Timing the Bluff: Predicting Deception in Poker through Timing

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1 Introduction

Poker is a game of skill, strategy, and deception. One of the most critical aspects of the game is the ability to bluff, convincing opponents that a weak hand is strong or vice versa. But would it be possible to use data and machine learning to detect when a player is bluffing? This project uses data collected from online poker games to explore bluffing based on various in-game factors, such as decision time, player position, and bet size, with a primary focus on whether the time it takes to bet can reveal deception.

Although past studies have investigated the psychological aspects of poker [1] and others have used field hand history data in their methodology [2], as far as the authors are aware, none have used detailed player actions and board data at the level of the present study. The results of multiple statistical models indicate that timing is of key importance in determining whether or not a player is bluffing.

The results of this study are pertinent to both poker as a theoretical object of study and the poker industry at large. Past academic research on poker has largely focused on the mathematical modeling of simulated poker games and the psychological aspects of betting. Here, the relevance of timing holds importance both for improving the accuracy of simulations and for understanding the cognitive processes involved in decision making. Furthermore, as of 2022 the global online poker industry represented a market worth more than 86.12 billion USD [3] such that gaining an advantage from information as minute as timing holds great financial value for both players and poker vendors.

2 Methods

2.1 Data Acquisition & Cleaning

This study collects hand histories from private, real-money cash games hosted on the PokerNow.club platform. These games featured blinds ranging from \$0.25/\$0.50 up to \$2/\$5 (\$50 to \$500 buy-in). After each session,we exported the detailed game logs, encompassing actions such as posting blinds, betting, raising, folding, and showdown results, into CSV files. We then processed and cleaned these logs, filtering out administrative lines and any incomplete or irrelevant records. The resulting dataset retained all pertinent game-play actions, including each player's decisions (e.g., bets, calls, raises, folds) and timing information. This allowed us to label each hand as a bluff or value scenario and engineer various features (such as bet size ratios, decision times, and positional context) for subsequent analyses.

Given the abundance in data values, we decided to discard any anomalies from standard Texas Hold'em 2-hand poker. From these data values, we extracted hands that went to showdown for verification of our dependent variable bluff/value.

2.2 Exploratory Data Analysis

The dataset consists of 32,304 total observations and 20 variables. Each row of the dataset indicates to a specific decision point of a player. The goal of our Exploratory Data Analysis is to understand the underlying structure of the dataset and be able to identify patterns and distributions of important variables before moving onto statistical modeling.

The distribution of our dependent variable handType was roughly evenly distributed between bluff and value. Distribution of other categorical variables all show roughly equal distributions with the exception of risk variables. This was to be expected, since the raw probability of there being a straight, flush or pair risk in a round of poker is fairly low.

Histograms of numeric variables show a severe right skew, with bet sizes, decision times and number of players in a game showing values close to 0. An analysis of bet times by hand type was performed, showing that bluff hands have a slightly shorter mean decision time of 5.17 seconds, compared to that of value hands of 5.2. This is most likely due to the pressure to display confidence when playing a bluff hand. The prevailing opinion is that the longer it takes a player to make a decision, the less confidence one has on their winning odds. However, this presumption can also backfire, giving rise to numerous psychological tactics in poker.

Further analysis was conducted on the relationship between categorical variables to find potential patterns in the data. The parallel plot in Figure 3 shows the flow

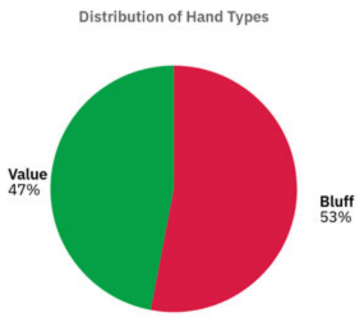

Fig. 1: Ratio of value hands to bluff hands.

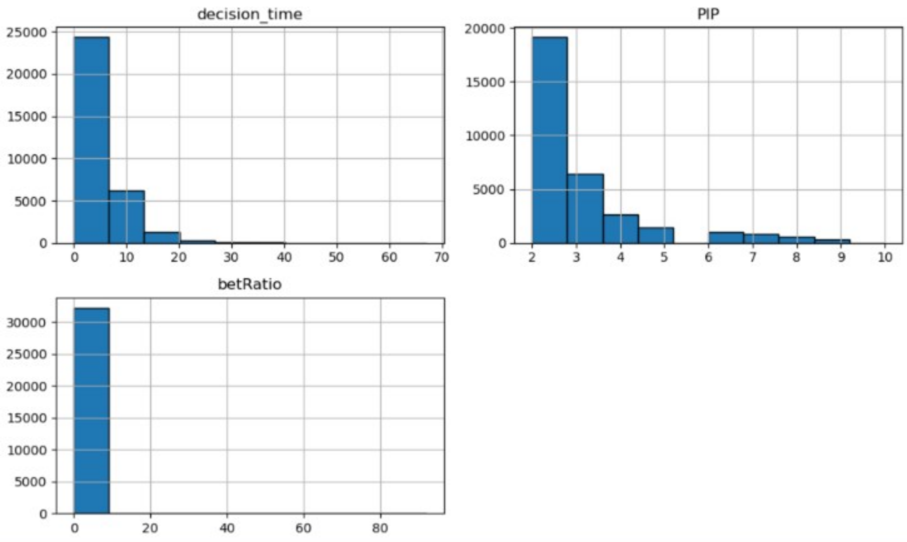

Fig. 2: Histograms of the numeric variables for decision time, bet ratio, and PIP (players in pot) with significant right skew.

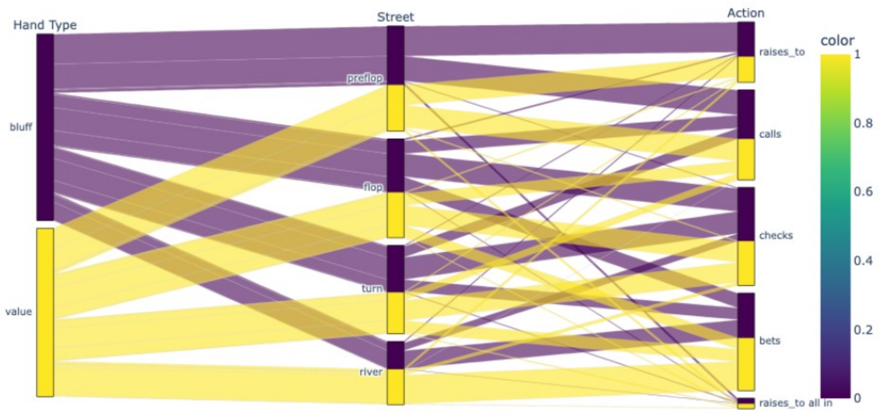

Fig. 3: Flow of hands types, street, and actions.

of hand types by street and action. The decision a player makes in each street is roughly similar for a bluff or a value hand, signifying that the participants are playing consistently, regardless of whether their hand is a bluff or value. The plot does show slightly higher proportions of bets and raises from the bluff players during the preflop, flop and turn stages, indicating that bluff players are encouraging the opposition to fold before all the cards are revealed.

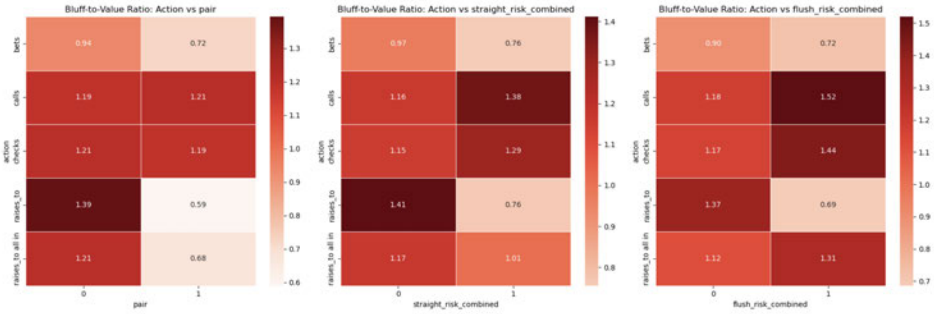

Fig. 4: Ratio Heatmaps of Bluff to Value by Action and Risk

Figure 4 provides a ratio heatmap of bluff to values each by pair, straight and flush risk and action taken. The most significant disparities seem to be when a player raises, with community cards containing a smaller risk having a higher ratio of bluff to value. This was expected, as a round with less risk would prompt players with bluff hands to assume an aggressive stance. A more interesting pattern arises in the call actions, where bluff to value ratios are higher for a round with a straight or flush risk. This phenomenon most likely arises because some players have a straight or flush draw, where they are one card away from a straight or a flush. Since there is a higher possibility of winning the round, the players follow the initial raise to see the next card revealed.

2.3 Assessing Risk

Under the rules of a standard 2-hand Texas Hold'em Poker game, a higher value of community cards signifies a higher risk in playing the round. Therefore, we deemed it crucial to understand the impact of community card combinations on bluff prediction. The basis for risk analysis was the assumption that a higher risk in the community cards would deter the player from raising or placing a bet. We also had to consider the possibility that the risk a player is willing to take largely depends on a player's style of play, and that a player with a bluff hand could possibly switch into a value hand with each community card revealed. The specifics of this type of risk prediction was too complicated to be analyzed without information from the hands of the other players. Therefore, risk was generalized into three distinct ways - straight risk, flush risk, and pair. Straight-risk and flush-risk returns True whenever the community cards show a potential for a straight or a flush. Similarly, pair returns True for any pair combinations within the community cards (one pair, two pair, three of a kind). An assessment of pair cards was important to gauge whether there was a potential for higher card combinations such as three-of-a-kind, full house, or a four-of-a-kind.

We explored other methods of calculating risk factors such as designating each combination risk into a numerical value and calculating a risk score for each turn, but the results were not as significant as the method mentioned above.

straight	flush	major_straight_risk	straight_risk	major_flush_risk	flush_risk
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
FALSE	FALSE	FALSE	TRUE	FALSE	TRUE

Fig. 5: Categorizing risk based on community cards.

2.4 Baseline Model Fitting

In order to properly assess the performance of our LSTM model, we must first see how more traditional models perform on the data set. The test accuracies of four popular models on the same 80-20 train-test are given in Table 1. Overall, none of the models could achieve much more than 60% test accuracy, or about 10% greater than random guessing which. This performance is not particularly impressive especially given that the provided data represents an essentially complete picture of any given poker table at a snapshot in time. Thus, the only real improvement could come from considering player actions in sequence such as in the LSTM model expanded upon in Section 2.5.

	Random Forest	xgBoost	SVM	Log. Reg.
Accuracy (%)	62.4	61.0	61.4	61.6
1st Variable	Player Type	**Dec. Time**	Bet Ratio	Player Type
2nd Variable	**Dec. Time**	Bet Ratio	Player Type	Flush Risk
3rd Variable	Bet Ratio	Player Type	PIP	Position
4th Variable	PIP	Ace is High	All In	**Dec. Time**

Table 1: Test accuracy of each fitted model with the four most important variables.

Further, three of the four models contain decision time as one of the top four models. However, in the Support Vector Machine model decision time holds very low importance, likely because it is highly correlated with the player's bet ratio. Overall, this indicates that while the mean difference in decision time is small between bluff and value hands, it is still relevant in prediction.

2.5 LSTM Model Fitting

A Long Short Term Memory model (LSTM) is a type of recurrent neural network designed to capture long-term dependencies in sequential data. LSTM units store and update a memory cell over time, allowing the network to retain relevant information from earlier in the sequence and effectively learn long-term dependencies. The model naturally handles variable-length sequences, matching the sequential nature of poker hand actions, and captures long-term dependencies in decision-making steps, improving classification of complex, time-dependent behaviors. Overall, it can learn complex

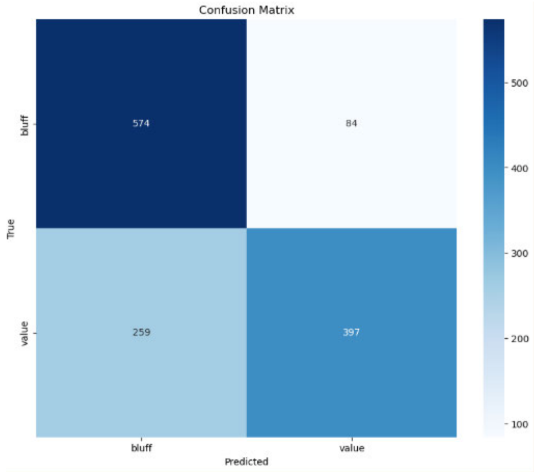

Fig. 6: Confusion matrix of the LSTM predicted values.

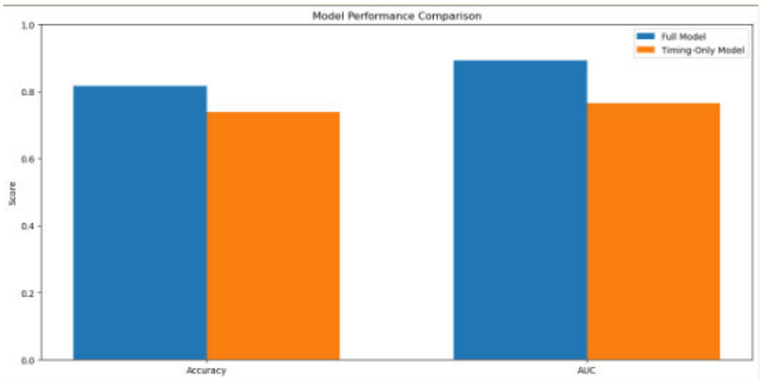

Fig. 7: Model Performance Comparison

patterns from the sequential nature of game actions and outcomes which is highly relevant to a game like poker. Thus, such a model should be capable of significantly outperforming the fitted baseline models.

After conducting the full LSTM model and finding that it yielded the best accuracy out of all the models we tried, we wanted to focus on the timing aspect more to dive further into our primary research question. Thus, we reran the LSTM model with the decision time as the only variable. This model found an accuracy of 0.74 and an AUC (Area Under the Curve) of 0.77.

To compare the accuracy of the full LSTM model and the timing-only LSTM model, we see that the full model performed better, thus indicating that timing is not the only important factor in determining whether or not a player is bluffing. Although the timing-only model performed relatively well, we should explore the relationship between other variables and how timing interacts with other features as well.

3 Conclusion

After thorough analysis of detailed player actions and hand data we have found that throughout multiple statistical models decision time proves highly important in predicting whether a player is bluffing. However, decision time alone is not enough to predict bluffing and it must be incorporated with other board factors. Our overall results indicate that reading and interpreting opponent decision time can give players a competitive edge, especially if taken as a single piece of an array of information. Thus, it seems reasonable to suggest that future models of player agents incorporate decision time as an element of player behavior.

Further, although multiple common statistical models showed poor performance in predicting bluffing, the Long Short Term Memory model proved highly effective, with more than 80% accuracy. This is likely due to the LSTM's ability to handle action in sequence rather than as discrete events. Thus, incorporating the temporal relationship between actions is crucial for properly predicting player behavior.

References

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