BlackJack

December 15, 2018

1 Monte Carlo Methods for Blackjack

In this notebook I wrote my own implementations of many Monte Carlo algorithms, in order to teach an agent how to play Blackjack.

1.0.1 Explore BlackjackEnv

This is an instance of the Blackjack environment.

```
In [1]: import matplotlib
        import numpy as np
        import sys
        import gym

        %matplotlib inline

        env = gym.make('Blackjack-v0')

        print(env.observation_space)
        print(env.action_space)
```

```
Tuple(Discrete(32), Discrete(11), Discrete(2))
Discrete(2)
```

Each state is a 3-tuple of: - the player's current sum $\in \{0, 1, \ldots, 31\}$, - the dealer's face up card $\in \{1, \ldots, 10\}$, and - whether or not the player has a usable ace ($\texttt{no} = 0$, $\texttt{yes} = 1$).

The agent has two potential actions:

- STICK = 0
- HIT = 1

1.0.2 Play Blackjack with a random policy.

This is designed to visualize the output that is returned as the agent interacts with the environment.

```
In [2]: for i_episode in range(3):
            state = env.reset()
            while True:
                print(f"State: {state}")
                action = env.action_space.sample()
                print(f"Action: {action}")
                state, reward, done, info = env.step(action)
                if action:
                    print(f"New state: {state}")
                if done:
                    print('End game! Reward: ', reward)
                    print('You won!!!\n') if reward > 0 else print('You lost...\n')
                    break
```

```
State: (15, 4, True)
Action: 0
End game! Reward:  -1.0
You lost...

State: (11, 10, False)
Action: 1
New state: (13, 10, False)
State: (13, 10, False)
Action: 1
New state: (20, 10, False)
State: (20, 10, False)
Action: 0
End game! Reward:  0.0
You lost...

State: (14, 10, False)
Action: 1
New state: (24, 10, False)
End game! Reward:  -1
You lost...
```

1.0.3 Generate an episode from action-value function estimate following the epsilon-greedy policy

The function accepts as **input**: - `env`: This is an instance of OpenAI Gym's Blackjack environment. - `Q`: This is a dictionary (of one-dimensional arrays) where `Q[s][a]` is the estimated action value corresponding to state `s` and action `a`. - `epsilon`: Value between 0 and 1, (probability of choosing a random action instead the Greedy action). - `nA`: Number of actions the agent can choose.

It returns as **output**: - `episode`: This is a list of (state, action, reward) tuples (of tuples) and corresponds to $(S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T)$, where T is the final time step. In particular, `episode[i]` returns (S_i, A_i, R_{i+1}), and `episode[i][0]`, `episode[i][1]`, and `episode[i][2]` return S_i, A_i, and R_{i+1}, respectively.

```
In [3]: def generate_episode_from_Q(env, Q, epsilon, nA):
            episode = []
            state = env.reset()
            while True:
                action = np.random.choice(np.arange(nA), p=get_probs(Q[state], epsilon, nA)) \
                                            if state in Q else env.action_space.sample()
                next_state, reward, done, info = env.step(action)
                episode.append((state, action, reward))
                state = next_state
                if done:
                    break
            return episode
```

1.0.4 Calculate the action probabilities corresponding to epsilon-greedy policy

The function accepts as **input**: - `Q_s`: This is a dictionary (of one-dimensional arrays) where `Q[s][a]` is the estimated action value corresponding to state `s` and action `a`. - `epsilon`: Value between 0 and 1, (probability of choosing a random action instead the Greedy action). - `nA`: Number of actions the agent can choose.

It returns as **output**: - `policy_s`: This is a list containing the probability of taking each action.

```
In [4]: def get_probs(Q_s, epsilon, nA):
            policy_s = np.ones(nA) * epsilon / nA
            best_a = np.argmax(Q_s)
            policy_s[best_a] = 1 - epsilon + (epsilon / nA)
            return policy_s
```

1.0.5 Update the action-value function estimate using the most recent episode

This algorithm has four arguments: - `env`: This is an instance of an OpenAI Gym environment. - `episode`: This is the number of episode that is generated through agent-environment interaction. - `Q`: This is a dictionary (of one-dimensional arrays) where `Q[s][a]` is the estimated action value corresponding to state `s` and action `a`. - `alpha`: This is the step-size parameter for the update step. - `gamma`: This is the discount rate. It must be a value between 0 and 1 inclusive.

The algorithm returns as output: - `Q`: This is the updated Q.

```
In [5]: def update_Q_alpha(env, episode, Q, alpha, gamma):
            states, actions, rewards = zip(*episode)
            # prepare for discounting
            discounts = np.array([gamma**i for i in range(len(rewards)+1)])
            for i, state in enumerate(states):
                # update Q using MC constant alpha
                # FORMULA -> Q(St|At) = Q(St|At) + alpha * (Gt - Q(St|At))
                Q[state][actions[i]] = Q[state][actions[i]] + alpha*(sum(rewards[i:]*discounts
            return Q
```

1.0.6 MC Control: Constant-α

This algorithm has four arguments: - `env`: This is an instance of an OpenAI Gym environment. - `num_episodes`: This is the number of episodes that are generated through agent-environment interaction. - `alpha`: This is the step-size parameter for the update step. - `gamma`: This is the discount rate. It must be a value between 0 and 1 inclusive.

The algorithm returns as output: - `Q`: This is a dictionary (of one-dimensional arrays) where `Q[s][a]` is the estimated action value corresponding to state `s` and action `a`. - `policy`: This is a dictionary where `policy[s]` returns the action that the agent chooses after observing state `s`.

```
In [6]: from collections import defaultdict


        def mc_control_alpha(env, num_episodes, alpha, gamma=1.0):
            nA = env.action_space.n
            # fraction of num_episodes in order to have 0.1 <= epsilon < 1
            fraction = num_episodes // 10
            # initialize empty dictionary of arrays
            Q = defaultdict(lambda: np.zeros(nA))
            # loop over episodes
            for i_episode in range(1, num_episodes+1):
                # monitor progress
                if i_episode % 10000 == 0:
                    print("\rEpisode {}/{}.".format(i_episode, num_episodes), end="")
                    sys.stdout.flush()
                # set the value of epsilon, after 1kk episodes it remains static to 0.1
                epsilon = 1.0/((i_episode/fraction)+1)
                if i_episode > 1000000:
                    epsilon = 0.1
                # generate an episode by following epsilon-greedy policy
                episode = generate_episode_from_Q(env, Q, epsilon, nA)
                # update the action-value function estimate using the episode
                Q = update_Q_alpha(env, episode, Q, alpha, gamma)
            # determine the policy corresponding to the final action-value function estimate
            policy = dict((k,np.argmax(v)) for k, v in Q.items())
            return policy, Q
```

Obtain the estimated optimal policy and action-value function.

```
In [7]: # obtain the estimated optimal policy and action-value function
        policy_alpha, Q_alpha = mc_control_alpha(env, 2500000, 0.005, gamma=0.85)
```

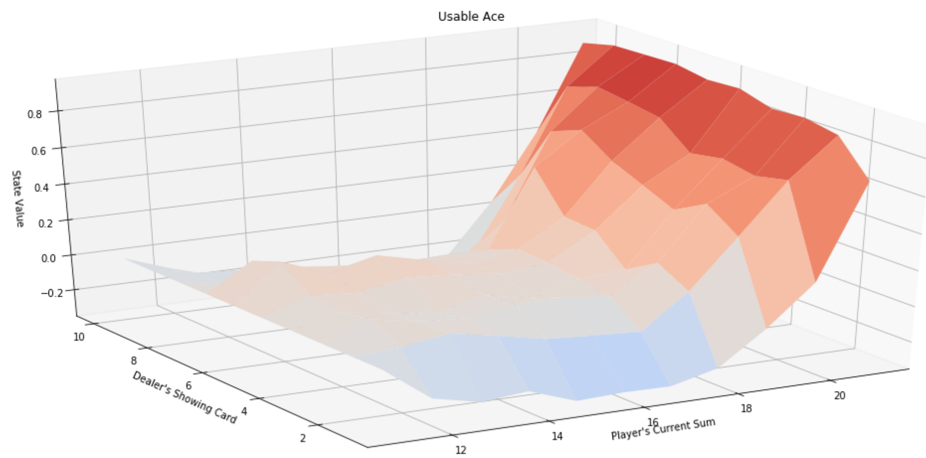
```
Episode 2500000/2500000.
```

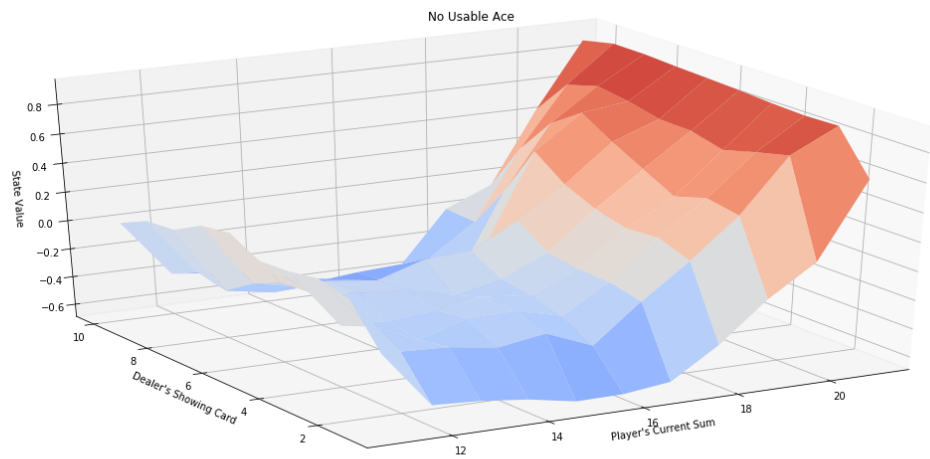
1.0.7 Plot the corresponding state-value function.

```
In [8]: from plot_utils import plot_blackjack_values
```

```
# obtain the state-value function
V_alpha = dict((k,np.max(v)) for k, v in Q_alpha.items())

# plot the state-value function
plot_blackjack_values(V_alpha)
```

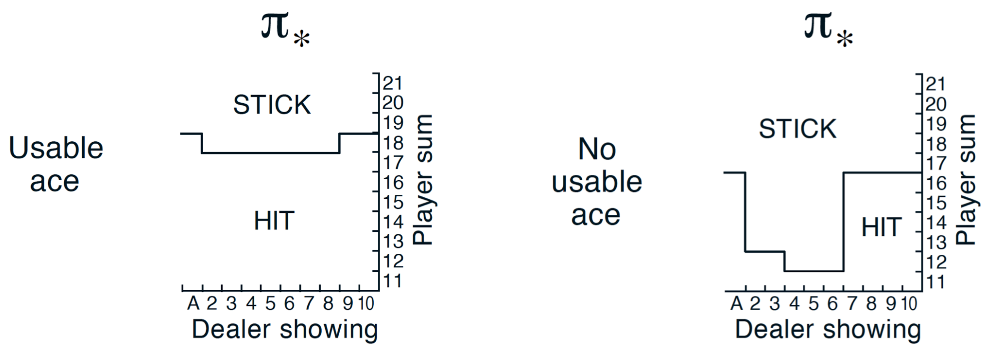




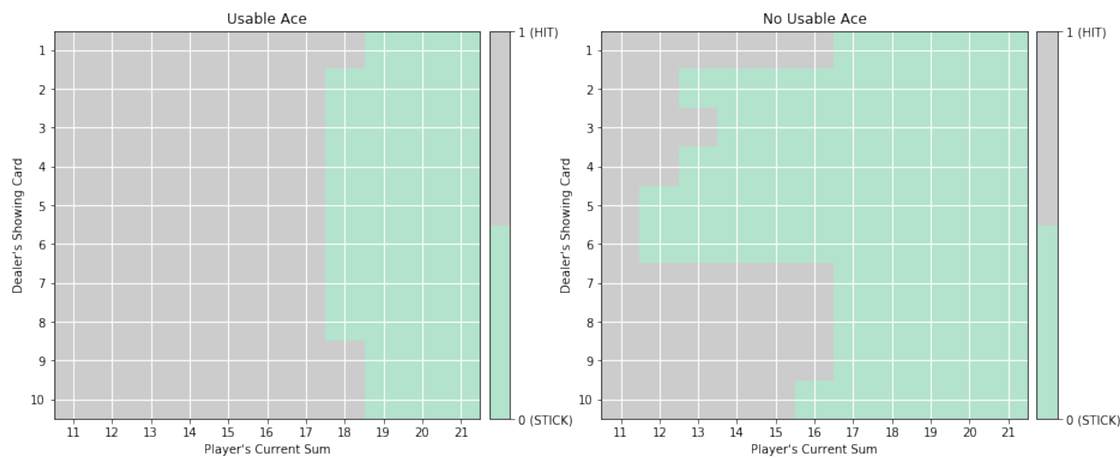
Visualize the policy that is estimated to be optimal.

```
In [9]: from plot_utils import plot_policy


        # plot the policy
        plot_policy(policy_alpha)
```



True Optimal Policy



In the following picture there is the **true** optimal policy, is not exactly like the optimal policy found by the agent but it is very similar.

```
In [ ]:
```