Maintenance Planning for Structures Using A Policy Gradient Approach

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Département des génies civil, géologique et des mines

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Transportation Ministry of Quebec (MTQ)

Quick Recap

An element with inspections

Quick Recap

An element with inspections

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An elements with inspections & repairs

Quick Recap

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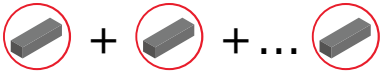
Category of elements



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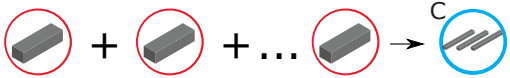

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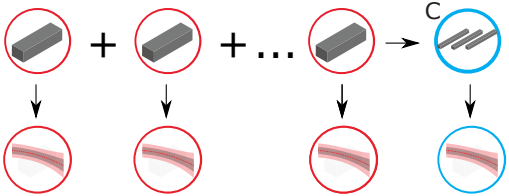

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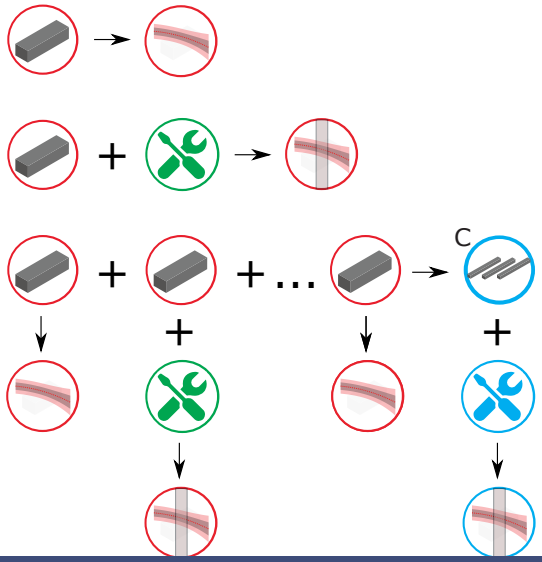
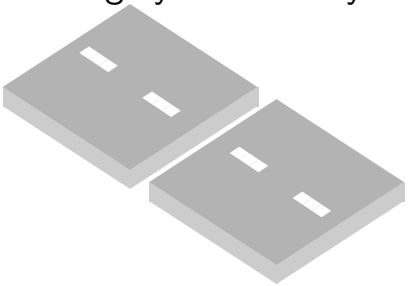
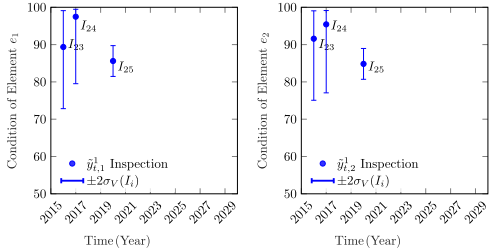


Structural Category-Level Analyses





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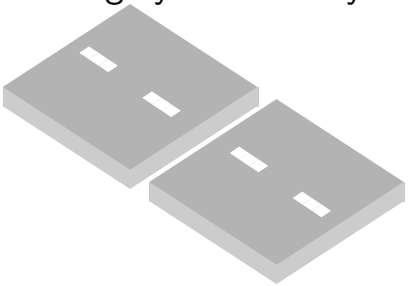

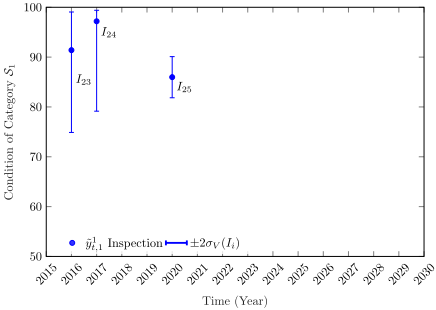

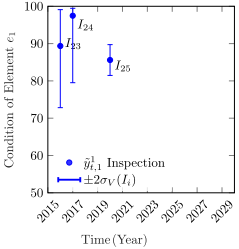

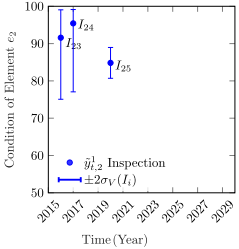

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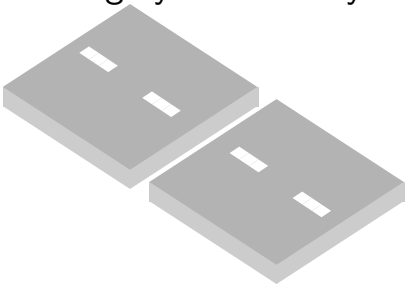

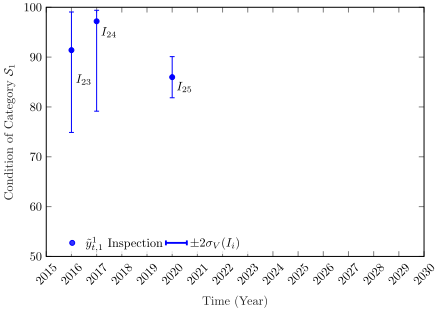

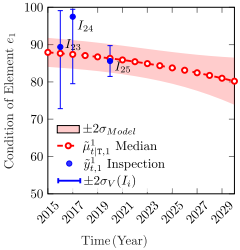

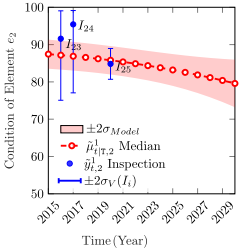

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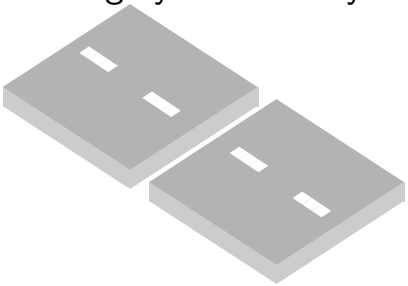

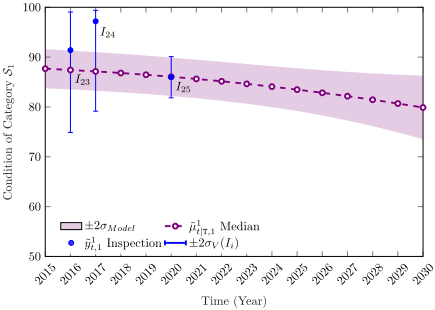

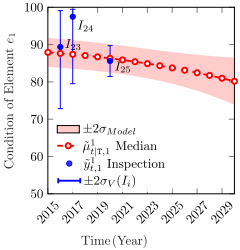

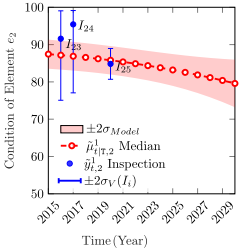

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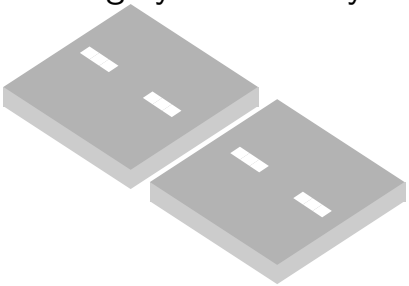

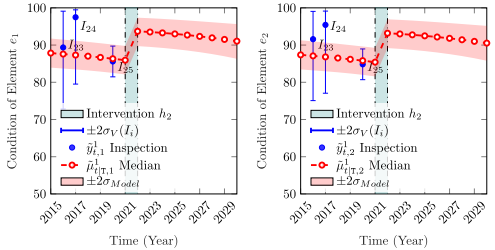

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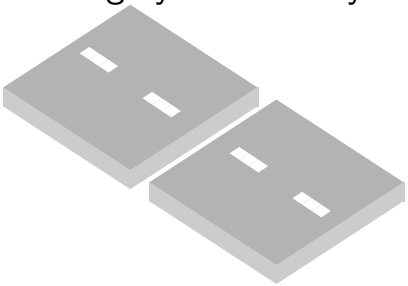

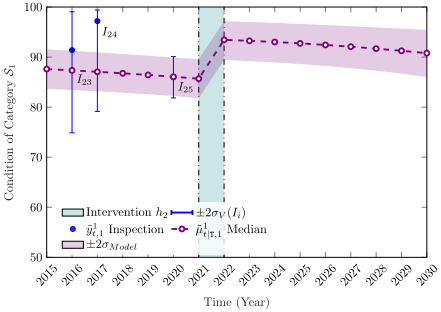

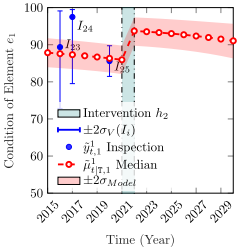

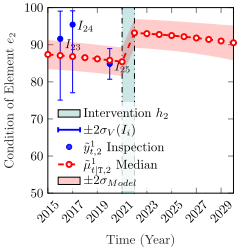

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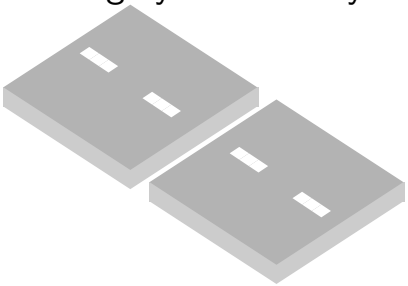

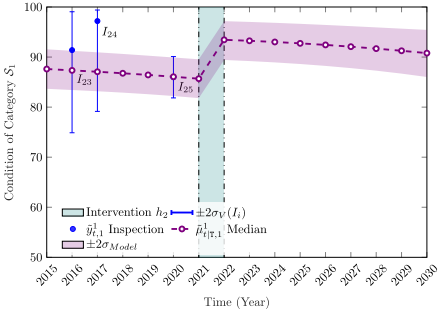

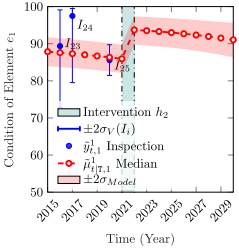

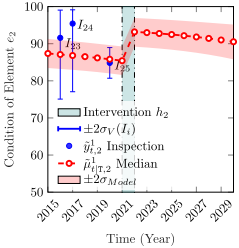

$$\underbrace{\mu^{\delta}}_{\text{Structure}} = \frac{1}{2}\Big(\underbrace{\mu_1^{\delta}}_{\text{Element 1}} + \underbrace{\mu_2^{\delta}}_{\text{Element 2}}\Big)$$

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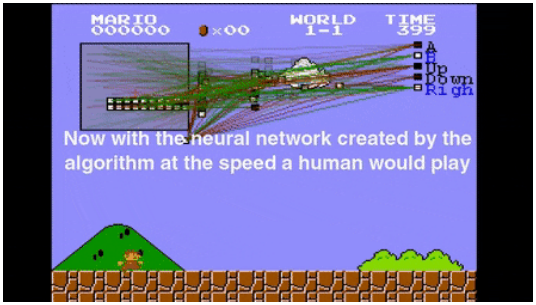
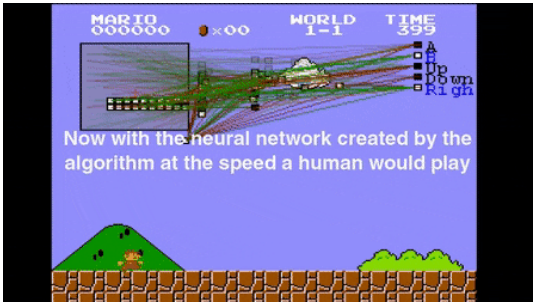
- ▷ Low-level policy: $\pi^{e} \left(\text{  } \right) \rightarrow$  , 

Reinforcement Learning



Source: Vansh Sethi

Reinforcement Learning



- ▷ Agent: decision maker.

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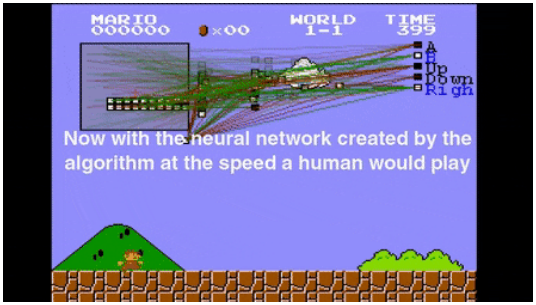

- ▷ Agent: decision maker.
- ▷ Environment: e.g., video game.

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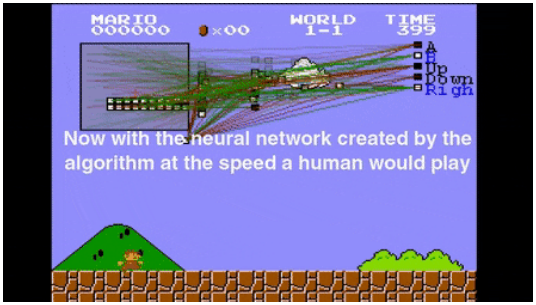

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- ▷ Environment: e.g., video game.
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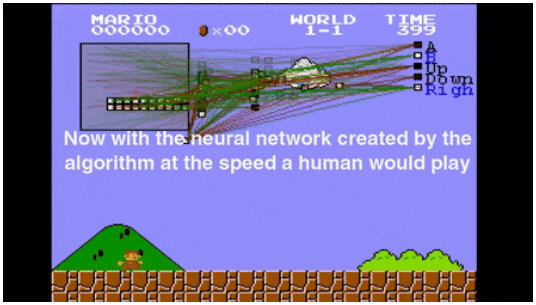

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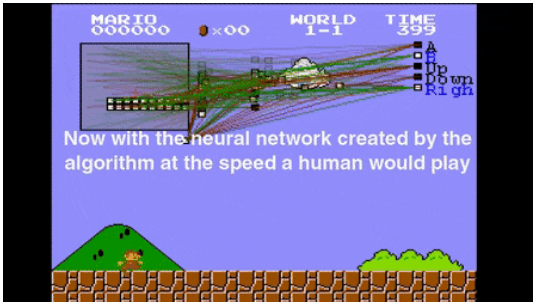

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- ▷ Environment: e.g., video game.
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Learn a policy that maximizes the total expected discounted rewards.

Source: Vansh Sethi

The Return and Action-Value Function:

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For a sequence of states s_t and rewards r_t, the return at time t:

$$G_t = r_{t+1} + r_{t+2} + r_{t+2} \cdots + r_{\mathrm{T}},$$

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$$G_t = \gamma^0 r_{t+1} + \gamma^1 r_{t+2} + \gamma^2 r_{t+2} \cdots + \gamma^{T-1} r_T, \text{ where, } \gamma \in [0, 1)$$

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$$Q^*(s_t, a) = r(s_t, a) + \gamma \max_{a'} Q^*(s_{t+1}, a')$$

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For a sequence of n samples, $y_1, y_2, \ldots, y_n$, the mean is computed as,

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&= \frac{1}{n}\left(y_n + n\mu_{n-1} - \mu_{n-1}\right)
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For a sequence of n samples, $y_1, y_2, \ldots, y_n$, the mean is computed as,

$$\begin{aligned}
\mu_n &= \frac{1}{n}\sum_{i=1}^{n} y_i, \\
&= \frac{1}{n}\left(y_n + \sum_{i=1}^{n-1} y_i\right), \text{by considering: } \left(\sum_{i=1}^{n-1} y_i = (n-1)\mu_{n-1}\right) \\
&= \frac{1}{n}\left(y_n + n\mu_{n-1} - \mu_{n-1}\right) \\
\mu_n &= \mu_{n-1} + \frac{1}{n}\left(y_n - \mu_{n-1}\right)
\end{aligned}$$

Q-Value Update:

From the incremental averaging equation,

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Q-Value Update:

From the incremental averaging equation,

$$\begin{aligned}\mu_n &= \mu_{n-1} + \frac{1}{n}(y_n - \mu_{n-1}) \\ &= Q(s_t, a) + \alpha(y_n - Q(s_t, a))\end{aligned}$$

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$$Q(s_t, a) = Q(s_t, a) + \alpha(\underbrace{r(s_t, a) + \gamma \max_{a'} Q(s_{t+1}, a')}_{\text{Target}} - Q(s_t, a))$$

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If a is continuous, then estimating $\max_{a'} Q(s_{t+1}, a')$ is challenging.

Deep Deterministic Policy Gradient (DDPG) and Actor-Critic Method:

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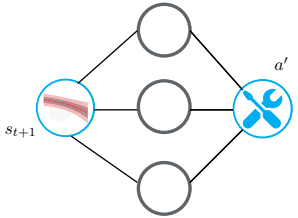
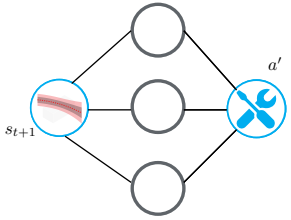
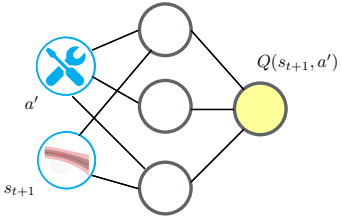


Actor Target

Deep Deterministic Policy Gradient (DDPG) and Actor-Critic Method:

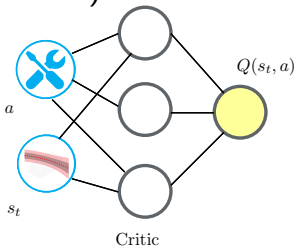


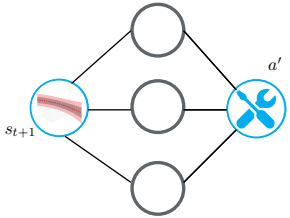
Actor Target



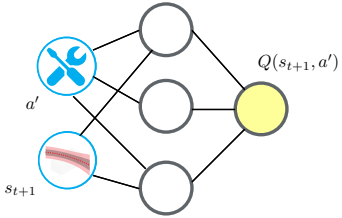
Critic Target

Deep Deterministic Policy Gradient (DDPG) and Actor-Critic Method:





Actor Target



Critic Target

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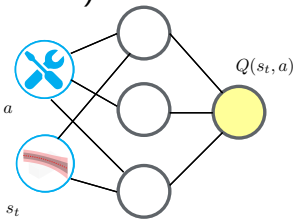
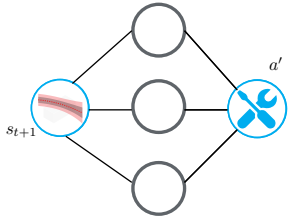
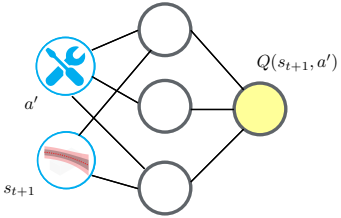


Critic

$$\text{Critic Loss} = \text{MSE}(r + \gamma Q(s_{t+1}, a') - Q(s_t, a))$$



Actor Target



Critic Target

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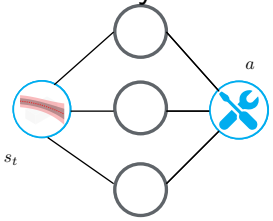
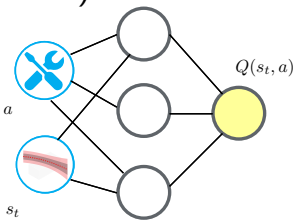
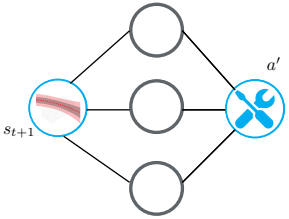


Actor

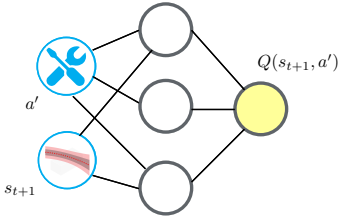


Critic

$$\text{Critic Loss} = \text{MSE}(r + \gamma Q(s_{t+1}, a') - Q(s_t, a))$$



Actor Target



Critic Target

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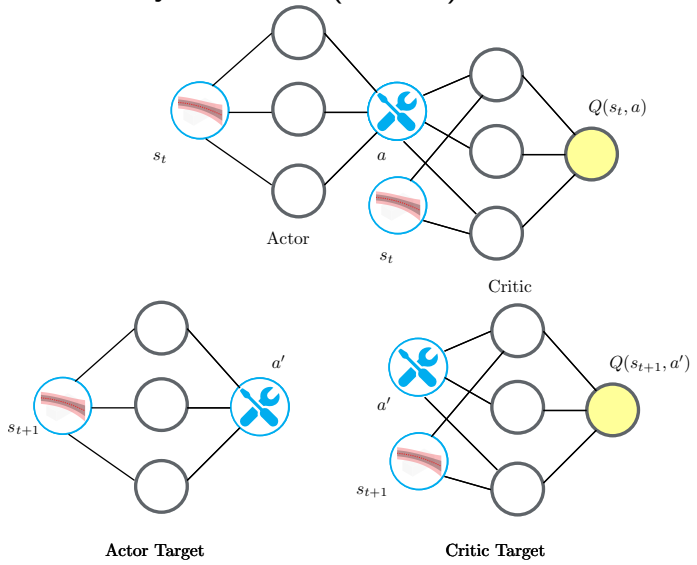

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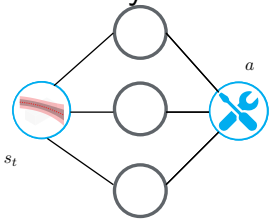
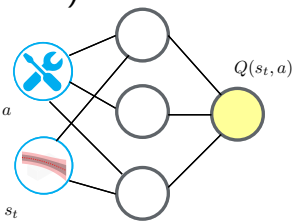
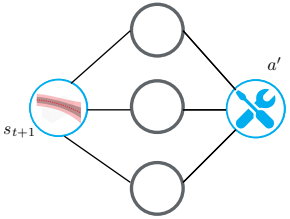


Actor

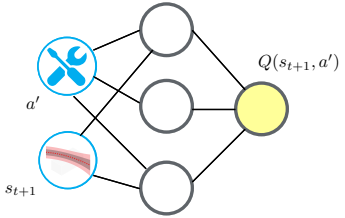


Critic

Delayed soft update for the target model parameters



Actor Target



Critic Target

Next Steps & Current Issues

- Design the reward functions.

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- ▷ Improve the sampling approach and/or the experience replay itself.

Next Steps & Current Issues

- Design the reward functions.
- Improve the sampling approach and/or the experience replay itself.
- Account for the budget in the framework.