Designing an Artificial Intelligence Poker Agent with Q-Learning

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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.

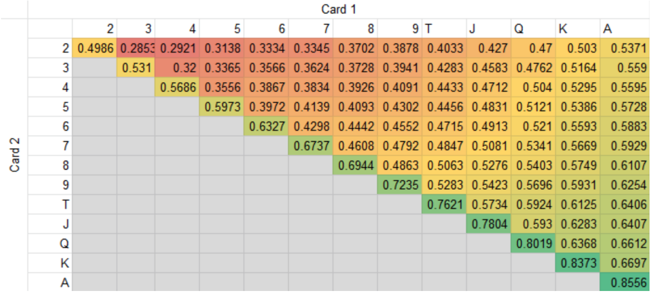
This paper outlines our design of an AI poker agent for Heads Up Limit Texas Hold'em, which aims to respond competently and accurately with limited information, within a limited amount of time. In tackling the issues above, we employed a three-pronged approach:

- Using Q-Learning, a reinforcement learning algorithm, to train our agent to play with the best possible strategy. (Section 3.1)
- Reducing the overall state size, by grouping similar states together. (Section 3.1, Clustering)
- Precomputing the estimated strength of hand ranks, storing them in look-up tables to allow for retrieval in linear time. (Section 3.3)

The following two sections explain our agent's strategy within preflop and postflop streets.

2 Preflop Street

In order to decide what action the agent would take based only on the limited amount of information it has during the preflop street, we introduce the use of hand strength (HS), which is an estimate determined by the probability of winning with the two hole cards currently in the agent's hand. To estimate HS, we perform a Monte Carlo simulation of 10,000 games for each possible starting hand. The total number of possible starting hands is 91, which is obtained by summing up the total number of possible pocket pairs and the total number of possible hands disregarding 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 the five community cards. Both players' hands are then revealed and the game result is 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 HS using the formula:

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

where the total games played is fixed at 10,000. The results of the Monte Carlo simulation are seen in Figure 1.

At every preflop street, the agent chooses an action [fold, call, raise] to take based on the HS of the starting hand:

$$\left.\begin{aligned} &raise\colon HS > k \\ &call\colon HS > j \\ &fold\colon HS \le j \end{aligned}\right\} \quad \text{where } 0 < j < k \le 1$$

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

3 Postflop Streets

The postflop streets consist of the Flop, Turn and River streets. In contrast to the preflop street, at least three community cards are revealed during the postflop streets, giving us more information to work with. Here, reinforcement learning is employed. Specifically, we use a modified version of the Q-Learning algorithm to train our agent.

3.1 Q-Learning

As per the Q-Learning algorithm, we maintain a table of states and actions as an input to the agent. Each state has a Q-Value for each action (Fold, Call or Raise), signifying

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

Table 1: Q-Learning Table

the expected reward for the action. An illustration of the Q-Learning table can be seen in Table 1.

The reward function is determined based on the pot size P - the total amount that has been bet by both players - at the end of the game, as seen in the formula below:

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

After each training round, the Q-Value of each state is obtained by summing up the previous Q-Value for that state and the reward function for that round. More formally,

$$Q\left(s', a'\right) = (1-l)Q(s,a) + l\lambda^t R(s,a)$$

where

t refers to the number of turns between the current move and the terminal node.

l refers to the learning factor.

R refers to the reward for that round.

λ refers to the discount factor.

s refers to the state of the agent.

a refers to the action taken by the agent.

P refers to the pot size.

Experience Replay

Additionally, we apply 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 it discovers 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 (highest Q-Value) 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, to avoid the scenario where the agent settles into a sub-optimal pattern of calling the same action repeatedly. At every street, the state of the agent is determined by the following attributes:

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

where

EHS refers to the agent's current Expected Hand Strength. More details can be found in Section 3.2.

S refers to the current street of the round.

P refers to the pot size.

#OR refers to the number of raises the opponent has made in the round so far.

#SR refers to the number of raises the agent has made in the round so far.

OPS refers to the Opponent Playing Style. More details can be found in Section 3.4.

Clustering

Using clustering to group information into buckets would reduce the massive state space, making it much more feasible to explore all possible states. We apply clustering to group the information for our Q-Learning algorithm as such:

- *EHS* is divided into groups with an increment of 0.01, from 0 to 1.
- *S* represents the three postflop streets - Flop, Turn and River.
- *P* ranges from \$0 to \$680 per game. We group it into increments of \$40, which is the 2 times the 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* simply ranges from 0 to 4.
- *#SR* simply ranges from 0 to 4.
- *OPS* is grouped into four categories. More details can be found in Section 3.4.

These groupings help to reduce the complexity and cut down the size of the total state space to: $101 \times 3 \times 18 \times 5 \times 5 \times 4 = 545{,}400$ states

3.2 Expected Hand Strength

The Expected Hand Strength, *EHS*, is the probability that a given player's current hand wins if the game reaches a showdown. It factors in all possible combinations for the opponent's hand and the remaining unrevealed board cards, and compares each of these hands to the agent's hand to determine which hand wins. The *EHS* of the agent's hand is calculated by finding the total number of times the agent's hand wins against the opponent's, out of all possible comparisons. More formally,

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

where the *Ahead*, *Tied*, and *Behind* functions respectively determine the number of times the given player's hand wins, ties or loses against its opponent's. The above formula used to derive the *EHS* was referenced from Teofilo *et al.* [2013a].

Note that the *EHS* may be required by the agent at any street of any round. However, the time required to accurately compute *EHS* based on large samples may exceed our time constraint of 200 milliseconds. This issue can be addressed by using a lookup table, which is explained in the next section.

3.3 *EHS* Lookup Table

We introduce a technique similar to the Average Rank Strength (*ARS*) heuristic [Teofilo *et al.*, 2013b] to improve the efficiency of *EHS*. In our method, three look-up tables are created - one for Flop, one for Turn and one for River. These tables consist of precomputed *EHS* values for all possible hand scores. The score of a particular hand refers to its strength, and is computed by PyPokerEngine's built-in $HandEvaluator.eval\_hand()$ function. For example, $HandEvaluator.eval\_hand()$ returns a numeric representation of the agent's hand score given some combination of hole cards and community cards which contain a Pair, which would be lower than if there were a Three-of-a-Kind. More details can be found in the PyPokerEngine repository.

Instead of computing *EHS* during gameplay, the agent now refers to the lookup table, to obtain its *EHS* based on its current hand score. The use of this technique allows the computation to run in linear time, and results in an approximate thousand-fold improvement in response time, while compromising negligibly on accuracy [Teofilo *et al.*, 2013b].

To enumerate the *EHS* table for the three postflop streets, for each street we performed a Monte Carlo simulation of 2.5 million samples of the agent's hand and the revealed community cards, also calculating the agent's hand score for each sample. Additionally, for each sample, we performed another simulation of 500 samples of the opponent's hand and the unrevealed community cards (if any) to calculate the *EHS* for the hand score. The results are displayed below:

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

Table 2: Results of *EHS* Lookup Table Simulation

We are aware that not all possible hand scores may appear in the tables generated during the simulation. However, our results from simulating 100,000 games reveal that approximately 99.87 percent of all hand scores can be found in each table, showing that the lookup tables remarkably maintain a high degree of reliability and accuracy. In the case where an agent looks up a hand score that is not enumerated in the lookup table, we perform a limited Monte Carlo simulation of 100 samples for that particular hand score and add it to the lookup table.

3.4 Opponent Playing Styles

The playing style of an opponent can be classified into four categories [Rupeneite, 2010]. Each style distinctly describes the opponent's frequency of play and style of betting. The four categories of playing styles are Loose/Passive, Loose/Aggressive, Tight/Passive and Tight/Aggressive. A brief description of each style is given 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

Aggressiveness Factor, AF, is the ratio of a given player's number of raises to the number of calls. More formally:

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

Players are classified as either Aggressive or Passive based on their Aggressiveness Factor. Based on research by Rupeneite [2010], a threshold of 1 is used:

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

Player Tightness, PT, is the ratio of a given player's number of folds to the total number of games. More formally:

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

Players are classified as either Loose or Tight based on their Player Tightness. Based on research by Rupeneite [2010], a threshold of 0.28 is used:

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

Later, a classification process, introduced by Dinis and Reis [2008], combined these two heuristics 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

4 Analysis

After several rounds of preliminary testing, we realized that the state space was still too large for the agent to be meaningfully trained with our resources. The following analysis was conducted with a limited set of features: Street, EHS, Pot, Action, which allowed us to generate tangible results within several hours of training.

4.1 Training and Results

Our poker agent was training with static agents, as detailed in Table 5.

Agent	Description
RandomPlayer	Chooses an action randomly.
RaisePlayer	Always raises.
HonestPlayer	Raises on a good hand, calls on a decent hand, folds on a bad hand.

Table 5: Static Agents used for Training

Early iterations of our agent performed rather well against Random and Raise but lost to HonestPlayer by a small margin. The average winnings per round were determined to be:

- Against RandomPlayer: 2.107 big blinds per round
- Against RaisePlayer: 0.4758 big blinds per round
- Against HonestPlayer: -0.1421 big blinds per round

Later iterations of our agent performed better; although our agent was still losing to HonestPlayer, it lost by an even smaller margin of 0.11 big blinds per round.

4.2 Limitations

Loss of Information from Clustering of *EHS*

Clustering of the *EHS* in by divisions of 0.01 was used with the intent of reducing the size of the state space. This results in different combinations of cards with similar *EHS* sharing the same state bucket. However, the action that the agent takes may also be dependent on its current combination of cards. Hence, information is lost from when we differentiate different combinations of cards merely by their *EHS*. Further work can be done to improve the decision process, such as by reducing the size of the buckets, or further classifying card combinations through the use of other heuristics such as the rank of the hand (High Card, Pair, Straight, Flush, etc.) or Hand Potential [Teofilo *et al.*, 2013a].

Non-Convergent Q-Values

The use of the ε-Greedy algorithm determines that every turn, there is a probability of ε that a random action is chosen, else the action with the highest Q-Value (best expected reward) is chosen. Ideally, reducing the value of ε after every game would cause the Q-Values of each state to converge, which would allow the agent to more reliably choose the best action at every state. Due to the time constraints of the project, we did not manage to derive a reliable formula for varying the value of ε. Our results show that our Q-Values did not converge after approximately 700,000 games with ε = 0.15 and l = 0.02. However, this could also be due to the fact that we did not have a large enough number of rounds for the Q-Values to converge, or that our clustering method needs to be improved to more accurately group the Q-Values.

Lack of Diversity in Training Opponents

The selection of opponents is an important factor in determining the type of agent we produce. For instance, training against an opponent who randomly selects actions will result in a greater probability of our agent selecting calls and raises, since the opponent has a substantial probability to fold throughout the round. Hence, training against opponents with different playstyles will produce a different set of biases for each opponent. We conclude that games against these static opponents would only be useful for initial training, and further generations should be trained by playing against itself. Further research can consider exploring a greater variety of opponent profiles to train the agent against.

5 Conclusions

There are still improvements that can be made to our agent for it to more effectively excel at Poker. While our research has resulted in a successful attempt at designing an agent with vast improvements to its decision time, better opponent modelling techniques and training methods can improve the overall competency of our agent.

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