Project Introduction for SSP/CSC-KUT

Game Informatics with Advanced Computer Players and Machine Learning Methods

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Background

After the development of AlphaGo [1] (and its successors AlphaZero [2] and MuZero) by Google DeepMind, research in game AI has undergone a significant innovative change. AI players that surpass human top players have been created for two-player perfect information games such as chess, shogi (Japanese chess), and go. However, the study of game AI is far from over. There remains considerable research potential in developing strong AIs for more complex games such as games with imperfect information, stochastic games, and multiplayer games. Advancing research on these types of games is a crucial step in advancing game AI research applicable to real-world problems.

[1] David Silver et al.: Mastering the game of Go with deep neural networks and tree search. *Nature* **529**(7587):484-489 (2016).

[2] David Silver et al.: A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science* **362**(6419):1140-1144 (2018).

Objective

Under the background above, this research project aims to apply both classical approaches (N-tuple network evaluation functions and Minimax/αβ search) and novel approaches (neural network evaluation functions and Monte Carlo tree search) to more challenging games including games with imperfect information (e.g., Geister, Daihinmin (a Japanese card game), DouDizhu,(a Chinese card game), and Mahjong), probabilistic games (e.g., 2048 and card games), and multiplayer games (Daihinmin, DouDizhu, Mahjong). The studies in this project will be conducted on the following three levels:

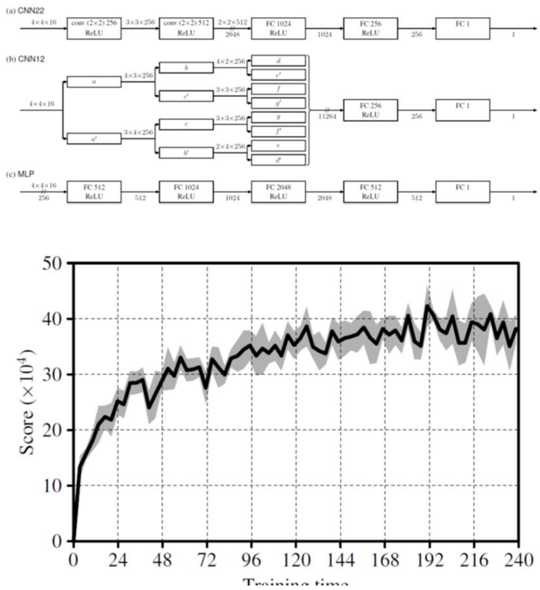
Level 1: Development of strong game AIs using classical and novel approaches,

Level 2: Experimental comparative evaluation of game AI technologies, and

Level 3: Qualitative/quantitative evaluation of the characteristics of the games themselves.

Selected Contribution 1:
“Developing DNN-Players for Game 2048”

Game 2048 is a stochastic single player game known for *its easy to learn but hard to master* characteristics. The mainstream of developing strong AIs for 2048 have been in classical approach: using N-tuple networks trained with extended TD learning. Our group tried developing strong AIs using novel approach using deep neural networks as evaluation functions. We designed and trained policy networks [3] as well as value networks [4, 5]. we achieved the state-of-the-art result, before renewed by the work from Google Deepmind.



(The images are from paper [4])

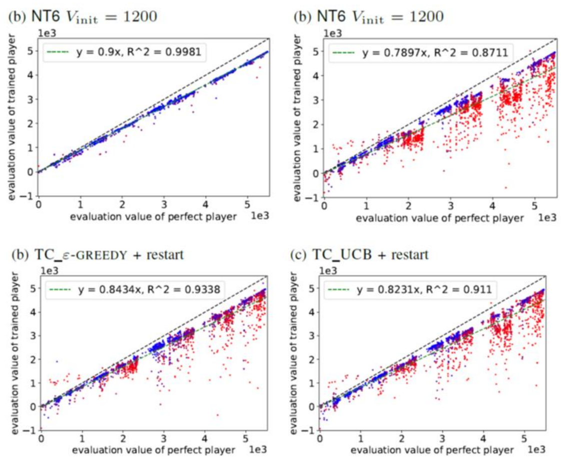
[3] Naoki Kondo and Kiminori Matsuzaki: Playing Game 2048 with Deep Convolutional Neural Networks Trained by Supervised Learning. *Journal of Information Processing* **27**:340-347 (2019).

[4] Kiminori Matsuzaki: Developing Value Networks for Game 2048 with Reinforcement Learning. *Journal of Information Processing* **29**:336-346 (2021)

[5] Wang Weikai, and Kiminori Matsuzaki: Improving DNN-based 2048 Players with Global Embedding. *IEEE Conference on Games* (*IEEE CoG*), pp. 628-631 (2022).

Selected Contribution 2:
“Analyzing AIs using Perfectly Analyzed Mini2048”

“Exploration-exploitation dilemma” is a fundamental issue in the reinforcement learning (RL). However, most of existing studies on RL-based 2048 AIs adopted exploration only without any exploration in the training. We tackled this issue by analyzing the trained AIs in details using the dataset given on game “Mini2048” that were perfectly analyzed (a.k.a. strongly solved) [6]. We identified the possible room for improvement by adopting exploration in the training and showed we can



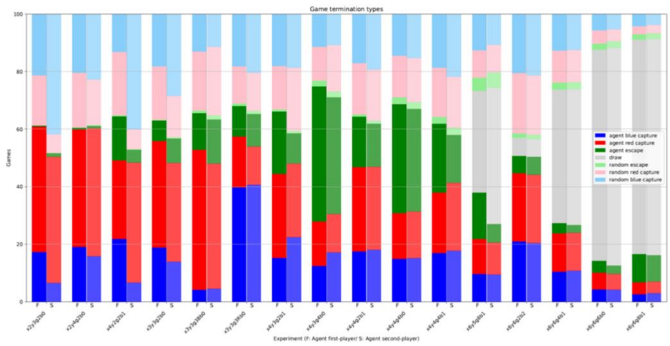
(The images are from paper [7])

develop better AIs by more exploration with extended strategies [7].

[6] Shunsuke Terauchi, et al.: Using Strongly Solved Mini2048 to Analyze Players with N-tuple Networks. *International Conference on Technologies and Applications of Artificial Intelligence* (*TAAI*), Vol. 2, pp. 165-178 (2023).

[7] Shunsuke Terauchi and Kiminori Matsuzaki: Yet More Optimistic Temporal Difference Learning for Game Mini2048, *IEEE Conference on Games* (*IEEE CoG*) (2024).

Selected Contribution 3: "Formalizing Properties of Games with Imperfect Information"



(The image is from paper [9])

After the success of research for games with perfect information, games with imperfect information will be the important targets in future research of game AIs. Most of the existing studies, however, are conducted on specific games, and discussion over multiple games are often missing. We identified the issue is in the missing metrices for characterizing games with imperfect information, and proposed two important notion, *visualization* and *impact*. We also developed techniques to qualitatively and/or quantitively assess those two properties, using variants of Geister [8, 9].

[8] Lucien Troillet and Kiminori Matsuzaki: Analyzing simplified Geister using DREAM. *IEEE Conference on Games* (*IEEE CoG*), pp. 1-8 (2021).

[9] Lucien Troillet and Kiminori Matsuzaki: Evaluating the Influence of Imperfect Information in Geister Using DREAM Trained Agents. *IEEE Transactions on Games* (2023).

Required Skills

The successful candidate for this project will have the following knowledge and skills:

(a) Excellent programming skill in C++, Java, Python, and similar programming languages,

(b) Experience of applying machine-learning techniques to solve (real) problems, and

(c) Mathematical capability to build a theory from new finding.