Maritime
Innovation
Update

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Priority-based Approach for timely Container Delivery

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Agenda

- Introduction
- Objective
- Simulation Scenario
- Modelling with Reinforcement Learning
- Results
- Conclusion

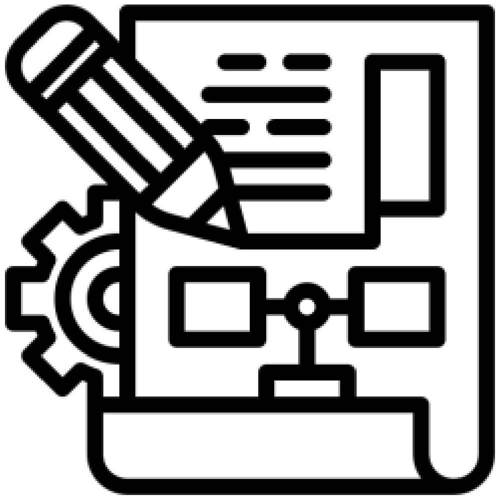
Introduction

- Exponential rise in number of shipping containers requires a Container Terminal to be efficient, stable and smooth in functioning.
- Overview of how simulation and reinforcement learning (RL) can be integrated and how practical it is to use these methods for logistics-related problems.
- Approach to reduce delayed/early delivery of containers by prioritizing containers and using a discrete event simulation.

Objective

The goal is to ensure timely container deliver by reducing the time difference between planned and actual container pick-up times and observe decisions made by the model. The study will help to answer the following questions:

- Is it possible to reduce delayed or early pickup of containers using RL ?
- Is each priority rule more suited to certain scenarios?
- Can delayed or early pickups be prevented by using optimum horizontal resources?



Simulation Scenario

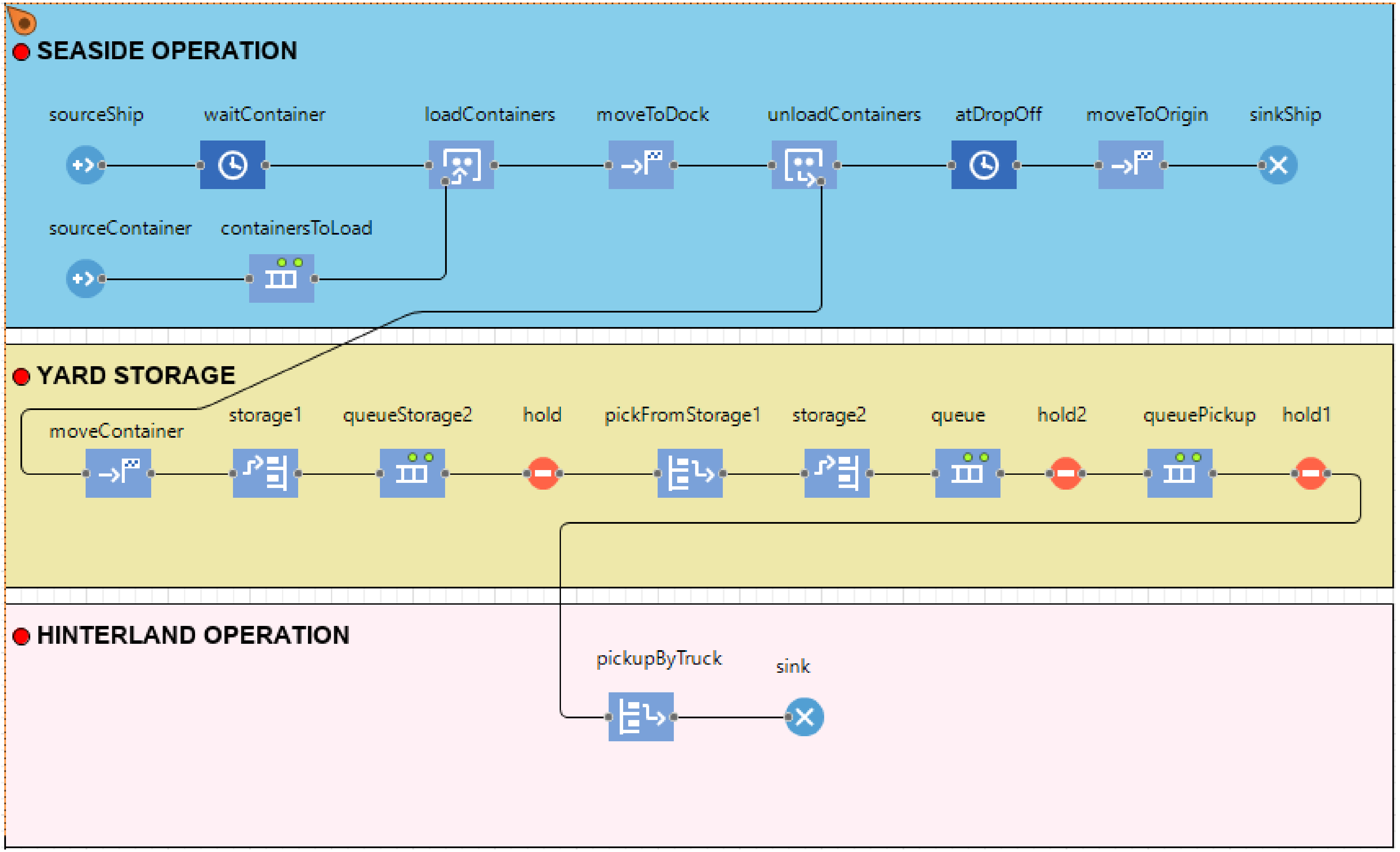
- A Discrete Event Simulation approach is used.
- Containers are stored randomly at storage1.

- Containers are stored separately based on their hinterland transport type in storage2. Heavier containers are placed in bottom while lighter ones in top.

- Containers are picked up on a priority basis from storage2. They are prioritized by either pickup time or wait time.

- The container has several parameters like carrier, weight, planned pick up time & location in storage2.

Figure 1: Model depicting basic workflow of a Container Terminal



Modelling with Reinforcement Learning

Introduction

- A form of machine learning where an agent is trained to make sequential decisions with a limited feedback.
- Tries to imitate behaviour of humans or animals and many of its core algorithms were originally inspired by biological learning systems.
- Has no knowledgeable external supervisor and has to explore all possible actions and eventually discover the correct one in a given situation.
- Relies on the reward signal to decide on next action rather than focusing on hidden structures of state, action pairs.
- Has five basic elements: environment, agent, policy, reward signal & value function.

Modelling with Reinforcement Learning

Model Parameters

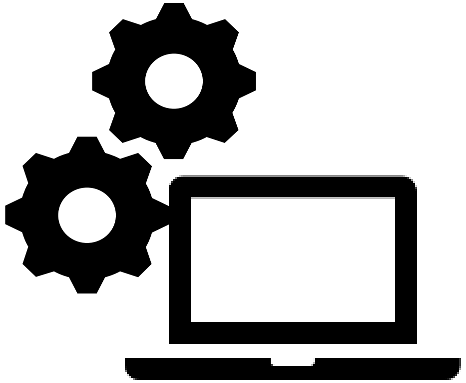
1. ***Observation Function***: Defined by total no. of containers present in the system, count of idle AGVs, count of idle trucks and mean squared time difference between planned pickup time of container and current model time.

2. ***Reward Variables***: The metrics used here are mean wait time of containers at second storage area and average squared time difference between actual and planned pickup times of containers.

3. ***Action Function***: Two queue priority rules (two discrete actions) were used to pick up containers. In one of them, containers with nearest due time were prioritized whereas in the other, containers that have waited the longest were picked up first.

4. ***Action Trigger***: An action was taken every three minutes as long as containers were available in the system to be picked up.

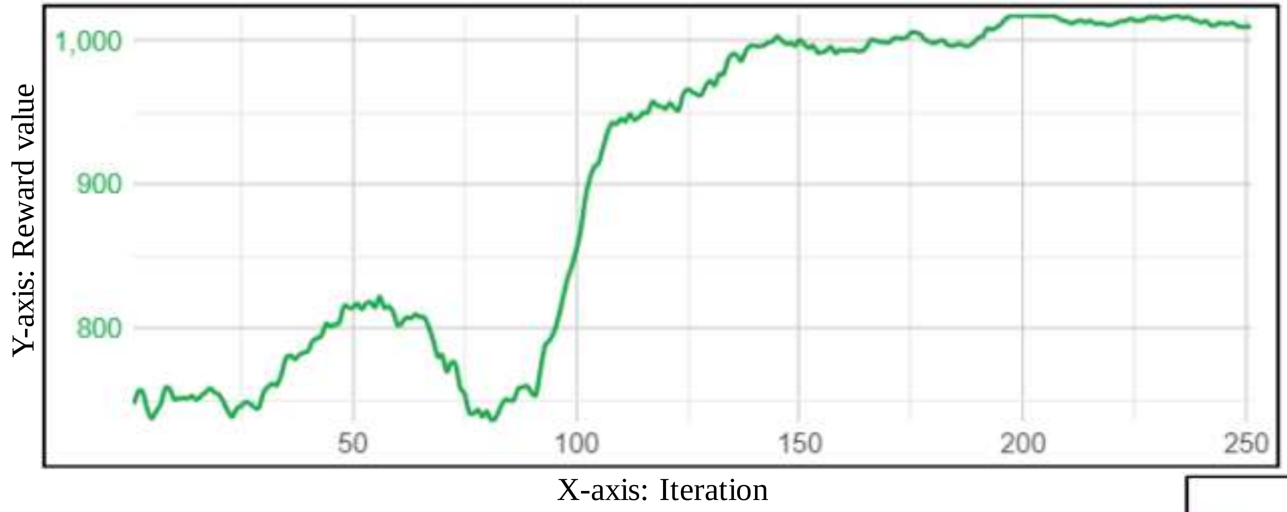
5. ***Reward Function***: It uses reward variables to calculate cumulative reward over the complete training process. The aim is to minimize container wait time in second storage area and gap between actual & planned pickup time.



Modelling with Reinforcement Learning

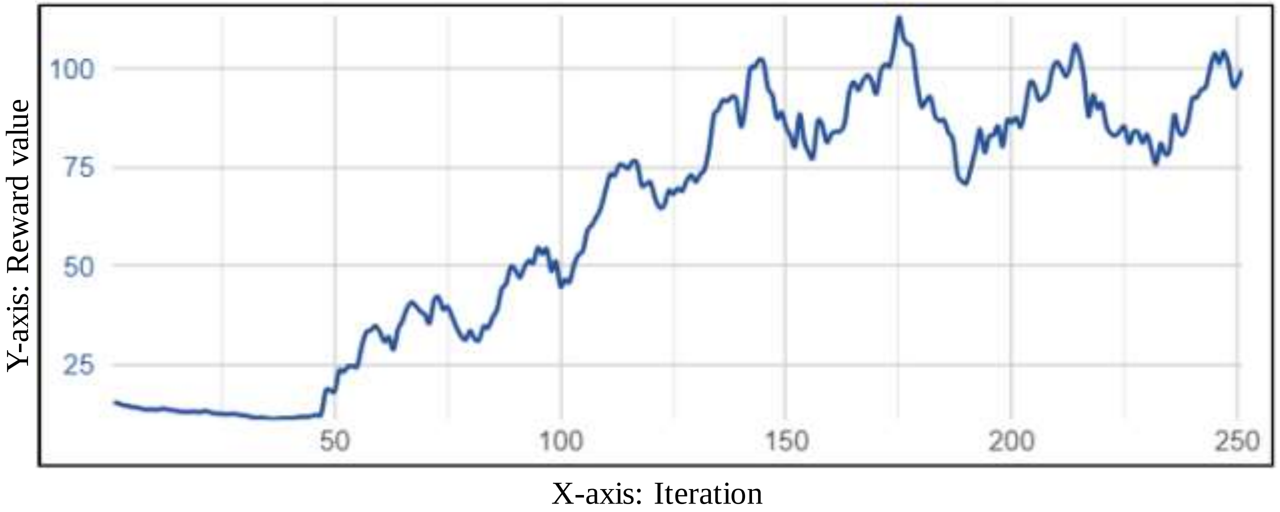
Model Training Results

Figure 2: Reward gained for action *A*



- Action *A* is prioritizing containers with high waiting times.
- Initially, agent takes actions that doesn't minimize container wait time, hence low reward score.
- Eventually, agents finds the right action and reward value becomes stable.

Figure 3: Reward gained for action *B*

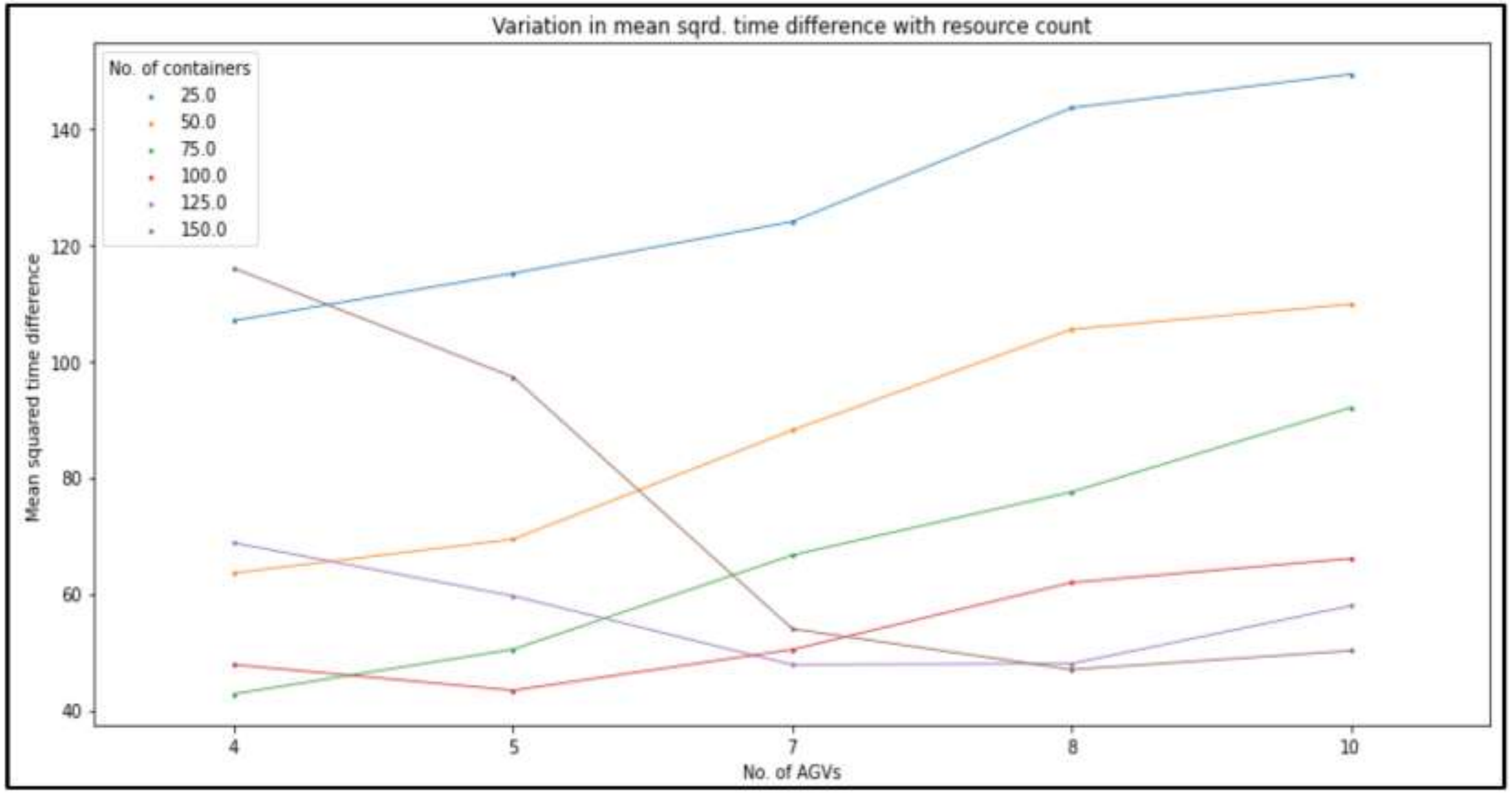


- Action *B* is prioritizing containers with nearest delivery time.
- Initially, agent takes unsuitable actions leading to decrease in reward score till 50 iterations.
- Reward score has an increasing trend and remains between 75-100 showing agent has learned the right action.

Results

- Lesser resources lead to delay in pickup of containers as they had to wait longer in the storage area.
- Increasing resources can help reduce the time difference but presence of too many of them leads to early pickup which is also not desired
- Using optimum resources showed the best results. Here, 4-5 resources for less containers (25-75) & 7-8 resources for more (100-150) containers yields minimum difference in pickup times.

Figure 4: Variation in mean squared time difference with resource count



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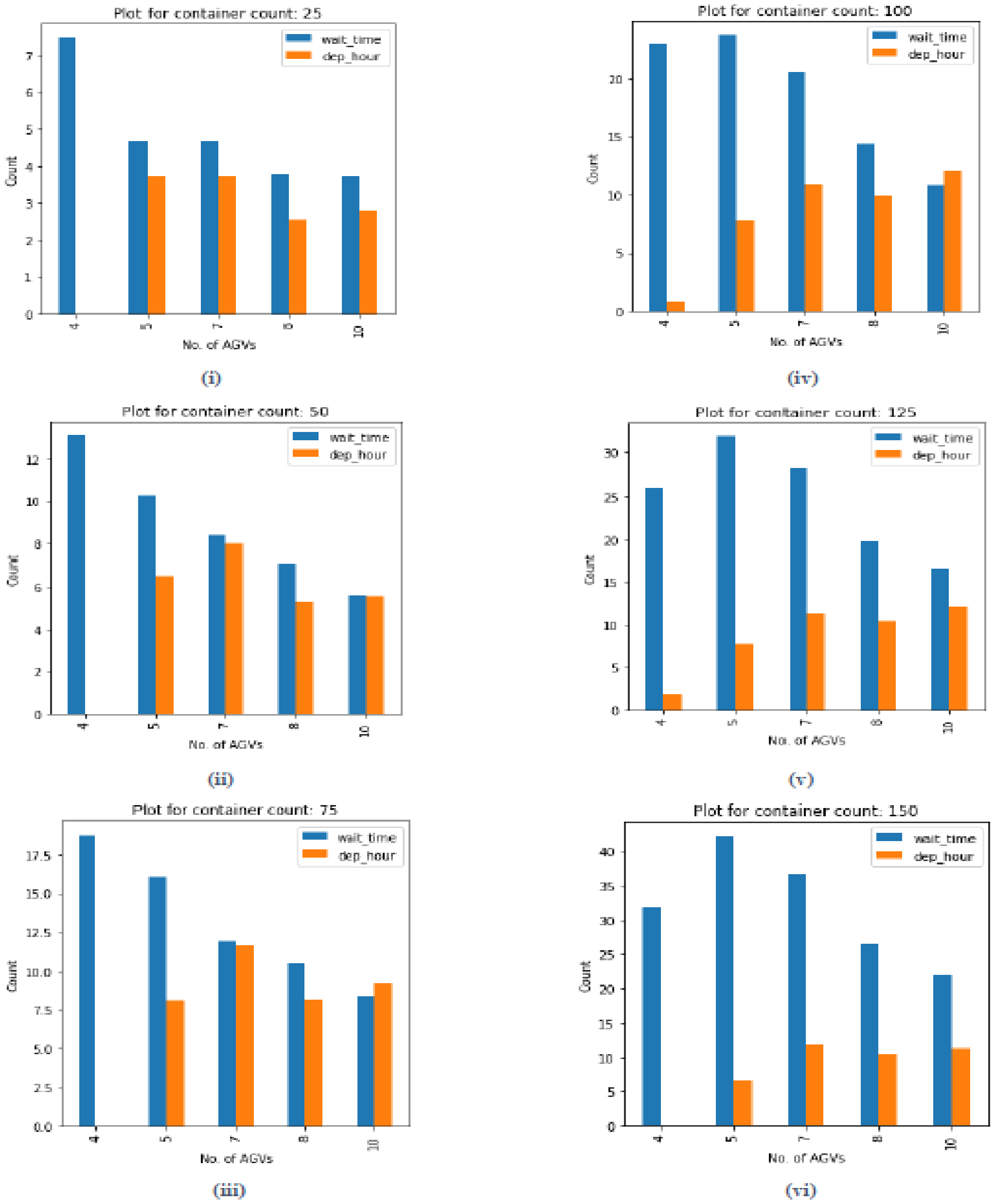
Results

- Picking containers that waited the most is visibly prioritized across all container counts. Less resources leads containers to wait longer and hence they are prioritized as an attempt to reduce delay.
- The disparity between priority rules decreases significantly with increase in resources. Containers don't have to wait much in presence of more resources and hence the ones with nearest pickup time are favoured.
- The model has learned to choose the desired action in presence of less resources. However, in the opposite situation it favours the desired action more.

Figure 5: Variation in chosen action with increasing resources



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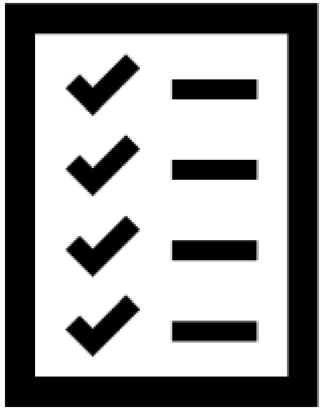
Conclusion

- Objective was to compare difference between actual & planned pickup time of containers in a priority-based & First in First out (FIFO) setting. No fixed pattern could be seen in the metric in either setting.

- Usage of simulation in logistics-related problems requires extensive domain knowledge and precise model parameters. It is also difficult to estimate which factors can affect the desired output.

- The model was able to learn successfully which actions to choose in certain scenarios and the choices were found meaningful.

- RL has the potential to be used in complex logistic-related problems. Tuning simulation model parameters and making it more realistic can help to achieve the same.



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Automatic Speech Recognition for Maritime Radio Communication

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