Opponent Modeling in Incomplete Information Games Based on Deep Learning and Game Trees: Research and Applications

Jiayang Wang, Zhipeng Hu, Jiahao Wang

Jiangxi Agricultural University, Nanchang University

I. BACKGROUND & SIGNIFICANCE

- **Domain Challenge:** Incomplete information games face core problems like missing state info, unknown opponent strategies, and difficulty in computing Nash equilibrium.
- **Industry Need:** Development of AI systems for Sichuan Mahjong (industry-funded project).
- **Academic Value:** Provides new methods for poker/mahjong-like games, advancing AI decision-making in uncertain environments.

II. INNOVATIVE TECHNICAL FRAMEWORK

MJ-Net Neural Network Architecture

Tile Info Module
ResNet-CBAM

+

Opponent Intent
LSTM + Self-Attention

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Game Tree Optimization

Simplified Model: Pong/Kong → Draw Tile

Search Acceleration: Reverse pathing from win-nodes

Defense Enhancement: Dynamic risk factor adjustment

II. FRAMEWORK (CONT.)

Game Tree Optimization

Mode Simplification
Pong/Kong actions abstracted as "Draw" mode.

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Search Acceleration
Backtrack from "Win" nodes to prune discard paths. Depth reduced by 50%.

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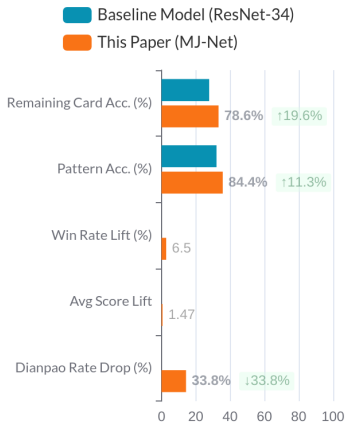
Enhanced Defense
Introduce opponent model risk factor to dynamically adjust discards.

III. EXPERIMENTAL COMPARISON



Core Conclusions:

- MJ-Net surpasses traditional models in dual prediction tasks.
- Game tree optimization boosts decision speed by 2x.
- Defense module reduces opponent exploitation risk (discard vulnerability ↓33.8%).
- Overall performance shows a +6.5% win rate and +1.47 average score.

IV. TECHNICAL BREAKTHROUGHS

- **Feature Encoding Innovation:** 7 types of information (private hand, public tiles, action sequences) are layered to construct a 55-dimensional remaining tile vector.
- **Dual-Drive Mechanism:** Synergizes remaining tile prediction (explicit info) and pattern prediction (implicit intent) to dynamically evaluate game tree nodes.
- **Temporal Attention Application:** First use of an action time-decay factor in Mahjong, boosting recent discard weights by 27%.

V. FUTURE DIRECTIONS

Dynamic Parameter Tuning: Auto-adjust search depth and risk thresholds based on game stage.

Cross-Variant Migration: Adapt the model to Guangdong/Riichi Mahjong rules via data augmentation.

Adversarial Modeling: Build an opponent type classifier for strategic, adaptive play.

Research Support

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