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Summary/Discussion #3

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Machine Learning

Schölkopf (2015) describes the concepts, ideas and process behind machine learning. Like humans, machine learning is an artificial intelligence (AI) system’s ability to process data and its surroundings and perform an action that gives the best outcome. Schölkopf briefly points at the basics of machine learning, stating that AI systems are trained by the system designer to observe a problem and with data provided will perform an output based on input known as supervised learning (para. 2). The systems size and complexity are a resemblance of what data the system designer thinks are useful depending upon the given problem. Schölkopf goes on to say that data sets are rapidly growing allowing the solution of exceedingly non-trivial inference problems (para. 3). This has led to the development of certain algorithms that allow AI to choose from a list of possible actions, where the AI chooses the action that gives the biggest possible reward. He also mentions the work of others, describing Q-learning as one of these action-and-reward type of learning styles. This type of learning opens access to teaching AI “to play a set of 49 vintage video games”, using the game score as the reward goal (Schölkopf, 2015, para. 5). He then continues to talk about Q-learning and the way it was designed and built. Schölkopf comes up on his conclusion by analyzing Q-learning stating that this is a great starting point and the dimensionality exceeds those of past reinforcement learning projects (para. 8). He concludes with questions that can only be answered with more research and experimentation, looking forward to future discovery.

Schölkopf (2015) statements are proven strong with the support of experimental data that he cites in his work. He refers to “Mnih et. al” throughout the article about the Q-learning mechanism they produced. With his brief explanation in the beginning of how machine learning works and then transitioning into higher-level machine learning with the support of the Q-learning project was very strong. Schölkopf states “In the early days of AI, beating a professional chess player was held by some to be the gold standard”, and this was very true. When Deep Blue (computer designed to play chess) beat the world champion in chess in 1996, people crazed over the fact a machine beat a human. Comparing that to a machine learning how to play 49 different vintage video games by “reading” the pixels on the screen figuring out what the best possible outcome is is a huge difference. They are only so many possible moves in chess and every state of the board can be physically coded into a computer thus the computer chooses what piece to move where to give it the best possible outcome. When Schölkopf uses Q-learning to support his article on the evolution of machine learning from something trivial to higher-order thinking, he represents the distance that machine learning has come. Q-learning reads all the pixels on the screen and by the state of all the pixels it decides what to do next and learns from when it made mistakes. Schölkopf also states that Q-learning might be the right tools for moving forward with machine learning, learning to play video games being a better real world model than learning to play chess (para. 10).

Schölkopf (2015) and Davis and Marcus (2015) both focus on about the same topic but in a different sense. Davis and Marcus describe the ways that have been designed for AI to learn commonsense and the many ways that it can do this. Schölkopf describes how machine learning works and focuses on one way of learning, Q-learning. The Q-learning that Schölkopf mentions could possibly be used towards AI learning commonsense. Schölkopf even hints towards Q-learning opening the window to real world problems, AI learning commonsense being one of them. Gil, Greaves, Hendler, and Hirsh (2014) focus on AI analyzing large quantities of data, understanding it, and sorting it. Schölkopf describes Q-learning as a teaching model for “highly trivial inference problems” and the complexity of the design is based on the data that is provided for the machine to learn from (para. 3). Dumping large amounts of experimental data for a machine to understand and learn from could be very prominent in the future of science.

References

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