Deep Neural Networks in the View of Ecological Holism

YUE Qiang\(^{1,b}\) and YUE Xun\(^{2,a}\)

\(^{1}\)College of Water Conservancy and Civil Engineering, Shandong Agricultural University, Tai’an, Shandong 271018, China
\(^{2}\)College of Information Sciences and Engineering, Shandong Agricultural University, Tai’an, Shandong 271018, China

\(^{a}\)yuexun@sdau.edu.cn, \(^{b}\)yueqiang406@163.com

Abstract. In the viewpoint of ecological holism, deep neural networks can be viewed as a machine cognitive agent with overall multi-level nested structure, the representation learning and problem-solving ability of machine cognitive agent with multi-modal perception function is also regarded as the result of the perception and judgment of ambient situation environment. In the paper, a machine cognitive method based on ecological holism was deconstructed. Then, two core questions to characterize learnability of AlphaGo were answered, one is how to explain the characteristics of the hierarchical gradient and update parameters between different layers of networks? Two is how to understand the effective ability to choose the drop sampling at the strongest level of game of Go. These core controlling structural and functional roles proposed in this study may be further improved to a new type of artificial intelligence law of machine cognitive system.

1. Introduction
Decision making system for cognitive machines is becoming the basic service system of digital ecosystem, deep neural network is considered to be the important advancement of machine cognitive system, which rely on its ability to extract complex patterns of underlying dataset \([1][2]\). For example, the mathematical model of single hidden layer fully-connected neural network is as follows \([3][4]\):

\[
F(x; \Theta) = \sum_{a=1}^{M} \beta_a \tanh (\omega_a \cdot x + b_a)
\]

(1)

\(x\) is the input representing the neural network, \(\Theta = [\beta_a, \omega_a, b_a]_{a=1}^{M}\) represent the parameter set of the neural network, \(M\) is the number of hidden layer neurons. \(x, y\) represent the training sample and the label assigned to the sample manually, an optimized parameter set \(\Theta^*\) can be gotten by the training sample set \(\{x_i, y_i\}_{i=1}^{T}\). How to understand the extracted hierarchical gradient and update parameters of the sample metadata features between different layers of networks, and how to explain the physical meaning of the distributed representation represented by the function parameter set \(\Theta^*\)?

In the viewpoint of ecological holism, deep neural networks can be viewed as a machine cognitive agent with overall multi-level nested structure, the representation learning and problem-solving ability of machine cognitive agent with multi-modal perception function is also regarded as the perception and judgment of ambient situation environment. Can ecological holism explain machine cognitive system of AlphaGo correctly? In the paper, a machine cognitive method in the viewpoint of ecological holism was deconstructed, which is different from reductionism and expand and upgrade...
the basic law of machine cognitive system. Then, two core questions of AlphaGo were answered, one is how to explain the characteristics of the hierarchical gradient and update parameters between different layers of networks? Two is how to understand the effective ability to choose the drop sampling at the strongest level of game of Go.

2. Machine cognitive method in the view point of ecological holism

Machine cognitive agent with multi-modal perception function can "understand" the unstructured data, such as language, images, video et al, the problem-solving ability of machine cognitive agent is regarded as the perception and judgment of ambient situation environment. The machine cognitive agent has the following cognitive characteristics:

- The external environment of machine cognitive agent is the set of external connected objects (things). The internal environment refers to the internal control elements, information transfer and the dynamic evolution process of spatial organization. The bounded time and space is called the system boundary.
- The relationship between machine cognitive agent and the external environment determines a dialectical relationship of interdependence. On the one hand, the changes of the external environment will stimulate and regulate the overall dynamic evolution of the internal environment; on the other hand, the dynamic evolution of information transfer and spatial organization will feedback the surrounding situation through information exchange with the external environment. Therefore, the representation learning and problem-solving ability of machine cognitive agent in specific application areas are in the process of dynamic exploration to unify the changes of the external environment.
- The spatial organization of internal control elements have the overall vertical multi-level nested structure, which follow the characteristics of stratification, classification, and subsection, each level of control elements has its own unique concepts, characteristics, and rules.
- Due to the vertical dimension hierarchy superposition non-linear structure, the internal information transfer of machine cognitive agent is not the single nature and the same direction, the gradient difference of the time space forms the difference of the information flow path or the movement mode, which include “top-down” and “bottom-up” in a single vertical dimension. “Top-down” reflects the system's downward causal relationship. “bottom-up” reflects the system's upward causality. The representation learning and problem-solving ability of machine cognitive agent lies in the hierarchical gradient difference of the time space and update parameters of the information flow path.
- Machine cognitive agent is often limited to a specific vertical dimension, however, decision making system for cognitive machines of digital ecosystem have the horizontal multi-dimensional dimensional synergy. The competition and cooperation of information transfer paths in different vertical dimensions will present two orderly rules of machine cognitive agent, one is the order of the information flow path; another one is the order of spatial organization.
- From the view point of dynamics and histology, the order of machine cognitive agent must be the dynamic evolution process of the information flow path and spatial organization. Orderly process of dynamic evolution depend on the direction of information transfer, which include “top-down” and “bottom-up” in a single vertical dimension, and the horizontal multi-dimensional dimensional synergy. The core technology of deep neural networks using deep reinforcement learning for machine cognitive system lies in the control parameters of information transfer paths and re-integration model of spatial organization.
- To cope with the external environment, machine cognitive agent at certain times of orderly process of dynamic evolution, which through a multistep of information transfer pathway in a single vertical dimension and the horizontal multi-dimensional dimensional synergy, can use
sophisticated and complex mechanisms to modulate the homeostasis between “top-down” and “bottom-up”.

- Machine cognitive agent with multi-modal perception function has the effective ability to deal with specific field problems through interaction with the external environment. In fact, the problem-solving ability of machine cognitive agent should be regarded as the perception and judgment of ambient situation environment, which depend on the dynamic evolution of information transfer paths and spatial organization.

3. The representation learning and problem-solving ability of AlphaGo under the view of ecological holism

AlphaGo can be view as a machine cognitive agent, play at the strongest level of game of Go. Using multi-modal perception function, each features of the input and outcome of game of Go was pre-processed into a set of $19 \times 19$ feature planes. Every board position or state determines the integer feature value, which is split into multiple $19 \times 19$ planes of binary values (one-hot encoding). Neural network architecture of AlphaGo (the policy and value networks) is the deep convolutional neural networks, which use convolutional layers to construct a representation of the position. The effective ability of AlphaGo, which choose the drop sampling at the strongest level of game of Go, selects actions to combine the policy and value networks.

3.1. Policy network sample actions

The effective ability to choose the drop sampling comes from policy gradient reinforcement learning of policy network, which depends on how to train the weight-sharing structure of the policy network [4] [5, 6]. As shown in Fig. 1: (a), 13 hidden layer SL policy network use stochastic gradient ascent to maximize the likelihood of the human move a selected in state. The parameter update of SL policy network training was based on mean squared error between the predicted values and the observed rewards.

For the first stage of the training pipeline, AlphaGo build on prior work on predicting expert moves in the game of Go using supervised learning, and applied an asynchronous stochastic gradient descent update to maximize the log likelihood of the action. The SL policy network alternates between convolutional layers with weights, and rectifier nonlinearities. A final soft-max layer outputs a probability distribution over all legal moves. Owing to its enormous search space (the number of legal moves per position and game length) and the difficulty of evaluating board positions and moves, the second stage of AlphaGo aims at improving the policy network by policy gradient reinforcement learning. The training pipeline is to receive high rewards between the current strategy network and the strategy network that randomly selects a previous iteration [5]. From the view point of dynamics and histology, The results using deep reinforcement learning for AlphaGo lies in the weights parameters (the characteristics of the hierarchical gradient and update parameters between different layers of nodes) of 13 hidden layer policy network, which will be “mapped” to the “top-down and “bottom-up” of vertical information transfer paths and the horizontal multi-dimensional dimensional synergy.

The representation learning of AlphaGo is not only to accumulate knowledge, when AlphaGo “read and understand” the change of board position or state, how to select the next-hand strategy? Problem-solving ability is more important. However, AlphaGo learn how to drop the sub-sampling for a specific situation and predict expert moves on a held out test set with an accuracy of 57.0% using the policy network.

3.2. Value network evaluate positions

As shown in Fig. 1: (b), the value network has a similar architecture to the policy network, the hidden layers 2 to 11 of the value network are identical to the policy network, hidden layer 12 is an additional convolution layer, hidden layer 13 convolves 1 filter of kernel size $1 \times 1$ with stride 1, and hidden layer 14 is a fully connected linear layer with 256 rectifier units. The output layer is a fully connected
linear layer with a single tanh unit, which outputs a single prediction instead of a probability distribution.

3.3. AlphaGo select actions to combine the policy and value networks for the effective ability as the strongest human players

As alternating Markov games, the highest state of the game of Go is the “balance and harmony”, which is not just kill the other party. The change of the game in the process of chess is unfolded step by step, the homeostasis of the chess process depend on the whole process of the game, which from balance to imbalance and then from balance to balance. In order to play at the level of the strongest human players, a way was found to capture the master significantly stronger “chess intuition” of experience. As shown in figure 1, using the regression, reinforcement learning of value networks, which is the final stage of the training pipeline, focuses on position evaluation, estimating a value function that predicts the outcome from positions of games played by using the policy network. AlphaGo select actions by evaluating positions using a value network, and sampling actions using a policy network. Systematic homeostasis of AlphaGo master the significantly stronger “chess intuition” of experience, AlphaGo has finally reached a professional level in Go.

4. Transcendence of reductionism: the symbolic framework s of machine cognitive agent from the view point of ecological holism

As the deep neural networks (DNNs), the main challenge feature powerful representation capability of AlphaGo is that the position evaluation functions, which means the hierarchical gradient and update parameters of the sample metadata features between different layers of networks, are typically highly non-linear and non-convex, non-linear model free reinforcement learning algorithms may not have enough representation capacity in modeling large-scale or high-dimension systems with nonlinear dynamics, which causes great difficulty for following decision making. It is really linear and non-linear algebra fashion for the mathematical model of deep neural networks? In the view point of ecological holism, the weights parameters of hidden layer for the policy and value networks can be evaluated by changes system of the whole concept of Chinese traditional cultures. The symbolic system of “Zhouyi: The book of Changes” can be further improved to a new type of artificial intelligence program. As mentioned mathematical model of single hidden layer fully-connected neural network, the parameter set of the neural network \( \Theta = \{ \rho_m, \psi_m, b_m \}_{m=1}^M \) can be explained by following parameters:

- \( M \) is the number of vertical multi-level nested structure
\{ \phi_m, b_m \} \text{ represent the hierarchical gradient and update parameters between different layers of the information flow path.}

\{ \beta_m \} \text{ represent the horizontal multi-dimensional dimensional synergy.}

The parameter set of the neural network \( \Theta = \{ \phi_m, \beta_m \}_m \), which represent the hierarchical gradient and update parameters between different layers of the information flow path, will “mapped” to the “top-down and “bottom-up” of vertical information transfer paths and the horizontal multi-dimensional dimensional synergy. The dynamic evolution process of the information flow path and spatial organization is

\[
\text{Number}(M; \beta) = 2^w \times \beta
\]

Instead of linear and non-linear algebra fashion for the mathematical model of deep neural networks, the outcome of the game can been determined by the unified systematic model based on the assignment of numbers, binary or decimal between different layers of the information flow path of the policy and value networks. Let \( \{ w = 3, \beta = 1 \} \), the number of the orderly process of dynamic evolution of machine cognitive system is \( 2^3 \times 1 = 8 \). \( M = 3 \) represent the three vertical dimension hierarchy superposition non-linear structure, “1, 0” represent the hierarchical gradient and update parameters between different layers of the information flow path of the policy and value networks, which represent the direction of information transfer of “top-down” and “bottom-up” in a single vertical dimension. \((\begin{array}{l} 111 \\ 110 \\ 101 \\ 100 \\ 011 \\ 010 \\ 001 \\ 000 \end{array})\) are used to describe the eight orderly process of machine cognitive system. This systematic construction framework seek out dynamic functional activity rather than to look for the fixed structures, which constitute an alternate way of understanding the machine cognitive agent from the view point of ecological holism. The representation learning and problem-solving ability of machine cognitive agent lies at the orderly process of \((\begin{array}{l} 111 \\ 110 \\ 101 \\ 100 \\ 011 \\ 010 \\ 001 \\ 000 \end{array})\), which depend on the direction of the information flow path and spatial organization, which include “top-down” and “bottom-up” in a single vertical dimension, and the horizontal multi-dimensional dimensional synergy.

As shown in figure 2, the nonlinear coupling structure between the orders of the hexagrams among eight orderly process is acceptance of the inevitability of change, the internal harmony through a system of mutual checks and balances cycles, and the dynamic evolution constitute the self-organized dynamic evolution global model of machine cognitive system. \( \{ w = 13, \beta = 2 \} \) is the policy and value networks of AlphaGo, the number of search control strategy in AlphaGo is \( 2^{13} \times 2 = 16384 \), which are from \((\begin{array}{l} 000000000000 \\ 111111111111 \end{array})\) to \((\begin{array}{l} 111111111111 \\ 000000000000 \end{array})\). Instead of linear and non-linear algebra fashion to evaluate the characteristics of the hierarchical gradient and update parameters between different layers of nodes, the symbolic system of the orders of the hexagrams among 16384 orderly proce can be further improved to a new type of artificial intelligence program.
5. Conclusions

With the development of the application (Internet of Things, 5G, machine cognition, big data, cloud computing technology and artificial intelligence) in the 21st century, machine cognitive system will become the basic service system of the digital ecosystem. In particular, machine cognitive system consisting of a certain number of agents will effectively improve the ability to solve large-scale complex problems. Recently, deep neural networks have achieved unprecedented performance in visual domains: for example, image classification, face recognition. AlphaGo and Alpha Zero make a better chess playing algorithm, but, it is not the right approach for most problems. However, machine cognitive system would discern and learn tasks without human intervention. Based on ecological holism, the core controlling structural and functional roles proposed in this study may be further improved to a new type of artificial intelligence law of machine cognitive system.

Acknowledgments

This work was financially supported by the State Key Laboratory of Crop Science, China (Grant No. 2013KF15), the National Key Technology Research and Development Program of the Ministry of Science and Technology of China (2015BAB07B05) and the Significant Application of Agriculture Technology innovation program of Shandong Province (SDNYCX1531963).

References

[1] CHEN Wei-Hong, AN Ji-Yao, LI Ren-Fa 2017 ACTA AUTOMATICA SINICA Review on Deep-learning-based Cognitive Computing (in Chinese). 43(11): 1886–1897

[2] David Silver, Thomas Hubert, Julian Schrittwieser 2017 Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm. arXiv:1712.01815v1,

[3] Luo T, Liu S L, Li L 2017 A neural network supercomputer. IEEE Transactions on Computers 66(1) 73–8

[4] Isma Hadji and Richard P. Wildes 2018 What Do We Understand About Convolutional Networks? https://arxiv.org/abs/1803.08834

[5] Manchun Tan and Desheng Xu 2016 Synchronization of Coupled Neural Networks with Nodes of Different Dimensions Advances in Neural Networks 9719 135–142

[6] David Silver, Aja Huang, Chris J Maddison 2016 Mastering the game of Go with deep neural networks and tree search. Nature.529 484 – 489