Deep Learning - Project Proposal

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1 Background/Related Work

Autonomous chess-playing agents have traditionally relied on rule-based systems like Stockfish or deep reinforcement learning approaches such as AlphaZero and Leela Chess Zero, which use MCTS and neural networks trained via self-play. Recent work[1] reveals that models like Leela may implicitly learn look-ahead reasoning, showing that internal representations of future moves play a causal role in decision-making.

2 Problem Definition

Most existing chess-playing AIs are trained using large amounts of game data(heuristic methods) or reinforcement learning, which can be time-consuming and complex. However, recent large language models have shown that they can solve tasks by receiving good prompts without additional training. In this project, we explore whether an LLM can play chess using only natural language prompts without specialized training. Our goal is to test if a general-purpose LLM can understand the rules and strategies of chess through prompting alone and generate valid and reasonable moves.

2.1 Conventional Methods

Traditional chess agents trained via reinforcement learning often come with high computational cost and lack interpretability. Once a move is made, it is difficult to understand the reasoning behind it, especially since these models are optimized solely for winning rather than playing in a human-like manner. As a result, they may make strong but unintuitive moves, and rarely make the kinds of mistakes or stylistic choices that humans do, which limits their usefulness in applications like tutoring or human-AI collaboration.

2.2 State-of-the-art Methods

Recent advancements have accelerated Large Language Models using novel prompting strategies like Think-on-Graph, enabling deeper reasoning with traceable knowledge paths. Graph-of-Thoughts further generalizes linear methods like Chain-of-Thought and Tree-of-Thought into flexible graph structures. Evaluations show GoT surpasses ToT in accuracy and computational efficiency. Its adaptability in correcting errors and managing multiple reasoning paths makes it highly effective for complex tasks like strategic reasoning in chess.

3 Proposed Idea/Method

In this project, we explore how Large Language Models can be used to create a general-purpose, strategically reasoning game AI through advanced prompting strategies, focusing initially on chess. We will evaluate the effectiveness of Chain-of-Thought and Graph-of-Thought prompting methods, aiming not only to improve chess performance but also to enable interpretable reasoning and strategic anticipation of moves. Insights gained may help generalize this approach for broader educational and reasoning applications.

References

References follow the acknowledgments in the camera-ready paper. Use unnumbered first-level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to `small` (9 point) when listing the references. Note that the Reference section does not count towards the page limit.

[1] Feng, Xidong, et al. "Chessgpt: Bridging policy learning and language modeling." Advances in Neural Information Processing Systems 36 (2023): 7216-7262.

[2] Jenner, Erik, et al. "Evidence of learned look-ahead in a chess-playing neural network." Advances in Neural Information Processing Systems 37 (2024): 31410-31437.

[3] Wei, Jason, et al. "Chain-of-thought prompting elicits reasoning in large language models." Advances in neural information processing systems 35 (2022): 24824-24837.

[4] Sun, Jiashuo, et al. "Think-on-graph: Deep and responsible reasoning of large language model on knowledge graph." arXiv preprint arXiv:2307.07697 (2023).

[5] Besta, Maciej, et al. "Graph of thoughts: Solving elaborate problems with large language models." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 38. No. 16. 2024.