## qlearning

June 5, 2024

```
[]: # Author: Till Zemann
     # License: MIT License
     from __future__ import annotations
     from collections import defaultdict
     import matplotlib.pyplot as plt
     import numpy as np
     import seaborn as sns
     from matplotlib.patches import Patch
     from tqdm import tqdm
     import gymnasium as gym
     # Let's start by creating the blackjack environment.
     # Note: We are going to follow the rules from Sutton & Barto.
     # Other versions of the game can be found below for you to experiment.
     env = gym.make("Blackjack-v1", sab=True)
     # Other possible environment configurations are:
     # env = gym.make('Blackjack-v1', natural=True, sab=False)
     # Whether to give an additional reward for starting with a natural blackjack, i.
     →e. starting with an ace and ten (sum is 21).
     # env = gym.make('Blackjack-v1', natural=False, sab=False)
     # Whether to follow the exact rules outlined in the book by Sutton and Barto.
      →If `sab` is `True`, the keyword argument `natural` will be ignored.
[]: # reset the environment to get the first observation
     done = False
     observation, info = env.reset()
```

# observation = (16, 9, False) Player current sum, value of dealers face-upu  $\hookrightarrow$  cards, bool if player holds usable ace (counts as 11 without busting)

```
[]: class BlackjackAgent:
         def __init__(
             self.
             learning_rate: float, # how much the agent should update its Q values_
      ⇒based on new experiences
             initial_epsilon: float, # starting exploration rate
             epsilon_decay: float,
             final_epsilon: float,
             discount_factor: float = 0.95, # defines how much to prefer future_
      ⇔rewards to imideate rewards
         ):
             """Initialize a Reinforcement Learning agent with an empty dictionary
             of state-action values (q_values), a learning rate and an epsilon.
             Args:
                 learning_rate: The learning rate
                 initial_epsilon: The initial epsilon value
                 epsilon_decay: The decay for epsilon
                 final_epsilon: The final epsilon value
                 discount factor: The discount factor for computing the Q-value
             self.q_values = defaultdict(lambda: np.zeros(env.action_space.n))
             self.lr = learning_rate
             self.discount_factor = discount_factor
             self.epsilon = initial epsilon
             self.epsilon_decay = epsilon_decay
             self.final_epsilon = final_epsilon
             self.training_error = []
         def get_action(self, obs: tuple[int, int, bool]) -> int: # what action_
      →to do based on curretn observation
             Returns the best action with probability (1 - epsilon)
             otherwise a random action with probability epsilon to ensure
      \hookrightarrow exploration.
             ,,,,,,
             # with probability epsilon return a random action to explore the
      \rightarrow environment
             if np.random.random() < self.epsilon:</pre>
                 return env.action_space.sample() # return random sample toe_
      →explore environment
```

```
# with probability (1 - epsilon) act greedily (exploit)
                                   else:
                                              return int(np.argmax(self.q_values[obs]))
                        def update(
                                   self,
                                   obs: tuple[int, int, bool],
                                   action: int,
                                   reward: float,
                                   terminated: bool,
                                   next_obs: tuple[int, int, bool],
                        ):
                                    """Updates the Q-value of an action."""
                                   future_q_value = (not terminated) * np.max(self.q_values[next_obs])
                                   temporal_difference = (
                                              reward + self.discount_factor * future_q_value - self.
                 →q_values[obs] [action]
                                    self.q values[obs][action] = (
                                              self.q_values[obs][action] + self.lr * temporal_difference
                                    self.training_error.append(temporal_difference)
                        def decay_epsilon(self):
                                   self.epsilon = max(self.final_epsilon, self.epsilon - epsilon_decay)
[]: # hyperparameters
             learning_rate = 0.001
             n = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 100 = 
             start epsilon = 1.0
             epsilon_decay = start_epsilon / (n_episodes / 2) # reduce the exploration over_
                \rightarrow time
             final_epsilon = 0.1
             agent = BlackjackAgent(
                        learning_rate=learning_rate,
                        initial_epsilon=start_epsilon,
                        epsilon_decay=epsilon_decay,
                        final_epsilon=final_epsilon,
             )
[]: env = gym.wrappers.RecordEpisodeStatistics(env, deque_size=n_episodes)
             for episode in tqdm(range(n_episodes)): #tqdm visual indicator of training_
                 \hookrightarrow progress
                        obs, info = env.reset()
```

```
# play one episode
while not done:
    action = agent.get_action(obs)
    next_obs, reward, terminated, truncated, info = env.step(action)

# update the agent
    agent.update(obs, action, reward, terminated, next_obs)

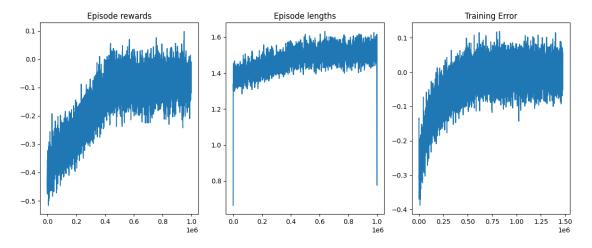
# update if the environment is done and the current obs
done = terminated or truncated
    obs = next_obs

agent.decay_epsilon()
```

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```
[]: rolling_length = 500
     fig, axs = plt.subplots(ncols=3, figsize=(12, 5))
     axs[0].set_title("Episode rewards")
     # compute and assign a rolling average of the data to provide a smoother graph
     reward_moving_average = (
         np.convolve(
             np.array(env.return_queue).flatten(), np.ones(rolling_length),__
      →mode="valid"
         )
         / rolling_length
     axs[0].plot(range(len(reward_moving_average)), reward_moving_average)
     axs[1].set_title("Episode lengths")
     length_moving_average = (
         np.convolve(
             np.array(env.length_queue).flatten(), np.ones(rolling_length),_
      omode="same"
         / rolling_length
     axs[1].plot(range(len(length_moving_average)), length_moving_average)
     axs[2].set_title("Training Error")
     training_error_moving_average = (
         np.convolve(np.array(agent.training_error), np.ones(rolling_length),_u
      →mode="same")
         / rolling_length
     axs[2].plot(range(len(training_error_moving_average)),__
      →training_error_moving_average)
```

```
plt.tight_layout()
plt.show()
```



```
[]: def create_grids(agent, usable_ace=False):
         """Create value and policy grid given an agent."""
         # convert our state-action values to state values
         # and build a policy dictionary that maps observations to actions
         state_value = defaultdict(float)
         policy = defaultdict(int)
         for obs, action_values in agent.q_values.items():
             state_value[obs] = float(np.max(action_values))
             policy[obs] = int(np.argmax(action_values))
         player_count, dealer_count = np.meshgrid(
             # players count, dealers face-up card
             np.arange(12, 22),
             np.arange(1, 11),
         )
         # create the value grid for plotting
         value = np.apply_along_axis(
             lambda obs: state_value[(obs[0], obs[1], usable_ace)],
             axis=2,
             arr=np.dstack([player_count, dealer_count]),
         value_grid = player_count, dealer_count, value
         # create the policy grid for plotting
         policy_grid = np.apply_along_axis(
             lambda obs: policy[(obs[0], obs[1], usable_ace)],
             axis=2,
```

```
arr=np.dstack([player_count, dealer_count]),
   )
   return value_grid, policy_grid
def create_plots(value_grid, policy_grid, title: str):
    """Creates a plot using a value and policy grid."""
    # create a new figure with 2 subplots (left: state values, right: policy)
   player count, dealer count, value = value grid
   fig = plt.figure(figsize=plt.figaspect(0.4))
   fig.suptitle(title, fontsize=16)
    # plot the state values
   ax1 = fig.add_subplot(1, 2, 1, projection="3d")
   ax1.plot_surface(
       player_count,
       dealer_count,
       value,
       rstride=1,
       cstride=1,
       cmap="viridis",
       edgecolor="none",
   )
   plt.xticks(range(12, 22), range(12, 22))
   plt.yticks(range(1, 11), ["A"] + list(range(2, 11)))
   ax1.set_title(f"State values: {title}")
   ax1.set_xlabel("Player sum")
   ax1.set_ylabel("Dealer showing")
   ax1.zaxis.set_rotate_label(False)
   ax1.set_zlabel("Value", fontsize=14, rotation=90)
   ax1.view_init(20, 220)
   # plot the policy
   fig.add_subplot(1, 2, 2)
   ax2 = sns.heatmap(policy_grid, linewidth=0, annot=True, cmap="Accent_r", u
 ⇔cbar=False)
   ax2.set title(f"Policy: {title}")
   ax2.set_xlabel("Player sum")
   ax2.set_ylabel("Dealer showing")
   ax2.set_xticklabels(range(12, 22))
   ax2.set_yticklabels(["A"] + list(range(2, 11)), fontsize=12)
    # add a legend
   legend_elements = [
       Patch(facecolor="lightgreen", edgecolor="black", label="Hit"),
       Patch(facecolor="grey", edgecolor="black", label="Stick"),
   ]
```

```
ax2.legend(handles=legend_elements, bbox_to_anchor=(1.3, 1))
    return fig

# state values & policy with usable ace (ace counts as 11)
value_grid, policy_grid = create_grids(agent, usable_ace=True)
fig1 = create_plots(value_grid, policy_grid, title="With usable ace")
plt.show()
```

## With usable ace State values: With usable ace Policy: With usable ace Stick 0.8 0.6 0.4 0.2 0.0 12<sup>13<sup>14</sup>15<sup>16</sup>17<sup>18</sup>19<sup>2</sup>0<sup>21</sup></sup> <sup>10</sup> <sub>9</sub> <sup>8</sup> <sup>7</sup> <sup>6</sup> <sub>5</sub> <sub>4</sub> <sub>3</sub> <sub>2 A</sub> Dealer showing 17 13 14 15 16 Player sum

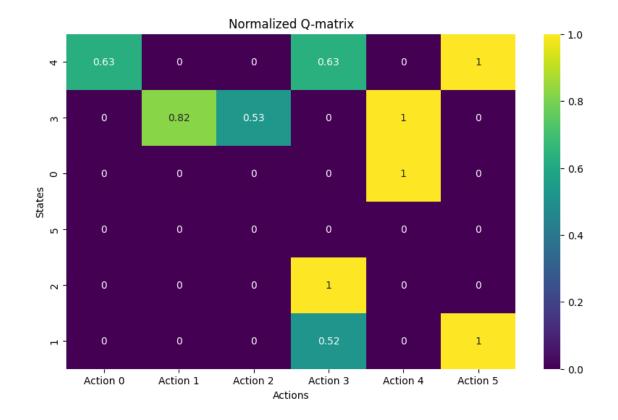
```
[]: # Author: Till Zemann
     # License: MIT License
    from collections import defaultdict
    import numpy as np
    import matplotlib.pyplot as plt
    import pandas as pd
    import seaborn as sns
    from tqdm import tqdm
    np.random.seed(42)
    R = np.array([
         [-1, -1, -1, -1, 0, -1],
         [-1, -1, -1, 0, -1, 100], # Action from state 1 to state 5
         [-1, -1, -1, 0, -1, -1],
         [-1, 0, 0, -1, 0, -1],
         [0, -1, -1, 0, -1, 100], # Action from state 4 to state 5
         [-1, 0, -1, -1, 0, 100] # Goal state, can loop to itself with high reward
    ])
```

```
# Q-Learning agent for the building environment
class BuildingAgent:
   def __init__(
       self.
       learning_rate: float,
        initial_epsilon: float,
        epsilon_decay: float,
        final epsilon: float,
       discount_factor: float = 0.8,
   ):
        # Initialize Q-values for each state-action pair
       self.q values = defaultdict(lambda: np.zeros(len(R)))
       self.lr = learning_rate
       self.discount_factor = discount_factor
       self.epsilon = initial_epsilon
       self.epsilon_decay = epsilon_decay
       self.final_epsilon = final_epsilon
       self.training_error = []
        self.episode_rewards = []
       self.episode_lengths = []
    # Select an action using epsilon-greedy policy
   def get action(self, state: int) -> int:
        if np.random.random() < self.epsilon: # using epsilon to explore in the
 ⇔beginning
            actions = np.nonzero(R[state] >= 0)[0] # non zero to avoid penalty
            return np.random.choice(actions)
        else:
            return int(np.argmax(self.q_values[state]))
    # Update Q-values based on the action taken
   def update(self, state: int, action: int, reward: float, next_state: int):
       best next action = np.max(self.q values[next state])
        td_target = reward + self.discount_factor * best_next_action
       td_error = td_target - self.q_values[state][action]
        self.q values[state][action] += self.lr * td error
        self.training_error.append(td_error)
    # Decay epsilon to reduce exploration over time
   def decay_epsilon(self):
        self.epsilon = max(self.final_epsilon, self.epsilon * self.
 ⇔epsilon_decay)
# Parameters for Q-learning
alpha = 0.1 # Learning rate
gamma = 0.8 # Discount factor
```

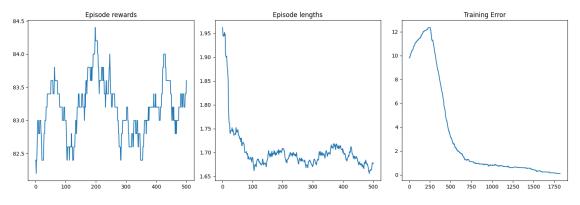
```
n_{episodes} = 1000
start_epsilon = 1.0
epsilon_decay = 0.99
final_epsilon = 0.1
# Initialize the agent
agent = BuildingAgent(
    learning_rate=alpha,
    initial epsilon=start epsilon,
    epsilon_decay=epsilon_decay,
    final epsilon=final epsilon,
    discount_factor=gamma
)
# Q-learning algorithm
for episode in tqdm(range(n_episodes)):
    state = np.random.randint(0, len(R))
    total_reward = 0
    length = 0
    while state != 5: # Goal state is 5
        action = agent.get_action(state)
       next state = action
        reward = R[state, action]
        agent.update(state, action, reward, next_state)
        state = next_state
        total reward += reward
        length += 1
    agent.episode_rewards.append(total_reward)
    agent.episode_lengths.append(length)
    agent.decay_epsilon()
# Normalize Q-matrix for better interpretability
Q_normalized = {state: q / np.max(q) if np.max(q) > 0 else q for state, q in_{L}
 ⇒agent.q_values.items()}
# Display the normalized Q-matrix in a prettier format
q_df = pd.DataFrame(Q_normalized).T.fillna(0)
q_df.columns = [f"Action {i}" for i in range(len(R))]
print(q_df)
# Heatmap visualization of Q-matrix
plt.figure(figsize=(10, 6))
sns.heatmap(q_df, annot=True, cmap="viridis", cbar=True)
plt.title("Normalized Q-matrix")
plt.xlabel("Actions")
plt.ylabel("States")
```

## plt.show()

```
| 1000/1000 [00:00<00:00, 56459.29it/s]
100%|
  Action 0
             Action 1
                       Action 2 Action 3 Action 4
                                                     Action 5
4 0.630542
             0.000000
                        0.00000
                                 0.634926
                                                0.0
                                                           1.0
                                                           0.0
3 0.000000
             0.823063
                        0.53469
                                 0.000000
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2
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                        0.00000
                                 0.520730
                                                0.0
                                                           1.0
```



```
axs[0].plot(range(len(reward_moving_average)), reward_moving_average)
axs[1].set_title("Episode lengths")
length_moving_average = (
    np.convolve(agent.episode_lengths, np.ones(rolling_length), mode="valid")
    / rolling_length
)
axs[1].plot(range(len(length_moving_average)), length_moving_average)
axs[2].set_title("Training Error")
training_error_moving_average = (
    np.convolve(np.array(agent.training_error), np.ones(rolling_length), u
 →mode="same")
    / rolling_length
axs[2].plot(range(len(training_error_moving_average)),__
 →training_error_moving_average)
plt.tight_layout()
plt.show()
```



```
[]: # Function to create value and policy grids

def create_grids(agent):
    state_value = defaultdict(float)
    policy = defaultdict(int)
    for state, action_values in agent.q_values.items():
        state_value[state] = float(np.max(action_values))
        policy[state] = int(np.argmax(action_values))

states = range(len(R))
    actions = range(len(R[0]))

value_grid = np.zeros((len(states), len(actions)))
```

```
policy_grid = np.zeros((len(states), len(actions)))
   for state in states:
        value_grid[state] = state_value[state]
       policy_grid[state] = policy[state]
   return value_grid, policy_grid
# Function to create plots
def create_plots(value_grid, policy_grid, title: str):
   fig, axs = plt.subplots(ncols=2, figsize=(12, 5))
   sns.heatmap(value_grid, ax=axs[0], cmap="viridis")
   axs[0].set_title(f"State values: {title}")
    sns.heatmap(policy_grid, ax=axs[1], cmap="Accent_r", annot=True, cbar=False)
   axs[1].set_title(f"Policy: {title}")
# Create value and policy grids
value_grid, policy_grid = create_grids(agent)
# Plot value and policy grids
create_plots(value_grid, policy_grid, title="Building Example")
plt.show()
```

