Study on Analogical Reasoning Methodologies For Developing Analogical Learning Systems

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Abstract: - In the last years, various reasoning methodologies have been proposed by the researchers in order to develop intelligent learning systems. These systems are based on the concepts and theories of the artificial intelligence (AI) science and technology. Many types of learning systems are in existence today and are applies to different domains and tasks, e.g., health care, business, commerce, and education. From the AI point of view, the research in the reasoning paradigms cover a variety of approaches. Analogical reasoning techniques (ARTs) play in developing an efficient and intelligent Analogical Learning Systems (ALSs). A number of computational models of analogy have been employed in a wide variety of research ALSs in different fields, acquiring features of how human compare representations, retrieve source analogues from memory, and learn from the results. This paper investigates the main features of some ARTs (namely, structured production rules, fuzzy rules, cognitive scripts, cases, and semantic networks) of used for the development of ALSs from the AI perspective.

Key-Words: - Analogical reasoning, analogical learning systems, structured production rules, fuzzy rules, cognitive scripts, cases, semantic networks.

1 Introduction

Knowledge and reasoning are the two main components for developing intelligent learning systems (ILSs) for any application. Although, a computer cannot have experiences and learn as the human mind can, it can acquire knowledge given to it by human experts. The knowledge consists of facts, concepts, theories, procedures, and relationships. Knowledge is also information that has been organized and analyzed to make it understandable and applicable to problem solving or decision making. Most knowledge bases are limited in that they typically focus on some specific subject area or domain.

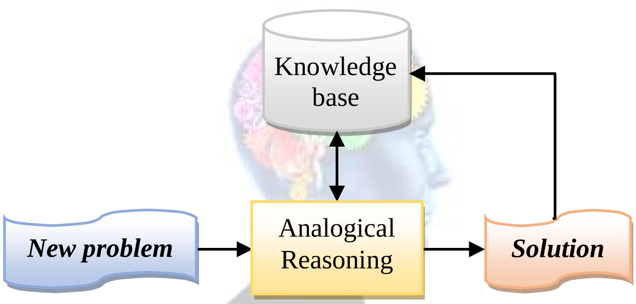

Fig.1. A simple ALS architecture with AR.

Once a knowledge base is built, artificial intelligence (AI) techniques are used to give the computer though and reasoning capability. The computer will be able to think, reason, and make inferences and judgments based on the facts and relationships contained in the knowledge base. It will be able to look through the knowledge base and reach conclusion based on the content.

The field of reasoning is very important for the development of ILSs. From the AI point of view, the research areas in this cover a variety of topics, e.g.; analogical reasoning, commonsense reasoning, automated reasoning, fuzzy reasoning, geometric reasoning, non-monotonic reasoning, model-based reasoning, probabilistic reasoning, causal reasoning, qualitative reasoning, spatial reasoning and temporal reasoning. In fact these methodologies receive increasing attention within the knowledge engineering AI-based learning systems community.

Since the early 1980s, cognitive scientists have been argued that analogical reasoning (AR) is the crucial cognitive mechanism and the core process in human learning, knowledge discovery, memory, problem solving and decision making [5, 6, 8]. With the progress in the understanding of the mechanisms underlying analogy, AR has occupied an important place in artificial intelligence, as a tool for problem solving, automated deduction and learning. Later, the interest for AR in AI has particularly focused on developing analogical learning systems (ALSs) that mimic the learning by analogy ability of humans.

The use of AR for learning has been discussed from various perspectives, including moral decision-making [2], real-time diagnostics and forecasting [3], and legal decision-making [4]. When facing a new situation, a human recognizes it as analogous to some previous experience and draws inferences from his previous decisions [2, 7, 8]. For that, developing ALSs with analogical reasoning techniques (ARTs) supports ALSs extending their knowledge across different or same domains, by resolving the high level similarities between these domains [1], where the solving of a new problem is based on the solutions of similar past problems stored in knowledge base as shown in Fig.1.

From the AI perspective, this paper discusses the advantages and disadvantages of five ARTs, used for developing ALSs in many fields, namely analogical reasoning with structured production rules, fuzzy rules, cognitive scripts, cases, and semantic networks. The paper is organized as follows: Section II defines analogical reasoning with highlighting the main challenges exist in it. Sections III, IV, V provide an overview of ARTs (structured production rules, fuzzy rules, cognitive scripts, cases and semantic networks, respectively). Comparison between the advantages and disadvantages of ARTs in developing ALSs is provided in Section VI. Finally, Section VII presents our conclusions.

2 Reasoning by Analogy

2.1 Overview

From what introduced above, reasoning by analogy is identified as a cognitive process of transferring information from a better-known domain (the base) to the less familiar domain (the target), on the basis of analogy (similarity) between these domains [8]. Hofstadter (1995, 2001) considers analogy as a kind of high-level perception, where one situation is perceived as another one [7] and has been argued that analogy is "the core of cognition" [6]. Therefore, reasoning by analogy is a powerful way of extending the one’s knowledge.

2.2 Relational Structure

AR involves the comparison of two structured representations. That is, the representations being compared typically include labeled relationships between entities and between other relations. Such representations contrast sharply with representations lacking internal structure, such as those based on independent features or multidimensional vectors [11]. This representational choice is dictated by a large set of findings indicating that people are sensitive to relational structure in processing analogy, and even in visual comparisons [11]. In addition that, Gentner (2012) has argued that two situations are relationally similar, if they share a common causal structure manifested in common relations to the both situations. And that what differentiate analogy from other many types of similarity measure used in computing similarity between two different situations, in which the two situations must be similar in their relational structure (i.e. sharing a common causal structure), to be analogical [8]. For example, used by Gentner (2011) to explain the behavior of an electric circuit; she describes the strength of an electric current in the electric circuit (the target) by analogy with a plumbing system (the base): the strength of water flow is determined by water pressure. As higher pressure leads to greater water flow in the plumbing system. Likewise, the strength of electric current is determined by electric pressure (voltage), so higher voltage leads to greater current in the electric circuit.

2.3 Processes

AR is decomposed into four sub-processes, as follows:

2.3.1 Retrieval (or reminding)

Given a situation (the target), discover similar situations to the target from the set of known situations. And return the most similar one (the base).

2.3.2 Mapping (or matching)

Given two structured situations (the target and the base), find how they are similar and align their elements structurally to produce a set of ono-to-one correspondences (mappings), on the basis of the common relational structure.

2.3.3 Transfer

Carry over some knowledge of the base to the target in accordance with a mapping, so the target is solved or a new knowledge is gained. There are three issues that face any computational model of analogical transfer: selecting an appropriate mapping, deciding transformable knowledge of the base, and transferring it to the target.

2.3.4 Evaluation

Once an analogical transfer has been done, the analogy and its inferences are evaluated. According to [8], the factors of evaluation are

a) Factual correctness of the inferences,
b) Goal relevance: Assure that the generated inferences are relevant to the goal, and
c) How much knowledge provided by analogy and its inferences.

2.4 Types

One type of analogy, according to whether the base and target situations belong to the same or different domains, is cross-domain analogy which gives the ability for people to adapt to new situations within different domains by using deep structural similarities between those new situations and old ones, while there are few systems have been developed which exhibit reasoning by cross-domain analogy, it is worth mention the work done by Baydin et al. (2012) for automated generation of diverse novel cases analogous to a given case in the basis of semantic networks using evolutionary computation [9]. By contrast, intra-domain analogy restricted to offer similarities within the same domain, such as case-based reasoning that relied on the assumption that the past cases and the new problem be in the same domain and described by the same set of features with different values.

As concluded in [20], reasoning by cross-domain analogy provides many challenges over reasoning by intra-domain analogy through reusing knowledge across different domains in which the sets of feature that describe an old situation and a new situation are different. On the other hand, allowing ALSs to act in different situations requires providing them with detailed knowledge about each of those situations.

3 Analogical Reasoning with Structured Production Rules

Production rules (PRs) are representations of a certain situation, by a set of conditions that yields to a specific consequent action, once are found to be true. A production rule of the form:

if <condition> then <action>

states that if condition is satisfied to be true, then the action is executed.

The first production rule-based systems, introduced during the 1970's by the Stanford Heuristic Programming Project led by Feigenbaum, who is sometimes referred to as the "father of expert systems". In fact, an expert system is the common term used to describe a rule-based processing system. Rule-based systems are very time-consuming to be built and maintained because rule extraction from experts is labor-intensive and rules are inherently dependent on other rules, making the addition of new knowledge to the system a complex debugging task.

The expert systems were one of the first large-scale commercial successes of AI research [14]. An expert system consists of two major elements, a knowledge base of know production rules and facts about the system's domain, and an inference engine, which deduces new knowledge from the knowledge base in order to provide a solution of a given problem.

Although the ease of PRs in encapsulating and representing experts' knowledge. There was a tendency towards enhancing them by means of structuring these PRs. Structured production rules (SPRs) are specific kind of PRs, in that rules are represented in a structure manner such as table or tree rather than traditional PRs. SPRs allow the rules to be accessed in a parallel manner, and to self-control access, in addition to allow each condition to preserve a richer semantic body of information [19]. For instance, ELI [19] represent traditional PRs using a two-dimensional representation as shown in Fig.2. In which, nodes representing conditions, edges representing links, and leaf nodes representing actions.

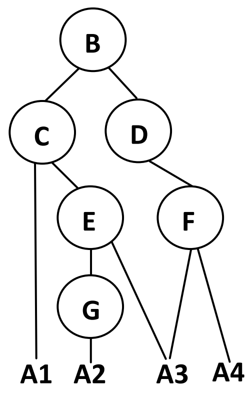

Fig.2. 2D representation of rules by ELI.

The rules of Fig.2 can be represented using traditional PRs as follows:

B & C => A1
B & C & E & G => A2
B & C & E => A3
B & D & F => A3
B & D & F => A4

From that, we can find that condition B will be tested only one time using SPRs, while using traditional PRs, four tests are required. This aspect allows the rules to the ability of self-access control and parallel accessing.

SPRs are easily manipulated by two main methods of reasoning. Forward chaining is also called data-driven reasoning, in which it begins with the given knowledge of the problem, and continues to extract new data from inference rules until satisfies a desired goal, and backward chaining is also called goal-driven reasoning, in which it begins with the desired goal, and continues working backwards through successive sub-goals until the goal conditions are satisfied. So, the forward chaining method can be used to generate new data by firing of the rules. As an inferencing procedure, forward chaining is very fast. Forward chaining is also used in real-time monitoring and diagnostic systems where quick identification and response to problems are required.

Unlike forward chaining, which uses rules and facts to produce new knowledge, backward chaining focuses on rules that are related to the desired goal to provide a logic conclusion about whether that is true or false. Also, It usually traverses the knowledge base using depth-first search trying to satisfy the goal. An advantage of backward chaining is that, because the inferencing is directed, any needed information can be gained from the user. Some reasoning systems also provide an explanation capability which allows the user to ask the inference engine why it asking for some piece of information, or why it derived some conclusion.

SPRs allow only the exact matching between the rules premises of the current situation and prior situations. For example, given the same exact problem situation, the system will go through exactly the same amount of work to come up with the solution. In other words rule-based systems don't inherently learn. In addition, given a problem that is outside the system's original scope, the system often can't render any assistance. From that, AR with structured production rules is one kind of reasoning by intra-domain analogy.

4 Analogical Reasoning with Fuzzy Rules

In everyday life, humans deals with vague terms which do not have well-defined boundaries. For example, many, high, tall, good, few, etc. These terms called fuzzy terms, which are true or false to some degree. Zadeh (1965) has introduced the fuzzy set theory for representing and manipulating fuzzy terms based on degrees of membership ranging between zero and one, rather than on complete crisp membership of classical binary logic [15].

For defining fuzzy set, let U denote the universe of discourse, then a fuzzy set A in U is defined in terms of a membership function (μA): U→ [0, 1] as a set of ordered pairs of the form $A = \{(x, \mu_A(x)\text{:}\ x\in U\}$, where

$$\mu_A(x) = \begin{cases} 0, & if\ x\ is\ not\ in\ A \\ 1, & if\ x\ is\ totally\ in\ A \\ > 0\ and < 1, & if\ x\ is\ partly\ in\ A \end{cases}$$

The membership degree μ_A of x, represents the degree of truth of the element x to A. The nearer the value $\mu_A(x)$ to 1, the better x verifies the property of A. The methods of choosing the proper membership function are empirical, based usually on statistical data of experiments performed with samples of the population under study. For reasons of simplicity many authors identify a fuzzy set A in U with the corresponding membership function μ_A. The following example illustrates the above presented definition of fuzzy set: consider a universe of discourse U of all non-negative integers between 1 and 100 representing the humans' ages. Suppose that a set A of U contains all the young citizens of a city. And as noticed that the definition of "young citizen" has not clear boundaries. Therefore, A can be defined as a fuzzy set in U of "young citizen" with a membership function $\mu_A(x)$ = [1+(0.04x)2]-1, if $x \leq 60$ and $\mu_A(x) = 0$, if $x > 60$. As shown in Fig.3, a citizen of the city aged less than one year has membership degree $\mu_A(0) = 1$ in A, one aged 30 years has $\mu_A(30)$ = [1+(0.04*30)2]-1 = 0.41, one aged 60 years has $\mu_A(60) \approx 0.14$, etc.

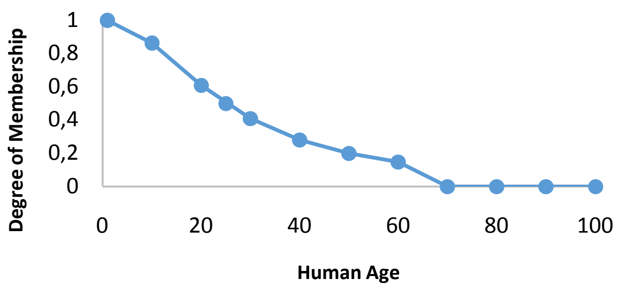

Fig.3. Fuzzy set of Human age.

In contrast, if A is defined as a set of all citizens aged less than or equal to 60 years old. Then A can be considered as a crisp set in U with a membership function $\mu_A(x) = 1$, if $x \leq 60$ and $\mu_A(x) = 0$, if $x >$ 60. As shown in Fig.4., that all citizens aged less than or equal to 60 years old have a complete membership of $A = 1$, otherwise, have no membership of A which equals 0.

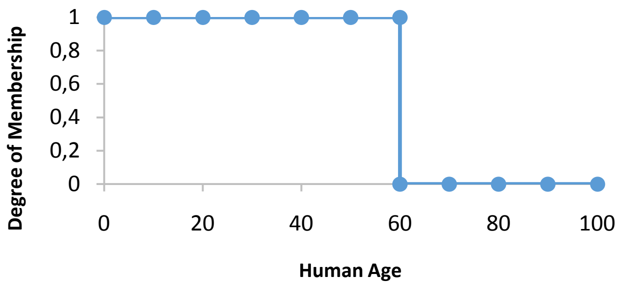

Fig.4. Crisp set of Human Age.

From what introduced above, fuzzy logic reflects how people think. It attempts to model our sense of words, our decision making and our common sense. As a result, it is leading to new, more human, intelligent systems. Traditionally, the inference engines of rule-based reasoning almost were based on Boolean logic which has only values (true or false). Fuzzy logic has provided a multi-valued logic-based systems, in which it deals with truth values which are real numbers in the interval range [0,1]. Thus something could be half true 0.5 or very likely true 0.9 or probably not true 0.1. Fuzzy logic represents knowledge in if-then rules, which called fuzzy rules. For example, "If speed is fast then stopping distance is long". The premise "speed is fast" is not strictly true or false. So, a membership function that maps the fuzzy set "fast" in the domain of the fuzzy variable "speed" to a truth value ranging from 0 to 1, is used to express that premise.
Reasoning with fuzzy rule systems is a forward chaining procedure. The initial crisp data are fuzzified, in which the degree to which these data belong to each of the appropriate fuzzy sets, is determined. Then, all fuzzy rules are evaluated, to also determine to which degree these rules are true. It is worthy mention that if a fuzzy rule has multiple premises combined using a fuzzy conjunction (and) operation, then it takes the minimum degree value of the fuzzy premises, while using fuzzy disjunction (or) operation, let it takes the maximum degree value. Next, the fuzzy sets specified in the consequent premises of all rules are combined into a single fuzzy set using the rule outputs (truth values) as scaling factors. So, the output is a single aggregate fuzzy set for each output fuzzy variable. Finally, given the aggregate output fuzzy set, the defuzzification technique produces the final output of a fuzzy system that has to be a crisp value. In [21] the authors stated that defuzzification can be described as a crisp decision making problem under fuzzy constraints, in case that there are several output variables.

Although, fuzzy rules allow the inexact matching between the rules premises of the current situation and prior situations. They cannot solve problems within different domains. From that, reasoning with fuzzy rules is another kind of reasoning by intra-domain analogy. A second notable disadvantage of fuzzy rules modeling is that they depend at a considerable degree on the modeler's personal criteria; e.g. choice of the proper membership function, correspondence of the crisp values to the linguistic fuzzy expressions, etc. Therefore, the validity of a fuzzy representation of a real situation must be strictly checked before its application in practice.

5 Analogical Reasoning with Cognitive Scripts

For people to act appropriately in different social situations and make believable actions, they require an amount of experiential knowledge of events that captures common social and cultural activities [20, 23]. These socio-cultural event sequences that define a particular context (well-known situation) can be represented in the form of cognitive scripts [23].
A cognitive script consists of slots (events) and temporal or causal links between these slots [24], and that what provides context to a particular script [22]. An example of a restaurant social situation represented using the multi-branched cognitive script is shown in Fig.5.

One example of analogical reasoning with cognitive scripts was proposed by Gawish et al. (2013). In that work, the authors proposed a cognitive model for learning by cross-domain analogy in social situations, which represented in cognitive scripts [20]. The model depends mainly on two modules; the retrieval module and the learning module. The retrieval module utilizes Pharaoh algorithm to retrieve the most relevant cognitive script (the base) to the target script, based on semantic similarity between a structured query cognitive script (the target) and registered cognitive scripts from different domains [24]. Whereas, the learning module aims to enrich the target script by extracting and transferring new experienced knowledge from the retrieved base script. From that, reasoning with cognitive scripts is a kind of reasoning by cross-domain analogy. In which, Pharaoh considers the timing of events execution in a script and the associated attributes to extract the degree of similarity. In addition to that, the model also shows that reasoning with cognitive scripts allows the inexact matching between the events of the current situation and prior situations. In which, Pharaoh does not consider two event names to be exactly similar unless they share the same context, not only by being lexically similar or having one event as a subclass of another [20].

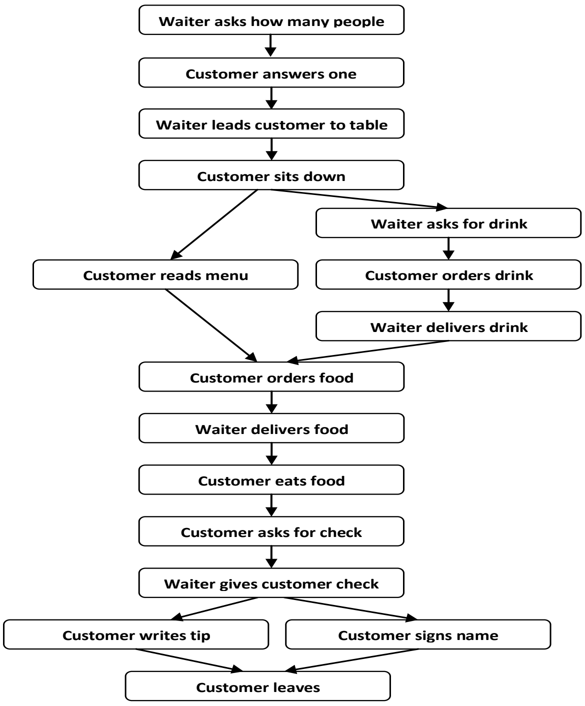

Fig.5. Multi-branched restaurant script [20].

6 Analogical Reasoning with Cases

A case is a piece of experience that consists of two main parts: (a) a problem part: contains a description of the problem as a list of features, and (b) a solution part: contains the solution of a particular problem. Reasoning with cases is the process of solving a new faced problem based on the solutions of old experiences (similar past problems stored in case-base) [26]. The main knowledge engineering task in case-based AI software is to determine the appropriate case features, by defining the terminology of the domain and gathering representative cases of problem solving by the expert [27]. The solved problem is memorized in order to solve new upcoming similar problems. Despite its big success in solving new problems and learning from pre-existing experience, where many systems have been developed in medical domain, such as ExpressionCBR [10] for helping in the diagnosis of different cancer types, and WHAT [11] for helping in the education of sports medicine students; as well as in manufacturing domain, such as CLAVIER [12] for helping in determining efficient loads of composite material parts to be cured in an autoclave, and Prism [13] in the banking domain, for helping in classifying bank telexes. It suffers from that new case structures are very difficult to manage with different structures of past cases [28]. Therefore, reasoning with cases is a kind of reasoning by intra-domain analogy. And it allows the inexact matching between the features of different cases in the same domain.

7 Analogical Reasoning with Semantic Networks

A widely used graph-based representation technique in many sub-fields of AI is semantic network. A semantic network is a directed graph for representing knowledge with sets of labelled vertices representing concepts, and arcs representing binary relations between concepts of a particular domain, as shown in Fig.6. There are two types of relations: (a) definitional relation, which describes an inheritable knowledge using *IsA*-relation that is true by definition (such as “apple IsA fruit”), (b) assertional relation, which describes assertions that are contingently true (such as “fruit AtLocation tree”) [9].

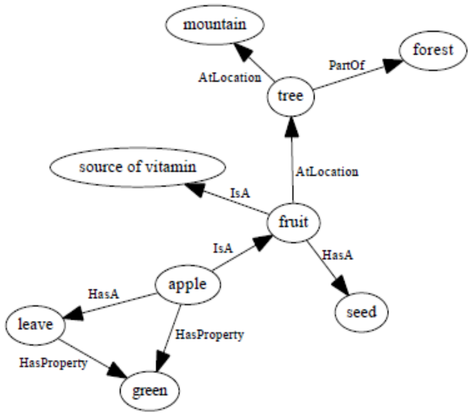

Fig.6. A semantic network with 9 concepts and 9 relations [9].

In 2012, Baydin et al. presented a new algorithm for automated generation of diverse novel cases analogous to a given case in the basis of semantic network using evolutionary computation [9]. In that work, the authors utilized the Structure Mapping Engine (SME) [25] to compute the analogical similarity score between the supplied semantic network (the target) and the existing ones from different domains. SME is based on the idea that an analogy is a one-to-one mapping from one domain (the base) into another (the target). The mapping is guided by the structure of relations between concepts in the two domains, ignoring the semantics of the concepts themselves; and is based on the systematicity principle, where connected knowledge

is preferred over independent facts and is assigned a higher matching score [9].
The advantages of semantic networks for knowledge representation are (a) its natural representation of structural information, and (b) its ease of updating in an open and dynamical problem domains. From that, reasoning with semantic networks considered as a kind of reasoning by cross-domain analogy. Which also allows the inexact matching between the concepts of different semantic networks.

8 Analysis
Table 1 presents an analysis of the ARTs presented previously.

Table 1. Analysis of analogical reasoning techniques.

	Reasoning with				
	Structured Production Rules	Fuzzy Rules	Cognitive Scripts	Cases	Semantic Networks
Intra-domain analogy	+	+	+	+	+
Cross-domain analogy	-	-	+	-	+
Exact Matching	+	+	+	+	+
Inexact Matching	-	-	+	+	+
Easy to be extended	-	-	+	+	+
Easy to validate	-	-	+	+	+
Fast, Direct Execution	+	+	-	-	-
Require interpretation	-	-	+	+	+
High level Data type	+	-	+	+	+
Deterministic	+	+	-	-	-
Preserve the context	-	-	+	-	-
Representational adequacy	-	-	+	+	+
Inferential adequacy	+	+	+	+	+
Acquisitional efficiency	-	-	+	+	+
Cognitive adequacy	less	less	more	less	more
Natural representation	-	-	+	-	+
Graph-based	+	-	+	-	+
Expressive	less	less	more	more	more
Dealing with fuzzy terms	-	+	-	-	-
Knowledge source	knowledge engineer	knowledge engineer	experience	experience	experience
The basic unit of knowledge	rule	rule	cognitive script	case	Semantic network

9 Conclusion
This paper conducted comparison analysis on the characteristics of five analogical reasoning techniques, namely, structured production rules, fuzzy rules, cognitive scripts, cases, and semantic networks, on the basis of analogy. For the purpose of developing an efficient and intelligent analogical learning systems. Systems that exhibit human-like learning ability from similar past situations (experiences) to behave in an acceptable manner in new situations of different domains, by using deep structural similarities between those new situations and old ones. The more the analogical reasoning technique can deal in different domains with inexact matching between domains' attributes, the more knowledge can be gained.

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