RL Lab 03 - Part 1- Monte Carlo predicition on BlackJack

1. Monte Carlo prediction

In these exercises, we will explore the **the Monte Carlo prediction algorithhm**.

The algorithm is shown on the course slide deck.
The algorithm will be tested on Blackjack.

1.1 Setup

In [1]:
```
!pip install gym
# !pip install plotting
!wget -nc https://raw.githubusercontent.com/lcharlin/80-629/master/week13-RL/blackjack.py
!wget -nc https://raw.githubusercontent.com/lcharlin/80-629/master/week13-RL/plotting.py
```

```
Requirement already satisfied: gym in /usr/local/lib/python3.7/dist-packages (0.17.3)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.7/dist-packages (from gym) (1.21.5)
Requirement already satisfied: cloudpickle<1.7.0,>=1.2.0 in /usr/local/lib/python3.7/dist-packages (from gym) (1.3.0)
Requirement already satisfied: pyglet<=1.5.0,>=1.4.0 in /usr/local/lib/python3.7/dist-packages (from gym) (1.5.0)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from gym) (1.4.1)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packages (from pyglet<=1.5.0,>=1.4.0->gym) (0.16.0)
--2022-02-23 22:05:35--  https://raw.githubusercontent.com/lcharlin/80-629/master/week13-RL/blackjack.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 4251 (4.2K) [text/plain]
Saving to: 'blackjack.py'

blackjack.py        100%[===================>]   4.15K  --.-KB/s    in 0s

2022-02-23 22:05:35 (31.1 MB/s) - 'blackjack.py' saved [4251/4251]

--2022-02-23 22:05:35--  https://raw.githubusercontent.com/lcharlin/80-629/master/week13-RL/plotting.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 3457 (3.4K) [text/plain]
Saving to: 'plotting.py'

plotting.py         100%[===================>]   3.38K  --.-KB/s    in 0s

2022-02-23 22:05:35 (38.1 MB/s) - 'plotting.py' saved [3457/3457]
```

In [2]:
```
# imports
%matplotlib inline

import gym
import matplotlib
import numpy as np
import sys

from collections import defaultdict

from blackjack import BlackjackEnv
import plotting

matplotlib.style.use('ggplot')
```

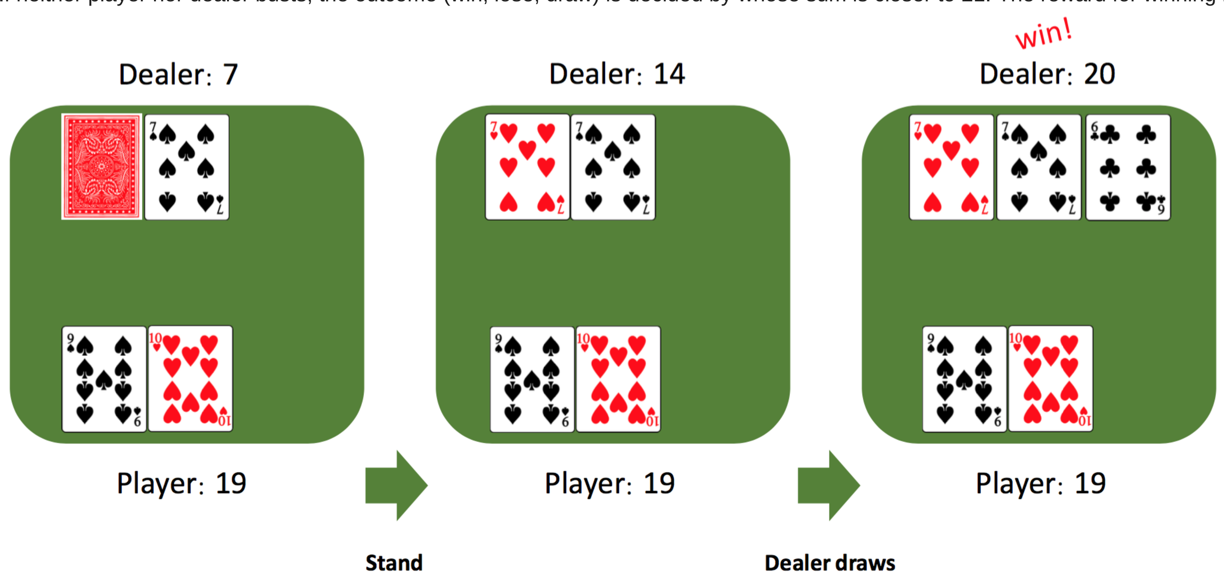
BlackJack Rules

First, we define the Blackjack environment:

- Black Jack is a card game where a player must obtain cards such that their sum is as close to 21 without exceeding it.
- Face cards (Jack, Queen, King) have point value 10. Aces can either count as 11 or 1, and it's called 'usable' at 11.
- In our example below, the player plays against a dealer. The dealer has a fixed policy of always asking for an additional card until the sum of their cards is above 17.
- Stationarity: This game is placed with an infinite deck (or with replacement).

Game Process:

1. The game starts with each (player and dealer) having one face up and one face down card.
2. The player can request additional cards (hit=1) until they decide to stop (stick=0) or exceed 21 (bust). After the player sticks, the dealer reveals their facedown card, and draws until their sum is 17 or greater. If the dealer goes bust the player wins.
3. If neither player nor dealer busts, the outcome (win, lose, draw) is decided by whose sum is closer to 21. The reward for winning is +1, drawing is 0, and losing is -1.



In [4]:
```
env = BlackjackEnv()
```

1.2 Monte Carlo prediction

Recall that the Monte Carlo prediction algorithm provides a method for evaluating a given policy (π), that is obtain its value for each state $V(s)\ \forall s \in S$.

It is similar to the policy evaluation step used in policy iteration for MDPs. The main difference is that **here we do not know the transition probabilities** and so we will have an agent that tries out the policy in the environment and, episode by episode, calculates the value function of the policy.

You need to write a function that evaluates the values of each states given a policy.

In [8]:
```
def mc_prediction(policy, env, num_episodes, discount_factor=1.0, plot_every=False):
    """
    Monte Carlo prediction algorithm. Calculates the value function
    for a given policy using sampling.

    Args:
        policy: A function that maps an observation to action probabilities.
        env: OpenAI gym environment.
        num_episodes: Number of episodes to sample.
        discount_factor: Gamma discount factor.

    Returns:
        A dictionary that maps from state -> value.
        The state is a tuple and the value is a float.
    """

    # Keeps track of sum and count of returns for each state
    # to calculate an average. We could use an array to save all
    # returns (like in the book) but that's memory inefficient.
    returns_sum = defaultdict(float)
    returns_count = defaultdict(float)

    # The final value function
    V = defaultdict(float)

    for i_episode in range(1, num_episodes + 1):
        # Print out which episode we're on, useful for debugging.
        if i_episode % 1000 == 0:
            print("\rEpisode {}/{}.".format(i_episode, num_episodes), end="")
            sys.stdout.flush()

        # Generate an episode.
        # An episode is an array of (state, action, reward) tuples
        episode = []
        state = env.reset()
        for t in range(100):
            action = policy(state)
            next_state, reward, done, _ = env.step(action) # YOUR CODE HERE #
            episode.append((state, action, reward))
            if done:
                break
            state = next_state

        # Find all states the we've visited in this episode
        # We convert each state to a tuple so that we can use it as a dict key
        states_in_episode = set([tuple(x[0]) for x in episode])

        for state in states_in_episode:
            # Find the first occurence of the state in the episode
            first_occurence_idx = next(i for i, x in enumerate(episode) if x[0]==state) # YOUR CODE HERE #
            # Sum up all rewards since the first occurance
            # YOUR CODE HERE #
            G = sum([x[2]*(discount_factor**i) for i,x in enumerate(episode[first_occurence_idx:])])
            # Calculate average return for this state over all sampled episodes
            returns_sum[state] += G # YOUR CODE HERE #
            returns_count[state] += 1  # YOUR CODE HERE #
            V[state] = returns_sum[state]/returns_count[state] # YOUR CODE HERE #

        if plot_every and i_episode % plot_every ==0:
            plotting.plot_value_function(V, title=f"{i_episode} Steps")

    return V
```

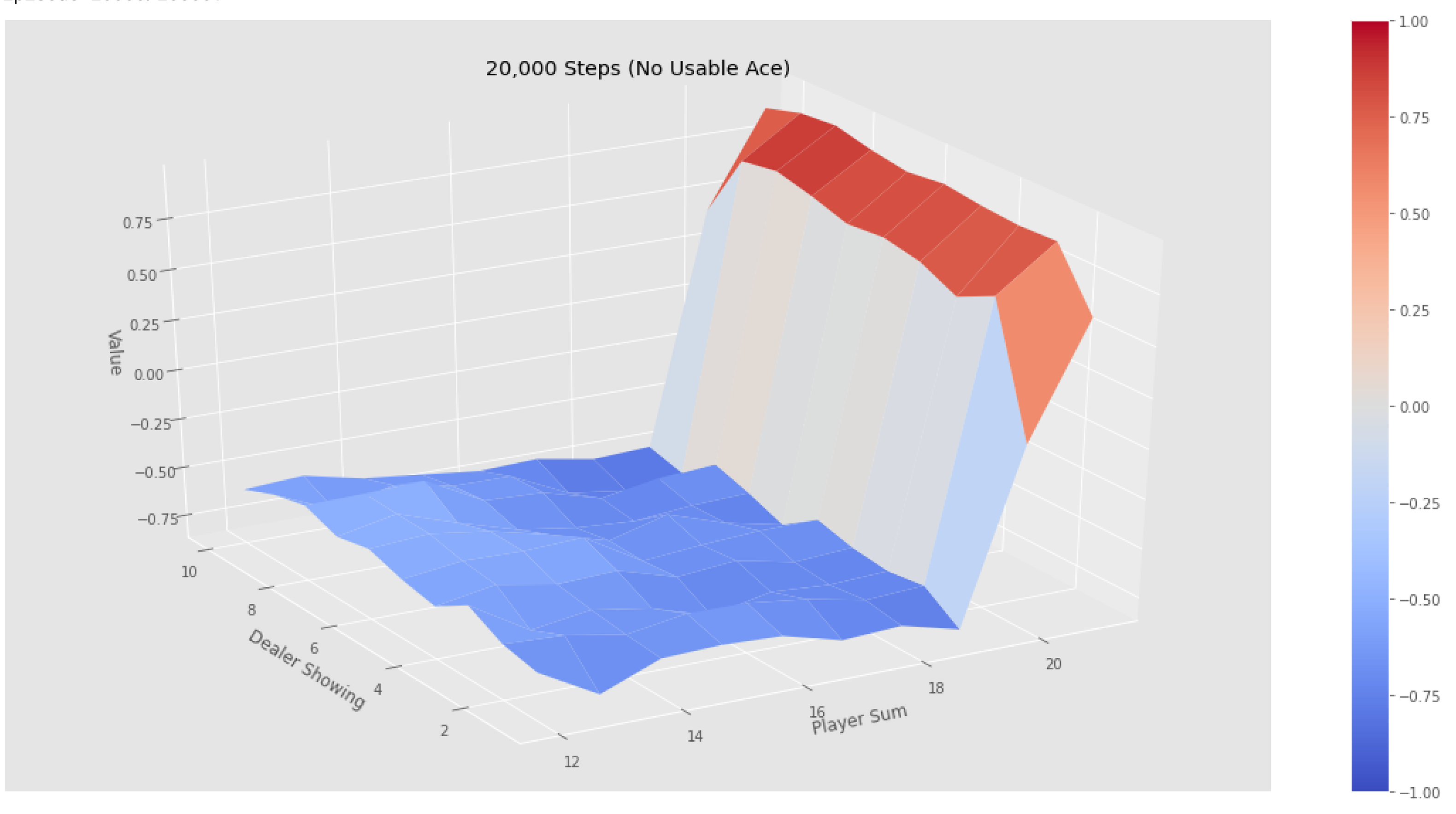
Now, we will define a simple policy which we will evaluate.
Specifically, **the policy hits except when the sum of the card is 20 or 21.**

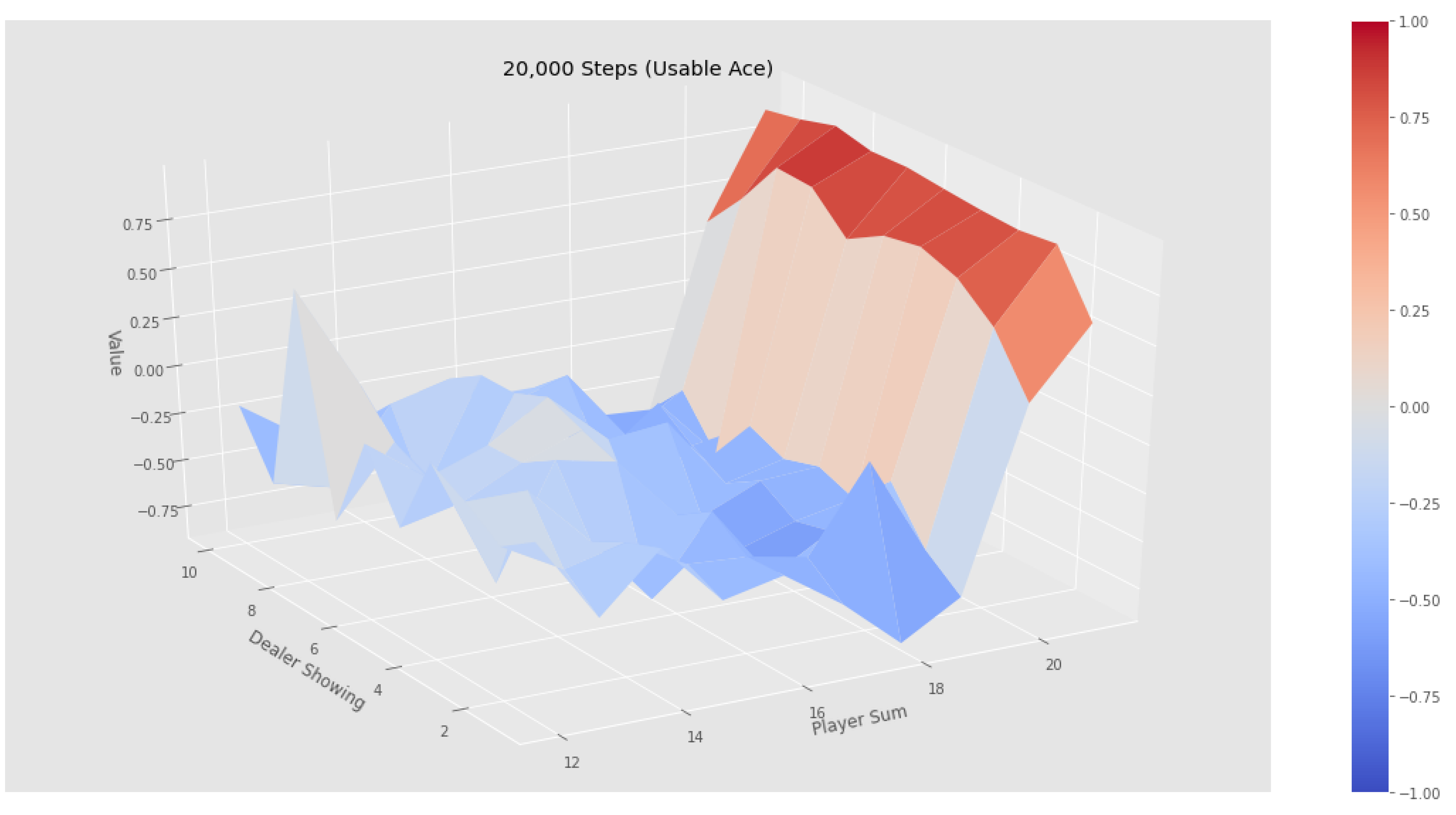
In [9]:
```
def sample_policy(observation):
    """
    A policy that sticks if the player score is >= 20 and hits otherwise.
    """
    score, dealer_score, usable_ace = observation
    return 0 if score >= 20 else 1
```

We now evaluate the policy for 20k iterations.

In [10]:
```
V_20k = mc_prediction(sample_policy, env, num_episodes=20000)
plotting.plot_value_function(V_20k, title="20,000 Steps")
```

```
Episode 20000/20000.
```





Question

Can you interpret the graph ?

Answer:

When with Ace, there are more variance in the values earned.

1.3 Monte Carlo prediction on multiple episodes

In this part we will analyze the effect of the number of episodes (num_episodes) on the learned value function.

In [11]:
```
V_20k = mc_prediction(sample_policy, env, num_episodes=200000, plot_every=10000)
```

```
Output hidden; open in https://colab.research.google.com to view.
```

Question

What's the effect of the number of episodes (num_episodes) on the learned value function ?

Answer:

As the number of episodes sampled increases, the variance of values when a player has a useable ace decreases before getting to 20/21. This indicates that the agent has been able to more precisely learn when to hit even with a useable ace.

Do not forget Part 2 of the Lab, refer to the second notebook

In [ ]: