DQN with experience replay

DEEP REINFORCEMENT LEARNING IN PYTHON

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Introduction to experience replay

- Barebone DQN agent learns only from latest experience
  - Consecutive updates are highly correlated
  - Agent is forgetful
- Solution: Experience Replay
  - Store experiences in a buffer
  - At each step, learn from a random batch of past experiences

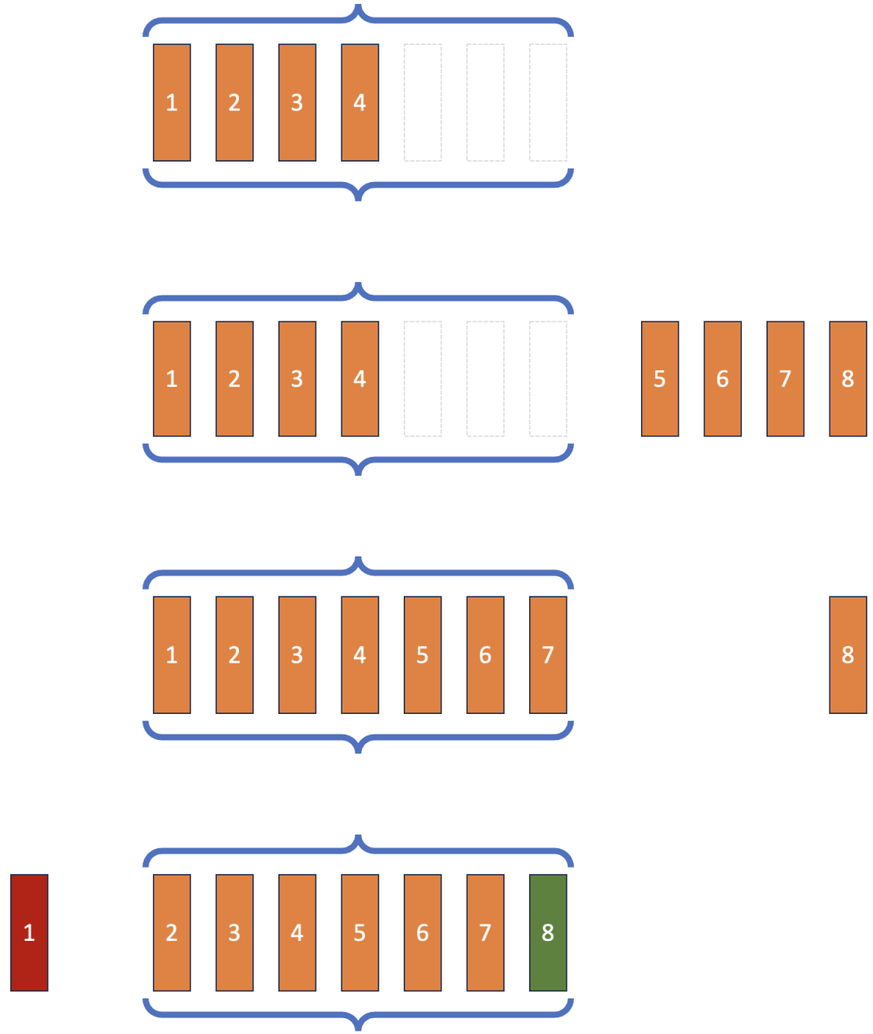
The Double-Ended Queue

```
from collections import deque

# Instantiate with limited capacity
buffer = deque([1,2,3,4], maxlen=7)

# Extend to the right side
buffer.extend([5,6,7,8])
```

- Beyond capacity, oldest items get dropped



Implementing Replay Buffer

```
import random

class ReplayBuffer:
    def __init__(self, capacity):
        self.memory = deque([], maxlen=capacity)

    def push(self, state, action,
             reward, next_state, done):
        experience_tuple = (state, action,
                            reward, next_state, done)
        self.memory.append(experience_tuple)

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

...
```

- Replay memory: `deque` with limited capacity
- `.push()`:
  - Experience as transition tuple
  - Append experience to buffer
  - At capacity: drops oldest experience

Implementing Replay Buffer

```
...
def sample(self, batch_size):
    batch = random.sample(self.memory, batch_size)
    states, actions, rewards, next_states, dones = (
      zip(*batch))

    states_tensor = torch.tensor(
      states, dtype=torch.float32)
    ... # repeat identically for
        # rewards, next_states, dones
    actions_tensor = torch.tensor(
      actions, dtype=torch.long).unsqueeze(1)

    return states_tensor, actions_tensor,
rewards_tensor, next_states_tensor, dones_tensor
```

- Randomly draw from past experiences
- `batch` : from list of transition tuples...
- ...to tuple of lists...
- ...to tuple of PyTorch tensors

Integrating Experience Replay in DQN

1. Before training loop:

   `replay_buffer = ReplayBuffer(10000)`

2. In training loop, after action selection:

```
replay_buffer.push((state, action,
                    reward, next_state, done))
if len(replay_buffer) >= batch_size:
    states, actions, rewards, next_states, dones = (
           replay_buffer.sample(batch_size))
    q_values = (
        q_network(states).gather(1, actions).squeeze(1))
    next_states_q_values = q_network(next_states).amax(1)
    target_q_values = (
                rewards +
                gamma * next_states_q_values * (1-dones))
    loss = nn.MSELoss()(target_q_values, q_values)
```

- Initialize replay buffer
- Push latest transition to buffer

If buffer length $\geq$ `batch_size` :

- Draw a random batch from the buffer and proceed with loss calculation
- Loss calculation conceptually unchanged
- Mean Squared Bellman Error on a replay memory batch
  - Learning is more stable and more efficient

Let's practice!

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The complete DQN algorithm

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The DQN algorithm

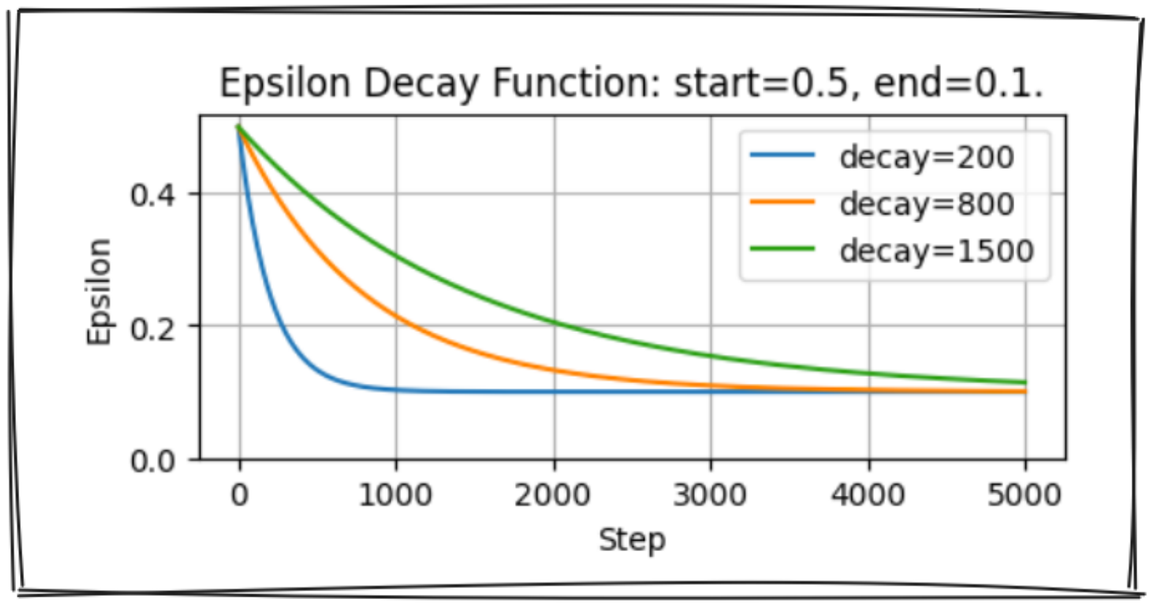
- We studied DQN with Experience Replay
- Close to DQN as first published (2015)
- We still miss two components:
  - Epsilon-greediness -> more exploration
  - Fixed Q-targets -> more stable learning

Epsilon-greediness in the DQN algorithm

- Implement Decayed Epsilon-greediness in `select_action()`

```
def select_action(q_values, step, start, end, decay):
    # Calculate the threshold value for this step
    epsilon = (
        end + (start-end) * math.exp(-step / decay))
    # Draw a random number between 0 and 1
    sample = random.random()
    if sample < epsilon:
        # Return a random action index
        return random.choice(range(len(q_values)))
    # Return the action index with highest Q-value
    return torch.argmax(q_values).item()
```

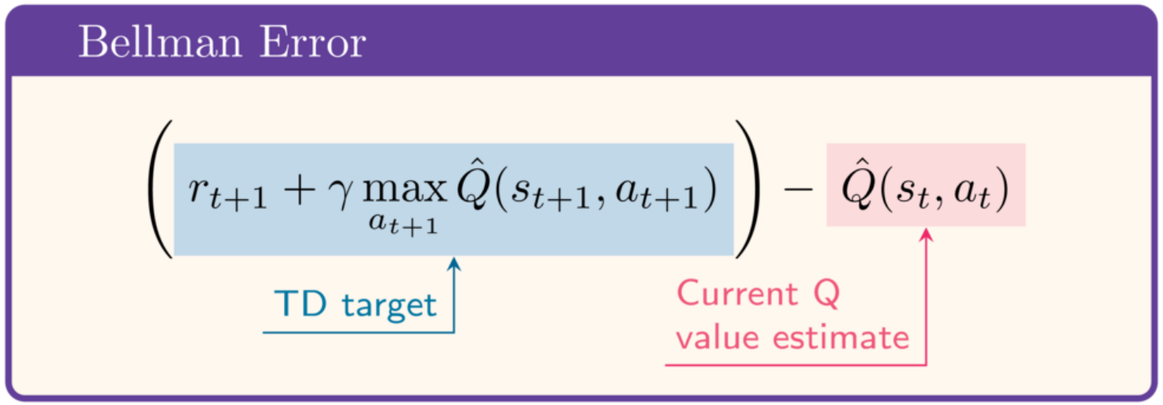
- $\varepsilon = end + (start - end) \cdot e^{-\frac{step}{decay}}$
- Take random action with probability ε
- Take highest value action with probability $1 - \varepsilon$

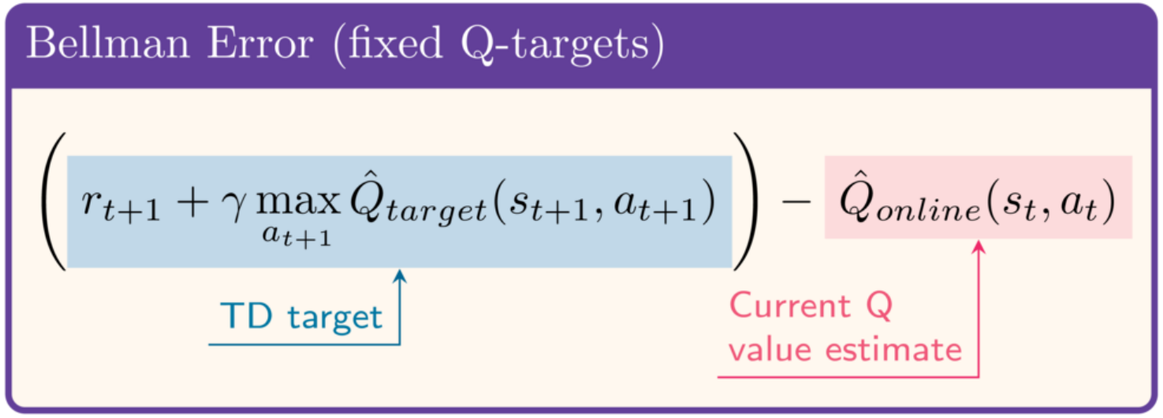


Fixed Q-targets

- In Bellman Error:
  - Q-Network in both Q-Value and TD-Target calculation
  - Instability from shifting target

- Introduce target network to stabilize target





Implementing fixed Q-targets

```
online_network = QNetwork(state_size, action_size)
target_network = QNetwork(state_size, action_size)
target_network.load_state_dict(
                        online_network.state_dict())

def update_target_network(
                    target_network, online_network, tau):
  target_net_state_dict = target_network.state_dict()
  online_net_state_dict = online_network.state_dict()
  for key in online_net_state_dict:
    target_net_state_dict[key] = (
         online_net_state_dict[key] * tau +
         target_net_state_dict[key] * (1 - tau))
    target_network.load_state_dict(
                          target_net_state_dict)
  return None
```

- Initially Online Network = Target Network
- A network's state dict contains all weights:

```
fc1.weight :
       tensor(
              [[-0.5059, -0.6368],
              [-0.4193,  0.6154]]
              )
fc1.bias :
       tensor([ 0.2465, -0.5916])
fc2.weight :
       tensor(
              [[-0.1208, -0.2308],
              [-0.2805,  0.5415]]
              )
```

- Each step, every weight of Target Network gets a bit closer to Online Network

Loss calculation with fixed Q-targets

```
# In the inner loop, after action selection
if len(replay_buffer) >= batch_size:
  states, actions, rewards, next_states, dones =
      replay_buffer.sample(64)
  q_values = (online_network(states)
              .gather(1, actions).squeeze(1))
  with torch.no_grad():
    next_q_values = (
        target_network(next_states).amax(1))
    target_q_values = (
        rewards + gamma * next_q_values * (1 - dones))
  loss = torch.nn.MSELoss()(target_q_values, q_values)
  optimizer.zero_grad()
  loss.backward()
  optimizer.step()
  update_target_network(
                target_network, online_network, tau)
```

- Q-values use `online_network`
- Target Q-values use `target_network`
- Use `torch.no_grad()` to disable gradient tracking for target Q-values
- Still use Mean Squared Bellman Error for loss calculation
- Use `update_target_network()` to slowly update `target_network`

Let's practice!

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Double DQN

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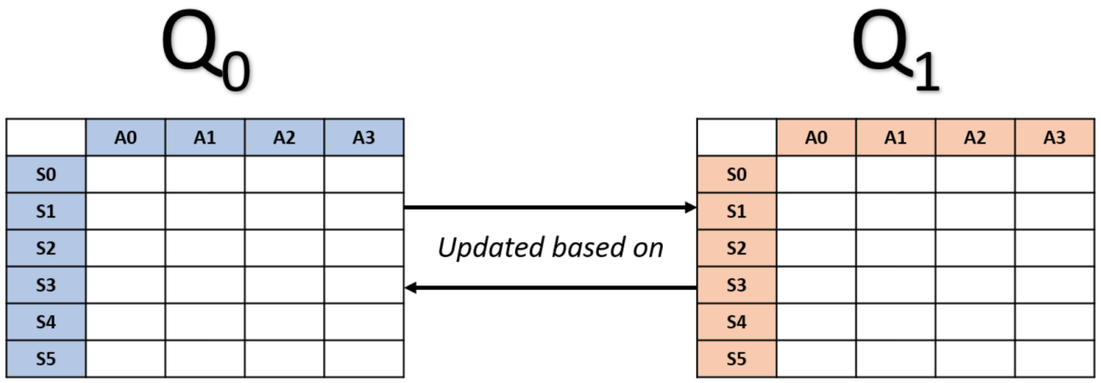
Double Q-learning

- Q-learning overestimates Q-values, compromising learning efficiency
- This is due to maximization bias
- Double Q-Learning eliminates bias by decoupling action selection and value estimation



$$max_a = argmax(Q_1(s'))$$

$$Q_1(s,a) = (1-\alpha)Q_1(s,a) + \alpha[r + \gamma Q_0(s', max_a)]$$

New Q value

Old Q value

Maximum Q value given the next state

The idea behind DDQN

- Start from complete DQN (with fixed Q-targets)
- In DQN TD target:
  - Action selection: target network
  - Value estimation: target network
- In DDQN TD target:
  - Action selection: *online* network
  - Value estimation: target network
- Not exactly double Q-learning (no alternating Q-networks)
- Most of the benefit, with minimal change

TD Error (DQN with fixed Q-targets)

$$\left(r_{t+1} + \gamma \max_{a_{t+1}} \hat{Q}_{target}(s_{t+1}, a_{t+1}) \right) - \hat{Q}_{online}(s_t, a_t)$$

TD target

Current Q value estimate

TD Error (DDQN)

$$\left(r_{t+1} + \gamma \max_{\tilde{a}} \hat{Q}_{target}(s_{t+1}, \tilde{a}) \right) - \hat{Q}_{online}(s_t, a_t)$$

TD target

Current Q value estimate

with $\tilde{a} = \arg\max_{a_{t+1}} \hat{Q}_{online}(s_{t+1}, a_{t+1})$

Double DQN implementation

DQN:

```
... # instantiate online and target networks
q_values = (online_network(states)
            .gather(1, actions).squeeze(1))
with torch.no_grad():
    #
    #
    next_q_values = (target_network(next_states)
        .amax(1))
    target_q_values = (rewards +
        gamma * next_q_values * (1 - dones))
loss = torch.nn.MSELoss()(q_values, target_q_values)
... # gradient descent
... # target network update
```

DDQN:

```
... # instantiate online and target networks
q_values = (online_network(states)
            .gather(1, actions).squeeze(1))
with torch.no_grad():




    target_q_values = (rewards +
        gamma * next_q_values * (1 - dones))
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Double DQN implementation

DQN:

```
... # instantiate online and target networks
q_values = (online_network(states)
            .gather(1, actions).squeeze(1))
with torch.no_grad():
    next_actions = (target_network(next_states)
       .argmax(1).unsqueeze(1))
    next_q_values = (target_network(next_states)
       .gather(1, next_actions).squeeze(1))
    target_q_values = (rewards +
        gamma * next_q_values * (1 - dones))
loss = torch.nn.MSELoss()(q_values, target_q_values)
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DDQN:

```
... # instantiate online and target networks
q_values = (online_network(states)
            .gather(1, actions).squeeze(1))
with torch.no_grad():
    next_actions = (online_network(next_states)
       .argmax(1).unsqueeze(1))
    next_q_values = (target_network(next_states)
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    target_q_values = (rewards +
        gamma * next_q_values * (1 - dones))
loss = torch.nn.MSELoss()(q_values, target_q_values)
... # gradient descent
... # target network update
```
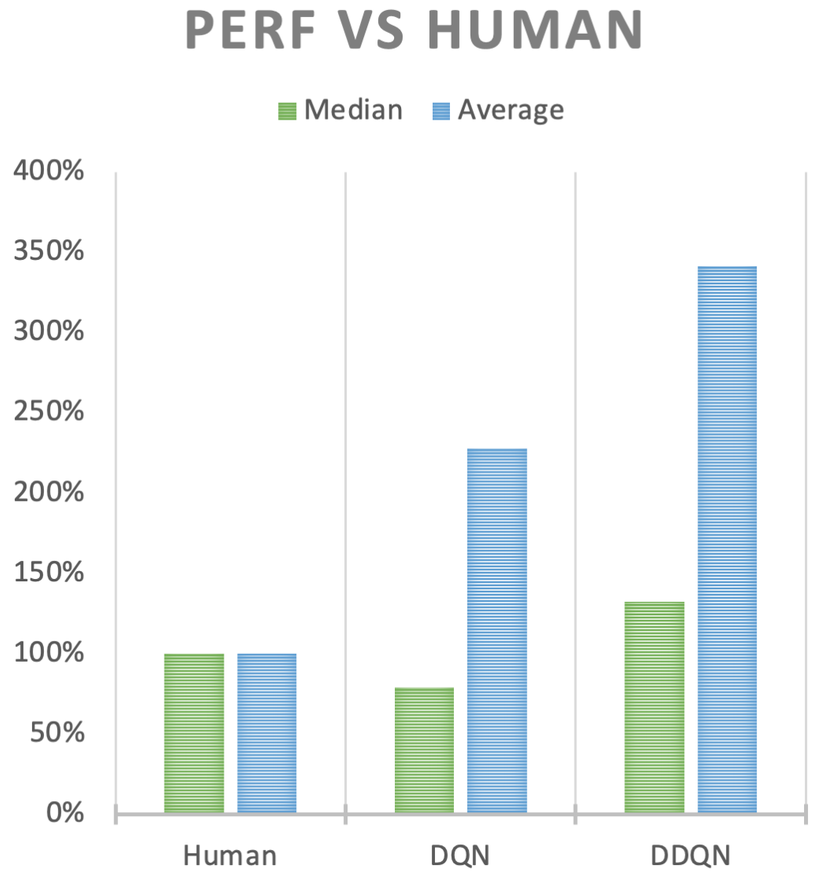

DDQN performance

- Compare performance of DDQN, DQN and human players on Atari games
- DDQN: higher scores than original DQN
- May not always be true -> try both



[1] https://arxiv.org/abs/2303.11634

Let's practice!

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Prioritized experience replay

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Not all experiences are created equal

- Experience Replay:
  - Uniform sampling of experiences may overlook important memories
- Prioritized Experience Replay:
  - Assign priority to each experience, based on TD errors
  - Focus on experiences with high learning potential

Prioritized Experience Replay (PER)

```
for step = 1 to T do:
    # Take optimal action according to value function
    # Observe next state and reward
    # Append transition to replay buffer
      # Give it highest priority (1)
    # Sample a batch of past transitions
      # Based on priority (2)
    # Calculate TD errors for the batch
    # Calculate the loss and update the Q Network
      # Use importance sampling weights (4)
    # Update priority of sampled transitions (3)
# Increase importance sampling over time. (5)
```

(1) New transitions are appended with highest priority $p_i = \max_k(p_k)$

(2) Sample transition i with probability

$$P(i) = p_i^\alpha / \sum_k p_k^\alpha \qquad (0 < \alpha < 1)$$

(3) Sampled transitions have their priority updated to their TD error: $p_i = |\delta_i| + \varepsilon$

(4) Use importance sampling weights

$$w_i = \left(\frac{1}{N} \cdot \frac{1}{P(i)}\right)^\beta \qquad (0 < \beta < 1)$$

(5) Progressively increase β towards 1

Implementing PER

```
def __init__(self, capacity, alpha=0.6, beta=0.4, beta_increment=0.001, epsilon=0.00
    # Initialize memory buffer
    self.memory = deque(maxlen=capacity)
    # Store parameters and initialize priorities
    self.alpha, self.beta, self.beta_increment, self.epsilon = (alpha, beta, beta_in
    self.priorities = deque(maxlen=capacity)


...
```

Implementing PER

```
...

def push(self, state, action, reward, next_state, done):
    # Append experience to memory buffer
    experience_tuple = (state, action, reward, next_state, done)
    self.memory.append(experience_tuple)
    # Set priority of new transition to maximum priority
    max_priority = max(self.priorities) if self.memory else 1.0
    self.priorities.append(max_priority)

...
```

Implementing PER

```
def sample(self, batch_size):
    priorities = np.array(self.priorities)
    # Calculate sampling probabilities
    probabilities = priorities**self.alpha / np.sum(priorities**self.alpha)
    # Randomly select sampled indices
    indices = np.random.choice(len(self.memory), batch_size, p=probabilities)
    # Calculate weights
    weights = (1 / (len(self.memory) * probabilities)) ** self.beta
    weights /= np.max(weights)
    states, actions, rewards, next_states, dones = zip(*[self.memory[idx] for idx in indices])
    weights = [weights[idx] for idx in indices]
    states, actions, rewards, next_states, dones = (zip(*[self.memory[idx] for idx in indices]))
    # Return tensors
    states = torch.tensor(states, dtype=torch.float32)
    ... # Repeat for rewards, next_states, dones, weights
    actions = torch.tensor(actions, dtype=torch.long).unsqueeze(1)
    return (states, actions, rewards, next_states, dones, indices, weights)
```

Implementing PER

```
...

def update_priorities(self, indices, td_errors: torch.Tensor):
    # Update priorities for sampled transitions
    for idx, td_error in zip(indices, td_errors.abs()):
        self.priorities[idx] = abs(td_error.item()) + self.epsilon

def increase_beta(self):
    # Increment beta towards 1
    self.beta = min(1.0, self.beta + self.beta_increment)
```

PER in the DQN training loop

1. In pre-loop code:

```
buffer = PrioritizedReplayBuffer(capacity)
```

2. At the start of each episode:

```
buffer.increase_beta()
```

3. At every step:

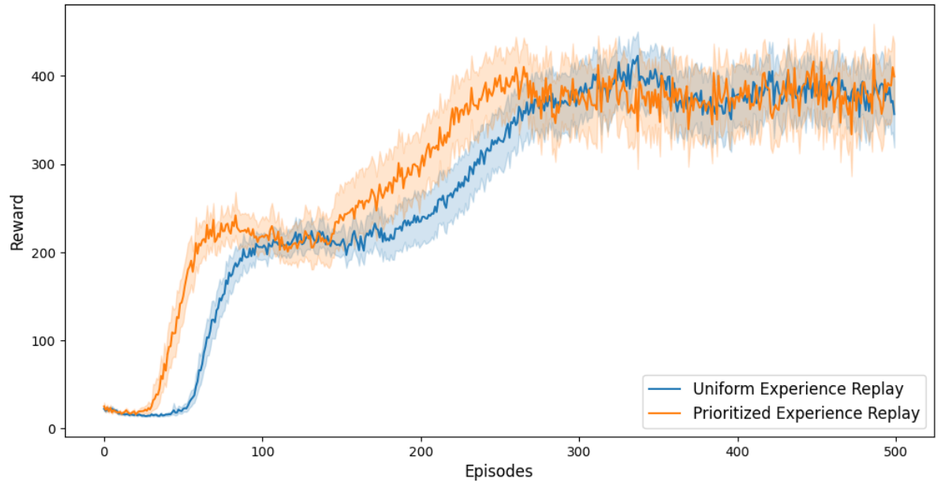
```
# After selecting an action
buffer.push(state, action, reward,
            next_state, done)
...
# Before calculating the TD errors:
replay_buffer.sample(batch_size)
...
# After calculating the TD errors
buffer.update_priorities(indices, td_errors)
loss = torch.sum(weights * (td_errors ** 2))
```

PER In Action: Cartpole

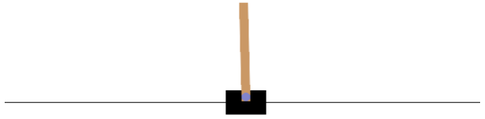
100 training runs in the Cartpole environment:

1. with Prioritized Experience Replay
2. with Uniform Experience Replay

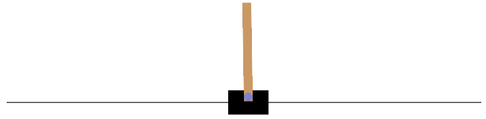
- **Faster** learning and **better performance** with PER than uniform experience replay



After 100 epochs:

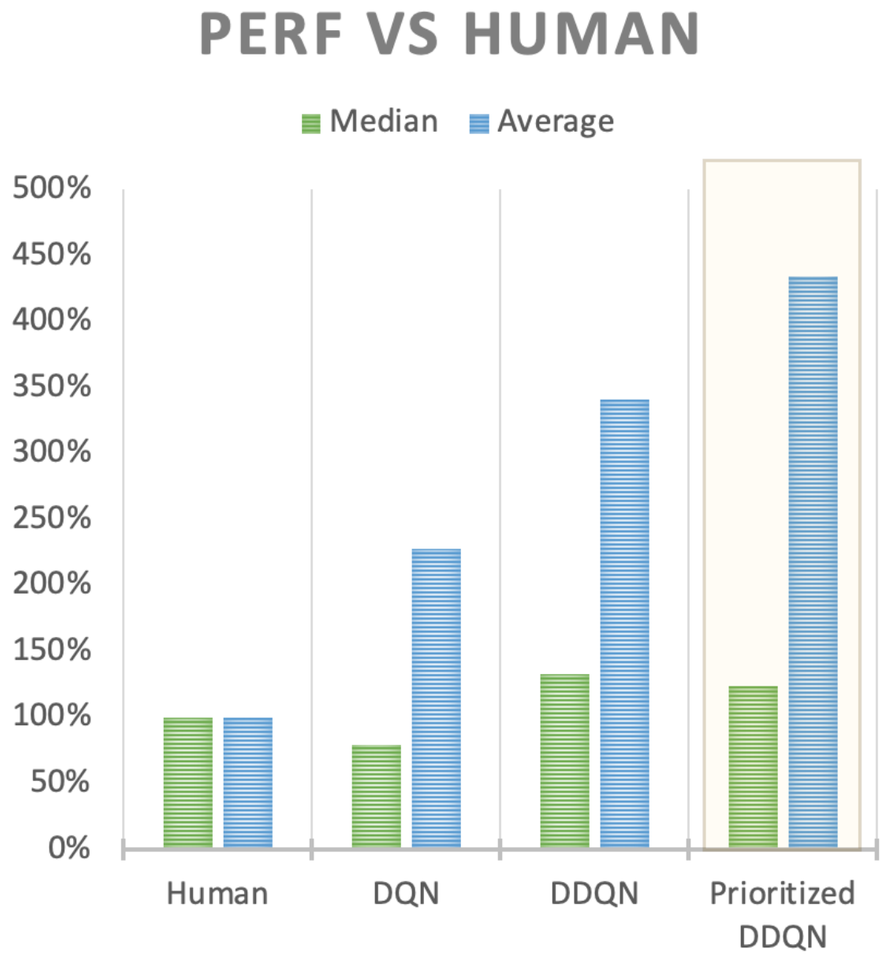


After 400 epochs:



PER In Action: Atari environments

- Substantial performance boost with PER in Atari environments



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