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Opponent Modelling in Texas Hold'em Poker as the Key for Success

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Abstract. Over the last few years, research in Artificial Intelligence has focussed on games with incomplete information and non-deterministic moves. The game of Poker is a perfect theme for studying this subject. The best known Poker variant is Texas Hold'em that combines simple rules with a huge amount of possible playing strategies. This paper is focussed on developing algorithms for performing simple online opponent modelling in Texas Hold'em Poker enabling to select the best strategy to play against each given opponent. Several autonomous agents were developed in order to simulate typical Poker player's behaviour and an observer agent was developed, capable of using simple opponent modelling techniques, in order to select the best playing strategy against each opponent. The results obtained in realistic experiments using eight distinct poker playing agents showed the usefulness of the approach. The observer agent is clearly capable of outperforming all their counterparts in all tests performed.

1 INTRODUCTION

Incomplete knowledge, risk management, opponent modelling and dealing with unreliable information are topics that identify Poker as an important research area in Artificial Intelligence (AI). Unlike games of perfect information, in poker, players face hidden information resulting from the opponents' cards and future actions. In such a domain, to be successful, players face the need to use opponent modelling techniques in order to understand and adapt themselves to the opponents playing style [1,2]. However, the huge amount of possible playing strategies in Poker makes opponent modelling a very hard task in this domain.

Poker is a popular card game in which players bet on the value of the card combination in their possession. The winner is the one who holds the highest valued hand according to an established hand rankings hierarchy, or otherwise the player who remains "in the hand" after all others have folded. Texas Hold'em is the most popular poker game. It is a community card game where each player may use any combination of the five community cards and the player's own two hidden cards to make a poker hand. This characteristic makes it a very good game for strategic analysis.

The main goal of the project is to prove that a poker agent that considers the opponent behaviour has better results, against players that use typical poker playing strategies, than an agent that doesn't, even when playing the same global betting strategy.

2 RELATED WORK

This project is based on previous betting strategies developed at the University of Alberta [1,2,3,4]. They are divided in betting strategy before the flop and after the flop [4]. There are 1326 possible hands prior to the flop. The value of one of these hands is called an income rate and is based on an off-line computation that consists of playing several million games where all players call the first bet [5,6]. The basic betting strategy after the flop is based on computing the hand strength (HS), positive potential (PPot), negative potential (NPot), and effective hand strength (EHS) of agent's hand relative to the board. EHS is a measure of how well the agent's hand stands in relationship to the remaining active opponents in the game. The hand strength (HS) is the probability that a given hand is better than that of an active opponent. Suppose an opponent is equally likely to have any possible two hole card combination. Thus it is possible to calculate the hand strength as:

```
HandStrength(ourcards, boardcards) {
  ahead = tied = behind = 0
  ourrank = Rank(ourcards, boardcards)
  for each case(oppcards) {
     opprank = Rank(oppcards, boardcards)
     if (ourrank>opprank) ahead += 1
       else if (ourrank==opprank) tied += 1
         else behind += 1
   }
  handstrength=(ahead+tied/2)/ahead+tied+behind)
  return(handstrength)
}
```

After the flop, there are still two more board cards to be revealed and it is essential to determine its potential impact. The positive potential (PPot) is the chance that a hand that is not currently the best improves to win at the showdown. The negative potential (NPot) is the chance that a currently leading hand ends up losing. PPot and NPot are calculated by enumerating over all possible hole cards for the opponent, like the hand strength calculation, and also over all possible board cards. The effective hand strength (EHS) combines hand strength and potential to give a single measure of the relative strength of a hand against an active opponent. A simple formula for computing the probability of winning at the showdown is: Pr(win)=HSx(1-NPot)+(1-HS)xPPot. Since the interest is the probability of the hand is either currently the best, or will improve to become the best, one possible formula for EHS sets NPot=0, giving: EHS=HS+(1-HS)xPPot.

3 OPPONENT MODELLING

No poker strategy is complete without a good opponent modelling system [7]. A strong poker player must develop an adaptive model of each opponent, to identify potential weaknesses. In poker, distinct opponents can make different kinds of errors that may be exploited [4]. The Intelligent Agents developed in this project observe the moves of the other players in the table. There are many possible approaches to opponent modelling [2,8,9], but in this work the observation model is based on basic observation of the starting moves of the players, so it could be created a fast, online estimated guess of their starting hands in future rounds.

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Players could be classified generally in four models that depend of two parameters: loose/tight and passive/aggressive. Knowing the types of hole cards various players tend to play, and in what position, is probably the starting point of opponent modelling. Players are classified as loose or tight according to the percentage of hands that he plays. These two concepts are obtained analysing the percentage of the time a player puts money into a pot to see a flop in Hold'em - VP$IP (voluntarily put money in the pot). The players are also classified as passive or aggressive. These concepts are obtained analysing the Aggression Factor (AF) which describes the player's nature.

4 INTELLIGENT AGENTS

Based on the player classification developed 8 intelligent agents were created, two for each player style: LA - Loose Aggressive (Maniac and Gambler); LP - Loose Passive (Fish and Calling Station); TA - Tight Aggressive (Fox and Ace); TP - Tight Passive (Rock and Weak Tight). A general observer agent was also created capable of keeping the information of every move made from the opponents and calculating playing information like the VP$IP and AF of each opponent in every moment of the game. The opponents are classified into 4 types of players: loose if VP$IP above 28% tight otherwise; aggressive if AF above 1, passive otherwise.

After player classification the agent could consider a different range of possible hands for different opponents. A general consideration is that tight players have a smaller range of possible hands than loose agents. In order to pass this information to Hand Strength calculation, for each player is determined a parameter that was called "sklansky". This parameter represents the lowest value of a hand that belongs to the most probable range of hands that the player plays with that specific movement (call or raise). Taking into account that many times the correct hand of the opponent is wrongly ignored, the better approach of Effective Hand Strength calculation given with this technique should give a better result that compensates this. The Hand Strength and Potential Hand Strength could now be calculated with a better approach. It is calculated only considering the hands with a rank better than the "sklansky" parameter.

5 RESULTS

In order to obtain results, several simulations were made with the agents created. In each simulation 8 normal agents and 1 observer were used at the table with the intention to give the Observer Agent the possibility to play in a table with all different kind of players: LA in the first round of simulations, LP in the second, TA in the third and TP in the final round of simulations.

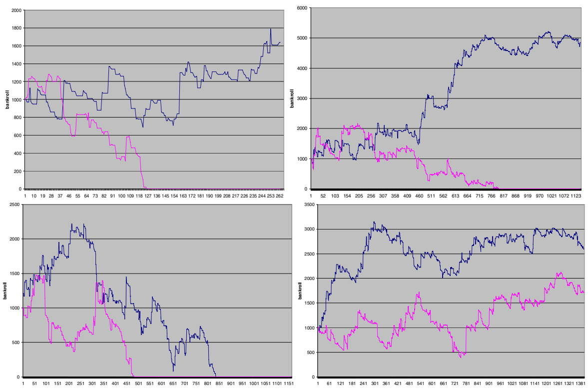

Figure 1: Bankroll of LA (top-left), LP (top-right), TA (bottom-left) and TP (bottom-right) observer agents (dark blue) compared with corresponding non-observer agents (magenta)

The hand selection in the pre-flop of the Observer was equal to the type of agent modelled using the opponent modelling strategy to change the hand strength potential accordingly to the opponents. Each one of the simulations performed was repeated 3 times and ends up when one of the two agents looses all his bankroll or after 2000 games. Figure 1 shows the bankroll variation of the four observer agents compared with corresponding non-observer agents.

In the 12 complete experiments performed (more than 10 000 games in total), the Observer achieved better results than the non observer agent that uses the same hand selection in pre-flop. The most conclusive results are with passive agents, Observer besides having always a big advantage from non observer, the results are also very good, reaching a good level of bankroll. With aggressive agents, the simulations seem to be a bit inconclusive due to big variations of bankroll that sometimes causes the end of the game too soon for an agent. Although, we can conclude that opponent modelling could help these kinds of agents to keep in game for a long time.

6 CONCLUSIONS AND FUTURE WORK

From the results achieved it is possible to verify that the Observer agent has better results than a non observer agent, even when the strategy of hand selection is not very good. This proves that even with simple opponent modelling strategies it is possible to achieve good results. However playing normal poker, due to the reduced number of games and the incomplete information gathered, only simple opponent models are possible to create online and thus, the approach proposed is very useful. At the end of this project, we have a good, stable simulator to test future work and an Observer Agent capable of playing poker at an acceptable level, improving the capabilities of the original agent, prepared to be explored, introducing new functionalities.

Future work may be concerned in exploring topics like learning to play depending on the position at the table and bluffing. Regarding opponent modelling in Texas Hold'em, future work may include: to consider more than the 4 type of players; analyse other player style variables; and retrieve information from the cards shown at showdown.

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