DQN

Goal: Approximate the optimal action-value function $Q^*(s, a) = \max_{\pi} \mathbb{E}\left[\sum_{t=1}^{\infty} \chi^{t}_{t} | s_0 = s, a_0 = a, \pi\right]$

Q*(s,c) = E[r+ x max (s', a') 1s, a] - Bellman ophinelity condition Classical Q-Learning and the Bellman equation

Q(s,a) = Q(s,a) + a[r+y max Q(s',a') - Q(s,a)]

Bellman equation

If d=1 -> Q(s,a) (- r+ymax Q(s',a'))
Approx: mation with a NN

Q(s, a; 0) & Q*(s, a)

Stabilize learning: Two-Nelwork Archilecture

Challenges: Instability due to non-stationary hargels
Policy Network: Estimate Q-values for current state
- Updated continuously at every braining step

Target Nelwork: Provides stable Earget Q-values during the braining of the Policy Network. - Copy of Policy Nelwork but updated less frequently Implementation: - Action solection: Policy Network (state) Experience replay - Environment interaction: Action executed +> 5', r - Experience storage: (s, a, r, s') stored in replay buffer - Sampling & Training: * - Sample from replay buffer - Alvoids overfilling, improves generalization - Compute luyer Q-value: y=r+y max Q larger (5', a') or Updale with gradient - Updaling the Policy Nelwork (Loss) dexel (Lectures 125) - L = [y- apolicy (s,a)] - dimension (balch-size, actions)

BILI 24, 12] Approxy q-value = policy-nel (shape) 62 L 13, 1] 49] policy-net. galher (1, actions) actions = [[0], => [[24], [13]] . squeeze() => [24, 13] = q-value,

target_net (next_state) b_1[[2,0],
b_1[03]]

target_net . max(1) +> ([2,3], [0,1])

[0] +> [2,3] = target_q_value if done==True=|

target_q_value = r + y · next_q_value · (1-dones)

Recall

Q(s,a) = r + y max Q(s',a') (Bellman equation

Policy_net

=) Loss = | 6aget_q_value - q_value|²