step of programming the knowledge of the human expert using some language, for instance, rules. The validation step consists in verifying that the expert system is useful for solving problems comparing the expert system results with those of the 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, in the example above the classification of pottery. If a rule can not be applied in all the situations, he associates a confidence based on probability—objective or subjective—that the rule may be applied when its

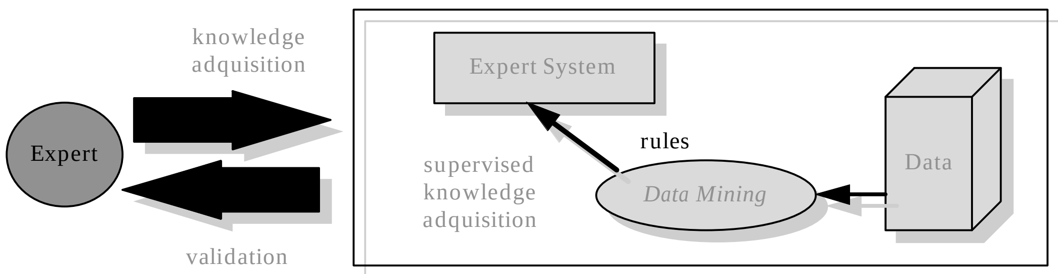

Figure 4. Discovery of association rules.

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 type black slip with chronology 1570 and the total of cases of pottery of type black slip.

At this point we should return to the origin of this section, the discovery of association rules. Notice that a database contains information about frequencies, objective probability. We will be able to profit this 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 we are interested in discovering knowledge from that database about pottery of type black slip.

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

From this example we can say 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 fulfil the goals of knowledge discovery [AMS+96].

Temporal Reasoning

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

If we look for applications of temporal reasoning to archaeology we will find a lot. For in-

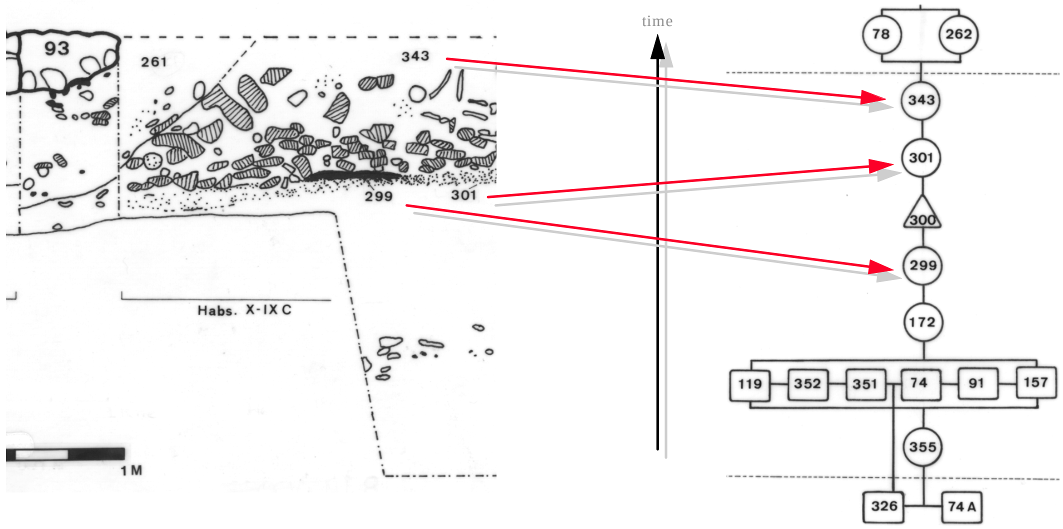

Figure 5. Representation of stratigraphic information.

stance, the chronology of archaeological findings or the stratigraphic study—which determine what is after or before—talk about time. We can use as an example the stratigraphy. In Figure 5 we can see a stratigraphic study of Vilauba excavation (Camós, Girona, Spain): the left part corresponds to the spatial stratigraphy, and the right one to the temporal stratigraphy.

We can see how to represent the knowledge contained in Figure 5. One form of representation is using the same formalism of rules, but temporaly 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 temporaly qualified, "*chronology(X,Y)*", where *Y* referres to time. For instance, we can say that "*chronology(E299,1570)*" is true.

Besides temporaly qualified rules we can use temporal predicates 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 relations would be different and dealing with other semantics.

Then we can think on rule programming using all those predicates, 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. We can think, similarly as in the previous Section, on the discovery of 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. Let me introduce it by means of an exam-

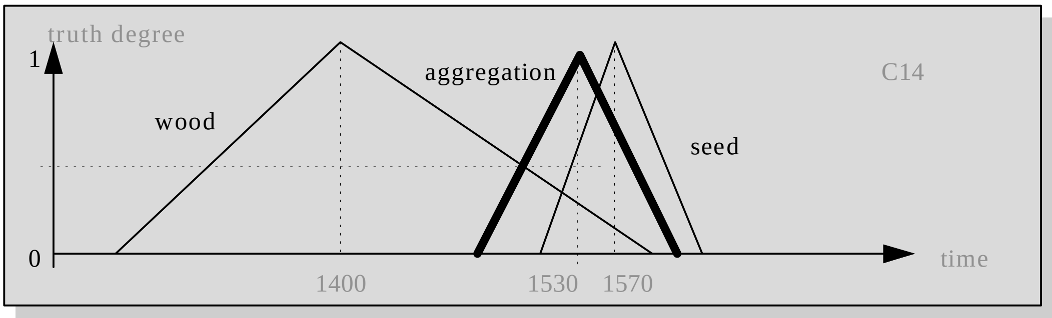

Figure 6. Fuzzy predicates.

ple. Imagine 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 about 1400, and for the seed about 1570. We know that wood is a long life sample and a seed is a short life one. Then a wood sample is less precise than a seed one. In this case we can talk about *vague* or *fuzzy predicates*. We can consider the predicate *chronology of the seed* as a function, named characteristic function, as depicted in Figure 6. The truth degree of that predicate is maximum (true) at 1570 and progressively decrease towards false as the data go far from 1570. Similarly the predicate *chronology of wood* is represented as another function, whit its maximum at 1400 and decreasing slower that 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 only true and 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 of the year 1300. It clearly belongs to the set of samples of 1570, and it has some membership degree to the set of samples of 1530.

We can define the chronology of the strata by means 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 of Figure 6).

Discovery of bayesian networks

Another formalism for knowledge representation is *bayesian networks,* also named *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 the Figure 7 we can see a bayesian network representing the reasoning process to determine if an excavation area is a *domestic area*.

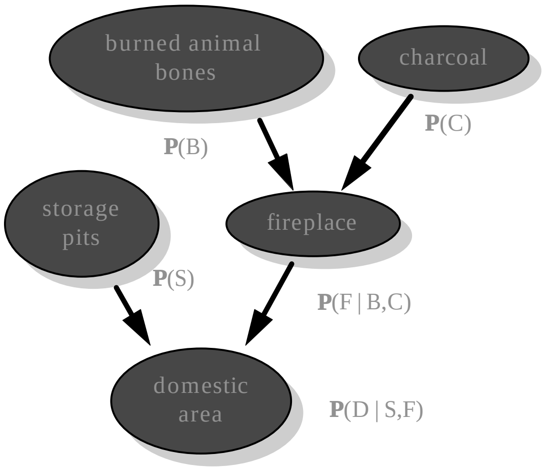

Figure 7. Probabilistic network example.

If we find burned animal bones and charcoal in an excavation, then we can think that this site could be a fireplace. Given these evidences, if we find also storage pits we can think this site is a domestic area.

After the drawing of dependencies we must assign probabilities to the nodes and 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.

S	F	**P**(D | 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 for 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 | B, C). Similarly the probabilities of domestic area are conditioned by the facts fireplace and storage pits, **P**(D | S, F). How we can give values to these probabilities? We should fill 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, which is the probability of finding a domestic area without other consideration, **P**(D)? Another example: which is the probability of finding a domestic area given that: we have found charcoal, there is no storage pits, and we ignore the truthness—it can be *true* or *false*—of burned animal bones? This probability can be expressed as **P**(D | C=*true*,S=*false*). Another one: which 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 those programs. They actualise the other probabilities from a given a set of evidences—the set of facts that are *true*.

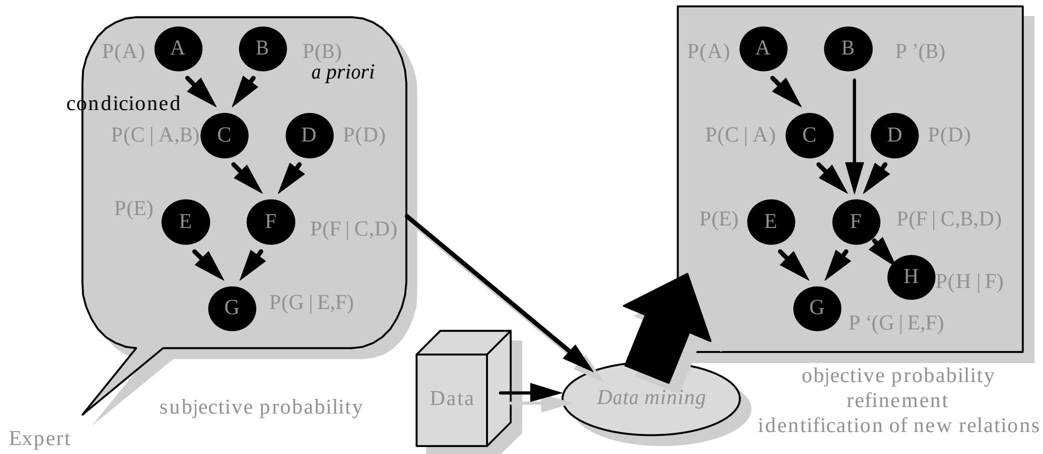

Figure 8. Discovery of probabilistic networks.

Similarly with the discovery of association rules in the previous section, we can think in 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 domain knowledge 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. The 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 new bayesian networks obtained to determine if he can consider that is really a discovery of knowledge.

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: 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.

The kind of questions when managing visual information is similar to those appearing in 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 the Figure 9. To do that the first problem is to isolate the different objects of the picture, that is called the segmentation problem. It is much more difficult to deduce that the four objects of the picture can share the same semantic label, alabastron.

Figure 9. Alabastrons. [MS89]

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

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

Figure 10. Roman coin from Empúries

Image features always belong to a region in the 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. This is an example of feature space. Typical operations in feature space are: finding boundaries; given an object feature, find 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 the space. We can imagine questions to a database of the following type: find pieces with circular geometrical characteristic, with copper colour, with a human face in the middle and letters around the perimeter. Of course, it is not easy to identify human faces, it is a more complex feature, but it could be a useful description to find coins in the database (see Figure 10). We can think in similar descriptions for the Figure 11. Which are the characteristics that combined will be useful to identify mosaics into an image? Given a set of mosaic examples, it is possible to obtain an automatic description of the object mosaic?

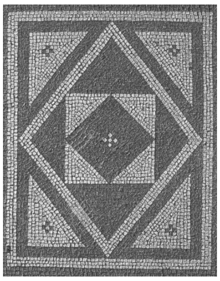

Figure 11. Mosaic [MS89]

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 a three-dimensional space. Each dimension is a feature chosen by the user. Then the images are ordered into that space following three features. The process is a cycle of navigating through the space till an image similar to that we are finding 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 repeated then approximating to the image we are finding.

Archaeological databases contain much visual information, then the discovery of knowledge has to be associated to visual 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.

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 the archaeological study, the people and their societies, the relations with the environment and other people, the commerce, hunting, etc. Multiagent systems for simulation of Palaeolithic societies has been yet used in the project EOS [Doran95].

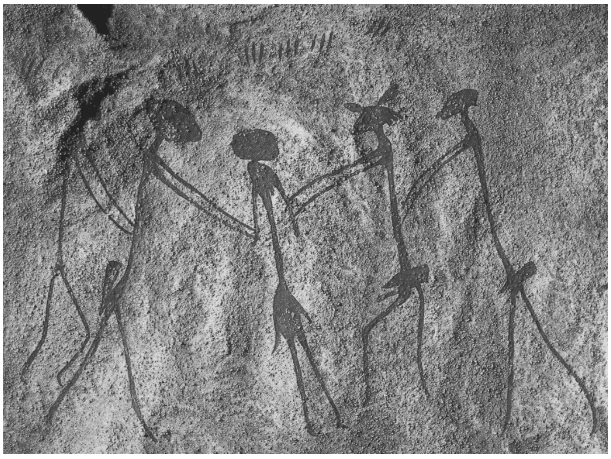

Figure 12. Rock-art from Tanzania

What is an agent from the point of view of artificial intelligence? Following Wooldridge [WJ95] 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 has control over their own actions; *sociability*, agents interact and communicate among them; *reactivity*, agents have perception of the environment—physical or virtual—and react to the changes on 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 to agents, as knowledge, beliefs, obligations, commitments, intentions 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 in the programming of agents, with their particularities—roles—in the society, the communication capabilities with other agents, the perception and reaction behaviour on the environment, etc. We can consider to define this behaviour by means of the rule formalism explained before.

Conclusions

Early in the future archaeologists will be able to use the results of these new areas on 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 to the understanding of the information sources. Artificial intelligence is especially useful for experience based knowledge.

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