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Concept Paper

An Heuristic Framework for Non-Conscious Reasoning

Felipe Lara-Rosano [1,2]

[1] Center for Applied Sciences and Technology, Universidad Nacional Autonoma de Mexico, Mexico City 04510, Mexico; flararosano@gmail.com; Tel.: +52-55-2300-8308

[2] Center for Complexity Sciences, Universidad Nacional Autonoma de Mexico, Mexico City 04510, Mexico

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Featured Application: This analysis of non-conscious reasoning can be applied in educational diagnostics and intervention, medical diagnostics and treatments, organizational and political decision making and design of artificial intelligence knowledge based systems, neuro-computers and similar devices for aiding people in the problem-solving process.

Abstract: Human non-conscious reasoning is one of the most successful procedures evolved for the purposes of solving everyday problems in an efficient way. This is why the field of artificial intelligence should analyze, formalize and emulate the multiple ways of non-conscious reasoning with the purpose of applying them in human problem solving tasks, like medical diagnostics and treatments, educational diagnostics and intervention, organizational and political decision making, artificial intelligence knowledge based systems and neurocomputers, automatic control systems and similar devices for aiding people in the problem-solving process. In this paper, a heuristic framework for those non-conscious ways of reasoning is presented based on neurocognitive representations, heuristics, and fuzzy sets.

Keywords: non-conscious reasoning; heuristics; fuzzy logic; approximate reasoning

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1. Introduction

Non-conscious reasoning procedures in daily human life are applied when it is urgent to solve a routine problem, time is limited, information unreliable, and the future uncertain. They are neither typical logical ones nor are they symbolic ones. They are based on simple heuristics also known as fast-and-frugal heuristics [1] but they are incredibly successful and efficient procedures in terms of its routine problem-solving capacity [1]. To give insight into how people reason, some theories like logic, probability, bounded rationality psychology and heuristics were developed in the past. Aristotle (384–322 B.C.) developed classic logic as the systematic study of the laws and forms of thought to obtain true new statements about the world by processing true premises. Today, logic has left the pure philosophical field to enter the area of discrete mathematics in the form of symbolic logic. As a part of mathematics, logic is a formal discipline using a highly developed abstract symbolic language.

However, to model human reasoning in a full way, logic should be able to define a one-to-one mapping between its conceptual elements: symbols, concepts, propositions, laws and processes, and the semantic contents of reasoning. At the present time, this is not yet the case. The subjective meaning of ordinary concepts is not absolute but depends on the context in which the concept is used. Likewise, the truth of a common proposition does not have an absolute value because the proposition's meaning may be dynamic and varies also with the context. This makes formal logic a necessary but insufficient instrument for handling human reasoning. Semantics, cognitive science, psychology and linguistics must then complement logic to form the appropriate analytical framework to understand and use conscious as well as non-conscious reasoning [2].

2. Precursors

In fact, since last century the mind has been modeled also by probabilistic approaches like Bayesian theories of cognition [3]. Moreover, for [1] heuristics are processes that, "ignoring some information, enable fast decisions". Gigerenzer, et al. [2] considered heuristics a comparatively recent means of understanding how the mind works. These authors argue that because of their cognitive limitations, humans are unable to perform fast rational calculations around complex problems and instead rely on approximate heuristics. A variant of this view says that even when people could compute the best decision, they often rely on heuristics in order to save effort at the price of sacrificing some accuracy. This approach is based on the principle of an accuracy—effort trade-off [2]. This trade-off, according to the theory of bounded rationality [4], is believed to be one of the few general laws of the mind. In fact, in situations where there is not enough resources to obtain all the needed information for an optimal solution, a bounded rationality must be used for finding at least a good feasible solution [5].

Other points of view around the necessity to consider fast-and-frugal heuristics as the base of non-conscious reasoning are those of [2] that proposed informal heuristic models "that do not make precise quantitative" statements and proposed and tested formal models of heuristics that "... when compared to standard benchmark strategies... can be faster, more frugal, and more accurate at the same time". These models include the few pieces of information that people use and specify the simple ways in which they process this information.

3. Methods

3.1. Psychological Heuristics

Psychological heuristics are formal models for making decisions that "(i) rely on core psychological capacities (e.g., recognizing patterns or recalling information from memory); (ii) do not necessarily use all available information, and process the information they use by simple computations (e.g., ordinal comparisons or unweighted sums); and (iii) are easy to understand, apply and explain" [4].

Psychological heuristics perform as well or even better than more complex standard models in decision problems such as multi-attribute choice, classification, and forecasting, and in domains as varied as health, economics and management.

Gigerenzer et al. [2] developed and tested formal models of heuristics that, "... when compared to standard benchmark strategies..., can be faster, more frugal, and more accurate at the same time" [2].

Katsikopoulos [6] proposed a definition of psychological heuristics which is a hybrid of these three interpretations. As in [2], this definition focuses on heuristics that not only are computational shortcuts but also have a psychological basis; and these heuristics are formalized.

3.2. Dual-Process and Dual-System Theories of Reasoning

Dual-process theories [7] hold that there are two distinct processing modes available for many cognitive tasks: one (type 1) that is fast, automatic and non-conscious, and another (type 2) that is slow, controlled and conscious. Typically, cognitive biases are attributed to type 1 processes, which are held to be heuristic or associative, and logical responses to type 2 processes, which are characterised as rule-based or analytical [7]. Dual-system theories go further and assign these two types of process to two separate reasoning systems, System 1 and System 2—A view sometimes described as 'the two minds hypothesis'. It is often claimed that System 2 is uniquely human and the source of our capacity for abstract and hypothetical thinking [7].

Dual-process and dual-system theories are empirical theories of human psychology. Operations Researchers have also proposed dual-process theories of learning and memory, one fast-access but slow-learning, the other slow-access but fast learning. In addition, it is often claimed that System 2 is evolutionary recent, uniquely human system, which is the source of our capacity for decontextualised abstract thinking in accordance with logical norms. There are now many dual process theories, developed across different disciplines. Evans, et al. [8] presents an interdisciplinary exploration of dual process theories, drawing together work from cognitive and social psychology, as well as philosophy. They encourage a dialogue between psychologists and philosophers about dual process theories, one that hitherto has been missing.

In real life problems, we find large amounts of information coupled with large amounts of uncertainty, that taken together constitute the ground of many of these problems today: its complexity [9]. As we become aware of how much we know and of how much we do not know, as information and uncertainty themselves become the focus of our concem, we begin to see our problems as centering around the issue of complexity.

3.3. Fuzzy Sets and Approximate Reasoning

Let us call a concept c the subjective logical representation of an object. The conceptual universe C is then a set of concepts used in a certain discourse, application or problem solving task.

The contents of a concept c can be represented as an ordered n-tuple $\{A_1(c), A_2(c), \ldots A_n(c)\}$ of attributes. The A's span a semantic space with n dimensions. Every attribute has a value that can be quantitative, logical, or linguistic. The pair (attribute, value) express a concept property. One must define for each attribute A_i valid ranges X_i for its values. Therefore, each attribute A_i is a function with domain C (the conceptual universe) and range X_i. The particular instances of the concept c are then represented in the semantic space by points (if they have quantitative values) or regions (if they have logical or linguistic fuzzy values).

A property can be (a) absolute, when it has a context-free meaning. Example: "this man is 1.70 m high" or "the car is red"; (b) relative, when its meaning depends from the context, i.e., from the current application of the concept. Example: "this man is not so tall" or "this car is very expensive".

Because of their variable, context dependent meaning, relative properties are fuzzy properties that have a broader range than absolute ones and are better expressed in linguistic terms. Their values can be represented as fuzzy membership functions in the sense of Zadeh [10].

From both kinds or properties, the absolute ones are more precise in a context-free semantics, because they represent concepts as points in the semantic space. However, when the meaning of the attributes depends from the context (and that is the rule in real world problem solving and communication), it is just the relative properties that convey the most information, because their fuzzy values express not only a region in the semantic space but the relative position of this region in the range (subspace) of the context meaning.

For instance, if we say "this boy is 1.70 m high", the value 1.70 m represent a point in the scale of height but it says nothing about the relative position of this point in the current context meaning. In fact, this value means very different things whether the boy is 10 years old or 20 years old. However, if we say "this boy is very tall" this presents not only a fuzzy region in the scale of height but also the relative position of the boy's height in our context meaning.

Therefore, if we have as only description of a concept property an absolute, numerical one, then to understand its meaning in our context, we should introduce additional information relating the absolute measure with the particular context. Even in hard science applications, where all relationships among concepts have a mathematical expression, the numerical results of a lenghty computation should be evaluated with additional qualitative criteria to decide whether they represent or not acceptable solutions for our purposes.

Considering relative properties as fuzzy sets, Ezhkova [11,12] has developed a method for translating absolute values to relative ones and vice-versa, introducing information about the context through an experience vector and mapping the absolute values on an universal space whose scales are the universal scales for measuring attributes in linguistic labels.

4. Results

Based on the models of psychological heuristics, dual-processes and dual-system theories of reasoning as well as fuzzy logic and fuzzy approximate reasoning, we have identified a set of heuristics that are the ground of the bounded rationality of non-conscious reasoning.

4.1. A Non-Conscious Reasoning Heuristic to Operate Preferably with Fuzzy, Non Measurable Object Properties

Fuzzy-trace theory [13] posits that people form two types of mental representations about a past event, called verbatim and gist traces. Gist traces are fuzzy representations of a past event (e.g., its bottom-line meaning), hence the name fuzzy-trace theory, whereas verbatim traces are detailed representations of a past event. Although people are capable of processing both verbatim and gist information, they prefer to reason with gist traces rather than verbatim. This implies, for example, that even if people are capable of understanding ratio concepts like probabilities and prevalence rates, which are the standard for the presentation of health- and risk-related data, their choice in decision situations will usually be governed by the bottom-line meaning of it (e.g., "the risk is high" or "the risk is low"; "the outcome is bad" or "the outcome is good") rather than the actual numbers. More importantly, in Fuzzy-trace Theory, memory-reasoning independence can be explained in terms of preferred modes of processing when one performs a memory task (e.g., retrieval of verbatim traces) relative to when one performs a reasoning task (e.g., preference for reasoning with gist traces).

Thus, we can identify a non-conscious reasoning heuristic to operate preferably with fuzzy object properties, because they are more meaningful than quantitative ones. In fact, they convey, semantic information not contained in quantitative scales.

4.2. A Non-Conscious Reasoning Heuristic to Operate Preferably with Linguistic, Non Numerical Values for Evaluating Object Properties

This heuristic is an extension of the former heuristic. Due to its fuzziness, the information provided by linguistic properties is easier to obtain than that of quantitative ones and therefore its cost is generally lower because of the accuracy—effort trade-off.

For example, in order to say "this boy is 1.70 m high" somebody must measure his height with a proper instrument, according to a methodological acceptable technique and make the data available to us without distortion. However, saying "this boy is very tall" the measurement procedure reduces to take a look at him or at his picture and compare his height with the mean height of boys in his context. Therefore, if we talk about his height, the linguistic communication process is more robust to noise distortion.

Thus, we can identify a non-conscious linguistic reasoning heuristic to operate preferably with linguistic relative properties because there is an accuracy—effort trade-off and the required information is easier, faster and cheaper to obtain than the quantitative one and its communication is more reliable.

4.3. A Non-Conscious Reasoning Heuristic Minimizing Problem Complexity by Reducing the Number of Necessary Significant Properties of the Concepts Involved

The attributes (properties) of a concept have different relevance in different contexts. Therefore we define significance s (A_i, c, a) of an attribute (property) A_i of a concept c in certain context a as the degree of relevance of the attribute (property) A_i of concept c in the given application a.

Concept meaning M (c, a) is the fuzzy set of significant properties of a concept c for a given application a, Expressing the significance s (A_i, c, a) of a property A_i as a number in (0, 1) it can be interpreted as the degree of membership μ [A_i, M (c, a)] of the property A_i to the fuzzy set meaning M (c, a).

$$s\ (A_i, c, a) = \mu\ [(A_i)], M\ (c, a) \tag{1}$$

Normalizing the significance s_i of the properties so that $\sum s_i = 1$ we get the relative significance of the properties. These can be interpreted as the relative contribution of the attributes to the meaning. [14] developed a linear algebra method to calculate the relative significance of the attributes (properties) of a given concept in certain context, by pairwise comparison of attribute significances.

Attribute significance permits to reduce the dimensionality of a semantic space and thus the amount of information to be processed and the complexity level of a problem by reducing the number of attributes to those above certain absolute or relative significance level [12]. This is done automatically by the human mind, which normally is not able to take into account more than seven different items at a time [15].

By combining two or more attributes we can define joint significances. In general, these joint significances are not functions of the single significances alone, but they depend also from conditional significances of an attribute or attribute combination given another. For two attributes then we have:

$$s\,(A_i \,\&\, A_j, c, a) = f\,[s\,(A_i, c, a), s\,(A_j, c, a), s\,(A_i, c, a) \mid s\,(A_j, c, a)] \quad (2)$$

Certain properties characterized by a high joint significance may dominate the meaning of a concept, so that they alone become sufficient to define it. To identify a concept is to find the concept most related with a set of properties. The minimal set of properties whose joint significance permits to identify a concept is a semantic cluster [16]. The minimal number of attributes defining a semantic cluster is the semantic dimensionality of the concept.

If we consider a concept as a region in the semantic space, then a semantic cluster is a projection of this region on the subspace defined by the semantic dimensions of the concept. This projection should be distinct enough to identify univocally a concept.

We may therefore identify a non-conscious reasoning heuristic to minimize problem complexity by reducing the number of necessary significant properties of the involved concepts.

4.4. A Non-Conscious Reasoning Heuristic to Assign Provisional Default Fuzzy Values to Uncertain Object Attributes

An uncertain concept is a concept that at least one of whose significant properties is uncertain. Every uncertain attribute may be modeled as a fuzzy set of values.

There are two ways to handle uncertain concepts: (a) To investigate the fuzzy membership functions of uncertain attributes; (b) To take as value of an attribute a default value according to some empirical criteria.

Assigning default values to uncertain attributes instead of doing research about the membership functions is an accuracy-effort trade-off. There are several strategies to assign default values to unknown properties. We will mention following:

(i) To consider our previous experience with similar cases. This is called the expert experience approach.
(ii) To minimize the maximal possible lost, in case of assigning the wrong value. This is the minimax or pessimistic approach.
(iii) To maximize the minimal possible gain in case of assigning the right value. This is the maximin or optimistic approach.

4.5. A Non-Conscious Reasoning Heuristic to Simplify Problem Complexity by Adopting a Hierarchical Philosophical Framework

A hierarchy or system of partitions of a conceptual world is a very adequate instrument to organize data, decodifying the information incoming from the environment. A partition of the world is always a qualitative or nominal one, even if the different qualities are mathematically defined, like the different types of numbers (integers, real numbers, imaginary numbers, complex numbers, etc.). Organization of instances in a set of partitions is called a classification.

A partition of a world according to some properties is called a class [17]. The operation defining a new class is called an abstraction. A set of classes sharing some properties is called a superclass. Superclasses constitute also partitions of the world. By combining classes and superclasses in a systematic way we get a hierarchy. A hierarchy, as a system of partitions of a conceptual world, represents a structural conceptual model to understand that world. For instance, the taxonomic hierarchy of living beings, introduced by Linnaeus, permitted for the first time to understand the whole biological world as well as to locate every living being in a conceptual framework. This partition approach is the base of the object oriented programming (OOP) that was a revolution in the computer programming technology [17].

In a hierarchy, according to the principles of Object Oriented Programming (OOP) [17] instances inherit the properties of its class and classes inherit the properties of its superclass. Syllogism is a logical operation that rules the inheritance of properties in a hierarchy when the assignment of properties is expressed by universal and partial quantified propositions that can be affirmative or negative.

This inheritance permits to extrapolate conclusions obtained for a class to all its corresponding instances. Therefore, reasoning with classes and superclasses, as in Object Oriented Programming, is a very economical procedure to model and analyze the world.

Non-conscious reasoning tends to reach a generalization level abstract enough to handle very extended classes and superclasses. This permits to state general laws and principles that model and explain the universe in qualitative terms.

4.6. A Non-Conscious Reasoning Heuristic to Extend the Truth of True Propositions to Fuzzier Predicates

A true proposition is a proposition fully supported by evidence, i.e., a proposition that states a fact. There are logical operations that guarantee to state new true propositions, if we depart from other true ones. Some of these logical operations are material implication, modus ponens and modus tollens. It is therefore very important to be able to state true propositions as foundations for our non-conscious reasoning.

A fuzzified proposition is a proposition where the predicate is replaced by a broader fuzzier concept implied by it. For instance, "Albert is intelligent" is a fuzzified proposition of "Albert is a genius".

A true proposition logically implies all its fuzzified propositions, i.e., if a proposition is true all the propositions derived from it through fuzzification are also true. For instance, if "Albert is a genius" is a departing non fuzzy true proposition, then its fuzzified proposition "Albert is intelligent" is also true.

Let $a \Rightarrow b$, a true proposition: "a implies b". Let us fuzzify the predicate b and call b ($\approx$) the fuzzified b then we have:

$$b \Rightarrow b\ (\approx)$$

Therefore, by transitivity of implication we have:

$$a \Rightarrow b \Rightarrow b\ (\approx)$$

This property let us, in an uncertain environment, to state a true proposition, by selecting a fuzzier predicate that we think contains (is implied by) a true non-fuzzy one.

Thus, a non-conscious reasoning heuristic extends the truth of true propositions to fuzzier predicates.

4.7. A Non-Conscious Reasoning Heuristic to Increase the Belief Value of a Verisimilar Proposition by Changing Its Context

A context is a set of empirical facts related with the conditions to be fulfilled for a proposition to be true. A context, being an expression of evidence, determines the belief value of a verisimilar proposition.

Therefore, we may increase the belief value of a verisimilar proposition by looking for an appropriate context.

5. Discussion

The process of non-conscious reasoning is applied by humans in numerous circumstances, and is an incredibly successful and efficient procedure in terms of its problem-solving capacity. As such, the increasing popularity of artificial intelligence systems could doubtless benefit from the construction of a well-formulated heuristic framework of non-conscious reasoning. However, as the principles of non-conscious reasoning are neither purely logical nor purely symbolic, the codification and formulization of this reasoning paradigm is a non-trivial problem. Thus, the present study applies the principles of bounded rationality, psychological heuristics, fuzzy and multivalued logic, dual-processes and dual-system theories of reasoning to develop a consistent framework of non-conscious reasoning. This framework should provide important guidelines for the analysis of non-conscious reasoning applied to education, medical diagnosis and treatment, organizational and political decision making and construction of fuzzy inference engines with the aim of realistically simulating human reasoning.

This paper introduces eight kind of heuristics that follow principles that underlie the logical structure of non-conscious reasoning, like the accuracy-effort tradeoff of [4] and the dual-process and dual-system theories of reasoning of [7]. Rigorous logical analysis of these principles enables realistic descriptions to be derived using the semantics of fuzzy sets [10], mult-ivalued logic [18] and object-oriented representations [17]. When combined, these fuzzified descriptions constitute an analytical framework for the construction of fuzzy inference systems that can be applied in the development of artificial intelligence [19].

Our results will be of great interest to those involved in the application of biological and neurological structures to the computational domain [20,21]. The codification of non-conscious reasoning has many potential applications in artificial intelligence and complex systems, which are an increasingly ubiquitous component of modern life.

6. Conclusions

In this paper, a heuristic framework for non-conscious ways of reasoning has been presented based on the accuracy-effort tradeoff of Keller and Katsikopoulos [4], the dual-process and dual-system theories of reasoning of Frankish [7], the semantics of fuzzy sets of Zadeh [10] and Dunn [22], the multivalued logic of Łukasiewicz [18] and the object-oriented world modeling representations [17]. This framework can serve as a guideline to analyze the theories and applications of non-conscious commonsense reasoning [23] and build fuzzy inference engines [24] able to model and simulate non-conscious reasoning [25,26].

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