

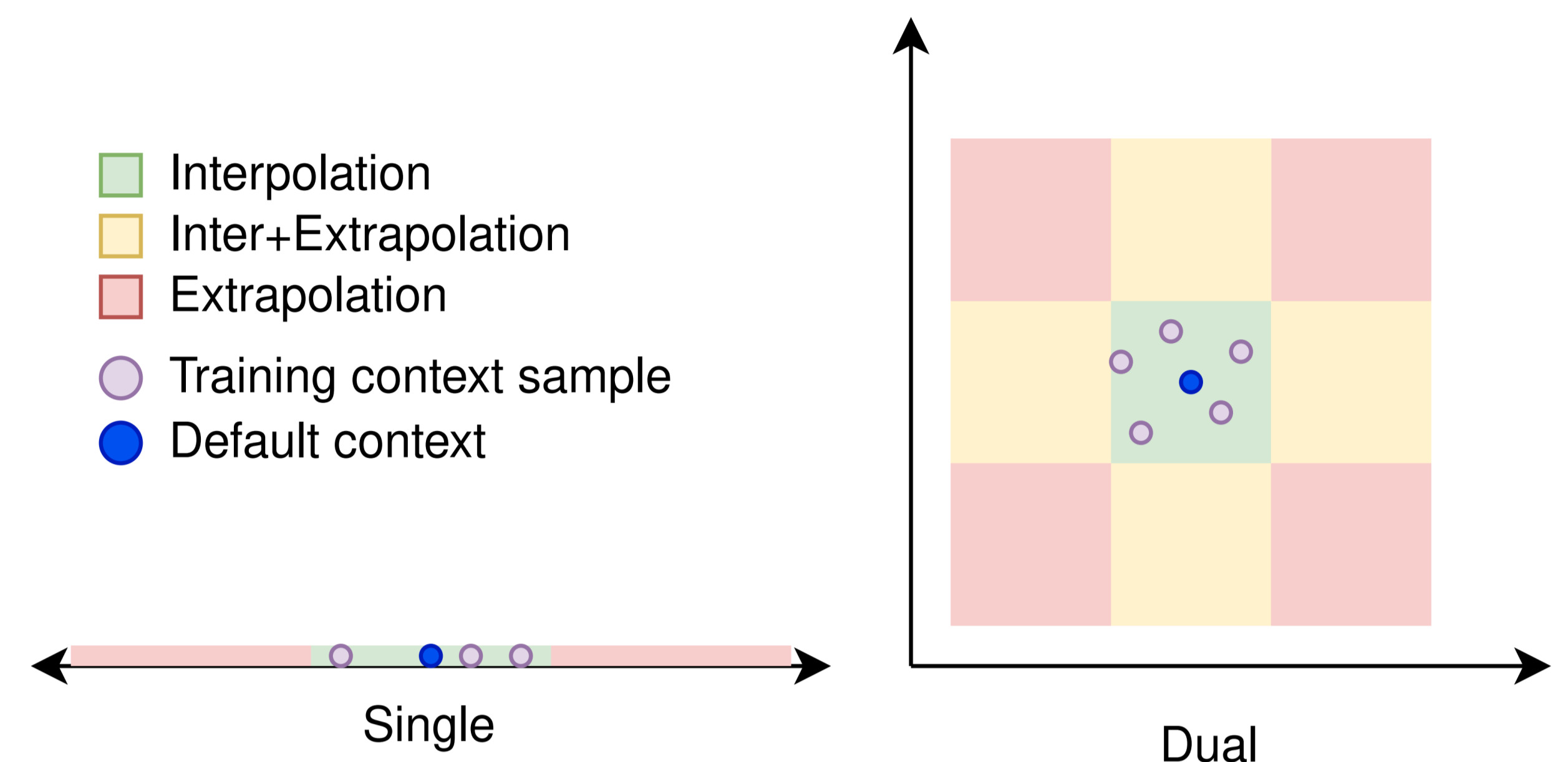
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<sup>1</sup>University of Freiburg, <sup>\*</sup>Equal contribution

Paper: <https://rlj.cs.umass.edu/2024/papers/Paper167.html>

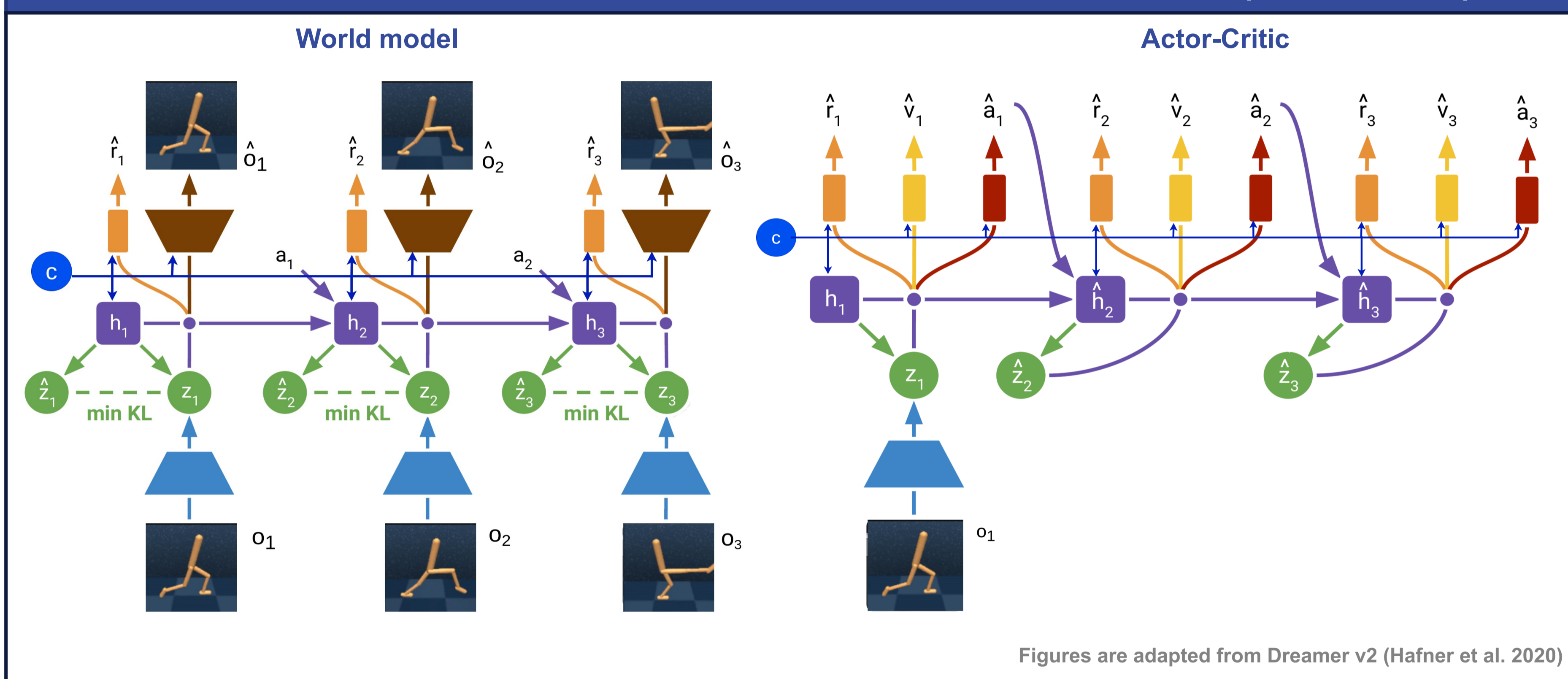
## Motivation

- Context:** parameters of a (PO)MDP that remain **unchanged** during an episode but can vary across episodes;
  - Affects the **dynamics** and **rewards**.
  - In this work, we assume the context is observable.
  - Examples: Height of a robot, mass of the load carried, actuator strength, etc.
- Zero-Shot Generalization (ZSG)** to context distributions without adapting weights.
  - Explicitly conditioning a SOTA MbRL agent, DreamerV3, should improve ZSG / OOD robustness.
- World models** could afford a promising avenue for ZSG.

## Zero-Shot Generalization



## Contextual Recurrent State Space Model (cRSSM)



## Experiments

### Incorporating context

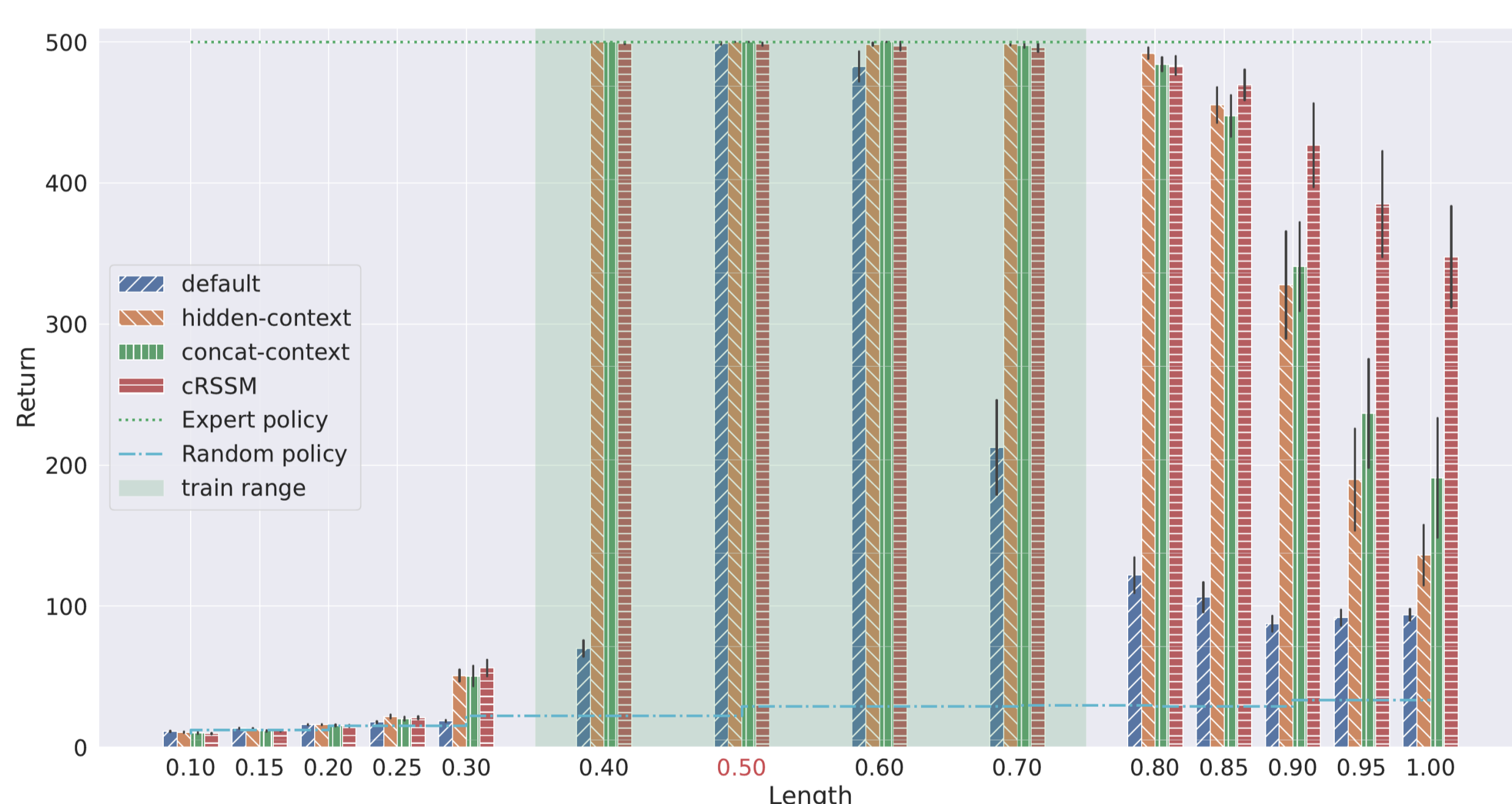
- Default:** train on only the "default" context
- Hidden Context:** train on multiple contexts without context being observable
- Concat Context:** context as an observation
- cRSSM:** appropriate conditioning of the world model and policy with context

### Environments & Context

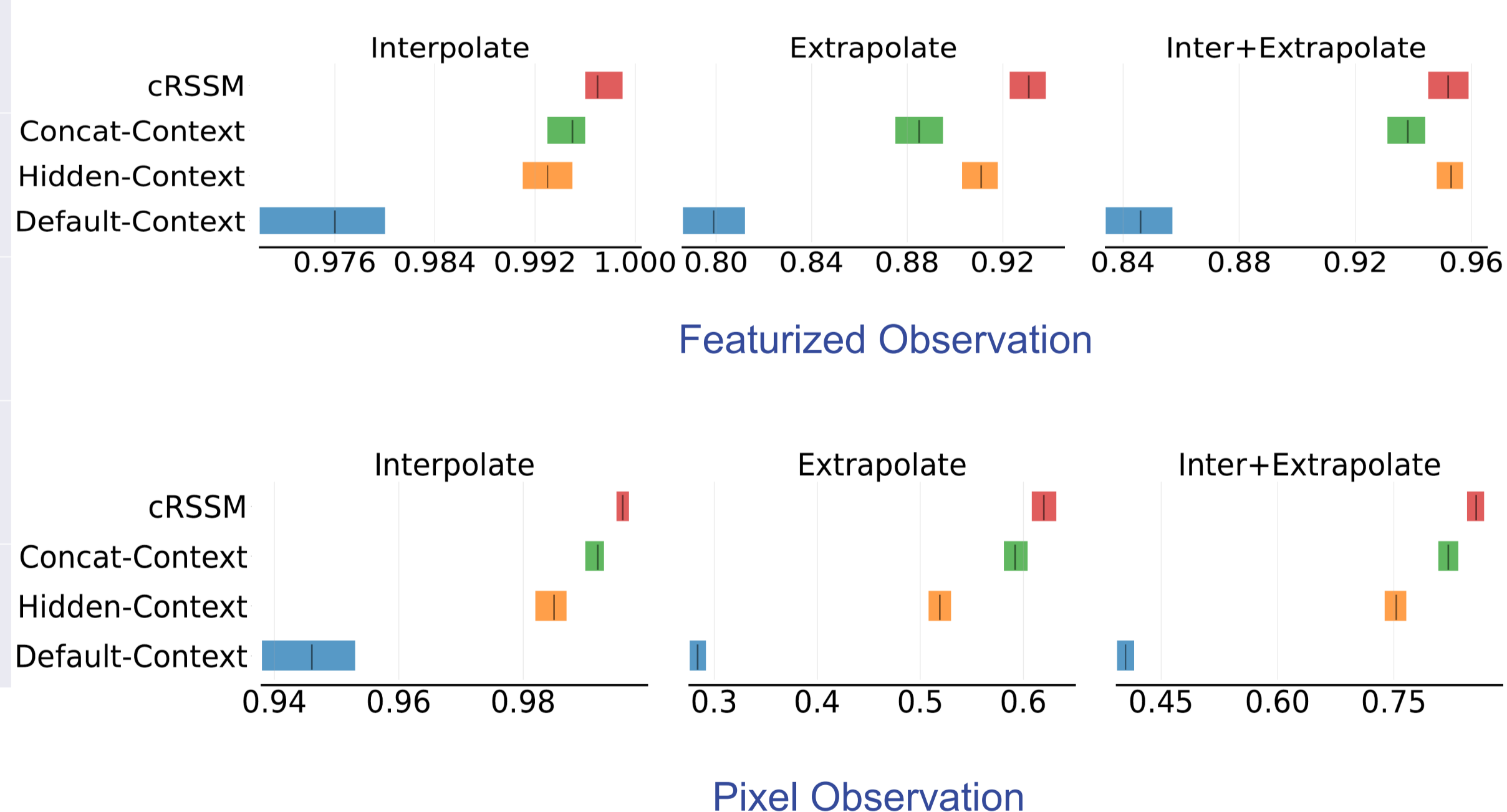
- Cartpole** — Discrete Control Task
  - Gravity, Length
- Walker Walk** — Continuous Control Task
  - Gravity, Actuator Strength

## Quantitative Evaluation

### Cartpole (Pixel) - Length



### Aggregated Normalized IQM

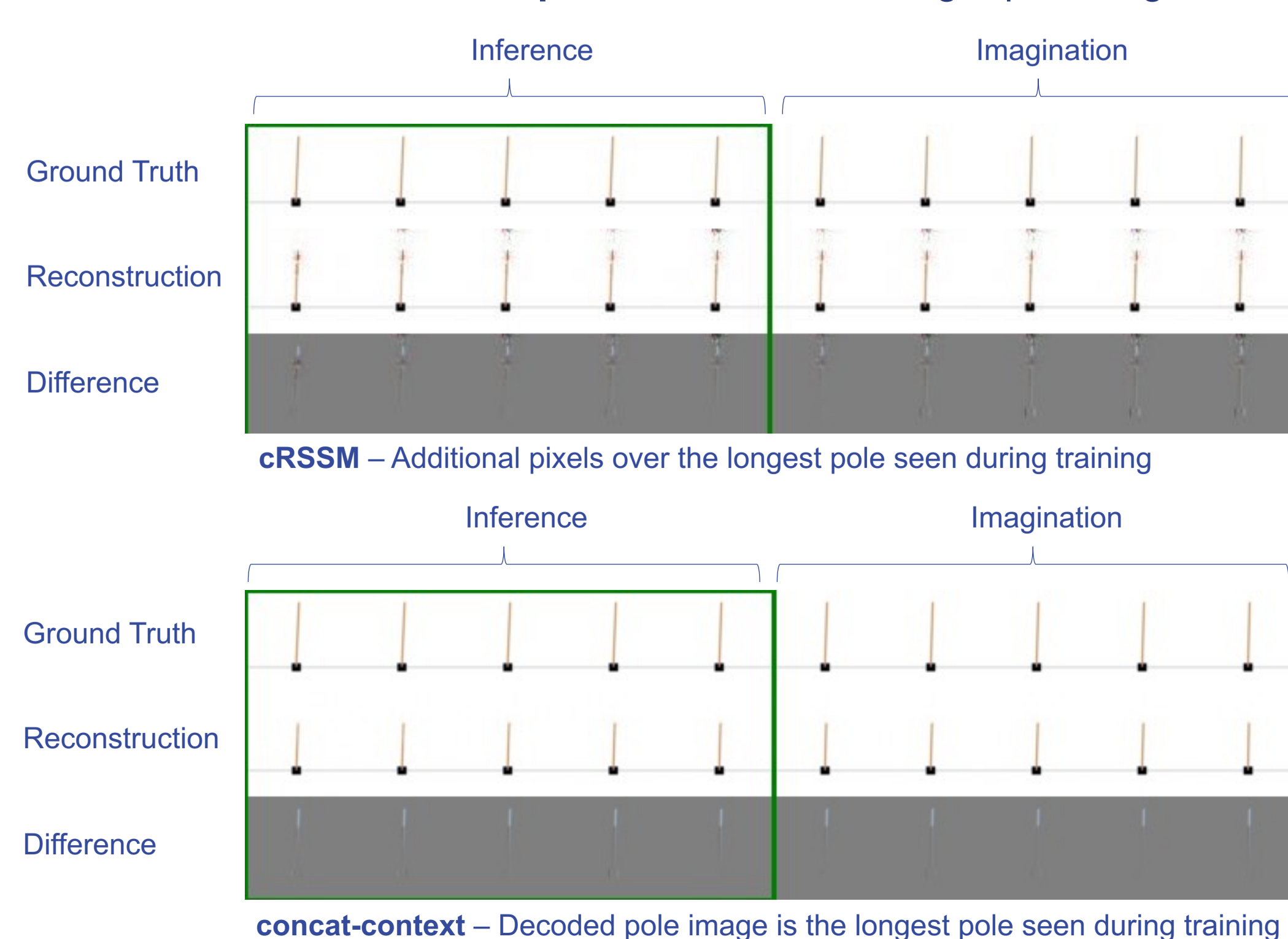


## Future Work

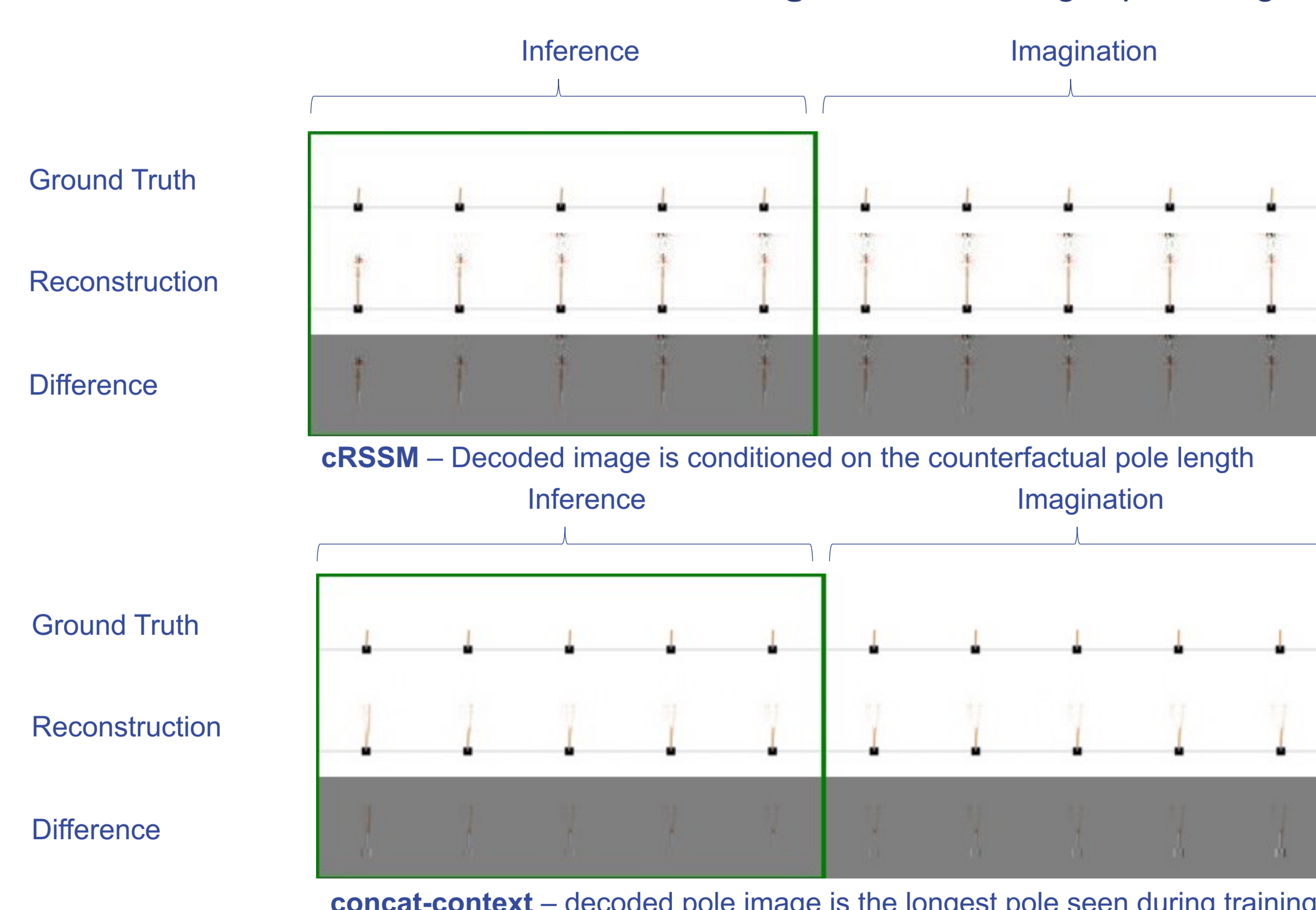
- Train in imagination in extrapolated contexts
- Inferring unobservable context and conditioning
- Standardized benchmarks for generalization with more appropriately designed environments

## Qualitative Evaluation

### 1. Extrapolation to unseen longer pole length



### 2. Counterfactual conditioning on unseen longer pole length



Paper



Code: [github.com/sai-prasanna/dreaming\\_of\\_many\\_worlds](https://github.com/sai-prasanna/dreaming_of_many_worlds)