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In [ ]: import numpy as np
        import gymnasium as gym #  use Gymnasium
        # -----
        # Create Taxi environment
        # ------
        env = qym.make("Taxi-v3")
        print("Number of states:", env.observation space.n) # 500
        print("Number of actions:", env.action space.n) # 6
        # Parameters
        qamma = 0.9
        theta = 1e-6
        # Value Iteration
        # -----
        def value iteration(env, gamma=0.9, theta=1e-6):
           value table = np.zeros(env.observation space.n)
           while True:
               delta = 0
               for state in range(env.observation space.n):
                   action values = np.zeros(env.action space.n)
                   for action in range(env.action space.n):
                       for prob, next state, reward, done in env.unwrapped.P[state][a
                           action values[action] += prob * (reward + gamma * value ta
                   best action value = np.max(action values)
                   delta = max(delta, abs(value_table[state] - best_action_value))
                   value table[state] = best action value
               if delta < theta:</pre>
                   break
           # Derive policy
           policy = np.zeros(env.observation space.n, dtype=int)
           for state in range(env.observation space.n):
               action values = np.zeros(env.action space.n)
               for action in range(env.action space.n):
                   for prob, next_state, reward, done in env.unwrapped.P[state][actic
                       action values[action] += prob * (reward + gamma * value table[
               policy[state] = np.argmax(action values)
           return policy, value table
        # Policy Evaluation
        # ---------
        def policy_evaluation(policy, env, gamma=0.9, theta=1e-6):
           value table = np.zeros(env.observation space.n)
           while True:
               delta = 0
               for state in range(env.observation space.n):
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V = 0
           action = policy[state]
           for prob, next state, reward, done in env.unwrapped.P[state][actic
               v += prob * (reward + gamma * value table[next state])
           delta = max(delta, abs(value table[state] - v))
           value table[state] = v
       if delta < theta:</pre>
           break
   return value table
# Policy Improvement
# -----
def policy improvement(value table, policy, env, gamma=0.9):
   policy stable = True
   for state in range(env.observation space.n):
       old action = policy[state]
       action values = np.zeros(env.action space.n)
       for action in range(env.action space.n):
           for prob, next state, reward, done in env.unwrapped.P[state][actid
               action values[action] += prob * (reward + gamma * value table[
       policy[state] = np.argmax(action values)
       if old action != policy[state]:
           policy stable = False
   return policy, policy stable
# -----
# Policy Iteration
def policy iteration(env, gamma=0.9, theta=1e-6):
   policy = np.random.choice(env.action space.n, size=env.observation space.n
   value_table = np.zeros(env.observation space.n)
   while True:
       value table = policy evaluation(policy, env, gamma, theta)
       policy, policy stable = policy improvement(value table, policy, env, g
       if policy stable:
           return policy, value table
# ------
# Run Both Algorithms
# ------
print("\n Running Policy Iteration...")
pi policy, pi value = policy iteration(env, gamma, theta)
print("Policy Iteration: Optimal Value Function shape =", pi value.shape)
print("Policy Iteration: Optimal Policy shape =", pi policy.shape)
print("\n Running Value Iteration...")
vi policy, vi value = value iteration(env, gamma, theta)
print("Value Iteration: Optimal Value Function shape =", vi value.shape)
print("Value Iteration: Optimal Policy shape =", vi policy.shape)
```

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# Quick check: same optimal policy?
 # -----
 print("\n Do both methods give same optimal policy? ->", np.array_equal(pi_pol
 # Demonstration: play one episode using optimal policy
 # -----
 state, = env.reset()
 done = False
 total reward = 0
 steps = 0
 print("\n Demo run with Optimal Policy:")
 while not done and steps < 20:
     action = pi policy[state]
     state, reward, terminated, truncated, = env.step(action)
     done = terminated or truncated
     total reward += reward
     steps += 1
     env.render()
 print("Episode finished in", steps, "steps with reward:", total reward)
Number of states: 500
Number of actions: 6
Running Policy Iteration...
Policy Iteration: Optimal Value Function shape = (500,)
Policy Iteration: Optimal Policy shape = (500,)
Running Value Iteration...
Value Iteration: Optimal Value Function shape = (500,)
Value Iteration: Optimal Policy shape = (500,)
Do both methods give same optimal policy? -> True
 Demo run with Optimal Policy:
Episode finished in 12 steps with reward: 9
/usr/local/lib/python3.12/dist-packages/gymnasium/envs/toy text/taxi.py:443: Us
erWarning: WARN: You are calling render method without specifying any render mo
de. You can specify the render mode at initialization, e.g. qym.make("Taxi-v3",
render mode="rgb array")
gym.logger.warn(
```