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The Advance of Chess Engines with Deep Learning

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Abstract:

Since IBM's "Deep Blue" computer defeated the world champion Garry Kasparov, chess is a vital evaluation scenario to verify the learning ability of artificial intelligence algorithms. Recently, with the rapid development of this neural network technology, deep learning and reinforcement learning technology based on neural networks has completely changed the chess artificial intelligence. Several mainstream neural networks, such as Convolutional Neural Networks (CNN), are good at recognizing chess pieces and extracting game features, while Recurrent Neural Network (RNNs) analyzes complex moving sequences. AlphaZero, based on deep reinforcement learning, can even surpass human champions in the field of Go through self-supervised learning, demonstrating the great potential of artificial intelligence in intellectual games. Although artificial intelligence has greatly enhanced the competitiveness and accessibility of the game, the interpretability of the deep learning model is still a limitation, especially in high-risk or high-trust areas, where it is essential to understand the model behaviour, decision-making process and transparency. In this paper, the development of deep learning in the chess system is deeply studied, the challenge of interpretability is explored, and the potential of causal reasoning is discussed to enhance the interpretability and the overall application value of chess artificial intelligence.

Keywords: Chess; Machine learning; Deep Learning; Interpretability.

1. Introduction

Chess has been widely spread as an intellectual sport and has become a testing ground for advances in artificial intelligence technology. 1997 IBM's supercomputer Deep Blue defeated world chess champion Garry Kasparov. This is the first time artificial intelligence has beaten humans at chess, marking machine intelligence's breakthrough in complex decision-making. This event widely promoted the research of artificial intelligence technology in chess. In recent years, the development of deep learning and reinforcement learning technologies has injected new vitality into chess AI. By simulating the connections between neurons in the human brain, deep neural networks can independently learn and extract advanced chess strategies from massive chess data. Reinforcement learning allows the AI to continuously adjust its strategy against itself or other AI opponents in countless games and gradually optimize its decision-making ability through trial and error. AlphaZero is an excellent example of this. It has mastered the top level of chess, Go, and Japanese chess games by playing millions of times without any input from human experience.

The application of deep learning in chess has made remarkable progress, bringing revolutionary changes to the performance of artificial intelligence in chess matches. Mainstream deep learning models include convolutional neural networks (CNNS). CNNS are excellent at image recognition and classification, making them ideal for dealing with the two-dimensional structure of a chessboard. In chess AI, the cnn can recognize the position and type of pieces and extract features that are relevant to the current situation. By using the 8x8 grid of the board as the pixels of the image, with the pieces in each position representing different types of pieces through their “channels,” CNNS can learn how to extract key information from the state of the board and assess the pros and cons of a given game - recurrent neural networks (RNNs). RNNS are excellent at processing sequence data. For chess AI, RNNS can be used to analyze chess’s evolution process and internal laws. RNNs can learn the sequence pattern of chess movement in the chess manual and predict the possible subsequent moves. By considering the previous chess records, RNNs can better understand the effectiveness of a particular strategy or combination in a specific situation to make decisions dynamically according to the current chess state—deep reinforcement learning. AlphaZero is a masterpiece in this field. It completely abandons the traditional chess manual and heuristic evaluation and only learns chess through self-playing. AlphaZero uses a deep residual network to predict the best way to achieve each step and its outcome, and it combines it with Monte Carlo Tree Search to explore more possibilities. Through millions of self-games, AlphaZero gradually improved its strategy and, after the game, evaluated its moves and adjusted network parameters to optimize future actions [1, 2].

The rapid development of AI improves chess’s competitive level and promotes its popularization and development. By introducing AI game platforms, smart chessboards and other products, more people can get in touch with the intellectual sport of chess and enjoy the fun and challenges. Although this board game represents the peak of human intelligence, the method based on deep learning has reached the height of surpassing the human world champion. It can self-learn and evolve. However, due to the interpretability of deep learning itself, the application of the model still needs to be expanded. For example, the current deep learning model is often used as a teaching tool to help players improve their chess skills. AI can provide a personalized learning experience for players by simulating opponents of different levels, providing chess game analysis and re-playing functions, Table 1 shows some popular chess AI engines. However, due to the transparency of its decision-making process, players need help understanding the potential logic of the model to make specific decisions.

Table 1. The five popular chess AI engine

ID	Name	link
1	HIARCS	https://www.hiarcs.com/
2	AlphaZero	https://deepmind.google/discover/blog/alphazero-shedding-new-light-on-chess-shogi-and-go/
3	Rybka	http://www.rybkachess.com/
4	Houdini	https://www.cruxis.com/chess/houdini.htm
5	Fritz	https://fritz.chessbase.com/en

The interpretability of deep learning mainly focuses on how to understand and explain the decision-making process and its output results of the deep learning model [3]. With the wide application of deep learning in various fields, its interpretability has become increasingly important, especially in areas that need high trust and reliability, such as medical care, finance, and law. In deep learning, interpretability can be defined as the ability to understand model behaviour and decision-making process. This understanding helps people to control and optimize the model better, thus improving its performance and reliability. Specifically, interpretability includes the following aspects: transparency, the model‘s structure, and parameters are visible and understandable. For example, decision trees and linear regression models are highly transparent because human beings can directly see and

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understand their structures and parameters. Interpretation of decision-making process: The model's decision-making process and output can be explained and understood. This includes understanding how the model uses features to make decisions and the basis of the model's output results. Traceability: The decision-making process of the model can be traced and explained. By tracing the model's decision-making process, we can understand how the model uses historical data or input information to make predictions.

This paper focuses on the development of the interpretability of the chess system based on deep learning. Specifically, the content of this paper is divided into three parts. The first part introduces the development of deep learning in the chess system, and the second part introduces the interpretability of the deep learning model and its research progress. The third part introduces the current mainstream interpretable deep-learning chess system. The fourth part discusses the possibility of causal inference to solve interpretable problems and focuses on improving the application value of the chess system based on the deep learning model.

2. The Chess with Deep Learning

AlphaZero uses Deep Residual Network to predict the best way of each step and the outcome and combines with Monte Carlo Tree Search, MCTS) to explore more possibilities. In AlphaZero, the residual network is the central part of its deep neural network. Specifically, the network architecture of AlphaZero includes a backbone network residual network (ResNet) and a separate Policy Head and Value Head. ResNet consists of layers of network blocks and skip connections, connected through residual connections, forming a unique network structure. ResNet is responsible for extracting helpful feature information from the input chess image in AlphaZero. This characteristic information, including the position, chess type, tightness, etc., is essential for the subsequent strategy selection and value evaluation. By introducing residual connection, ResNet can effectively alleviate the problem of gradient disappearance or gradient explosion that quickly occurs in the training process of deep networks. This will help AlphaZero converge more steadily in the training process and improve efficiency. With the introduction of ResNet, AlphaZero can achieve a higher performance level in less training time. Through continuous self-playing and intensive learning, AlphaZero can gradually master the complex changes in chess and strategic choices, thus surpassing the level of top human players.

AlphaZero's training process is a typical reinforcement learning process. It starts with a neural network with random initialization parameters and collects training data by playing games with itself repeatedly. In the training process, AlphaZero will choose each step according to the current network parameters and Monte Carlo Tree Search (MCTS) results and update the network parameters according to the game results.

During the training process, the weight of ResNet will be constantly adjusted and optimized to extract the chess features better and predict the moves of each step and the outcome. At the same time, the Policy Head and Value Head will also make strategy selection and value evaluation according to the feature information extracted by ResNet, thus forming a complete decision-making process. The training process of AlphaZero is wholly based on self-playing and reinforcement learning, and it does not depend on the chess game of human masters or pre-written rules. By playing against itself millions of times, AlphaZero constantly learns from its mistakes and improves its game strategy. This way of self-learning enables AlphaZero to quickly adapt to different opponents and game situations and show strong competitiveness in actual combat.

MuZero is a reinforcement learning model introduced by DeepMind after AlphaZero [4]. It inherits many advantages of AlphaZero and makes essential improvements. MuZero's main contribution is that it can predict the future state and value through model learning without knowing the environmental dynamics (the rules of state transition). MuZero's model consists of three parts: representation, dynamics and prediction.

MuZero uses Monte Carlo Tree Search (MCTS) in the search process, but unlike AlphaZero, MuZero does not need a priori environmental model when searching, but relies entirely on its internal model for prediction and decision-making. This enables MuZero to be applied to a wider range of tasks and environments, not just those where environmental dynamics are known. EfficientZero is another improved model based on AlphaZero, which mainly focuses on improving the efficiency and scalability of the model [5]. By introducing new technologies and optimization methods, EfficientZero enables the model to converge faster and adapt to new environments and tasks while maintaining high performance.

However, these methods make decisions through deep learning and reinforcement learning, and their internal mechanism is complex and difficult to explain directly. This makes it difficult for people to understand how AlphaZero makes a specific decision, so verifying and trusting its decision-making process is complex. Although AlphaZero can perform well in board games, it cannot explain the reasons and logic behind its decisions with language or concepts like humans. This lack of intuitive explanation limits the application of AlphaZero in fields that need high transparency and interpretability. In addition, although AlphaZero has made remarkable achievements in chess games such as Go and Chess, its training and learning process highly depend on specific game rules and environments. AlphaZero may only be directly applied to other games or fields if much retraining and adjustment are carried out. If the rules of the game change or a new set of rules is introduced, AlphaZero may need to learn and adapt again. This may require a lot of time and computing resources, and it may not be guaranteed that its performance will not degrade.

3. The Interpretability of Deep Learning

The interpretability of deep learning is difficult mainly because of the following reasons:

Model complexity. 1) Nonlinear and multi-level structure: Deep learning models, such as convolutional neural networks (CNN), recurrent neural networks (RNN) and Transformers, usually have complex nonlinear structures and multiple hidden layers. This complexity makes it challenging to understand the internal working mechanism of the model intuitively, and the output and decision-making process of each layer involve complex mathematical operations and parameter adjustment. 2) Many parameters: The deep learning model contains many weight and bias parameters, which are adjusted by an optimization algorithm in the training process to minimize the loss function. However, the vast number of these parameters makes it extremely difficult to manually analyze or understand their specific functions. However, the improvement of deep learning performance mainly comes from the rapid growth of model parameters, as shown in Figure 1.

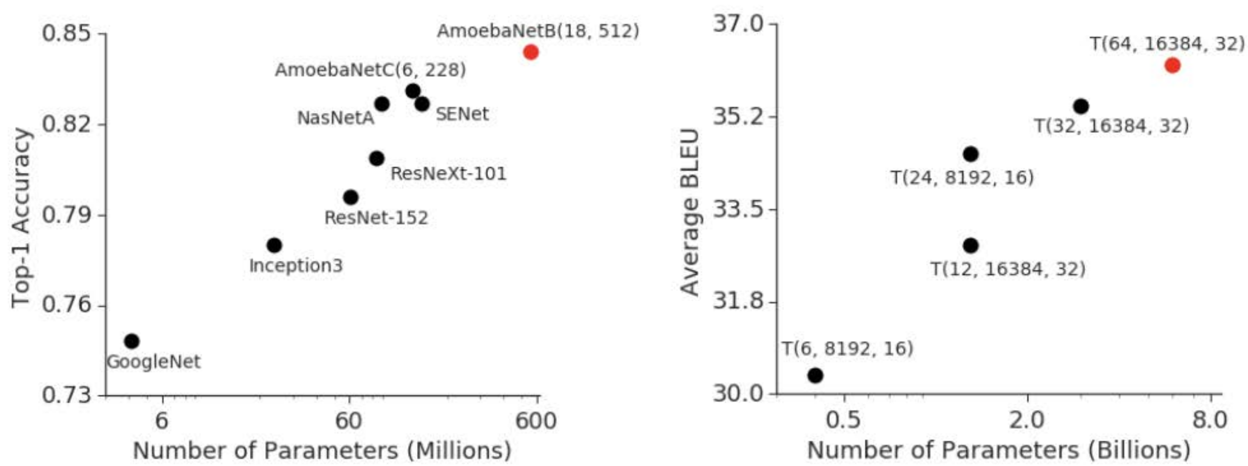

Fig. 1 The correlation between Model parameters and performance [6].

Black box characteristics. The relationship between input and output is unclear: deep learning models are usually regarded as „black boxes“ because they can automatically learn features from input data and make predictions. However, this process is opaque to external observers. There needs to be a more intuitive explanation of how the input data is converted into the output forecast and how the decision is made inside the model.

Data dependence. Impact of data quality: The performance of the deep learning model is highly dependent on the quality and quantity of training data. If there is deviation or noise in the training data, the prediction result of the model may also be affected, resulting in inaccurate interpretation. Complexity of data distribution: Data in the real world often has complex distribution characteristics, including imbalance, diversity and noise. These characteristics make the deep learning model show different behaviours when processing these data, which increases the difficulty of model interpretation.

The stability of the algorithm. Uncertainty in the training process: The deep learning model may encounter problems such as gradient disappearance, gradient explosion, and over-fitting or under-fitting during the training process. These problems may lead to instability in the training results of the model and then affect the interpretability of the model. Limitations of optimization algorithms: Although gradient descent has been widely used in deep learning training, it only sometimes guarantees finding the global optimal solution. In addition, the choice of optimization algorithm and parameter setting may also impact the model‘s interpretability.

Differences in domain knowledge. Interdisciplinary knowledge demand: The interpretability of deep learning requires basic knowledge of computer science and

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mathematics and in-depth knowledge of specific application fields. This demand for interdisciplinary knowledge increases the difficulty of understanding and explaining the deep learning model. Domain-specific interpretation requirements: Different domains may have different interpretation requirements for deep learning models. For example, more detailed and accurate explanations may be needed in the medical field to ensure that the model's decision meets the medical norms and ethical requirements. In the financial field, more attention may be paid to the model's stability and prediction accuracy.

Although researchers have developed some methods to explain the deep learning model, such as feature visualization, feature importance analysis, and local explanatory models (such as (local interpretable model-agnostic explanations) lime), these methods can only provide limited explanations. They may not fully reveal the internal working mechanism of the model. Taking LIME as an example, the core idea is to use local proxy models (such as linear models, decision trees, etc.) to approximate the prediction behaviour of black box models near specific sample points. By slightly disturbing the input data and observing the prediction results of the black box model for these disturbed data, LIME can train a simple and easy-to-understand model to explain the black box model's prediction partially. However, the LIME method provides a local explanation, not a global explanation. Therefore, it may not fully reflect the overall behaviour of the black box model. In addition, the performance of the LIME method is affected by many parameters, such as disturbance range, neighbourhood size and proxy model type. The selection of these parameters requires some experience and skills.

4. Improve the Interpretability with Causal Inference

As a large chess neural network model like AlphaZero challenges the most advanced level in computer chess, two challenges lie ahead: how to explain the internalized domain knowledge of this model and the problem that this model cannot be used publicly. Using a large open-source chess model with comparable performance. They obtained results like those on AlphaZero, relying only on open-source resources [7]. They also proposed a new interpretable artificial intelligence (XAI) method, which guarantees that the information used in the expo will be highlighted in a native model. This method generates visual explanations suitable for fields characterized by discrete input spaces. However, the above method has defects similar to those of the LIME method.

Recently, the combination of structural causal inference and deep learning methods to improve the interpretability of the model has attracted wide attention from researchers. The structural Causality Model (SCM) was put forward by Pearl and others, and a Graphical Model of production described the causal mechanism [8]. This model contains the mathematical relationship between variables and defines the causal direction and path between variables, as shown in Figure 2.

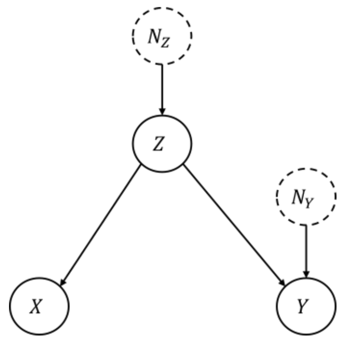

Fig. 2 the Structural causal Model with exogenous variable

SCM can clearly show which variables are the cause, which is the result, and how the causal relationship between them is transmitted. In SCM, the relationship between variables is usually represented by a Directed Acyclic Graph (DAG) called a causal graph. Nodes in the causality diagram represent variables, and directed edges represent causality between variables. In the causality diagram, if all the paths between two variables are blocked by a set of variables Z (d- separation), then under the condition of given Z, the two variables are probabilistically independent. This is an essential concept in causal inference used to judge the independence between variables. In SCM, given all the direct causes (parent nodes) of a node (variable), the node is independent of all other nodes that are not its descendants. This basic assumption in SCM simplifies the complexity of causal inference.

Causal inference can improve the interpretability of the deep learning model: Through causal inference algorithms to explain the prediction results and decision-making process, people can better understand how the model works and find potential deviations and problems. In the medical field, researchers can use deep learning models to predict patients' disease risks and use causal inference algorithms to explain these prediction results. By combining these two methods, doctors can better understand the patient's condition and treatment effect to make a more reasonable treatment plan. In autonomous driving, researchers can use deep learning models to identify road obstacles and pedestrians and explain how the model makes obstacle avoidance decisions according to these goals through a causal inference algorithm. This helps to improve the safety and reliability of self-driving cars. This paper holds that combining structural causal inference with deep reinforcement learning is the leading research direction for chess-related research to solve the interpretability problem of models.

5. Conclusion

Deep learning and reinforcement learning methods have changed human stereotypes about AI at the board game level. While AI has dramatically enhanced the competitiveness and accessibility of chess, the interpretability of deep learning models remains a barrier, especially in high-stakes or high-trust contexts where understanding model behaviour, decision-making frameworks, and transparency are critical. This paper delves into the progress of deep learning in chess systems, takes a closer look at interpretability challenges, and examines the potential of causal reasoning to support chess AI's interpretability and overall practical value.

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