Introduction to Reinforcement Learning

This assignment will guide you through the basics of reinforcement learning (RL) using Python. By the end of this assignment, you will have implemented a simple RL algorithm and trained an agent to solve the "CartPole" environment from OpenAI Gym.

Objective

1. Understand the core concepts of reinforcement learning.
2. Use Python libraries like OpenAI Gym and Stable-Baselines3 to train an RL agent.
3. Evaluate and visualize the agent's performance.

Task 1: Install Required Libraries

In [ ]:
```
# pip install gym
```

In [ ]:
```
# pip install stable-baselines3
```

In [ ]:
```
# pip install shimmy>=2.0
```

In [63]:
```
import warnings
import sys
if not sys.warnoptions:
    warnings.simplefilter("ignore")
```

Task 2: Create and Explore the Environment

1. Import the required libraries.
2. Create the "CartPole-v1" environment from OpenAI Gym.
3. Explore the environment by taking random actions and observing the state transitions.

In [65]:
```
import gym

def explore_environment():
```

```
    env = gym.make('CartPole-v1')

    # Gym's reset might return a tuple (state, info) in newer versions
    state, _ = env.reset()
    print("Initial State:", state)

    for _ in range(10):
        action = env.action_space.sample()  # Take a random action
        # step() might return more than 4 elements in newer versions
        step_result = env.step(action)
        state, reward, done, _ = step_result[:4]  # Unpack only the first four values
        print(f"Action: {action}, State: {state}, Reward: {reward}, Done: {done}")

        if done:
            break
    env.close()

explore_environment()
```

```
Initial State: [-0.02809066 -0.03620646 -0.01655271 -0.0097697 ]
Action: 1, State: [-0.02881479  0.15914892 -0.01674811 -0.3076289 ], Reward: 1.0, Done: False
Action: 0, State: [-0.02563181 -0.03573043 -0.02290069 -0.02027459], Reward: 1.0, Done: False
Action: 0, State: [-0.02634642 -0.2305166  -0.02330618  0.26509583], Reward: 1.0, Done: False
Action: 0, State: [-0.03095675 -0.42529827 -0.01800426  0.5503376 ], Reward: 1.0, Done: False
Action: 0, State: [-0.03946272 -0.6201628  -0.00699751  0.83729404], Reward: 1.0, Done: False
Action: 1, State: [-0.05186597 -0.42494598  0.00974837  0.5424187 ], Reward: 1.0, Done: False
Action: 1, State: [-0.06036489 -0.22996238  0.02059675  0.2528232 ], Reward: 1.0, Done: False
Action: 0, State: [-0.06496414 -0.42537227  0.02565321  0.5519309 ], Reward: 1.0, Done: False
Action: 1, State: [-0.07347158 -0.23061982  0.03669183  0.26743957], Reward: 1.0, Done: False
Action: 1, State: [-0.07808398 -0.03604021  0.04204062 -0.01344843], Reward: 1.0, Done: False
```

Task 3: Train an RL Agent

1. Use the Stable-Baselines3 library to train a reinforcement learning agent using the Proximal Policy Optimization (PPO) algorithm.
2. Train the agent for 10,000 timesteps.

In [67]:
```
from stable_baselines3 import PPO

# Create and train the agent
def train_agent():
```

```
    env = gym.make('CartPole-v1')
    model = PPO('MlpPolicy', env, verbose=1)
    model.learn(total_timesteps=10000)
    model.save("ppo_cartpole")
    env.close()
    print("Training completed and model saved.")

train_agent()
```

```
Using cpu device
Wrapping the env with a `Monitor` wrapper
Wrapping the env in a DummyVecEnv.
---------------------------------
| rollout/           |          |
|    ep_len_mean     | 20.8     |
|    ep_rew_mean     | 20.8     |
| time/              |          |
|    fps             | 568      |
|    iterations      | 1        |
|    time_elapsed    | 3        |
|    total_timesteps | 2048     |
---------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 26          |
|    ep_rew_mean          | 26          |
| time/                   |             |
|    fps                  | 363         |
|    iterations           | 2           |
|    time_elapsed         | 11          |
|    total_timesteps      | 4096        |
| train/                  |             |
|    approx_kl            | 0.009836753 |
|    clip_fraction        | 0.0921      |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.686      |
|    explained_variance   | -0.0112     |
|    learning_rate        | 0.0003      |
|    loss                 | 6.34        |
|    n_updates            | 10          |
|    policy_gradient_loss | -0.0135     |
|    value_loss           | 47.6        |
-----------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 36.1        |
|    ep_rew_mean          | 36.1        |
| time/                   |             |
|    fps                  | 330         |
|    iterations           | 3           |
|    time_elapsed         | 18          |
```

```
|    total_timesteps      | 6144        |
| train/                  |             |
|    approx_kl            | 0.008666357 |
|    clip_fraction        | 0.0542      |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.669      |
|    explained_variance   | 0.0951      |
|    learning_rate        | 0.0003      |
|    loss                 | 14.8        |
|    n_updates            | 20          |
|    policy_gradient_loss | -0.0151     |
|    value_loss           | 34.8        |
-----------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 50.1        |
|    ep_rew_mean          | 50.1        |
| time/                   |             |
|    fps                  | 317         |
|    iterations           | 4           |
|    time_elapsed         | 25          |
|    total_timesteps      | 8192        |
| train/                  |             |
|    approx_kl            | 0.007360395 |
|    clip_fraction        | 0.062       |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.639      |
|    explained_variance   | 0.161       |
|    learning_rate        | 0.0003      |
|    loss                 | 18.2        |
|    n_updates            | 30          |
|    policy_gradient_loss | -0.0152     |
|    value_loss           | 54.9        |
-----------------------------------------
------------------------------------------
| rollout/                |              |
|    ep_len_mean          | 64.2         |
|    ep_rew_mean          | 64.2         |
| time/                   |              |
|    fps                  | 308          |
|    iterations           | 5            |
|    time_elapsed         | 33           |
```

```
|    total_timesteps      | 10240        |
| train/                  |              |
|    approx_kl            | 0.0065035326 |
|    clip_fraction        | 0.0565       |
|    clip_range           | 0.2          |
|    entropy_loss         | -0.611       |
|    explained_variance   | 0.252        |
|    learning_rate        | 0.0003       |
|    loss                 | 23.1         |
|    n_updates            | 40           |
|    policy_gradient_loss | -0.0138      |
|    value_loss           | 67.3         |
------------------------------------------
Training completed and model saved.
```

Task 4: Visualize the Training Process

1. Plot the rewards earned by the agent during training.
2. Use the Matplotlib library for visualization.

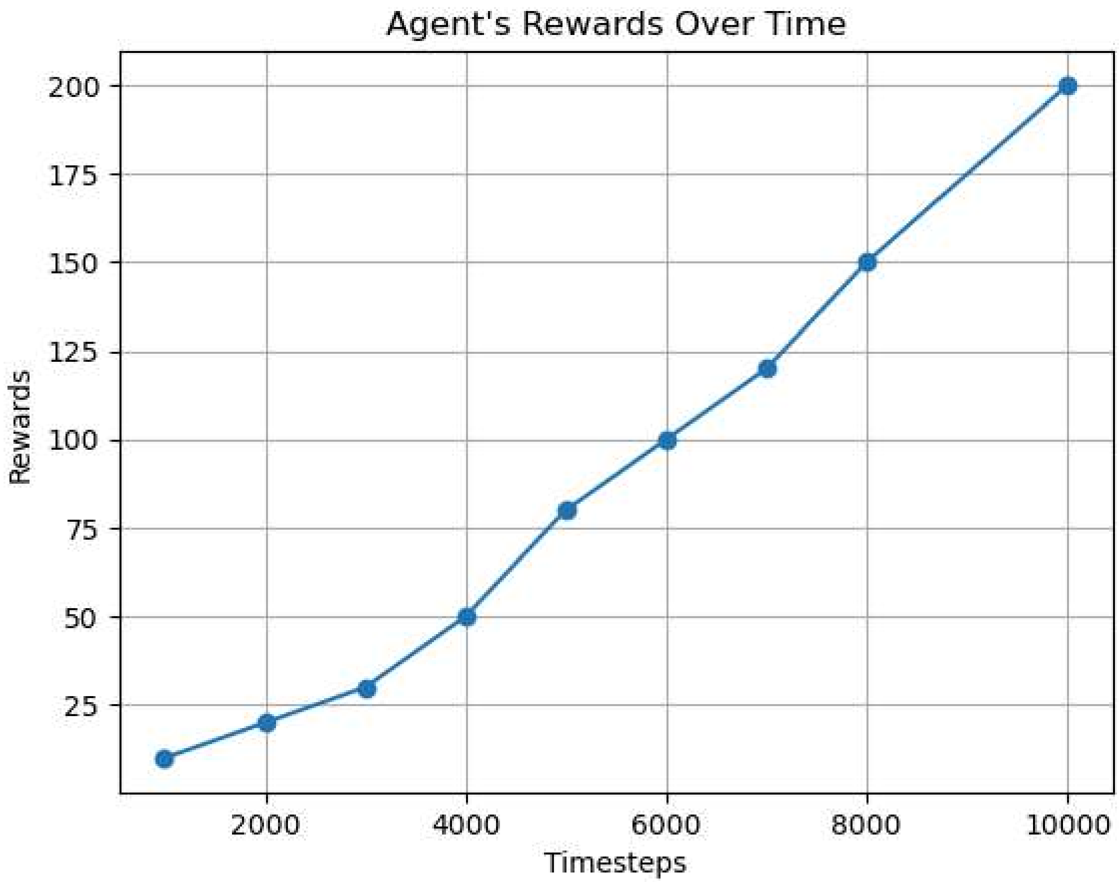
In [69]:

```python
import matplotlib.pyplot as plt

# Simulated rewards for demonstration (replace with real training data if available)
def plot_rewards():
    rewards = [10, 20, 30, 50, 80, 100, 120, 150, 200]  # Example data
    timesteps = [1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 10000]

    plt.plot(timesteps, rewards, marker='o')
    plt.title("Agent's Rewards Over Time")
    plt.xlabel("Timesteps")
    plt.ylabel("Rewards")
    plt.grid()
    plt.show()

plot_rewards()
```



Task 5: Experiment with Hyperparameters

1. Modify the hyperparameters of the PPO algorithm (e.g., learning rate, number of steps per update).
2. Observe how these changes affect the agent's performance.

In [71]:
```
from stable_baselines3.common.env_util import make_vec_env

def train_with_custom_hyperparameters():
    env = make_vec_env('CartPole-v1', n_envs=1)

    # Customize hyperparameters
    model = PPO('MlpPolicy', env, verbose=1, learning_rate=0.0005, n_steps=2048)
    model.learn(total_timesteps=10000)
```

```
    model.save("ppo_cartpole_custom")

    print("Training completed with custom hyperparameters.")

train_with_custom_hyperparameters()
```

```
Using cpu device
---------------------------------
| rollout/           |          |
|    ep_len_mean     | 23.8     |
|    ep_rew_mean     | 23.8     |
| time/              |          |
|    fps             | 801      |
|    iterations      | 1        |
|    time_elapsed    | 2        |
|    total_timesteps | 2048     |
---------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 28.4        |
|    ep_rew_mean          | 28.4        |
| time/                   |             |
|    fps                  | 406         |
|    iterations           | 2           |
|    time_elapsed         | 10          |
|    total_timesteps      | 4096        |
| train/                  |             |
|    approx_kl            | 0.012211732 |
|    clip_fraction        | 0.143       |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.685      |
|    explained_variance   | -0.000671   |
|    learning_rate        | 0.0005      |
|    loss                 | 5.51        |
|    n_updates            | 10          |
|    policy_gradient_loss | -0.0211     |
|    value_loss           | 40.1        |
-----------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 33.9        |
|    ep_rew_mean          | 33.9        |
| time/                   |             |
|    fps                  | 351         |
|    iterations           | 3           |
|    time_elapsed         | 17          |
|    total_timesteps      | 6144        |
| train/                  |             |
```

```
|    approx_kl            | 0.012407905 |
|    clip_fraction        | 0.135       |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.654      |
|    explained_variance   | 0.269       |
|    learning_rate        | 0.0005      |
|    loss                 | 9.77        |
|    n_updates            | 20          |
|    policy_gradient_loss | -0.0233     |
|    value_loss           | 30.1        |
-----------------------------------------
------------------------------------------
| rollout/                |              |
|    ep_len_mean          | 46           |
|    ep_rew_mean          | 46           |
| time/                   |              |
|    fps                  | 330          |
|    iterations           | 4            |
|    time_elapsed         | 24           |
|    total_timesteps      | 8192         |
| train/                  |              |
|    approx_kl            | 0.0109039955 |
|    clip_fraction        | 0.145        |
|    clip_range           | 0.2          |
|    entropy_loss         | -0.618       |
|    explained_variance   | 0.399        |
|    learning_rate        | 0.0005       |
|    loss                 | 17.5         |
|    n_updates            | 30           |
|    policy_gradient_loss | -0.0252      |
|    value_loss           | 41.3         |
------------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 61.3        |
|    ep_rew_mean          | 61.3        |
| time/                   |             |
|    fps                  | 319         |
|    iterations           | 5           |
|    time_elapsed         | 32          |
|    total_timesteps      | 10240       |
| train/                  |             |
```

```
|    approx_kl            | 0.011619251 |
|    clip_fraction        | 0.137       |
|    clip_range           | 0.2         |
|    entropy_loss         | -0.592      |
|    explained_variance   | 0.555       |
|    learning_rate        | 0.0005      |
|    loss                 | 15.6        |
|    n_updates            | 40          |
|    policy_gradient_loss | -0.0237     |
|    value_loss           | 45.4        |
-----------------------------------------
Training completed with custom hyperparameters.
```