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Personal considerations about creativity and artificial intelligence

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Abstract. It presents an original model of human creativity, as well as a series of personal considerations about creativity within Artificial Intelligence (AI). It is believed that when human creativity it will be known, it can be implemented in AI, such as a number of major challenges such as pattern recognition, process simulation, optimal control, and so on.

Keywords: human creativity, artificial intelligence, artificial neural nerworks, artificial consciousness, artificial creativity**.**

1. Human creativity

A personal, original model of human creativity is presented in Fig. 1.
An existing real fact from real world is transformed via abstractization (coding) in an existing abstract fact in subconscious mind. Now, in subconscious mind, an analogy of this existing fact is made with a very different abstract fact. This is the core of creativity, and unfortunately the mechanism of this process is today unknown. By this analogy is created in subconscious mind a new abstract fact, which is then decoded in a real fact in real world.
Almost all the theory and applications of the present artificial intelligence are based on artificial neural networks (ANNs). These are very useful and performance in applications such as pattern recognition or forecast. But creativity need an intelligence much more close to the human brain. The ANNs are based on a lot of analogies with the central nervous system. But, there is an important restriction: the quantity which modify the quality. The human brain has 150 000 neurons/ m^2 and an average surface of approx. 200 000 mm^2 which gives a total number of neurons

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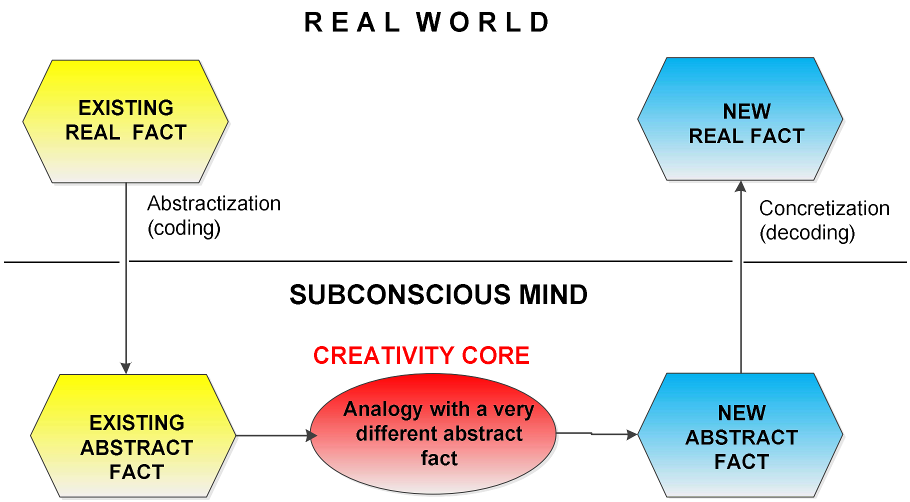

Fig. 1. A proposed original model of human creativity.

$3 \cdot 10^{10}$ which means in computer terms 30 Gb. An usual actual laptop has an installed memory of 16 Gb.Therefore the total number of neurons of the brain is not too high. The big difference consists in the interconnexions of the natural neurons through 10^{15} synaptic connexions. Thus, while a neuron in an ANN store one digit, a natural neuron in the brain participate simultaneously at a huge number of informational connexions. There are also huge differences of the velocity of information processing: the human brain make 10^{16} interconnexions/s, while a performat computer realise 10^{8} interconnexions/s.

2. AI creativity

Despite this major differences between natural and artificial intelligence, there are some promising facts that AI will be in time a tool in creativity: the abilities to make analogies, developing the knowledge of thinking mechanisms such as learning, memorization, creativity, and the huge continuous progress in computers performances.

A first step to the implication of ANNs in creativity was made by professor Igor Aleksander from Imperial College London, UK. He has developed the research programme, “Artificial Consciousness”. This title was invented to signify a general approach to researching neural versions of a long list of cognitive tasks, mainly associated with human beings. Previously, in AI and ANN, very few attempts had been made to look at issues such as memory, planning, natural language and so on within the same framework. In the frame of this research programme, an ANN call Magnus has been created and used to see if a bunch of artificial neurons can carry out some of the feats that their living counterparts, the cells of human or animal brains, perform in going about their daily lives. The feats are feats which when performed by humans are described as the result of "conscious thought".

These investigation was the base of the fascinating book Impossible Minds My Neurons, My Consciousness [1] published by Aleksander at Imperial College Press (revised edition in 2015).

The core of this book is the so called **The Basic Guess. Neurons and Thoughts**: *The personal sensations which lead to the consciousness of an organism are due to the firing patterns of some neurons, such neurons being part of a larger number which form the state variables of a neural state machine, the firing patterns having been learned through a transfer of activity between sensory input neurons and the state neurons.*

On the base of this Basic Guess, Alexander proposed four consequences.

Consequence 1: **The brain is a state machine:** *The brain of a conscious organism is a state machine whose state variables are the outputs of neurons. This implies that a definition of consciousness be developed in terms of the elements of automata theory.*

Consequence 1 simply recommends the use of the language of automata to talk about the brain becauseit is a language in which one can express the three major elements which make the brain do anything at all: structure, function of the components which make up the structure, and the way these two lead to the totality of what the system can do expressed as a statestructure. In fact it says even more. It says that if a statement is tobe made of how a brain can be conscious, such a statement mightbenefit from being made in terms of state structures, recognising these to be a product of physical structure and the function of neurons (learned or inherited).

Consequence 2: Inner neuron partitioning: *The inner neurons of a conscious organism are partitioned into at least three sets: 1.Perceptual inner neurons: responsible for perception and perceptual memory; 2.Auxiliary inner neurons: responsible for inner "labelling" of perceptual events; 3.Autonomous inner neurons: responsible for "life support" functions — not involved in consciousness.*

Consequence 2 follows from the notion that it would be a mistake to suggest that consciousness is due to the firing of all the neurons of a neural state machine. A very high proportion of the brain's neurons are found in the cerebellum — the organ which involved in the refinement of the control of movement. This is the classical unconscious function.

Consequence 3: Conscious and unconscious states: *The contribution to consciousness of the inner neurons and the sensory neurons has three major modes: 1.Perceptual: which is active during perception — when sensory neurons are active; 2.Mental, conscious: which is an act of thinking in the same neurons even when sensory neurons are inactive or otherwise engaged;3.Mental, unconscious: which is activity generated by the neurons involved in conscious activity, but which does not cause sensations of consciousness.*

Where Consequence 2 distinguishes between conscious and unconsciousevents in space, Consequence 3 distinguishes between conscious and unconscious states in time within the same physical groups of neurons. Consequence 3 suggests that a neural system will develop both the “asleep” and “repressed memory” aspects of unconsciousness and distinguishes between conscious and unconscious states in time within the same physical groups of neurons. Consequence 3 clearly classifies states that can occur within the same perceptual inner neurons.

There is a danger that talk of mental imagery being like perception might be overdone. Mental imagery is different from perception in two important ways. First, it seems not to have the sharpness of actual vision; then, it has a fleeting, slipping quality, easily distracted and altered either from within or through sensory events.

Consequence 4: Iconic learning: *To qualify for a contribution to consciousness, firing patterns in the inner perceptual/conscious neurons need to be created through dominant neural inputs which sample the activity of outer sensory neurons and influence the function of the inner neurons. This has been called “iconic learning”.*

Psychophysical effects, such as arousal and attention, come into focus from Consequence 4.

Consequence 4 concentrates onthe learning mechanism which leads to this memory structure — the “inner eye” of awareness. In Consequence 4 that a learning model exists which explains how these mental images get there, while Consequence 3 merely suggests that given the belief in the Basic Guess that the firing of neurons causes consciousness, “being conscious of something” makes use of the same neural circuitry whether this is actually perceived or imagined.

The more difficult question to answer is: “Where do the conscious states among the neurons that cause consciousness come from?” Consequence 4 deals with this question and explains the “iconic transfer” mentioned in the Basic Guess.

Alexander [1] believe that in future the performances of ANNs, respectively in AI, will strong evolve in the field of Artificial Consciousness.

Our brains are really very complex machines and that working with automata theory applies to simplified forms of brains — the idea that simplified forms of brains may give us a clue to consciousness, albeit a simplified form of consciousness.

The basic operational difference of the natural (electrochemical) and artificial (computational) neuron implies an important functional difference consisting of the more subtle, nuanced activity of the natural neuron [2]. In order to increase the performance of the artificial neuron I consider beneficial to introduce into its model the multiple input, activation and output functions with the possibility of their logical selection.

Here I present some personal considerations about implementation of AI creativity in ANNs based on the biological analogies of ANNs [2].

Current ANNs do not use specialized neurons (except Kohonen's ANN type with "localized responses").

I consider that the idea of ANNs composed of different types of neurons (with different models and functions) is a way of improving ANN's performance.

From neurophysiology there are known the mutual influences that exist between the states of activation of certain areas of the brain. These mutual influences are usually represented by the "sombrero" function (Fig. 2) with the following interpretation: up to a certain distance, the activity of a neuron has an exciting effect on neighboring neurons, then an inhibiting action, and at a greater distance the influence becomes negligible.

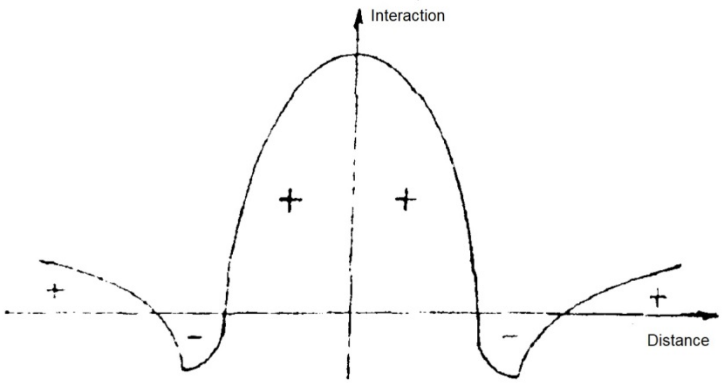

Fig. 2. "Sombrero" function.

This aspect was successfully enforced in Kohonen's ANN, which, along with the specialization of neurons, has made this type of network more extensive biological analogies, factualised by a series of successful pattern recognition applications [3].
I suggest that this development can be also made for multilayers ANNs with several hidden layers.
The most outstanding and spectacular results obtained with the ANNs are those related to learning and memorizing processes. Unfortunately, the mechanisms of thinking, and in particular creativity, are very little known to be an analogous way of transposing ANNs.
Due to the research in the field of neurophysiology, it is also remarkable to establish the importance of dreams and forgetfulness in the processes of information restructuring and preservation. Of course, it can not be about the ANN implementation of dreams! But forgetting in the form of a "purge" of information can lead to the elimination of errors, of incorrect knowledge in the learning process. This has been achieved through the implementation of "partial forgetting" within the ANN-tip Hopfield [4].

3. Conclusions

Decripting of human creativity is a task of extraordinary difficulty, but all the more tempting. AI through ANNs has solved a wide range of major issues such as pattern recognition, process simulation, optimal control, etc. If the mechanism of human creativity will be known, it can will be simulated by AI.

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