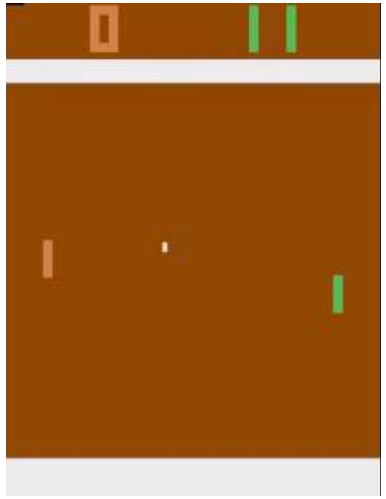
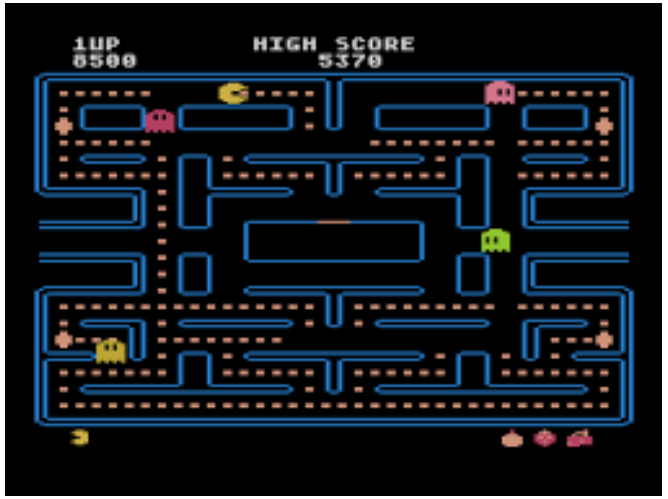
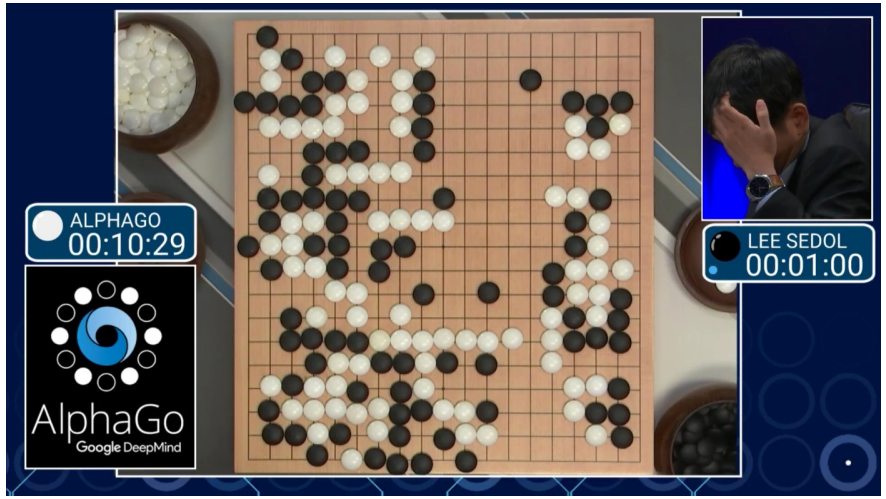
Verifiable Reinforcement Learning via Policy Extraction

Osbert Bastani, Yewen Pu, Armando Solar-Lezama

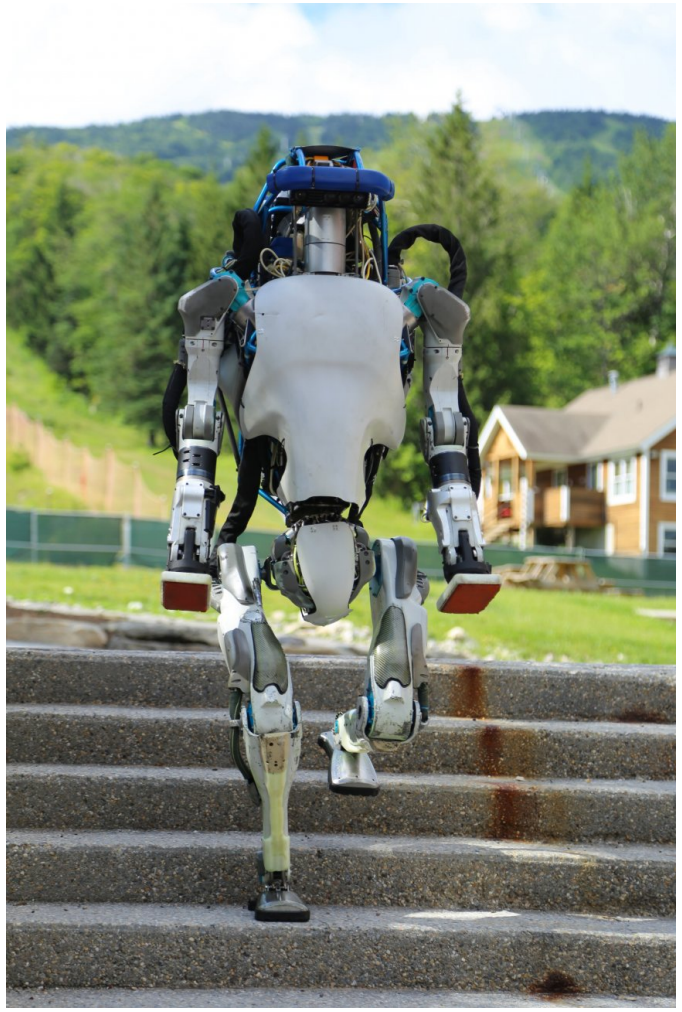
Deep Reinforcement Learning Successes

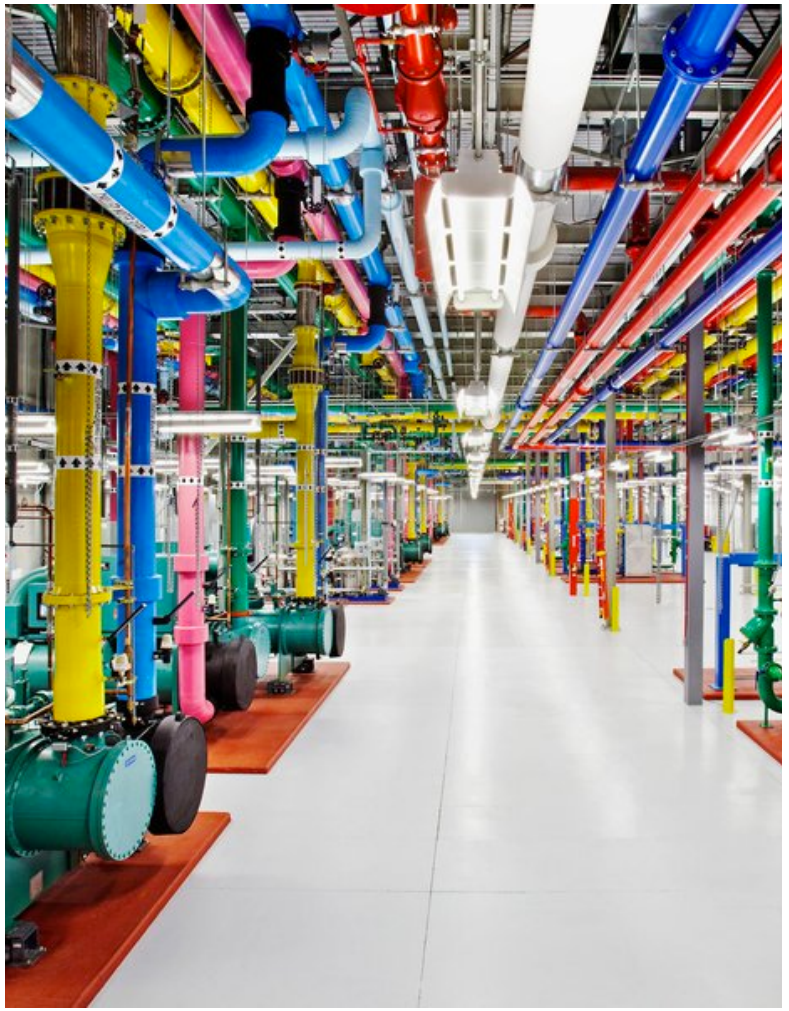




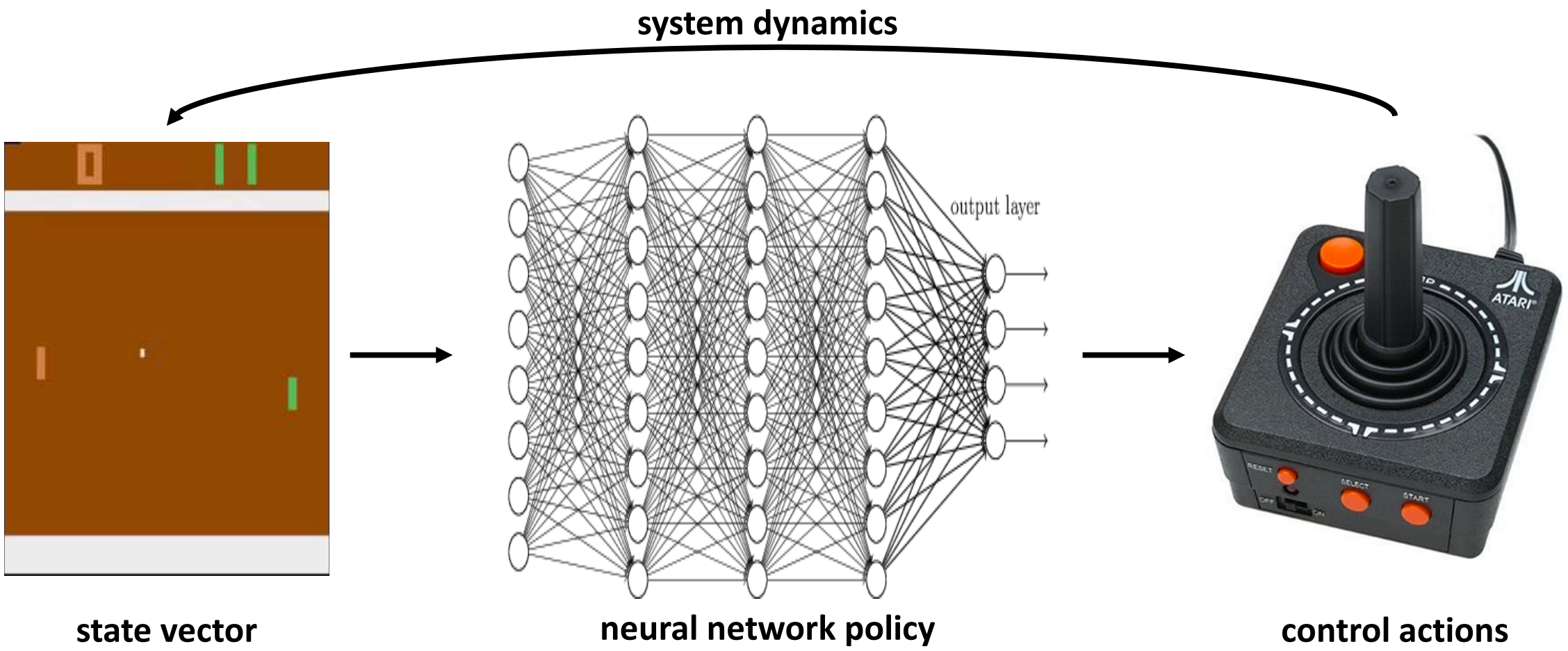


Safety Critical Applications

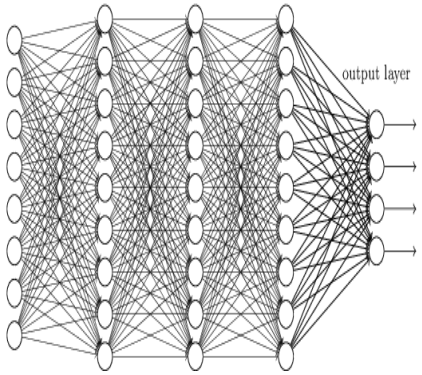


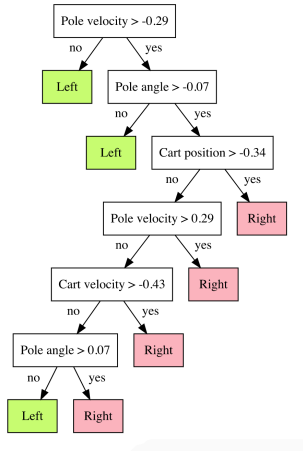


Deep Reinforcement Learning



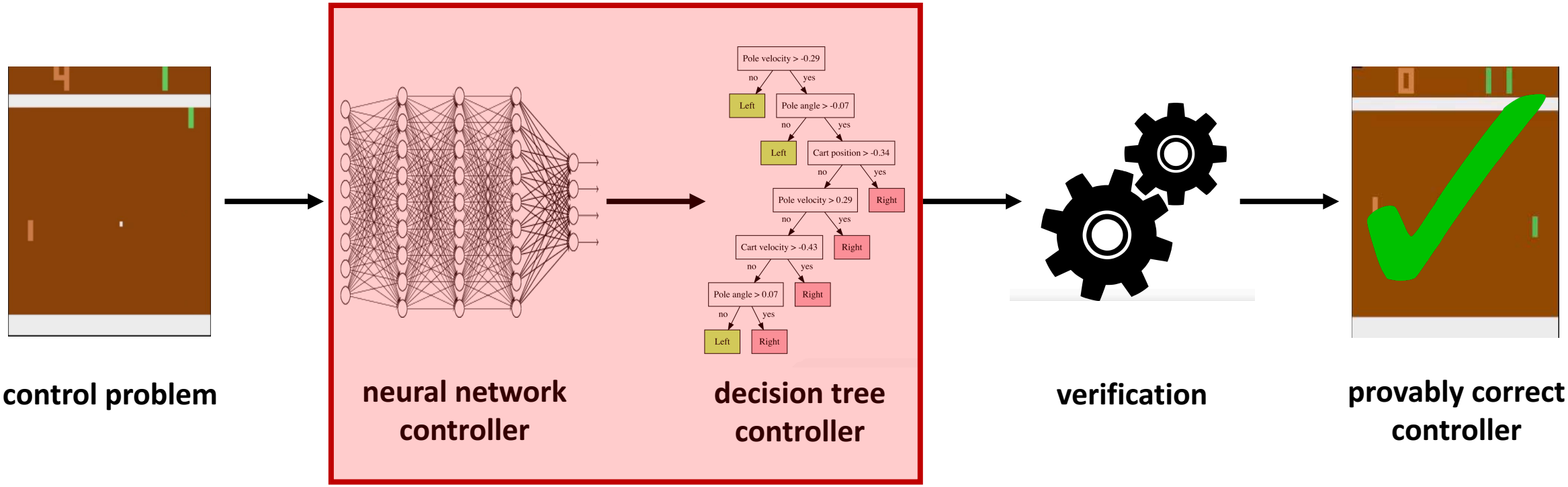
Learnability vs. Verifiability





Complex policies	✓	✓
Easy to verify	✗	✓
Easy to train	✓	✗

High-Level Approach



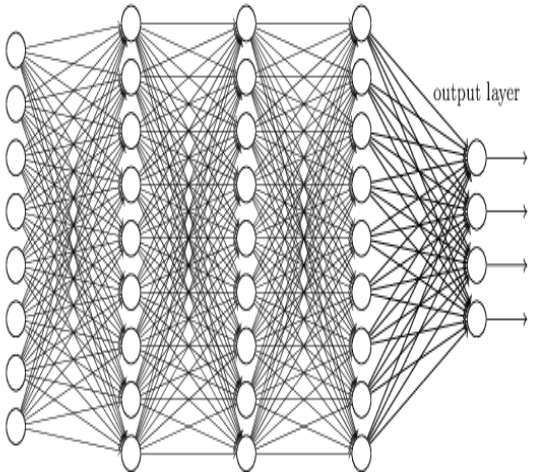
Imitation Learning

Examples from Human Expert

Autonomous Controller

Abbeel & Ng 2004

Imitation Learning

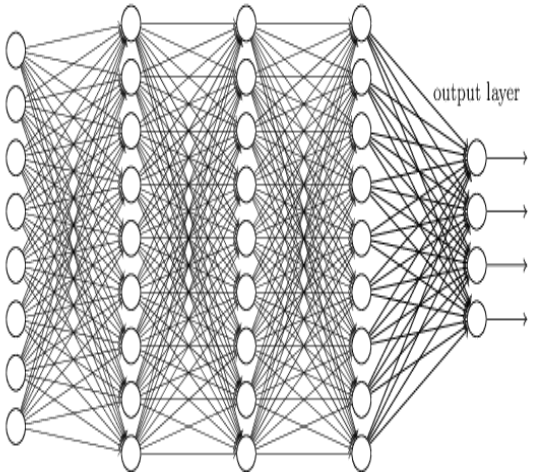


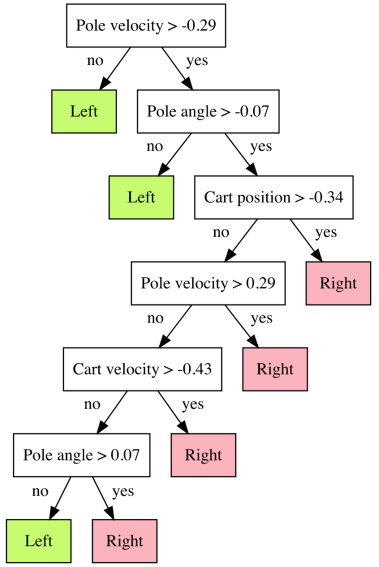
Examples from Neural Network

Autonomous Controller

Abbeel & Ng 2004

Imitation Learning



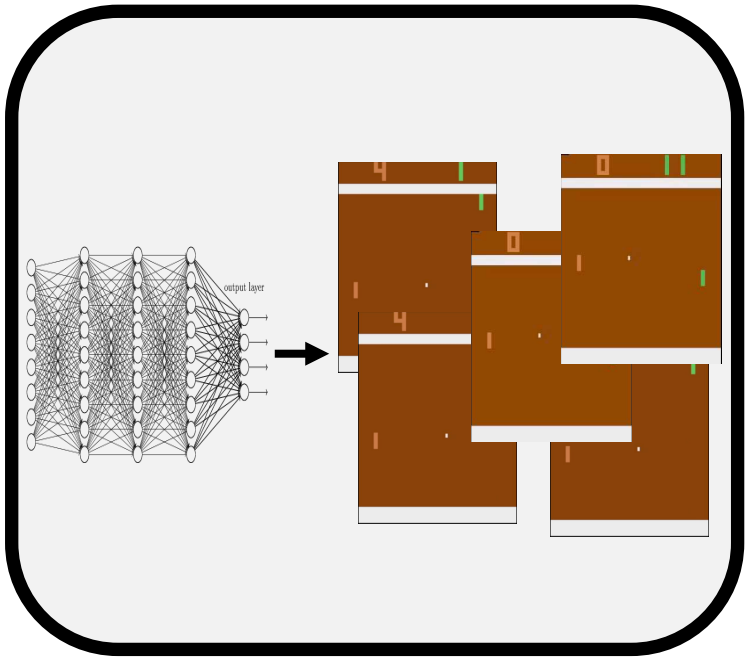


Examples from Neural Network

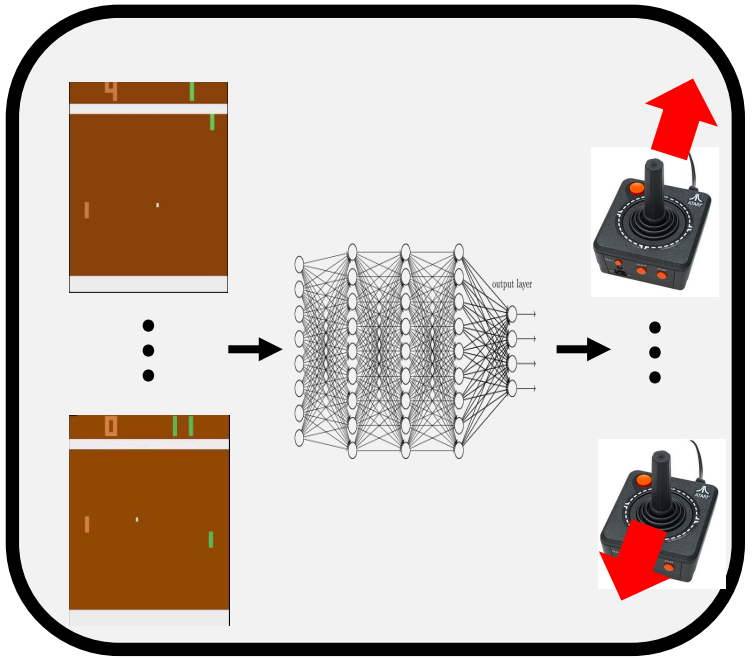
Decision Tree Controller

Abbeel & Ng 2004

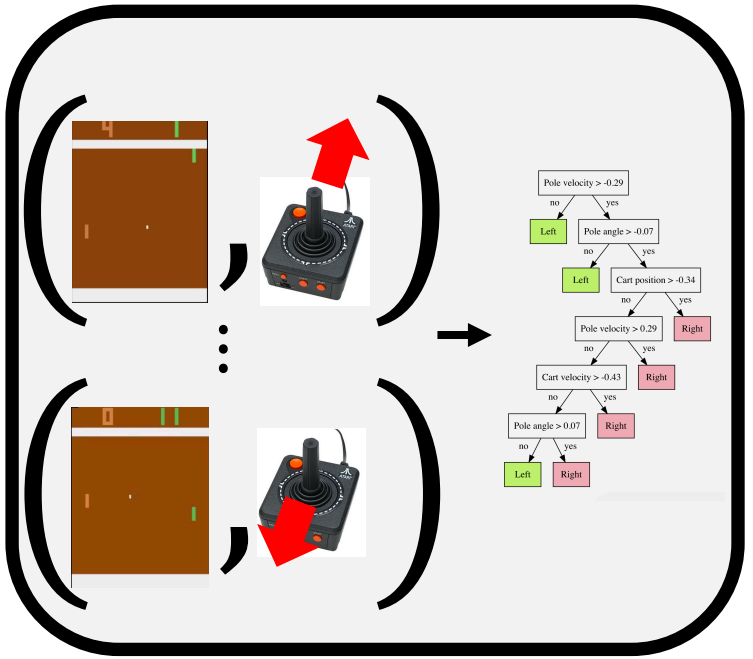
Imitation Learning (Supervised)



Step 1: Use NN to generate states



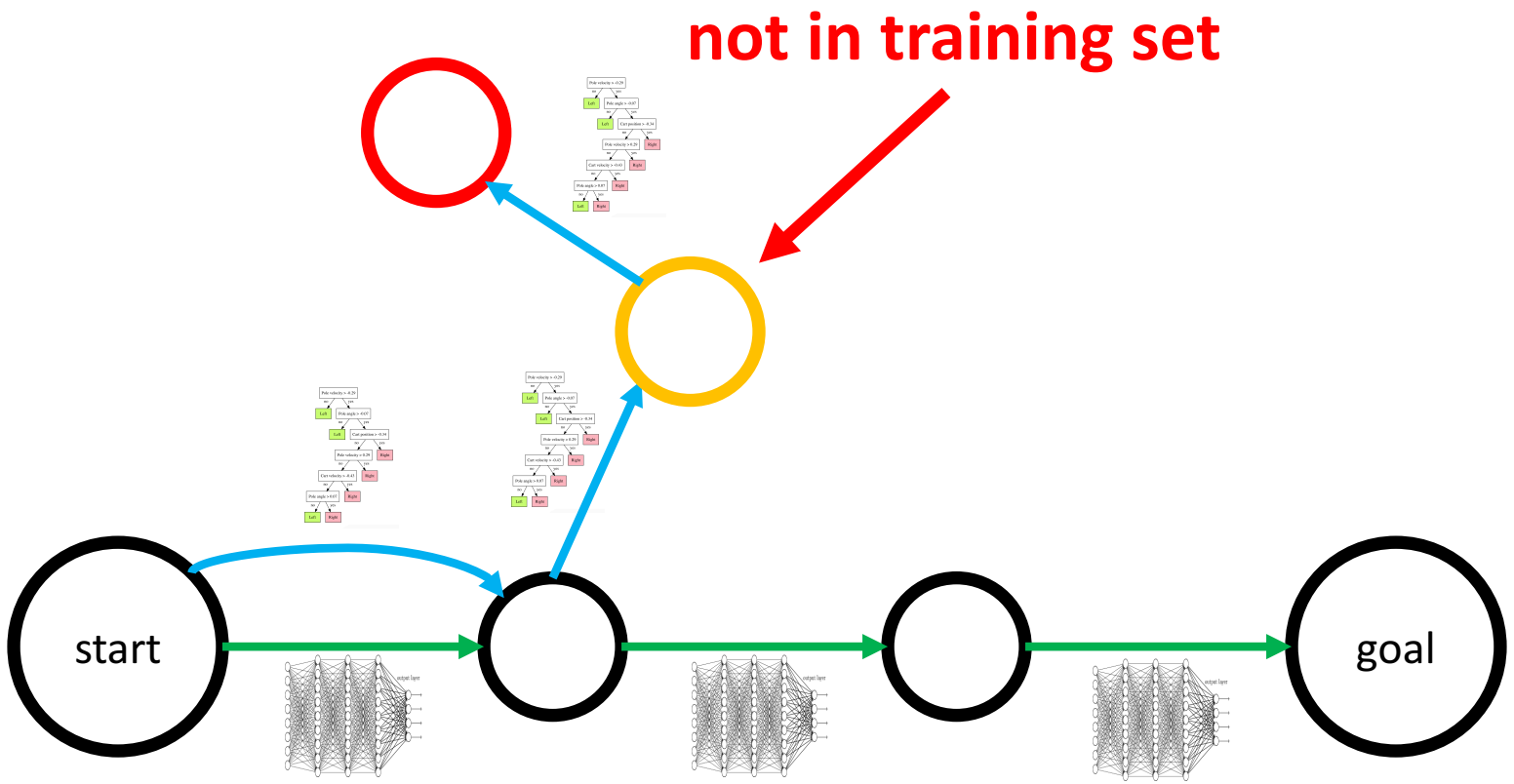
Step 2: Use NN to obtain actions



Step 3: Use supervised learning to train a decision tree

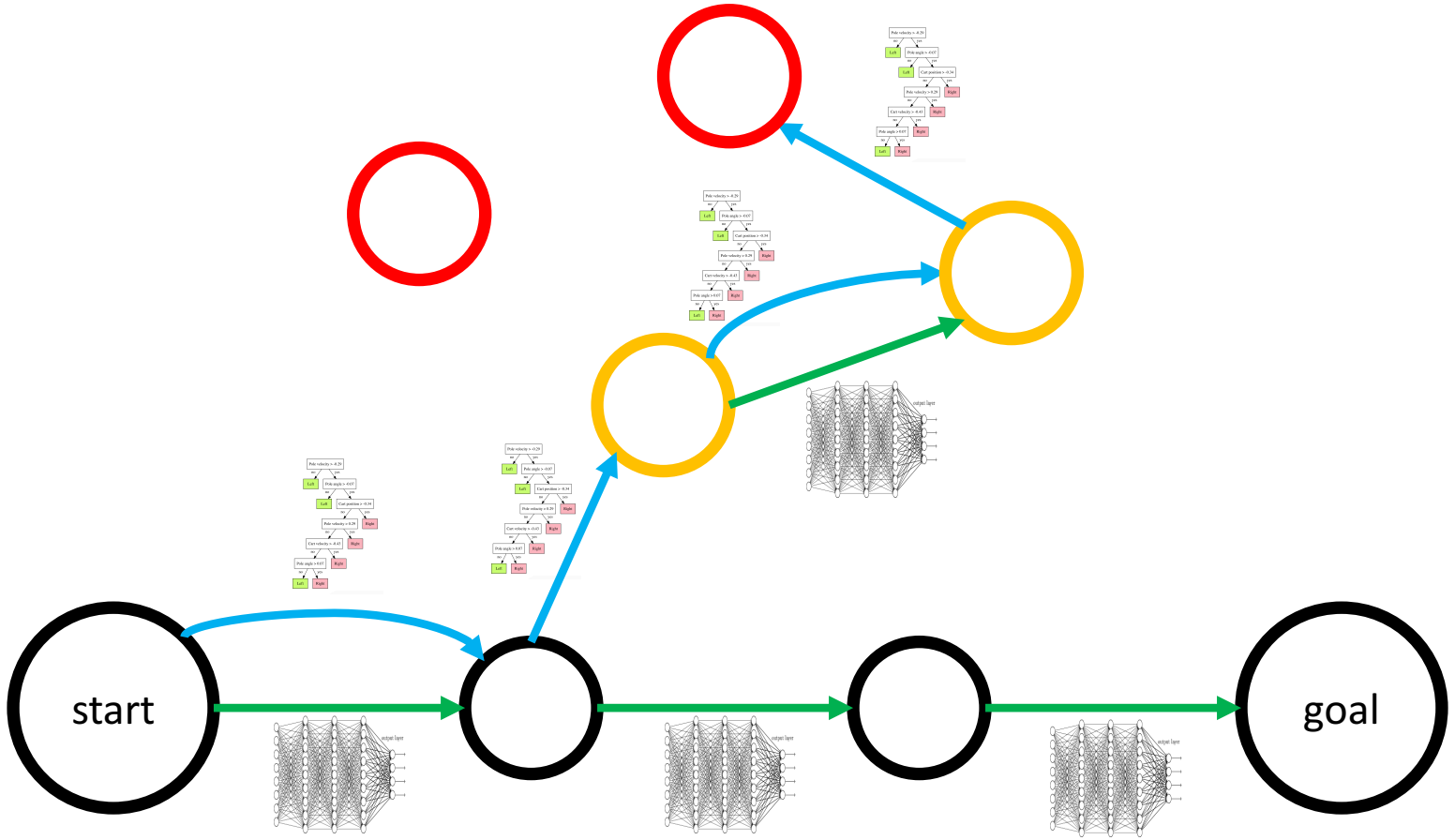
Ross & Bagnell 2011

Imitation Learning (Supervised)



Ross & Bagnell 2011

Imitation Learning (Dataset Aggregation)



Ross & Bagnell 2011

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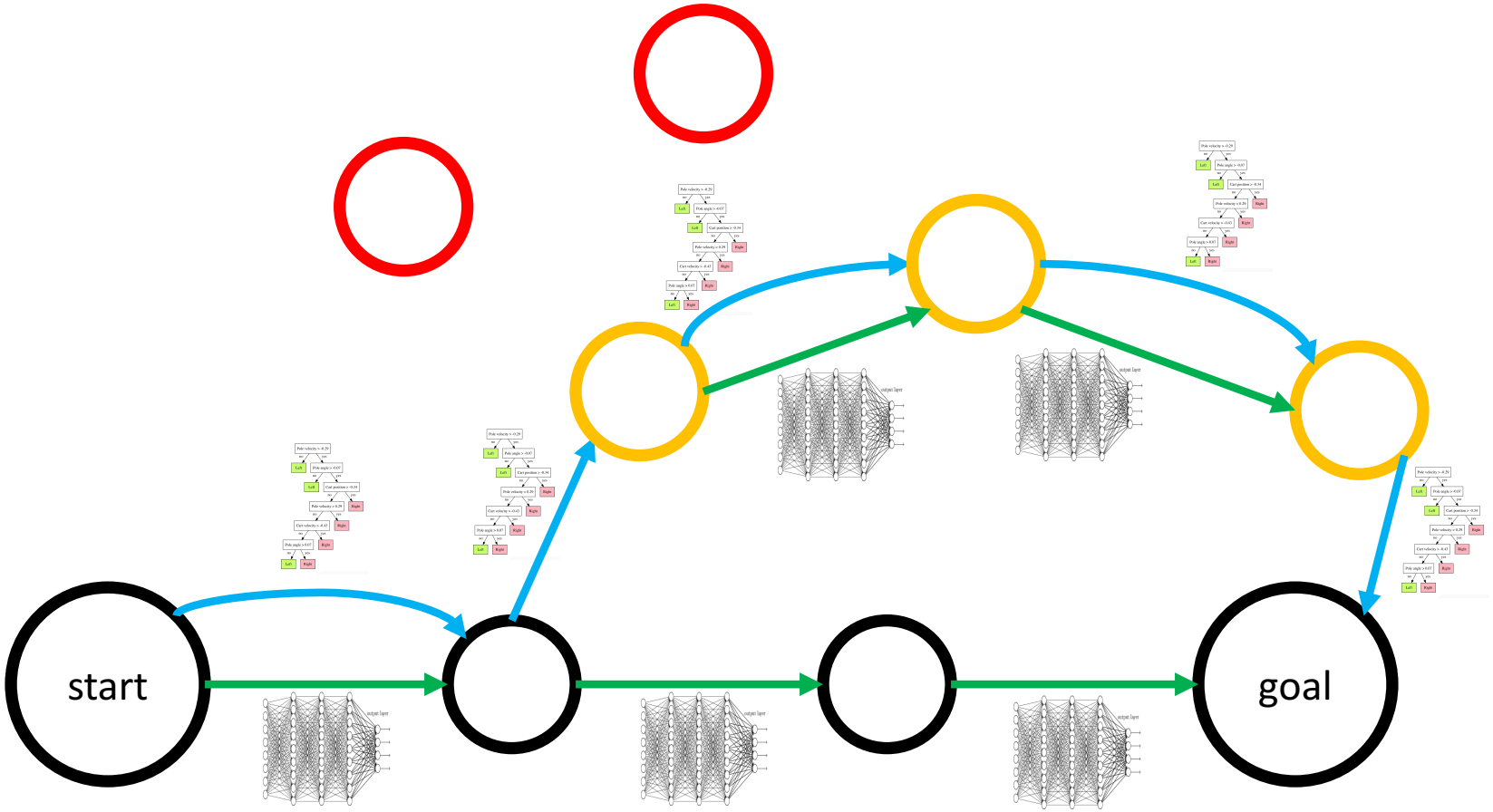
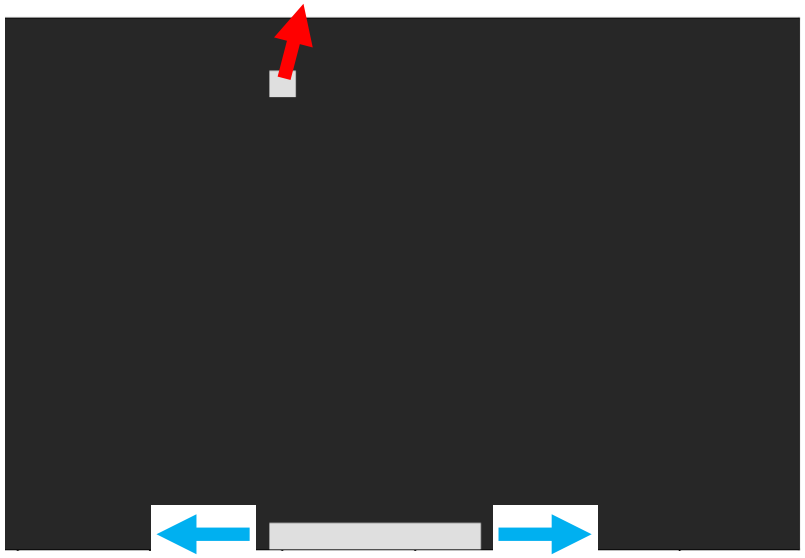
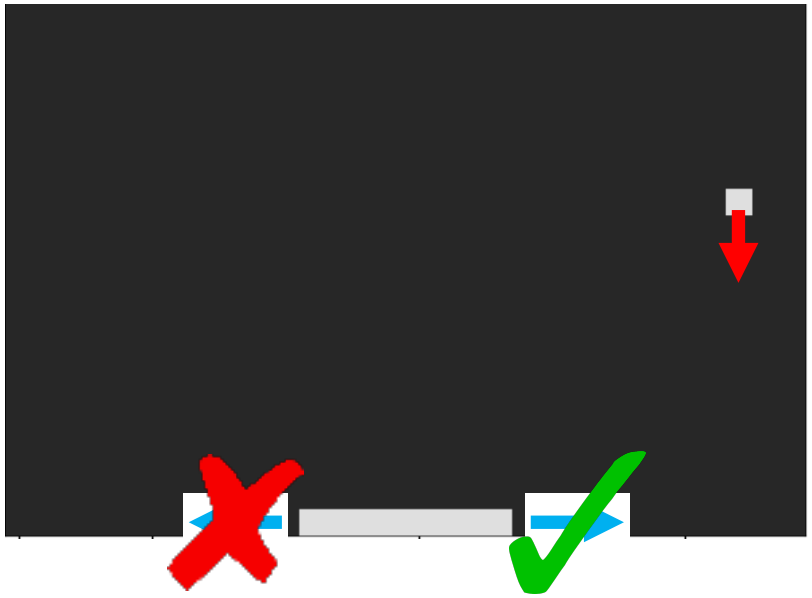


Ross & Bagnell 2011

Problem: Critical Actions



actions are similar



must move right!

Solution: Leverage $\boldsymbol{Q}$-Function

$Q(s, a) =$ “how good is action a in state s?”

Q-Dagger Algorithm

- Dataset Aggregation (Dagger) treats all state-action pairs equally:

$$\pi^* = \arg\min_{\pi} \sum_{(s,a)\in D} \mathbb{I}[\pi(s) = a]$$

- Q-Dagger weights state-action pairs by the Q-function

$$\pi^* = \arg\min_{\pi} \sum_{(s,a)\in D} Q(s,a) - Q\big(s,\pi(s)\big)$$

Theoretical Guarantees

Theorem. *For any $\delta > 0$, there exists a policy $\hat{\pi} \in \{\hat{\pi}_1, ..., \hat{\pi}_N\}$ such that*

$$J(\hat{\pi}) \leq J(\pi^*) + T\epsilon_N + \tilde{O}(1)$$

with probability at least $1 - \delta$, as long as $N = \tilde{\Theta}(\ell_{max}^2 T^2 \log(1/\delta))$.

Viper

- Extends Q-Dagger to extract decision tree controllers

Algorithm 1 Decision tree policy extraction.

procedure VIPER($(S, A, P, R), \pi^*, Q^*, M, N$)
  Initialize dataset $\mathcal{D} \leftarrow \varnothing$
  Initialize policy $\hat{\pi}_0 \leftarrow \pi^*$
  for $i = 1$ **to** N **do**
    Sample M trajectories $\mathcal{D}_i \leftarrow \{(s, \pi^*(s)) \sim d^{(\hat{\pi}_{i-1})}\}$
    Aggregate dataset $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$
    Resample dataset $\mathcal{D}' \leftarrow \{(s, a) \sim p((s, a)) \propto \tilde{\ell}(s)\mathbb{I}[(s, a) \in \mathcal{D}]\}$
    Train decision tree $\hat{\pi}_i \leftarrow \text{TrainDecisionTree}(\mathcal{D}')$
  end for
  return Best policy $\hat{\pi} \in \{\hat{\pi}_1, ..., \hat{\pi}_N\}$ on cross validation
end procedure

Evaluation

- Comparison to baselines
- Verified desirable properties

Comparison to Fitted $\boldsymbol{Q}$-Iteration (on Cart-pole)

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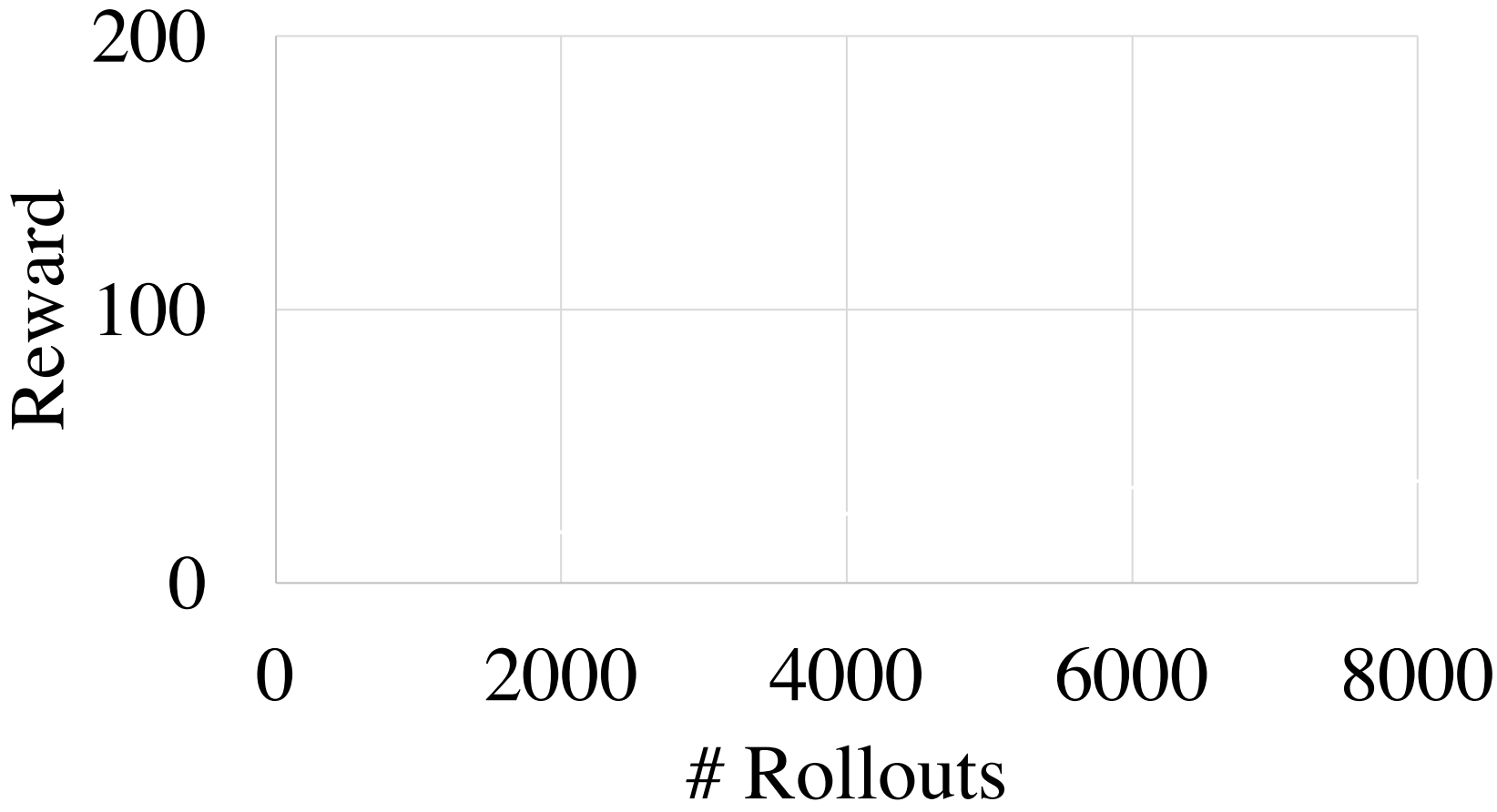
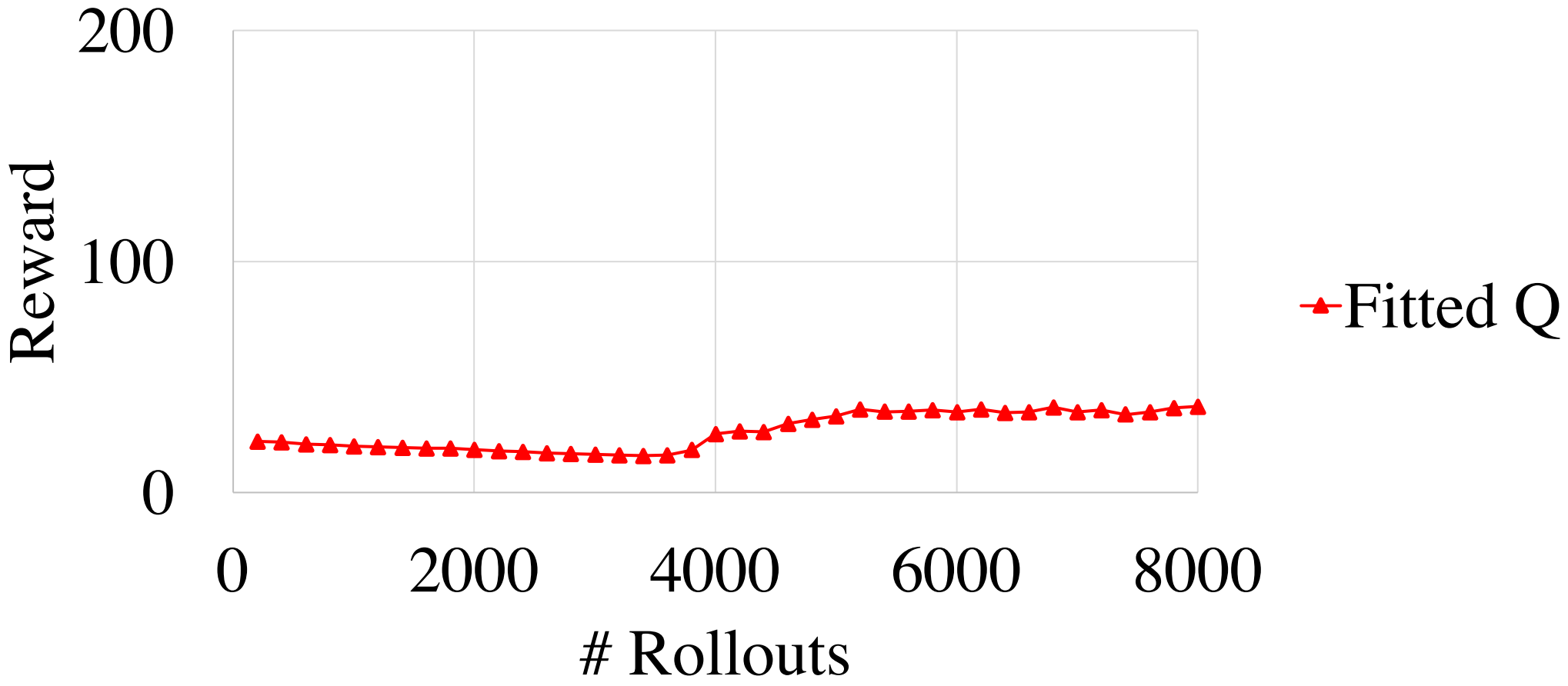
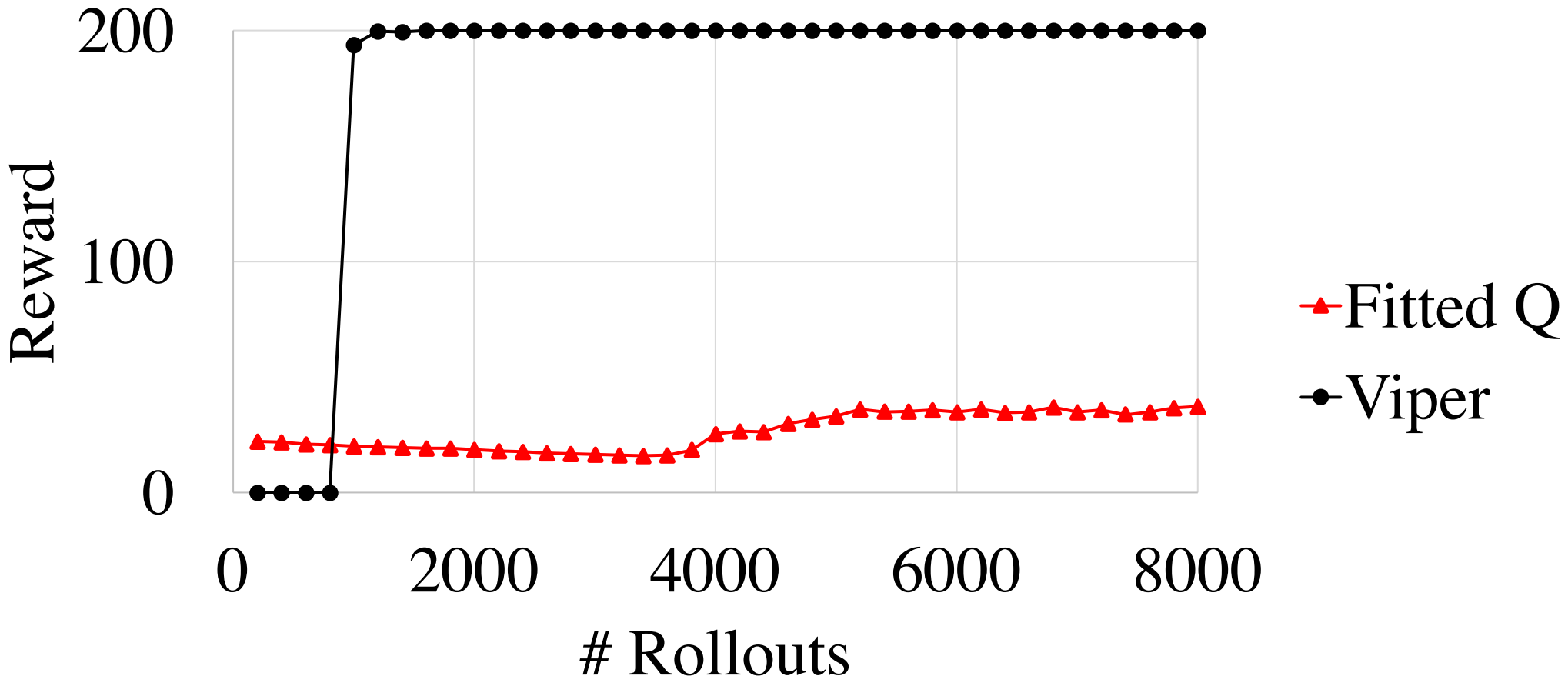


Comparison to Fitted $\boldsymbol{Q}$-Iteration (on Cart-pole)



Comparison to Fitted $\boldsymbol{Q}$-Iteration (on Cart-pole)



Comparison to Dagger (on Atari Pong)

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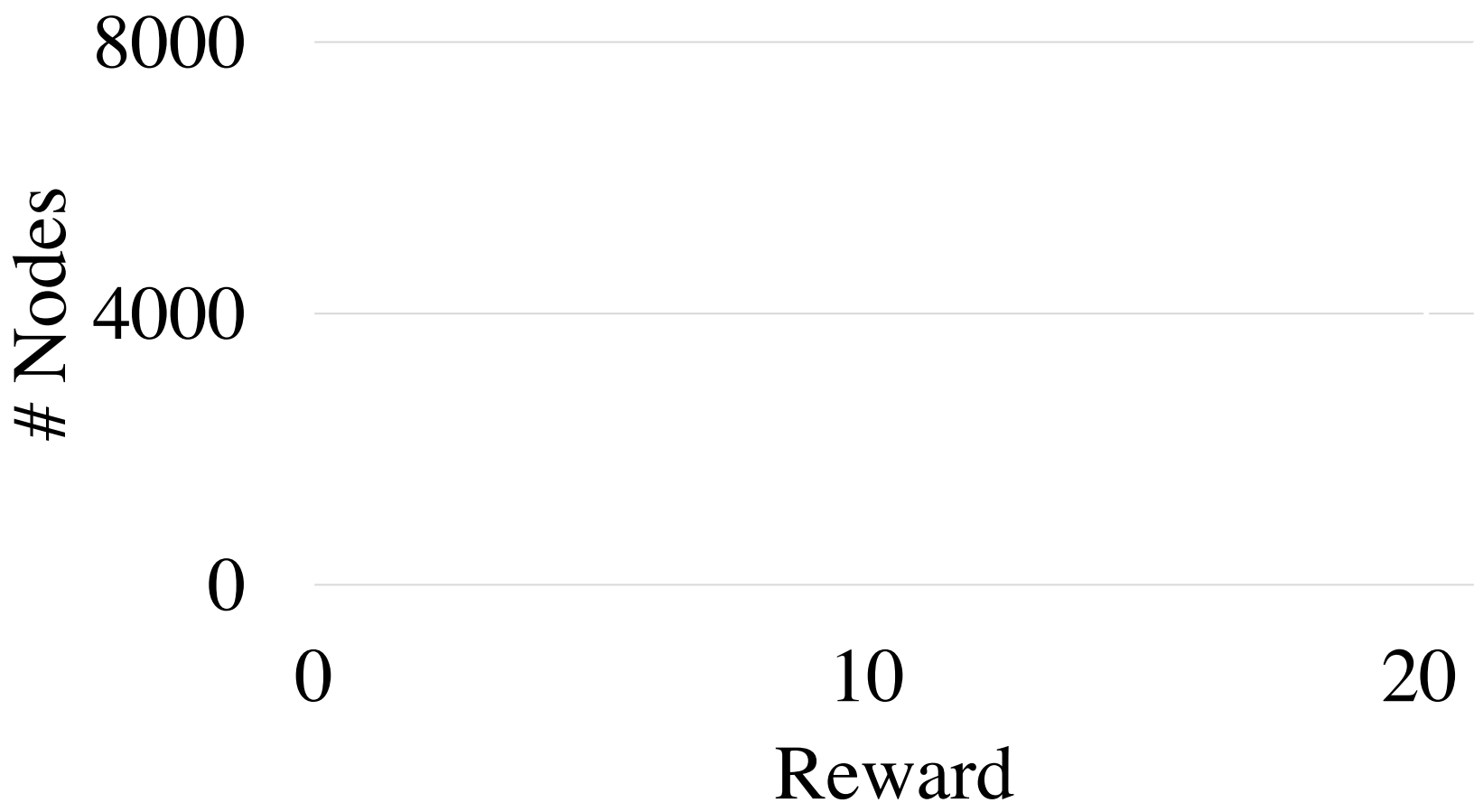

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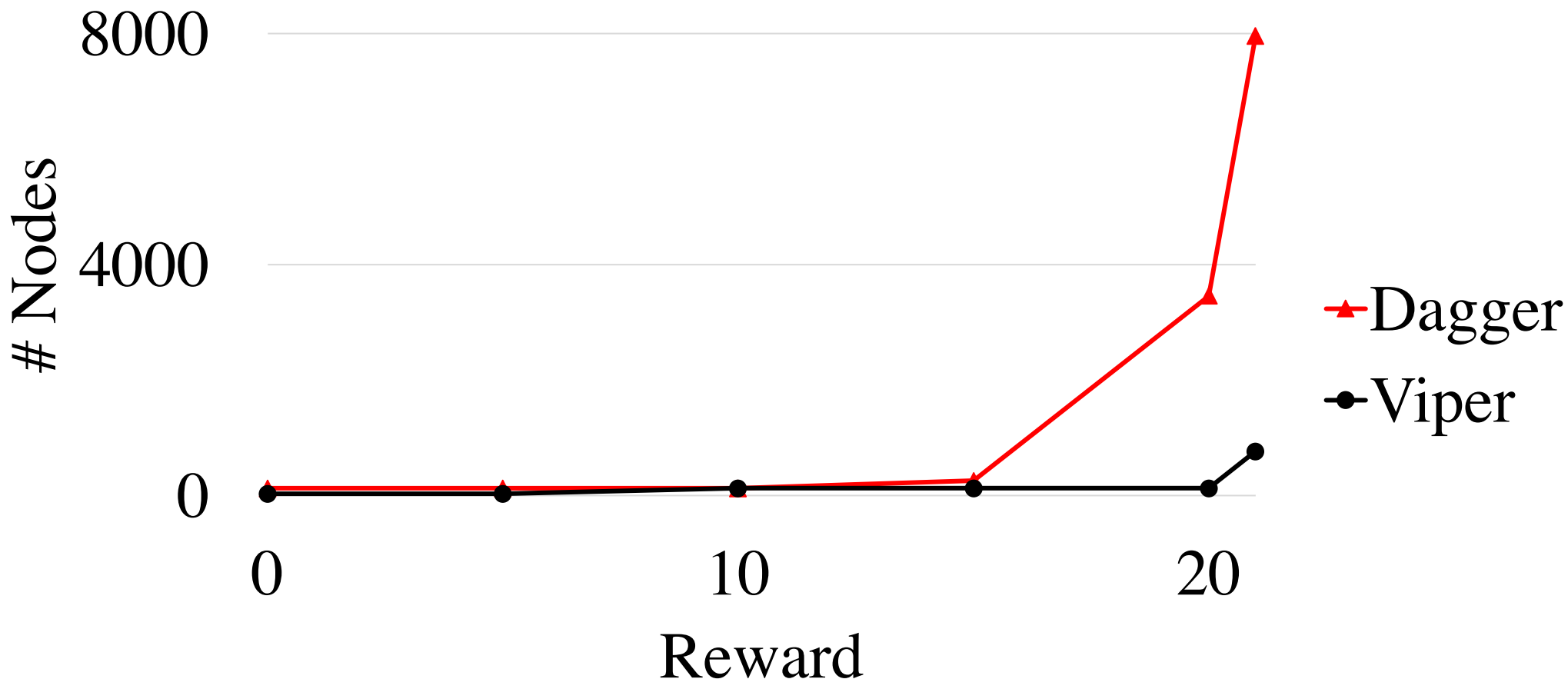
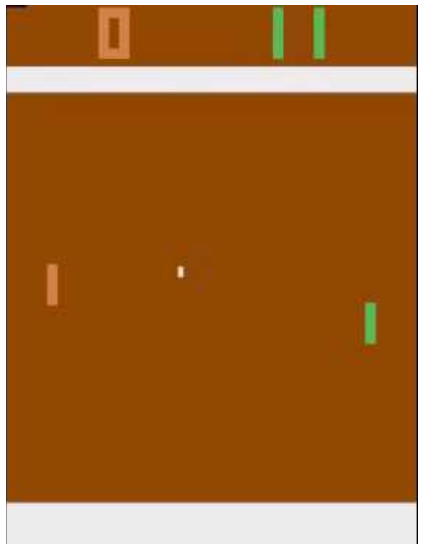
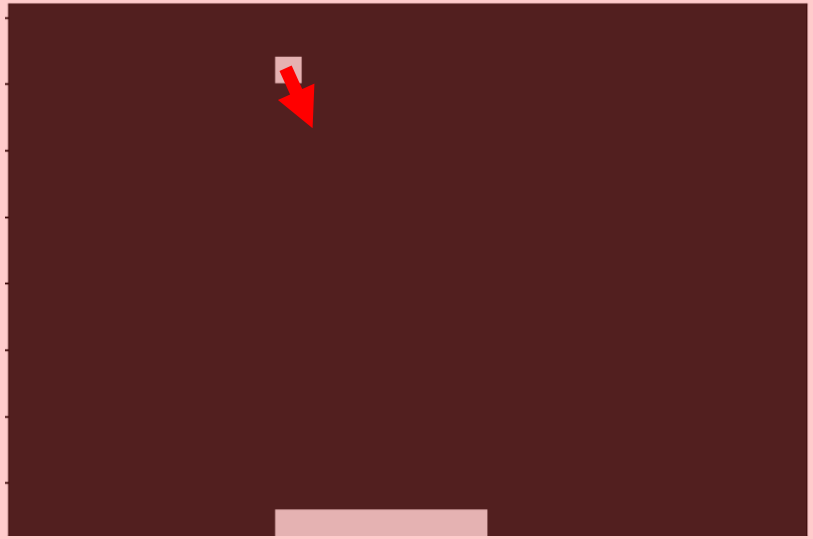


Verification



robustness

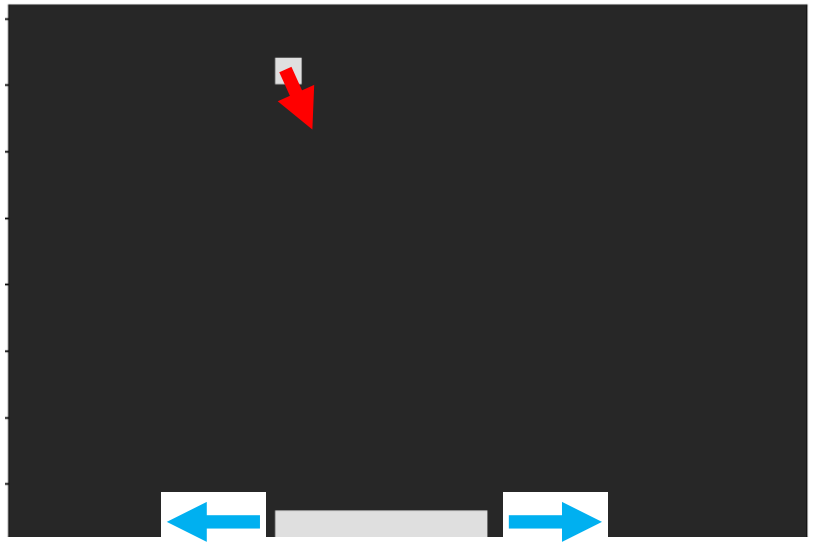


correctness
(never loses)

stable

Verifying Correctness of a Toy Pong Controller

- **Toy Pong**
  - states $= \mathbb{R}^5$
  - actions $= \{\text{left}, \text{right}, \text{stay}\}$
- **Neural network:**
  - trained using policy gradients
  - 600 neurons
- **Decision tree:**
  - extracted using Viper
  - 31 nodes



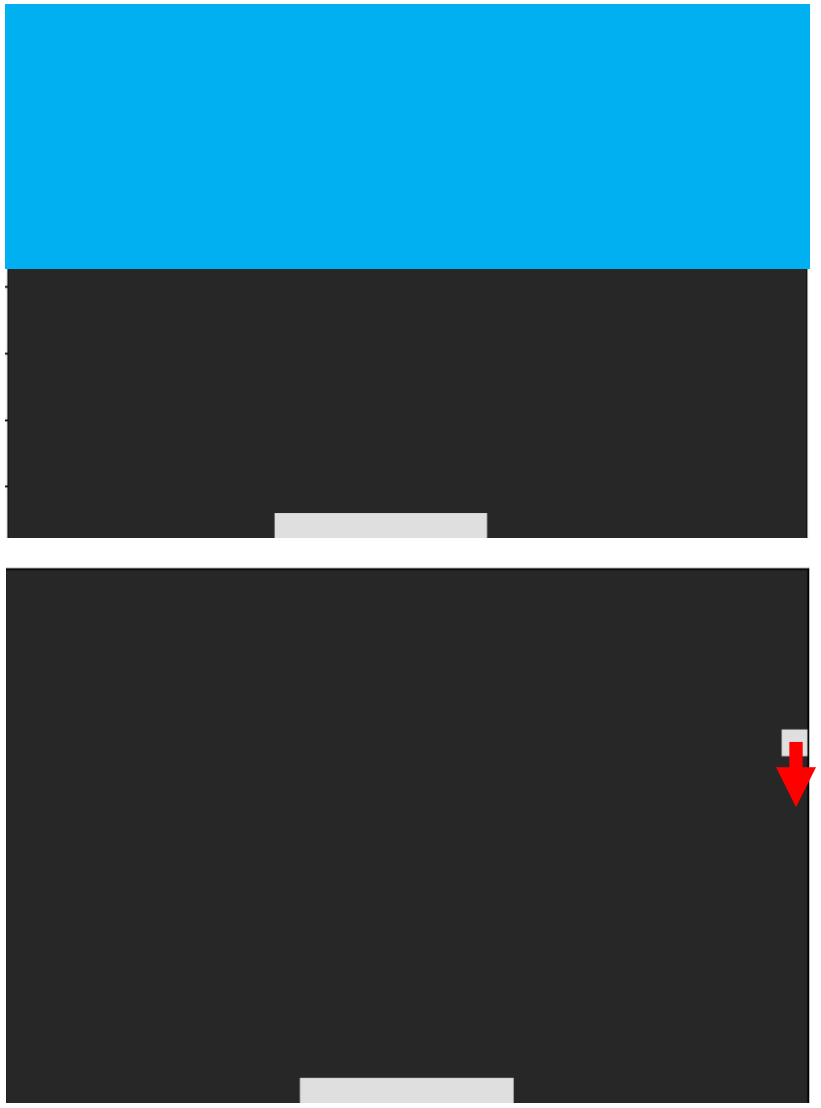
Verifying Correctness of a Toy Pong Controller

- **Inductive invariant:**

$$s(0) \in \text{blue} \Rightarrow s(t) \in \text{blue}$$

- **Verification algorithm**
  - dynamics are piecewise linear
  - SMT formula over linear arithmetic
  - solved by Z3 in < 5 seconds

- **Results:**
  - error when ball starts on the right
  - fixed when paddle is slightly longer!



Conclusion

Verifiability is critical to enabling application of deep reinforcement learning to safe-critical systems