Work-in-Progress: What Recent Artificial Intelligence Breakthroughs in the Game of GO Mean for Human Learning and Engineering Education

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***Abstract*—Artificial intelligence, led by the method of deep learning, has generated enormous interest in both professional circle and general public in the last two years thanks to Deepmind's AlphaGo's stunning mastery of Go, the most sophisticated board game. While most interest since then has been shown in exploring the applications of AlphaGo's algorithms in machine learning, it is the potential impact of its learning strategy on human learning that captures our attention. Can AlphaGo's success, aside from taking advantage of superior computing power, lead to more effective learning for humans? Does AlphaGo's learning lend support to any of the learning theories? Or does the training data reveal any notable pattern or trajectory that may suggest new perspectives on human cognition? In this work-in-progress paper, we try to make connection between human and machine learning using the technical details revealed by the Deepmind team, and examine what insights can be gained from AlphaGo's training on human cognitive development and more specifically, engineering education.**

I. Introduction

Artificial intelligence and machine learning have witnessed some significant developments in the last two years, and none is catching more interests and creating more excitement in the research world than its success in the ancient board game of Go.

The game of Go has long been viewed as the Holy Grail of classic games for artificial intelligence to master owing to its enormous search space and the difficulty of evaluating board positions and moves. Even after IBM's DeepBlue defeated Kasparov in 1997, people in the AI community generally believed it would still take at least five decades before computers can compete with professional Go players, and it would be in an even more distant future that machines can win matches against world champions of the game. However, in a shocking and fast-paced development, Google's AlphaGo became the first machine to beat professional player in 2015, and defeated one of the world's top players by an aggregate score of 4:1 in 2016. In 2017, Master, AlphaGo's 2.0, beat the world's champion in three straight sets. The exclamation came in late 2017 when Deepmind announced that AlphaGo Zero, the latest Go program defeated AlphaGo by 100 games to 0.

While professional Go players are intensively studying AlphaGo's moves, many of which have toppled centuries-old Go doctrine, what is even more remarkable is the learning ability demonstrated in successive versions of Deepmind's Go programs. The complexity of the game prohibits the use of brute force to search for optimal move, therefore from the very beginning AlphaGo settled on machine learning algorithm. While previous versions of AlphaGo were initially trained on thousands of human amateur and professional games using supervised learning, AlphaGo Zero skips this step and learns to play simply by playing games against itself using a novel form of reinforcement learning. The system progressively accumulates thousands of years of human knowledge and learns the game of Go during a period of few days.

We are not overlooking the computing power of machine, which unequivocally plays a major part in the programs' quantum leap. However, the rapid gain of the knowledge and innovative moves by the programs should be seen as a testament of the efficacy of the learning algorithm. Therefore, can men benefit from similar learning activity to rapidly increase their own cognitive understanding and become more creative?

The study on the connection between artificial intelligence and human learning has been narrowly focused on using AI to help develop computer-aided tools for better learning environment. In this paper, we will use technical details released by the Deepmind team on the machine's cognitive development and learning ability to explore the connection between machine learning and human learning, and see how the machine learning activities can be adapted to practices that may lead to better engineering education outcomes.

The rest of the paper is organized as follows. Section II reviews basic learning theories and pertinent cognition psychology. We then examines the application of general learning

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sciences to engineering education in Section III. Finally, we introduce in Section IV AlphaGo's learning strategy and some noteworthy discoveries from its training data, and examine their connections to human learning.

II. Learning Theory Review

Learning, in one definition, is described as "a persisting change in human performance or performance potential[which] must come about as a result of the learners experience and interaction with the world". According to [1], this definition encompasses many of the attributes commonly associated with learning theories, i.e., learning is a lasting changed state (emotional, mental, physiological (i.e. skills)) brought about as a result of experiences and interactions with content or other people.

Learning theory has a rich and diverse heritage. As a result of this heritage, numerous viewpoints (or paradigms) concerning the learning process exists. According to [2], the first paradigm is *functionalistic*, which reflects the influence of Darwinism in that it stresses the relationship between learning and adjustment to the environment. The second paradigm is referred to as *associationistic*, since it studies the learning process in terms of the laws of association. This paradigm originates with Aristotle and is perpetuated and elaborated by Locke, Berkeley, and Hume. The third paradigm originates with Plato and evolves through Descartes, Kant, and the faculty psychologists. The fourth paradigm is referred to as neurophysiological since it attempts to isolate the neurophysiological correlates of such things as learning, perception, thinking, and intelligence.

All learning theories hold the notion that knowledge is an objective (or a state) that is attainable (if not already innate) through either reasoning or experiences. Behaviorism, cognitivism, and constructivism (built on the epistemological traditions) attempt to address how it is that a person learns. [1] summarizes the features of the main learning theories as follows.

Behaviorism states that learning is largely unknowable, that is, we can't possibly understand what goes on inside a person (the "black box theory"). Behaviorism is being seen as comprised of several theories that make three assumptions about learning: *a*) Observable behaviour is more important than understanding internal activities; *b*) Behaviour should be focused on simple elements: specific stimuli and responses; *c*) Learning is about behaviour change. Cognitivism, which often takes advantage of computer information processing model, views learning as a process of inputs, managed in short term memory, and coded for long-term recall. Constructivism suggests that learners create knowledge as they attempt to understand their experiences. Among the three, behaviorism and cognitivism view knowledge as external to the learner and the learning process as the act of internalizing knowledge. Constructivism assumes that learners are actively attempting to create meaning. Learners often select and pursue their own learning. Constructivist principles acknowledge that real-life learning is messy and complex. Classrooms which emulate the "fuzziness" of this learning will be more effective in preparing learners for life-long learning.

Details about learning theory and cognition can be found in many well written monographs[3, 4, 5, 6, 7].

III. Engineering Education

Engineering education, as a field of scholarship, has started to gain significant traction over the last decade. Still, the emphasis of the scholarship has been on improving teaching pedagogy and engineering research methodologies. For example, a series of papers published in the Chemical Engineering Education in 2000, such as [8, 9], discusses the future of engineering education from different angles. One of the papers, [10], touches on the teaching methods. As noted in [11], the broadest movement over the past few decades is a shift from passive, lecture-style teaching to more active, learner-centric activities. Felder et al.[10] recognize that mainstream teaching methods in general education, technical education and educational psychology had relatively little impact on engineering education, and survey some instructional methods that are easy to implement and consistent with learning theories. In [12], the authors summarize seven emerging engineering education research methodologies, which are Case Study, Grounded Theory, Ethnography, Action Research, Phenomenography, Discourse Analysis, and Narrative Analysis. These methodologies might allow engineering educators to better study key challenges such as students' responses to innovative pedagogies and the changing requirements for engineering graduates in the 21st century. However, Johri [13] brings up the debate in research community about engineering education being too theory-driven versus the lack of emphasis on theory that could hamper the pragmatism of education. Johri believes that making theory more serviceable to engineering education research by developing broader frameworks that can help solve classes of problems. For this goal, he suggests more review articles to get insights from psychology/sociology/anthropology on theoretical paradigms with emphasis on its applicability to engineering education. Felder et al. are among the first to propose the concept of learning styles of engineering students. They follow that concept up with a well received metric for assessment in engineering educators, the Felder-Soloman's Index of Learning Styles. The Felder model of learning styles focus on five aspects of learning dimensions: Processing (Active/Reflective), Perception (Sensing/Intuitive), Input (Visual/Verbal), Understanding (Sequential/Global) and Organization (Inductive/Deductive). In the highly cited work [14], Felder et al. describe the student learners with the following characterizations. Sensing learners are concrete thinker, practical and oriented toward facts and procedures. The intuitive students are abstract thinker, innovative and oriented toward theories and underlying meanings. The students in the visual category are visual learner of presented material, such as pictures, diagrams and flow charts. The verbal students prefer written and spoken explanations. The active students are hands-on learner who learn by trying things out and enjoy working in groups. The reflective students are more of solitude learner who learn by thinking things through and prefer working alone or with a single familiar partner. The students in the sequential group are linear thinker who learn in small incremental steps. The global students like holistic thinking process and learn in large steps. Each of the above stated dimensions has parallels in other learning style models.

Though learning sciences and general learning theory have been research focus for many decades, they have not made significant inroads in the engineering education. What it means is the engineering education research to lack theoretical and empirical work on engineering learning that could supported by learning sciences. This is probably due to the fact that engineering as a whole, concerns with cognitive understanding than sensory-motor tasks. Nonetheless, there have been some studies that try to link learning theories with specific perspectives.

In [15], Hassan argues that because learning method should dictate the assessment framework, and because learning method should be built upon certain learning theory, ultimately the assessment method should be aligned with respective learning theory, for instance, the behavioristic method of learning for engineering students should include some cognitive aspects (e.g. let the student learn using his/her own way of thinking) and the socio-cultural factor(e.g. in the form of group work, artefacts, project demonstration, etc.).

Engineering education is generally believed to have to cover three learning domains: cognitive, affective, and psychomotor domain. While learning with cognitive domain has received the most attention, Alias et al. propose a framework that combines methodologies for achieving learning in cognitive domain with the support of affective dimension of learning, which include emotional elements such as empathy, enthusiasm and motivation. The authors identify key affective constructs that influence cognition based on analysis of four learning theories.

One specific perspective, situative learning, is investigated in [17]. Situativity refers to the central role of context, including physical and social aspects of the environment, on learning. Johri and Olds outlines and discusses analytical aspects of situative learning: the importance of social and material contexts on learning; the role of activities and interactions in situated learning; and the ideas of participation and identity in relation to situativity.

Students' performance in engineering programs is analyzed in [18] using their learning styles. For this purpose, [18] separates the students into four groups: assimilators, which account for majority of the students; divergers and convergers are two groups who normally follow the assimilators; and accommodators whose number is very limited. Under these categories, he fouhe relationship between engineering students' learning styles and their performance is found: assimilators and convergers performed better than the divergers and accommodators. The performance difference between assimilators and divergers is statistically significant. The results of this study show that the learning style theory is a potential tool for guiding the design and improvement of courses and helping students to improve their individual performance.

IV. AlphaGo's Revelations

AlphaGO came on the scene in 2016, and in two years the Deepmind creation has sent shock waves to the AI community with back to back versions that bested a professional Go player, an 18-time international champion, and then No. 1 player in the world. The culmination occurred in late 2017 when AlphoZero beat the previous version of AlphaGo by an aggregate goal of 100 to zero, after only 72 hours of training where over 4.9 million games of self-play were generated.

So what do we learn from the training other than the staggering number of self-played games? According to [19], AlphaZero is trained solely by self-play reinforcement learning, starting from random play, without any supervision or use of human data. This is the most significant difference from its predecessors where a mixture of supervised learning and reinforcement learning are used to train two deep neural networks. In fact, the developers of AlphoZero compare the performance of reinforcement and supervised learning on the same architecture and find that notably, while supervised learning achieves a better initial performance and is better at predicting human professional moves, the self-learned player performs much better overall and defeats the human-trained player within the first 24 hours of training. In other words, the human knowledge gives the program an edge at the beginning, which is readily understandable, but seems to restrict the machine's creativity and inhibit its progress to discover non-standard Go strategies beyond the scope of traditional Go knowledge.

Another important fact is that AlphaGo Zero does not outperforms its early versions with superior computing power. On the contrary, AlphaGo Zero only runs on a single machine with four TPUs as opposed to 48 and 176 TPUs for the first two generations of the AlphaGo programs. Therefore, the learning efficiency has tremendously improved with Deepmind's latest training algorithm using much less resources and utility.

The success of AlphaGo Zero seems to suggest the feasibility of reinforcement learning as a better learning strategy, especially for learners to unleash their imagination and unearth more inherent dynamic of the are under study. This is consistent with Gregory Kimble's definition that learning results from reinforced practice, or can trace its origin to Aristotle who argues "Truth is found outside of ourselves using our senses" and develops a scientific method of gathering data to study the world around him.

More broadly, what AlphaGo Zero has accomplished seems to be in line with the views held by behaviorists who believe that learning is the reinforcement of formation, strengthening, or weakening of the observable connections between stimuli and responses . However, we cannot underestimate the positive influence of supervised learning at the beginning stage of human cognition because just as AlphaGo Zero tests show, supervised learning with *a priori* knowledge does jump start the learning cycle quickly.

Interestingly, there are some researchers who have already produced cognitive models building on similar ideas. One example is the study done by the team led by Dr. Ron Sun from Rensselaer Polytechnic Institute. His work in the modeling of cognitive agents, especially in their abilities to learn, reason and act in the real world has resulted in a hybrid connectionist model CLARION [20, 21, 22]. CLARION combines both procedural knowledge and declarative knowledge in one framework. The most important feature of learning in this architecture, besides being accomplished by reinforcement learning, is that it is supplemented with rule induction. This means that the resulting model is parsimonious in structure and possesses a variety of reasoning and decision-making capabilities. Another notable work is modular reinforcement learning that allows multiple modules (agents) to compete or collaborate. This is similar to AlphaGo Zero and AlphaGo Master's self-play games. The end results from AlphaGo program training prove its potential in human learning, and it is a direction of research worth paying attention to. For more of Prof. Sun's research pertinent to AlphaGo's machine learning techniques, please refer to his web page: https://sites.google.com/site/drronsun/.

V. Summary

In this paper, we have offered preliminary analysis of possible correlation between machine learning and human learning based on Deepmind's AlphaGo performance. We try to see if the findings from AlphaGo provide some form of validation to any of the fundamental learning theory, and if and how these results can potentially lead to more effective engineering teaching strategies. What we know now is that the latest AlphaGo program relies purely on reinforcement learning and follows a bottom-up learning paradigm. However, supervised learning with human knowledge can provide the machine a good head start as much to shortening the learning curve. It is reasonable to suggest that as engineering educators, we should feel more comfortable of moving towards behaviorism based learning paradigm. The framework may incorporate supervised learning at the beginning for implicit knowledge but reinforcement type learning later for explicit knowledge on its basis.

Of course, this is still work-in-progress and the conjuncture needs more in depth research for two reasons. First, due to the "black-box" nature of deep neural networks, it is impossible for us to decipher the thought process of the AlphaGo programs. In other words we know the moves AlphaGo makes, but we do not understand the internal mechanism that drives the machine to reach those conclusions. Although the traditional behaviorism theory accepts the premise of learning process as a "black box", if supervised learning is involved, it would still be beneficial to interpret the decision making and cognitive understanding in the process. We hope the development of machine learning such us fuzzy logic can help us with the extraction of explicit knowledge (or rules) to enable explicit reasoning. Second, the eventual goal of any theory is to help design and construct better learning environment. To achieve better learning outcomes, epistemology which represents our belief about the nature of knowledge, and learning theory which represents our belief about how people learn, must align to produce the most reasonable and effective strategies for teaching/learning practice. Assuming behaviorism based learning theory is the foundation for future engineering education, we still need to develop a guiding framework, narrative structure, discourse, or schema for actual implementation of the learning strategy. There is a lot work to be done in this area.

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