AI Mellontology e-Symposium 2021

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AI grand challenges

Organizer: Prof. Ioannis Pitas, Aristotle University of Thessaloniki, Greece, Coordinator of International AI Doctoral Academy (AIDA), pitas@csd.auth.gr

In the eve of the 20th century, the famous German mathematician Hilbert issued his 23 **Hilbert's problems** in Mathematics. They were all unsolved in 1900 and many of them proved to be very influential for 20th-century Mathematics. Such AI challenges do exist today and, if properly defined and addressed, they can greatly boost AI research.

AI grand challenge definition procedure

Proposals (and short descriptions) for such grand challenges are welcomed from anybody by email to: pitas@csd.auth.gr They will be debated in the AI Mellontology e-Symposium each year and defined (or updated or deleted) in a more formal/detailed definitions after the debate. Proposals can be co-defined by more than one scientist/lab.

R&D cooperation will be sought within Horizon2020 ICT48 projects and AIDA to address these challenges.

Subsequently, I define three such problems: knowledge quantification, knowledge evolution/adaptation and knowledge education. Actually, it can be debated, whether they are indeed three independent problems.

AI grand challenge list 2021

Knowledge quantification. The ability of an AI/autonomous system to really operate as such depends on its knowledge of the environment and of itself (self-awareness). Unfortunately, *Knowledge* is such an elusive, yet pervasive and ubiquitous term, as it forms the basis of our society. It is found in philosophy and education texts since antiquity. Yet, the following proverb, attributed to Socrates, applies to it: 'The only thing I know is that I do not know' (εν οίδα ότι ουδέν οίδα). Even its formal definitions do not really converge. Therefore, a proper, epistemologically correct, quantifiable and practical definition of a knowledge is one of the major challenges we face today. This goes hand-in-hand with knowledge quantification. (Proposed by Prof. Ioannis Pitas)

Learning interventional representations. A central problem of contemporary AI is causal representation learning, that is, the discovery of high-level causal variables from low-level observations. While many successful applications of AI rely on learning statistical data representations based on large-scale collections of i.i.d. data, future systems must be able to interact with the world and with other learning systems in complex feedback loops, where the actions taken affect the data the system is trained on. This requires learning causal representations, which support intervention, planning, and reasoning. (Proposed by Prof. N.

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Cesa-Bianchi)

Generalization in large neural networks. One of the most striking successes of AI and machine learning is the ability to learn efficiently by fitting large neural networks using specific algorithms that optimize a given loss function. The generalization performance of the resulting classifier is potentially affected by a large number of interacting factors, including the network architecture, the optimization geometry, the type of loss function, the initialization, the hyperparameters (stepsize, momentum, etc.), and the randomness in the optimization algorithm. Understanding the role of these factors in the final performance is one of the main open problems of machine learning. (Proposed by Prof. N. Cesa-Bianchi).

Knowledge evolution/adaptation. Another equally pressing issue is knowledge acquisition and evolution/adaptation. In recent decade, many advances have happened in using Machine Learning for knowledge acquisition, typically in the form of Deep Neural Networks (DNNs). Knowledge adaptation has also been addressed in a rather fragmented way, e.g., through transfer/lifelong/continual learning. Despite all this progress, major issues are still unsolved. We cannot quantify AI system (notably DNN) knowledge in a satisfactory way. As a result, we cannot quantify its evolution, when trying to learn e.g., with more/new data or new tasks. And, of course, we cannot optimize knowledge evolution. This is a major issue to be solved that will really boost system adaptation and autonomy. (Proposed by Prof. Ioannis Pitas)

Knowledge education. It defines the processes of transferring knowledge from AI system(s) and/or human(s) to other AI system(s). In this sense, its scope is much broader than the current knowledge transfer theory. Actually, I claim that the 'teacher-student' model that prevails in human education, as well as other human education theories and paradigms can be adapted to an AI education environment. Such advances can greatly boost both knowledge acquisition and knowledge evolution in AI/autonomous systems. Going the opposite way, novel Knowledge education theories can be adapted and can quantify/improve human education. (Proposed by Dr. Ioannis Mademlis, Prof. Ioannis Pitas)

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