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ESSAY

Your Artificial Intelligence, Connectionism or Augmented Fuzzy Cognitivism?

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Warning

Abstract

Artificial Intelligence (AI) is more than 60 years old and its many operational applications are beginning to revolutionise society by questioning the future distribution of functions and professions: in the near future, which positions will be dedicated to intelligent robots and which positions will still be the prerogative of men? In this essay, we present the two competing approaches of AI by showing their respective epistemological and practical limits: on the one hand, Cognitive AI, a logical and psychological approach, which allowed the development of Expert Systems on the basis of decision-making rules; on the other hand, Connectionist AI, a biomimetic approach, which produced the concept of Neural Networks, promoted since the 1990s under the expression "Deep Learning". To try to overcome the limitations of these two approaches, we propose a hybrid approach, which we will call "Augmented Fuzzy Artificial Intelligence".

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Biography

Prof. Zyed ZALILA, 53, is the CEO-Founder of the Intellitech [intelligent technologies] R&D company and its R&D director. He holds a PhD degree in fuzzy mathematics from Université de Technologie de Compiègne (UTC), a M.Sc. in Applied Mathematics and Artificial Intelligence from UTC and an Authorisation to Oversee Research. Since 1993 Prof. Zalila has taught fuzzy theory and its applications in this same university.

In 1990, he applied his fuzzy research to invent the concept of "virtual driver" and "lounge in motion": his first *ADAS* (*Advanced Driver Assistance Systems*) are operational on open roads, in partnership with RENAULT.

In 1998, Prof. Zyed Zalila created Intellitech, a company specialising in decision-making software that integrates the latest advances in Artificial Intelligence (fuzzy theory, machine learning theory). Since 2003, he has implemented a pivotal part of Intellitech's strategy: to offer a universal professional solution for Automatic Discovery of Predictive Decision-making Systems from Big/Smart Data, which does not require computer programming and offers improved predictive reliability compared to Open Source techniques.

Prof. Zalila has led numerous research projects in fuzzy mathematics and their applications. He is co-inventor of 8 patented fuzzy ADAS in 15 countries, and in 2000 invented xpark!® the world's first automatic parking system, operational in the most difficult situations. Since 2002, he has been the co-inventor of the various generations of the xtractis® intelligent robot for Robust Predictive Modelling of complex processes by Augmented Fuzzy Artificial Intelligence, whose rights are protected worldwide.

Awards and Recognition

Since 2004, Intellitech has been a member of the Comité Richelieu, the French association for high technology SMEs. Since 2005 it has been registered by the French General Secretariat of Defense and National Security, placed with the Prime Minister on the list of companies belonging to the strategic sectors for the preservation and promotion of national strategic interests.

In 2005, Intellitech received the *Award of the Picardy Economic Pres*s in the category *Innovative Enterprise of the year* rewarding its efforts of innovation of very high level, materialized in particular by its xpark!® automatic parking system.

Prof. Zalila was awarded the *Researcher of the Year 2006* Award as part of the *Nouvel Economiste's Men of the Year* trophy for his work on xpark!® and xtractis®.

In 2008, the international firm Frost & Sullivan awarded xpark!® the award for *Best Product Innovation in Automotive Safety Systems market*.

In 2012, Intellitech received the "*Coup de Coeur of the Jury*" Award as part of the *Deloitte Technology Fast 50 North of France* award for its xtractis® robot.

xtractis® has won several national and international benchmarks competing against Open Source techniques: Polynomial Regression, Logistic Regression, PLS (Partial Least Squares), Neural Networks / Deep Learning, Bayesian Networks, CART Decision Trees, Random Forests, Boosted Trees, SVM (Support Vector Machines).

Intellitech has distinguished itself in the *Deloitte Technology Fast 50 North of France 2011 and 2012* Awards, recognizing the 50 fastest growing independent technology companies in Haute-Normandie, Picardie and Nord-Pas de Calais regions.

Intellitech also won the *2011* and *2012 Deloitte Technology Fast 500 EMEA* Awards, recognizing the 500 fastest growing independent technology companies in the Europe / Middle East / Africa region.

I. Did you say AI?

Considered to be the father of Artificial Intelligence (AI), in 1936 the British mathematician Alan Turing imagined a programmable machine capable of rapidly performing all sorts of calculations [Turing 1936][1]. He was convinced that an automaton could be as intelligent as man if it were able to reproduce his mental activity.

Benefiting from the cryptographic breakthroughs achieved by the Polish mathematician Marian Rejewski in the 1930s, Alan Turing put his intuition into practice by designing, as early as 1941 for the services of English decoding, *the Bombe*, an electromechanical machine capable of taking only a few hours to discover the specific key to decrypt the encoded messages exchanged between the German High Command and the Nazi army[2]. Turing very quickly realised that such a task was humanly insurmountable[3]: he thus proposed to develop a logical and automated analysis of the space of possibilities and probabilities, based on any slips by the German cipherers and on the knowledge held by the Poles on the internal functioning of the machine. After the war, he continued his philosophical reflections and suggested that a machine could claim the qualifier of "intelligent", as long as it was capable of impersonating human intelligence [Turing 1950][4].

Exploring the Turing paradigm of thinking machines, Marvin Minsky, a cognitive scientist, invented the SNARC[5], the first self-learning neural network simulator [Minsky 1952, 1954]. In August 1956, he organised a conference at Dartmouth College (Hanover, New Hampshire, USA) with his fellow John McCarthy mathematician, Claude Shannon, father of information theory and Nathaniel Rochester, IBM's scientific director. Their ambition was to launch a new research discipline, "Artificial Intelligence", whose objective would be the development of new concepts, techniques and methods allowing the creation of an "artificial brain" thanks in particular to the availability of cryptanalysis mainframes developed during the 2nd world war [Wikipedia 1].

Following this seminal conference, which brought together several researchers from diverse disciplines, two competing approaches emerged: according to the paradigm of a rational calculation thought defended by Leibniz and Turing, cognitive logicians and psychologists, under the aegis of McCarthy, purported that Man's thought was based on his ability to manipulate symbols by applying formal rules; therefore, an intelligent machine had to know how to calculate with the help of symbols. This branch was named "Symbolic AI" or "Cognitivist/Cognitive AI" or "Computational AI" of which philosopher of the mind Jerry Fodor was one of its fervent defenders. At the same time, neurobiologists, neurophysiologists and neuro-psychologists, led by Minsky and Rosenblatt, argued that Man's intelligence emanates rather from the neuronal structure of his/her brain; indeed, an intelligent machine would need to integrate an artificial model of the brain. This biomimetic branch was given the name "Sub-Symbolic AI" or "Connectionist AI".

In this essay, we will expose the boundaries of Cognitive AI and Connectionist AI and present a hybrid approach, which we will call "Augmented Fuzzy Artificial Intelligence", in an attempt to overcome the limitations of the two approaches mentioned above.

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1 Its mathematical concept of a universal computing machine was supposed to represent a virtual person performing a well-defined procedure, in the form of instructions (transitions table). The machine was endowed with an infinite memory (ribbon composed of an infinity of contiguous boxes) and a reading and writing unit; it was programmable and reprogrammable. Nowadays, Turing machines are called computer programs or by extension, computers.

2 From 1939 to 1941, in the Victorian mansion of *Bletchley Park*, between Oxford and Cambridge, secretly sheltering the decoding services of English intelligence, Turing wrote the specifications of *the Bombe* and improved it with his colleagues Gordon Welchman and Richard Pendered: a machine able to determine every day, among the 159 10^{18} possible keys of the *Enigma* Nazi coding system, the key that would give access to messages between the German General Staff and its submarines crossing the North Atlantic. Historians believe that the decoding of the *Enigma* code shortened the 2nd World war by at least two years, saving more than 14 million lives.

3 If a team of 10,000 men could check 10,000 keys per minute, 24 hours a day, 7 days a week, 365 days a year, it would have taken a year to test 5.256 billion different keys and thus more than 30 billion years to test all possible combinations as part of an exhaustive search!

4 During the *Imitation Game* test created by Turing, judges discuss at a distance with interlocutors whose nature (automaton or human) they do not know. If, after five minutes of conversation, the automaton manages to pass as a human to at least 30% of the judges, then the test is successful and the automaton is qualified as "intelligent".

5 SNARC = *Stochastic Neural Analog Reinforcement Calculator*

II. Bivalent Cognitive AI and its (many) limits

Logic and cognitive psychology postulate that Man reasons through the inference of decision rules[6], Cognitive AI researchers have developed artificial systems that make decisions by manipulation of symbols: from a collection of "If...Then" rules that are supposed to be true, an inference engine makes it possible to infer a decision for observed facts about a particular situation. The goal being to model the knowledge of an expert in the field, so that it can be used anytime and anywhere, they quickly acquired the name of "Expert Systems".

Bivalent Logic? Rather simplistic...

The first expert system MYCIN developed in 1972 focused on the medical diagnosis of blood pathologies [Shortliffe & Buchanan 1975]. Despite a benchmark won against physicians specialised in infectious diseases, the limits of such an approach soon became apparent. Indeed, the paradigms implemented in an Expert System are those inherited from the bivalent Logic of Aristotle[7]: its founding axiom states that the world is governed by two mutually exclusive states, the "True" and the "False". It is thus impossible to be both "True" and "False" (Principle of Non-Contradiction), just as it is impossible to be in a third state other than "True" or "False" (Principle of Excluded Middle). If such theorems are precious for mathematical demonstrations, they prove to be very little applicable in the real world. The physician could not use bivalent decision rules to model his/her expertise: if one of his/her diagnostic rules was almost always true, this other rule would be sufficiently true, but not always true. Shortliffe and Buchanan were then obliged to introduce coefficients of likelihood or certainty to weigh the veracity of the deductions made from each of the binary rules of the Expert System. In addition to the logical inconsistencies induced by such probability coefficients[8], no expert was able to define the value of certainty of each of the rules he/she used. Indeed, the Expert System developed a mechanism of reasoning that diverged, both in terms of similarity and in terms of outcome, from the cognitive mechanism developed by the Expert that it was supposed to model.

It was not until the beginning of the 20th century, and the development of quantum mechanics, that certain thinkers dared to question the simplistic axiom imposed by Aristotle and thus the binary reasoning of classical logic. The Polish logician Jan Lukasiewicz thus proposed in 1920 a ternary logic, that in addition to the "True" and the "False" accepted a third state: the "Possible" or the "Uncertain" [Lukasiewicz 1920-1939a, 1920-1939b]. All the mathematics would be turned upside down, since they would have lost *de facto* the strong algebraic properties induced by the bivalence axiom. He went so far as to propose a logic accepting an infinity of nuances of truth: his *aleph* logic is thus the first infinite uncountable-valent logic, that is, a logic accepting an uncountable infinity of nuances of truth.

In the early 1960s, obsessed with the control of complex systems, Lotfi Zadeh, American-Azerbaijani control system scientist, admitted that it was very difficult for him to model a complex system thanks to nonlinear analytical equations and even less to analytically reverse such a model to construct the control law of the complex system. In love with the very young Cognitive AI, he ended up finding an operational solution by relocating the problem of automation: instead of modelling the complex process and failing during the inversion of the model, he decided to model the resolution strategy developed by a human expert who would solved the problem through a qualitative empirical approach, without the use of mathematical equations; thus, he tried to model the expert thanks to a system of decision rules that he would have managed to make explicit. Zadeh's touch of genius was to abandon Aristotelian logic, retained by the promoters of Cognitive AI for Expert Systems, and replace it with the *aleph* logic of Lukasiewicz, which he rebranded with a more marketable name: *Fuzzy Logic*[9] [Zadeh 1965, 1968, 1973, 1975]. The

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6 From the 4th century BC, Aristotle was the first philosopher and scientist to attempt a modelling of human discourse: his intention was to propose a tool or instrument (*Organon*) that would allow to arbitrate the oratorical jousting organised between schools of philosophy in the Agora. He is the author of the essential concepts of inference rule and inference scheme (syllogism) that would create the foundations of Logic. The formal and mathematised version of this discipline would become in the 19th and 20th centuries, the foundation of all modern mathematics. In this sense, we believe that Aristotle could also be considered to be the founding ancestor of Cognitive AI.

7 Aristotelian bivalent logic is also called binary logic because the two possible states False/True can be coded in binary system as 0/1.

8 The coefficients of certainty were proposed *a posteriori* to attempt to fill a notable difference between the logical rule proposed by Aristotle (a rule used to make a deduction is always true) and the nuanced rule that would be used by the Expert (presumably true, almost always true, very possibly true, more or less true). A coefficient of likelihood is therefore attached to each rule, assuming that the rules are independent of each other. Let us assume in the expert system the presence of three redundant rules R1: A→B, R2: A→B, R3: A→B with a likelihood coefficient of 0.3. With the combination of the certainty coefficients of MYCIN, these rules would conclude B with a likelihood of 0.657. In Logic, the proposition "(A→B) or (A→B) or (A→B)" forms a tautology, meaning that the redundancy of the same knowledge does not provide any additional information, and in fact the system would be reduced to R1 to conclude B with a likelihood of 0.3. Paradoxically, the management of uncertainty in MYCIN means that if several distinct rules are unsafe to conclude B, *in fine* they would eventually reinforce each other to conclude B with certainty (group mimicry effect)!

9 Fuzzy Theory, also called Fuzzy Mathematics, extends all the branches of classical mathematics by postulating the existence of an uncountable infinity of degrees of truth. This rigorous theory is intended

gradually intrinsic to fuzzy logic thus naturally integrated the vagueness, uncertainty and subjectivity with which the human expert perceives the real world in order to make nuanced decisions. However, this approach, which we call "**Fuzzy Cognitive AI**" remains strongly constrained, as is Bivalent Cognitive AI, by the manual acquisition of expert knowledge.

Manual acquisition of expert knowledge? No need to worry about that anymore...

From the 4th century BC, Socrates advocated for the expert to give birth to his knowledge through a process of interpersonal interrogation known as "maieutics". Several pitfalls quickly appeared.

The non-explicability of tacit knowledge

Cognitive psychology shows that if neophytic experts still rely on reasoning by inference of explicit rules, super-experts aggregate, during their years of experience, learning and practice, all successively accumulated knowledge strata. Thus, they would no longer reason by activating rules, but would quickly decide by using intuition, instinct, and heuristics, thanks to an unconscious decision mechanism [Marewski & Gigerenzer 2012]. This type of reasoning called "pattern recognition" associates a decision with a multidimensional abstract form recognised by the expert. The more the expert is able to recognise forms composed of several variables AND the more they are able to recognise a large number of such forms AND the more they are able to associate the right decision with each of these forms, the more their expertise will be judged to be at a high level.

Since super-experts use a pattern of reasoning based on tacit or implicit knowledge that cannot be explained in a maieutic process, the very principle of Cognitive AI is found to be *de facto* defeated [Dreyfus 1965]. Could you ask a Grand Master of the game Go to explain his decision strategy? No, he lets himself be guided in his choices of moves by a pictorial and qualitative perception of the game configurations, difficult to translate into formal rules of strategy. "*We, the pros, have a hard time defining how we make these choices, never mind talking about teaching it to a computer*", as told to *Science* by the American Michael Redmond, the first Western player to have reached 9th Dan, the "divine" rank, the highest grade of professional players [De Pracontal 2016].

Experts in sensory evaluation also use tacit knowledge[10]. Thus, the "Nose" in perfumery will know how to accurately measure the intensity of the jasmine scent of a perfume, without being able to explain how he/she was able to make his/her decision. The typical example of a decision made by intuition!

On the limitation of human understanding

Thanks to his "Bounded Rationality" paradigm of the decision-making agent, Herbert Simon[11] demonstrated that the capacity of the human mind to formulate and solve complex problems is very small in view of the size of the problems to be solved [Simon 1957].

His work upset the neo-classical economy and its decision-making agent with Perfect Rationality: until then, *Homo œconomicus* was supposed to make his/her decision rationally, independently of other agents, in order to maximise his/her utility or profit, on the basis of complete and perfect information (on past, present and future[12]). Although it simplifies the development of mathematical models of the Efficient Market, this axiom is misleading since it has never been verified in reality: in order to make a decision, the agent has only incomplete and uncertain information and often acts in an emotional and subjective way, depending on the present context, far from any optimisation of profit or utility [Kuhnen & Knutson, 2005]; hence a theoretical mathematical model developed *ab initio* based on erroneous behavioural assumptions, describing a pure and perfect economy, but incapable of describing and predicting the complexity of the market's real behaviour[13] [von Mises 1949].

Several researches in experimental cognitive psychology have shown the limit of Man to consciously process a great deal of information in decision-making: from 1 to 3 variables

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to represent and exploit data and knowledge tainted by vagueness, epistemic uncertainty and/or subjectivity. Fuzzy Logic is the branch that tries to model approached and nuanced human reasonings [Zalila 1993-2016, 2006-2013].

10 A sensory analyst uses his/her senses and his/her experience to evaluate, as objectively as possible, the sensorial descriptors describing a product as a measuring instrument. Due to the intra and inter-inherent variability of any human sensation, we describe these expert opinions as "objectivo-subjective".

11 An economist, sociologist and psychologist, Herbert Simon was one of the fathers of AI and participated in the Dartmouth founding conference of 1956: according to him, computers allow to reproduce and systematise human thought [Partenay 2005]. With Newell and Shaw, he developed the *General Problem Solver*, a universal solver that would prove limited to solving simple problems [Newell & al 1959]. In 1978, he obtained the Prize in Economics from Sweden's Central Bank in memory of Alfred Nobel (Nobel Prize for Economics) for his work on Bounded Rationality.

12 *Homo œconomicus* is expected to be fully aware of all past and present information that will enable him/her to decide, as well as all future consequences of his/her decision, **before** making his/her rational decision. In such a case, would it be better to "invoke" a *Deus œconomicus* (Economic God)?

13 From the axiom of Perfect Rationality, the neoclassical economy inferred the mathematical model of general equilibrium. The Sonnenschein-Mantel-Debreu theorem makes this model unusable by stating that general equilibrium can be stable only at the price of too restrictive hypotheses [Wikipedia 2].

simultaneously for normal people, up to 7 to 9 variables simultaneously for the most gifted among us [Miller 1956].

Thus, we consider that a decision maker with bounded rationality is a decision-maker in a fuzzy environment: he/she is led to make a decision based on a limited number of vague, uncertain and subjective pieces of information and knowledge, while using often ill-defined decisional knowledge (heuristics, know-how, fuzzy rules) [Simon 1955]. Moreover, Simon even introduces the *satisficing solution*[14] concept to express the fact that the agent will not seek the optimal solution at all costs if the discovery of it would cost him/her dear; very often, he/she will content himself/herself with a sufficiently satisfactory solution, that is to say, sufficiently close to the optimum. It is the definition of an optimal fuzzy solution, discovered thanks to a slight violation of one or more constraints[15].

<u>On the rejection of Systems that are not quite so Expert</u>

The aforementioned limitations of human understanding definitively put an end to the classical approach of knowledge acquisition, as advocated by Cognitive AI: limitation of the Expert to conceptualise his/her pieces of information, either because they are complex and would require a large number of variables, or because they are implicit and therefore not expressible on the one hand; limitation of the Cognitive Psychologist and the Cognitive Engineer who attempt to model the knowledge of the Expert while being overwhelmed by the large number of variables involved, or constrained by the impossibility of the Expert to express their knowledge. Let us not forget another insidious pitfall: the maintenance of knowledge. Since the process of acquiring expertise is often long, several years can pass before the decision-making system is finalised. But in the meantime, the expert will have been able to develop his/her knowledge and the previously coded rules would then need an update, delaying the availability of the updated Expert System!

Consequently, the expert knowledge gathered and modelled in the Expert System would be at worst, false, incoherent, biased, outdated and at best sub-optimal. All these reasons explain the many failures experienced by the Expert Systems and therefore their rejection by those who thought that this new paradigm of AI would rapidly revolutionise the world.

Call upon Descartes to solve complex problems? A myth…

In his *Discourse on the Method of Rightly Conducting One's Reason and Seeking Truth in the Sciences*, the French philosopher and mathematician René Descartes proposed a systematic approach to the solution of complex science problems [Descartes 1637]. He suggested that we decompose the complex problem into a sum of simple sub-problems[16]; it would be sufficient to combine the elementary solutions to the sub-problems in order to find a solution to the original complex problem. Although this physicalist reductionist approach[17] has been promoted in all scientific and academic formations up to the present day, it seems to us to be very limited, if not erroneous. Indeed, in a complex system, it is necessary not only to consider all the parts, but also to take into account all the interactions that may appear between the parts. Thus, by dividing, more subjectively, the original system into subsystems, one would inevitably break these interactions which could prove to be as important as the components themselves.

Moreover, a complex system is often governed by a large number of weak signals: a variable whose individual influence is limited but whose synergies with other weak signals or other strong signals would explain the behaviour of the system. This would *de facto* prevent us from using the incremental modelling approach advocated by Descartes[18], which focuses exclusively on the few most influential variables.

When analysing the intellectual approach used in Cognitive AI for the design of Expert Systems, it is distressing to realise that the Cartesian approach is built on dogma. Because of the limitation of human understanding, no expert can grasp more than a few variables simultaneously to express his/her decision strategy [Hayes 1962]; accordingly, each decision rule would contain at most 2 to 3 premises[19]. Worse, the decision tree paradigm, often used in AI to model a classification decision strategy, imposes itself as the ultimate expression of the Cartesian approach. A strategy involving 10 variables would be summarised to test sequentially, and

14 Combination of *satisfying* and *sufficing*.

15 Optimal fuzzy solutions are often the only possible solutions to a highly constrained multi-objective optimisation problem. If all the requests of the optimisation problem were validated, except for just one of them, the problem would not admit an optimal solution in a bivalent Aristotelian logic. Now, in the real world, a manager would in no way stop the operation of his/her factory if such a perfect solution did not exist; on the contrary, he/she would be happy to discover a new formulation of his/her product, very close to the optimal solution, which would satisfy all the requests, for example, with a degree of at least 0.98 (i.e., by accepting a tiny violation of one of the requests).

16 According to the second precept of Descartes.

17 Physicalism argues that things can be explained from the understanding of their constituent parts.

18 According to the third precept of Descartes.

19 A, B are the two premises of the rule (A and B)→C.

binary each of the variables, one at a time, in an order subjectively determined by the designer!

Similarly, as we have seen, the neo-classical economy imagines a Market composed of economic agents that are all identical, and which make decisions without any interaction between them. A Cartesian and simplifying vision of the Market, which is however totally false.

Had Descartes thus confused the Complex with the Complicated? If the Complicated can be broken down into the sum of its elementary parts and can be treated separately and sequentially, the Complex forms an inseparable whole and requires holistic reasoning in an attempt to apprehend it[20]. Thus, if 10 variables are involved in a Complex Process/Phenomenon (CPP) to be studied, it would be necessary to be able to reason by mobilising the 10 variables simultaneously; which is, as we have just seen and in the state of our current scientific advances[21], impossible for any human, independently of their Intellectual Quotient: a "Cognitive Ceiling" would forbid our reason to access the highly complex, multidimensional and interactive world in which we live.

But some would argue that it would be enough to reduce the number of variables through a multivariate analysis of data by applying the principle of parsimony[22] so dear to science. On the contrary, we maintain that **the complexity of a Process/Phenomenon (PP) is intrinsic to the PP and in fact cannot be reduced or simplified**: thus, a simple and efficient model for a CPP cannot exist; otherwise it would mean that the PP being studied was not complex, but simple. Consequently, the objective is to *a posteriori* determine the level of complexity of the CPP being studied by taking a holistic approach, without having to *a priori* and subjectively eliminate variables that could be important through their interdependencies or interactions with other variables. We would therefore support an extension of the Shadoks principle: "**Why make it simple and false, when you can make it complex and true?**".

Deployment of the Experimental Scientific Method? Interesting, but can do better...

The experimental scientific method was originally proposed by Alhacen Ibn al-Haytham, Arab mathematician, philosopher and physicist of the late 10th century in order to develop his work on geometric and physiological optics: he was one of the first physicists to appeal to mathematics to explain the Real. His works enabled the Franciscan monk and scholar Roger Bacon to theorise in 1267, in *De Scientia experimentalis*, experimental scientific reasoning; by this means, Roger Bacon paved the way for the philosopher Francis Bacon to, in the 17th century, develop an empirical theory of knowledge and the foundations of modern science [Hackett 1996]. Roger and Francis Bacon both promoted reasoning by induction in the sciences: on the basis of experimental measurements and observations carried out, using appropriate instruments, on the phenomenon studied, the scientist called upon his personal intuitions (in addition to mystic illuminations according to Roger Bacon) to develop a model or mathematical law M of the phenomenon that confirmed the observations that had been carried out. In a second step, new experiments were carried out to confirm the predictions made by deduction from the M model presumed to be true. If some of these new observations were to invalidate M's predictions, the scientist had to amend M into an M' model so that it conformed both to the old experiments confirming M and to the new ones which refuted it. The theoretical models imagined by the scientist and the observations made on the real phenomenon had to be mutually reinforcing: no scientific model should be accepted if it were invalidated by experimental observations[23].

However, the M model is created by the scientist with all the cognitive limitations inherent in his/her humanity. Consequently, we are entitled to question the veracity of such models, especially when the observations do not always confirm the supposedly true models. Should Economic sciences go by the name of "Science" when very few theoretical models which are laid out *ab initio* by scientists, even Nobel laureates, are confirmed by real

[20] Greek ὅλος *holos*, meaning "all", "whole". Anglo-Saxons speak of *holistic processing/reasoning* or *configural thinking*. Holism emphasises the importance of a whole as something that goes beyond the sum of the parts, where it is necessary to retain the importance of the interdependence of these. Taoist thought is intrinsically holistic.

[21] If in the near future, we were able to develop a drug that allows us to massively interconnect our 100 billion neurons (statistically a neuron is connected to only 10,000 neighbouring neurons) and to be able to mobilise all of them simultaneously, Man could undoubtedly reach a maximum multidimensional perception and unlimited intellectual capacity, like Lucy in Luc Besson's eponymous science-fiction film (2014). On the other hand, the functioning of all the neurons would require an enormous amount of unavailable energy: after consuming all the carbohydrates in the body, the brain would break down the fat and then the muscles to find the carbohydrates it would need to power all the neurons simultaneously, and this would remain insufficient! In normal operation, the human brain already uses about 20% of the daily energy consumed by the body.

[22] Also called "principle of simplicity" or "principle of economy", it could be translated as: "why make something complicated when it could be simple?" [Wikipedia 3].

[23] This experimental science approach raises questions in theoretical physics, particularly when no sensor allows the measurement of the phenomenon studied in the present state of technical advances. Thus, gravitational waves, deformations in space-time displacement following the brutal collision of two black holes, could only be detected in September 2015 by an international team of the Ligo Observatory of the California Institute of Technology (USA), 100 years after Albert Einstein predicted them in his theory of general relativity [Thorne & al. 2016].

experiences? Should we be content with simplified models that distort reality, postulated by scientists to describe a CPP, or should we try to overcome our cognitive limit by using a smart robot deploying an automatic inductive method to discover the more faithful behaviour of the CPP, without being limited in its capacity to apprehend a strongly multidimensional real world with interactions?

Is your model accurate? Concentrate more on its robustness...

A scientific model or a decision-making system is supposed to offer good performances in regards to both known and unknown situations. **Precision** is the metric used to estimate the descriptive capacity of a model: it evaluates the performance of the model to provide the right values for the situations already known. Most scientists and engineers are often satisfied with this unique estimator. But how would a specific model behave in regards to unknown situations? **Robustness** is precisely the metric that estimates the predictive capacity of the model. Robustness, or generalisation capacity, is a more pessimistic estimator than precision; so if the model is not precise, it will have no chance of being robust. On the other hand, a precise model is not necessarily robust. It is also the most feared situation in predictive modelling, that of learning by heart or overfitting: the model gives the impression of being perfect for known cases, but as soon as it is asked to make predictions for new situations, it is mistaken. In reality, and without it being known, the model will have modelled the noise inherent to the experimental measurements, thinking that the reference data were perfect!

Figure 2 shows the example of a decision-making system in financial risk analysis carried out within the framework of the European Sun & Sup project, aimed at incubators and investment fund managers [Kuhn 2006]: the objective is to predict whether a young innovative company is likely to survive to the 3 year mark? Each company is described by a hundred quantitative and qualitative variables, characterising human resources, as well as the product, financing, alliances, marketing and intellectual property. The M1 fuzzy model discovered by the xtractis® robot is perfectly accurate (Figure 2a): on the "actual survival / predicted survival" graph, the 150 companies are all aligned on the diagonal (correlation R = 1.000, root of the quadratic error (RMSE)[24]= 0.01%)! This means that the model has been able to perfectly describe the known records. By looking at its structure, it can quickly be concluded that no human scientist could have conceived such a model: it uses 77 predictive variables and is composed of 16 fuzzy rules of decision, a system of 16 nonlinear equations! If M1 is very precise, its robustness estimated by a Monte Carlo cross-validation of 10,000 cycles at 15% (10,000 x MC15%) is incredibly poor: for unknown corporate files, the model is very much mistaken (R = 0.408, RMSE = 15.73%) and therefore cannot be used to make predictions. However, this situation is rather frequent in science: "But why does the author of this leading publication claim that his model is a good explanation of the phenomenon under study, whereas I find that his model no longer correctly predicts new experiments that I have just carried out?". Most definitely a situation that has been experienced before...

The M2 xtractis® fuzzy model is a bit less accurate (R = 0.970, RMSE = 3.94%), but its 10,000 x MC15% robustness is much better (R = 0.849, RMSE = 8.61%), it would be able to predict the survival of new cases with a limited error (Figure 2b).

If such a metric seems so important, why would we not systematically calculate the robustness of the models we create? We could mention three possible reasons for this:

1. The Engineer or the Scientist has not learned the existence of such a metric. Gaps in education.
2. They do not want to calculate the metric for fear of having to discard their model if its robustness turns out to be weak. Scientific dishonesty.
3. They throw in the towel mainly because of the cumbersome process involved in estimating robustness. Help would not be too much.

Let us assume that a scientist develops a cognitive strategy S that is specific to him/her, in order to conceive by the inductive experimental approach a model M conforming to the observations O that have already been carried out. If they wanted to evaluate the robustness of their model M, that is, its predictive capacity, they would have to deploy the following Monte-Carlo Cross Validation process at x%:

They randomly divide the set O into two classes: a validation set V_i containing x% of the observations and a training set A_i containing (100-x)% of the observations. Then, they apply their cognitive strategy S to design a new model M_i in accordance with observations A_i. M_i is indeed a different model from M since it was developed from a different set of observations; but all the same we can consider M_i as a "first cousin" of M, since it was developed from the same strategy S. It remains only to ask M_i to make predictions about observations V_i which are totally unknown to it. We obtain V_i predictions for unknown situations. And we iterate this process N times. Little by little, the cloud of predictions will grow and its Actual/Predicted correlation, as well as its RMSE will eventually stabilise. Would a human be able to scrupulously develop N times the same cognitive strategy S

[24] RMSE = *Root Mean Square Error*

for N distinct training sets? Would he/she be able to reproduce this for N tending to around 10,000 just to estimate the reliability of their original model? The answers are obviously negative! And yet, the deployment of this process would be necessary to validate any new decision-making system, be it a scientific model or an Expert System. Worse, if he/she followed the recommendations of Roger Bacon to the letter, the Scientist would be led to refine his/her model incrementally as new observations arrive that would contradict the model. Hence the strong risk resulting from learning by heart (overfitting). In reality, on the basis of a certain level of invalidation, the Scientist should accept he/she will need to throw away the old model in order to imagine a new one, even if the latter is in breach with the previous one. Science has always progressed in this way through the adoption of new paradigms that were previously considered rebellious, blasphemous and heretical! The geocentric representation of Ptolemy[25] was thus supplanted by the heliocentric model of Copernicus[26], itself corrected by Kepler's elliptic system[27], whose experimental laws have been proved theoretically by Newton's theory of universal gravitation[28], itself encompassed and supplanted by Einstein's general relativity, which has is in turn been called into question by String theory since the end of the 20th century.

In conclusion, because of the limitation of our understanding, we cannot ensure the robustness of the decision-making systems we *ab initio* create, whether it is from an experimental inductive approach or from our past expertise. However, robustness is a necessary condition to ensure the future reliability of a predictive model [Zalila & al 2006a, 2007, 2013]. Hence the necessity of using an automaton to support us in the completion of this task.

You have every right to assume that you do not know! Did you know that?

Aristotelian logic reinforces our certainties: it forces us to be sure that it is true or to be sure that it is false, no other outcome being possible. Yet many situations in real life leave us full of possibilities and uncertainties. An uncertainty not stochastic, linked to a random phenomenon but rather epistemic, which denounces an incompleteness of information. If the first type of uncertainty is directly managed by probability theory, the second type is governed by the theory of possibilities and necessities [Zadeh 1978] [Dubois & Prade 1986] [Zalila 1993], one of the fundamental bases of Fuzzy Theory.

At the beginning of the 20th century, the French physicist and mathematician Jacques Hadamard established a binary categorisation of mathematical problems: "well-posed" problems, which have a unique solution, and "ill-posed" problems that may have different equi-efficient solutions or no solution [Hadamard 1902].

In doing so, we should be allowed to answer that a problem has no solutions or that it accepts several solutions by displaying them. For example, a complex industrial process that would induce an extremely high reject rate, despite several attempts to control production quality, is a problem that currently has no solution. On the other hand, if several different experts succeed in controlling a complex chemical process with a sufficient level of quality, we could say that the problem has several different, though equivalent, solutions. This would invite us to develop as many different Expert Systems as we would have high-level experts. The strategy used by Cognitive AI is rather to aggregate experts' knowledge into a single Expert System, even if some knowledge from different experts leads to serious inconsistencies, which is all the more acute if the acquisition of knowledge is spread over several years[29].

Opting for Fuzzy Cognitive AI? Very efficient, but anything can be improved...

We have just seen that Fuzzy Cognitive AI, commonly called Fuzzy Logic, filled the pitfalls of Aristotelian logic by proposing to qualify the veracity of propositions or the degree of possibility of occurrence of an event during the construction of a decision system. The concept of a decision fuzzy rule of the type "If (X is A) and (Y is B) then (Z is C)" is central because it linguistically and implicitly defines a non-linear fuzzy relation linking the variable Z to be predicted to the predictive variables X and Y used in the premise part of the rule. Its main advantage remains its interpretability by any professional expert, even a non-mathematician. Thus, a fuzzy rule represents a local model and a collection of fuzzy rules allows to define the global model covering the decision space. If a fuzzy rule proves insufficient to correctly model a certain region of the decision space, it would be enough to

[25] Geocentrism is an ancient and erroneous physical model according to which the Earth is stationary in the centre of the Universe.

[26] Heliocentrism is a physical theory that places the Sun at the centre of the Universe, or, depending on the variants, only the solar system. The planets follow perfect circular orbits around the Sun.

[27] Kepler proposed a heliocentric model in which planets follow elliptic trajectories.

[28] Newton's equations provided an exact solution in the case of an isolated body orbiting another, called a 2-body problem. For the solar system, they are only an approximation since they neglect the interactions of the planets (N-body problem).

[29] Suppose two experts E_1 and E_2 in the same profession respectively develop equi-efficient strategies $\{R_{1i}\}_i$ and $\{R_{2j}\}_j$, where R_{1i} and R_{2j} are the decision rules. If the R_{1i} from E_1 (respectively R_{2j} from E_2) are coherent with one another, it is quite possible that the decision strategy $\{R_{1i}, R_{2d}\}_{i,j}$ aggregating the expertise of the expert group $\{E_1, E_2\}$ is no longer valid.

replace it with a set of more local rules, more specific because covering finer grains. Thanks to these properties of locality and granularity, a decision-making system based on fuzzy rules, also called "Fuzzy Inference System" or "Fuzzy Expert System", is a universal approximator of non-linear functions [Kosko 1992] [Wang & Mendel 1992][30]. This pragmatically explains the many successes of Fuzzy Expert Systems since the late 1980s in managing complex control-command, supervision and diagnostic problems [Terano & al 1989] [Japan IA 1989] [Zalila & Lézy 1993, 1995] [Zalila & Coffin 1996] [Zalila & al 1998a, 1998b, 1998c, 1998d, 1998e, 2000a, 2004a], while the Expert Systems using bivalent conventional logic did not cease to accumulate failures.

Remember that most autofocuses use a Fuzzy Expert System to take sharp, high-quality photos by simulating the professional photographer's expertise, or that the most energy-efficient washing machines rated A+, A++... all incorporate a Fuzzy Expert System to adjust the amount of powder required, the amount of water, the drum rotation speed, the water temperature and the wash time, based on the fuzzy estimates of the dirtiness of the clothing, the amount of clothing and its fragility! Or that the world's first automatic parking system xpark!® integrated a large number of fuzzy systems, simulating the expertise of a professional driver and allowing a minivan to be parked in a parking spot with only 30 cm at the front and 30 cm at the back! [Zalila & Gueydan 2000] [Gueydan & Zalila 2003] [Auto-innovations 2008]. In paragraph V, we will briefly present two applications of Fuzzy Expert Systems in personalised predictive medicine.

However, in spite of its many successes, Fuzzy Cognitive AI drags along with it the original limitation of Bivalent Cognitive AI: the acquisition of knowledge proceeds according to the manual process of maieutics, hence is intrinsically constrained by the aforementioned limitations of human understanding. Fuzzy Expert Systems, even if they look powerful, do not display intensive metrics of robustness guaranteeing this displayed performance. Faced with the complexity of the process to be apprehended, the human expert develops tacit knowledge and the Cognitive Engineer cannot grasp several variables at the same time to code this implicit knowledge, and resigns himself/herself to adopting the Cartesian reductionist approach or the manual experimental method to design their fuzzy Expert System.

III. Connectionist AI: limits and assets

However, Connectionist AI, a competing branch of Cognitive AI, had early proposed an automated method for modelling an artificial neural network [Hebb 1949] [Rosenblatt 1957] [Lettvin & al 1959]. Used primarily for classification (image processing) and artificial perception (automatic vision, automatic recognition of speech and writing), a neural network is an oriented graph composed of nodes (the "neurons") connected to other nodes by weighted arcs and activation functions (the "synapses"). The upstream neurons which are excited combine their signals with the synaptic coefficients and transmit the resulting signal to the downstream neuron[31]. The idea is to reinforce connections when the network produces a good response and weaken them when the response is poor[32]. Early versions of formal neural networks, in particular the *Perceptron* proposed by Rosenblatt, were rejected by Minsky and Papert because of their inability to deal with non-linear and non-convex problems [Minsky & Papert 1969]. Yet, as early as 1965, Ivakhnenko and Lapa proposed the *Multilayer Perceptron* to erase this original limitation [Ivakhnenko & Lapa 1965]. Werbos and Rumelhart & al supplemented the concept by adding the error gradient retro-propagation algorithm [Werbos 1974, 1981-1982] [Rumelhart & al 1986], initially proposed by Linnainmaa to adjust the values of the synaptic weights [Linnainmaa 1970]. The denomination *Deep Learning*, which is currently more fashionable, embraces exactly this same paradigm, originally proposed more than 50 years ago! Schmidhuber presents in a very exhaustive manner all the work carried out in this field since the beginning [Schmidhuber 2015].

However, we oppose the connectionist paradigm with several major disadvantages:

i. Its main shortcoming is its non-interpretability: being a super-connected graph, no human would be able to understand or interpret the solution modelled by the

[30] If the works of Kosko, Wang and Mendel prove the theoretical existence of a fuzzy system allowing to approximate any non-linear and non-monotonic multidimensional function in the most **precise** way, they give no indication on how to proceed to discover this fuzzy system. By a manual human approach, it becomes unlikely that such a precise solution could be systematically discovered, even less probable to prove the existence of a **robust** solution to the problem posed, and almost impossible that such a robust solution could be discovered if it existed.

[31] The weighted sum of the signals emitted by the upstream neurons is transformed by an activation function (threshold, linear, radial, stochastic); the result is transmitted to the downstream neuron.

[32] This method is that of "supervised learning". It presupposes the existence of a reference dataset which sets out the decisions to be made for each of the reference situations.

neural network. The neural network provides a response but is unable to justify its response. Moreover, neural network specialists still do not know how such a network succeeds in finding a solution to the problem posed! This is a serious limitation, especially when the decision-making system has to be audited and approved by a regulatory body, for example in the fields of Finance, Medicine, Transport, Nuclear, Defence or Health. In fact, whenever the decision made by the neural network, being unexpected, could result in extremely costly financial, human, industrial or environmental damage.

ii. The neural network requires a very large volume of data to stabilise itself. In fact, several problems cannot be solved by this concept, simply because of lack of data.[33] In addition, the larger the volume of data, the more it will be necessary to deploy a large computing capacity to discover the solution neural network.

iii. The neural network models a decision system with global behaviour: as soon as a network parameter changes, the behaviour of the network would change. This complicates and lengthens the process of discovering a solution neural network for the problem posed.

iv. The Connectionist Engineer will have to make *a priori* choices concerning the architecture of the neural network: how many input neurons, how many hidden layers, how many neurons for each of the hidden layers, presence or absence of feedback loops, which activation functions for each neuron? This subjective approach slows the design work, does not encourage the Engineer to test a large number of architectures and leads to often biased, generally sub-optimal solutions.

v. Finally, the neural network has the unfortunate tendency to over-learn from the actual observations submitted to it. Thus, the decision strategy it proposes will often be very accurate, but less robust, i.e. its predictions on unknown situations will be less reliable. Of course, so-called regularisation techniques will avoid the neural network being too complex by penalising the high values of the structure parameters (number of neurons, number of hidden layers). As already mentioned above, we hardly ever know *a priori* the complexity of the new Process/Phenomenon that we are about to study. Applying *a priori* and systematically the principle of parsimony, the Connectionist Engineer would then risk obtaining a model that is indeed simple, but false: **the Complex cannot be simplified!**

However, the neural network has two major advantages. On the one hand, it shares with the fuzzy rules-based inference system the property of universal approximator of non-linear functions [Cybenko 1989] [Hornik 1991]; but its main advantage is its capacity for self-learning, i.e. to discover on its own the optimal values of the synaptic weights, making it possible to minimise the error of prediction on the cases observed. The combination of these two characteristics explains why a neural network tends to discover solutions that are very accurate, but not always robust!

IV. Augmented Fuzzy Cognitive AI, or the best of both worlds

Fervent defender of Fuzzy Theory and its multiple advantages compared to the standard approaches, I was often distressed to not always be able to prove the existence of a Robust Fuzzy Expert System solution that would model the Complex Process/Phenomenon (CPP) under study, and even less to discover if such a fuzzy system existed. Hence the idea of using learning algorithms as a neural network would do, i.e. mathematical optimisation techniques coming from *Machine Learning* [Mitchell 1997].

Hybrid, so-called neuro-fuzzy approaches have emerged that combine fuzzy systems and neural networks [Jang 1993] [Leondes 1998] [Liu & Li 2004]. In 2002, we decided to hybridise the theory of Fuzzy Relations of order N [Zalila 1993][34] with *Machine Learning* in order to develop a Learning Fuzzy Robot, without using neural networks to avoid their aforementioned disadvantages [Zalila 2003]. The guiding idea was to design a Universal Solver Robot capable of:

1. mobilising an infinite family of original, robust and rapid learning strategies,

[33] The *AlphaGo* program of *DeepMind* which managed in 2016 to defeat a 9th Dan Grand Master of Go was composed of two neural networks with 13 layers each. It began its initial learning from the analysis of 30 million game configurations; and for each of these configurations it had access to the best move proposed by a good player. The second step was to make it play against itself so that it could develop its "personal" experience of the game [De Pracontal 2016].

[34] The Fuzzy Relations of order N theory, proposed in my PhD thesis, extends the theory of fuzzy sets to a multidimensional space and to an infinite family of fuzzy logic operators. It defines new algebraic structures and exposes the maximum structures that can be attained according to the logic operators involved. It proposes an infinite family of *c*-dual generalised fuzzy measures of possibility and necessity, and demonstrates that these fuzzy measures are reduced to particular cases of composition by anchoring of fuzzy relations (fusion multiplication).

2. automatically discovering the hidden laws of the studied CPP[35], from a set of actual observations made on the CPP (logical process of Induction[36]),
3. translating the N-order Fuzzy Relations that have been discovered into a collection of fuzzy linguistic rules which could be interpreted by humans,
4. systematically assessing the stability or robustness of[37] the knowledge discovered, i.e. the reliability of the predictions made, based on this knowledge, on new observations,
5. automatically updating this knowledge as soon as the behaviour of the CPP evolves,
6. using robust knowledge to predict the future state of the CPP (logical process of Deduction[38]),
7. using robust knowledge to discover possible values of the predictive variables (input variables) to satisfy a multi-objective request defined from the variables to be predicted, while respecting constraints imposed on the predictive variables (logical process of Abduction[39]).

Such a robot would provide the Engineer or Scientist with three types of new results:

- an unprecedented set of Fuzzy Expert Systems **that are as robust and compact as possible**[40],
- the unprecedented decisions predicted by the Fuzzy Expert Systems for any new situation encountered,
- novel **optimal prescriptions** which, if placed at the input of the Fuzzy Expert Systems, would make it possible to achieve the desired objective-request[41].

It should be noted that with such an approach, the Engineer or the Scientist no longer has to assume *a priori* design hypotheses. They only need to define the superset of potentially predictive variables from which the robot will have to select the predictive variables to build a set of fuzzy decision rules. In order to preserve weak signals, the robot is obliged to approach the CPP, not according to Cartesian physicalist reductionist precepts, but rather by a holistic systemic approach.

The xtractis® Intelligent Robot, designed and developed by Intellitech, meets the aforementioned specifications: it combines all the advantages inherited from Fuzzy Cognitive AI and Connectionist AI, to which it adds a systematic and intensive evaluation of the robustness of the fuzzy decision systems that it creates [Zalila & al 2008, 2008-2013]. In this sense we call it **Augmented Fuzzy AI** (AFAI) or Robot for Knowledge and Optimal Solutions Discovery[42]. Thanks to what we call **Exobrain** or Cognitive Orthesis, the Engineer and the Scientist are thus able to access a multidimensional perception of the real world. Paradoxically, our AFAI robot helps them to understand this complex and interactive world, by **making explicit in the form of linguistic "If ... Then" rules the non-explicit and tacit knowledge they did not grasp**! Thus, our Exobrain is composed of a super right hemisphere[43] that is able to reason holistically and a super left hemisphere[44] that is able to translate linguistically the implicit decision strategies mobilised by the right hemisphere.

In order for this AFAI robot to be able to handle CPPs with very large dimensionality in a reasonable time, in 2008 we equipped it with a massively parallel calculation capacity in CPU[45] and GPU[46], similar to the first GPU acceleration work carried out by [Oh & Jung 2004] on neural networks. Note that if a large computing power is needed for the discovery of the model and the evaluation of its robustness, the use of the knowledge discovered to make predictions is real-time

[35] The laws are defined by N-order Fuzzy Relations connecting N-1 predictors to the output to be predicted. The robot must therefore succeed in discovering non-linear decisional fuzzy forms in a multidimensional space.

[36] Induction: We assume the premise A and the conclusion B. We induce the causal relation: A→B.

[37] The robustness estimator is also called "generalisation capacity": is the knowledge discovered sufficiently general to explain unknown cases other than the learning cases used to discover this knowledge?

[38] Deduction: We assume the causal relation A→B and the premise A. From this we deduce conclusion B.

[39] Abduction: We assume the causal relation A→B and conclusion B. We abduct the possible premise A. This is the technique used to solve police puzzles or medical diagnoses. In Bivalent Cognitive AI, it is also called "backward chaining".

[40] By "compact" we mean a model with the lowest possible complexity. But a compact model can be very complex, in the case of a CPP! The robustness of the model remains the dominant criterion when selecting the models: with an equal robustness level, we will select the most compact models.

[41] The prescriptions discovered are fuzzy optimal solutions, i.e. they validate the objective-requests with a sufficiently high degree of satisfaction, but not necessarily to 1 as would be required by conventional binary optimality. They are therefore *satisficing solutions* in the sense of Herbert Simon's Bounded Rationality.

[42] The objective assigned to a scientist being the discovery of knowledge models to describe and predict CPPs in the real world, we also describe such an AFAI robot as a "Virtual Scientist" or "Virtual Modeller".

[43] The right hemisphere of the brain is dedicated to the holistic and parallel treatment of information. It is often the seat of creativity, emotions, visuo-spatial aptitudes, perception of faces; i.e. unconscious decision-making.

[44] The left hemisphere of the brain is dedicated to the local and sequential processing of information. It is often the seat of analysis, of rationality, of abstraction, of logic, of numeration, of language; i.e. conscious decision-making.

[45] The CPU board (*Central Processing Unit*) is the motherboard of the computer. The new CPUs integrate multiple processors with N physical cores and 2N logical cores allowing parallel multi-core computing.

[46] A GPU card (*Graphics Processing Unit*) is a graphics card designed primarily to streamline video games and computer graphics. It incorporates a powerful processor with M cores allowing to parallelise the many mathematical calculations necessary for the representation of realistic computer graphics. We use this computing power for the parallel, inductive, predictive and abductive reasoning algorithms of the AFAI robot. In 2017, an HPC computing station (*High Performance Computing*), equipped with 4 latest-generation GPU cards, is able to deliver a calculation power of 51.70 Tflops in 32-bit single precision!

on a standard computer and in tens of seconds for the search of optimal prescriptions[47].

Figure 1 shows an example of a model discovered by our AFAI robot. The aim was to explain the implicit strategy of a sensory expert evaluating a fresh tomato in regards to several sensory descriptors such as pulpy, juicy, acidic, mealy, sweet, firm... using fifteen instrumental variables characterising seventeen varieties of tomatoes (mass, colour, amount of gel, amount of sugar, amount of acid, etc.). The most robust and compact model discovered to predict the *sweet* perception of tomato is composed of four fuzzy rules, a system of four non-linear equations. It is interesting to note that the robot, proceeding from a holistic approach, has eliminated thirteen variables to retain only two, thus confirming that the sensory decision-making process studied, although unconscious, was relatively simple. An interaction between the total acidity and the quantity of sugars is highlighted. Rule 1 states that the human brain does not detect a sweet taste as long as the total acidity and amount of sugars in the tomato are low. Rule 2 shows that sweetness is perceived when the quantity of sugar is greater than the total acidity. Rule 3 is the most interesting and intriguing; xtractis® discovered for the tomato a strategy used by the soda manufacturers to make us ingest up to 120g of sugars per litre[48]: when the total acidity is large relative to the quantity of sugars, then the human brain is deceived and is no longer able to detect the excessive amount of sugars, which are nevertheless harmful to health[49]. Due to the amount of phosphoric acid it contains, soda has the same acidity as a lemon[50]!

The paradox of automatic cognitive induction

As previously stated, the complexity of the Process/Phenomenon (PP) studied is intrinsic to the PP. Thus, if the PP proves to be complex, the most robust and compact model discovered by the AFAI robot will be equally complex. In fact, even if the strategy is expressed in the form of decision rules, it is very likely that a human expert would not be able to comprehend it in its total multi-dimensionality. On the other hand, it will always be possible to force the simplification of this complex model (by reducing its dimensionality) so that we can understand the underlying decision strategy, even if it degrades its performance; however, the simplified model will be less robust than the best original model and will no longer fit the CPP it was supposed to represent.

V. Augmented Fuzzy AI for Personalised Predictive Medicine

Since 2003, xtractis® has been successfully applied in several domains and sectors, for both public and private reference datasets [Zalila & al 2004b, 2004c, 2005, 2006b, 2009, 2011a, 2011b, 2014-2016] [Zalila 2014a] Kuhn 2006] [Amamou 2008] [Grès & al 2012, 2014, 2015] [Bernard 2013] [Jollivet & al 2012]. The most complex processes/phenomena that were successfully solved relate to the early diagnosis of human diseases in epigenetic and metabolic personalised predictive medicine, involving up to 26,000 variables in interactions with one another![51] [Zalila 2014b]. And the most robust and compact models discovered combine up to fifty epigenetic variables, proof of which is that this class of problems is indeed part of the CPP. So what about the tests marketed to the general public by several US biotech companies and which promised to create, from the sequencing of your genome[52], a diagnosis report for several pathologies after only analysing one or two genes? The US agency *Food & Drug Administration* made no mistake and decided in 2013 to ban these companies from any commercialisation of genetic testing to determine the risks of cancer, diabetes and Alzheimer, arguing that these tests were not reliable in the slightest and could result in unfortunate health consequences[53] [Fréour 2016] [Rambaud 2016].

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47 The process of model induction and validation is generally performed on HPC computing stations, while the validated models can be operated on "small" embedded processors, such as those of laptops or even smartphones.

48 Our reptilian brain is dependent on sugar, carbohydrates representing the energy source of the body.

49 WHO advises adults to get a maximum daily intake of 25g free sugars to prevent dental caries, diabetes and obesity [Lindmeier 2015].

50 The potential of Hydrogen (pH) measures the acidity or the basicity of a solution. In an aqueous medium at 25°C, a solution of pH = 7 is said to be neutral; it will be more acidic when its pH is less than 7 (minimum pH = 0) and be more basic when its pH is higher than 7 (maximum pH = 14). pH of Pepsi Cola® = 2.3, pH of Coca Cola® = 2.48, pH of lemon = 2.3.

51 Epigenetics demonstrates the influence of the environment on gene expression. It is therefore necessary to include all the criteria describing the living environment of the person to be diagnosed, in addition to nearly 24,500 intensities of gene expression and variables describing the metabolism of the person.

52 The full-scale genetic sequencing (24,500 genes) at high throughput of a human being can easily be achieved in a few hours from a sample of saliva or hair, for less than a thousand euros.

53 In October 2015, the *FDA* re-authorised the commercialisation of genetic tests, but limited to monogenic disorders (cystic fibrosis, sickle cell disease), hereditary intolerance (lactose, alcohol, caffeine), physical traits (eye colour, hair type) or parentage (geographic origin of ancestors, paternity test, Neanderthal gene).

Example 1

A pharmaceutical company or a Biotech company wishes to minimise the discovery cycle of a drug with the aim of eradicating a virus (*Drug Discovery*). From a reference dataset containing the molecular descriptors of different molecules and, for each of the molecules, its efficiency on viruses, but also its toxicity on healthy cells, xtractis® robots GENERATE, PREDICT and OPTIMISE will respectively allow:

- to discover the decision rules to predict the efficacy of a molecule on the virus and its toxicity on healthy cells,
- then to use the stable knowledge discovered in order to:
  - carry out a *Virtual Screening* of new molecules, testing them virtually to predict their efficacy on the virus and their toxicity on healthy cells
  - and discover optimal molecular profiles that simultaneously maximise toxicity to the virus and minimise toxicity to healthy cells, while verifying regulatory or manufacturing or cost constraints.

The pharmaceutical laboratory will then only have to synthesise the molecules having these optimal molecular profiles in order to test them in real-life conditions on the virus and the healthy cells, and then manufacture the corresponding therapeutic formulation. This means that the cycle time for designing new products is excessively reduced, avoiding unnecessary expenditure of time and money during numerous test/error cycles.

Example 2

A medical laboratory in anatomical pathology wishes to accelerate and make a reliable medical diagnosis for breast cancer[54]. The reference dataset is composed of 569 patient images: 357 cases correspond to a malignant diagnosis (positive case = "1") and 212 cases to a benign diagnosis (negative case = "0"). Each image represents three mammary cells from biopsies. After pre-processing, 30 characteristics of each image are calculated defining the potential predictors of this classification problem.

Figure 3 shows the performance of one unitary model (Individual Virtual Expert or IVE) among the most robust and compact of those discovered by xtractis®, after deploying 900 different learning strategies across all 30 predictors. Note that the dimensionality of the predictive model is important (21 predictors, 3 rules) which *a posteriori* confirms the high level of complexity of the process studied, well beyond the human cognitive limit.

By analysing the individual influences of each predictor, we find that two predictor variables stand out: *Cell 2 radius* which is the most influential[55], i.e. the one which, if it were not filled in, would lead to the most important degradation of the prediction; then *Cell 3 texture* with an influence of 0.436. On the other hand, we find that our AFAI robot has selected 19 other predictors with low or even excessively low individual influences ranging from 0.274 to 0.021. The robustness of the model for sensitivity[56] is 95.22% and the specificity[57] is 98.98% (Figure 3a). What does this mean? Simply put, for new patient records to be diagnosed, the AFAI robot estimates the ratio of "false negatives" of the predictive model at 4.78% (the patient had breast cancer and the model was mistaken in its diagnosis) and the "false positive" ratio at 1.02% of the predictive model (the patient did not have breast cancer and the model was mistaken in its diagnosis). In the case of a "false negative", the patient returns home reassured, at the risk of developing metastases in the months that follow; the consequences are disastrous for both the patient and the virtual doctor which could be accused of not saving its patient. In the case of a "false positive", the patient will be anguished, undergo unnecessary aggressive chemotherapy treatment, or even a preventive breast removal, suffer physically and psychologically for nothing, and the health insurance company will waste money on an expensive and pointless treatment. But the virtual doctor will be happy to have saved its patient, who was never in danger in the first place!

We could then ask why the AFAI robot kept 21 variables. Let us develop a reasoning by the absurd by adopting an incremental reductionist Cartesian modelling approach: by keeping only the two most influential predictors, the best possible model that could be built by the AFAI robot, after having deployed 350 different learning strategies, would maintain the order of the individual influences of the two variables, but would heavily impair the predictive performances of the model. The sensitivity and specificity robustness of the model drops to 77.54% and 82.04% respectively with the simplified model (Figure 3b). Cases of false negatives are in fact multiplied by 4.7 and cases of false positives by 17.6!! Thus, the 19 weak signals in synergy with each other and in synergy with the 2 strong signals made it possible to make a good model of the CPP under study. To deprive ourselves of these weak signals, trying at all costs to "simplify" complexity just to achieve the illusion of

[54] Reference database: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian – University of Wisconsin [UCI Machine Learning Repository] (USA)

[55] By convention, the most influential predictor has an individual influence of 1.

[56] Sensitivity refers to the percentage of "true positives", i.e. cases of cancers that are predicted by the model as such.

[57] Specificity refers to the percentage of "true negatives", i.e. cases of non-cancers that are predicted by the model as such.

controlling it is an ineptitude: it inevitably leads to erroneous decisions with consequences that can prove costly, if not disastrous.

In reality, faced with this ill-posed mathematics problem in the sense of Hadamard, our AFAI robot discovers several robust models corresponding to as many IVE: each IVE has a decision strategy of its own, even if all IVE are experts in the same field. They will certainly use a common subgroup of predictive variables, but will complement them with other predictive variables that are personal to them. As early as 2005, we proposed combining these EVIs into a college of virtual experts in order to make the final decision even more robust. We thus move from the theory of individual decision to the theory of group decision. In this case study, the college consists of 1,000 EVI[58]. Its robustness performance estimated on the basis of validation[59] is 98.10% in sensitivity and 99.16% in specificity; on the basis of test records[60], sensitivity is 97.17% and specificity at 98.60%, confirming the very good estimation of the predictive performance of the model.

As a comparison, in 1979 the MYCIN expert system for the medical diagnosis of blood disorders, and with only 65% good diagnoses, had already succeeded in beating the five experts in infectious diseases of the *Stanford University Medical Center* judged in the same conditions: their individual performances ranged from 42.5% to 62.5% of correct diagnoses [Yu & al 1979]! This proves the ability of the AI to compete with the most specialised expertise hitherto reserved for human intelligence alone. The wide inter-variability of diagnoses by medical experts with the same academic background is puzzling: a patient would thus have an additional 47% chance of having a good diagnosis if they met the most qualified doctor, as opposed to being diagnosed by the least qualified doctor! The Expert System has the advantage of being deterministic (always the same decision for the same file) and duplicable to ensure the availability of its expertise anywhere and at any time.

Note that ethical issues should always be addressed in the development of predictive intelligent systems for Epigenetic Predictive Medicine. Indeed, such an aid originally designed for very early diagnosis of the risk of the future onset of pathologies and therefore to avoid their consequences, could easily be used in a malicious way: refusal to hire, to insure, or grant credit to anyone whose medical diagnosis as predicted by the AI would be unfavourable. Given that the genome forms at the time of conception of the foetus, some might even be tempted to revisit eugenic human selection...

VI. Conclusions

With the development of GPU graphics cards and the democratisation of their significant computing power[61], various applications of Artificial Intelligence are emerging, in medicine, finance, industry, robotics, natural language processing, customer relationship management, and even in court or in the detection of malicious behaviour. If the AI algorithms developed since the 1960s struggled to express themselves on the computers of the time, in a few years from now, robots will be able to help us on a daily basis to diagnose our state of health, coach us during our purchases or in our professional career, to drive vehicles autonomously, decide on investments to be made, or hiring to be carried out, help judges in their decision, or even train politicians how to run their country. After the defeat of Garry Kasparov in 1997, no chess player has been able to compete with AI without a handicap, and since the defeat in 2016 of South Korean Lee Sedol, one of the best 9th Dan players in the world, no Grand Master of Go will either. Tomorrow, only Grand Master Robots will compete for world titles, and it is certain that grades higher than divine 9th Dan will have to be created!

We could also cite another AI "success" that passed unnoticed in 2016: one of the most experienced fighter pilots of the US Air Force lost all his aerial duels against a Fuzzy AI program[62], conducted on a training simulator over a long day of intense effort and concentration. The Fuzzy AI even managed to beat degraded flight situations (speed, manoeuvrability, sensors, weapons systems). "*It is the most*

58 Results obtained by xtractis®GENERATE 9.1.16139 (07/2016).

59 The validation dataset contains records of unknown patients from the predictive model, which were not used to create the model. However, this dataset is used to select the most successful EVIs, those that would be part of the final college of EVIs.

60 The test dataset contains records of patients unknown to the predictive model, which are not used to create or to select the model. It is the most reliable estimator of the real performance of the predictive model.

61 *IBM Deep Blue*, the first computer to defeat a Grand Master Chess World Champion in title (Garry Kasparov) in a full game, in May 1997 deployed a computing power of 11.38 Gflops [Wikipedia 2]. In 2017, a High Performance computing station equipped with 4 Nvidia Titan Xp GPUs delivered a computing power of 51.70 Tflops, 4,540 times more than that of *Deep Blue*!

62 This Fuzzy AI named *Alpha*, developed by the *University of Cincinnati* and its spin-off *Psybernetix*, with the support of the *US Air Force Research Laboratory*, had already managed to beat other AI opponents in air combat. It was able to analyse in detail and in real time each new dynamic combat scenario, then to decide the actions to be undertaken, all in less than 1 millisecond! Or 250 to 300 times faster than the blink of a human fighter pilot...

aggressive, responsive, dynamic and credible AI I have seen to date (...) It seemed to be aware of my intentions (...) It moved instantly between defensive and offensive actions as soon as needed." according to Colonel Gene Lee [Reilly 2016]. And what if tomorrow, robot soldiers, police robots or smart drones were allowed to kill autonomously? Without doubt, some politicians would be tempted to deploy them, claiming the preservation of the lives of human soldiers on new battlefields (urban guerrilla warfare, defence against terrorist attacks). Today, heads of state are ordering special services to "neutralise" terrorist or political leaders; tomorrow, a Spy Robot could be in charge of this "outlaw" task.

Undoubtedly, Intelligent Robots will be involved to help us in our daily lives. However, they will eventually replace human beings in almost all the tasks they have carried out up to now, from the most routine ones (cleaning, collecting garbage, searching the shelves of a large warehouse for items ordered online, transporting goods or persons[63]), to the most dangerous (clogging a breach in a nuclear power plant, working in mines or on high-altitude sites, exploring the abyss or other parts of the universe), and the most intellectual (call centres, medical diagnosis, surgery, financial risk analysis[64], legal decisions), to the most artistic (writing music, painting, sculpture, literary work).

Throughout this article, we talked about the capacity of the xtractis® AFAI robot to reliably model CPPs. The numerous studies, public and private, which we have carried out since 2003 show that it virtually systematically beats the Domain Expert, the Modelling Engineer or the Scientist. Moreover, I have even suggested that my fellow academics use it to analyse the veracity of works in experimental sciences: it would suffice to submit to it the reference dataset from which the authors of a scientific publication would have succeeded in producing their models, so that our AFAI robot can evaluate whether a robust predictive model exists, by exhibiting it, or, if not, to refute the results presented and refuse the publication of the said article! A great turnaround in scientific publication in perspective, previously ruled by the famous law of "Publish or Perish"... [Barthélémy 2013]

If a robot were to discover major scientific results in Medicine, Economics, Physics or Chemistry, who would be the holder of the Nobel Prize? The Intelligent Robot or the Human Scientist who provided the datasets and who published the results of the discoveries made by the robot? Maybe would we witness a scientific battle between robots to win these prestigious awards? With the automated processing of Natural Language becoming more and more effective, it could even be that the Nobel Prize for Literature is no longer out of the reach of a robot writer! Who would then hold the copyright of an intellectual work entirely created by a robot? Several legal questions will arise and will undoubtedly impose an extension of the legal arsenal.

The Nobel Peace Prize would be the only prize that Humans could hope of winning, at least as long as a robot is unable to show empathy and interpersonal emotional intelligence. But taking everything into consideration, perhaps the robot could achieve this by discovering original solutions to current conflicts or by predicting the political, diplomatic, economic or societal actions to be taken to avoid the emergence of such conflicts. If a robot had been able to objectively assess the level of well-being and happiness of the Arab populations, other than by means of biased economic indicators based almost exclusively on tourism rents, could Western diplomats have anticipated the direct or collateral consequences suffered by the countries of the whole world since the Tunisian Jasmine revolution carried out in January 2011?

The new economy of well-being or happiness [Davoine 2009] invites us to revisit our standard metrics of the wealth or economic development of a country. Who would still accept this measure of GDP if they knew that its increase was also directly related to the increase in the number of sick people or traffic jams or conflicts as a consequence of increased consumption of the number of drugs, fuel and weapon systems? Worse still, did you know, for example, that the two rules of good fiscal behaviour in the Maastricht Treaty of 1992, limiting the public deficit to 3% and the public debt to 60% of GDP, were enacted subjectively and arbitrarily in 1981 by three senior officials of François Mitterrand [Charrel 2017]. Yet such mono-criteria and binary reasoning do not distinguish the "good" deficit in future investments in education and research that would support future growth, from the bad debt induced by increases in the State's operating expenditures. Similarly, Japan does not seem to be on the brink of a precipice with a debt bordering 240% of the GDP, proving that the sustainability level of the sovereign debt is a multi-criteria issue! Indeed, it would be much more difficult for the Economist to have to combine multiple objective and subjective factors relating to the lives of citizens to invent new complex indicators that are more faithful to the level of well-being and happiness of citizens. But, as we have just seen in detail, the Human brain is incapable of managing a CPP alone. Hence its unfortunate tendency to want to simplify the CPP to give the impression of mastering it. Do not worry dear fellow citizens, everything is under control! In reality, few politicians admit that the very

[63] A report published by the US government highlights the direct threat posed by AI autonomous vehicles on 2.2 to 3.1 million jobs in the transport sector [Porrometo 2016].

[64] The Japanese life insurance company *Fukoku Mutual Life Insurance* has announced that the AI *IBM Watson Explorer* will replace 34 jobs held by its employees (25% of staff) [Porrometo 2017].

existence of the various international crises (societal, economic, financial, environmental, societal, political) is the indisputable proof of man's powerlessness to curb such crises. Multiple endogenous and exogenous factors in interactions and the CPP will not fail to knock on your door... Since the 19th century, thinkers have proposed several politico-economic models. All without exception have failed, from communism to ultra-liberalism, inviting Man to overcome the bivalence of his thought that he imposed on himself: Right against Left, Democrat against Republican, Labour against Conservative... Politics is often the sterile battle of duality: Aristotle would feel right at home in our assemblies to arbitrate the oratorical jousts of political parties. More than 2,350 years later, Western societies are unfortunately still stuck in this dualistic vision of the World inherited from the thinkers of Ancient Greece. Like Oriental societies, let us dare to introduce more nuances and harmony, by allowing complementarity in differences, to be both "Black and White"[65], "Male and Female", "Right and Left" and we could certainly create viable solutions to contribute to the progress of Humanity. At the risk of offending the fervent defenders of Greek non-contradiction, the World is in constant change and full of contradictions [Nisbett 2003].

The main question that we are entitled to ask is more an economical and sociological one: if mechanised and repetitive work has ended by alienating Man who only lives to work, instead of working to live, what kind of work will still remain, in the near future, when most of the tasks will be completed in their entirety by Intelligent Robots? How can we live without working and therefore without receiving the income of a job that has disappeared? Economists have already reflected on this highly probable situation and propose that the State distributes to each of its citizens a single universal unconditional income, throughout their lifetime, which the recipient can supplement by any other source of income [Damgé 2016][66]. Perhaps the most intelligent of our fellows would supplement their income by creating Intelligent Robots whose services would be leased to carry out the above tasks[67]. But in such a case, could the robot with full autonomy refuse to work for a Man for free? *In fine*, could we not imagine that an Intelligent Robot might have the ability to create other Intelligent Robots and rent the services of its fellows to customers, in fact reproducing the power held over one's own kind already practiced by Man towards Man for millennia? Will we ever have to enact the "Robot and Citizen-Robot Rights" that will govern Robot's freedom of thought and speech, Robot-Man and Robot-Robot relations? Moreover, the European Parliament has published a report calling for a "*classification of autonomous and intelligent robots*" and to impose an "*individual registration*". The report proposes to oblige companies to "*notify the extent of the contribution of robotics (...) to their financial results, for purposes of taxation and calculation of social contributions*" and "*to seriously consider the introduction of a universal basic income*". Moreover, the Members of the European Parliament advocate legislation on the civil liability of robots by "*the creation of a robot-specific legal personality so that at least the most sophisticated autonomous robots can be considered as electronic people with specific rights and duties*" [Perrotte 2017].

In this case, why would the Intelligent Robot still accept orders from humans with much more limited cognitive abilities, and why would it not try to use its Artificial Intelligence maliciously to enslave Human Intelligence, or even destroy it? The British astrophysicist Stephen Hawking thus estimates that "*AI could spell the end of the human race*", while Elon Musk, the founder of the companies *Tesla* and *SpaceX*, thinks that "*it could be more dangerous than nuclear bombs*" [Tual 2016]. But this is another long story, and we will not fail to tell you the latest advances in an upcoming episode. I am obliged to leave you, xtractis® has just announced that it has solved the complex strategic problem in Financial Risk Analysis, which we submitted to it less than three weeks ago...

Epilogue

We therefore suggest a new test of "machine intelligence", which is more extensive than the *Imitation Game* created by Turing in 1950.

We will qualify a Robot as **Intelligent** if it is able to discover independently, from its past experiences, the best possible decision-making strategies that enable it not only to explain previous situations, but also to make the best possible decisions when confronted with unknown situations: an excellent example of Darwinian adaptation to a dynamically changing environment!

By using the above definition of robustness, we state that an **Intelligent Robot must be able to independently discover the most robust learning strategies possible, which, based on its past experiences, enable it to discover the most robust decision-making strategies**

65 The Yin-Yang Taoist symbol of Chinese philosophy is a fine example: White and Black interpenetrate and are mutually included in each other.

66 Since January 2017, Finland has been the first European country to try out universal basic income at the national level, for a period of two years [Geoffroy 2017a]. Since February 2017, the German association *Mein Grundeinkommen* has used crowdfunding to finance a monthly net income of 1,000 euros for 1 year, to persons drawn at random without any nationality or age requirement [Geoffroy 2017b].

67 This is already the case for AI companies, such as *IBM* or **intelli**tech, who rent the intellectual work of Smart Robots to corporate customers to help them solve various complex problems!

possible[68]. Thus the Augmented Fuzzy AI, which we defend, is freed from its original mimetic shackles of Human Intelligence, and it redesigns its object of study around the design of Intelligent Robots in all its forms.

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e AFAI xtractis® robot validates this definition.

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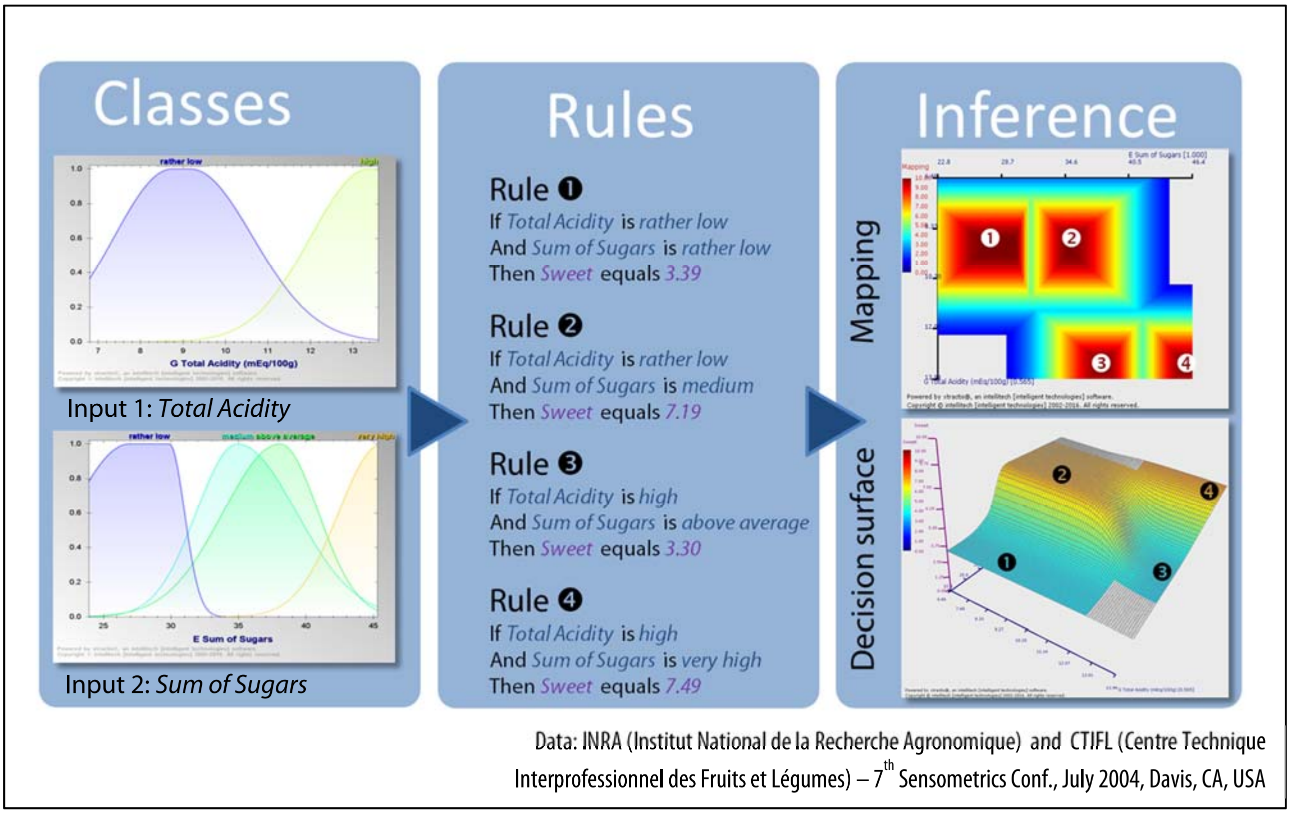

Figure 1: xtractis® modelling (GENERATE 9.1.16325) of the sweet perception of a fresh tomato: 2 predictive variables, 4 decisional rules.

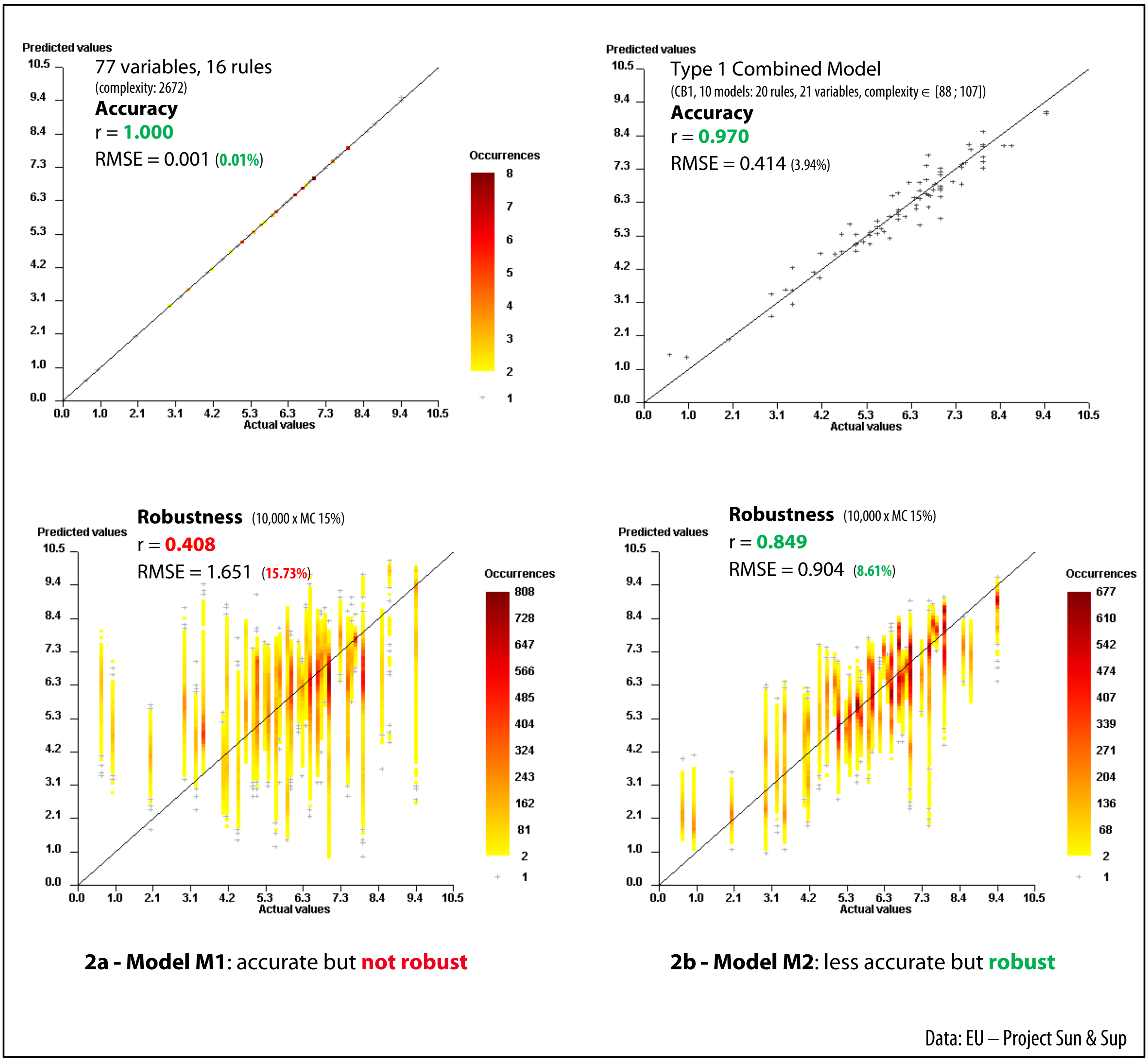

Figure 2: Comparison of the performance of two xtractis® models (GENERATE 9.1.16139)
for the survival analysis of a European technology start-up.

Actual class

Predicted class

Decision	0	1
0	98.98%	4.78%
1	1.02%	95.22%
Non-mapped	0.41%	2.55%

Robustesse 1,000 x MC 15%

Rank	Var. ID	Label	dividual influen	Missing value
1	11	radius Cell 2	1	0,00%
2	22	texture Cell 3	0,436	0,00%
3	8	concave points Cell 1	0,274	0,00%
4	29	symmetry Cell 3	0,147	0,00%
5	23	perimeter Cell 3	0,12	0,00%
6	28	concave points Cell 3	0,105	0,00%
7	21	radius Cell 3	0,103	0,00%
8	15	smoothness Cell 2	0,078	0,00%
9	2	texture Cell 1	0,066	0,00%
10	16	compactness Cell 2	0,063	0,00%
11	1	radius Cell 1	0,052	0,00%
12	25	smoothness Cell 3	0,049	0,00%
13	12	texture Cell 2	0,046	0,00%
14	18	concave points Cell 2	0,045	0,00%
15	10	fractal dimension Cell 1	0,044	0,00%
16	24	area Cell 3	0,039	0,00%
17	3	perimeter Cell 1	0,039	0,00%
18	27	concavity Cell 3	0,033	0,00%
19	4	area Cell 1	0,025	0,00%
20	7	concavity Cell 1	0,022	0,00%
21	30	fractal dimension Cell 3	0,021	0,00%

Predictors with a weak individual influence

3a – Modelling by holistic approach: 21 predictors, 3 rules

Actual class

Predicted class

Decision	0	1
0	82.04%	22.46%
1	17.96%	77.54%
Non-mapped	0.88%	1.04%

Robustness 1,000 x MC 15%

Individual influence

Rank	Var. ID	Label	Individual influence	Missing value
1	11	radius Cell 2	1,000	0,0 %
2	22	texture Cell 3	0,570	0,0 %

3b – Modelling by Cartesian approach: 2 predictors, 8 rules

Data: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian – University of Wisconsin (USA)

Figure 3: Diagnosis of breast cancer by image analysis of mammary cells. Differences in the robustness of xtractis® modelling (GENERATE 8.0.10349): holistic and Cartesian approaches.