PokerBot Analysis Report v3

1. Project Overview

This report documents the evolution of the PokerBot from a basic legal-action bot to an advanced decision-making system incorporating probability theory, Monte Carlo simulation, opponent modeling, and strategic poker concepts derived from academic literature and poker theory texts.

2. Core Mathematical Foundations

The bot is based on expected value maximization under uncertainty. Decisions are evaluated using Monte Carlo equity estimation and pot odds comparison:

Equity ≈ Wins / Simulations
Pot Odds = Call / (Pot + Call)

A call is profitable when Equity > Pot Odds.

These principles originate from probability theory and the law of large numbers, which ensures simulation estimates converge to true probabilities over many trials.

3. Architecture Evolution

Initial Version:
• Legal move selection only.

Intermediate Versions:
• Hand evaluation using Treys.
• Monte Carlo win probability estimation.
• Expected value decision framework.
• Pot-based raise sizing.

Current Version:
• Preflop range engine with positional awareness.
• Adaptive opponent modeling (fold rate, aggression).
• Mixed-strategy randomization.
• Semi-bluff logic with draw detection.

4. Key Strategic Modules Implemented

Preflop Ranges:
Position-based opening ranges prevent weak hand mistakes and improve long-run EV.

Position Awareness:
Aggression increases in position and decreases out of position due to information advantage.

Monte Carlo Equity:
Random sampling estimates win probability, supported by simulation theory.

Opponent Modeling:
Statistics such as fold frequency and aggression influence bluff and value decisions.

Semi-Bluff Detection:
Draws increase bluff probability because they provide two paths to winning: fold equity and improvement equity.

5. Insights from Literature

Probability and Simulation:
Monte Carlo methods converge with increasing sample size. Adaptive simulation counts can optimize performance while maintaining accuracy.

Poker Theory:
The Fundamental Theorem of Poker states profit arises when opponents make mistakes relative to your strategy. Bluff frequency should depend on pot odds and opponent tendencies.

Game Theory:
Mixed strategies prevent exploitation. Controlled randomness in decision-making improves robustness.

6. Current Bot Strength Assessment

Strength Level: Advanced Student Competitive Bot

Capabilities:
• Equity-based decision making
• Opponent exploitation
• Position-aware aggression
• Value betting and bluff balancing
• Legal action safety and modular architecture

Limitations:
• No board texture awareness
• No stack depth (SPR) logic
• No opponent range inference
• Limited bet sizing diversity

7. Experimental Observations

Testing confirms:

• Strong hands raise consistently.
• Weak hands fold when pot odds unfavorable.
• Medium-strength hands mix between call and raise.
• Bluff frequency adapts to opponent fold tendencies.
• Semi-bluff module increases aggression when draws are present.

8. Future Development Roadmap

Next Modules:
1. Board texture classification and aggression adjustment.
2. Stack depth and SPR-aware decisions.
3. Dynamic bet sizing based on polarization.
4. Opponent range estimation using Bayesian inference.
5. Range vs range equity simulation.
6. Reinforcement learning or regret minimization (optional advanced stage).

9. Key Learnings

Poker is fundamentally a decision problem under uncertainty. Cards determine probabilities, but profits arise from exploiting deviations from optimal play. Long-term expected value, not short-term outcomes, defines success.

Simulation accuracy, opponent modeling, and strategic balance collectively determine bot strength.

10. Conclusion

The PokerBot has progressed from a rule-based prototype to a probabilistic decision system with strategic reasoning grounded in mathematics and poker theory. With continued incremental improvements, the bot can reach high competitive performance suitable for algorithmic poker competitions.