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The Underlying Issues in Knowledge Elicitation

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Abstract

Eliciting knowledge out of an expert is essentially the major focus of studies in knowledge engineering. Although the collection of documents, manuals, specification, procedures and research materials readily available in electronic libraries constitute knowledge, the real knowledge needed in organizations for crafting expert systems exists 'between the ears' of workers, otherwise experts. Harvesting this knowledge poses the greatest challenge in the development of expert systems. Elicitation of knowledge and its transfer to a knowledge-based system is not only complex, but involves a range of diverse activities. This paper presents the important issues underlying the elicitation of explicit and tacit knowledge and also proffers solutions based on experiences acquired from research and development in the area of expert systems technology.

Keywords: Knowledge engineering, knowledge elicitation, machine learning, knowledge acquisition, knowledge-based system, implicit knowledge, explicit knowledge, tacit knowledge

Introduction

Knowledge Engineering, an activity in knowledge creation, is the process by which an engineer has to elicit knowledge out of an expert. This knowledge then needs to be modeled such that it could be represented as a set of rules in a ruled-based or expert system. Hsia, Lin, Wu, and Tsia (2006) described knowledge creation as identifying and selecting content from relevance, creating knowledge source catalog, capturing and discovering new knowledge. Knowledge elicitation is roundly defined by McGraw (1992) as the transfer and transformation of problem solving expertise and domain knowledge from a source into a program. Figure 1 shows the basic knowledge engineering model (Gaines & Shaw, 1995). Working with the domain expert(s), the knowledge engineer elicits, encodes and continuously refines the knowledgebase until an acceptable performance is achieved. A suitably designed shell uses the knowledgebase to draw inferences on cases that may be specified by users/clients. The inferences then help clients obtain advice on particular cases.

The knowledge elicitation problem entails the hindrances or discouragements encountered when prompting people to divulge what they know in their area of specialization. Essentially, these are the impediments to extracting or obtaining useful knowledge from experts for use in developing knowledge-based systems. These problems are as old as expert systems development itself which dates back to the mid 1960's.

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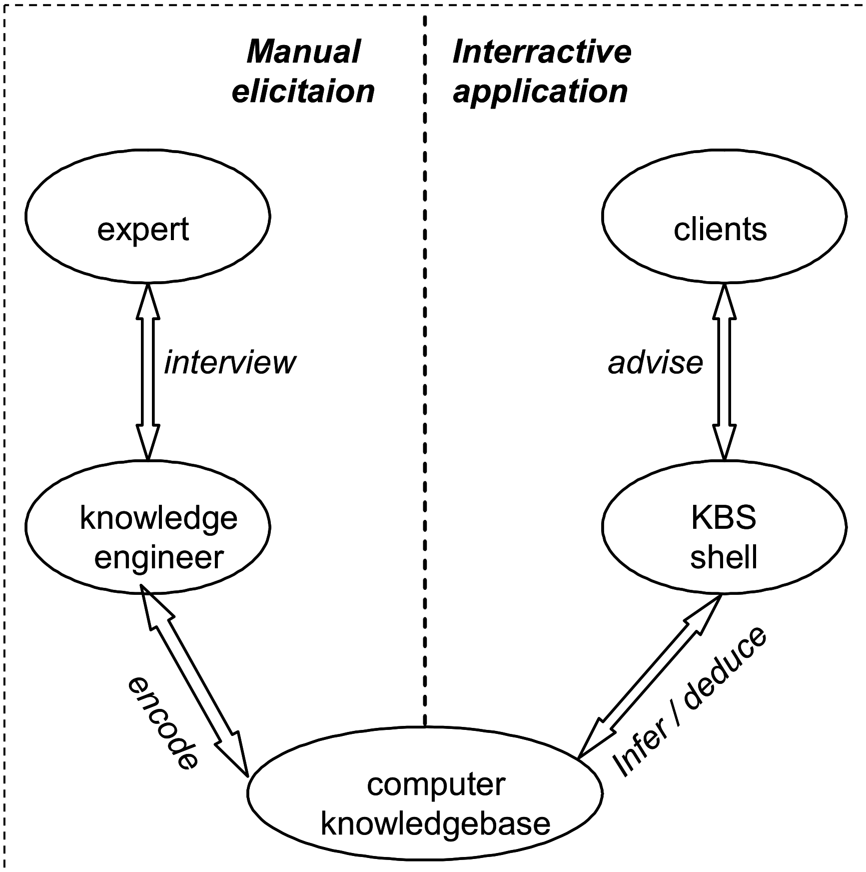

Figure 1: Basic knowledge engineering

To elicit knowledge consists of defining the main problem, including participants, characteristics, resources and goals.

All knowledge is not quickly accessible and knowledge as symbolic descriptions is especially very difficult to capture (Garavelli, Gorgoglione, & Scozzi, 2002). Furthermore, a clear distinction has to be made between explicit knowledge (that can be verbalized) and implicit knowledge (that is tacit). In fact, Nonaka (1994) and Nonaka and Takeuchi (1995) posit that the process of knowledge conversion (the dynamic interrelationship between tacit and explicit knowledge – Figure 2) lies at the heart of knowledge creation. Binotto, Hamer, Nakayama, and Silveira (2004) presented an analysis of this process in agricultural properties from the perspective of producers.

Research into knowledge management aims at capturing the tacit knowledge residing in heads of experts and making them explicit for general use. Tacit knowledge is essentially the driving force behind such innovations as new technologies, processes or techniques (Maqsood, Finegan, & Walker, 2004).

The creation of knowledge starts with an individual and spirals through successive conversion modes as shown in Figure 2. This essentially results in its amplification as large number of individuals, groups, and eventually the organization relate to the newly created knowledge (Vat, 2003).

Repetition of certain tasks over time usually results in the execution of such tasks without need for conscious thought. Also verbalizations may not be valid descriptions of real processes espe-

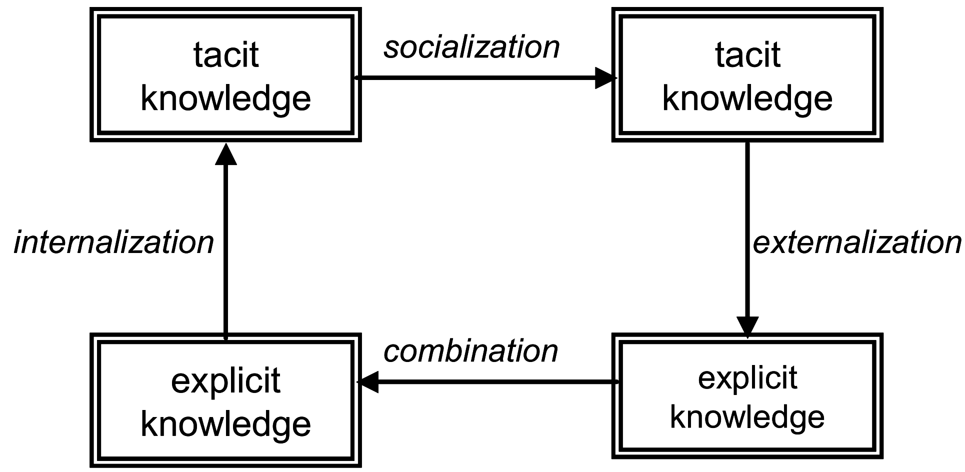

Figure 2: Two-by-two table with four modes

cially for those very difficult for an expert to verbalize. Interviews may also encourage experts to speculate about their cognitive processes. Again, a number of studies have shown that people can display consistent and accurate behaviour without being able to report verbally the concepts utilized. These points essentially constitute the knowledge elicitation bottleneck and must be kept in mind by the knowledge engineer when eliciting knowledge.

There are two broad classes of knowledge elicitation – *manual* and *automated* (or *machine learning*). This article initially considers start-up and in-elicitation issues for manual elicitation of implicit and explicit knowledge. This is followed by suggestions on determining suitable elicitation method(s) for different applications. Issues in automated elicitation as well as problems of knowledge analysis and transfer are also treated. The closing pages articulate measures aimed at reducing the knowledge elicitation bottleneck.

Manual Knowledge Elicitation

Start-up Problems

Nagao (1990) defines knowledge as understanding, awareness, or familiarity acquired through education, or experience, anything that has been learned, perceived, discovered, inferred or understood and the ability to use information.

Hence, the first problem a knowledge engineer faces is that of identifying the *most valuable knowledge*.

To overcome this, the engineer has to review the goals and purposes of embarking on knowledge elicitation. The question "*why do I need this knowledge*?" may lead to the review of the plans and strategies of the benefiting organization and a closer look at the target audience (or end-users) of the elicited knowledge. The elicitation process is then expected to converge on the knowledge that supports these objectives and strategies.

The next problem is to find where this expert knowledge is available and convenient to harvest. This question discards the easily found knowledge on textbooks, journals, reports, et cetera. It also strikes out the prohibitively expensive or clearly prohibited trade secrets of organizations. Nowadays, knowledge can be embodied, embrained, encoded, embedded, and/or encultured (Blackler, 1995). Hence the goal is to work out a means of getting the best of the defined knowledge at the least cost; and that is another bottleneck.

To successfully execute this requires experts that can willingly give relevant data, behaviors and rules that help to get good result; who can point out exceptions, preferences and reasons for each of these. One can identify these experts either through works they have authored or from managers and stakeholders of the organization, company expertise profiles like yellow pages, white pages and knowledge and skills databases. Hanes and Gross (2002) noted that the individual should posses the following qualities amongst others:

- Be recognized as being one of a few experts about something important
- Posses expertise in handling rare or infrequent events
- Should not be one that possesses expertise for system, etc about to be replaced with different technology involving different skills.

Another start-up problem is that of choosing competent elicitors. Good elicitors go for details and can critically focus, listen, reflect, filter and refine simultaneously. To choose those who can effectively work on a specific elicitation job demands knowing the experts involved. Some working knowledge about them on the following will be of immense assistance:

- Work profile, job description and other related information about current roles and responsibilities.
- Work experience (job type, geographies/cultures worked with)
- Education and training
- Relevant/essential work documents
- Contacts (phone no, location, e-mail, etc)
- Personal preferences (for setting timing, etc).

Is the expert willing to divulge his/her knowledge? There are a variety of reasons for experts to feel eager to share their knowledge:

- Realizing how important and invaluable his/her contributions are.
- Understanding that it is right to immortalize his/her expertise.
- Being aware of the financial and statutory payoff.
- Receiving assurances of minimum time usage in each elicitation session.

Also some experts are not willing to share their expertise due to a variety of reasons that include but are not limited to:

- Fear of lay-off or loss of status because of the perception that unique knowledge guarantees job protection while the opposite may increase vulnerability.
- Fear of losing relevance on surrendering expertise or knowledge.
- Expert may feel he/she has no valuable knowledge. Neve (2003) noted that a problem with tacit knowledge is that the individual is not fully aware of what he/she knows.
- Alienation against the organization due to perceived unfair treatment and/or lack of motivation.
- Where there is a feeling that the elicited knowledge will not be put to use, hence the entire process is a waste of the experts time.

- For an expert that is quite busy, current schedules may leave no time for elicitation sessions.

The essential and desirable features of a potential knowledge-based system application as proposed by Slagle and Wick (1988) are shown in Table 1.

Table 1: Essential and desirable features for a potential knowledgebase system application (Slagle & Wick, 1988)

ESSENTIAL FEATURES	DESIRABLE FEATURES
Recipients agree on high payoff	Management committed to follow on
Recipients have realistic expectations	Insertion into work place smooth
Project has management commitment	System interacts with user
Task is not natural language intensive	System can explain reasoning
Task is not knowledge intensive	System can intelligently question user
Test cases are available	Task identified as problem area
Incremental growth is possible	Solutions are expandable
Task requires no common sense	Task does not require real-time response
Task will be performed in the future	Similar expert system built before
Task does not require optimal solution	Task performed in hostile environment
Task not essential to deadline	Task involves subjective factors
Task easy but not too easy	Expert unavailable in future
An expert exists	Expert intellectually attached to project
Expert is a genuine expert	Expert does not feel threatened
Expert is committed to entire project	Expertise loosely organized
Expert is co-operative	
Expert is articulate	

Eliciting implicit (tacit) knowledge usually demands more work and must be handled diligently (Wilson & Holloway, 2000). First, one must determine whether the expert is articulate enough to express his knowledge as a clear set of modifiable facts, objects and rules, and give reasons for each decision. In line with the foregoing, elicitation techniques are either classified as *direct* or *indirect.*

- Direct methods involve questioning the domain expert directly. They are used for cases where the expert is articulate, willing and can express his knowledge. These direct methods include all forms of interviews, case studies, protocols, critiquing, simulation and prototyping, teach-back, observations, et cetera (Burge, 2001). Most often these methods elicit *procedural knowledge*.
- Indirect methods are more adapted to situations of *implicit knowledge*. These methods include role playing, construct elicitation, card sorting, 20 questions, and document analysis, et cetera (Burge, 2001). More often than not, we get classes, categories or hierarchies of knowledge from these.

In-Elicitation Problems

These are problems encountered during knowledge elicitation proper. Good elicitation seeks to identify:

- The expert's decision making strategies
- The consequences of such strategies
- Methods of improving on such strategies.

The problems usually vary depending on the technique(s) of elicitation chosen (Diaper, 1989; Hudlicka, 1997).

Problems of Eliciting Explicit Knowledge

Eliciting explicit knowledge entails extracting knowledge from an expert who can articulate his expertise and express or verbalize it. Here, the elicitor usually starts with an unstructured interview or protocol (thinking aloud) where the expert renders a lecture on what he knows while the elicitor listens, reflects, restates and refines/harmonizes the flow of knowledge. The possible scenarios are:

Expert presents unbalanced knowledge

Most experts, at the start, are usually tempted to present only procedure (steps) taken to achieve a task. This is only one of three aspects of a piece of knowledge. The other two are:

- Problem-solving strategies - how the expert makes each decision, that is, his/her considerations.
- Goals and sub goals - why a task is performed and the expected outcome. The elicitor uses his/her own discretion to ask '*how or why*' on any point that is unbalanced or not clarified. This probing must be done carefully to avoid interruptions when a point is being made. Using *interrupt analysis*, only one elicitor interrupts at a time while others carefully monitor and analyze the interruption.

Expert presents scanty knowledge

Every expert is usually busy but some will rather not tell. This becomes apparent from their being brief and never detailed unless on deep enquiry. For this type of expert, a good approach will be not to demand details at the first contact sessions. Instead, those topics, points and concepts raised should just be recorded and other follow-up sessions scheduled. These sessions will then provide ample opportunities for detailing using "structured interviews" like problem discussion, semantic nets, cognitive structure analysis, et cetera.

No insight into what informed a decision

A teach-back or any prototyping session provides an opportunity for the elicitor to teach-back all that has been grasped to the expert so as to correct misconceptions and misrepresentations. Prototyping also entails designing a prototype of the envisaged system, explaining the system design to the expert; while he criticizes and corrects how it works and certain orders adopted.

Several experts, many conflicts

Having all the experts work at each stage of the elicitation would most likely introduce conflict of ideas and options. Eliciting knowledge fully from one and refining with the others via say critiquing, system validation, prototyping generally provides solution to this. In critiquing, one meticulously compares and contrasts problem-solving strategies with alternatives; while prototyping presents a model of the actual system either for the expert to criticize or for other experts to appraise.

Problems of Eliciting Implicit Knowledge

This poses more challenges to the knowledge engineer both in the preparation for and the actual elicitation of the expert knowledge. Elicitors usually start by making informal visits to build trust and rapport with the expert or contributor. To do this effectively one must posses a pleasant character, be time conscious, allow the expert to lead conversations and be informal enough. Wilson and Holloway (2000) raised the following issues underlying implicit knowledge elicitation:

Expert is nervous or intolerant

This usually happens where the expert feels handicapped or insecure in giving the knowledge. Constantly reassuring the expert of how safe and secure the exercise is to his/her job and future may resolve this. Also, there is need to make the environment and setting of the session conducive for the expert. Highly *visual experts* should be provided with necessary tools while the highly *kinesthetic* should be provided with the actual work environment for physical demonstrations.

Expert does not understand questions

This usually infers a language and/or expression mismatch. Background reading on both the domain area and the expert is usually helpful. This tends to provide not only updates on the vocabulary of both but also on the mental model of the expert too. It may also be necessary to prepare a handy list of technical questions that would break into the needed nuggets of knowledge hidden in the expert.

Most elicited knowledge is irrelevant

This usually results when the expert is not constantly reminded of the scope of knowledge needed with respect to the target audience or end-users. Video and audio recording of sessions (with the expert's consent) ensures that all responses are fully captured for future analysis.

Expert knowledge about uncertainties

Some expert knowledge could have some degree of truthfulness and validity as well as some degree of falsity and invalidity. Expert systems that handle uncertain information all have some kind of probability-like measure to weigh and balance conflicting evidence. Two methods can be applied to elicit probabilities from experts. In the *direct method*, the expert states the possibility of an event occurring or not using '1' or '0' respectively. The assessment may also be expressed in odds. For example, odds of 8 to 3 for an event occurring implies a probability of 0.73 that the event will happen and 0.27 that it will not.

The *indirect method* is about indifference bet method allowing the extraction of subjective probability without the expert explicitly stating his/her degree of belief. An example is to create two wagers for the expert and ask for his preference of any. The other wager is then increased to a point that an expert has equal preference for both. The subjective probabilities in both cases are the same.

Mental processes that construct and shape knowledge are mostly complex and not easily communicated or made explicit. Hence, the quality of tacit knowledge elicited is usually influenced by certain factors including perception and recognition, cognitive styles, heuristics and biases in judgment, functional fixedness and mental set, mental models, et cetera (Maqsood et al., 2004).

Elicitors should also strive to capture tacit knowledge without bias. Instead, the context in which knowledge is constructed must be extracted in order to ensure its effectiveness when shared.

Which Elicitation Method?

The suitability of any method depends on the kind of information being elicited. Interviews are most suitable for gaining an overview or scope of an experts knowledge. Protocol analysis may then follow when trying to get more valid knowledge not available from probing questions. *Concurrent protocols* should be used for knowledge that can be verbalized while *retrospective protocols* are better used for information that is tacit.

Multidimensional scaling techniques elicit experience and relationship between objects from the view of an expert. Hence, they are more suitable for eliciting perceptions that are not accessible with protocol-based methods. Also, protocol and interview methods are both dependent on natural language used which may be ambiguous and open to many interpretations.

In elicitation about uncertainty, a method of accessing subjective probability that is more reliable could be applied at different times given that assessor's knowledge of the event is unchanged. A comparison of the results should produce a high degree of agreement. FORECAST, an automated elicitation tool applies this scheme and checks for consistencies between direct and indirect methods of assessments. The result is fed back to the expert for resolution. The system then checks for coherence in probability using probability laws.

Automated Knowledge Elicitation (Machine Learning)

Automated knowledge elicitation handles elicitation, analysis and transfer of knowledge almost simultaneously. The emphasis is on the development of knowledgebase systems that give straight set of rules from examples or samples of knowledge acquired interactively from the domain expert. This saves money, time and energy for the knowledge engineer.

Rule Induction

Interactive knowledge acquisition and encoding tools can greatly reduce the need for the knowledge engineer to act as an intermediary. But in most applications, they leave a substantial number of roles for the knowledge engineer as shown in Figure 3 (Gaines & Shaw, 1995).

Interactive elicitation can be combined with manual elicitation so that with available interactive tools, the knowledge engineer proceeds more efficiently and effectively with the experts. These roles however tend to pose some problems:

Inadequate initial dataset

In many cases of automated knowledge elicitation, the problem of insufficient prior dataset with which to build the knowledge base shell arises. So, in addition to data from textbook, reports, et cetera, the knowledge engineer still needs to manually elicit certain first-hand expert knowledge essential for modeling the shell. The shell contains classes, objects and pattern-matching rules used to weigh and elicit further rules.

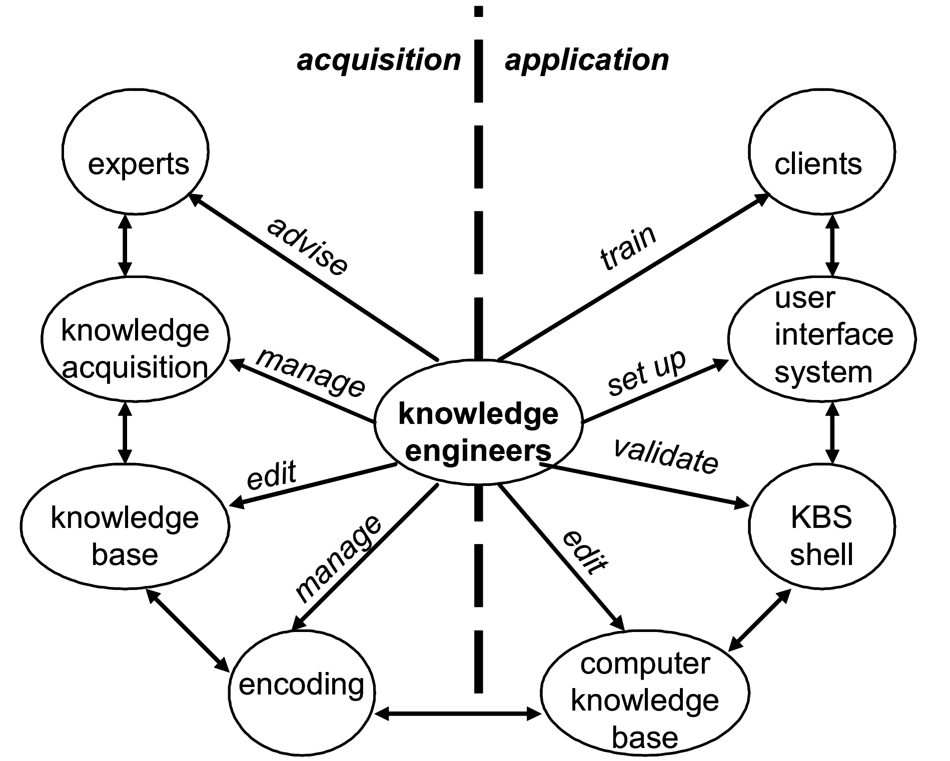

Figure 3: Knowledge engineering with interactive tools

Large and complex dataset

Proper abstractions at most worthy and needed facts are essential in modeling this situation. Also proper skills in software engineering that would minimize redundant questions go a long way to reduce size and complexity of the rule sets generated from it.

Noise or error-infested data

Decision tree techniques such as ID3 (Quinlan, 1987) may be used to analyze data which is subsequently converted to a set of rules by tracing the paths to each decision. However, Cendrowska (1987) proposed the *PRISM* algorithm which generates rules directly without going through decision trees and also removes redundancies. Generally ID3 copes better with noisy data while PRISM is best suited for error-free data. Other techniques like INDUCT (Gaines, 1989) generate rule sets directly as well as filter them statistically to cope with error-infested data.

Uncertainties and spurious correlations

These are encountered when experts enter incorrect, incomplete or low-precision answers to some of the inquiries of an automated knowledge elicitation tool. The resultant spurious correlations would appear alright, but show illogical sequences of reasoning on closer examination. A good solution is to educate and enlighten the experts on the best uses of the auto-elicitation tool and environment.

Training an expert to effectively use a computerized or automated elicitation tool could pose a bottleneck of its own. Depending on the approach, it could get as tedious as manual elicitation – *time and energy consuming*.

But in all cases, the knowledge engineer starts by getting enough background on the expert's domain so as to guide entries as well as correct errors in the knowledge base built.

The expert can also learn these skills of expertise transfer by trial and error, which is supported only by well-programmed elicitation environments - friendly enough to guide the learning.

Genetic Algorithms and Neural Networks

Most times the IF-THEN rules of auto-induction method is grossly inadequate to define and handle the particularities and peculiarities of certain data. Good solution to this is a pattern-matching cum weight-matching technology called *neural network* – an attempt to model the neurons (processing elements) in human brain. It is well suited for:

- Uncertainties (incomplete, partially correct, conflicting data)
- Spontaneous generalization and analogical reasoning
- Simultaneous consideration of competing hypothesis about solutions to problems and matching patterns
- Display of best-match facilities
- Fuzzy classification
- Self-training and improvement
- Large and complex data sets

Genetic algorithms on the other hand are methods developed to search parameter spaces and to optimize a set of parameters for a given function. It encodes parameters into binary strings, and then combines them with other binary strings to create better "guesses" to the solution. It more or less mimics biological genetic inheritance. The example of Figure 4 is a simple demonstration that uses sixteen binary digits.

1. Encode the two numbers into binary strings.
   Parent 1 = 3.273672 => 11.0100011000001
   Parent 2 = 3.173294 => 11.0010110001011
2. Randomly choose a crossover point, and split the "genes" at that point. This particular example splits the gene at bit six
   Parent 1 = 3.273672 => 11.010 ----0011000001
   Parent 2 = 3.173294 => 11.001 ----0110001011
3. Swap the two tail ends of the binary strings – ten bits in this example
   Child 1 => 11.010---0110001011
   Child 2 => 11.001---0011000001
4. Recombine the two strings to get two new "children".
   Child 1 => 11.0100110001011
   Child 2 => 11.0010011000001
5. Decode the two binary strings back into floating point numbers.
   Child 1 = 3.298218
   Child 2 = 3.148560

Figure 4: Simple demonstration of genetic algorithm

The resulting guesses are close to, but not exact replicas of the two parents. Note that in this case, the first three bits remain unchanged (11.0) no matter what, so that the offspring of these two parents would have to be between 3.0 and 3.5. In this way, good 'genes' are passed down from generation to generation, while bad 'genes' are bred out of the population because the parents with the bad 'genes' are not often given the chance to breed.

Genetic algorithms are used to program neural nets as each can handle the other's randomness of approach to both learning and solving expert problems. So in these two there is provision for the weighing of incoming signals at the input neurons (processing elements) level and matching them with built-in perfect models. Then, the decoded match/decision is output via the output level neurons.

Knowledge Analysis and Transfer Problems

Problems do arise from the analysis and transfer of elicited knowledge to a knowledge-based system. Before the transfer, elicited knowledge has to be modeled according to a suitable pattern of reasoning.

Improving on Expert Judgment

Expert judgment can be improved on by statistical modeling. This is needed to adapt the evolving expert system to solve a greater range of problems in its domain. Experts are usually skilled in knowing 'what to look for" and not in the ability to integrate information. Improving expert judgment focuses on this aspect. Linear modeling serves only in repetitive situations where the set of cue variables are constant from one diagnosis to another. Thus linear models are valid but limited in application as a replacement for expert judgment. Standard regression analysis, black boarding (Burge, 2001) are some of the techniques used to model a knowledge base in order to improve on expert judgment.

Modeling Uncertainties

This is another terminal problem of knowledge elicitation. Fuzzy logic provides good and modern solution to reasoning with uncertainty. Neural Nets also work when modeled using fuzzy logic, decision trees; and to a less extent flowcharts and state diagrams.

Structuring the Knowledgebase

This problem opens up a vast new world called *structural informatics*. Simultaneously, this field addresses such problems as accommodating the large volume of knowledge involved, indexing them rapidly and how to acquire all new knowledge efficiently. The focus is on:

- Representational and inferential adequacies
- Inferential and acquisitional efficiencies

Employing the most suitable "search strategies" is a positive step towards solving this impediment.

Owoc (2003) treated current research directions, managerial context and development determinants for knowledgebases.

No Rare Cases Covered

It is very usual to encounter only common and usual situations during elicitation. The rare cases usually pop up during refining or use of the resultant expert system. This is remedied through system validation before use. It may be necessary to mention here that handcrafting as an elicitation mode is almost outdated and rarely used today except in complimentary scales to automated elicitation. Many automated modes are available now and include rule induction, genetic algorithm, neural networks, mixed modes and chaos theory.

Reducing Knowledge Elicitation Bottleneck – The Future

McGraw and Harbisson-Briggs (1989) traced the impediments to effective knowledge acquisition to lack of management and organization, incompletely trained knowledge engineers and translating knowledge from source to code.

Some of the measures that promise to reduce the elicitation bottleneck are:

- Adequate training of knowledge engineers in relevant psychological techniques. Most knowledge engineers are computer-oriented people.
- Improvements in the field of knowledge engineering automation. The emphasis is on the development of 'smart' machines that give straight set of rules from examples or samples. Such samples could even be visual definitions of certain features in graphical form, which is more concrete and less subject to misinterpretation (Crowther & Hartnett, 1997). KAGES (Knowledge Acquisition for Geographic Expert Systems) is a toolkit which provides a series of knowledge acquisition techniques including interview manager, several graphics acquisition tools and a rule editor.

Full automation of knowledge engineering is still being pursued, given the underlying issues and difficulties in knowledge elicitation.

Currently, the trend is to enrich knowledge acquisition and creation, a scheme that requires more sophisticated ontology to underline the process (Davey & Tatnall, 2004).

Conclusion

The above discourse has exposed the different problems of both manual and automated knowledge elicitations. But in today's functional expert systems, there is usually a tactical application of several methods and tools to elicit, analyse, model and properly transfer expert knowledge to a knowledgebase system. This guarantees that it effectively replaces a human expert in the specified domain of expertise. Manual elicitation is employed to obtain prior knowledge needed to model the expert system shell and train the system to acceptable functionality; while automated tools, in turn, save the knowledge engineer the strenuous ordeals of eliciting implicit expert knowledge. Knowledge elicitation bottlenecks are real. This presentation gives it a face instead of leaving it as intrinsic parts of discourses on knowledge elicitation techniques.

Outside these technical problems of knowledge elicitation there are other inhibitions peculiar to third world countries:

- Poor capital base minimizes production, and essentially makes expert systems and consequently knowledge elicitation needless.
- Low government involvement in and encouragement to technological development is also quite apparent.
- Poverty and fear of losing one's job may hinder an expert from divulging his wealth of knowledge. The cause may be due to some psychological enslavement to the job.
- Very poor and underdeveloped record keeping culture in third world countries is arguably one of the greatest hindrances to knowledge elicitation.

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Biographies

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