DIARIA: AN INTEGRATED INFERENCE ENGINE

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Abstract
To date all inference engines have been based on *modus ponens* which is, of course, a deductive inference rule. However, when making inferences, human beings do not only use modus ponens or any other deductive inference rule, they also employ inductive, abductive and deductive inference rules, as required by the circumstances. In this paper, after having studied the different kinds of inference in AI: deductive, inductive, abductive and retroductive, we present a design of an inference engine which incorporates three of these kinds of inference and uses each of them when most appropriate, depending on the data, information and knowledge with which it is supplied at any time. Thus we have a true data-driven inference system.

Keywords
Reasoning models, deduction, induction, abduction, retroduction, hybrid systems

1.- Introduction

The way in which human beings reason remains a mystery. Though we know which reasoning models are used, that is deduction, induction, abduction and retroduction, many questions remain to be answered:

* When is each reasoning model used? Which circumstances lead us to use just one model or a combination of them?
* Why do we use one model and not another? What leads a person to opt for a way of reasoning?
* How do the results obtained by each model overlap? That is, how is it that the conclusions of one inference system may be the starting point for another type of inference and how can we link similar conclusions obtained from different reasoning processes?
* What relationships exist between each reasoning model? Are there hidden relationships that lead to predetermined behaviour with respect to reasoning?
* How can the use of two or more models improve the final results of the reasoning process?
* Are there any combinations of widely used models?

In this paper, we propose a system whose objective it is to go deeper into these questions and thus improve the reasoning methods that can be programmed in a computer, never losing sight of the possibility of answering some of these questions from the human point of view. All four models will be operational in this system (leaving the retroduction model aside for the time being), such that they can interact with each other, share all the knowledge acquired by each one, etc., so as to improve the results on the basis of cooperation.
The paper is composed of this introduction, where the objectives of the system are set out and five other sections. Section 2 analyses previous work on reasoning models. Section 3 describes the design of the system's inference engine and its control mechanisms. Finally, Section 4 gives an example of the system's performance and Section 5 outlines future research.

2.- Reasoning Models

Throughout history, many philosophers and scientists have analysed the nature of intelligence, knowledge and how it is stored in the human brain, trying to discover and sketch a map that reflects the dynamics of thought. Bertrand Russell [1] said that it seemed that Aristotle was the first to explicitly proclaim that man was a rational being. This opinion was based on the fact that some people were able to add up. However, nobody would really consider a machine to be intelligent just because it can perform arithmetic operations. It is its capacity for working with large amounts of data, that is knowledge that can be used to solve problems efficiently or infer new knowledge, that gives it this quality.

An inference is a logic operation by means of which a new fact (proposition, consequence or conclusion) is obtained from other propositions. There are four types of inference, and we will take the following formal schema to examine them:

$$\begin{array}{rl} \forall x\ F(x) \rightarrow G(x) & : R \\ \underline{F(a) \qquad\qquad} & : F \\ G(a) & : DF \end{array}$$

where R is the rule, F a known fact and DF is a deduced fact. Let´s now consider the four types of inference or reasoning models.

2.1 Deduction

Deduction is a process of deriving new sentences or theorems from the sentences of a theory by applying a set of deductive inference rules [2]. Its formal schema is R, E -> DF, that is, a new fact is deduced from the rule and a known fact. Some of the most widely used deductive inference rules are: purely hypothetical syllogisms, modus ponens, modus tollens.

Deduction does not provide any really new knowledge, as all the information obtained was implicitly contained in the premises. Using deduction, however, we can be absolutely sure that the conclusion is true, provided that we are sure that the premises are so.

This is the most suitable reasoning model for using previously acquired knowledge, which means that it is often employed as an inference mechanism in Expert Systems so as to arrive at particular solutions to problems, based on expert judgements. Mycin [3] and Prospector [4] are examples of deductive Expert Systems.

2.2 Induction

Induction is a process of deriving more general hypotheses or rules from individual known facts by applying a set of inductive inference rules. Generally, we have a domain theory and a set of facts to be generalized that meet the conditions of non-redundant facts, unknown conclusion, consistency and generalization.

Its formal schema is F,DF -> R, that is, we could make a generalization on the basis of the pairs of observations (F(a), G(a); F(b), G(b); ...) and obtain the rule "Every F is G".

The most common inductive inference rules according to Gries [5] and Michalski [6] are: standard generalization, restriction of the conjunction, extension of the disjunction, interval closure, specialization tree.

Induction supplies new knowledge that was not contained in the premises, though we have no assurance that the conclusion is true. Nevertheless, provided that we start from a wide and diverse enough set of premises, we can be sure enough about the conclusion to be able to accept it. This really is a creative reasoning model.

Due to its great capacity for obtaining new knowledge, this model has been used in knowledge acquisition tools, usually confined to classification tasks. The most well-known inductive systems are ID3 and successors [7] and AQ [6].

2.3 Abduction

Charniak and McDermott [8] say that abduction is a process of inferring hypotheses that explain given sentences. A hypothesis may in fact be considered as an explanation of another sentence if there is a causal relation between them.
Its formal schema is R, FD -> F, that is, we start from a rule and the consequence of that rule to arrive at the premise of the rule. Abduction supplies new knowledge because we could not deduce the truth of F.
This reasoning model is used in medical diagnostics, for example, where we must abduce -not deduce- the illness causing the symptoms from the latter. There are very few abductive systems, Dendral [9] and RED [10] being the most important examples.

2.4 Retroduction

Retroduction can be seen as second-order induction, which consists in searching for a general abstract law which matches the experimental data. Let´s suppose that we have induced the laws that explain the planets' movement around the sun. If we were to take each one of these laws as a fact and apply induction again, it would be possible to obtain the universal law of gravitation. There are no systems that can be called retroductive. Perhaps Bacon [11] is the nearest there is to retroduction.

2.5 Conclusion

Retroduction is an inference process for creating inventions, scientific laws and general theorems, abduction is a process by which we are able to outline new explanatory hypotheses, induction confirms or refutes such hypotheses and, finally, deduction is an inference mechanism that allows these laws, theories or hypothesis to be used. Induction, abduction and retroduction generate new knowledge about the world but are not formally valid, while deduction only reformulates the knowledge, though it is formally valid.
No knowledge-based system combining all four reasoning models exists as yet. The biggest efforts towards integration have been the predetermined combination of two reasoning models as in the case of learning by analogy and reasoning mechanisms. In this paper, we present a design of an inference engine that works with these four models and provides for any kind of interaction and combinations between them.

3.- System architecture

There are two premises underlying the design of the system, based on the objectives we were pursuing:
- Firstly, we aimed to design as open an architecture as possible. Therefore, we tried not to place any constraints on the behaviour of the system, since we have very little knowledge about reasoning model interaction.
- Secondly, we should make it clear that computational efficiency was not an objective in the early stages of the project. So we were not looking for a system that did things quickly, just that it did them.

3.1 Inference engine design

Taking these two premises as a starting point, we developed the architecture of an inference engine which will support a working memory shared by all the reasoning models. There will only be one knowledge base, where all the facts and hypothesis inferred by the system will be introduced and updated.
In order to achieve maximum flexibility in the system, we decided to divide each inference model into the steps or subgoals that make it up, allowing for the possibility of each step being performed at any moment in combination with any other step of different inference model. This idea will increase the system's possibilities with regard to different reasoning chains.
Figure 1 is an example of how we broke down the first level of the abductive reasoning model [10].

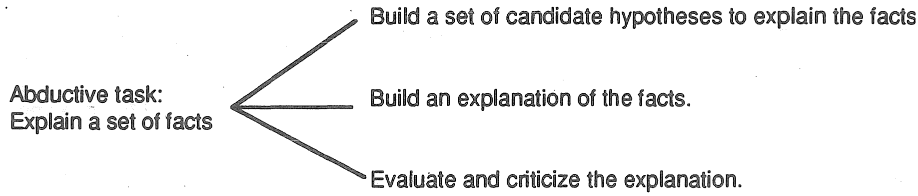

Figure 1

In order to put together an explanation of a set of facts, that is, perform an abductive task, we generally have to take three steps: obtain a set of hypotheses that can explain a general set of facts, select a subset of these hypotheses as the explanation of the facts in question, and finally evaluate and criticize that explanation in order to improve it. In our system, these steps will not necessarily have to be carried out consecutively, any combination with another step of a different reasoning model being feasible.
The other deductive and inductive models have be broken down similarly (we will not take into account the retroductive model in this first version of the system) to arrive at the hierarchy of tasks shown in Figure 2. This Figure shows a two-level decomposition of each reasoning model.

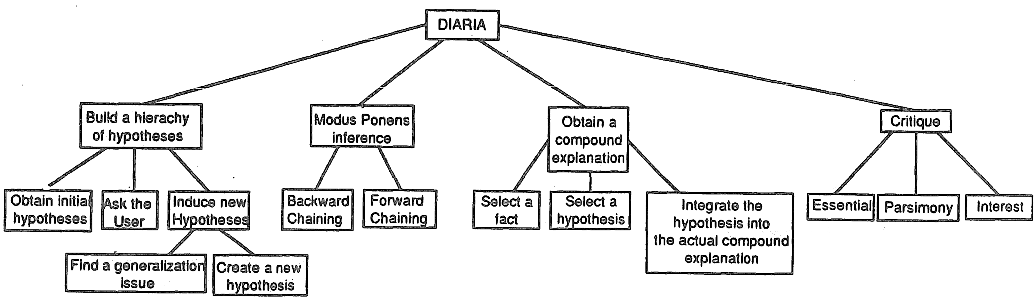

Figure 2

In this Figure, we have grouped tasks with similar objectives under a common branch, irrespective of which reasoning model they belong to.
Let´s examine the purpose of each of these major branches:

* Build a hierarchy of hypotheses module: obtain rules or hypotheses that will later be used to perform abduction or deduction. We have provided for the possibilities of obtaining an initial set from a

previous knowledge base, asking the user for a hypothesis interactively or, finally, inducing new rules from a particular set of facts.

* Modus ponens inference module: We have grouped the two most usual deductive mechanisms, forward and backward chaining, here.
* Obtain compound explanations module: its three components perform the task of finding an explanation of a fact or set of facts.
* Critique module: This groups three types of conclusion evaluation. Essential critique will be used in induction and abduction to determine the need for a characteristic in an induced rule or explanation, parsimony critique which determines whether any explanation is redundant, and interest critique that evaluates the interest of a deductive conclusion or an induced rule by means of characteristics like utility, etc.

3.2 Control mechanisms

The use of control mechanisms is not a contradiction to the objective of achieving a flexible system. These mechanisms will provide for one or other task to be selected, depending on the state of the KB, making it possible to carry out different experiments on reasoning lines.
The control mechanisms must provide a way to evaluate each task's appropriateness of invocation and then select one task. Each of these tasks will have a sponsor which will indicate at all times the appropriateness of invocation of the task it represents. There is a selector governing this set of sponsors, whose mission it is to select which task has to be performed, taking into account the rates supplied by the sponsors and other knowledge, such as whether a task has ever been carried out, etc.
Each sponsor will have a set of heuristics on the state of the KB, and these will indicate whether it is the moment to perform a given operation. For example, if there are many relations F(a)->G(a), F(b)->G(b), ..., in the KB, it may be the right time to perform an induction to create the rule $\forall x\ (F(x) \rightarrow G(x))$. The set of heuristics needed to define every sponsor is now being developed, this being the main reason for the results shown in next section being provisional.
These sponsor mechanisms mean that the system can be used in three different ways:

* Data-driven strategies: Based on the heuristics of the sponsors, the system will solve the problems it was asked to. This is a true data-driven model which is of great interest as an alternative to traditional instruction-driven models.
* Interactive strategies: Users will be able to define the values for the sponsors and thus analyse variations on a particular reasoning line.
* Predefined strategies: The most useful strategies can be stored in order to examine which reasoning lines are most suited for each problem class. Purely deductive, inductive or abductive reasoning models can also be reproduced.

4.- An Example

The system is still under development, so we cannot offer any definitive results. However, we can give an example of the type of things the system will be able to do.
It goes without saying that human beings don't use just one reasoning model. Instead, they use the one which gives better results, depending on the circumstances. The example we are going to explain is about an episode in history in the field of scientific discovery, involving a combination of deduction, abduction and induction.
The case starts with the phenomenon of water level in a suction pump repeatedly observed by Galileo. This water level never rose higher

than 10.5 metres. The observation of this strange coincidence led to the formulation of the following inductive rule:

E: water level in a suction pump
A: level higher than 10.5 metres.

$$\frac{E(a) \cap A(a),\ E(b) \cap A(b)\ \ldots}{\forall x\ (E(x) \rightarrow A(x))}$$

In the 18th century, Torricelli, intrigued by the same phenomenon, outlined the hypothesis that the 10.5 ceiling was caused by there being a sea of air that exerted pressure on the water, that is:

S(x) x is a sea of air
R(x) x is around the Earth
P(x) x exerts pressure on the Earth

$$\forall x\ \forall y\ (M(x) \cap R(x) \rightarrow P(x)) \rightarrow (E(y) \rightarrow A(y))$$

This retroductive inference has been simulated in our system through an interactive introduction of this rule through the user facility.
At this point Torricelli carried out another experiment with mercury instead of water. As mercury is 14 times the density of water, the rise in the level of the mercury would be 10.5/14=0.76 m, if the hypothesis were true. The experiment was successful and led Torricelli to perform the next abductive inference:

Hg(y): mercury level in a suction pump
L(y): level to 0.76 m.

$$\frac{\begin{array}{c}\forall x\ \forall y\ (M(x) \cap R(x) \rightarrow P(x)) \rightarrow (Hg(y) \rightarrow L(y)) \\ Hg(a) \rightarrow L(a)\end{array}}{M(b) \cap R(b) \rightarrow P(b)}$$

The probability of Torricelli's theory being true has increased, and from here we can deduce, making only minor changes, the level of any liquid element in a suction pump, if we accept that the abduction is valid.

5.- Future work

The main priority of our work in the short term is to implement the full system and finish defining the heuristics for all the sponsors, as well as carry out a large number of experiments in several predefined domains so as to obtain conclusions on the objectives of the systems.
In the future, we plan to enlarge the system to encompass retroductive inference - we are now doing some work in this respect -, and another important idea is to design a learning module that would be able to learn decisions on improving reasoning strategies in particular domains by tracing the operation of the system.

Acknowledgments

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