Introduction to policy gradient

DEEP REINFORCEMENT LEARNING IN PYTHON

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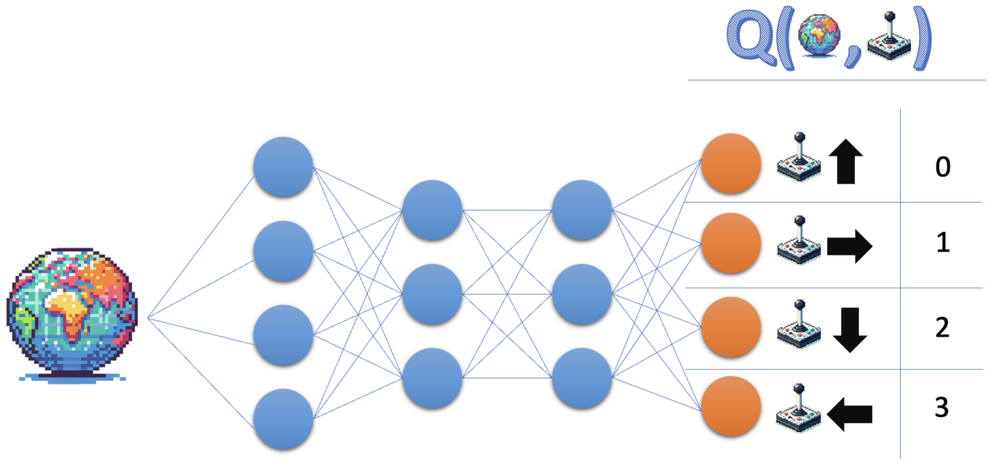
Introduction to Policy methods in DRL

Q-learning:

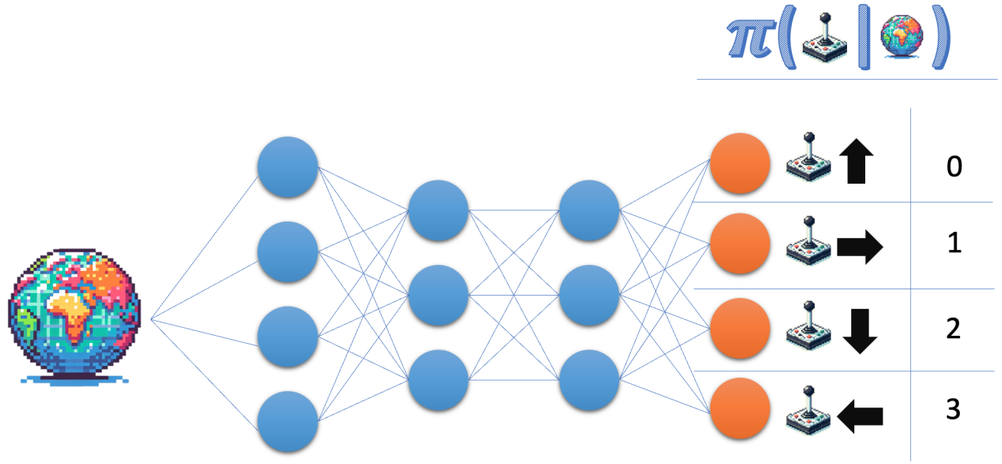
- Learn the action value function Q



- Policy: select action with highest value

Policy learning:

- Learn the policy directly



Policy learning

- Can be stochastic
- Handle continuous spaces
- Directly optimize for the objective
- High variance
- Less sample efficient

- In Deep-Q learning: policies are deterministic

$\pi_\theta(a_t|s_t)$:

- Probability distribution for a_t in state s_t, with:
  - a_t, s_t: action and state at step t
  - θ: policy parameters (network weights)

The policy network (discrete actions)

```
class PolicyNetwork(nn.Module):
  def __init__(self, state_size, action_size):
    super(PolicyNetwork, self).__init__()
    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 = torch.relu(self.fc1(torch.tensor(state)))
    x = torch.relu(self.fc2(x))
    action_probs = torch.softmax(self.fc3(x), dim=-1)
    return action_probs

action_probs = policy_network(state)
print('Action probabilities:', action_probs)
```

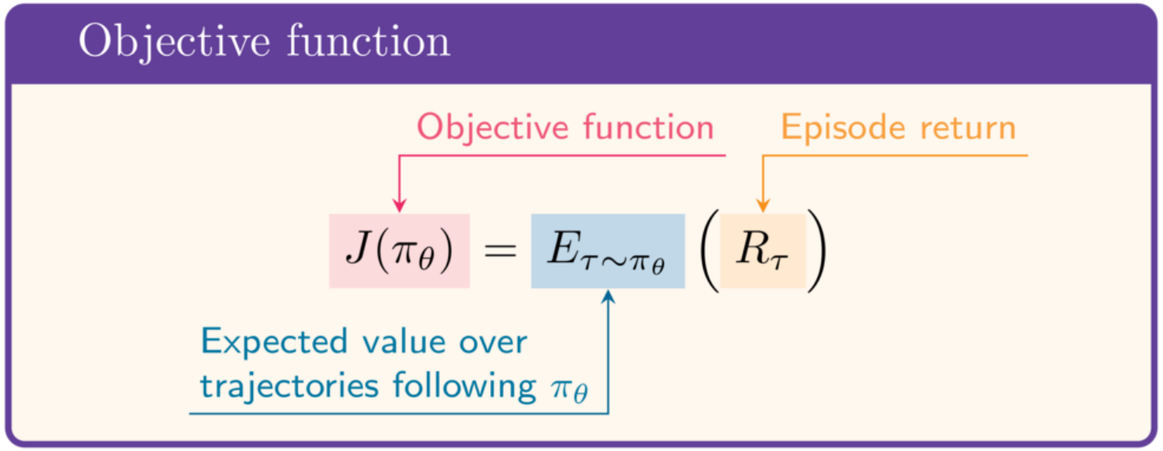
```
Action probabilities: tensor([0.21, 0.02, 0.74, 0.03])
```

Action	index	$\pi(\text{action} \mid \text{state})$
	0	0.21
	1	0.02
	2	0.74
	3	0.03

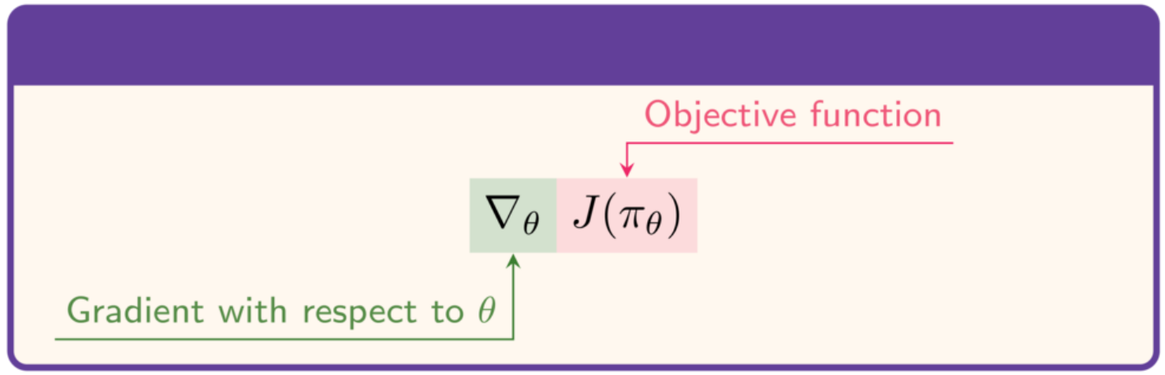
```
action_dist = (
    torch.distributions.Categorical(action_probs))
action = action_dist.sample()
```

The objective function

- Policy must maximize expected returns
  - Assuming the agent follows π_θ
  - By optimizing policy parameter θ
- Objective function:



- To maximize J: need gradient with respect to θ:



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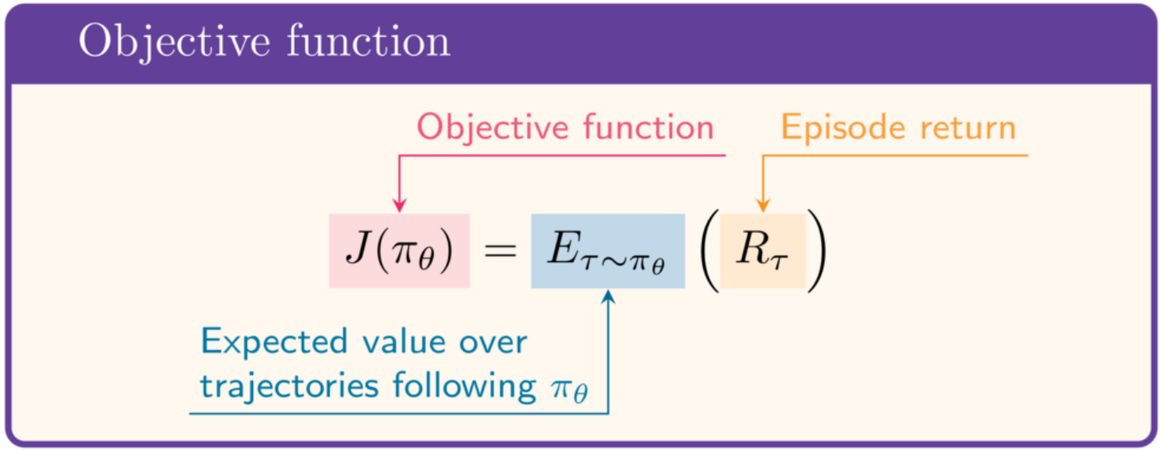

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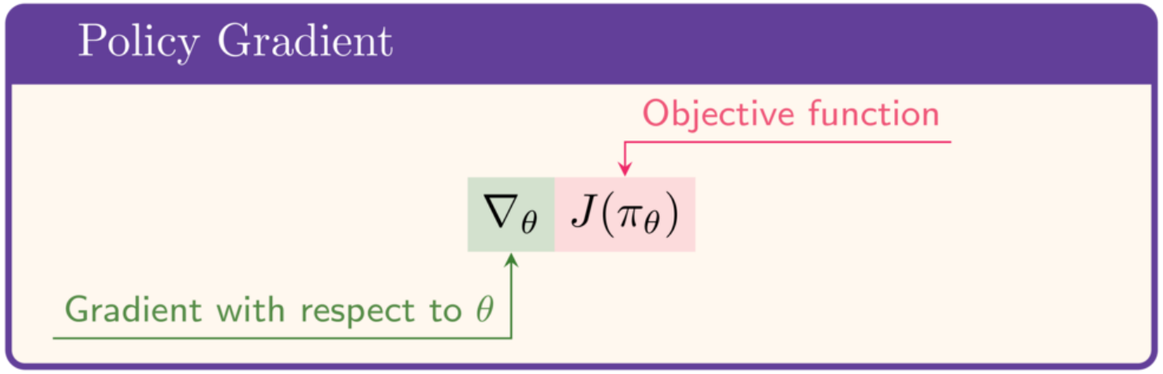
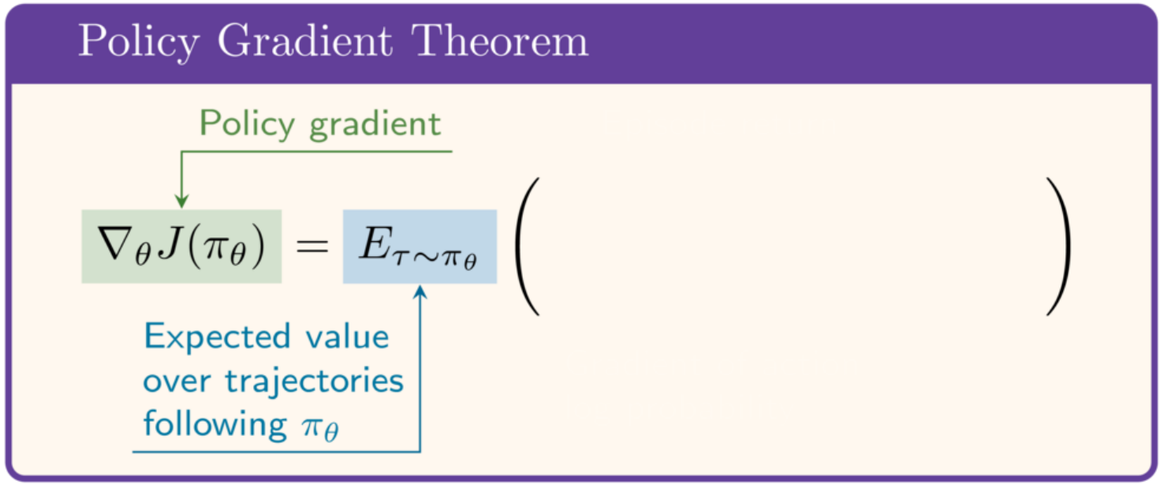


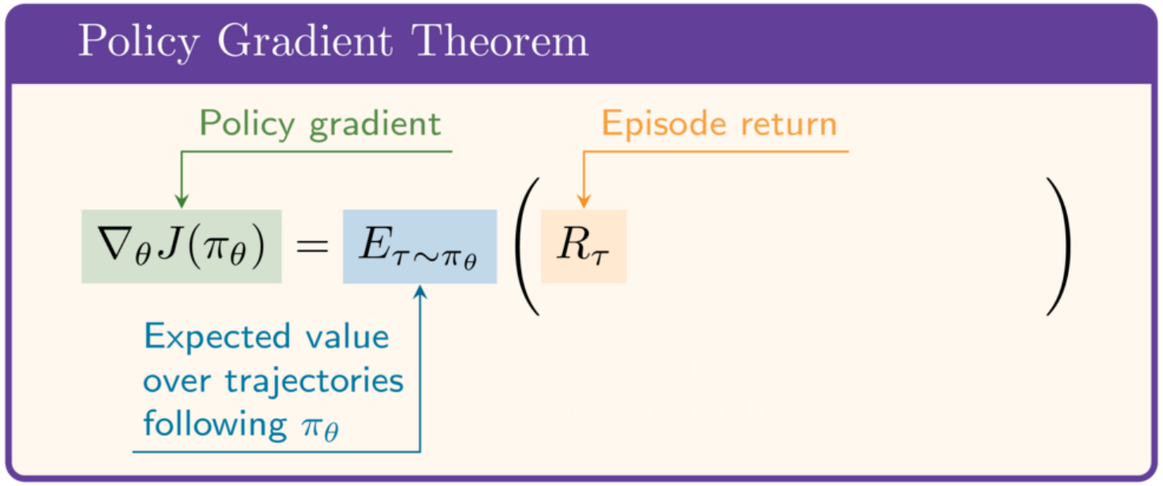
The policy gradient theorem

- Gives a tractable expression for $\nabla_\theta J(\pi_\theta)$
- Expectation over trajectories following π_θ
  - Collect trajectories and observe the returns



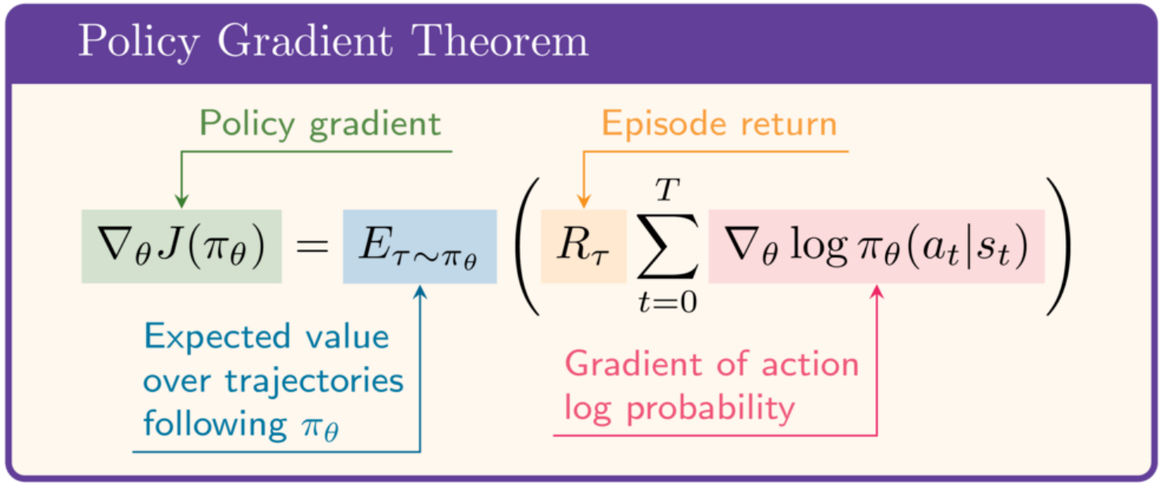
The policy gradient theorem

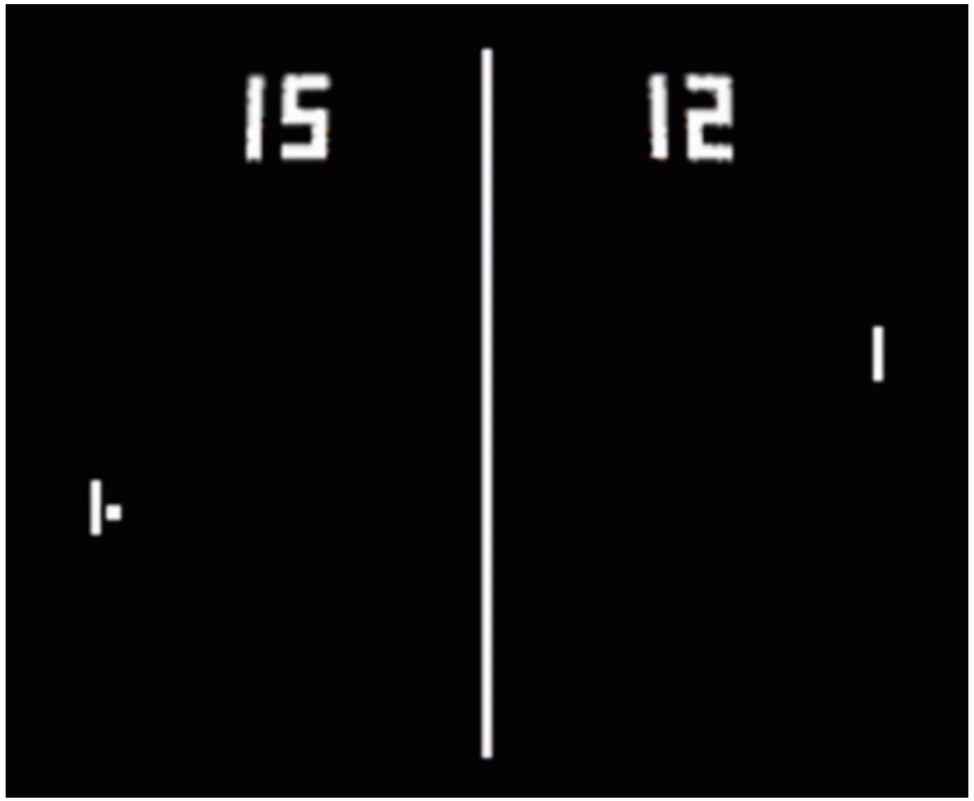
- Gives a tractable expression for $\nabla_\theta J(\pi_\theta)$
- Expectation over trajectories following π_θ
  - Collect trajectories and observe the returns
- For each trajectory: consider return R_τ



The policy gradient theorem

- Gives a tractable expression for $\nabla_\theta J(\pi_\theta)$
- Expectation over trajectories following π_θ
  - Collect trajectories and observe the returns
- For each trajectory: consider return R_τ
- Multiply by the sum of gradients of log probabilities of selected actions
- Intuition: nudge theta in ways that increase probability of all actions taken in a 'good' episode

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Let's practice!

DEEP REINFORCEMENT LEARNING IN PYTHON

Policy gradient and REINFORCE

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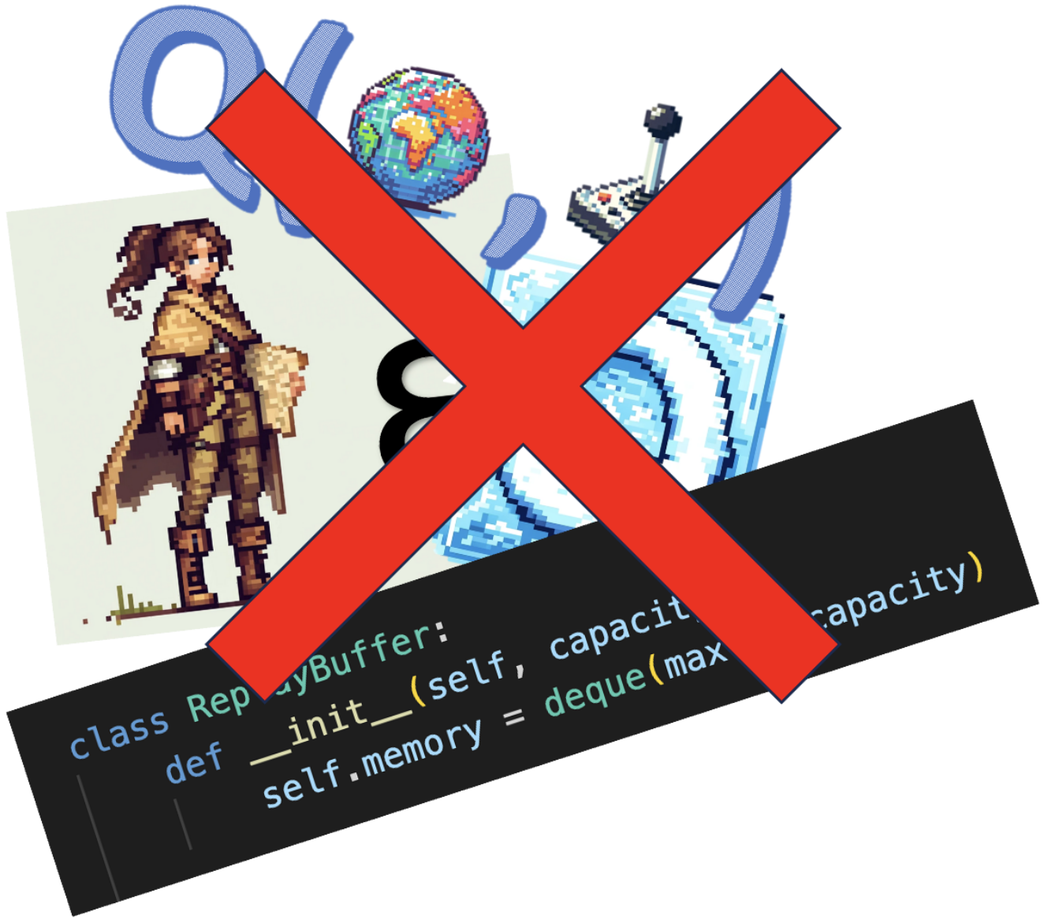
Differences with DQN

- REINFORCE: Monte-Carlo, not Temporal Difference
  - Update at the end of the episode, *not* at every step
  - Can update after several episodes instead
- No value function
- No target network
- No epsilon-greediness
- No experience replay



The REINFORCE training loop structure

```
for episode in range(num_episodes):
  # 1. Initialize episode
  while not done:
    # 2. Select action
    # 3. Play action and obtain next state and reward
    # 4. Add (discounted) reward to return
    # 5. Update state
  # 6. Calculate loss
  # 7. Update policy network by gradient descent
```

Action Selection

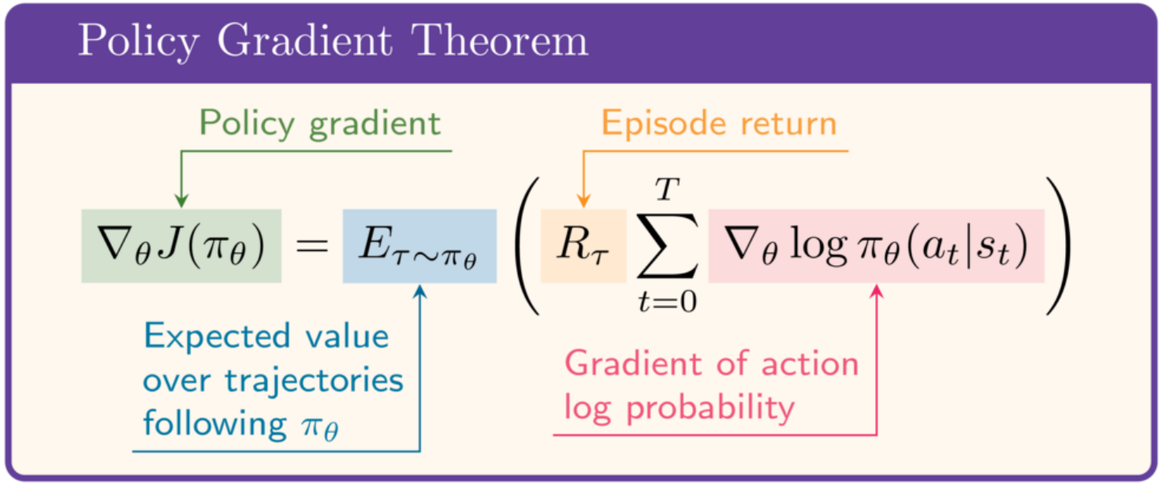
```
from torch.distributions import Categorical

def select_action(policy_network, state):
  action_probs = policy_network(state)
  action_dist = Categorical(action_probs)
  action = action_dist.sample()
  log_prob = action_dist.log_prob(action)
  return action.item(), log_prob.reshape(1)

action, log_prob = select_action(
                        policy_network, state)
```

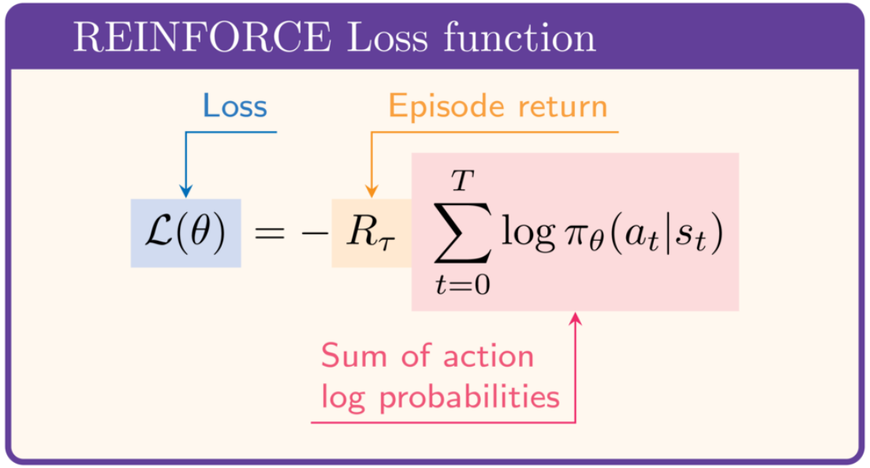
- Obtain probabilities from network
- Sample one action
- Return action and corresponding log probabilities

```
Sampled action index: 1
Log probability of sampled action: -1.38
```

Loss Calculation

Recall the policy gradient theorem:





In Python:

- R_τ as `episode_return`
- Vector of $\log \pi_\theta(a_t|s_t)$ as `episode_log_probs`

```
loss = -episode_return * episode_log_probs.sum()
```

The REINFORCE training loop

```
for episode in range(50):
  state, info = env.reset(); done = False; step = 0;
  episode_log_probs = torch.tensor([])
  R = 0
  while not done:
    step += 1
    action, log_prob = select_action(policy_network, state)
    next_state, reward, terminated, truncated, _ = env.step(action)
    done = terminated or truncated
    R += (gamma ** step) * reward
    episode_log_probs = torch.cat((episode_log_probs, log_prob))
    state = next_state
  loss = - R * episode_log_probs.sum()
  optimizer.zero_grad(); loss.backward(); optimizer.step()
```

Let's practice!

DEEP REINFORCEMENT LEARNING IN PYTHON

Advantage Actor Critic

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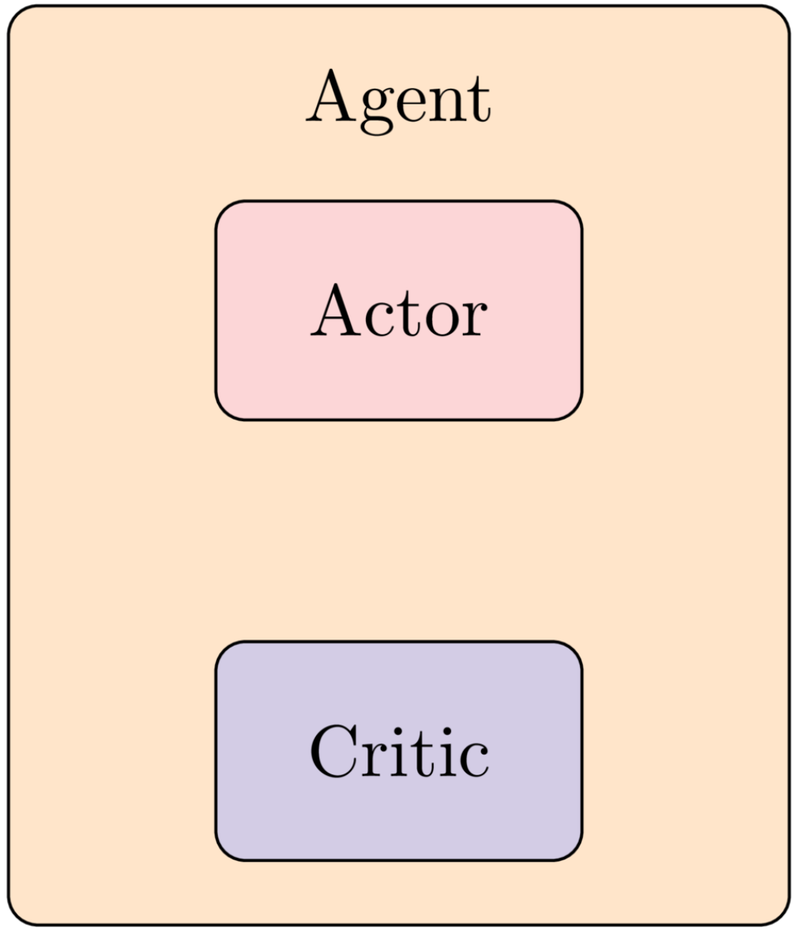
Why actor critic?

- REINFORCE limitations:
  - High variance
  - Poor sample efficiency
- Actor Critic methods introduce a critic network, enabling Temporal Difference learning

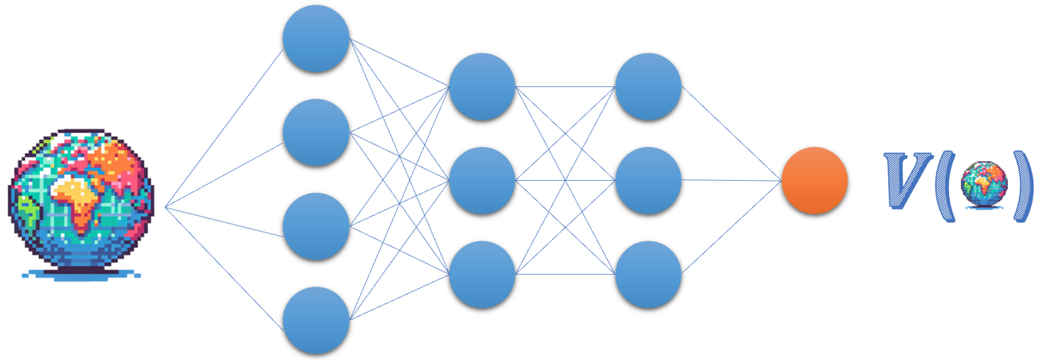


The intuition behind Actor Critic methods

- Actor network:
  - Makes decisions
  - Cannot evaluate them
- Critic network:
  - Provides feedback to actor at every step

The Critic network

- Critic approximates the state value function



- Judges action a_t based on the advantage or TD-error

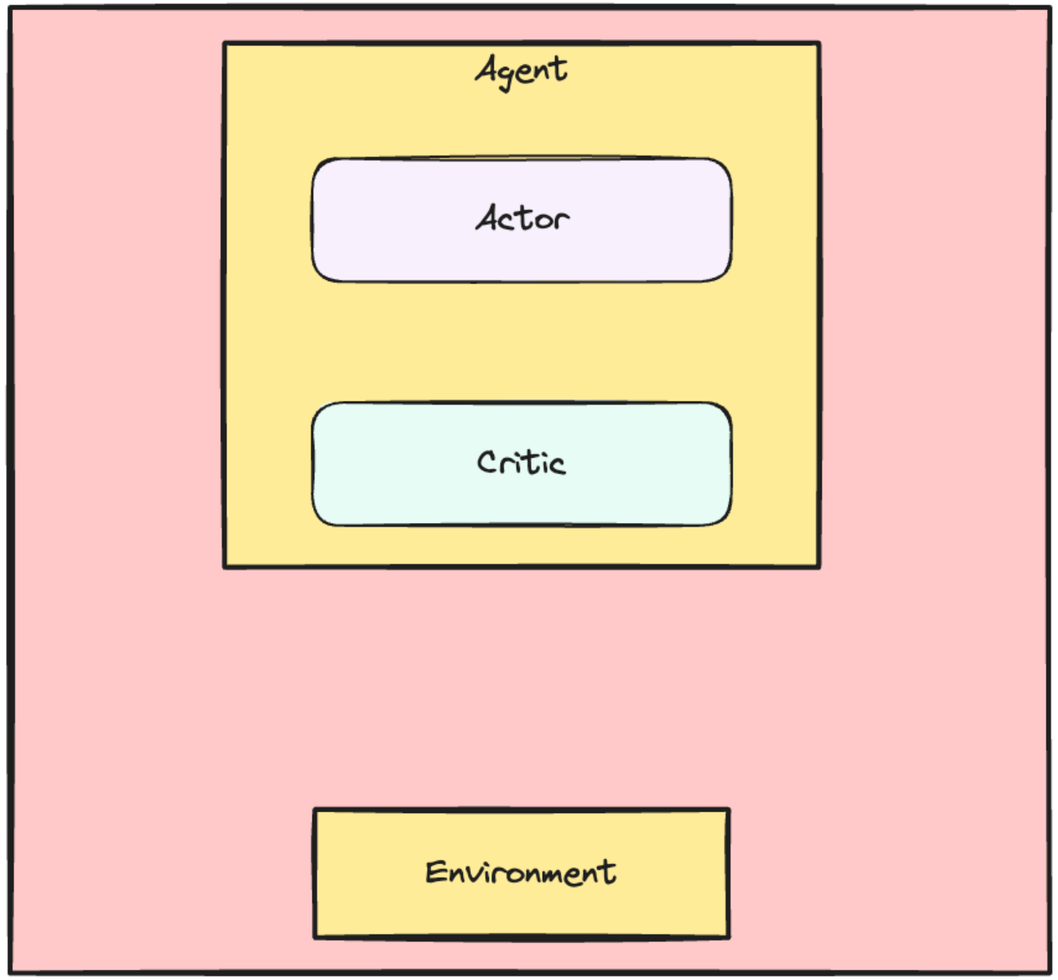
```
class Critic(nn.Module):
    def __init__(self, state_size):
        super(Critic, self).__init__()
        self.fc1 = nn.Linear(state_size, 64)
        self.fc2 = nn.Linear(64, 1)

    def forward(self, state):
        x = torch.relu(self.fc1(torch.tensor(state)))
        value = self.fc2(x)
        return value

critic_network = Critic(8)
```

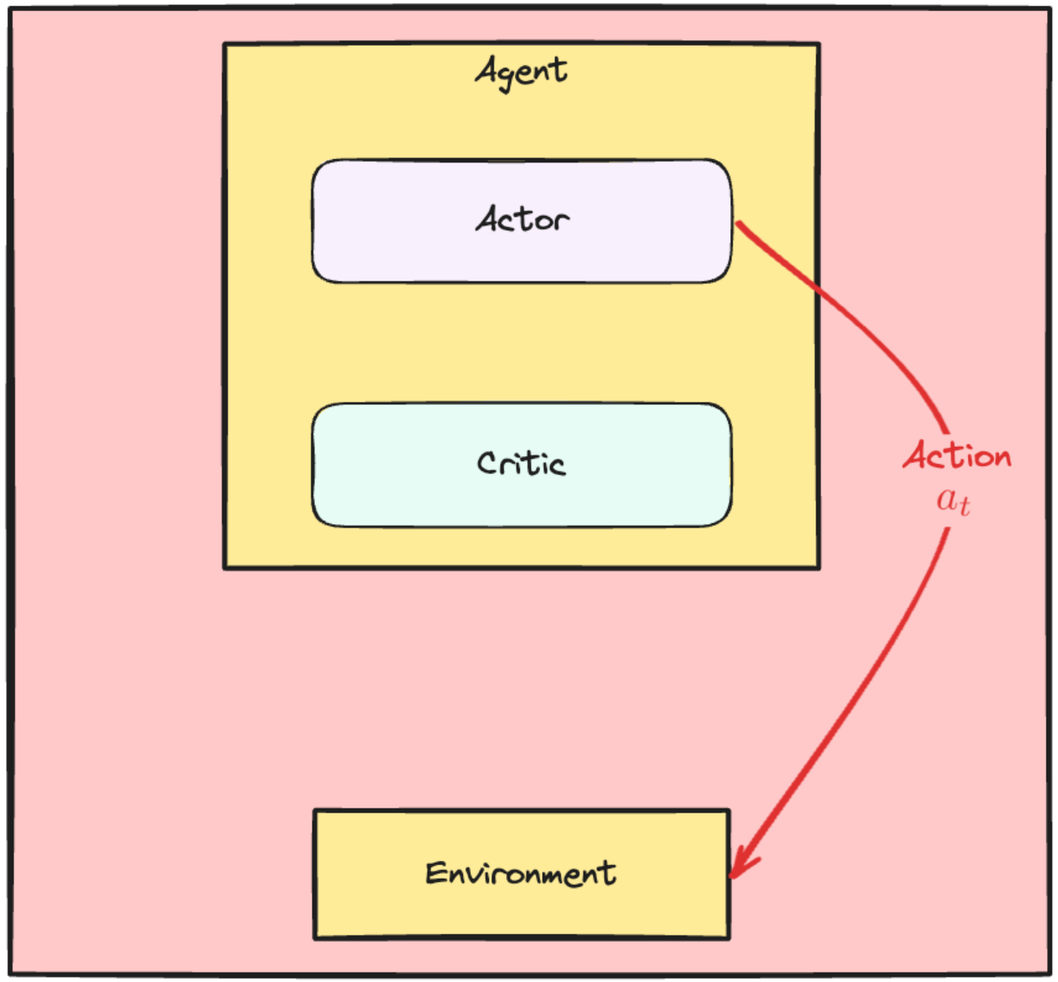
The Actor Critic dynamics

- At every step:
  - Actor chooses action (same as policy network in REINFORCE)



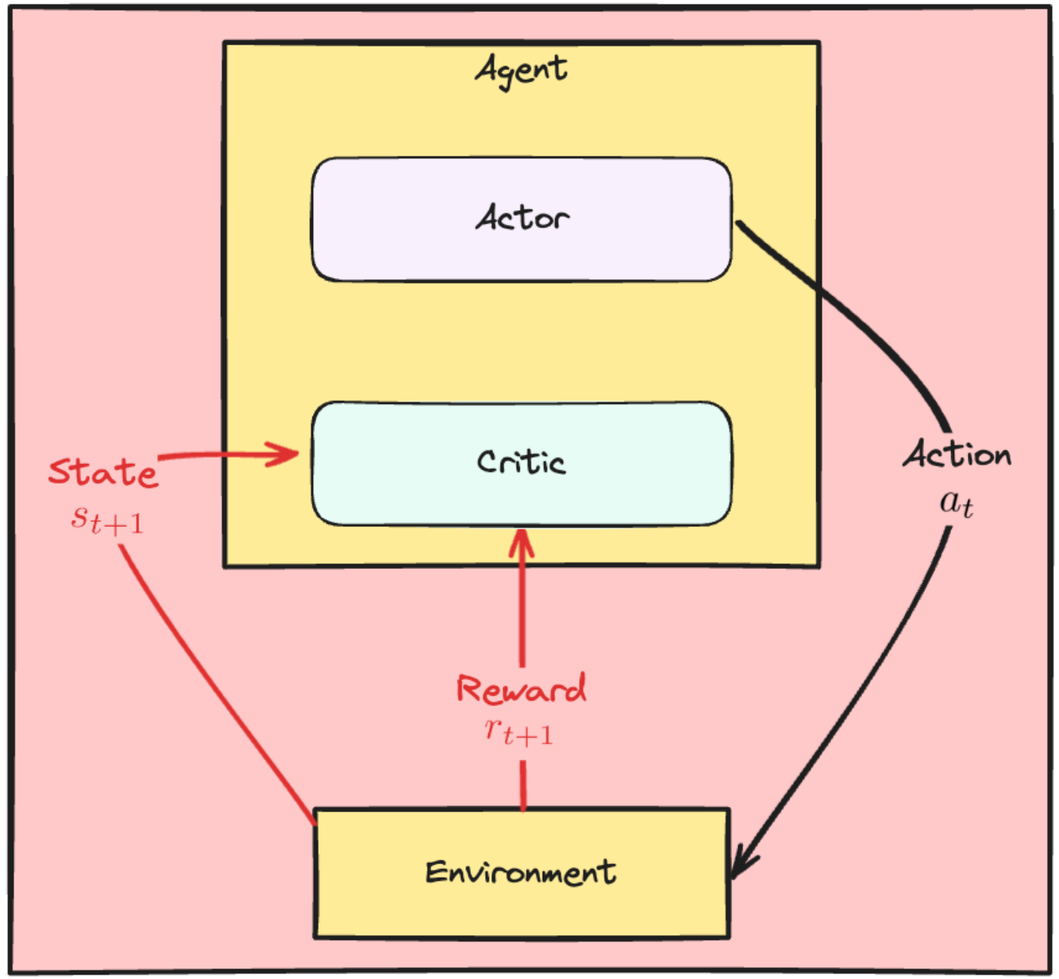
The Actor Critic dynamics

- At every step:
  - Actor chooses action (same as policy network in REINFORCE)
  - Critic observes reward and state



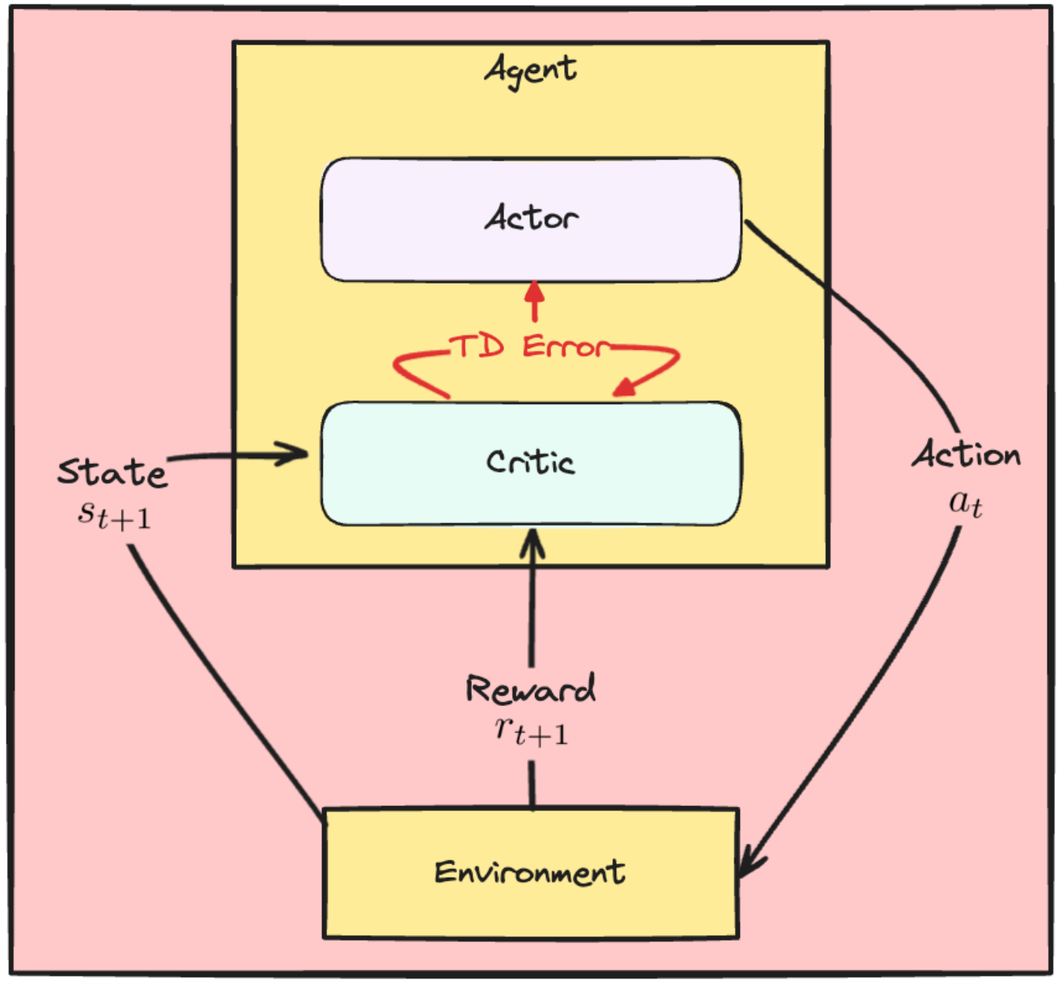
The Actor Critic dynamics

- At every step:
  - Actor chooses action (same as policy network in REINFORCE)
  - Critic observes reward and state
  - Critic evaluates TD Error
  - Actor and Critic use TD Error to update weights



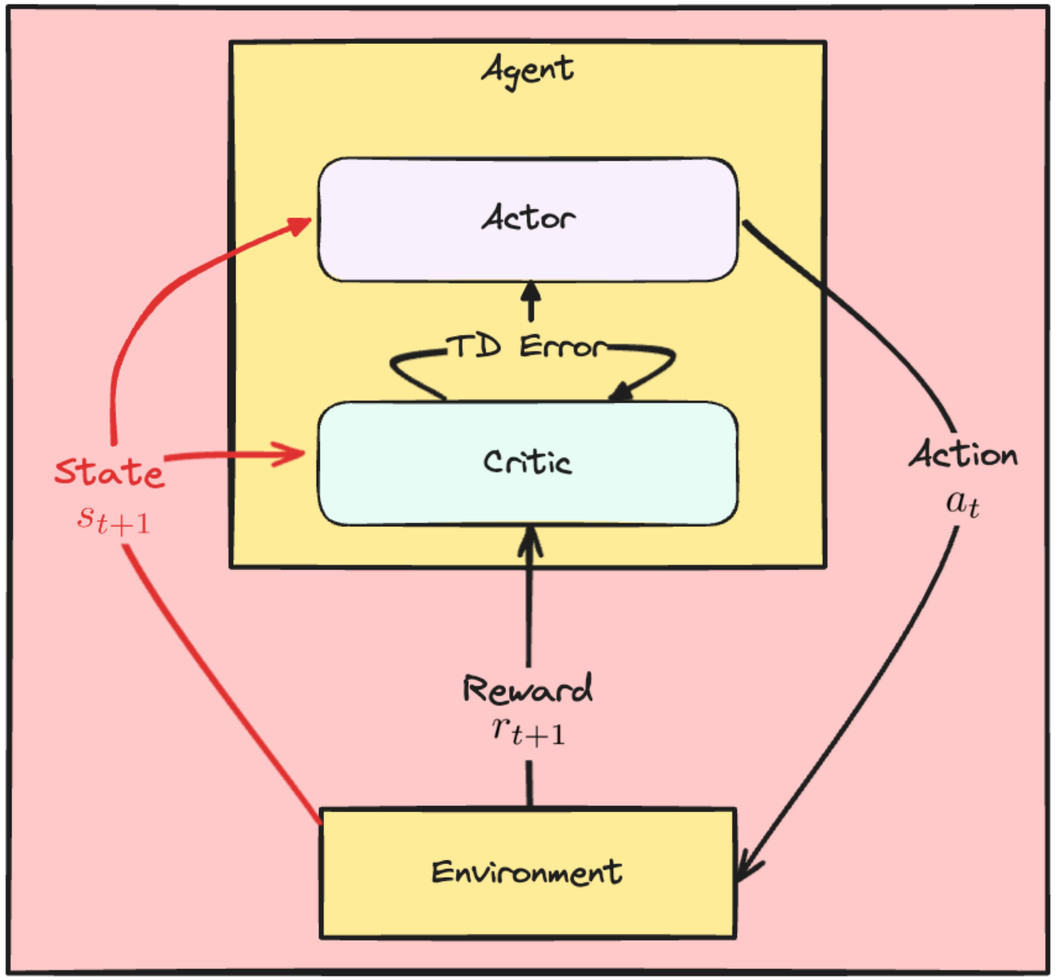
The Actor Critic dynamics

- At every step:
  - Actor chooses action (same as policy network in REINFORCE)
  - Critic observes reward and state
  - Critic evaluates TD Error
  - Actor and Critic use TD Error to update weights
  - Updated Actor observes new state



The Actor Critic dynamics

- At every step:
  - Actor chooses action (same as policy network in REINFORCE)
  - Critic observes reward and state
  - Critic evaluates TD Error
  - Actor and Critic use TD Error to update weights
  - Updated Actor observes new state
- ... start over

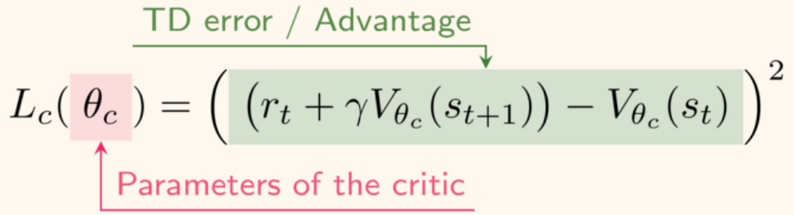


The A2C losses

Critic

Critic loss function

Use the Squared TD Error for the Critic:

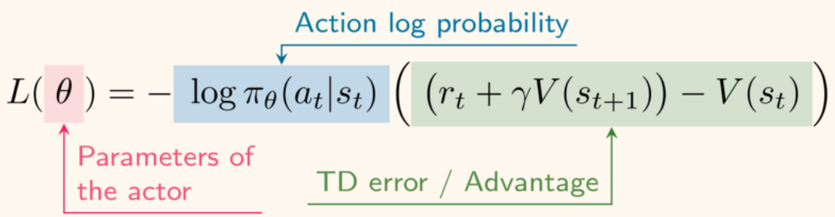


- Critic loss: squared TD error

Actor

Actor loss function

It can be shown that we can use, at every step t, this loss function for the Actor:



- TD error captures critic rating
- Increase probability of actions with positive TD error

Calculating the losses

```
def calculate_losses(critic_network, action_log_prob,
                     reward, state, next_state, done):
    # Critic provides the state value estimates
    value = critic_network(state)
    next_value = critic_network(next_state)
    td_target = (reward + gamma *
                     next_value * (1-done))
    td_error = td_target - value

    # Apply formulas for actor and critic losses
    actor_loss = -action_log_prob * td_error.detach()
    critic_loss = td_error ** 2

    return actor_loss, critic_loss
```

- Calculate TD-Error
- Calculate actor loss
  - Use `.detach()` to stop gradient propagation to critic weights
- Calculate critic loss

The Actor Critic training loop

```
for episode in range(10):
  state, info = env.reset()
  done = False
  while not done:
    # Select action
    action, action_log_prob = select_action(actor, state)
    next_state, reward, terminated, truncated, _ = env.step(action)
    done = terminated or truncated
    # Calculate losses
    actor_loss, critic_loss = calculate_losses(critic, action_log_prob, reward, state, next_state, done)
    # Update actor
    actor_optimizer.zero_grad(); actor_loss.backward(); actor_optimizer.step()
    # Update critic
    critic_optimizer.zero_grad(); critic_loss.backward(); critic_optimizer.step()
    state = next_state
```

Let's practice!

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