Deep Deterministic Policy Gradients - Components and Extensions

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Deep Deterministic Policy Gradient

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- **Actor-Critic Method**
  - Approximated critic $Q(s, a|\theta^Q)$
  - Approximated actor $\pi(s|\theta^\pi)$
- **Deep Q-Learning**
  - Q-Learning with approximated critic by nn
  - $\nabla_{\theta^Q} L(\theta^Q) = \mathbf{E}\left[\left(r + \gamma \max_{a'} Q(s', a'|\theta^Q) - Q(s, a|\theta^Q)\right) \nabla_{\theta^Q} Q(s, a|\theta^Q)\right]$
  - Experience Replay Buffer
  - Target Network(s)
- **Deterministic Policy Gradient**
  - $\nabla_{\theta^\pi} J(\theta^\pi) \approx \mathbf{E}\left[\nabla_a Q(s, a)|_{a=\pi(s|\theta^\pi)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)\right]$
  - Enables to learn a deterministic policy while following a stochastic exploratory policy

DDPG Pseudocode

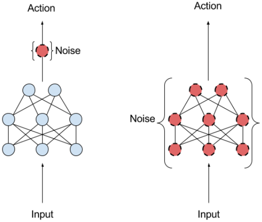
Algorithm 2 Deep Deterministic Policy Gradient (DDPG)

Initialize: Replay buffer D with high capacity
Initialize: Critic network $Q(s, a|\theta^Q)$ and actor network $\pi(s|\theta^\pi)$ with random weights θ^Q and θ^π
Initialize: Initialize target networks Q' and π' with weights $\theta^{Q'} \leftarrow \theta^Q$ and $\theta^{\pi'} \leftarrow \theta^\pi$

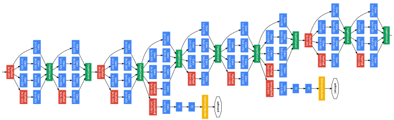
for episode 1 **to** M **do**
  Initialize random process N for action exploration
  Reset environment to state s_1
  for $t = 1$ **to** T **do**
    Select action $a_t = \pi(s_t|\theta^\pi) + N_t$ from local actor
    Execute action a_t and observe reward r_t and next state s_{t+1}
    Save (s_t, a_t, r_t, s_{t+1}) in replay buffer D
    Sample mini-batch $(s_i, a_i, r_i, s_{i+1})_k$ with size k from D
    Set TD-target from target networks:
      $y_i = r_i + \gamma Q'(s_{i+1}, \pi'(s_{i+1}|\theta^{\pi'})|\theta^{Q'})$
    Update the critic by minimizing the loss:
      $L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor using the sampled policy gradient:
      $\nabla_{\theta^\pi} J \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\pi(s_i)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)|_{s=s_i}$
    Update the target networks:
      $\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$
      $\theta^{\pi'} \leftarrow \tau\theta^\pi + (1-\tau)\theta^{\pi'}$
  end for
end for

Improvements for DDPG

- **D4PG**
  - Importance Weighted Experience Sampling
  - Utilizing N-Step return
  - Parallelized Actors
- **Parameter Noise for Exploration**



- **Deep Changes**



Sources

- For publication references please see our paper "Deep Deterministic Policy Gradients: Components and Extensions"
- GoogLenet: https://towardsdatascience.com/an-intuitive-guide-to-deep-network-architectures-65fdc477db41
- Parameter noise for exploration: https://openai.com/blog/better-exploration-with-parameter-noise/