Betting Strategies in Poker

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1 Introduction

Poker is a set of card games that has become one of the most popular games globally with an estimated 14 million players worldwide. It is also a huge boon to the economy netting approximately $15 billion in 2006. Most say the draw of the game is that it imitates life, offering incomplete information and a combination of chance and skill. It is this element of missing information that makes poker a fascinating study for data scientists. Skilled players will decide whether to bet based on complex probabilities and their analysis of the available information. In a game where not all information is known, poker players must be continually predicting what the best action is based on an assessment of current and past information. Unlike games like chess or Go where there is perfect or complete information, poker is game of imperfect and incomplete information. Only recently have AI systems like Watson or AlphaGo been able to defeat world champions in the most complex complete information games. However, imperfect information games like poker offer an additional challenge for AI and the computer scientists, data scientists, statisticians, and others who study these games. Bayesian analysis is one method that can be used to answer some of the questions raised by this interesting game. For the scope of this project, our goal was to see if players exhibit certain betting strategies and if those strategies, independent of what cards they have or what pot size they start with, can determine the probability of winning. To this end, we chose to analyze the poker game limit Texas holdem where there is a pre-specified bet and raise amount.

2 Data and Feature Selection

The data that we are using is from the first online poker environment called the Internet Relay Chat (IRC) [1]. This server was the foundation of many of the online poker sites and attracted many students of the game who would go on to be World Champions. This data has been used for many of the poker AI systems being tested today as well as analytical studies of the game. The limit Texas hold'em data that we used for this project was collected monthly from 1995-2001. We used the games from 2000 and limited it to the top 1% of players who played the most hands to minimize the data, which still left us with over 500,000 observations. Also, players who have played many hands are likely to have played with an assortment of different players under a variety of circumstances which decreases the likelihood of dependence between hands.

[1] Data can be found here:
https://web.archive.org/web/20040622065852/http://games.cs.ualberta.ca:80/poker/IRC/IRCdata/

For our feature selection, we used a combination of normal logistic regression and the Boruta package in R which is a feature selection wrapper algorithm. We took out all the variables that weren't relevant to our question such as cards, player count, and money variables among other unnecessary and highly correlated variables. This left us with who won the game (winner), whether the player bet first in a round (flopInitBet, turnInitBet, riverInitBet), the average number of raises and times chips were voluntarily put into the pot per round (avgRaises, avgPip), and the number of check raises per hand (num_CheckRaises). It is to be noted that avgRaises and avgPip are highly correlated, but that is to be expected since avgPip includes any raises plus calls and these are important varaibles to include to answer our question.

3 Our Model

There are a variety of factors that can influence a betting strategy, but the two we chose were experience level and the proportion of times (out of all hands played) a player voluntarily put chips into the pot pre-flop (VPIP). Experience level was determined by the data from 1995-1999 where those players who had played more than 7500 hands were considered expert, less than 7500 hands played was deemed mediocre, and those players who started playing in 2000 were assigned to be beginners.

The most common statistic used in poker is VPIP and it is also used to determine a player's type. A low VPIP means a player is tight, in that he or she folds more often before the flop unless the player was dealt a strong hand. A high VPIP means a player is loose and is more likely to continue to play even with a weaker starting hand. Typically VPIP is used along with the proportion of times a player raises preflop out of all hands played (PFR) to create 4 player types, but these types are not strictly defined, so we decided to use just VPIP. Because the IRC data does not represent a modern style of poker play, we were not able to define the VPIP types according to the modern standards. Instead we broke up the VPIP types into three equal categories based on the distribution of VPIP such that loose players had the highest VPIP and tight players had the lowest, with semi-loose players in the middle.

We made these categories for VPIP and experience in order to create three hierarchical models that allowed us to explore the natural differences in betting strategy based on these groupings. Additionally, using a hierarchical model could help us get more accurate estimates of our parameters. We used a logistic regression model that predicted if a player would win the hand because you don't need linearity between variables, we have several ordinal variables, and a large amount of data. Thus, we created a double hierarchy model where we assume that our data comes from a normal population with uniform variance which feeds into our normal distribution of each experience level with uniform variance which informs the normal distribution of each VPIP type with uniform variance which funnels to the logistic regression model and our prediction variables. We also ran two separate single hierarchy models, on VPIP and experience level with the same logistic regression model.

4 Results

When comparing the results from the single hierarchical model based on VPIP type, we find results that are consistent with our prior knowledge. Tight players are found to have a greater average of chips in the pot per round (Figure 1) and a greater average of raises per round (Figure 2) compared to semi-loose and loose players with statistical significance. This makes sense since tight players will continue to play when they have a strong hand and therefore are more willing to bet.

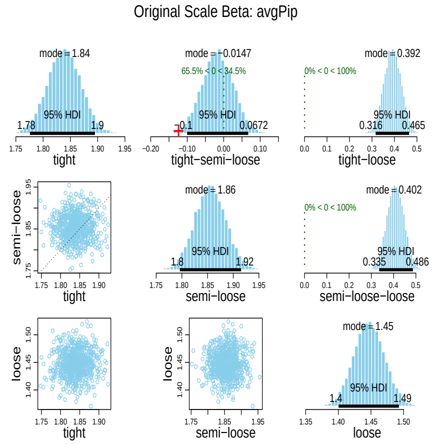

Figure 1

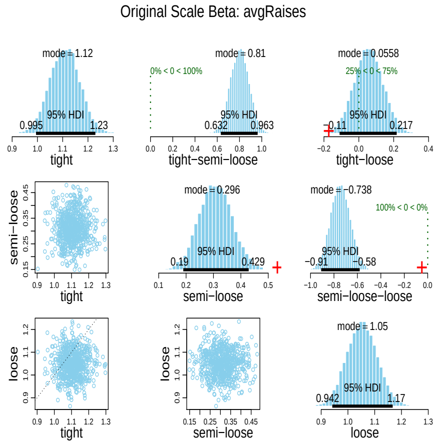

Figure 2

On the other hand, loose players, which are those players that are more likely to play a hand, even if the starting hand is weaker, are statistically less likely to make the initial bet in a round compared to tight and semi-loose players (Figure 3, Figure 4, Figure 5). Loose players have a smaller average of chips in the pot compared to both tight and semi-loose players with statistical significance (Figure 1). The interesting result though is that loose players are more likely to raise on average per round compared to the semi-loose players with statistical significance (Figure 2). This may be a result of the loose players attempting to bluff an opponent away.

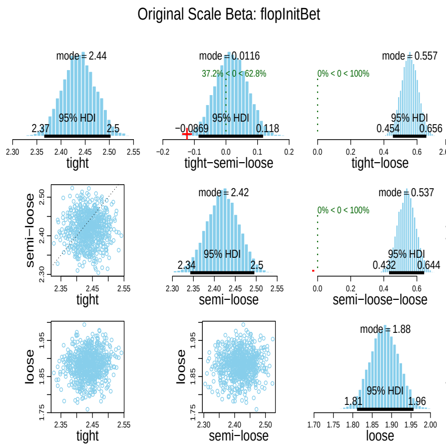

Figure 3

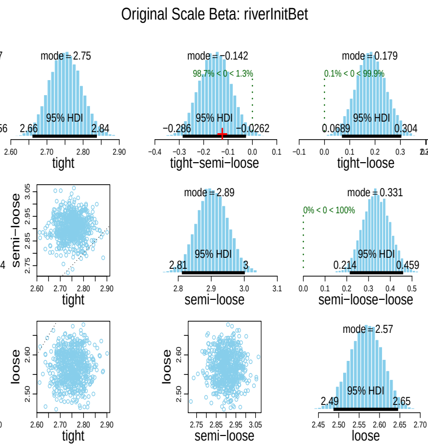

Figure 4

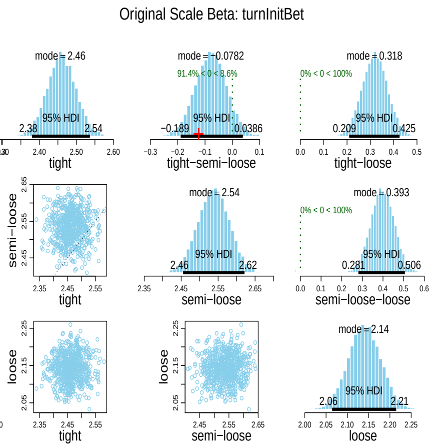

Figure 5

Overall, these results claim that tight players, when they play a hand, are more likely to be an aggressive better and play a hand to the end, which again makes sense given that they normally only play hands with strong cards. That being said, loose players, which are more likely to gamble and play hands with weaker cards, are less aggressive than tight players and may try to bluff more than semi-loose players given that they on average raise more per round.

Looking at the results from the single hierarchical model using prior experience, it is interesting to see that experts have a much greater average of chips in the pot per round when compared to both mediocre players and beginners (Figure 6). However, mediocre players have a greater average of raises per round (Figure 7). These results show that mediocre players are more aggressive than experts but experts are more likely to stay in a hand longer.

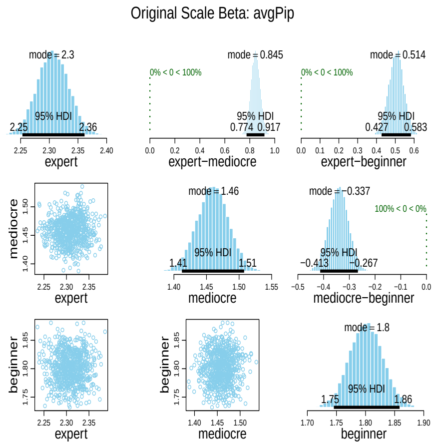

Figure 6

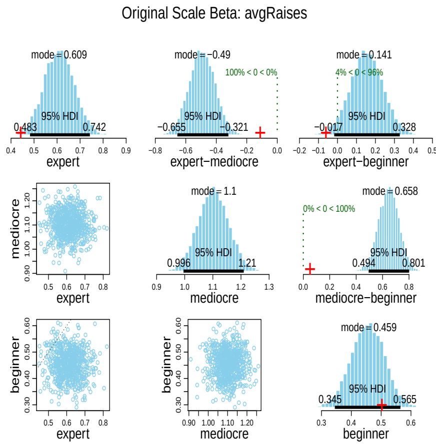

Figure 7

The results get stranger as both experts and beginners have a significantly greater number of initial bets in each of the three betting rounds than mediocre players (Figure 8, Figure 10, Figure 11). These results claim that while mediocre players are more likely to raise, they are less likely to be the first person in a round to bet. Overall, it seems that experts also do more check raises compared to beginners (Figure 9), which make sense given that a check raise can be considered a more advanced move when trying to lure an opponent in and then either raising on top to win more money or to bluff an opponent off.

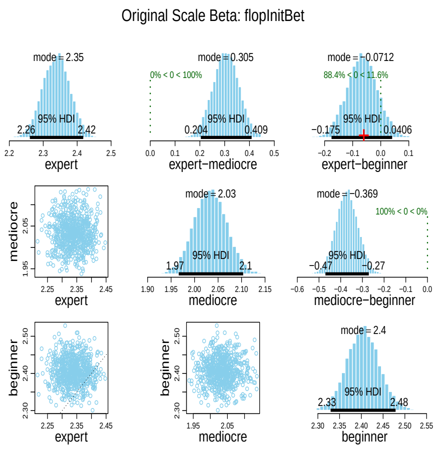

Figure 8

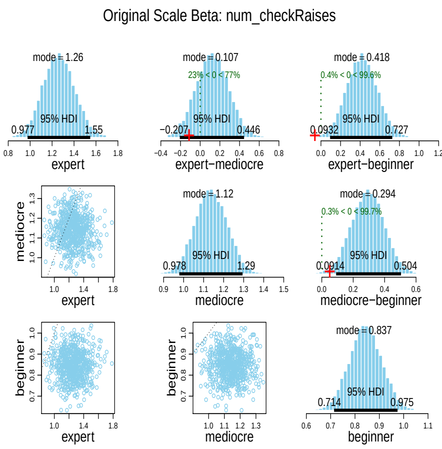

Figure 9

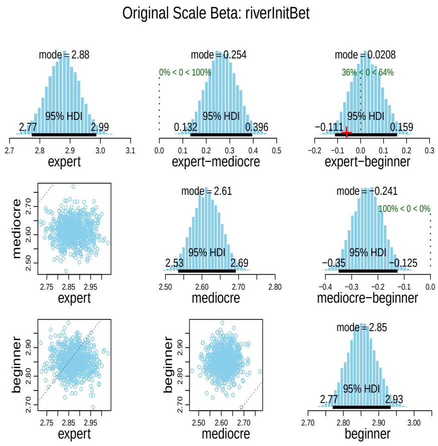

Figure 10

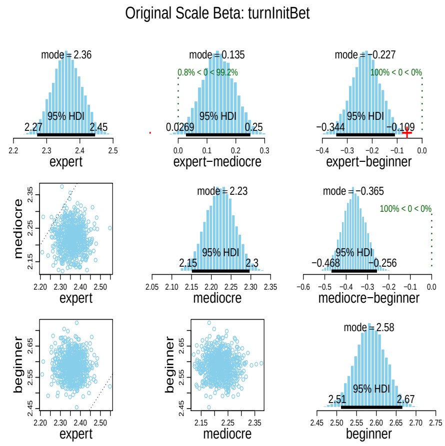

Figure 11

Lastly, when examining the double hierarchical model, where players prior experience determines the distribution of the players VPIP type, which in turn affects the coefficients of the predictors, the prior experience distributions seem skewed in that expert players have an extremely wide distribution compared to mediocre and beginner players (Figure 12 and Figure 13). This can be seen in the scatter plots in that the scale of the expert players is between -150 and 150 while the beginner and mediocre players are between 0 and 1. This signals that the players within the expert group may play very different from one another compared to the other groups. However, despite these differences, there is no statistically significant difference between the three group means, meaning that the prior knowledge between all three groups should be exhibiting about the same influence on the player VPIP.

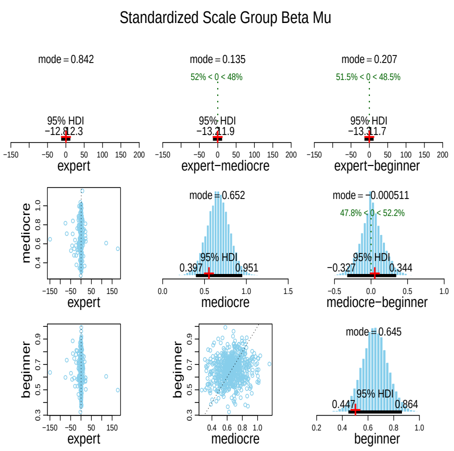

Figure 12

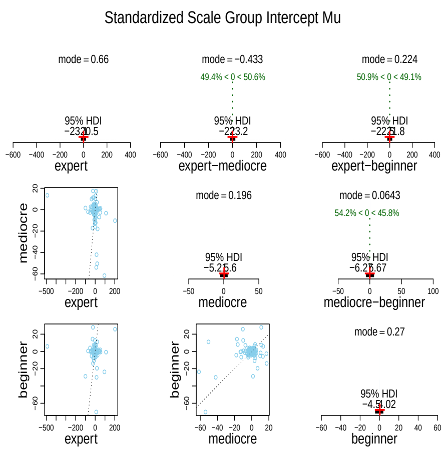

Figure 13

We find further proof of that when looking at the plots of the beta where we see that the analysis is the exact same analysis that we determined when looking at the single hierarchy for VPIP (Figure 14 and Figure 15). It is interesting to note however, that while the analysis is the same there is stronger statistical evidence shown by the double hierarchy model. Therefore, we are led to conclude that players with different VPIP types do not exhibit different betting strategies based on their prior experience. This means that an expert with a tight playing type exhibits the same strategy as a beginner with a tight playing type.

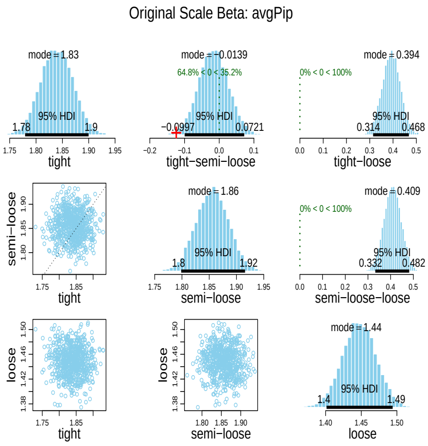

Figure 14

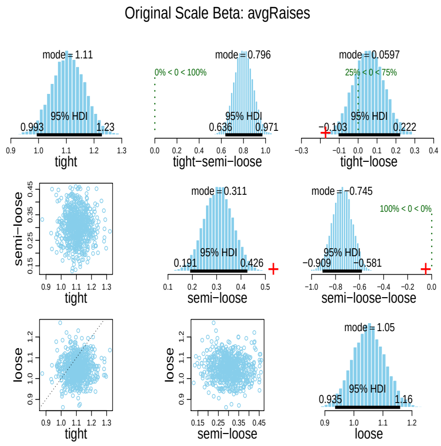

Figure 15

5 Conclusion

From our three models, we find that on their own, players with different experience backgrounds and players of different VPIP types have different betting strategies. However, we found little evidence that a combination of prior experience on VPIP type has any influece on a player's betting strategy.

There are several ways that this project could be extended and adapted. First, we ran our three hierarchical models on a limited portion of the data, which took days for the models to run, but in the future we could increase the pool of players that we use for our analysis. Second, we could chose different parameters to use in our model since in poker average VPIP and average Raises aren't as useful as other statistics like regular VPIP and PFR. Third, we could add in different grouping parameters. These could be number of players in a hand, number of players in a round, player position, the PFR, or others. Finally, we could separate our dataset into test and train data sets and see how well our models predict the test data to expand this analysis from a parameter comparison to a model prediction comparison.