IWSSL Introduction to this volume

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1. Introduction

This collection of papers was presented at the second annual international workshop on self-supervised learning (IWSSL2021) held in virtually, between August 13 and August 14, 2021. They represent the state of the art in an expanding field of research that attempts to build systems that can learn without human intervention with little or no hard-wired domain knowledge, as would a new-born child or animal.

As we try to build increasingly complex A.I. systems, including robots and other complex cyber-physical systems (CPS), and as these systems increasingly depend upon machine learning in order to be effective in their intended environments, the role of human involvement is becoming a limiting factor.It is in this light that the need for and the potential benefits of "Self-Supervised Learning" (SSL) have become apparent.

How do intelligent systems, such as human beings and software agents, learn about the world? They should primarily learn about themselves and their environment, and how the two interact effectively, by exploration and self-motivated experimentation. We continue to ignore the fundamental mechanisms underlying self-motivated learning through experience in the open world that could ultimately lead to intelligent behaviors such as, for example, how to recognize objects through visual and other senses, how to move another object to reach an object otherwise out of reach, and how to use those objects as tools, by experimenting.

2. What is Self-Supervised Learning

The traditional view of machine learning has been that it is an offline process.This was largely due to computational cost of machine learning. The fact of it being considered an offline computation has invited certain shortcuts that are ultimately limiting.

In AI in general, the role of the human in describing the world has been the standard model.It is researchers that establish the ontologies that structure our world for A.I. systems and as a consequence these models tend to be limited to the problem being tackled, and are thus limited in their applicability to other, even similar domains.A baby, human or animal, is not born into the world with a rich ontology, it is left to find out what is important and how things are related.

In the rush to produce high-performing intelligent systems (e.g. problem solvers, classifiers), and to work within the constraints of limited memory and processing power, we have jumped directly to hand-crafted actions, often encoded using PDDL (Planning Domain Definition Language). Such systems are notoriously brittle as the number of rules tends to be small and overly specified. These do not address the core features of cognition and are not the intelligent robotic systems of the future that we are expecting.

Rules learned through experimentation or mimicking tend to be more numerous and less brittle. Moreover, we may need other knowledge representation structures than rules to account for incremental open-ended learning and cognitive development. We believe that ultimately self-motivated learning will fuel the next wave of intelligent systems. These will depend less on hand-crafted design and, in contrast to existing systems, will be adaptable to new environments, and more robust in the face of complexity and uncertainty in the real world.

The world is continually changing as are the demands that we put on our would-be intelligent systems. The cost of continually updating ontologies, rules and training data sets is ultimately limiting.We wish to build intelligent and autonomous systems that have as a primary capability the intelligence to learn the rules, learn the ontologies, absorb the training data, and to learn, without the supervision of its human creators.

Today, machine learning is almost entirely a victim of this view of the role of human designers to model the learning process and the notion that learning is an offline process.These will ultimately limit what can be done.In short the approach suffers from many weaknesses including that it doesn't scale.It takes too much human involvement of a complex nature to scale to having A.I. systems proliferate.They also suffer in that they do not generally have the ability to learn from their experience without a human in the loop.

With current methods (Deep Learning), when learning to recognize objects, we collect a very large number of examples which are hand- annotated using annotations that come from a human designed ontology. It is human designers that decide what is important and what represents good examples of the objects being recognized.This is a very costly endeavor which is often times unacceptable.The use of mechanical Turk to annotate images has allowed some early success stories but for specialized domains including, for example, classified objects, the approach is not viable long term.

For systems that see and act, in order to generate massive amounts of training data, we employ simulators that can run many times real life speed and can perform millions of iterations without wearing out the hardware for which it is designed to control.In many experiments, the transfer to a robot never happens, either because the transfer from a simulated world to a real world doesn't work well, or because for the experiment it is deemed sufficient to show off a simple simulation of a game world.There are many examples of such experiments in reinforcement learning that at first glance appear promising, but are ultimately limited by their human designers. A recent example is the success of Alpha-GO Zero to achieve a level of competence that exceeds the best living player after several millions of self-play games.The best living GO player has not played millions of games!

We are presently experiencing an explosion of machine learning systems due in large part to the recent availability of low cost massively parallel computer architectures originally targeted at computer graphics (GPUs). These allow massive computations and high-speed simulations to perform learning and show that certain learning algorithms, given enough data and enough iterations can perform well. Hand-in-hand with the growth of affordable massive computation has come large affordable memory.These are the driving forces behind the current revolution in applications of machine learning.

In self-supervised learning, we can redirect the massive parallelism to serve the role of understanding the world through exploration, as would a baby or a new-born animal. The system, and not a human designer would decide what is important and what is not.What is related to what else would be learned too. In the self-supervised learning view of the world, it is the A.I. system, and not the human designers that would determine the ontology, the training sets, when to seek new examples, and when to update learning when new evidence suggests significant differences, such as between a leopard and a tiger.

Self-supervised learning is not just about a learning algorithm, it encompasses a range of learning related issues, such as motivation, intrinsic and extrinsic and the decision to explore versus act. As with Deep-Learning, tentative approaches and algorithms have been around for a long time, and as with Deep-Learning, the key to why SSL is ready to change the world is rooted in the availability of fast inexpensive, massively parallel processing architectures and large inexpensive memory. Similarly, as with Deep-Learning, we believe that ultimately, specialized chipsets for SSL will emerge to provide higher performance at a lower power utilization and a lower price.

2.1. Benefits of a Self-Supervised Learning Approach

Robots and learning enabled systems that can continue to grow once deployed will be ultimately more robust to a changing world and more useful.By removing the (expensive) human from the loop, we can look forward to affordable intelligent devices, including robots and CPS.

Self-supervised learning means that the ground rules for a particular problem domain will not be baked in and so the systems will be able to learn to perform multiple different tasks, or to recognize different sensory patterns than were necessary for any particular problem.

Letting massively parallel machines learn what is important and how to act to achieve desirable outcomes will be dramatically cheaper than having humans define the learning problems for point problems.The principal reason why the self-supervised approach will come to dominate is that computing devices are cheaper than humans.In addition, learning systems can build models of the world based upon exploration much better than humans can reduce their knowledge to design rules.

3. In this volume

This volume presents four papers from the pandemic workshop, held virtually. Working from home without access to the laboratories invites reflection on our work and in the first paper of this volume, *The Explanation Hypothesis in General Self-Supervised Learning*, Kristinn Thórisson argues that general self-supervised learning requires (a particular kind of) explanation generation. In the second paper, *A Unified Model of Reasoning and Learning*, Pei Wang describes the NARS architecture for artificial general intelligence (AGI) which brings together reasoning and learning within a coherent architecture. In the third paper, *Comparison of Machine Learners on an ABA Experiment Format of the Cart-Pole Task*, Leonard Eberding et. al. analyze the autonomous transfer learning capabilities of five different machine learning approaches, an **Actor-Critic**, a **Q-Learner**, a **Policy Gradient Learner**, a **Double-Deep Q-Learner**, and the *OpenNARS for Applications*. Finally, in the fourth paper, Artificial Emotions for Rapid Online Explorative Learning, Paul Robertson describes the neuroscience underpinnings of the CARL architecture.

4. Conclusion

We believe that despite the current fascination with human-intensive machine-learning methods, ultimately, self-supervised learning systems will come to dominate because they will be more robust in an ever- changing world and will be cheaper to build and maintain.

SSL devices will be more readily accepted as truly intelligent systems, due to their ability to learn from their own mistakes and to apply themselves to disparate domains not defined by the human designers.A general intelligence does not come from building point solutions to specific problems.

Achieving the goals of self-supervised learning will take time and funding.There are significant technical barriers to overcome.Like the non-SSL approaches, success will critically depend upon the availability of cheap memory and computation.

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