Hold'Em or Fold'Em: Machine Learning in Online Poker

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Abstract

As the field of machine learning grows, for decades we have challenged world champions at their own game. In 1997, DeepBlue was victorious against a Chess grandmaster. Since then, AI has surpassed itself taking on much more difficult feats. With the advent of the Internet came the surge in popularity of Texas Hold'Em thanks to the online poker room. Online gaming has enabled millions of instances of data to be generated. With this data, we have the possibility for AI gaming to take on a new stage and become a world poker champion. This study will demonstrate data mining techniques for the progression of such an AI by determining the value of data generated from online poker rooms and its effectiveness with machine learning classification algorithms.

Contents

1 Introduction

The classic card game of poker began circulating the United States in the early days of the 19th century. As player-ship increases and the game becomes more widespread, it evolves and different cultures or communities develop a multitude of playstyles and variants. Arguably, the most popular variant since its development is Texas Hold 'Em. However, it wasn't until the late 1960's until it began ascertaining its dominance in the gambling world. Over the next few decades, while the variant was being introduced throughout casinos outside of Texas and Las Vegas, the advent of the World Series of Poker (WSoP) and broadcast television formed the foundation of its popularity. With the turn of the 21st century, the game's widespread portrayal in television and movies such as *Rounders* (1988) and *Casino Royale* (2006) is only surpassed by the online poker room.

The popularity of Texas Hold 'Em is undeniably attributed to the growth of the Internet and consumer-at-home computing. From gaming to shopping, every vice imaginable can be supplemented through the Internet. Gambling is no different. Nowadays, there are thousands of betting, fantasy sports, sweepstakes, and of course, online poker sites. The top online poker stars have won millions of dollars in online competition. Famously, by gaining entry to the World Series of Poker from these online rooms, it has been shown that any amateur with discipline and skill can be a top competitor. However, before its popularity surged, the real-money online poker servers were predated by the Internet Relay Chat (IRC) poker server. These servers have been training grounds hosting some of the top WSoP champions along with newcomers and students of the game alike. From 1995-2001, Michael Maurer introduced an Observer program that logged the details of all the games it witnessed in the IRC poker channels. With 100's of millions of hands played in online poker, the IRC Poker Database [1] consists of over 10 million complete hands from this time period.

As the field of machine learning and artificial intelligence continues to grow, common experiments have been in the development of bots to beat the world's best players in a variety of games. Two decades ago, IBM's Deep Blue supercomputer defeated Chess champion Kasparov in a first of its kind feat [2]. Similarly, twenty years later Google's DeepMind AI was able to easily defeat world champions and previous AI at Go, Shogi, and Chess. Able to compute millions of operations per second, computers are able to envision thousands of possible moves. Obviously, these games' rules and board state are relatively transparent and well-developed strategies are readily available to be taught to any person or program. With our current technology, it would be safe to assume that an AI could easily defeat any range of player. However, the difference that makes DeepMind so remarkable is that, unlike classical machine learning, the program taught itself without training during its play sessions to defeat the champions [2]. That does not go without saying the deep learning algorithms employed by DeepMind are not perfect. There is still progress to be made in terms of efficiency and human interaction for AI [3].

When it comes to Hold 'Em, the hidden information and multitude of opponents introduces new problems for a bot to become world champion. While strategies can be taught and observed, the variability of both cards dealt and cards revealed from the deck is difficult to account for. Moreover, opponents may, willingly or otherwise, not always play optimal to strategy. As player count fluctuates and with a possible four rounds of betting, an AI could reasonably have a difficult time forming a playstyle of its own. However, recently researchers at Carnegie Mellon University developed an AI bot capable of defeating professionals in heads up, no-limit Hold 'Em [4]. With this feat, AI continues to do the unthinkable.

My research in this report intends to demonstrate an introduction into the data obtainable from online poker rooms, determine efficient and accurate classifiers, and useful attributes in predicting winning hands and plays for machine learning in online Texas Hold 'Em. Firstly, in the next section with the data obtained from the IRC Poker Database [1], the data obtained from the Observer bot will be deconstructed and explained. Secondly, various attributes will be selected as the player files are scrubbed for complete showdown hands and preprocessed into the proper formatting for data mining. In Section 3, I will demonstrate my use of WEKA [5] as a tool for data mining in the evaluation of various classifiers and attributes. After discussing my findings, I will briefly describe related works from this domain and further considerations for improvements of the study.

2 Data Preprocessing

With the preprocessing process, the goal is to parse through the millions of logged hands and transform the data recovered into a set of readable values and selective attributes for use with WEKA. The process involves analyzing the raw data, parsing it with a special tool, preparing the data into a useful structure, and outputting attribute values in a readable form.

2.1 Raw Structure Data Analysis

The IRC Poker Database contains tens of millions of hands played across 17 channels over seven years. The entire play of each hand including player actions, bets, winnings, bankroll and hole cards at the showdown is shown in the player database. Folded hands are omitted in our research as well as hands won before the showdown.

```
HAND INFORMATION (in hdb file)
------------------------------
timestamp      hand #     #players/starting potsize
         dealer    #play flop    turn    river  showdn     board
766303976   1   455  8  6/600   6/1200  6/1800  3/2400  3s Jc Qd 5c Ah

ROSTER INFORMATION (in hroster file)
------------------------------------
766303976  8  Marzon spiney doublebag neoncap maurer andrea zorak justin

PLAYER INFORMATION (in pdb.* files)
-----------------------------------
player             #play prflop    turn         bankroll    winnings
          timestamp     pos   flop       river          action     cards
Marzon    766303976  8  1 Bc  bc    kc    kf      12653  300    0
spiney    766303976  8  2 Bc  cc    kc    f       10237  300    0
doublebag 766303976  8  3 cc  r     b     bc       7842  500    0 Jh Qh
neoncap   766303976  8  4 f   -     -     -        7857    0    0
maurer    766303976  8  5 f   -     -     -       12711    0    0
andrea    766303976  8  6 cc  c     c     f        7190  300    0
zorak     766303976  8  7 r   c     c     cc       4460  500    0 As Kc
justin    766303976  8  8 c   c     c     r        4304  500 2400 Ad Qs
```

Figure 1: Raw Data Structure from IRC Poker Database.

From the seventeen channels, data is excluded from poker variants Omaha and 7-stud as well as bot only channels. The IRC has channels for variants of Hold'Em of various limits, minimum buy-in, and tournaments. Each channel contains data directories separated by month from which the Observer participated in the channel. For each month, there is a file for hand information (hdb), roster information (hroster) and player information (pdb.*). Each entry in each file has a timestamp as a primary key for the hand being played. An entry in the hroster file denotes the number of players at the table followed by their nicknames. An entry in the hdb file denotes the game number, number of players dealt cards, the players and pot size in each betting round, and finally the board at the end of the hand (0, 3, 4, or 5 cards). For each player, there is a pdb file associated with their nickname. Each entry in their respective file shows the player's position at the table, their action during each betting round, current bankroll, total bet, winnings, and hole cards for each hand completed. Figure 1 shows an example of the data displayed in tabular format.

2.2 Data Transformation and Preparation

Using a python script [6], all 212,069 files in the database were scanned. The information gathered from the player's database were the number of dealt cards for a particular hand, the player's position, their total bet, their winnings, and their hand revealed at showdown. Whether the cards revealed were suited was gathered, however, the individual suit from each card was not taken into account. As well, the ordering of the cards in the hand matters. From this set, every hand revealed had their total bets and winnings across all rooms stored as well as a metric *profitability* attributed to it. The *profitability* of a hand is the quotient of the total winnings over the bets.

From the hand database, the board cards were obtained for the timestamp of the hand played as well as the number of players dealt cards.

The number of completed hands resulted in 9,745,525 with 325 distinct hands. Some entries in the data base had to be deleted from corruption during unpacking but the amount was negligible.

2.3 Data Training and Testing

Due to the size of the resultant dataset, the ARFF files were split into 9 with 1,000,000 records each and a 10th with 745,525 records. To simplify the model for WEKA, betting actions and board cards were omitted as attributes because of high variance and the resulting number of features that would be added to the already computationally heavy dataset. The only feasible betting actions to collect would be betting or raising however the data would be skewed because of limit table regulations on betting. This is the same reason as why profitability was chosen as an attribute instead of total action of the hand. The attributes described in Table 1 were used with the WEKA tool.

Attribute	Description	Trying to Measure	Value
Cards dealt	The number of cards dealt at the table for the hand	Correlation with class	numeric
Player position	The player's position at the table	Correlation with class	numeric
Profitability	Profitability of player's hand	Correlation with class, likelihood of hand appearing in showdown	numeric
card1	The first card dealt to the player for the hand	Number of winning classifications	Nominal 2, , A
card2	The second card dealt to the player for the hand	Number of winning classifications	Nominal 2, , A
suited	True if card1 and card2 are the same suit	Number of winning classifications	Nominal True, False
win	True if the player's hand won the showdown	class	Nominal True, False

Table 1: Attributes for classifying instances.

3 Data Mining

The data mining process aims to test the effectiveness of a set of classifiers used for each dataset in the WEKA tool. It is also to gain insight on the attributes used in the classifiers. The WEKA tool aids us in determining the number of instances of each attribute for the dataset and its correlation to the classification. This section will show the results of the averages of the classifiers, visualizations from the most effective classifier, evaluation of the attributes, and observations of patterns from the results.

3.1 Result of Classifiers

Figure 2 shows the average prediction quality of the set of classifiers used. 5 of the classifiers were chosen to demonstrate the accuracy and speed for different methods of tree growth and regression. Naive Bayes was used because it is the fastest overall and provides depth for the classification of attributes. Each classifier performed a 10-fold cross-validation with default configurations in the WEKA tool. The classifiers JRip and IBk were considered, however, for a dataset of this size and since there were no missing attributes, they were ruled as computationally infeasible. The relatively low percentages of correctly classified instances can possibly be a consequence of not being able to train the entire dataset or to the high variance of the numeric attributes which are scored highest in the attribute evaluation.

As the most accurate classifier, Figure 3 shows a summary of output from the Classification with Regression model with one of the datasets. Figure 4a shows the trees generated from the classifier and the attributes chosen in their construction. Figure 4b shows an example of rules generate to calculate the linear model used to predict the class. Figure 5 shows a J48 tree for comparison.

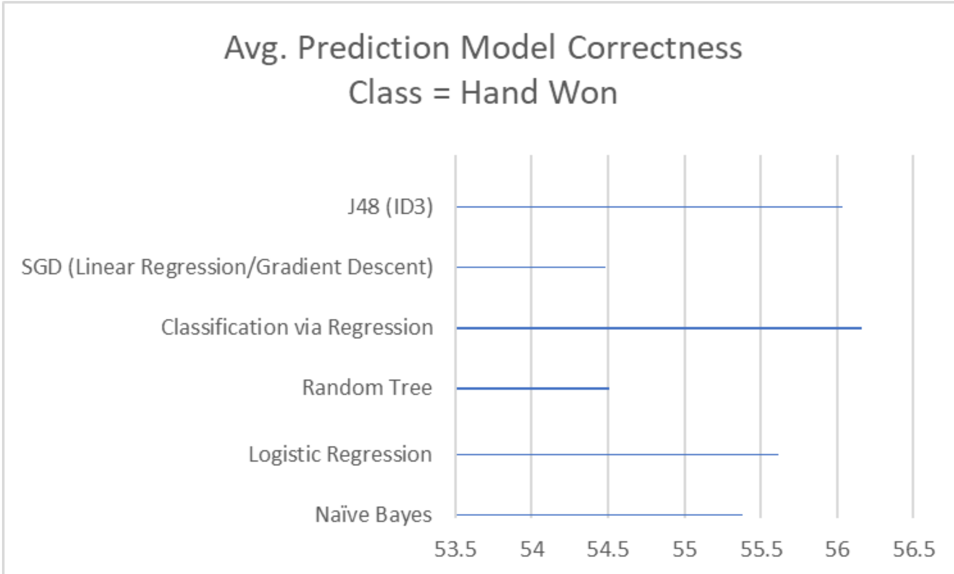


Figure 2: The results of the correctness of classifiers in WEKA.

```
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      562316              56.2316 %
Incorrectly Classified Instances    437684              43.7684 %
Kappa statistic                          0.0993
Mean absolute error                      0.4882
Root mean squared error                  0.4942
Relative absolute error                 98.0641 %
Root relative squared error             99.0497 %
Total Number of Instances          1000000

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.336    0.240    0.552      0.336    0.418      0.107    0.576     0.540     yes
                 0.760    0.664    0.566      0.760    0.649      0.107    0.576     0.594     no
Weighted Avg.    0.562    0.465    0.560      0.562    0.541      0.107    0.576     0.569

=== Confusion Matrix ===

      a      b   <-- classified as
 157211 310072 |      a = yes
 127612 405105 |      b = no
```

Figure 3: Summary output of Classification via Regression model

```
=== Run information ===

Scheme:       weka.classifiers.meta.ClassificationViaRegression -W weka.classifiers.trees.M5P -- -M 4.0
Relation:     poker
Instances:    1000000
Attributes:   7
              cards_dealt
              player_position
              profitability
              card1
              card2
              suited
              win
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

Classification via Regression

Classifier for class with index 0:

M5 pruned model tree:
(using smoothed linear models)

card1=J,Q,K,A <= 0.5 :
|   cards_dealt <= 4.5 :
|   |   card2=9,T,J,Q,K,A <= 0.5 :
|   |   |   profitability <= 1.034 :
|   |   |   |   card1=8,9,T,J,Q,K,A <= 0.5 :
|   |   |   |   |   profitability <= 0.962 :
|   |   |   |   |   |   profitability <= 0.711 :
|   |   |   |   |   |   |   profitability <= 0.376 : LM1 (2645/100.123%)
|   |   |   |   |   |   |   profitability >  0.376 : LM2 (3125/97.802%)
|   |   |   |   |   |   profitability >  0.711 : LM3 (22717/97.921%)
|   |   |   |   |   profitability >  0.962 : LM4 (9336/99.094%)
|   |   |   |   card1=8,9,T,J,Q,K,A >  0.5 :
|   |   |   |   |   card2=8,9,T,J,Q,K,A <= 0.5 : LM5 (15215/99.066%)
|   |   |   |   |   card2=8,9,T,J,Q,K,A >  0.5 : LM6 (5250/99.217%)
|   |   |   profitability >  1.034 :
|   |   |   |   profitability <= 1.138 :
|   |   |   |   |   card1=8,9,T,J,Q,K,A <= 0.5 : LM7 (8660/99.639%)
|   |   |   |   |   card1=8,9,T,J,Q,K,A >  0.5 : LM8 (5305/99.627%)
```

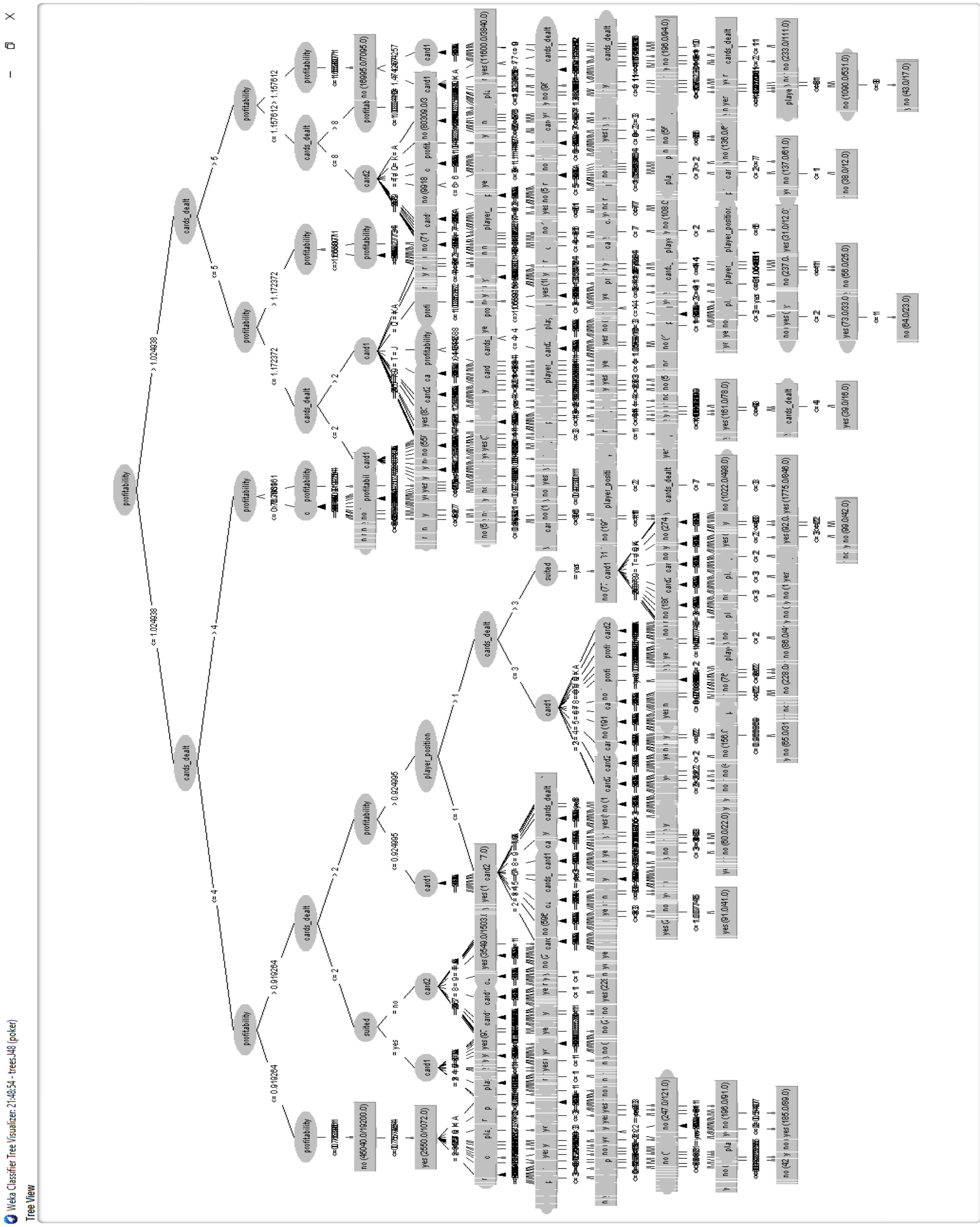


Figure 5: J48 Tree Structure from an instance of the dataset

3.2 Observations

3.2.1 Attribute Evaluation

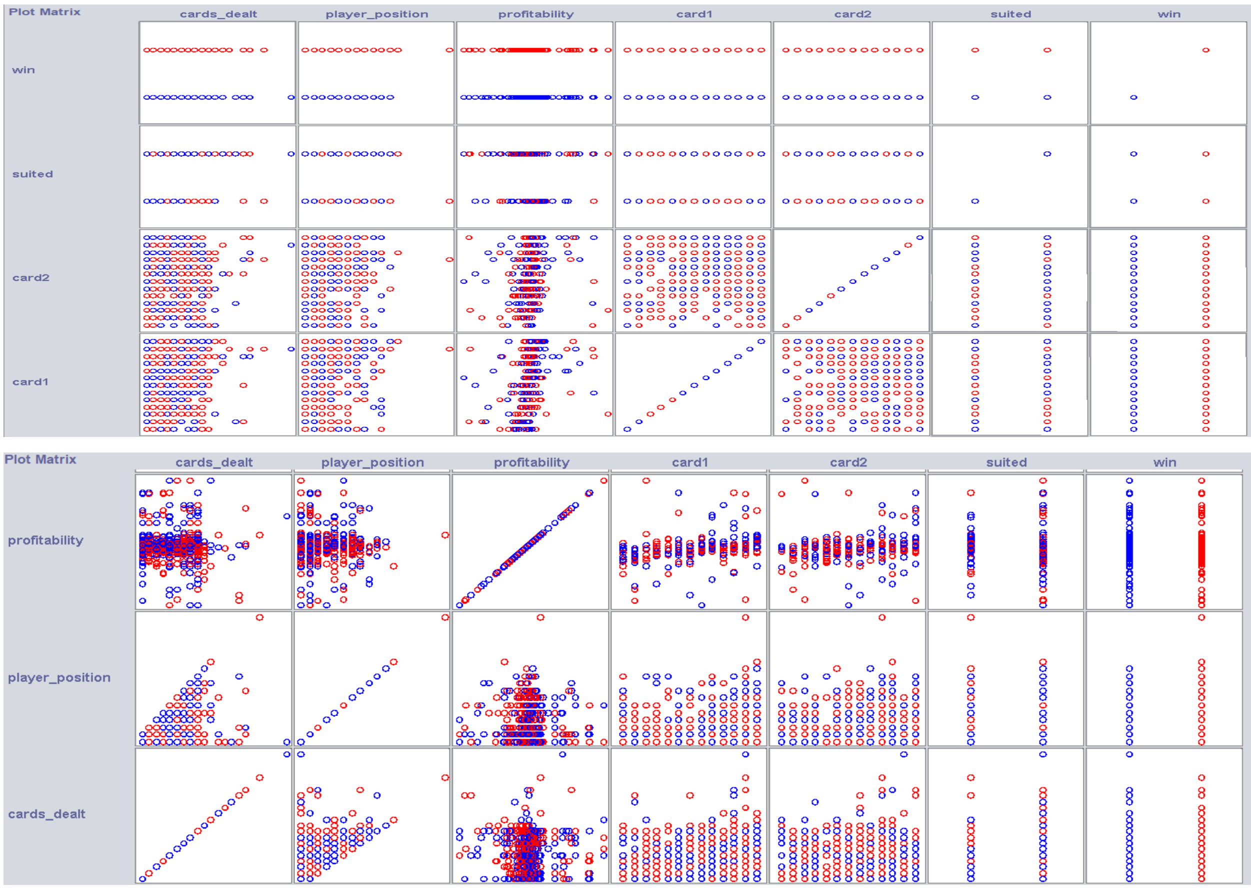


Figure 6: Distribution of Attribute values.

Figure 6 shows the distribution of attribute values. It is important to note that the plots have a relatively uniform distribution amongst each other. Table 2 shows the results of various WEKA evaluations. From the evaluation, we may infer:

- *Profitability* has the highest information gain for winning hands, as expected. Hands that tend to win the pot more frequently will have more winnings resulting in a positive correlation. However, profitability is generally an indicator for a good hand and not a winning one.
- *Cards dealt* has a surprisingly high evaluation score. It may be seen that when a player has a good hand, they are likely to win if the value of cards dealt is low. However, from the visualized plot, the distribution of cards dealt and wins (as well as its correlation with other features) quite uniform.
- *Card1* and *Card2* unsurprisingly have a high evaluation score considering the better cards are more likely to win. Surprisingly, the ordering of cards was not an important factor in predictions as their evaluation scores were very marginally different.
- *Player position* surprisingly has a low evaluation for information gain. In Texas Hold 'Em, having a high player position is a major advantage for deciding player action. This attribute could better be correlated with player's bankroll, player actions, or folded hands.
- *Suited* came in dead last in for every evaluation. This is surprising because, despite card quality, suited hole cards are less likely to be folded. However, since the data proves that majority of hands played,

both winning and losing, are not suited, it is reasonable that this attribute does not contribute highly to any prediction model. Moreover, paired hole cards, which are inherently not suited, have a higher likelihood of winning than other opening hands.

Evaluator	Search	Attribute
CfsSubsetEval	BestFirst	Cards dealt Profitability Card1 Card2
InfoGainAttributeEval	Ranker	Profitability Card1 Card2 Cards dealt Player position suited
GainRatioAttributeEval	Ranker	Profitability Card1 Card2 Cards dealt Player position suited
CorrelationAttributeEval	Ranker	Cards dealt Profitability Player position Card1 Card2 suited

Table 2: Evaluation of Attributes with WEKA

3.2.2 Analysis of Results

As seen in Figure 2, the Classification vs Regression model ended up being the most effective at correctly classifying the winnings hands. Figure 3 shows us in the confusion matrix, that the majority of incorrect classifications were hands that won but were classified as losing. This may be a result from the majority of the data containing losing hands. In Figure 4a, we see that the card attribute at the root making it one of the most important factors in predicting the class. Following along the cards dealt branches gives to pruning at either the profitability leaves or other card attribute leaves. The linear model rule in Figure 4b shows that the subsets of nominal values for the card attributes are barely considered and it is the other attributes, even if marginal, that decide the outcome. The card attributes are mainly for guiding along the tree to the appropriate linear model.

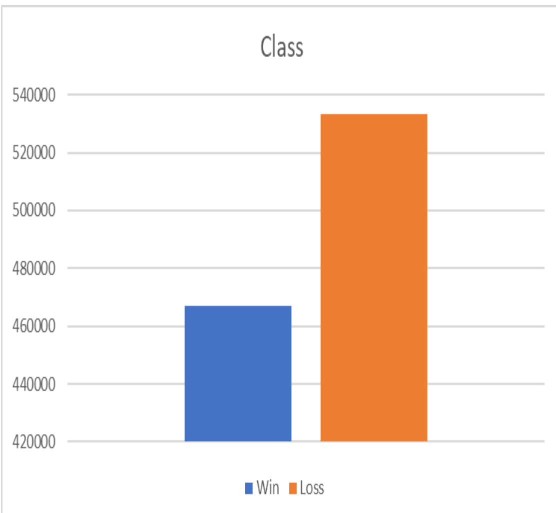
4 Evaluation

As discussed in Section 1, the goal of this study was to determine possible attributes and classifiers to effectively predict winning Texas Hold'Em hole cards for machine learning poker bots. From Figure 2, we see that with the given attributes, no classifiers used were able to sufficiently predict winning hands from the online poker dataset. Although the predictions were correct for the majority of the instances, the quality of prediction can be greatly improved.

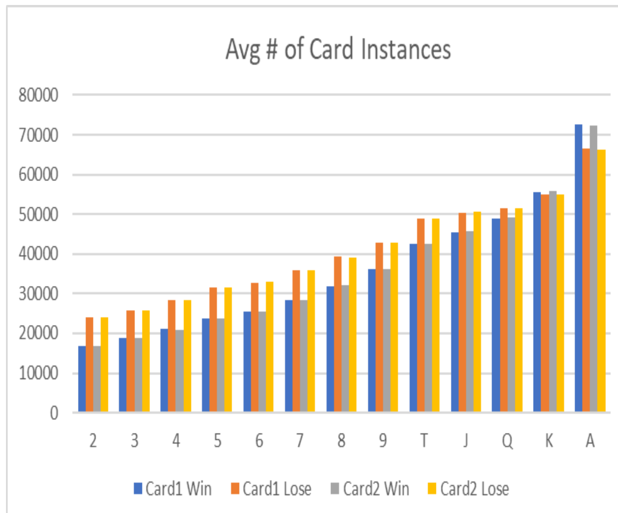
The best classifier model was the Classification via Regression model as discussed in Section 3. As for the attributes, for our model, suited and player position were effectively not considered. As predicted, the cards and profitability were key attributes for information gain yet the decision came down to the correlation between the class and cards dealt. In further studies, possible attributes to consider would be the betting actions of the player, the suit of the individual cards, and the board of cards at showdown.

Interesting patterns recognized during the data mining process include:

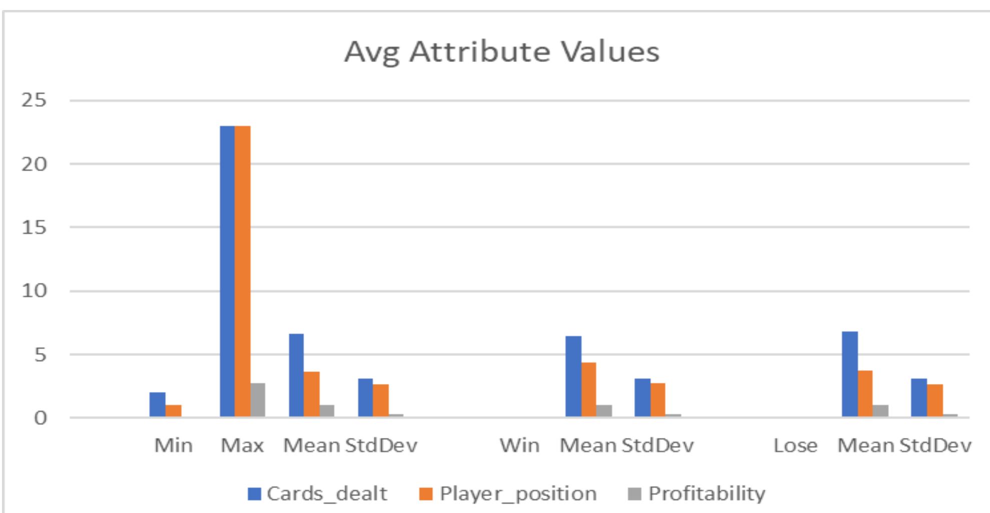
- There were more losses on average recorded than wins (see Figure 7a).
- The number of instances on average of a card steadily increases with value (see Figure 7b).
- The mean profitability is relatively the same for wins and losses (see Figure 7c).
- The mean player position is greater for wins than losses (see Figure 7c).
- The mean cards dealt is greater for losses than wins (see Figure 7c).
- The most profitable hands aren't necessarily the highest winning or most betted on (see Table 3).



(a) Win vs Loss



(b) Card Instances



(c) Attribute Instances

Figure 7: Data collected from Naive Bayes classifier

Most Profitable	Profitability	Highest Winnings	Chips earned	Most Bets	Chips bet
6 10	2.731	Q 8 suited	1,331,584,695	K A suited	862,802,860
4 4	2.028	4 4	961,040,437	10 A suited	595,458,167
6 7 suited	2.018	K K	730,873,294	K K	489,618,855
7 A	1.849	J J	703,683,725	Q Q	455,155,624
2 Q	1.836	A 10	197,614,274	J J	424,398,968

Table 3: Data collected from Naive Bayes

5 Related Work

The Libratus bot discussed in Section 1 has not been the only data science project involving the game of poker. A study on the profitability of Texas Hold'Em hole cards used the data from real money tables consisting of over 115 million hands. The researchers developed their profitability using distinct pairs, suit, and player position at the table [7]. A similar study was conducted using the data of 120 million hands from former online site *Pokerroom* [8]. These studies take into account the type of players found in certain channels. They high correlation between the hole cards being suited and the effect of player position on profitability were reasons for choosing those attributes in my study. It is found from the latter study that less than a quarter of possible hands are profitable and that the top five of those hands account for half of the profits.

A data scientist used the data from the IRC Poker database to plot the likelihood of betting with a pair in hole cards and analyzed the efficiency of classification algorithms for predicting if the player has a pair [9]. His study formed the basis for my interpretation of the raw data structures discussed in Section 2.

Further related work comes from the curator of the IRC Poker database on the variance of Hold'Em using the data he provided us [10].

Discovery of these studies provided not only a glimpse of the amount of data created by online poker but the extensiveness of attributes contributing to each hand played as it showed me that from these attributes sensible data may be predicted.

6 Conclusion

As discussed in Section 1, with the advent of the Internet, online gaming and online gambling has brought Texas Hold'Em to the peak of its popularity. With hundreds of millions of hands by millions of users globally, any one of them can be the next world champion. That is, until the AI bots take over. As we've seen before with many strategical games, sophisticated machine learning is capable of dethroning the brightest of us all. By utilizing the data created by the millions, finding improvements to predicting classifications is essential to strengthen these programs.

With millions of instances of data, finding the right classifiers and attributes in the records becomes challenging. Improvements can always be made as seen with the results of this paper. In Section 2, we demonstrated that given the data from the IRC Poker database, when mined to gather values, we could determine a selective group of meaningful numerical and nominal attributes to be tested. With some of the most efficient classification algorithms, we were able to determine the correctness of their predictiveness and ascertain the value of those attributes. In Section 3, we observed that with the best of those algorithms producing only correct predictions for nearly half of the millions of instances, the evaluation of attributes still gave insight for further improvements. Analysis of the classifier and attributes provided details for which attributes were effective and why. Patterns within the values of the data were recognized providing a real-world perspective for comparison with the algorithmic predicted outcomes as shown in Section 4.

Finally, the evaluation and analysis contribute to further considerations of related studies for efficiency and selection of attributes and classifiers for the predictiveness of winning poker hands.

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