

Is Boredom an Indicator on the way to Singularity of Artificial Intelligence? Hypotheses as Thought-Provoking Impulse

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Abstract. In the past, the question regarding the point of singularity in artificial intelligence - when machines become more intelligent than humans - has been raised again and again. In this publication, a crucial point of human intelligence and the impact on this discussion will be postulated in the form of 3 hypotheses as thought-provoking impulse based on the basic hypothesis, that only systems which can be bored are intelligent. First, boredom is discussed from the perspective of psychology with its influence on human intelligence before deductions are drawn from this to artificial intelligence resp. machine learning. Finally, the hypotheses are formulated and the resulting future investigations are outlined.

1 Introduction

At the latest with the fictional intelligence of Skynet [1], the question of the singularity in artificial intelligence (AI) was brought into broader focus. Starting with the comments of von Neumann paraphrased by Ulman [2] ("One conversation centered on the ever accelerating progress of technology and changes in the mode of human life, which gives the appearance of approaching some essential singularity in the history of the race beyond which human affairs, as we know them, could not continue.") and the postulation of Vinge [3], the evolution and acceleration of technological progress arose the question when machines will be more intelligent than humans. According to [3], among others, large computer networks may "wake up as a superhumanly intelligent entity". Opinions about reaching the point singularity in AI are quite diverse. A review about the opinions is given in [4].

Caused by the problem that a common accepted and detailed definition of intelligence is still controversial, the point of singularity is already vague to find in terms of a technical definition - cognition and emotions are additional issues. Even though it is recognised as an important part of the human nature and human intelligence in psychology, to the best of my knowledge, one characteristic of human mental property has not been taken into account in the discussion about intelligence: boredom. In psychology boredom is recognised as an important mental state often intermediary between states of e.g. full awareness and/or mental demanding working and/or moments of findings etc.. Even though in some publications boredom such as [8] is mentioned in order to propose better learning results, it is not regarded as a state an AI system can fall in while processing its assigned task it is designed for. Thus, assuming that a key feature

of an intelligent system is the presence of boredom, it should be investigated, if machine learning (ML) based networks resp. AI can be bored in order to postulate intelligence within AI.

The paper is organised as follows: First, boredom will be introduced from the psychological point of view in respect to intelligence. Based on these findings, AI/ML is commented regarding boredom. From these point of views hypotheses to different AI approaches (Classical Machine Learning, Reinforcement Learning and Spiking Neural Networks) will be formulated regarding their abilities to be bored in the psychological sense - and thus to be intelligent. The paper in hand concludes with an outlook for future research work.

2 Boredom

Boredom is a condition that all of us have experienced in our lives. For example, it is often said that the best ideas come to us in the shower or in other situations where we are not fully mentally challenged. Children often complain about boredom before they start coming up with new ideas to relieve the state of boredom. In the following, we will try to contextualise these perception from the perspective of psychology and artificial intelligence.

2.1 Psychological view

In psychology, boredom has been an object of research for decades. As in the question of the definition of intelligence, there is no generally accepted definition for boredom [5]. Depending on the different schools of thought, different definitions have been proposed [6]. Eastwood et al. [6] proposed on page 482 the probably most commonly employed definition of boredom: "an aversive state of wanting, but being unable, to engage in satisfying activity?". An important problem is, that people experience individually the state of boredom in different ways. According to [7] the state of boredom can be of different length (not speaking about trait boredom) and can as well be interrupted by awareness before falling back to boredom state. In addition, boredom must be "capable of both being induced and alleviated by proximal situational factors" [7]. Furthermore, Elpidorou postulates the sense of boredom: boredom signals an uninteresting state with the aim of getting out of it. The purpose of boredom is therefore to escape from the state of boredom and, according to the definition of Eastwood et al. [6], to return into a state of satisfying activity. Therefore, one can state, that intelligence is needed to recognise boredom and - more important - to escape from this state into a state of satisfying activity. Thus, boredom is an essential part of intelligence what consequently is needed in machines as well if we want to reach the point of singularity of AI or even to obtain intelligent ML.

2.2 Artificial Intelligence View

Following the above mentioned definition of boredom in the sense of psychology, there is, to the best of the author's knowledge, no corresponding transfer into AI

or ML - despite the use of the term boredom eg. in [8]. Bolland et al. describes a state of "boredom" when a machine is in a state in which it does not receive any new information and is therefore in a state of complete knowledge about a process or a task to be learned. In this sense, boredom is a state in which a machine has reached the end of its learning task and cannot learn any further. Consequently, the machine must then be supplied with new information (either from outside or actively through its own exploration) in order to learn the task up to complete knowledge of the presented data set or situation (what might be named overfitting as well). Accordingly, one could interpret that every machine that has completed its learning task is bored. Thus, if the machine is not fed with new knowledge or not programmed to explore further a certain task ad infinitum, a machine will fall either automatically in the state of boredom after the end of learning or will not be able to reach the state of boredom.

Now, since the status of boredom is, from the point of view of psychology, a status of transition occurring again and again in an intelligent system whereas the intelligent system can escape from this state itself, one can interpret that such described systems of AI as described above are not to be called intelligent. The author is well aware that this view is debatable and depends on the definition of boredom and intelligence.

3 Hypotheses on Boredom in Artificial Intelligence

Based on the argumentations in chapter 2 the basic hypotheses in order to be a human-like intelligent system is postulated:

Hypothesis 1 *A system, which claim to possess human-like intelligence, needs to be able to get bored and to get out of the state of boredom by itself.*

Accepting this hypothesis, the following hypotheses will be postulated in regards to different general classes of approaches and algorithms used in ML resp. AI. Hereby, it is always assumed that the number of neurons or connections as well as the choice of architecture is not a limiting factor.

3.1 Classical Machine Learning

Under "Classical" ML the currently commonly used algorithms such as Back-propagation [9], Long Short Term Memory [10], Hopfield nets [12], Neocognitron [11] or Deep Learning [18] to name just a few as well as its successors resp. further developed algorithms based on their learning principles are considered:

Hypothesis 2 *Classical Machine Learning approaches cannot be bored.*

All these approaches have one goal in common: based on a given data set, a well defined goal or task should be reached in terms of the best accuracy resp. precision possible. For this reason, a well defined learning algorithm adopted to the problem in question is applied - what is well justified from an engineering point of view. Since the learning algorithm follows precisely defined

rules, the trained system will always follow accordingly, regardless of whether the algorithm is interested in the task or not. Thus, the system cannot fall into a status comparable to boredom from a psychological point of view.

3.2 Reinforcement Learning

Reinforcement Learning (RL) [14] follows a different learning philosophy compared to classical ML algorithms: RL allows a "free" search including try and error resp. exploration in a given data space, but still with the clear goal of fulfilling a given task:

Hypothesis 3 *Reinforcement Learning might be bored under certain circumstances.*

Even if RL basically follows a different learning philosophy than classical ML, the applied reward algorithm ultimately used in RL is decisive. If, for example, a greedy learning is used, learning ultimately follows a similar procedure to classical ML in order to find the most optimal solution. In this case, RL cannot fall into the status of boredom as well as classical ML. However, if other learning methods are used, such as rate-based Hebbian learning [15] p.366ff, it cannot be ruled out that a state of boredom in the psychological sense could be achieved.

3.3 Spiking Neural Networks

In contrast to ML and RL Spiking Neural Networks (SNN) do not follow the commonly used coding schemes in computer architecture to define data and thus information in bit based data words. SNNs are based on neurological plausible neurons, thus coding the information in a spike-time-dependent code [16], what is already hard to handle with current computer architectures. In addition, SNNs are using originally neurological plausible learning algorithms [15, 16].

Hypothesis 4 *Spiking Neural Networks can be bored if they follow neurological plausible learning.*

If one uses SNNs in the sense of neuromorphic information processing - with neurological plausible information coding and neurological plausible learning procedures and under the condition of disregarding limiting resources of neurons and networks - they will be able to organise themselves similarly to the networks existing in the human brain and behave accordingly. As the state of boredom can occur in human neural networks, consequently they can occur in SNNs as well: An SNN can be bored. Moreover, it will be able to free itself from the state of boredom towards a more satisfying state. Remark, we are postulating this hypothesis explicitly for SNN with neurological plausible data coding and learning. SNNs using other non neurological plausible and thus classical ML learning algorithms like Backpropagation [17, 18] will not be able to be bored and they will fall back to hypothesis 2.

4 How to proof the hypotheses - Modus Operandi

In order to proof the above postulated hypotheses, a self regulating system needs to be implemented. This self-regulating systems will represent different populations of neurons connected to themselves based on neurological plausible areas responsible for the regulatory paths in the brain following the propositions of the psychological and neurological background as described above. First, we will start with SNNs based on population coding [15] using neurological plausible learning incorporating not only synaptic plasticity but also synaptic dynamic [19, 20]. Once this approach proof the correctness of hypothesis 4, the same self-regulating system will be transferred to RL and ANN including the use of appropriate learning algorithms.

5 Conclusion and Future Work

In this thought-provoking publication, the question of whether ML and AI can reach the point of singularity, that means they can become as intelligent or even more intelligent than humans, is explored. As a line of reasoning, the status of boredom is introduced from a psychological perspective. Based on the psychological definition of boredom the basic hypothesis is postulated that only intelligent systems can be bored. Following this assumption, the hypotheses of classical ML, RL and SNNs were then postulated. The hypotheses 2 and 3 state that classical ML cannot become bored but RL could possibly be bored under special conditions. Only SNNs in their original form with neurological plausible information coding and neurological plausible learning procedures are said in the hypothesis 4 to have the possibility of boredom. In combination with the basic hypothesis, this means SNNs can form intelligent systems in the sense of human-like intelligence, but classical ML procedures cannot. In the case of RL, there is a possibility, but from our point of view it is currently not given, since neurologically plausible learning procedures tend not to be used in RL.

In future work it must and currently is investigated whether it is possible to implement a self-regulated system with SNNs that can become bored. Once, this system has been proofed to be bored, it will be transferred to RL and ANN with appropriate learning algorithms.

The author is aware that provocative hypotheses postulated are being put forward and hopes that this new approach to the status of boredom as indicator for intelligence will provide a thought-provoking impulse for future discussion.

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