Expert Systems as a tool for Knowledge Representation in teaching & learning Process

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Abstract :

In the last years, Intelligent Tutoring Systems have been a very successful way for improving teaching & learning experience. Many issues must be addressed until this technology can be defined mature. One of the main problems within the Intelligent Tutoring Systems is the process of contents authoring: knowledge acquisition and manipulation processes are difficult tasks because they require a specialized skills on computer programming and knowledge engineering.

In this research we discuss a general framework for knowledge management in an Intelligent Tutoring System and propose a mechanism based on first order data mining to partially automate the process of knowledge acquisition that have to be used in the ITS during the tutoring process. Such a mechanism can be applied in Constraint Based Tutor and in the Pseudo-Cognitive Tutor.

We design and implement a part of the proposed architecture, mainly the module of knowledge acquisition from examples based on first order data mining. We then show that the some topics of intelligence tutoring system. Finally, we discuss the limitation of current approach and the possible improvements of the whole framework for Expert tutoring Programs in teaching & learning process.

1. Concept of Expert System:

An expert system is a computer system that emulates the decision-making ability of a human expert, i.e. it acts in all respects as its human counterpart .

The term expert may be misleading. In the early days expert systems only contained expert knowledge . Presently however, any system using expert system technology (even if not containing highly specialized expertise in a certain domain) is called an expert system. Therefore, the term knowledge-based system is more appropriate, although most people use the term expert system because it is shorter.

Expert systems have emerged from early work in problem solving, mainly because of the importance of domain-specific knowledge. A human expert's knowledge is specific to a problem domain . In much the same way, expert systems are designed to address a specific domain, called the knowledge domain.

showS the concept of a knowledge-based expert system. The expert system receives facts from the user and provides expertise in return. The main components of the expert system (invisible from the outside) are the knowledge base and the inference engine . The inference engine may infer conclusions (solutions) from the knowledge base, based on the 'facts' supplied by the user. The following Fig (1) represents that [1]:

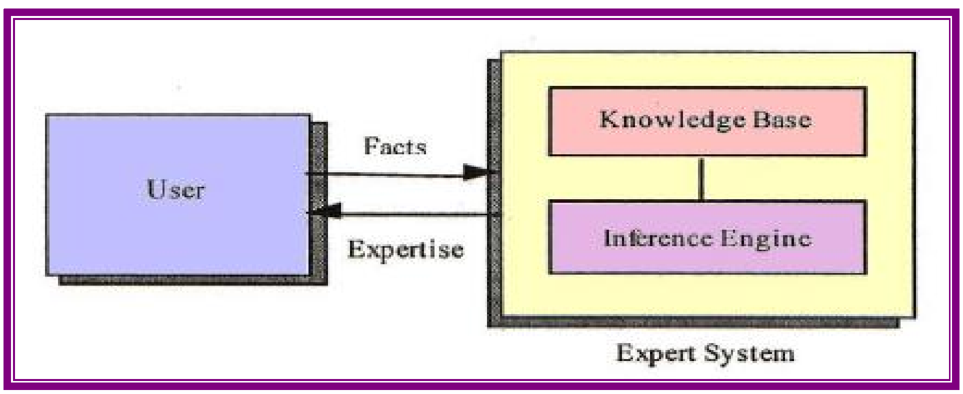

Figure 1. Represent of basic concept of an expert system

Resource (1)

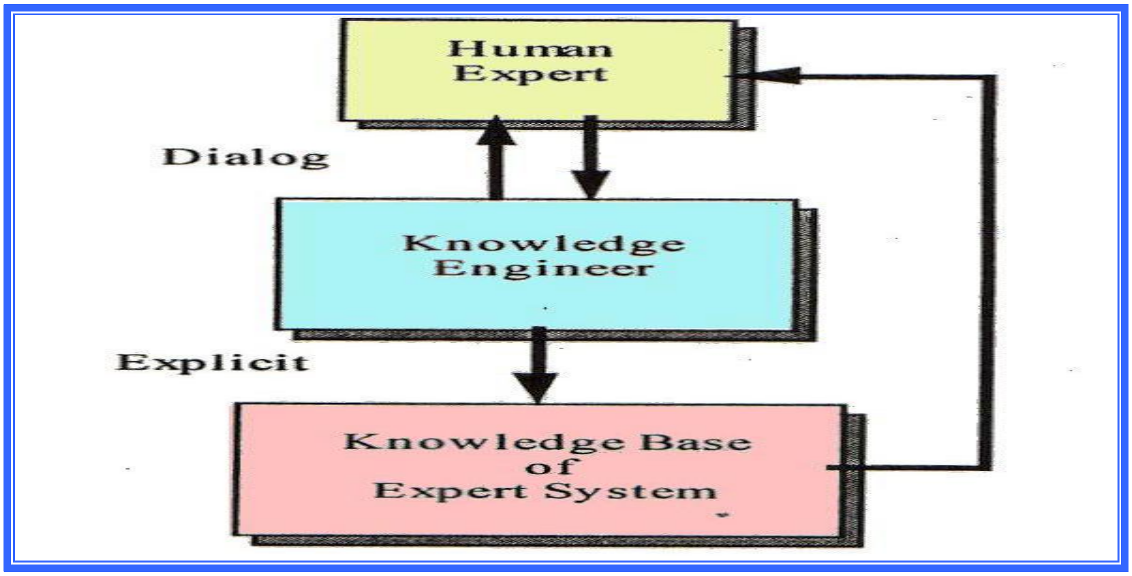

Figure 2. Basic Factors of an expert system

Resource (1)

2. General concepts.

A. Rule-based expert systems.

Knowledge representation in expert systems may be *rule-based* or encapsulated in *objects*. The rule-based approach uses IF-THEN type *rules* and it is the method currently used in constructing expert systems. IF-THEN rules take the following form:

IF there is a flame THEN there is a fire.

The modern rule-based expert systems are based on the *Newel and Simon* model of human problem solving in terms of long-term memory (rules), short-term memory (working memory) and cognitive processor (inference engine).

Elaborate expert systems may be based on thousands of rules (e.g. XCON/R1 system from Digital Equipment Corporation, used for configuring computers) and surpass a human expert in a particular field. However, even smaller sized

expert systems, based on several hundred rules may be extremely efficient in very specialized areas.

While a knowledge-based system may rely on knowledge commonly available, a true 'expert' system will be based on unwritten expertise, acquired from a human expert.

In the conditions where no algorithm is available to solve a particular problem, a *reasonable* solution is the best we can expect from an expert (system or human). The expert system will *infer* a solution from the facts provided by the user and the rules in the knowledge base. Therefore, it should be able to *explain* the reasoning employed to achieve the solution. The *explanation facility* is an important feature of the rule based expert systems, since it provides a mechanism for a human to follow and check the correctness of the solution achieved by the expert system. A further enhancement to this facility is the availability of *what-if* scenarios (employing *hypothetical reasoning* questions), where the user may examine the outcomes of several possible situations[2].

B. Development of an expert system.

The process of building an expert system is commonly known as *knowledge engineering*. This implies knowledge acquisition from a human or other source and coding it into the knowledge base of the expert system (refer Fig. 3).

The main phases in the knowledge engineering process are[1]:

. The *dialog* process represented in Fig. 3 is similar to the task of a system designer discussing the requirements of the program with the client, in conventional programming. After acquiring knowledge from the human expert, the knowledge engineer has to *explicitly* code it into the expert system knowledge base.

. After the coding stage, the human expert evaluates the expert system and gives feedback/critique to the knowledge engineer.

. The knowledge engineer alters the knowledge base in order to reflect the human expert's comments.

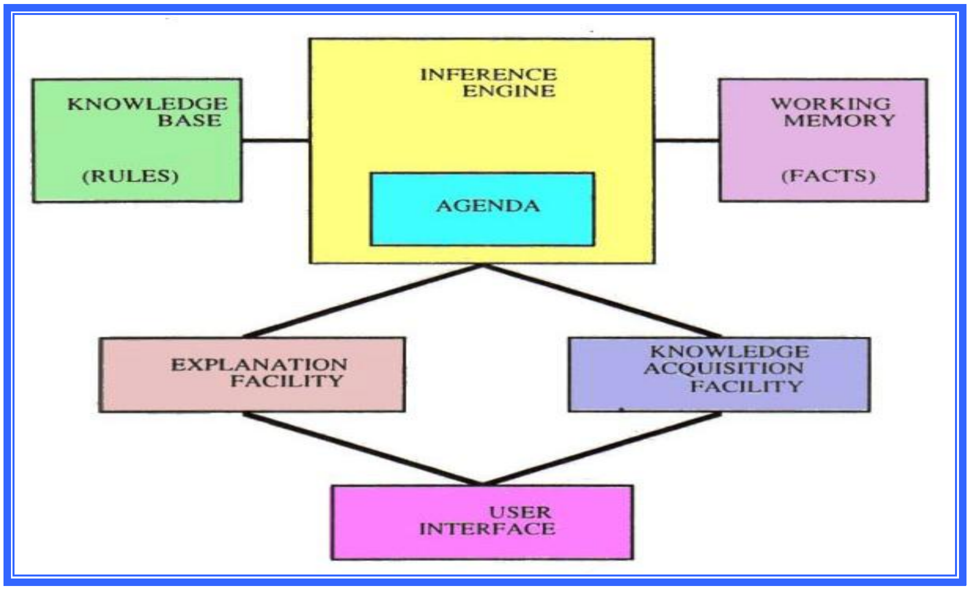

Figure 3. Structure of a Rule based expert system

Resource (1)

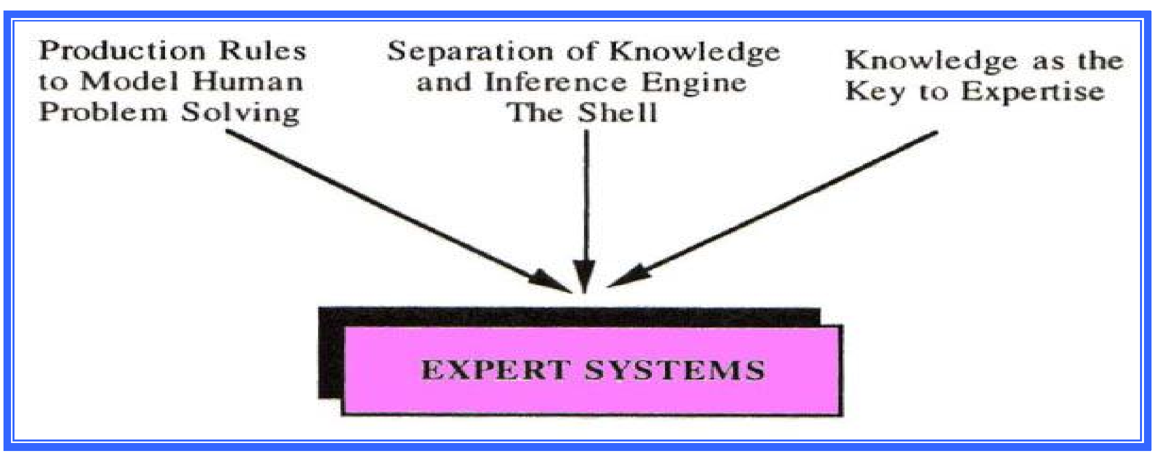

Figure 4. Creation of the modern rule-based expert system

Resource (1)

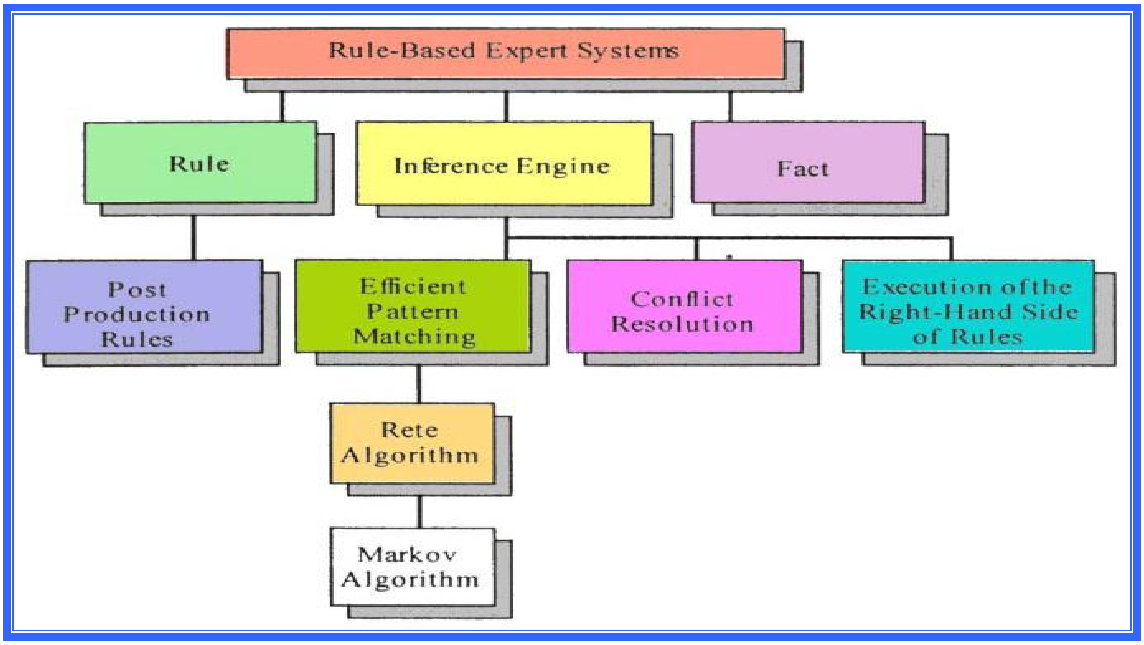

Figure 5. The foundation of the rule based expert systems

Resource (1)

3.Concept of Intelligence tutoring systems

Early systems that were developed for teaching purpose were known variously as Computer Aided Instruction or Computer Aided Learning systems. These traditional systems were developed to provide users with knowledge in a particular area and then assess the user retained knowledge by posing questions, usually multiple choice, to direct the course of study. The structure of such a system is shown in figure. 6 [3].

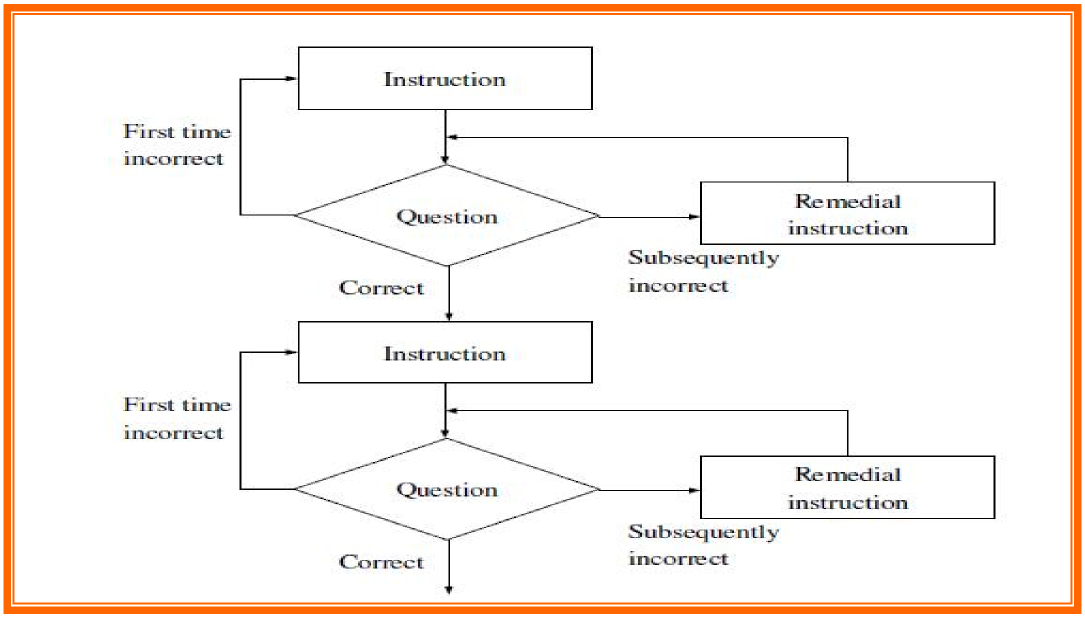

Figure 6: Routing within a Computer Aided Instruction System

Resource (3)

Examinees are presented with information after which a series of question are asked. If the user answers correctly the next phase of instruction is entered. There may be a summary set of questions at the end of the instruction to gauge how well the student has performed.

If an examinee answers the questions incorrectly the instructional material is presented again, perhaps in a slightly different format. If, after the material has been repeated, the examinee again answers incorrectly then remedial instruction may be presented. In this kind of systems, the instruction was not individualized to the learner's needs. In general the decisions about how to move a student through the material were script-like, such as "if question 21 is answered correctly, proceed to material 54; otherwise go to material 33". Such systems can appear to imitate intelligence by being able to adapt to student misconceptions [4].

However, this appearance is a result of the system designer anticipating all possible errors that the student may make. These are built into the system at design time and encoded within the branching structure. If the designer of the system has not anticipated an incorrect interpretation of the instructional material then the system will not be able to provide feedback to help the examinee resolve the misunderstanding.

These systems are incapable of dynamically generating a response to a particular situation as a human tutor would be able to do. So, while CAI may be somewhat effective in helping learners, they do not provide the same kind of individualized attention that a student would receive from a human tutor. For a computer based educational system to provide such attention, it must implement more advanced algorithms to parse the knowledge domain and related learner feedback. During last few years there have been many systems developed for this purpose each having its own characteristics. Until now the majority of such ITSs are specialized in a specific knowledge domain. In literature we can find many examples of specialized ITS operating in various

knowledge domain.

4. Intelligent Tutoring Systems: overview

Recognizing the deficiencies of traditional Computer Aided Instruction systems Intelligent Tutoring Systems were subsequently developed which attempted to adapt the speed and level of presentation to that required by a student. Typically this kind of systems can be seen as a number of independent components which can communicate between them [5]:

⇒ **the student module forms a framework for identifying a student's current state of understanding of the subject domain. The knowledge that describes the student's current state of mind is stored in a student model. In order to make any learning environment adaptable to individual learners, it is essential to implement a student model within the system. The student module should permit the system to store relevant knowledge about the student and to use this stored knowledge to adapt the instructional content of the system to the student's needs;**

⇒ **the pedagogical module contains the knowledge of how to teach, that is, a teaching or tutoring strategy. It orchestrates the whole tutoring process and deals with issues like which topic to present, when to present a new topic, when to present a problem, when to review, and when to offer remedial help;**

⇒ **the domain knowledge module contains the knowledge of what to teach. It represents an area of syllabus and usually requires knowledge engineering in its construction. Domain knowledge is usually represented as skills, concepts, procedures and problems of the subject domain under study;**

⇒ **the expert model is strictly related to domain knowledge. The expert model uses the domain knowledge to advise other parts of the system. It may indicate the relative difficulty of curriculum sections or problems, such that the pedagogical module can select the next task. Furthermore, this module aims to provide expert like solutions to problems in the domain to be taught;**

⇒ **the communication module controls interactions with the learner, including the dialogue and the screen layouts. The interaction scheme between the five modules is shown in figure .7 Knowledge representation and tutoring methodologies are areas suitable for the application of intelligence [6].**

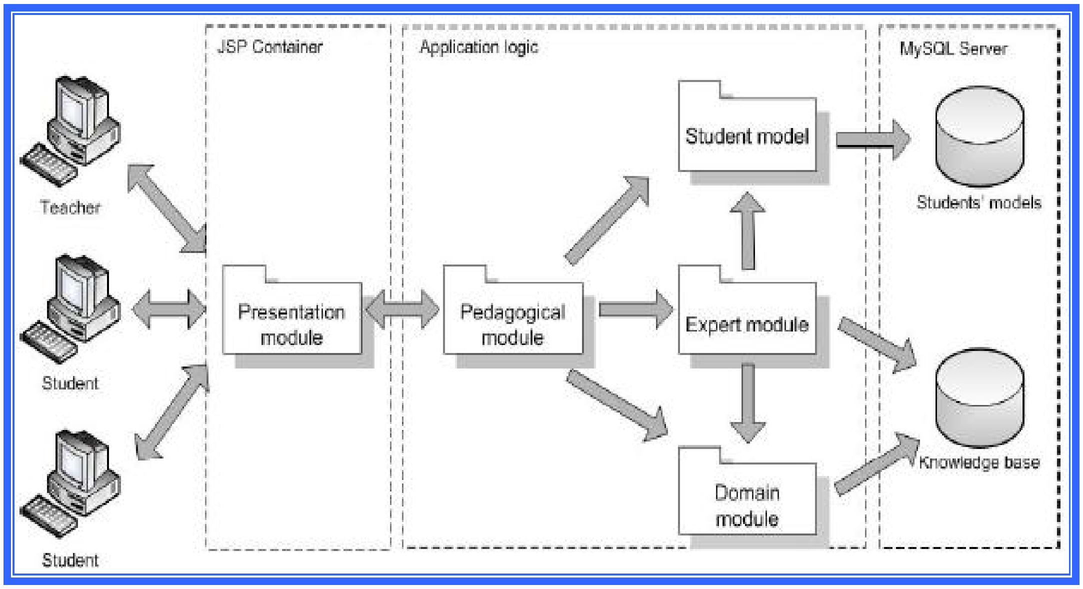

Figure 7: Interaction of components in an Intelligent Tutoring System

Resource(6)

5.Knowledge Representation in Expert Systems.

This research will try to present the meaning of knowledge and some commonly used representations of knowledge for expert systems [7].

What *is* knowledge ?

Knowledge is a very hard to define term and it has many meanings. *Data*, *facts*, *information* are terms also being used with the meaning of knowledge. The study of knowledge is *epistemology*. It contains:

- **philosophic theories (Aristotle, Plato, Descartes, Kant, etc)**
- ***a priori* knowledge (considered to be universally true);**
- ***A posteriori* knowledge (derived from the senses).**

Knowledge may be classified in:

• Procedural knowledge (*know-how)*;

• Declarative knowledge (declarative statements);

• Tacit knowledge (*unconscious knowledge*) - cannot be expressed by language. A good example is *how to contract a muscle*. Knowledge is of central importance to expert systems.

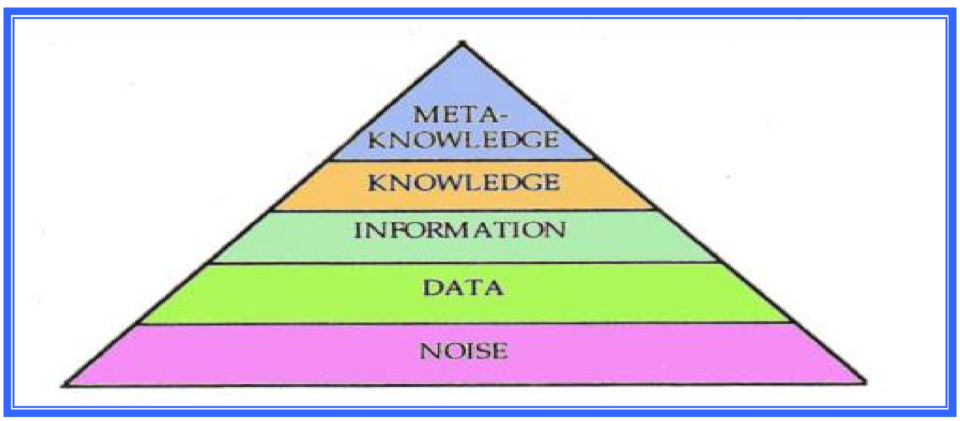

Figure .8: The hierarchy of knowledge

Resource(7)

Figure. 8. Shows a possible hierarchy of knowledge. The of this structure foundation is *noise*, meaning items of little interest and obscure data. Items of potential interest make up the next level, the *data*. Processed data represents *information*, and sits on top of the *data*. The knowledge layer, consisting of specialized information, is next. The last and most interesting layer is the *meta-knowledge*, (*Meta* meaning *above*).Meta knowledge is knowledge about knowledge.

For example in an expert system with knowledge in several domains, the meta-knowledge would specify which knowledge is applicable for a particular domain. Within a particular domain, meta-knowledge may be used to determine which set of rules is applicable for a specific problem. The hierarchy of knowledge. The Evolution of Expert Systems Knowledge Representation in Expert Systems [8] .

6.Knowledge representation techniques.

1.6 Productions.

Production rules are commonly used in the knowledge bases of expert systems. A formal notation for defining productions is the Backus-Naur form(BNF).BNF represents *Meta language* for defining the *syntax* of a language. While syntax defines the form, the *semantics* refers to the meaning of the language. A grammar is a complete set of production rules that uniquely defines a language. There is a wide variety of languages that BNF can define, such as natural, logic, mathematical, computer [9].

2.6 Semantic Nets.

Semantic network (nets) is also known as *propositional* nets. A proposition is a statement that can either be true or false, and is a form of *declarative* knowledge (they state facts).

The structure of a semantic net may be shown graphically in terms of nodes (*objects*) and arcs (*links* or *edges*) connecting them. Nodes represent objects, concepts or situations. The links show the relationships between nodes .If the links are directed arrows, then the net becomes a *directed graph* (refer

Relationships give the knowledge contained in the nodes a cohesive structure about which other knowledge may be inferred

3.6 Semantic net problems.

Unfortunately, semantic nets have some limitations in representing knowledge[10]:

• Lack of link name standards and naming rules for the nodes. Only if the link and nodes are unambiguously defined may the semantic net represent *definitive* knowledge (knowledge that can be defined).

• Semantic nets cannot define knowledge in a similar way to logic;

• Heuristics (rules of thumb) on how to efficiently search the net *cannot* be embedded in a semantic net. Heuristics play a *major* role in expert systems.

The Evolution of Expert Systems Knowledge Representation in Expert Systems , although a number of approaches have been tried to correct the above-mentioned problems, little improvement has been achieved at the expense of the natural expressiveness of the semantic nets.

4.6 Schemata.

All the knowledge in a semantic net is contained in the links and nodes. Therefore, a semantic net is an example of *shallow knowledge structure* . In contrast, a *deep* knowledge structure may explain why something occurs via *causal* knowledge. In a human expert's case, deep knowledge is usually called upon when causal knowledge fails to solve the problem [11].

Schemas are used to represent more complex knowledge structures. Conceptual schemas are *abstractions* in which specific objects are classified by their general properties. Schemas are used to focus on the *general* properties of an object without being distracted by irrelevant details. Schemas have an internal structure to their nodes, in contrast with the semantic nets. A semantic net is like a data structure in computer science. The schema is more like a data structure in which nodes contain records that can further contain records, data or pointers to other nodes.

5.6 Frames.

Two types of schemas have been used in many AI applications: the *frame* and the *script* (a time-ordered sequence of frames) Frames are very suitable for representing objects typical to a particular situation (stereotypes) .

7.Commonsense

Knowledge is very difficult to master by the computers, and frames can be of great help. While semantic nets are used to represent broad knowledge, frames are efficient at representing a narrow subject containing much *default* knowledge. Special purpose language have been designed for frames, such as FRL, SRL, KRL, etc [2]

An analogy can be made between a frame and a *record* in Pascal or an *atom* in LISP.

The correspondent frame elements to the fields and values of the record are the *slots* and slot *fillers* of a frame. The fillers may be values (e.g. a property) or a *range* of values (a *type* slot). Slots may contain attached procedures which can be *if-needed* (when a filler value is needed but none present), *default* (expectations of a situation), or *if-added* (when a value is added to a slot).

Sophisticated frame systems have been used in discovering mathematical concepts and describing mathematical understanding in linear algebra.

Frame systems that allow unrestricted alteration or cancellation of slots may however display major problems. Most frame systems do not provide a way to define unchangeable slots. This leads to a system where nothing is really certain and no universal statements can be made. Building composite elements from simpler frames is also restricted.

5. Logic and Sets

Knowledge may also be represented by symbols of *logic* (the study of exact reasoning). Logic is extremely important in expert systems, as the inference engine reasons from facts to conclusions. The term of *automated reasoning systems* would include both logic programming and expert systems. Two common formal logic methods of representing knowledge are:

The Evolution of Expert Systems Knowledge Representation in Expert Systems

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Syllogisms . Invented by Aristotle in the fourth century B.C., they have two *premises* and one

8. Student knowledge and skills Acquisition Process in Tex-SYS

TEx-Sys is structured according to the cybernetic model of systems, hence interpreting the education process as a feedback system [12]. Within the model student knowledge and skills acquisition is a guided process, with a referent value defined through goals and tasks pertaining to subject matter to be learned. We define the model of a "good student" which is based on certain. Evaluation criteria according to a specified student knowledge level [13].

The control function in TEx-Sys is based on:

1) measurement and diagnostics of student knowledge,
2) determination of differences between actual student knowledge and the referent model one, and ,
3) Evaluation of student knowledge with recommendations for future work.

TEx-Sys is structured

- *Login*: legalization of work on the system;
- *T-Expert*: building the base of freely chosen domain knowledge (for teachers, and in particular cases for students, too);
- *Learning and Teaching* of freely chosen domain knowledge (for students);
- *Exploring*: access to knowledge in the knowledge base; effectively this is a subsystem with a limited set of predefined sentences (nine questions and two

  Statements) which the user is not allowed to freely form ; there also exists a dictionary containing object names and properties as well as object attribute

  Names and values;

- ***Examination***: evaluation of a student's knowledge within a teaching scenario, according to Piaget's theory of "guided free play" [14]and combinations of scenarios of teaching by "articulated experts" and "dialogues of divided initiatives" [15];
- ***Evaluation***: access to the achieved results of learning and teaching (for teachers);
- ***Courseware***: installation of lessons or even complete curricula of a subject matter (for students).into the following modules, see Fig.9:

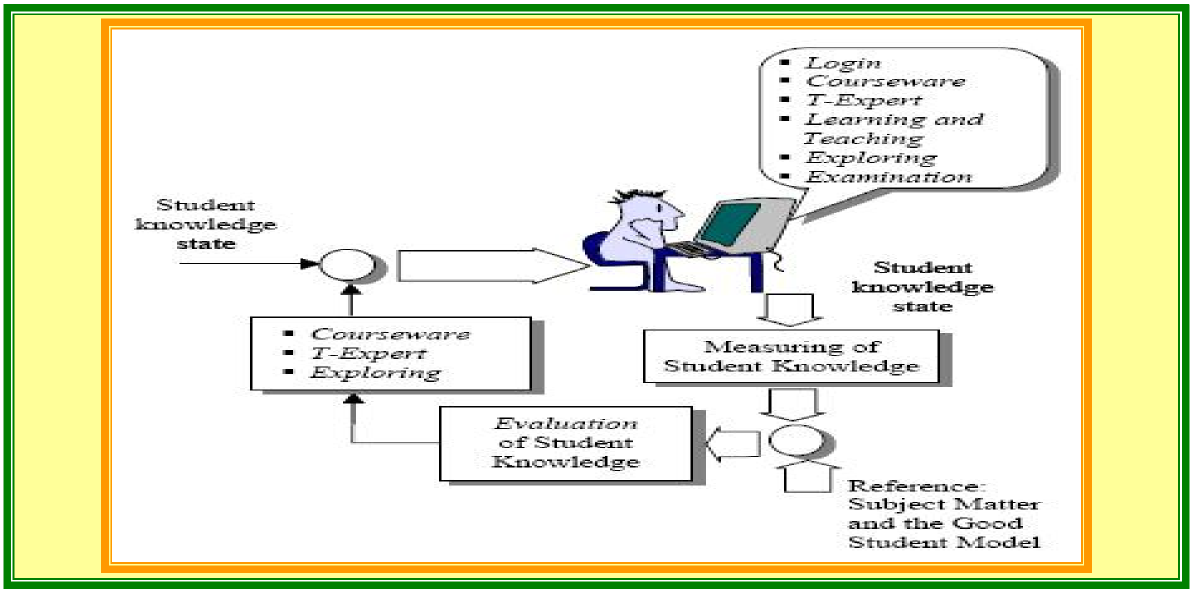

Figure9:Interaction of TEx-Sys module in student knowledge and skills acquisition process

Resource(13)

9. Samples of Knowledge Representation in TEX-SYS

Within TEx-Sys knowledge is represented by semantic networks with frames (specifically in T-Expert, as well as in knowledge learning and teaching, exploring, examining and courseware modules) and production rules (in the examining module). The basic components of TEx-Sys semantic networks are nodes and links (see Fig. 10).

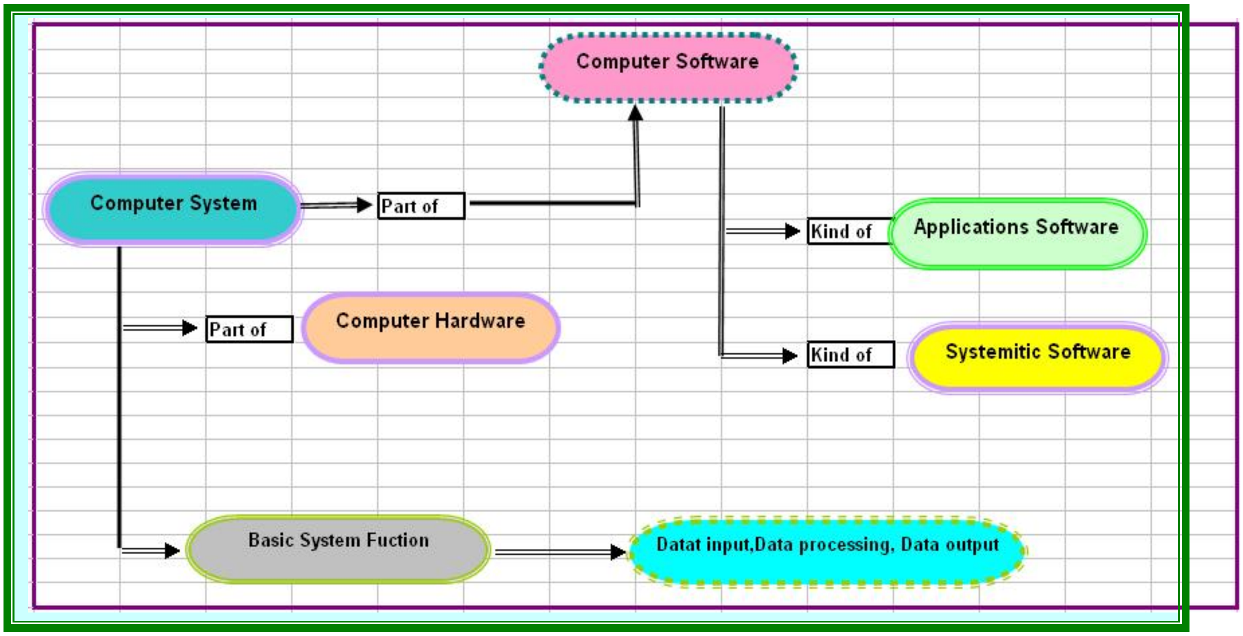

Figure10: A simple semantic network with frames in the TEx-Sys

Resource(13)

Nodes are used for presentation of domain knowledge objects, while links show relations between pairs of objects. Beside nodes and links, the system supports properties and frames (attributes and respective values), along with property inheritance. The system relies heavily on modern supporting technologies, such as multimedia, with the following structure attributes: picture, animation, slides, URL addresses and hyper textual descriptions.

In the following we especially consider knowledge representation for :

1. **domain knowledge and**
2. **student knowledge and**
3. **Skills acquisition.**

A. <u>Domain Knowledge Representation</u> The domain knowledge base is implemented according to the entity-relationship model for databases and is built upon the following five objects, see Figure.11:

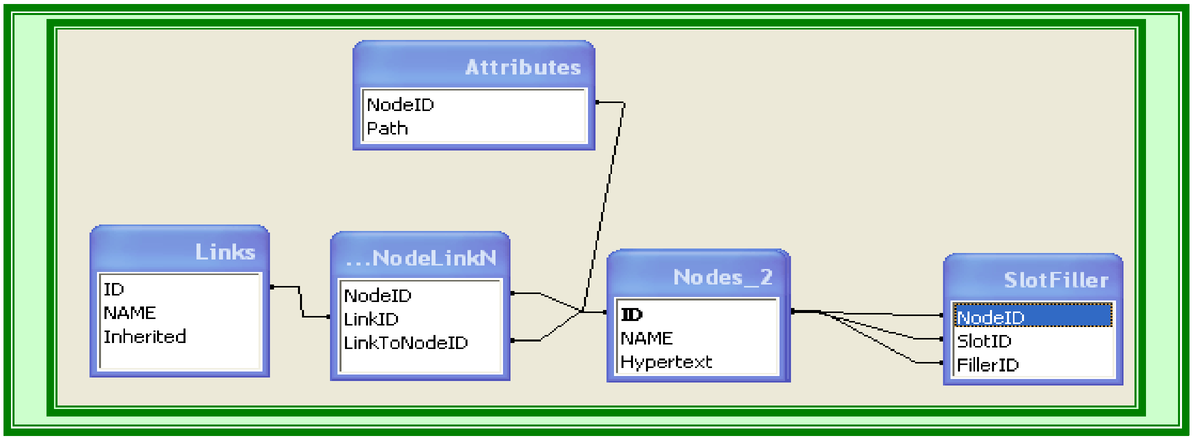

Figure.11: A simple semantic network with frames in the TEx-Sys

Resource(14)

B. Student Knowledge Representation

The formalization of student knowledge in TEx-Sys is based on the same syntax and semantics for nodes and links, and harmonized with knowledge representation using semantic networks with frames. Student knowledge is developed by overlaying it with the teacher one, including misconceptions and missing conceptions [13], using the following three knowledge bases, sees Figure.12.

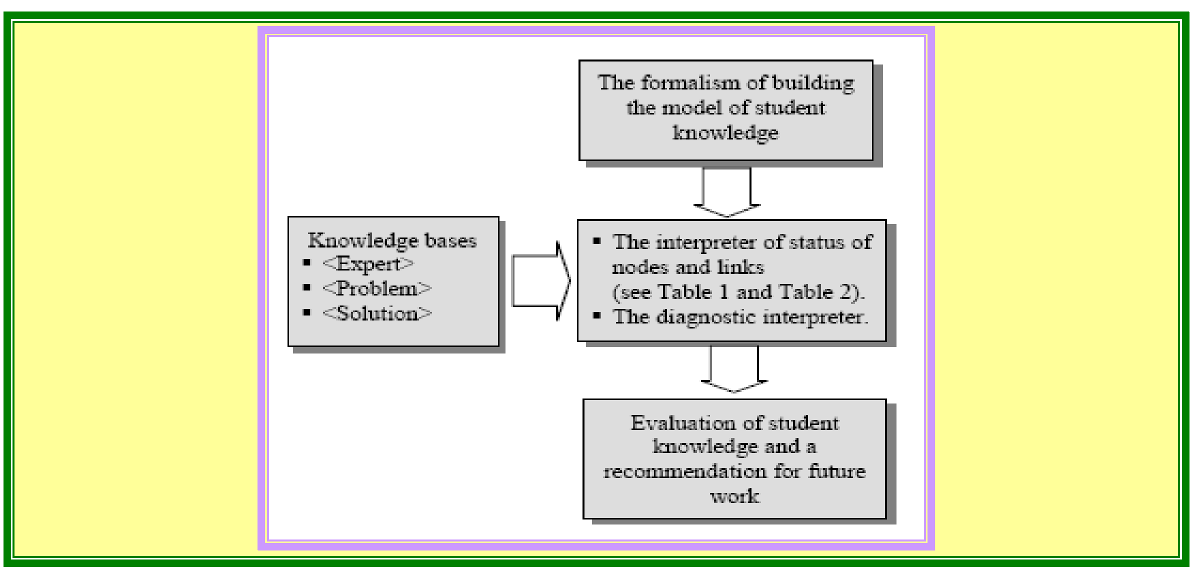

Figure . 12:Process of student knowledge evaluation Resource(13)

- ⇒ . **Expert knowledge base for chosen domain knowledge, which is denoted with <Expert>,**
- ⇒ . **Problem knowledge base, denoted with <Problem>,**
- ⇒ . **Solution knowledge base, denoted with <Solution>.**

Problem generation in TEx-Sys allows the evaluation of student knowledge of a chosen domain.

Modern Techniques For Knowledge Discovery & Representation & Data Mining (KDR) Data mining and knowledge discovery & representation in databases have been attracting a significant amount of research, industry, and media attention of late. What is all the excitement about? This article provides an overview of this emerging field, clarifying how data mining and knowledge discovery in databases are related both to each other and to related fields, such as machine learning, statistics, and databases. The article mentions particular real-world applications, specific data-mining techniques, challenges involved in real-world applications of knowledge discovery, and current and future research directions in the field.

Across a wide variety of fields, data are being collected and accumulated at a dramatic pace. There is an urgent need for a new generation of computational theories and tools to assist humans in extracting useful information (knowledge) from the rapidly growing volumes of digital data.

These theories and tools are the subject of the emerging field of knowledge discovery in databases (KDR). At an abstract level, the KDR field is concerned with the development of methods and techniques for making sense of data. The basic problem addressed by the KDR process is one of mapping low-level data (which are typically too voluminous to understand and digest easily) into other forms that might be more compact (for example, a short report), more abstract (for example, a descriptive approximation or model of the process that generated the data), or more useful (for example, a predictive model for estimating the value of future cases). At the core of the process is the application of specific data-mining methods for pattern discovery and extraction.1 This article begins by discussing the historical context of KDR and data mining and their intersection with other related fields.

A brief summary of recent KDR real-world applications is provided. Definitions of KDR and data mining are provided, and the general multi-step KDR process is outlined. This multi-step process has the application of data-mining algorithms as one particular step in the process.

The data-mining step is discussed in more detail in the context of specific data-mining algorithms and their application. Real-world practical application issues are also outlined.

Finally, the article enumerates challenges for future research and development and in particular discusses potential opportunities for AI technology in KDR systems.

Knowledge discovery & representation from data can be understood as a process that contains, at least, the steps of application domain understanding, selection and preprocessing of data, Data Mining, knowledge evaluation and consolidation and use of the knowledge.

A representative outline containing all these steps is illustrated in Figure (1). The KDR process begins with the understanding of the application domain, considering aspects such as the objectives of the application and the data sources. Next, a representative sample (e.g. using statistical techniques) is removed from database, preprocessed and submitted to the methods and tools of the Data Mining stage with the objective of finding patterns/models (knowledge) in the data. This knowledge is then evaluated as to its quality and/or usefulness, so that it can be used to support a decision-making process. It should be emphasized that, in spite of the visualization tools being used mostly in the knowledge evaluation step, they have great relevance in understanding and evaluating the results of each stage, especially for the Final User [16].

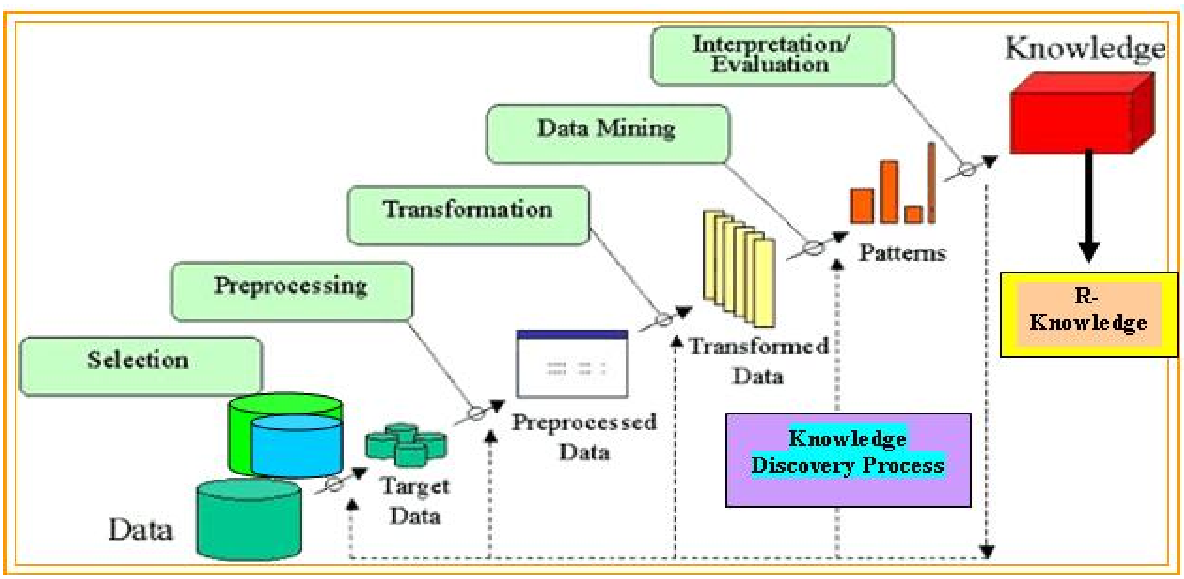

Figure 13: KDR Process main steps Resource(16)

Using of ES in DM

Developing intelligent tools to extract information that supports research and decision making has been of critical importance in fields such as knowledge discovery, information retrieval, pattern recognition, databases, and increasingly in medicine and biology. Quantitative and intelligent biomedical data analysis is a fast-growing interdisciplinary area of applied computer science, artificial intelligence, and biomedical science with the potential of introducing very important developments in these fields.

Looking for complex patterns within large biomedical data repositories and discovering previously unexpected associations can be of particular interest for understanding the physiology and functionality of the human body as well as tracing the roots of several diseases.

Data mining is the process of extracting patterns from data. As more data are gathered, with the amount of data doubling every three years,[17] data mining is becoming an increasingly important tool to transform these data into information. It is commonly used in a wide range of profiling practices, such as marketing, surveillance, fraud detection and scientific discovery.

While data mining can be used to uncover patterns in data samples, it is important to be aware that the use of non-representative samples of data may produce results that are not indicative of the domain. Similarly, data mining will not find patterns that may be present in the domain, if those patterns are not present in the sample being "mined". There is a tendency for insufficiently knowledgeable "consumers" of the results to attribute "magical abilities" to data mining, treating the technique as a sort of all-seeing crystal ball. Like any other tool, it only functions in conjunction with the appropriate raw material: in this case, indicative and representative data that the user must first collect. Further, the discovery of a particular pattern in a particular set of data does not necessarily mean that pattern is representative of the whole population from which that data was drawn. Hence, an important part of the process is the verification and validation of patterns on other samples of data.

The term data mining has also been used in a related but negative sense, to mean the deliberate searching for apparent but not necessarily representative patterns in large numbers of data. To avoid confusion with the other sense, the terms *data dredging* and *data snooping* are often used. Note, however, that dredging and snooping can be (and sometimes are) used as exploratory tools when developing and clarifying hypotheses.

The overall KDR process (Figure 14) includes the evaluation and possible interpretation of the \mined" patterns to determine which patterns may be considered new \knowledge."[18].

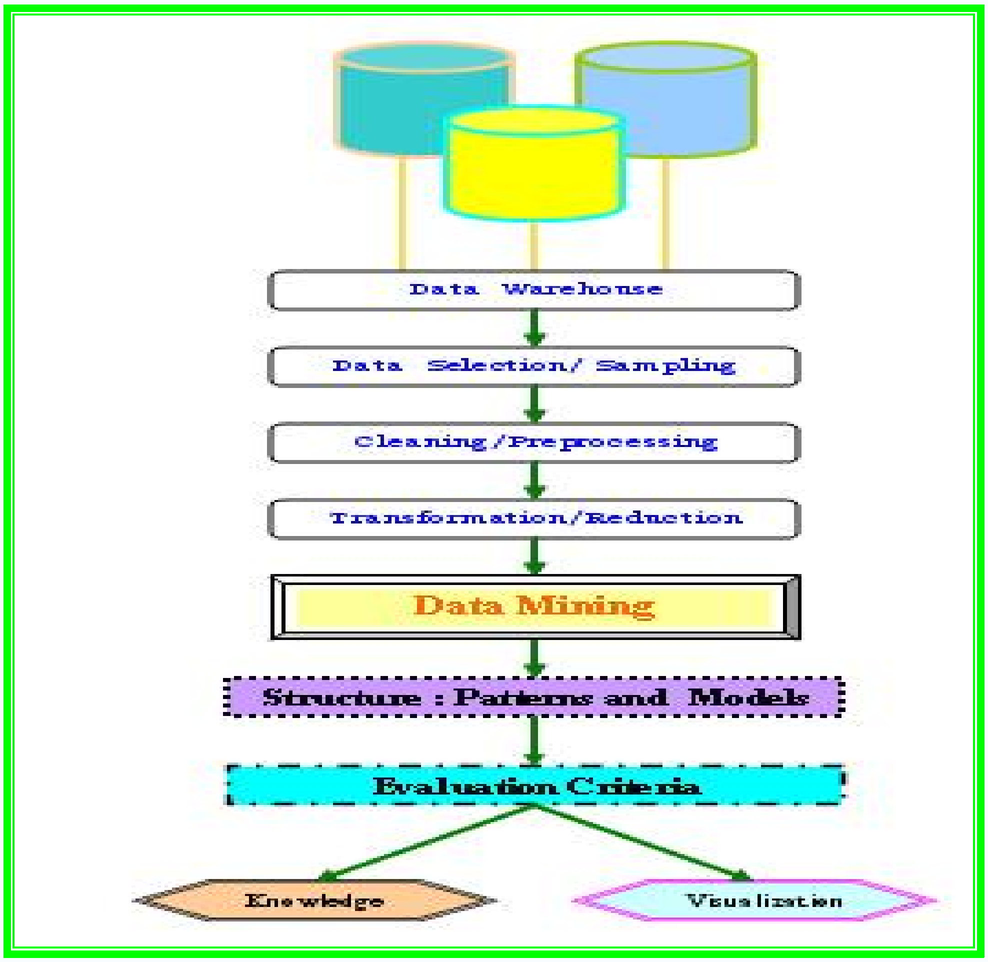

Figure (14) : An overview of the steps comprising the KDR Process

Resource (18)

Data mining commonly involves four classes of task:[19]

- **Classification - Arranges the data into predefined groups. For example an email program might attempt to classify an email as legitimate or spam. Common algorithms include Nearest neighbor, Naive Bayes classifier and Neural network.**
- **Clustering - Is like classification but the groups are not predefined, so the algorithm will try to group similar items together.**
- **Regression - Attempts to find a function which models the data with the least error. A common method is to use Genetic Programming.**
- **Association rule learning - Searches for relationships between variables. For example a supermarket might gather data of what each customer buys. Using association rule learning, the supermarket can work out what products are frequently bought together, which is useful for marketing purposes. This is sometimes referred to as "market basket analysis".**

Subject-based data mining

"Subject-based data mining" is a data mining technique involving the search for associations between individuals in data. In the context of combating terrorism, the National Research Council provides the following definition: *"Subject-based data mining uses an initiating individual or other datum that is considered, based on other information, to be of high interest, and the goal is to determine what other persons or financial transactions or movements, etc., are related to that initiating datum."*[20]

Games

Since the early 1960s, with the availability of oracles for certain combinatorial games, also called tablebases (e.g. for 3x3-chess) with any beginning configuration, small-board dots-and-boxes, small-board-hex, and certain endgames in chess, dots-and-boxes, and hex; a new area for data mining has been opened up. This is the extraction of human-usable strategies from these oracles. Current pattern recognition approaches do not seem to fully have the required high level of abstraction in order to be applied successfully. Instead, extensive experimentation with the tablebases, combined with an intensive study of tablebase-answers to well designed problems and with knowledge of prior art, i.e. pre-tablebase knowledge, is used to yield insightful patterns. Berlekamp in dots-and-boxes etc. and John Nunn in chess endgames are notable examples of researchers doing this work, though they were not and are not involved in tablebase generation.

Business

Data mining in customer relationship management applications can contribute significantly to the bottom line. Rather than randomly contacting a prospect or customer through a call center or sending mail, a company can concentrate its efforts on prospects that are predicted to have a high likelihood

of responding to an offer. More sophisticated methods may be used to optimize resources across campaigns so that one may predict which channel and which offer an individual is most likely to respond to — across all potential offers. Additionally, sophisticated applications could be used to automate the mailing. Once the results from data mining (potential prospect/customer and channel/offer) are determined, this "sophisticated application" can either automatically send an e-mail or regular mail. Finally, in cases where many people will take an action without an offer, uplift modeling can be used to determine which people will have the greatest increase in responding if given an offer. Data clustering can also be used to automatically discover the segments or groups within a customer data set.

Businesses employing data mining may see a return on investment, but also they recognize that the number of predictive models can quickly become very large. Rather than one model to predict which customers will churn, a business could build a separate model for each region and customer type. Then instead of sending an offer to all people that are likely to churn, it may only want to send offers to customers that will likely take to offer. And finally, it may also want to *determine which customers* are going to be profitable over a window of time and only send the offers to those that are likely to be profitable. In order to maintain this quantity of models, they need to manage model versions and move to *automated data mining*.

Data mining can also be helpful to human-resources departments in identifying the characteristics of their most successful employees. Information obtained, such as universities attended by highly successful employees, can help HR focus recruiting efforts accordingly. Additionally,

Strategic Enterprise Management applications help a company translate corporate-level goals, such as profit and margin share targets, into operational decisions, such as production plans and workforce levels.[21]

Another example of data mining, often called the market basket analysis, relates to its use in retail sales. If a clothing store records the purchases of customers, a data-mining system could identify those customers who favour silk shirts over cotton ones. Although some explanations of relationships may be difficult, taking advantage of it is easier. The example deals with association rules within transaction-based data. Not all data are transaction based and logical or inexact rules may also be present within a database. In a manufacturing application, an inexact rule may state that 73% of products which have a specific defect or problem will develop a secondary problem within the next six months.

Market basket analysis has also been used to identify the purchase patterns of the Alpha consumer. Alpha Consumers are people that play key roles in connecting with the concept behind a product, then adopting that product, and finally validating it for the rest of society. Analyzing the data collected on these types of users has allowed companies to predict future buying trends and forecast supply demands.

Data Mining is a highly effective tool in the catalog marketing industry. Catalogers have a rich history of customer transactions on millions of customers dating back several years. Data mining tools can identify patterns among customers and help identify the most likely customers to respond to upcoming mailing campaigns.
Related to an integrated-circuit production line, an example of data mining is described in the paper "Mining IC Test Data to Optimize VLSI Testing."[22] In this paper the application of data mining and decision analysis to the problem of die-level functional test is described. Experiments mentioned in this paper demonstrate the ability of applying a system of mining historical die-test data to create a probabilistic model of patterns of die failure which are then utilized to decide in real time which die to test next and when to stop testing. This system has been shown, based on experiments with historical test data, to have the potential to improve profits on mature IC products.

Conclusions.

The use of Intelligent Tutoring System in recent years has proved effective in improving the learning experience in various domains of knowledge. The technologies for distance learning spread ever faster, but giving little weight to the system "intelligence" that allows to develop a real interoperability with user. The ITS can fill the GAP but they are extremely difficult to create and maintain because many skills are required for their development. This research aimed to achieve two objectives:

- **ü • give a basic coverage on some important areas of expert systems, and maybe incite the reader into further individual expert systems technology reading and research;**
- **ü • allow the author to train its own *natural* neural net (pun intended) with knowledge in the field of AI and expert systems.**

The history of Artificial Intelligence and expert systems started in fact very early, with the ancient philosophers and then Renaissance scientists. The foundations of modern expert systems are quite recent though (i.e. 1943 onwards). In terms of *computer* history however, this is equivalent to hundreds of years of human history.

While Artificial Intelligence is far from being perfect and expert systems still have a long way to go to fully model a human expert, the progress achieved in such a short period is astonishing. And better still, the development pace is accelerating constantly, in step with computer hardware technology.

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نظم الخبرة كأداة لتمثيل المعرفة في عملية التعليم والتعلم

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المستخلص :

في السنوات الأخيرة قد تطورت نظم التعلم الخبيرة بشكل واسع ، وأصبحت من الطرق الناجحة في تحسين وزيادة الخبرة في عملية التعليم والتعلم والتربية، والعديد من الأصدارات والمؤلفات في هذا المجال ساهمت وتساهم في نشر وتطبيق تلك التكنولوجيا ، ومن بين المشاكل الرئيسية ضمن نظم التعلم الخبيرة ، هي عملية التأليف وأكتشاف ومعالجة المعرفة ، والتي تكون من المهمات الصعبة والمعقدة ، التي تتطلب مهارات وخبرات متخصصة في برمجة الكومبيوتر وهندسة المعرفة.

وفي هذا البحث سنناقش الأطار العام لأدارة المعرفة في نظام تعلم الخبرة، وألية التنقيب عن البيانات، وأكتساب المعرفة في أستخدام نظم التعلم الخبيرة من خلال عملية التعليم والتعلم، مثلا انشاء المعلم وأدراكه ومهارته.. وسوف يتم عرض النماذج الخاصة بالهيكل المقترح (لموديلات نظم الخبرة) ، وموديل أكتشاب المعرفة الموضوع على التنقيب عن البيانات، وسنناقش بعض المواضيع الخاصة بنظم التعلم الخبيرة ومحدودية الطرق الجارية وأمكانية تحسين الأطار العام لبرامج التعلم الخبيرة في عملية التعليم والتعلم.