Hierarchal Intelligence

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Current Stage

Navigating through a chemical plant is difficult

Navigation in 2D space is similar to that in 3D space, but they are not the same

Treat different skill acquisitions as separate problems

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Key Concepts

Multi-task Learning

Learn multiple tasks

Learn new task while maintaining the knowledge learned before

Able to automatically allocate resource for learning

Visual Navigation

Find the location of a given view

Prior knowledge not required for similar scene

Navigate through large space with minimum sensor requirement

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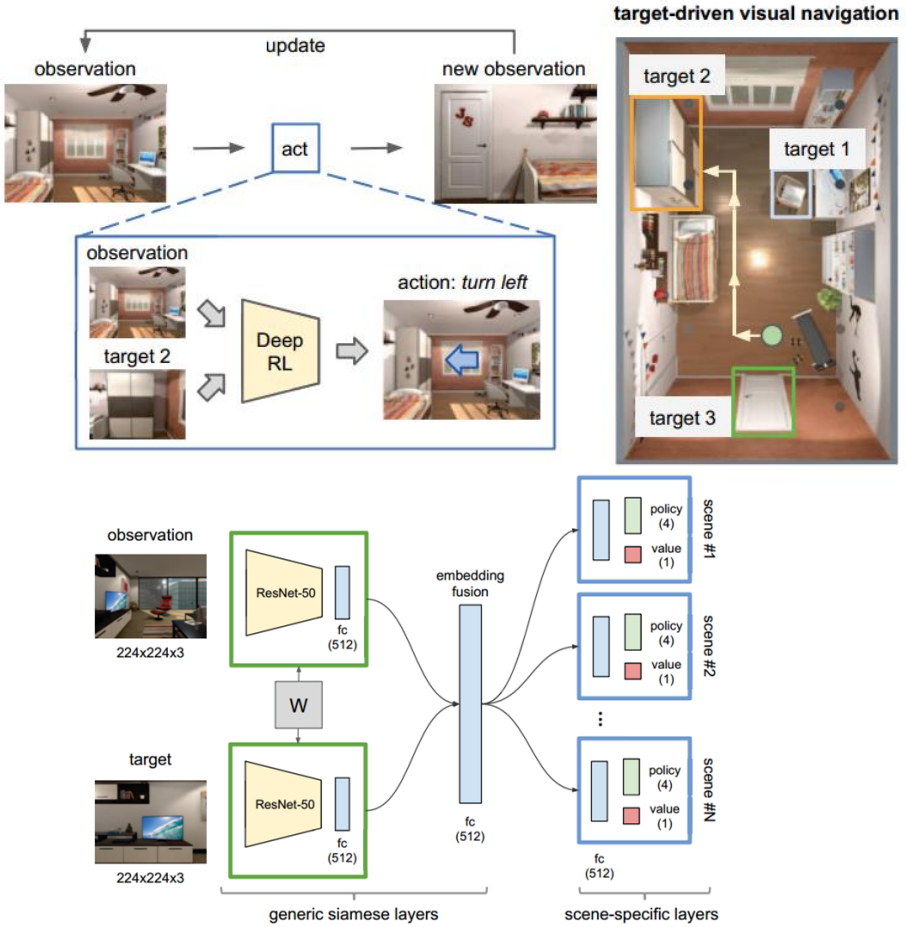
Visual goal driven navigation task

- The robot will be trained for scene specific model
- Find the location of a given view
- Prior knowledge not required for similar scene
- Navigate through large space with minimum sensor requirement



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Multi-task Learning

- Multi-task learning aims to help improve the learning of a model for a **task** by using the knowledge contained in multiple tasks where all the tasks or a subset of them are **related** but not identical

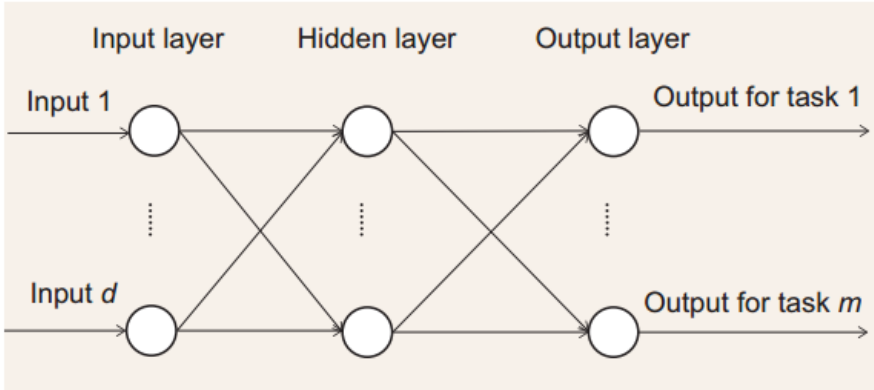

Figure 1. A multi-task feedforward neural network with one input layer, hidden layer and output layer.

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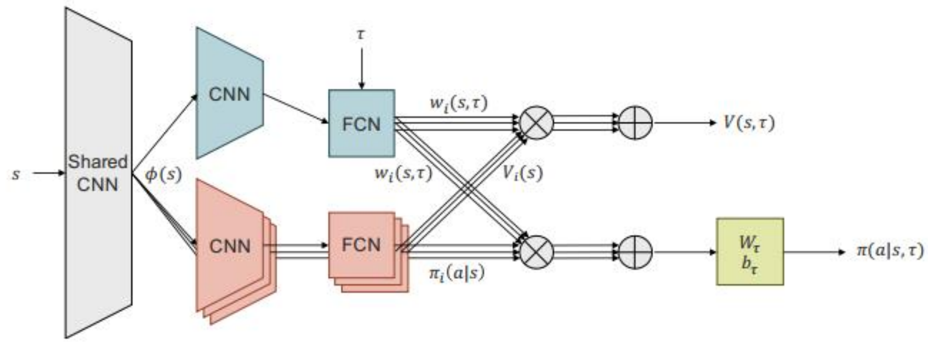
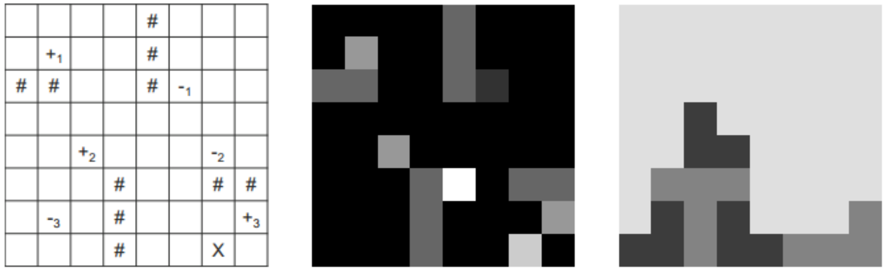
Multi-task Learning

- Attentive multi-task deep reinforcement learning
- learns multiple tasks
- Simultaneously
- Without guidance
- Conflicting tasks in separate network





(a) # are walls and X is the target. $+$ ($-$) denote objects giving positive (negative) rewards. If only one bonus (penalty) object is present, it is located at $+_1$ ($-_1$).

(b) A state space of a grid world task. The player is the white square. Walls, the target, three bonus objects and one penalty object are present.

(c) Example state of the connect four task. The agent controls the dark tokens, the random opponent controls the gray tokens.

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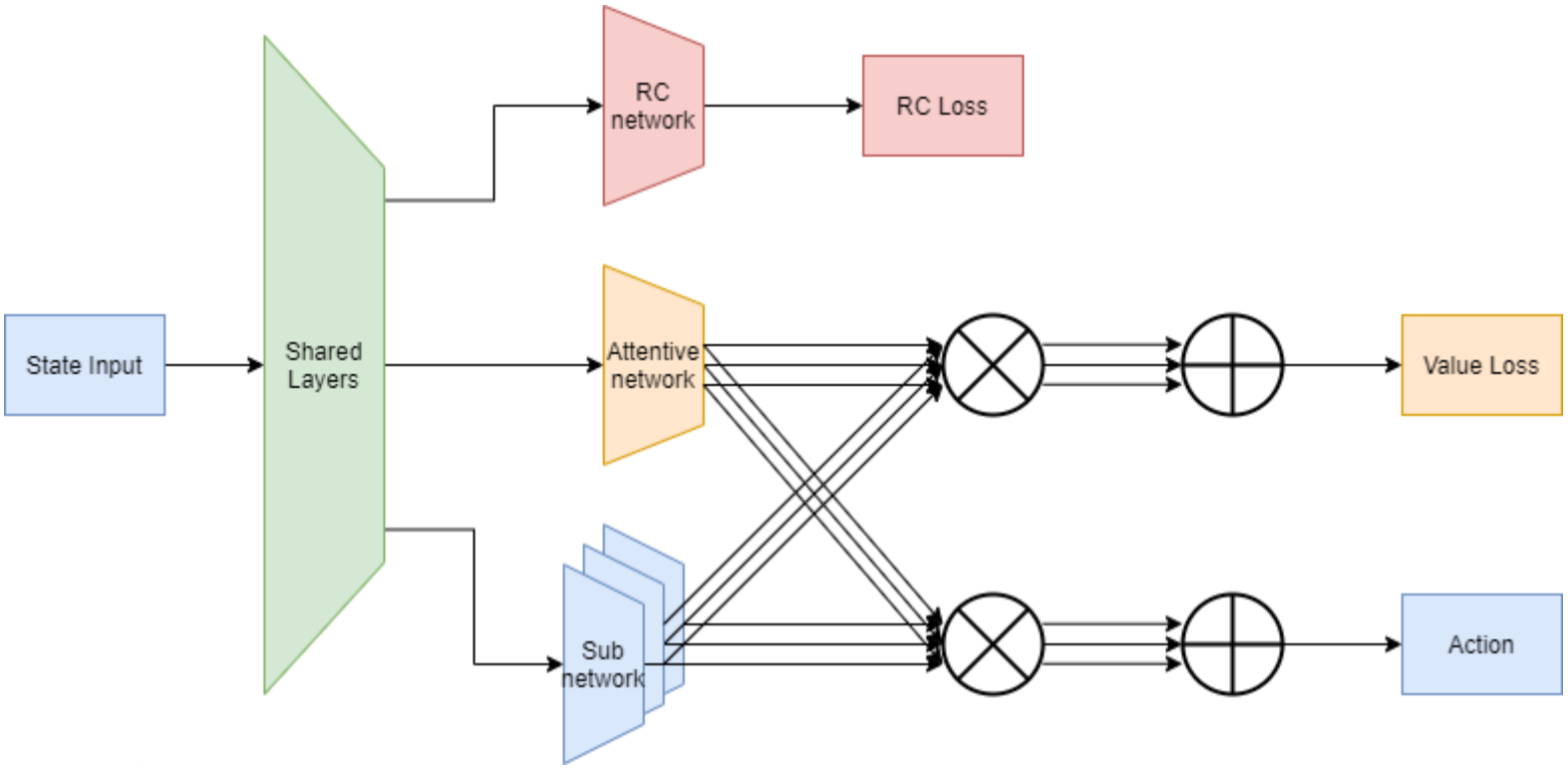
Multi-task Visual Navigation



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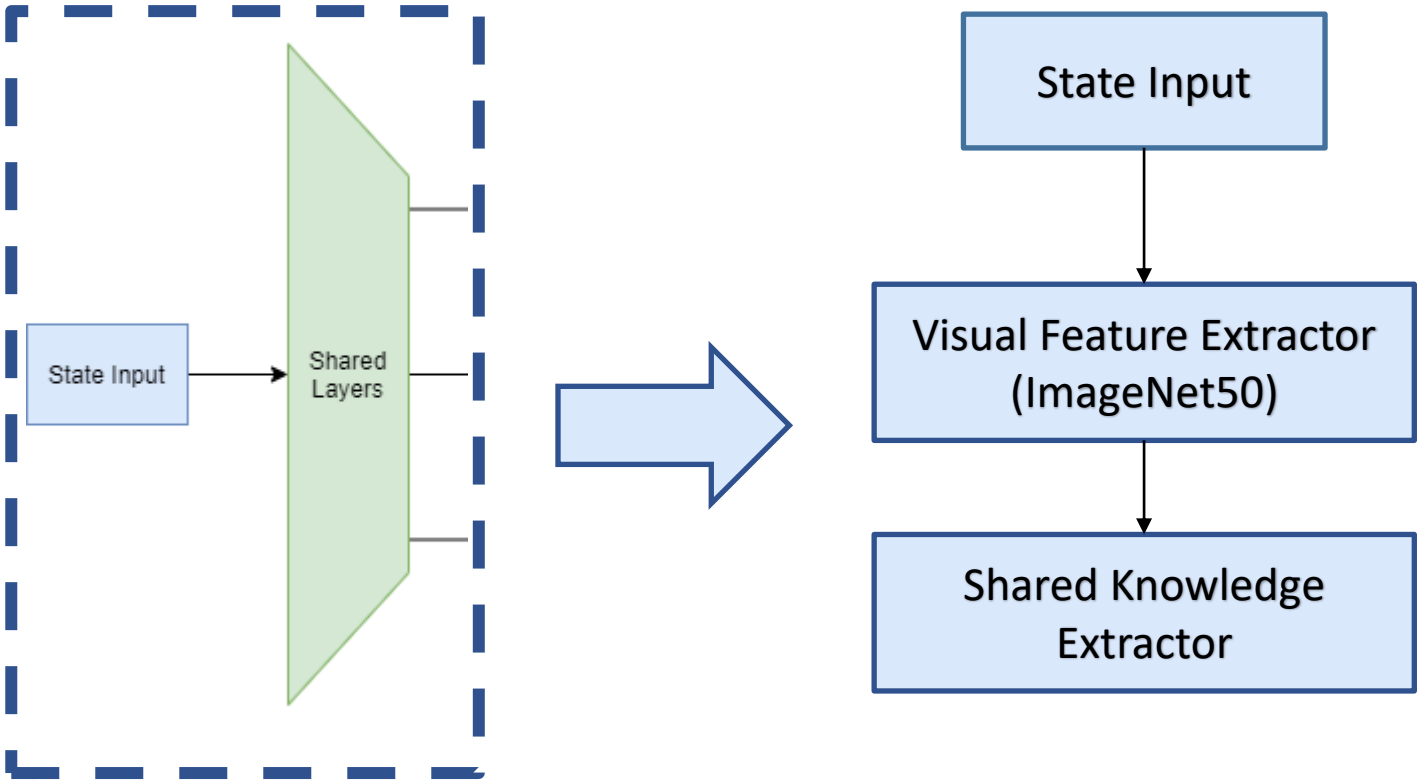
Multi-task Visual Navigation



The Shared Layers learns the shared knowledge

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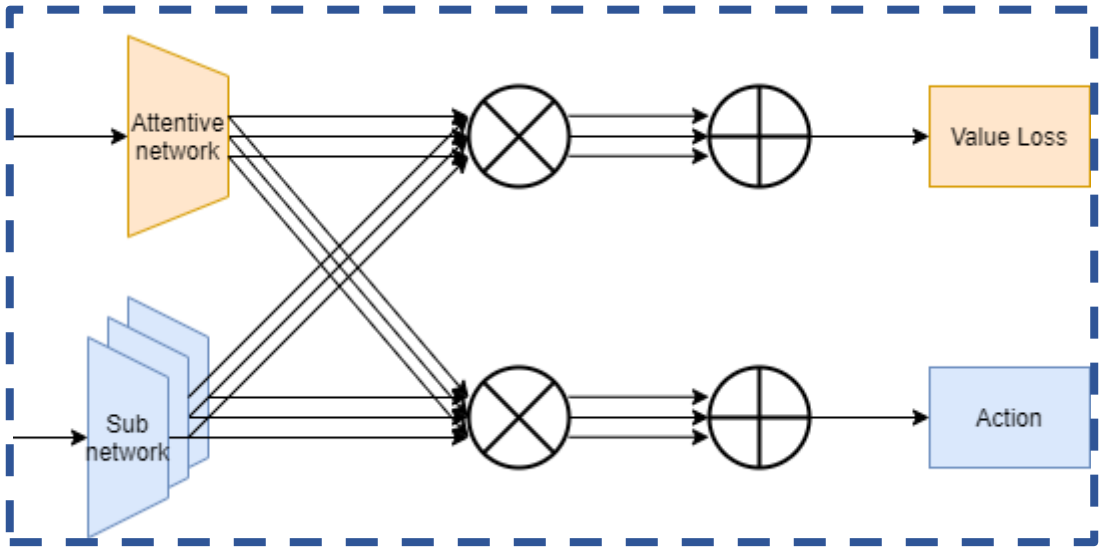
Multi-task Visual Navigation



$$V(s,\tau) = \sum_{i=1}^{N} w_i(s,\tau) V_i(s)$$

$$\pi(a|s,\tau) = \text{softmax}\left(W_\tau \cdot \left(\sum_{i}^{N} \pi_i(a|s) w_i(s,\tau)\right) + b_\tau\right)$$

The Subnetworks learns and perform each task

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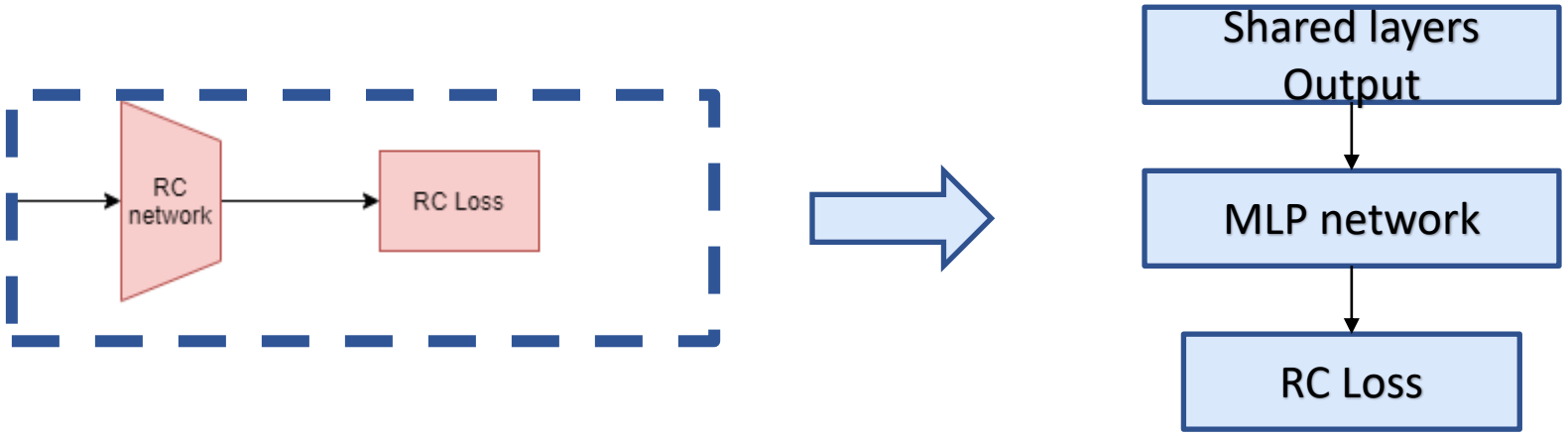
Multi-task Visual Navigation



The RC loss branch of the network takes input from the shared layers.

It has a separate update function that update the RC network itself and the shared layers. It will not effect the subnetworks and the attentive network

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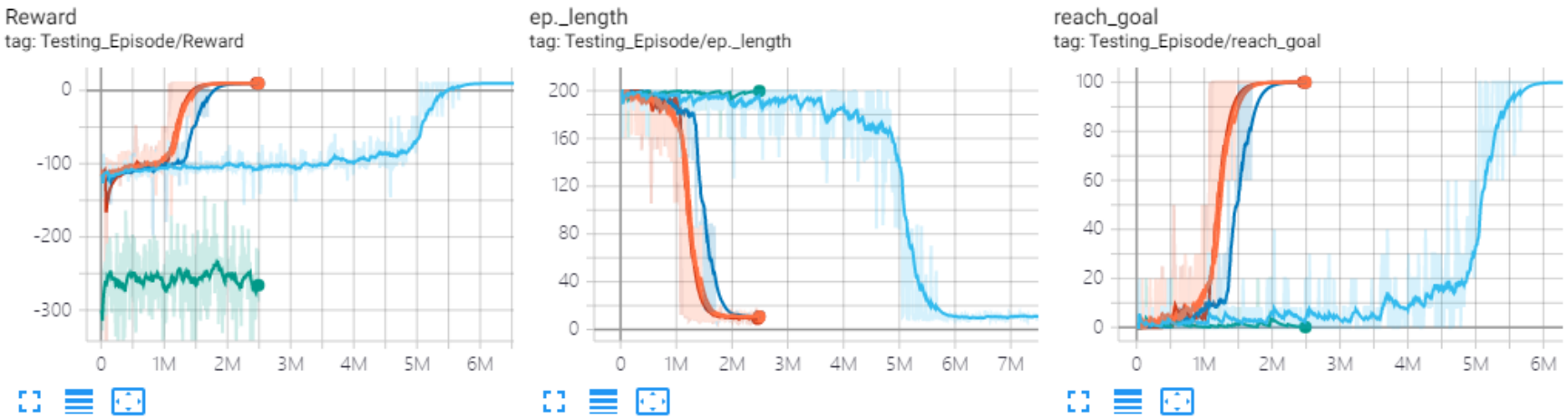
Experiment and Evaluation



- Light Blue: State of the Art multi-task agent
- Navy Blue: Multi-task visual navigation agent
- Orange: Multi-task visual navigation with RC loss
- Green: Random baseline

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Summary

- Finished the research goal for multi-task visual navigation
- Currently working on Evaluation and Benchmark
- Currently working on publication (ICRA) in Sept./Oct.

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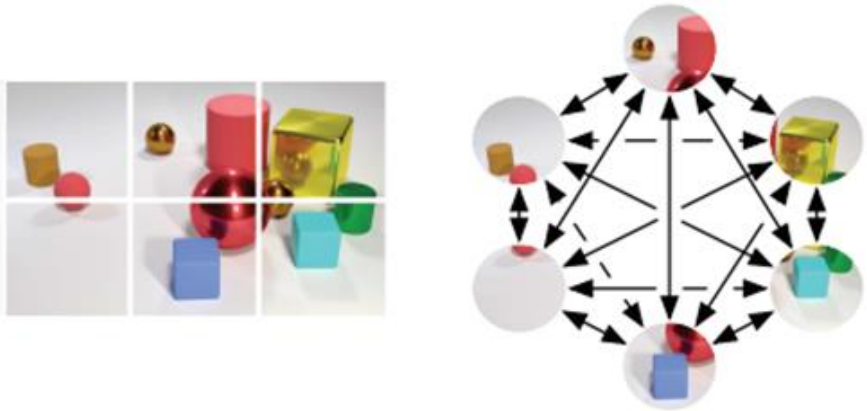
Moving Forward

- Combine attentive network with graph network
- Relational Biased Induction
- Adaptation to more complex environment
- More complex task

Image and Fully-Connected Scene Graph



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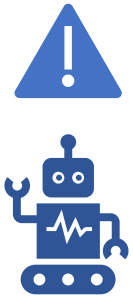
Moving Forward

- Automatic schedule optimal behavior through AI
- Improve performance in complex environment through learning
- Schedule patrol and inspection routes in response to **unexpected** plant behavior
- Explore the possibility of the AI suggesting or taking remote remedial action



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Q&A

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