L16: Advanced Off-Policy RL

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Contents are based on website

Agenda

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Key Ideas of Off-policy RL

Off-Policy RL

Key ideas:

- Use a replay buffer to store samples that might be collected from long before.
- Build a value network approximator $Q_\theta(s, a)$ and learn θ by minimizing the TD loss with samples from the replay buffer.
- Had Q_θ been learned, policy $\pi(s)$ can be considered as solving an optimization problem over the value network:

$$\pi(s) = \mathbf{argmax}_{a \in \mathcal{A}} Q_\theta(s, a)$$

- For discrete action space, the optimum a can be computed by enumerating all possible actions (recall the DQN algorithm).

Recall: Q-Learning for Tabular RL

1. Given transitions $\{(s, a, s', r)\}$ from some trajectories, how to improve the current Q-function?
   - By Temporal Difference learning, the update target for $Q(S, A)$ is
     - $R + \gamma \max_a Q(S', a)$
   - Take a small step towards the target
     - $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_a Q(S', a) - Q(S, A)]$
2. Given Q, how to improve policy?
   - Take the greedy policy based on the current Q
     - $\pi(s) = \text{argmax}_a Q(s, a)$
3. Given π, how to generate trajectories?
   - ϵ-greedy policy in the environment.

Continous Q-Learning

- The major challenge for continous Q-learning is in how we compute $\max_a Q_\theta(s, a)$.
- For discrete action space, the optimum a can be computed by enumerating all possible actions (recall the DQN algorithm).
- However, for continuous action space, computing $\max_a Q_\theta(s, a)$ cannot be achieved by enumeration.
- *Q: How to do Q-learning if the action space is continuous?*

Continous Q-Learning

- The most straight-forward idea: Solving an optimization problem to compute a:

$$\underset{a}{\text{maximize}} \qquad Q_\theta(s, a)$$

- Limitations:
  - Very slow!
  - May get stuck in local minima.

Continous Deterministic Policy Network

- If optimizing a every time is too slow, let us use a neural network to memorize the decisions in the past!
- We consider a simple policy family - deterministic policies. Deterministic policies can be approximated as a network $\pi_\phi : \mathcal{S} \mapsto \mathbb{R}$.
- Suppose that we have a learned value network $Q_\theta(s, a)$. Then, the optimal policy can be obtained by "fine-tuning" our policy network:

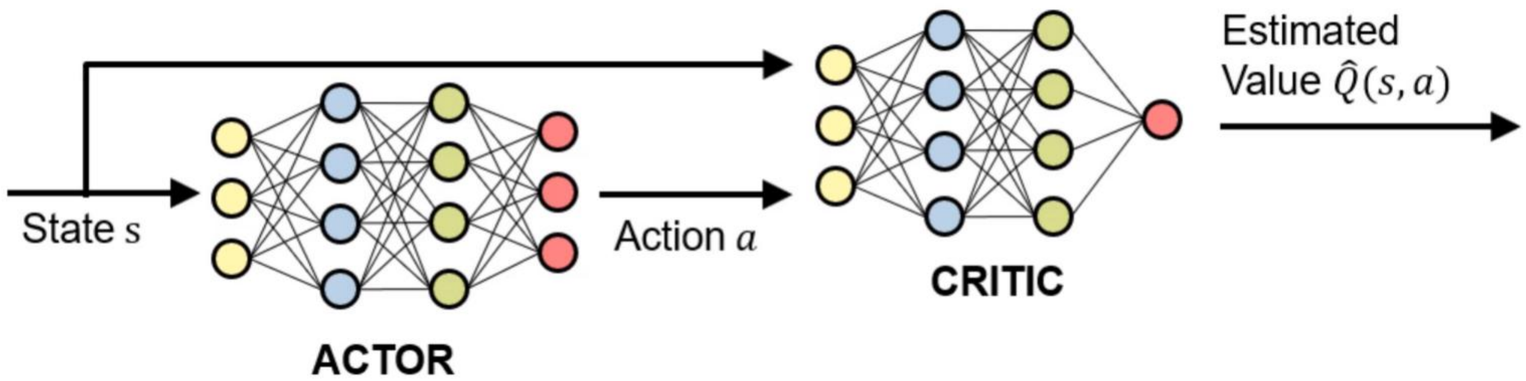
$$\underset{\phi}{\text{maximize}} \qquad Q_\theta(s, \pi_\phi(s))$$

- *Q: What are the potential benefit of using a policy network other than being faster?*

TD-based Q Function Learning

We can still use TD-loss to learn Q_θ. Given a transition sample (s, a, s', r):

- In tabular Q-learning, the update target for $Q(s, a)$ is $r + \gamma \max_a Q(s', a)$;
- In continuous deterministic Q-learning, the update target becomes $r + \gamma Q(s', \pi_\phi(s'))$.
- In literature, the policy network is also referred as "actors" and the value network referred as "critics"



Have We Finished? Revisit the Three Questions

1. Given transitions $\{(s, a, s', r)\}$ from some trajectories, how to improve the current Q-function?
   - We have derived the update target for $Q(S, A) = r + \gamma Q(s', \pi_\phi(s'))$.
2. Given Q, how to improve policy?
   - We introduced a policy network π_ϕ and update it by solving

$$\underset{\phi}{\text{maximize}} \qquad Q_\theta(s, \pi_\phi(s))$$

3. Given π, how to generate trajectories?
   - We also need exploration in contious action space!

Exploration in Continuous Action Space

- For discrete action space, we can use ϵ-greedy.
- For continuous action space, we can add small perturbations to the actions output by the policy network to do exploration.
- Example:
  - Gaussian noise: $\mathcal{N}(0, \sigma^2)$;
  - Ornstein-Uhlenbeck random process (temporally correlated random noises).

Deep Deterministic Policy Gradient (DDPG)

- Initialize replay buffer D, Q network Q_θ and π_ϕ.
- For every episode:
  - Sample the initial state $s_0 \sim P(s_0)$
  - Repeat until the episode is over
    - Let s be the current state
    - **select $a = \pi_\phi(s) +$ random noise**
    - Execute a in the environment, and receive the reward r and the next state s'
    - Add transitions (s, a, s') in D
    - Sample a random batch from D and build the batch TD loss
    - Perform one or a few gradient descent steps on the TD loss
    - **Perform one or a few gradient descent steps on the policy loss**

Continuous control with deep reinforcement learning

Trouble and Tricks in Practice

- DQN and DDPG are concise, but they cannot get state-of-the-art performance in practice.
- Troubles in practice:
  - Value overestimation
  - Rare beneficial samples in replay buffer
  - Slow reward propagation
- Tricks in practice:
  - Dueling Network
  - Distributional action-value network
  - State-conditional exploration noise

Tricks - Value Overestimation

Value Overestimation

- Value network approximates the value. Policy networks are optimized over value networks. If Q of some sub-optimal action a' is overestimated and larger than the optimal one, policy network tends to choose suboptimal actions and hurts the performance.
- Theoretical intuition in Q-Learning
  - Target of TD update is $Q_\theta^{target}(s) = R(s,a,s') + \gamma \max_{a'} Q_\theta(s',a')$
  - Assume $Q_\theta(s,a) = Q_{gt}(s,a) + \epsilon$ with $\mathbb{E}[\epsilon] = 0$, where Q_{gt} is the ground-truth Q function
  - $E_\epsilon[\max_{a'} Q_\theta(s',a')] = E_\epsilon[\max_{a'} Q_{gt}(s,a) + \epsilon] \geq \max_{a'} E_\epsilon[Q_{gt}(s',a') + \epsilon] = \max_{a'} Q_{gt}(s',a')$
  - In practice $E_\epsilon[\max_{a'} Q_\theta(s',a')] > \max_{a'} Q_{gt}(s',a')$ which make target of TD update also overestimated.

Issues in using function approximation for reinforcement learning

Double Q-Learning

- The max operator in Q-learning uses the same values both to select and to evaluate an action. This makes it more likely to select overestimated values, resulting in overoptimistic value estimates.
- Solution: decouple the selection from the evaluation with double value functions $Q_{\theta_i}(s, a), i = 0, 1$.
  - Random choose one of the Q function to collect samples from the environment.
  - TD error of Q_{θ_i} is $TD_{\theta_i}(s, a) = \|Q_{\theta_i}(s, a) - [R(s, a, s') + \gamma Q_{\theta_{1-i}}(s', \text{argmax}_{a'} Q_{\theta_i}(s', a'))]\|^2$.
- In theory and practice, Double Q-Learning has advantages over Q-Learning in some cases.

Double Q-learning
Deep Reinforcement Learning with Double Q-learning

Clipped Double Q-Learning

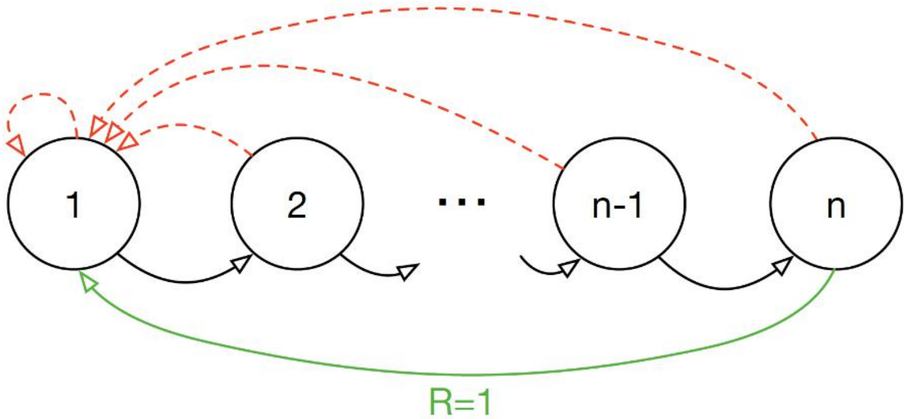
- In practice, Double Q-Learning in continuous action space can provide better performance, because it does not entirely eliminate the overestimation.
- Solution: Clipped Double Q-Learning
  - TD error of Q_{θ_i} is $TD_{\theta_i}(s,a) = \|Q_{\theta_i}(s,a) - [R(s,a,s') + \gamma \min_j Q_{\theta_j}(s', \pi_\phi(s'))]\|^2$.
- With Clipped Double Q-learning, the value target is smaller than that with one value function.
- While this update rule may induce an underestimation bias, this is far preferable to overestimation bias, as unlike overestimated actions, the value of underestimated actions will not be explicitly propagated through the policy update
- In practice, two value functions are enough. Using more cannot provide extra benifits.

Addressing function approximation error in actor-critic methods

Tricks - Prioritized experience replay

Rare beneficial samples in replay buffer

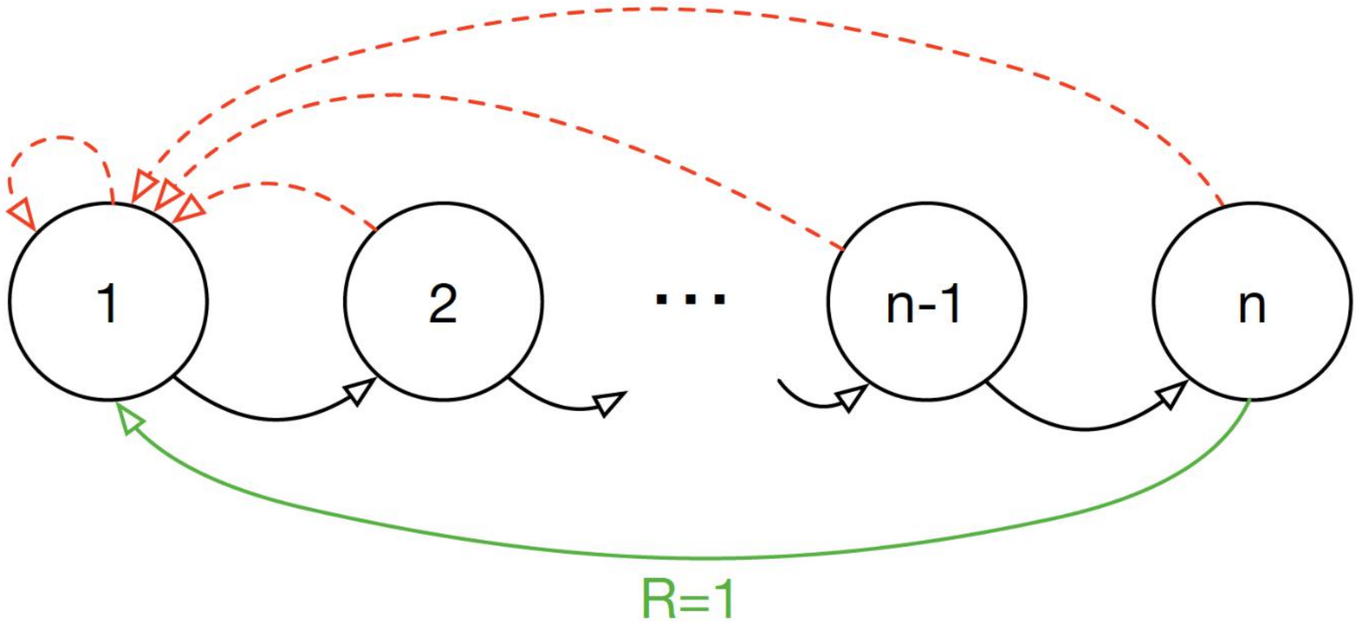
- In environment that suffers from hard exploration, reward singals are rare in replay buffer. It is not efficient to uniformly choice training samples from th buffer.
- Example: Montezuma's revenge, Blind Cliffwalk.



Prioritized experience replay

Blind Cliffwalk

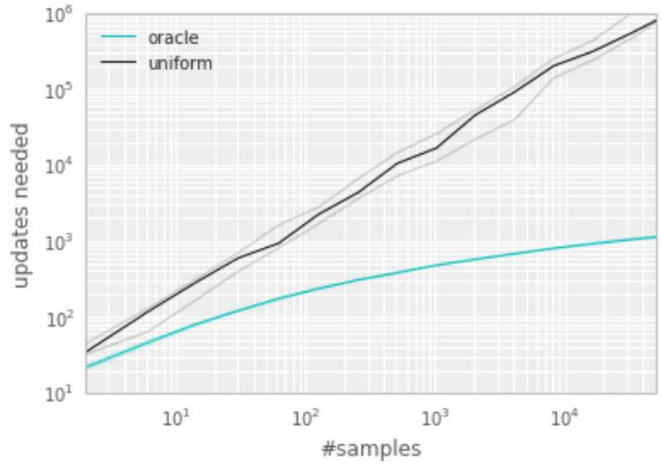
- Two actions at each state: right and wrong.
- Episode is terminated whenever the agent takes the wrong action.
- Agent will get reward 1 after taking n right actions.



Prioritized experience replay

Analysis with Q-Learning

- In expectation, they are $O(2^n)$ transitions with reward 0 in replay buffer before the agent get the first reward 1.
- With uniform sampling, the agent learn from successful transitions with probability $O(2^{-n})$ in the begining stage and this will dramatically slow down the reward propagation.
- Compare performance between uniform sampling and oracle sampling. Oracle greedily selects the transition that maximally reduces the global loss in its current state.



Prioritized experience replay

Prioritized experience replay

- Define a priority p_i of a transition pair $i = (s, a, s')$ with TD error $\delta = Q_\theta(s) - (R + \gamma Q_\theta(s', \pi_\phi(s')))$.
  - **proportional prioritization**: $p_i = |\delta| + \epsilon$, where ϵ is a small positive constant.
  - **rank-based prioritization** $p_i = \frac{1}{\text{rank}(|\delta_i|)}$, where $\text{rank}(|\delta_i|)$ is the rank of absolute value of TD error in the replay buffer.
- Probability of sampling transition i as $P_i = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$ where $p_i > 0$ is the priority of transition i.
- Prioritized replay introduces bias because it changes this distribution. As a result, importance sampling is necessary to help the convergence.
  - $w_i' = (NP_i)^{-\beta}, w_i = \frac{w_i'}{\max_j w_j'}$. Noramlized importance weights due to the numerical stablity
  - TD loss with importance sampling is $\sum_i w_i ||\delta_i||^2$.
  - In practice, β is linearly aannealed from its initial value $beta_0$ to 1.
- Comment: probability of being sampled is monotonic in a transition's priority and guaranteeing a non-zero probability even for the lowest-priority transition.

Prioritized experience replay

Tricks - Slow reward propagation

Slow reward propagation

- Q-learning accumulates a single reward and then uses the greedy action at the next step to bootstrap. The propagation speed is very slow when horizon is long and reward signal is sparse.
- Solution: $TD(n)$ can be used to update vaule network.
  - $TD^n_{\theta_i}(s_t, a_t) = \|Q_\theta(s_t, a_t) - [\sum_{i=0}^{n-1} \gamma^i R(s_{t+i}, a_{t+i}, s'_{t+i}) + \gamma^n Q_\theta(s'_{t+n}, \pi_\phi(s'_{t+n}))]\|^2$.
  - $n = 3$ are used in Rainbow for Atari games.

Rainbow: Combining Improvements in Deep Reinforcement Learning

Tricks - Dueling Network

Dueling Network

- For discrete action space, researchers find that decoupling $Q(s,a)$ into $V(s)$ and $A(s,a)$ can help.
- Intuitively, V only depends on s, which may capture features from states only and generalize to similar state. A should focus on how action will impact the performance.
- A simple idea is represent $Q_\theta(s,a)$ with $V_{\theta_S}(s) + A_{\theta_A}(s,a)$. However, adding any constant C to $V_{\theta_V}(s)$ and subtracting C from $A_{\theta_A}(s,a)$ also works. This decomposition isunidentifiable, and $V_{\theta_V}(s)$ may not recover the value function.
- One possible solution: $Q_\theta(s,a)$ with $V_{\theta_V}(s) + (A_{\theta_A}(s,a) - \max_{a' \in \mathcal{A}} A_{\theta_A}(s,a'))$. Now, for $a^* = \text{argmax}_{a' \in \mathcal{A}} Q_\theta(s,a') = \text{argmax}_{a' \in \mathcal{A}} A_{\theta_A}(s,a')$. So $Q_\theta(s,a^*) = V_{\theta_V}(s)$, which means $V_{\theta_V}(s)$ really represents the value function.

  In practice, average is used to replace the max operator in $V_{\theta_V}(s) + (A_{\theta_A}(s,a) - \max_{a' \in \mathcal{A}} A_{\theta_A}(s,a'))$. max operator can change the $A_{\theta_A}(s,a) - \max_{a' \in \mathcal{A}} A_{\theta_A}(s,a')$ non-smmothly, which can cause the instability.

Dueling network architectures for deep reinforcement learning

Tricks - Distributional RL

Stochasticity in the environments

- In stochastic environment, for example, stepping with an action can provide different results. Then scalar Q value can only provide the mean and lost the information about the reward distribution.
- Even in deterministic environments like ALE(Atari games), stochasticity does occur in a number of guises:
  - from state, for example image, aliasing
  - learning from a nonstationary policy
  - from approximation errors.

A Distributional Perspective on Reinforcement Learning

Value Network with Discrete Distribution

- In stead of one value, value network predicts a discrete distribution on a set of atoms $\{z_i = V_{MIN} + i\Delta_z | 0 \leq i < N\}, \Delta z := \frac{V_{MAX} - V_{MIN}}{N-1}$. The probability of atom z_i is p_i.
- $Q_\theta(s, a) = \sum_i p_{\theta,i}(s, a) z_i$.
- Update rules of Q, x_t is state at time-step t.

Algorithm 1 Categorical Algorithm

input A transition $x_t, a_t, r_t, x_{t+1}, \gamma_t \in [0, 1]$
  $Q(x_{t+1}, a) := \sum_i z_i p_i(x_{t+1}, a)$
  $a^* \leftarrow \arg\max_a Q(x_{t+1}, a)$
  $m_i = 0, \quad i \in 0, \ldots, N-1$
  for $j \in 0, \ldots, N-1$ **do**
    # Compute the projection of $\hat{\mathcal{T}} z_j$ onto the support $\{z_i\}$
    $\hat{\mathcal{T}} z_j \leftarrow [r_t + \gamma_t z_j]_{V_{\text{MIN}}}^{V_{\text{MAX}}}$
    $b_j \leftarrow (\hat{\mathcal{T}} z_j - V_{\text{MIN}})/\Delta z$ # $b_j \in [0, N-1]$
    $l \leftarrow \lfloor b_j \rfloor, u \leftarrow \lceil b_j \rceil$
    # Distribute probability of $\hat{\mathcal{T}} z_j$
    $m_l \leftarrow m_l + p_j(x_{t+1}, a^*)(u - b_j)$
    $m_u \leftarrow m_u + p_j(x_{t+1}, a^*)(b_j - l)$
  end for
output $-\sum_i m_i \log p_i(x_t, a_t)$ # Cross-entropy loss

Tricks - State-conditional exploration noise

State-conditional exploration noise

- Using the same exploration policy for all the states is not efficient in practice.

Rainbow: Combining Improvements in Deep Reinforcement Learning

Noisy Nets (For Discrete Action Space)

- For discrete action space, we can replace the last linear layer of the value network Q_θ with a **noisy linear layer** to form a noisy Q network and generate exploration actions directly from the noisy Q.
- Let original linear layer be $y = wx + b$, **noisy linear layer** will be $y = wx + b + (\sigma^w \circ \epsilon^w x + \sigma^b \circ \epsilon^b)$, where $\circ$ represents element-wise multiplication, σ^w, σ^b are learnable paramters, ϵ are noise random variables.
- Greedly selecting on the noisy Q value has already provided exploration. Other parts are simlar to DQN. The only difference is that noisy Q network is used to replace the classical Q network.
- Updating Q network with TD loss,

Rainbow: Combining Improvements in Deep Reinforcement Learning

Parameterized Squashed Gaussian policy (For Continuous Action Space)

- For continuous action space, the policy network can output a parameterized Gaussian distribution.
- $\pi_\phi(s) = \tanh(\mu_\phi(s) + \sigma_\phi(s) \circ \epsilon)$, where $\epsilon = (0, I)$.
- $\mu_\phi(s)$ is the mean value of the agent's policy at state s, which can be used in evaluation.
- $\sigma_\phi(s)$ is the standard deviation of the exploration noise.
- In practice, policy network predicts $\log \sigma$ and clip it in to range $[\log \sigma_{min}, \log \sigma_{max}]$. In SAC, $\log \sigma_{min} = -20, \log \sigma_{max} = 2$.
- To train $\sigma_\phi(s)$, we need entropy regularization which will be discussed in SAC in the next lecture.

Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

Off-Policy RL Frameworks in Practice

Practical Off-Policy Algorithms

- In practice, a good off-policy algorithm needs to ensemble tricks ans solve exploration problem.

  Example algorithms:

  - Rainbow
  - Soft-Actor-Critic

Rainbow: Combining Improvements in Deep Reinforcement Learning

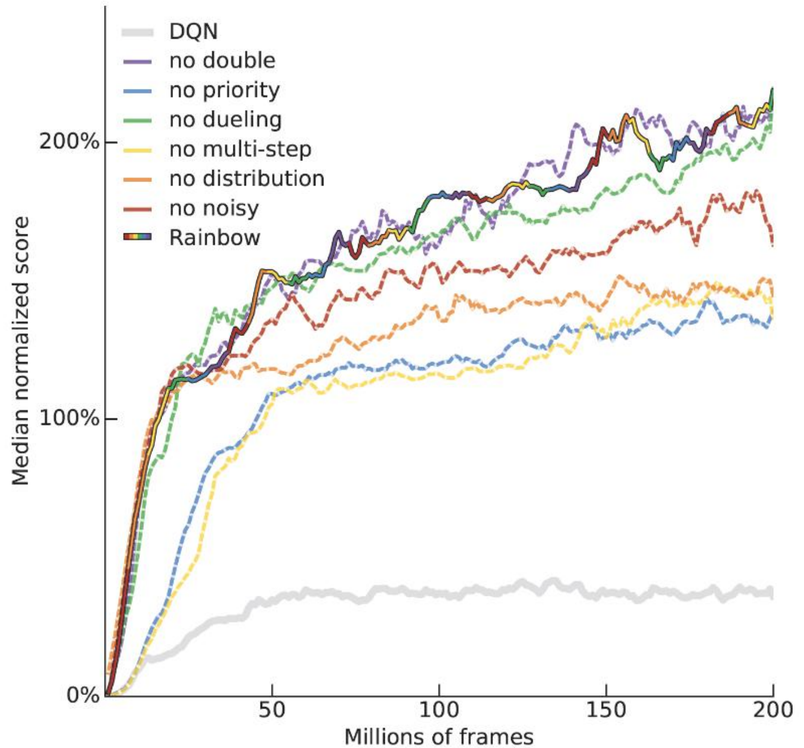
Rainbow

- For discrete action space, Rainbow is a famous algorithm which ensembles all the tricks to get better performance.
- Tricks used in Rainbow:
  - Prioritized replay
  - Multi-step learning / TD(3)loss
  - Distributional RL
  - Noisy Net
  - Double Q-learning
  - Dueling Q-learning

Rainbow: Combining Improvements in Deep Reinforcement Learning

Ablation study of tricks in Rainbow

- Prioritized replay, multi-step learning, distributional RL are most important tricks in Rainbow.



Rainbow: Combining Improvements in Deep Reinforcement Learning

Soft-Actor-Critic(SAC)

- For continuous action space, Soft-Actor-Critic is a famous algorithm which combines some tricks with an entropy-based exploration method.
- Tricks used in SAC:
  - Clipped Double Q-Learning
  - Parameterized Squashed Gaussian policy

Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor