Deep Learning
Lab17: Deep RL

Pin-Yu Wang & Datalab

Outline

- From RL to Deep RL
- Deep *Q*-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Outline

- From RL to Deep RL
- Deep Q-Network
    - Naïve Algorithm(TD)
    - Experience Replay
    - Delayed Target Network
    - Complete Algorithm
    - Implementation
- Assignment

From RL to Deep RL

- (Tabular) RL
  - Q-learning:

    $$Q^*(s,a) \leftarrow Q^*(s,a) + \eta[(R(s,a,s') + \gamma \max_{a'} Q^*(s',a')) - Q^*(s,a)]$$

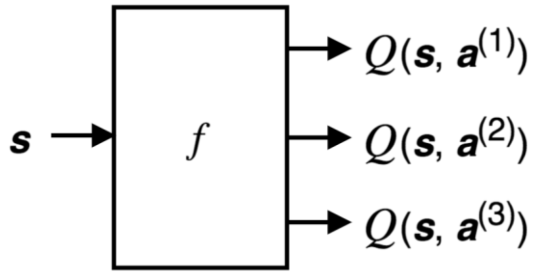
  - It requires a large table to store Q^* values in realistic environments with large state/action space.
    - Flappy bird: $O(10^5)$, Tetris: $O(10^{60})$, Automatic car: ? ? ?
  - Hard to visit all $(s,a)'s$ in limited training time.
  - Agents must derive efficient representations of the environment from high-dimensional inputs and use these to generalize past experience to new situations.

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Deep Q-Network

- To learn a function $f_{Q^*}(s, a; \theta)$ that approximates $\mathrm{Q}^*(s, a)$
  - Trained by a small number of samples.
  - Generalize to unseen states/actions.
  - Smaller θ to store.



Deep Q-Network

- Naïve Algorithm(TD)
  1. Take action a from s using some exploration policy π' derived from f_{Q^*} (e.g. ε-greedy).
  2. Observe s' and reward $R(s,a,s')$, and update θ using SGD:

$$\theta \leftarrow \theta - \eta \nabla_\theta C, \text{ where}$$

$$C(\theta) = [(R(s,a,s') + \gamma \max_{a'} f_{Q^*}(s',a';\theta)) - f_{Q^*}(s,a;\theta)]^2$$

❖ Recall the Q-learning update formula:

$$Q^*(s,a) \leftarrow Q^*(s,a) + \eta[(R(s,a,s') + \gamma \max_{a'} Q^*(s',a')) - Q^*(s,a)]$$

Deep Q-Network

- However, the naïve TD algorithm diverges due to:
  1. Samples are correlated (violates i.i.d. assumption of training examples).
  2. Non-stationary target ($f_{Q^*}(s', a'; \theta)$ changes as θ is updated for current a).

- As a result, the Deep Q-Network applies two stabilization techniques to solve each problem respectively:
  1. Experience Replay
  2. Delayed Target Network

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Deep Q-Network

- Experience Replay
  - To remove the correlations in the observation sequence.
  - Use a replay memory $\mathbb{D}$ to store recently seen transitions (s, a, r, s')'s.
  - Sample a mini-batch from $\mathbb{D}$ and update θ.
    - The sample from the mini-batch is not a sequence now.

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Deep Q-Network

- Delayed Target Network
  - To avoid chasing a moving target.
  - Set the target value to the output of the network parameterized by old θ^-.
  - Update $\theta^- \leftarrow \theta$ every K iterations.

❖ Update formula of naïve TD algorithm:

$$C(\theta) = [(R(s,a,s') + \gamma \max_{a'} f_{Q^*}(s',a';\theta)) - f_{Q^*}(s,a;\theta)]^2$$

❖ Update formula after applying Delayed Target Network:

$$C(\theta) = [(R(s,a,s') + \gamma \max_{a'} f_{Q^*}(s',a';\theta^-)) - f_{Q^*}(s,a;\theta)]^2$$

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Deep Q-Network

- Complete Algorithm
  - Naïve algorithm(TD) + *Experience Replay* + *Delayed Target Network*
  - Initialize θ arbitrarily and set $\theta^- = \theta$. Iterate until converge:
    1. Take action a from s using some exploration policy π' derived from f_{Q^*} (e.g. ε-greedy).
    2. Observe s' and reward $R(s,a,s')$, add (s,a,R,s') to $\mathbb{D}$.
    3. Sample a mini-batch of (s,a,R,s')'s from $\mathbb{D}$, do:

$$\theta \leftarrow \theta - \eta \nabla_\theta C, \text{ where}$$

$$C(\theta) = [(R(s,a,s') + \gamma \max_{a'} f_{Q^*}(s',a';\theta^-)) - f_{Q^*}(s,a;\theta)]^2$$

    4. Update $\theta^- \leftarrow \theta$ every K iterations.

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Outline

- From RL to Deep RL
- Deep Q-Network
  - Naïve Algorithm(TD)
  - Experience Replay
  - Delayed Target Network
  - Complete Algorithm
  - Implementation
- Assignment

Assignment – state-based DQN

- What you should do:
  - Change the input from stack of frames to game state(as Lab 16).
  - Change the network structure from CNNs to Dense layers.
  - Train the state-based DQN agent to play Flappy Bird.
- Evaluation metrics:
  - Code (Whether the implementation is correct) (50%).
  - The bird is able to fly through at least 1 pipes (50%).
- Requirements:
  - Upload the notebook and html file to google drive, and submit the link to iLMS.
    - Lab17_{student_id}.ipynb
    - Lab17_{student_id}.html
  - Deadline: 2020-12-31(Thur) 23:59.