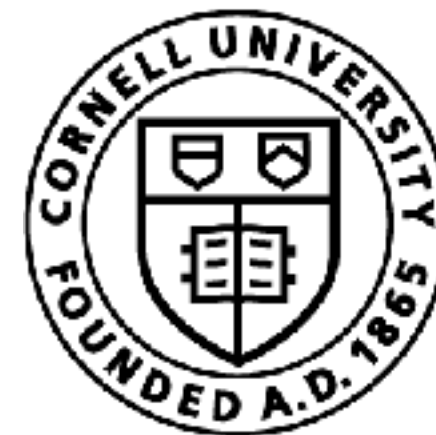


Model-based Reinforcement Learning

Sanjiban Choudhury



Cornell Bowers CIS
Computer Science

Do not worry about prelims!

We will grade on a curve (and try to be lenient!)

It's only 20% of the grade

Instead focus on final project (20%) and in-class quiz (10%)

[This is totally in your control to get full marks!]

Final Project

Will be posting doc with full instructions + partner finding today

Deliverables: Project proposal (in 2 weeks), final project, video, peer review

Groups of upto 3

Expectations (next slide)

Final project expectations

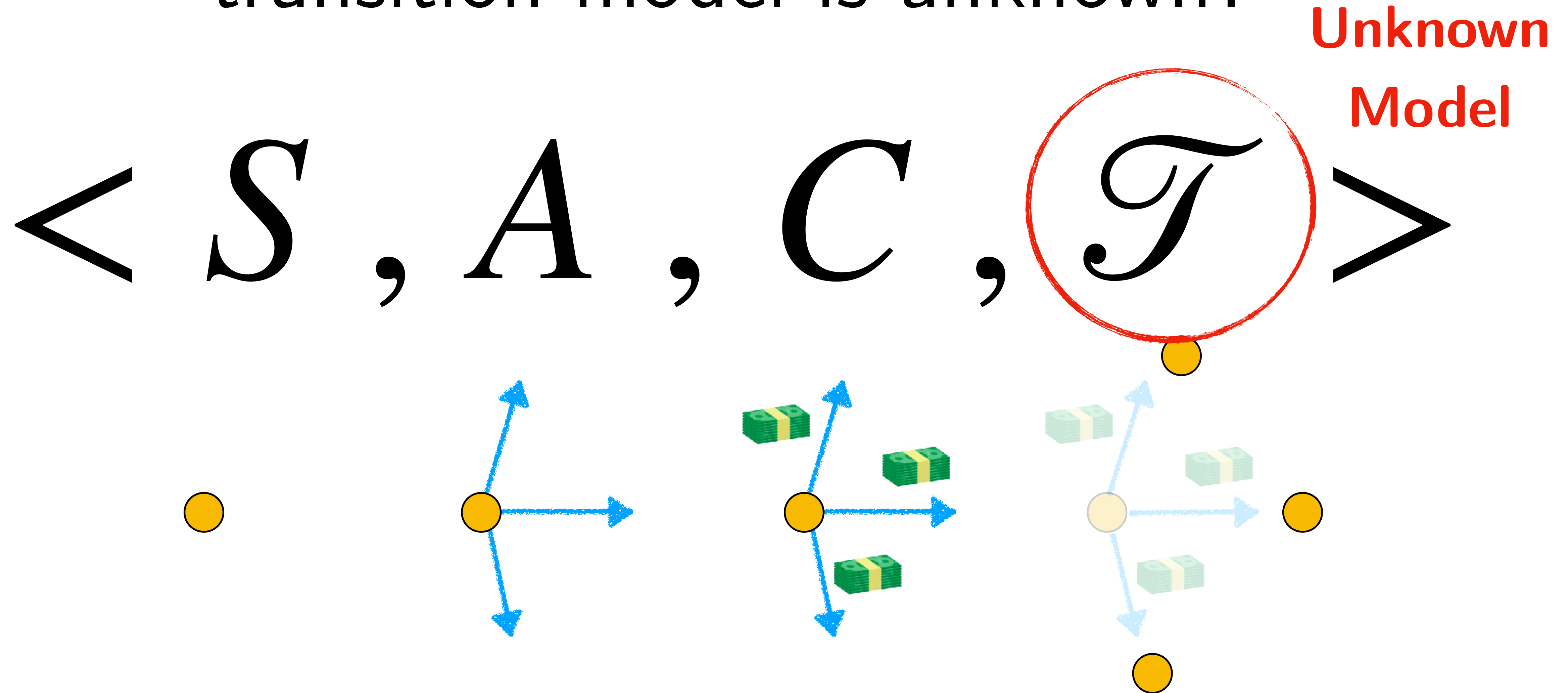
We have the following expectations for the final project:

- * You should apply a concept that you learned in class
 - * Your project should be well-scoped so it is achievable in the short time that you have
 - * Your project should have some degree of science. It can't just be "I tried X algorithm on Y environment and here are the results".
 - * Instead, clearly state a hypothesis that you are testing
- E.g. We expect warm starting RL from BC in this environment would lead to faster convergence because it reduces the need to explore.*

Today's class

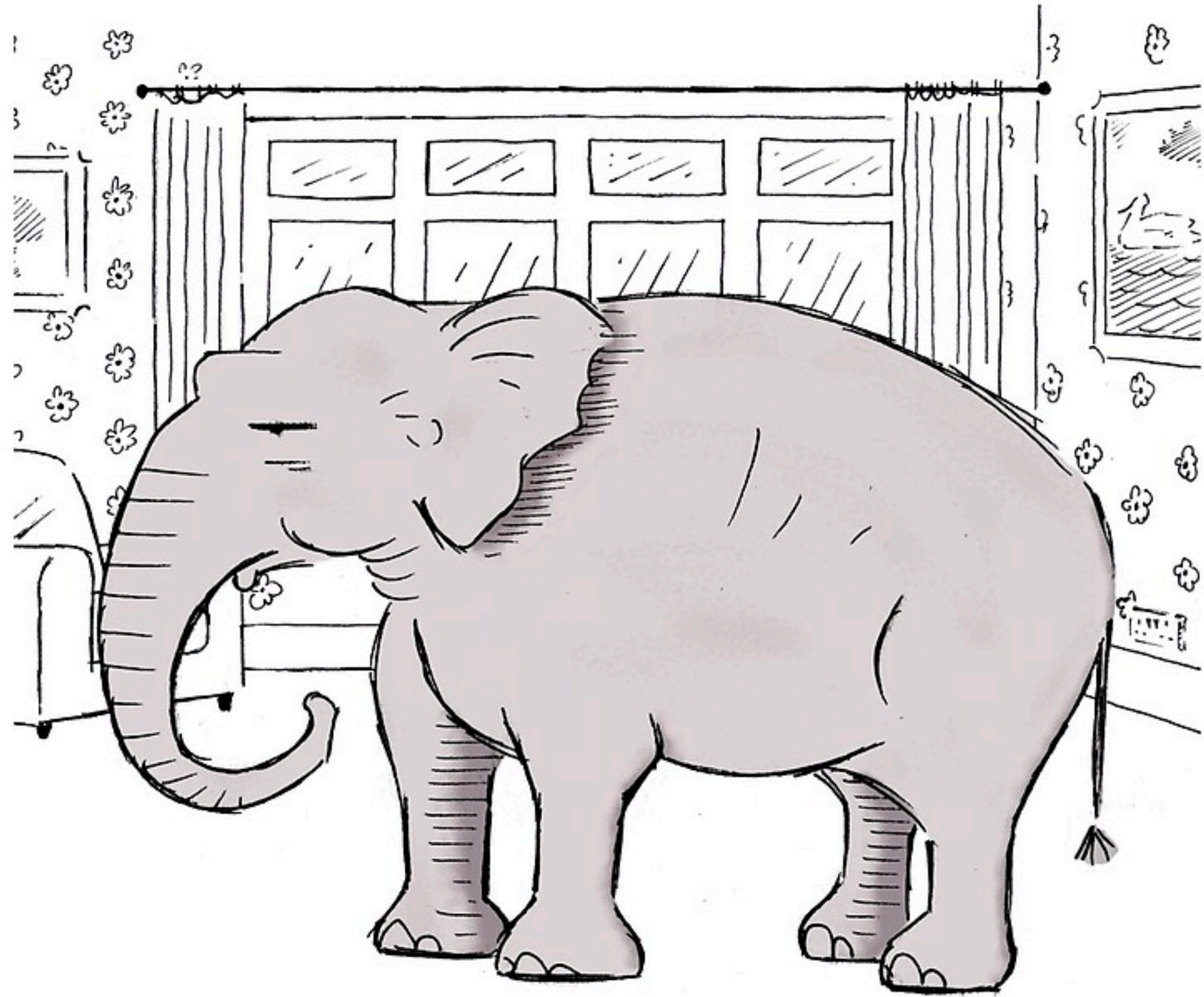
- What is model-based RL?
- How NOT to learn a model?
- DAgger for model-based RL

How do we solve the MDP if the transition model is unknown?



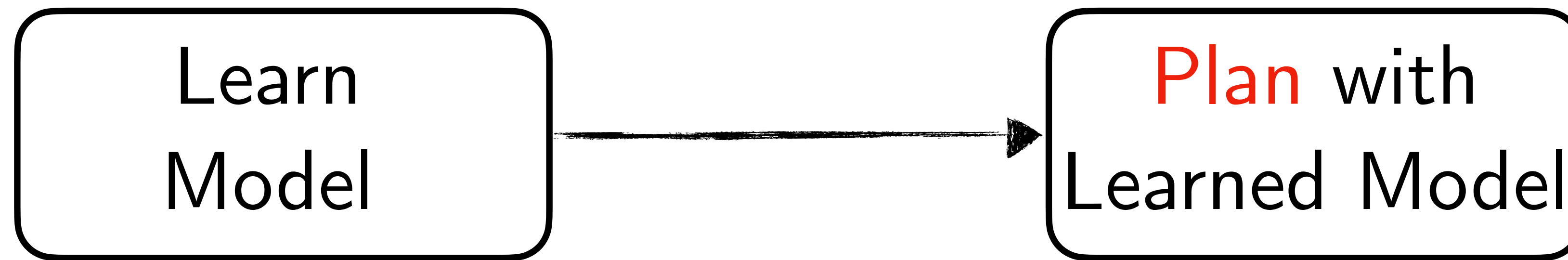
All the RL you learned up
until now is
Model-Free RL

RL
=
Learn model
+
Plan with model



“Just pretend I’m not here...”

Model Based Reinforcement Learning

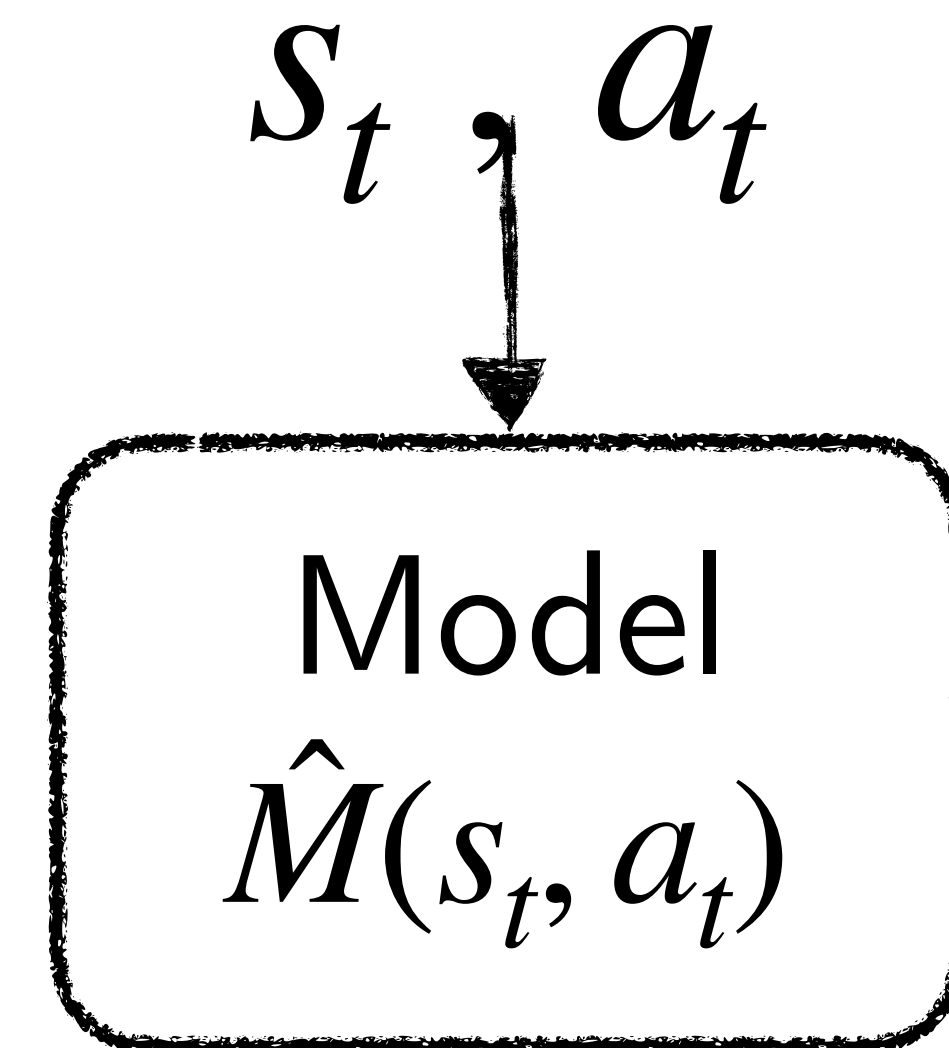


Use *any* **planning** algorithm you like:

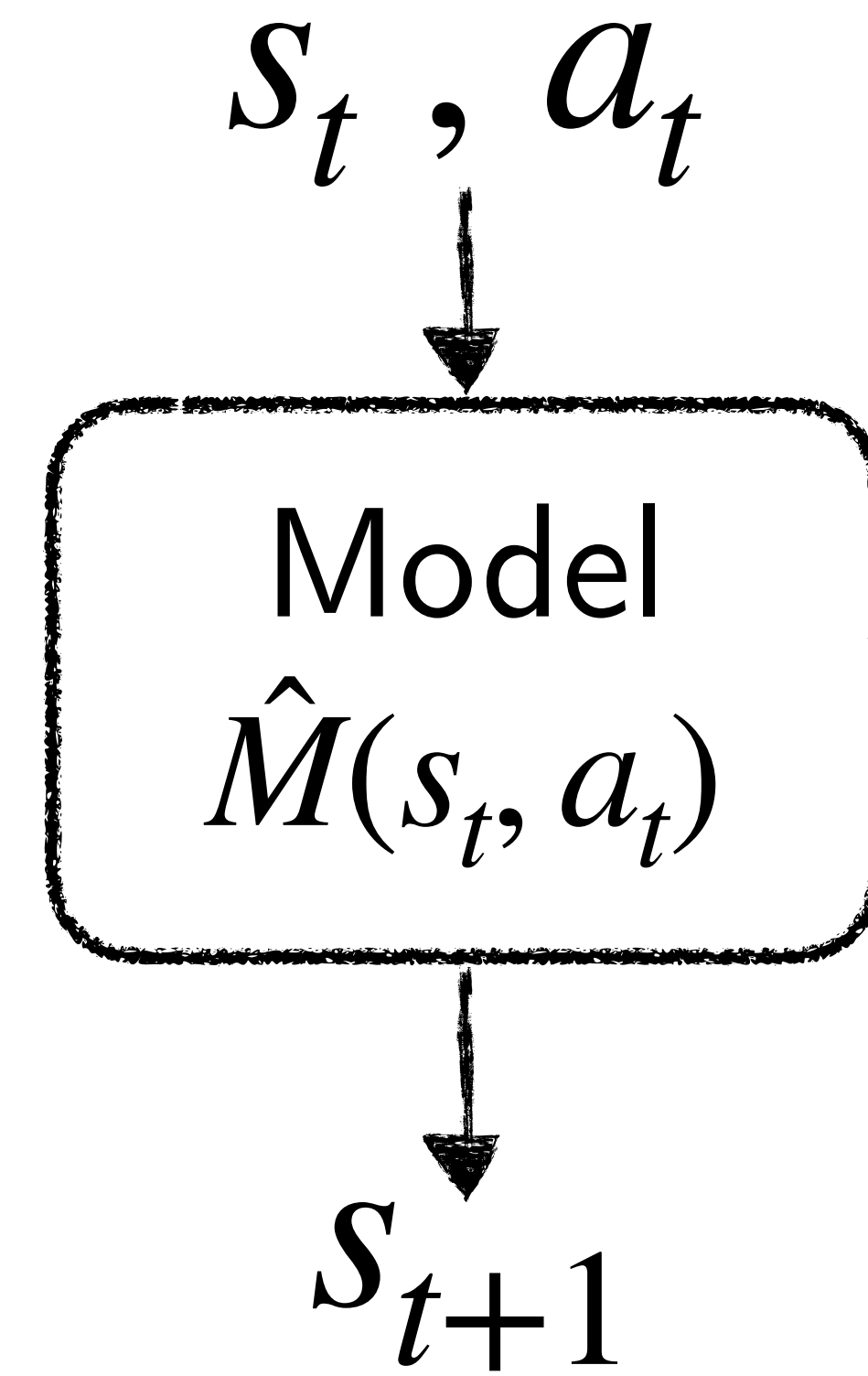
Value iteration / Policy iteration / LQR / A* search / RRTs ...

What is a model?

What is a model?



What is a model?



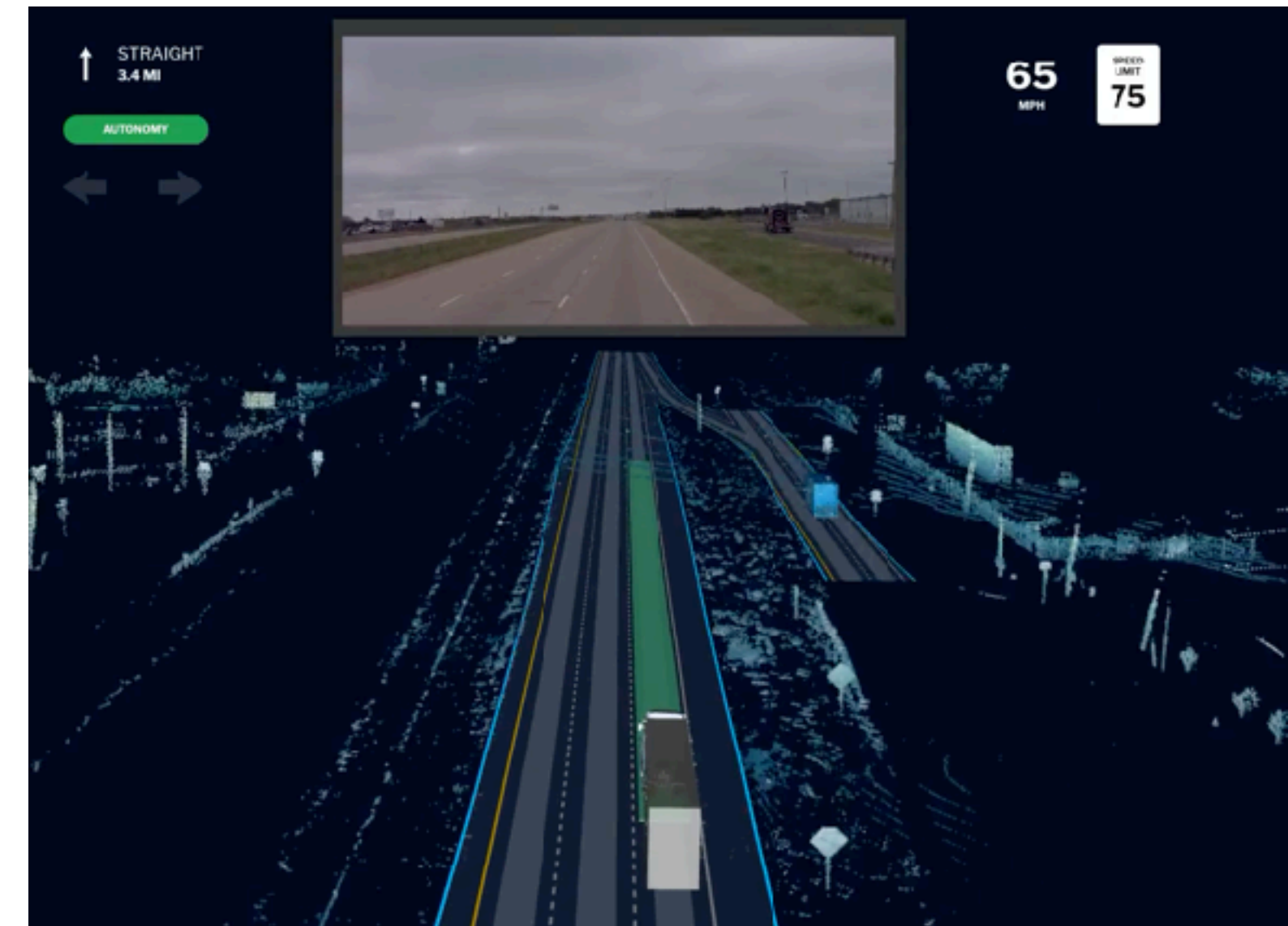
Models are simulators of the
real world dynamics

Why model-based RL?

What happens if we run model-free RL in the real world?



All practical robotics rely on evaluating policies in a simulator before deploying



Models work very well in *theory*

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

Alekh Agarwal

Microsoft

alekha@microsoft.com

Sham Kakade

University of Washington

sham@cs.washington.edu

Lin F. Yang

University of California, Los Angeles

linyang@ee.ucla.edu

April 7, 2020

Models work in *practice*

Hafner et al. 2023



Learning Models.

What is the machine learning setup for learning models?

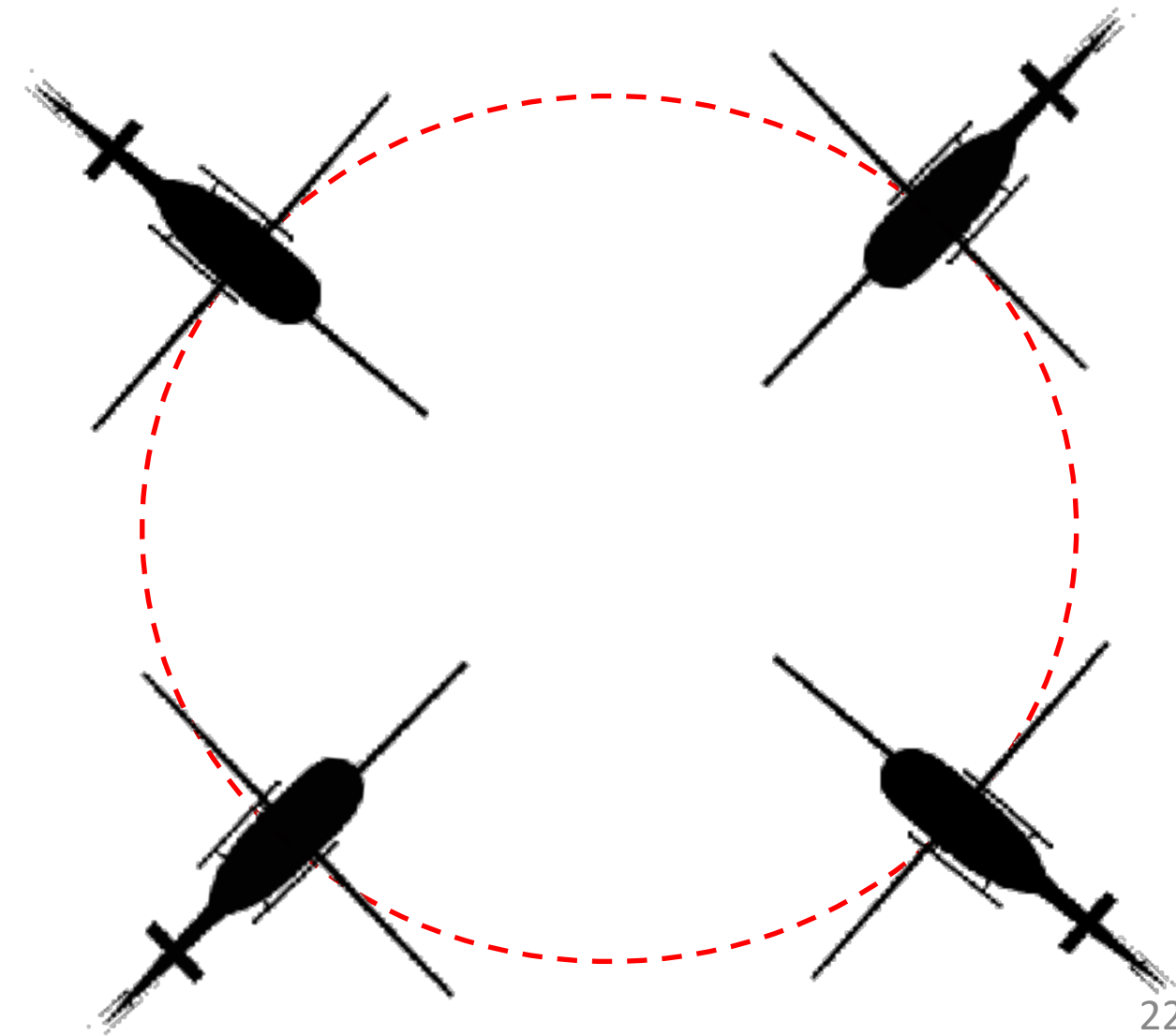
Goal: We want to fit a model $\hat{M}(s, a)$
to the real world dynamics $M^*(s, a)$

What is the Input? Output? Loss? Model Class? Data?

Activity!



Example: Helicopter Aerobatics



(Super cool work by Pieter Abeel et al. https://people.eecs.berkeley.edu/~pabbeel/autonomous_helicopter.html)

Suppose I want to learn a helicopter model.
What is input / output / loss?

When poll is active respond at Pollev.com/sc2582

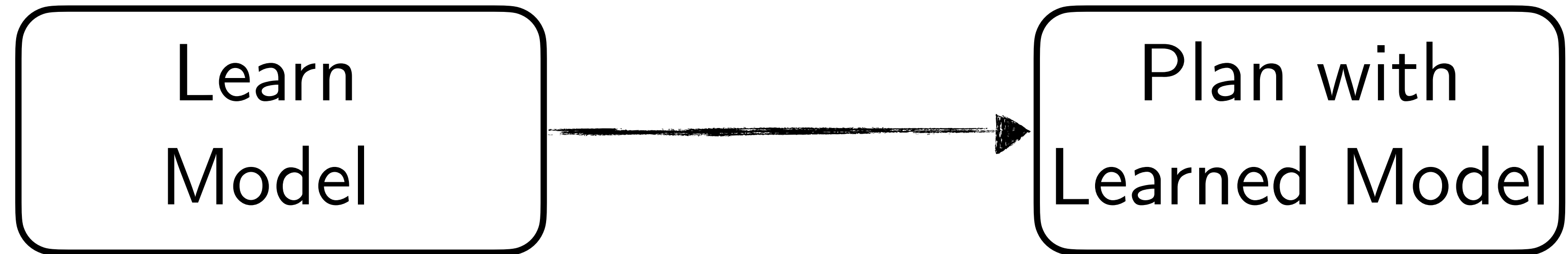
Send **sc2582** to **22333**



Think-Pair-Share

Think (30 sec): What model will you use for learning?
What planner would you use to execute a maneuver?

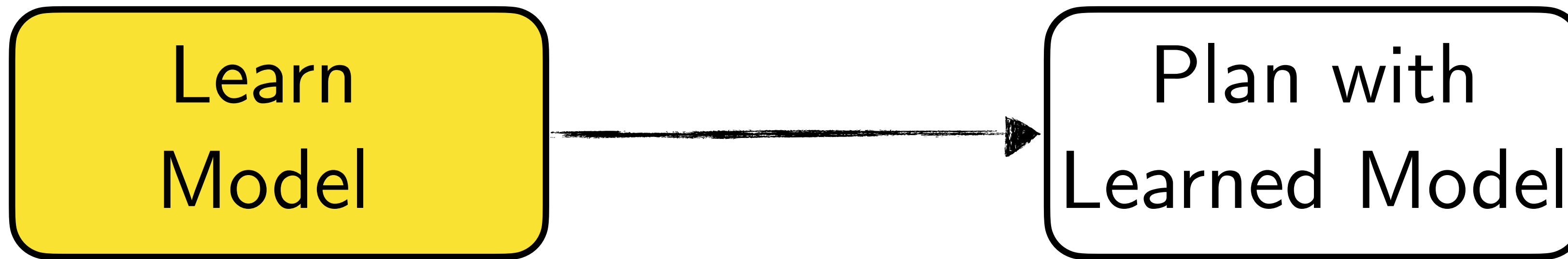
Pair: Find a partner



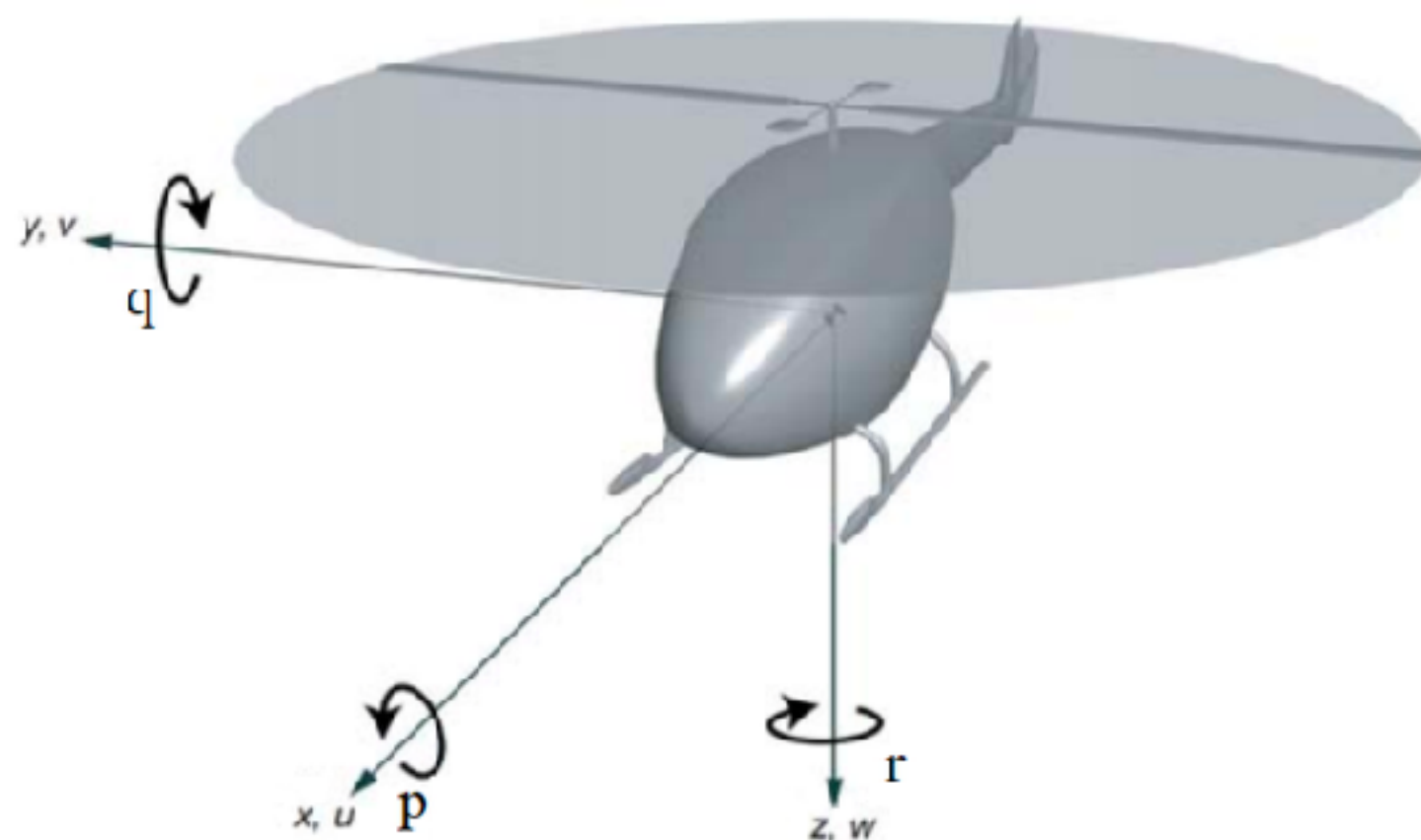
Share (45 sec): Partners exchange ideas

What did Abeel and Ng do?

Part 1: Learn a Model

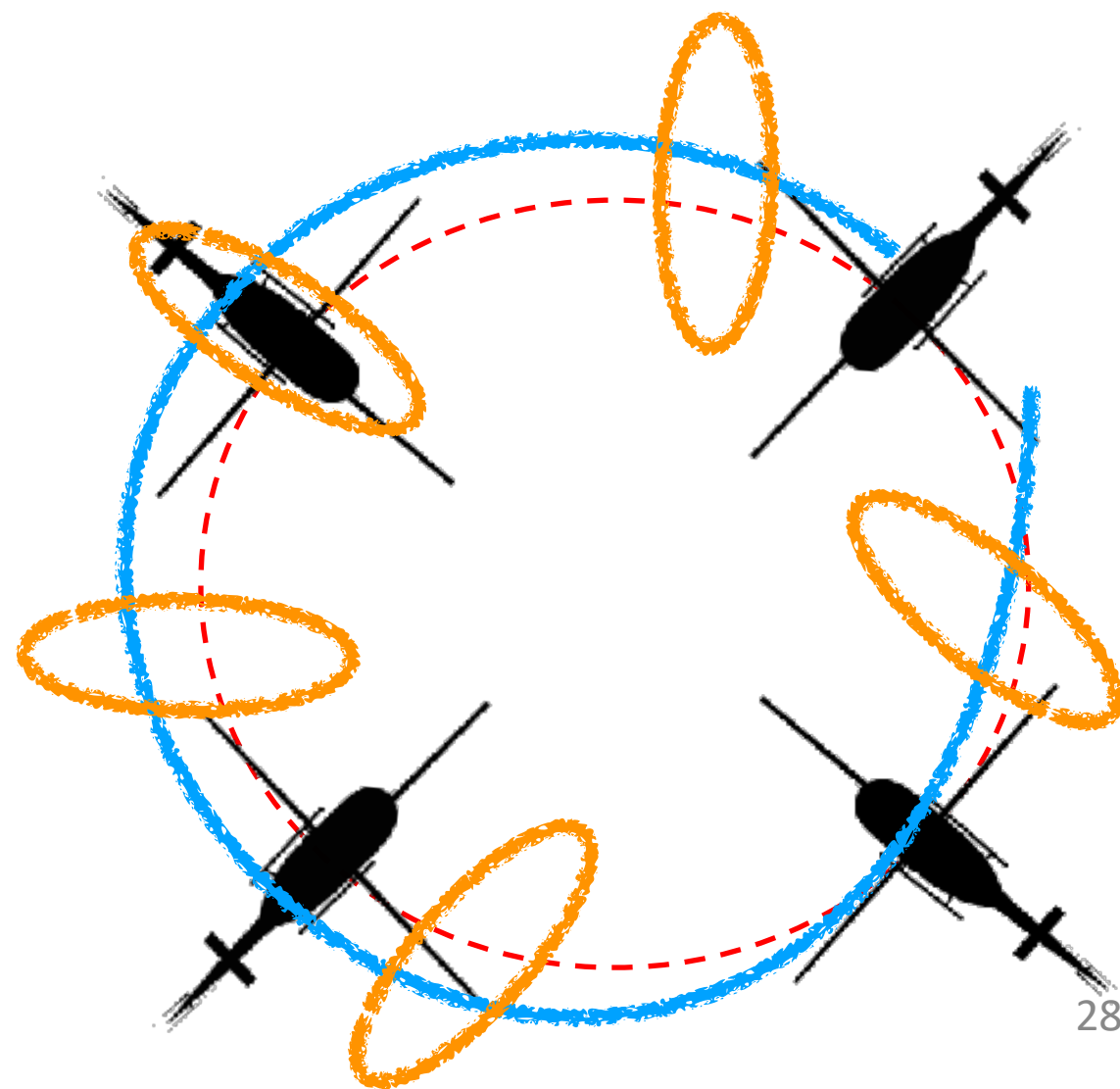
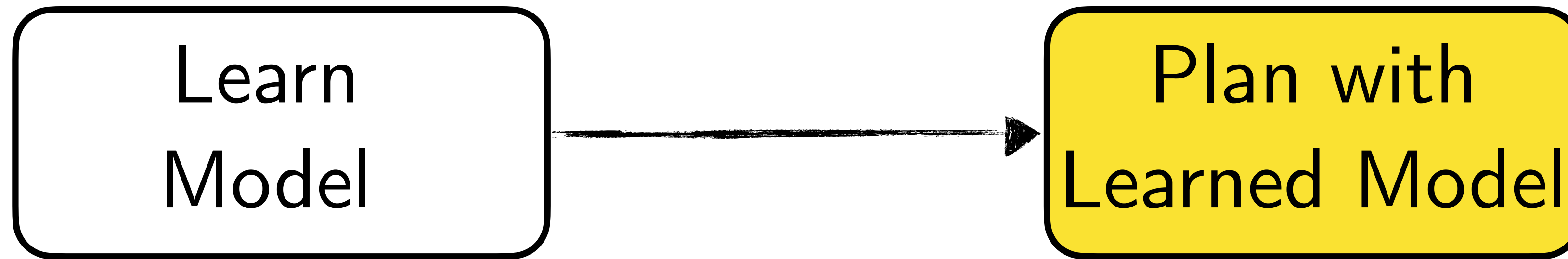


Write down a physics model and learn parameters



$$\begin{aligned}\dot{u} &= vr - wq + A_x u + g_x + w_u, \\ \dot{v} &= wp - ur + A_y v + g_y + D_0 + w_v, \\ \dot{w} &= uq - vp + A_z w + g_z + C_4 u_4 + D_4 + w_w, \\ \dot{p} &= qr(I_{yy} - I_{zz})/I_{xx} + B_x p + C_1 u_1 + D_1 + w_p, \\ \dot{q} &= pr(I_{zz} - I_{xx})/I_{yy} + B_y q + C_2 u_2 + D_2 + w_q, \\ \dot{r} &= pq(I_{xx} - I_{yy})/I_{zz} + B_z r + C_3 u_3 + D_3 + w_r.\end{aligned}$$

Part 2: Plan with Learned Model



Use LQR by *linearizing* the model

Today's class

- What is model-based RL?

Learn a model, plan with learned model

- How NOT to learn a model?

- DAgger for model-based RL

Question: How do you collect data for learning model?



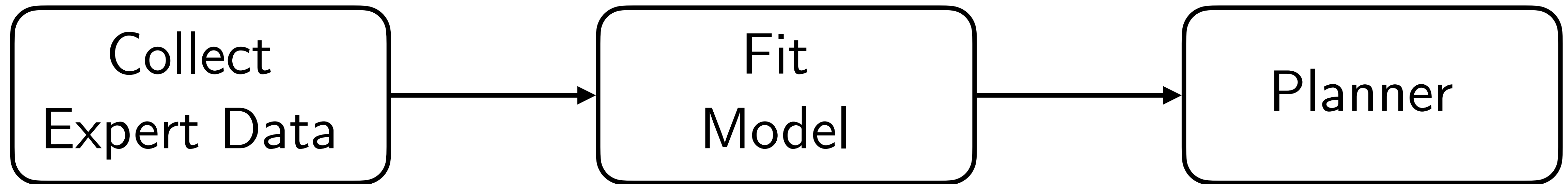
Inverted Hover

(Super cool work by Pieter Abeel et al. https://people.eecs.berkeley.edu/~pabbeel/autonomous_hover.html)

Strategy

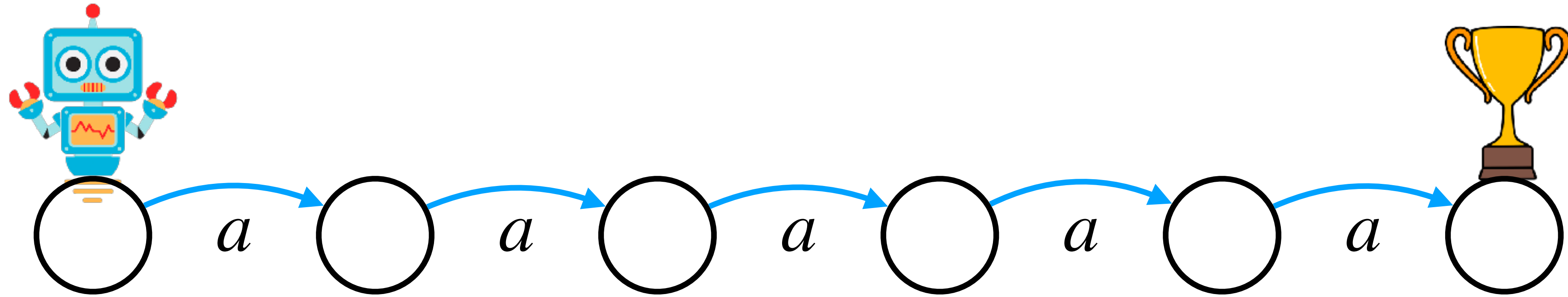
Train a model on state actions visited by the expert!

Model Based RL v1.0



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

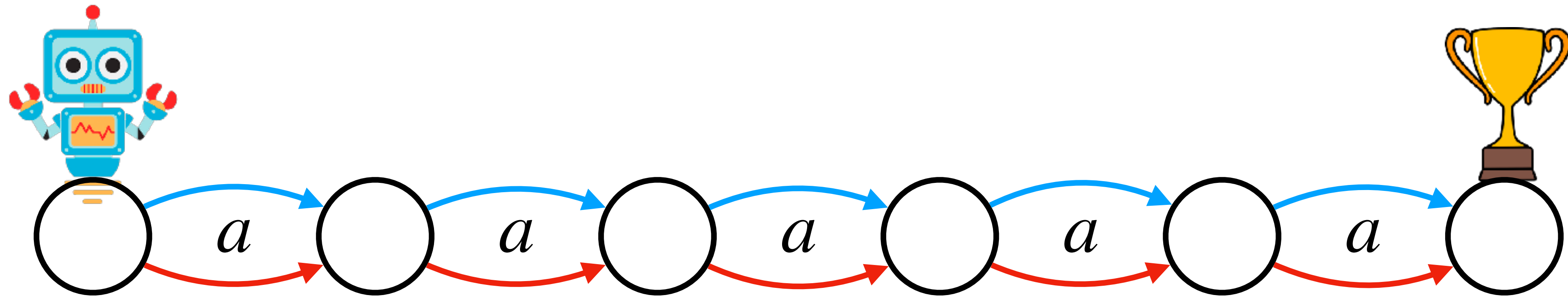
World
 $s' = M^*(s, a)$



Experts picks action a to go to the goal

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

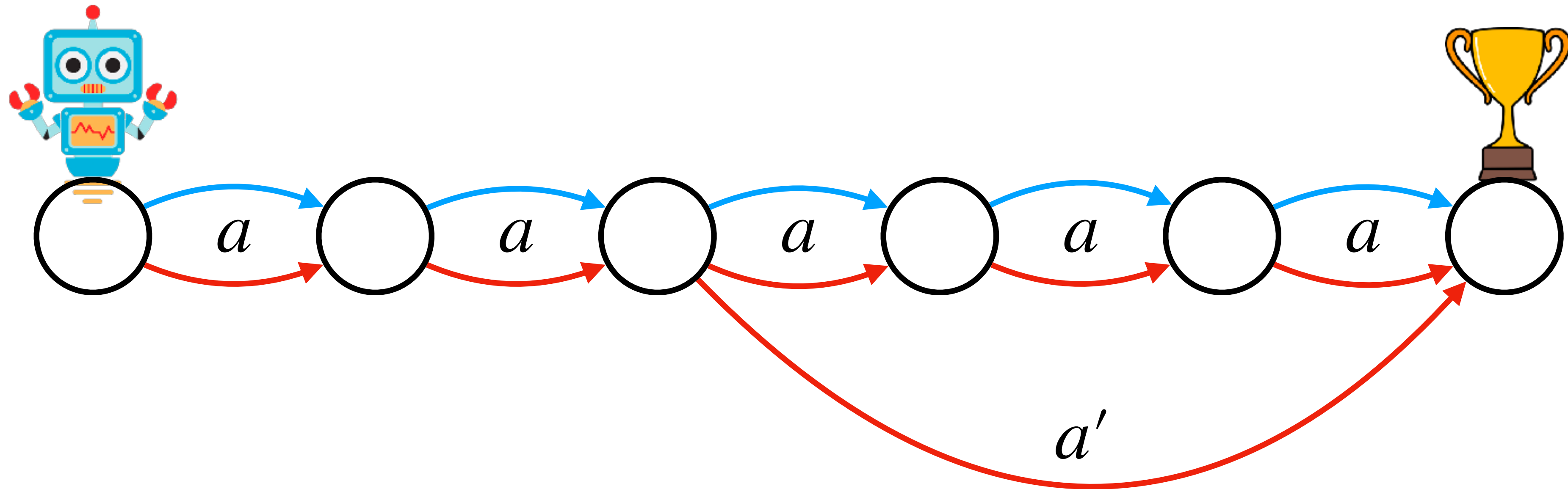
World
 $s' = M^*(s, a)$



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

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

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

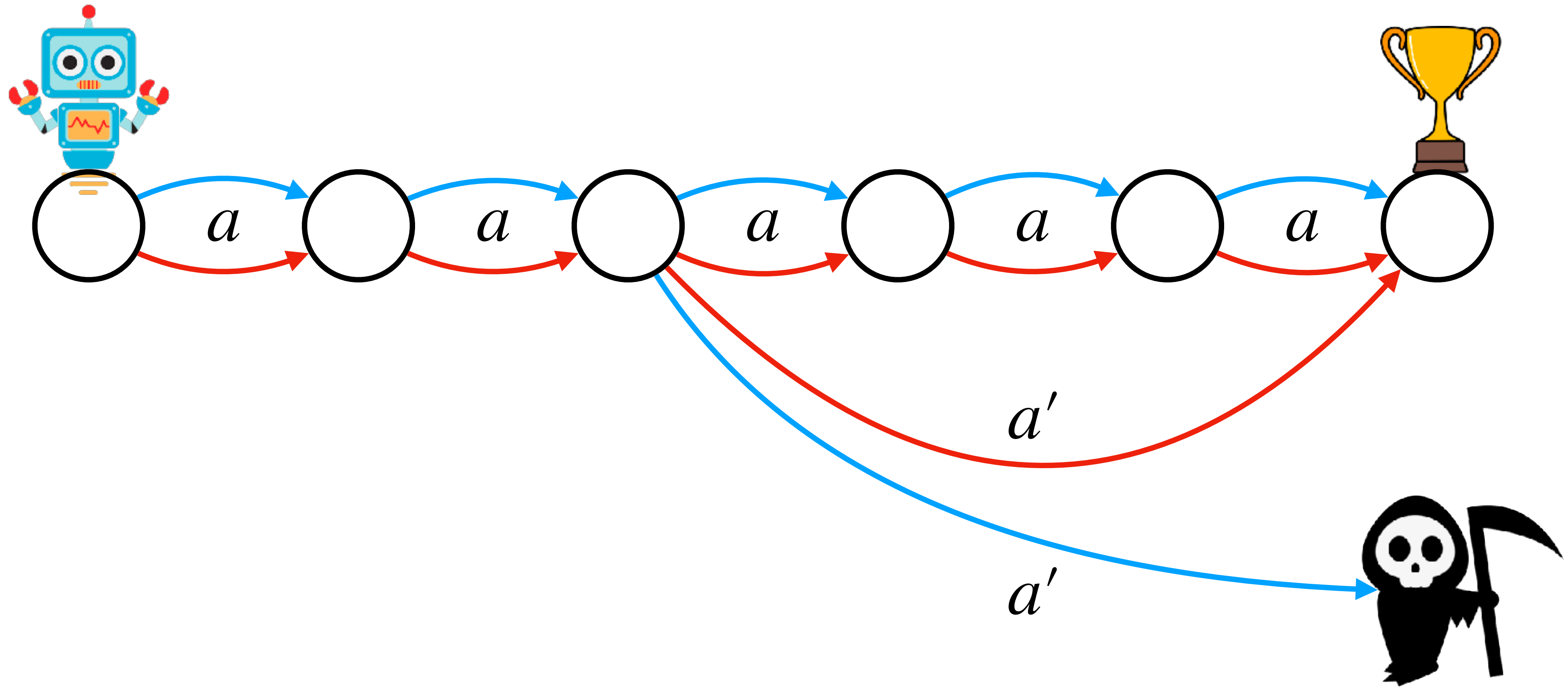


What if the model is optimistic?

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

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

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



In reality the shortcut ends in death ...

Training just on expert data may
result in *optimistic* models

Training on
Expert Data

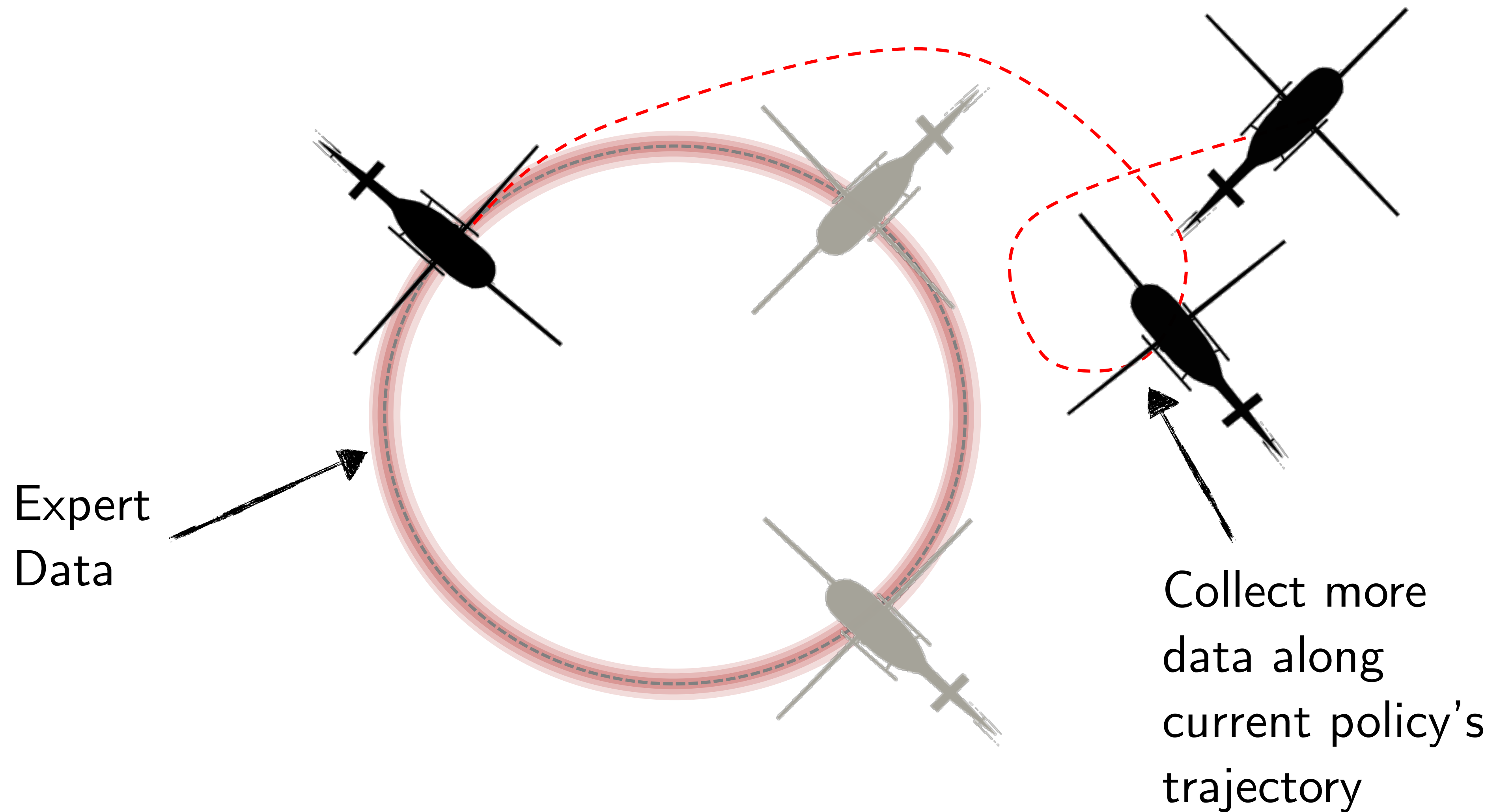
(From Ross
and Bagnell,
2012)

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

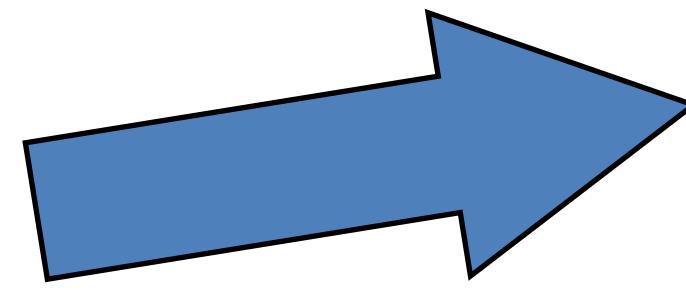
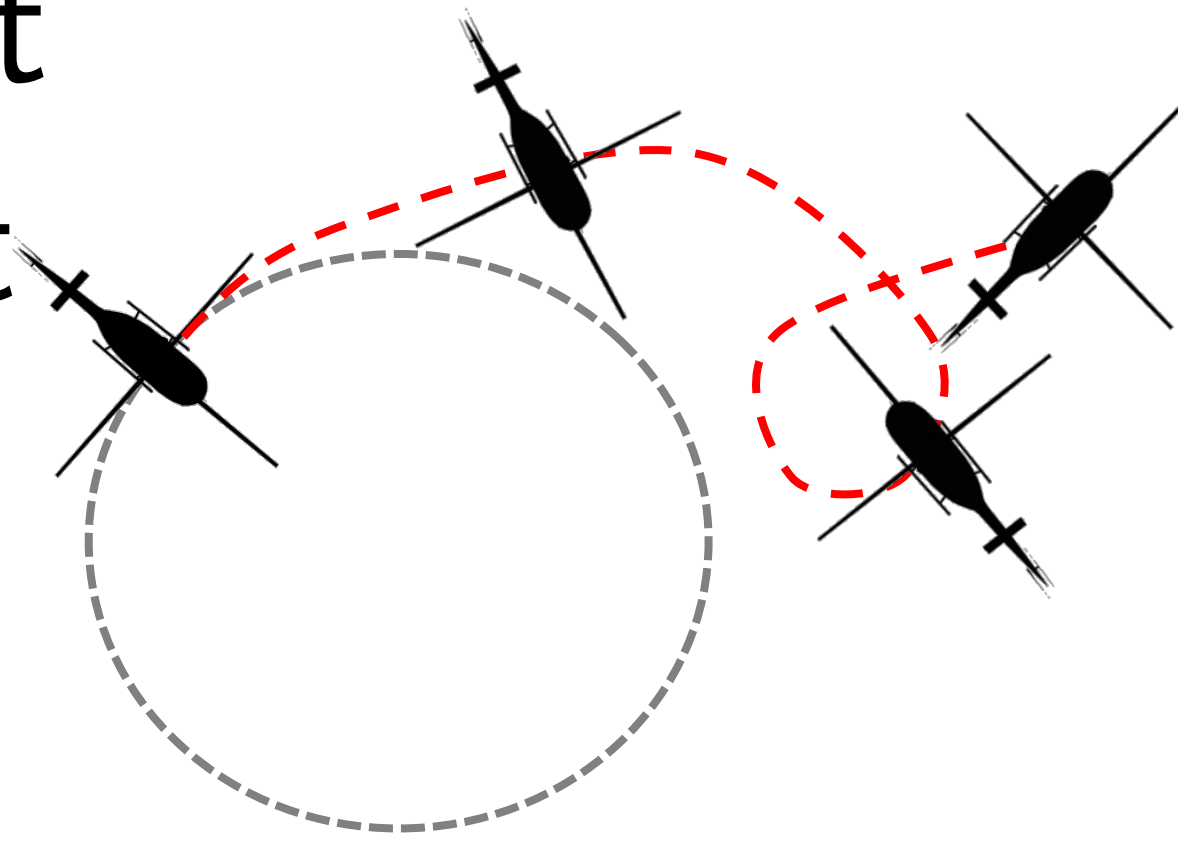


Don't we know an
algorithm that does this?



DAGGER for Model-based RL!!

Roll-out
current
policy



New Transitions

State	Action	Next State
	⋮	



All previous transitions

	⋮	

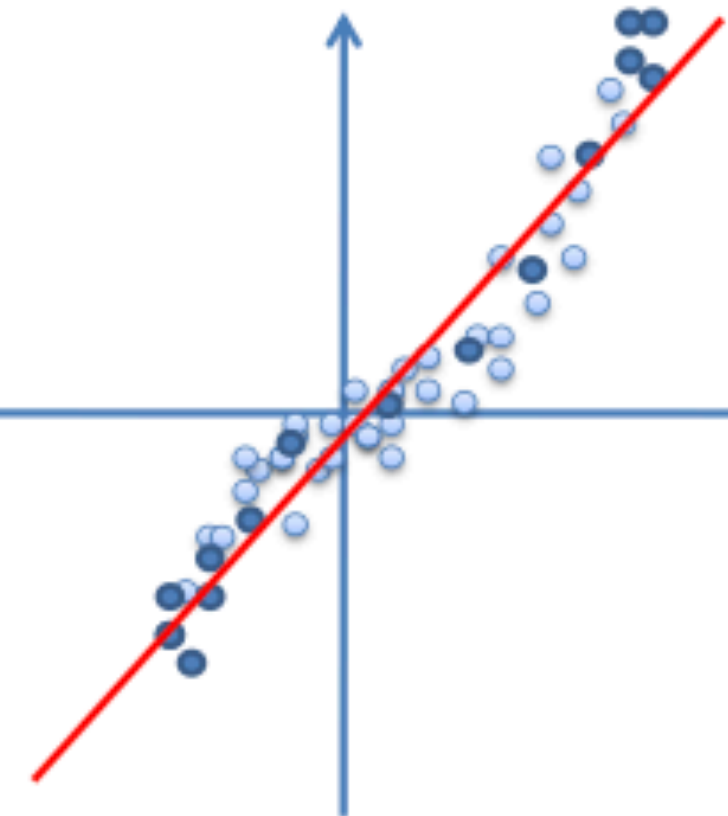
Planner

New Policy

New Model

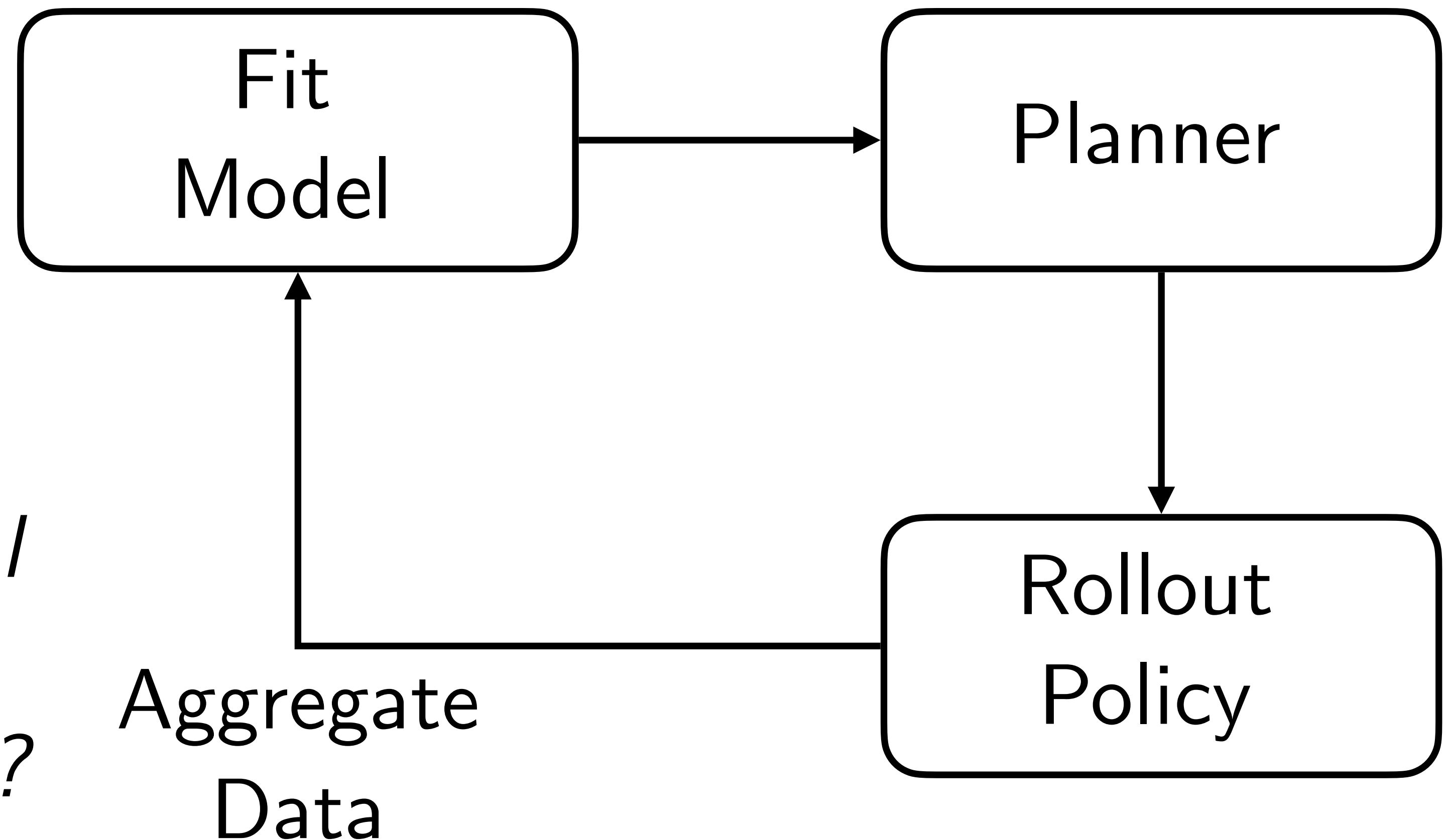
Fit Model

Aggregate
Dataset



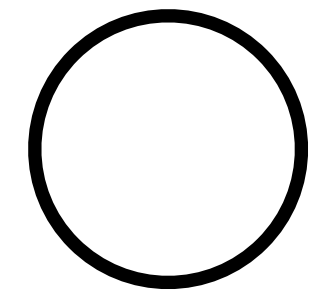
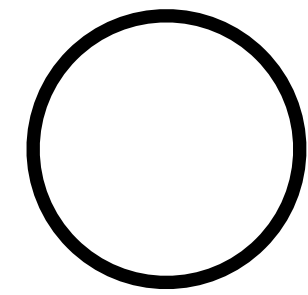
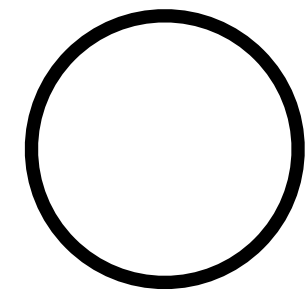
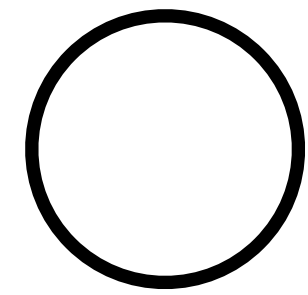
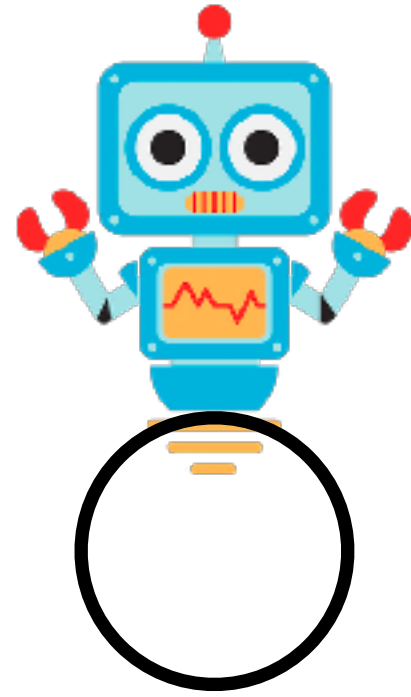
Model Based RL v2.0

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



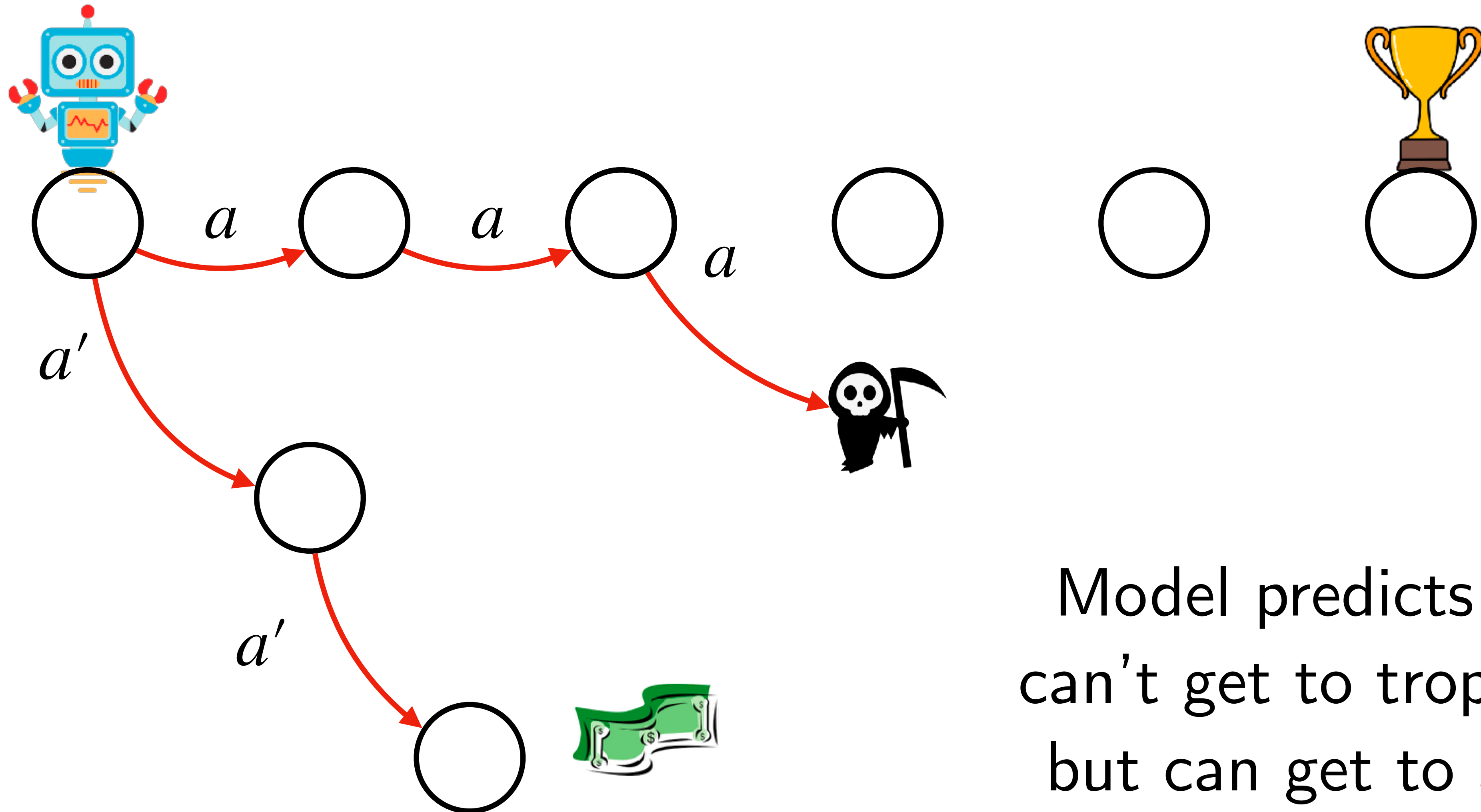
Model
 $s' = \hat{M}(s, a)$

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



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

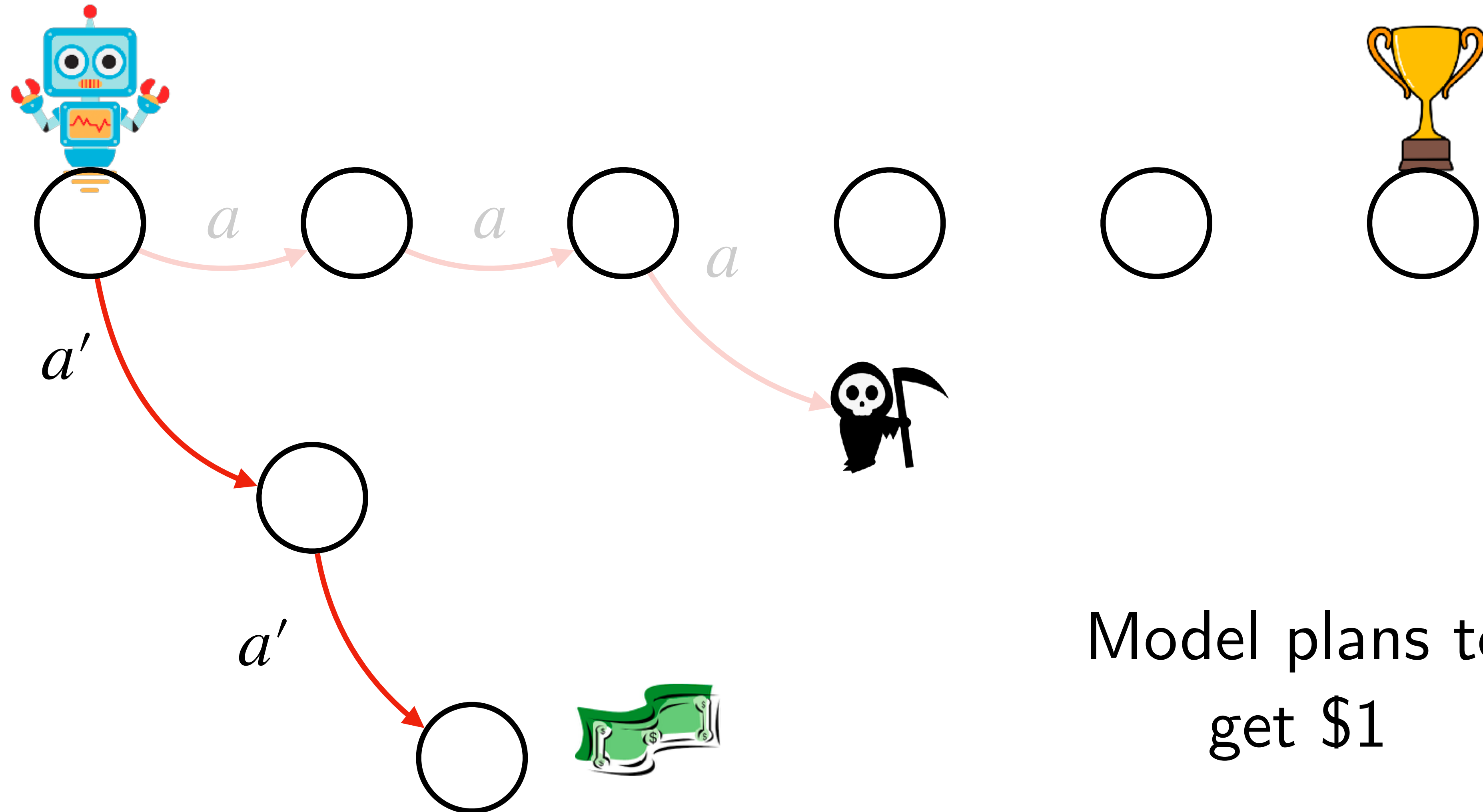
World
 $s' = M^*(s, a)$



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

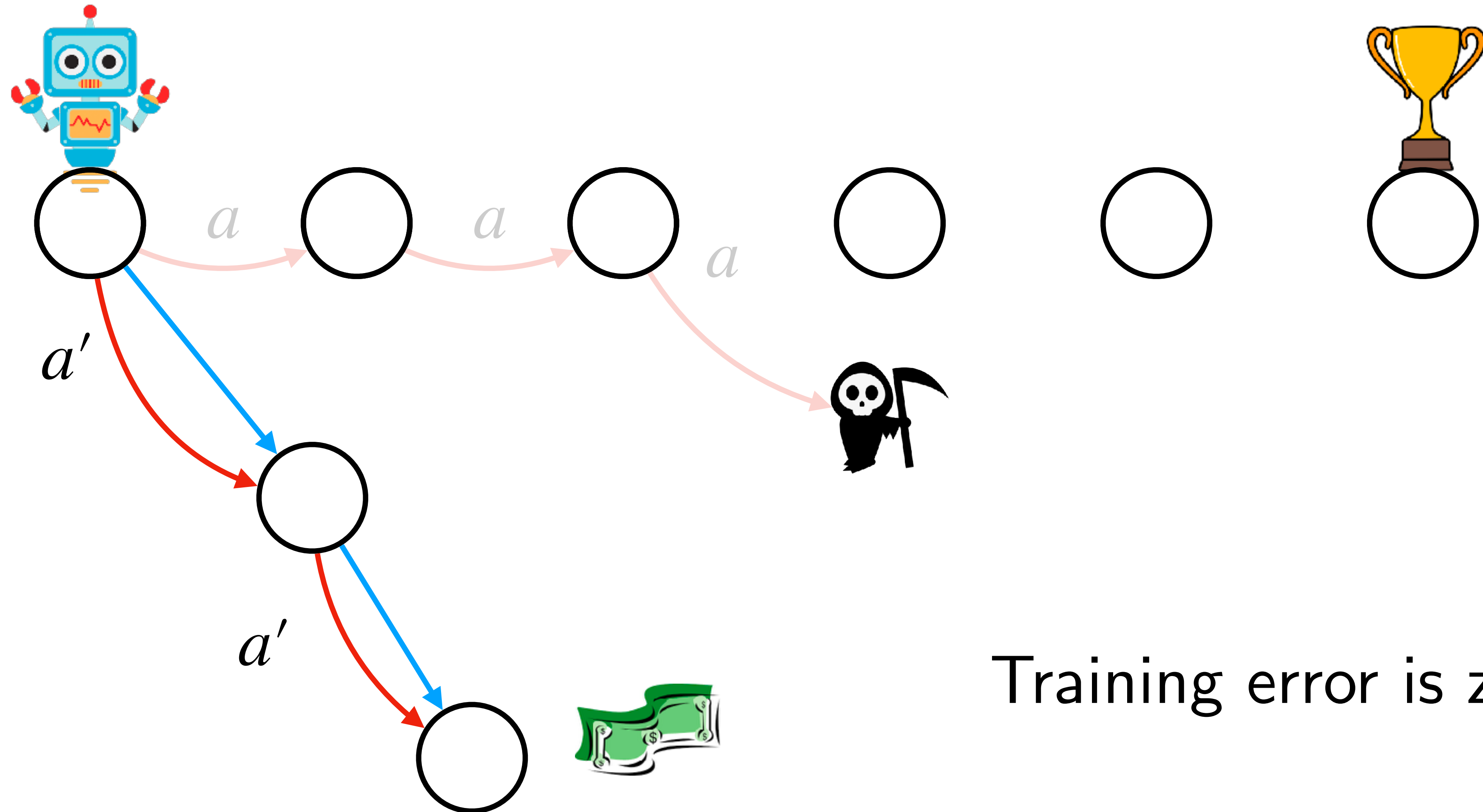
Model
 $s' = \hat{M}(s, a)$

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



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

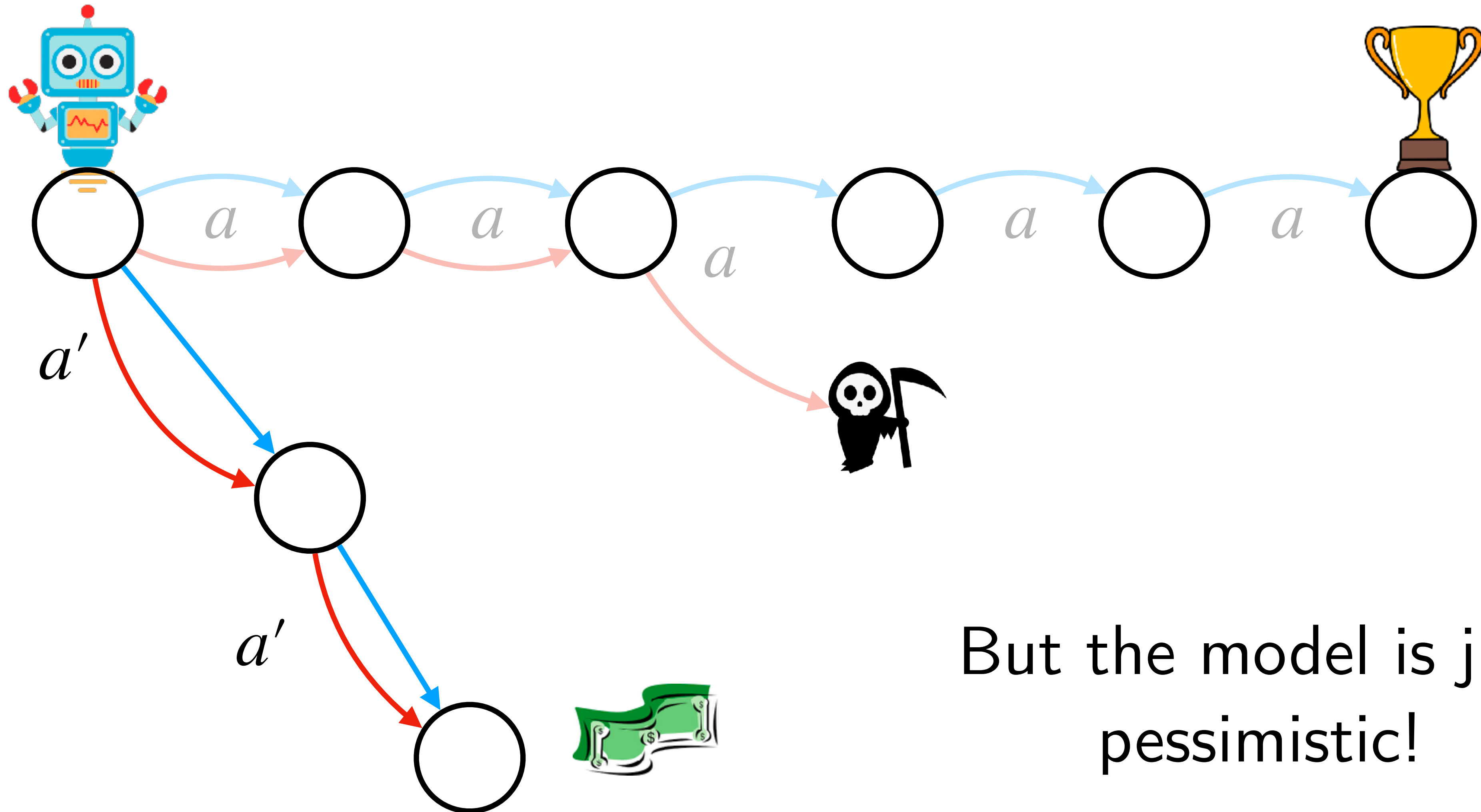
World
 $s' = M^*(s, a)$



Training error is zero!

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

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



But the model is just pessimistic!

Training just on learner data may
result in *pessimistic* models

Today's class

What is model-based RL?

Learn a model, plan with learned model

How NOT to learn a model?

Don't train on only **expert** data (too **optimistic**),

Don't train on only **learner** data (too **pessimistic**).

DAgger for model-based RL

Strategy

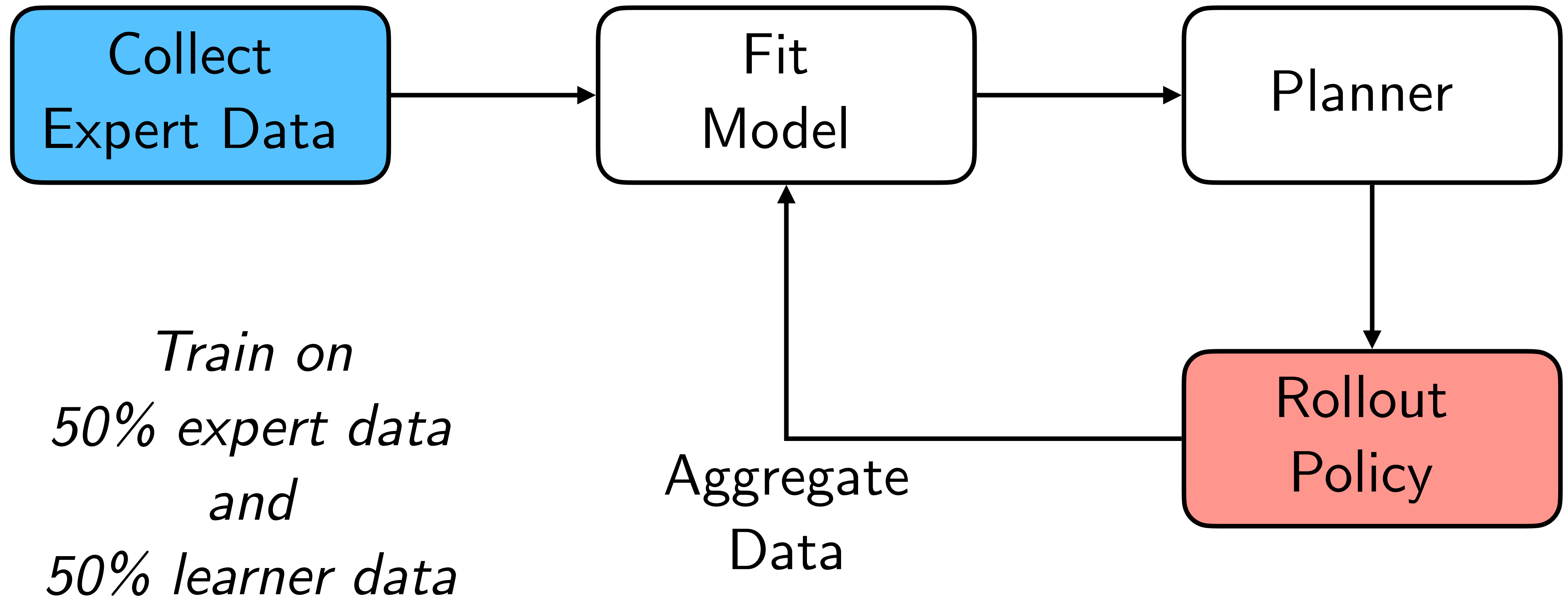
~~Train a model on state actions visited by the expert!~~

~~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)



Training on 50% learner, 50%
expert

(Not too optimistic or pessimistic)

Model Learning with Planner in Loop

Collect data from an expert $\mathcal{D}_{\text{expert}} = \{(s, a, s')\}$

Fit a model \hat{M}_1 . Compute a policy $\hat{\pi}_1$ in the model via planning

Initialize empty data buffer $\mathcal{D}_{\text{learner}} \leftarrow \{\}$

For $i = 1, \dots, N$

Execute policy $\hat{\pi}_i$ in the real world and collect data

$$\mathcal{D}_i = \{(s, a, s')\}$$

Aggregate data $\mathcal{D}_{\text{learner}} \leftarrow \mathcal{D}_{\text{learner}} \cup \mathcal{D}_i$

Train a new model on 50% expert + 50% learner data

$$\hat{M}_{i+1} \leftarrow \text{Train}(0.5 * \mathcal{D}_{\text{expert}} + 0.5 * \mathcal{D}_{\text{learner}})$$

Train a new policy π_{i+1} in the model \hat{M}_{i+1}

Select the best policy in $\pi_{1:N+1}$

Model Learning with Planner in Loop

Collect data from an expert $\mathcal{D}_{\text{expert}} = \{(s, a, s')\}$

Fit a model \hat{M}_1 . Compute a policy $\hat{\pi}_1$ in the model via planning

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Train a new policy π_{i+1} in the model \hat{M}_{i+1}

Select the best policy in $\pi_{1:N+1}$

Model learning
on both expert
and learner
data works!

(From Ross &
Bagnell, 2012)

Today's class

- ☑ What is model-based RL?
- ☑ How NOT to learn a model?
- ☑ DAgger for model-based RL

Why is 50-50 the right thing to do?

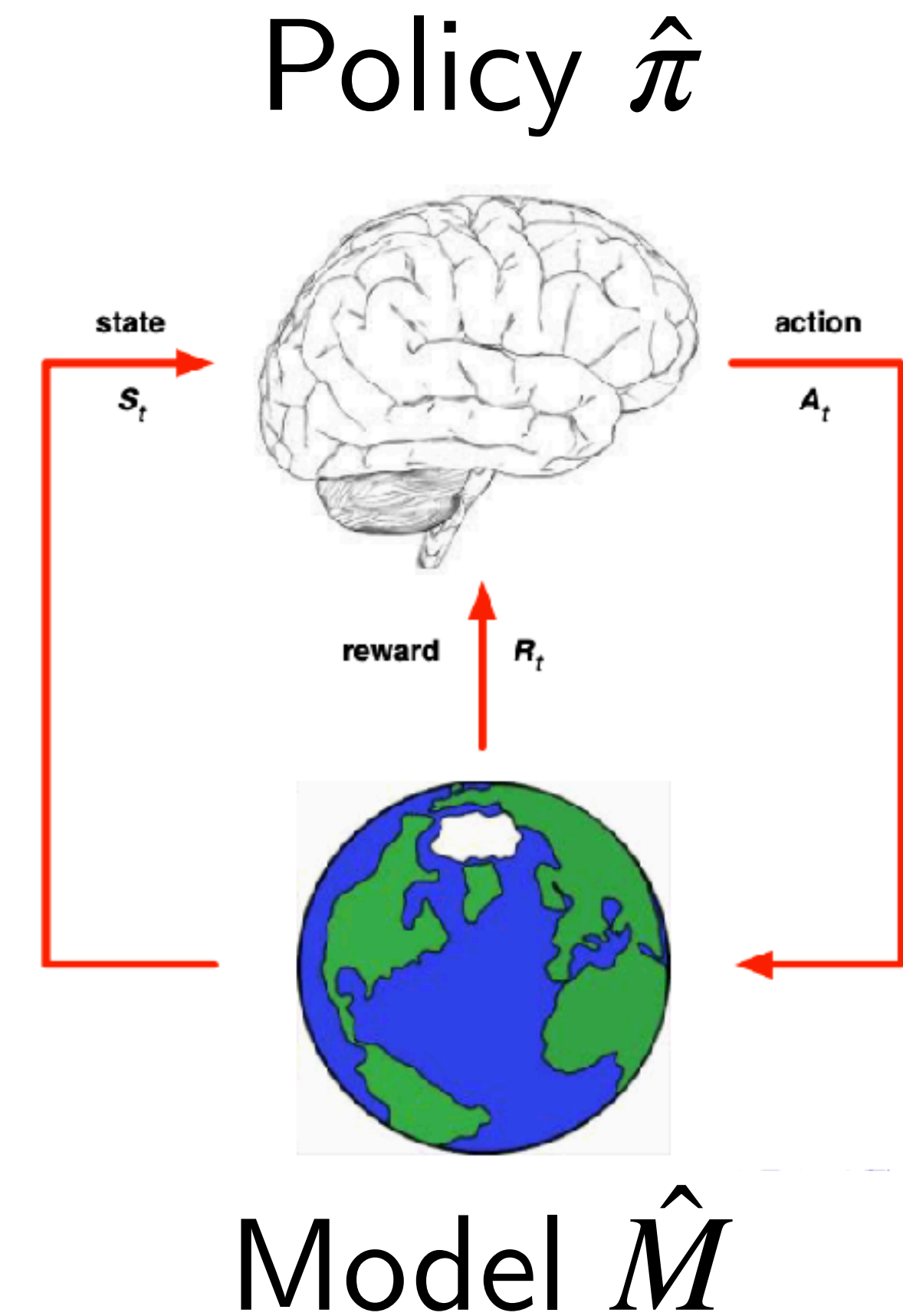


Performance Difference via Planning in Model Lemma

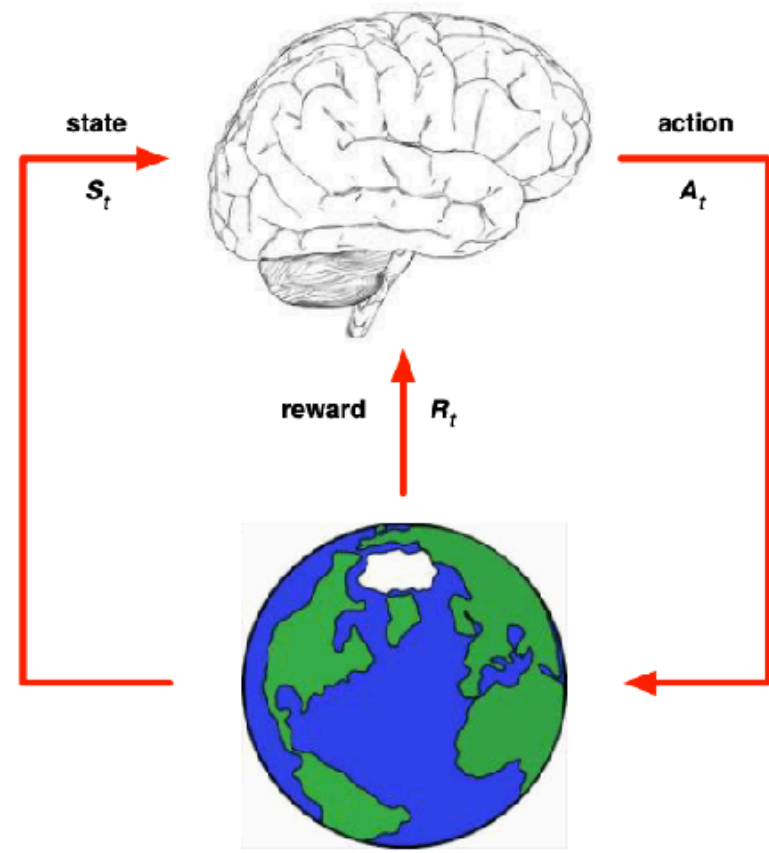


What makes for a good model?

A good model is one such that if
we plan with the model
we get a good policy



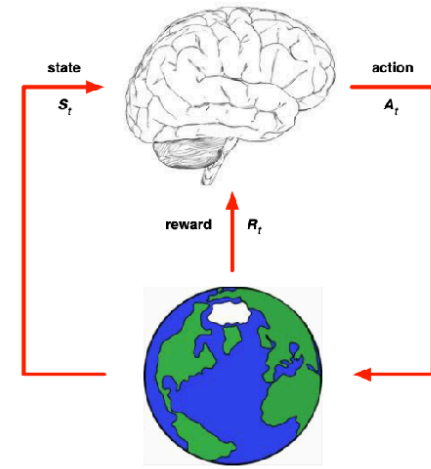
What makes for a good model?



$$V^{\hat{\pi}}(s_0) - V^{\pi^*}(s_0)$$

A good model gives a good policy that has bounded performance difference

What makes for a good model?



$$V_{M^*}^{\hat{\pi}}(s_0) - V_{M^*}^{\pi^*}(s_0)$$

Two globe icons are positioned below the terms of the equation, one under $V_{M^*}^{\hat{\pi}}(s_0)$ and one under $V_{M^*}^{\pi^*}(s_0)$, representing the real world.

A good model gives a good policy that has bounded performance difference **in the real world**

What makes for a good model?

$$\left[\underset{\text{Earth}}{V_{\hat{M}^*}^{\hat{\pi}}(s_0)} - V_{\hat{M}}^{\hat{\pi}}(s_0) \right] + \left[V_{\hat{M}}^{\pi^*}(s_0) - \underset{\text{Earth}}{V_{M^*}^{\pi^*}(s_0)} \right]$$

Learner in real-world vs model

Expert in real-world vs model

$$+ \left[\underset{\text{Earth}}{V_{\hat{M}}^{\hat{\pi}}(s_0)} - V_{\hat{M}}^{\pi^*}(s_0) \right] \text{Learner vs Expert in model}$$

What makes for a good model?

