Modeling the Intuitive Decision-Maker's Mindset

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Abstract: Today, the term, Working Memory, is closely associated with intelligence. We propose that in addition to improving and speeding-up analysis, Artificial Intelligence (AI) can also be useful as a supplement to Working Memory. It is generally accepted that working memory plays a crucial role in cognition and models by computers, can help us understand the human mind. Building an artificial working memory can bring further benefits; for example, it can separate retrieval from reasoning and therefore, can acquire new concepts. The aim of this research is to solve the capacity shortage problem of Working Memory, by using AI as a supplement. In order to develop our argument, we characterize the ID3 algorithm as a way of looking for a consistent solution in the existing Case Based Graph; as the ID3 algorithm builds it from an empty graph, to an increasingly complex one. Methodologically, our study is based on observation of several Digital Natives (DNs) playing different games at Mobilis Interactive Exhibition Center in Győr, Hungary. The aim is to explore the behavior of the DN generation. By identifying the different mindset patterns of DNs, we will be able to observe how different DNs can be facilitated, to enjoy the games, rather than being bored, anxious or even, becoming addicted.

Keywords: Artificial Intelligence; Knowledge-based System; Machine Learning

1 Introduction

A published overview of expert systems shows the kinds of articles published in the field [1]. Even though intuitive Decision-Makers emphasize that the knowledge bases of their tools cannot have more knowledge than the experts whose knowledge has been represented, sometimes the illusion still arises. The knowledge base in the expert system will not be able to think differently than the decision maker who was the source of that knowledge. As Liao [2] said, the development of methodological approaches in expert systems shows expert-orientation in ICT-related disciplines, and suggests that there is a possibility of a different orientation in human and social studies. One of the novelties of our DoctuS Knowledge-based System [3] is its ability to show the informativity of the attributes of the Decision-Maker through the ID-3 algorithm. The intuitive Decision-Maker's mindset can be discovered through the informativity of these attributes. At the Mobilis Interactive Exhibition Center, we observed Digital Natives during play and built up a knowledge base of their behavior to illustrate the functional novelty of the Doctus Knowledge-based System. We argue for a transdisciplinary approach, in which the two otherwise parallel research paths may meet. Transdisciplinarity examines what lies beyond the different disciplines. It seeks to have an overall picture, an integration of a fuller understanding [4]. To understand the reality of decision making, one has to "pick and choose" from the fields of Philosophy, Cognitive Psychology, Cybernetics and Artificial Intelligence. In this article we aim to provide a demonstration of the ID-3 algorithm-based, Doctus Knowledge-based System, through a case, where the attributes, as indicated by the descriptor, are classified and a graph is developed. The descriptive indicator is a statistical value, which is called entropy, in information theory.

A contemporary Decision-Maker can only work together, with a smart tool, if the model created by the latter, distorts the thinking of the former, only minimally. In this study, we show how to map Working Memory, through the inductive reasoning of the Doctus Knowledge-based System, to create an artificial Working Memory.

2 Background

Daniel Kahneman states, "fast thinking includes both variants of intuitive thought – the expert and the heuristic – as well as, the entirely automatic mental activities of perception and memory, the operations that enable you to know there is a lamp on your desk or retrieve the name of the capital of Russia" [5]. Not having understood the intuitive Decision-Maker's mindset, expert systems have not yet found their domain of validity. "There were many published cases of systems that did not go beyond the basic validation of the application rules and so this pulled down the overall averages" [6].

Knowledge gathered in the knowledge-based system always comes from the memory of the intuitive Decision-Maker. The mind is not tuned for arithmetic, but to the memories of experience. We not only tell stories when we decide we are going to tell stories. Our memory is also telling us stories, in other words, what we have kept from our experiences is the story. As Daniel Kahneman says in his talk entitled "The riddle of experience vs. memory" at the TED2010 Conference, "We actually don't choose between experiences, we choose between memories of experiences. And even when we think about the future, we don't think of our future normally as experiences. We think of our future as anticipated memories. And, basically, you can look at this, you know, as a tyranny of the remembering self, and you can think of the remembering self-sort of dragging the experiencing self through experiences that the experiencing self doesn't need" [7].

If we examine cognitive psychology, from a meta-level, we find a vast amount of results from just as numerous experiments. It is not the aim of this paper to predict when cognitive psychology will present a few theories, nor if that is even possible. We interpret this situation on the basis of Karl Popper, who declared that the research of human-created organizations does not have its own Galilei. Both Popper and we hope that it will always be so, because the understanding of human organizations is different than that of physical or biological ones. With the efforts of Galilei and Newton, the successes of physics have surpassed all expectations, and so physics leapt far ahead of all other disciplines. Ever since Pasteur appeared as the Galilei of biology, biology has also been almost as successful [8].

In the wake of George Armitage Miller's idea of "The Magical Number Seven, Plus or Minus Two", published in 1956, the research results of Working Memory experiments have been just as defining for cognitive psychology [9]. "The proposal of the episodic buffer clearly does represent a change within the Working Memory framework, whether conceived as a new component, or as a fractionation of the older version of the central executive. By emphasizing the importance of coordination, and confronting the need to relate WM and LTM [long-term memory], it suggests a closer link between our earlier multi-component approach and other models that have emphasized the more complex executive aspects of WM. The revised framework differs from many current models of WM in its continued emphasis on a multi-component nature, and in its rejection of the suggestion that WM simply represents the activated portions of LTM. It also rejects the related view that slave systems merely represent activations within the processes of visual and verbal perception and production. Although WM is intimately linked both to LTM and to perceptual and motor function, it is regarded as a separable system involving its own dedicated storage processes" [10].

Howard Gardner defined ten types of intelligence [11] and is one of the people who has spent the most effort on defining the concept of intelligence. In his newest book, co-authored with Katie Davis, they examine the interaction between Apps and the human mind. "The second opportunity entails the capacity to make use of diverse forms of understanding, knowing, expressing, and critiquing – in terms that Howard has made familiar, our multiple forms of intelligence. Until recently, education was strongly constrained to highlight two forms of human intelligence: linguistic and logical-mathematical. Indeed, until the end of the nineteenth century, linguistic intelligence was prioritized; in the twentieth century, logical-mathematical intelligence gained equal if not greater importance" [12]. Nothing guarantees that the intuitive Decision-Maker behaves according to mathematical intelligence. It is impossible to prove, that mathematical intelligence leads to better decisions than other forms of intelligence.

This might indeed be at the core of the difficulty in understanding the intuitive Decision-Maker's mindset; the different disciplines are captive in their respective cages. Developers of machine learning held to their own concepts and methods, occasionally looking to cognitive psychology. Cognitive psychologists, for example Amos Twersky and Daniel Kahneman [13] have occasionally considered decision-making. Researchers in decision-making, often looked to cognitive psychology, but almost never paid attention to machine learning. To make matters worse, all three disciplines neglected philosophy, especially the problem of induction [14] [15]. Whatever may have happened, it is now clear that we must free ourselves from the cages of disciplines and hope to reach another result through meta-knowledge and a transdisciplinary approach. In this approach we must also decide on what level we wish to examine reality: through models, methods or tools. "We describe decision making with the following three levels of reality: (1) Models of decision makers' behavior, (2) Methods used to support intuitive decision makers, (3) Tools we use to implement the support of intuitive decision makers" [16].

3 Rejuvenating Machine Learning

For laymen, a computer is a machine that 'computes', that is, calculates faster than a human. This is still the basic approach, even though humans 'compute' very little. On trams and in pubs, we see people use the machine, but we do not see them calculating with it. The rejuvenation of machine learning, if it was rejuvenation at all, did not bring a paradigm shift. Based on the work of Thomas Kuhn [17], if two people stand in the same place and look in the same direction, then, avoiding solipsism, we conclude that they receive the same stimuli. If their eyes could be in the same place, the stimuli would be identical. However, people do not see stimuli. People have impressions and feelings, and nothing requires that we make the assumption that the two observers' impressions are the same.

At the time of the rejuvenation of machine learning, we are still not able to rethink it. We still tell digital natives what the digital outsiders believed. It is a matter of debate who first introduced the concepts of digital natives and digital immigrants. According to Marc Prensky, it was he himself, that used it first in 2001 [18], but that is beside the point right now. Our narrow field of vision and lack of courage allows us to see only what others have accepted. "What we refer to with the `meta-' is a very high level of abstraction, something that we can call meta-level.

At a high level of abstraction, where the details of reality dissolve, such knowledge loses direct touch with reality. However, it can be ’concretized’ by zooming into reality, and in this ‘concretization’ the meta-knowledge can take radically different forms. For instance, it may take the form of some knowledge with reference to one reality and some different knowledge with reference to some other reality. For this reason, meta-knowledge does not consist of concepts but of meta-concepts, which are extremely high-density essences of many concepts” [19].

Nick Bostrom in his book, Superintelligence [20] said that we cannot expect Artificial Intelligence to be motivated by love or hate or pride or other such common human sentiments. Let us first emphasize, that if we have understood reality at the level of the individual, then the modeling of the intuitive Decision-Maker’s mindset can be represented with an algorithm. We also posit that the ID3 algorithm, originally developed by J. Ross Quinlan would be fit for that purpose. If it were not, we could not choose any other existing algorithm, we would have to create a new one. In the next chapter, we will demonstrate that the ID3 algorithm is suitable for adequately describing the intuitive Decision-Maker’s mindset. Developed by us and actively applied for two decades, the inductive reasoning of the Doctus Knowledge-based System is based on the aforementioned ID3 algorithm. A tool is a tool, which grows more effective as its validity domain narrows. One must never search for the problem matching the tool, one must search for the most suitable, or least inadequate tool, for the problem.

4 Informativity in Mindset Patterns

Digital Natives are trained as if they would need the same tools as the Digital Immigrants and their ancestors. This new generation knows a little about everything, which is not necessarily a bad thing [21]. If we arouse their attention, they can deepen their knowledge easily, because knowledge is just ‘a click away’. This generation of Digital Natives do not need to be specialized in a strict way but rather become de-specialized, with the ability to search for knowledge efficiently and thus to become competitive. The capacity of long term memory, or what can be called meta-knowledge, defines the personal level of knowledge and experience acquired, the levels of which can be gained through many learning hours: novice (10 hours), expert (100 hours), master (1,000 hours) or grand master (10,000 hours). Short-term Memory or Working Memory, however, can contain and hold only 7 plus or minus 2 items.

Due to technological acceleration, the use of the term ‘content specific knowledge’ has grown significantly in recent decades, in large part because educators now commonly use the term as shorthand to articulate a useful technical distinction between knowledge and skills. It refers to the body of knowledge and information that teachers teach and that students are expected to learn in a given subject or content area, generally referring to the facts, concepts, theories, and principles that are taught and learned in specific academic courses, rather than to related skills – such as reading, writing, or researching – that students also learn in school. It is incontestable that Working Memory plays a crucial role in cognition and that models created with computers can help us understand the human mind. On the other hand, building an artificial Working Memory can result in many other positive outcomes: it can for example separate retrieval from reasoning and therefore can acquire new concepts. "By placing Working Memory between an agent's sensors and its decision-making element, we can give it the ability to recognize existing contexts, and reason using precedents – even analogies. This, in turn, allows the designer to focus on the agent's heuristics. Another reason to create an artificial Working Memory system is that doing so will also give us a framework within which to investigate different types of similarity, measures of uncertainty, and knowledge bases" [22]. In order to examine our topic, we observed several Digital Natives playing different games at Mobilis Interactive Exhibition Center in Győr, Hungary. Figure 1 depicts the attributes of meaningful play. The selection of observed attributes is based on gamification literature [23, 24, 25, 26, 27].

Figure 1

Observed attributes (Source: Screenshot by Authors from Doctus)

The aim was to explore the behavior of the DN generation by observing how the structure of the games affected their viability. By understanding the different mindset patterns of DNs, we would be able to observe how different DNs can be facilitated to enjoy the games, rather than getting bored, getting anxious or becoming dependent. We have selected five primary categories based on feedback from randomly selected players on the overall experience of the game, grade M1 became the lowest and grade M5 was the highest ranking in connection to the meaningfulness of the game. We then faced the following question: Which attribute should be first examined, in other words, which has the greatest descriptive power? We have chosen inductive reasoning as the categories are used when we would like to predict the value of an attribute with a discrete value based on a given situation and the knowledge we have on values of other descriptive attributes. Thus, we have a Case Based Graph, which is based on the previously described examples for a similar simulation we want to observe, hence we will be able to provide the expected value of the requested attribute. The ID3 (inductive learning) algorithm creates (or learns) the Case Based Graph based on the examples provided [28], which are built up from the bottom to the top. The basic idea of this machine learning algorithm is to select an attribute which we are interested in – this will be the target function, at first a binary attribute. Then, we find the additional attributes which best define the output value of the target function – this will give the root of the Case Based Graph and the possible values of each attribute will be the branches. We continue this process for the remaining levels and for each attribute until complete. Then ID3 classifies the attributes based on the descriptor and builds the graph – the descriptive indicator is a statistical value, which is called entropy in information theory. We shall characterize the ID3 algorithm by looking for a consistent solution in the existing Case Based Graph – as the ID3 algorithm builds the tree of decision (hypothesis) from an empty graph to an increasingly complex one. We use the Formula (1), where S is the set of examples, B is the binary target attribute, S_{plus} is positive, S_{minus} is a set of examples with negative target attributes, therefore $s \in S_{plus}$, if B(s) = ↑, and $s \in S_{minus}$, if B(s) =↓. For each Entropy count, log 0 should be 0.

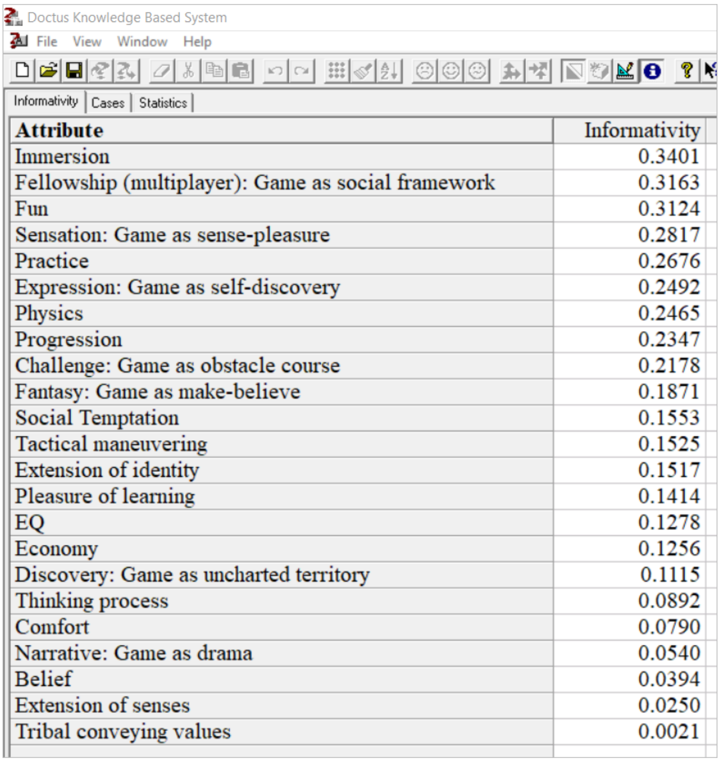
$$Entropy\ (S) = -\left(\frac{|S_{plus}|}{|S|} log2 \frac{|S_{plus}|}{|S|} + \frac{|S_{minus}|}{|S|} log2 \frac{|S_{minus}|}{|S|}\right) \quad (1)$$

The Entropy (S) specifies the minimum number of bits in an encoded bit sequence for a given example. If it is 0, then the target function in S is the same, so it does not have to be encrypted as we know what it was. If this is 1, it cannot be compressed and encoded, as positive and negative examples are equally likely. If it is a number between 0 and 1 (e.g. 0.7), then at least 0.7 bits must be used when encoding. We got the following values in Figure 2.

Entropy (S, Immersion) = 0.3401

Entropy (S, Fellowship) = 0.3163

Entropy (S, Fun) = 0.3124



Attribute	Informativity
Immersion	0.3401
Fellowship (multiplayer): Game as social framework	0.3163
Fun	0.3124
Sensation: Game as sense-pleasure	0.2817
Practice	0.2676
Expression: Game as self-discovery	0.2492
Physics	0.2465
Progression	0.2347
Challenge: Game as obstacle course	0.2178
Fantasy: Game as make-believe	0.1871
Social Temptation	0.1553
Tactical maneuvering	0.1525
Extension of identity	0.1517
Pleasure of learning	0.1414
EQ	0.1278
Economy	0.1256
Discovery: Game as uncharted territory	0.1115
Thinking process	0.0892
Comfort	0.0790
Narrative: Game as drama	0.0540
Belief	0.0394
Extension of senses	0.0250
Tribal conveying values	0.0021

Figure 2

Informativity of Attributes (Source: Screenshot by Authors from Doctus)

As Immersion, Fellowship and Fun had the strongest explanatory force, the root of the Case Based Graph will be Immersion and the resulting edges will be matched to its possible values. Subdivisions that fit into new branches will not be built on the whole set of S, but only with the examples in which the Immersion attribute takes the value corresponding to that branch. We could characterize the ID3 algorithm by looking for a consistent solution in the existing Case Based Graph. Based on the ID3 algorithm, we developed the following graphical model seen in Figure 3.

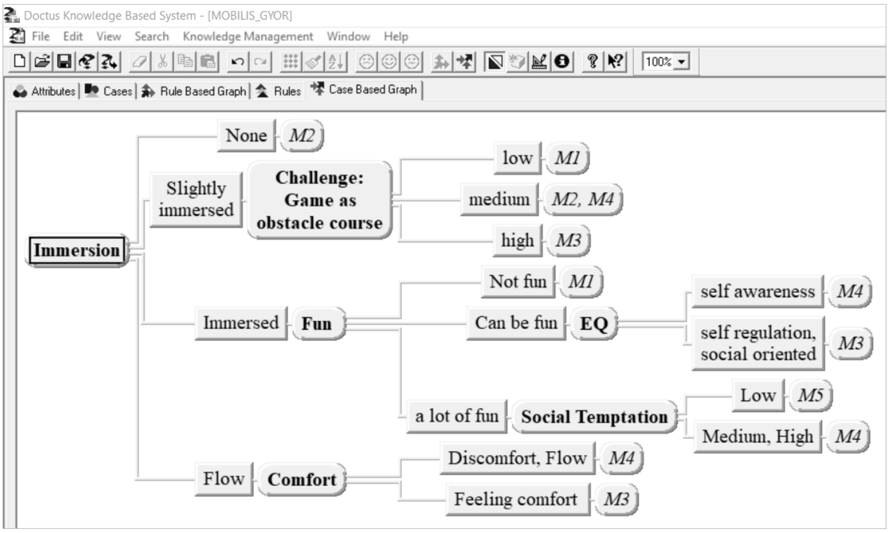


Figure 3

Case Based Graph (Source: Screenshot by Authors from Doctus)

As the Case Based Graph is founded on the statistics for all given attribute values in our examples and because we may have been using faulty data, we will need to modify the termination condition of the machine learning algorithm, to make it work better – we have to accept some imperfect consistencies. Experience shows that the more examples we work on, for a particular situation, produce more precise Case Based Graph. This observation is also valid for problem scenarios: The bigger the graph is, the more precisely we can set the value of the target attribute, but, surprisingly, after approximately 25 leafs, the accuracy decreases constantly.

5 Conceptual Model

Based on Nassim Taleb [29] those living in Mediocristan were satisfied with using arithmetic-based, Multiple Criteria Decision Analysis (MCDA) systems; they were perhaps afraid of new knowledge and the losses that come with change. Those living in Extremistan [29], are practically waiting for some new knowledge to challenge the current knowledge. If we say that it is currently possible to model the Working Memory of the intuitive Decision-Makers, then we will appear frightening in Mediocristan. We may cause a lot of trouble, if we rob someone of their belief in numbers. Life in Mediocristan is nice and calm, if we believe that Artificial Intelligence will bring the faster recalculation of the past. Very few intuitive Decision-Makers live in Extremistan, but they are always happy to see the knowledge representations modeled by knowledge-based systems.

The weak point of Doctus Knowledge-based System is that it is only able to show the mindset patterns of those who have them. In other words, machine learning is only able to help those who have natural intelligence. Perhaps even the concept of intelligence will need further clarification. Let us not dream of a world where every puzzle can be solved by a crutch. Puzzles were created for people who, every now and then, succeed with a good shot. Not everyone has to be a puzzle solver, that is, to try to reach the one true solution quickly.

It is possible that knowledge-based expert systems have to pull themselves out of their predicament. Bootstrapping is a commonly used phrase today. Bootstrapping in Artificial Intelligence and machine learning, according to one definition, is a technique used to interactively improve performance, in other words, recursive self-improvement. For example, Ryan Smith talks about why every start-up should be a bootstrap [30]. The new wave of Artificial Intelligence can start the third S-curve found in Figure 4.

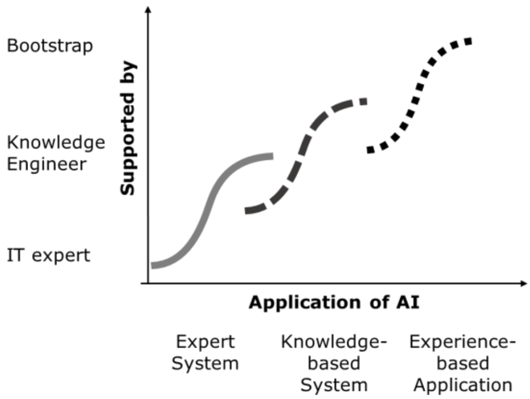


Figure 4
The third S-curve (Source: Drawn by Authors)

The harmony between the model and algorithm presented herein, can lead to the development of a tool that conforms to the already established user habits of digital natives who behave according to bootstrap patterns. This generation is already on the stage in the business world as well, but is often still forced to use the legacy tools of digital outsiders. Let us not forget, however, that the generation of the future, who grew up on computer games, does not want to read help files and does not really want to attend a course where they will only learn the use of one tool.

Conclusions

Although more and more data is being analyzed in the world, the decision-making process will not become smarter. Smartly prepared business decisions are born, based on knowing. An intuitive Decision-Maker can only be in balance with a smart tool if the invisible model between them, distorts as little as possible. In this paper, we demonstrated that Working Memory can be mapped to artificial Working Memory. This means that the tool does not replace the intuitive Decision-Maker by making a decision for them; it simply frees up their memory capacity limits. In this case, nothing stands in the way of a Decision-Maker, if they want to use further, new attributes, in a new decision. The tool can, however, help make the new attributes consistent and congruent with those already established. Knowledge-based systems, if they can be rejuvenated, will always remain tools, they will never become scary monsters that overcome humans. Just like all other tools, these can also help augment and expand the capacity limits of Working Memory.

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