CAROL: **C**ertifi**a**bly **Ro**bust Reinforcement **L**earning through Model-Based Abstract Interpretation

Chenxi Yang[1], Greg Anderson[2], Swarat Chaudhuri[1]
[1]The University of Texas at Austin, [2]Reed College

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Background: RL in Safety-Critical Tasks

- Reinforcement learning (RL) is an established approach for various tasks, including safety-critical ones.

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Reinforcement learning AI model improves accuracy of skin cancer diagnoses

Article | Published: 22 March 2023

Dense reinforcement learning for safety validation of autonomous vehicles

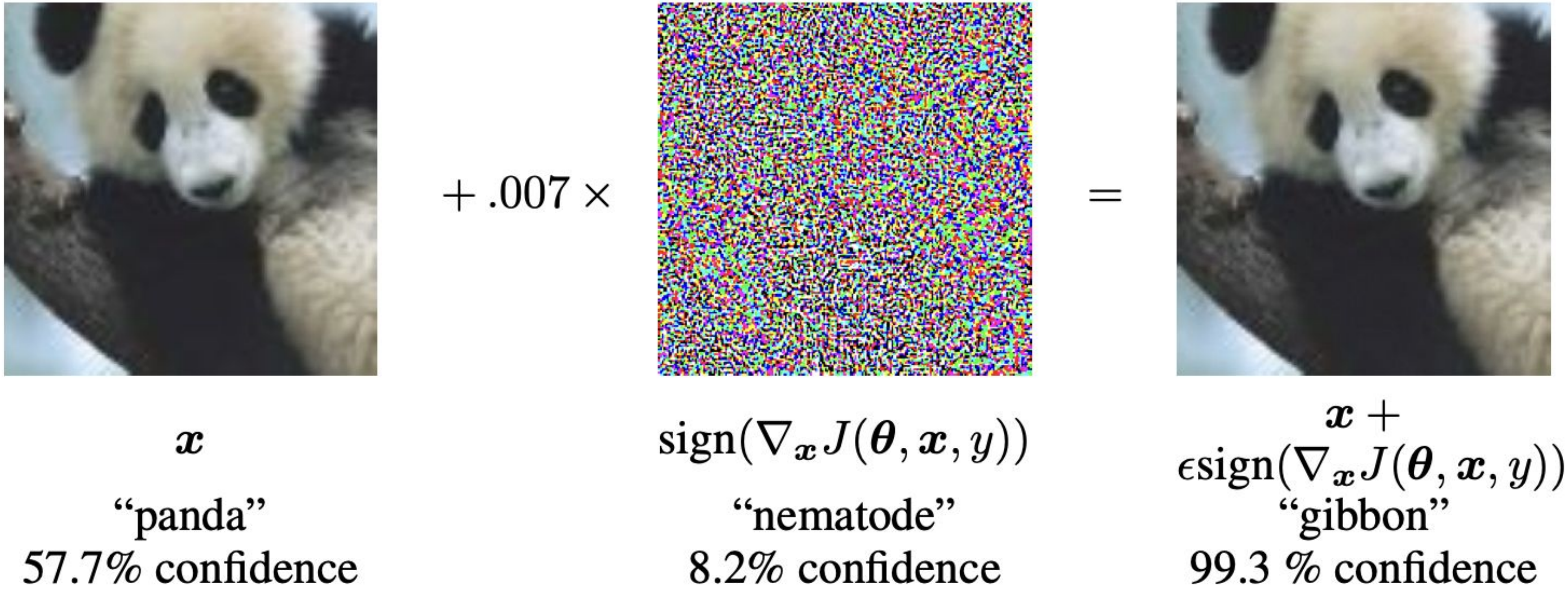
Shuo Feng, Haowei Sun, Xintao Yan, Haojie Zhu, Zhengxia Zou, Shengyin Shen & Henry X. Liu

Nature **615**, 620–627 (2023) | Cite this article

- State-of-the-art RL methods use neural networks as policy representations.

Background: RL with Neural Network Policies is Vulnerable

Neural networks are vulnerable.

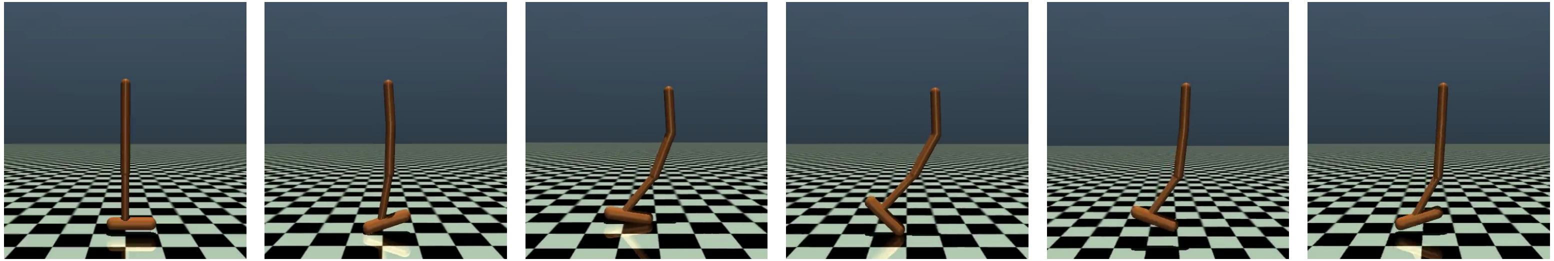


[1] Goodfellow et, al. Explaining and Harnessing Adversarial Examples. ICLR 2015.

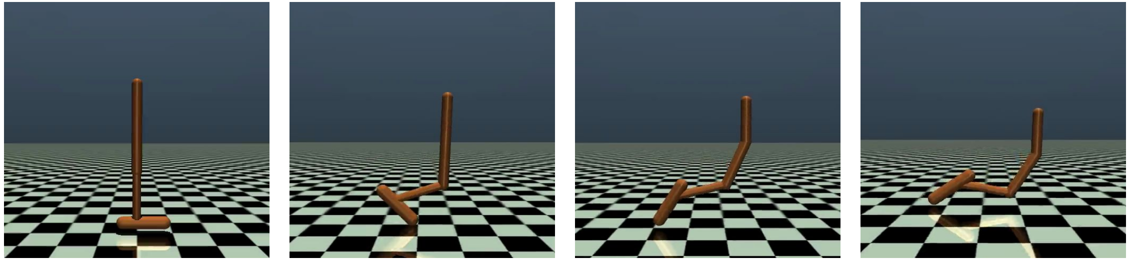
Background: RL with Neural Network Policies is Vulnerable

Problems are more severe in RL as mistakes can cascade.

A hopper moves forward



Under attacks



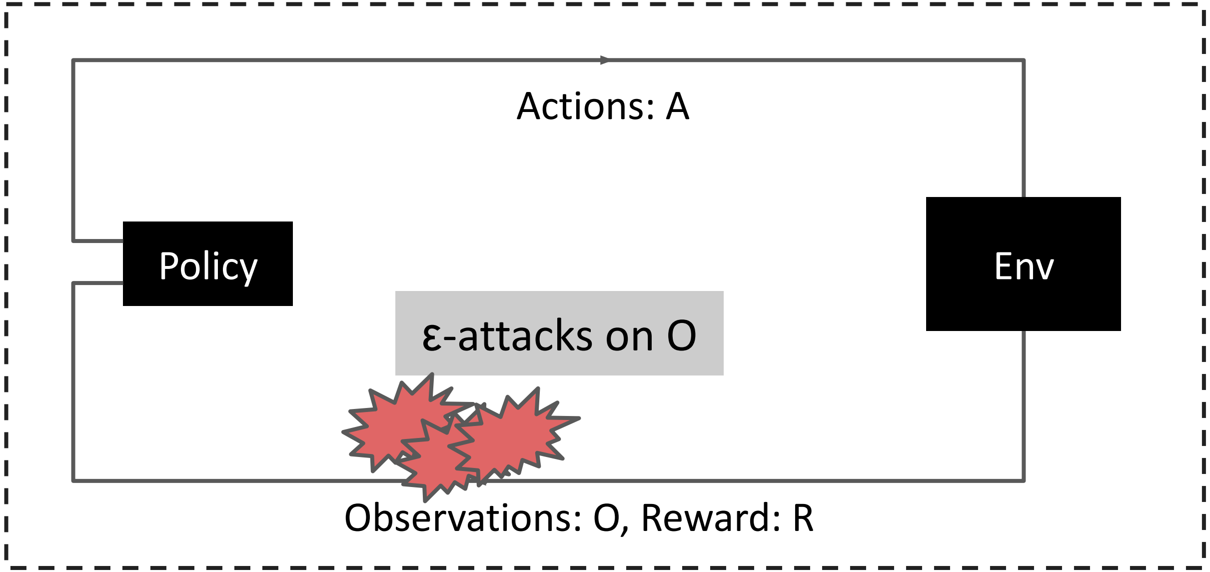
Background: Certified Defenses

Certified Neural Networks in Supervised Learning	Defenses are still heuristic in RL
DiffAI (Mirman et al. 18), k-ReLU (Singh et al. 19), RNN Verification (Ryou et al. 21)	SA (Zhang et al. 20), PA-AD (Sun et al. 22), RADIAL (Oikarinen et al. 21)

Heuristic defenses are defeated by **counter** attacks.

Can we train a **certifiable** RL policy against **arbitrary** attacks?

Goal: Train Certifiable Robust Reinforcement Learning Policies



Challenges

- How to represent and quantify worst-case attacks?

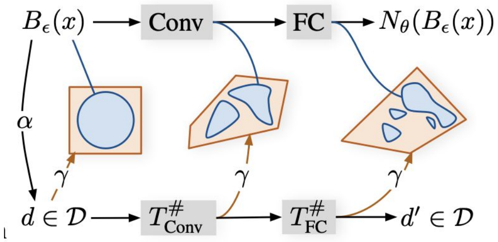
We use abstract interpretation, covering all the attacks.

- How to reason over the black-box environment?

Goal: Train Certifiable Robust Reinforcement Learning Policies

Abstract Interpretation[1]: A well-established method to effectively compute bounds over functions.

It can be used to certify neural networks[2].



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[1] Cousot et, al. Abstract Interpretation. POPL 1977.
[2] Mirman et, al. Differentiable Abstract Interpretation for Provably Robust Neural Networks. ICML 2018.

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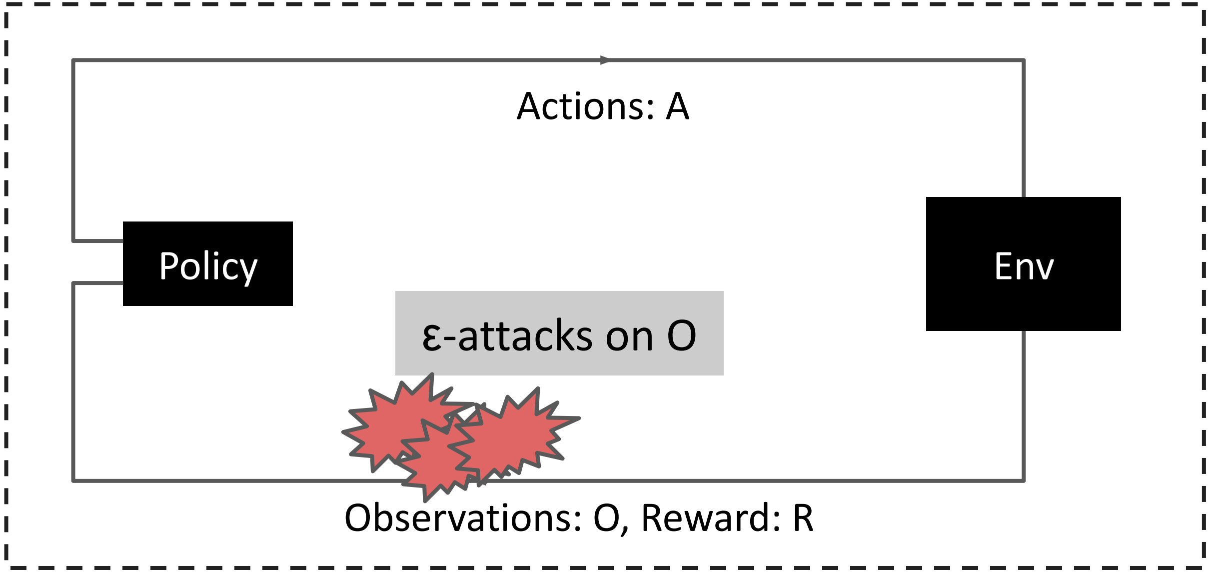

Challenges

- How to represent and quantify worst-case attacks?

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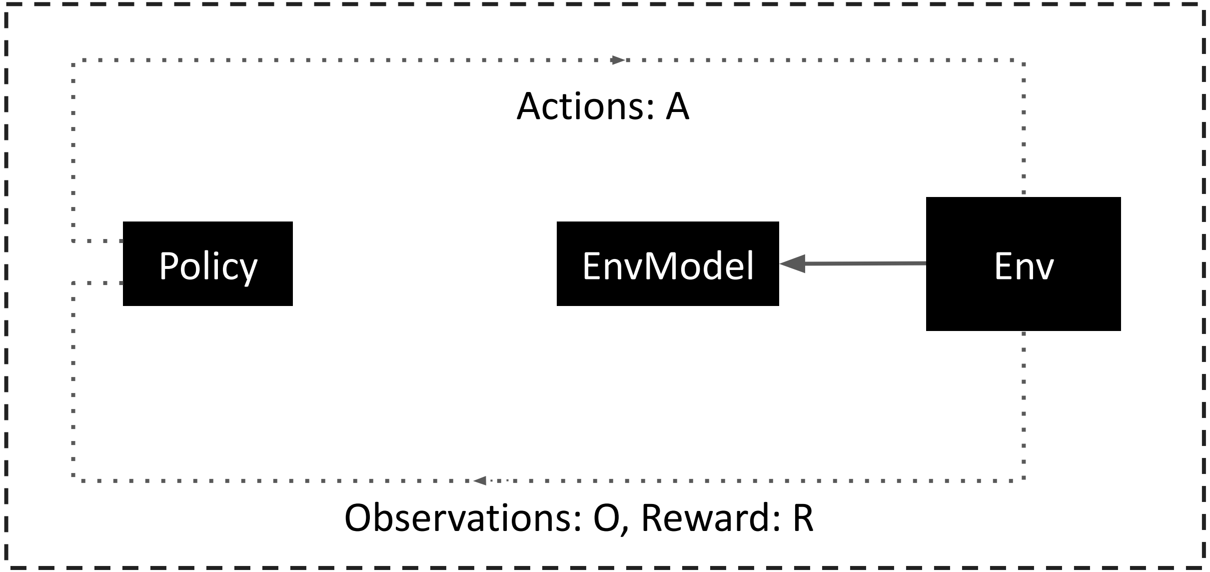
- How to reason over the black-box environment?

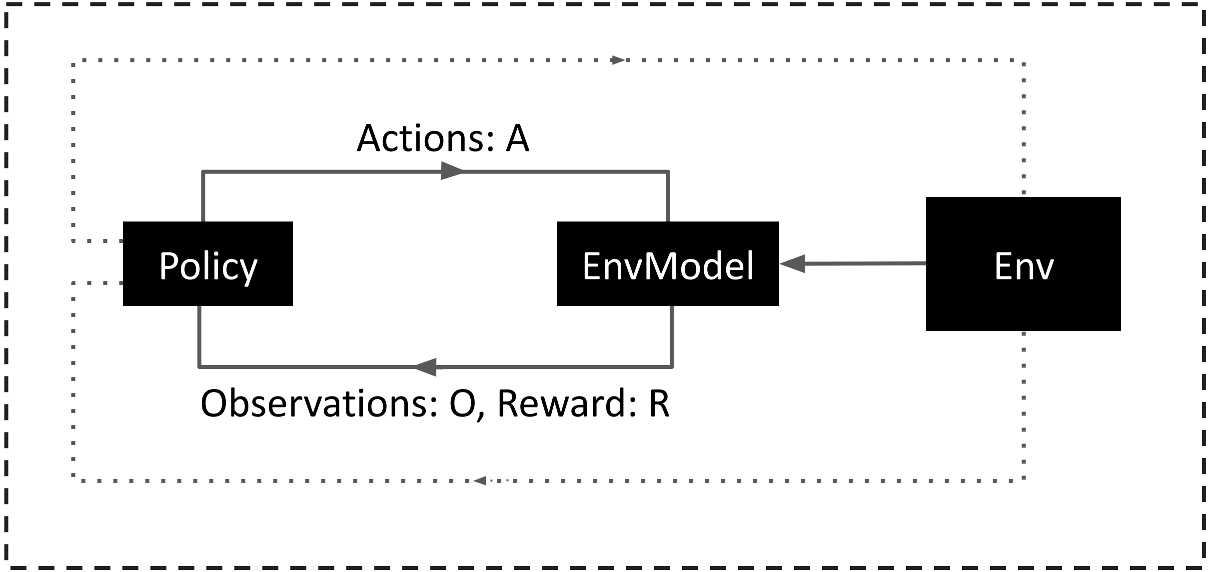
Learn a white-box transition representation of the environment with the policy.

Carol: Certifiably Robust Reinforcement Learning



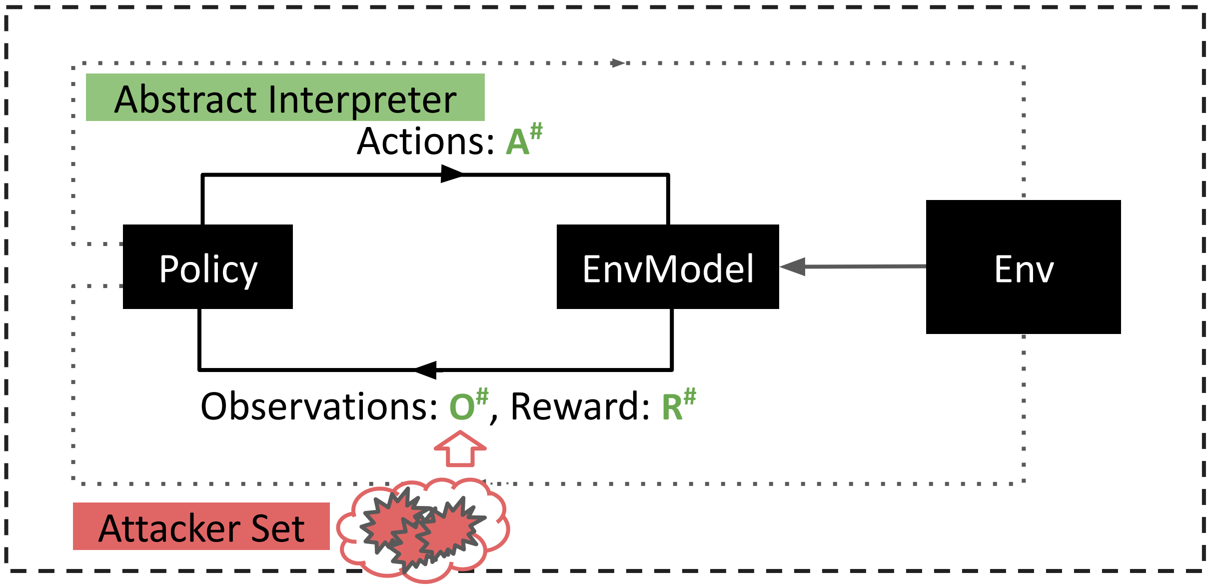
Step 1: Train a NN represented **model** (verifiable) for the black-box environment during normal training.

Carol: Certifiably Robust Reinforcement Learning



Step 1: Train a NN represented **model** (verifiable) for the black-box environment during normal training.
Step 2: Train the **policy** over the NN model of the real environment.

Carol: Certifiably Robust Reinforcement Learning



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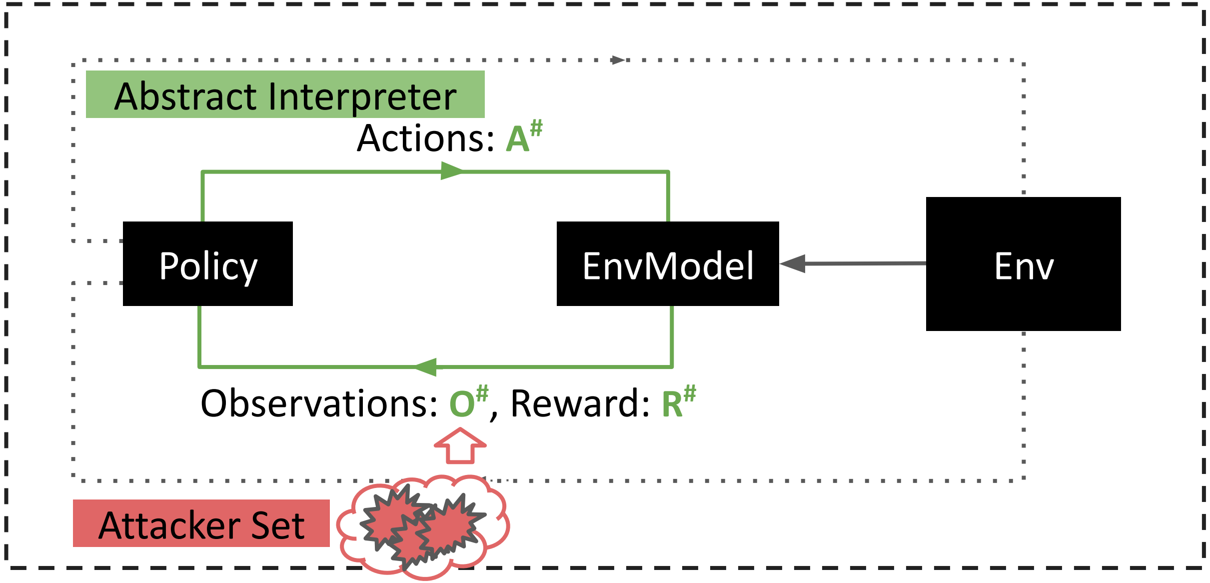
Carol: Certifiably Robust Reinforcement Learning



Step 1: Train a NN represented **model** (verifiable) for the black-box environment during normal training.
Step 2: Train the **policy** over the NN model of the real environment.
Step 3: A **symbolic** RL algorithm: **RL$^{\#}$** : with the learnt symbolic reward **R$^{\#}$**.
Step 4: In each iteration: we use the accumulative reward lower bound to guide the training: $\hat{R}^{\#}$ = LowerBound[**RL$^{\#}$**(**A$^{\#}$**, **O$^{\#}$**, **R$^{\#}$**)]

Theoretical Bound of Reward

With probability 1 - δ, the reward (R) under the worst attack is bounded by,

$$R \geq \hat{R}^{\#} - \frac{1}{\sqrt{\delta}}\sqrt{\frac{Var[R^{\#}]}{N}} - \left(1 - (1 - \delta_E)^T\right) C.$$

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1. The bound grows as the δ shrinks.
   ⇨ We pay the price of a looser bound as we consider higher confidence levels.
2. The bound depends on $Var[R^{\#}]$ and N in an intuitive way.
   ⇨ Higher variance makes it harder to measure the true reward, more samples make the bound tighter.
3. As δ_E increases, the last term grows.
   ⇨ A less accurate environment model leads to a looser bound.
4. The bound grows with T.
   ⇨ Over longer time horizons, our reward measurement gets less accurate.

Results: Certifiable Accumulative Reward Bound

Reward
Bound under
Worst-case
Attack

Time Horizon (T)

Results: Certifiable Accumulative Reward Bound

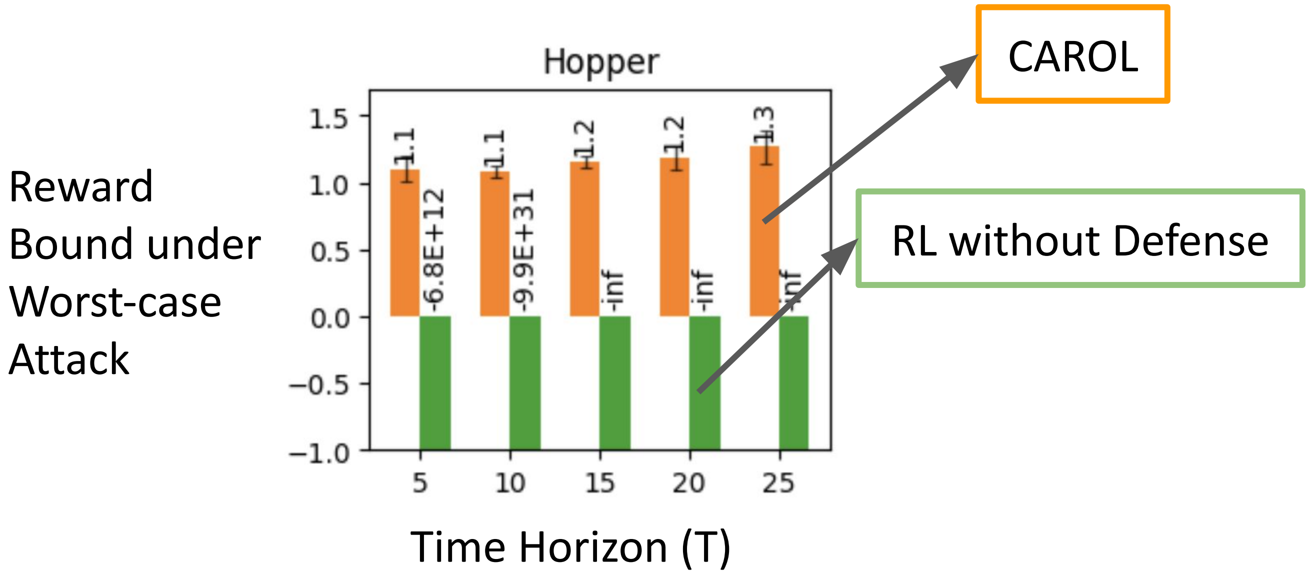
CAROL

Reward
Bound under
Worst-case
Attack

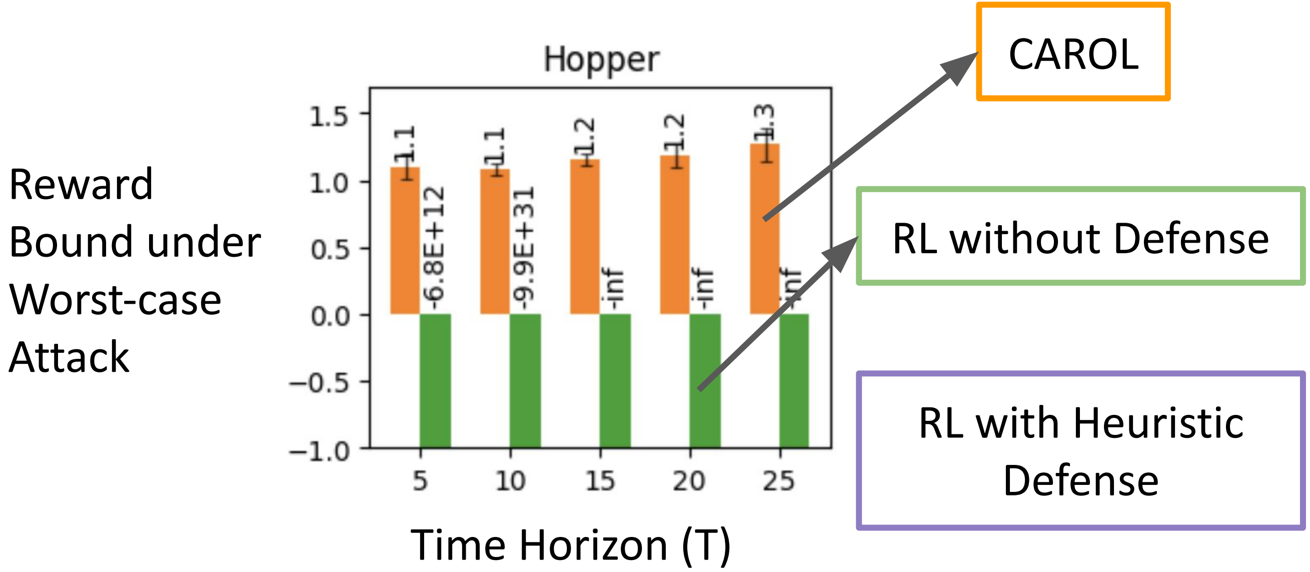
RL without Defense

Time Horizon (T)

Results: Certifiable Accumulative Reward Bound

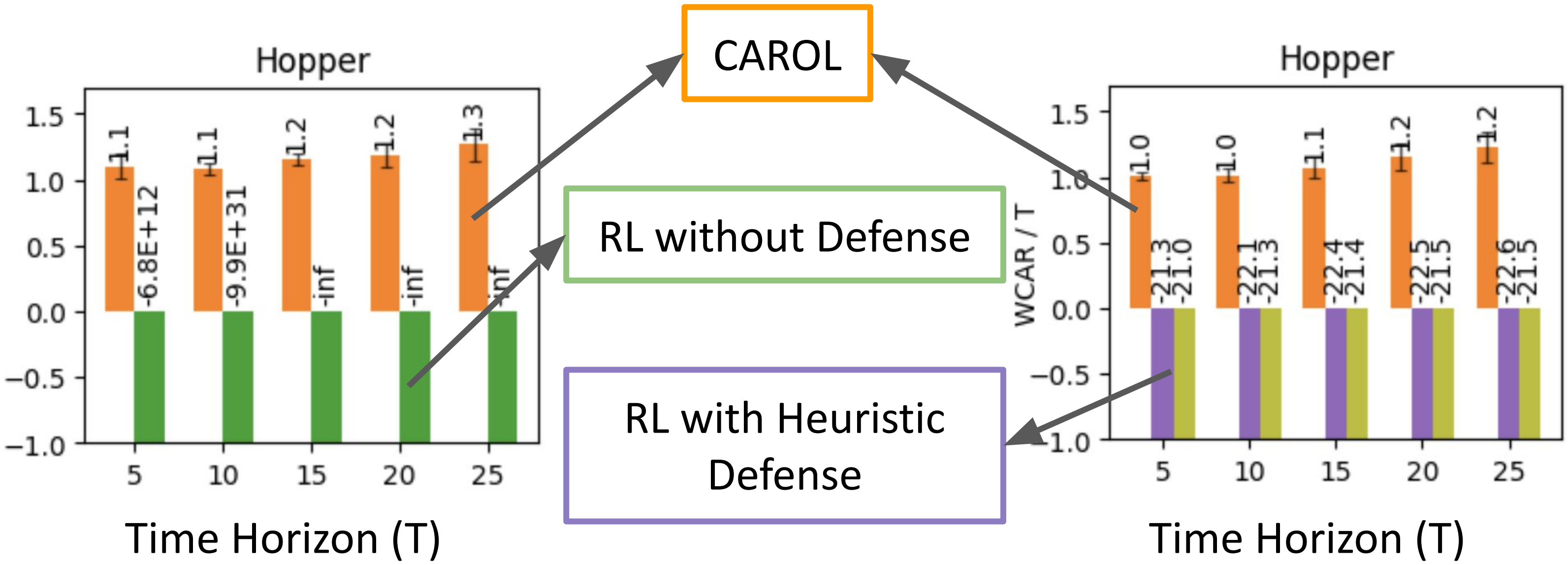


Results: Certifiable Accumulative Reward Bound



Results: Certifiable Accumulative Reward Bound

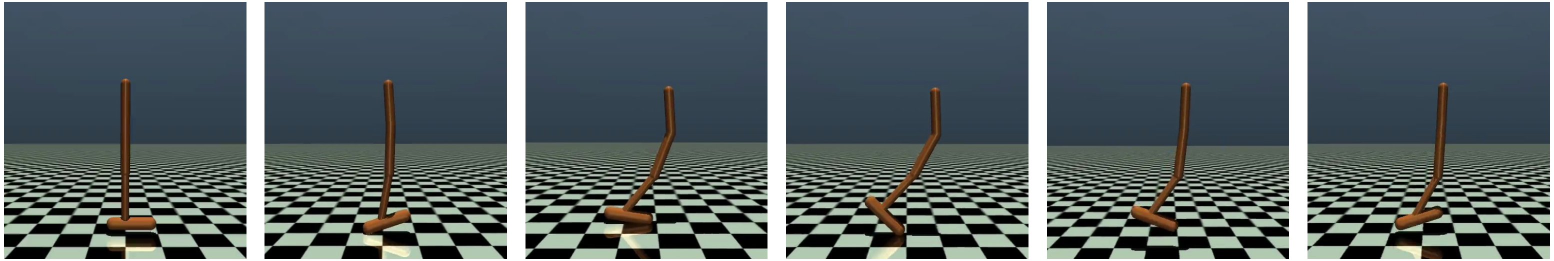
Reward Bound under Worst-case Attack



Summary: CAROL

CAROL: **Certifiable** Robust Reinforcement Learning with **Long-Horizon** Reward Bound

Key Idea: Abstract Interpretation for **Verification** in the Learning Loop
White-Box Environment Representation Learning



Code: https://github.com/chenxi-yang/carol

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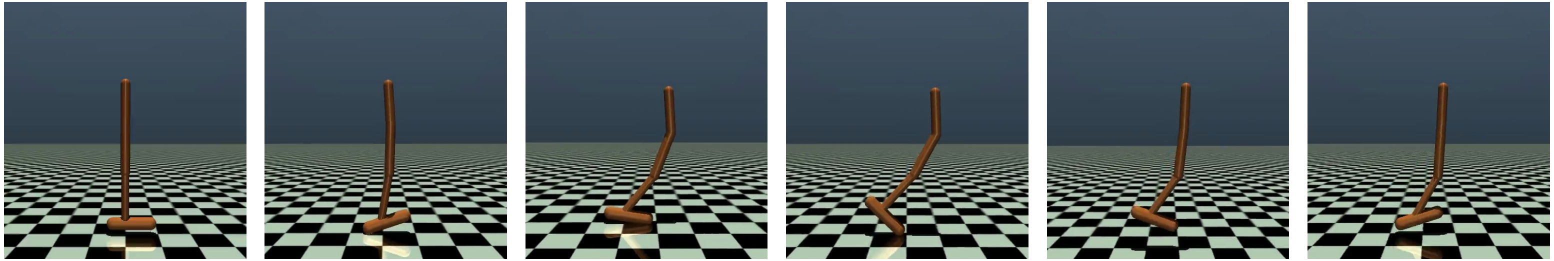

Future: More **Accurate** and **Scalable** Certified RL

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Summary: CAROL

Thank you!

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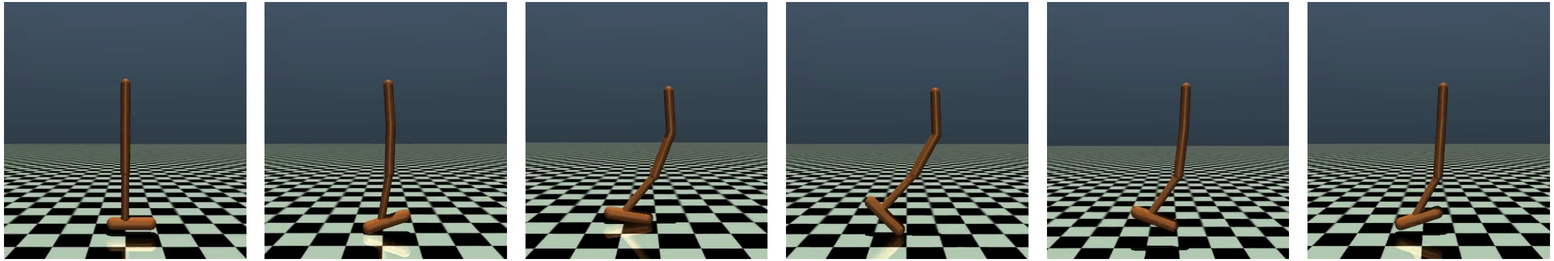
White-Box Environment Representation Learning



Future: More **Accurate** and **Scalable** Certified RL

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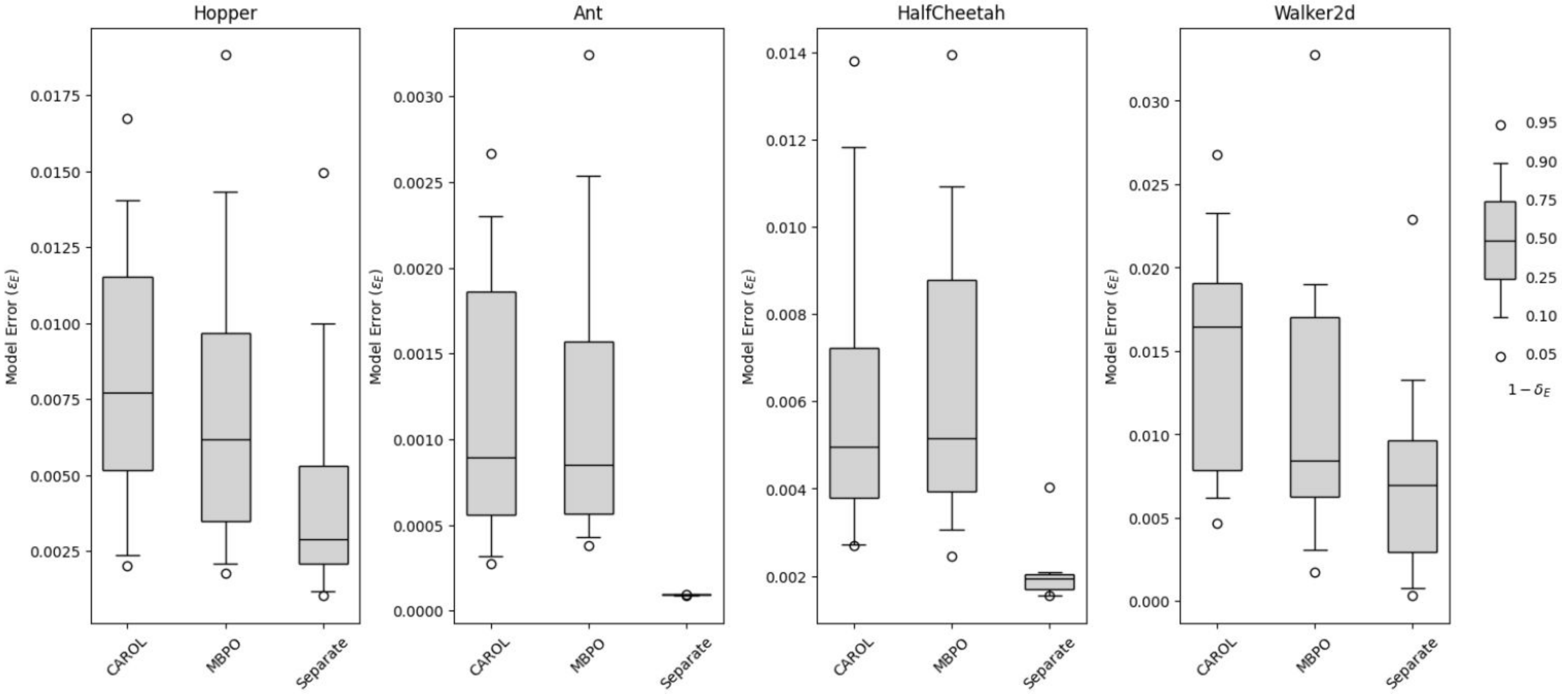
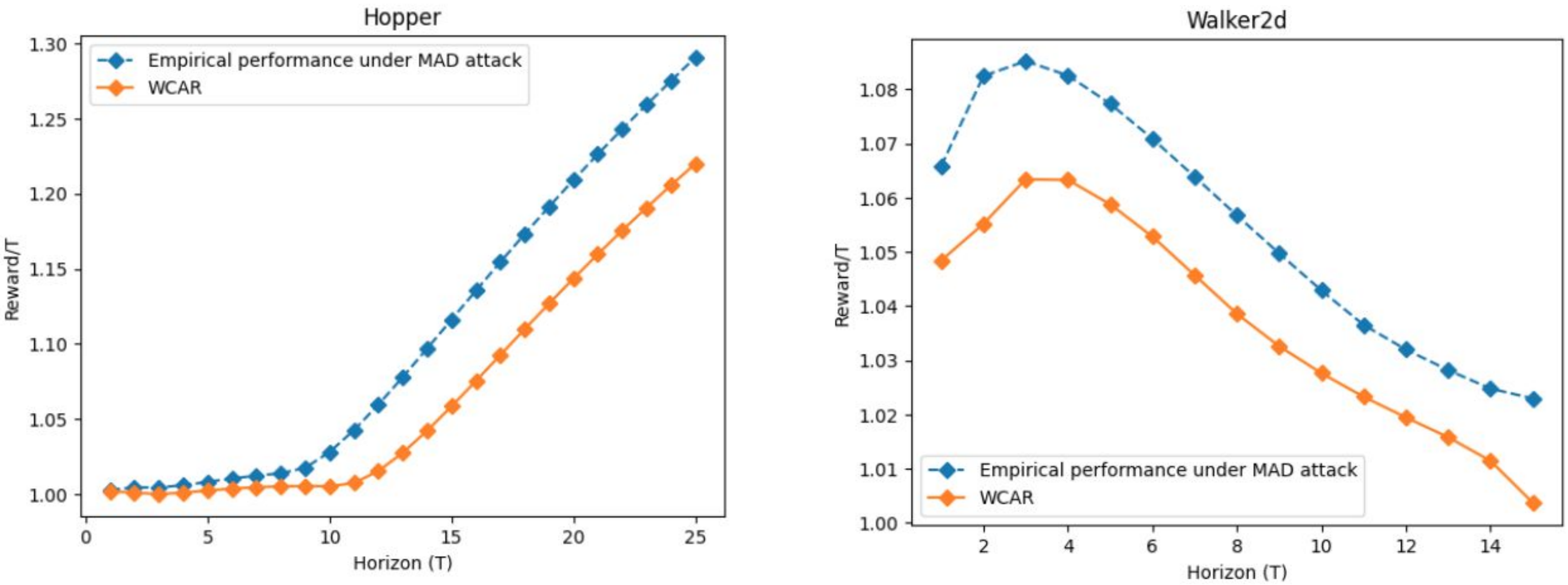
Backup Materials

Model Error



Hopper
Ant
HalfCheetah
Walker2d
Model Error (ϵ_E)
CAROL
MBPO
Separate
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0.95
0.90
0.75
0.50
0.25
0.10
0.05
$1-\delta_E$

Bound Tightness



Certifiable Bound Physical Meaning