Poker Project - Team 07

Arielyte Tsen Chung Ming, Devarajan Preethi, James Pang Mun Wai, Lee Yi Wei Joel, Yip Seng Yuen
National University of Singapore
chungming.tsen@u.nus.edu, e0203237@u.nus.edu, jamespang@nus.edu, lywjoel@u.nus.edu, yip@u.nus.edu

1 Introduction

The game of poker has long been a field of interest for artificial intelligence (AI) researchers. There are many challenges with developing an AI poker agent capable of competing with humans, since poker is a complex game that forces players to make decisions with incomplete and imperfect information. AI poker agents are hence faced with the task of having to make the best decision at every street under such informational constraints. Additionally, conventional poker matches impose a time limit on players to make a decision, adding another constraint for AI poker agents to work with.

This paper outlines our design of an AI poker agent for Heads Up Limit Texas Hold'em, which aims to respond competently and accurately with limited information, within a limited amount of time. In tackling the issues above, we employed a three-pronged approach:

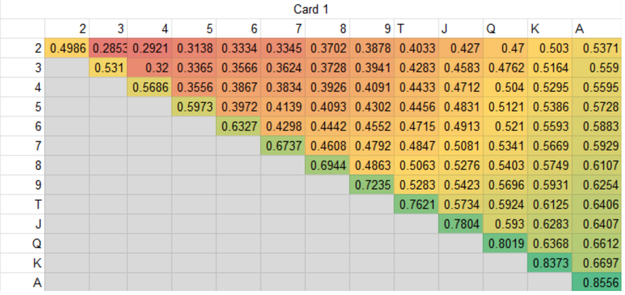
- Using Q-learning, a reinforcement learning algorithm, to train our agent to play with the best possible strategy. (Section 3)
- Using the Average Rank Strength (ARS) heuristic and other methods of abstracting information sets to reduce the overall state size. (Sections 3.1, 3.3)
- Precomputing the estimated hand strength of possible card sets to allow the agent to retrieve information in linear time.

The following two sections will explain our agent's strategy within each betting round, namely the pre-flop and post-flop round.

2 Pre-Flop Hand Strength

To begin with, we wanted to decide how the agent would determine the strength of its hand, based only on the pre-flop round. Due to the limited amount of information that we can manipulate during the pre-flop round, the strength of a hand, HS, at pre-flop is determined by the probability of winning, $Pr(Win)$, based on the prior knowledge of the two hole cards currently in hand.

To estimate HS, we simulated 10,000 games for each possible combination of starting hand. The total combination of starting hands is 13 + $\binom{13}{2}$ = 91, obtained by summing up the combinations of pocket pairs and the combinations of possible hands, ignoring the suits. For each game, we first pick the two starting cards for the agent, followed by randomly picking two starting cards for the opponent and five community cards. Both players' hands are then revealed and the game result determined as a win or a loss for the agent.



		Card 1												
		2	3	4	5	6	7	8	9	T	J	Q	K	A
Card 2	2	0.4986	0.2853	0.2921	0.3138	0.3334	0.3345	0.3702	0.3878	0.4033	0.427	0.47	0.503	0.5371
	3		0.531	0.32	0.3365	0.3566	0.3624	0.3728	0.3941	0.4283	0.4583	0.4762	0.5164	0.559
	4			0.5686	0.3556	0.3867	0.3834	0.3926	0.4091	0.4433	0.4712	0.504	0.5295	0.5595
	5				0.5973	0.3972	0.4139	0.4093	0.4302	0.4456	0.4831	0.5121	0.5386	0.5728
	6					0.6327	0.4298	0.4442	0.4552	0.4715	0.4913	0.521	0.5593	0.5883
	7						0.6737	0.4608	0.4792	0.4847	0.5081	0.5341	0.5669	0.5929
	8							0.6944	0.4863	0.5063	0.5276	0.5403	0.5749	0.6107
	9								0.7235	0.5283	0.5423	0.5696	0.5931	0.6254
	T									0.7621	0.5734	0.5924	0.6125	0.6406
	J										0.7804	0.593	0.6283	0.6407
	Q											0.8019	0.6368	0.6612
	K												0.8373	0.6697
	A													0.8556

Figure 1: Estimated winning probabilities with starting hands

We then calculate $Pr(Win)$ using the formula:

$$Pr(Win) = \frac{\#\,of\ wins}{Total\ games\ played}$$

Where the total games played is fixed at 10,000 in our case. The results of our simulation are seen in Figure 1.

At every pre-flop street, the agent chooses an action to be performed based on the starting hand's estimated probabilities of winning, which are:

$$\left.\begin{aligned} &raise\colon Pr(Win) > k \\ &call\colon Pr(Win) > j \\ &fold\colon Pr(Win) \leq j \end{aligned}\right\} \quad \text{where } 0 < j < k \leq 1$$

Where j and k are pre-determined thresholds set for the agent.

3 Post-Flop Rounds

3.1 Q-learning

In subsequent post-flop rounds, reinforcement learning is employed. Specifically, the technique of Q-learning - which was described in the introduction - was used to train our agent.

In Q-learning, we maintain a table of states and actions as input for the agent. Each state has a Q-value that corresponds to each action. An illustration of it can be seen in Table 1.

State	**Action**		
	fold	*call*	*raise*
1			
2			
3			
...			
S			

Table 1: Q-learning Training

After each training round, the Q-value of each state is calculated and updated based on the formula given below:

$$Q\left(s',a'\right) = Q\left(s,a\right) + \sum_{0}^{t} \lambda^{t} R_{t}\left(s,a\right)$$

Where t is the number of turns between the current move and the terminal node, R_t is the reward for round t, λ is the discount factor, s is the state, a is the action and P is the pot size.

$$R_t = \begin{cases} +\frac{P}{2} & \text{if win,} \\ -\frac{P}{2} & \text{otherwise} \end{cases}$$

$$\lambda = \text{discount rate for future reward}$$

Additionally, we applied the technique of experience replay to achieve more efficient use of previous experiences. We store the agent's experiences based on the formula

$$e_t = (s_t, a_t, R_t, s_{t+1})$$

The agent stores the data discovered for each round in a table, and reinforcement learning takes place based on random sampling from the table. This reduces the amount of experience required to learn, replacing it with more computation and memory which are cheaper resources than the agent's continuous interactions with the environment [Schaul *et al.*, 2016].

ε-Greedy Algorithm

At every turn, with a probability of ε, a random action is chosen to be performed, otherwise an action with the best expected reward is chosen.

The value of ε will slowly decrease as the agent acquires more training. A relatively large initial value ensures that all possible paths will be explored before the agent settles into a sub-optimal pattern. The i-th *State* and possible *Actions* for the ε-Greedy Algorithm is

$$State_i = \{EHS_i,\ S_i,\ P_i,\ \#OR_i,\ \#SR_i,\ OPS_i\}$$

$$Actions = \{fold,\ call,\ raise\}$$

Where

EHS refers to the current Expected Hand Strength of a given player. More details can be found in Section 3.2.

S refers to the current Street that the game is in, which is the start of each new round.

P refers to the Pot Size, which is the total amount in the player's bet.

#OR refers to the number of Opponent Raises per street.

#SR refers to the number of Self Raises per street.

OPS refers to the Opponent Playing Style.

Abstraction of states

Without abstracting the states into groups, the total size of the state space will be very large and it would be infeasible to calculate all possible states. Therefore, we can apply abstraction by grouping some of the features in increments.

- *EHS* is grouped in increments of 0.01.
- There are three streets - Flop, Turn and River.
- *P* in a game ranges from \$0 to \$680, but by grouping it in increments of \$40, which is the 2 x big blind amount, since every raise (big blind amount - \$20) must minimally be matched by the opponent, we get a range of 0 to 17.
- *OR* is grouped into five different groups, i.e. from 0 to 4.
- *SR* is grouped into five different groups, i.e. from 0 to 4.
- *OPS* is grouped into four categories. More details can be found in Section 3.4.

These groupings helped reduce the complexity and cut down the size of the total state space to: 101 x 3 x 35 x 5 x 5 x 4 = 1,060,500 states

3.2 Expected Hand Strength

The Expected Hand Strength, *EHS* is the probability of the current hand of a given player winning if the game reaches a showdown. It factors in all possible combinations of the opponents' hands, the remaining hidden board cards, and performing a comparison between the agent's hand and the hands in the enumeration to see which is better. The quality of the hand is then measured based on the number of times the hand turns out to be better. For our ε-Greedy Algorithm, the *EHS* is grouped in increments of 0.01. The remaining cards, *Rem* is given by:

$$Rem = [\alpha \backslash \beta]^5$$

Where α is the set of all cards in the deck, and β is the set of all hole cards of a particular player. The formula to calculate the rank of each hand, $Rank(h)$ is:

$$Rank(h) = max(\forall x \in [\beta \cup \Omega]^5 : s(x))$$

Where Ω is the set of community cards. Having *Rem* and $Rank(h)$, it is now possible to calculate *HS* through the formulas below:

$$Ahead(h) = \#\{\forall x \in Rem : s(x) > Rank(h)\}$$
$$Tied(h) = \#\{\forall x \in Rem : s(x) = Rank(h)\}$$
$$Behind(h) = \#\{\forall x \in Rem : s(x) < Rank(h)\}$$

Thus, the *EHS* for player h against 1 opponent is given by:

$$EHS(h) = \frac{Ahead(h) + \frac{Tied(h)}{2}}{Ahead(h) + Tied(h) + Behind(h)}$$

The above formulas used to derive the *EHS* was referenced from Teofilo *et al.* [2013a]. Note that the *EHS* may be used at any round of the game. However, the time required to compute an accurate EHS exceeds the time constraint of 0.2s set by the project guidelines, as the number of iterations needed to compute it for a single hand at the pre-flop street is very high. This issue is addressed by using the Average Rank Strength technique which is explained in the next section.

3.3 Average Rank Strength

A technique developed by Teofilo *et al.* [2013b] called Average Rank Strength (*ARS*), is used to improve the efficiency of *EHS*. *ARS* consists of using the hand score to estimate the future outcome of the match, without having to generate all card combinations. This is simply done by storing the average *EHS* of a hand for each score in three lookup tables, one for Flop, one for Turn and one for River. Since we are not considering suits, the number of possible scores is reduced. The pre-computation of a given score is as follows:

$$ARS_5\left(C_1,C_2\right) = \left(\frac{\sum_i X_i \in [\alpha\backslash\beta]^5 : Rank\left(X_i \cup \{C_1,C_2\}\right)}{\#[\alpha\backslash\beta]^5}\right.$$

Where X_i is a distinct subset of size 5 of the deck except the pocket cards.

Thus, compared to *EHS*, *ARS* had a three orders of magnitude faster response time when querying the lookup table, while also doing so with negligible error [Teofilo *et al.*, 2013b]. This is due to the fact that getting the EHS from the lookup table runs in constant time.

To find out the estimated *EHS* for the three post-flop streets, we simulated 2,500,000 rounds each. Additionally, for each round of simulation, we ran the Monte Carlo sampling algorithm 500 times to obtain the *EHS*. The results are displayed below:

Street	**Number of Combinations**
Flop	5133
Turn	13,408
River	17,470

Table 2: Result of *ARS* Simulation

The reason for the high number of simulations is that we want to sample as many score combinations as possible.

Based on the results from simulating 100,000 rounds, approximately 99.87% of the scores can be found in the table. This goes to show that our three *ARS* tables are highly reliable.

3.4 Opponent Playing Styles

According to Rupeneite [2010], the playing style of an opponent can be classified into four categories. Each style is distinct, in that it describes the opponent's frequency of play and how the player bets. The four categories of playing styles are Loose/Passive, Loose/Aggressive, Tight/Passive and Tight/Aggressive. A brief description of each style is shown in Table 3 below:

Playing Styles	**Description**
Tight	Plays few hands and often folds.
Loose	Plays multiple and varied hands.
Aggressive	Bets and raises a lot, almost always never checking or call.
Passive	Usually checks and call, unlikely to take the lead.

Table 3: Description of Playing Styles

The Aggressive Factor, *AF*, is used to classify a player as either Aggressive or Passive. The formula for *AF* is as follows:

$$AF = \frac{\#\,raises}{\#\,calls}$$

Players can be classified into either Aggressive or Passive by the percentage of games they have played. Based on research by Rupeneite [2010], a threshold of 1 is used:

- Aggressive if $AF > 1$
- Passive if $AF \leq 1$

The Player Tightness, *PT*, is used to classify a player as either Loose or Tight. The formula for *PT* is as follows:

$$PT = \frac{\#\,folds}{\#\,games}$$

Players can be classified into either Loose or Tight by the percentage of games they have played. Based on research by Rupeneite [2010], a threshold of 0.28 is used:

- Tight if $PT < 0.28$ hands
- Loose if $PT \geq 0.28$ hands

Later, a classification process, introduced by Dinis and Reis [2008], is conducted to classify the opponent's style of play into four categories, as seen in Table 4.

	AF ≤ 1	**AF > 1**
PT ≥ 0.28	Loose Passive	Loose Aggressive
PT < 0.28	Tight Passive	Tight Aggressive

Table 4: Style of Play Classification

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