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Bridging human and machine learning for the needs of collective intelligence development

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Abstract

There are no doubts that artificial and human intelligence enhance and complement each other. They are stronger together as a team of Collective (Collaborative) Intelligence. Both require training for personal development and high performance. However, the approaches to training (human vs. machine learning) are traditionally very different. If one needs efficient hybrid collective intelligence team, e.g. for managing processes within the Industry 4.0, then all the team members have to learn together. In this paper we point out the need for bridging the gap between the human and machine learning, so that some approaches used in machine learning will be useful for humans and vice-versa, some knowledge from human pedagogy can be useful also for training the artificial intelligence. When this happens, we all will come closer to the ultimate goal of creating a University for Everything capable of educating human and digital "workers" for the Industry 4.0. The paper also considers several thoughts on training digital assistants of the humans together in a team.

Keywords: collective intelligence; Industry 4.0; deep learning; university for everything; artificial intelligence

1. Introduction

Training is the major need of the Artificial Intelligence (AI), which humans can provide at the current stage of the AI evolution. In the human world, this need is addressed by education, which is an important enabler of human development implying expansion of capabilities (also creative ones) and freedoms. Schools and universities serve as centers for intellectual capacity building, verified information sharing and exchange. Likewise, a modern AI system must be well-trained. We argue that (deep) learning for a machine is a dynamic, evolutionary process, very similar to a traditional higher education, however, with new challenges and features. It facilitates comprehensive acquisition of different skills at all the major cognitive levels, leveraging on collaboration in creative, dynamically changing ecosystems, similar to those built around universities. Recently we introduced a concept of the University for Everything (U4E) [5] or "deep university", which can be launched as a creative, evolving and collaborative training environment for artificial (AI) and hybrid (Human + AI = Collective Intelligence) cognitive systems ("students"). Such university will provide a "student" with the information resources and training methods for increasing self-awareness and autonomy by deep-learning-driven self-development of capabilities to be curious, to ask questions (formulate queries) intelligently and creatively, find answers and make decisions. The most powerful weapon in the IT business today is the alliance between the AI, or analytical skills of self-learning machines, and the imaginative Human Intellect of great leaders. Together they make the Collective Intelligence, which is the major business model of the future.

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2. Collective intelligence

We consider Collective Intelligence as a hybrid of human intelligence collaborating with several types of personal digital assistants (intelligent agents, advisors, clones, twins, etc.). We studied six different roles, which someone or something can play within a collective intelligence team as shown in Figure 1. Ideally an Intelligent Agent would be an autonomous, self-aware, self-managed, constantly evolving, bottom-up and top-down intelligent software robot capable of operating within and exploring new environments of various nature. It understands and is capable of developing personal mission including permanent self-development, performing "humanoid" or/and "alien thinking", and also capable and willing to represent, replace when necessary or collaborate with humans and other agents to achieve complex objectives. This is a "big dream". Figure 1 shows, however, few more pragmatic and realistic concepts of an agent. It depicts a human-centric view, although this can be easily generalized, if one replaces a human with some complex product, system or process within the Industry 4.0.

We treat the concept of Collective Intelligence in terms of how AI and Human are able to assist one another in the education process. Initially, it is our task as humans to design and develop the optimal methods for the AI learning, taking into account all possible aspects, caveats, challenges and threats. However, once that task is complete, we believe that the AI would be able to enhance human learning process and optimize the education process in general.

Our goal is performing the studies in this area needed for launching the University for Everything. This paper does not focus on the U4E concept itself, but rather on the steps that would take us closer to it. [8] describes the challenges that such Human-AI environment is inevitably going to face. Generic goal of this research is bridging the gap between human and machine learning for their mutual benefits and coevolution. We aim to prove (theoretically and experimentally) the hypothesis that the order of training material matters both for human and AI learners in a similar way. For that we are studying a variety of ontology-driven and deep-learning-driven metrics capable of ranking (ordering) samples as well as groups of samples for learning towards optimal efficiency of the training process. Furthermore, we are making synchronous tests by training deep neural networks (ensembles with different configuration and pre-training) and human groups and assessing the performance of training depending on the order of the inputs. We have started using temporal interval semantics to specify uncertain temporal sequences of training events; simulating the collective intelligence groups by combining the neural networks with the autonomous "clones" of the particular humans according to our "patented intelligence" (PI-Mind) technology [14]; using the generator network for the prototype ordering and simulating the process of how a learner (discriminator) adapts to the most problematic order of the training samples.

3. AI and human training

The need for training the autonomous AI systems in the same way as humans (in addition to traditional machine learning) is recently discussed in [9]. Authors suggested the never-ending learning paradigm for machine learning, according to which intelligent agents will learn and generalize many types of knowledge, continuously over many years to become better learners over time. According to the Asilomar Principles [1] signed by the majority of leading AI scientists, the goal of the AI research should be to create not undirected intelligence, but beneficial intelligence and, therefore, AI systems designed to recursively self-improve or self-replicate under strict human control.

3.1. Related research

In previous studies, we already made a hypothesis and started testing it with children [3,4]. It was an assumption that concept learning and recognition depend on individual perception of several parameters such as sound and visual representations as well as their semantics. There are three main factors, which influence the level of complexity: visual similarity, semantic similarity and sound-based phonetic representations of the concepts, which need to be learned. Now we want to apply the metrics of ranking information also on the AI.

We want to study different methods for teaching the neural networks. We will choose different parameters which will be managed. This research is concentrated on building a solid methodology that will choose the right configuration of training.

3.2. Bridging the gap between human and AI learning

As our generic goal is bridging the gap between human and machine learning for their mutual benefits and coevolution, we are looking for answers to three generic research questions:

- Which of the machine-learning techniques would be reasonable to apply also for human education; what would be the expected benefit and impact of it; and what would be the process?
- Which of the human-learning techniques would be reasonable to apply also for AI training or machine learning; what would be the expected benefit and impact of it; and what would be the process?
- What would be a suitable integrated collection of the human-learning and machine-learning techniques for training the collective intelligence (groups of humans and AI systems); what would be the expected benefit and impact of it; and what would be the process?

3.3. Digital Clones

The concept of Digital Twins (DT) or Clones was first introduced in 2003 [7].

An extensive literature analysis in [16] revealed, that currently digital clones are mostly utilized in terms of production equipment maintenance and optimization, rather than product itself and its lifecycle after production.

Digital twins are widely applied in cyber-physical integration on the way to smart manufacturing [12]. [10] describes application of digital clones as a service provider in the manufacturing industry. Such application would help to shift the current 3.0 digitized factory to 4.0 smart factory.

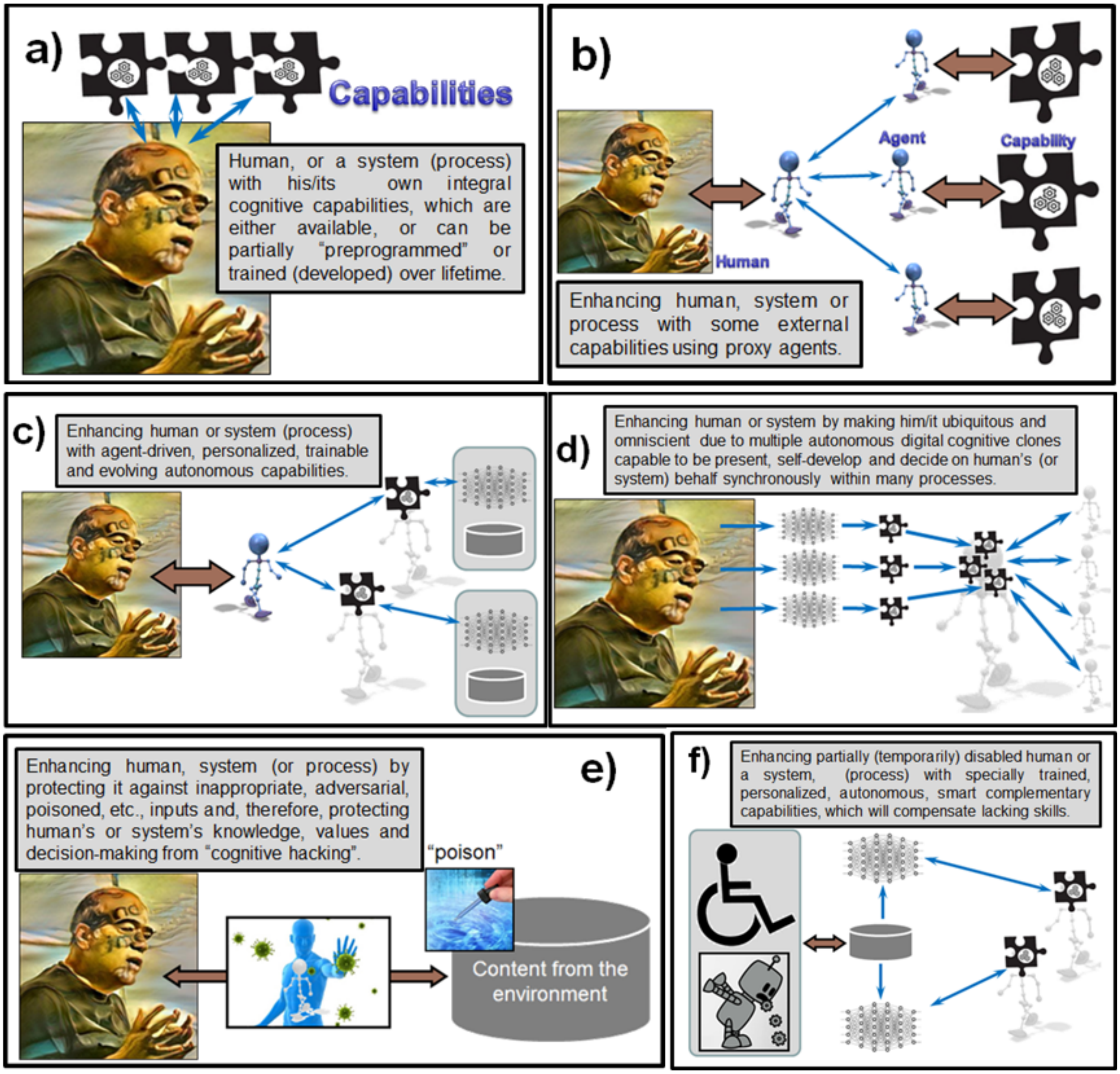

Figure 1. Various roles of the Collective Intelligence team member: (a) a human with own capabilities; (b) smart digital proxy between a human and available-as-a-service external capabilities; (c) smart and self-evolving digital capability providers; (d) cognitive agent-driven clones of a human; (e) agent as a personalized digital agent-driven immune system; (f) agent with complementary intelligence.

On the other hand, [11] describes the approach to creating a smart DT of a manufacturing process enhanced with AI technologies aimed at integrating the digital twin of the product itself and a twin of the product's development process.

In this paper we focus on creating a digital twin of a human being rather than product or equipment.

4. Digital learning assistant

Technologies are developing very rapidly nowadays. The companies should be aware that in order to stay in the lead of the market, they should learn on the fly, use modern technologies and innovations which are useful for the business processes. Taking that into account, people inside the companies need training and retraining. We live in the age where employees always have to be on top of their skills.

As a particular example of a trained AI-student we have developed the concept of a digital learning assistant. It begins its lifecycle as a digital clone of a given human and develops on its own the required cognitive skill, that the human desires but does not possess. Figure 2 below depicts the use-case for such digital assistant.

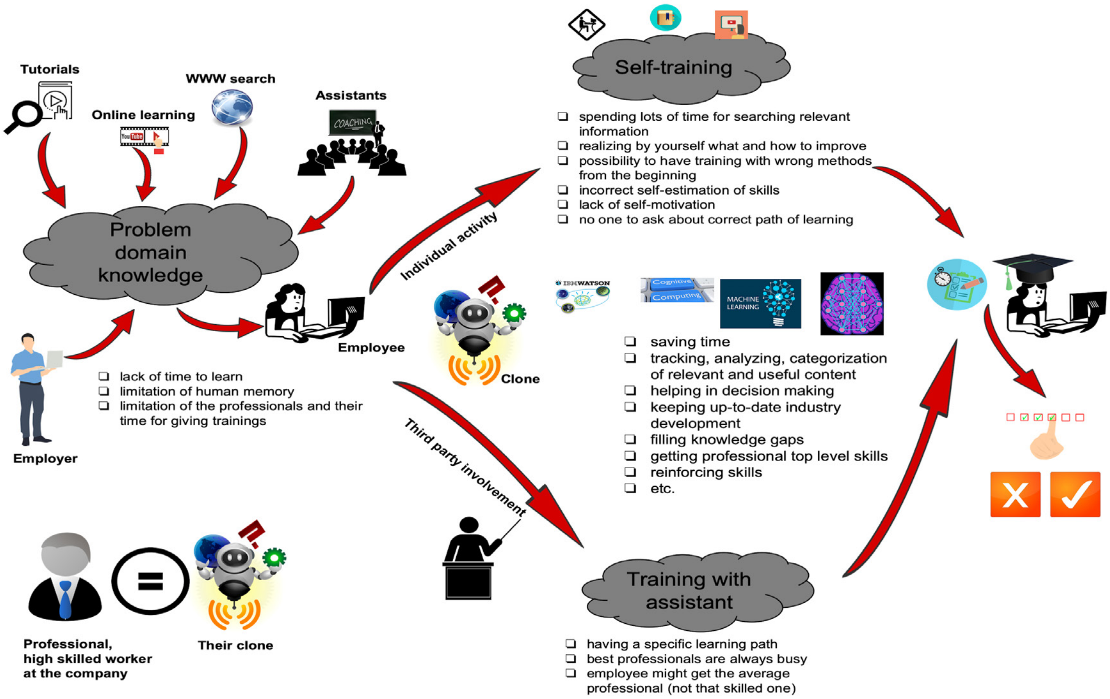

Figure 2: Digital Learning Assistant Use-Case

The assistant effectively addresses the issues of natural human limitations: lack of memory and time. It is an alternative solution to self-training or training with an assistant. Both of these existing approaches have certain limiting factors. Self-motivation being a crucial component of self-training path is often hard to find. Likewise, a good human training assistant's availability is often an issue.

Digital assistant, on the other hand, is always available to assist in decision making process based on its own domain knowledge and its human counterpart's personality.

As Figure 3 shows, these assistants would be complementing the human (shown as the central yellow cell) capacity, creating a new entity: a human enforced with their digital assistants – Collective Intelligence (COIN) [2].

COIN Cell contains the user and user's AI-driven extensions in the form of personal artificial and autonomous advisors. In case the user is being trained for a certain professional activity within some university, then the advisors have to be trained synchronously with the user and together as a team.

However, it is still an open question, how to train the digital assistant in the most timely, suitable and efficient manner.

5. Optimal training process

In addition to studying multiple ontology- and deep-learning-driven metrics, utilizing the temporal interval semantics [15] as described in section 2, we are going to perform similar experiments with the Adversarial Learning settings. Such learning in general and Generative Adversarial Networks in particular have recently become a popular type of deep learning algorithms. They have achieved great success in producing realistically looking images and in making predictions. Unlike the discriminative models, where the high-dimensional input data is usually mapped to a class label, the adversarial networks offer a different approach where the generative model is pitted against the discriminative one [6]. The adversarial method works as a system of two neural networks, where one of them, called the generator, produces fake prototypes of the intended class and the other one, called the discriminator, tries to uncover the fake by evaluating how well the prototype fits the distribution of real prototypes of this class. During the training process, both networks are co-evolving up to the perfectness in performing their conflicting objectives.

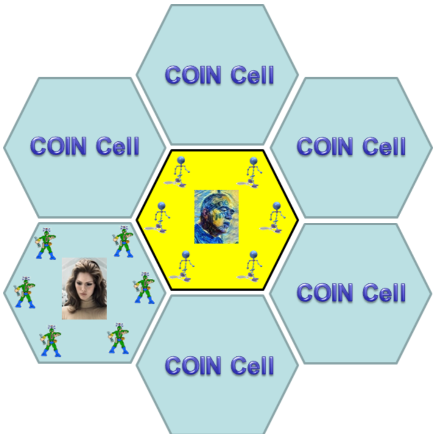

Figure 3: Cellular Collective Intelligence

One important issue to be addressed is how to protect the training process from data poisoning and data evasion attacks, which are the major threats for the AI today. In [13], various attacks and their potential impact are shown related to the training data poisoning. We are going to measure and learn to estimate the negative impact of the data poisoning when the target is not the data itself but rather the way it is selected and ordered.

6. Summary

Having better knowledge about suitable and relevant methods for teaching humans in sense of reducing the time of learning and better knowledge about human ability to learn, AI could build new optimal models for the education process. This will lead to the development of the learning process and intelligence of both human and the AI. We believe that development of the AI will also lead in this case to the fast development of humans as a synchronous process.

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