## IEOR 8100 Lab 3: Pseudocode for DQN

## March 2, 2018

## Algorithm 1 DQN

- 1: INPUT: target network update period  $\tau$ , total number of episodes E, initial time steps before update init, learning rate  $\alpha$ , exploration prob  $\epsilon$ , batchsize for training N
- 2: INITIALIZE: DQN principal network  $Q_{\theta}(s, a)$  with parameters  $\theta$ , target network  $Q_{\theta^{-}}(s, a)$  with parameters  $\theta^{-}$ , time steps counter counter  $\epsilon$  0, empty buffer  $R \leftarrow \{\}$
- 3: **for** e = 1, 2, 3...E **do**
- 4: while episode not terminated do
- 5: Execute actions
- 6:  $counter \leftarrow counter + 1$
- 7: Given state  $s_t$ , for prob  $\epsilon$ , take action uniformly random; otherwise, take action by being greedy  $a_t \leftarrow \arg\max_a Q_{\theta}(s_t, a)$
- 8: Save experience tuple  $\{s_t, a_t, r_t, s_{t+1}\}$  to buffer R
- 9: Training  $\theta$  by gradients
- 10: Sample N tuples  $\{s_i, a_i, r_i, s_i'\}$  from replay buffer R (uniformly)
- 11: Compute target  $d_j = r_j + \max_{a'} Q_{\theta_j^-}(s'_j, a')$  for  $1 \le j \le N$
- 12: Compute empirical loss

$$L = \frac{1}{N} \sum_{j=1}^{N} (Q_{\theta}(s_j, a_j) - d_j)^2$$

- 13: Update  $\theta \leftarrow \theta \alpha \nabla_{\theta} L$
- 14: Update target network  $\theta^-$
- if  $counter \mod \tau = 0$  then
- 16: Update target parameter  $\theta^- \leftarrow \theta$

There are multiple ways to improve the efficacy of the algorithm.

- Sampling: Instead of sampling uniformly from buffer, sample using adaptive distribution (prioritized replay buffer).
- Double DQN: DQN overestimates Q values. To mitigate the issue, use Double DQN.
- Architecture: Decompose Q value into Q(s,a) = V(s) + A(s,a) and use Dueling DQN architecture.
- Soft update:  $\theta_{\text{target}} \leftarrow (1 \beta)\theta_{\text{target}} + \beta\theta$ .
- Exploration constant: Exploration constant can be made adaptive. Start with large  $\epsilon$  and gradually decrease  $\epsilon$  to be small.