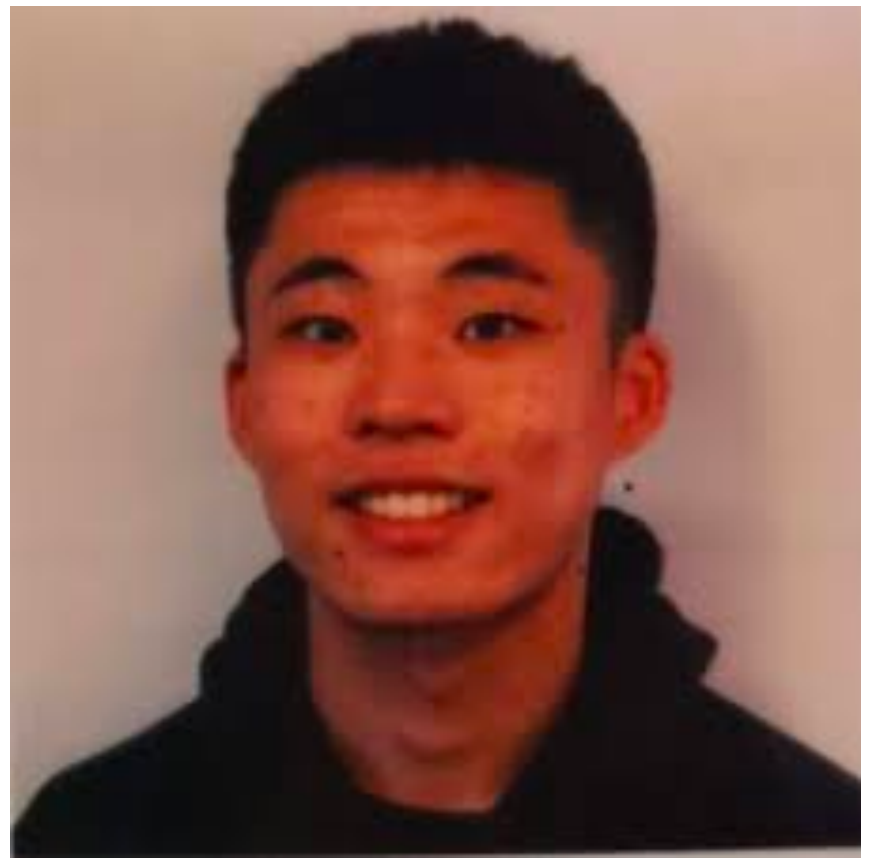
The Virtues of Laziness in Model-based RL

Anirudh Vemula



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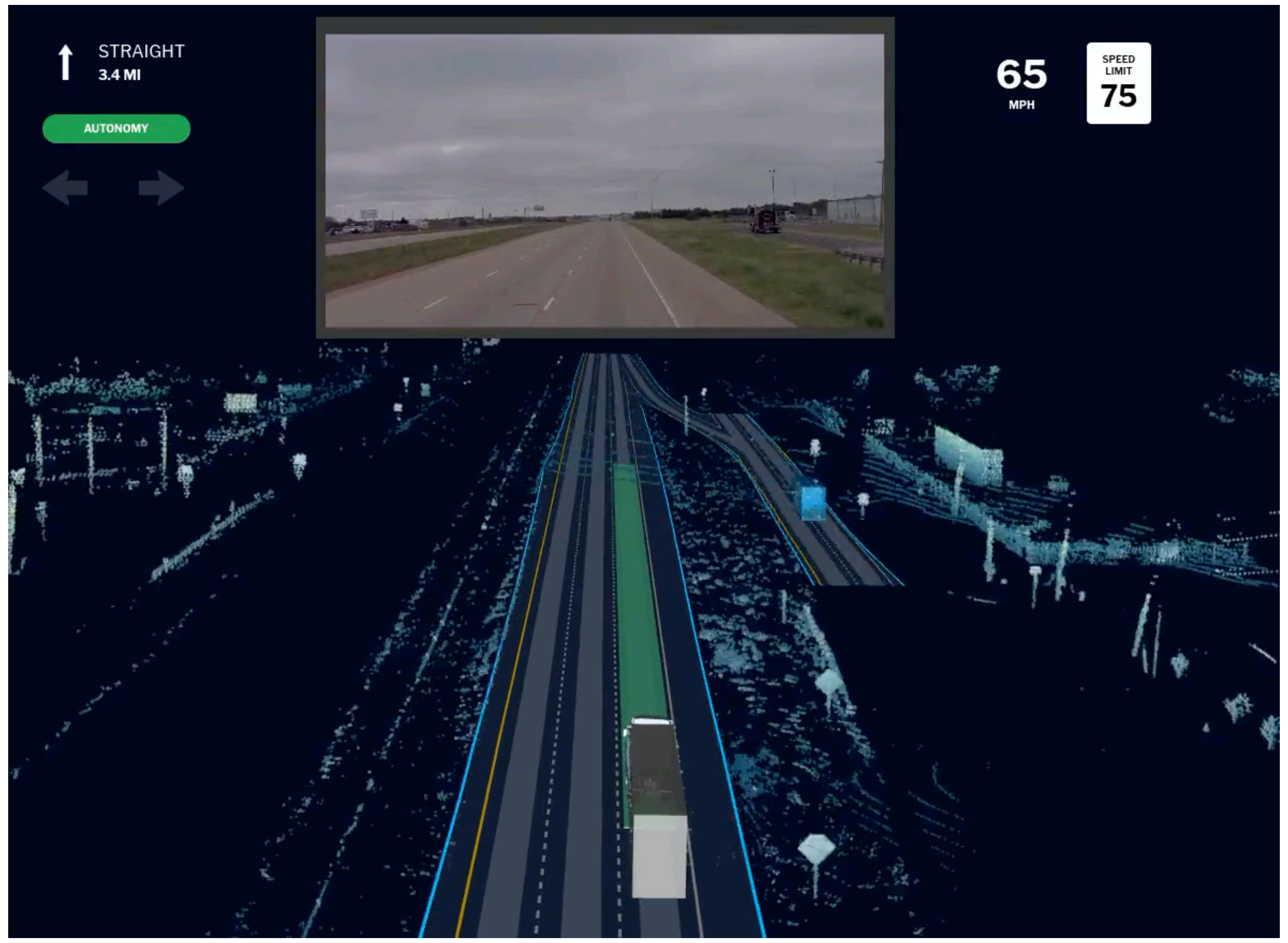
Why Model?

Models are *necessary*

Robots can’t just try out random actions in the world!

Models are *necessary*

We invested heavily in simulators for helicopters and self-driving to verify behaviors before deployment



Models work in *theory*

Model-Based Reinforcement Learning with a Generative Model is Minimax Optimal

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April 7, 2020

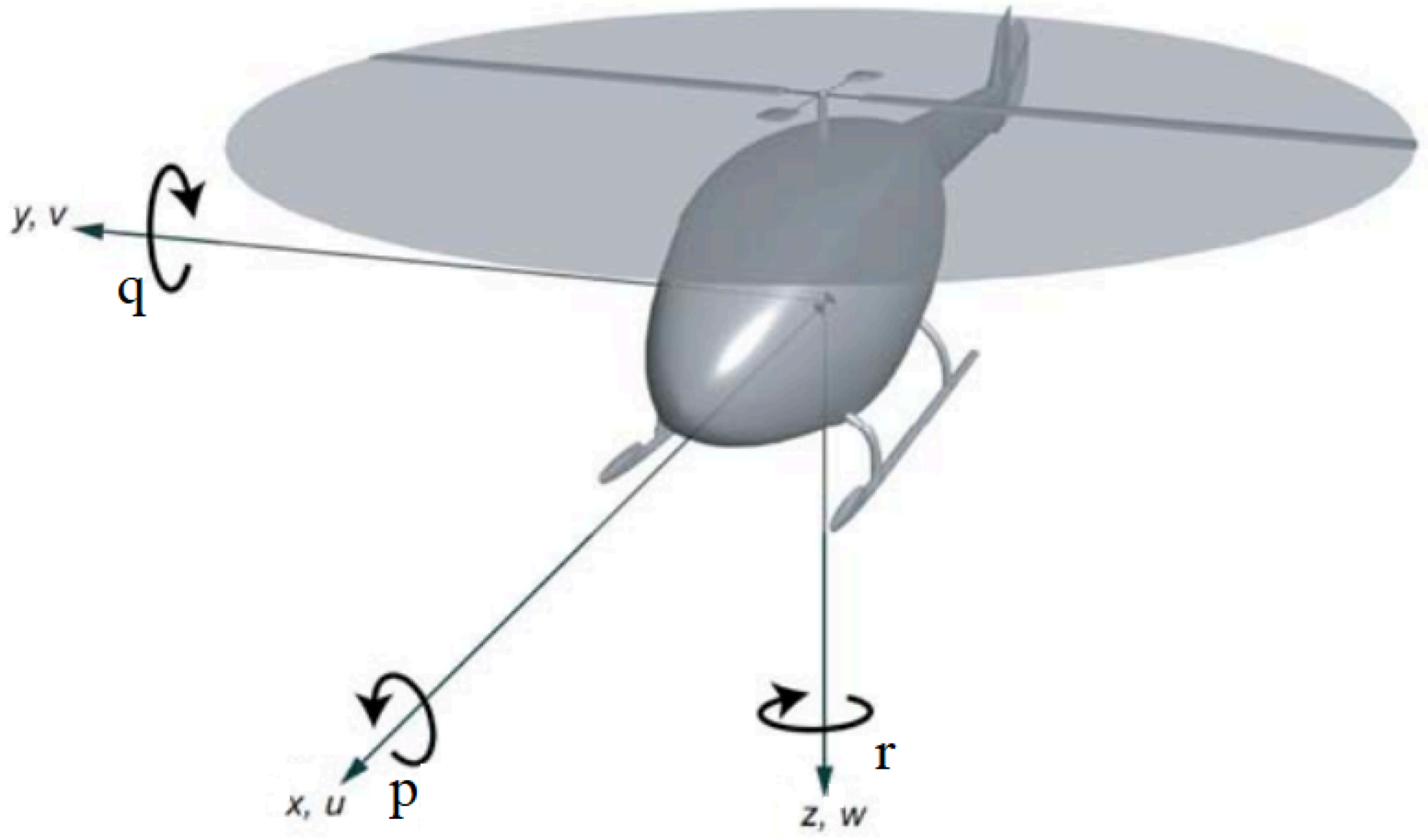
Models work in *practice*

Hafner et al. 2023

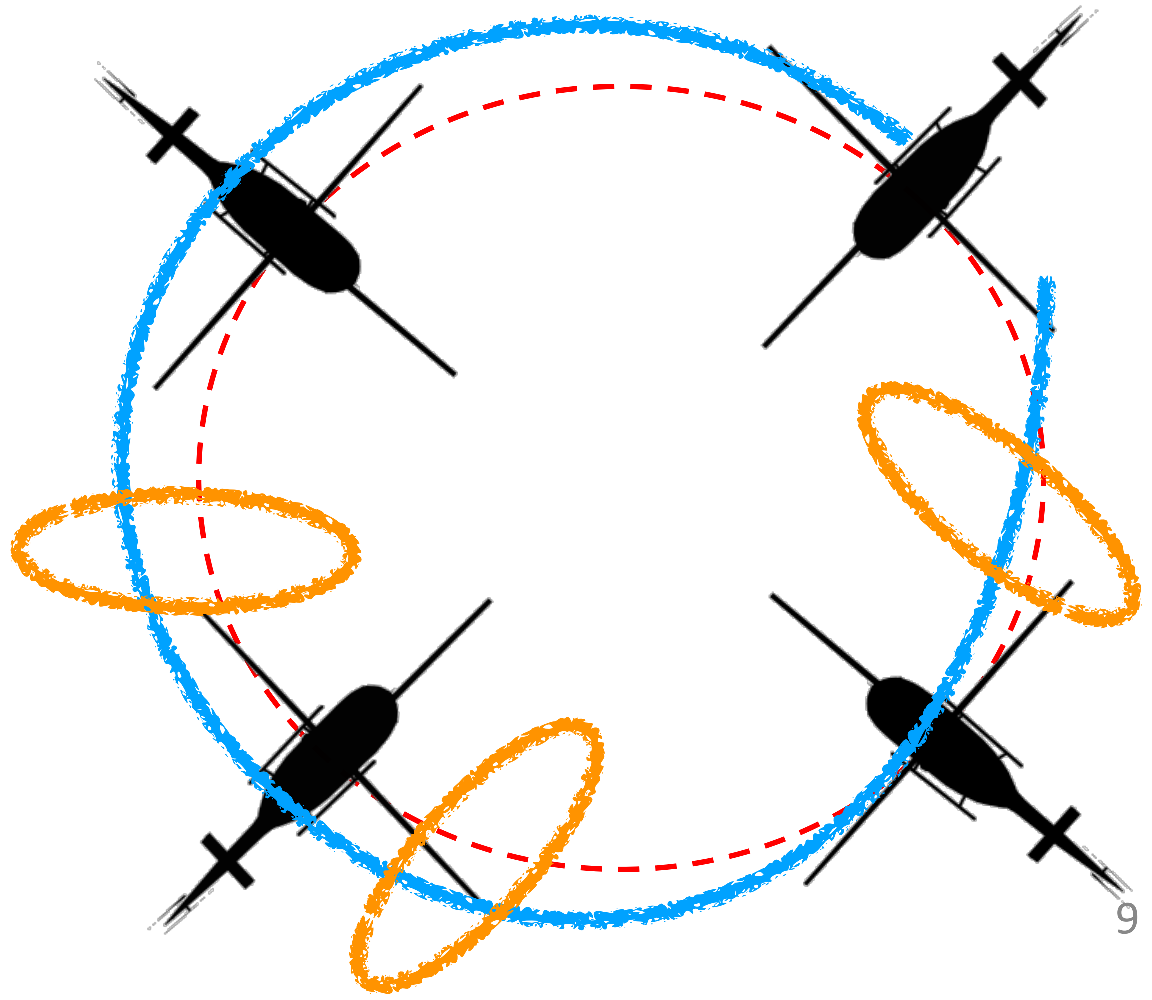
Learning Models.

(Early work in Model Based RL by Pieter Abeel et al. 2010
https://people.eecs.berkeley.edu/~pabbeel/autonomous_helicopter.html)

Learn Model → Plan with Learned Model



Least Squares Fit

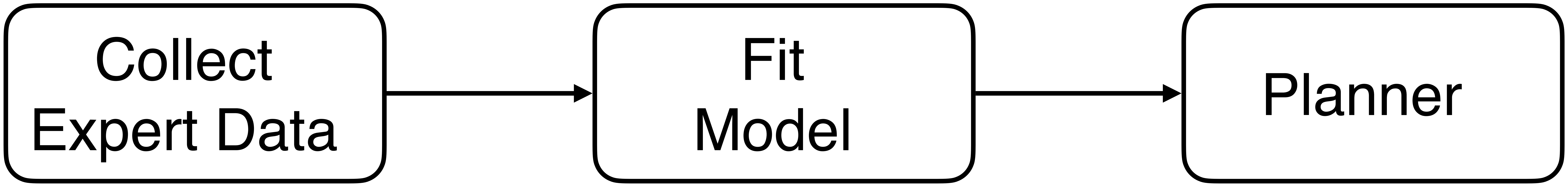


ILQR

Strategy

Train a model on state actions visited by the expert!

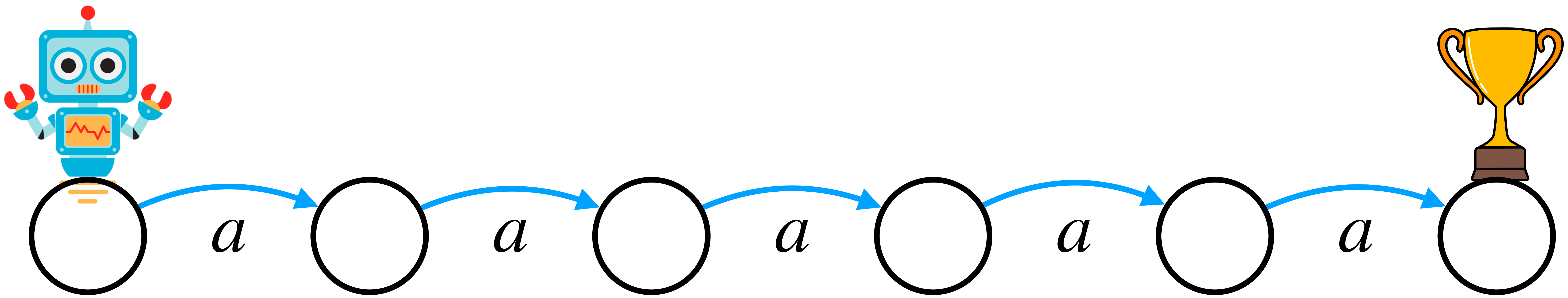
Model Based RL v1.0



*If I **perfectly** fit a model (i.e. training error zero),*
this should work, right?

World

s'=$M^*(s, a)$



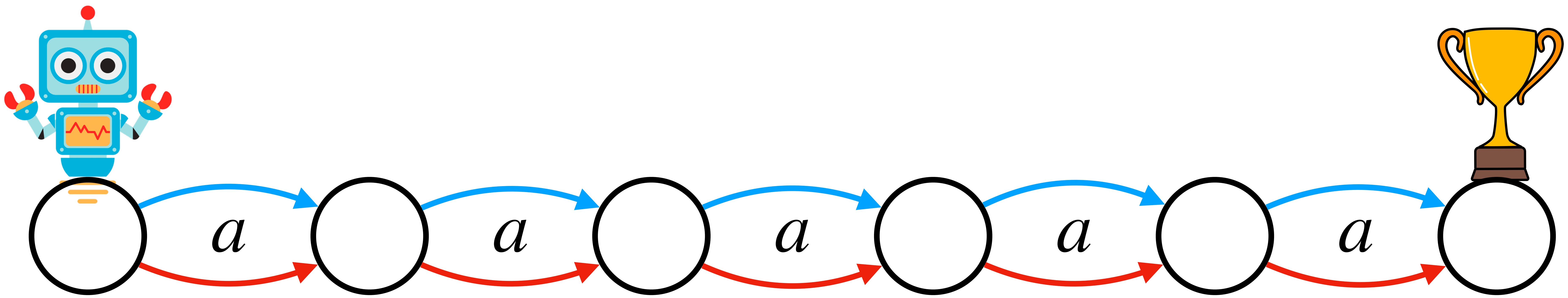
Experts picks action a to go to the goal

Model

s'=$\hat{M}(s, a)$

World

s'=$M^*(s, a)$



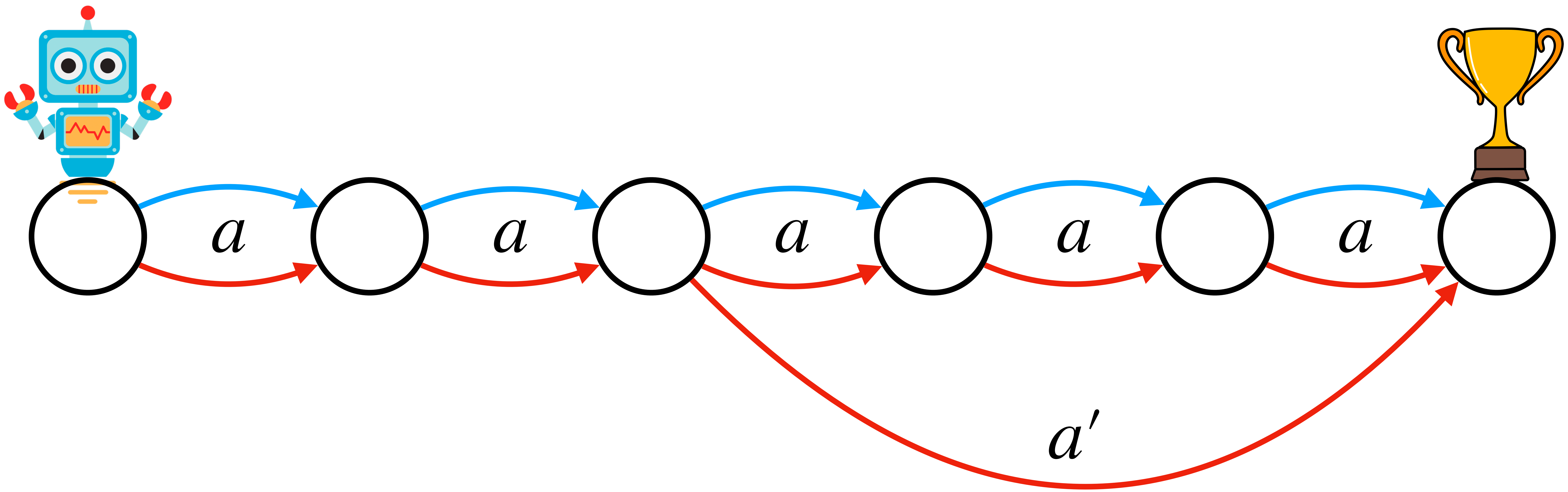
Model agrees with world, i.e. train error zero!

Model

s'=$\hat{M}(s, a)$

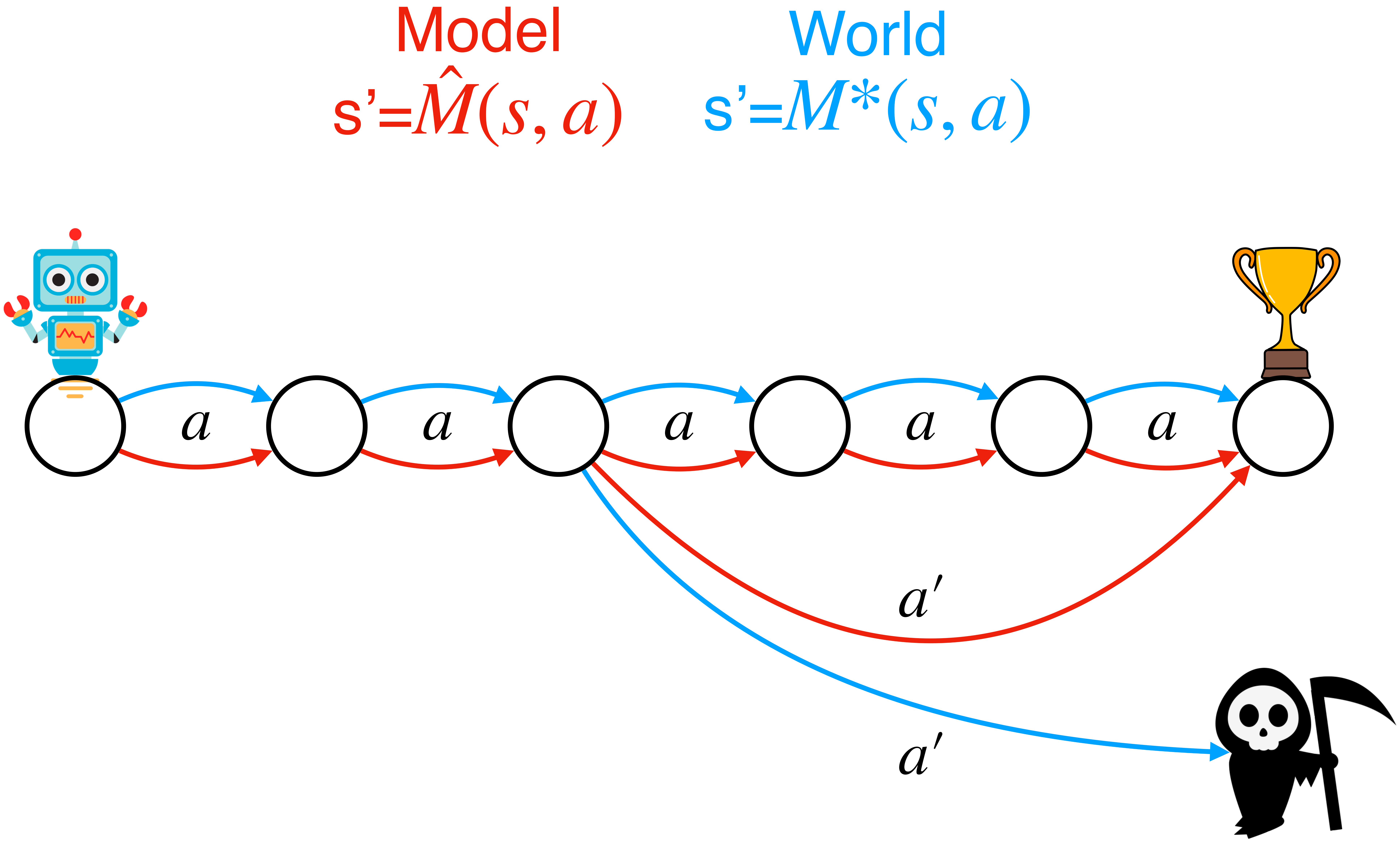
World

s'=$M^*(s, a)$

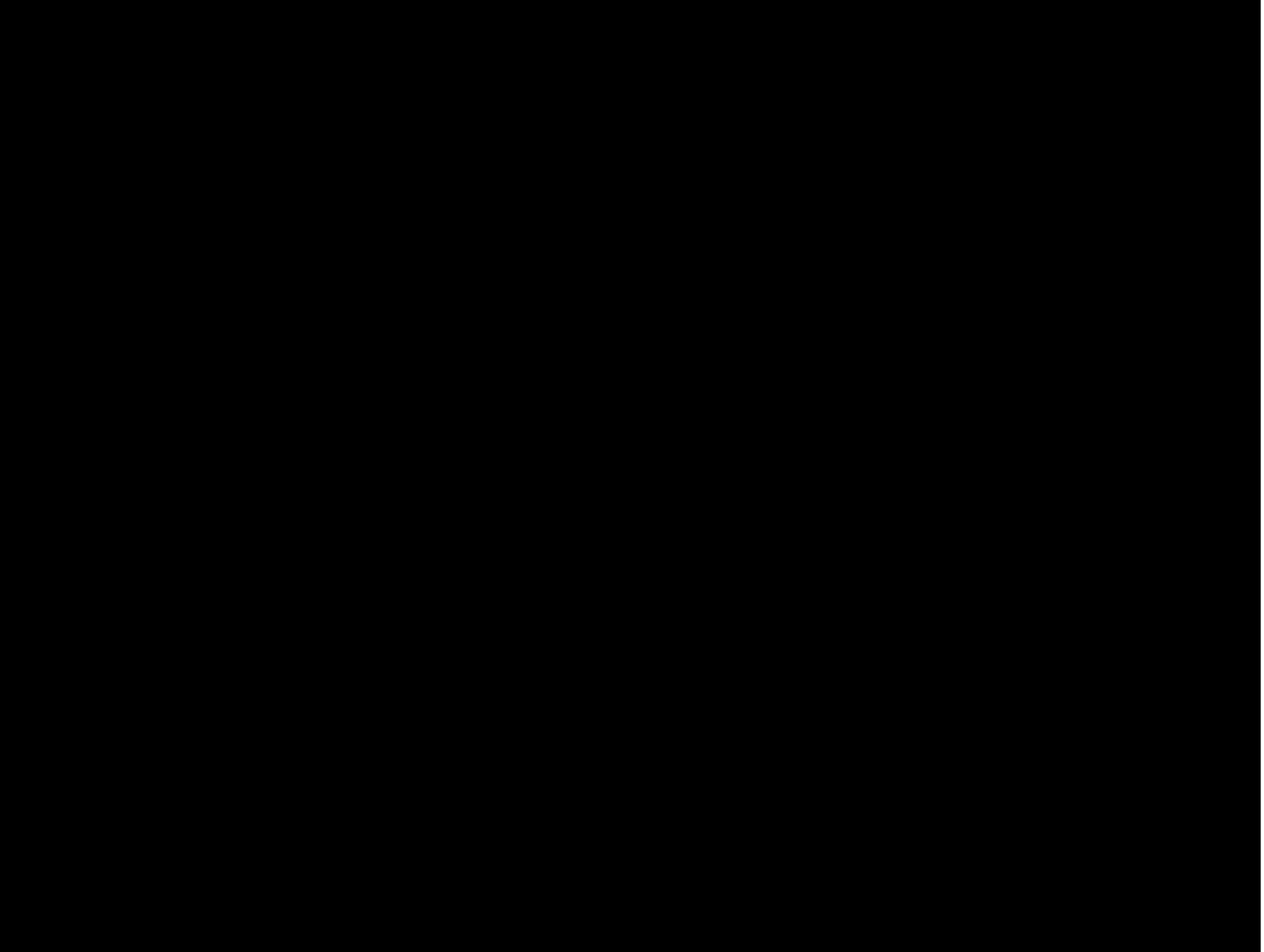


What if the model is optimistic?

Predicts a short cut to the goal by taking action a'



In reality the shortcut ends in death …



Training on Expert Data

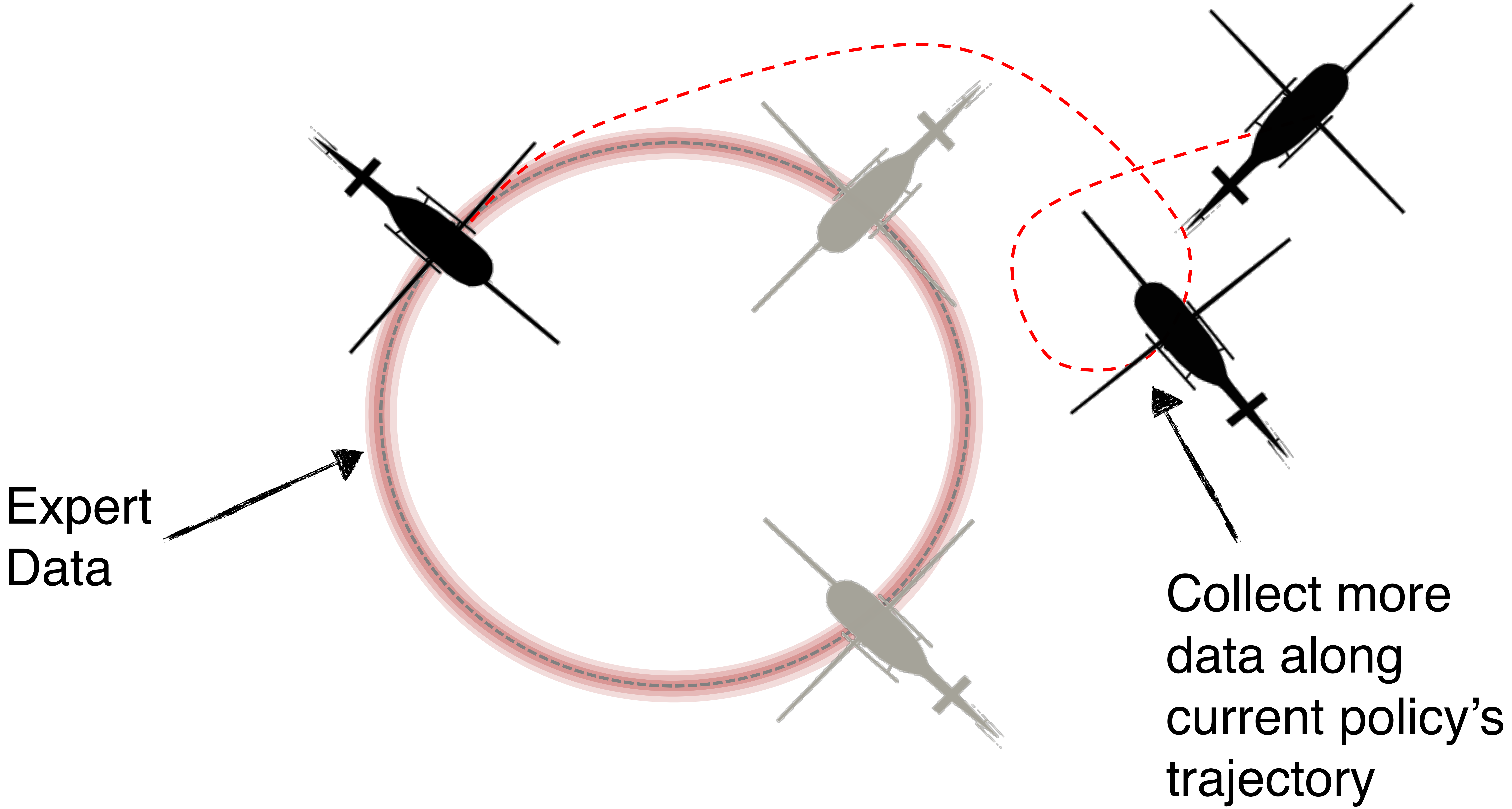
(From Ross and Bagnell, 2012)

Strategy

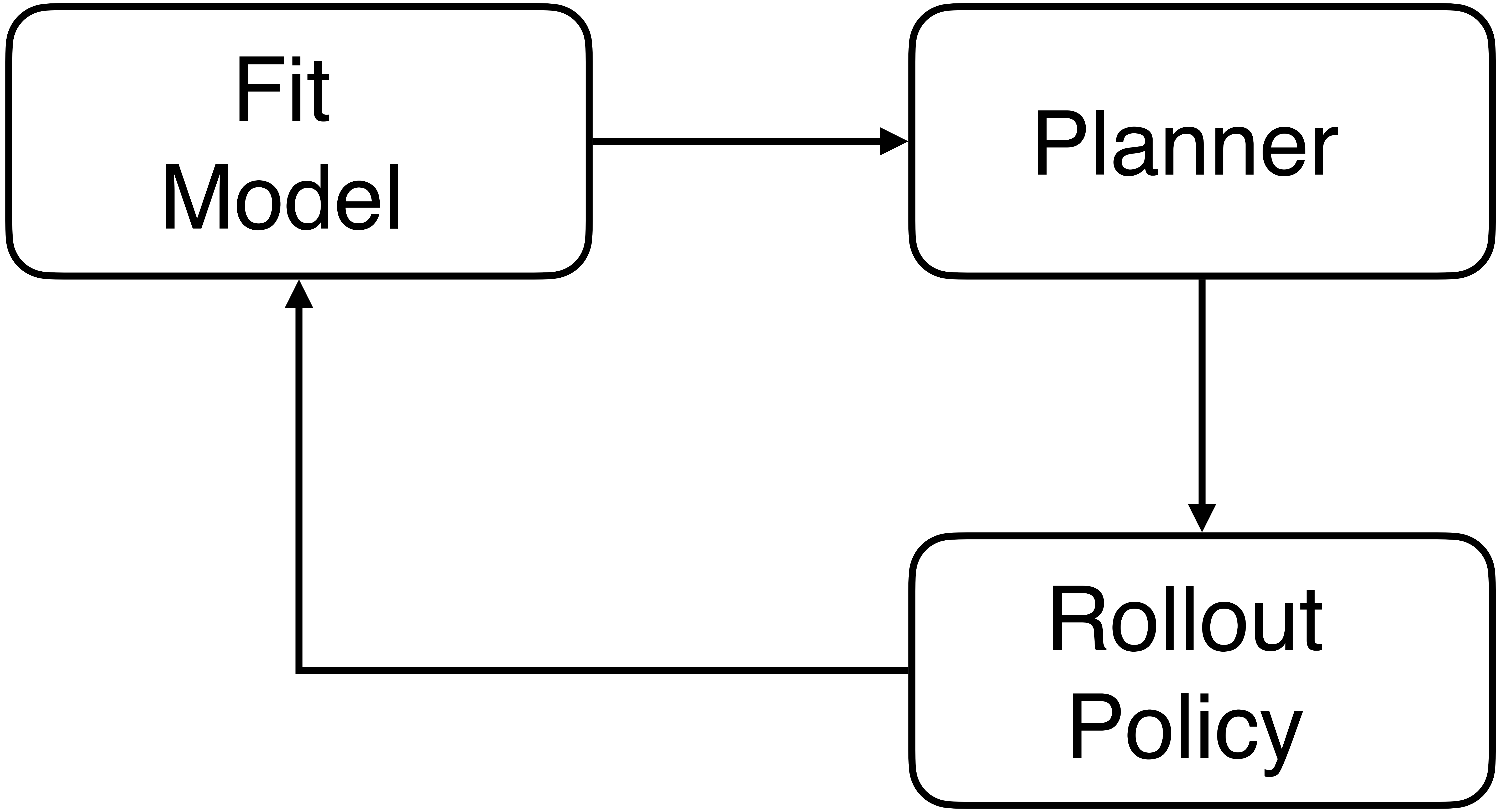
~~Train a model on state actions visited by the expert!~~

Train a model on state actions visited by the learner!

Improve model where policy goes



Model Based RL v2.0



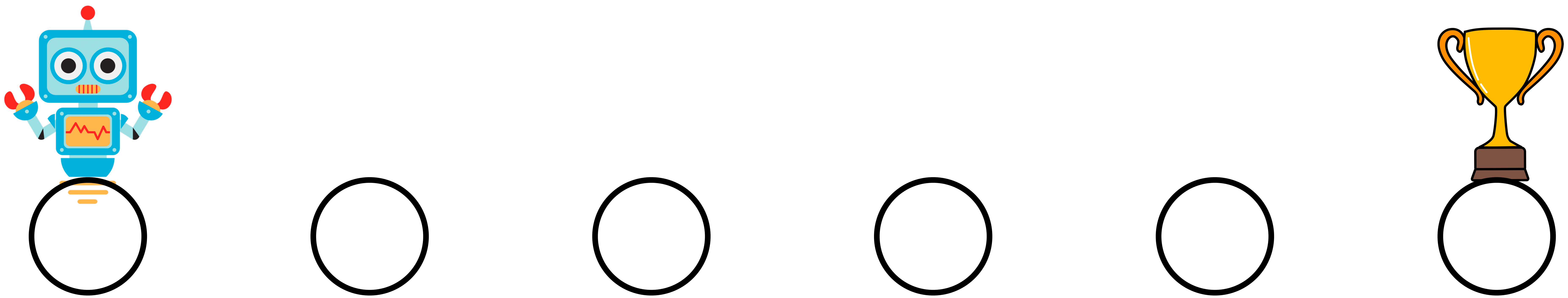
*If I **perfectly** fit a model (i.e. training error zero), this should work, right?*

Model

s'=$\hat{M}(s, a)$

World

s'=$M^*(s, a)$

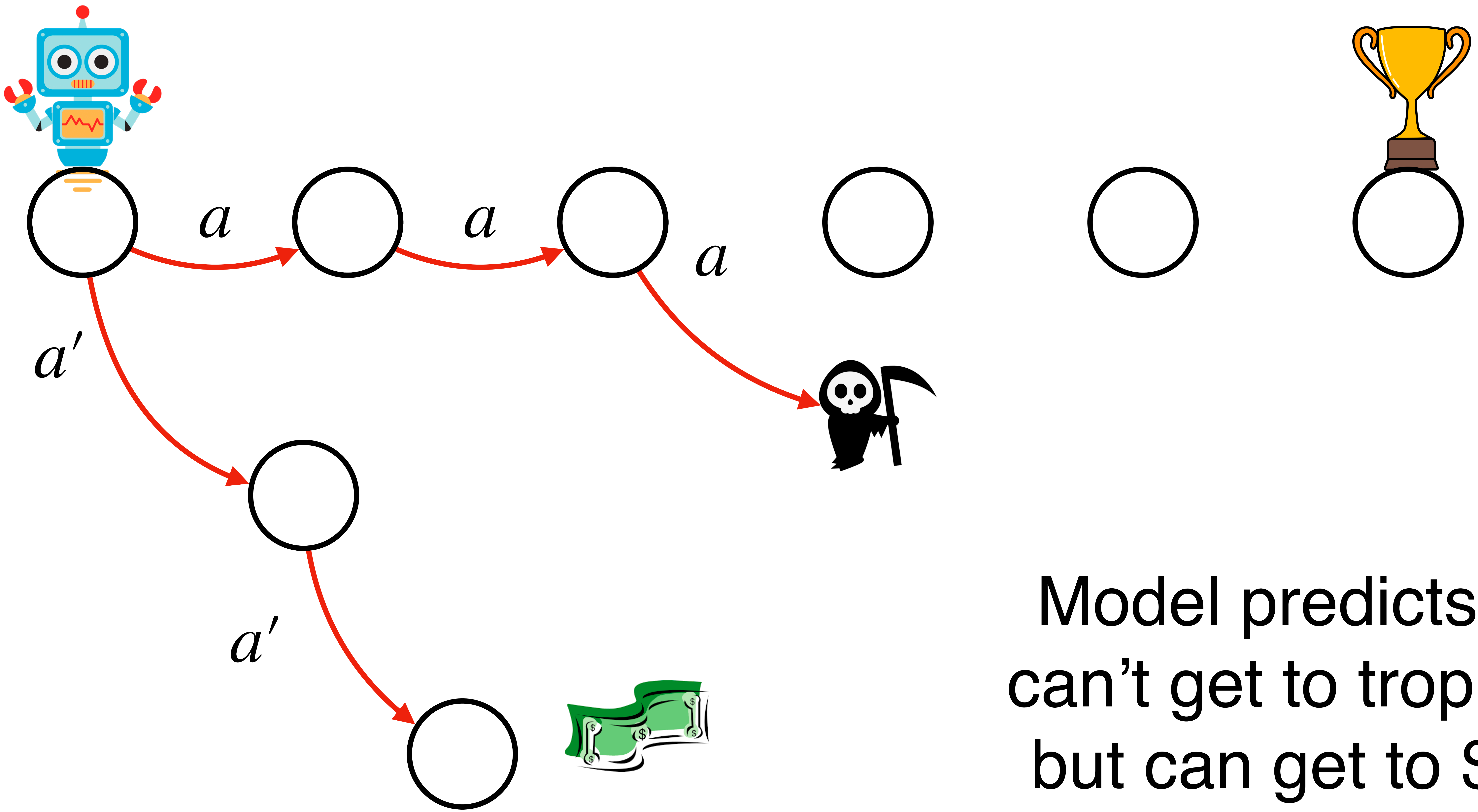


Model

s'=$\hat{M}(s,a)$

World

s'=$M^*(s,a)$



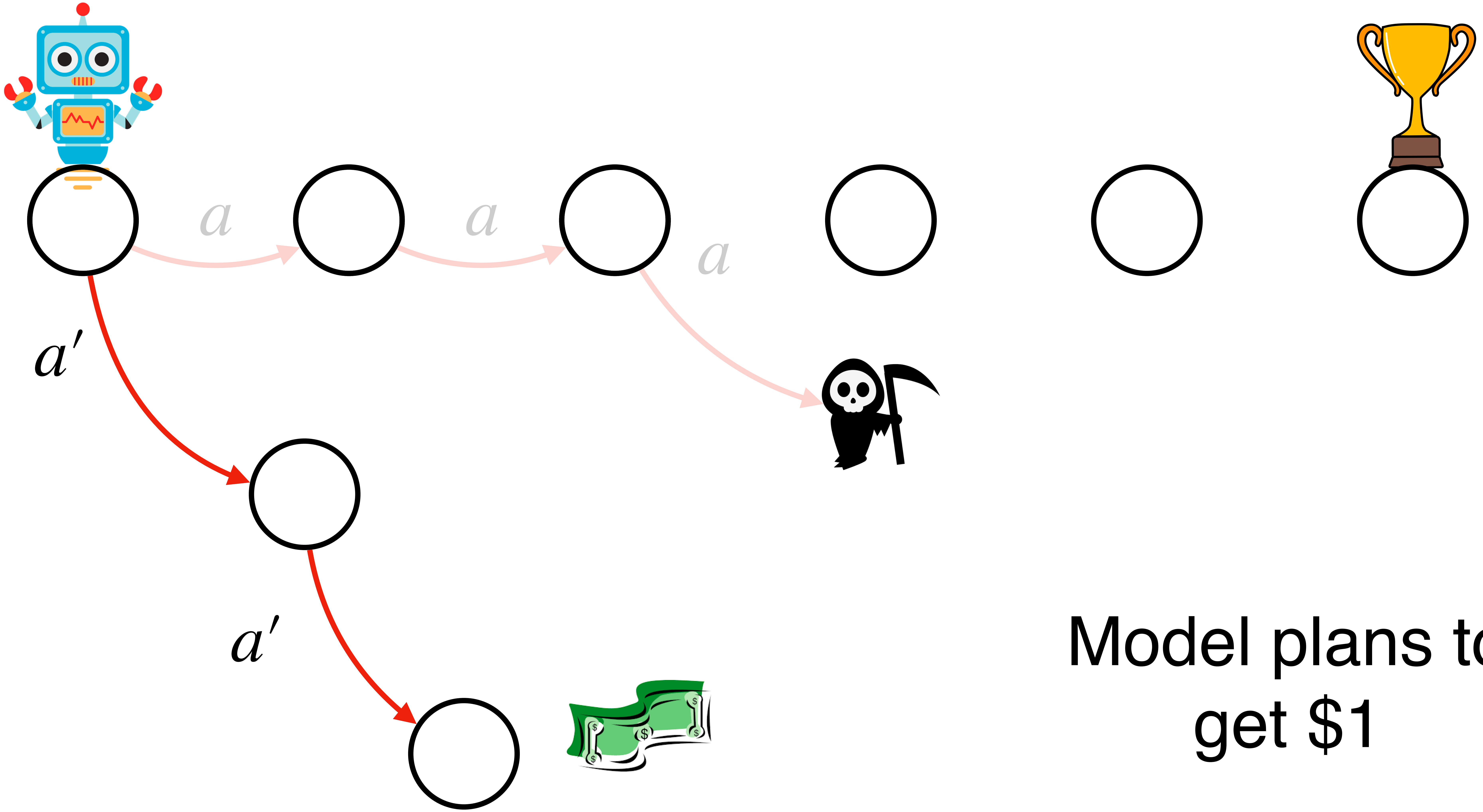
Model predicts it can't get to trophy, but can get to $1

Model

s'=$\hat{M}(s, a)$

World

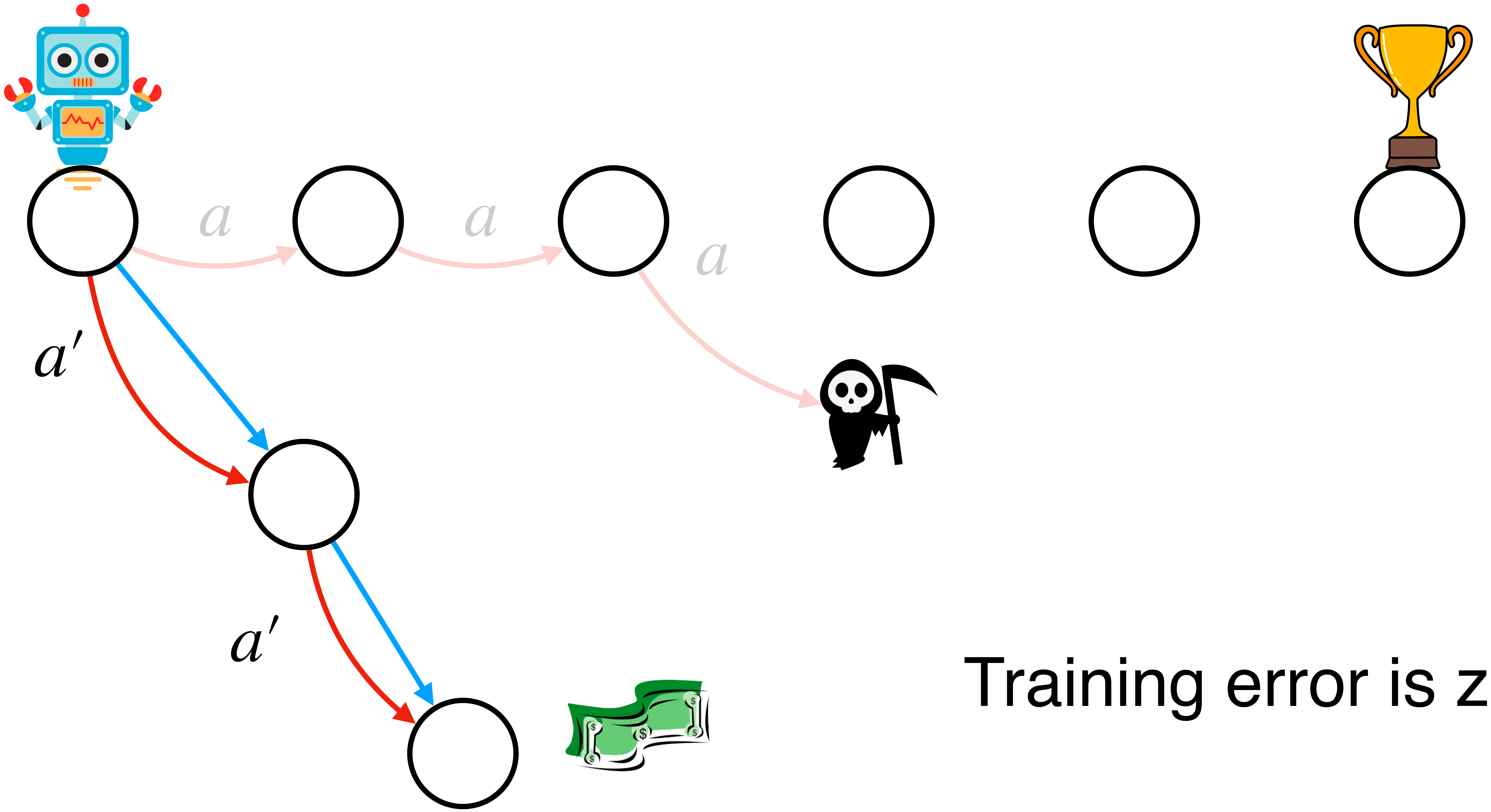
s'=$M^*(s, a)$



Model plans to get $1

Model
s’=$\hat{M}(s, a)$

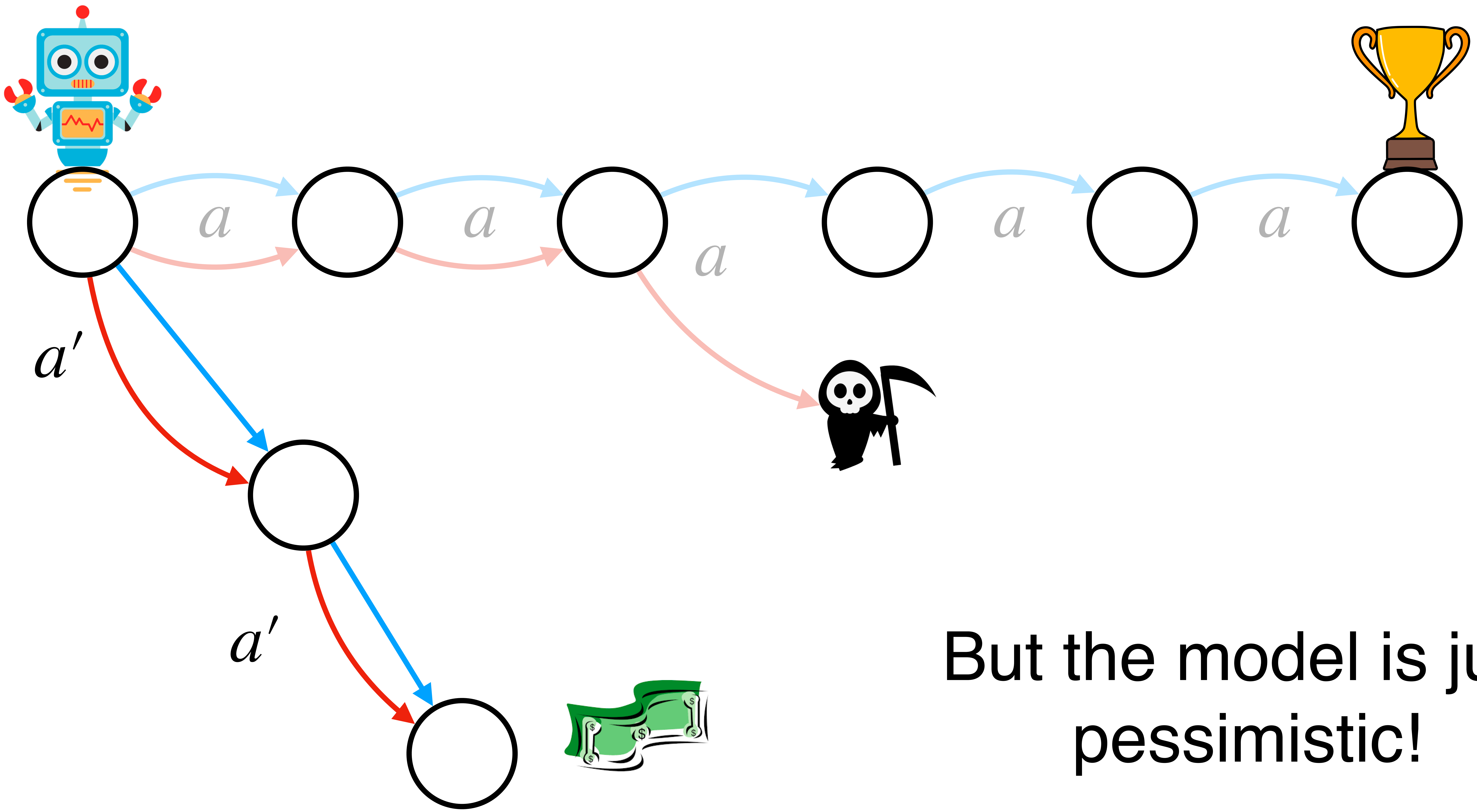
World
s’=$M^*(s, a)$



Training error is zero!

Model
s'=$\hat{M}(s, a)$

World
s'=$M^*(s, a)$



But the model is just pessimistic!

Strategy

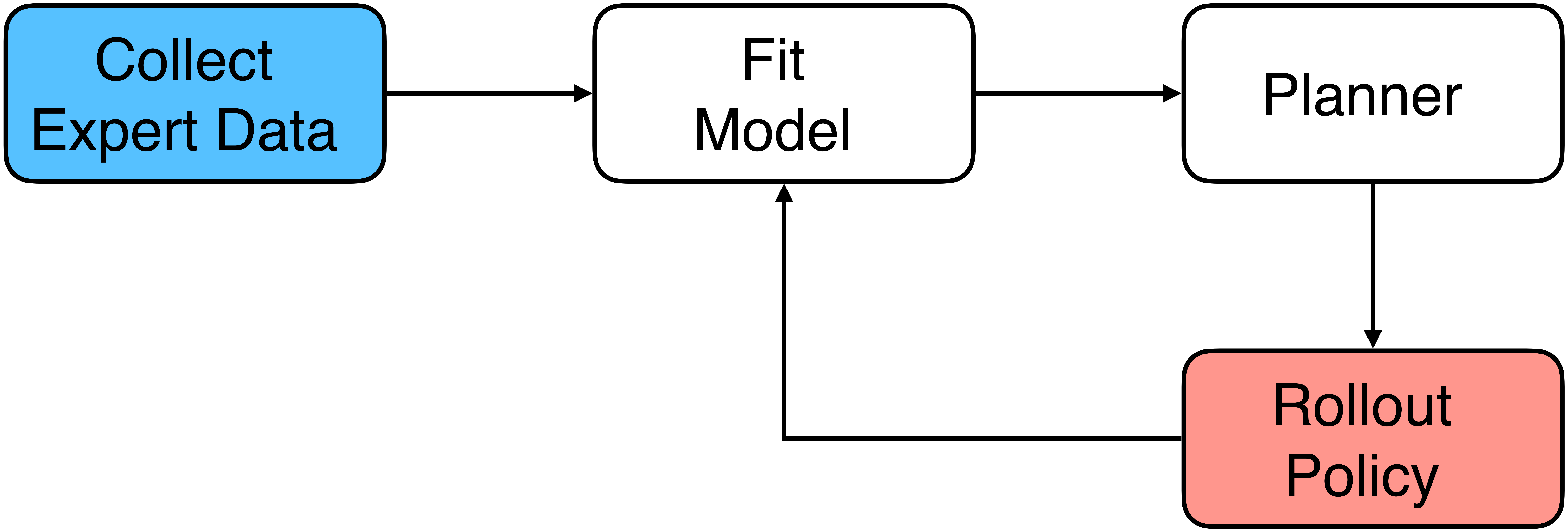
~~Train a model on state actions visited by the expert!~~

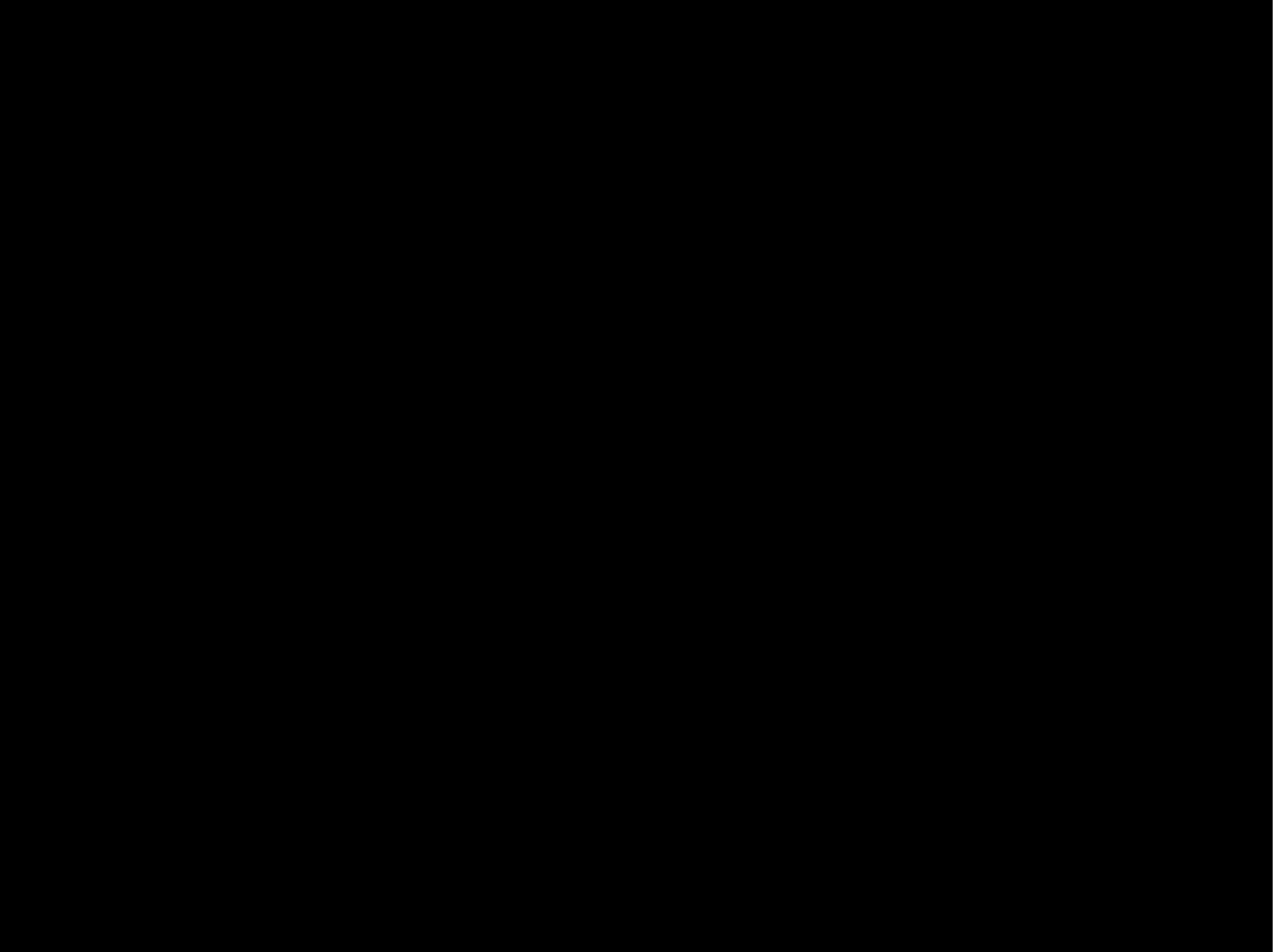
~~Train a model on state actions visited by the learner!~~

Train a model on state actions visited by
both the expert and the learner!

Model Learning with Planner in Loop

(Ross & Bagnell, 2012)





Model learning on both expert and learner data works!

(From Ross & Bagnell, 2012)

Theoretical Foundations for Model Based RL

Agnostic System Identification for Model-Based Reinforcement Learning

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Lemma: Performance Difference via Planning in Model

$$J_{M^*}(\pi^*) - J_{M^*}(\hat{\pi})$$

$$\leq \mathbb{E}_{s_0}\left[V^{\hat{\pi}}_{\hat{M}}(s_0) - V^{\pi^*}_{\hat{M}}(s_0)\right] \quad + TV_{\max}\mathbb{E}_{s,a\sim\pi^*}||\hat{M}(s,a) - M^*(s,a)||$$

Planning error — *Model fit on expert states*

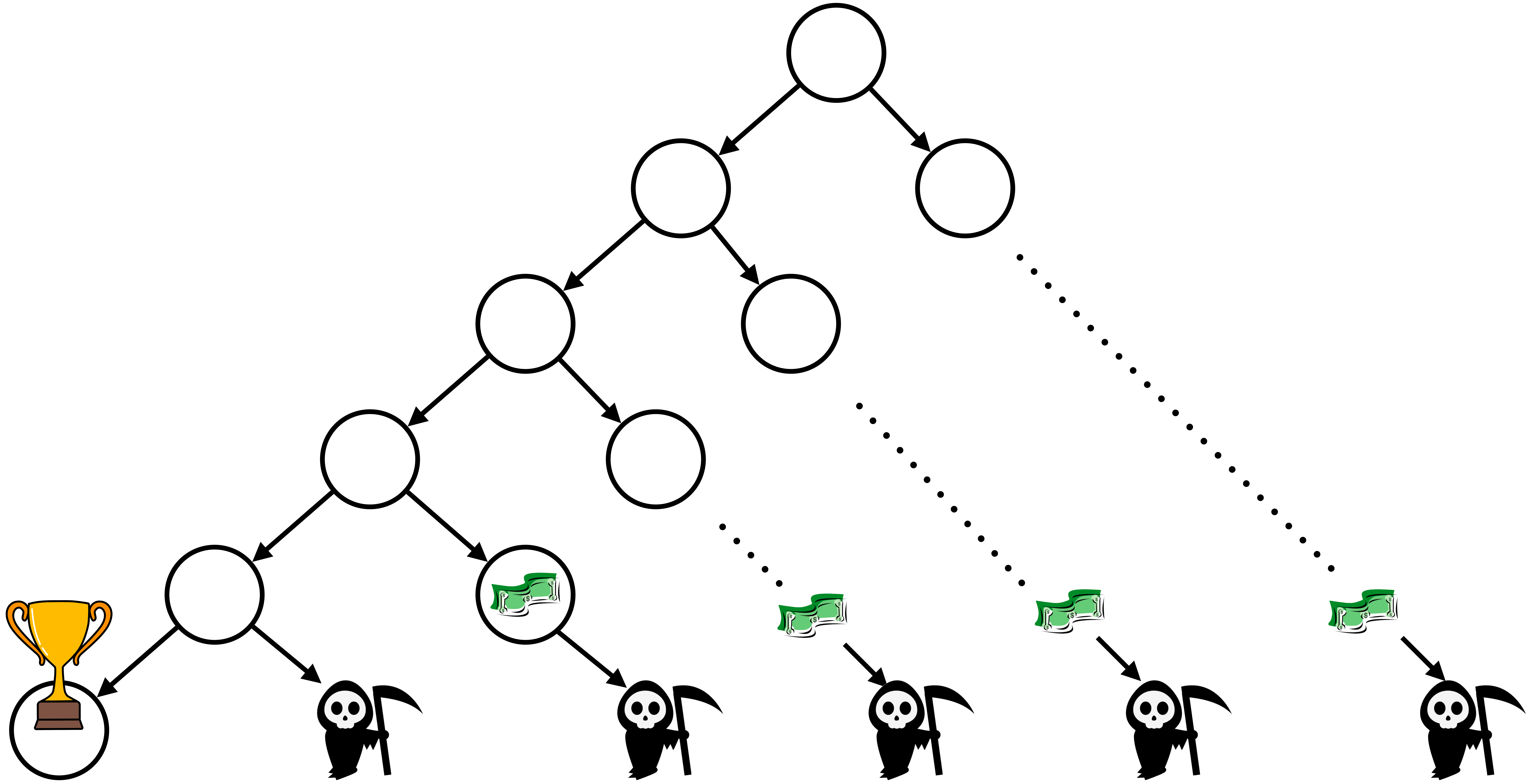
$$+ TV_{\max}\mathbb{E}_{s,a\sim\hat{\pi}}||\hat{M}(s,a) - M^*(s,a)||$$

Model fit on policy states

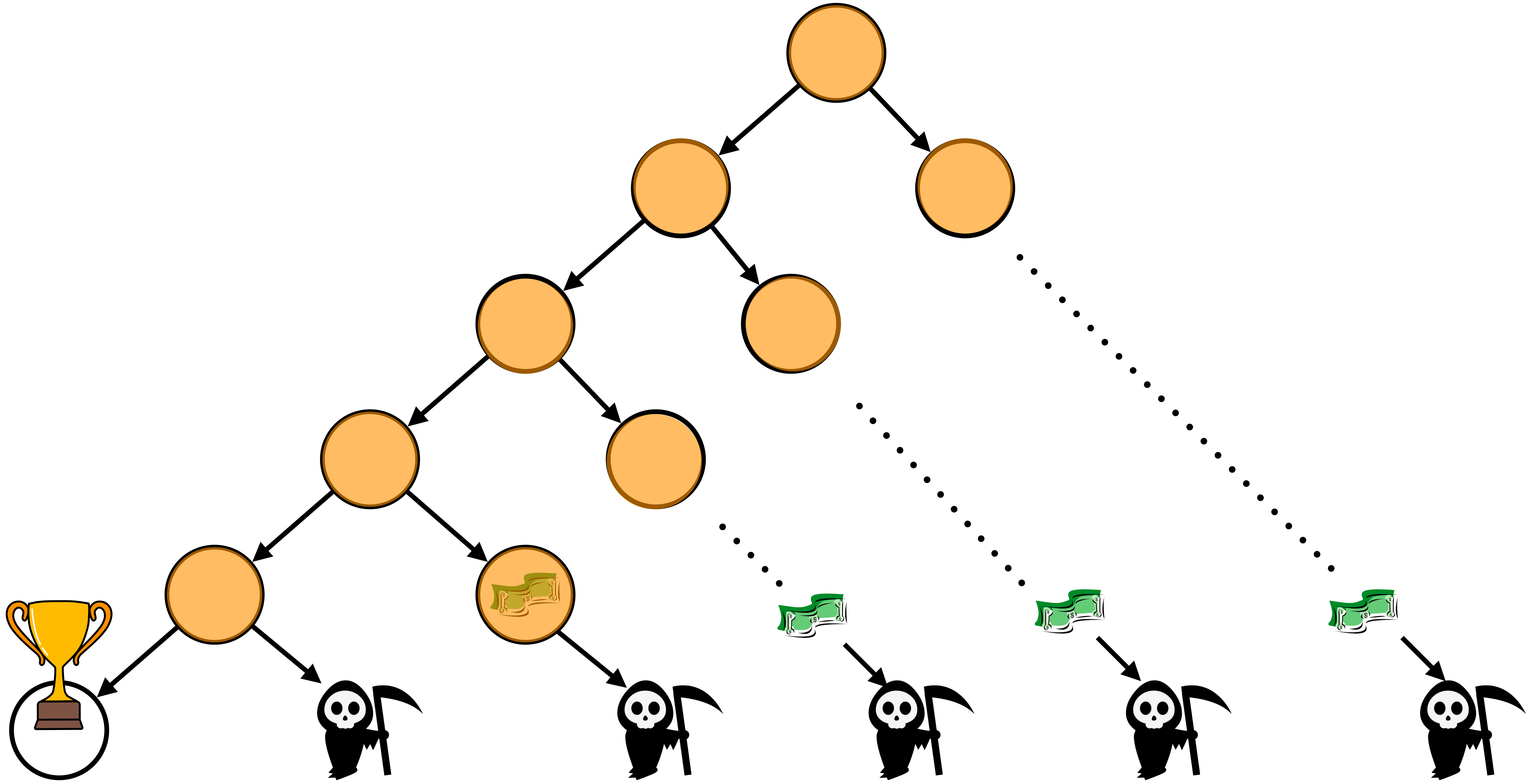
The Challenge.


Planning is like finding a
needle in an exponential
haystack

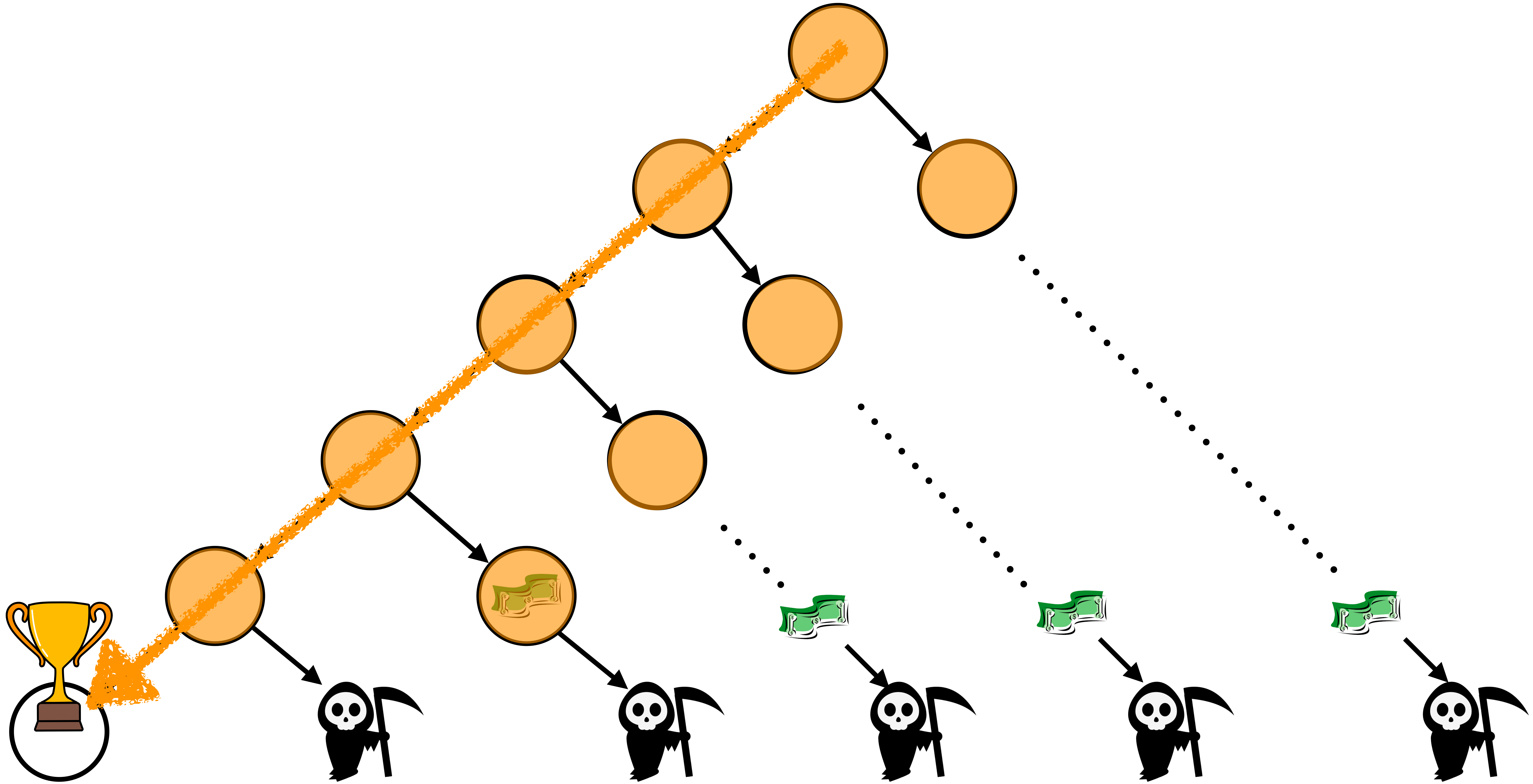
A Tree MDP



Planning is exp(T)!



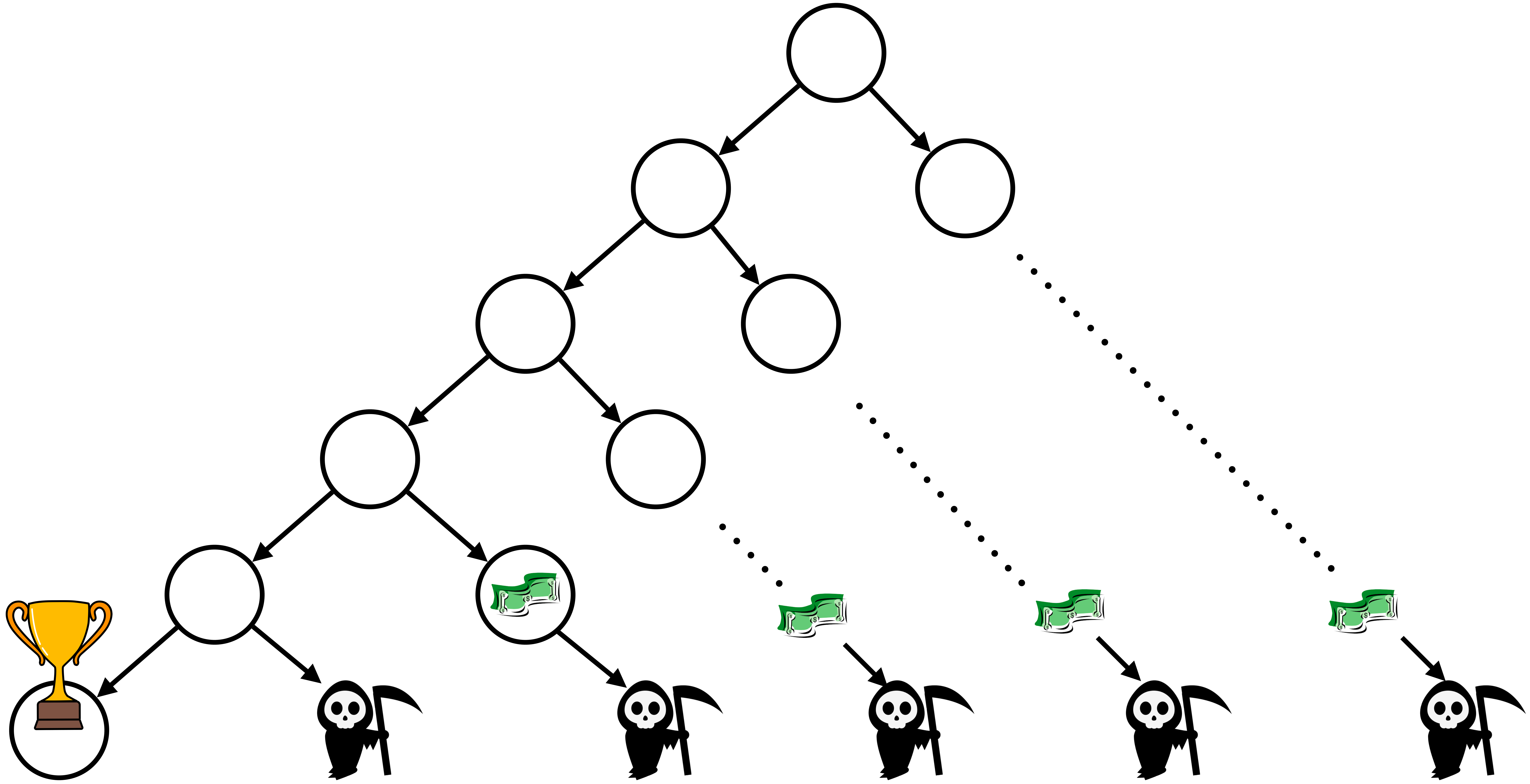
Planning is exp(T)!



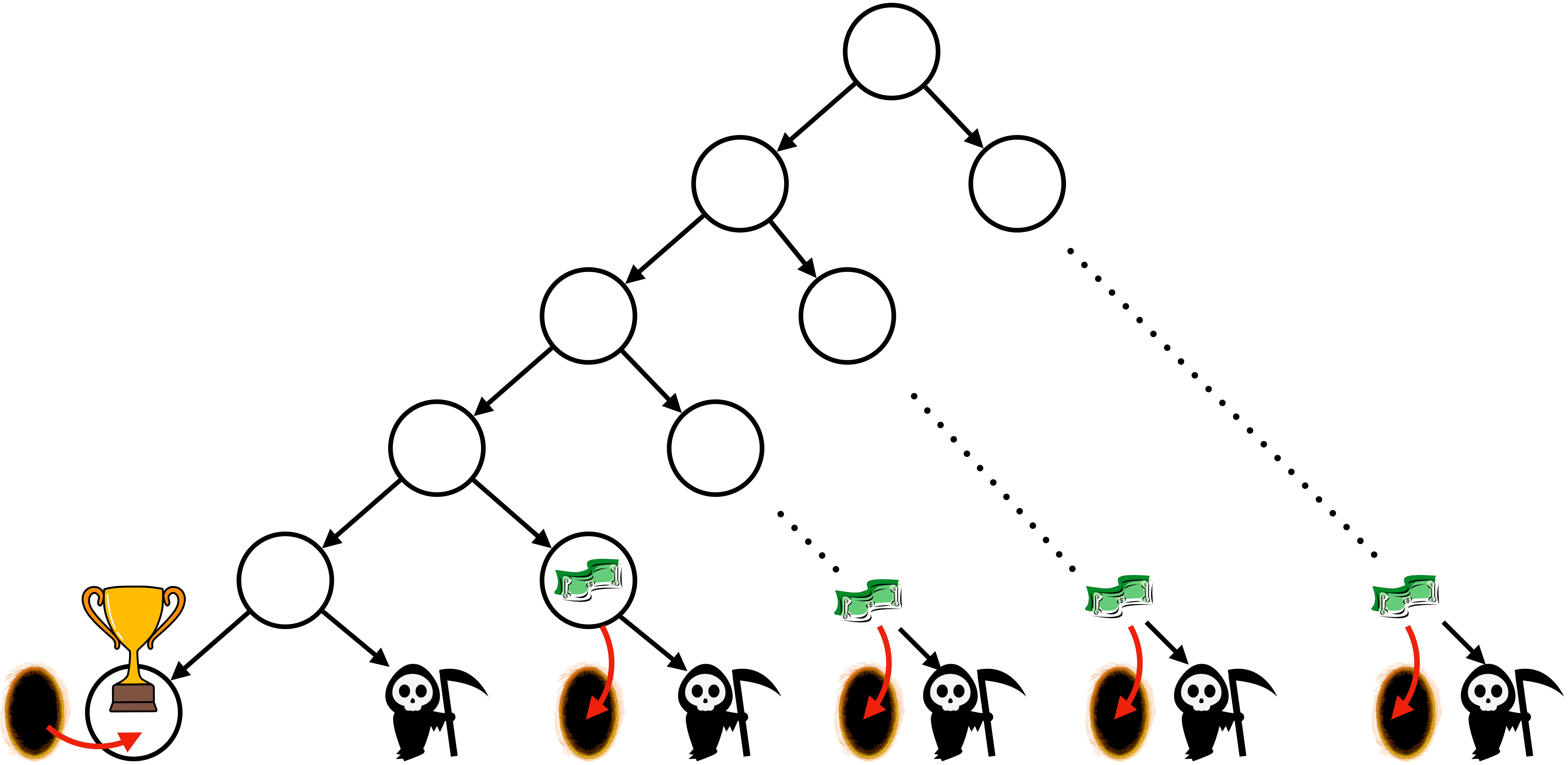
How much planning do we need when learning models?

Models can have many hidden portals

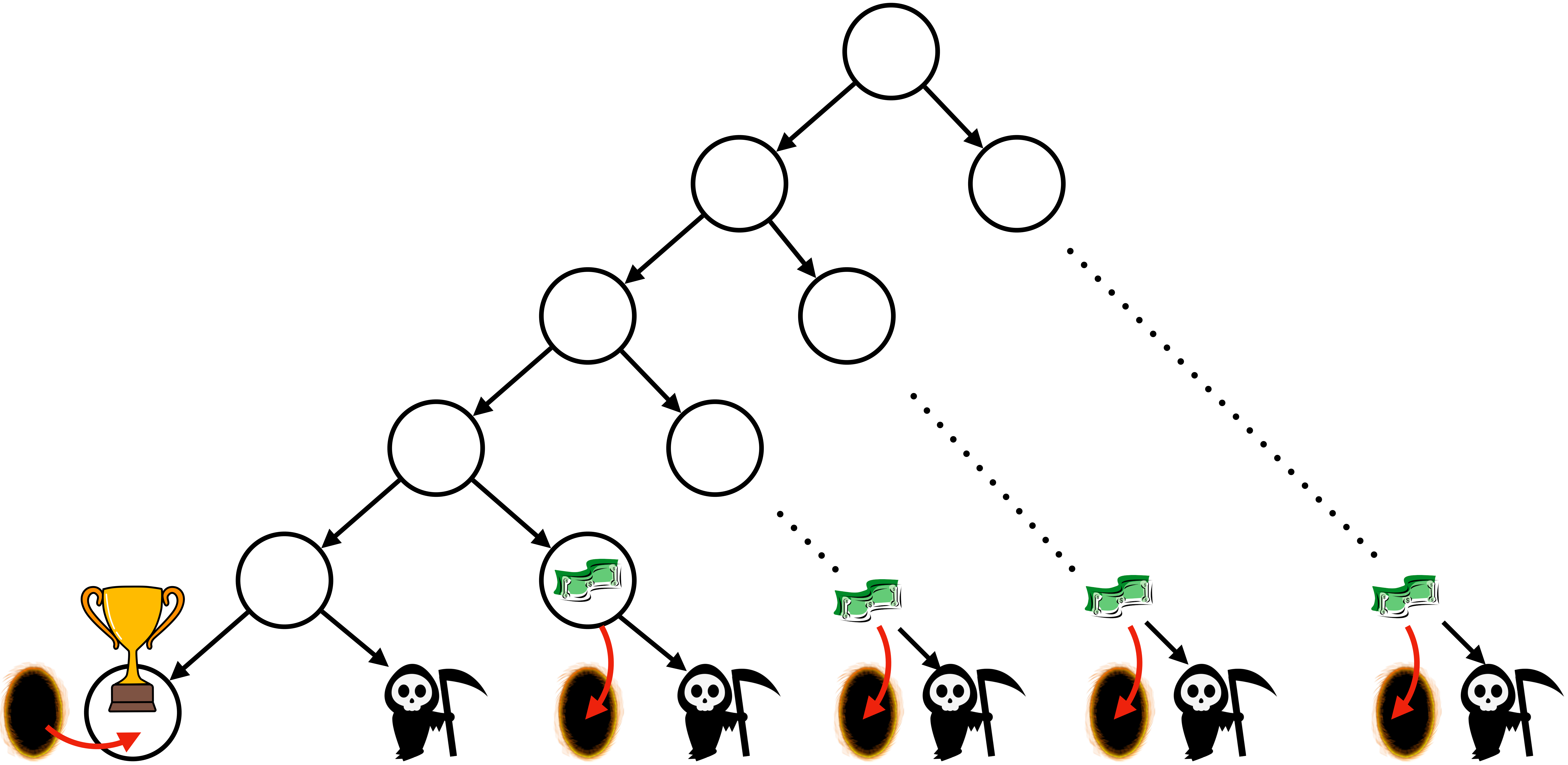
The True Dynamics



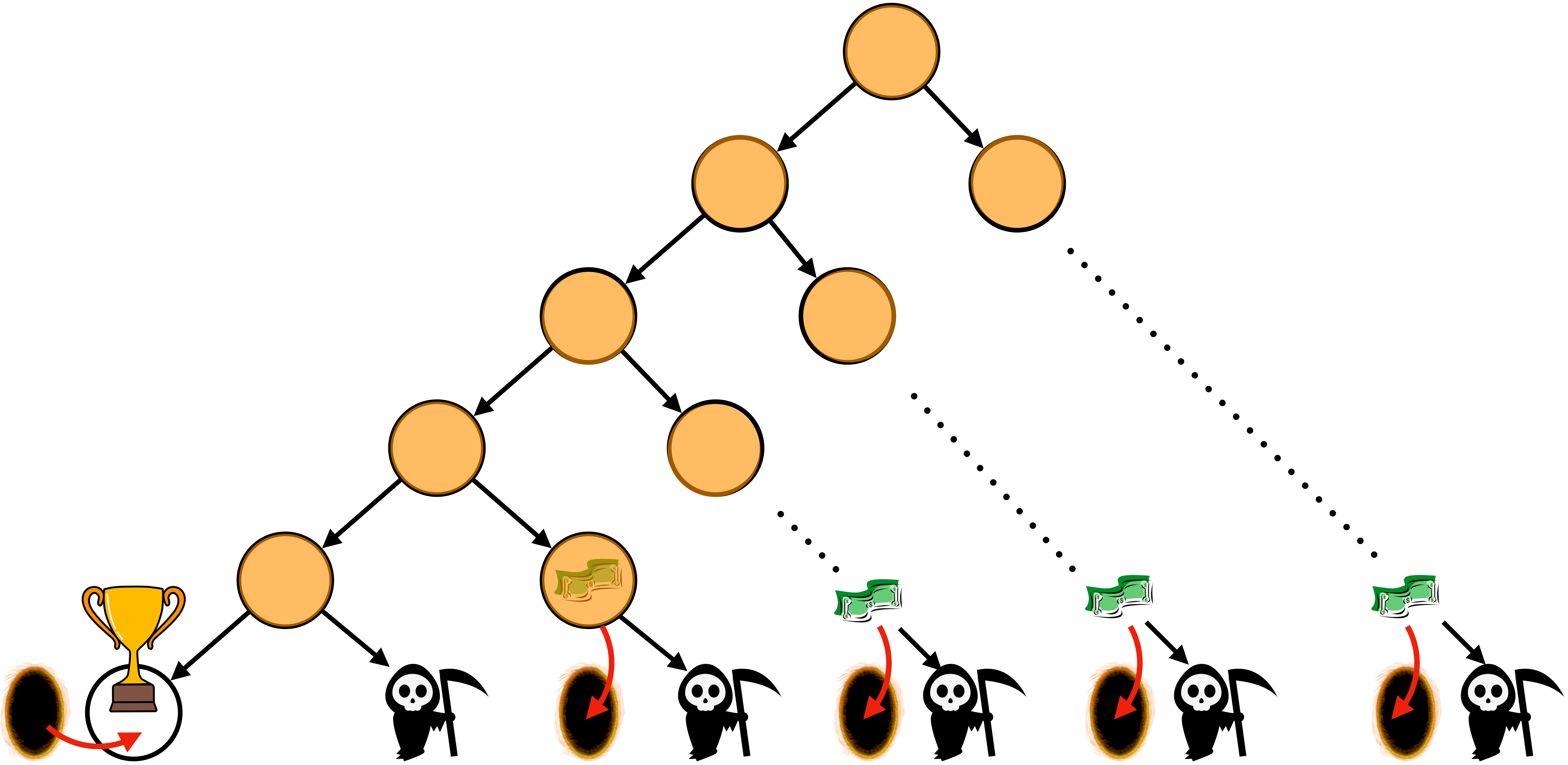
Learnt model has hidden portals!



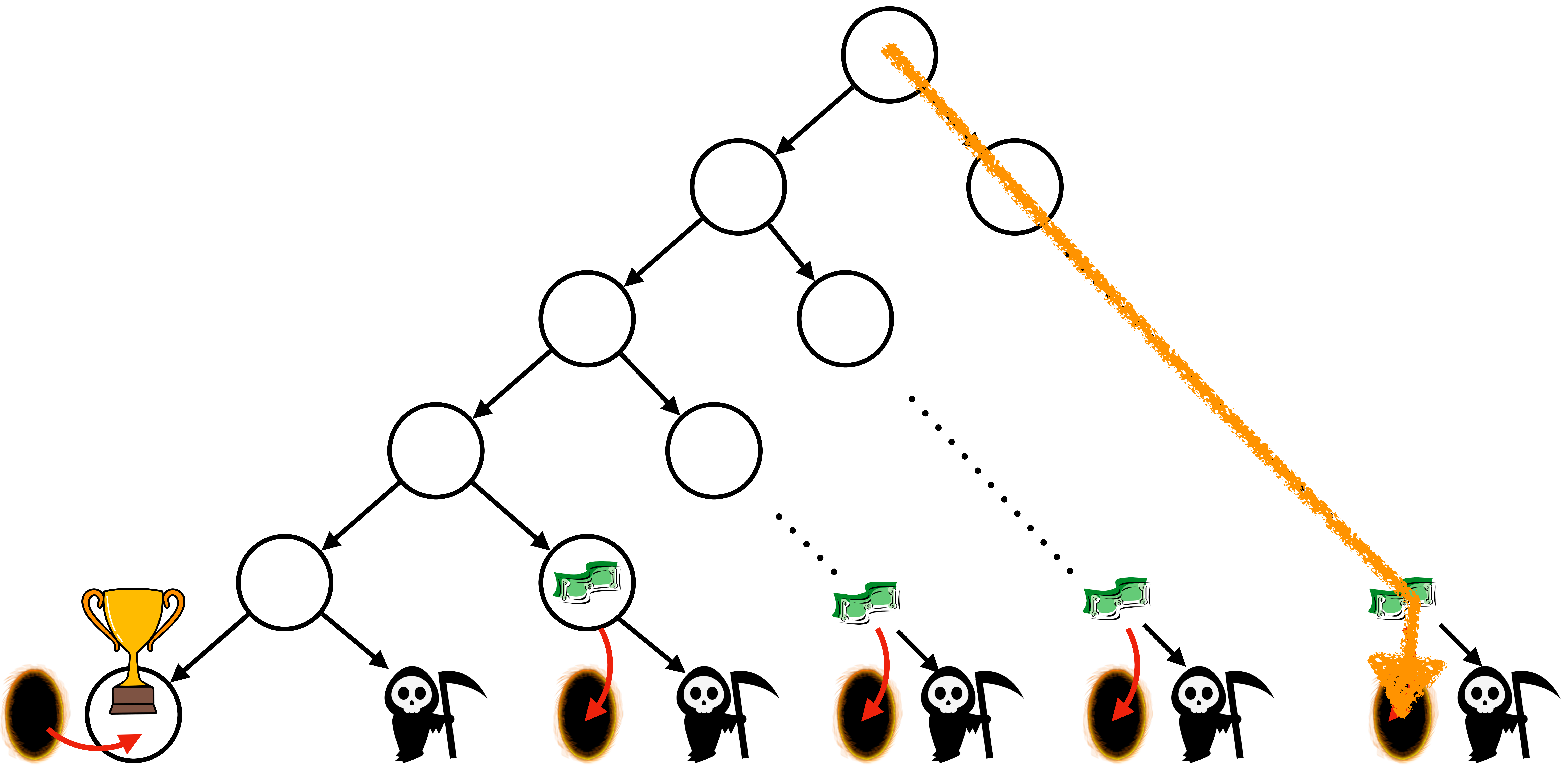
Model at iteration 0



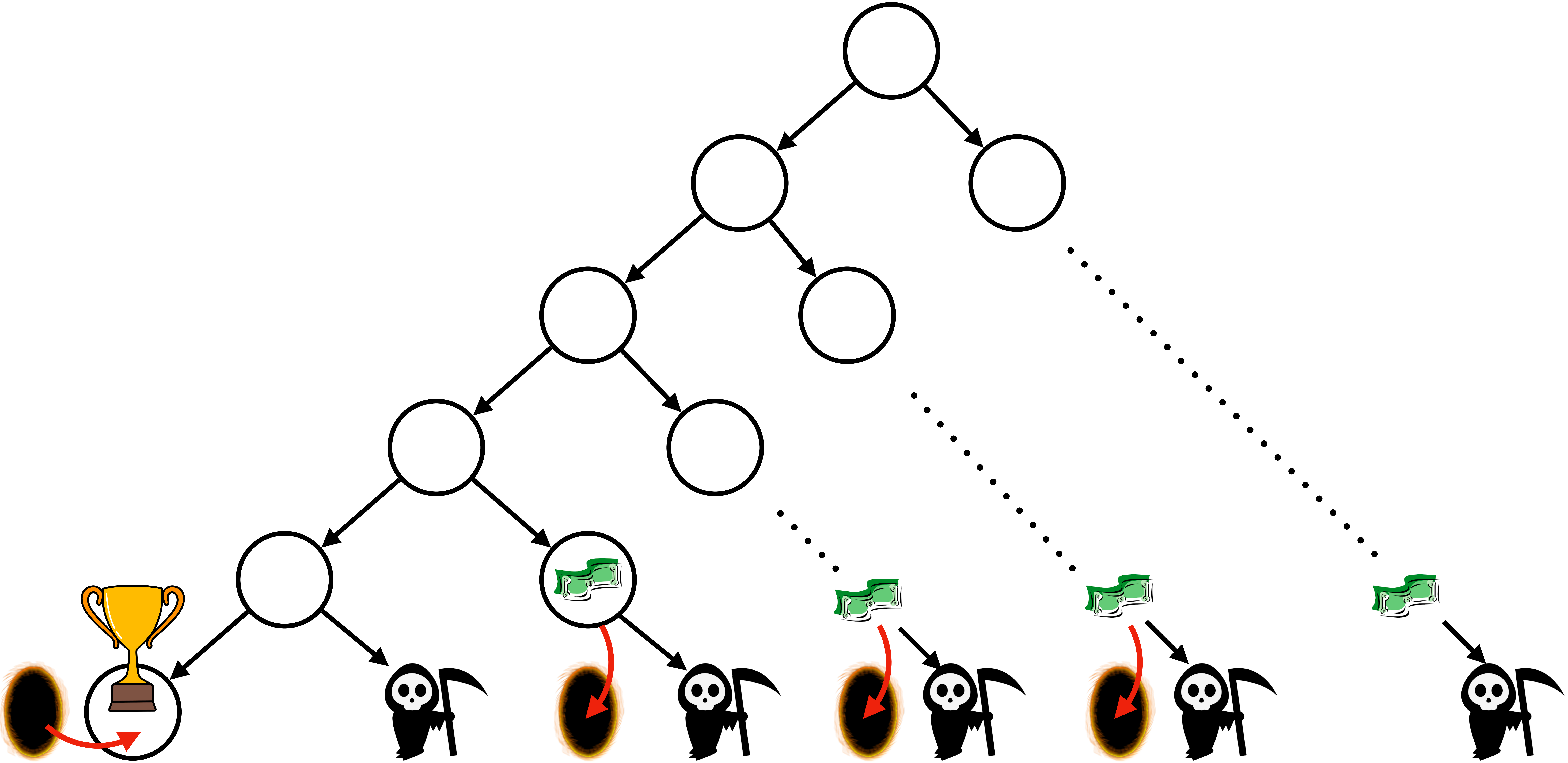
Run planning for exp(T)



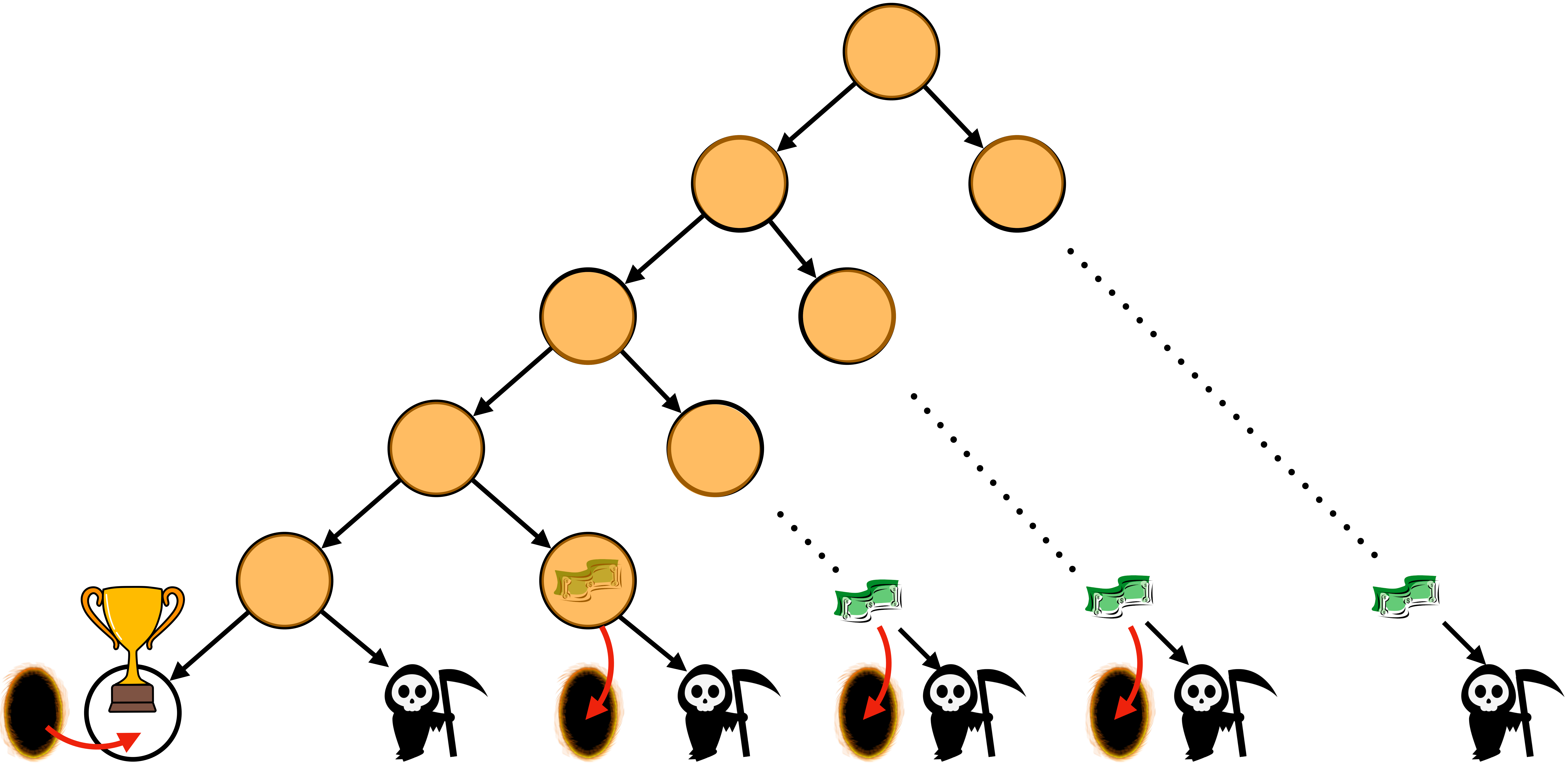
Policy at iteration 0



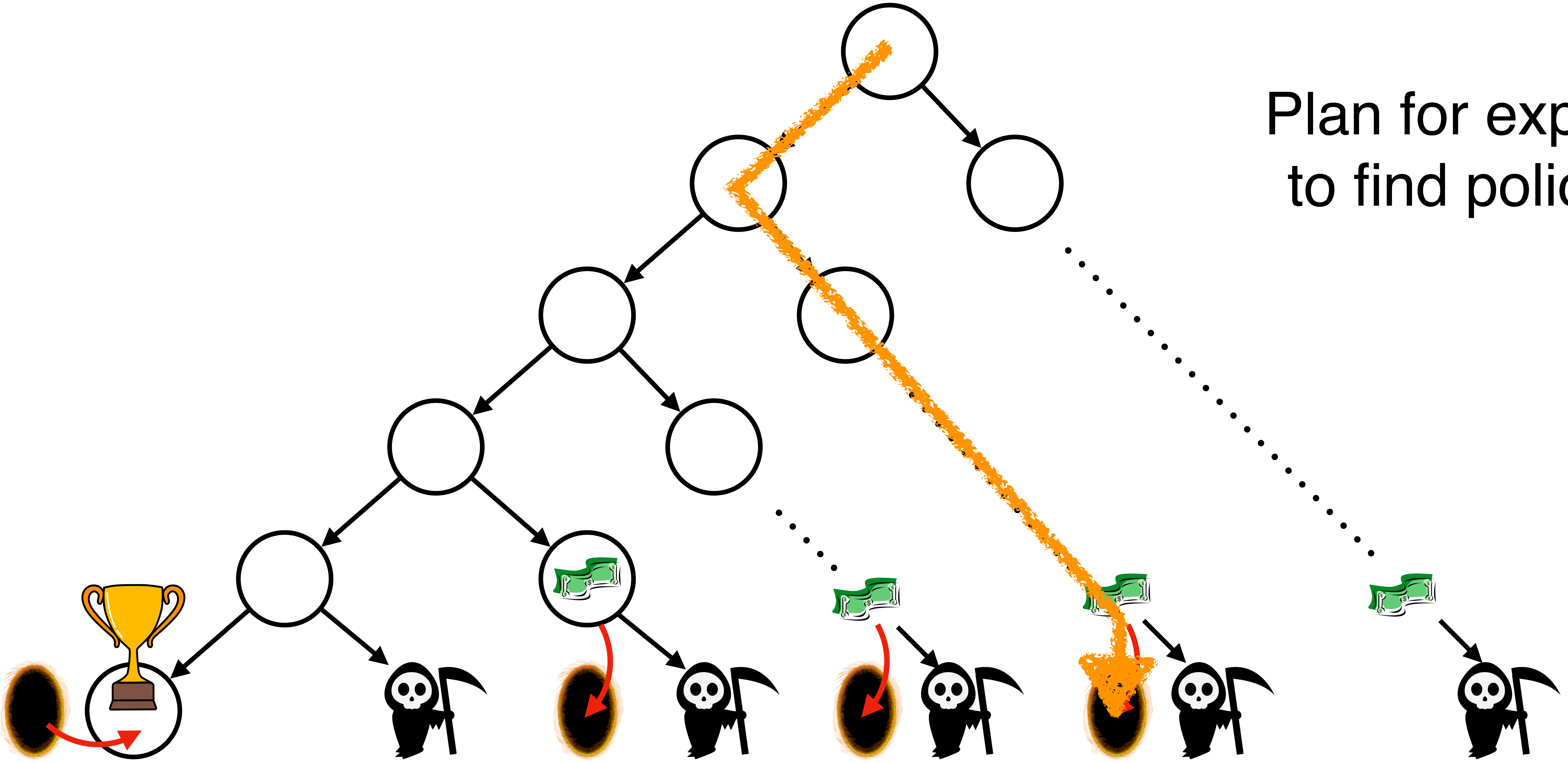
Model at iteration 1



Run planning for exp(T)

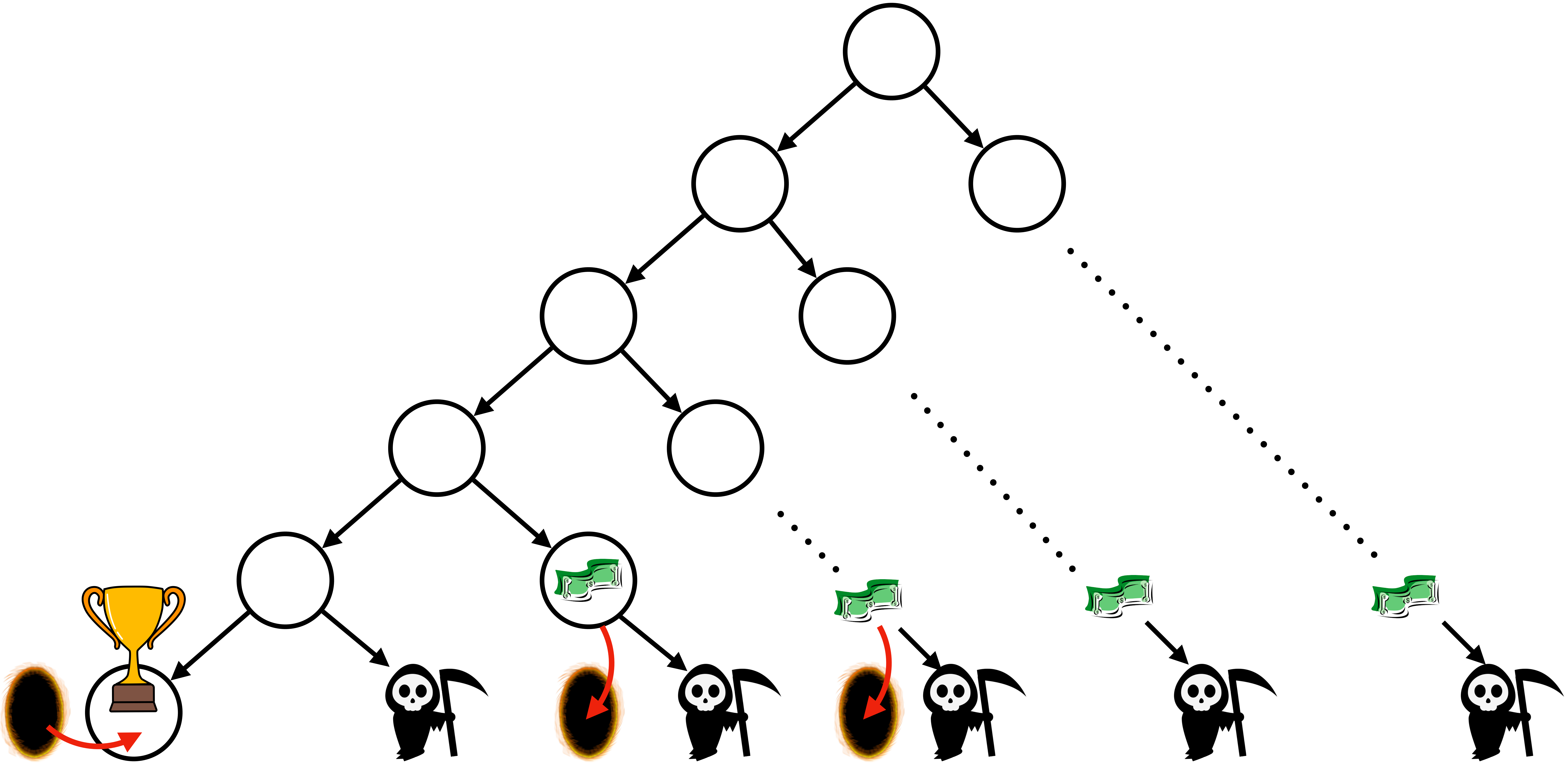


Policy at iteration 1

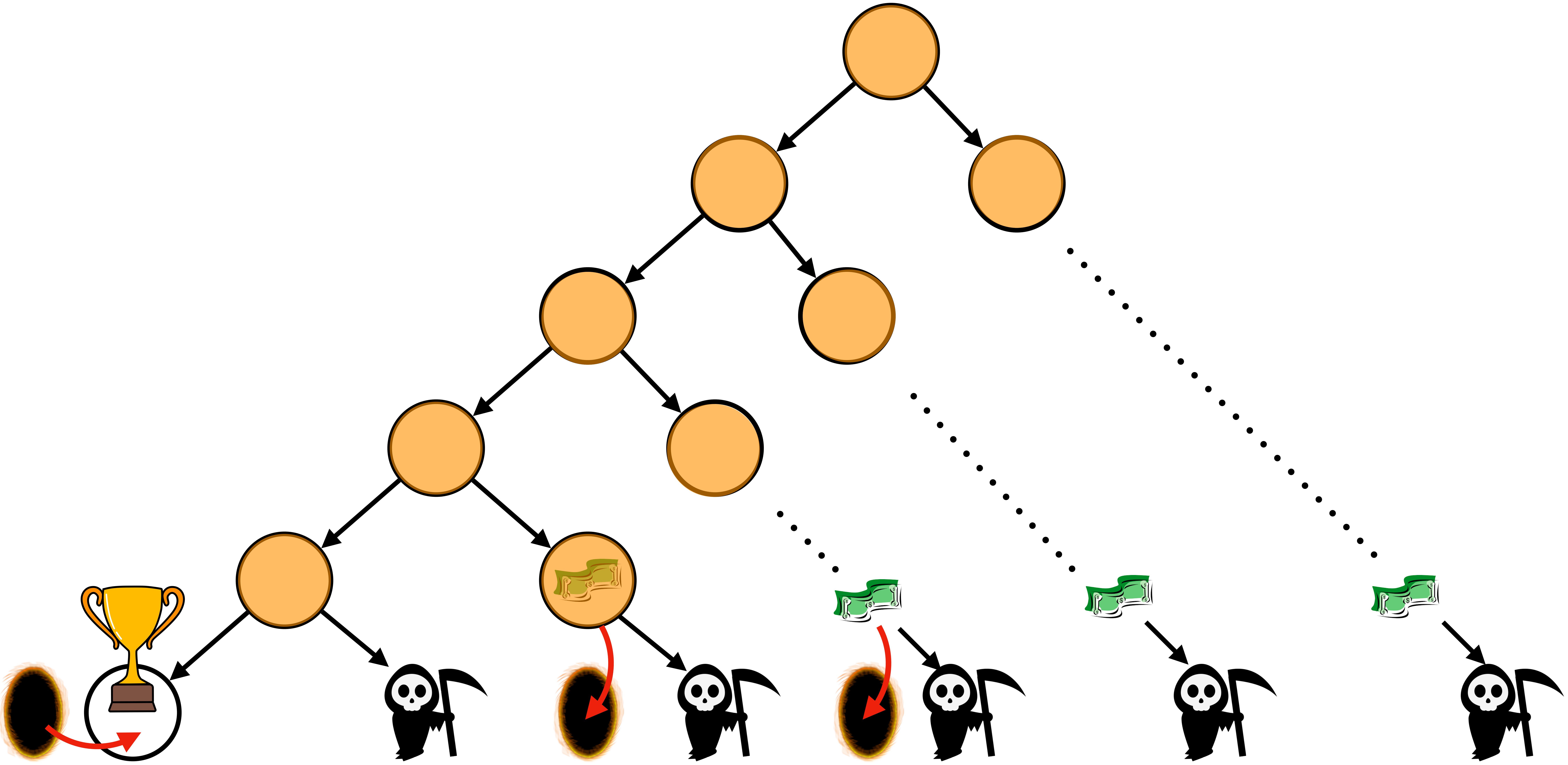


Plan for exp(T)
to find policy!

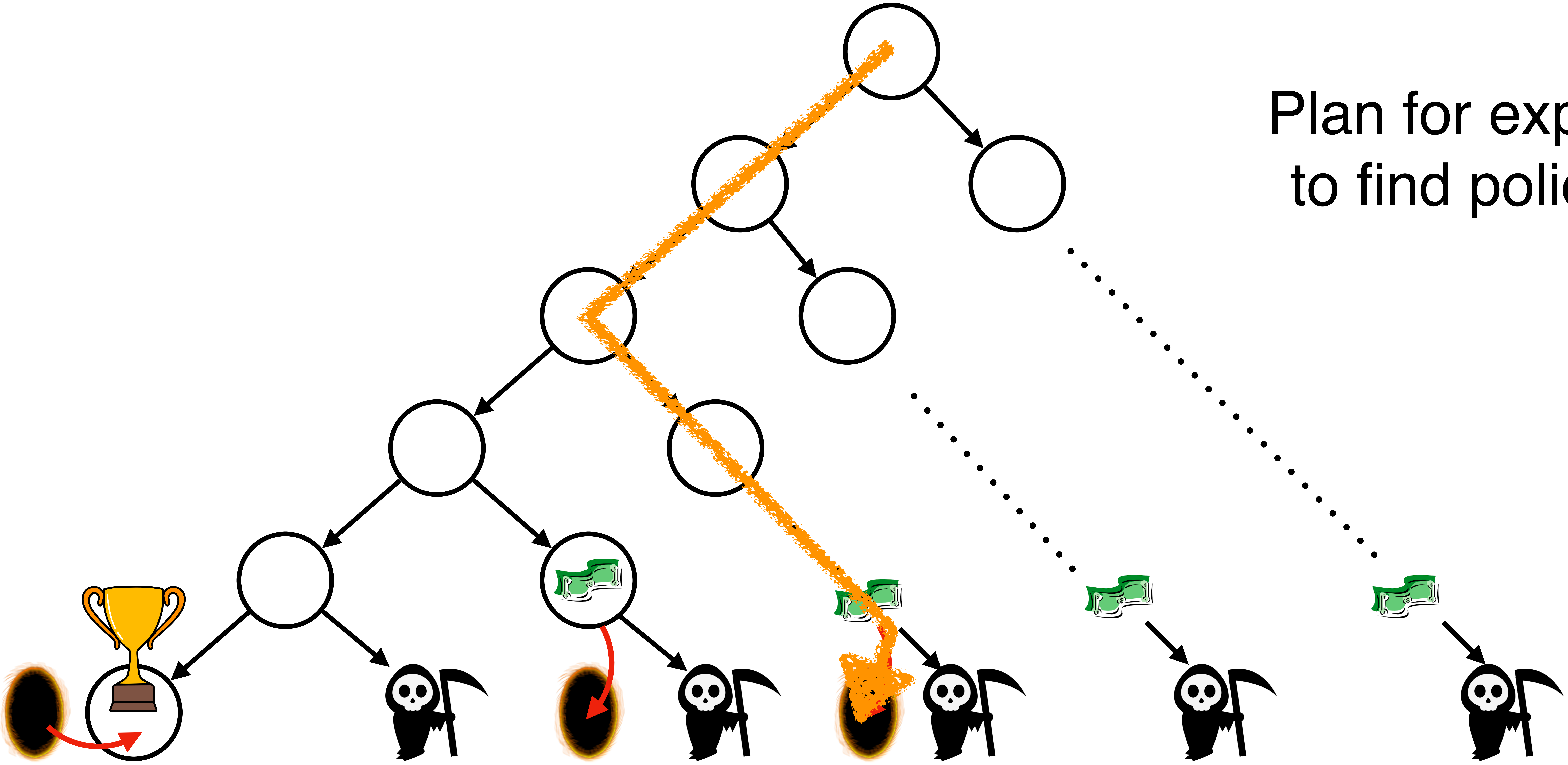
Model at iteration 2



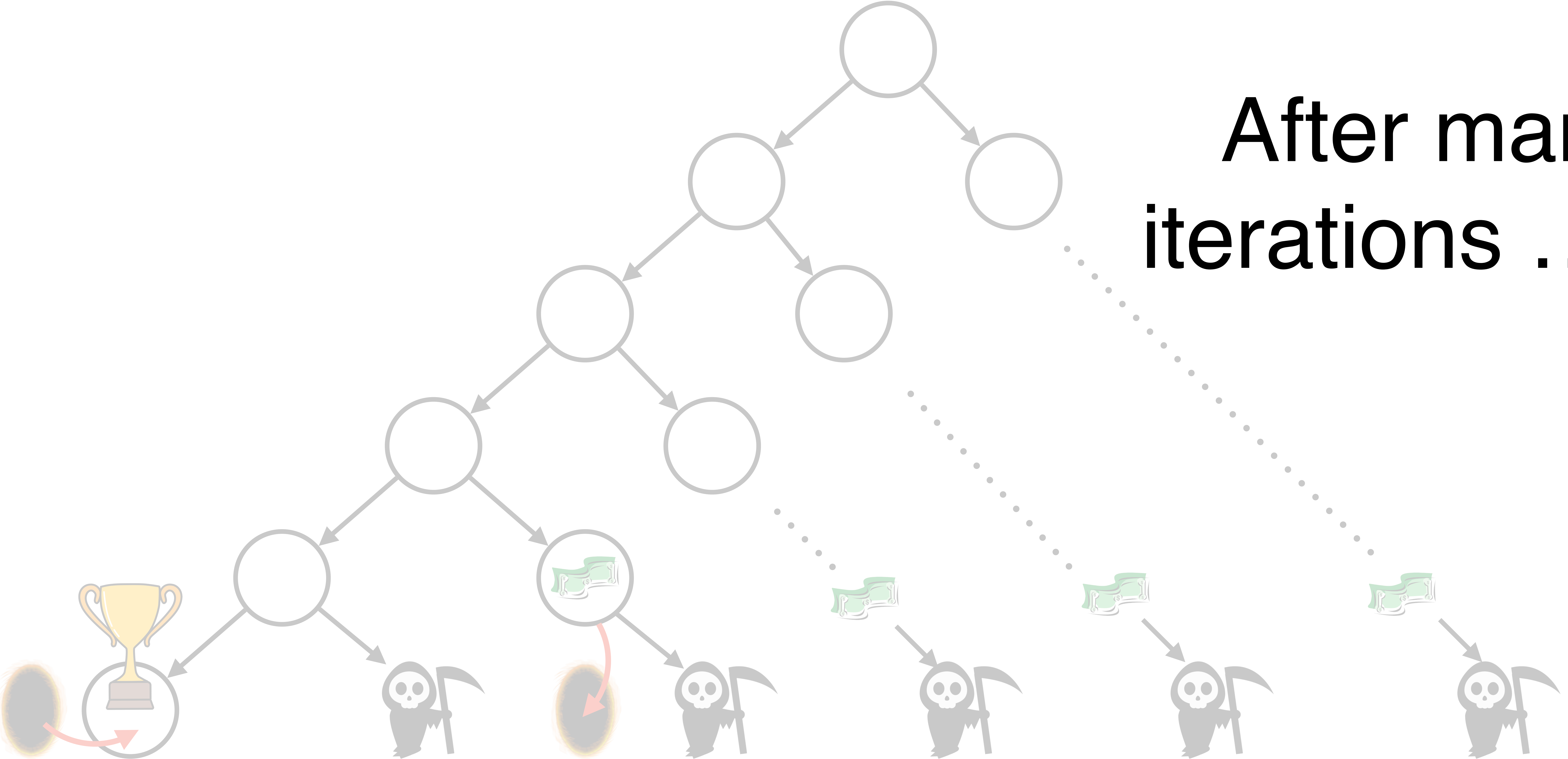
Run planning for exp(T)



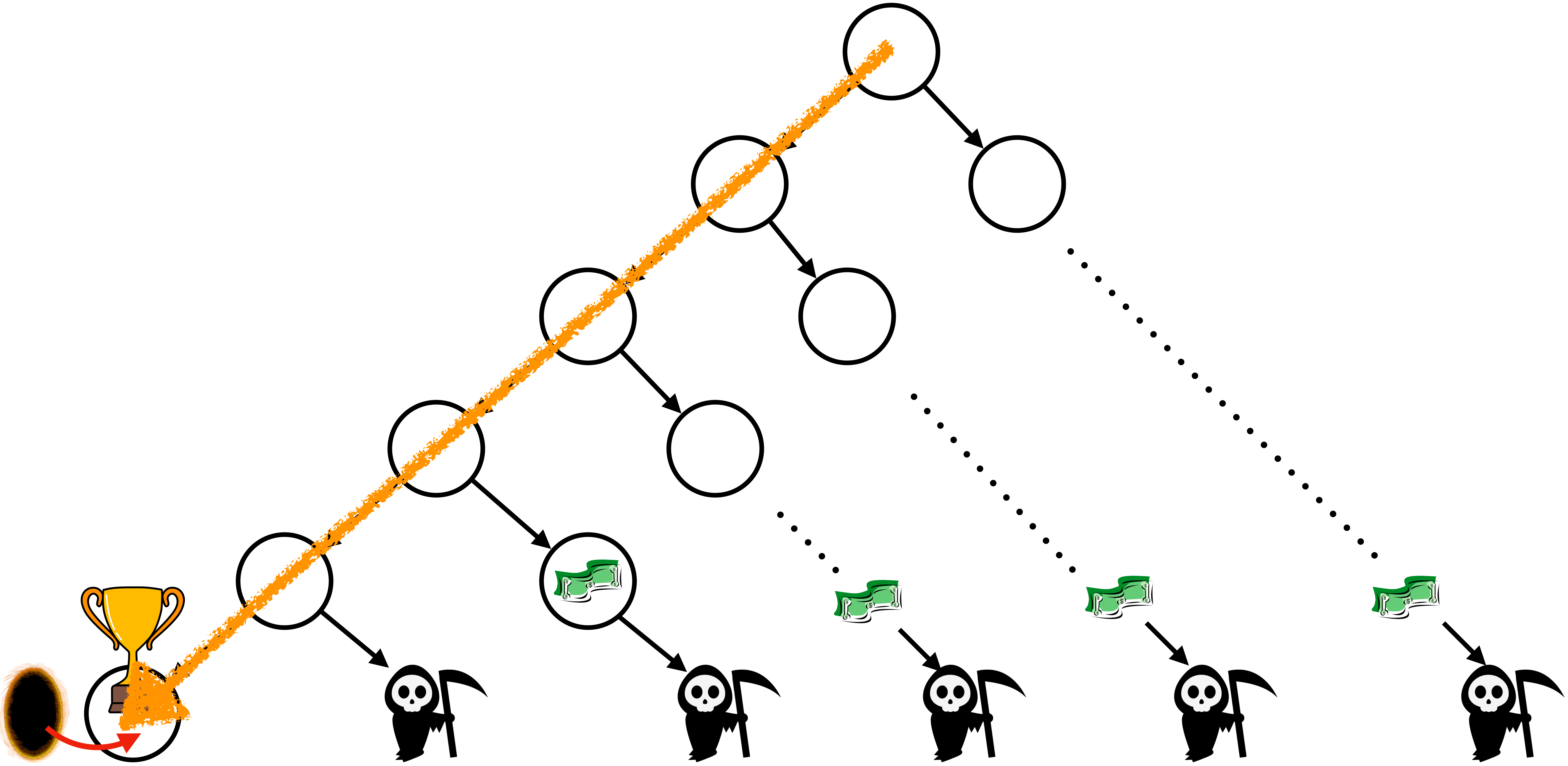
Policy at iteration 2



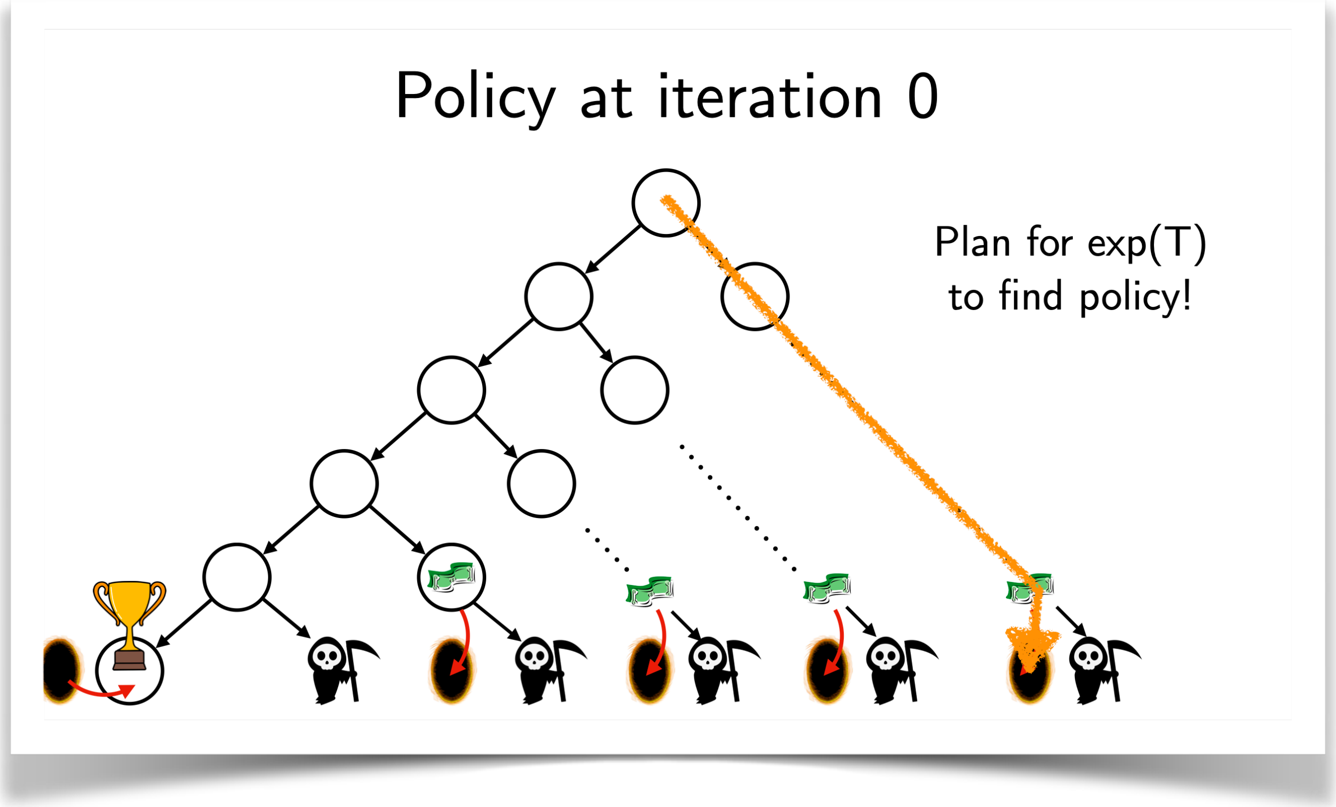
Plan for exp(T) to find policy!

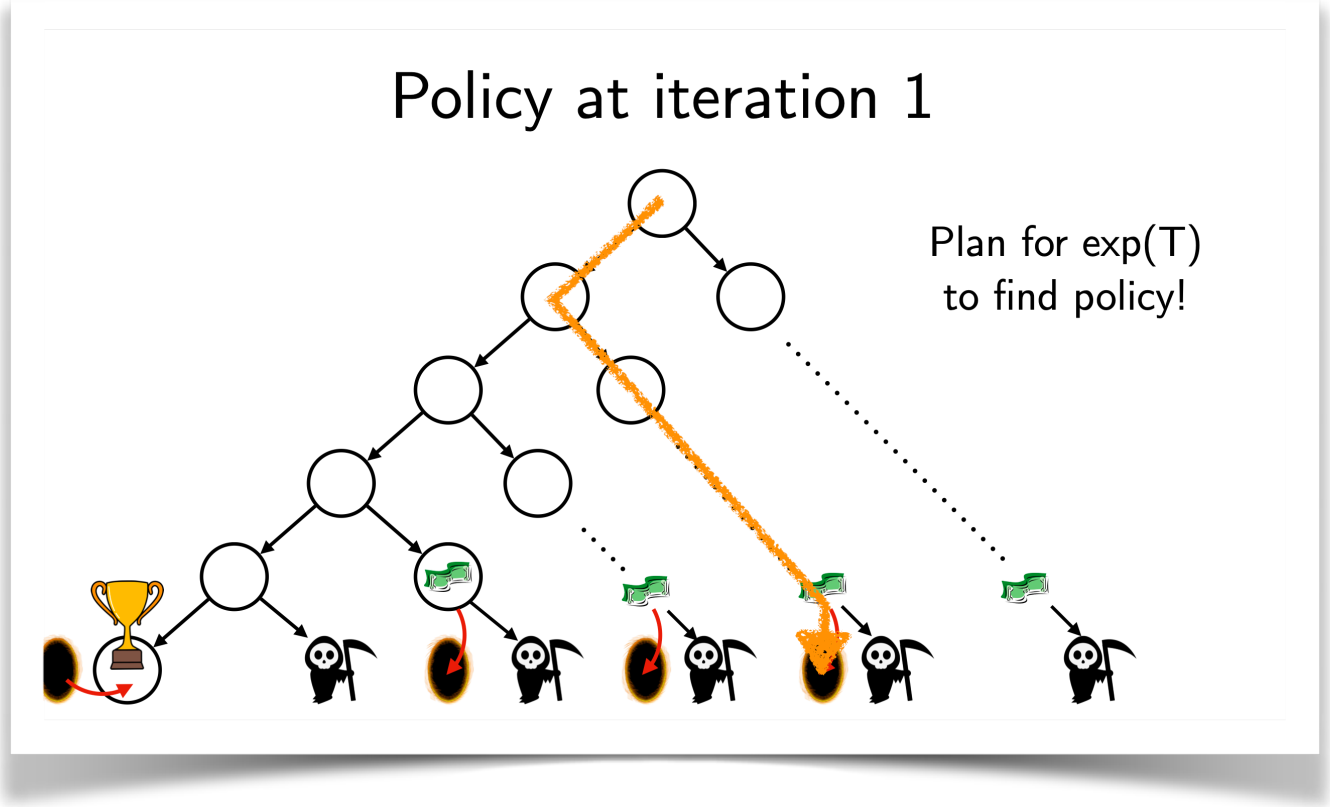


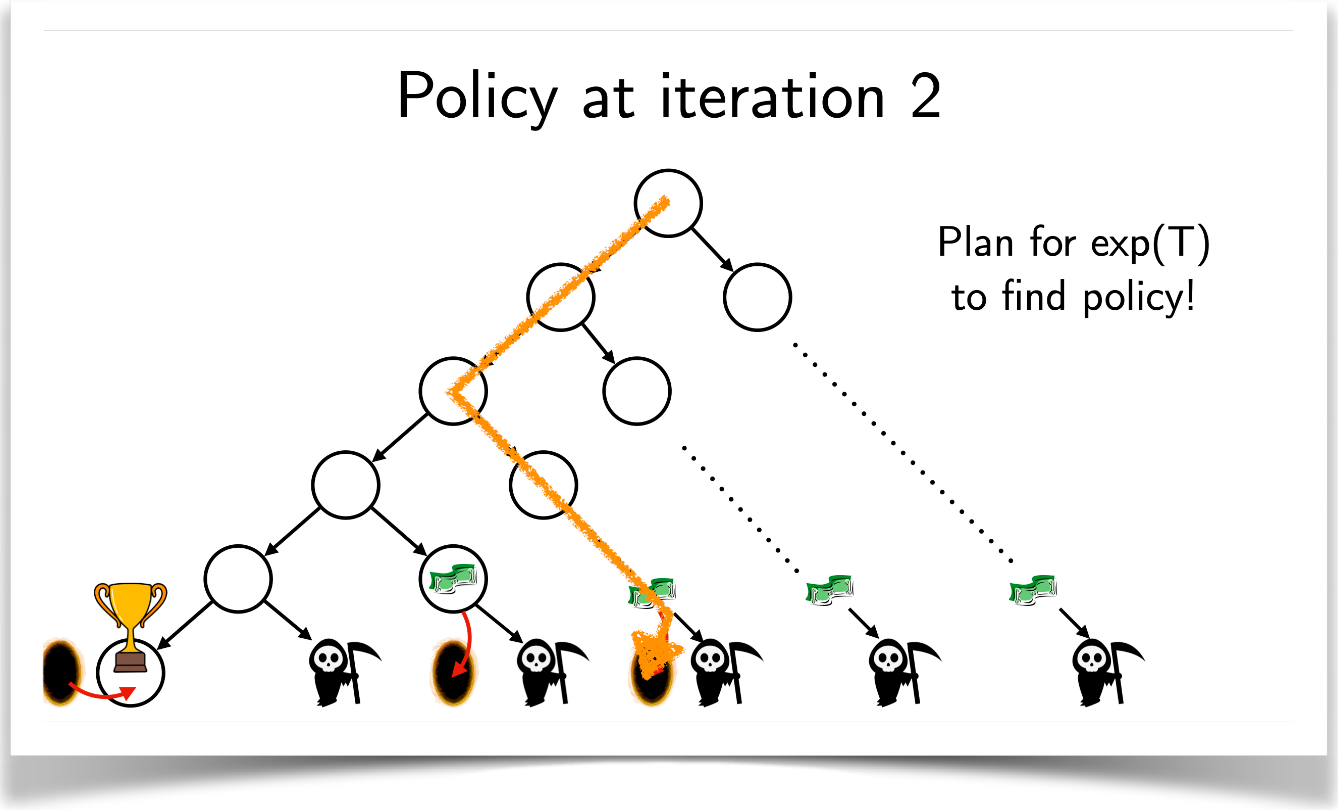
After many iterations ....



Exponential Complexity of Model Learning







.....

Every iteration, planning is exp(T) computation

Repeat for many iterations to eliminate all portals

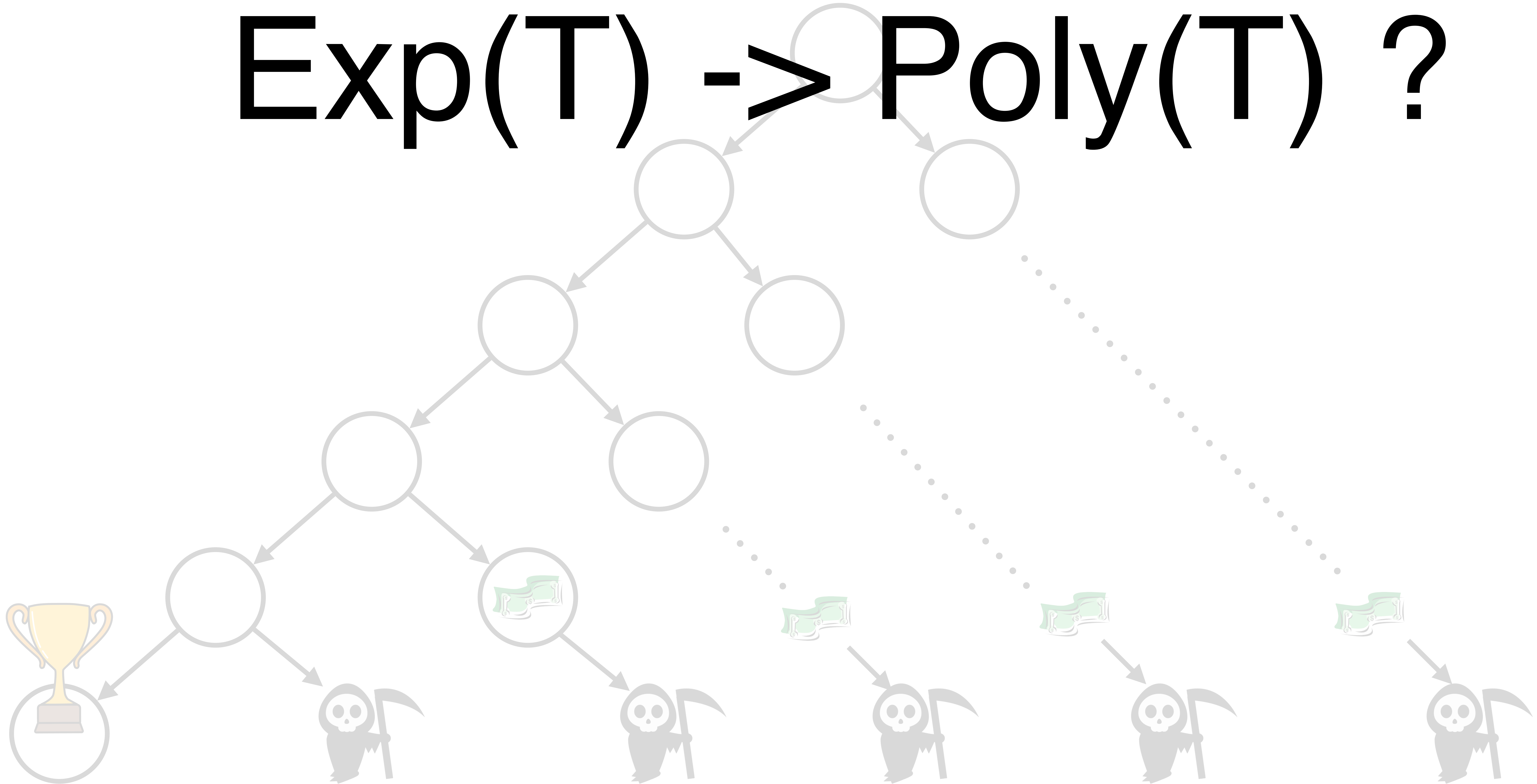
Key Insight.

Be Lazy.

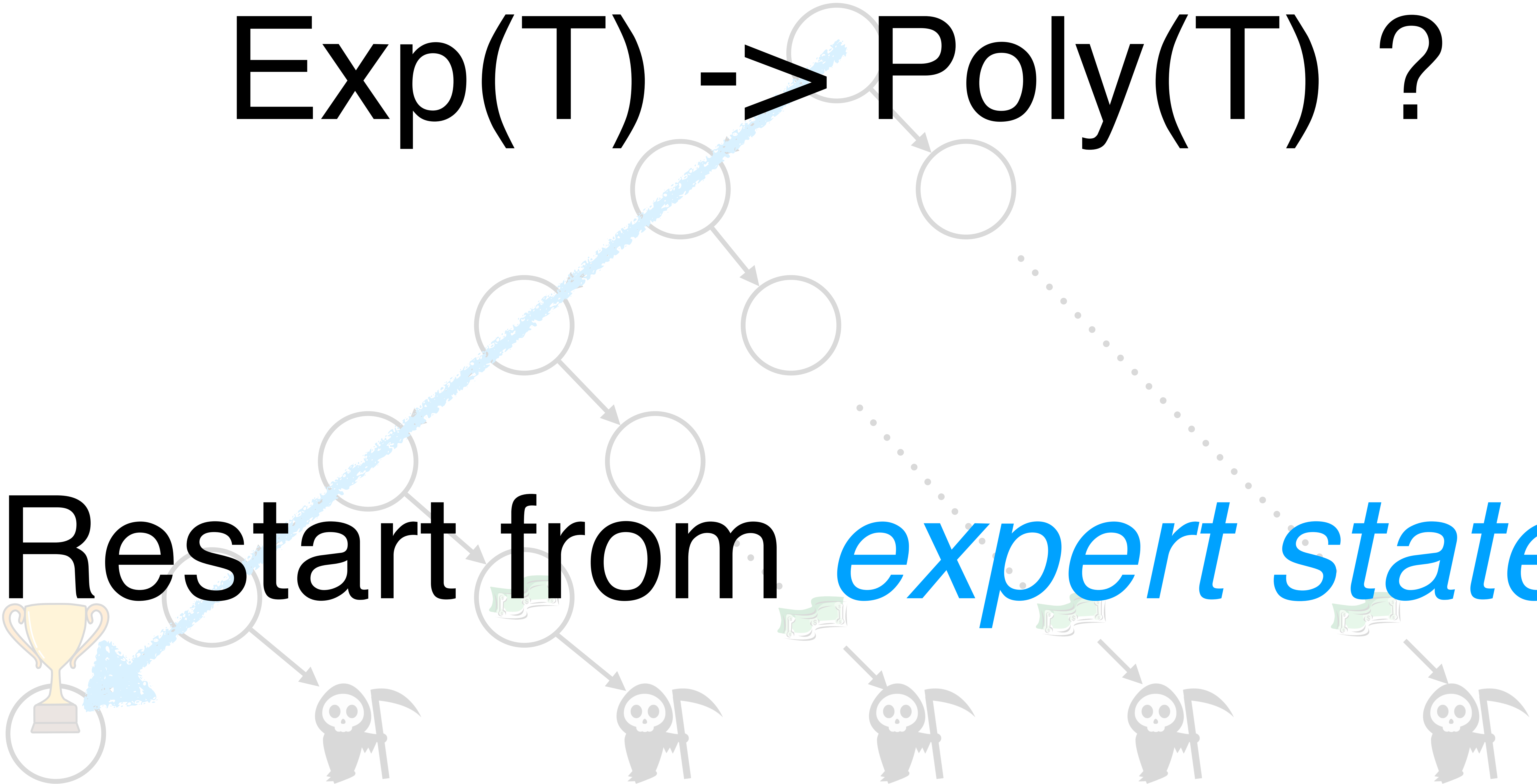
Don’t compute optimal plan.

Just do better than expert.

How do we turn planning Exp(T) -> Poly(T) ?



How do we turn planning Exp(T) -> Poly(T) ?



Restart from *expert states*

Policy Search via Dynamic Programming (PSDP)

(Bagnell, et al. 2003)

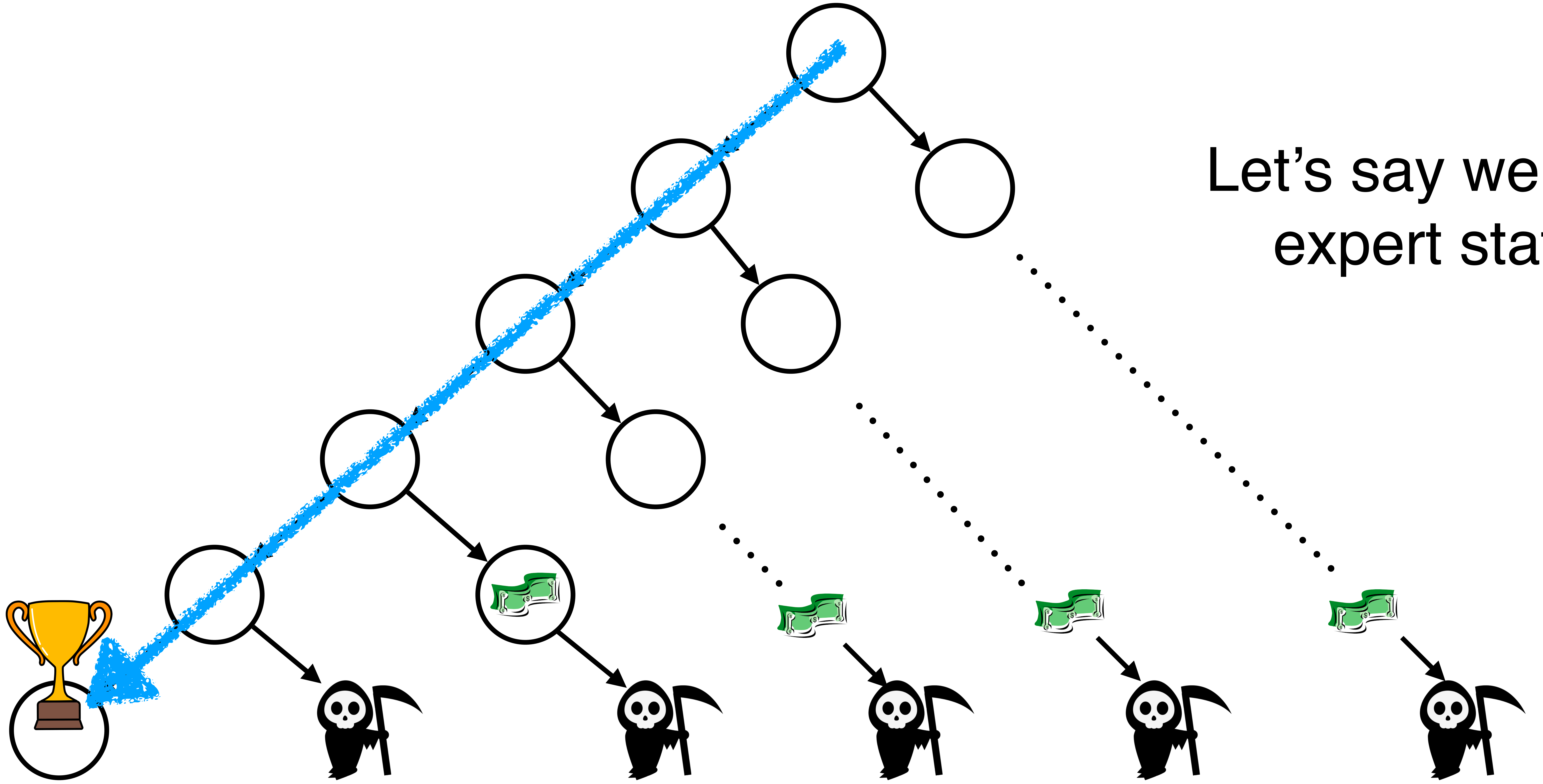
Iterate from T-1 and go back in time

At each time t, restart from expert state s_t^*

Solve for best policy π_t , *given future policies* $\pi_{t+1}, \pi_{t+2}, \cdots \pi_T$

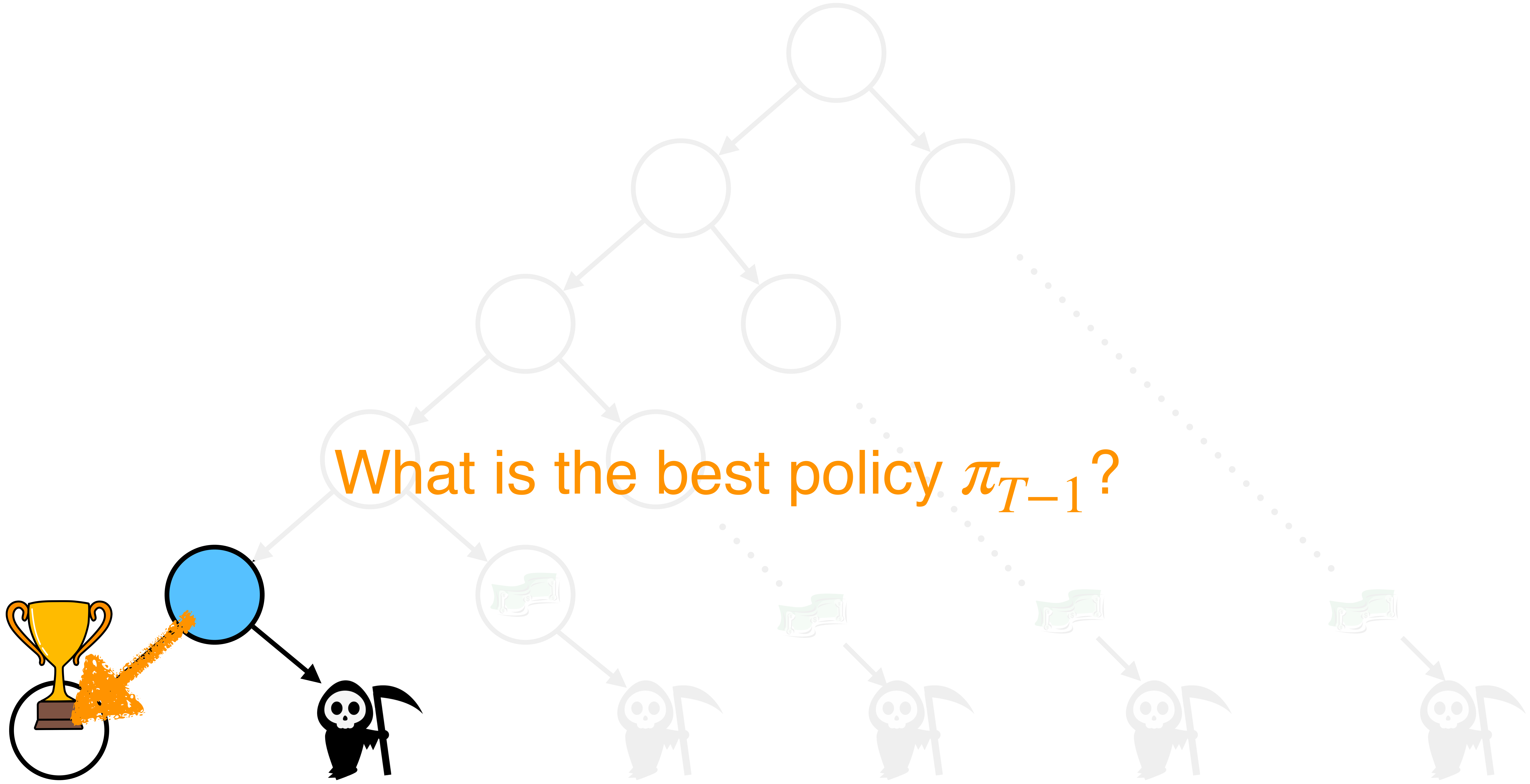
$$\pi_t = \arg\max_{\pi} r(s_t^*, \pi(s_t^*)) + \mathbb{E}_{s_{t+1}} V^{\pi_{t+1:T}}(s_{t+1})$$

Policy Search via Dynamic Programming (PSDP)



Let's say we have expert states

Policy Search via Dynamic Programming (PSDP)



What is the best policy π_{T-1}?

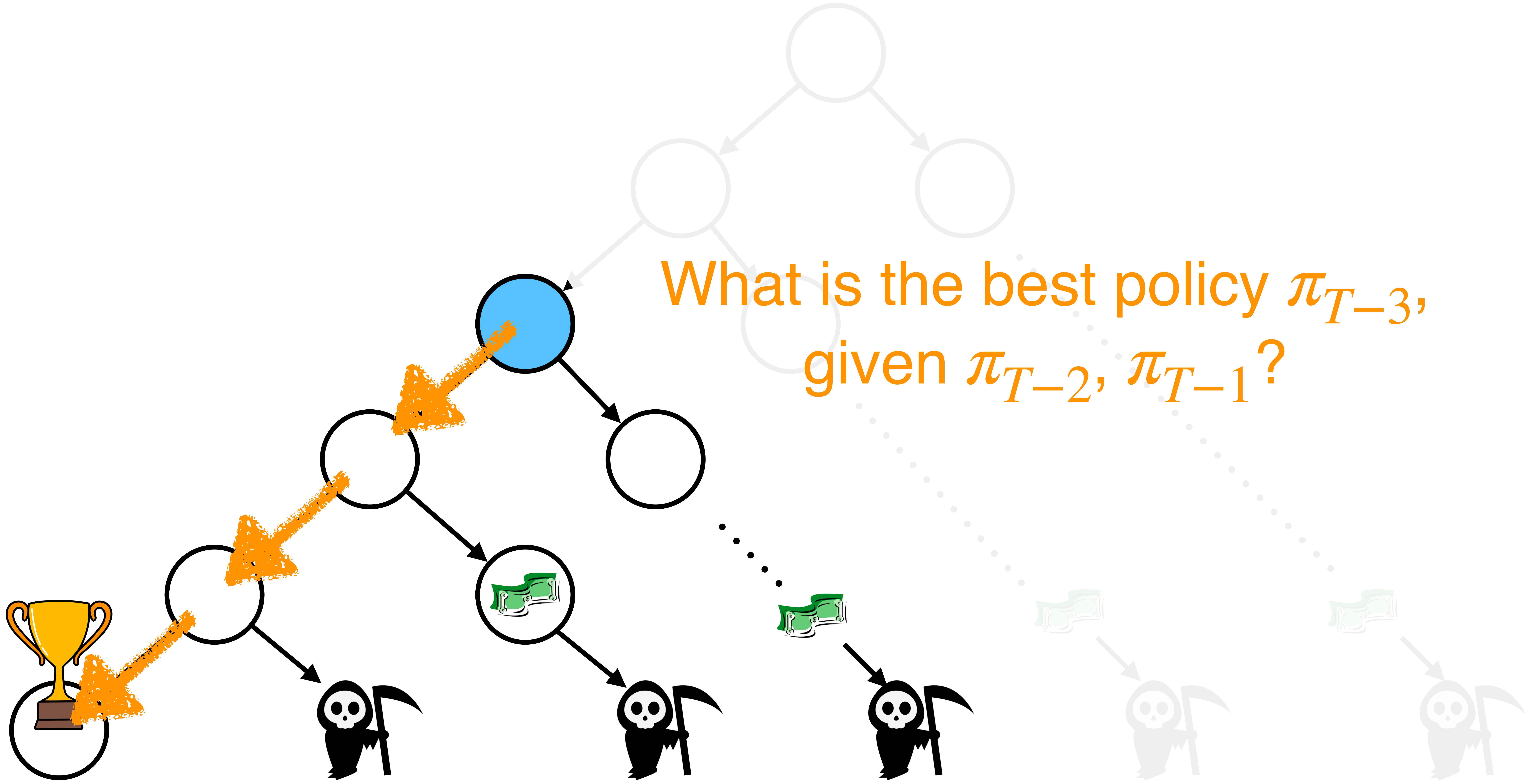
Policy Search via Dynamic Programming (PSDP)

What is the best policy π_{T-2}, given π_{T-1}?

Policy Search via Dynamic Programming (PSDP)

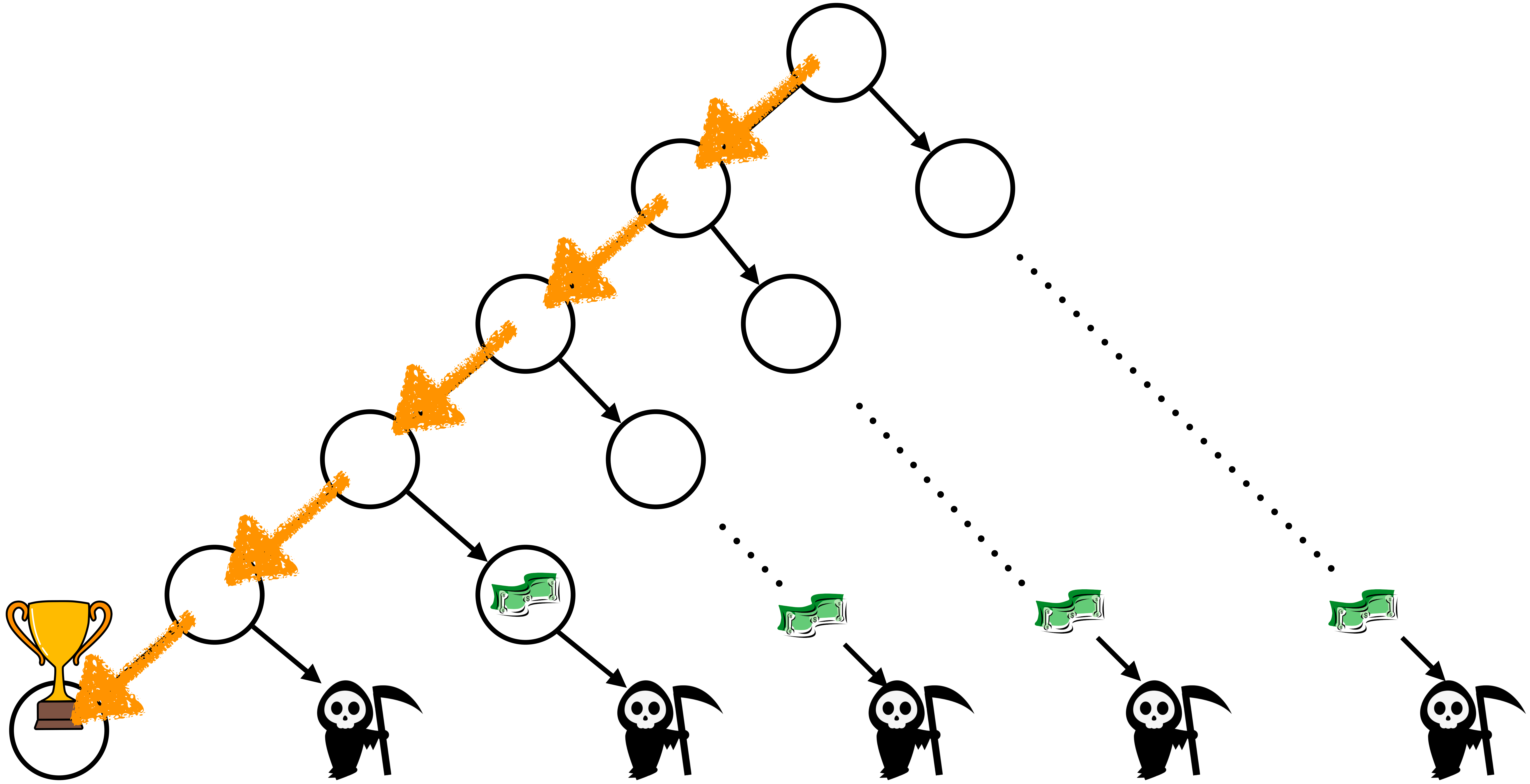
What is the best policy π_{T-2}, given π_{T-1}?

Policy Search via Dynamic Programming (PSDP)

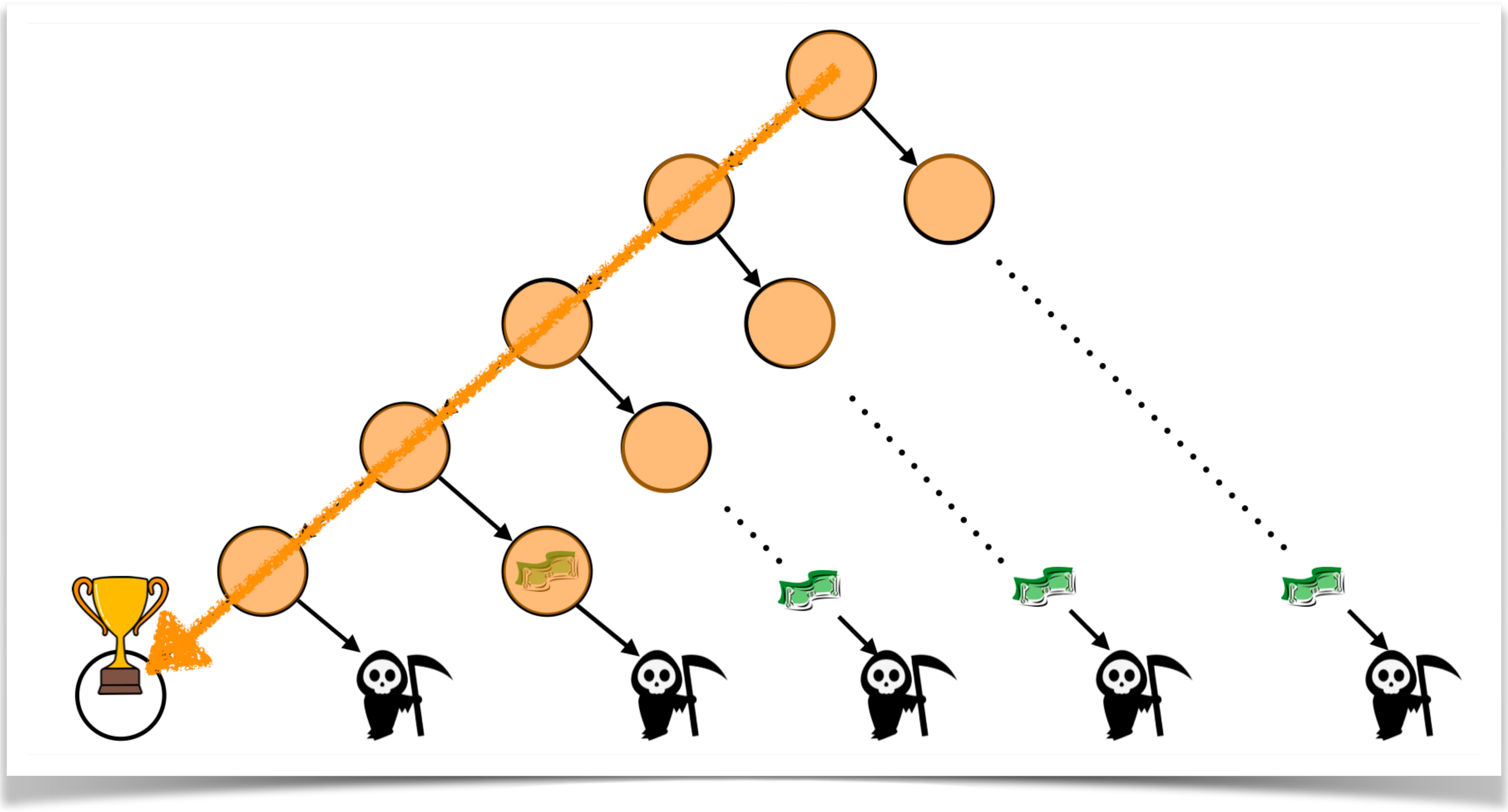


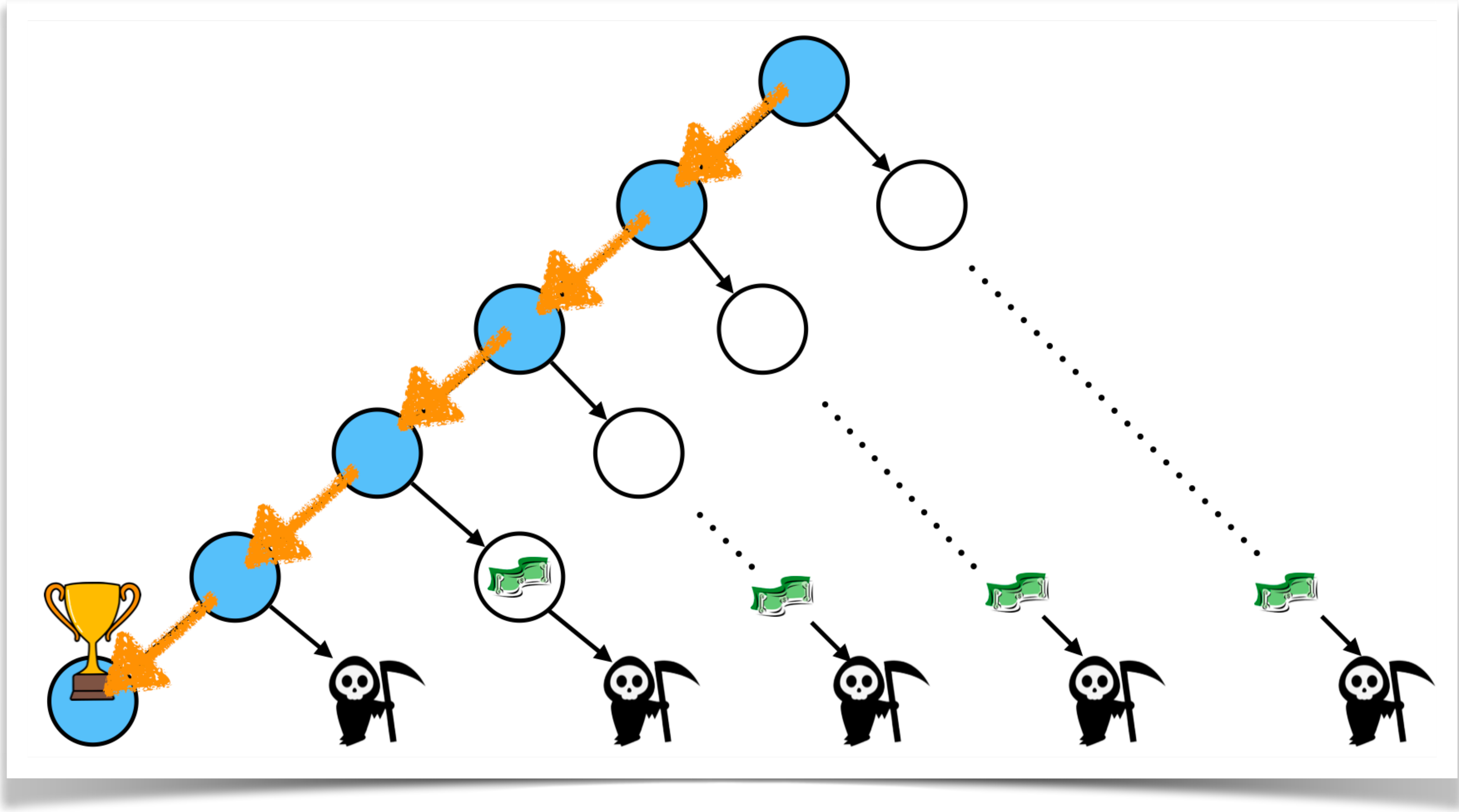
What is the best policy π_{T-3}, given π_{T-2}, π_{T-1}?

Only took poly(T) steps!



PSDP is Lazy



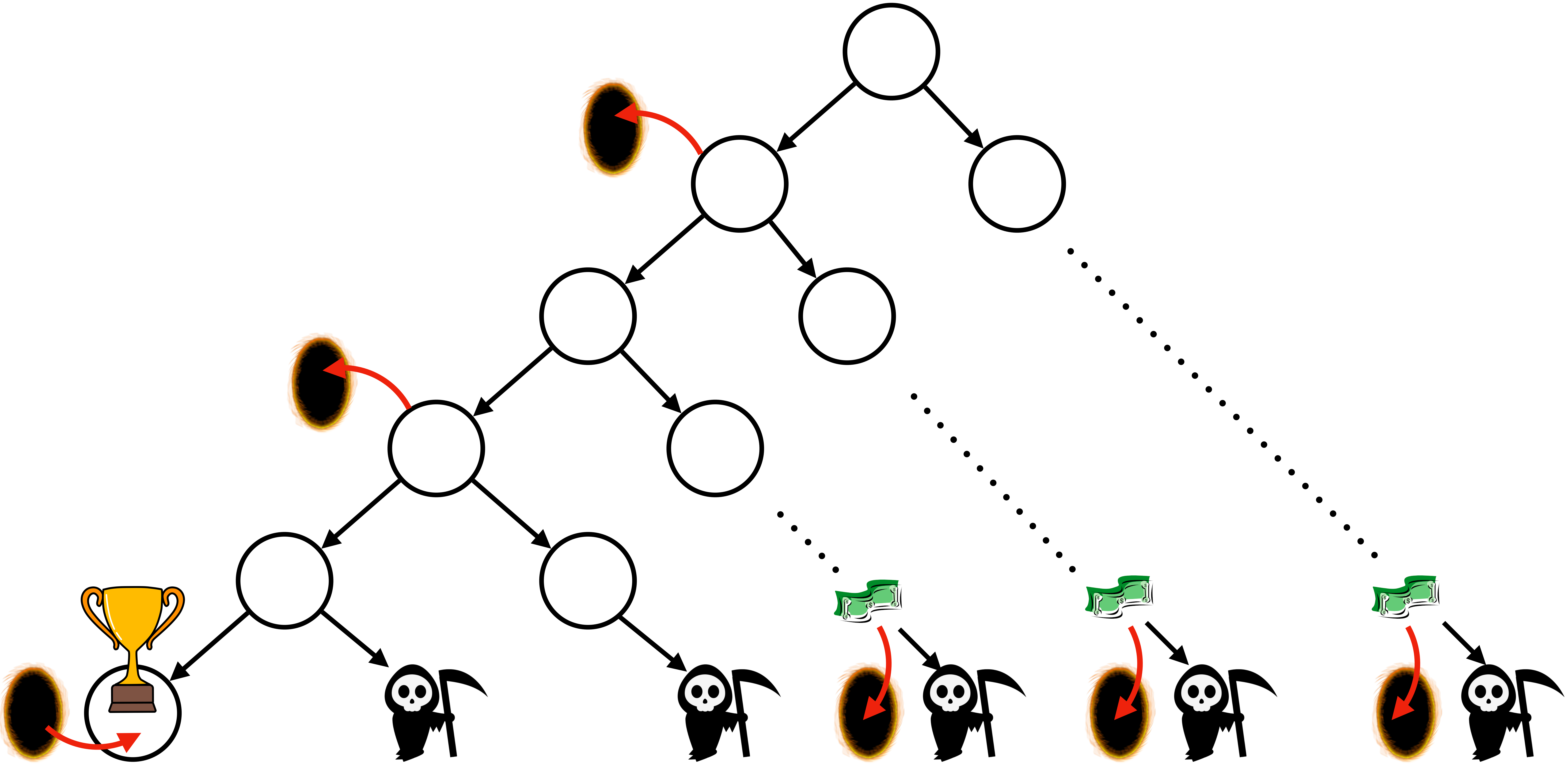


Instead of searching all states to find the best policy

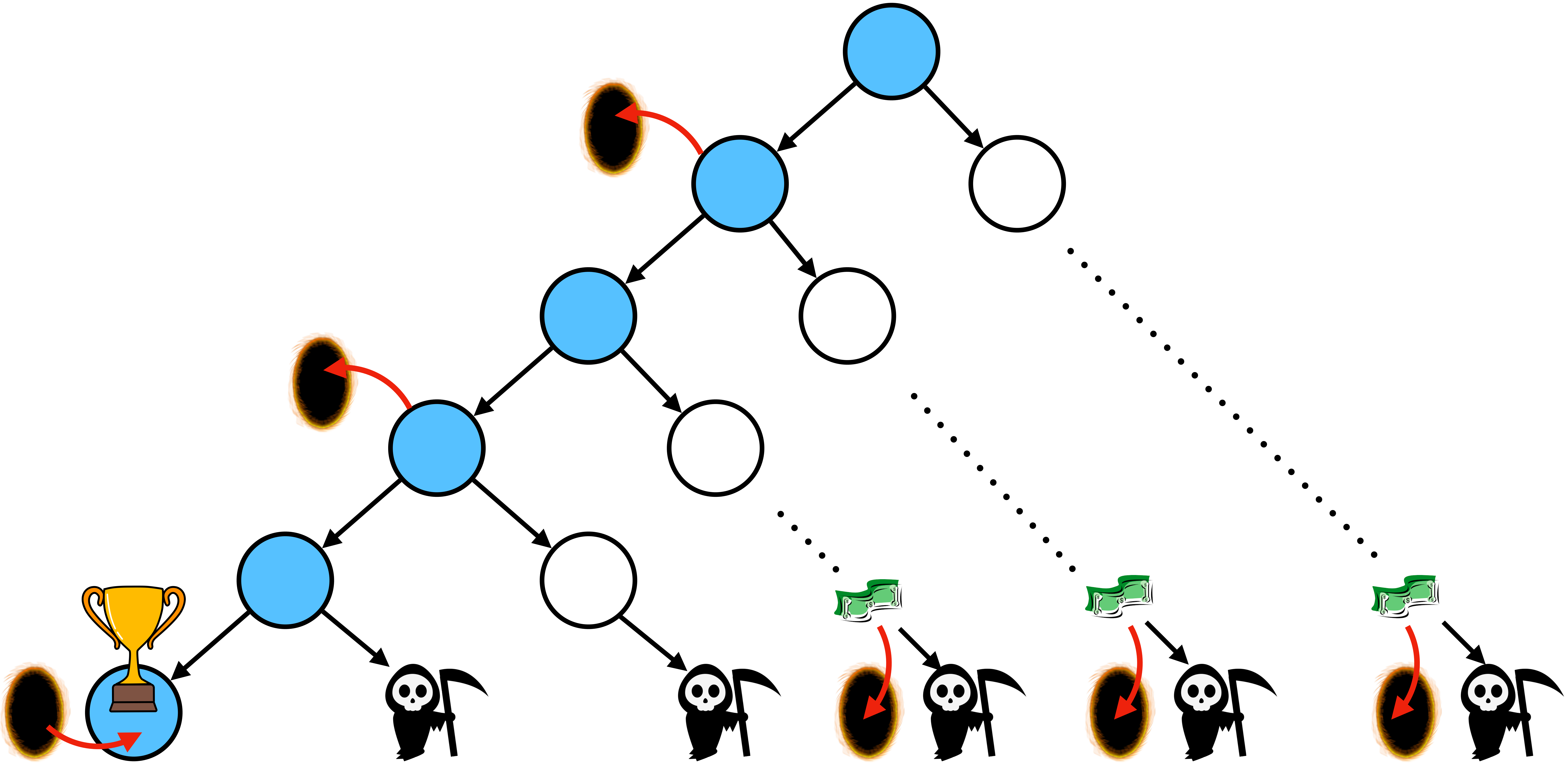
Just do better on states the expert visits

Is being lazy
a good idea
for model learning?

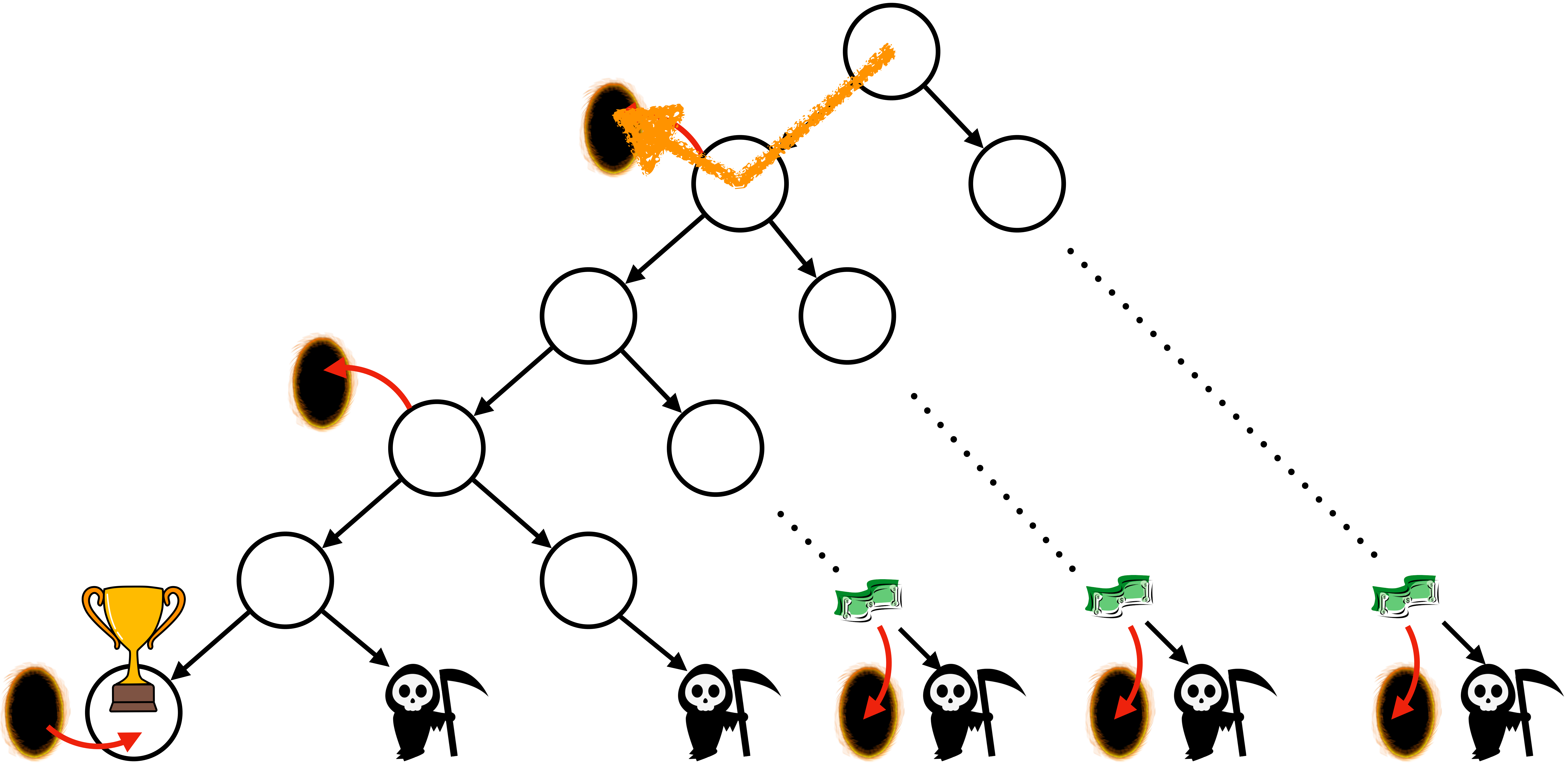
Model at iteration 0



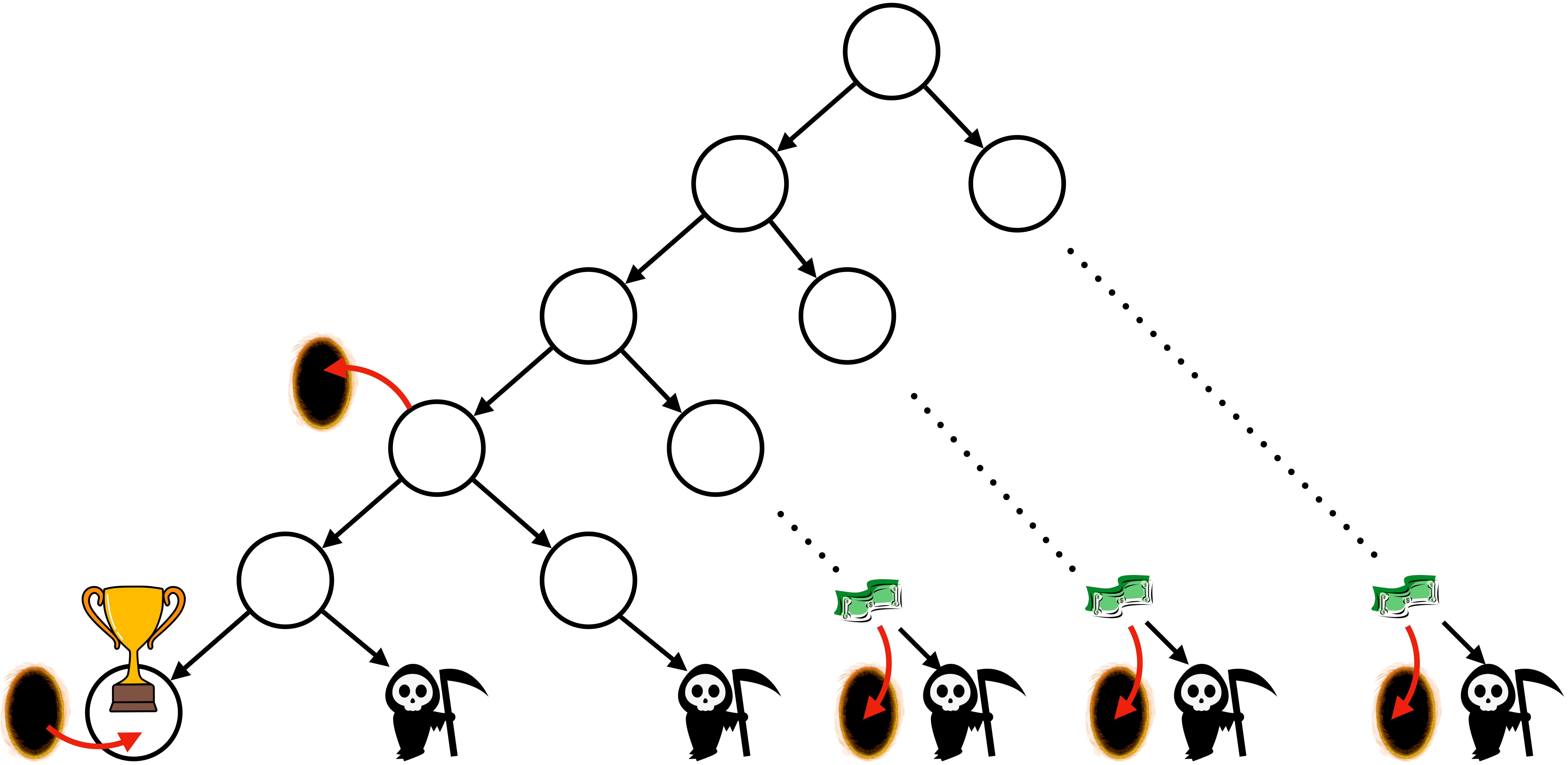
Run lazy policy search poly(T)



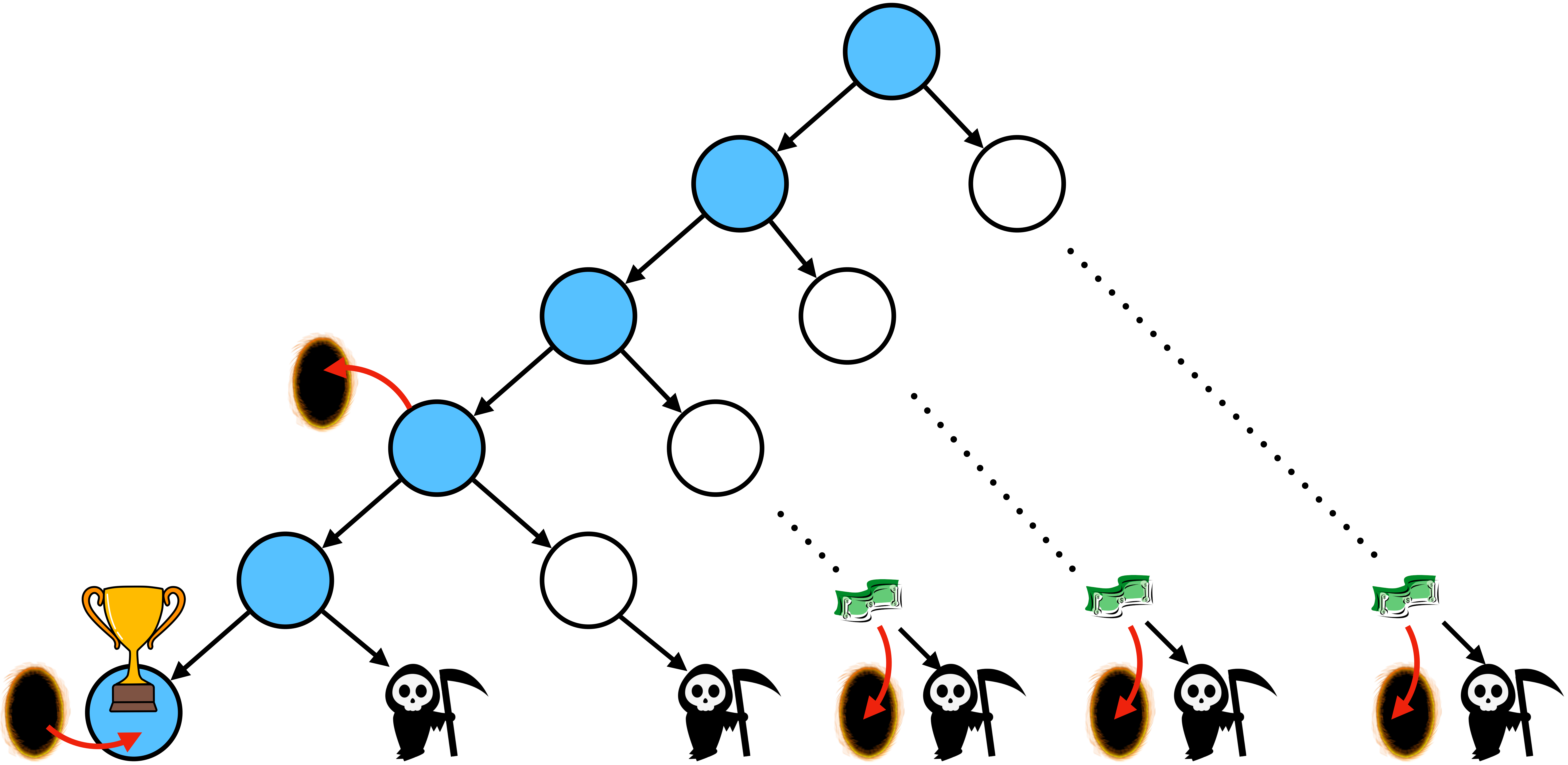
Policy at iteration 0



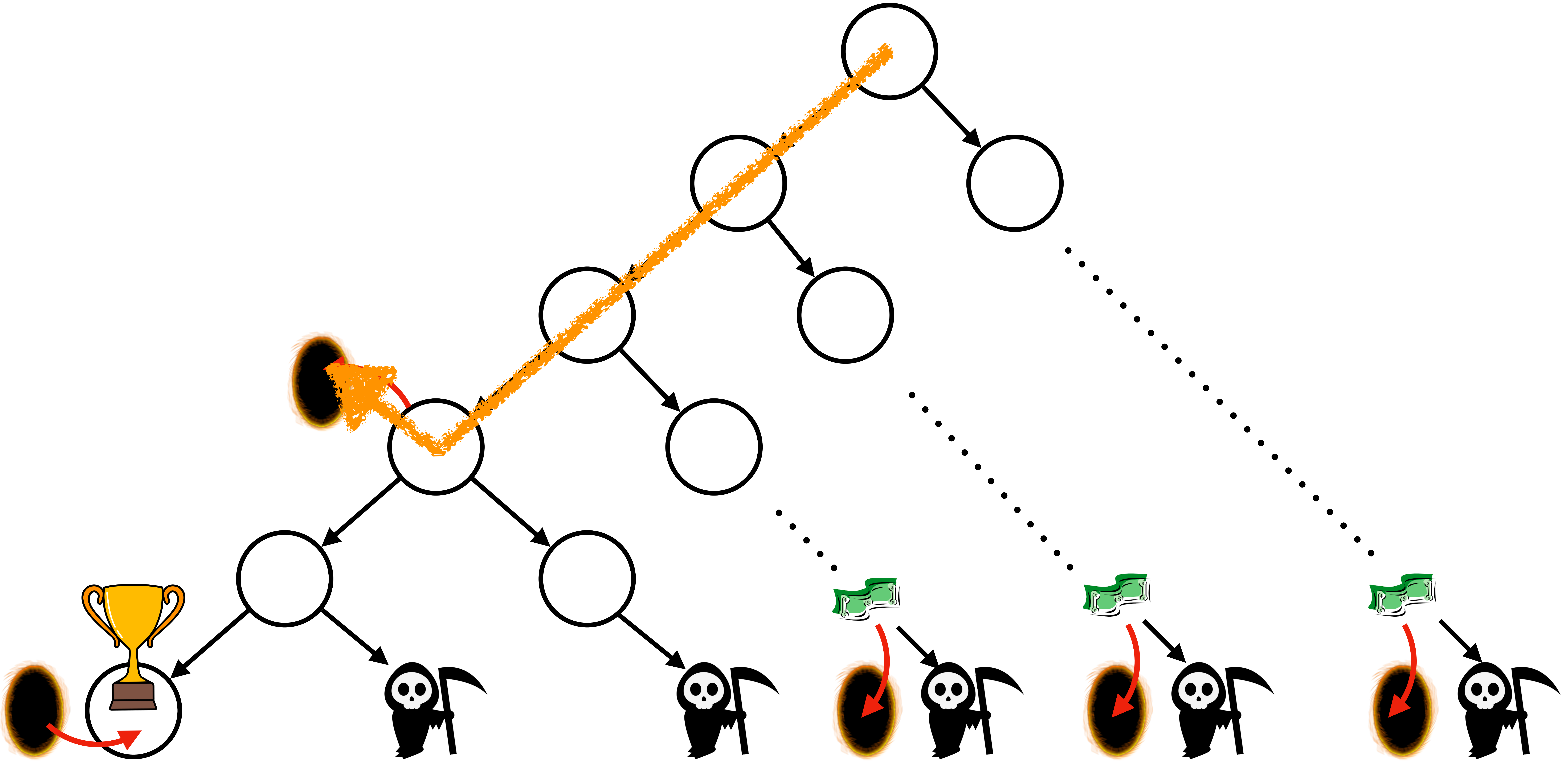
Model at iteration 1



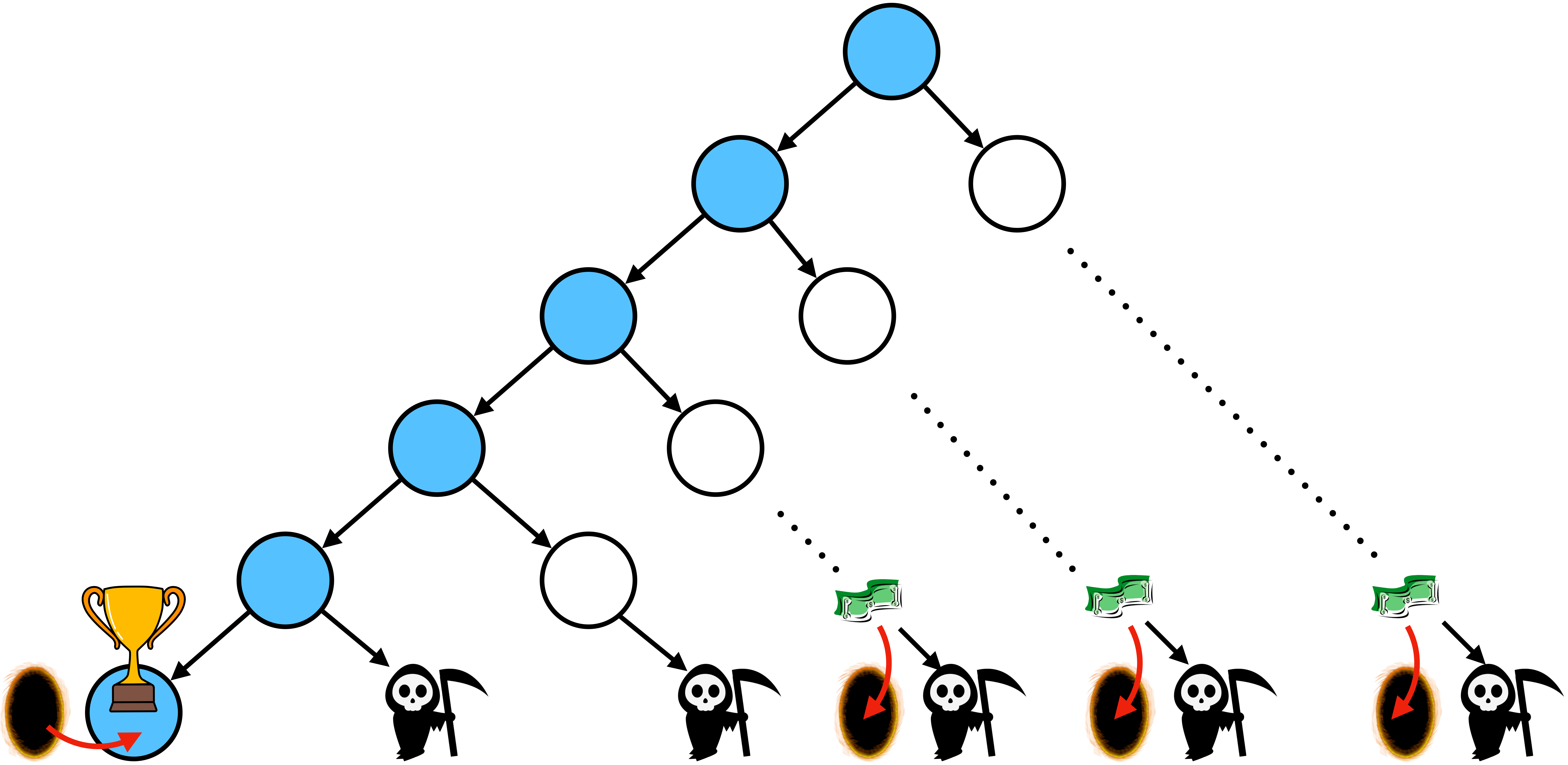
Run lazy policy search poly(T)



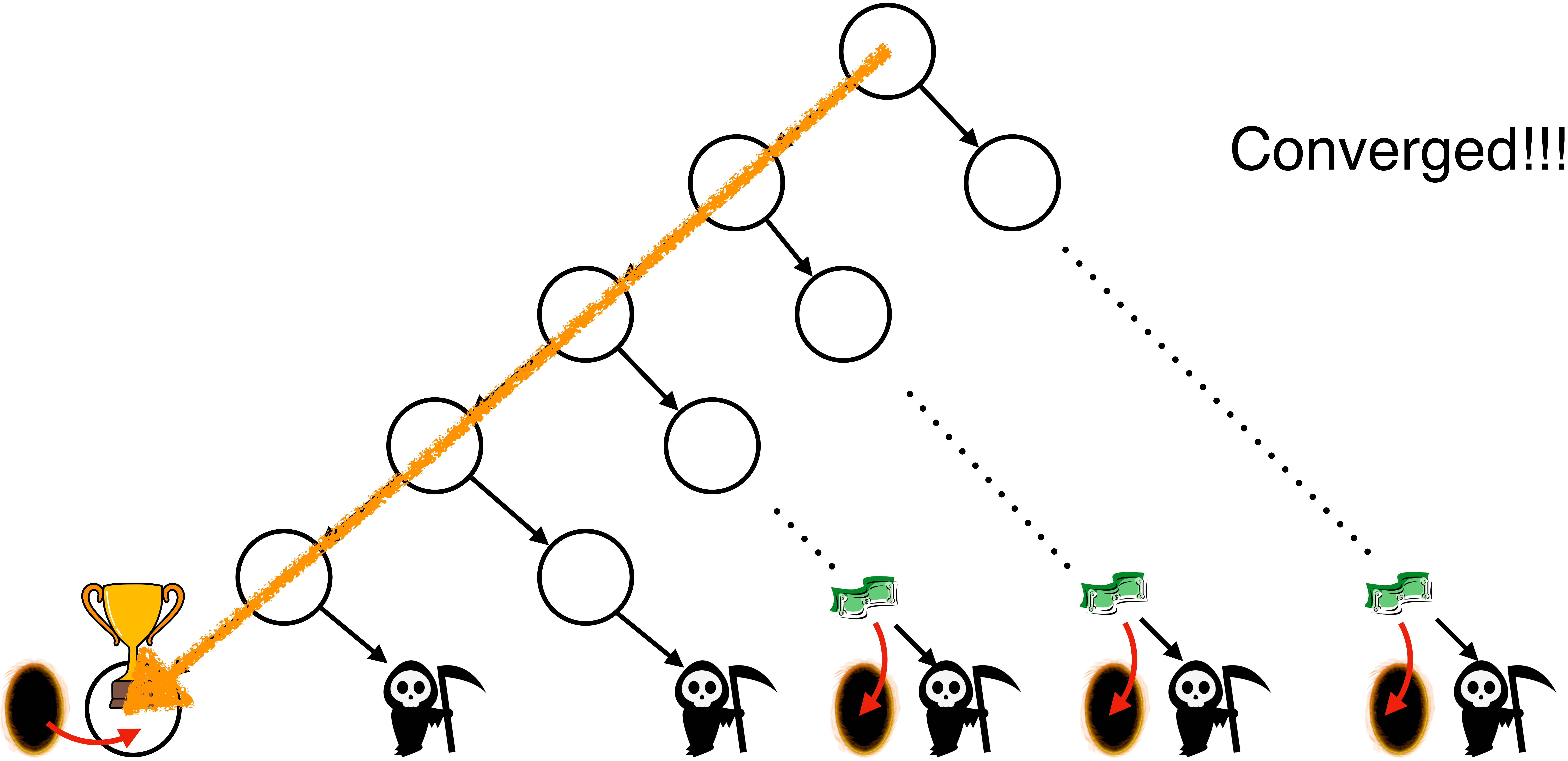
Policy at iteration 1



Run lazy policy search poly(T)

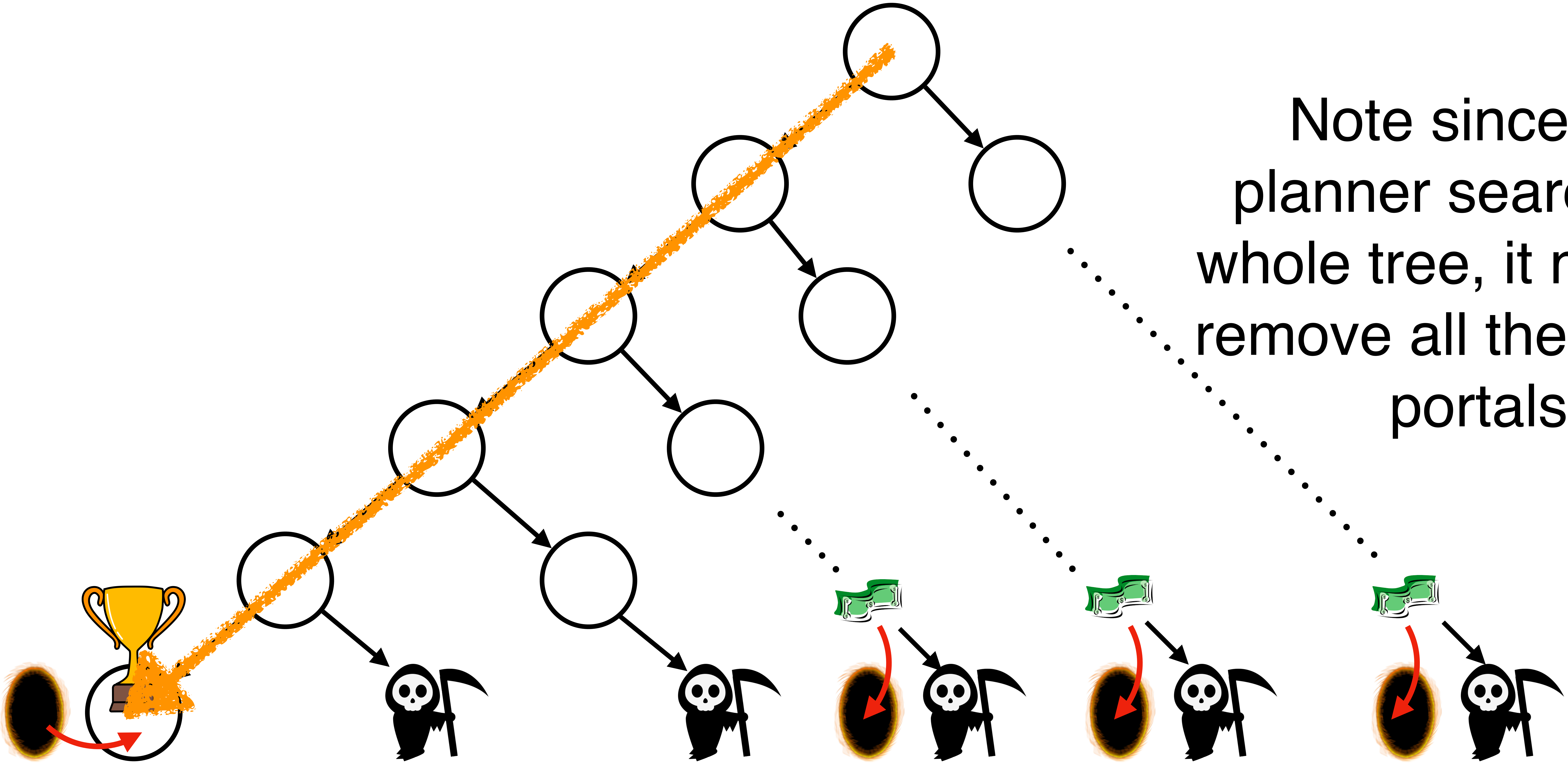


Policy at iteration 2



Converged!!!

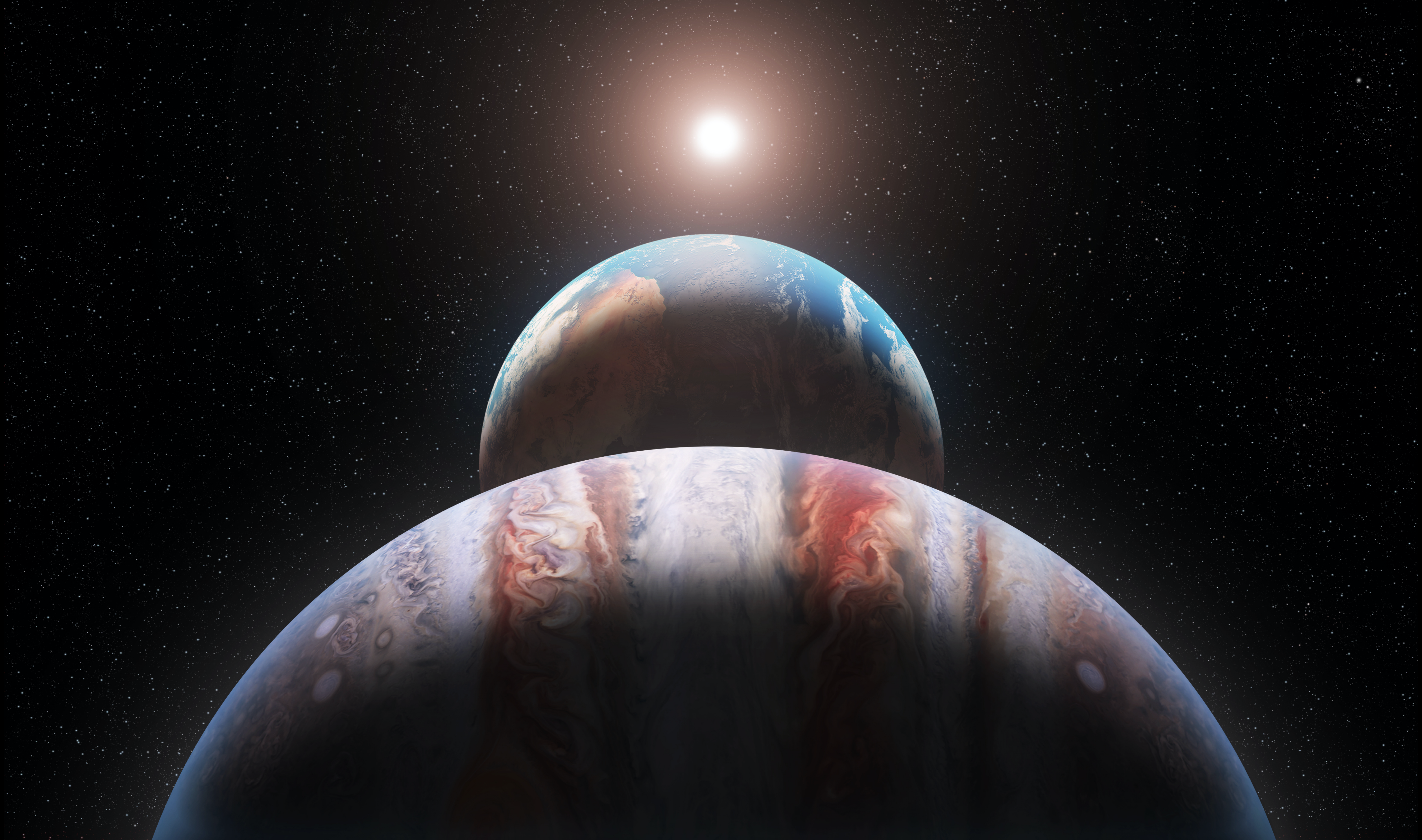
Final Model + Policy



Note since the planner search the whole tree, it may not remove all the hidden portals

But can we prove that lazy is good for model learning?

A New Lemma!



Lemma: Performance Difference via Advantage in Model

$$J_{M^*}(\pi^*) - J_{M^*}(\hat{\pi})$$

$$\leq \mathbb{E}_{s^* \sim \pi^*}\left[A^{\pi}(s^*, a^*)\right] \quad + TV_{\max}\mathbb{E}_{s,a\sim\pi^*}||\hat{M}(s,a) - M(s,a)||$$

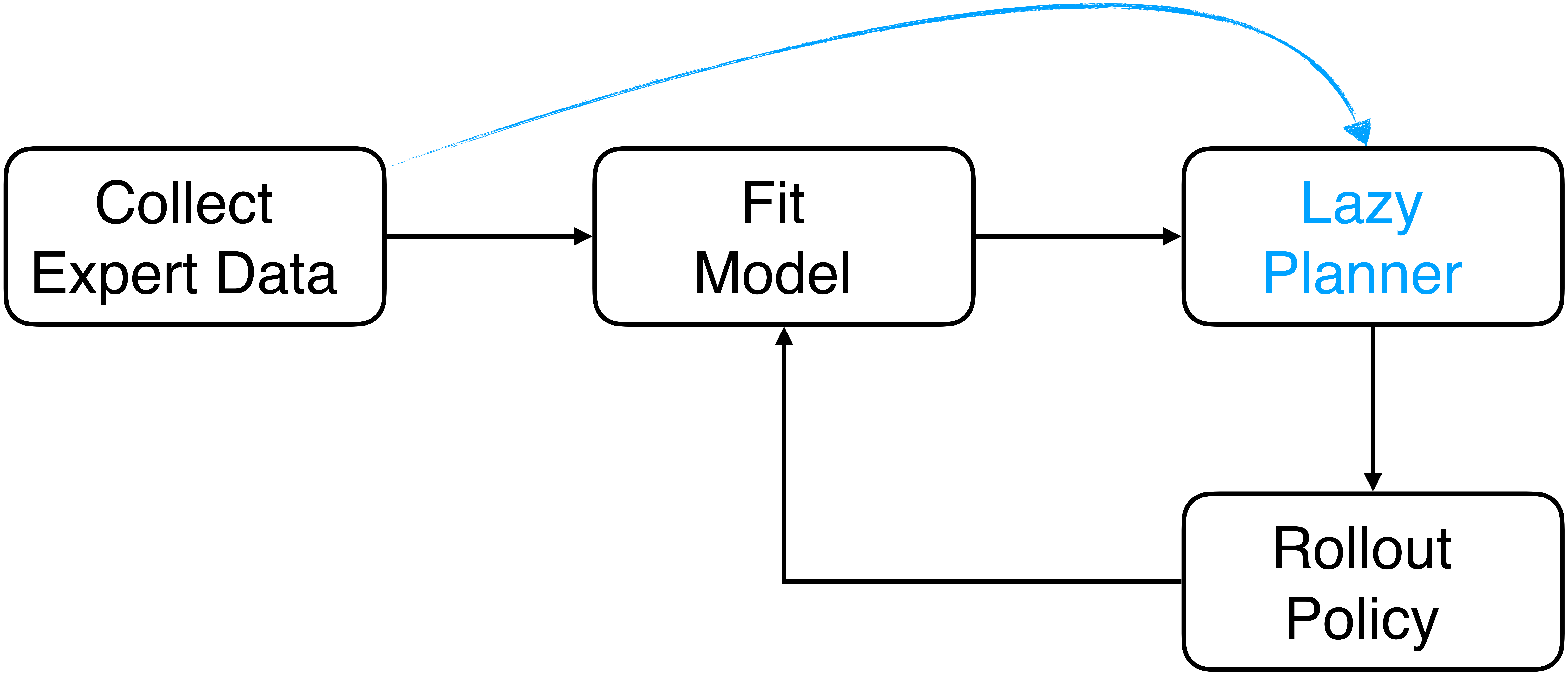
Advantage of expert in model

Model fit on expert states

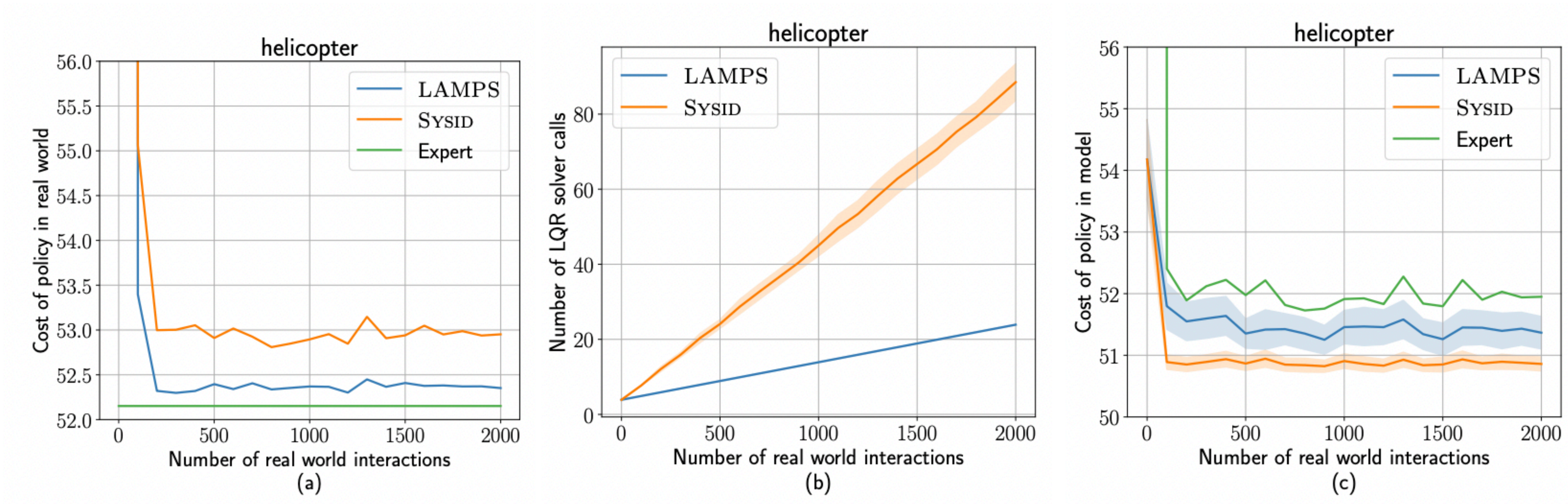
$$+ TV_{\max}\mathbb{E}_{s,a\sim\pi}||\hat{M}(s,a) - M(s,a)||$$

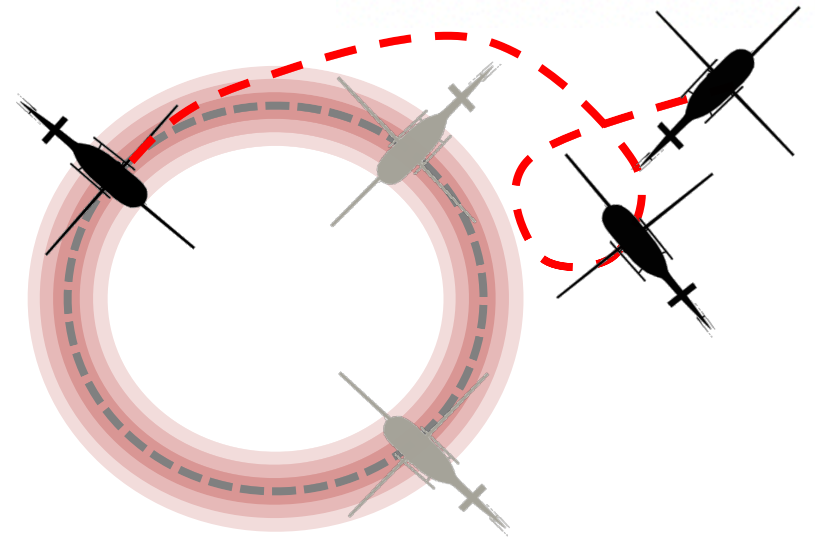
Model fit on policy states

Lazy Model-based Policy Search (LAMPS)



LAMPS finds a better policy with fewer samples + fewer computation

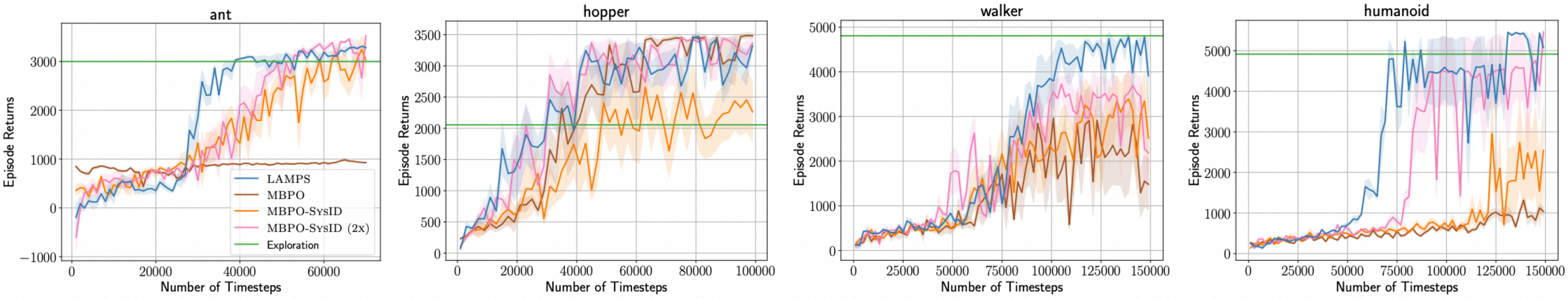




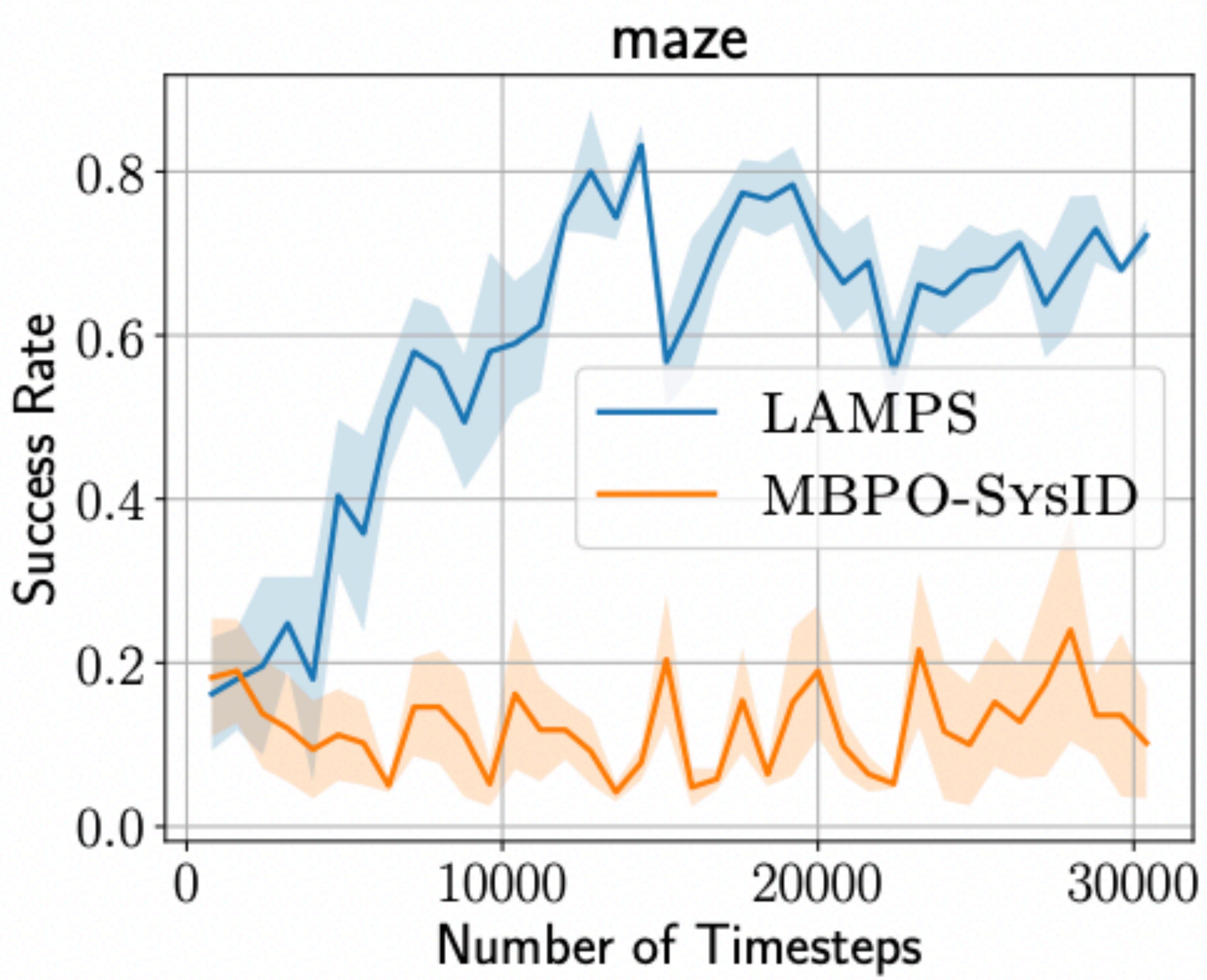
SysID: Use planner (iLQR)

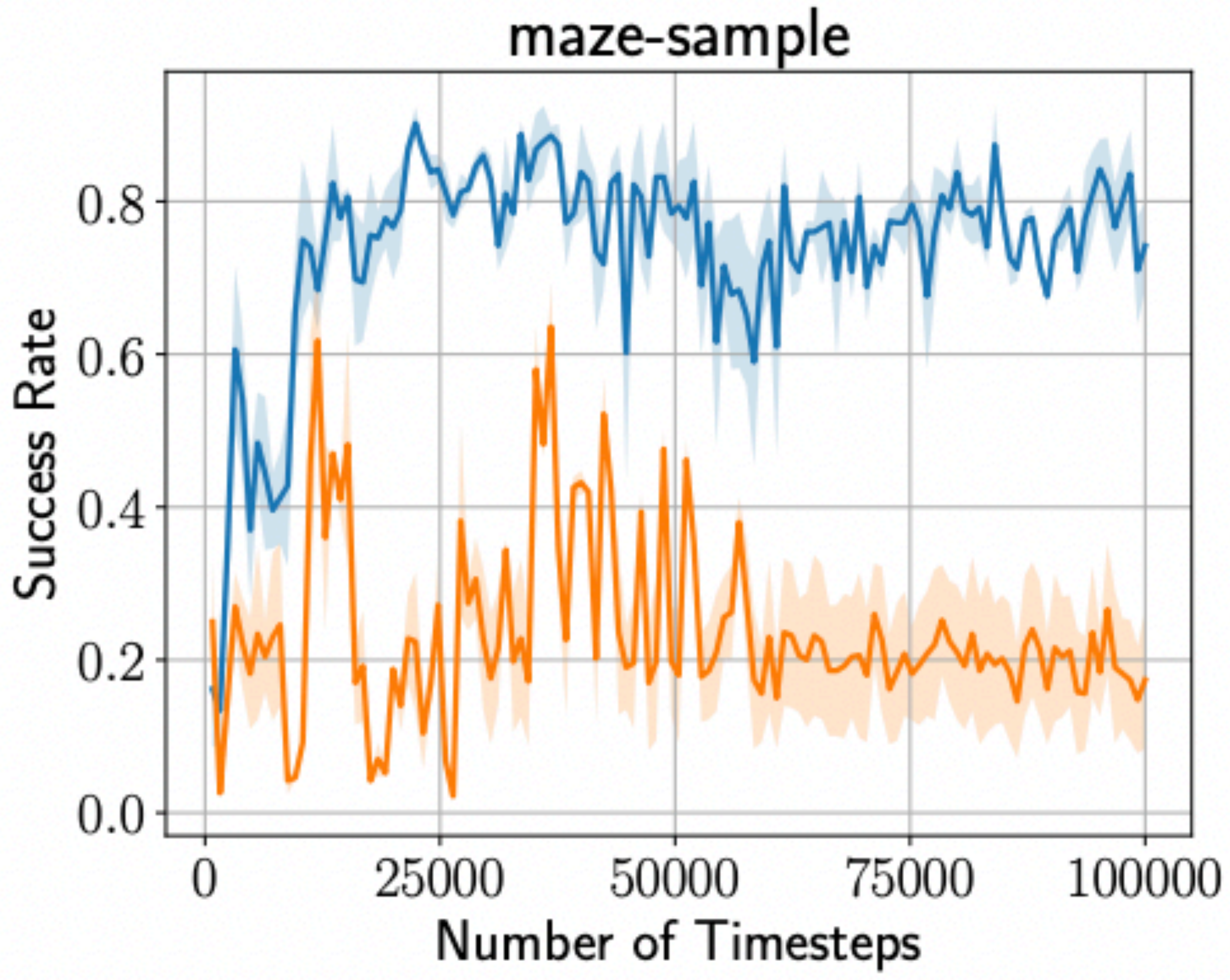
LAMPS: Use PSDP (LQR on expert traj)

LAMPS converges faster than both SysID and MBPO



LAMPS makes better use of Expert Data

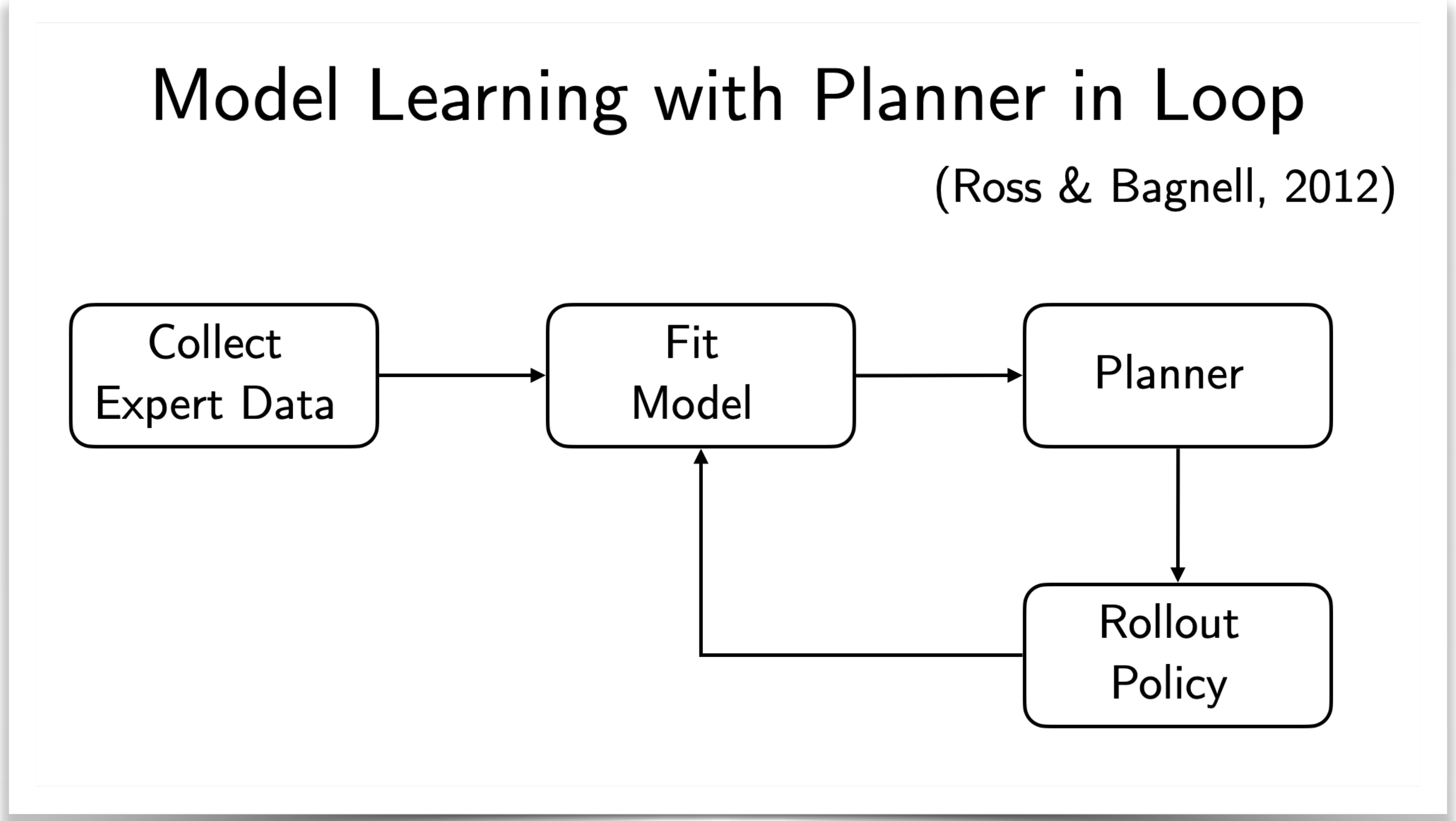


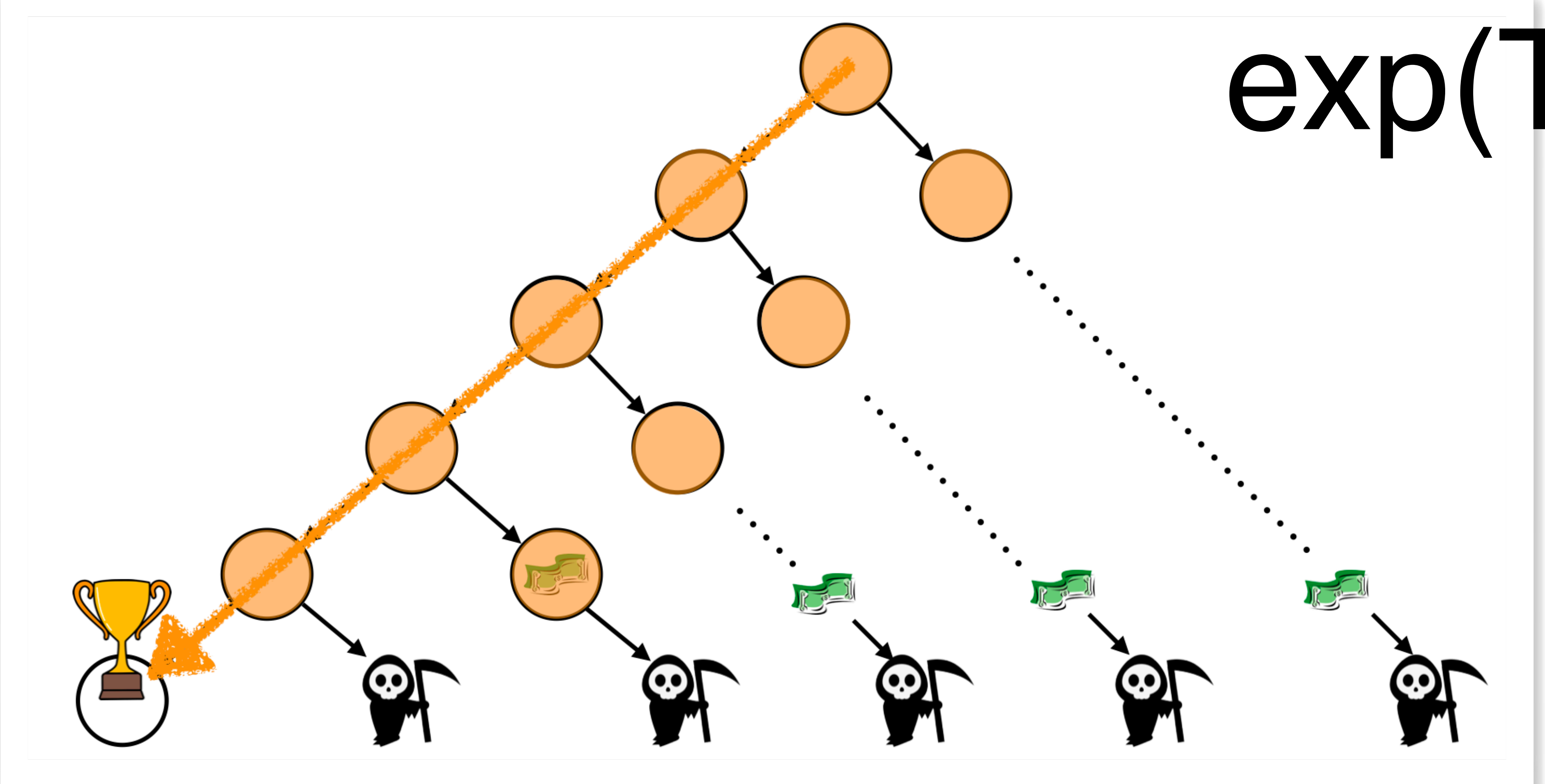


10000 samples

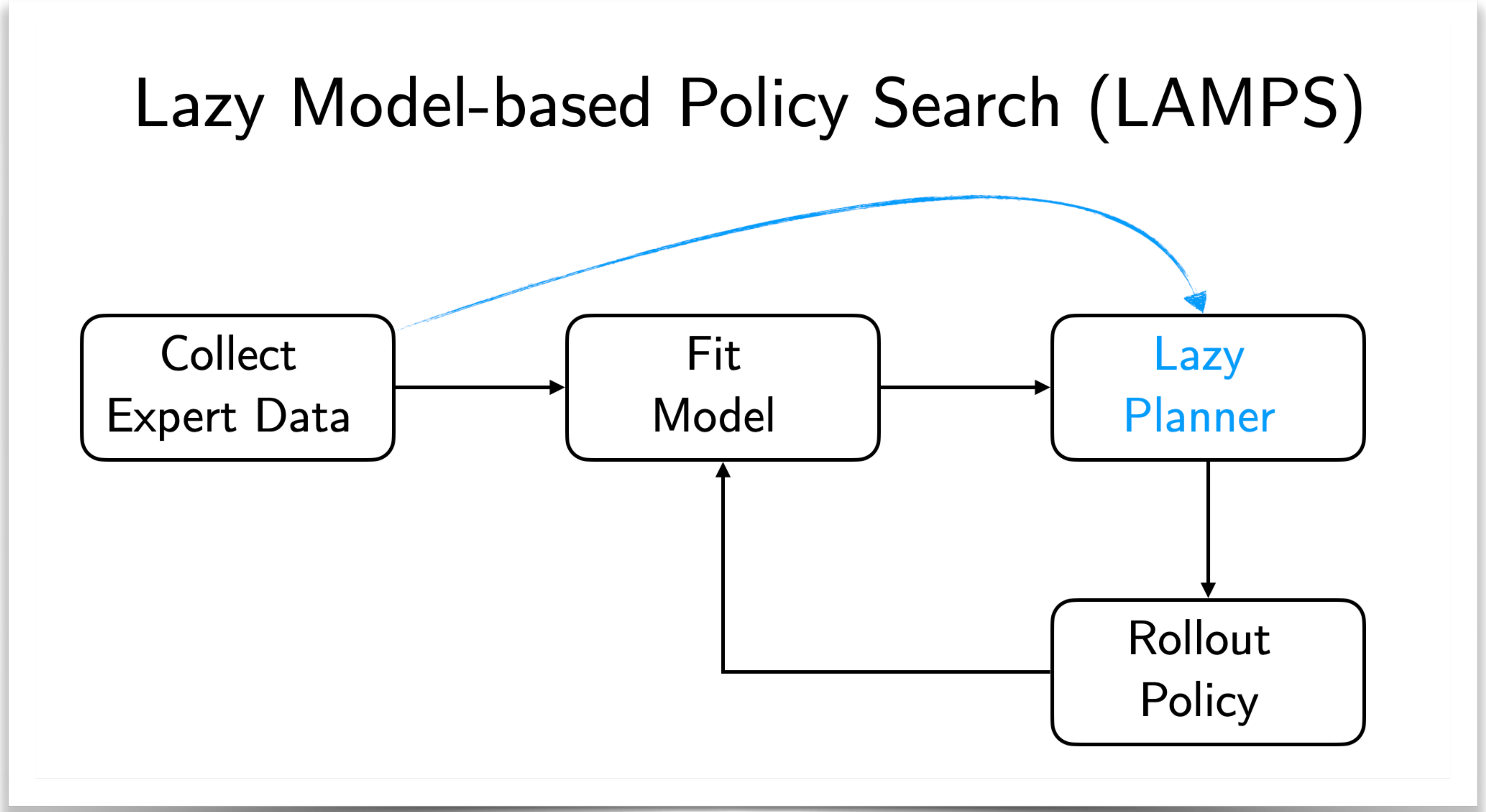
50000 samples

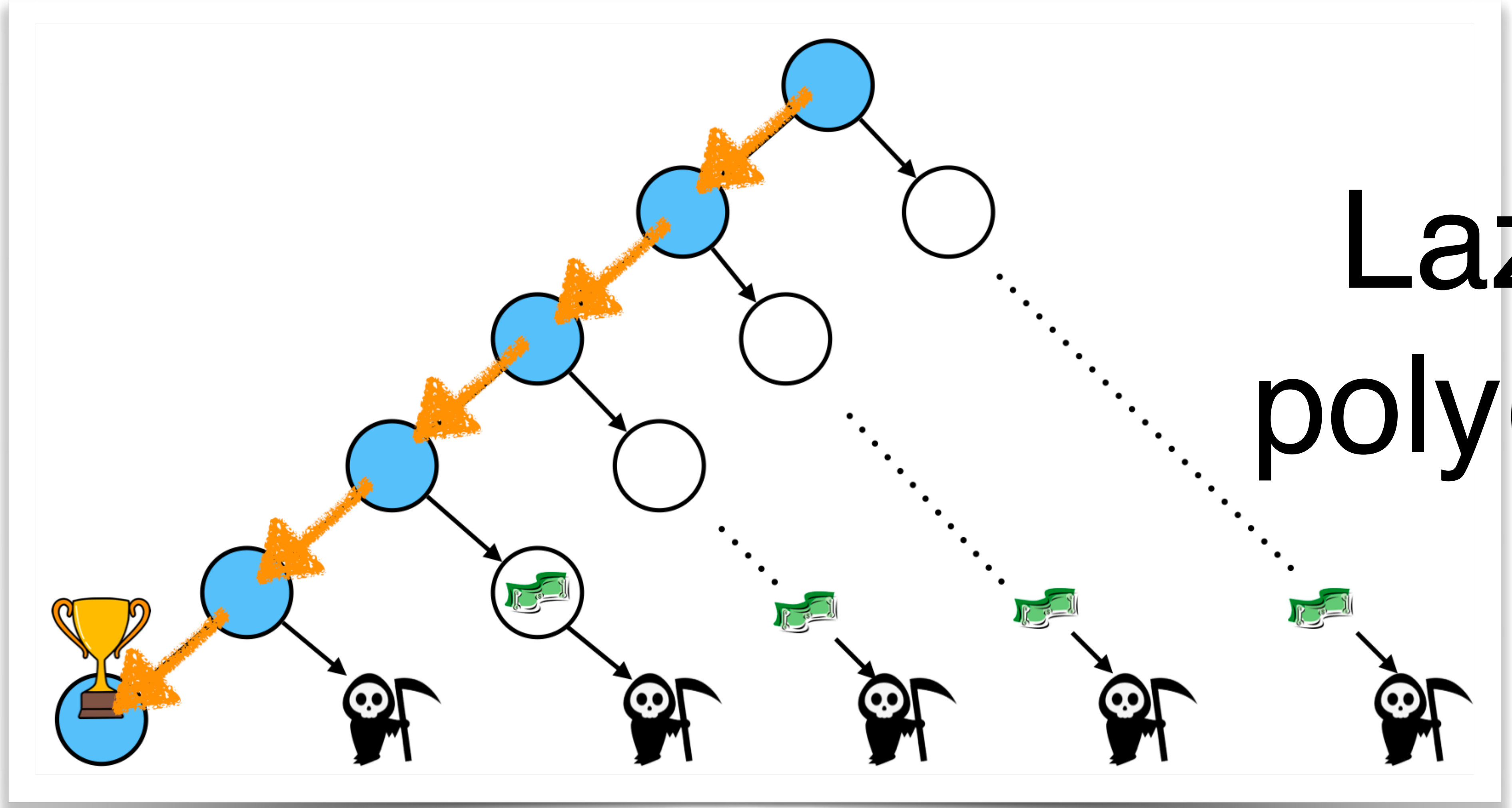
Recap





Planning
exp(T)!





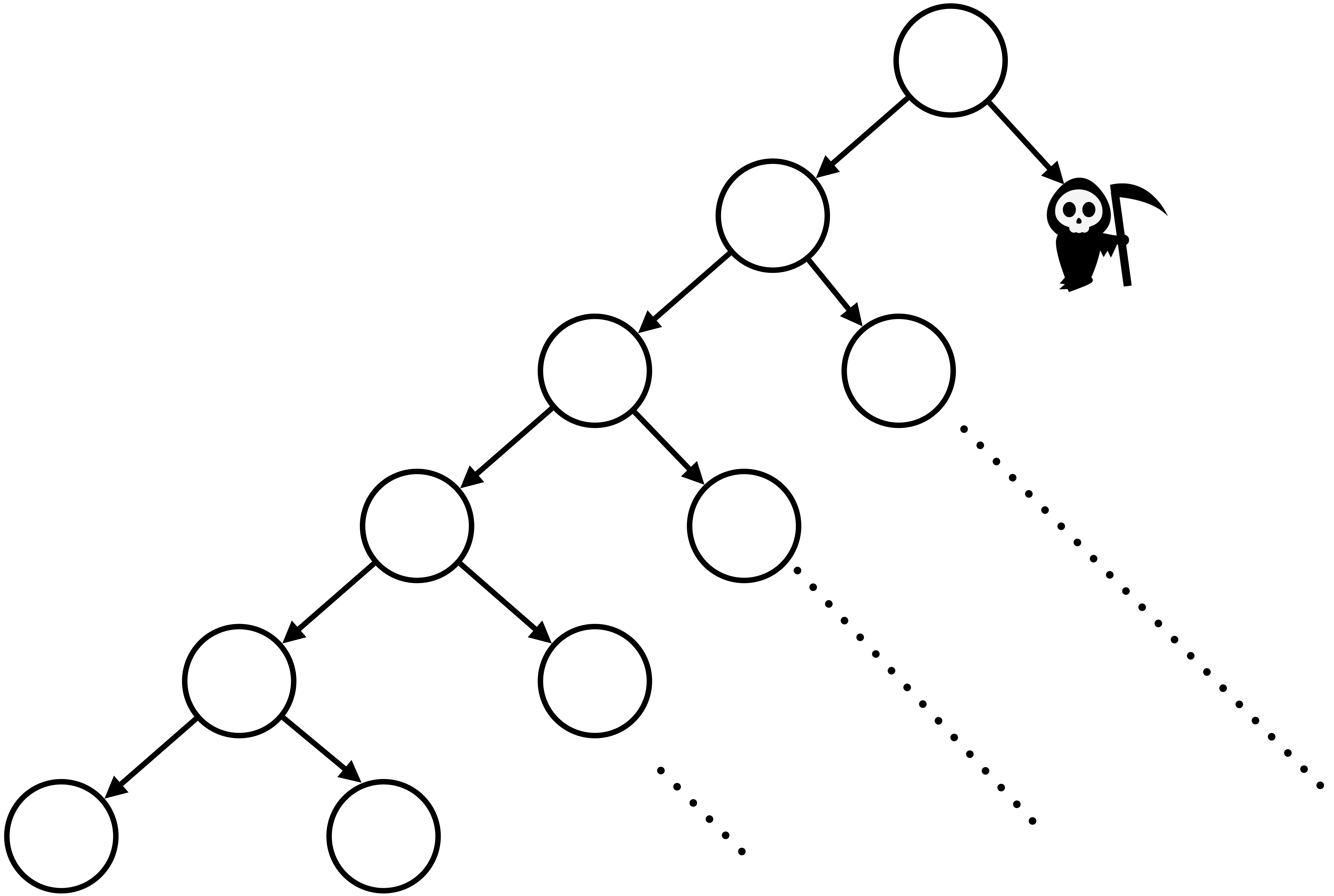
Lazy
poly(T)!

Another challenge.

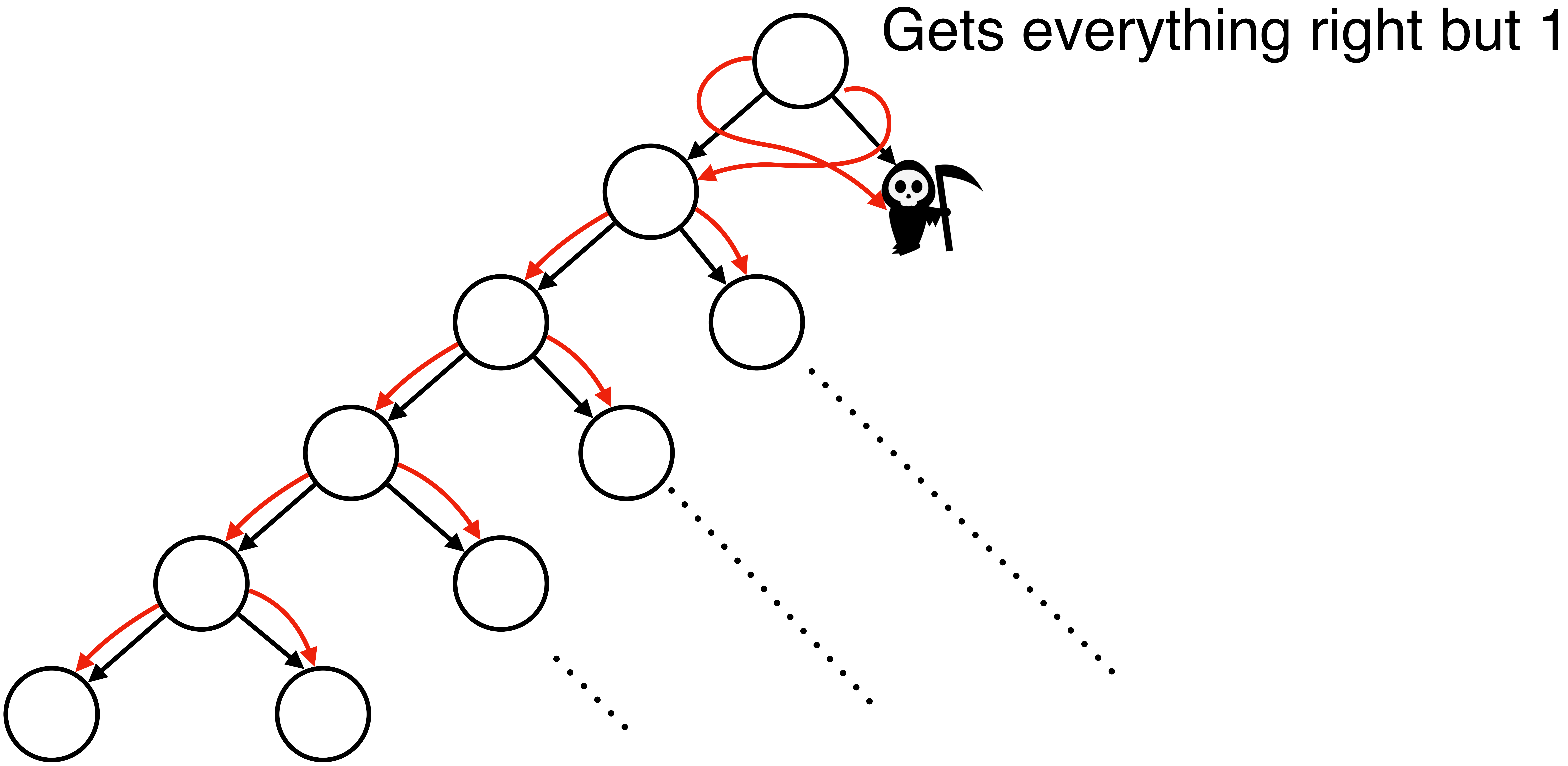
Mismatched Objectives

Fitting model with L2 loss
is mismatched
with how good
the resulting policy is

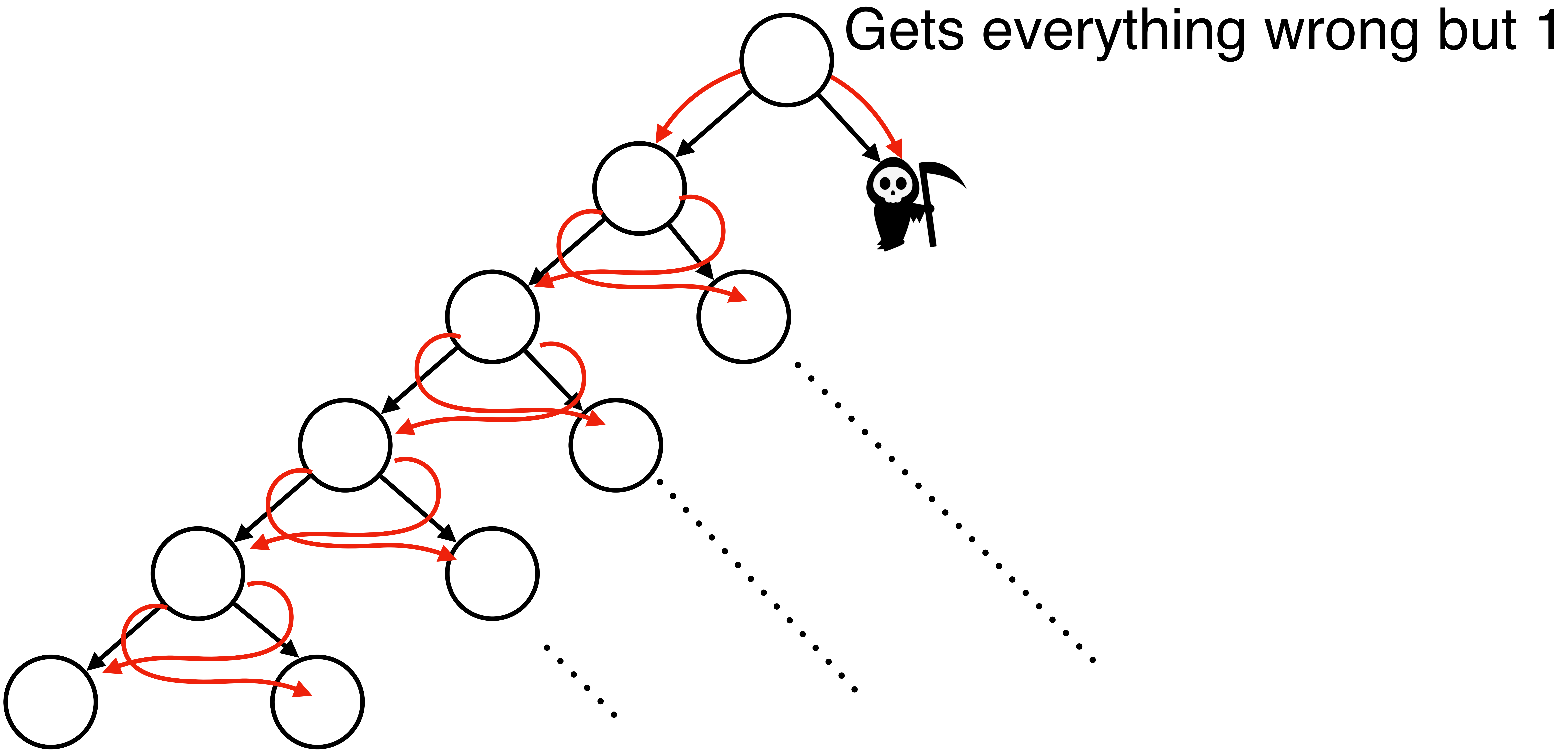
True Dynamics



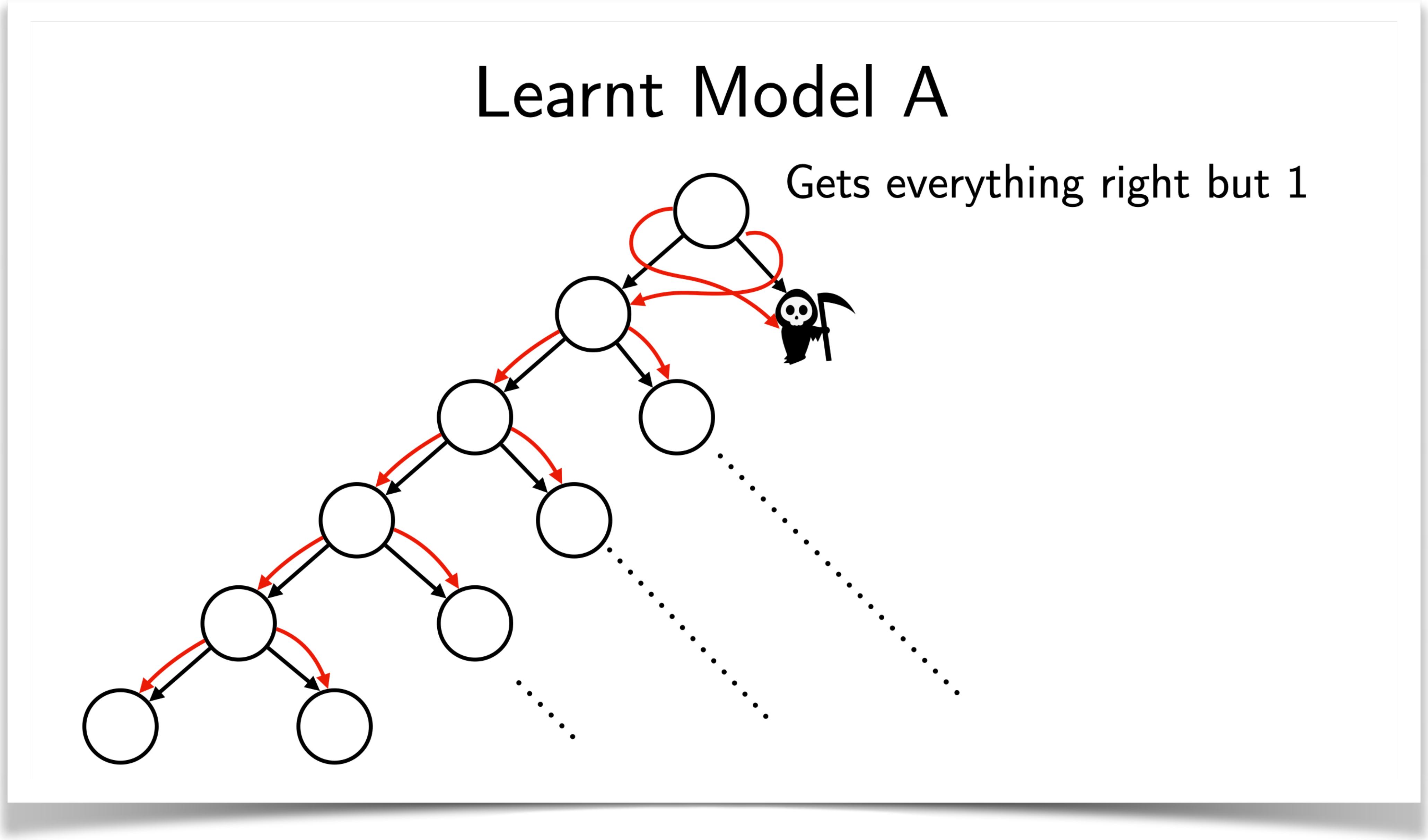
Learnt Model A

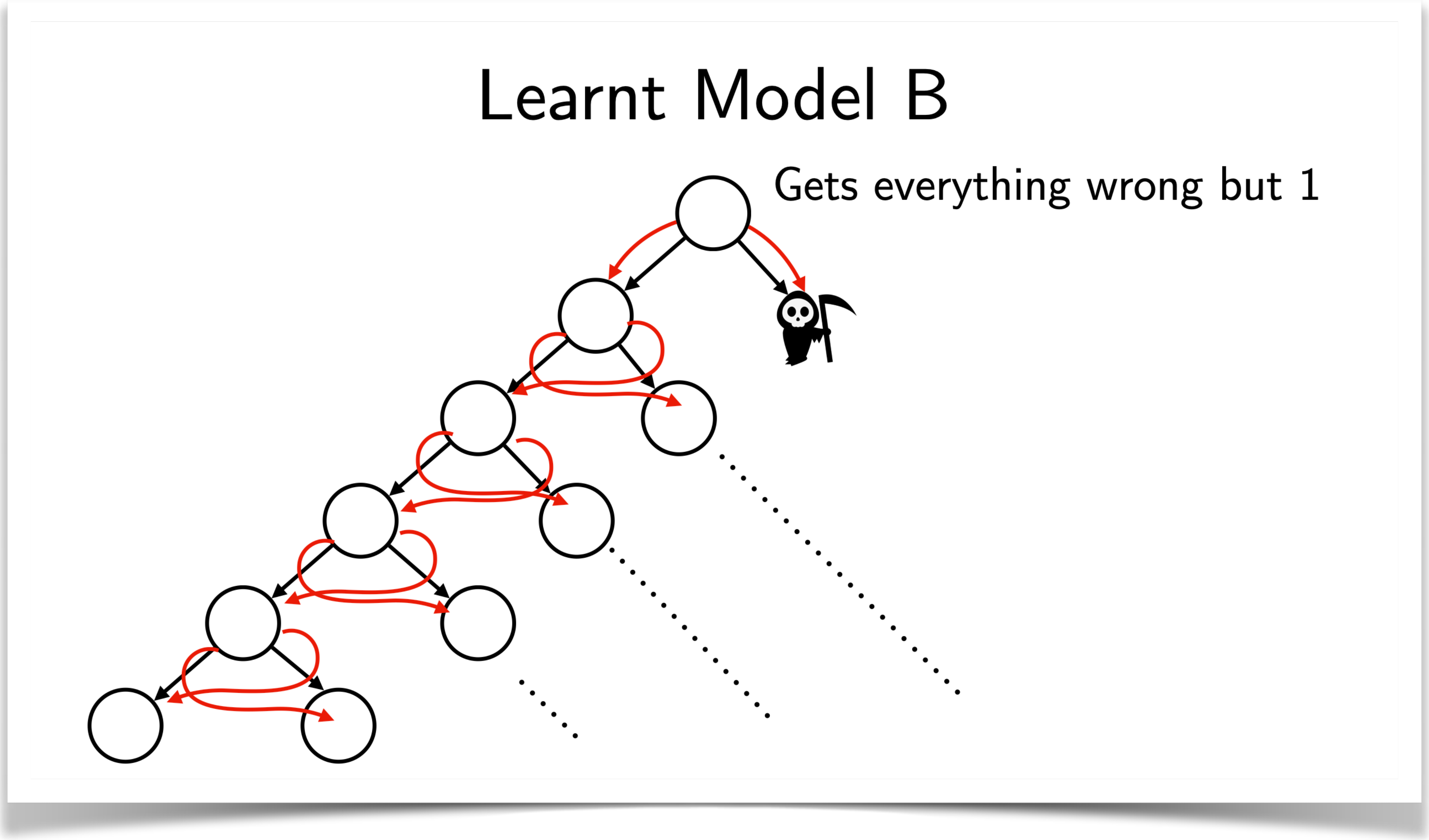


Learnt Model B



Which model has lower loss? Which one do we prefer?





Can we have change the loss for how we fit the model?

Our new lemma actually prescribes matching values!

$$J_{M^*}(\pi^*) - J_{M^*}(\hat{\pi})$$

$$= \mathbb{E}_{s^* \sim \pi^*}\left[A^{\hat{\pi}}(s^*, a^*)\right] \quad + T\mathbb{E}_{s,a \sim \pi^*}\left[E_{s' \sim \hat{M}} V^{\hat{\pi}}(s') - E_{s'' \sim M^*} V^{\hat{\pi}}(s'')\right]$$

Advantage of expert in model

Value matching on expert states

$$+ T\mathbb{E}_{s,a \sim \hat{\pi}}\left[E_{s' \sim \hat{M}} V^{\hat{\pi}}(s') - E_{s'' \sim M^*} V^{\hat{\pi}}(s'')\right]$$

Value matching on learner states

$$J_{M^*}(\pi^*) - J_{M^*}(\hat{\pi})$$

$$= \mathbb{E}_{s^* \sim \pi^*}\left[A^{\hat{\pi}}(s^*, a^*)\right] \quad + T\mathbb{E}_{s,a \sim \pi^*}\left[E_{s' \sim \hat{M}} V^{\hat{\pi}}(s') - E_{s'' \sim M^*} V^{\hat{\pi}}(s'')\right]$$

Advantage of expert in model

Value matching on expert states

$$+ T\mathbb{E}_{s,a \sim \hat{\pi}}\left[E_{s' \sim \hat{M}} V^{\hat{\pi}}(s') - E_{s'' \sim M^*} V^{\hat{\pi}}(s'')\right]$$

Value matching on learner states

Lemma: Performance Difference via Advantage in Model

$$J_{M^*}(\pi^*) - J_{M^*}(\hat{\pi})$$

$$\leq \mathbb{E}_{s^* \sim \pi^*}\left[A^{\pi}(s^*, a^*)\right] \qquad + TV_{\max}\mathbb{E}_{s,a \sim \pi^*}||\hat{M}(s,a) - M(s,a)||$$

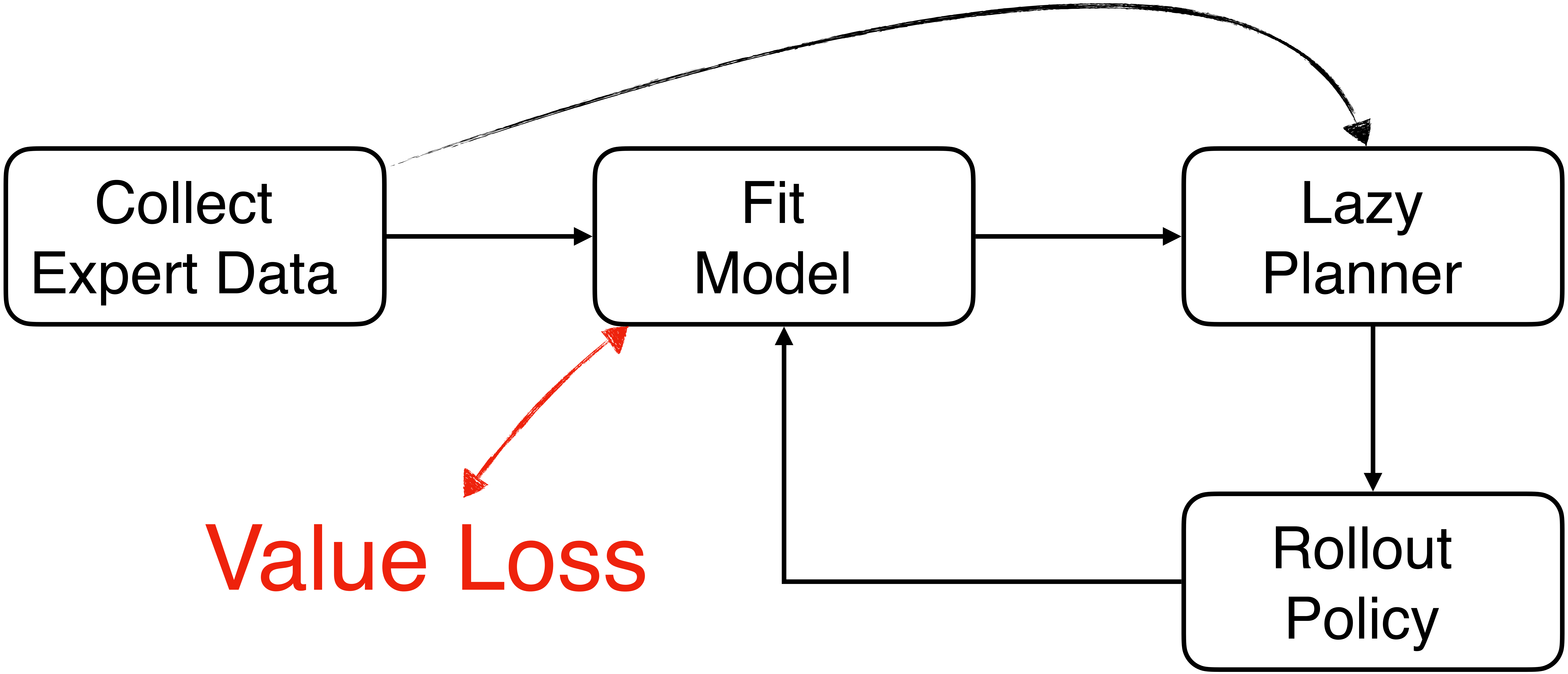
Advantage of expert in model

Model fit on expert states

$$+ TV_{\max}\mathbb{E}_{s,a \sim \pi}||\hat{M}(s,a) - M(s,a)||$$

Model fit on policy states

LAMPS with Moment Matching (LAMPS-MM)



New Lemma: Performance Difference via Advantage in Model

Solution 1:
Be lazy, restart
from expert states

Solution 2:
Match value loss