Lunar Landing Program Using RL

February 23, 2026

0.1 Importing the Important Libraries

[1]:
```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import torch.autograd as autograd
from collections import deque, namedtuple
import gymnasium as gym
from gymnasium.wrappers import RecordVideo
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
```

0.2 Environment Setups

[2]:
```
base_env = gym.make("LunarLander-v3",
                    continuous=False,
                    gravity=-10.0,
                    enable_wind=False,
                    wind_power=15.0,
                    turbulence_power=1.5,
                    render_mode="rgb_array")


env = RecordVideo(base_env, video_folder='./video_training',␣
 ↪episode_trigger=lambda x: x % 25 == 0)

state_size = env.observation_space.shape[0]
action_size = env.action_space.n
print("State Size:", state_size, "| Action Size:", action_size)
```

```
State Size: 8 | Action Size: 4
```

0.3 Defining the Hyperparameter for the agent

[3]:
```
learning_rate = 5e-4
minibatch = 150
gamma = 0.99
replay_buffer_size = 100000
interpolation_parameter = 1e-3
number_episodes = 5000
max_time_steps = 1000
epsilon_starting_value = 1.0
epsilon_ending_value = 0.01
epsilon_decay_value = 0.995
scores_100_episodes = deque(maxlen=100)
```

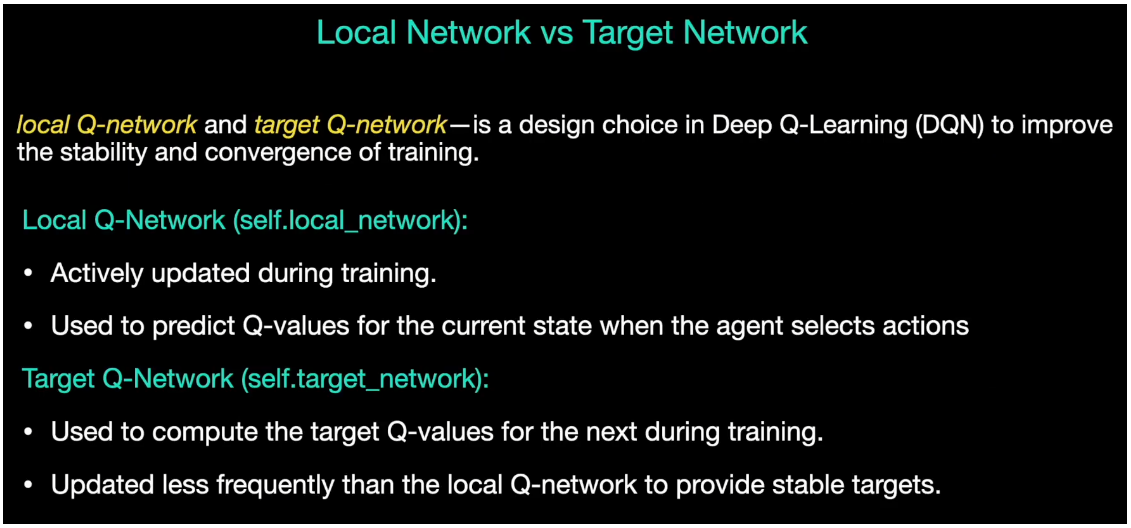
0.4 Defining the Neural Networks

[4]:
```
class ANN(nn.Module):
        def __init__(self, state_size, action_size, seed =42):
                super(ANN, self).__init__()
                self.seed = torch.manual_seed(seed)
                self.fc1 = nn.Linear(state_size, 64)
                self.fc2 = nn.Linear(64, 64)
                self.fc3 = nn.Linear(64, action_size)

        def forward(self, state):
                x = self.fc1(state)
                x = F.relu(x)
                x = self.fc2(x)
                x = F.relu(x)
                return self.fc3(x)
```

0.5 ReplayMemory:

- The ReplayMemory class is designed to manage the agent's memory of game experiences. It stores the state, action, reward, next state, and whether the episode ended(done) for each step in the game.

```
experience = (state, action, reward, next_state, done)
```

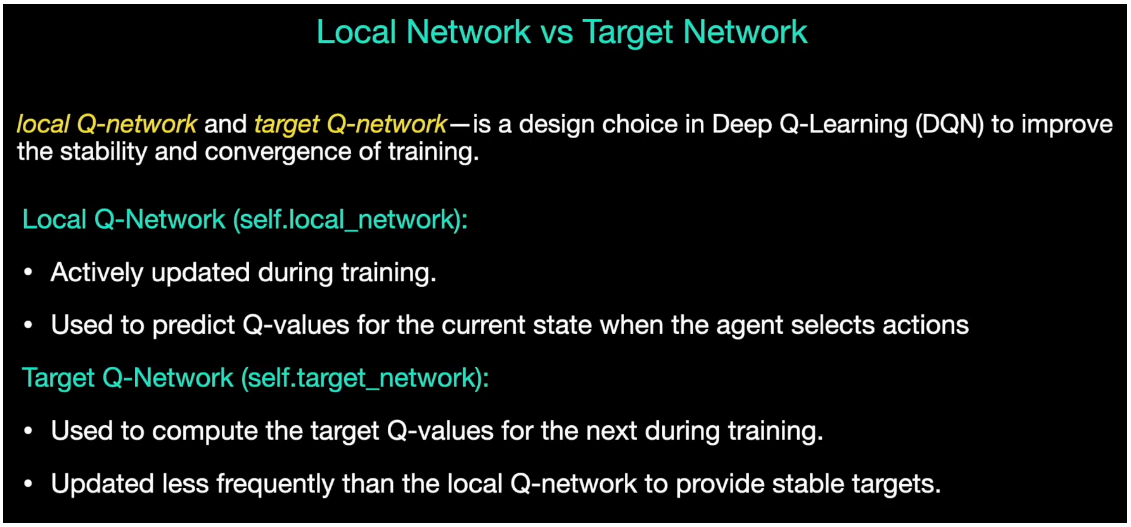


[5]:
```python
class ReplayMemory(object):

        def __init__(self, capacity):
                self.capacity = capacity
                self.memory = []


        def push(self, event):
                self.memory.append(event)
                if len(self.memory) > self.capacity:
                        del self.memory[0]


        def sample(self, batch_size):
                experiences = random.sample(self.memory, batch_size)
                states = torch.from_numpy(np.vstack([e[0] for e in experiences if e is not None])).float()
                actions = torch.from_numpy(np.vstack([e[1] for e in experiences if e is not None])).long()
                rewards = torch.from_numpy(np.vstack([e[2] for e in experiences if e is not None])).float()
                next_state = torch.from_numpy(np.vstack([e[3] for e in experiences if e is not None])).float()
                dones = torch.from_numpy(np.vstack([e[4] for e in experiences if e is not None]).astype(np.uint8)).float()

                return states, actions, rewards, next_state, dones
```

0.6 Defining the RL Agent

•

0.7 Local Vs Target Q-Network

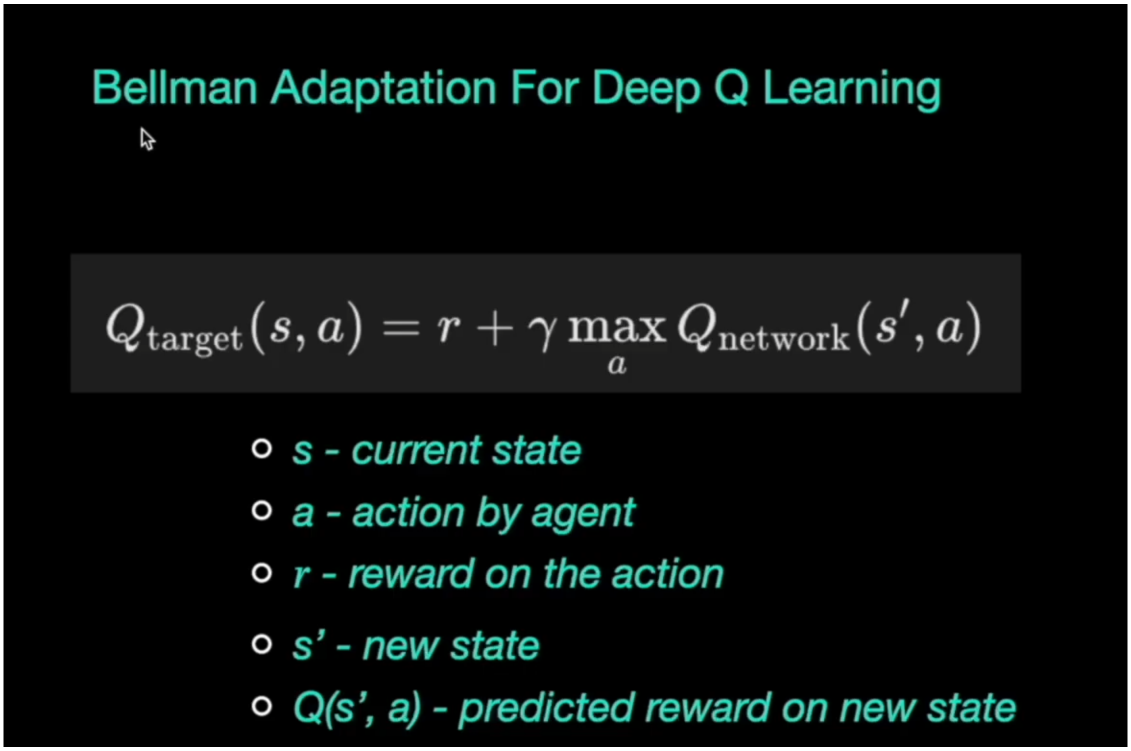


•

0.8 Exploration Vs Exploitation Tradeoffs

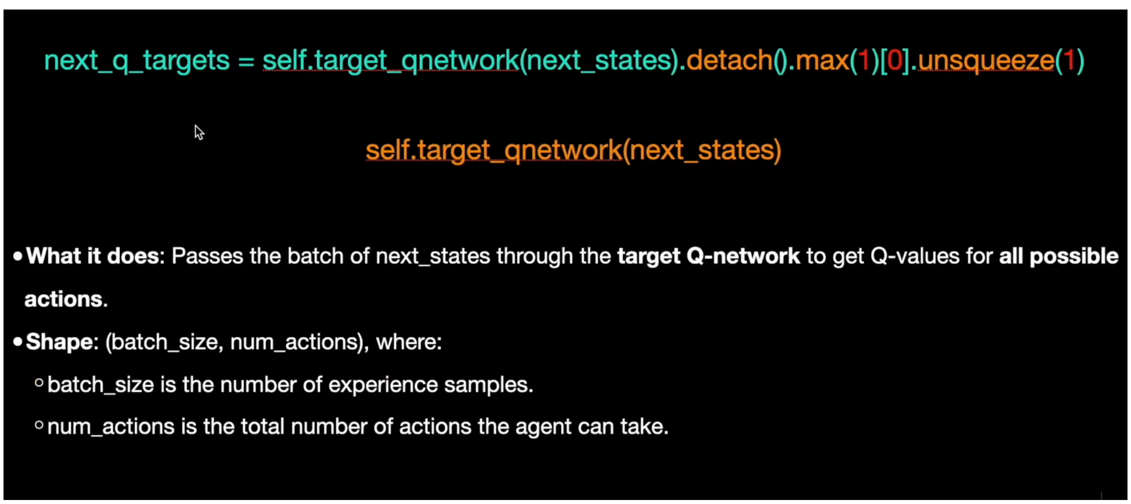
•

0.9 Bellmen Equation



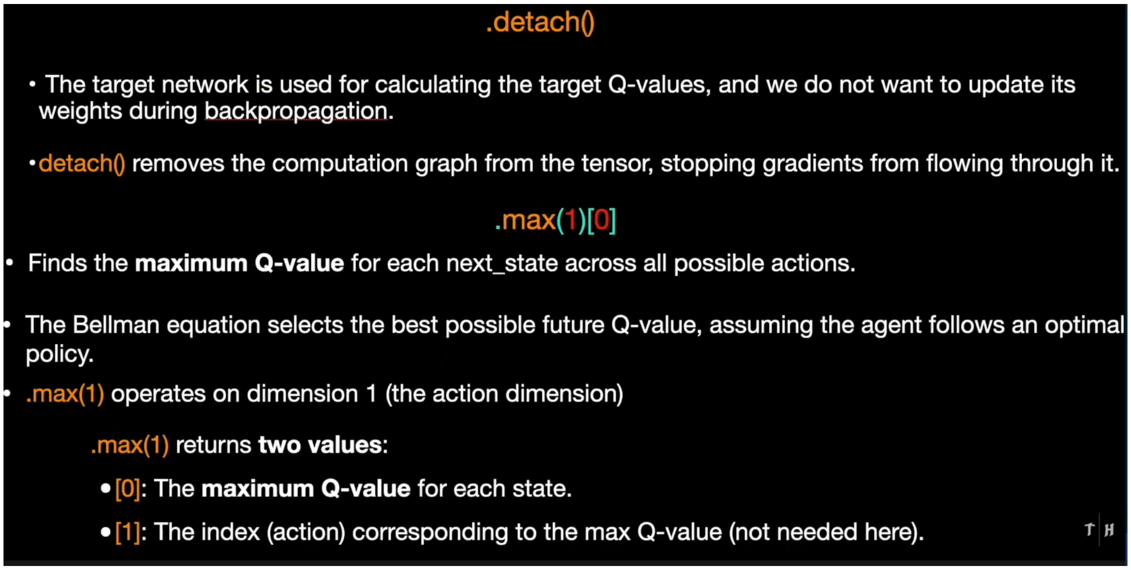
•

0.10 Next-Q-Target State



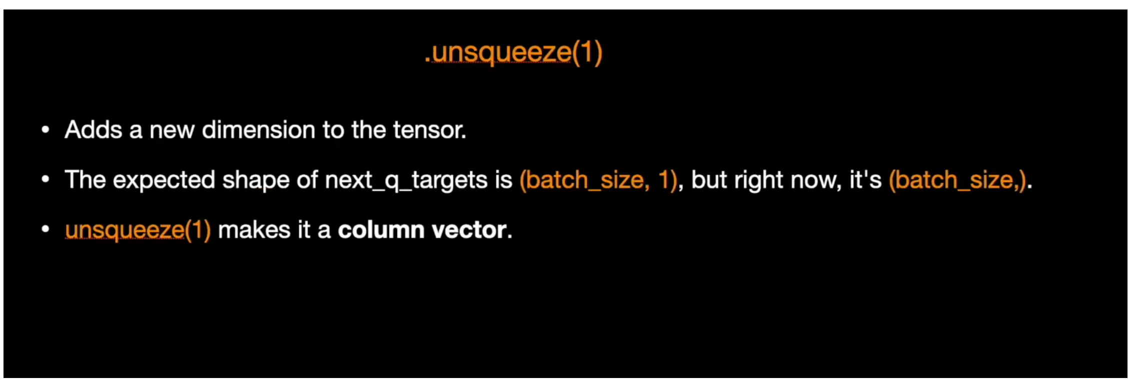
•

0.11 Detach() method.



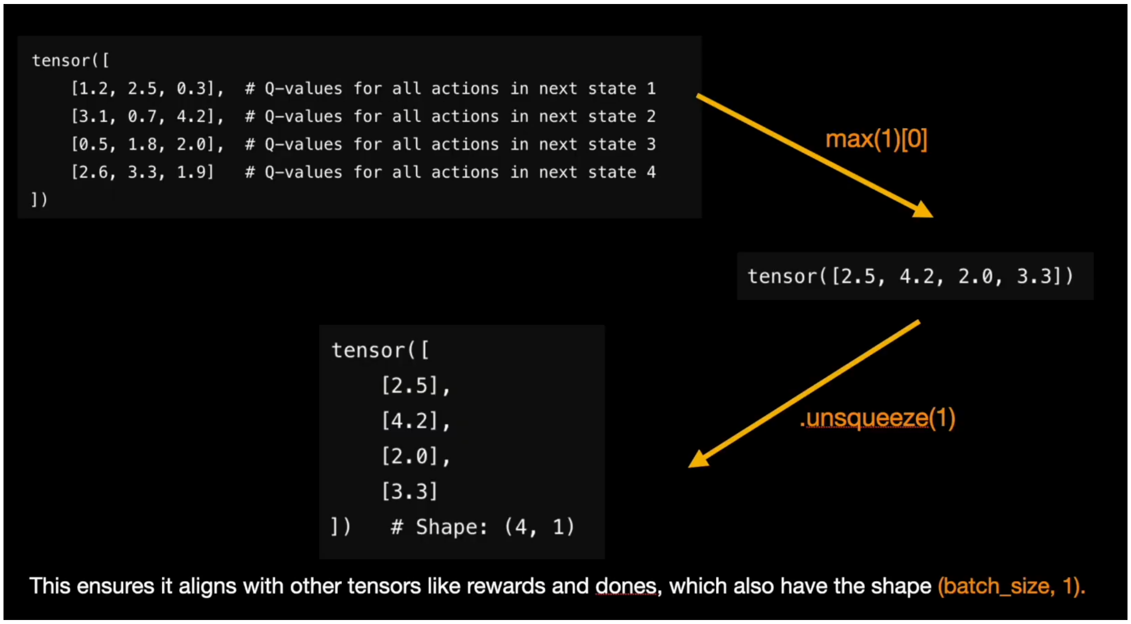
•

0.12 Unsqueeze() method.



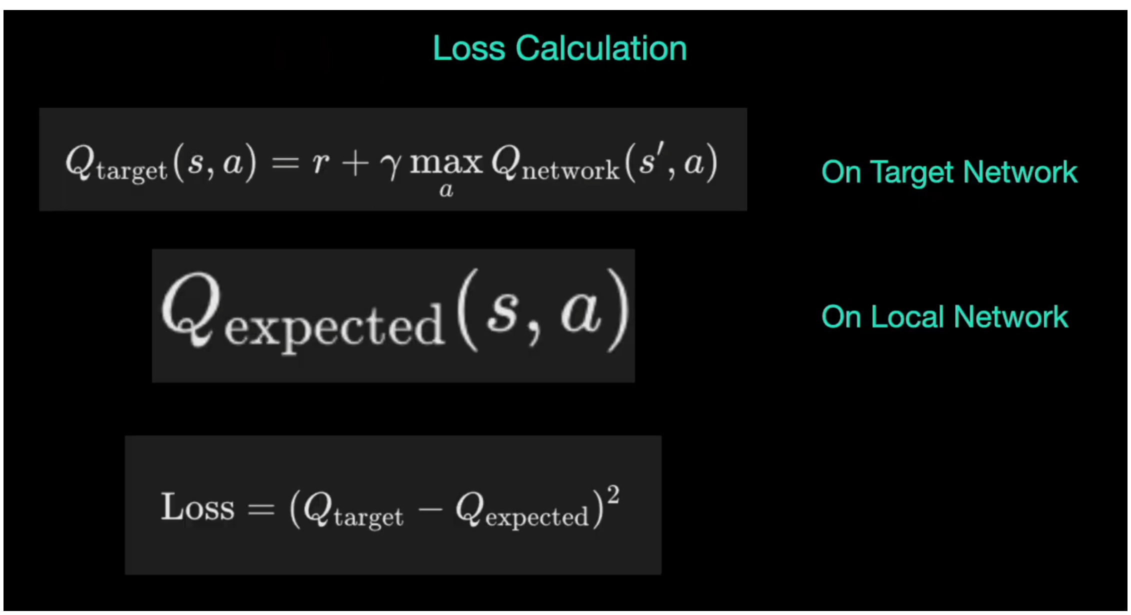
•

0.13 Example for the Next-Q-Targets.



-

0.14 Loss Calculation



-

0.15 Loss Functions()

loss = F.mse_loss(q_expected, q_targets)

- Calculates the Mean Squared Error (MSE) between predicted Q-values (q_expected) and target Q-values (q_targets).

self.optimizer.zero_grad()

- Resets gradients from the previous step to prevent accumulation.

loss.backward() - Backpropagate Loss

- Computes gradients of the loss with respect to model parameters.

self.optimizer.step() - Update Weights

- Adjusts model parameters using the computed gradients to minimize the loss.

-

0.16 How Soft Update Function Works

How soft_update works

Parameters:

1. `local_model`: The neural network actively learning (local Q-network).
2. `target_model`: The more stable network (target Q-network).
3. `interpolation_parameter` (τ): A factor between 0 and 1 that controls the update speed.
   - If $\tau = 1$: The target model immediately copies the local model's weights (hard update).
   - If $\tau = 0.01$: The target model updates very slowly, blending in only 1% of the local model's parameters at a time.

Key Idea:

The target network parameters are updated using:

$$\theta_{\text{target}} \leftarrow \tau \cdot \theta_{\text{local}} + (1 - \tau) \cdot \theta_{\text{target}}$$

Where:

- θ_{target}: Parameters of the target network.
- θ_{local}: Parameters of the local network.
- τ: Interpolation parameter.

[6]:

```
class Agent():

        def __init__(self, state_size, action_size):
                self.state_size = state_size
                self.action_size = action_size
                self.local_qnetwork = ANN(state_size, action_size)
```

```python
        self.target_qnetwork = ANN(state_size, action_size)
        self.optimizer = optim.Adam(self.local_qnetwork.parameters(), lr = learning_rate)
        self.memory = ReplayMemory(replay_buffer_size)
        self.t_step = 0

    def step(self, state, action, reward, next_state, done):
        self.memory.push((state, action, reward, next_state, done))
        self.t_step = (self.t_step+1) % 4
        if self.t_step == 0:
            if len(self.memory.memory) > minibatch:
                experiences = self.memory.sample(minibatch)
                self.learn(experiences, gamma)

    def get_action(self, state, epsilon):
        state = torch.from_numpy(state).float().unsqueeze(0)
        self.local_qnetwork.eval()
        with torch.no_grad():
            action_values = self.local_qnetwork(state)  # [Q(sate, action[0]), Q(state, action_1), ..... ]

        self.local_qnetwork.train()
        if random.random() > epsilon:
            return action_values.argmax().item()
        else:
            return random.choice(np.arange(self.action_size))

    def learn(self, experiences, gamma):
        states, actions, rewards, next_states, dones = experiences
        next_q_targets = self.target_qnetwork(next_states).detach().max(1)[0].unsqueeze(1)
        q_targets = rewards + (gamma * next_q_targets * (1 - dones))
        q_expected = self.local_qnetwork(states).gather(1, actions)
        loss = F.mse_loss(q_expected, q_targets)
        self.optimizer.zero_grad()
        loss.backward()
        self.optimizer.step()
        self.soft_update(self.local_qnetwork, self.target_qnetwork, interpolation_parameter)

    def soft_update(self, local_qnetwork, target_qnetwork, interpolation_parameter):
        for target_params, local_params in zip(target_qnetwork.parameters(), local_qnetwork.parameters()):
            target_params.data.copy_(interpolation_parameter * local_params.data + (1.0 - interpolation_parameter) * target_params.data)
```

1 Training the Agent

[7]:
```
agent = Agent(state_size, action_size)
```

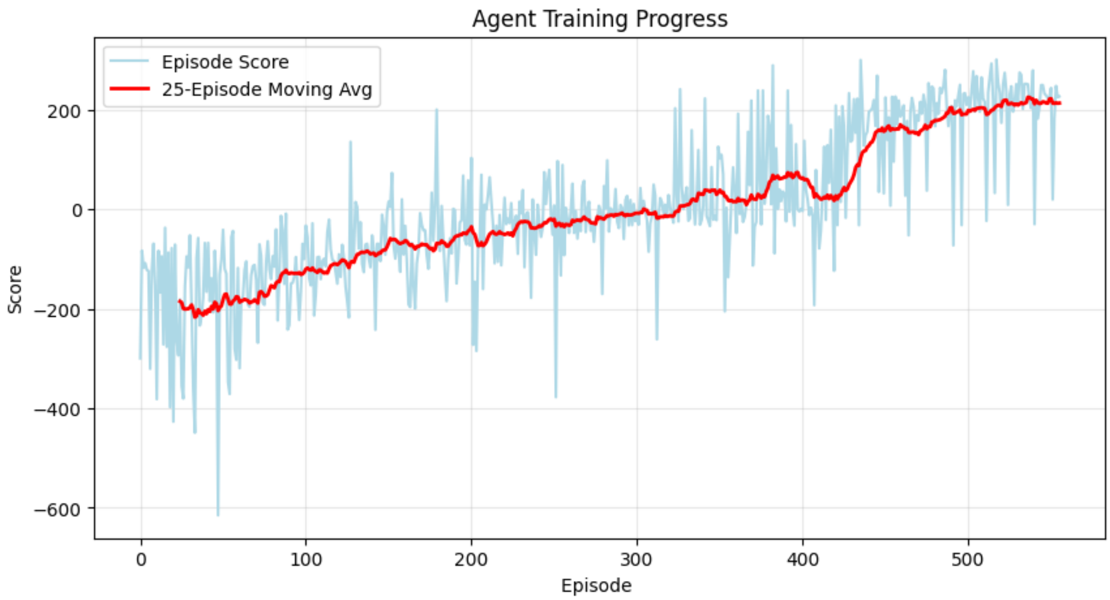
[8]:
```
scores_100_episodes = deque(maxlen=100)
all_scores = []
epsilon = epsilon_starting_value

for episode in range(0, number_episodes):
    state, _ = env.reset()
    score = 0

    for st in range(0, max_time_steps):
        action = agent.get_action(state, epsilon)

        if torch.is_tensor(action):
            action = action.item()


        next_state, reward, terminated, truncated, _ = env.step(action)
        done = terminated or truncated

        agent.step(state, action, reward, next_state, done)
        state = next_state
        score += reward

        if done:
            break

    scores_100_episodes.append(score)
    all_scores.append(score)

    epsilon = max(epsilon_ending_value, epsilon * epsilon_decay_value)

    if episode % 25 == 0:
        print('\rEpisode {}\tAvg Score: {:.3f}'.format(episode, np.
 ↪mean(scores_100_episodes)))

    if np.mean(scores_100_episodes) >= 200:
        print('\nCongratulations! Solved in {:d} episodes \t Avg Score: {:.2f}'.
 ↪format(episode, np.mean(scores_100_episodes)))
        torch.save(agent.local_qnetwork.state_dict(), 'Lunar_Landing_agent.pth')
        break

env.close()
```

```
Episode 0       Avg Score: -299.712
Episode 25      Avg Score: -191.956
```

```
Episode 50      Avg Score: -187.072
Episode 75      Avg Score: -183.146
Episode 100     Avg Score: -166.305
Episode 125     Avg Score: -147.237
Episode 150     Avg Score: -118.699
Episode 175     Avg Score: -94.803
Episode 200     Avg Score: -73.482
Episode 225     Avg Score: -59.097
Episode 250     Avg Score: -47.202
Episode 275     Avg Score: -34.711
Episode 300     Avg Score: -27.888
Episode 325     Avg Score: -15.602
Episode 350     Avg Score: -0.951
Episode 375     Avg Score: 11.950
Episode 400     Avg Score: 29.657
Episode 425     Avg Score: 41.699
Episode 450     Avg Score: 71.719
Episode 475     Avg Score: 106.522
Episode 500     Avg Score: 140.427
Episode 525     Avg Score: 182.351
Episode 550     Avg Score: 198.218

Congratulations! Solved in 555 episodes         Avg Score: 200.71
```

2 Demonstration of Lunar Lander Learning

[9]:
```
fig = plt.figure(figsize=(10, 5))
ax = fig.add_subplot(111)
plt.plot(np.arange(len(all_scores)), all_scores, label='Episode Score',␣
 ↪color='lightblue')


rolling_mean = pd.Series(all_scores).rolling(window=25).mean()
plt.plot(np.arange(len(all_scores)), rolling_mean, label='25-Episode Moving␣
 ↪Avg', color='red', linewidth=2)

plt.ylabel('Score')
plt.xlabel('Episode ')
plt.title('Agent Training Progress')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```


Agent Training Progress
Episode Score
25-Episode Moving Avg
200
0
−200
−400
−600
Score
0
100
200
300
400
500
Episode