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Natural Language Processing With Deep Neural Network Architecture

Since the invention of computer in 1941, artificial intelligence become one of the most controversial and concentrated domains in computer science. In the past 60 years, computer scientists have re-defined the meaning of artificial intelligence as a machine mimics "cognitive" functions that humans associate with other human minds, such as natural language processing and self-learning abilities. (Russell, Norvig, 2) Many scientists believed that natural language processing remain one of the most difficult topic to complete in artificial intelligence. While researchers conducted some significant progress in machine learning, the ability for a machine to process human language remained steady. In recent years, the development of deep neural network architecture and the success of AlphaGo provides a new sign to improve the efficiency and correctness of natural language processing.

In 1950, Alan Turing, one of the pioneer computer scientist in the field of artificial intelligence, proposed the measurement of machine intelligence, known as the Turing Test. In his work, *Computing Machinery and Intelligence*, Turing suggested a machine should be considered "intelligence" if it can pass the Turing Test. According to his original work, the test can be described in terms of an imitation game with three players, a man A, a woman B and an interrogator C who may be of either sex. The interrogator is separated from both man and woman. The objective of the interrogator is to identify the sexuality of both humans by asking series of question via typewritten. While A try to give false information to mislead the interrogator, B should help interrogator to make the correct decision. In the Turing test, human A is replaced by a computer, which does exactly what human A does in the game. Turing stated, if the correct rate of the interrogator is lower when the game is played with the computer as he does when the game is played with two humans, should one conclude the machine can think? (Turing, 434) In other word, if a computer program can successfully pass the test and let the interrogator conclude it is female, one can conclude that the machine have the ability to act as a human being. After Alan Turing published *Computing Machinery and Intelligence*, the Turing Test become one of the main methods scientist used to determine whether a program should be consider intelligent or not.

According to the Turing Test, a machine should be considered intelligent if it can think as human and act as human. In order to fulfill this goal, natural language processing become one of the important topic in modern AI development. In the early history of artificial intelligence, the first, and probably the most well- known natural language system that has been programmed is ELIZA. According to Saygin, Cicekli and Akman's paper, *Turing Test: 50 Years Later*, ELIZA was developed by Joseph Weizenbaum at MIT during the years 1964-1966. The system "act" as a psychotherapist and rephrase the interrogator's statements as questions and urges him/her to continue talking. The system parsed the input string and formulated a suitable replay by simple pattern recognition and substitution of keywords. (Saygin, Cicekli, and Akman, 504) The ELIZA system symbolized the early skill level of natural language processing. In the past 50 years, although machine's natural language processing skill has improved, it is still not close to perfect at all. According to Huma Shah and his research team's article, *Can machine talk? Comparison of Eliza with modern dialogue systems,* the authors compared the early ELIZA with the modern ELIZA that manifests as a web-based version. The result shows that the modern version of

ELIZA performed more human like compare to the original one. However, when the conversation goes deeper, people can still notice the difference between the program and actual human. As authors addressed in the paper, “These descendants of Eliza’s question- answer conversationalist are not ‘empty vessels’ though they still have a long way to go in levels of conversational sophistication to respond to questions in a sustained satisfactory manner”. (Shah, et al. 282) In later section of the paper, Shah and his collogues performed a comparison of ELIZA with other modern dialogue systems. In the experiment, 116 human participants were selected and asked to rate the six online artificial chat bots. For the purpose of fair play, all the systems were indicated with entity number so the participants won’t be affect by outside factors. After the results were collected and carefully analyzed, ELIZA received the lowest mean conversational ability score of 24.86 on the scale ranging from 0 = poor-machinelike, 50 = good, but machinelike, 100 = humanlike. The highest score was Eugene Goostman with score number 63.56. (Shah, et al. 286) These scores not only indicated the ranking of modern artificial chatbots, but also emphasized the difficulties of natural language processing. The ability for a machine to understand human language and reply naturally remain as one of the hardest problem in artificial intelligence.

Unlike natural language processing, the progress of machine learning has rapidly developed due to the usage of deep neural network. In October 2015, AlphaGo, a computer program developed by Google DeepMind became the first computer Go program to defeat the human European Go champion by 5 games to 0. In the following year, AlphaGo defeated Lee Sedol, one of the top ranking professional Go player in a five- game match. The event is considered a significant breakthrough in modern machine learning. As explained David Siver and his DeepMind research team in *Mastering the game of Go with deep neural networks and* *tree search*, the reason why AlphaGo was able to calculate such complicate game is because it uses the Monte Carlo tree search algorithm. The key features of this searching algorithm is, as more simulations are executed, the search tree grows larger and the relevant values become more accurate. (Silver, et al. 484) AlphaGo also has two deep convolutional neural networks called value network and policy network. The value network is used to evaluating positions and the policy network is used to sampling actions. Researchers train the neural networks using a pipeline consisting of serval stages of machine learning. It first began with a supervised learning of the two neural networks directly from expert human moves. AlphaGo has over 30 million positions from the KGS Go Server. By imitating human player’s moves, it can provide fast, efficient learning updates with immediate feedback and high quality gradients. After AlphaGo finishes the supervised learning, it began to optimizing the final outcome of games by reinforcement learning against itself. (Silver, et al. 484) By allowing AlphaGo to repeatedly play against itself, it gain the ability to generalizing to new positions. According to the table 2.b in the paper, games played with reinforcement learning policy network has the lowest chance of error. (Silver, et al. 485) The ability to self-train its neural network allows AlphaGo to improve its skill even when it play against real player. When AlphaGo against Lee Sedol, it stores the new information from the game into its networks so it can analyze it later.

Many scientists believed that similar neural network architecture from AlphaGo can also be used in natural language processing to improve its efficiency and correctness. According to Ronan Collobert and Jason Weston’s *A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning*, the performance of natural language processing (NLP) can be significantly improved under the convolutional neural network with multitask learning. Unlike to the traditional NLP approach where the program parsed the input string and fed to a classical shallow classification algorithm, with deep neural network, the input sentence is processed by several layers of feature extraction. The features in deep layers of the network are automatically trained by backpropagation to be relevant to the task. (Collobert, Weston, 161) With the feature of multitasking learning, the program can learn several tasks at the same time with the aim of mutual benefit. In the paper, Collobert and Weston also stated that multitasking is significantly useful when considers related task. For example, in some standard natural language processing tasks, the Part-of-Speech tagging task is related to semantic role labeling and named entity recognition. When the neural network automatically learns features for the desired tasks in the deep layers of its architecture, the deepest layer implicitly learns relevant features for each word in the dictionary. (Collobert, Weston, 163) This means when training neural network on related tasks, sharing deep layers in these neural network would improve features produced by these deep layers, and thus improve generalization performance. The experiment results presented by Collobert and Weston shows that the program with deep neural network and multitask learning can process part of speech tagging with 2.91% error and chunking with 3.8% error, which both are lower than the experiment without multitask learning. In particular, the neural network architectures achieved state-of-the art performance of 14.30% error rate when performing semantic role labeling task without any explicit syntactic features. (Collobert, Weston, 167) These results show how deep neural network and multitask learning can help to improve natural language processing. On September 26 2016, the Google research team published a paper about using neural network to improve the correctness of Google Translator. In *Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation*, Yonghui Wu and his collogues presented a similar neural network architecture with different level of layers and training procedures. According to the result of the experiments, the new Google's Neural Machine Translation reduces translation errors by more than 60% compared to Phrase-Based Machine Translation model on some of the popular languages. (Wu, et al. 19)

The improvement in natural language processing and machine learning due to deep neural network emphasized a new era of modern AI development. With the neural network architecture, the program can process its task in several layers of feature extraction. This not only improve the correctness of the task, but also provides the ability to learn, which is significant in artificial intelligence. The ultimate goal of artificial intelligence is to create an intelligent machine that is able to solve problems and maximize its chance to success the goal. As Alan Turing concluded in his paper, "We can only see a short distance ahead, but we can see plenty there that needs to be done." (Turing, 460) However, one thing we can be sure right now is the importance and effeteness of neural network architecture in modern AI technology.

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