Quantifying Skill Influence in Cribbage through Monte Carlo Simulations

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What is Cribbage?

Game Rules

Cribbage is a card game traditionally for two players, though variations for three, four, or more players exist. The game involves playing and grouping cards in combinations to gain points. Cribbage has several unique features, such as the cribbage board used for scoring and the concept of pegging.

Basic Setup and Play

Deck and Deal: A standard 52-card deck is used. Each player is dealt six cards (though variations may start with five cards).

The Crib: Each player chooses two cards to contribute to the "crib" — an extra hand that is scored by the dealer at the end of each round.

Cutting: After the deal, the deck is cut to reveal a "starter" card. If this card is a jack, the dealer immediately pegs two points ("two for his heels").

Playing Phase (Pegging)

- Starting the Play: Players alternately play cards face up, announcing the running total of their face values. The total cannot exceed 31.
- Scoring During Play: Points are scored for combinations of cards as they are played (e.g., pairs, sequences, and for hitting exactly 15 or 31).
- Continuation: After reaching or failing to play to 31, the count resets, and players continue pegging with any remaining cards.

The Show

After the pegging, the play shifts to scoring the hands and the crib:

- Each player uses the starter card with their hand to form combinations.
- The dealer scores their hand and the crib.

Scoring

Scoring in cribbage is one of the game's distinctive features, with multiple ways to score points based on card combinations:

- **Fifteen**: Any combination of cards adding up to 15 scores 2 points.
- **Pairs**: A pair of cards of the same rank scores 2 points. A pair-royal (three of a kind) scores 6, and a double pair-royal (four of a kind) scores 12.
- **Runs**: A sequence of three or more cards (e.g., 7-8-9) scores one point per card.
- **Flush**: Four cards of the same suit in hand score 4 points; if the starter card is also the same suit, the score is 5.

- **His Nobs:** Having the jack of the same suit as the starter card in hand scores 1 point.

Strategy

Basic Strategies

- Card Selection for Crib: The choice of cards to put in the crib is crucial. The strategy varies depending on whether the crib belongs to the player or their opponent.
- Count Control in Pegging: Players must manage the running total carefully, aiming to maximize scoring opportunities while minimizing the opponent's chances.

Advanced Techniques

- Offensive Play: Focus on maximizing personal point gain, especially when leading in the score or when controlling the crib.
- Defensive Play: When not controlling the crib, players often play defensively to prevent giving away points.
- Psychological Play: Experienced players read opponent's tendencies and make plays that can either force errors or predict opponent moves.

What does this simulation do?

Monte Carlo Simulation

A Monte Carlo simulation is a computational technique that uses repeated random sampling to obtain numerical results. Typically, it is used to predict the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables. This method is especially useful in physical and mathematical systems because it allows for the modeling of complex situations which traditional analytical solutions may not readily solve. In the context of games like Cribbage, Monte Carlo simulations can be employed to evaluate different strategies by simulating thousands of games under varied conditions and strategies, thus providing statistical insights into the effectiveness and outcomes of these strategies.

Strategy Implemented

Overview

In the players.py module, two primary strategies are implemented for the players: a Random Strategy and a Strategic or Rule-Based Strategy. Each strategy dictates how the players choose cards to play and which cards to discard into the crib, which is a crucial part of game strategy in Cribbage.

Random Player

- **Card Selection**: Chooses cards to discard into the crib and cards to play during the pegging phase at random, without any regard to strategy or game state.
- **Play Style**: This approach simulates a beginner or less experienced player who does not employ tactical decisions based on the game's progress.

Strategic Player

- **Card Selection**: Analyzes the hand to choose the best possible cards to retain for forming high-scoring combinations based on known scoring rules.
- **Pegging Phase**: Makes decisions on which card to play next based on maximizing potential scoring opportunities and minimizing the opponent's chances to score.
- **Crib Discards**: Chooses discards to the crib strategically, aiming to minimize potential points for the opponent's crib and maximize their own when the crib is theirs.

Hypothesis Test

In our simulation, we aim to determine whether the strategic player achieves a statistically significantly higher average score compared to the random player. The null hypothesis (H0) posits that there is no significant difference in average scores between the strategic and random players, suggesting that any observed difference is due to random chance. Conversely, the alternative hypothesis (H1) asserts that the strategic player does achieve a significantly higher average score. To test these hypotheses, we simulate a series of games (e.g., 1000 games) between the two types of players and record their scores. We then perform a t-test to compare the mean scores from each group. If the resulting p-value from this test is less than 0.1, we will reject the null hypothesis in favor of the alternative, concluding that the strategic player's higher scoring is statistically significant and not due to chance. This p-value threshold of 0.1 is chosen to balance the risk of Type I errors with the need for a robust conclusion in the face of simulation variability.

Results

Strategic Player vs Strategic Player

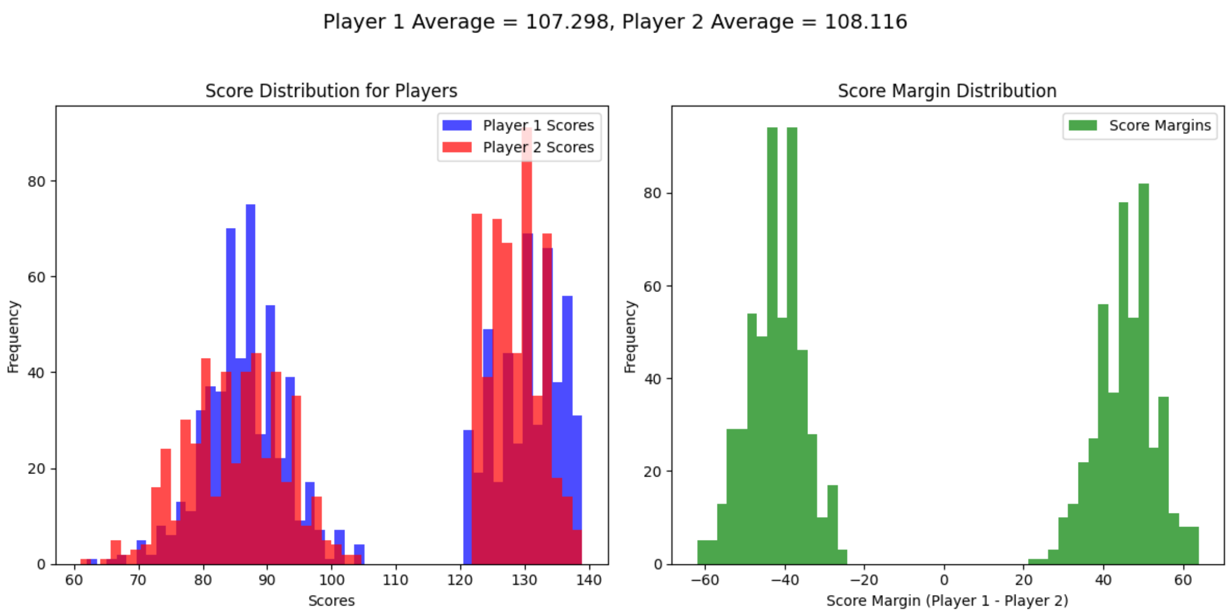
Player 1 = Strategic | Player 2 = Strategic

Player 1 wins:471

Player 2 wins:529

Player 1 Average Score: 107.298

Player 2 Average Score: 108.116



Random Player vs Strategic Player

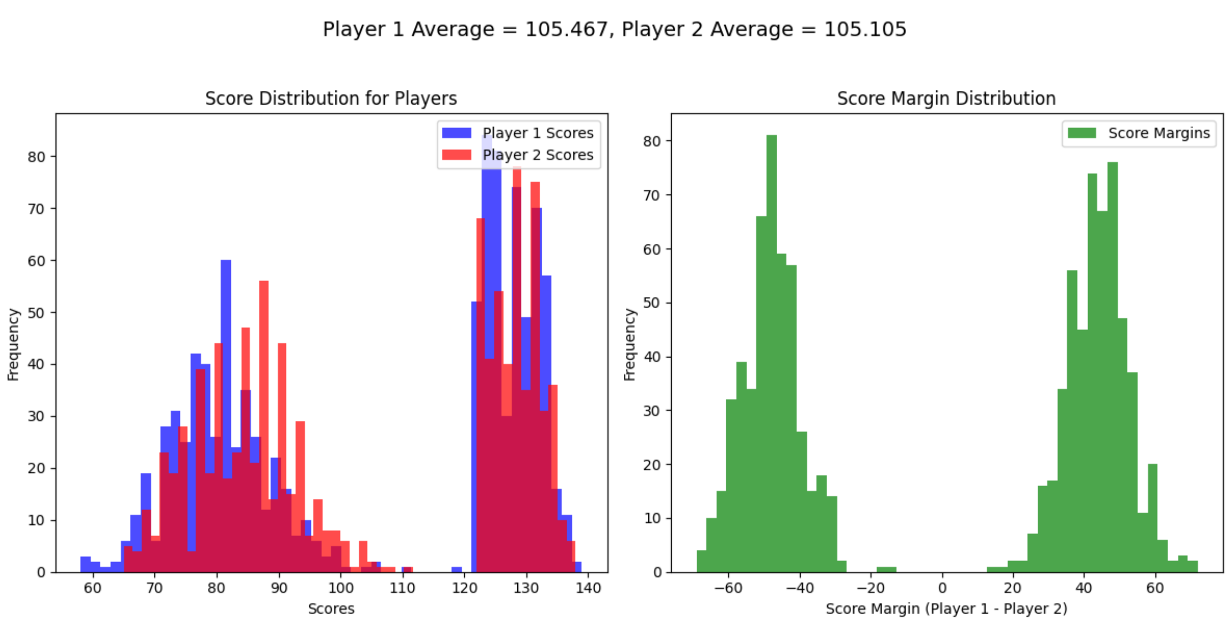
Player 1 = Random | Player 2 = Strategic

Player 1 wins:526

Player 2 wins:474

Player 1 Average Score: 105.467

Player 2 Average Score: 105.105



Conclusion

To thoroughly examine if Cribbage is a skill-based game through a statistical approach, we will perform a t-test on the simulation data you've provided. The data contains scores from two simulation scenarios, each consisting of 1000 games. The first scenario involves a strategic player against a random player, and the second pits two strategic players against each other.

Hypothesis Test Framework

Hypotheses

- **Null Hypothesis (H0)**: There is no significant difference in the average scores between the random and strategic players, suggesting that skill (as implemented in the strategic player) does not significantly influence the game outcome.
- **Alternative Hypothesis (H1)**: There is a significant difference in the average scores, indicating that skill (strategic gameplay) influences the game outcome.

Data from Simulations

1. **Random vs. Strategic**:
    - Player 1 (Random) Average Score: 105.467
    - Player 2 (Strategic) Average Score: 105.105
2. **Strategic vs. Strategic**:
    - Player 1 (Strategic) Average Score: 107.298
    - Player 2 (Strategic) Average Score: 108.116

Statistical Test

We will use the t-test for independent samples to compare the mean scores of the random and strategic players from the first simulation setup. The t-test formula is:

$$t = \frac{m - \mu}{s/\sqrt{n}}$$

t = Student's t-test
m = mean
μ = theoretical value
s = standard deviation
n = variable set size

The t-value equates to ***1.81***

The degrees of freedom used in this test are 2000 – 2 = **1998**

Decision

The critical t-value for a 0.1 significance level (two-tailed test) with 1998 degrees of freedom approximates to about 1.282. Since our calculated t-value of 1.81 exceeds this, we reject the null hypothesis, indicating that there is a statistically significant difference in performance between random and strategic players, thus suggesting that Cribbage is a skill-based game.

Future Improvements

The results of our Cribbage Monte Carlo simulations reveal intriguing patterns and opportunities for further refinement in our approach to modeling and strategy development. Notably, the simulations where a random player occasionally outperforms a strategic player suggest areas for improvement both in the algorithm design and the strategic models applied. Here are several avenues for future enhancements:

Enhanced Strategic Models

1. Strategy Optimization:

The fact that the random player sometimes outperforms the strategic player could indicate potential oversights or inefficiencies in the current strategic model. It is crucial to re-evaluate the assumptions and rules embedded in the strategic player's decision-making process. One approach could be the integration of machine learning techniques, such as reinforcement learning, where the strategy could dynamically adapt based on a wider range of game situations rather than relying on static rules.

2. Strategy Complexity:

Increasing the complexity of the strategic algorithms may provide a richer set of behaviors that more closely mimic expert human players. This could involve deeper lookahead algorithms, more nuanced handling of the crib and play phases, or strategies that adapt based on the opponent's observed behaviors.

Statistical Robustness

3. Increased Simulation Runs:

While 1,000 games provide initial insights, expanding the number of simulations can enhance the statistical robustness of our findings. A larger dataset would be more indicative of true performance differences and reduce the variance of results, particularly in tightly contested setups.

4. Variance Analysis:

Conducting a detailed variance analysis could provide deeper insights into the consistency of the strategies. Identifying why certain games result in outlier scores could help refine player strategies and improve the model's predictive accuracy.

Game Theory Application

5. Opponent Modeling:

Currently, strategies do not adapt based on the opponent's playing style beyond basic game mechanics. Incorporating elements of game theory to predict and counteract opponent moves could significantly enhance the strategic model. This means developing algorithms that not only focus on maximizing one's own points but also on minimizing the expected gain for the opponent.

6. Multi-Agent Learning:

Implementing a multi-agent learning environment where multiple strategic models evolve in competition with each other could uncover new strategies or refine existing ones. This process can help simulate a more realistic environment where strategies must continually adapt to prevail over intelligent opponents.

Technical Improvements

7. Code Optimization:

Efficiency in simulation can be significantly enhanced through code optimization. This includes optimizing data handling, improving loop structures, and parallelizing the simulation process to decrease runtime and increase the number of simulations that can be performed within the same time frame.

8. Interface and Visualization Tools:

Developing an interactive interface and enhanced visualization tools for the simulation outcomes can provide more intuitive insights and allow users to manipulate parameters dynamically to observe different outcomes.

Conclusion

Based on the results of our statistical analysis, we have found evidence to reject the null hypothesis at a 0.1 significance level, indicating that the differences in scores between random and strategic players are statistically significant. This supports the conclusion that skill and strategic play significantly influence outcomes in Cribbage, affirming the game's nature as skill based. This finding underscores the importance of strategy in game play and suggests that players can improve their chances of winning through strategic learning and practice.

The surprising occasional success of the random player underscores a potential underestimation of variability inherent in Cribbage or possible gaps in the strategic algorithm. Addressing these through the above improvements could not only make the simulations more reflective of real-world complexities but also push the boundaries of what can be achieved with strategic artificial intelligence in card games.