

Episode \rightarrow Change in point

$$q^{\text{new}}(s, a) = (1 - \alpha) \underbrace{q(s, a)}_{\text{old value}} + \alpha \left(R_{t+1} + \gamma \max_{a'} \overbrace{q(s', a')}^{\text{learned}} \right)$$

Episode loop

- \rightarrow start env
- \rightarrow check for initial flag for stopping
- \rightarrow initial reward

Time-step loop

- \rightarrow take action based on exploitation, exploration
- \rightarrow ~~temp~~ update q table
- \rightarrow update reward
- \rightarrow check if episode is complete
- \rightarrow add reward of current step to all rewards

Learning \equiv Using value iteration to compute optimal Q-value function.

Deep Q learning \equiv Use neural networks to approximate Q-value function

Experience replay

\downarrow
we store the agent's experience at each time step in a DS called replay memory.

$$C_t = (s_t, a_t, r_{t+1}, s_{t+1})$$

⑧ Why use replay memory?

- \rightarrow To break correlation.

Summary of Steps

1. Initialize replay memory capacity
2. Initialize the network with random weights / Xavier initialization
3. For each episode
 1. Initialize the starting state
 2. For each time step
 1. Select an action
 - via exploration or exploitation
 2. Execute selected action in an emulator
 3. Observe reward and next state
 4. Store experience in replay memory.

5. Sample random Batch from replay memory
6. Preprocess states from batch
7. Pass batch of pre-processed states to policy network
8. Calculate loss between target Q-values & Q-values
 - Requires second pass to the network for next state
9. Gradient descent updates weights in the policy network to minimize loss.

Target network

- When calculating loss between present Q-values and target Q-values, we use the target network [a clone of the original network] to compute target Q-values.
- The weights of target network are updated after every τ timesteps where τ is a hyperparameter

Code

