Network-Scale Maintenance Planning for Infrastructures Using Reinforcement Learning (Formulation, Part 2)

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Transportation Ministry of Quebec (MTQ)

Outline

Recap & Definitions

Reinforcement Learning - Context

Problem Formulation

Recap & Definitions

Visual Inspections (VI): Network-scale monitoring technique

Source: Google images

Recap & Definitions

Visual Inspections (VI): Network-scale monitoring technique

Network:

Source: Google images

Recap & Definitions

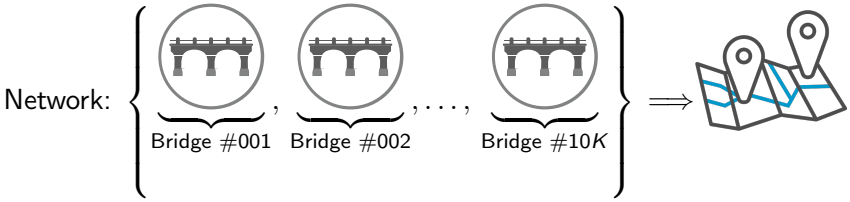
Visual Inspections (VI): Network-scale monitoring technique

Network: $\left\{ \underbrace{\text{  }}_{\text{Bridge \#001}}, \underbrace{\text{  }}_{\text{Bridge \#002}}, \ldots, \underbrace{\text{  }}_{\text{Bridge \#10}K} \right\}$

Source: Google images

Recap & Definitions

Visual Inspections (VI): Network-scale monitoring technique



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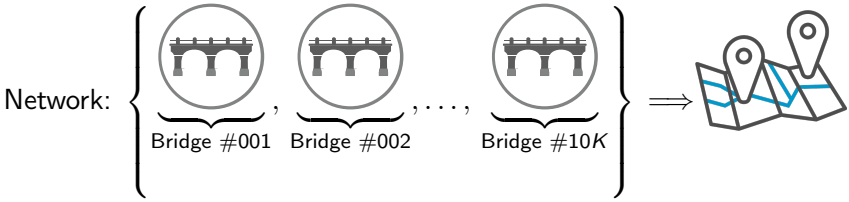
Recap & Definitions

Visual Inspections (VI): Network-scale monitoring technique



Bridge: {type, material, traffic, location,...}

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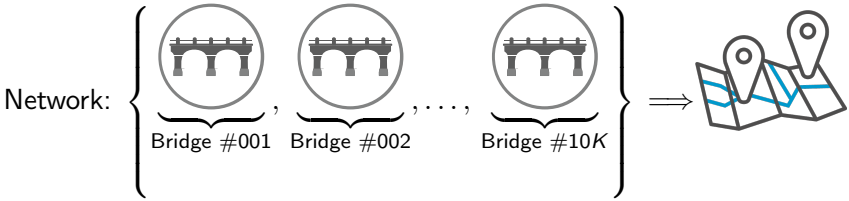
Recap & Definitions

Visual Inspections (VI): Network-scale monitoring technique



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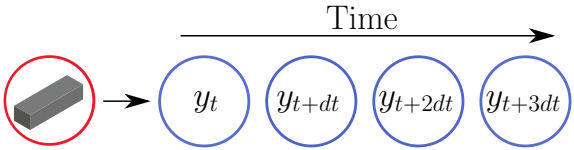
Deterioration Framework

Deterioration Framework



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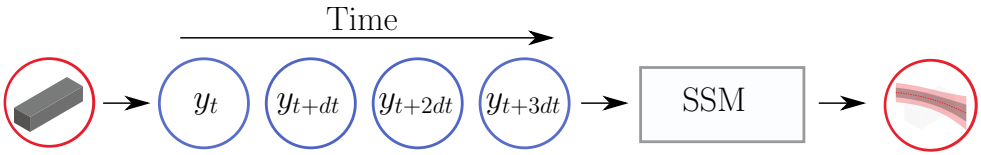

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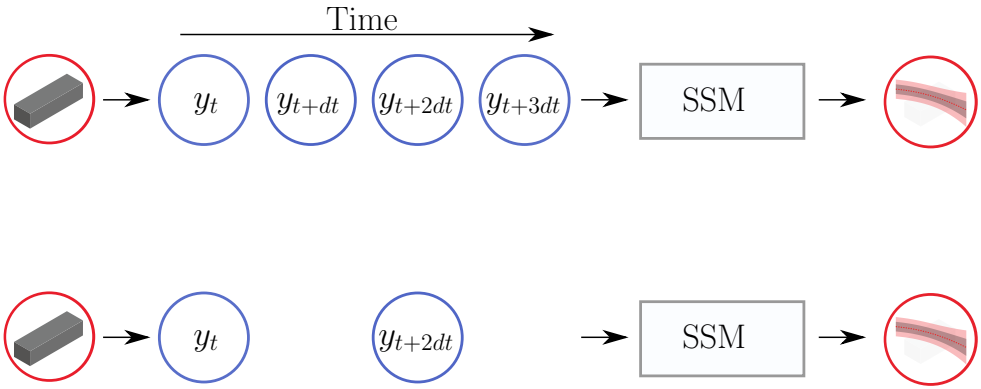

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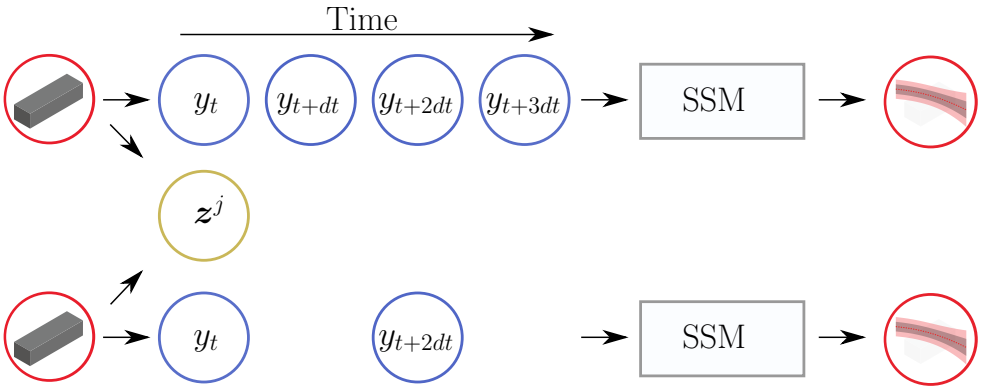

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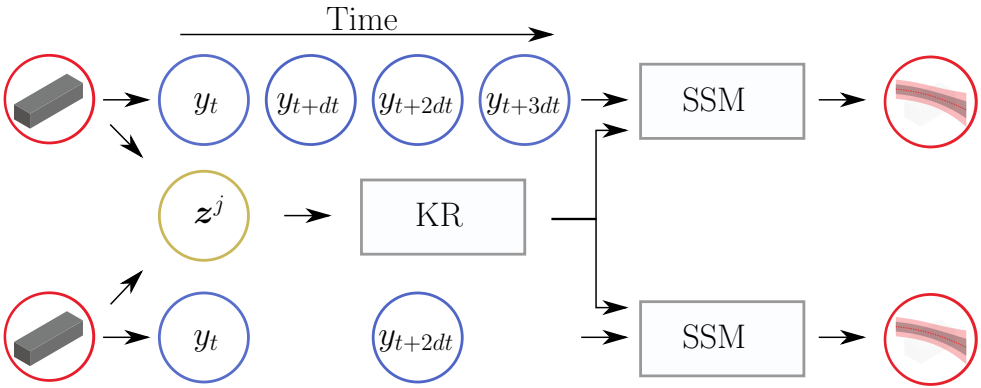

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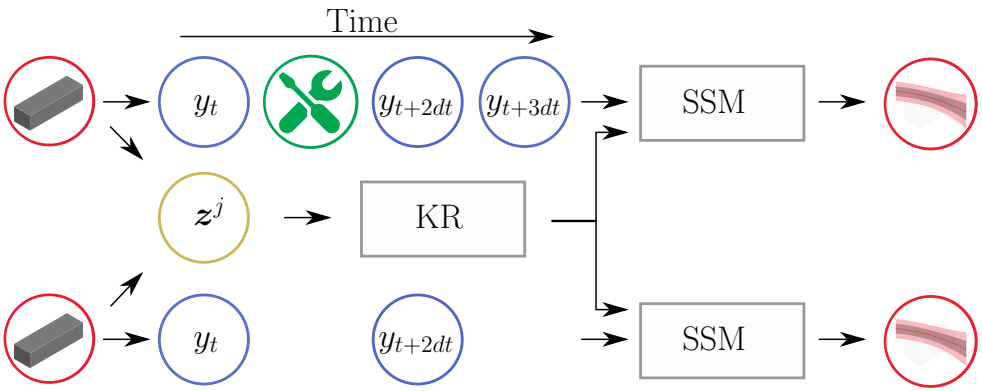
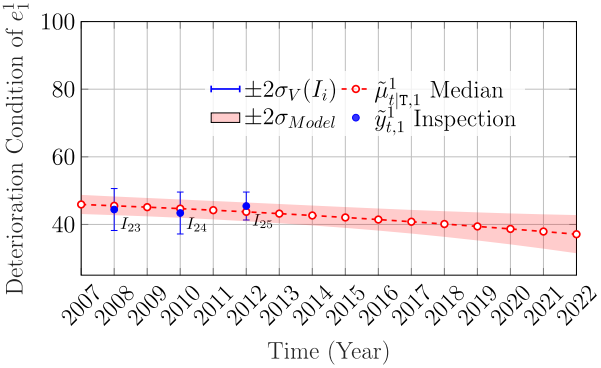
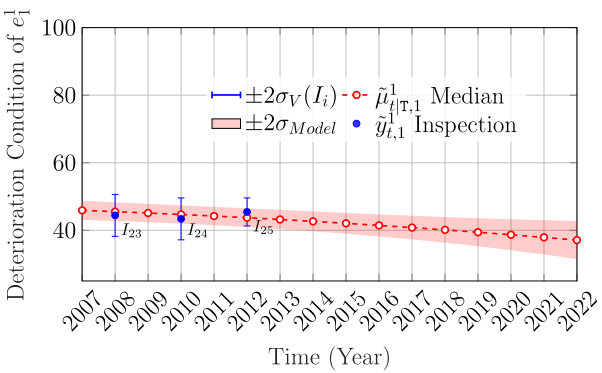


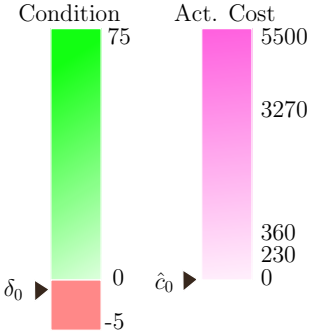
Element-Level Analyses



Source: MTQ, Manual of Inspection

Element-Level Analyses





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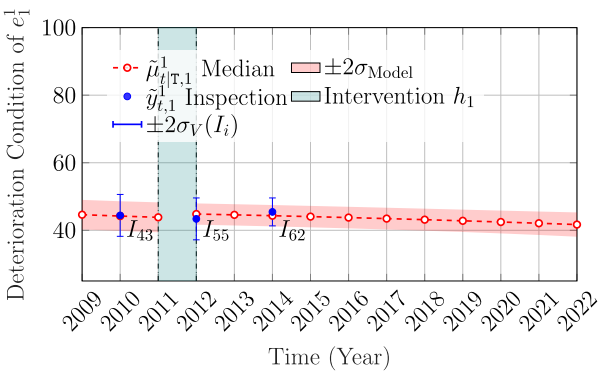

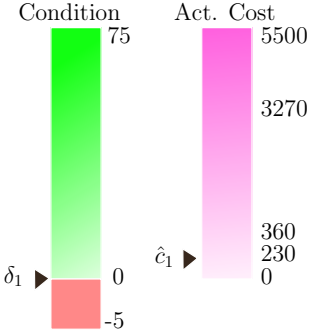

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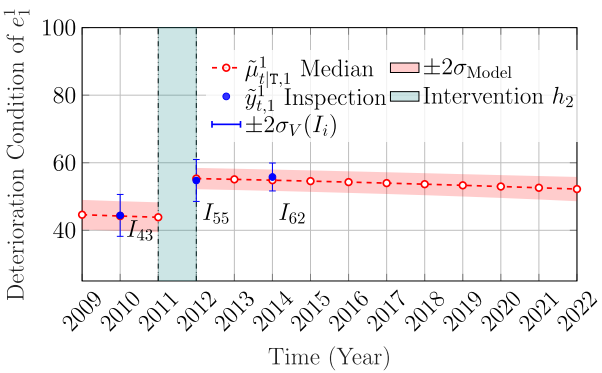

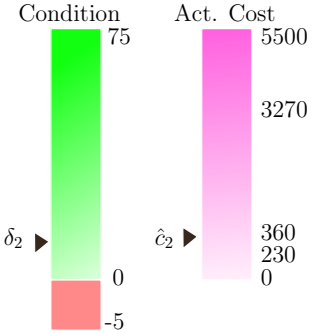

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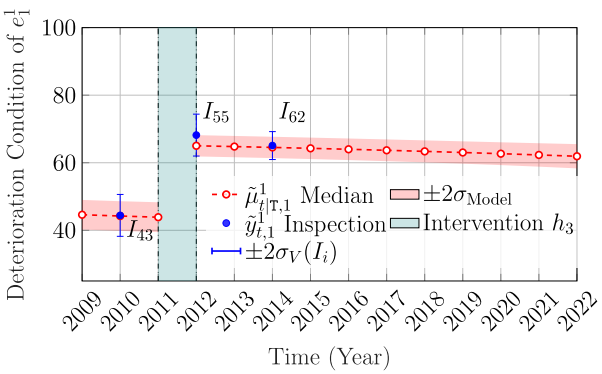

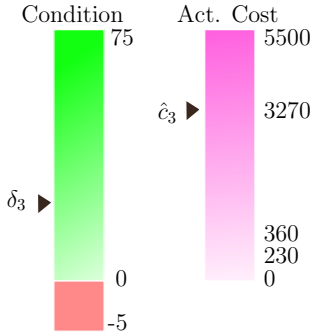

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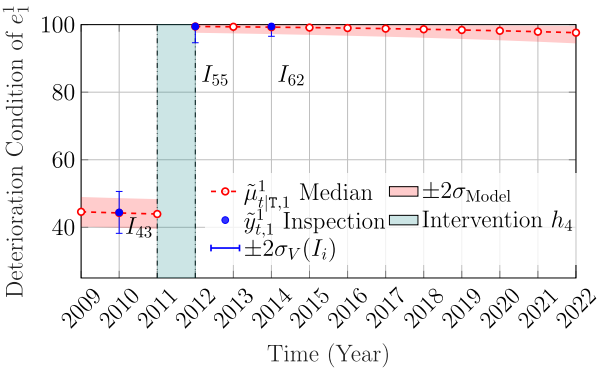

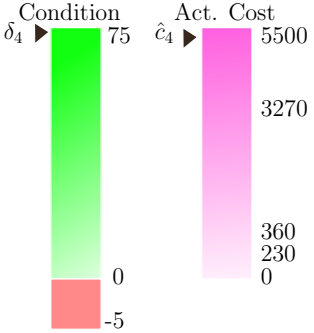

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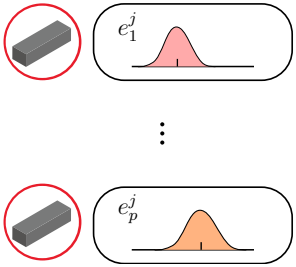
System-Level Analyses

At any time t:



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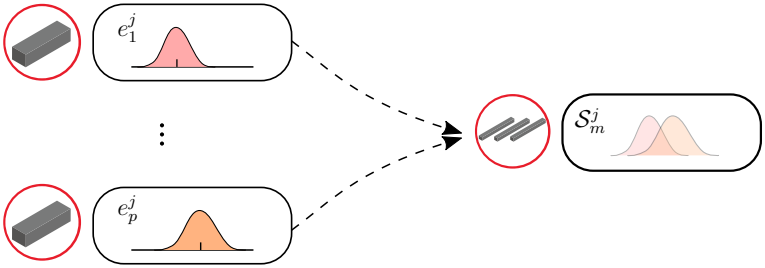

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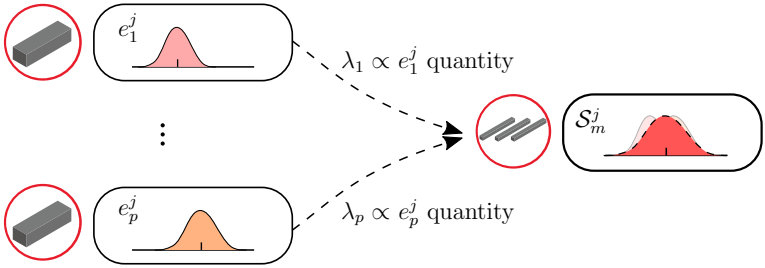

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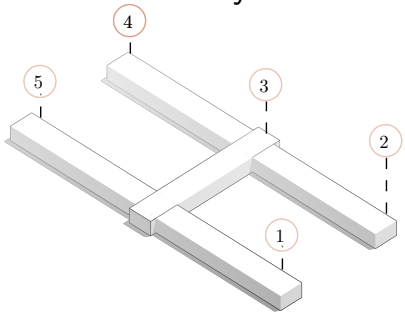

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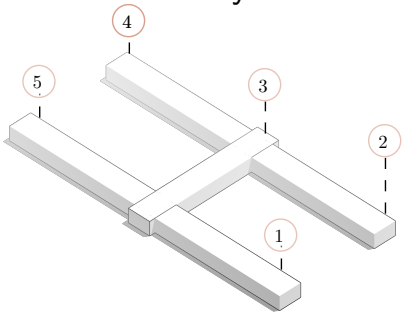

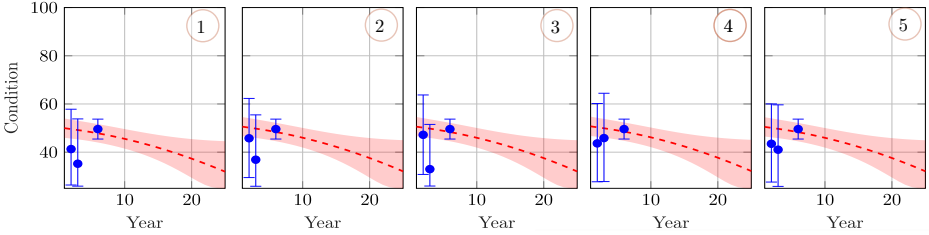

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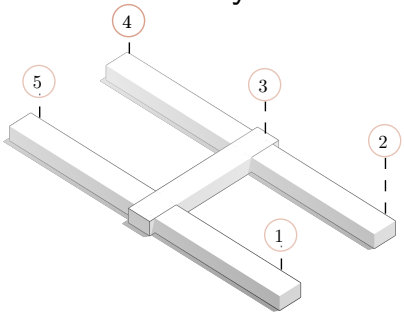

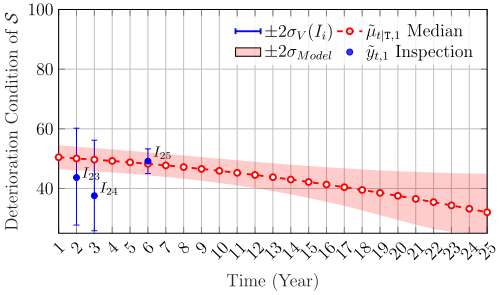

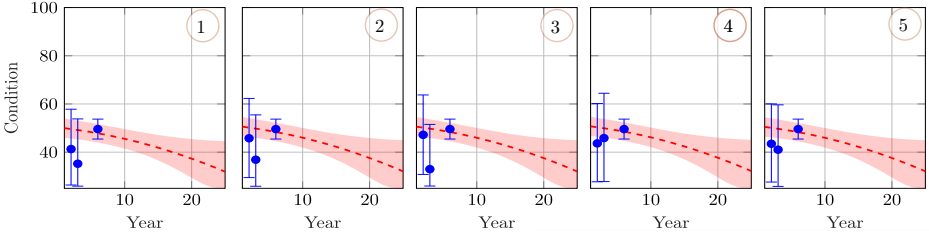

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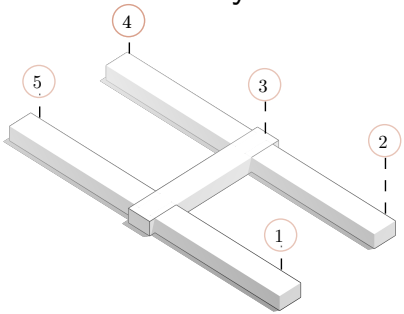

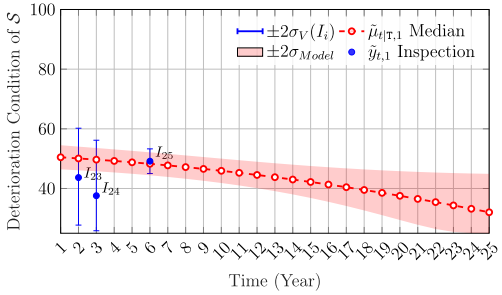

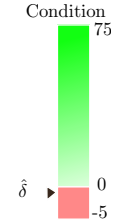

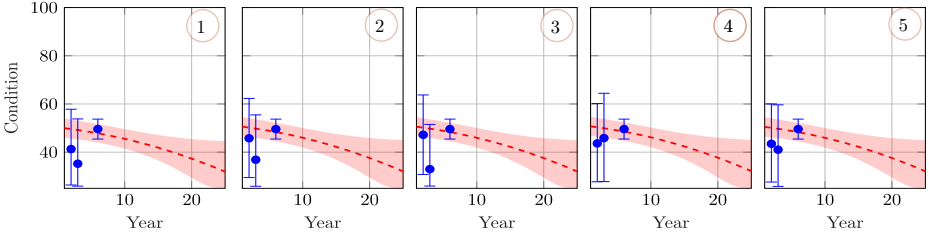

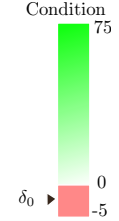

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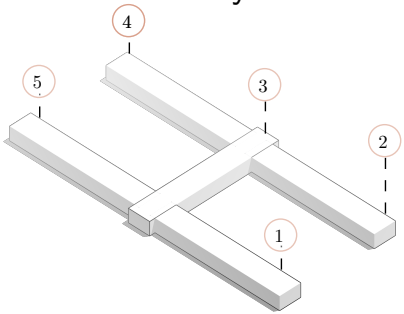

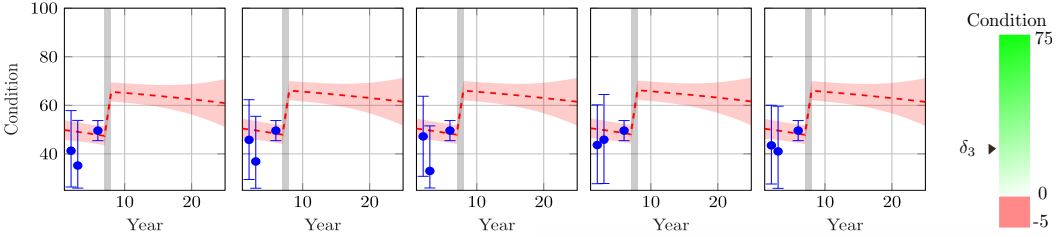

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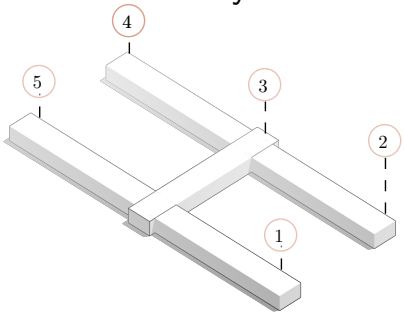

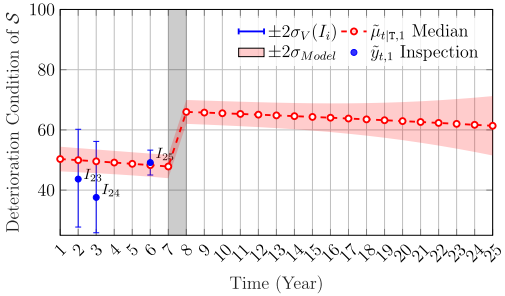

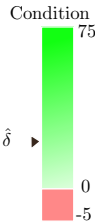

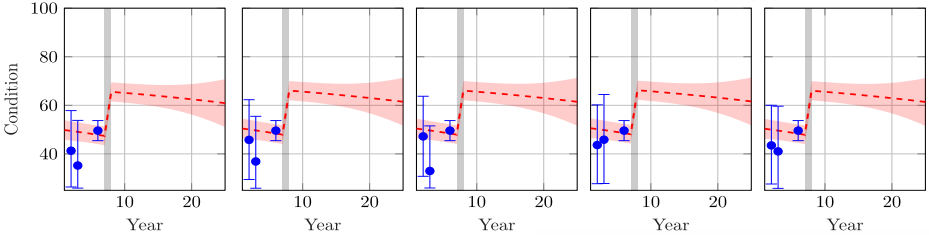

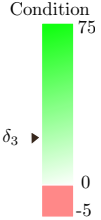

Research Objective

Find a policy for maintenance:

$$\pi\left(\text{  }, \text{  }, \text{  }, \text{  }, \text{  }\right)$$

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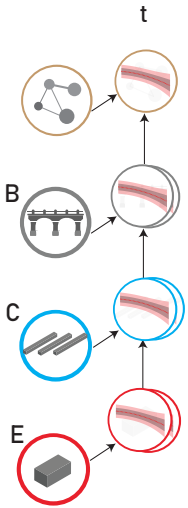
Research Objective

Find a policy for maintenance:

$$\pi \left(\text{[network]}, \text{B}, \text{C}, \text{E}, \$ \right)$$



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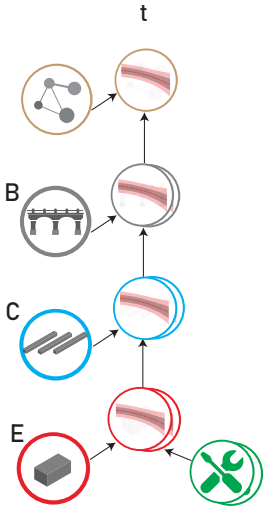
Research Objective

Find a policy for maintenance:

π (, B, C, E, $)



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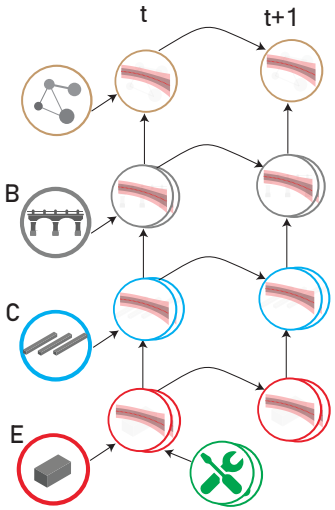

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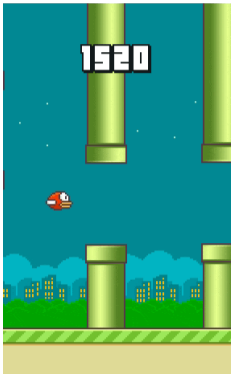
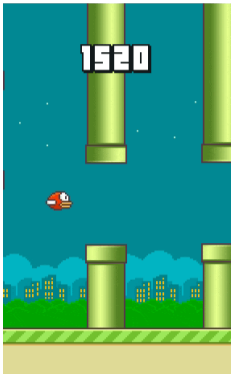
Reinforcement Learning



Source: Google Images

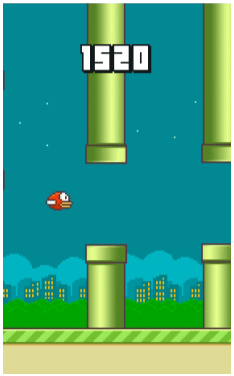
Reinforcement Learning



- Agent: decision maker.

Source: Google Images

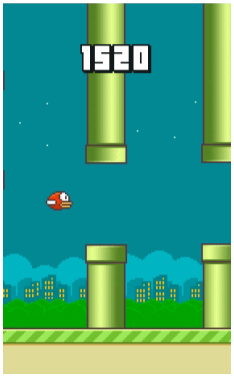
Reinforcement Learning



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

Source: Google Images

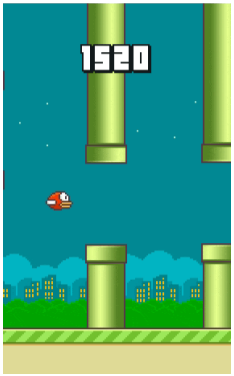
Reinforcement Learning



- ▷ Agent: decision maker.
- ▷ Environment: e.g., video game.
- ▷ Actions: e.g., key press or movement.

Source: Google Images

Reinforcement Learning



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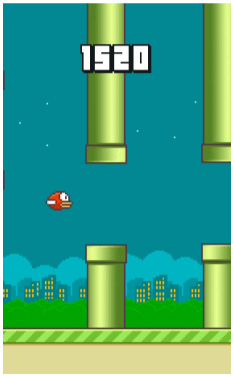
- ▷ Actions: e.g., key press or movement.
- ▷ Rewards: e.g., achieving the goal.

Source: Google Images

Reinforcement Learning



- ▷ Agent: decision maker.
- ▷ Environment: e.g., video game.
- ▷ Actions: e.g., key press or movement.
- ▷ Rewards: e.g., achieving the goal.

Learn a policy that maximizes the total expected discounted rewards.

Source: Google Images

Environment

Employing the deterioration model as an environment requires:

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- ▷ Adjustments for the actions' exploration:

Environment

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- ▷ Adjustments for the actions' exploration:
  - ✓ Account for the boundaries of the feasible condition.

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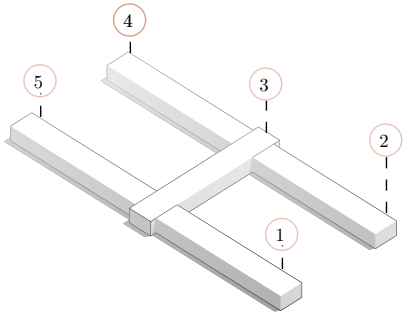
  - ✓ Criticality (Elements and Category).
  - ✓ Variability (Elements).
  - ✓ Action frequency (Category).


4
5
3
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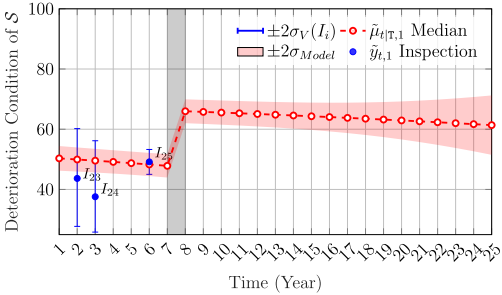
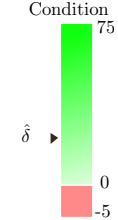
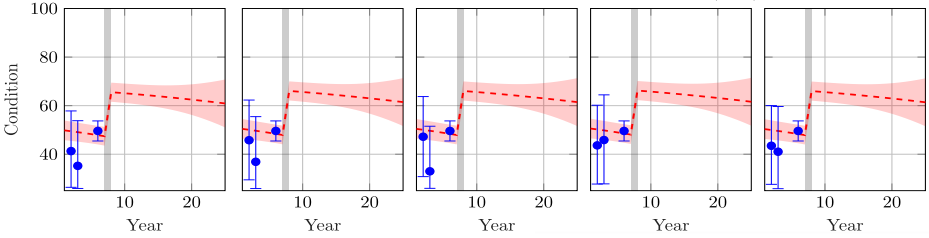
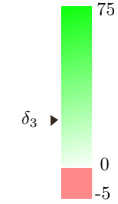
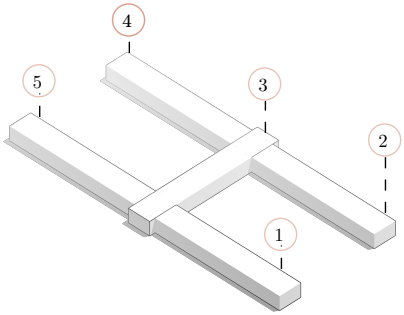
1


Deterioration Condition of $\mathcal{S}$
$\pm 2\sigma_V(I_i)$
$\tilde{\mu}_{t|\mathrm{T},1}$ Median
$\pm 2\sigma_{Model}$
$\tilde{y}_{t,1}$ Inspection
I_{23}
I_{24}
Time (Year)


Condition
75
$\hat{\delta}$
0
-5


Condition
Year


Condition
75
δ_3
0
-5


4
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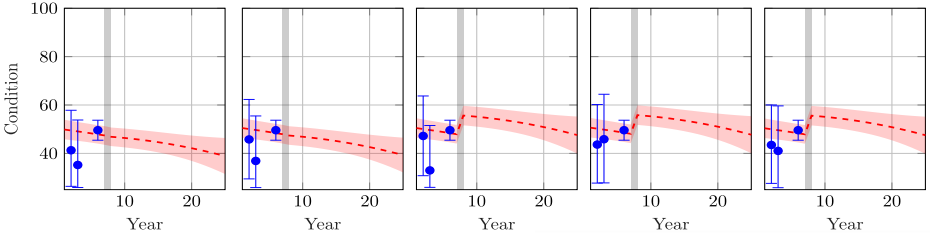
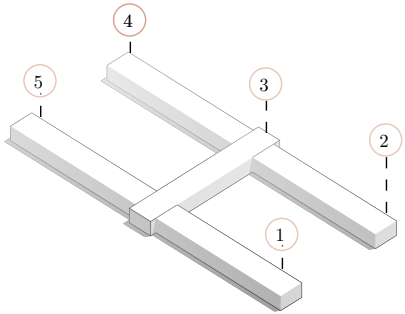

Condition
100
80
60
40
10
20
Year
Condition
75
0
-5
δ_2
δ_1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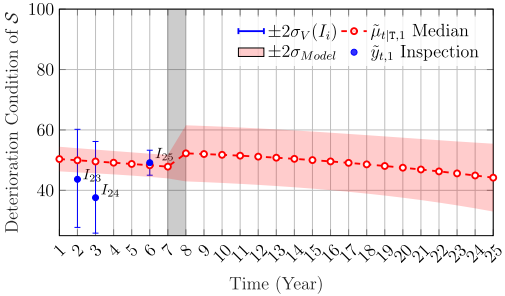
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$\pm 2\sigma_{Model}$
$\tilde{\mu}_{t|\mathbf{T},1}$ Median
$\tilde{y}_{t,1}$ Inspection
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I_{24}
I_{25}
Time (Year)
Condition
$\hat{\delta}$
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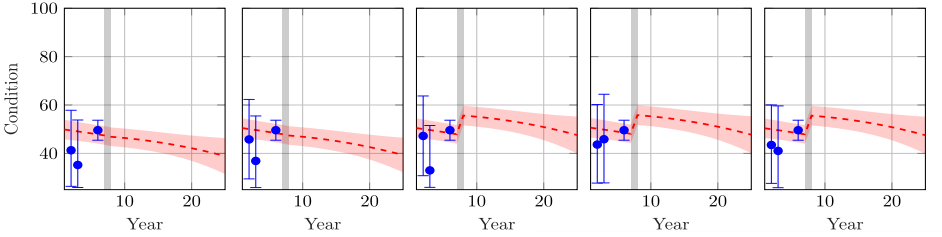
-5


Condition
Year
Condition
δ_2
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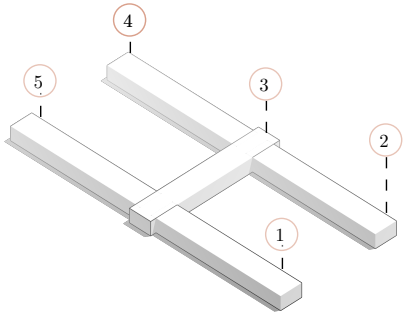
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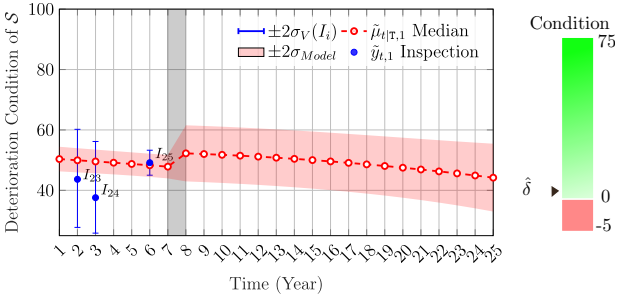
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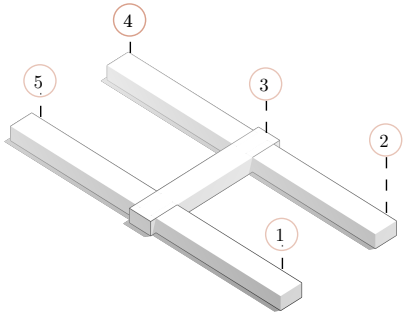
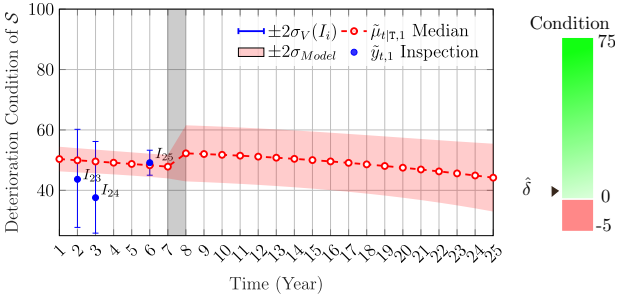
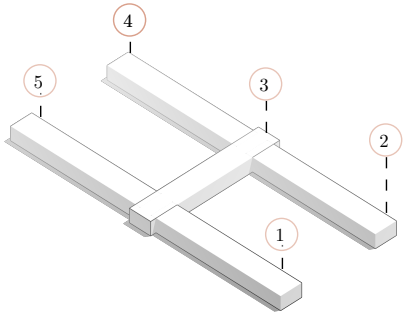
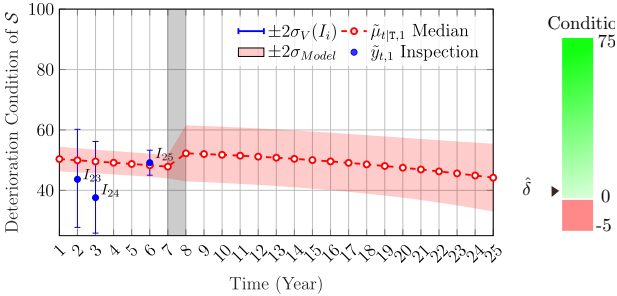
$\hat{\delta}$





$$L = \|\mathbb{E}[\boldsymbol{\delta}] - \hat{\delta}\|$$





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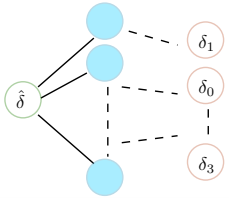
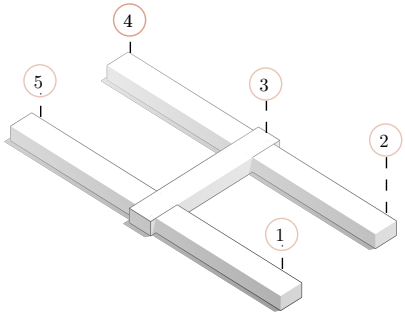
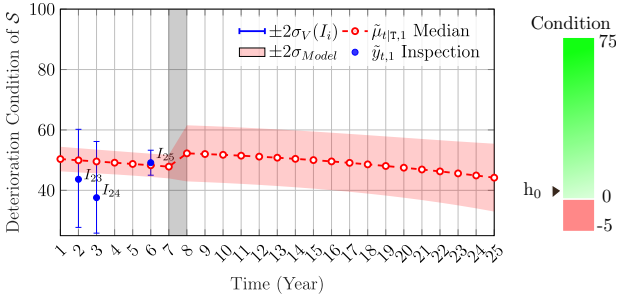
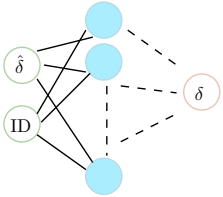
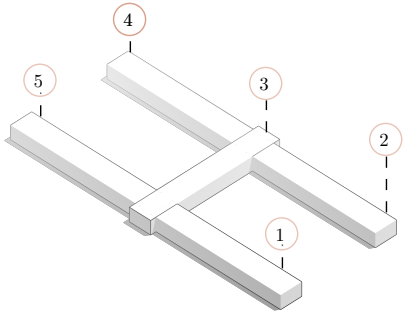


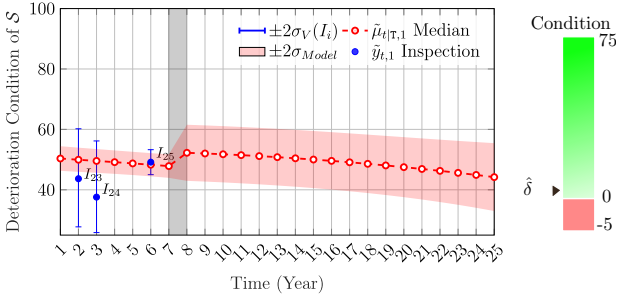




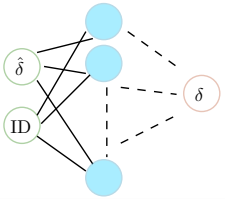
$$L = \|\frac{\delta_i}{\mathbf{E}} - \hat{\delta}\|$$







$$L = \|\tfrac{\delta_i}{\mathbf{E}} - \hat{\delta}\| \times \hat{c}_i$$



RL Sub-task (Local Policy π^e):

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- ▷ state: $\hat{\delta}_i$, ID

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- ▷ transition model: $\hat{\delta}_{i+1} = \hat{\delta}_i - \frac{\delta_i}{\mathrm{E}}$.

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Use Q-learning to find the policy π^e for the RL problem.

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Use Q-learning to find the policy π^e for the RL problem.

But, what about the maintenance policy π ?

RL Main Task (Global Policy π):

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- ▷ state: $\mu_{t|\mathrm{T}}, \dot{\mu}_{t|\mathrm{T}}$

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- ▷ actions: $\hat{\delta}_t$ (continuous action)
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Use Q-learning (with policy gradient) to solve the RL problem.

Simultaneous Training for π^e and π (HRL):

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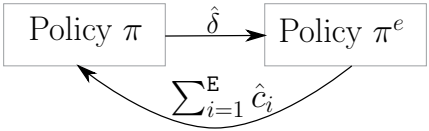

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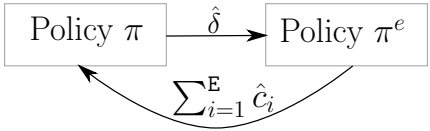

Problem: $\|\mathbb{E}[\delta] - \hat{\delta}\| \gg 0$

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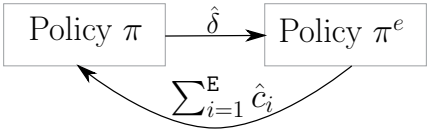

Problem: $\|\mathbb{E}[\delta] - \hat{\delta}\| \gg 0 \rightarrow \sum_{i=1}^{\mathbf{E}} \hat{c}_i$ and $\hat{\delta}$ do not correspond to each other.

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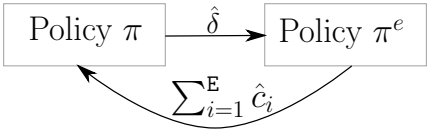

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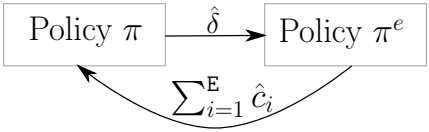

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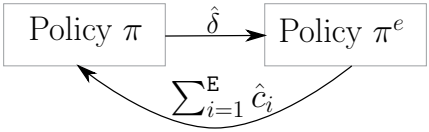
$$\log \pi^e(a_i|\bar{\delta}) \propto -\frac{1}{2} \sum_{i=1}^{\mathbf{E}} \|a_i - \pi^e(\bar{\delta}_i, \mathrm{ID})\|$$

Simultaneous Training for π^e and π (HRL):



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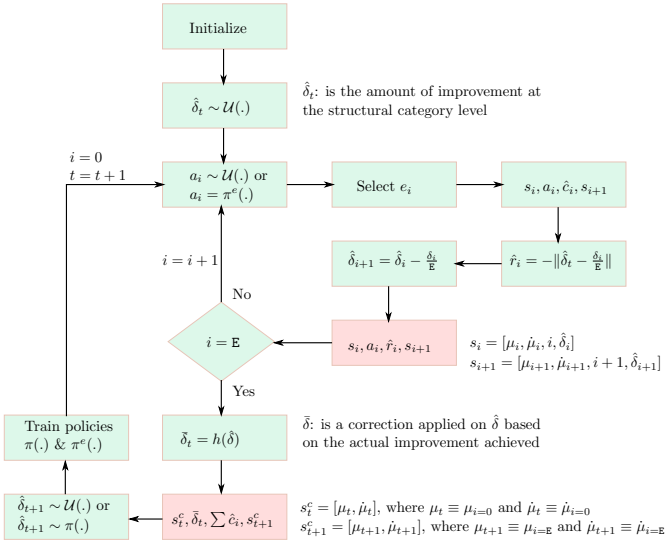
To maximize this quantity, candidate goals $\bar{\delta}$ are sampled based on the original goal $\hat{\delta}$.

Full HRL Framework

Full HRL Framework



Next Steps

- Improve environment design (e.g., repeating actions).

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- ▷ Design the reward functions.

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- ▷ Improve environment design (e.g., repeating actions).
- ▷ Design the reward functions.
- ▷ Account for the budget in the framework.