Building Poker Bot with Reinforcement Learning (December 2020)

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No-limit Texas Hold'em is one of the most popular card games in the world. Leduc Hold'em is a simplified version, where new implementations can be easily tested. We present a poker bot that learns to play Limit-Hold'em and Leduc Hold'em by training against a random agent. For this purpose, we use the RLCard environment. Our bot uses Deep Q Learning and it is implemented in PyTorch. We also introduce various strategies that even though are quite simple, yet sometimes effective. In the process, we use a replay buffer to store past experiences and another Q-network to aid the learning process. We also take a look at how long-term-planning poker machines perform against our implementation by creating a sample one that uses Counterfactual Regret Minimization. Lastly, we compare the results of each unique strategy to the others, thus giving the reader a better understanding of how poker should be played (in a really simple manner).

***Index Terms*—poker, AI bot, reinforcement learning, Deep Q-Network**

I. Introduction

THE current results in reinforcement learning have always been important for humanity. Not so long ago we managed to reach what some considered to be impossible, namely beating the current best Go player by using artificial intelligence [1]. This was a huge milestone, even though perfect-information games were considered to be easier to solve than their imperfect-information counterparts. The reason for that is obvious: imperfect information games require more complex reasoning than similarly sized perfect-information games. We have to balance our strategy so that our opponent does not find out too much about our way of playing, hereby the hidden information we have. To give an example, in poker if we always raise when we have a pair of kings, our opponents will recognize that and punish us for doing it, either by folding their cards or by raising if the current public cards favour them. As we can see from the previous explanation, poker is intuitively easy to understand and captures the challenges of hidden information effectively and elegantly. For this reason, it has been widely used to illustrate game theory concepts. [2]

The classical solution for games is a Nash equilibrium. This strategy ensures that no player can increase his or her expected utility by altering their strategy. All finite extensive-form games have at least one Nash equilibrium.

In order to have a better understanding of the Nash equilibrium, we illustrate it with an example. The prisoner's dilemma is commonly analyzed in game theory. The problem is the following: two criminals are arrested but the police have no evidence. To catch someone for the crime, they offer the pair the opportunity to either betray the other person and say he/she did the crime, or remain silent. If both prisoners betray each other, each serves five years in prison. If A betrays B but B remains silent, prisoner A is set free and prisoner B serves 10 years in prison or vice versa. If each remains silent, then each serves just one year in prison. The Nash equilibrium tells us that the best decision for both players is to betray each other. Even though mutual cooperation leads to better results, if player one alters from this but player two does not, then player one's outcome is worse.

II. Literature review

In the past few years, the media has been constantly covering breakthroughs in reinforcement learning. For example, in 2019 OpenAI Five [3] became the first AI system to defeat the world champions at an esports game. Some thought it was inevitable that the precision of the computers will outshine their human opponents, and it was bound to happen. Later that year Pluribus shocked the world: a superhuman AI has been made that managed to consistently beat human professional players. Beating humans in poker is not something we have not seen before.

First, in 2015 a paper claimed that Heads-up Limit Hold'em Poker is essentially solved [4]. Cepheus (the name of the supercomputer) was trained for 68 days with CPUs, using a special version of Counterfactual Regret Minimization (CFR). Cepheus heavily outperformed Polaris, the poker bot made in 2008. This triggered a snowball effect in the world of poker AIs.

In 2016 another paper [5] argued that their NFSP (Neural Fictitious Self-Play) is the first deep reinforcement learning method known to converge to approximate Nash equilibria in self-play.

In early 2017 DeepStack [6] achieved expert-level artificial intelligence in Heads-Up No-Limit Poker. It became the first poker AI that managed to beat professional poker players in Heads-Up No-Limit Texas Hold'em. DeepStack allows computation to be focused on specific situations that arise when making decisions and the use of automatically trained value functions while using minimal domain knowledge.

To completely isolate these machines from humans, in 2018 Libratus [7] was created without any domain knowledge and also greatly reduced the required training time. It defeated four top human specialist professionals in a 120,000-hand competition in Heads-Up No-Limit Texas Hold'em. It consisted of a blueprint strategy for the overall strategy, an algorithm that provided more information on the details of the strategy for subgames that were reached during play, and a self-improver algorithm that fixes potential weaknesses that the opponents might identify.

To top it all, in 2019 Pluribus [8] crushed multiple humans simultaneously. It was tested in six-player No-Limit Texas Hold'em poker, the most commonly played poker format in the world.

III. Methodology

During our project, we used RLCard card environments [9] that are designed for reinforcement learning research. A simple sketch illustrates its main components in Fig. 1. It is an easy-to-use toolkit that provides Limit Hold'em and Leduc Hold'em environment. The latter is a simplified version of Limit Texas Hold'em and it was constructed to have a more tractable game [10].

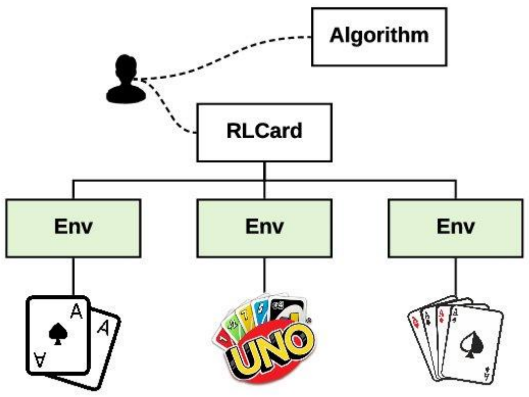


Fig. 1. An overview of the RLCard toolkit [9]

Both types have the same actions: *check*, *call*, *raise* and *fold*. During *checking* the action passes to the next player without betting. In the case of someone bets, this action is not possible anymore. *Calling* means matching a bet or a raise. If the player chooses to *raise*, he/she increases the size of an existing bet in the round. *Folding* is discarding one's hand.

The payoff is identical as well in both environments. It is based on the big blinds per hand. The player gets the positive or negative R reward if he/she wins or loses R times the amount of the big blind, respectively.

Limit Hold'em is played with 52 cards. Each player has 2 hole cards and there are 5 community cards with 3 phases, called the *flop*, the *turn* and the *river*. The players have 4 *raise* actions per round each with 4 betting rounds in total. The state representation is a vector of length 72 in this game. The first part contains the known cards, namely the hole cards and the already revealed community cards. The first 13 element represents the cards from the Ace of Spade to the King of Spade, followed by the Heart, the Diamond and the Club similarly. The rest of the vector is the number of *raise* actions in each round.

A more simplified version is the Leduc Hold'em. It is limited to 6 cards, which are two pairs of King, Queen and Jack. This game is played by 2 players with 2 rounds, where there are 2 *raise* actions in the first one and 4 in the second one. The game is fixed with two-bet and 14 chips maximum.

After describing the used environments and their features, we present the classical algorithm, DQN, and its modified version in the remaining part of this section.

We have chosen the DQN algorithm and implemented it in PyTorch. For this, we used the TensorFlow code from RLCard [11] as a base and created a more powerful, more manageable, and easy to use code in PyTorch. This implementation is an advanced Q-learning agent in two aspects. First, it uses a replay buffer to store past experiences. As we simulate the environment and make an action, we add the state, action, reward and next state to it. When we train our network, we sample from this replay buffer for a more consistent result. Second, to make the training more stable, another Q-network is used as a target network in order to backpropagate through it and train the policy Q-network. These features were first described in [12].

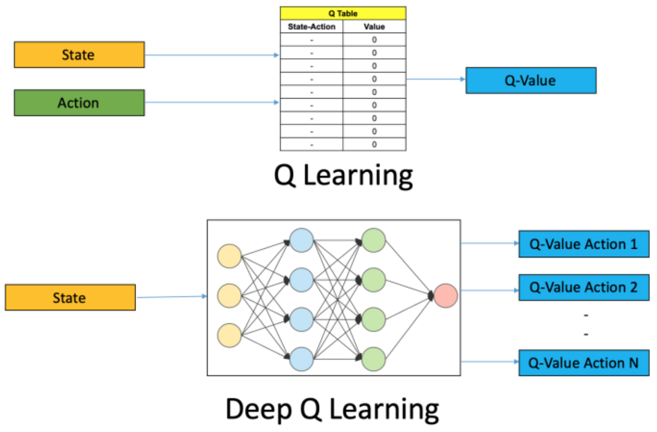
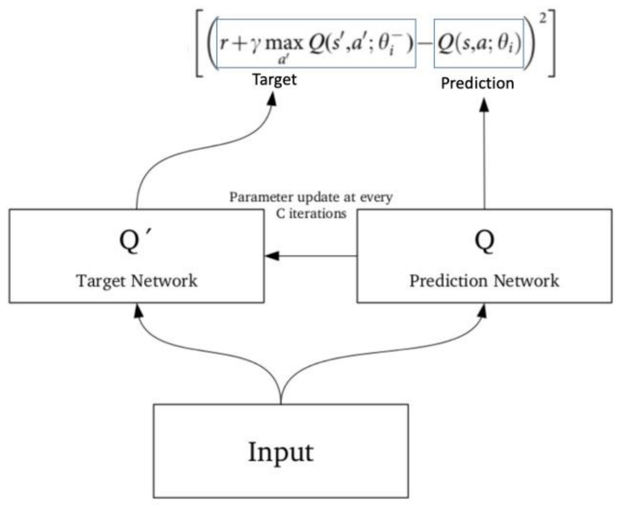


Fig. 2. The architecture of the Deep Q-networks [13]

The purpose of these networks is to estimate a Q-value given the current state, which can be used to determine which action the agent will take. They consist of a simple neural network with the states as its input layer and the action values for the current policy as its output layer. This structure is illustrated in Fig. 2.

Every step the agent first makes an action based on the epsilon value which is responsible for exploration. If epsilon is high, the agent is more likely to take a random action if it is low, it will use the Q-network to determine the best action. In the early stages of the game, the epsilon starts with a high value "exploring" the environment, and each step its value is reduced by a small amount to the point when it will be near zero.

The agent learns by sampling a minibatch from the replay memory and gets a Q-value for the next state using the policy network and determines the best action for this state. Then it determines the target Q-value using the target network. It calculates the target action using the reward from the replay memory and the target Q-value. Afterward, it backpropagates using this value. The figure below [Fig. 3] presents the target network and the policy or prediction network in other words.



$\left[\left(r+\gamma \max_{a'} Q(s',a';\theta_i^-)-Q(s,a;\theta_i)\right)^2\right]$
Target
Prediction
Parameter update at every C iterations
Q′
Target Network
Q
Prediction Network
Input

Fig. 3. The inner structure of the DQN networks [13]

First, the agent explores the environment making random actions and getting positive/negative rewards and updating its Q-network accordingly. But as it plays more and more it will take less random actions and has more accurate Q-values for the given states, playing better and better.

Furthermore, as an extra component, we added the opportunity of a more aggressive playing strategy. In case of the given action has the maximum Q-value, the agent chooses the *raise* action as a replacement for it if *raising* is a valid action. Hence, the 3 possible extra settings are to encourage the agent to *raise* instead of *calling*, *checking* and *folding*. For referring to these alternative versions, we use the abbreviation of these actions next to the name of the DQN, namely the DQN-CAR, DQN-CHR and DQN-FR, respectively.

At the first glimpse, DQN-FR, where the agent is encouraged to prefer *raising* to *folding*, seems a bit too extreme, but the other two methods can make sense in several situations. In the next section, we investigate their impact on the performance of the agent.

IV. Results and Discussion

We trained the DQN agents with 215 different hyperparameter settings against random agents in both environments. During the hyperparameter tuning the number of layers, the replay memory size, the batch size, the discount factor and the learning rate were examined.

The best parameter combinations are shown in Table I. It is interesting to observe that 3 parameters, which are the replay memory size, the batch size and the discount factor, lead to the best performance in both environments. The difference is in the parameter of the network layers and the learning rate.

TABLE I.
TUNED MODELS

Hyperparameter	Leduc Hold’em	Limit Hold’em
network layers	[128, 128, 128]	[128, 128]
replay memory	2000	2000
batch size	64	64
discount factor	0.99	0.99
learning rate	0.1	0.001

Next, we investigate how the proposed agents affect the results in both environments. We trained them 1000 episodes long and they were evaluated with 100 games in each tenth episode. The reward is calculated from the last 10 evaluations. Table II.and Table III. display the average rewards and their variance in Leduc Hold’em and Limit Hold’em.

The most important finding is that the different versions of the traditional DQN agent have an effect on the performance. Moreover, if the agent prefers *raising* to *calling*, the performance is significantly better.

In the case of the Leduc Hold’em environment, the DQN-CAR algorithm exceeds the baseline DQN by more than 30% with respect to the achieved average reward. Furthermore, it also performs better than the CFR agent. Meanwhile, the other two methods underperform the classical DQN and CFR as well.

TABLE II.
BEST PERFORMANCE IN LEDUC HOLD'EM ENVIRONMENT

	mean reward	reward variance
CFR	0.734	0.300
DQN	0.960	0.265
DQN-CAR	**1.261**	**0.352**
DQN-CHR	0.682	0.285
DQN-FR	0.723	0.202

Similar results come from the Limit Hold’em environment, where the DQN-CAR outperforms the DQN algorithm by almost 40% improvement. In this game, the CFR agent learns far slower, because it requires full traversals of the game tree [14], which is infeasible in a larger game. To overcome this situation, abstraction is typically applied before running CFR, where determining a good abstraction can be a huge challenge [15]. We found this to be a part that falls outside the scope of this paper. For this reason, there is no comparison with the CFR agent in the Limit Hold’em environment.

TABLE III.
BEST PERFORMANCE IN LIMIT HOLD'EM ENVIRONMENT

	mean reward	reward variance
DQN	2.057	0.258
DQN-CAR	**2.870**	**0.465**
DQN-CHR	1.806	0.433
DQN-FR	1.713	0.276

These results with the proposed DQN-CAR algorithm against a random agent shows great performance in both environments. However, it is important to note its limitations. While the aggressive strategy works well against a random agent, the opposite can happen against a stronger opponent. As suggested from [9], the problem of the DQN policy is that it may be highly exploitable since it is easy to find its weaknesses. Indeed, if we train the algorithms against a pre-trained NFSP agent, their performance drops drastically. These evaluation results are shown in Table IV.

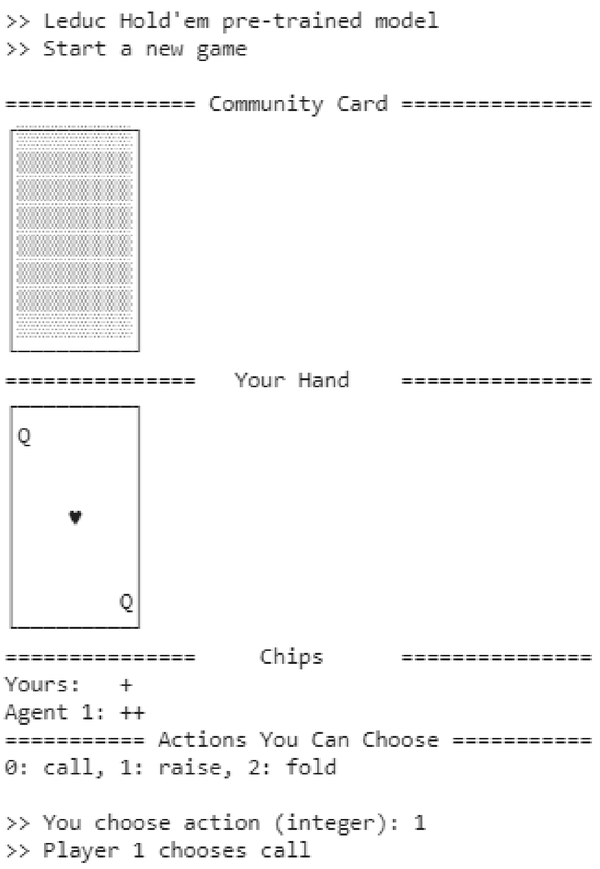
TABLE IV.
PERFORMANCE AGAINST PRE-TRAINED AGENT IN LEDUC HOLD'EM

	mean reward	reward variance
CFR	**0.484**	**0.288**
DQN	-0.049	0.350
DQN-CAR	0.023	0.350
DQN-CHR	0.093	0.353
DQN-FR	-0.001	0.3671

The 3 new methods slightly perform better than the classical DQN, but the differences are not considerable. This also confirms the fact that the CFR agent can learn better in a difficult scenario. These results with playing against the pre-trained NFSP agent show that the DQN algorithm is not able to adapt in stochastic environments. They also support the findings in recent research [9][12]. It would be worth investigating the same question in the Limit Hold'em environment with a strong pre-trained agent, but such a model is not yet presented for this environment. However, the team of the RLCard proposed to develop more pre-trained agents in the future [9]. Although it is possible to train a strong agent by ourselves, as mentioned before, abstraction in the case of the CFR agent in a complex environment is tricky. Hence, it is not dealt with in this paper.

After comparing the results, we used the DQN-CAR algorithm and created a poker-bot from it in the Leduc Hold'em and Limit Hold'em environment as well. We added a human player and an easy-to-use interface to the game. In this part, we highly relied on the offered elements from the RLCard library [11].

The final poker-bot is available with Docker container and in Google Colab notebook format in our Github repository. The user can choose from them based on which suits better her/his requirements.



```
>> Leduc Hold'em pre-trained model
>> Start a new game

=============== Community Card ===============

===============   Your Hand    ===============

===============     Chips      ===============
Yours:   +
Agent 1: ++
=========== Actions You Can Choose ===========
0: call, 1: raise, 2: fold

>> You choose action (integer): 1
>> Player 1 chooses call
```

Fig. 4. Snippet from the Leduc Hold'em game in our notebook

Long-term planning poker bots have not been in the main focus of research. To handle this problem, we created a simple CFR agent by editing its code in the RLCard library. For computational reasons, our implementation only deals with 2 rounds of play, and it is specialized in a curious way: its main goal is to have more chips at the end of the round than the opponent has. As CFR learns by traversing the tree and correcting its policy by the calculated regrets, moving beyond two rounds resulted in a really slow learning speed.

TABLE V.
RESULTS IN REGARDS OF WHO HAS MORE CHIPS IN LEDUC HOLD'EM

	Win percentage
DQN	71.2
DQN-CAR	**76.99**
DQN-CHR	70.86
DQN-FR	70.98
CFR	75.88

In Table V. we can see that our DQN-CAR bot is heavily outperforming the others in this regard. It is important to mention that these results happened against a random agent, so this should not be so surprising. Intuitively, what DQN-CAR does is encouraging the bot to choose *raise* over *call*. Against a random agent who happened to raise randomly, *raising* instead of *calling* could very often be beneficial. Still, this experimentation should not be treated as a proof that the modern poker playing machines are performing well in every circumstance. These special types of long-planning problems are yet to be explored even in the field of poker, meaning that this field can not be ignored, even though some argued against its importance after Pluribus was made.

V. Conclusions

In this paper, we have presented the methodology for creating a poker-bot based on a reinforcement learning algorithm. For this purpose, we selected the classical DQN agent, which performs well in Atari games [12].

As an additional component, we created 3 different versions of the original method to encourage the agent to play more aggressively. After comparing our results, the DQN-CAR algorithm against a random agent outperformed the other ones, including DQN and CFR. However, further investigations lead us to the fact these results highly vary from a game with a strong pre-trained opponent.

In conclusion, the power of the DQN agent in imperfect-information games is limited compared to stronger agents like CFR. Our agents have excellent performance against random agents but not against strong pre-trained agents. Due to this fact, we recommend our poker bot for beginner and intermediate level players especially.

As also recommended above, future research should consider the potential training of a strong CFR or NFSP agent to explore the performance of our proposed algorithms against them in complex environments. Aside from this, interesting topics would be training an advanced level poker AI and creating a poker bot at any level in No-Limit Texas Hold'em environment.

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