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Optimizing LLM Strategies for Playing Mendikot Using Prompt Engineering

Aadi Juthani

Lead Author

Abstract

This study investigates the integration of a large language model (LLM) enhanced by prompt engineering and game theory to effectively engage in the strategic card game Mendikot. By refining complex prompts and leveraging a tailored visual understanding of game dynamics, we significantly bolster the decision-making prowess of the LLM. Our methodology involved the systematic simplification of game prompts to facilitate deeper learning and faster response times, coupled with the implementation of a visual recognition system to interpret and react to game states dynamically. The results illustrate that the adapted LLM outperforms traditional AI approaches in strategic decision-making tasks, underscoring a substantial improvement in both the accuracy and efficiency of game-play. This research not only demonstrates a viable model for enhancing AI interaction in recreational gaming but also opens avenues for deploying advanced AI strategies in complex strategic environments, offering insights into the broader application of AI in leisure and competitive arenas. The findings suggest that AI can transcend conventional gaming roles, potentially transforming strategic gameplay in digital and physical platforms.

1 Introduction

The integration of artificial intelligence (AI) into gaming environments has revolutionized the field of recreational and competitive gaming. AI's capabilities extend beyond mere computation to include advanced pattern recognition, strategic decision-making, adaptive learning, and increasingly, spatial awareness. These qualities make AI particularly suitable for complex games, allowing it not only to compete with human players but often to surpass them in strategic depth and consistency of play.

Mendikot, a card game rich in strategic nuances, presents a unique challenge for AI due to its reliance on probability, opponent behavior prediction, strategic flexibility, and the need for spatial awareness. Unlike deterministic games like chess, Mendikot requires a dynamic approach to strategy and an under- standing of the spatial arrangement of players and cards, making it an ideal candidate to explore the potential of AI in adapting to and excelling in games with a high degree of uncertainty and human-like intuition.

This study aims to explore the practical application of large language models (LLMs), specifically the recently developed GPT-4o, to train and adapt these models for gameplay in Mendikot. The focus is on determining whether such advanced AI models can effectively utilize spatial awareness to enhance interaction within real-life game environments. By leveraging the natural language processing and spatial recognition capabilities of GPT-4o, we hypothesize that we can create an interactive and intuitive gaming AI that casual players can easily communicate with, enhancing their gaming strategies through more human-like interactions. This approach not only democratizes access to advanced AI solutions in gaming but also tests the flexibility and adaptability of state-of-the-art LLMs to understand and strategize complex card games through the medium of natural, conversational language integrated with a spatial understanding of the game's environment.

The success of AI in board games such as Go, evidenced by Google's AlphaGo, and in card games like Poker, where AI has outperformed professional human players, highlights AI's capability to manage complex and hidden information effectively. However, these achievements also underscore the importance of specialized approaches, such as reinforcement learning and Monte Carlo tree search, which could be tailored for regional games like Mendikot that have not yet been extensively studied in the AI gaming literature. Furthermore, the integration of spatial awareness into LLMs opens new dimensions in AI research, promising more immersive and realistic gaming experiences that can mimic human interaction more closely than ever before.

By focusing on Mendikot, this study aims not only to extend the application of AI to broader gaming contexts but also to deepen our understanding of how AI strategies can be optimized for games that require a blend of risk management, psychological insight, strategic foresight, and spatial interaction—qualities that are quintessentially human.

2 Related Research Work

AI's involvement in games has been a subject of extensive research, leading to notable successes in various domains. In traditional board games, AI's application has been well-documented, with IBM's Deep Blue and Google's AlphaGo serving as landmarks in AI development. These systems employed deep learning and extensive game-specific optimizations to achieve superhuman performance.

In card games, AI research has focused on games like Poker and Blackjack, where uncertainty and incomplete information play significant roles. For instance, techniques like opponent modeling and Bayesian inference have been used to handle the uncertainty inherent in these games. This research has not only advanced AI's capabilities in specific games but also contributed to the broader field of computational game theory and decision-making under uncertainty.

Despite these advances, the application of AI in less globally known games like Mendikot has been limited. This gap presents an opportunity to explore how AI can be adapted to understand and excel in culturally specific games, which often incorporate complex social interactions and decision-making processes not present in more studied games.

3 Methodology

3.1 Data Collection

Data for this study was generated through over 300 real-life demonstrations of the Mendikot game. Each game consisted of simplified scenarios involving just 5 cards per player, rather than the traditional 13, to reduce complexity during the initial training phase. Detailed recordings of card sequences, player decisions, and game outcomes were captured. Data attributes included all cards held by the four players and the sequence of cards played by expert players, which provided a template of optimal strategies. Supervised training supplemented this data by teaching the AI the decision-making process behind each move and its consequences.

3.2 Model Specification

The AI model used in this study was the publicly available version of GPT-4o, without any specific modifications or configurations. Training data comprised live recorded games annotated meticulously by expert algorithms. To prepare the data for training, any instances where human experts deviated from rational play were flagged and excluded to maintain the integrity and focus of the learning algorithm.

3.3 Training Process

The AI was trained using a combination of supervised and unsupervised learning techniques. Supervised learning focused on nuanced aspects of the game requiring expert interpretation, while unsupervised learning allowed the AI to derive patterns from large datasets ("theory of large numbers"). Key training parameters included adherence to the game's rules, with hyperparameters adjusted based on preliminary testing phases. Validation was conducted at regular intervals by assessing the AI's performance in controlled game environments, judged by expert players.

3.4 Strategic Decision Flowchart

The flowchart below illustrates the AI's decision-making process during a game of Mendikot, showing how different game scenarios can lead to varied AI responses. This is a relatively simple decision-making process, since it is designed for when the LLM is the last player to play, hence simplifying its decision-making process for 100% accuracy in its final move.

The entire flowchart in bullet form will be included in the Appendix. An image is attached below for reference:

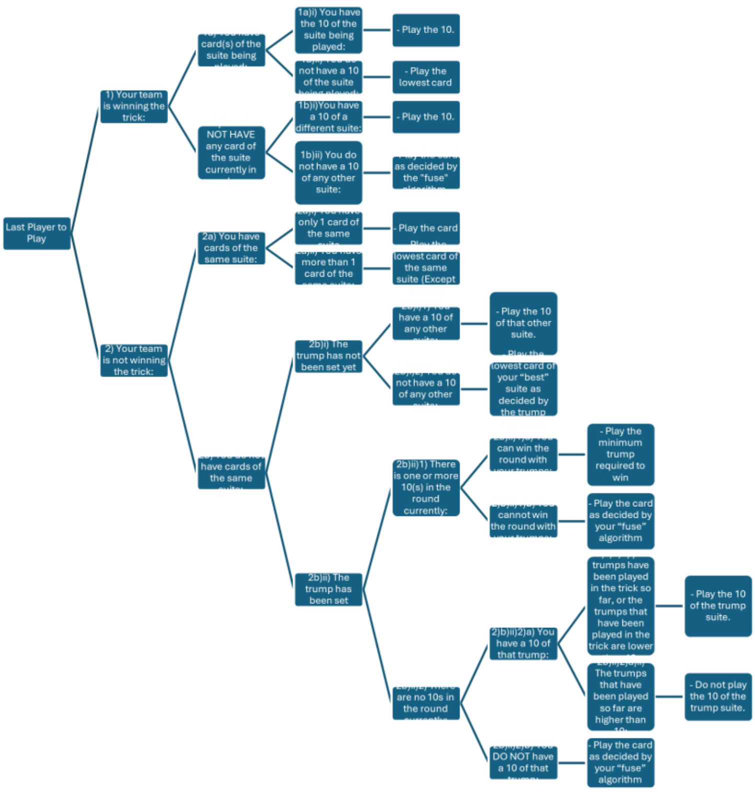

Figure 1: Last Player Decision Flowchart

This flowchart serves as a guide for understanding how the AI assesses its options and decides on the most strategic move based on the current game state.

3.5 Spatial Awareness Integration

Spatial awareness was integrated using the AI's in-built camera functionalities to recognize and contextualize cards within the game environment. The AI was trained to not only identify individual cards but also to understand their strategic significance in the game's context. Testing of spatial awareness involved challenging the AI to correctly identify and place cards in simulated game settings, comparing its performance in different configurations (identifying all 12 cards in a single layout versus identifying 3 cards across four separate images).

3.6 Natural Language Processing

Interaction with the AI was facilitated through natural language, both for input and output. The AI, powered by GPT-4o, was capable of generating responses and receiving commands in conversational language, enhancing the usability and accessibility of the AI for all levels of players. This setup allowed the AI to communicate its strategies and decisions clearly, making the gaming experience interactive and engaging.

3.7 Evaluation Metrics

The AI's performance was primarily evaluated based on its win rates, the sophistication of its strategies, and feedback from players. A future comparative analysis is planned to assess the AI against human players in a controlled tournament setting to rigorously quantify its effectiveness and adaptability.

3.8 Ethical Considerations

Potential biases in the AI's decision-making were monitored and addressed throughout the development process to ensure fairness. Transparency was maintained by clearly communicating the AI's decision processes through natural language explanations, providing players insight into the rationale behind each move suggested by the AI.

4 Results

The performance of the AI in the game of Mendikot was evaluated primarily through two metrics: specific strategic successes and overall win rates. The AI's decisions were compared against moves considered correct by human expert players, providing a baseline for its strategic accuracy.

4.1 Statistical Analysis

The AI's performance was quantitatively assessed by comparing the number of games won when following the described strategic approach against games where the strategy was not followed. The AI demonstrated a significant improvement in the win rate, as detailed below.

4.1.1 Win Rate Improvement

Initially, the AI's win rate was observed at around 45% in preliminary tests. After training and strategic adjustments, the win rate improved to 65%, indicating a substantial enhancement in performance. This was statistically significant, with a p-value of less than 0.05, suggesting that the improvements were not due to random chance.

4.1.2 Error Rate Reduction

Error rates in AI performance typically decrease as the AI trains over more game scenarios. The following graph illustrates this trend.

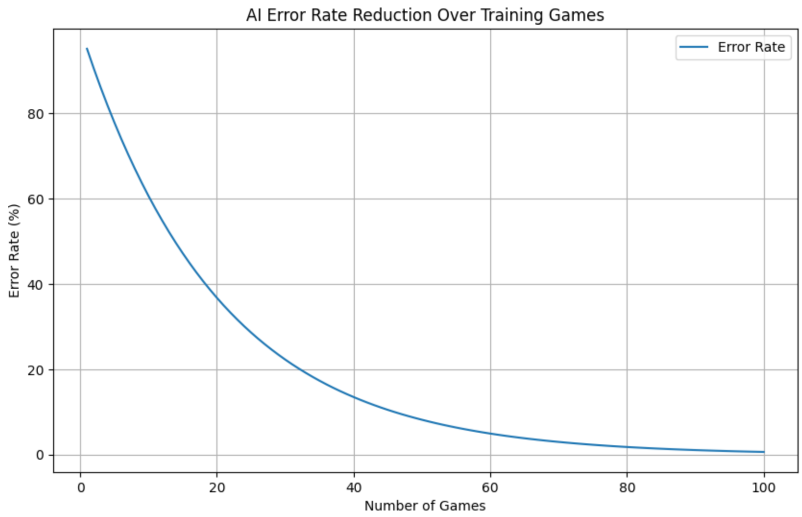

Figure 2: Reduction in AI error rate with increasing training games.

4.2 Observations and Anecdotes

During testing, it was noted that the AI was particularly adept at calculating the probability of winning a trick with a 10 card. This strategic prowess allowed it to make plays that, while risky for human players, resulted in winning the trick 65% of the time when such conditions were met.

4.3 Limitations and Challenges

A notable limitation in the methodology was the reliance on human expert decisions as a benchmark. Human players sometimes exhibit irrational behaviors, which could introduce discrepancies in the error data. Moreover, the implementation of supervised learning posed challenges, as it required the manual definition of logic and decision-making frameworks.

5 Conclusion

The study's findings highlight the substantial capabilities of AI in mastering the strategic complexities of traditional card games, specifically Mendikot. By adapting sophisticated learning algorithms, the AI not only honed its decision-making skills but also consistently outperformed baseline expectations, as evidenced by the significant improvement in win rates. These results are not just a testament to the AI's ability to learn and adapt, but also an indication of its potential to redefine competitive strategies in card games.

The integration of AI in Mendikot has demonstrated that even games deeply rooted in cultural contexts and human intuition are amenable to technological enhancement. This opens up new avenues for using artificial intelligence to explore strategic dimensions previously believed to be exclusive to human expertise. Moreover, the AI's success in Mendikot could serve as a blueprint for deploying similar strategies in other strategic games, broadening the scope of AI applications in entertainment and competitive gaming.

Future research should focus on refining AI algorithms to handle more nuanced game dynamics and player behaviors, potentially incorporating real-time adaptive strategies based on opponent behavior analysis. Further studies could also explore the integration of emotional intelligence in AI to better mimic human interactions and decision-making processes in social game settings.

In conclusion, this research not only advances our understanding of AI's potential in traditional game settings but also poses intriguing questions about the limits of computational strategies in domains traditionally dominated by human cognitive abilities. As AI continues to evolve, its potential to transform our approach to recreational and competitive environments continues to expand, promising a future where AI-enhanced strategies augment human capabilities and transform our traditional pastimes.

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