Outline

Part 1: Agents in Reinforcement Learning

- Agent and Environment in RL
- Markov Decision Process
- Q-learning

Part 2: Deep Q-learning

- DQN
- PyTorch implementation of DQN
- Extensions of DQN

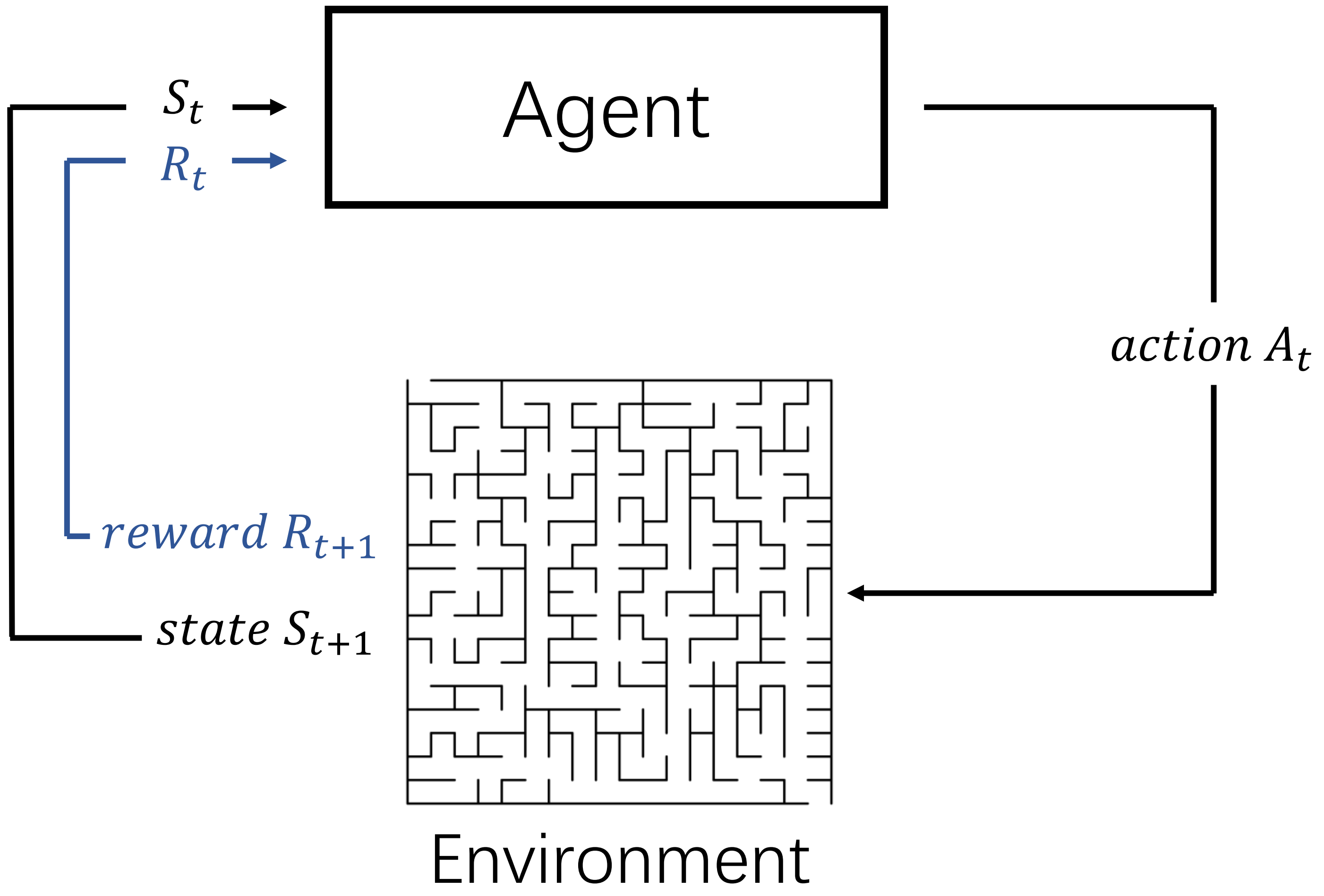
Part 3: Policy Gradient based Methods

- DDPG
- A3C
- DQN vs Policy Gradient

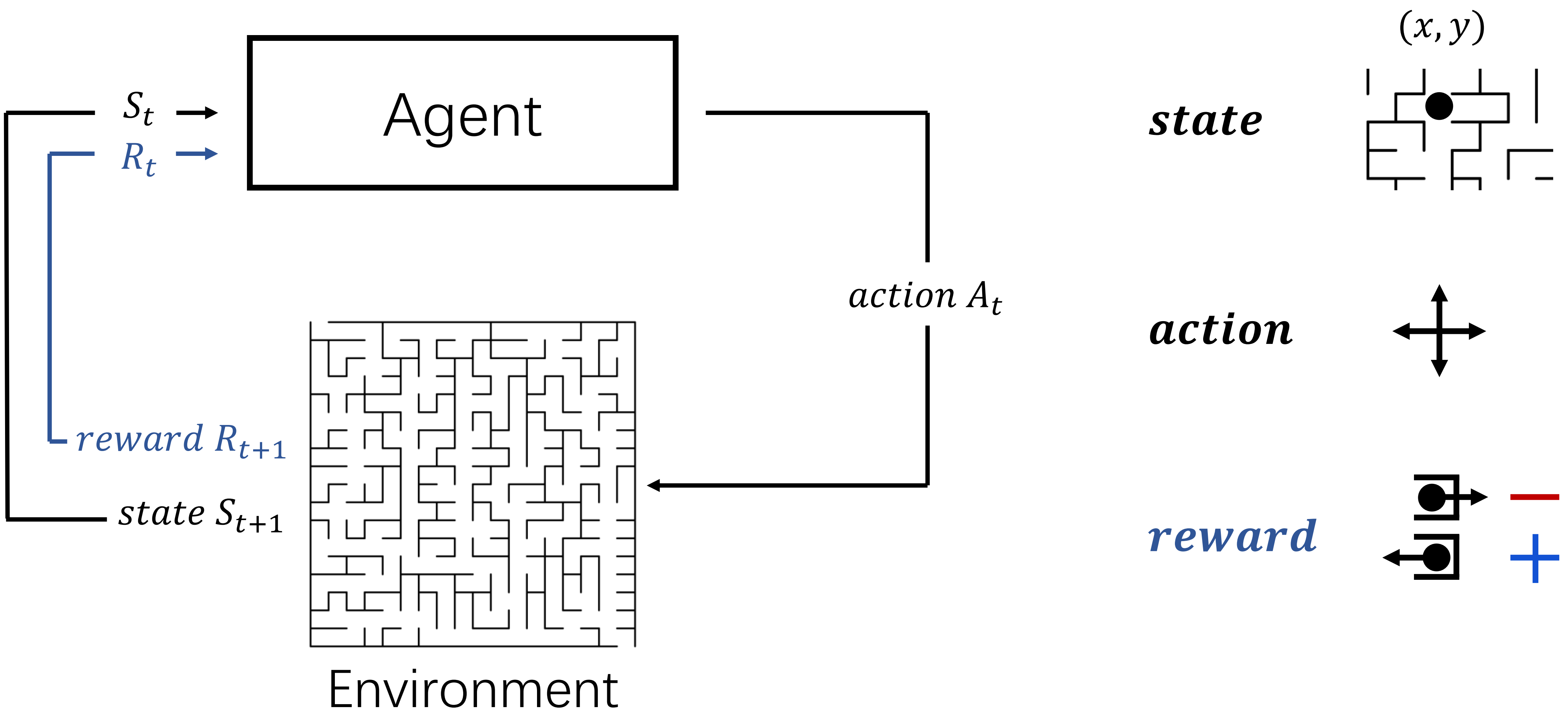
Lab Assignment

Part 1: Agents in Reinforcement Learning

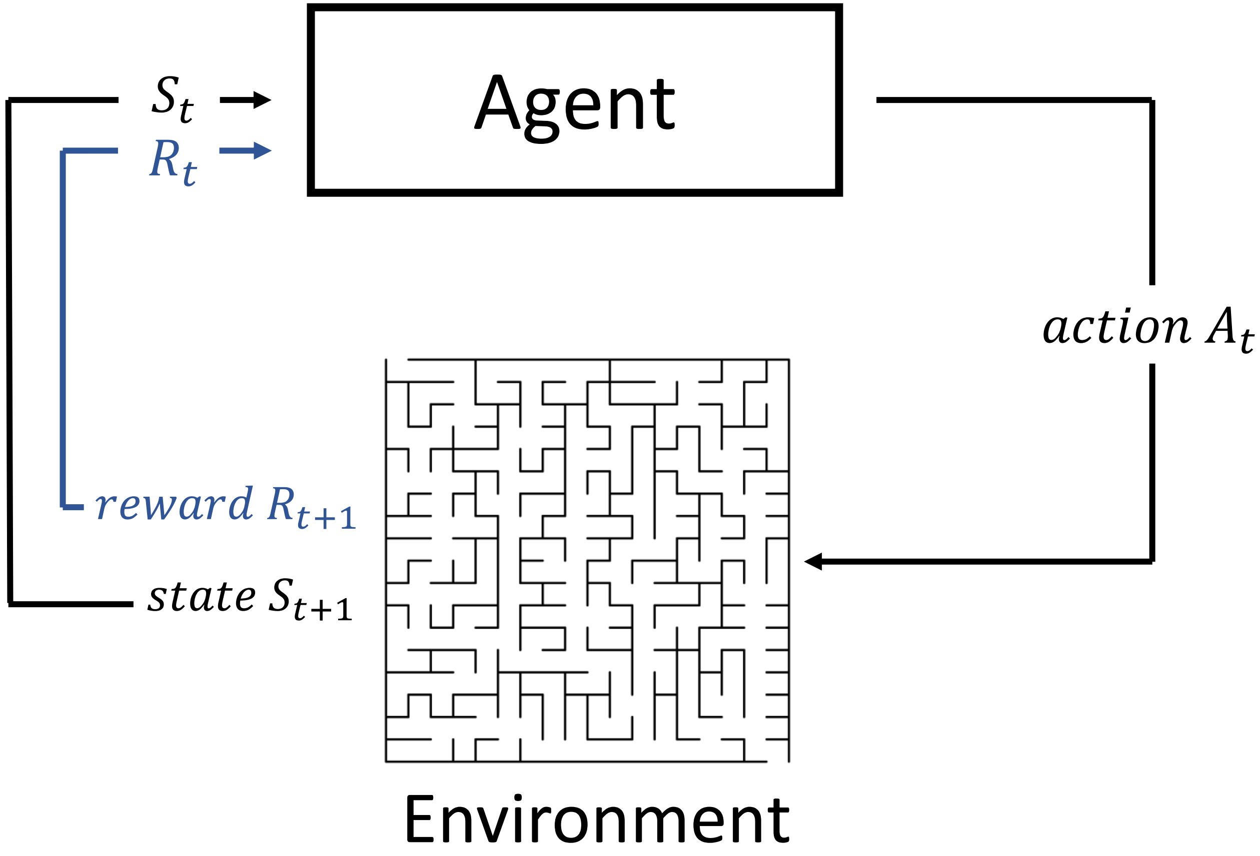
Agent and Environment in RL



Agent and Environment in RL



Markov Decision Process (MDP)



MDP Tuple

$[S, A, T, r, \gamma]$

State transition function

$T(s, a, s') = P[S_{t+1} = s' | S_t = s, A_t = a])$

$\pi(s, a)$ Mapping of state to action

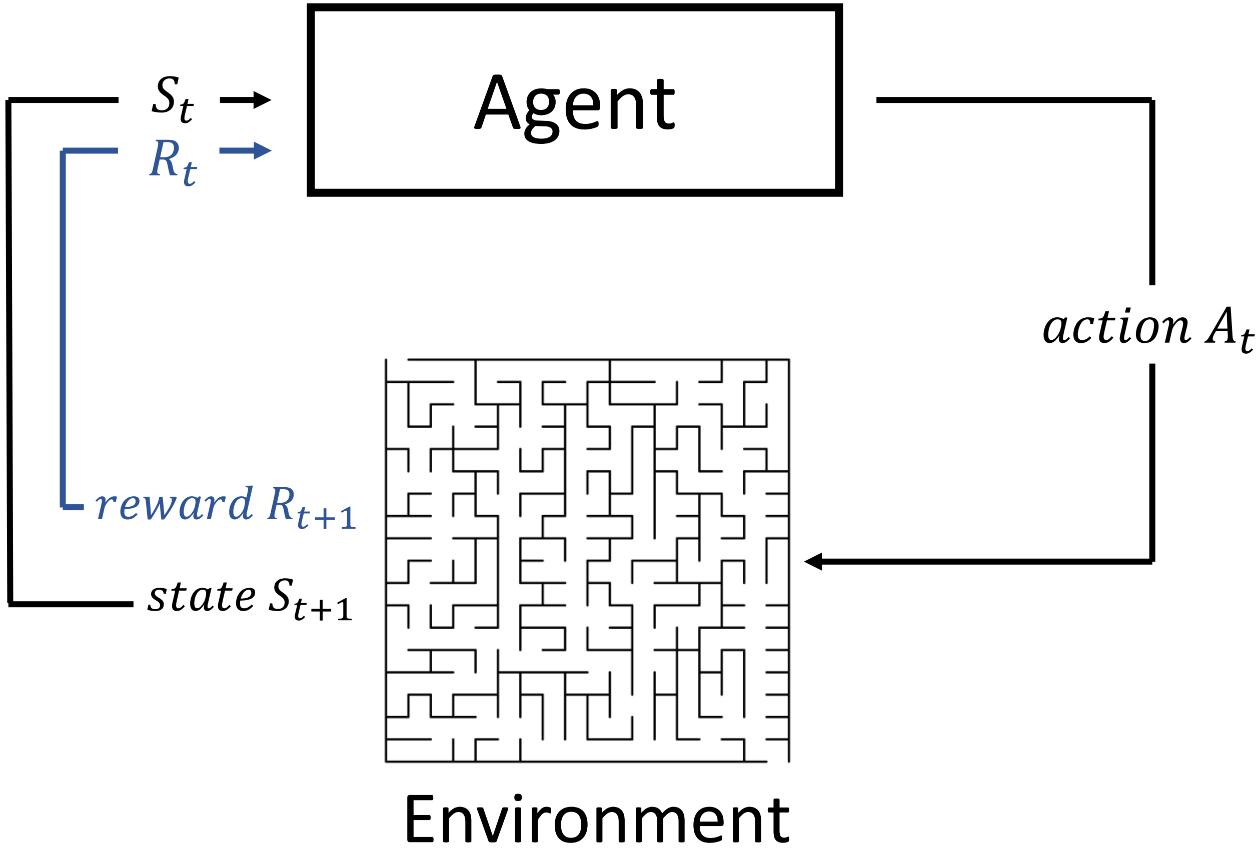
Reward function

$$R_t = \sum_{k=t}^{T} \gamma^{k-t} r_k(s_k, a_k)$$

$\pi^*(s, a) = argmax(R_t)$ for $\forall t$

Optimal Policy

Q-Learning



Markov Decision Process

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Optimal Policy

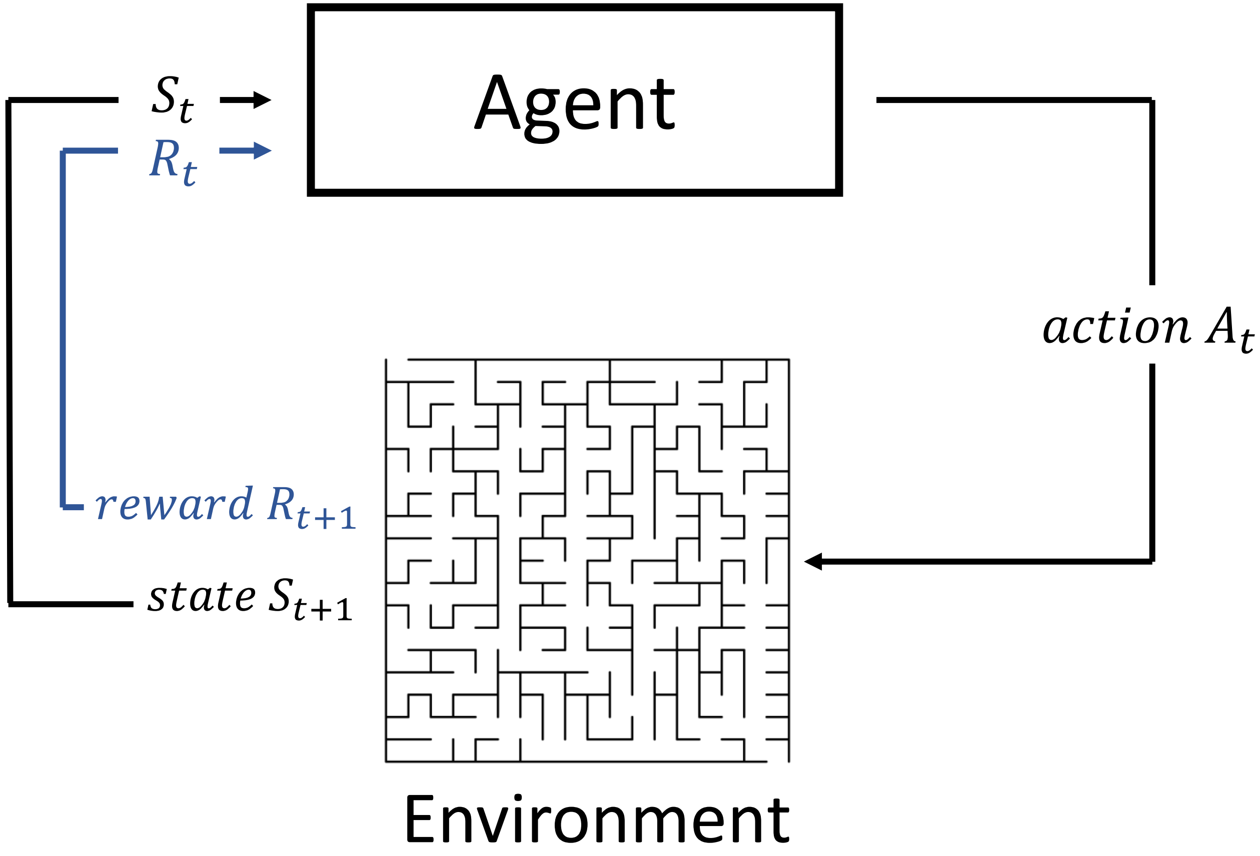
Q-Learning

$q^\pi(s, a) = E_\pi[R_t | S_t = s, A_t = a]$

Policy as a function of R_t (q-values)

$\pi^*(s, a) = argmax_a q^\pi(s, a)$

Q-Learning



Not efficient with large S_t and A_t

Markov Decision Process

$[S, A, T, r, \gamma]$

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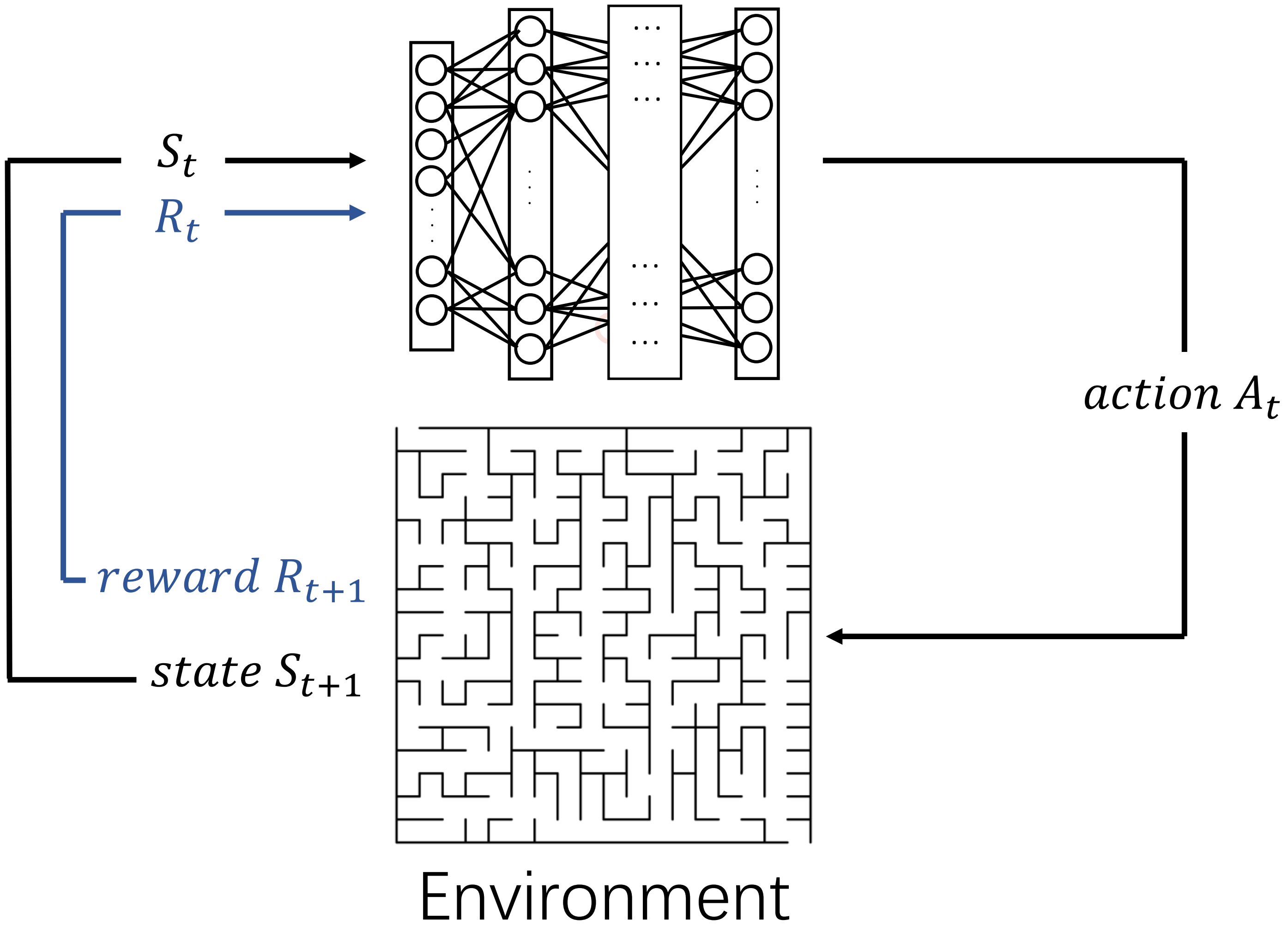
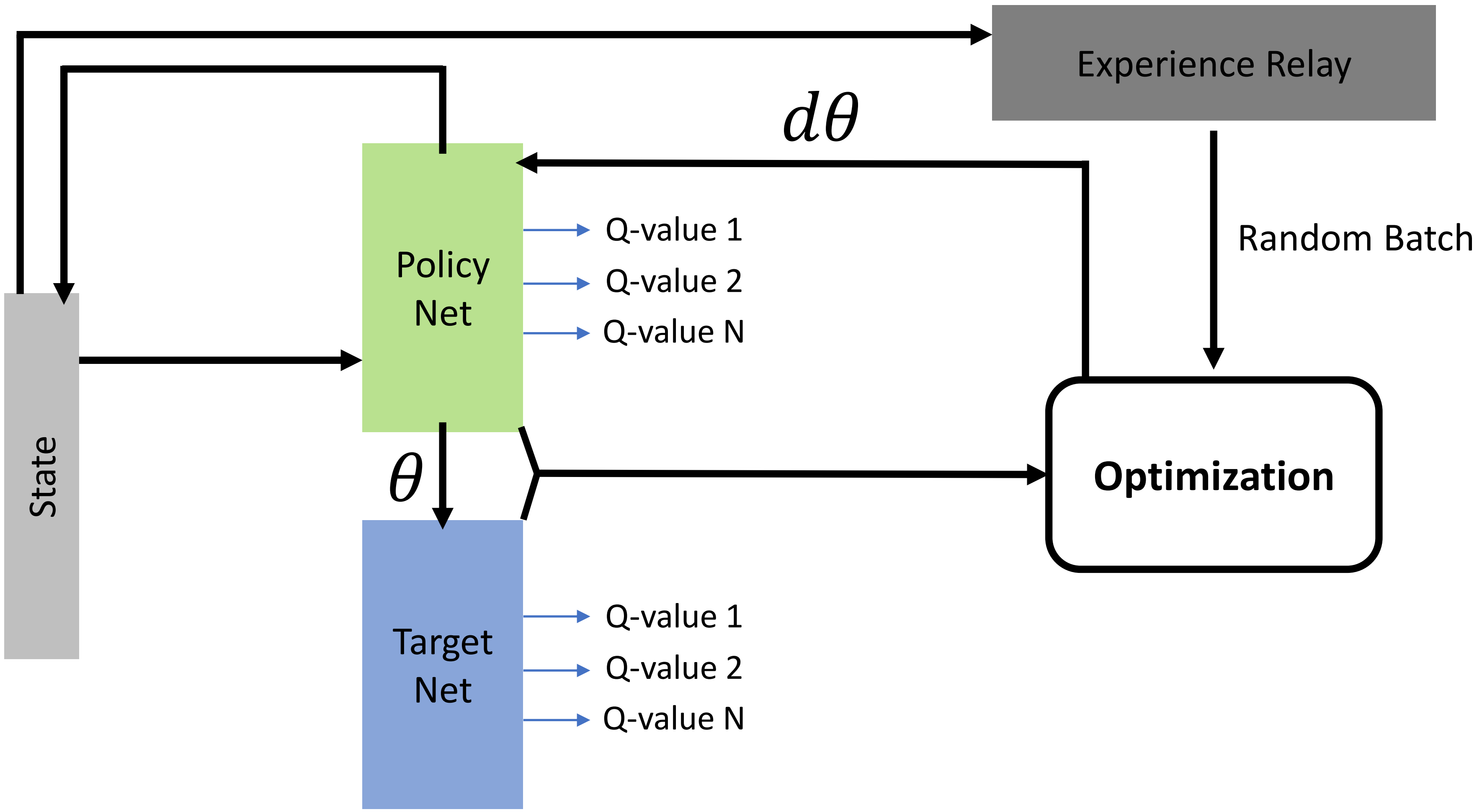
Part 2: Deep Q-Learning

Deep Q-Network (Mnih et al., 2014)

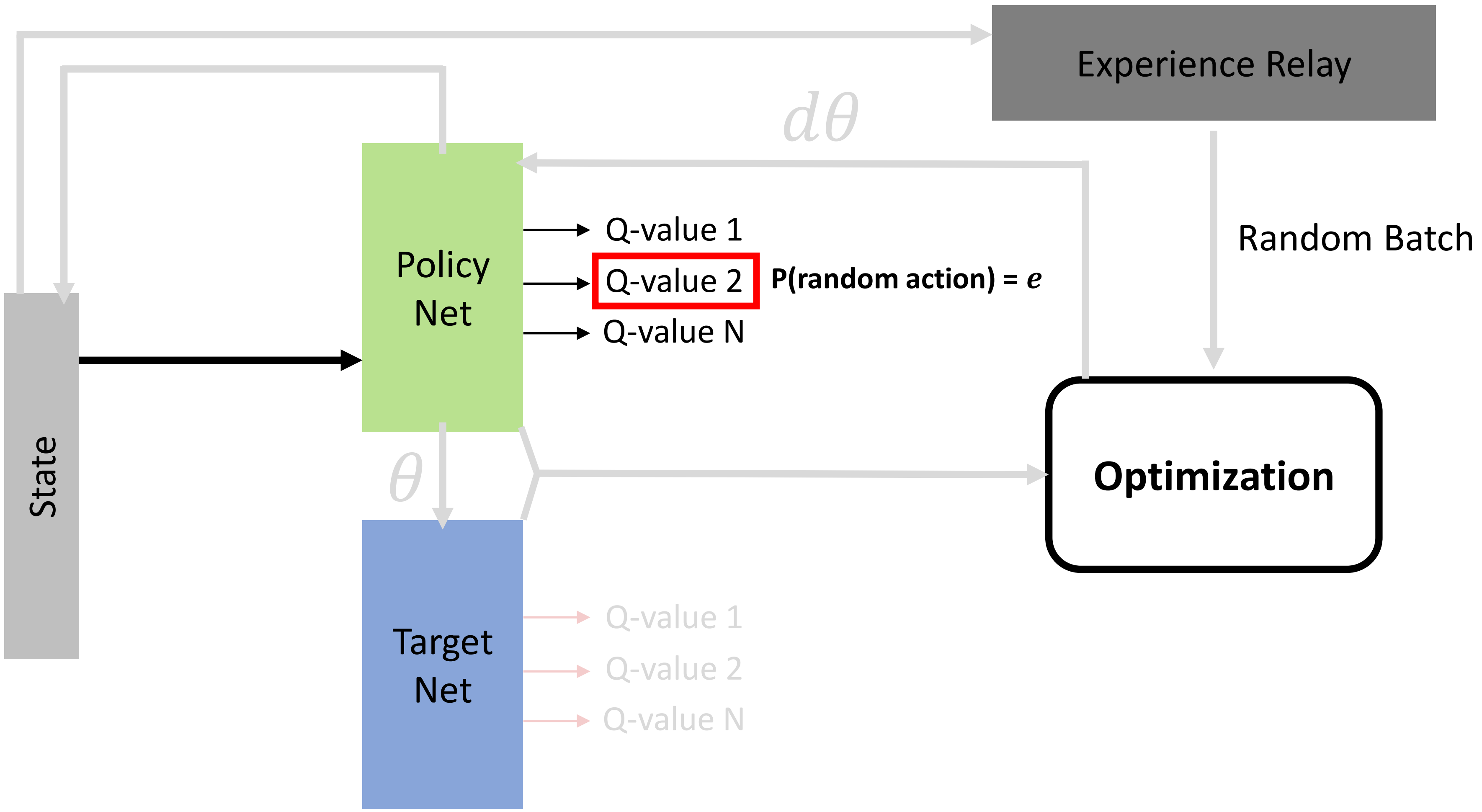


Q-values are approximated by a neural network

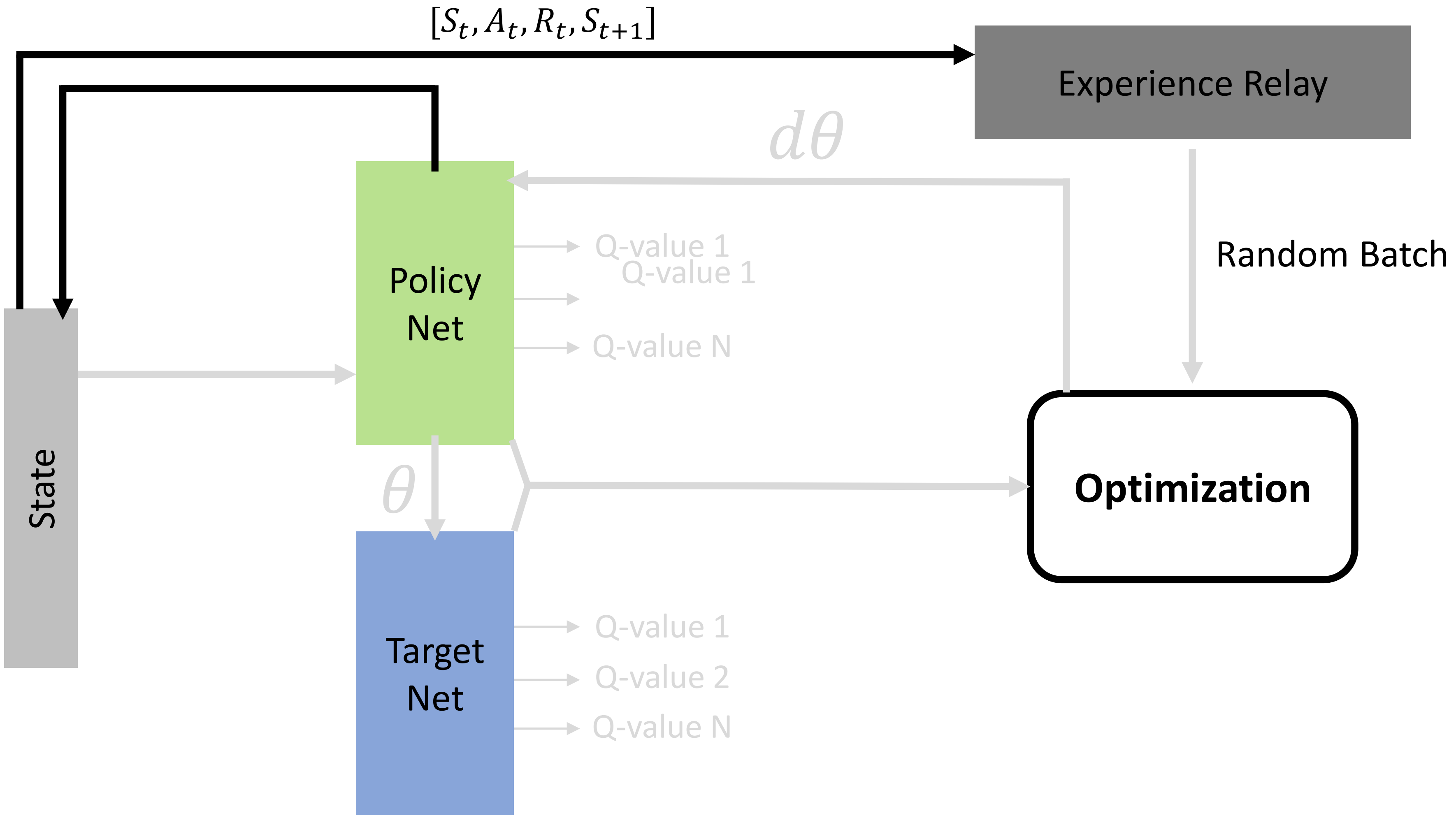
DQN Architecture



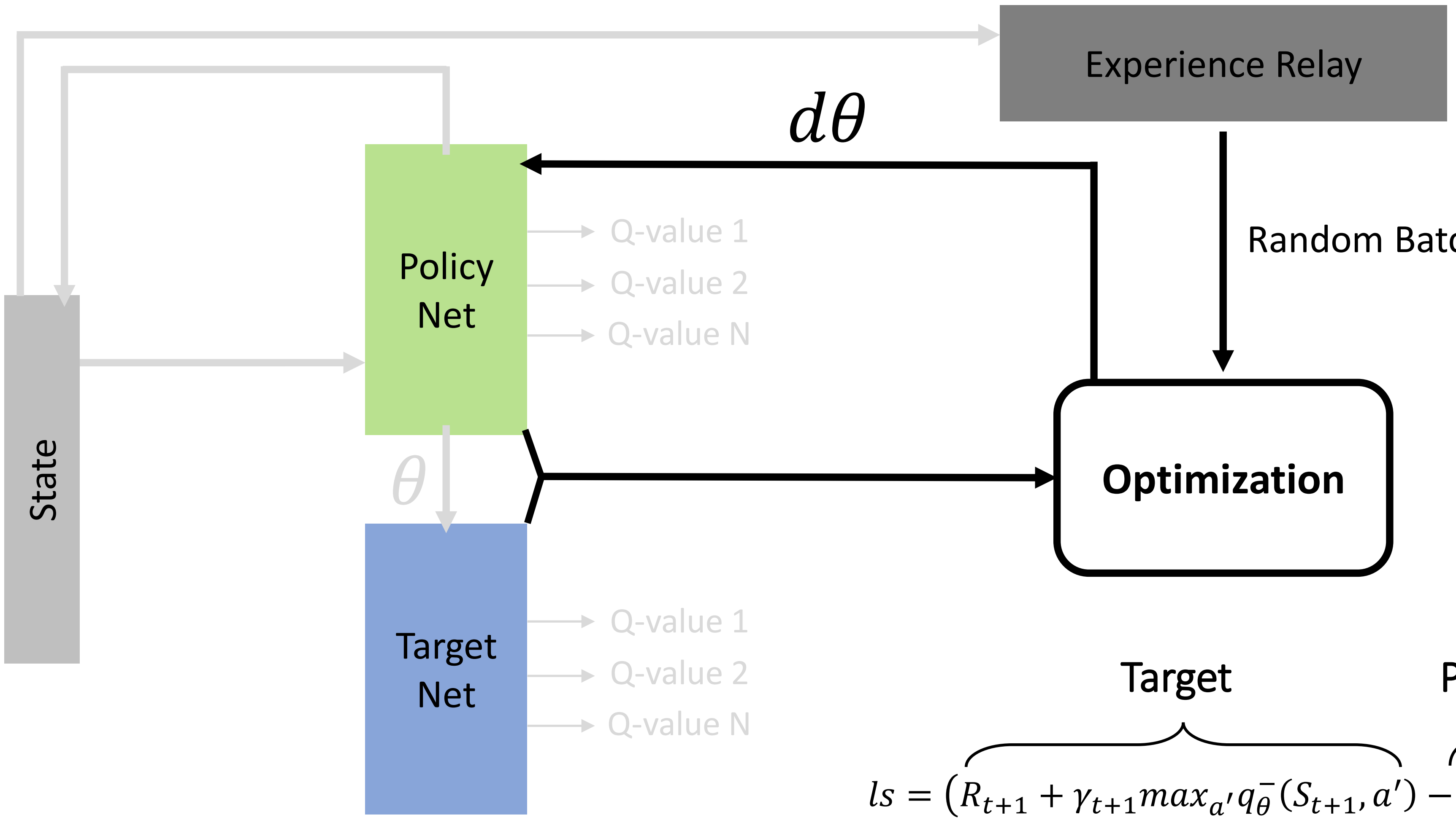
DQN Architecture



DQN Architecture

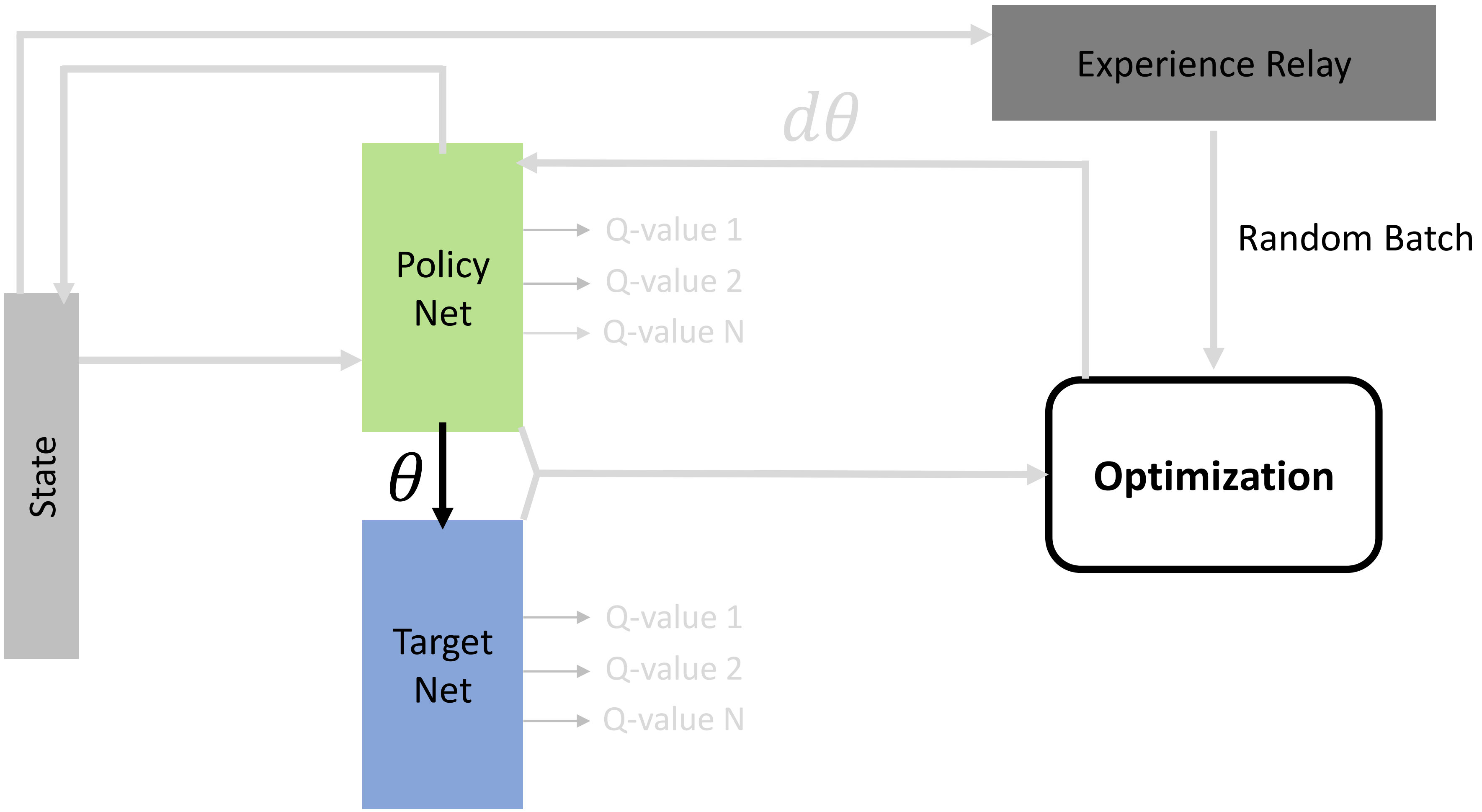


DQN Architecture



$$ls = \Big(\overbrace{R_{t+1} + \gamma_{t+1} max_{a'} q_{\bar{\theta}}(S_{t+1}, a')}^{\text{Target}} - \overbrace{q_{\theta}(S_t, A_t)}^{\text{Prediction}}\Big)^2$$

DQN Architecture



PyTorch Implementation: Policy/Target networks

```
class Q_network(nn.Module):

    def __init__(self, state_size,action_size, seed, fc1_unit,
                 fc2_unit):

        super(QNetwork,self).__init__()
        self.seed = torch.manmual_seed(seed)
        self.fc1= nn.Linear(state_size,fc1_unit)
        seed.fc2 = nn.Linear(fc1_unit,fc2_unit)
        seed.fc3 = nn.Linear(fc2_unit,action_size)

    def forward(self,x):

        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        return self.fc3(x)
```

State_size : Dimension of each state

Action_size : Dimension of each action

Seed : random seed

Fc1_unit : # of neurons in first hidden layer

Fc2_unit : # of neurons in second hidden layer

PyTorch Implementation: Agent (initialization)

```
class Agent():

    def __init__(self, state_size, action_size, seed):

        self.state_size = state_size
        self.action_size = action_size
        self.seed = random.seed(seed)

        #Q- Network
        self.qnetwork_policy = Q_network(state_size, action_size, seed).to(device)
        self.qnetwork_target = Q_network(state_size, action_size, seed).to(device)

        self.optimizer = optim.Adam(self.qnetwork_policy.parameters(),lr=LR)

        # Replay memory
        self.memory = ExperienceRelay(action_size, BUFFER_SIZE,BATCH_SIZE,seed)
        # Initialize time step (for updating every UPDATE_EVERY steps)
        self.t_step = 0
```

Network initializations

Define optimizer

Memory initializations

PyTorch Implementation: Agent (ENV interactions + Memory Retrieval)

```
def step(self, state, action, reward, next_step, done):
    # Save experience in replay memory
    self.memory.add(state, action, reward, next_step, done)

    # Learn every UPDATE_EVERY time steps.
    self.t_step = (self.t_step+1)% UPDATE_EVERY
    if self.t_step == 0:
        # If enough samples are available in memory, get radom subset and learn

        if len(self.memory)>BATCH_SIZE:
            experience = self.memory.sample()
            self.learn(experience, GAMMA)

def act(self, state, eps = 0):

    state = torch.from_numpy(state).float().unsqueeze(0).to(device)
    self.qnetwork_policy.eval()
    with torch.no_grad():
        action_values = self.qnetwork_policy(state)
    self.qnetwork_policy.train()

    #Epsilon -greedy action selction
    if random.random() > eps:
        return np.argmax(action_values.cpu().data.numpy())
    else:
        return random.choice(np.arange(self.action_size))
```

Store [s, a, r, s’] to memory

Retrieve memory and learn every learning steps

Choose action based on e-greedy action selection

PyTorch Implementation: Agent (Learning + update Target network)

```
def learn(self, experiences, gamma):

    states, actions, rewards, next_state, dones = experiences
    criterion = torch.nn.MSELoss()
    self.qnetwork_policy.train()
    self.qnetwork_target.eval()
    predicted_targets = self.qnetwork_policy(states).gather(1,actions)

    with torch.no_grad():
        labels_next = self.qnetwork_target(next_states).detach().max(1)[0].unsqueeze(1)

    labels = rewards + (gamma* labels_next*(1-dones))

    loss = criterion(predicted_targets,labels).to(device)
    self.optimizer.zero_grad()
    loss.backward()
    self.optimizer.step()

    # ------------------- update target network ------------------- #
    self.soft_update(self.qnetwork_policy,self.qnetwork_target,TAU)

def soft_update(self, local_model, target_model, tau):

    for target_param, local_param in zip(target_model.parameters(),
                                         local_model.parameters()):
        target_param.data.copy_(tau*local_param.data + (1-tau)*target_param.data)
```

Set policy network to train mode and target network to eval mode

Compute Loss (target - predicted)

Backpropagate gradients

Soft transfer weights to target network

PyTorch Implementation: Experience Relay

```
class ExperienceRelay:

    def __init__(self, action_size, buffer_size, batch_size, seed):

        self.action_size = action_size
        self.memory = deque(maxlen=buffer_size)
        self.batch_size = batch_size
        self.experiences = namedtuple("Experience", field_names=["state",
                                                                "action",
                                                                "reward",
                                                                "next_state",
                                                                "done"])
        self.seed = random.seed(seed)

    def add(self,state, action, reward, next_state,done):
        e = self.experiences(state,action,reward,next_state,done)
        self.memory.append(e)

    def sample(self):
        experiences = random.sample(self.memory,k=self.batch_size)

        states = torch.from_numpy(np.vstack([e.state for e in experiences if e is not None])).float().to(device)
        actions = torch.from_numpy(np.vstack([e.action for e in experiences if e is not None])).long().to(device)
        rewards = torch.from_numpy(np.vstack([e.reward for e in experiences if e is not None])).float().to(device)
        next_states = torch.from_numpy(np.vstack([e.next_state for e in experiences if e is not None])).float().to(device)
        dones = torch.from_numpy(np.vstack([e.done for e in experiences if e is not None]).astype(np.uint8)).float().to(device)

        return (states,actions,rewards,next_states,dones)

    def __len__(self):
        return len(self.memory)
```

Store [s, a, r, s’] as tuple

Uniform sample the batch

Extensions of DQN

Double DQN

Prioritized Experience Relay

Dueling DQN

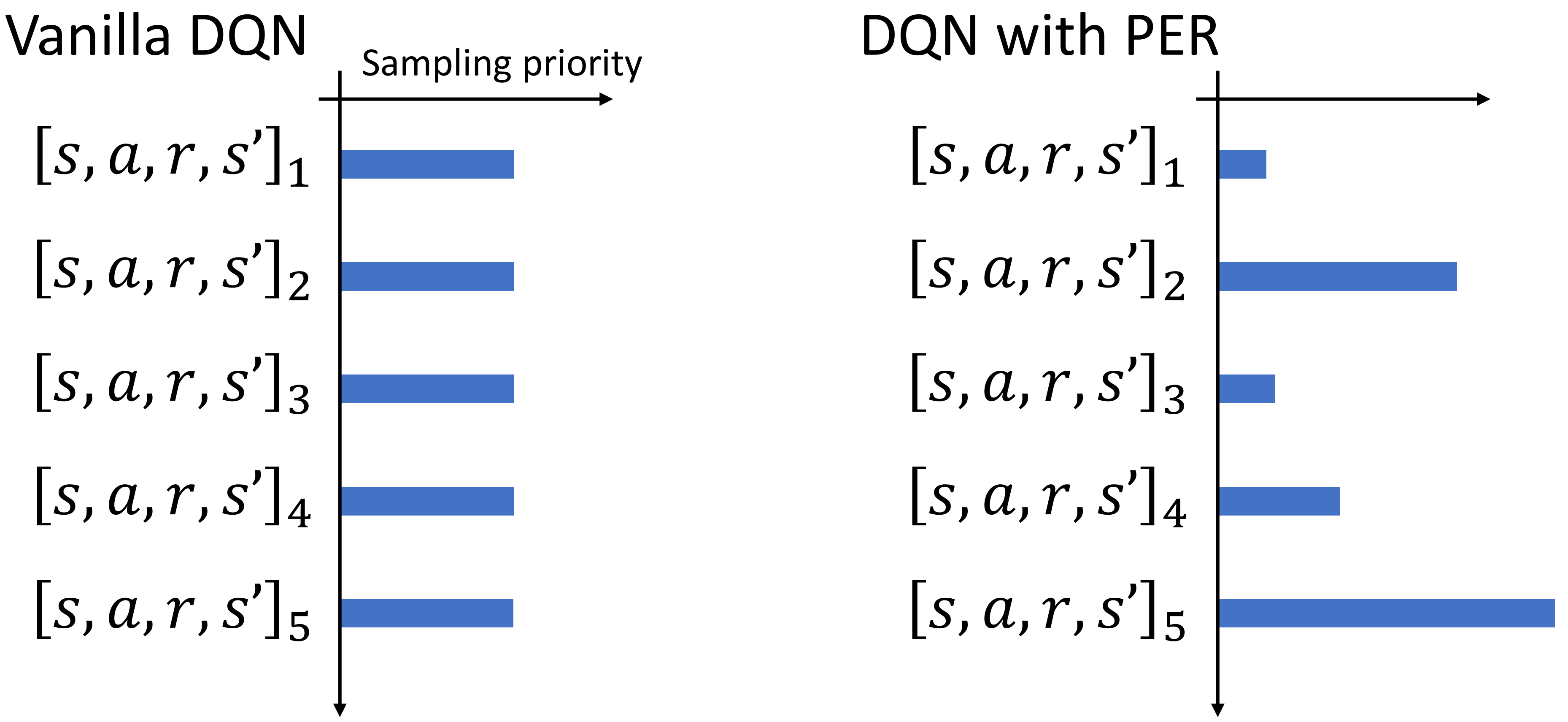
Extensions of DQN – Double DQN

$$ls = \left(R_{t+1} + \gamma_{t+1} \overbrace{max_{a'} q_{\bar{\theta}}(S_{t+1}, a')}^{\text{Q-values and action chosen by target network}} - q_\theta(S_t, A_t)\right)^2$$

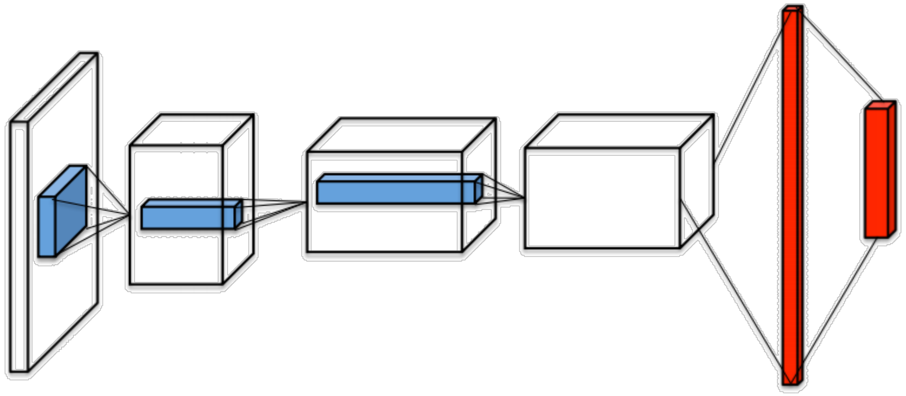
$$ls\_double = \left(R_{t+1} + \gamma_{t+1} \overbrace{q_{\bar{\theta}}(s', \underbrace{argmax_{a'} q_\theta(S_{t+1}, a')}_{\text{Action chosen by policy network}})}^{\text{Action evaluated by target network}} - q_\theta(S_t, A_t)\right)^2$$

Extensions of DQN – Prioritized Experience Replay

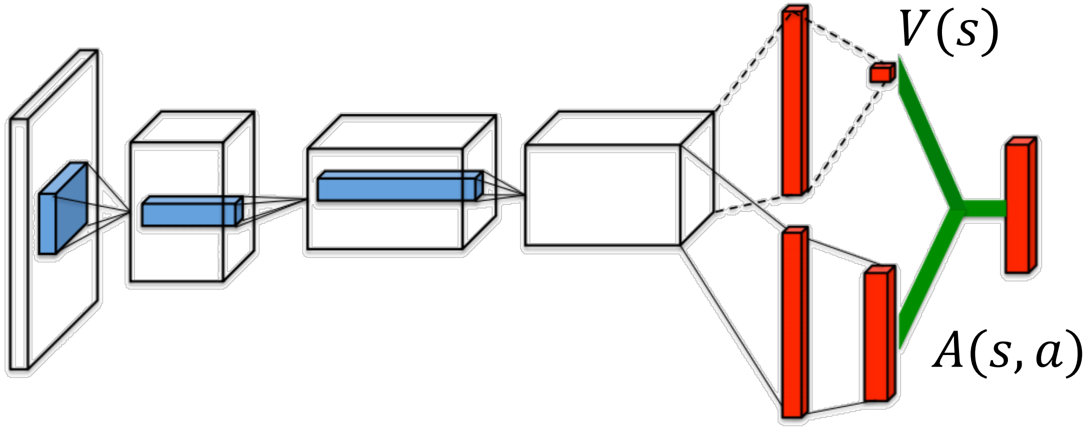
$$p_t \propto \left| R_{t+1} + \gamma max_{a'} q_{\bar{\theta}}(S_{t+1}, a') - q_\theta(S_t, A_t) \right|^\omega$$



Extensions of DQN – Dueling DQN



Vanilla Deep Q-Network



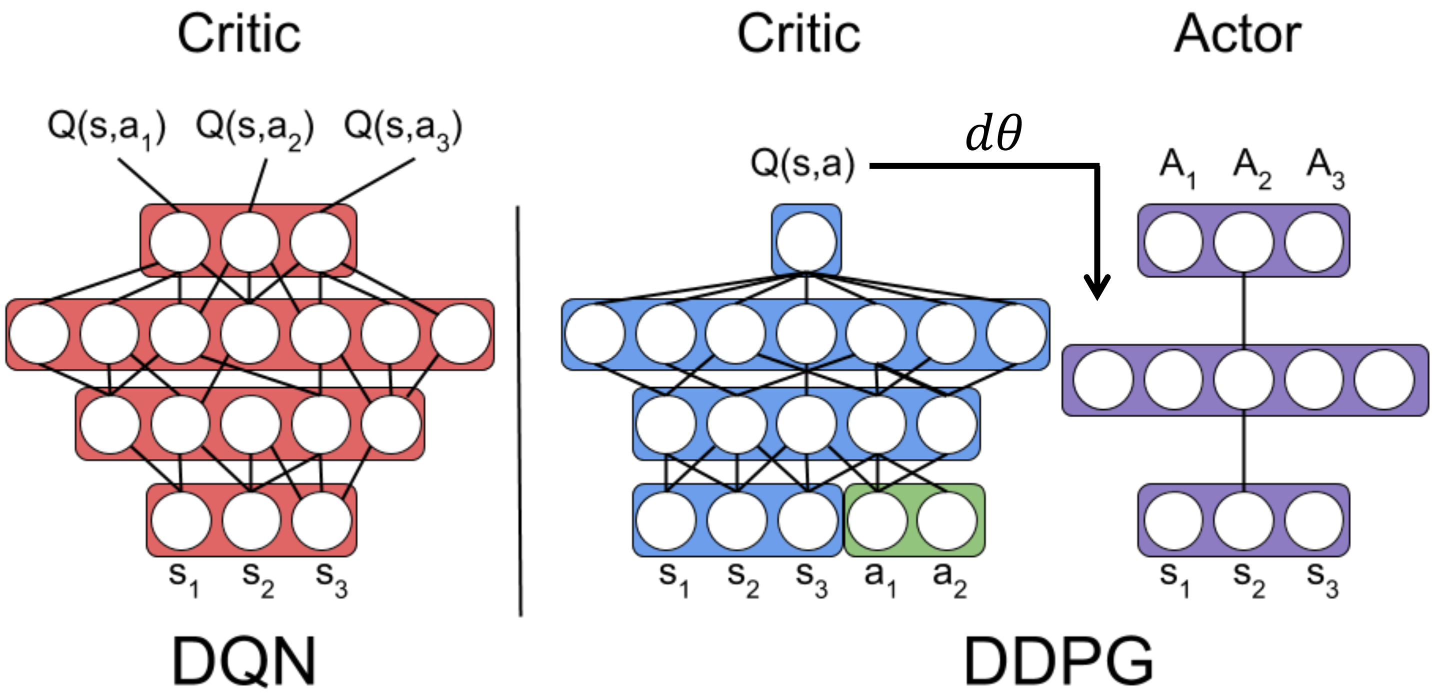
Dueling Deep Q-Network

$$Q(s,a) = V(s) + \left(A(s,a) - \frac{1}{|\boldsymbol{A}|} \sum_a A(s,a) \right)$$

Image credit: https://arxiv.org/pdf/1511.06581.pdf

Part 3: Policy Gradient based Methods

Deep Deterministic Policy Gradient (DDPG)



DQN – Network

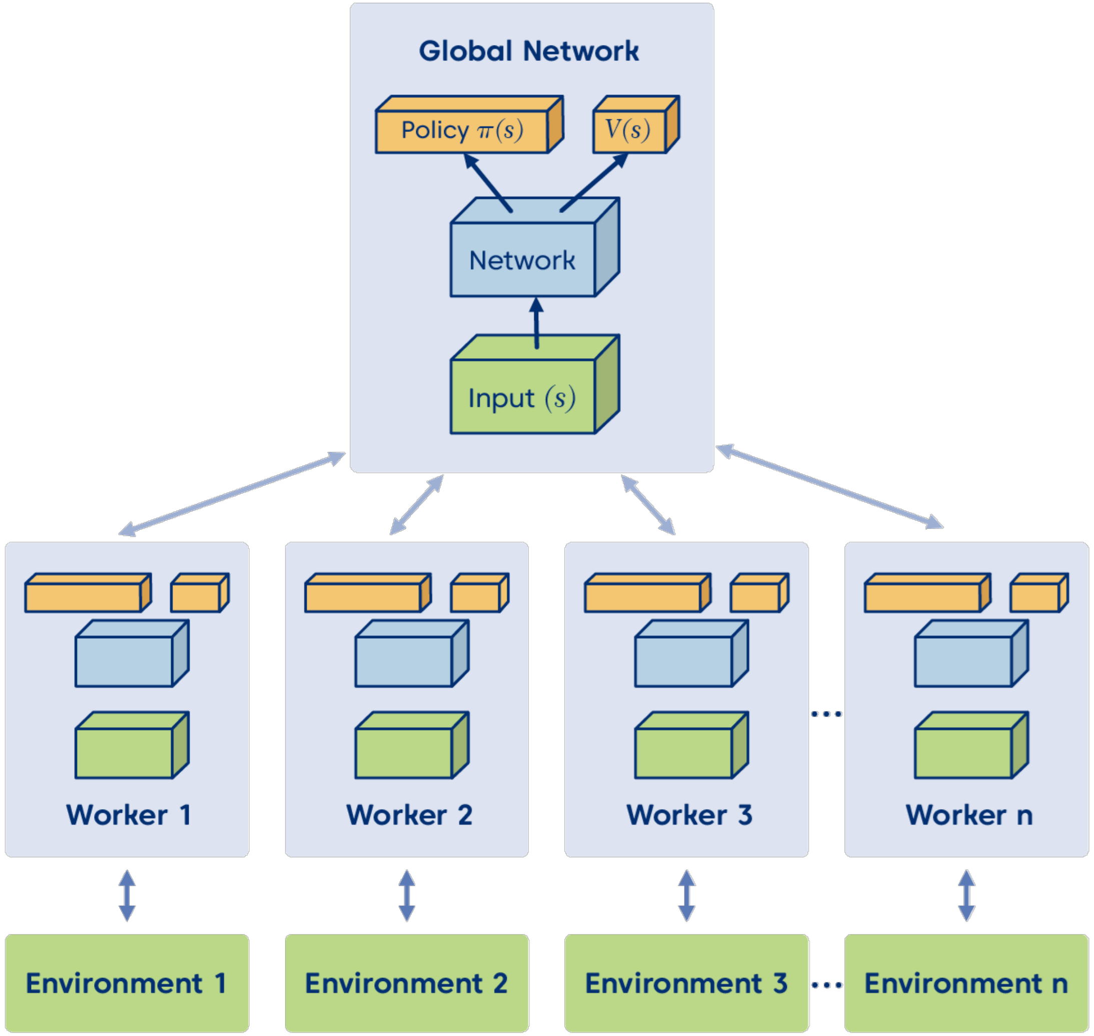
approximates ***Value*** function

DDPG – Network

approximates ***Policy*** function

Implementation in PyTorch: https://towardsdatascience.com/deep-deterministic-policy-gradients-explained-2d94655a9b7b

Asynchronous Advantage Actor-Critic (A3C)



Asynchronous: Utilizes multiple agents each with unique experiences

Actor-Critic: Agent uses the value – V(s) estimate (critic) to update – $\pi(s)$ policy (actor)

Advantage: discounted rewards – V(s)

Implementation in PyTorch:
https://github.com/ikostrikov/pytorch-a3c

DQN vs Policy Gradient

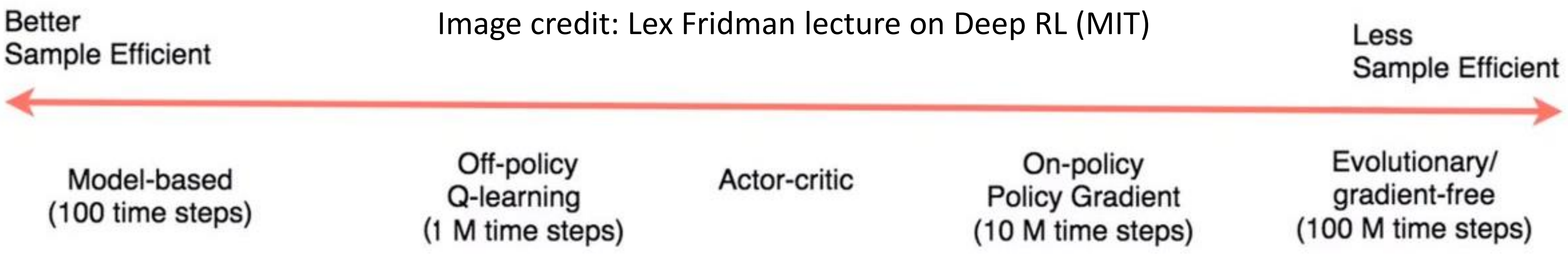


Image credit: Lex Fridman lecture on Deep RL (MIT)

+ vs DQN

- Better with env where Q-function is difficult to learn
- Can be applied on continuous action space
- Can learn stochastic policies
- Relatively faster to convergence

– vs DQN

- Relatively sample inefficient
- Less stable during training
- Tendency to converge to local minima
- Poor handling of delayed rewards

Lab Assignment:

Solve OpenAI cartpole problem using Deep RL

OpenAI Gym - Cartpole_v1

Cartpole documentation:
https://gym.openai.com/envs/CartPole-v1/

State space:
- Position of a cart
- Velocity of a cart
- Angle of pole
- Rotation rate of pole

Action space
- Move left (-1)
- Move right (+1)

Performance evaluation:

Attain average rewards (frames lasted) of >475 over 100 consecutive trials.

Generate a cartpole rendering controlled by trained agent

OpenAI Gym - Cartpole_v1

*Training loop code template + rendering function included in the lab8_template.ipynb

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