Predicting actions in the first stage of poker hand using Random Forest algorithm

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1. INTRODUCTION

It is often said, ''it takes ten minutes to learn poker, however lifetime to master.'' One of the simplest versions – **Limit Hold 'em Heads Up[1]** contains $1.38 * 10^{13}$ information sets. Three of orders of magnitude more than any other game solved via computation. (except ''Go'') However in 2015, it was solved by algorithm CFR+ (Bowling et al., 2015) It took 68.5 days and 10.2 TB of disk space. It is important, to note that solving, does not necessarily mean beating human players consistently over long period of time. To this day, poker bots fail against humans.

The motivation of this paper, comes from the authors' personal opinion, that any solution to games with imperfect information could be further improved via human/machine interaction. Statistical software programs, like Poker Tracker 4, and Holdem Manager 2, provides players with huge number of real time statistics to dive in, while making a decision. This paper investigates some of the most important variables affecting decisions in poker, on two levels. First are variables, available at any single poker **hand**[2] – ''hand environment''. Second part, are sticky characteristics calculated as sum of actions, for the fixed time into the past. Latter is much more difficult to incorporate into the modern algorithms, as it increases computational needs substantially, acting as agents' short-term memory.

Paper is divided into: *domain overeview*, where poker rules are briefly outlined, as well as some poker theory and questions in interest; *preprocessing* – where data cleaning, and transforming operations are presented; methods applied are addressed in *anlaysis* section; then goes *results and limitations; conclusion* follows at the end.

2. DOMAIN OVERVIEW

There are many different poker variants. Six most popular ones are Texas hold 'em, Omaha high-low, Razz, Seven card stud and Seven Card Stud eight or better. This list is often abbreviated as **H.O.R.S.E.**[1] Three properties attributable to most poker types:

- *Imperfect information.* Opponent cards is the most important piece of information which only becomes available, if players go through all stages of poker hand, or player decides to disclose it. (which is very uncommon practice)
- *Stochastic outcomes.* There is always element of chance involved, as a consequence of the cards being dealt randomly.
- *Non-cooperative multi-player*. Players are actively trying to deceive each other.

This paper addresses variant of poker called No Limit Texas Holdem. Variant was chosen due to many reasons, most important being authors personal interest and overall popularity on this type in particular.

2.1 Texas Hold 'em rules

Number of players at each **table**[2] varies between 2 and 9. There are four stages in every Texas Hold 'em poker hand**.** Players take one of four actions in turns (succession does not change for the duration of a hand), at every stage. Goal is to win as many **chips**[3] as possible by making the best possible 5 hand card combination[4], with two cards in hand and up to 5 available **community cards**[2]; or through forcing your opponents give up their hands before the **showdown** [2]. Stages of poker hand:

- *Pre-flop*. First stage, players are dealt two hole cards[2]. Before any action, players to the left of the dealer are forced to bet small and big blinds[2].
- *Flop***.** Three **community cards**[2] are randomly drawn from a deck and made available for all players to see.
- *Turn.* After all players competed at the *flop* stage took action, one more community card is drawn.
- *River*. Last stage, after all players still competed in the *turn* stage took action, one more community card is drawn. Winner is decided through the possession of a best combination or through the folding of every opponent.

Actions:

- *Fold*. Player who folds stops participating in a hand and loses all chips put in the pot up until this action.
- *Check*. This is the action of taking no action, and is only available if no one bet[2] before the player.
- *Call*. This action is only available if someone bet/raised. Player who calls, accepts the amount of chips put by player(s) before him, and puts

[1] More on poker variants: http://www.gamblingsites.org/poker/games/
[2] Glossary of poker terms: https://en.wikipedia.org/wiki/Glossary_of_poker_terms
[3] Chips and money used synonymously in this paper, both define store of value in poker.
[4] Poker hand combinations could be found: https://www.partypoker.com/how-to-play/hand-rankings.html

same amount into the shared pot. As a result - continues participating in a hand.

- *Bet/Raise*. is when a player commits a greater amount than the current bet size. The action is a bet if no one has previously placed any chips into to the pot, and it is a raise if someone has previously bet.

2.2 Questions

Main goal of this paper is to distinguish and rank features according to the importance in predicting actions in the first stage of poker hand. Study is focused exclusively on actions taken in pre-flop stage because of tight limits on the scope and time available for project completion; availability of data – all hands start at this stage, therefore information loss is minimized; the importance of hole and community cards increases with every successive stage, players' actions are analyzed in the absence of this information, therefore, stage where omitted variable is least important, is more appropriate.

Harrington (Harrington and Robertie, 2004) suggests that any poker hand in any given session could described by ten variables:

1. Number of players at a table.
2. The type/style of players.
3. Stack[2] size in ratio to the blinds and ante.
4. Stack size in ratio the other stack sizes.
5. Where is player sitting in relation to aggressive and passive players.
6. What actions is player facing.
7. Number players left to act.
8. Pot Odds[2] offered.
9. Players' position at table after flop.
10. Cards player hold and any community cards.

As basis for this paper, list was reduced even further, motivated by potential simplification without significant loss of information. Variables 1, 5, 7 all describe the total number of opponents and position of a current player in relation to the opponents. Potential variable defining players' position in relation to the total number of players,[5] is viable alternative. Number of players left to act is not of significant importance pre-flop, because, all players participate in the pre-flop stage.

Features 3, 4 describes the significance of players' bankroll. Variable that takes players bankroll as numerator, and total bankroll of a table as denominator captures information from both variables well, especially in No-Limit variation of Holdem, where blinds and antes are not that important.

Feature 6 is left as it is. Variables 8 and 10 describe hand ''strength''**,** which is not being evaluated in this paper.

Player type/styles is a very interesting feature, which had been primary focus of poker researchers worldwide. (7, 8, 9). Even though this feature is of great importance and interest, this particular study substitutes player profiles with short term action dynamics. Which, could be seen as ''sticky'' styles.

Updated list, which is made of two parts, first one we call ''pre-flop environment'' list:

1. Player position relative to total number of players.
2. Player bankroll relative to total bankroll of all the players in the session.
3. Recent opponents' action.

Second part – ''short-term dynamics'':

1. N-hand lagged aggressiveness.
2. N-hand lagged passiveness.
3. N-hand lagged submissiveness.
4. N-hand lagged deceptiveness.
5. N-hand lagged outcome.[6]

3. PREPROCESSING

Data from famous University of Alberta poker research group was used. Source contains more than 10 million hands, played between 1995 and 2001, over internet relay chat (IRC) channel. Players competed for play money, however every player had limited amount of. Also, the participants were known to be mostly computer science geeks and poker enthusiasts. As a result, overall quality of information is considered to be quite good and applicable to recent times.

3.1 Cleaning and importing

All files containing No-Limit Hold 'em games were downloaded. There were 10folders in total, each containing one file for hands database, where each row contained information unique for every hand (hdb); one file for roster (hroster) database, where each row was also unique for every hand and contained player names**.** There was also a folder containing one file for each player in the database (pdb), in each file rows were unique for hand and contained information on players' bankroll, actions and hand results.

Files were of unknown format and effort was made to contact authors of (Bensson et al,. 2013) to consult about parsing it, however without success. After quite some experimentation with Python, files were read and written into three text files. One for hand roster, one for hand database and one for player database. Files were uploaded into Oracle SQL for initial investigation and formatting. Overall, as expected from data archived automatically, it seemed pretty clean without any duplicate values, unexpected characters or data types. Shortly after that, data was exported as csv files and read into python using *pandas* library, for further transformation, exploration and analysis.

3.2 Transforming and merging

First, binary numerical variables were created from strings, describing four different actions types preflop. (grey color in Appendix A) These actions were:

- Aggressiveness. Dummy 1 for bet, raise, all-in.
- Passiveness. Dummy 1 for check or call.
- Submissiveness. Dummy for fold.

[5] $\frac{POS}{N_{Players}}$ = Players position in relation to the number of players.

[6] With lagged outcome variable we hope to capture opponents who are more likely to play loosely because they lost a lot recently (tilting) , and players who play tighter, as they had won a lot.

- Deceptiveness. Dummy for raise and fold; or check and raise in the same stage.

Initially, intention was to make these variables mutually exclusive and analyze them all together, however it required to ‘’give’’ some of the data from aggressiveness, and submissiveness to deceptiveness[7]. Also, deceptiveness is an aggregation of actions, while other actions are only last moments. Therefore, splitting analysis in two parts one for deceptiveness; one for aggressiveness/passiveness/submissiveness seemed more appropriate.

Then, variables to describe current ‘’preflop environment’’ (blue Appendix A) and ‘’short term dynamics’’ (pink in Appendix A) were created. Final dataframe had form of 26380 rows x 45 columns. Lowest number of non-null rows is 16506[8]. Rows with nan values are discarded, if variable used in the model.

4. ANALYSIS

Before the onset of analysis an expectation matrix was drawn, from the authors viewpoint. It could be found in the appendix. Some of environmental variables are expected to have quite strong effect. No expectation had been made on variables affecting deceptiveness, due to lack of studies. No relationship is expected from short term dynamics, because every is hand is independent from one another. Tilting, and other short term player characteristics is more an anomaly rather than any important pattern.

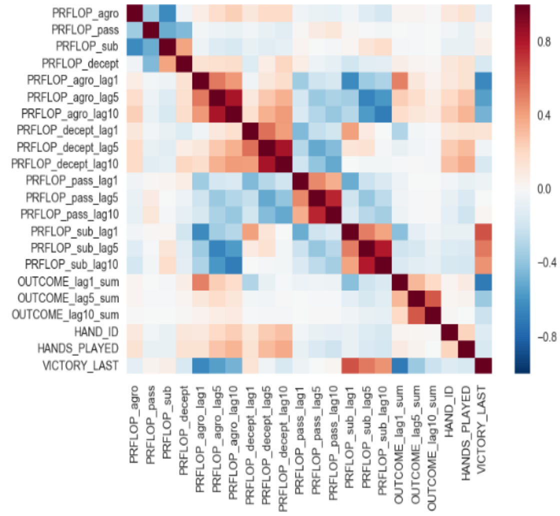
4.1 Exploration

First we set the probability thresholds which we hope to surpass with chosen classification method. 31% of all actions are aggressive; 22% passive; 47% submissive and 42% deceptive. So any, method predicting action with less accuracy is better of just choosing positive class for whole sample space and is considered a bad model.

Second, correlation matrices are calculated and heatmaps drawn (figure 1), using both spearman and pearson correlation methods. As we expect some linearity as well as monotonicity. Both, methods return quite similar results:

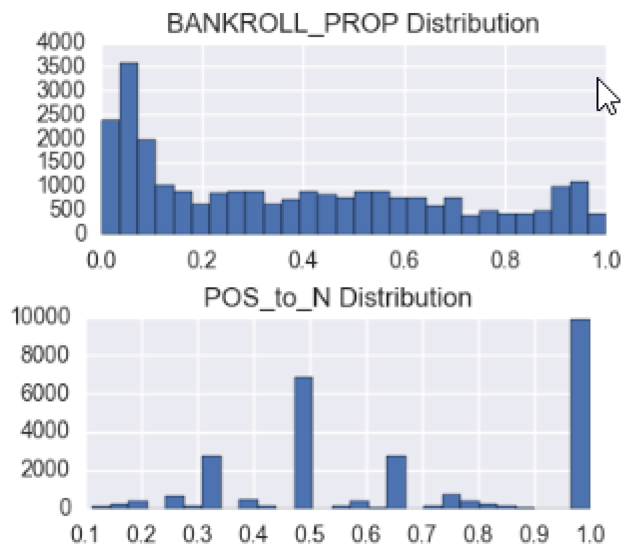
Short term dynamics variables, as anticipated, fail to show any significant correlations. Variables, that display correlations of >|0.3|, have expected signs and follow common sense in poker.

Figure 1. Spearman correlation. Short term dynamics



Finally, normality is investigated. Frequency diagrams point to non-normal distributions. (example in figure 2). Finding is later confirmed with qq plots.

Figure 2. Frequency distributions of bankroll proportion and players relative position.



Box-Cox transformations on variables[9] was performed, however qq plots still expressed strong non-normality. Wilko-Shapiro tests on subsets of samples (n < 5000) , had p-value <0.1 – an additional evidence against normality.

Linear probability model was rejected. Plan was to proceed with logistic in this case, but logistic regression performs poorly when there is important variable omitted, and tends to capture false patterns. Author, decided to use random forest algorithm. (Breinman, 2001)

[7] Where 1 occurs in any two action columns including deceptiveness – only deceptiveness must remain as sole column 1.

[8] NaN values occupy in opponent action columns where position is 1, as there is no opponent before.

[9] More on box-cox transformation http://itl.nist.gov/div898/handbook/eda/section3/eda336.htm

4.2 Predicting deception.

First, random forest classifier is fit with default parameters, using only ''environment'' variables .[10] Shockingly, it returns accuracy of 92%, which is very unlikely due to variables omitted. Immediately, 10 fold k-cross validation is implemented, which returns accuracy of 72%. Aim is to reduce the difference between cross-validated score and fitted score. *GridSearchCV*[11] was used to evaluate different parameters. However, best parameters' do not differ much from default ones. Except for min_samples_leaf, which defines the number of samples required to split every leaf node, suggested is 25. After some experimentation, 25 was found to increase the difference even more, 3 was chosen. Next, out-of-bag error rate is drawn as a function of number of trees. (figure 3) Error rate stabilizes below 0.2 at little less than 100 trees. This number used in final model. Investigation of learning curves confirms the quality of parameters, difference between fitted and cross-validated-score stabilizes at around 0.05. (figure 4)

Figure 3. OOB error rate. Predicting deception, environment only.

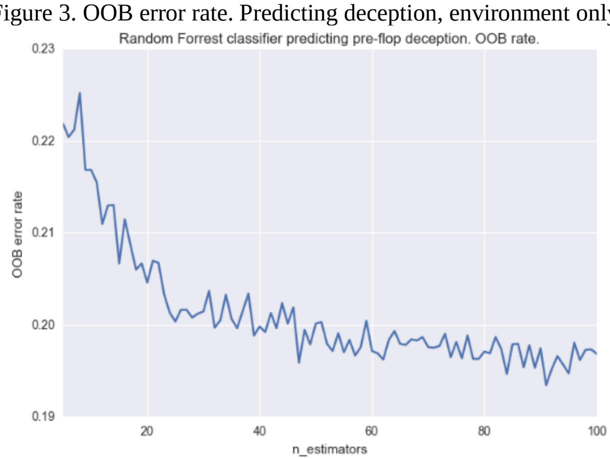
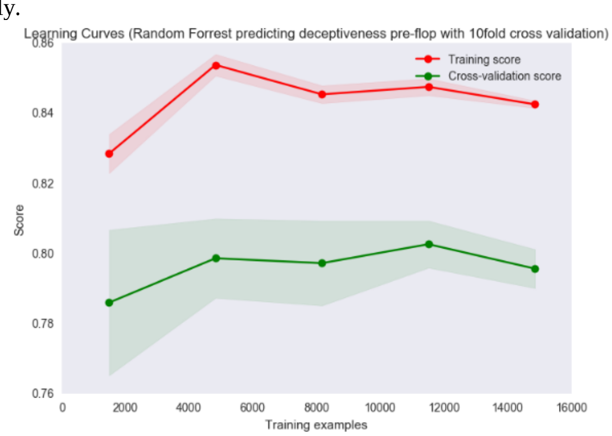


Figure 4. Learning curves. Predicting deception with environment only.



F1 score for 0 class (no deception) is 0.91, mainly arising from 0.99 recall rate. Precision is also high 0.84 for positive class, however recall is only 0.15. Algorithm predicts mainly negative class, however in the small subset it predicts positive, it is quite accurate.

Importances are evaluated using integrated GINI scoring function, which measures to quality (purity) with which variables split the data. BANKROLL_prop is clearly the most significant, with >0.9 GINI score. However, random forest with few features tend to be biased towards one, with greater number of distinct values. Therefore, it is curious whether the significance will remain in full model.

Similar sequence of steps was taken in full model analysis. Three models were fitted: with 1, 5 and 10 hand lagged dynamics. They all were calibrated using *gridsearchcv*. Parameters chosen were similar to the best 'environment only' model, except for number of trees (n_estimators), which was increased to 500. Initially, accuracy differed, 83% for model with 1 hand lagged dynamics, 98% - 10 hand lagged dynamics. However, when cross-validated after tuning, all converged to about 77%.

All models, were better in positive class recall (0.26, 0.49, 0.77), and in positive class precision (0.91, 0.93, 0.96). It is important to note, that these results are still higher beyond any expectation, however as long as cross validated score is way above our probability thresholds of 0.48, feature significance is investigated.

There were five features that showed distinct - higher than average GINI importance level. In order, to understand the relationship better, the direction (sign) had to be found. There is small python module, created by Ando Saabas[12], which calculates contributions of each feature, towards each prediction. It is important to note, that contributions are calculated as linear sum, and therefore does note capture non-linear relationships, accounted for by GINI importance. However, comparison of these two measures is valuable.

All three models are very similar. Interestingly, short term dynamics show distinct contributions here, specifically: lagged deceptiveness (distinct[13] positive), lagged aggressiveness (distinct negative), lagged outcome (distinct negative), lagged passiveness (positive) are four top variables. Suggesting, that short term dynamics might be a valuable tool in predicting deception pre-flop, after all.

4.3 Predicting aggressiveness/passiveness/submissiveness.

Onevsrest[14] classifier was used. Classifier takes three random forests, separate for each class as argument. First attempts to fit the model showed very low cross-validated score, despite returning high fitted score. Numerous implementations of *gridsearch* followed, with f1-score as scoring function as well as accuracy-score. Default parameters proved to be superior. Fitted accuracy – 0.49, cross-validated accuracy 0.22, which is much worse than not differentiating and predicting same class throughout dataset.

Despite, low overall accuracy, precision remained high (>0.8), however recall was low for aggressiveness (0.44) and passiveness especially (0.26). Learning curve showed no convergence, meaning

[10] Default features: http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
[11] More on gridsearchcv: http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
[12] Saabas, Ando. "Random Forest Interpretation with Scikit-learn." *Diving into Data*. N.p., 12 Aug. 2015. Web. 13 Dec. 2016.
[13] Relationship is considered strong if aggregated cont./number of trees > average. Threshold was chosen arbitrarily.
[14] More on the classifier: http://scikit-learn.org/stable/modules/generated/sklearn.multiclass.OneVsRestClassifier.html

that algorithm fails to detect a pattern with increase in training sample. Importances and contributions expressed distinct signficance for BANKROLL_prop (>0.9). Result confirmed suspicion that variable with greater number of levels leads to overestimated significance in the problem with few dimensions.

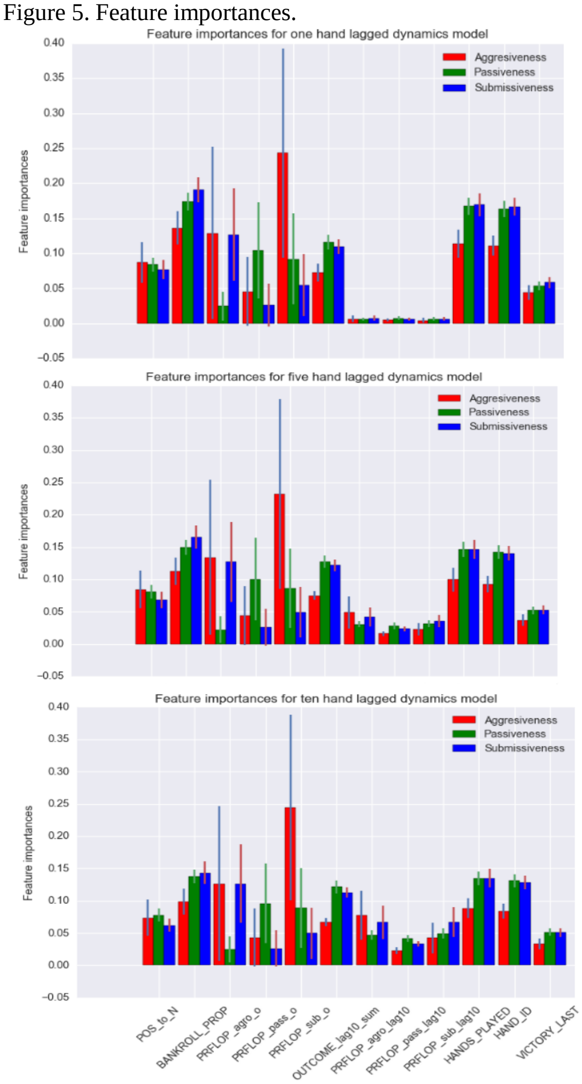
Models with lagged dynamics are fitted. After calibration, cross-validated scores converge to 0.55. Which is not great, however, in multi-classification problem it is still much better than chance.

Confusion matrices, and classification reports show that model struggles in passiveness recall. Remaining scores are high, and increasing with the length of the lag.

Result confirmed with importance graphs, as lagged variables are gaining importance with increase in lag, however they still remain insignificant. Remaining variables express similar importance measures in all three models.

Opponent submissiveness strikes as most distinct variable predicting aggressiveness, consistent with correlation matrices. Passiveness and submissiveness (unlike aggressiveness) express similar patterns, as they share 4 out of five most important variables. (except for opponent aggresiveness) It is surprising, that control variables for player experience, and table familiarity emerged as important factors.

Figure 5. Feature importances.



5. RESULTS AND LIMITATIONS

This paper is an attempt to find predictors for actions pre-flop in the absence most important variable – hand-strenght. As a result, author refrain from deducing precise numeric effects, but rather intends to spot the variables that possess strongest informational merit on differentiating between actions pre-flop. Expectation matrix in appendix B, consists of authors expectations arising from studies as well as personal experience. Matrix had been colored according to the results of this study.

Criteria for the quality of results.

- Variable is above average in GINI importance measure and aggregated contribution measure= Confirmation of importance, with sign as in contribution measure.
- Variable is above average in one either GINI, or aggregated contribution measure. = Inconclusive relationship.
- Variable is below average in both GINI and aggregated contribution measure. = Variable not important.

5.1 Results

The one, who is skilled at deceiving, as well as the one who is sharp in detecting deception possess a significant advantage in poker. It looked like we managed to detect deception, with high accuracy using only proportional bankroll. However, full model spread the importance to 6 variables evenly. Three of them - lagged deceptiveness; lagged passiveness and relative position also showed high positive contributions. Players, who played deceptively recently, are more likely to do it again. Prolonged passiveness shows up as a sign of a deceptive player and requires careful evaluation. Later position (POS_to_N) is associated with deceptive action pre-flop, which is different from what correlation matrices suggested. Relative bankroll-size still shows importance, however aggregated contributions are small. It means that positive and negative contributions cancel each other out and relationship is complex non-monotonic.

Aggressive play is the one that earns you the money. Successfully predicting it without knowing the hand strength is bluff catching skill. Predicting it using only ‘’environment’’ variables seem of little use. However, full model gives some hope. Opponent actions, specifically passiveness and submissiveness score highest in importance measure. Opponents’ submissiveness is also one of the most contributed variables (positively). Player experience (HANDS_PLAYED) express strong monotonic relationship, even though does not appear in importance graph. Seems, like aggressiveness tends to increase with experience, and is mostly affected by actions of the most recent opponent.

Passiveness rather than submissiveness, is generally a sign of a weak poker player. Passive play gives more flexibility to your opponents, and ability to spot the high likelihood of passive play is of great use in poker. All four variables that showed high importance, also contributed the most. namely BANKROLL_prop; HANDS_PLAYED; HAND_ID and OUTCOME_lag10_sum. Fact that relative bankroll is strong positive predictor for deceptiveness as well as passiveness, points to interesting, and dangerous interaction. Therefore, features should always be considered in combinations. Greater experience, table familiarity and recent success adds more weight on the likelihood of a passive action.

Folding, or giving up a hand at the right time is one of the hardest skills to learn and can define long term winner from looser. If one could spot potential for submissive pre-flop action, one could profit steadily via pressuring. Expectation was to spot strong negative relationship, with opponent aggressiveness, surprisingly PRFLOP_agro_o appeared only in importance measure. Table familiarity (HAND_ID) as well as sum of recent winnings (OUTCOME_lag10_sum) shows most robust, positive effect. (positive) Similarity of variables and signs in predicting passiveness and submissiveness leads to challenges in deducing reliable distinctions between these actions.

5.2 Issues and limitations

Script had to be re-run at least 5 times. One instance was result of not including all-in action in transformation, resulted in some 0 rows for all action columns. There were couple system crashes and all variables, stored in IPYTHON kernel were lost. Common cause of crashes or significant system slowdowns, were computationally intensive operations, particularly calculations of aggregated contributions of interaction variables, for full models. Theese calculations, if completed required several hours.

Variable interactions are important part of any non-linear analysis, which could be addressed with more depth, either with more efficient method or more powerful machine. Hand strength being the main factor beyond any decision in poker, it is curious to see how the importances and contributions would change in the presence of it. Data is another factor, there is millions of poker hands played online every day and quality of analysis could usually be improved via integrating more data.

6. Conclusion

This analysis glimpses into everyday complexities of poker. Players are continuously striving to achieve an edge through better ‘’reading’’ skills, so to reduce the bias between true information and personal opinion. Predicting players’ actions can never be perfect, as long as player is human. Humans are inconsistent, often irrational, vulnerable to emotions and also, able to change and adapt. However, there where lies the challenge lies the immense fun and excitement. Learning never stops.

“Every time you play a hand different from the way you would have played it if you could see all your opponents cards, they gain; and every time you play your hand the same way you would have played it if you could see all their cards, they lose” (Sklansky, 1994, p. 16)

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APPENDIX A

GROUP	NAME	NUMBER OF NON-NAN VALUES	DESCRIPTION	MEASUREMENT
INDEX (level 0)	TIMESTAMP_ID	26380	Unique id for every hand.	Unique integer.
INDEX (level 1)	NAME_ID	26380	Unique id for every player.	Unique string.
ACTIONS BEFORE FLOP (DEPENDENT VARIABLES)	PRFLOP_A	26380	Action before flop.	String.
	PRFLOP_agro	26380	Players' aggressive action before flop	Dummy variable 1 or 0.
	PRFLOP_sub	26380	Players' submissive action before flop	Dummy variable 1 or 0.
	PRFLOP_pass	26380	Players' passive action before flop	Dummy variable 1 or 0.
	PRFLOP_decept	26380	Players' deceptive action before flop	Dummy variable 1 or 0.
HAND OUTCOMES (USED FOR INITIAL TRANSFORMATIONS)	BANKROLL	26380	Players' bankroll.	Floating positive number.
	WINNINGS	26380	Total winnings after the hand.	Floating positive number.
	ACTION	26380	Total money put in the pot during the hand.	Floating positive number.
	PLAYERS_POS	26380	Players' position at the table.	Integer [1,9].
	PLAYERS_N	26380	Number of players at the table	Integer [1,9].
	OUTCOME	26380	Money outcome after the hand. ((WINNINGS - ACTION)/BANKROLL))	Proportion [-1, 1]
	PLAYERS_PRFLOP	26380	Number of players before flop.	Integer [1,9].
	POT_PRFLOP	26380	Amount of money in the pot.	Floating positive number.
ENVIRONMENT (INDEPENDENT VARIABLES)	BANKROLL_PROP	26380	Player bankroll as proportion to total table bankroll	Porportion [0,1].
	POS_to_N	26380		
	PRFLOP_agro_o	16506	Aggressive action of the last opponent.	Dummy variable 1 or 0.
	PRFLOP_decept_o	16506	Deceptive action of the last opponent.	Dummy variable 1 or 0..
	PRFLOP_pass_o	16506	Passive action of the last opponent.	Dummy variable 1 or 0.
	PRFLOP_sub_o	16506	Submissive action of the last opponent.	Dummy variable 1 or 0.
SHORT TERM PLAYER DYNAMICS (INDEPENDENT VARIABLES)	PRFLOP_agro_lag1	26293	Players' aggressive action before flop, lagged sum 1	Integer [0,1].
	PRFLOP_agro_lag5	25964	Players' aggressive action before flop, lagged sum 5 hands in the past.	Integer [0,5].
	PRFLOP_agro_lag10	25568	Players' aggressive action before flop, lagged sum 10 hands in the past.	Integer [0,10].
	PRFLOP_decept_lag1	26293	Players' deceptive action before flop, lagged sum 1 hand in the past.	Integer [0,1].
	PRFLOP_decept_lag5	25964	Players' deceptive action before flop, lagged sum 5 hands in the past.	Integer [0,5].
	PRFLOP_decept_lag10	25568	Players' deceptive action before flop, lagged sum 10 hands in the past.	Integer [0,10].
	PRFLOP_pass_lag1	26293	Players' passive action before flop, lagged sum 1 hand in the past.	Integer [0,1].
	PRFLOP_pass_lag5	25964	Players' passive action before flop, lagged sum 5 hands in the past.	Integer [0,5].
	PRFLOP_pass_lag10	25568	Players' passive action before flop, lagged sum 10 hands in the past.	Integer [0,10].
	PRFLOP_sub_lag1	26293	Players' submissive action before flop, lagged sum 1 hand in the past.	Integer [0,1].
	PRFLOP_sub_lag5	25964	Players' submissive action before flop, lagged sum 5 hands in the past.	Integer [0,5].
	PRFLOP_sub_lag10	25568	Players' submissive action before flop, lagged sum 10 hands in the past.	Integer [0,10].
	HANDS_PLAYED	26380	Number of hands played before current hand.	Integer positive.
	HAND_ID	26127	Number of hands dealt in this session before current hand	Integer positive.
	VICTORY_LAST	26293	Number of hands ago las victory occurred	Integer positive.
	OUTCOME_lag1	26293	Money outcome after the hand, lagged 1 hand mean.	Proportion [-1, 1]
	OUTCOME_lag3	26293	Money outcome after the hand, lagged 3 hand mean.	Proportion [-1, 1]
	OUTCOME_lag5	26293	Money outcome after the hand, lagged 5 hand mean.	Proportion [-1, 1]
	OUTCOME_lag10	26293	Money outcome after the hand, lagged 10 hand mean.	Proportion [-1, 1]
	OUTCOME_lag1_sum	26210	Money outcome after the hand, lagged 1 hand cumulative sum.	Float positive/negative number.
	OUTCOME_lag5_sum	26210	Money outcome after the hand, lagged 5 hand cumulative sum.	Float positive/negative number.
	OUTCOME_lag10_sum	26210	Money outcome after the hand, lagged 10 hand cumulative sum.	Float positive/negative number.

Appendix A. Metadata.

APPENDIX B

EXPECTATION MATRIC	PRFLOP_agro	PRFLOP_sub	PRFLOP_pass	PRFLOP_decept
BANKROLL_PROP	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP	NO EXPECTATION
POS_to_N	POSITIVE	NEGATIVE	NO EXPECTATION	NO EXPECTATION
PRFLOP_agro_o	NEGATIVE	POSITIVE	NEGATIVE	NO EXPECTATION
PRFLOP_decept_o	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION
PRFLOP_pass_o	POSITIVE	NO RELATIONSHIP	NEGATIVE	NO EXPECTATION
PRFLOP_sub_o	POSITIVE	NEGATIVE	NO RELATIONSHIP	NO EXPECTATION
PRFLOP_agro_lag10	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP
PRFLOP_decept_lag10	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP
PRFLOP_pass_lag10	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP
PRFLOP_sub_lag10	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP	NO RELATIONSHIP
HAND_ID	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION
VICTORY_LAST	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION
HANDS_PLAYED	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION	NO EXPECTATION
OUTCOME_lag10_sum	POSITIVE	NEGATIVE	NEGATIVE	NO EXPECTATION

Appendix B. Expectation matrix.

Green color represents the expectation being consistent with the study.
Orange meaning result is very inconclusive.
Red meaning result was different from expectation.

APPENDIX C

MODEL	TUNED PARAMETERS	FITTED ACCURACY	CROSS VALIDATED ACCUARCY	F1-SCORE	TOP FEATURES (GINI importance)	TOP FEATURES (CONTRIBUTIONS PER T
Deception\Environment	1. min_samples_leaf=3 2. n_estimators=100	0.84	0.79	0.79	1. BANKROLL_prop = 0.94	1. BANKROLL_prop=0.09
Deception\Full (10 hand lag)	1. min_samples_leaf=3 2. n_estimators=500	0.87	0.78	0.87	1. PRFLOP_decept_lag10 = 0.12 2.BANKROLL_prop=0.12 3.PRFLOP_agro_o = 0.115 4.POS_to_N= 0.115 5.PRFLOP_pass_lag10 = 0.11 6.PRFLOP_sub_o=0.105	1.PRFLOP_decept_lag10=0.32 2.PRFLOP_pass_lag10=0.06 3. POS_to_N= 0.06 4.OUTCOME_lag10_sum= -0.057
Agressiveness\Environment	1. min_smaples_leaf=3 2.n_estimators=500	0.49	0.22	0.58	1. BANKROLL_prop = 0.94	1. BANKROLL_prop=0.06
Passivness\Environment	1. min_smaples_leaf=3 2.n_estimators=500	0.49	0.22	0.41	1. BANKROLL_prop = 0.93	1. BANKROLL_prop=0.13
Submisivness\Environment	1. min_smaples_leaf=3 2.n_estimators=500	0.49	0.22	0.73	1. BANKROLL_prop = 0.93	1. BANKROLL_prop=0.06
Agressiveness\Fulll (10 hand lag)	1. min_samples_leaf=3 2.n_estimators=1000	0.86	0.55	0.92	1. PRFLOP_sub_o=0.25 2.PRFLOP_agro_o=0.13	1.HANDS_PLAYED=0.038 2.POS_to_N=0.032 3.VICTORY_LAST=0.025 4.PRFLOP_sub=0.019
Passiveness\Full (10 hand lag)	1. min_samples_leaf=3 2.n_estimators=1000	0.86	0.55	0.84	1. BANKROLL_prop=0.14 2.HANDS_PLAYED=0.14 3.HAND_ID=0.13 4.OUTCOME_lag10_sum=0.12	1.HANDS_PLAYED=0.057 2.OUTCOME_lag10_sum=0.052 3.BANKROLL_prop=0.043 4.HAND_ID=0.038 5.VICTORY_LAST=0.032
Submisiveness\Full (10 hand lag)	1. min_samples_leaf=3 2.n_estimators=1000	0.86	0.55	0.91	1. BANKROLL_prop=0.145 2.HANDS_PLAYED=0.14 3.HAND_ID=0.135 4.PRFLOLP_agro_o=0.135 5.OUTCOME_lag10_sum=0.11	1. POS_to_N= -.032 2.OUTCOME_lag10_sum=0.029 3.VICTORY_LAST= -0.028 4.HAND_ID=0.023

Appendix C. Results. Top models and their properties.