ON COMPUTATIONAL INTELLIGENCE HISTORY

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Abstract: *Computational Intelligence history is the fusion of the history of its pillars: Neural Networks, Evolutionary Computation, Computational Swarm Intelligence, Imprecision Modeling (Fuzzy sets/logic/systems and extensions), and Immunological Computation.*

1. Introduction

In “Frames of Mind”, Howard Gardner (1983) defines intelligence as “the ability to solve problems or to create products that are valued within one or more cultural settings”. Howard Gardner's theory of multiple intelligences argues that “people are not born with all the intelligence they will ever have”, and that each person increases their intelligence level by processing information in a more specific/personalized way. He divides intelligence into nine different intelligences that include: Bodily-Kinaesthetic Intelligence, Existential Intelligence, Interpersonal Intelligence, Intrapersonal Intelligence, Linguistic Intelligence, Logical-Mathematical Intelligence (LMI), Musical Intelligence, Naturalist Intelligence, and Visual-Spatial Intelligence. Following Gardner, naturalistic intelligence is "the ability to identify, classify and manipulate elements of the environment, objects, animals or plants." However, to solve problems we need not only LMI, but also methods nature inspired as those promoted by the new field called "Computational Intelligence", mainly in the era of computing and Artificial Intelligence developments.

Computational Intelligence (CI) is a fascinating and broad field that intersects with many aspects of artificial intelligence (AI). Covering Neural Networks (NN), Fuzzy Systems (FS), Evolutionary Computation (EC), Swarm Intelligence (SI) and Artificial Immune Systems (AIS), CI is applied in optimization problems, control systems, robotics, and decision-making processes.

NN is also a subfield of Machine Learning (ML), while CI and ML have distinct focuses and methodologies. ML involves training algorithms on large datasets to identify patterns and make predictions. It uses statistical methods and data-driven approaches using various types of learning (supervised[1], unsupervised[2], and reinforcement[3]) to solve complex problems like image and speech recognition, recommendation systems, and predictive analytics.

According to Duch (2007), "CI studies problems for which there are no effective algorithms, either because it is not possible to formulate them or because they are NP-hard and thus not effective in real life applications". In this paper, the pillars of CI are considered and historical aspects are discussed.

2. The history of CI

The history of CI has many intersections with history of ML and AI. Developments in CI have been and will continue to be influenced by IEEE Computational Intelligence Society (CIS). CIS was approved in 2004 and is oriented to bring together biologically-inspired computational paradigms for problem solving.

The first pillar of CI is considered to be NN, and the beginning of CI models can be found in 1943, when **P**itts (an American logician) and **M**c**C**ulloch (an American neurophysiologist and cybernetician[4]) published the first mathematical modeling of a neural network to create algorithms that mimic human thought processes, called **MCP** ("**M**c**C**ulloch – **P**its") neuron. They set out to understand how the brain can produce highly complex patterns using multiple basic cells linked together.

Even, the name ML was coined in 1952 by Samuel Arthur (a pioneer in the field of computer gaming), the learning principles were discovered by Hebb (1949) that explained how the brain activity is modeled by neural networks. The first NN, called SNARC, composed by 3000 vacuum tubes to

[1] Supervised machine learning uses labeled data, where each input comes with a corresponding correct output.

[2] Algorithms learn patterns exclusively from unlabeled data.

[3] Perform a task through repeated "trial and error" rounds with a simulated/real field when maximizing a reward metric.

[4] Cyberneticist

simulate 30 neurons was implemented in January 1952 by Marvin Minsky and Dean Edmonds. It uses Hebb synapses model and is considered to be the first artificial self-learning[5] machine.

A theory of machine intelligence was developed by Alan Turing in 1950, but only in 1956, the term “artificial intelligence” was coined by McCarthy during the workshop at Dartmouth[6], according to McCorduck et al (1977). When look to history of AI, a promoter of the field is the International Joint Conferences on Artificial Intelligence (IJCAI), founded in 1969. IJCAI conferences were held biennially in odd-numbered years since 1969 till 2015, and annually starting with 2016.

Between 1956 and 1969 much research was done in the field of mathematical modeling of biological neurons. The most important results were obtained on perceptrons by Rosenblatt[7] and "ADALINES" by Widrow[8] and Hoff[9]. In fact, the perceptron is an MCP neuron in which the inputs first pass through some "preprocessors", which have been called *association units*. These association units will detect the presence of certain features in the inputs. As the name suggests, the perceptron model has been designed as a pattern recognizer and the association units act as feature or pattern detectors. ADALINE (Adaptive Linear Neuron) is similar to the perceptron, but instead of a *step activation* function, it uses a *linear activation* function. This NN model consists of an input layer, an output

[5] Self-learning systems are artificial entities that are capable of learning and correcting information on their own during a training session without supervision.

[6] “John McCarthy won't swear he hadn't heard it before, but he was the first to apply it to the kind of work which was going on in this field, he promoted the term, and despite some other proposals and certain grumbling, artificial intelligence has stuck.”

[7] Rosenblatt proved four main theorems. The first theorem states that elementary perceptrons can solve any classification problem if there are no discrepancies in the training set (but enough elements of type A and/or R.) The fourth theorem states the convergence of the learning algorithm if this elementary perceptron model can solve the problem.

[8] Widrow has developed a reinforcement learning algorithm known as "penalty/recompensation" or "bootstrapping ", which can be used to solve problems where supervised learning methods are impractical due to uncertainty about error signals.

[9] In 1960, Hoff and Widrow published an improved learning rule for artificial neurons. Unlike the perceptron, where the error was defined based on the predicted outcome, here the result of the activation function was used to define a loss function or cost function. The purpose of this loss function is to find the minimum that corresponds to the optimal solution to the problem at hand.

layer, and a feedback layer that adjusts the weights of the input layer according to the result obtained by minimizing the *mean squared error* (MSE[10]) between the desired output and the actual result of the network.

Rosenblatt was very enthusiastic about the power of perceptrons, while Minsky was involved in symbolic artificial intelligence. So, in 1969, Minsky and Papert "caused a major setback" in research on artificial neural networks, as Engelbrecht (2007) explained. In the book entitled " Perceptrons: an introduction to computational geometry", they concluded that extending simple perceptrons to multilayer perceptrons would not improve computational power. This led to a decline in neural network research until the mid-1980s.

However, during this "winter" period, a few researchers, notably Grossberg, Carpenter, Amari, Kohonen, and Fukushima, continued to work on various aspects of NNs, according to Widrow and Lehr (1990).

Based on biological principle, Klopf (1972) developed a basis for learning in artificial neurons. Fukushima (1975) has developed a step-by-step trainable multilayer neural network for interpreting handwritten characters. Grossberg's research on neural networks culminated in 1976 with adaptive pattern classification and universal registration based on feedback and short-term memory.

Gail Alexandra Carpenter and Grossberg developed in 1987 a massively parallel architecture for self-organizing neural pattern recognition machine. By 1992, they had extended adaptive resonance theory (ART)-based learning algorithms to take fuzzy concepts into account, along with the fuzzy ART, ARTMAP and fuzzy ARTMAP projects. ART and ARTMAP neural networks were update by Carpenter (1997) to support distributed learning, recognition, and prediction.

Self-organizing networks, which learn from externally given patterns or sequences of patterns as stimuli that remember some of them as stable steady states or state transition sequences, were introduced by Amari (1972). A special type of self-organizing network, called self-organizing map (SOM), was introduced by Teuvo Kohonen in the 1980s, as a type of artificial neural network which is trained by competitive learning, rather than the error-corrective learning (gradient descent learning based on backpropagation) used by other artificial neural networks.

[10] The MSE is a metric used to measure the mean square difference between predicted and actual values in a dataset.

Hopfield networks are a type of recurrent neural network (RNN) invented by John Hopfield in 1982. These networks are capable of reconstructing modified information. Essentially, they allow storage and reconstruction of patterns. Geoffrey E. Hinton co-developed in 1986 the backpropagation algorithm that revolutionized the way neural networks are trained. His research spans diverse innovations including Boltzmann machines[11], deep belief networks[12], and the revolutionary AlexNet[13], which significantly advanced image recognition technologies. For their contributions to artificial neural networks and advances in machine learning, John Hopfield and Geoffrey Hinton have been awarded the Nobel Prize in Physics in 2024.

EC is the second pillar of CI. Genetic or evolutionary search was proposed by Turing as early as 1948, a natural selection in which a combination of genes is sought, the criterion being survival value. In 1962, Bremermann (a German-American mathematician and biophysicist) was conducting computer experiments on "optimization by evolution and recombination". The roots of this way of thinking can be found in Darwinian Theory. In the 1960s, three different implementations of the basic idea were developed in different places: the USA (evolutionary programming introduced by Fogel and genetic algorithms introduced by Holland) and Germany (evolutionary strategies invented by Rechenberg and Schwefel). These fields developed separately, but since the early 1990's they have been regarded as different representatives ("dialects") of a technology that came to be known as evolutionary computation (EC). In the early 1990's a fourth stream emerged, namely genetic programming advocated by Koza (1982). Contemporary terminology calls the whole field *evolutionary computation*, the algorithms involved are called *evolutionary algorithms*, and considers evolutionary programming, evolutionary strategies, genetic algorithms and genetic programming as subdomains of evolutionary computation. Genetic Algorithms (GAs) are based on techniques such as

[11] "A Boltzmann Machine is a network of symmetrically connected, neuron-like units that make stochastic decisions about whether to be on or off. Boltzmann machines have a simple learning algorithm that allows them to discover interesting features in datasets composed of binary vectors."
(https://www.cs.toronto.edu/~hinton/csc321/readings/boltz321.pdf)

[12] https://www.cs.toronto.edu/~hinton/absps/fastnc.pdf

[13] https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

mutation, crossover (the combination of features from two individuals in offspring), and selection to evolve solutions to optimization problems. GA is a subset of EC, where a final population of individuals is provided as candidates to the problem solution.

The next important pillar of CI is based on Nature Inspiring Computing containing SI. Swarm Intelligence (SI) is a term that was first introduced by Gerardo Beni and Jing Wang in 1989. SI is part of a large plethora of Nature inspired approaches, often referred to as nature-inspired algorithms, which are methodologies derived from natural processes to solve complex, non-algorithmizable problems. These approaches are particularly useful in optimization, ML, and other computational fields where traditional algorithms may fall short, or for solving NP-hard problems[14]. One type of biological inspired CI approach is the genetic algorithm, considered above. Some other types of nature-inspired algorithms that already proved value consists of:

- Particle Swarm Optimization (PSO): PSO mimics the social behavior of birds flocking or fish schooling. It optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. According to Sengupta et al (2019), the PSO algorithm uses a swarm of particles (traversing a multidimensional search space to find the optimal solution. It was formally introduced in 1995 by Eberhart and Kennedy through an extension of Reynold's work.
- Ant Colony Optimization (ACO): ACO was developed by Dorigo and Stützle (2004) and is based on the foraging behavior of ants and proved to be effective for solving computational problems which can be reduced to finding good paths through graphs, for example.
- Artificial Bee Colony (ABC): ABC is inspired by the foraging behavior of honey bees and is used for optimizing numerical problems.

[14] In computer science there are two classes of problems, P and NP. A problem is said to belong to the class P if there exists an algorithm that can solve it in polynomial time in the worst-case. The NP class consists of problems that can be solved by some algorithm (without a statement about its running time), and any solution can be verified in polynomial time by another algorithm. Therefore P is a subset of NP.

- Firefly Algorithm (FA): FA was developed by Xin-She Yang (2007) and is based on the flashing behavior of fireflies; this algorithm is used for solving optimization problems by attracting other fireflies based on their brightness.
- Simulated Annealing (SA): SA is a technique inspired by the annealing process in metallurgy, and is used for finding an approximate global optimum in a large search space a search space (the collection of all points of interest including the solution we are seeking). SA was invented by Enrico Fermi and Stanislaw Ulam in the context of "Monte Carlo" simulations (1949).

PSO, ACO, ABC and FI are "Computational Swarm Intelligence" methods. Optimization algorithms inspired by nature and biology are usually designed after observing a natural process or the behavior patterns of biological organisms, which are then converted into a computational method. These algorithms are powerful because they can handle complex, multi-dimensional, and dynamic problems that are difficult to solve using traditional methods.

Another pillar of CI arise from solving the problem of representing fuzziness in logic, physics, linguistics and the questioning of the notion of a set. This challenge led to many of the first suggestions for fuzzy set theory. However, it was Lukasiewicz who, in 1920, published the first extension of two-valued logic in his work on three-valued logic - later extended to an arbitrary number of values, together with Moisil (see Lukasiewicz-Moisil algebra). But, it was Lotfi Zadeh who developed on *fuzzy sets* in 1965. Unlike classical sets where elements either belong to the set or do not belong to the set, fuzzy sets allow for degrees of membership, represented by a membership function that assigns a value between 0 and 1 to each element. Also, Lotfi A. Zadeh invented in 1965 the fuzzy logic as an extension of fuzzy set theory to provide a way of reasoning about data that is not exact, allowing more flexible and humane reasoning in computers. Fuzzy logic has been widely used in various fields such as control systems (fuzzy systems), decision making (fuzzy relations) and artificial intelligence (fuzzy expert systems).

Until 2000, *fuzzy systems* was an active field developed by Mamdani and Assilian (1975), Sugeno and Takagi (1985), and Zadeh (1994) who coined the *soft computing* term when refers to fuzzy logic and neural networks. With this occasion, Zadeh introduced MIQ ((machine intelligence

quotient) to describe a measure of intelligence of human-made systems. Therefore, an intelligent system should have a high MIQ.

In 1983, Atanassov presents the definition of Atanassov Intuitionistic Fuzzy Set (AIFS). Every element of an AIFS has both a membership degree, and a non-membership degree, but their sum can be below one, not equal to one as in the case of fuzzy sets. Smaradache introduces the concept of Neutrosophic Set in 2002. În Neutrosophic framework, every element has three attributes (membership, non-membership, and indeterminacy), but their sum can be above three.

Recently, a new pillar of CI was considered: Immunological Computation (IC). IC methods were developed in the framework of Artificial Immune Systems (AIS) taking into account the principles of Biological Immune Systems (BIS). Since 1985 there has been a major research interest in immunity-based techniques and their applications. According to Dasgupta and Niño (2009), some theories were established in time: 1) Burnet (1959) developed “clonal selection theory” to describe the “proliferation” of immune cells reacting to an antigen; 2) Niels K. Jerne (1974) developed the "immune network (IN) theory" to explain the formation of immune memory; 3) Bretscher and Cohn (1970) and Hoffmann (1975) considered the classical “self/nonself (SNS) discrimination theory” and its value for the “detection and recognition processes” used by the Danger Theory (1994), the self-assertion model (1999), and the integrity model (2000).

From computational point of view, the main characteristics of BIS to be modeled by AIS are: pattern matching, feature extraction, learning and memory, diversity, distributed processing, self-regulation and self-protection. In this way, AIS methods can be seen as ML approaches. The well known algorithms of AIS are Negative selection (1994, computational model of self/nonself discrimination) and Clonal selection (2000, similar to EC). Applications in software engineering were proposed by Popențiu and Albeanu (2017) when considering imprecision models in various contexts like fuzzy, intuitionistic fuzzy, and neutrosophy.

As it can be seen from above, CI is more than just “the study of the design of intelligent agents, it includes also study of all non-algoritmizable processes that humans (and sometimes animals) can solve with various degree of competence, and the engineering approaches to solve such problems using hardware and software systems”, as Duch (2007) remarked.

3. Conclusion

Computational Intelligence can be seen as inspired by the Naturalist Intelligence (of Gardner), but also as a set of computational methods inspired by nature to be used for Machine Learning approaches. Therefore, both Human Intelligence and Machine Intelligence may learn from environment, store knowledge, and adapt the behavior when solving problems or create products.

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