Model-based Offline RL with Partial Coverage

Wen Sun

CS 6789: Foundations of Reinforcement Learning

Potential Applications of Offline RL

Robotics manipulation:

[Kalashnikov et.al, 18]

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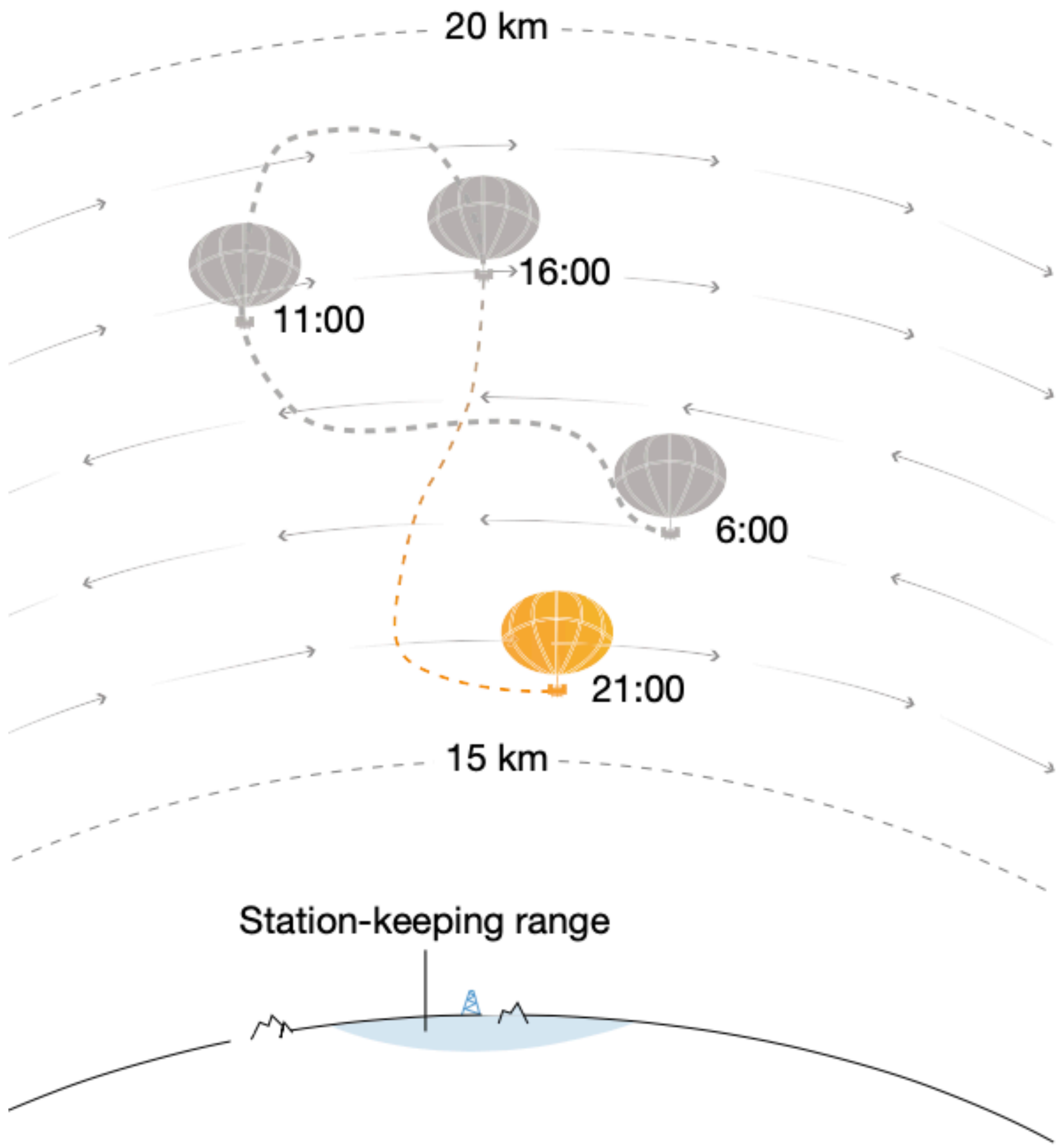
Stratospheric balloon navigation



[Bellemare et.al,21, Nature]

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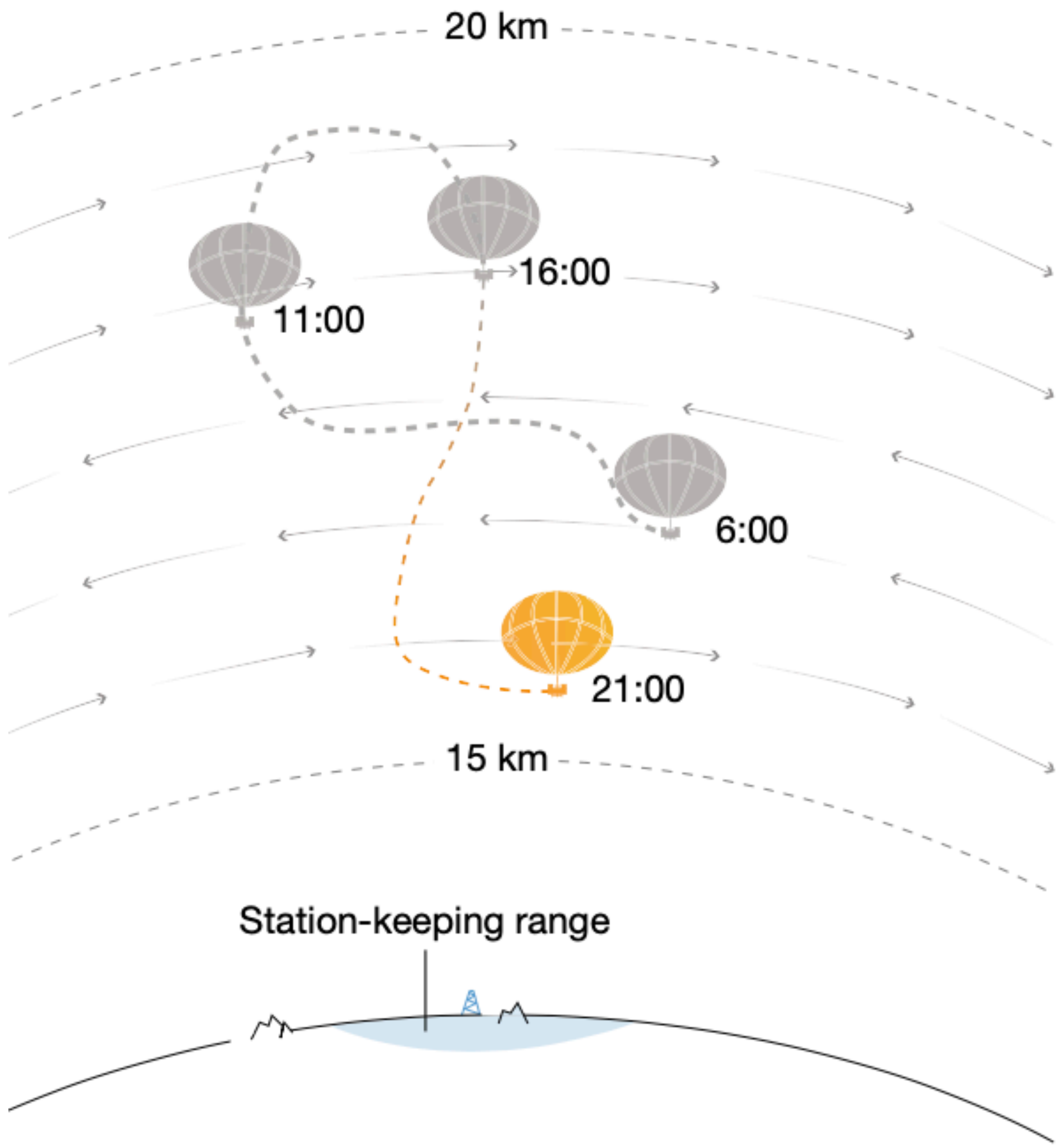

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AND healthcare applications!

(See Levine et.al for a list of applications and existing works)

Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems

Why offline RL is challenging?

Let's contrast it to traditional Supervised Learning

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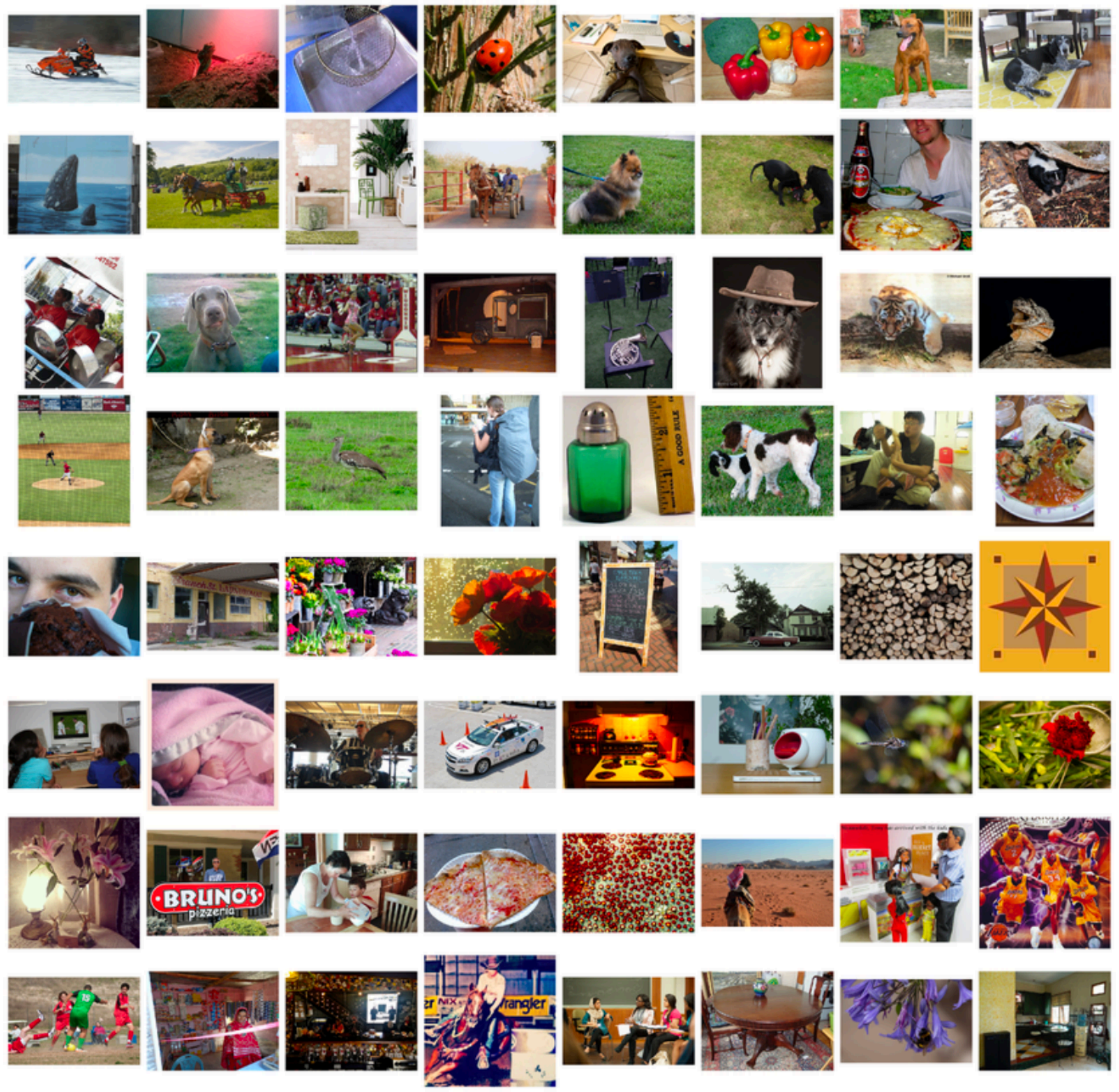
e.g., image classification



[ImageNet]

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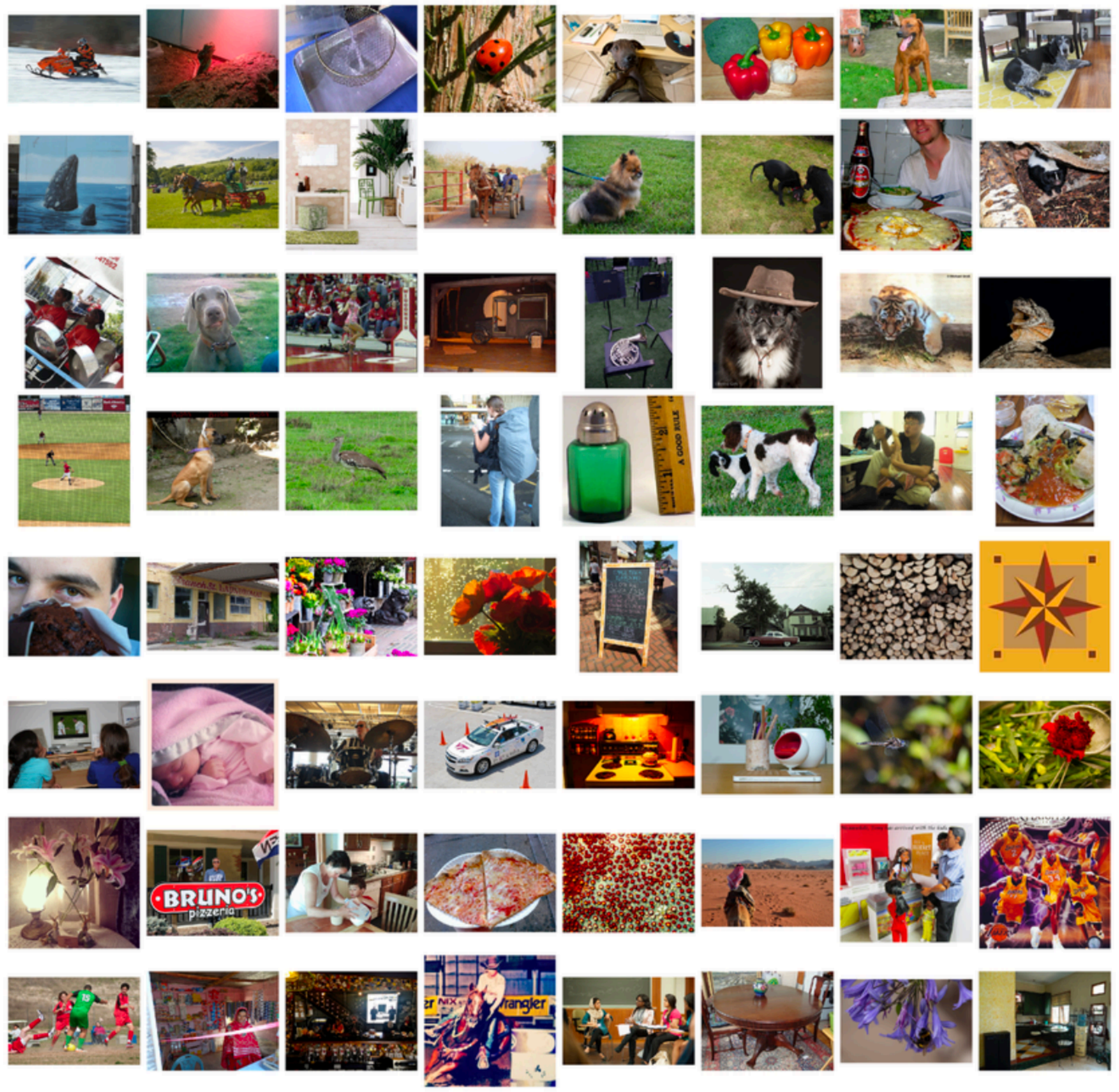

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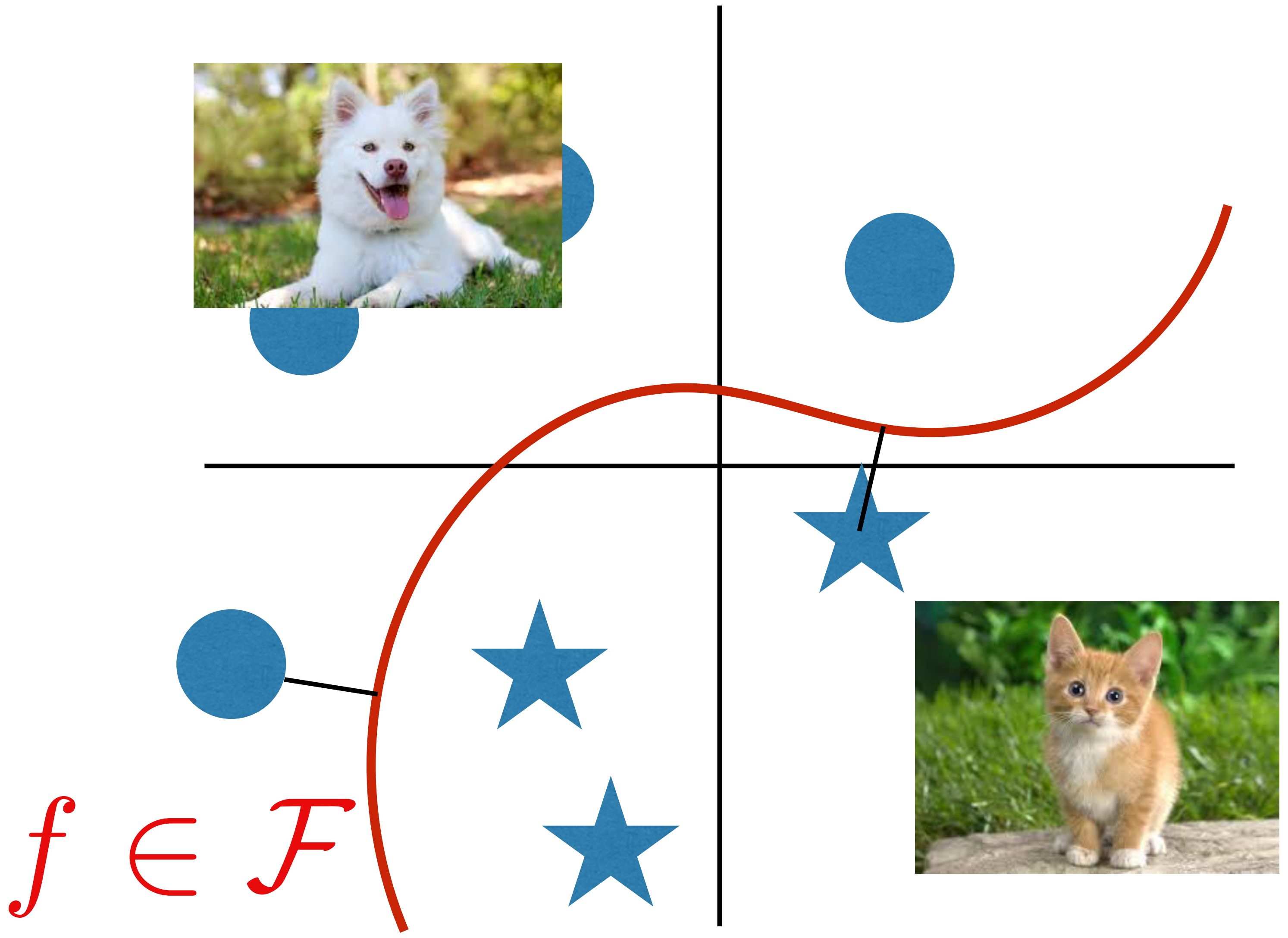

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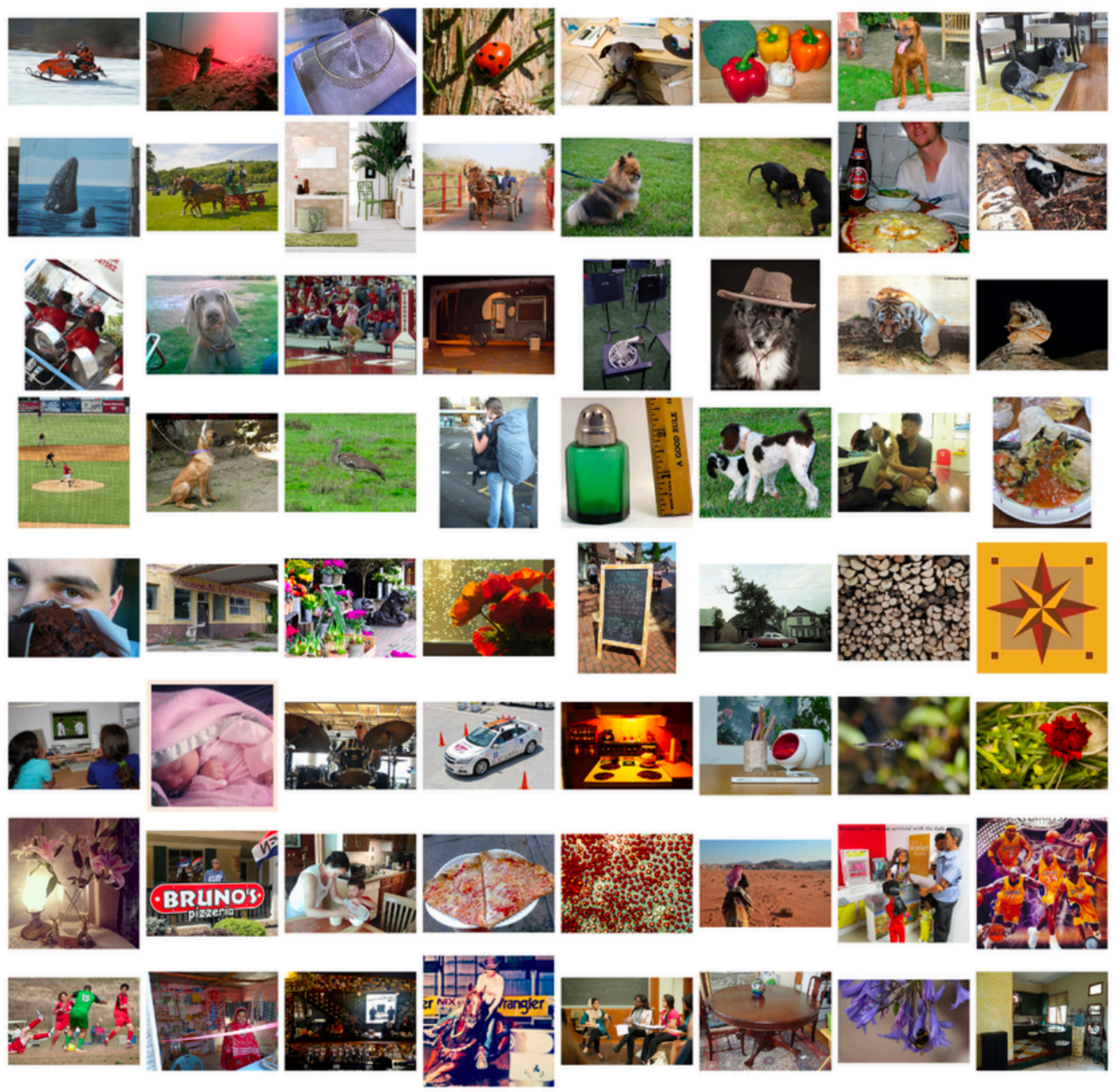

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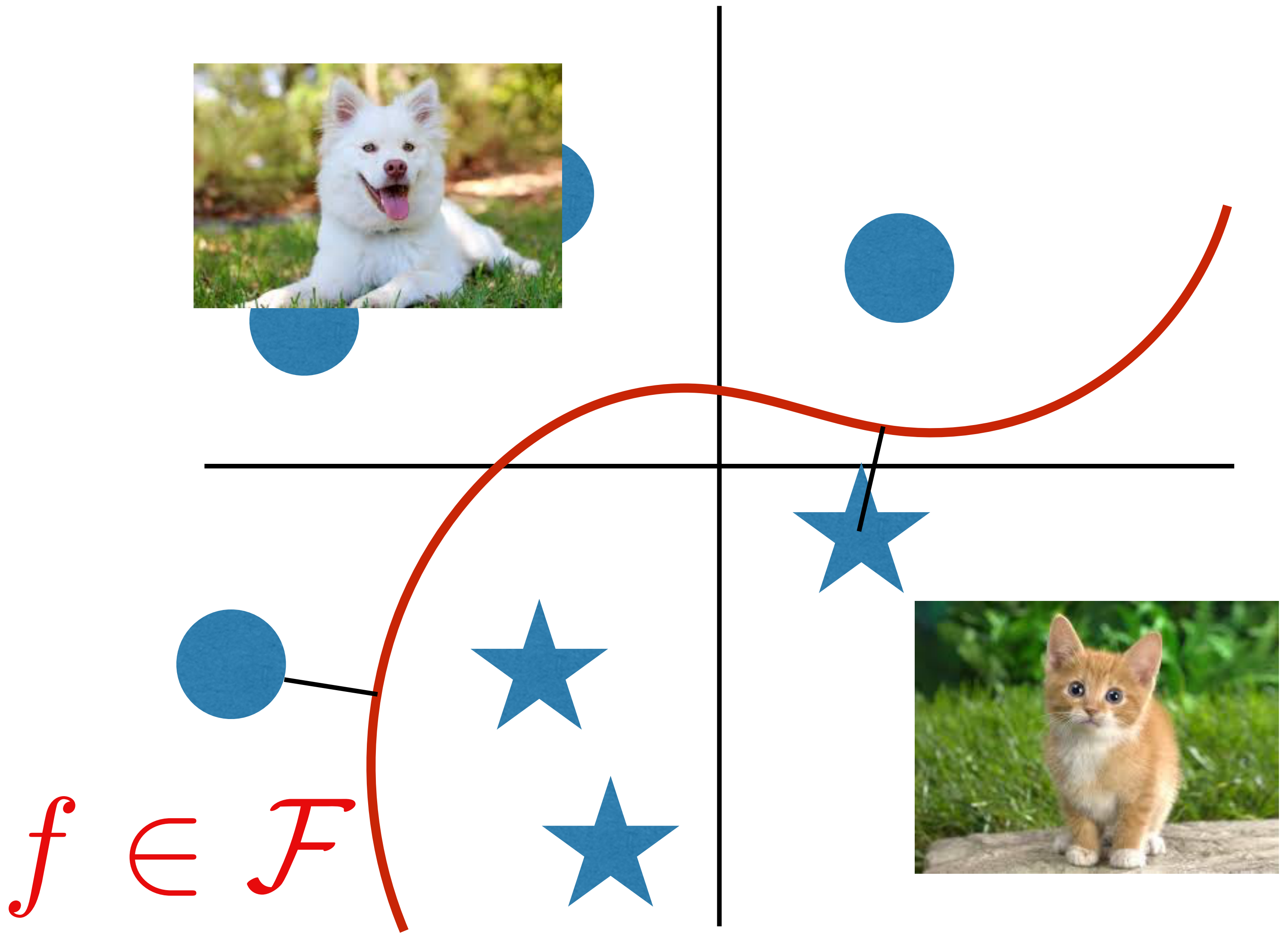
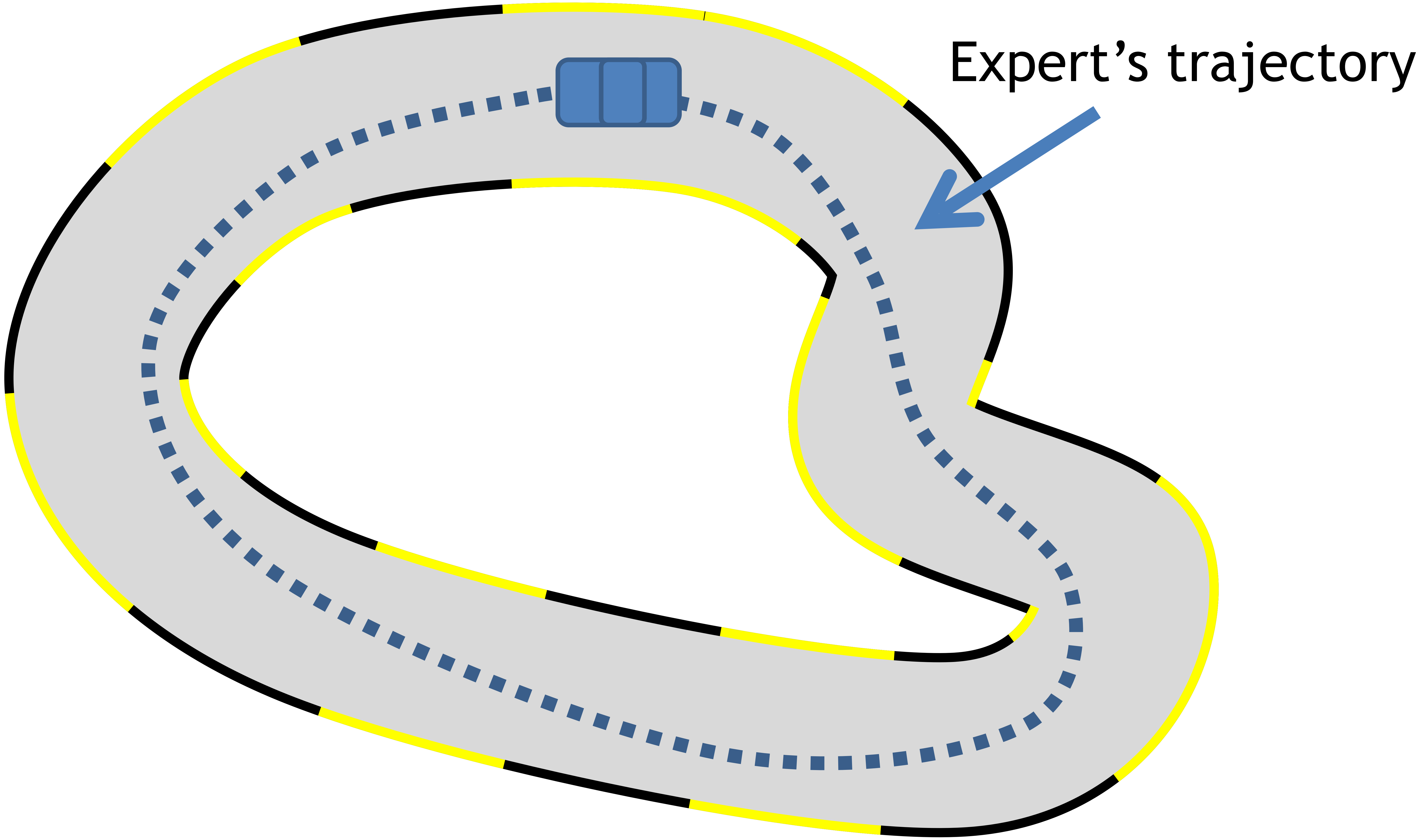


Training distribution $=$ Testing distribution

Why offline RL is challenging?

In RL, we are facing **distribution shift!**



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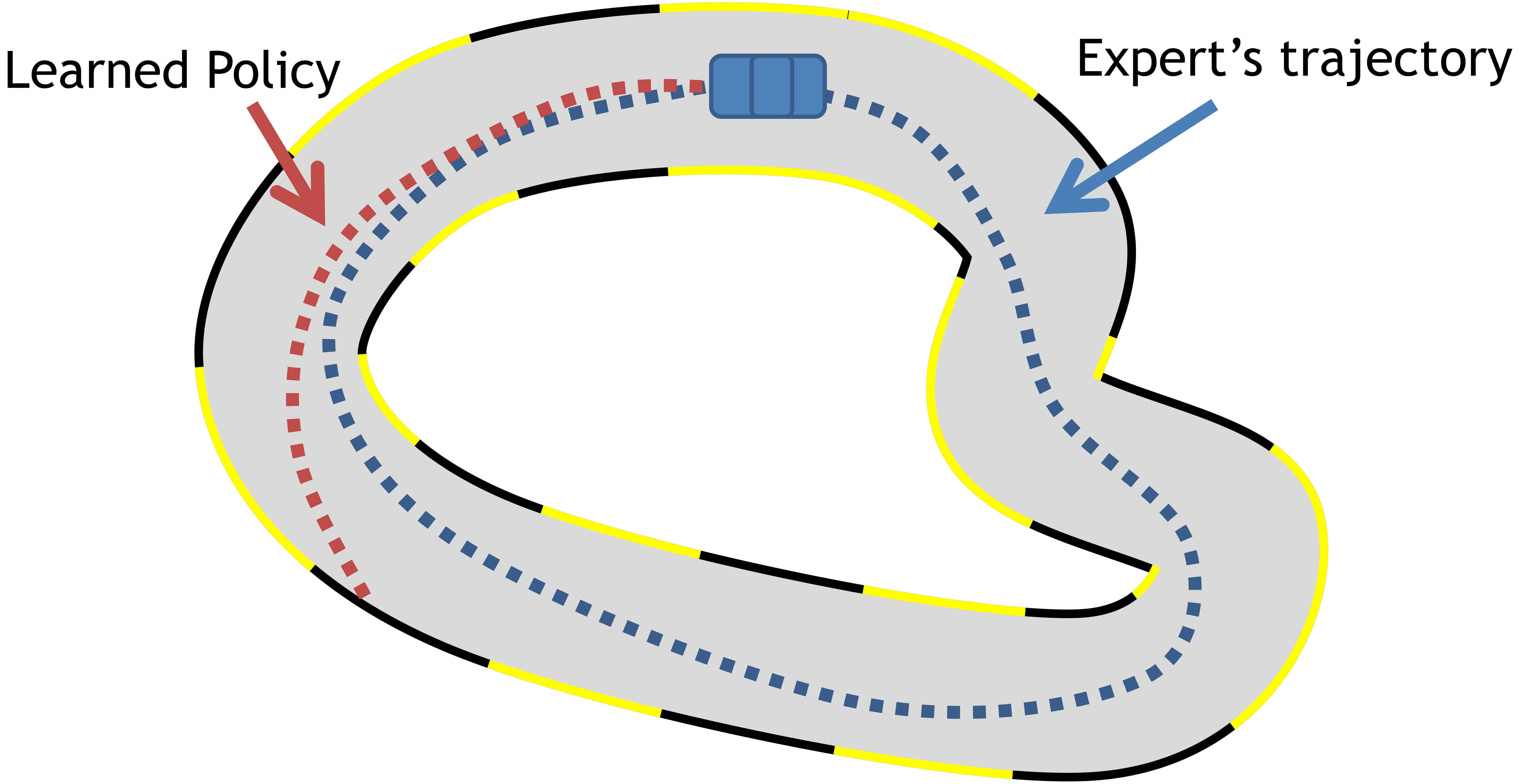

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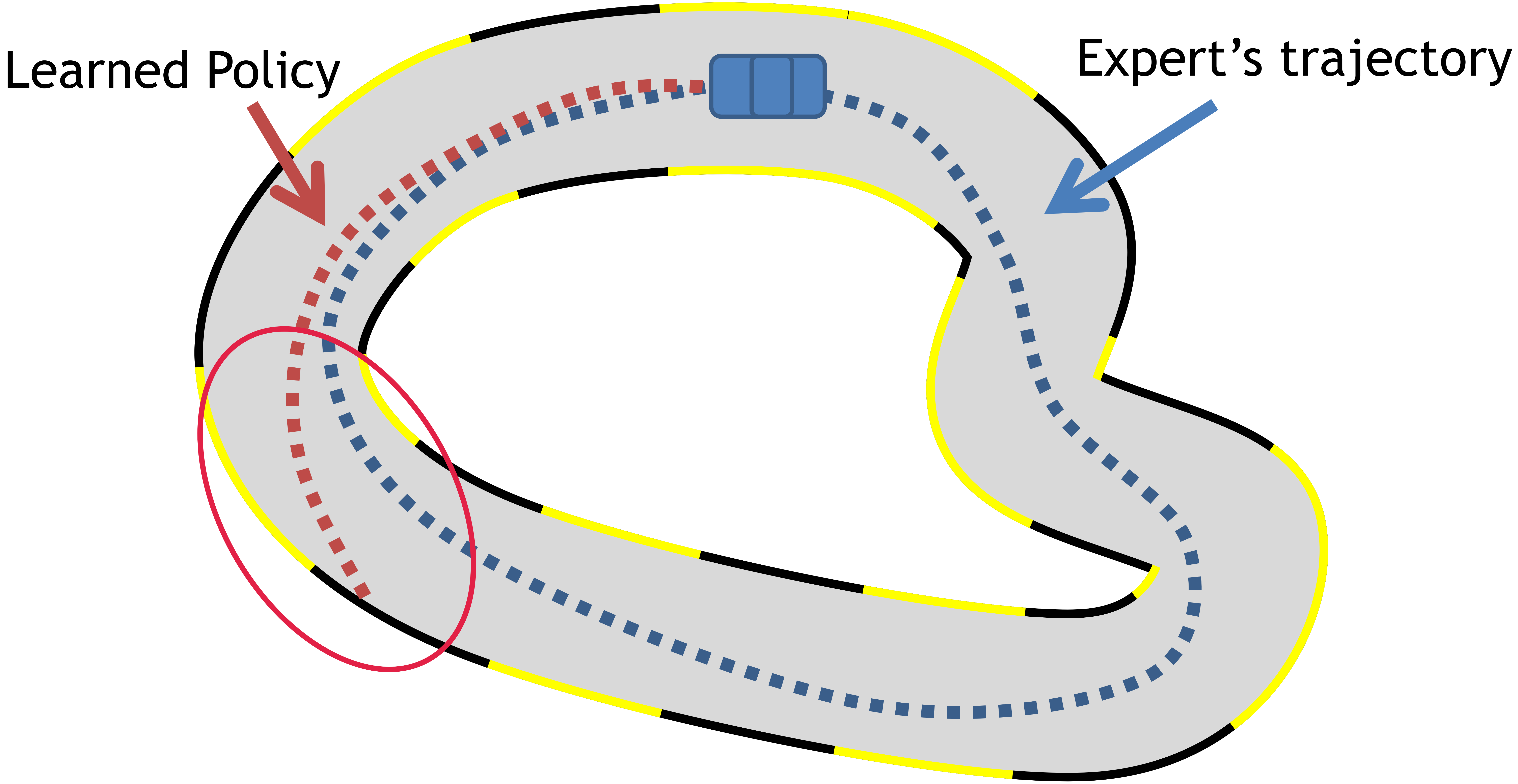


Today:

How should we tackle offline RL (e.g., settings, goals)

when offline data has insufficient coverage?

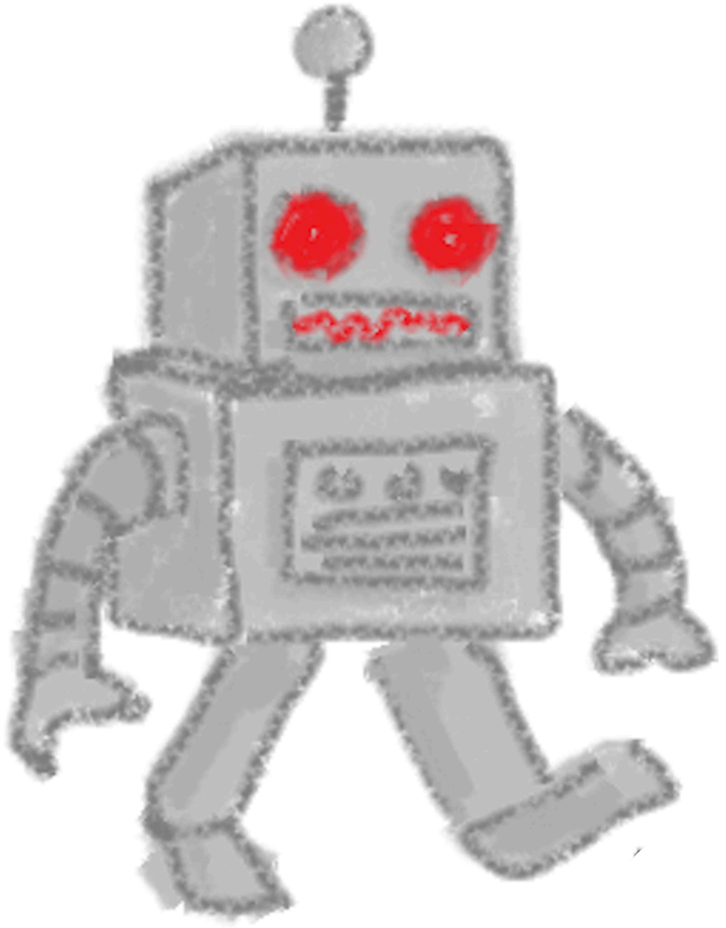
Outline:

1. Rethinking the goal in offline RL: Robustness

2. Can we achieve the goal?

Finite Horizon MDPs

agent



Policy: state to action

$$\pi(s) \rightarrow a$$

Reward & Next State

$$r(s,a), s' \sim P^\star(\cdot \mid s,a)$$

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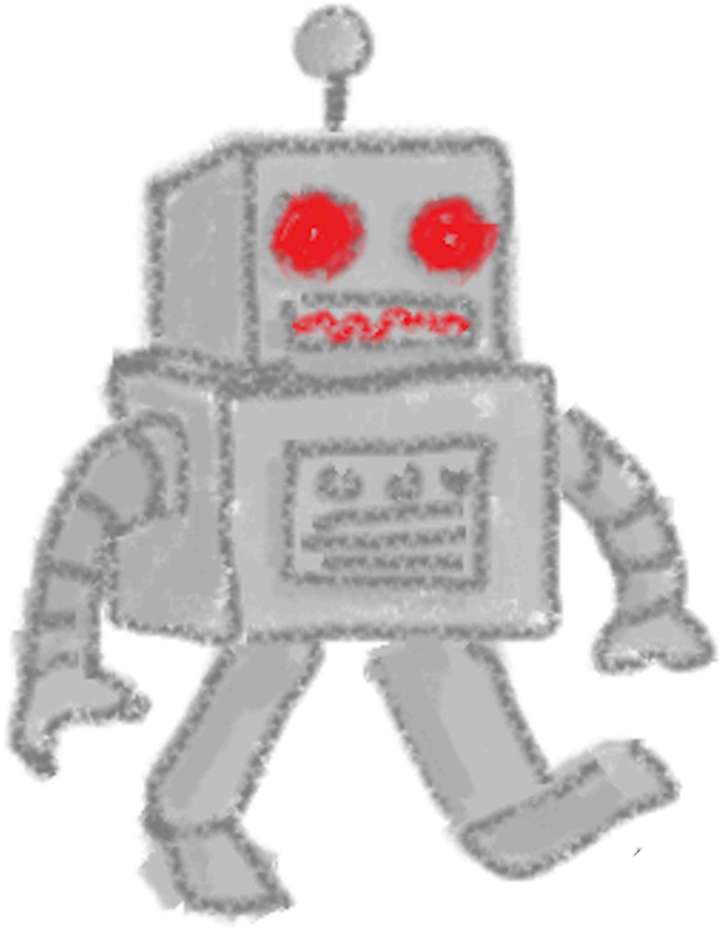

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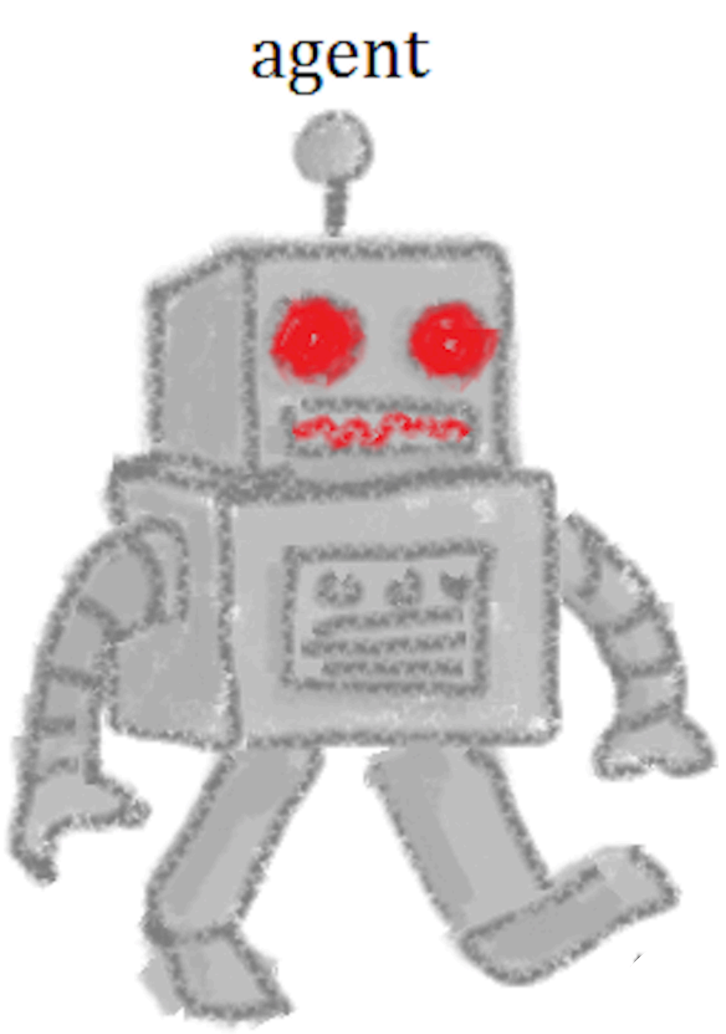

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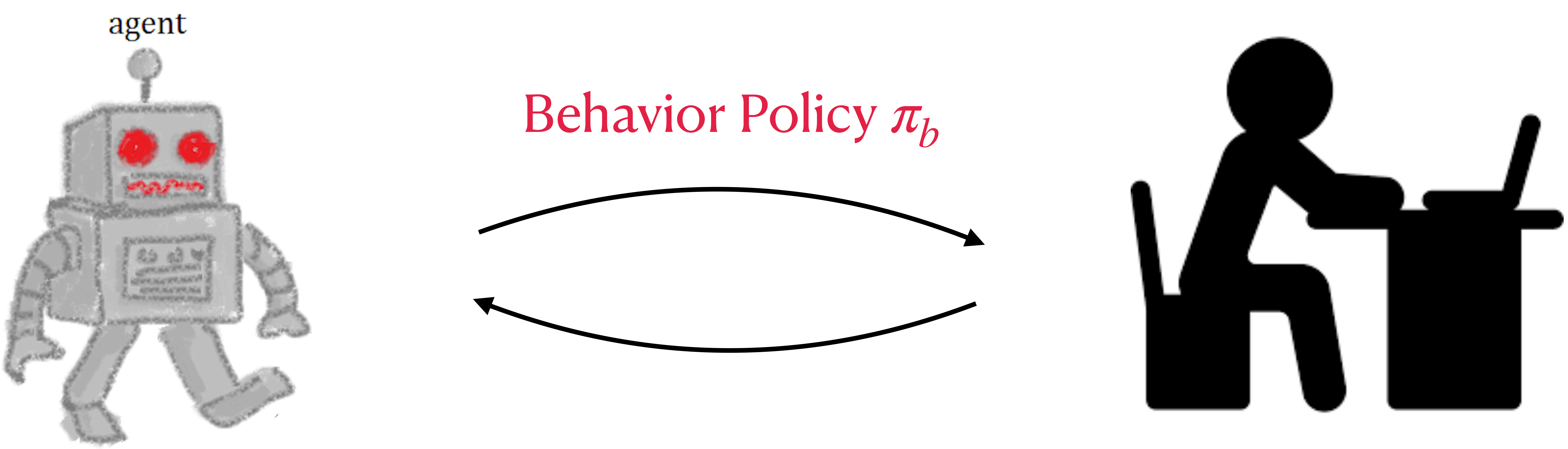
Objective: $\max_\pi J(\pi; P^\star, r)$, where $J(\pi; P^\star, r) := \mathbb{E}\left[\sum_{h=0}^{H-1} r(s_h, a_h) \,|\, a \sim \pi, P^\star\right]$

Offline Data Collection



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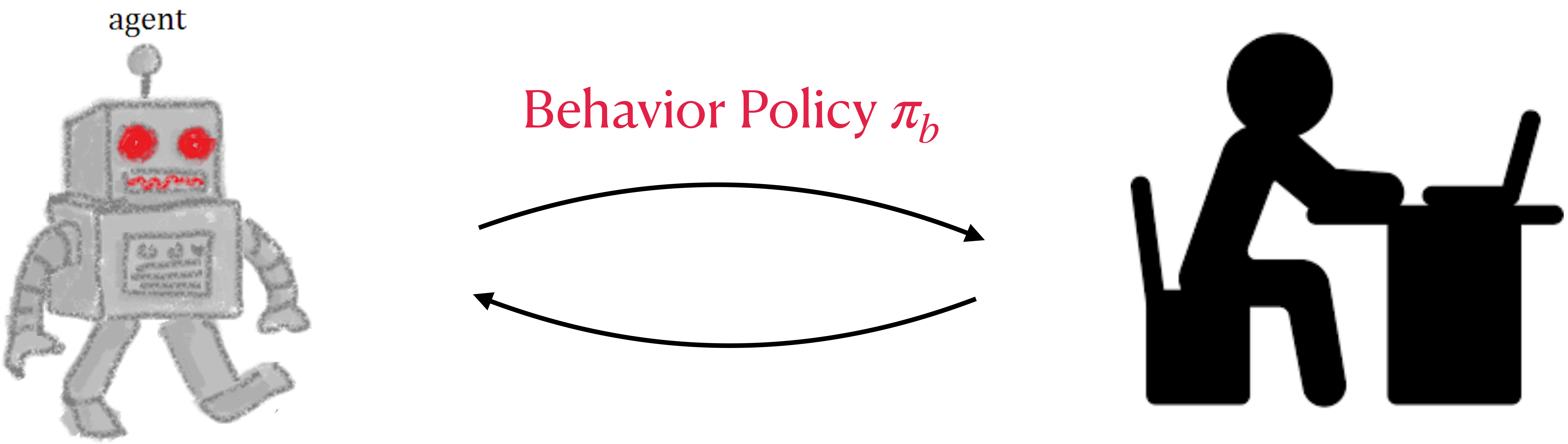

Induced state-action distribution of π_b:

$$d^{\pi_b} \in \Delta(S \times A)$$

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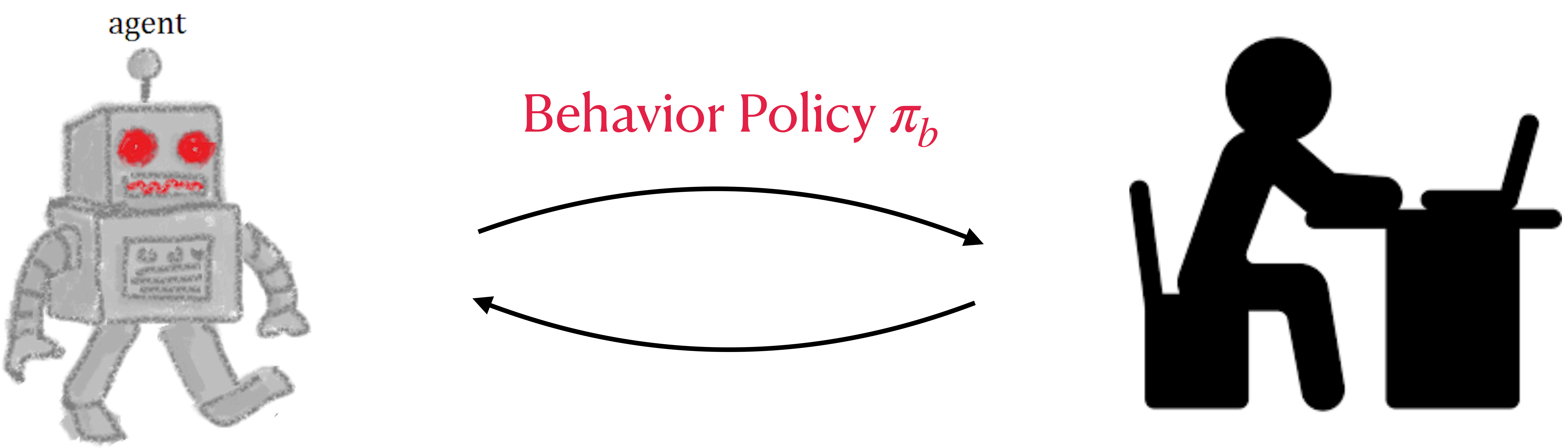

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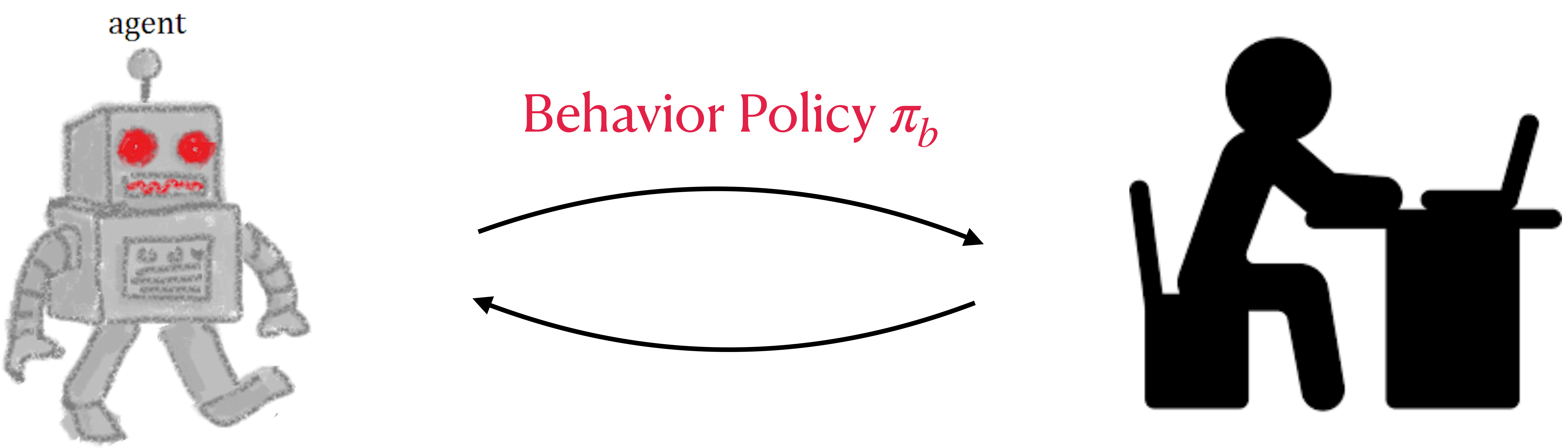

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i.i.d triples

Offline Data Coverage

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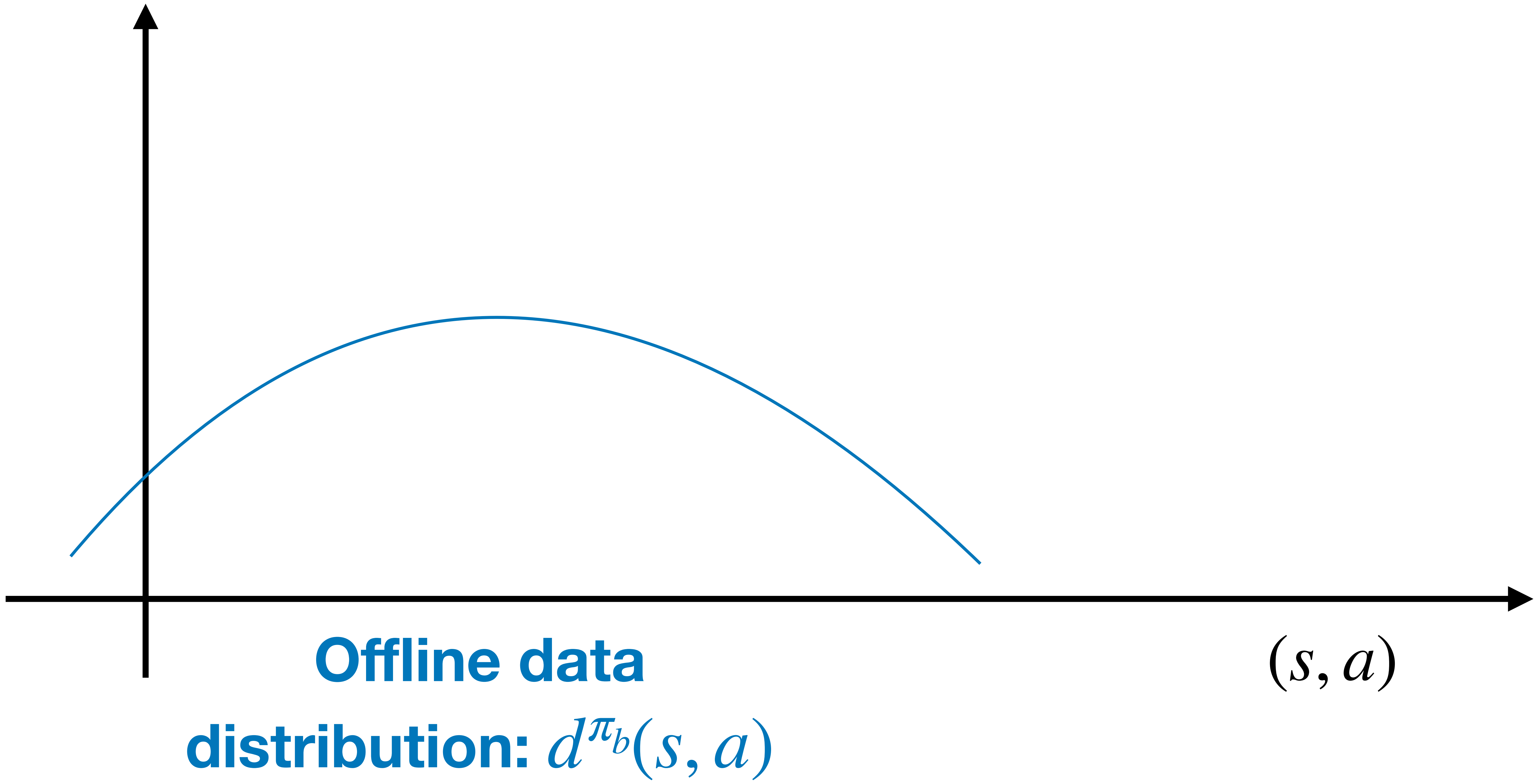

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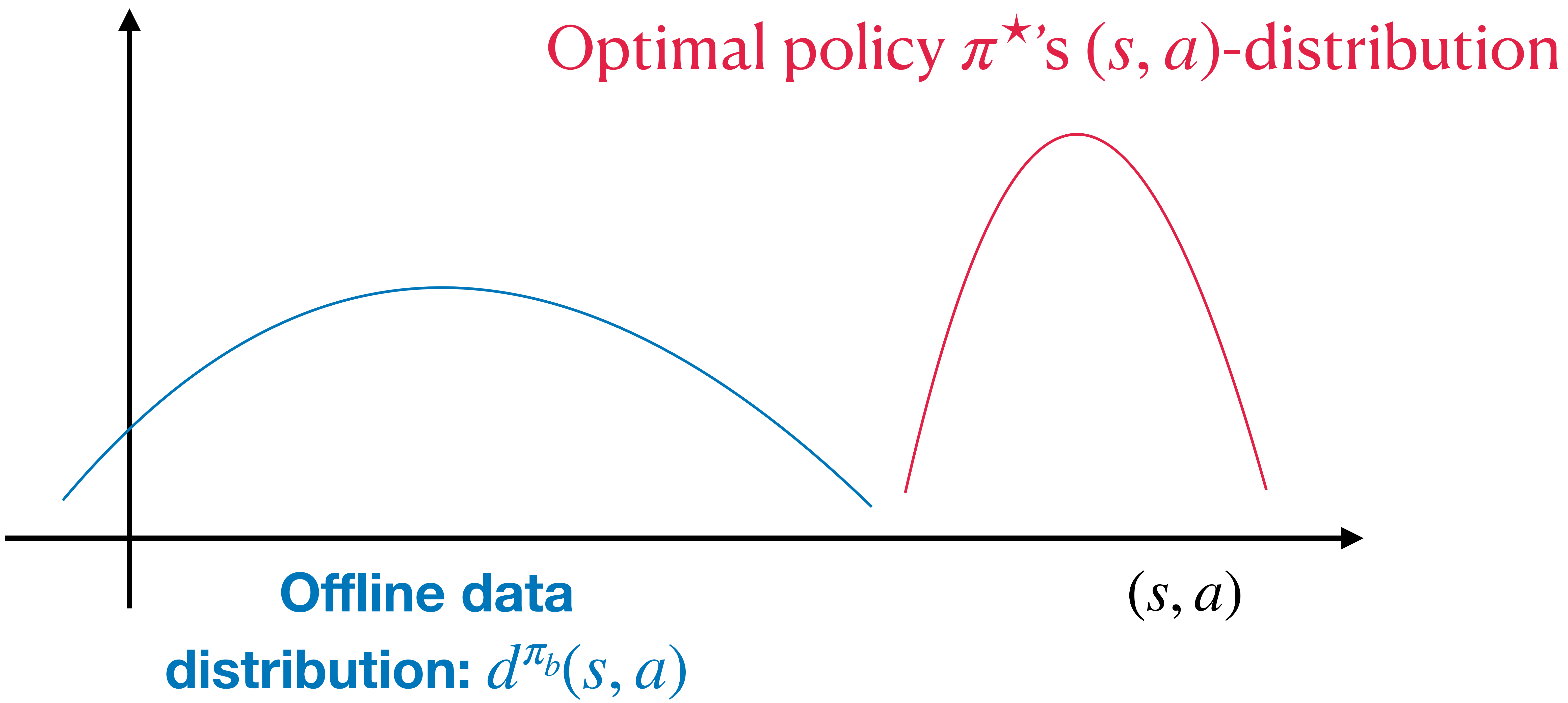

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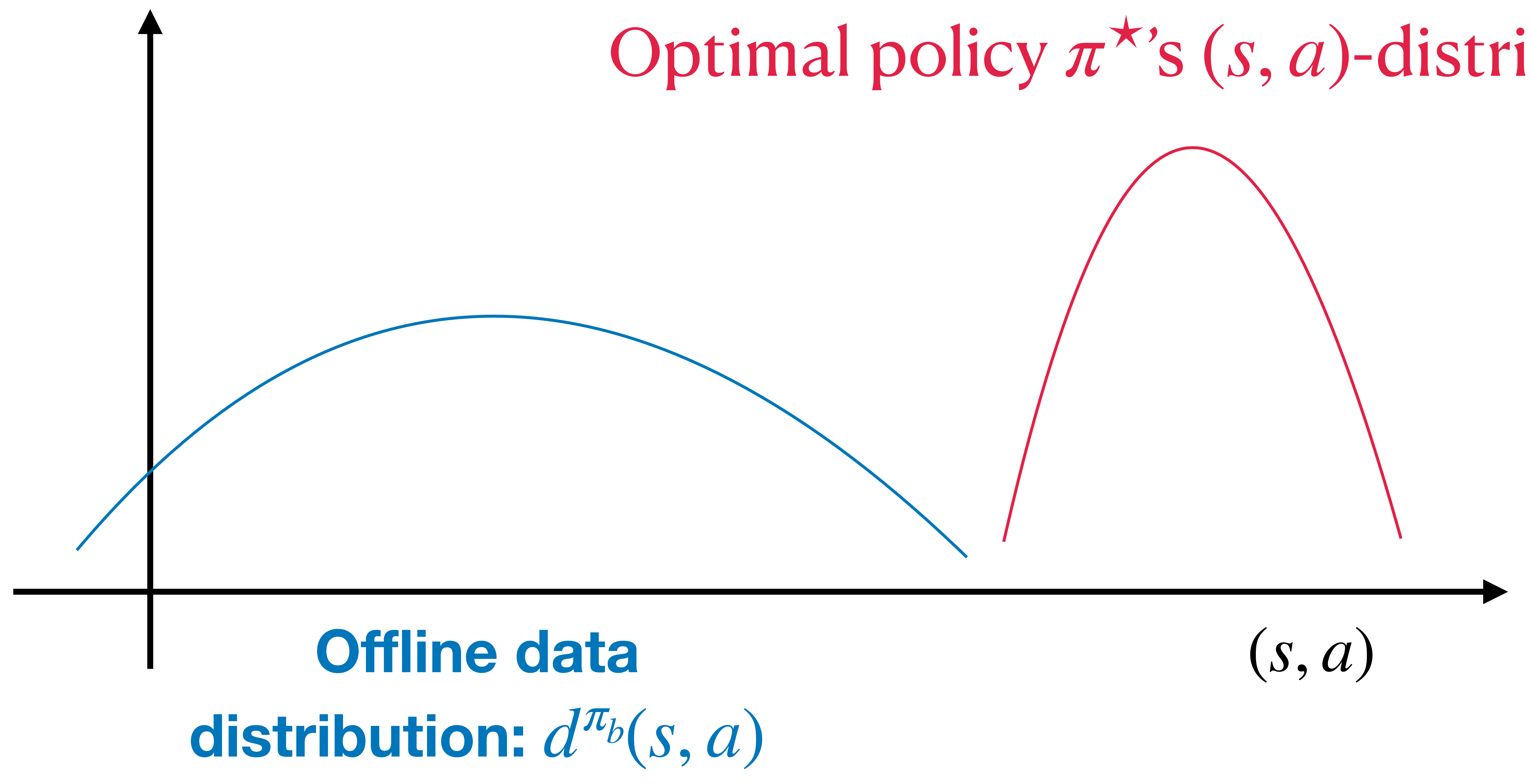

Finding $\pi^\star$ seems hopeless!

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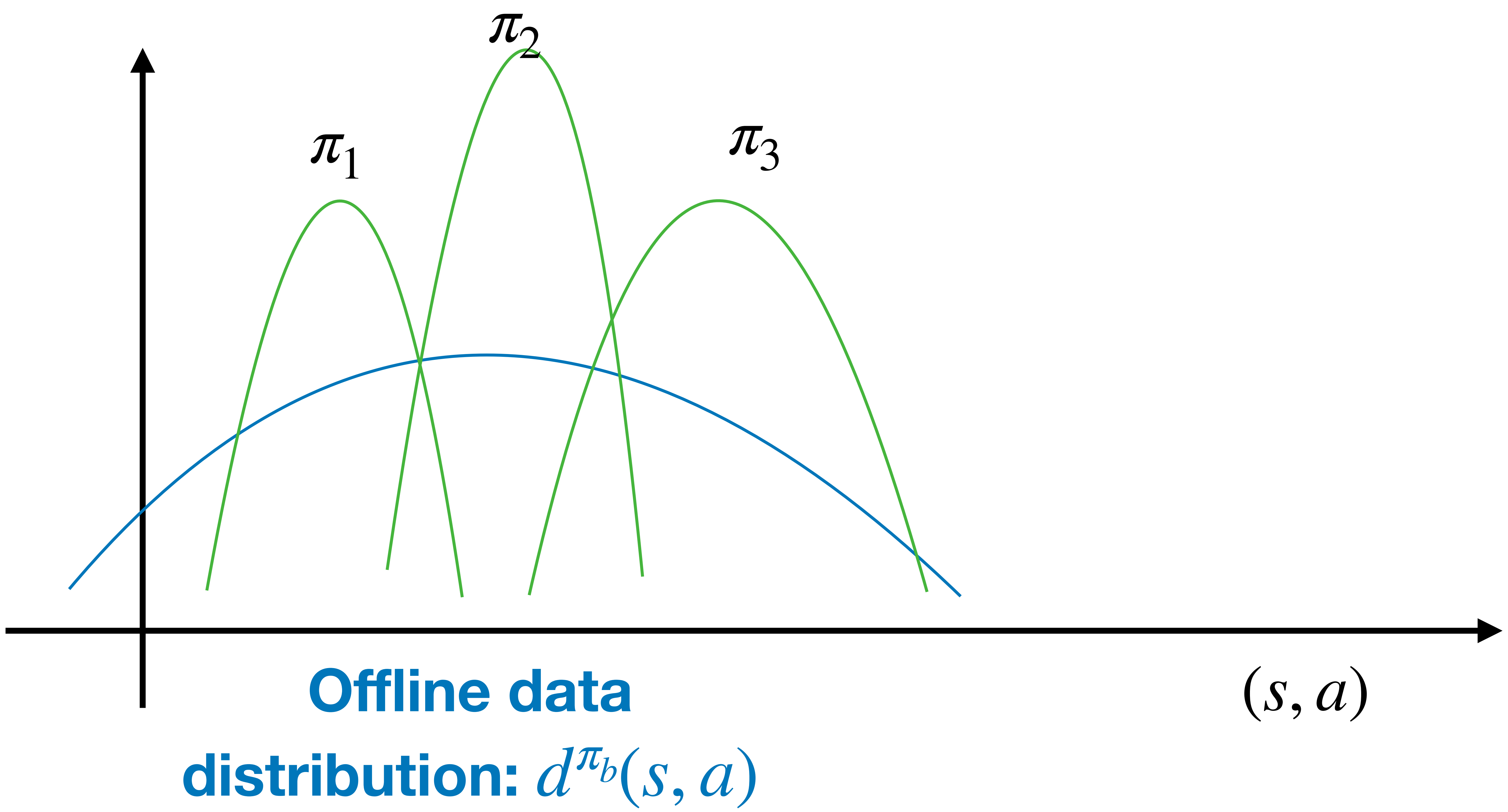

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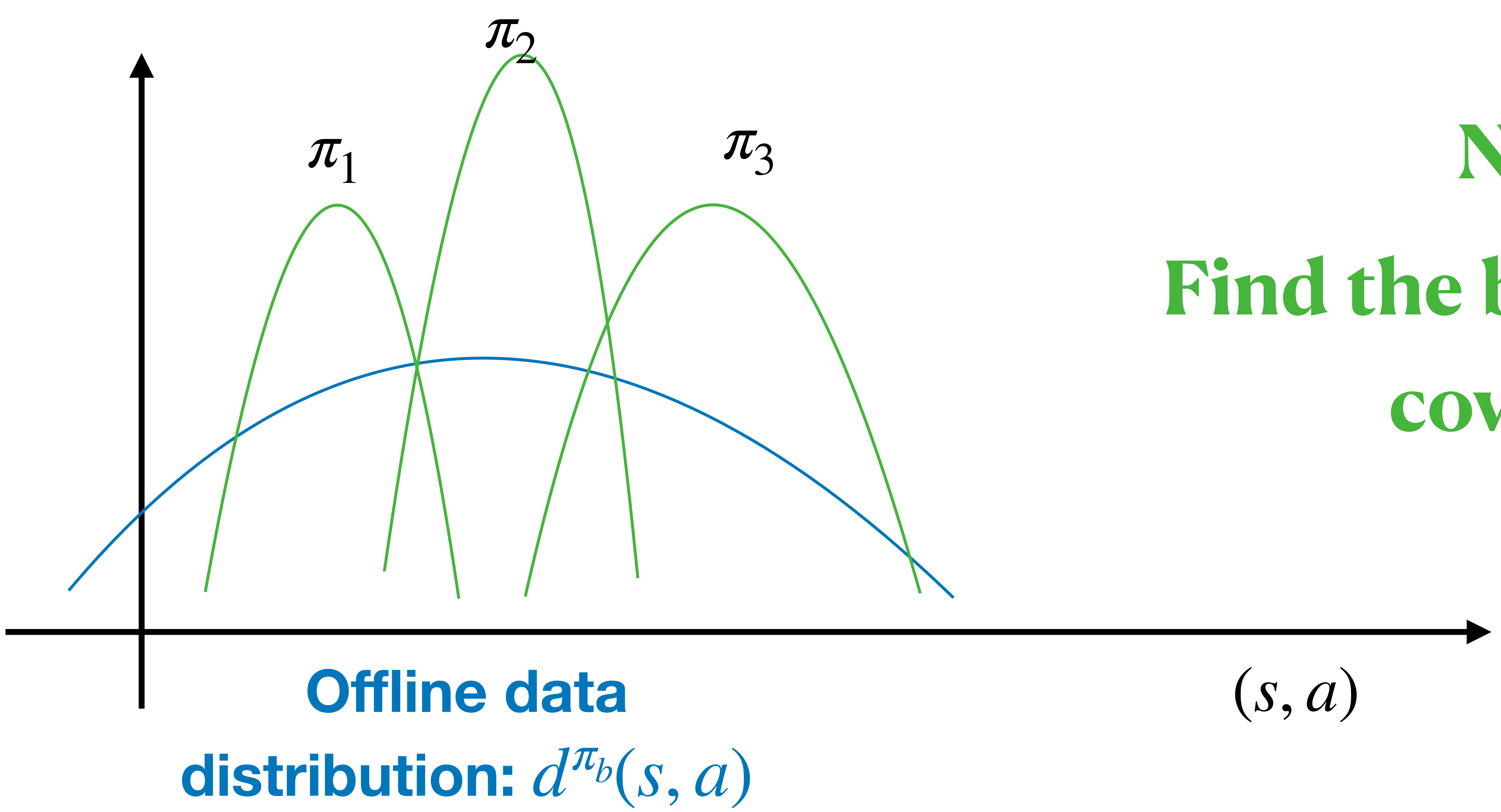
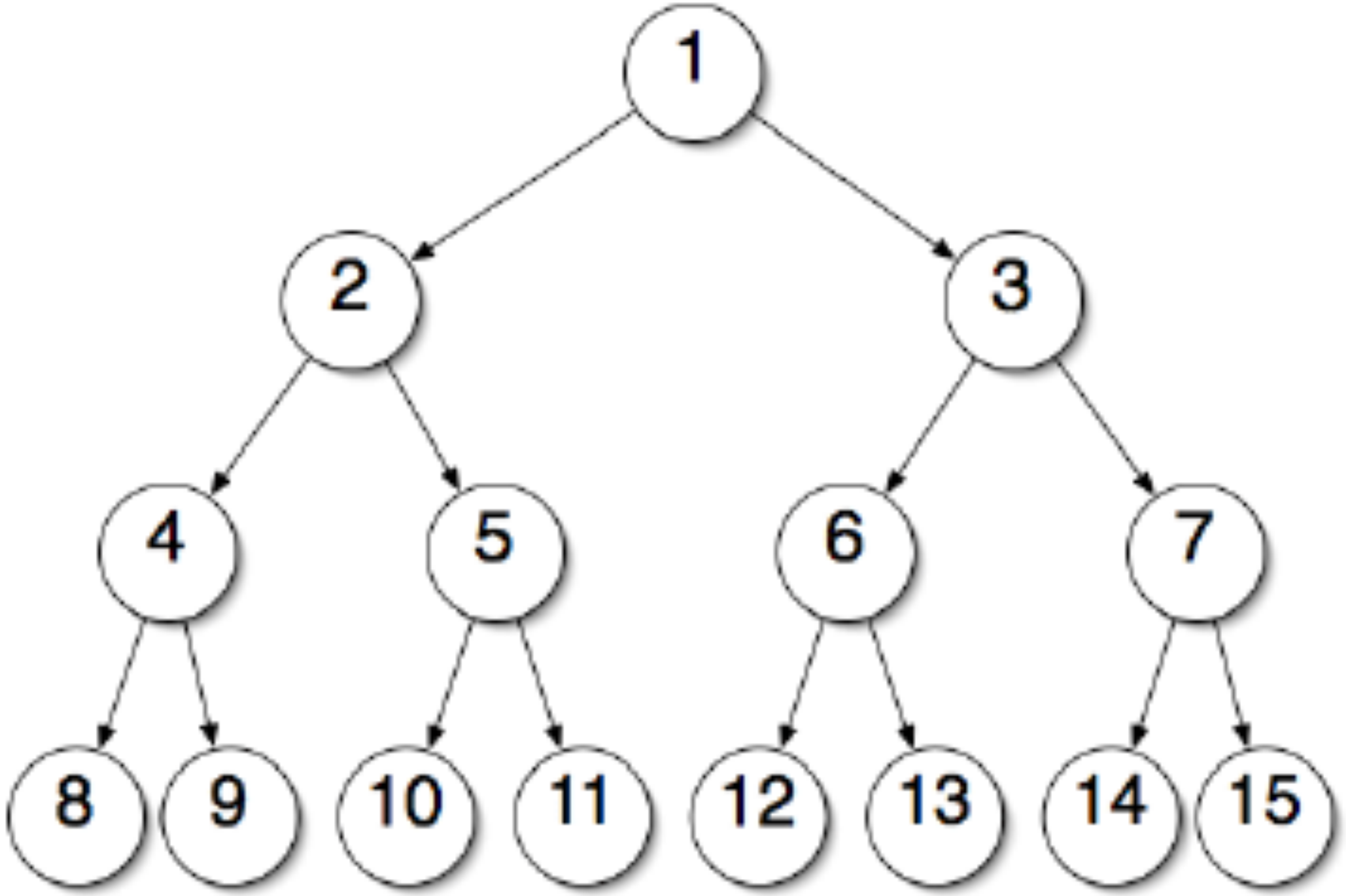


New Goal:

Find the best among those covered by d^{π_b}

Learning goal in Offline RL: Robustness



$r(15) = 1$

$r(10) = 0.9$

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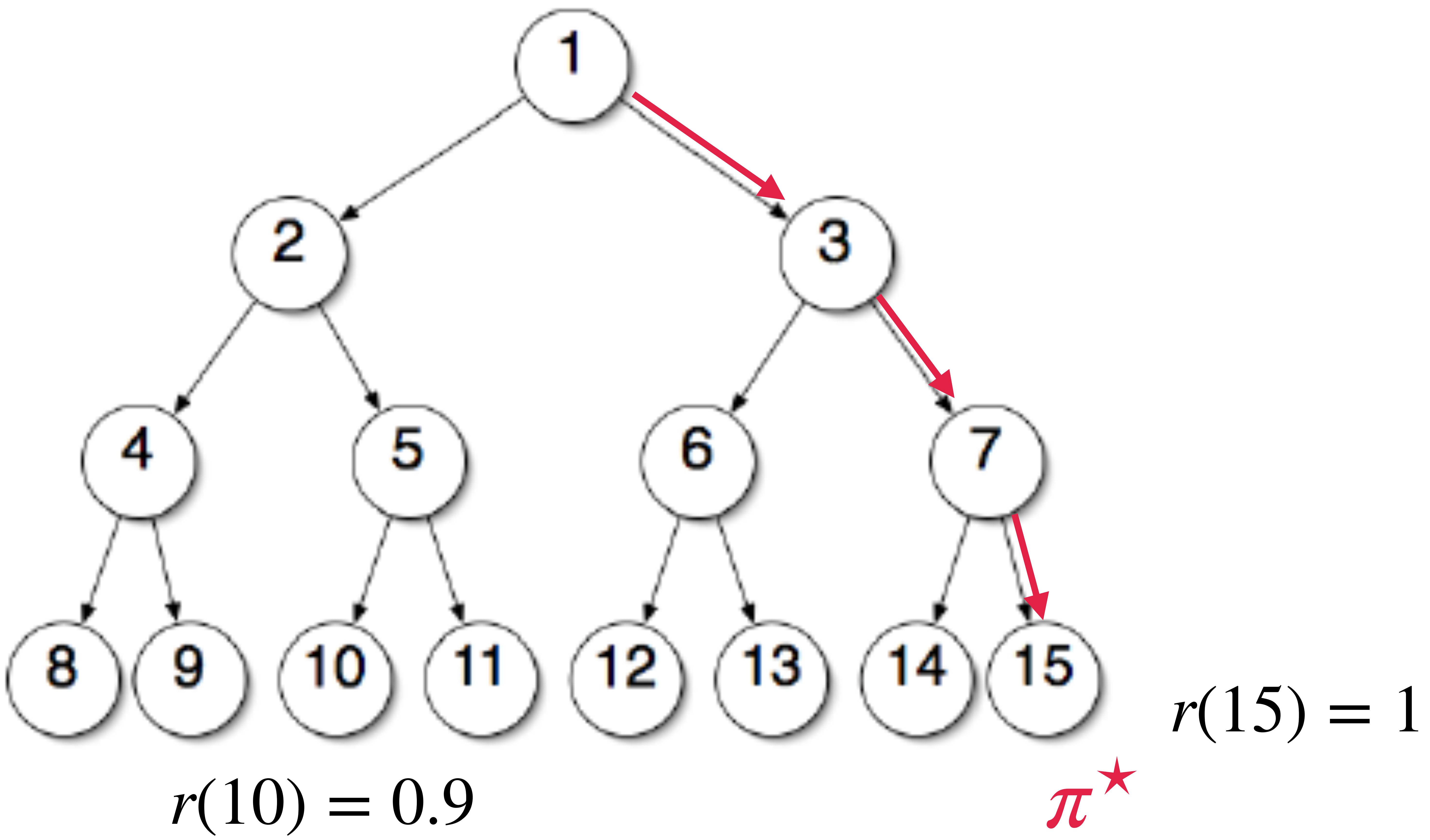

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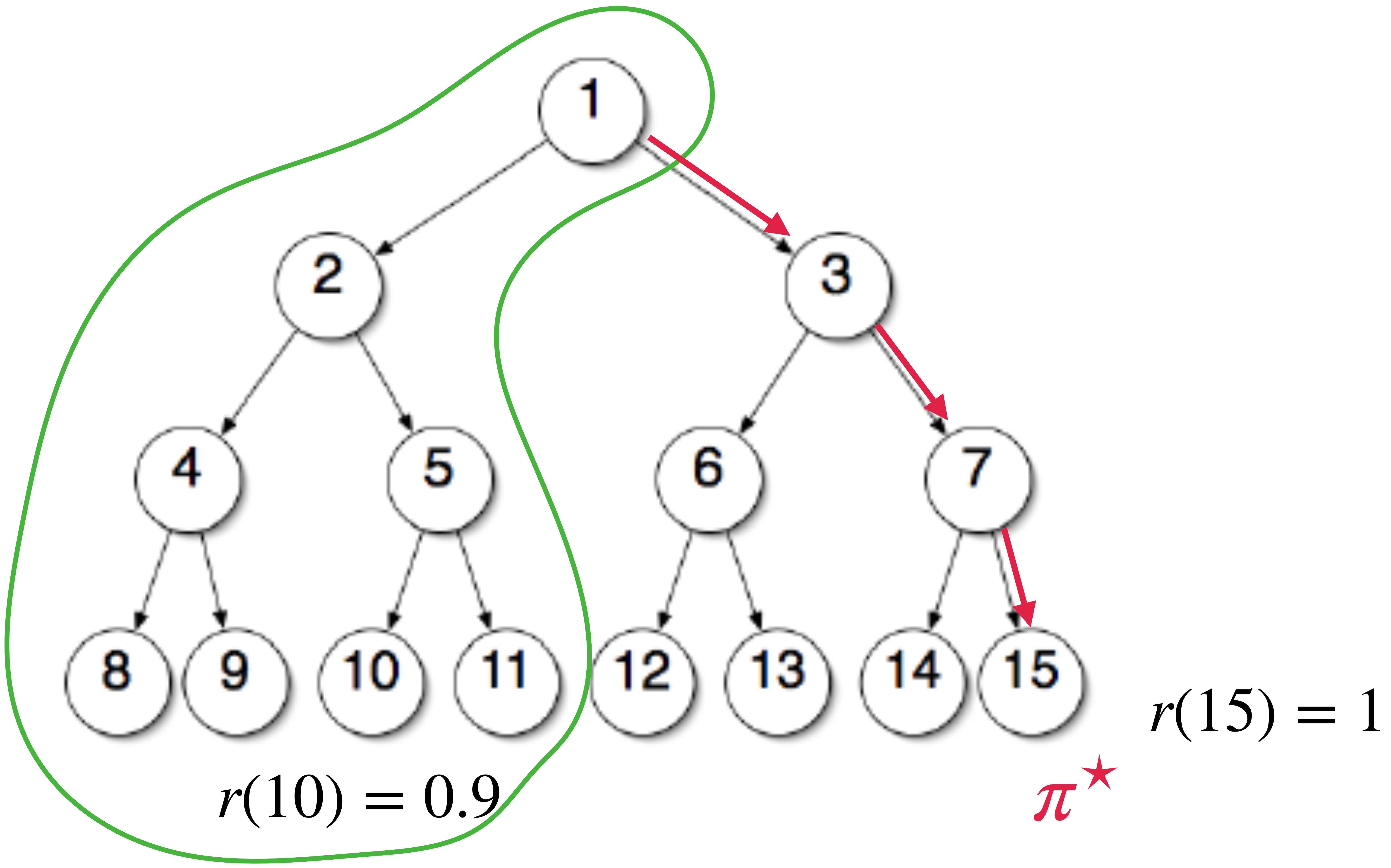

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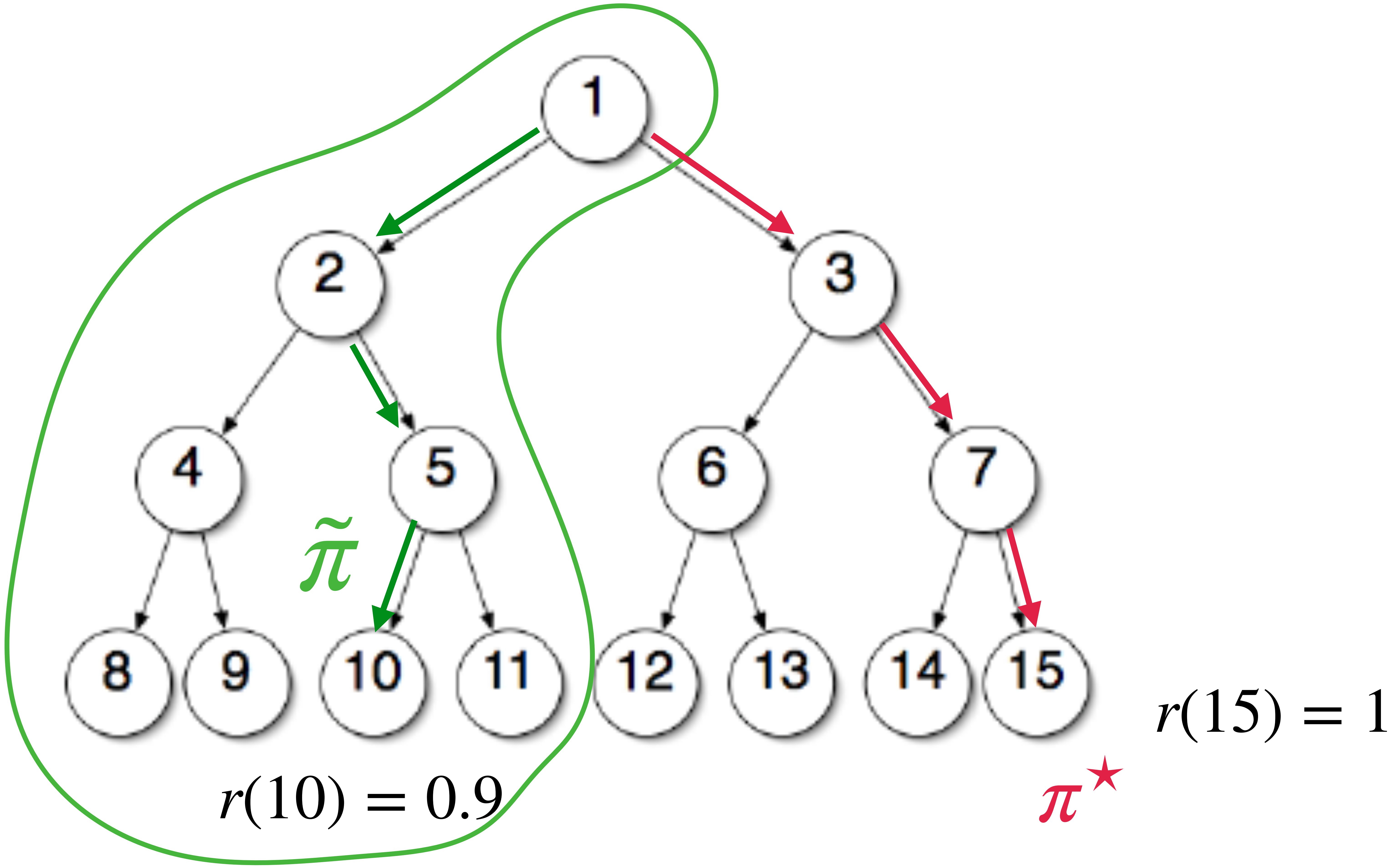

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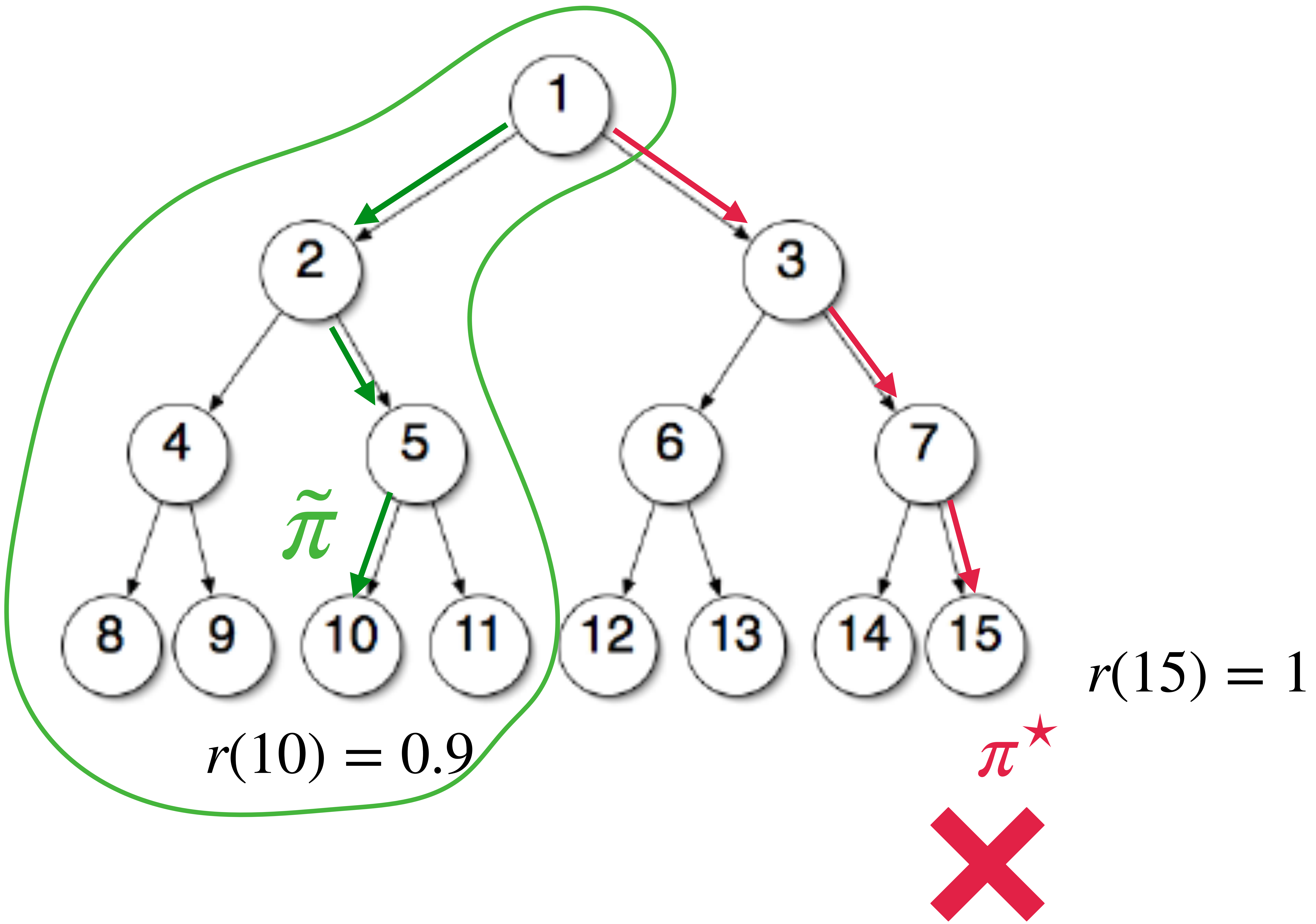

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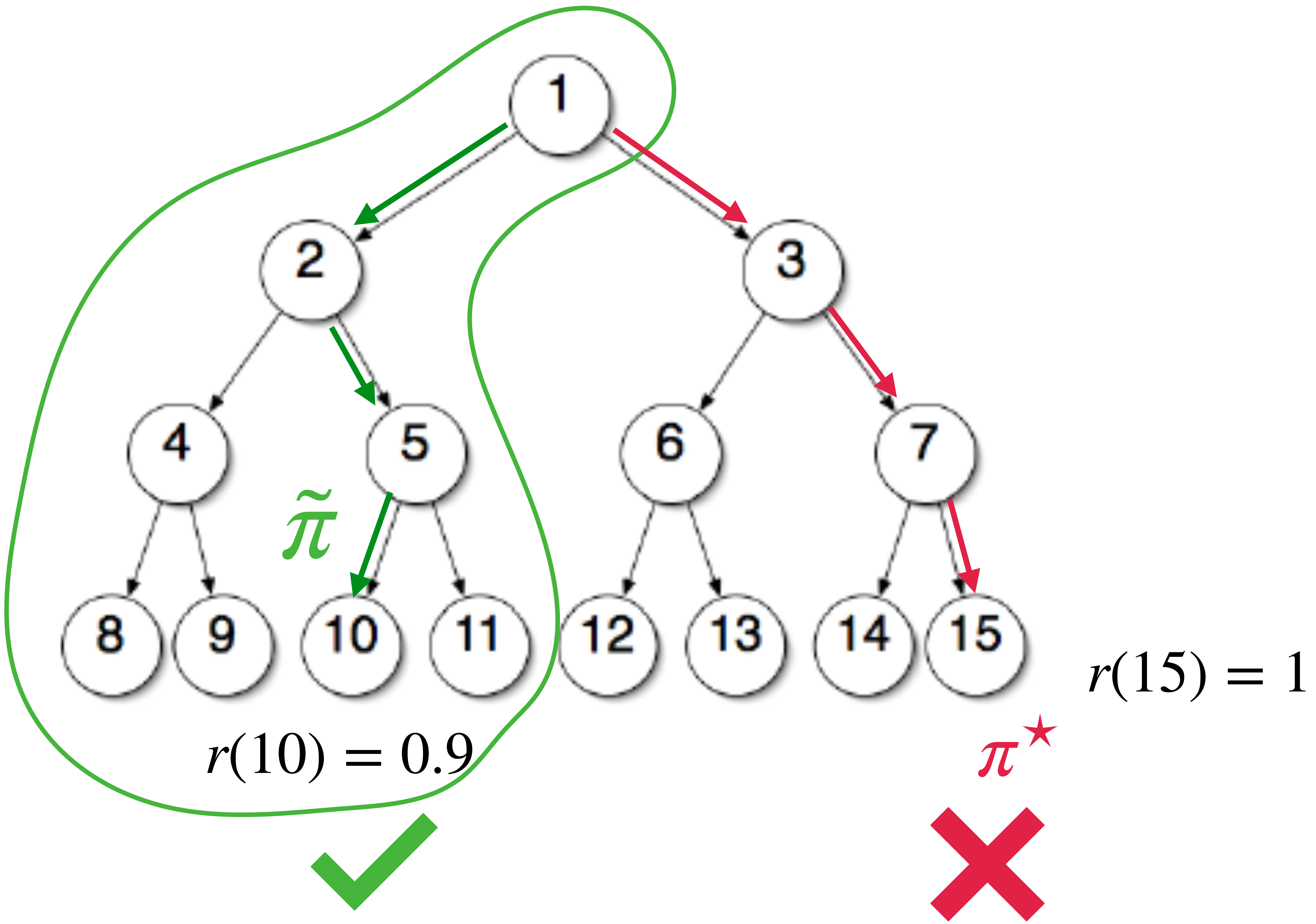

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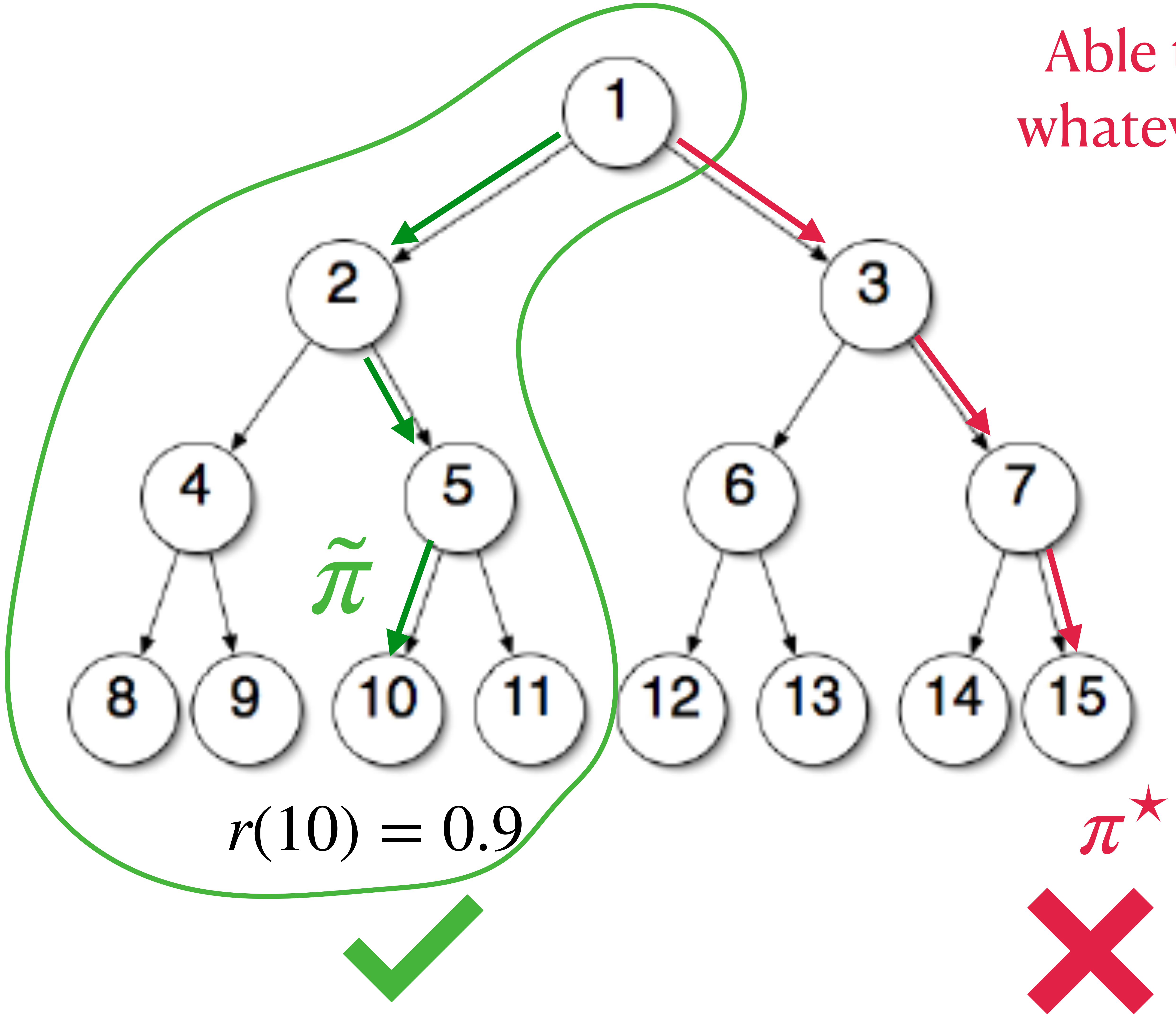

Able to compete against whatever is covered by the offline data

Learning goal in Offline RL: Generalization

Supervised Learning:

Offline RL:

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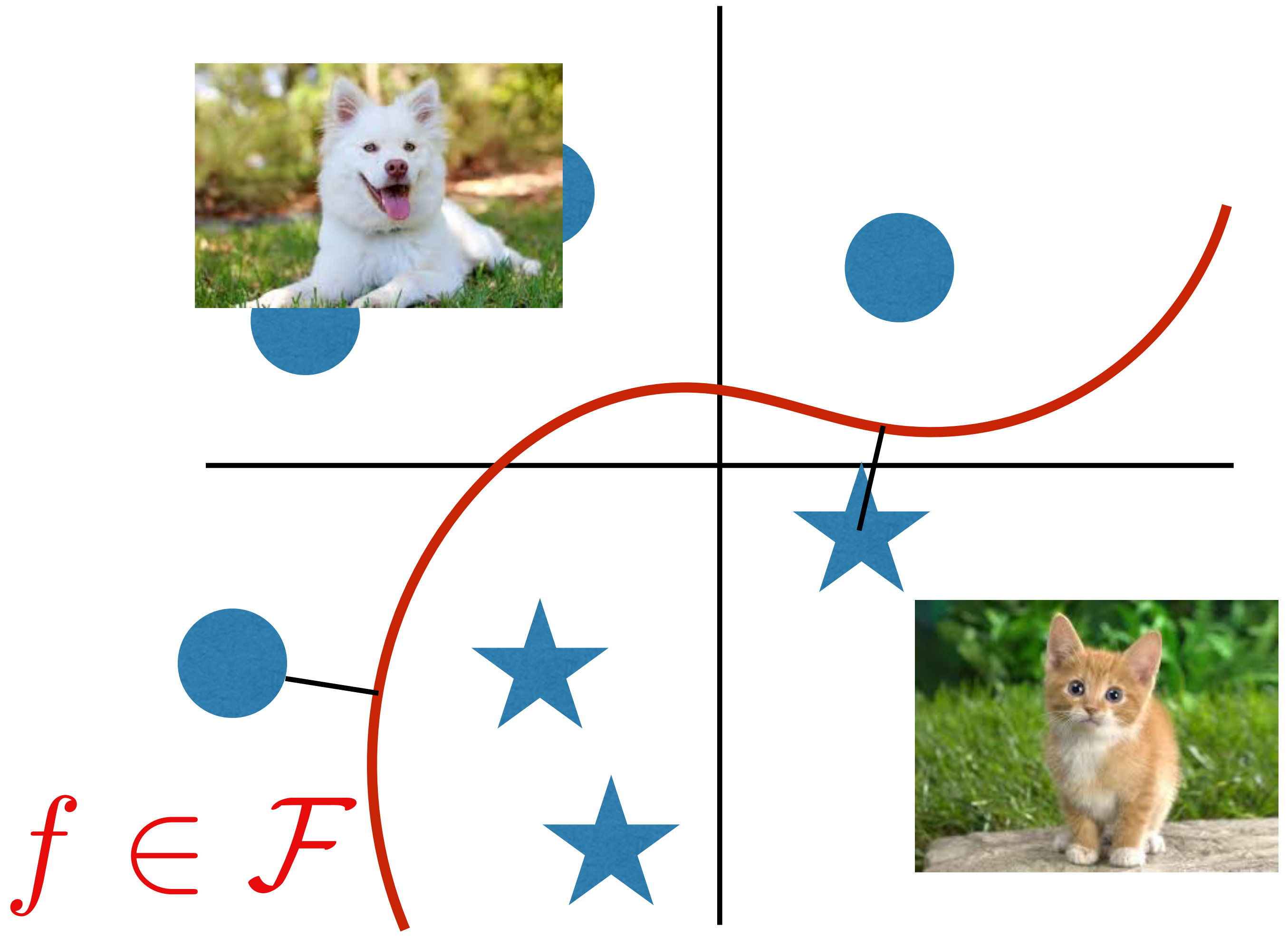
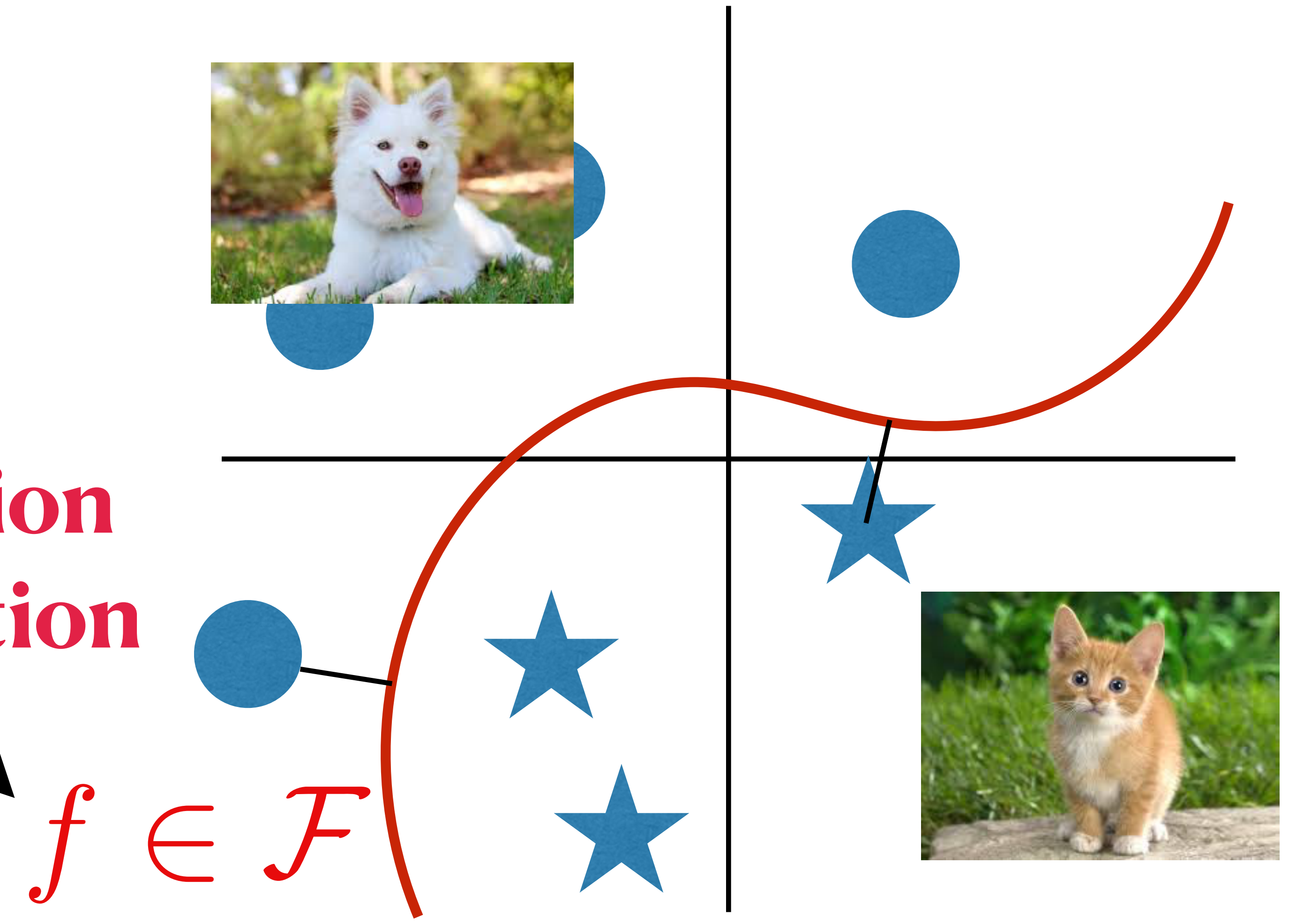


Offline RL:

Learning goal in Offline RL: Generalization

Supervised Learning:

Rich Function Approximation



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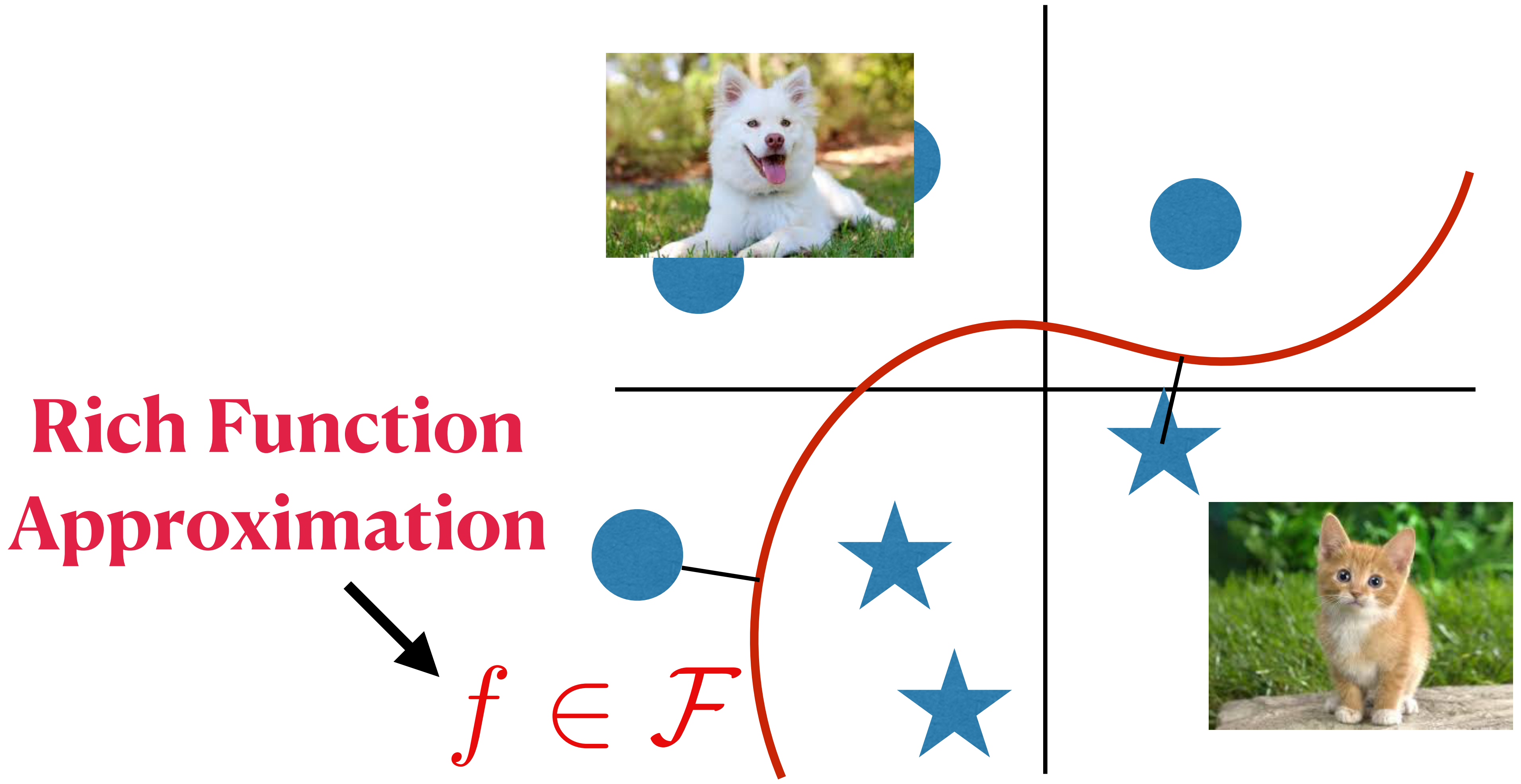
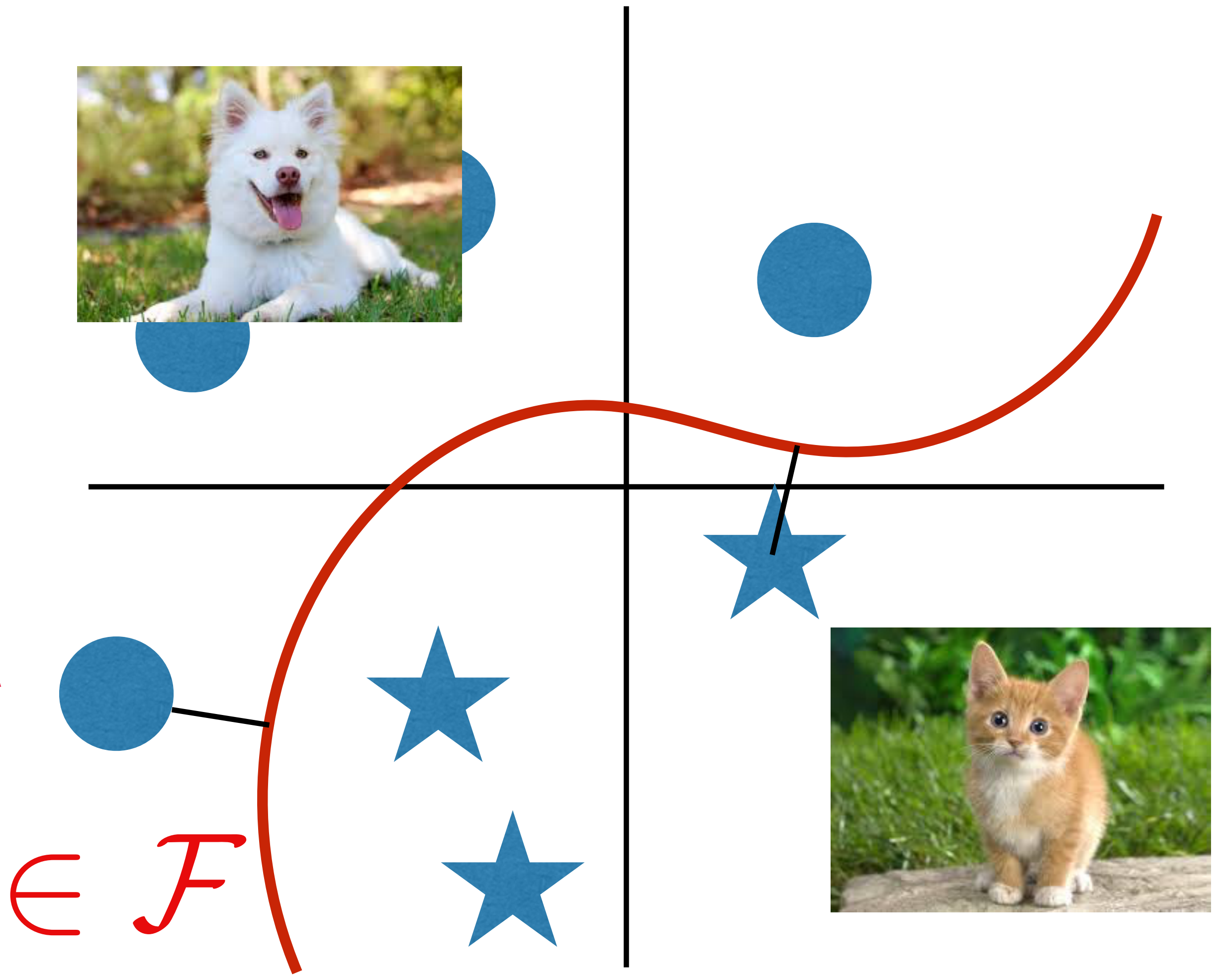


Sample complexity depends on **complexity of $\mathscr{F}$** (e.g., VC-dim, Rademacher, covering dim)

Offline RL:

Learning goal in Offline RL: Generalization

Supervised Learning:



Rich Function Approximation

$f \in \mathcal{F}$

Offline RL:

Learning goal in Offline RL: Generalization

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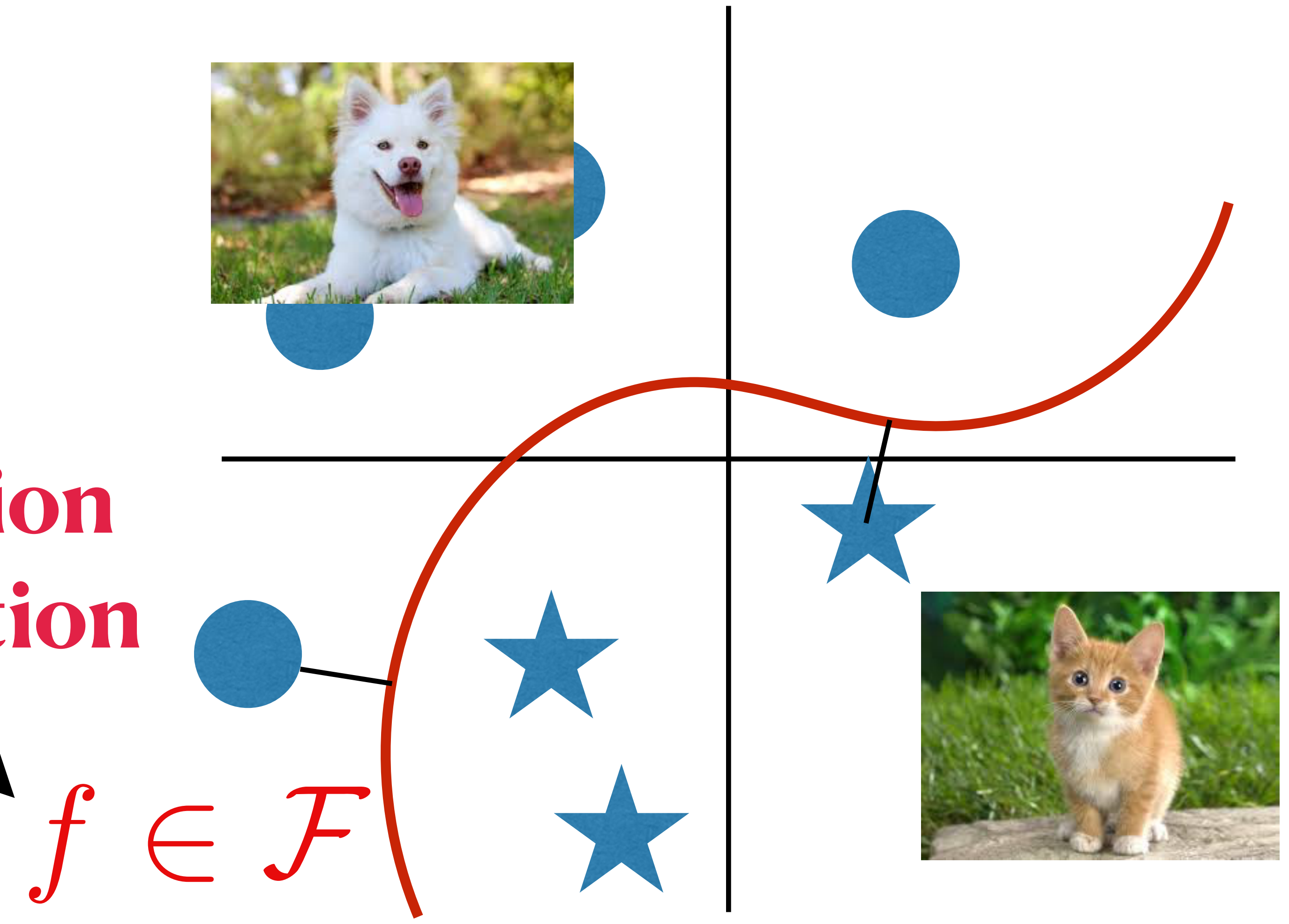

Polynomial Dependency of #
of unique images

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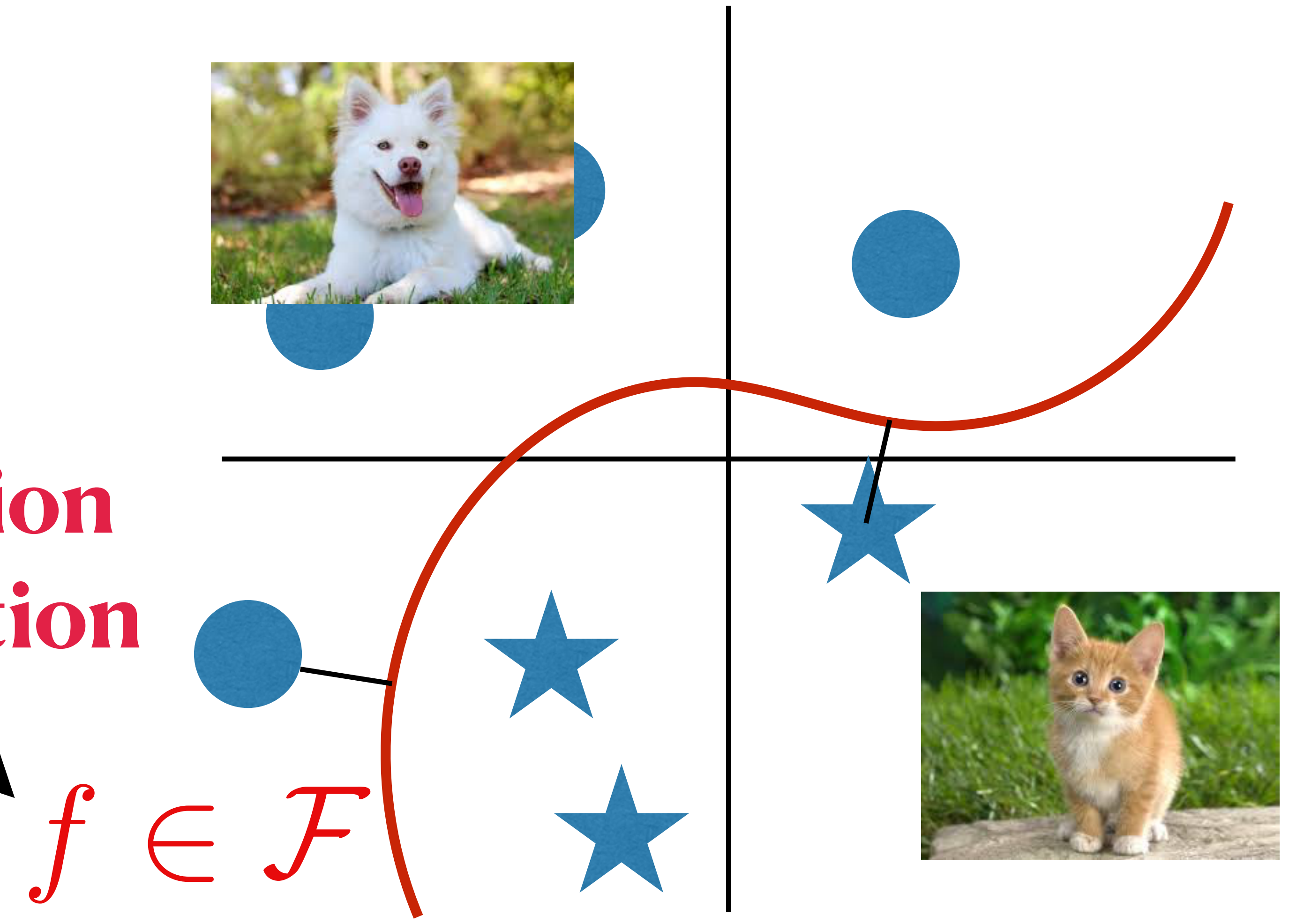

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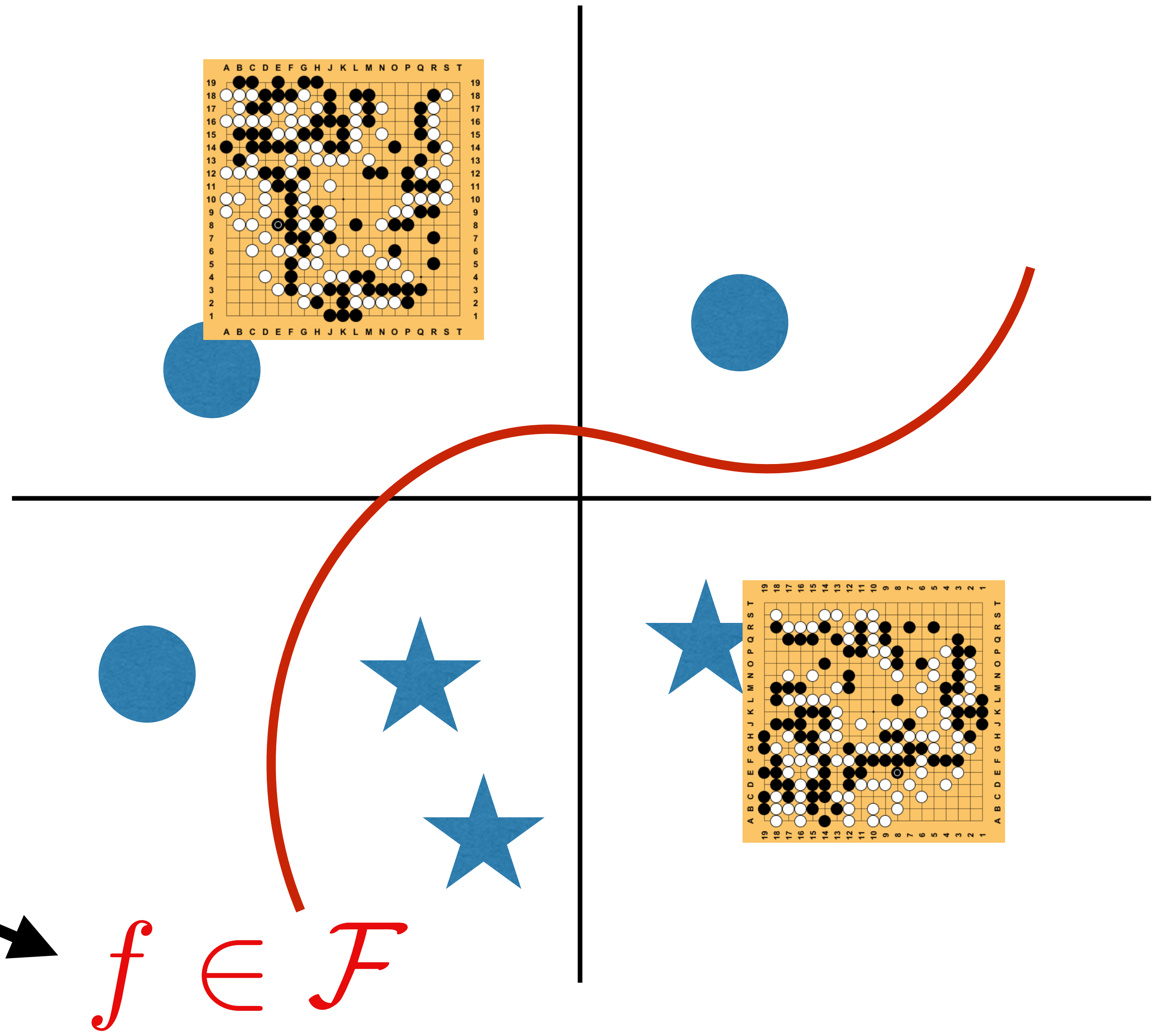

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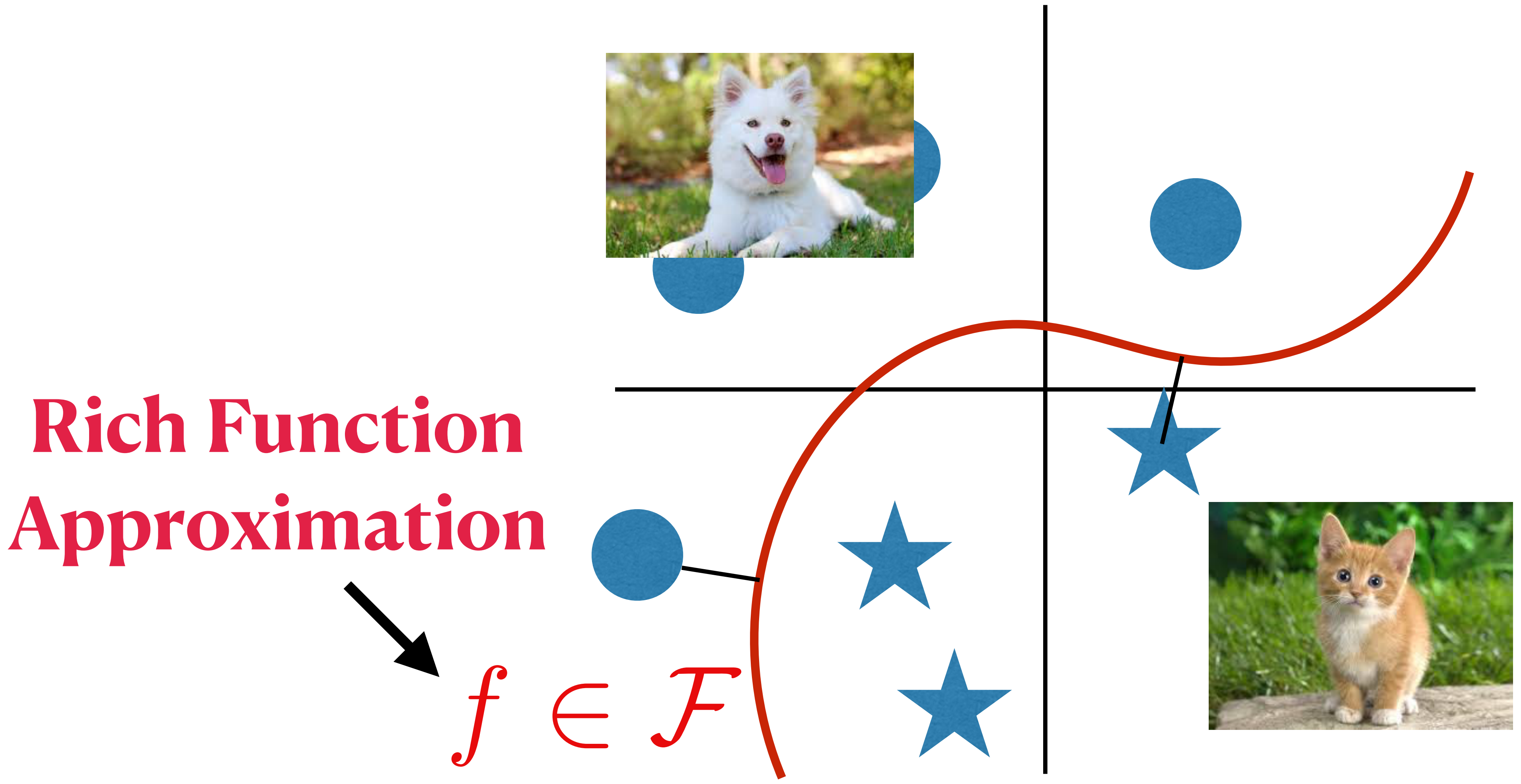

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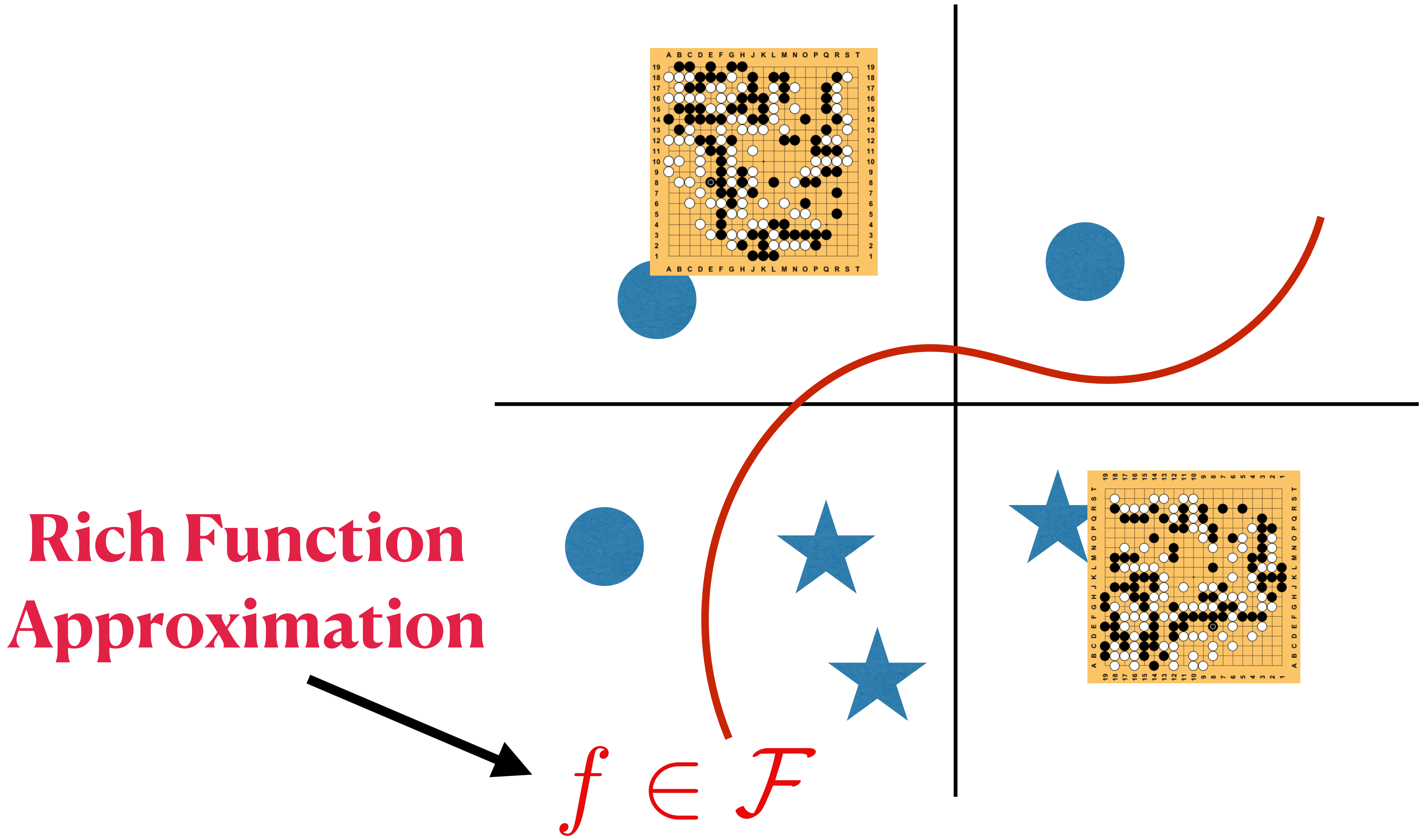

Identify a high quality policy w/ # of offline samples scaling wrt complexity of $\mathscr{F}$

Learning goal in Offline RL: Robustness & Generalization

Can we

(a) compete against the best policy among those covered by d^{π_b},

(b) w/ # of offline samples scaling polynomially wrt the complexity of $\mathscr{F}$?

Outline:

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A Naive Model-based Approach

Certainty Equivalence:

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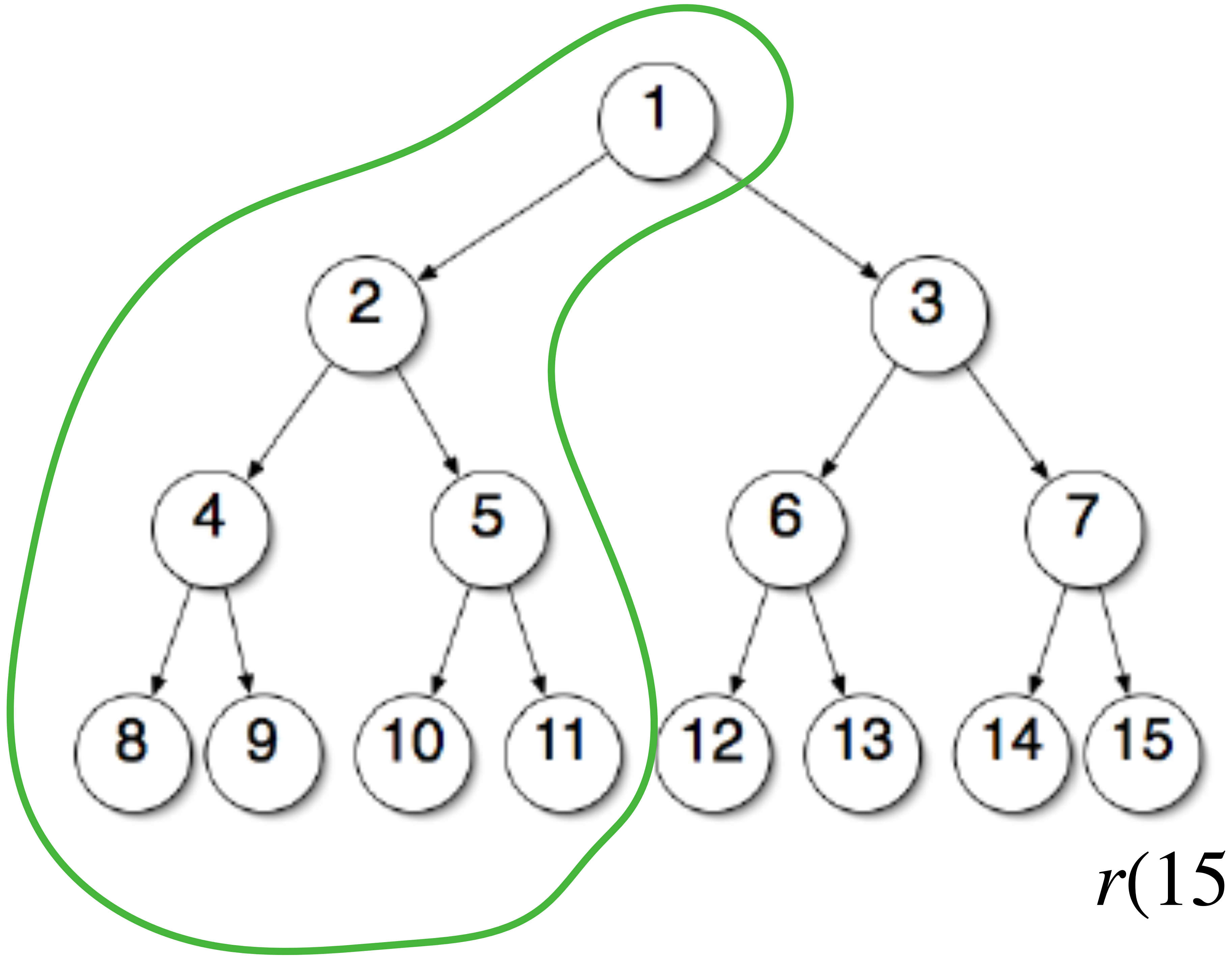

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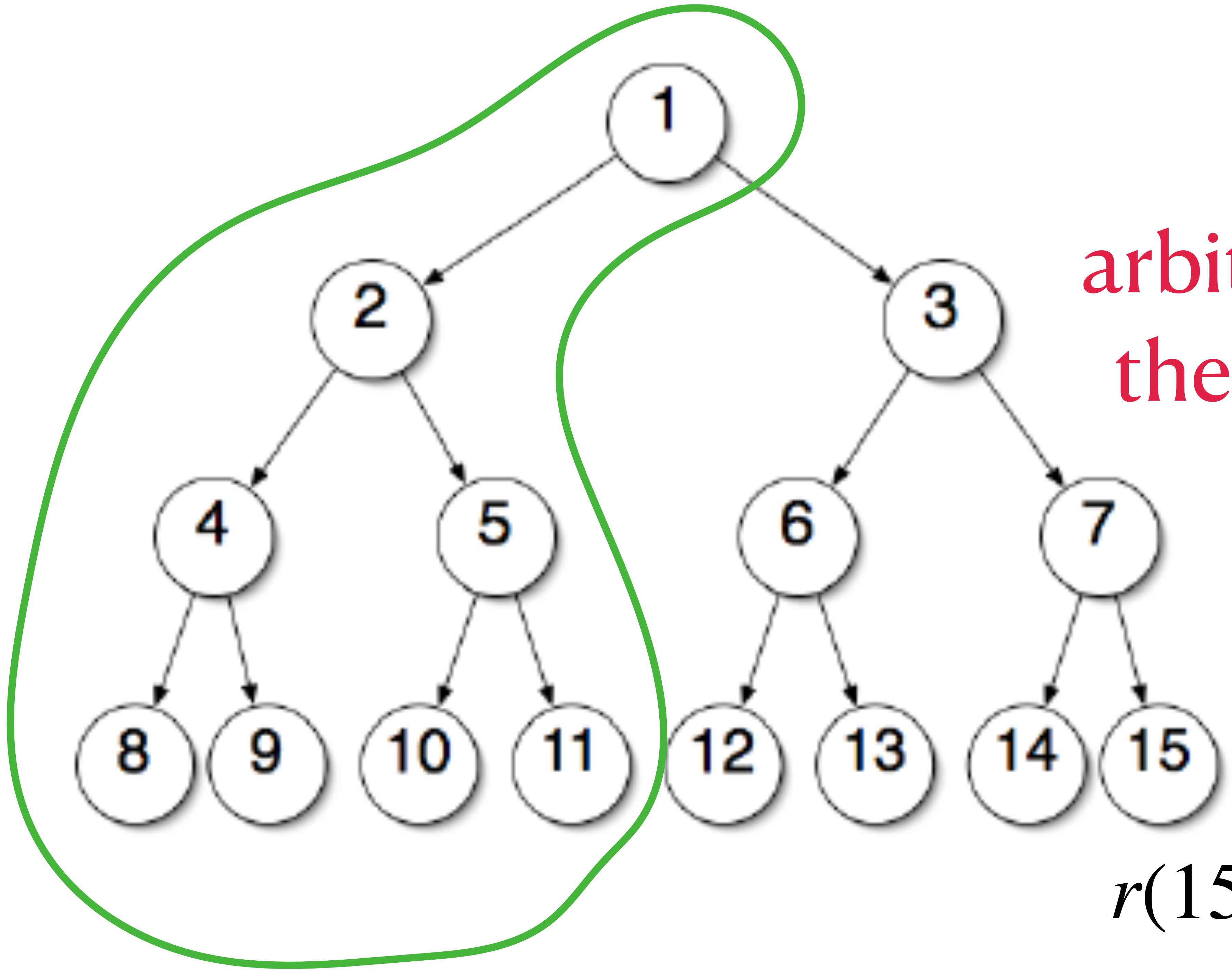

$\hat{P}$ could be arbitrarily wrong in the right sub-tree

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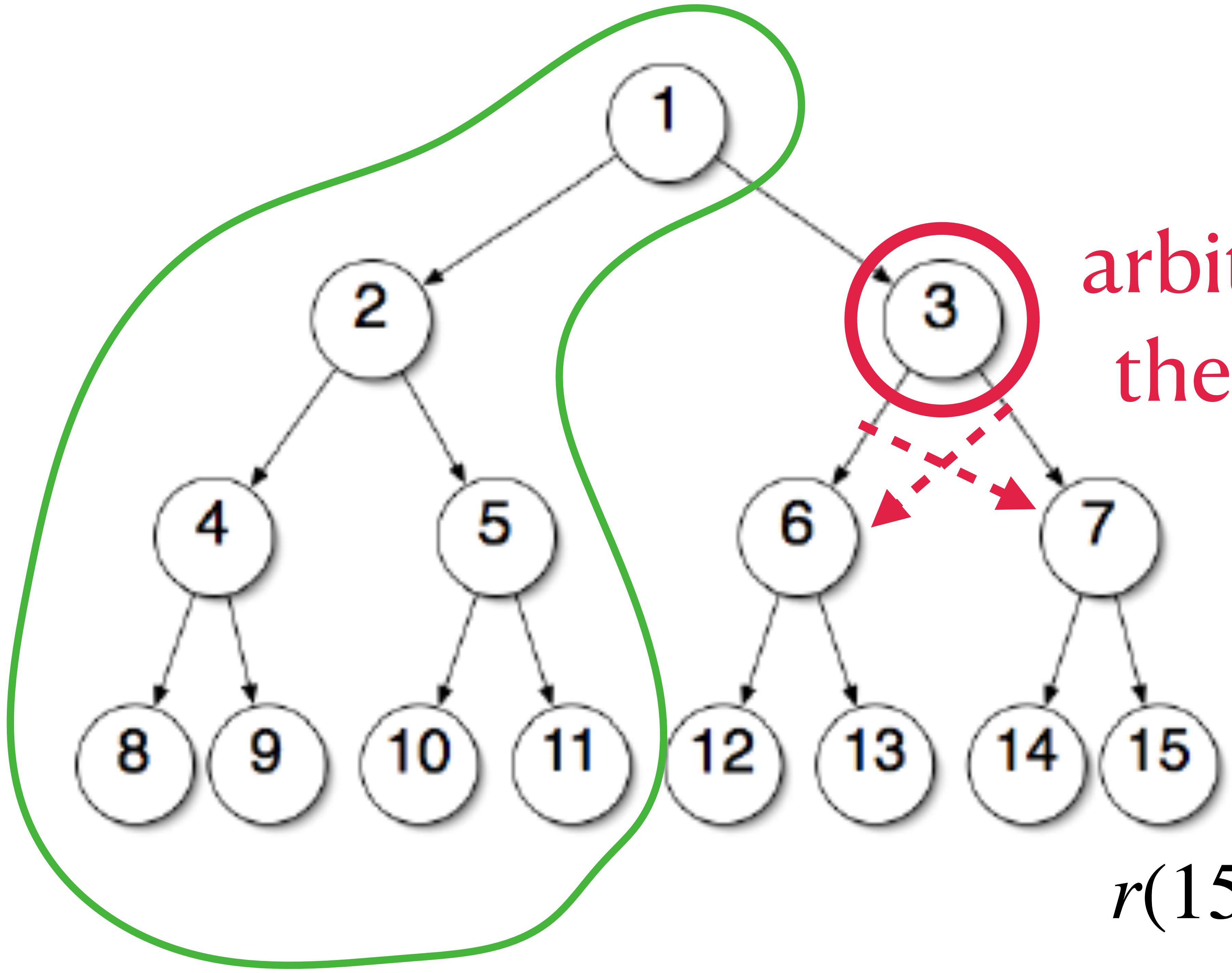

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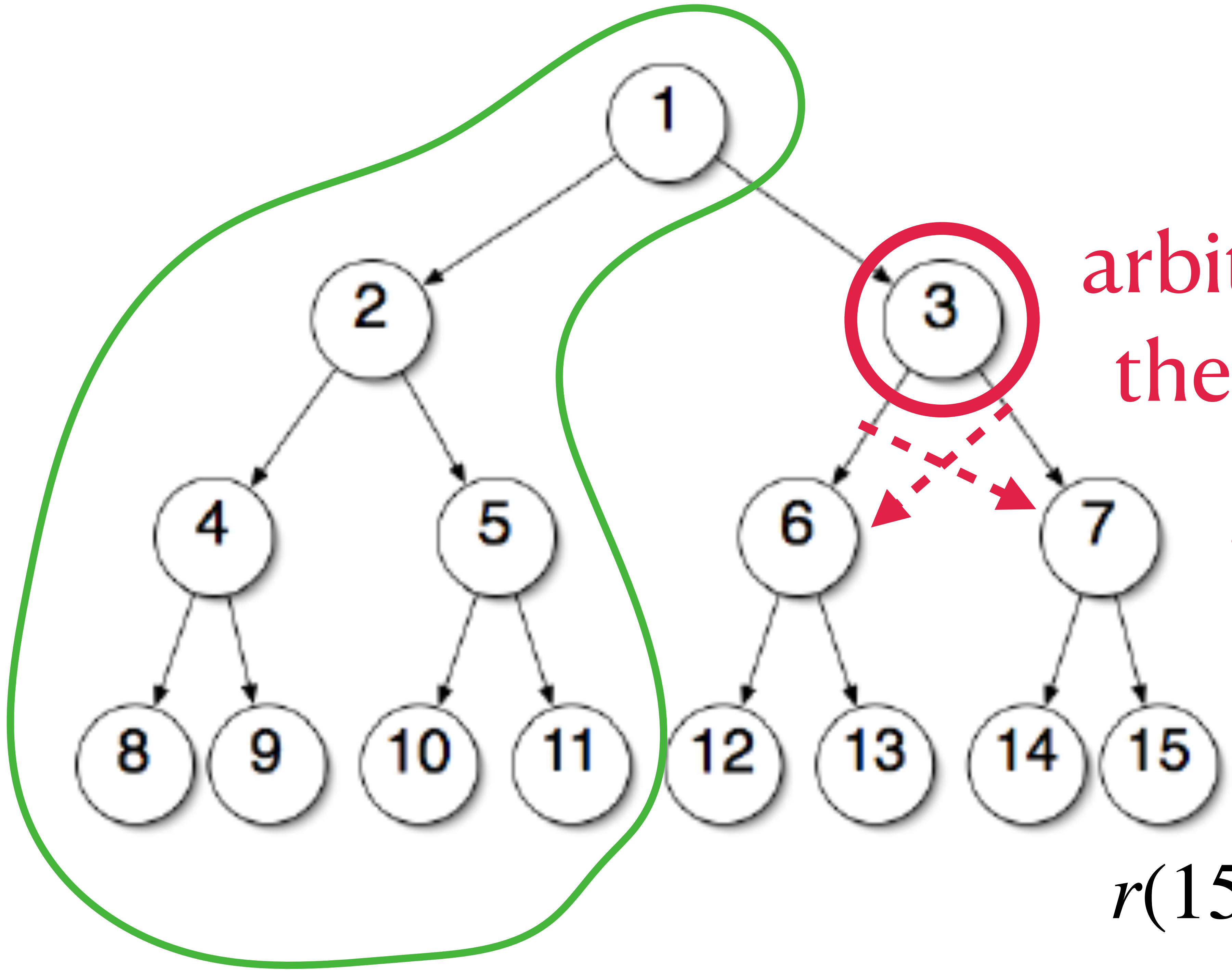

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$\hat{\pi} = \{\text{right, left, right}\}$

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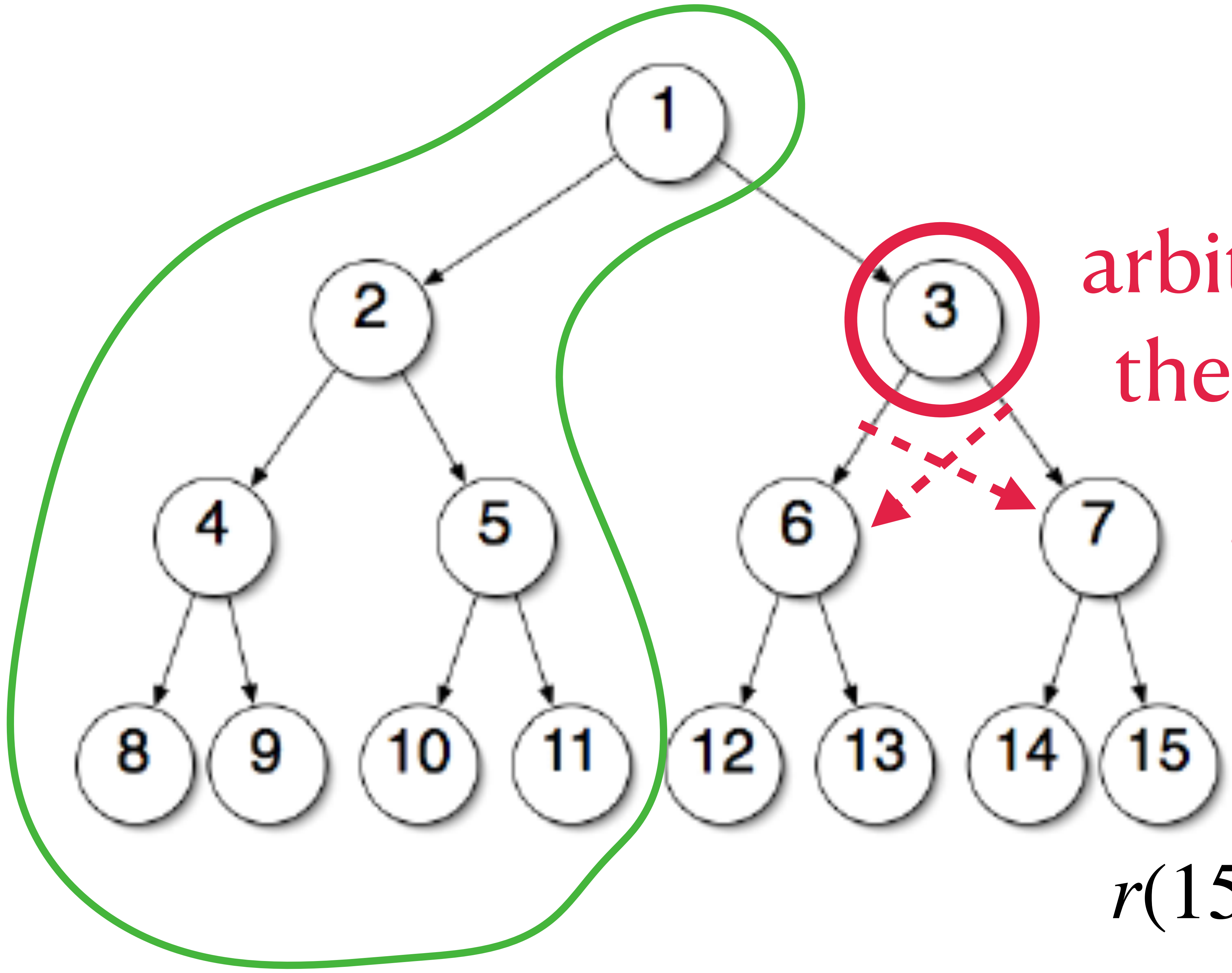

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$\hat{P}$ could be arbitrarily wrong in the right sub-tree

$\hat{\pi} = \{\text{right, left, right}\}$

In real $P^\star$, $\hat{\pi}$ not only miss $r(15)$, also miss **good policies inside the green!**

Constrained Pessimistic Policy Optimization (CPPO)

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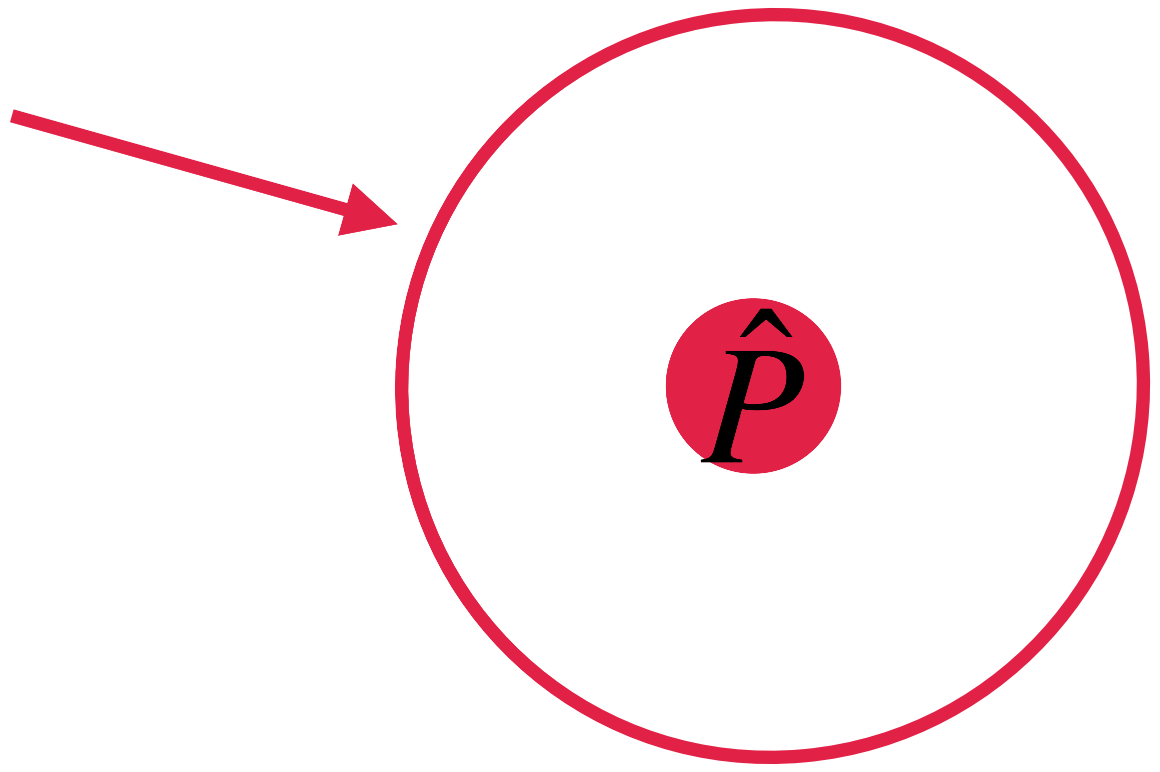

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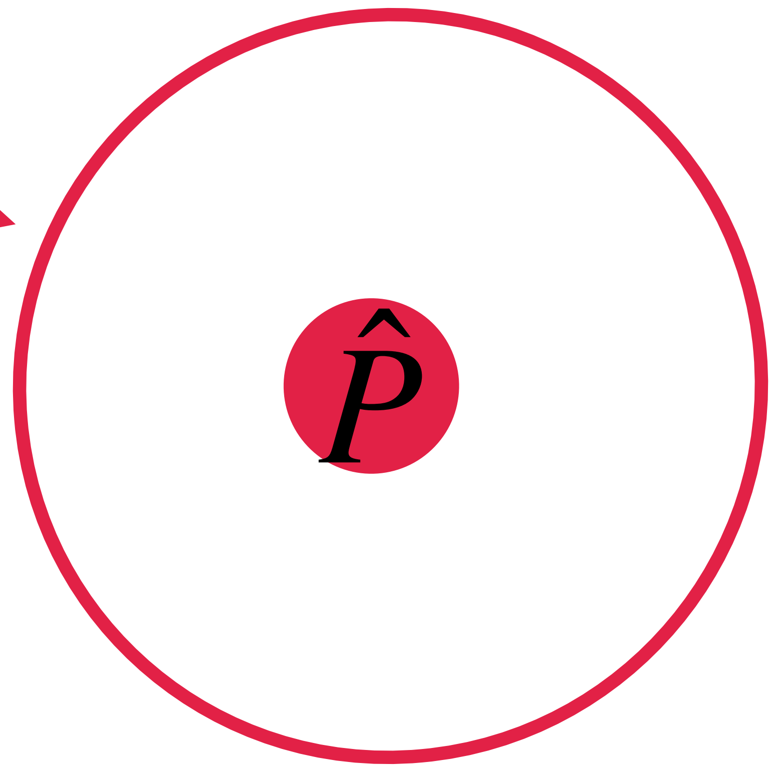
$$\left(\text{or } \frac{1}{|\mathcal{D}|} \sum_{s,a,s' \in \mathcal{D}} \ln P(s' \mid s, a) \geq \frac{1}{|\mathcal{D}|} \sum_{s,a,s' \in \mathcal{D}} \ln \hat{P}(s' \mid s, a) - \delta \right)$$



Constrained Pessimistic Policy Optimization (CPPO)

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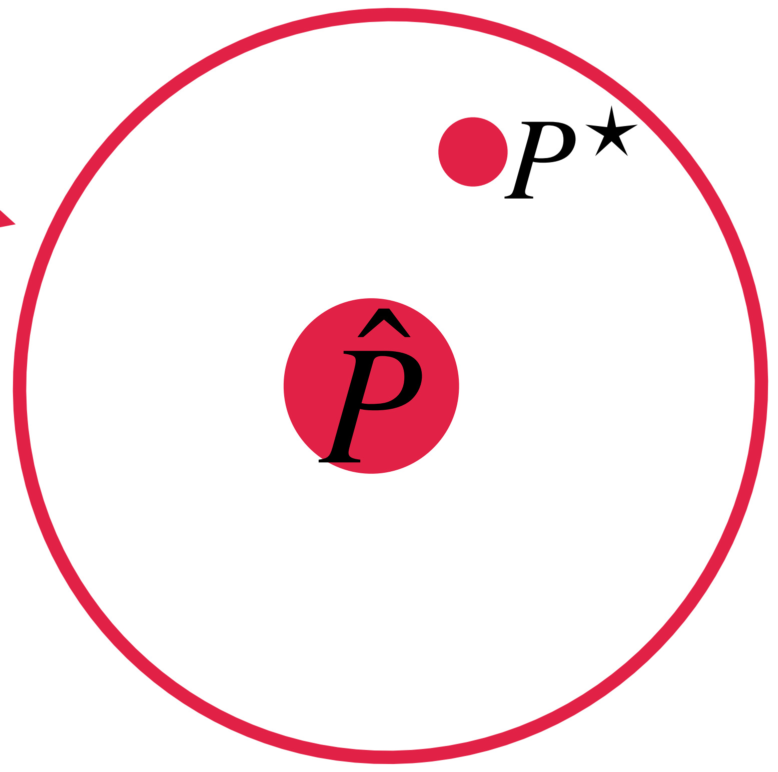

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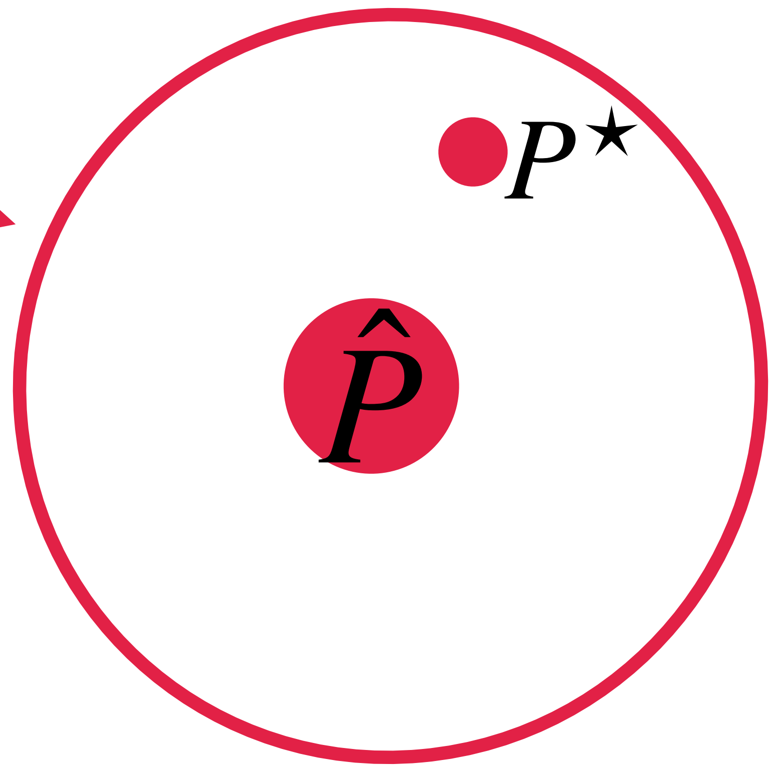
Select the least favorable model!



Formal Theoretical Guarantee for CPPO

1. Definition of offline data coverage

Given a policy π, define:

$$C_\pi^\dagger = \sup_{P' \in \mathscr{P}} \frac{\mathbb{E}_{(s,a)\sim d^\pi}\left[\|P'(\cdot \mid s,a) - P^\star(\cdot \mid s,a)\|_1^2\right]}{\mathbb{E}_{(s,a)\sim d^{\pi_b}}\left[\|P'(\cdot \mid s,a) - P^\star(\cdot \mid s,a)\|_1^2\right]}$$

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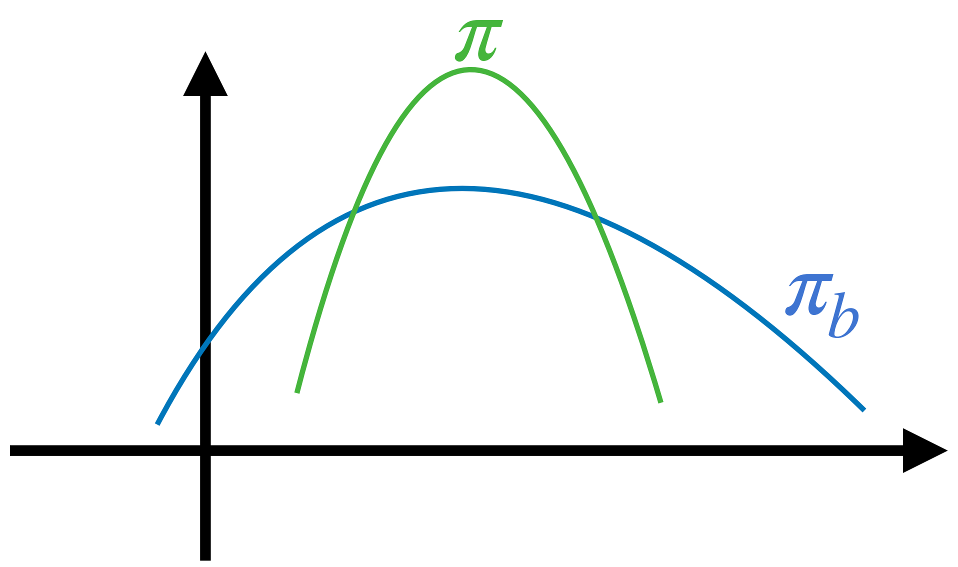

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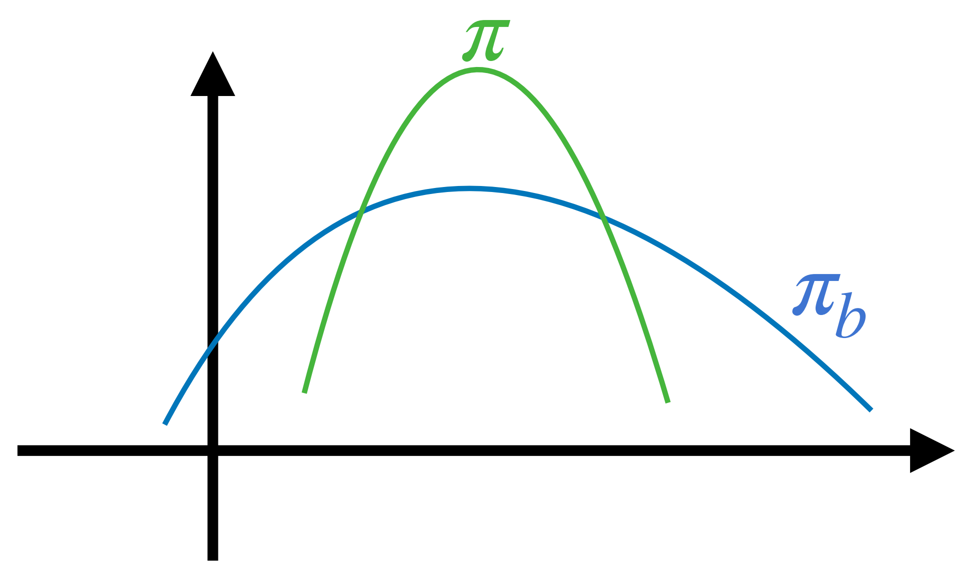

Remark 2: when $P = P^\star, \forall P \in \mathscr{P}$, we have $C_\pi^\dagger = 1$

Formal Theoretical Guarantee for CPPO

2. CPPO's Sample Complexity:

Given n (i.i.d) offline data points, with high probability:

$$\forall \pi^*; V_{P^\star}^{\pi^*} - V_{P^\star}^{\hat{\pi}} = O\left(H^2 \sqrt{\frac{C_{\pi^*}^{\dagger} \ln(|\mathscr{P}|/\delta)}{n}} \right)$$

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SL-style Generalization!

CPPO and its general bound applies to many examples...

The non-parametric kernel model

$$s_{t+1} = f^\star(s_t, a_t) + \epsilon, \epsilon \sim \mathcal{N}(0, \sigma^2 I),$$

where $f^\star$ is from some RKHS w/ kernel $k([s, a], [s', a']) = \langle \phi(s, a), \phi(s', a') \rangle$

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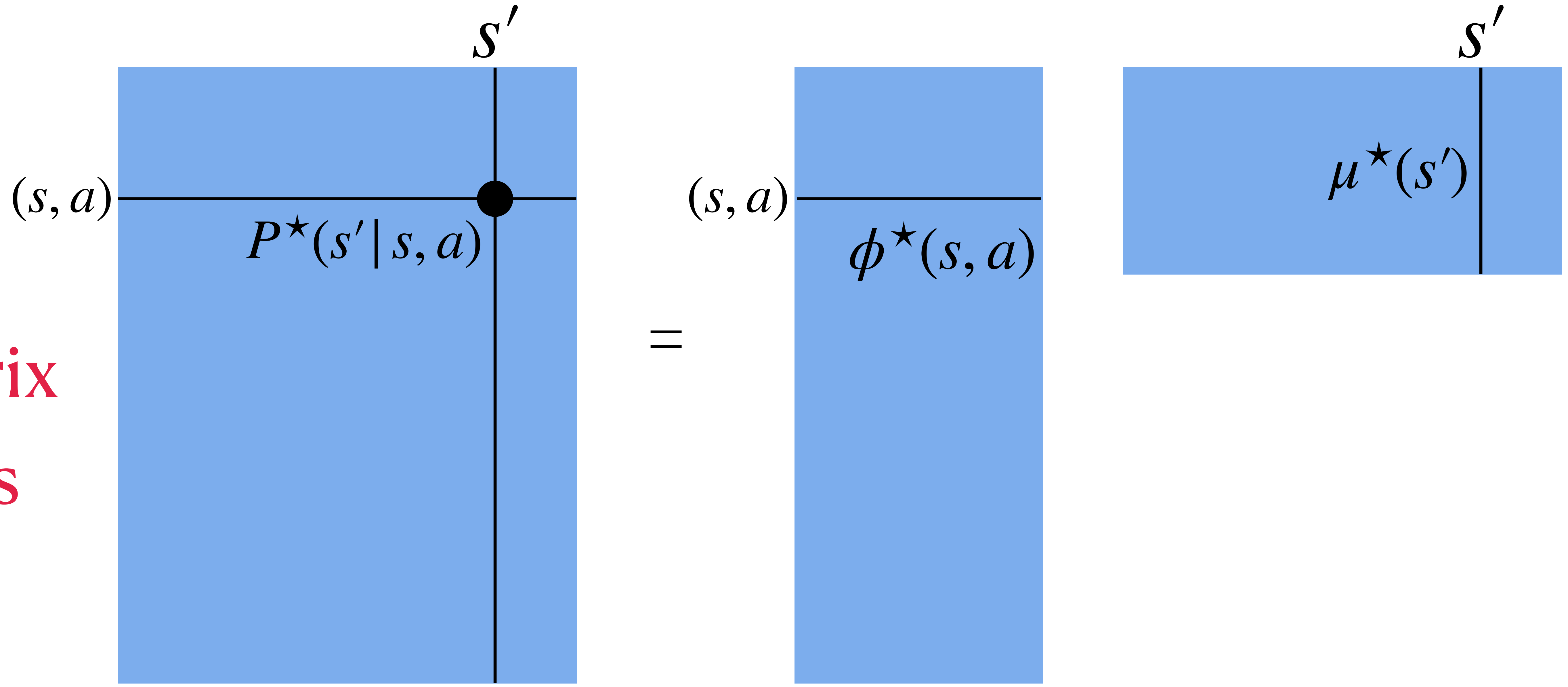
i.e., measuring coverage using subspace..

CPPO for Low-rank MDPs

Transition matrix
$P \in \mathbb{R}^{SA \times S}$ has
rank d



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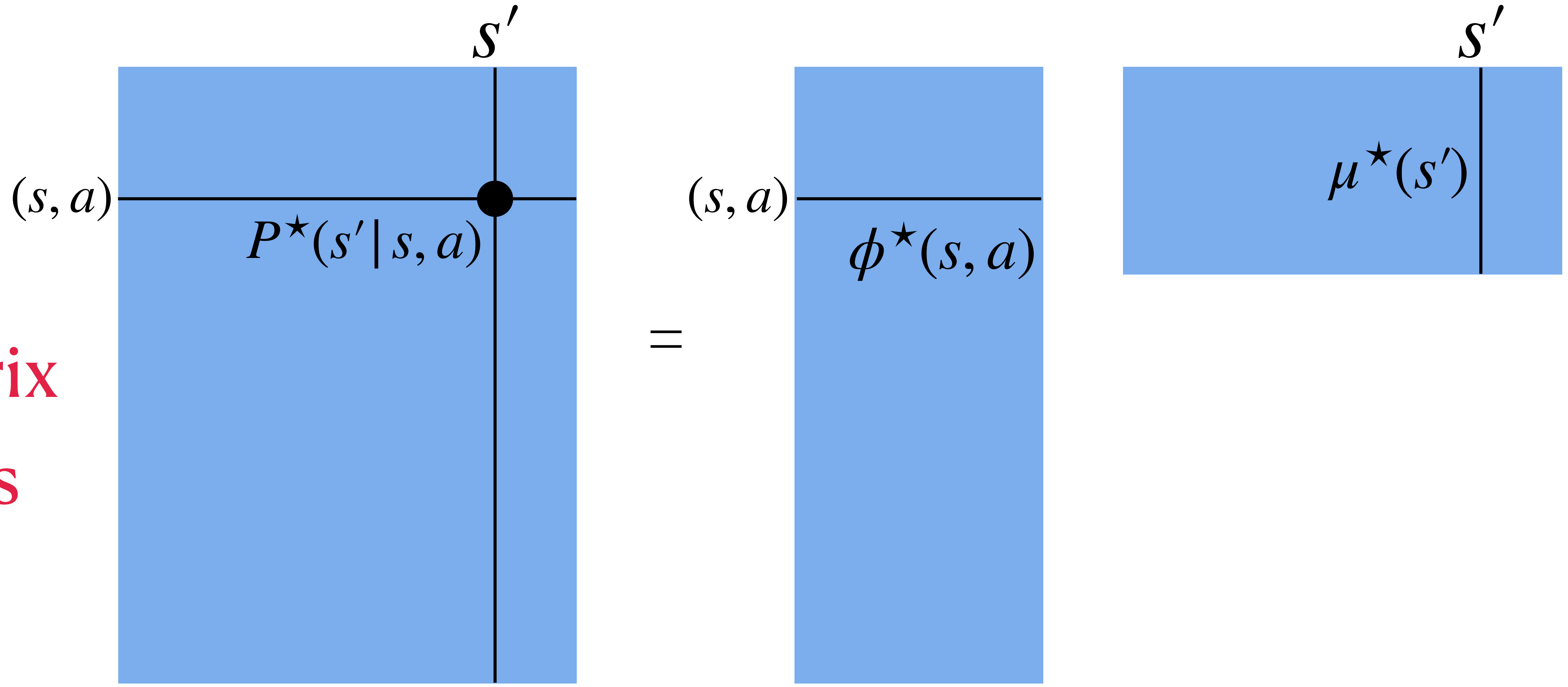

$$\exists \mu^\star, \phi^\star : \quad \forall s, a, s', P^\star(s' \mid s, a) = \mu^\star(s')^\top \phi^\star(s, a)$$

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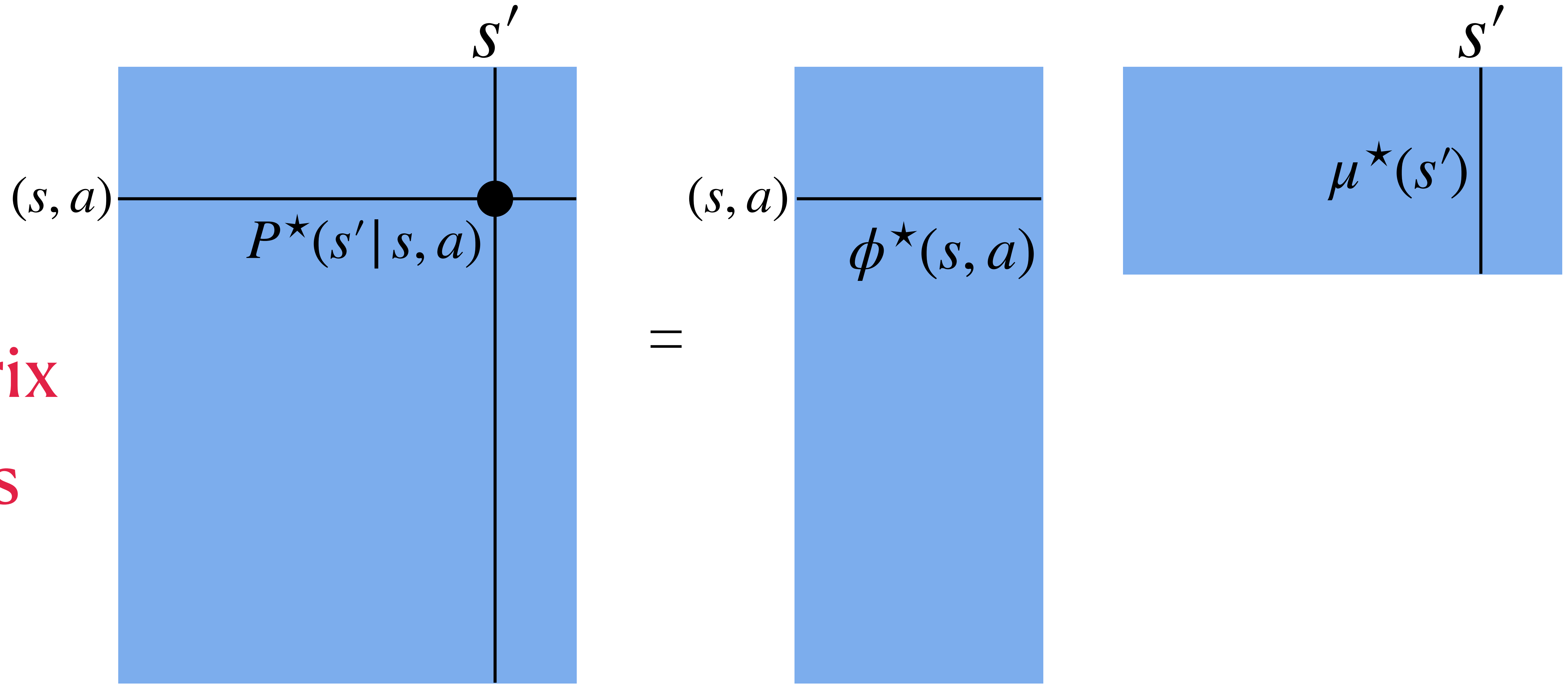

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In low-rank MDP, neither $\mu^\star$ nor $\phi^\star$ is known

CPPO for Low-rank MDPs

Two Function classes Γ & Φ

Realizability: $\mu^\star \in \Gamma$, $\phi^\star \in \Phi$

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(Many more interesting examples: linear mixture MDP, factored MDP, etc)

Implementation

1. MLE: $\hat{P} = \max_{P \in \mathscr{P}} \sum_{s,a,s' \in \mathscr{D}} \ln P(s' \mid s, a)$

2: Treat constraint as a penalty w/ Lagrangian multiplier:

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Practical version of CPPO (Rigter et al. Neurips22)

“Uehara et al. (2021) provides the theoretical motivation for solving Problem 1. In this work, we focus on developing a practical approach to solving Problem 1.”

CPPO

Practical version of CPPO

		Ours	Model-based baselines				Model-free baselines		
		RAMBO	**RepB-SDE**	**COMBO**	**MOPO**	**MOReL**	**CQL**	**IQL**	**TD3+BC**
Random	HalfCheetah	40.0 ± 2.3	32.9	38.8	35.4	25.6	19.6	-	11.0
	Hopper	21.6 ± 8.0	8.6	17.9	4.1	53.6	6.7	-	8.5
	Walker2D	11.5 ± 10.5	21.1	7.0	4.2	37.3	2.4	-	1.6
Medium	HalfCheetah	77.6 ± 1.5	49.1	54.2	69.5	42.1	49.0	47.4	48.3
	Hopper	92.8 ± 6.0	34.0	94.9	48.0	95.4	66.6	66.3	59.3
	Walker2D	86.9 ± 2.7	72.1	75.5	-0.2	77.8	83.8	78.3	83.7
Medium Replay	HalfCheetah	68.9 ± 2.3	57.5	55.1	68.2	40.2	47.1	44.2	44.6
	Hopper	96.6 ± 7.0	62.2	73.1	39.1	93.6	97.0	94.7	60.9
	Walker2D	85.0 ± 15.0	49.8	56.0	69.4	49.8	88.2	73.9	81.8
Medium Expert	HalfCheetah	93.7 ± 10.5	55.4	90.0	72.7	53.3	90.8	86.7	90.7
	Hopper	83.3 ± 9.1	82.6	111.1	3.3	108.7	106.8	91.5	98.0
	Walker2D	68.3 ± 20.6	88.8	96.1	-0.3	95.6	109.4	109.6	110.1
MuJoCo-v2 Total:		826.2 ± 33.8	614.1	769.7	413.4	773.0	767.4	692.6*	698.5

SOTA

Summary

Rethinking offline RL's learning objective:

Generalization & Robustness

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Generalization & Robustness

Like SL, learning via function approximation, i.e., generalization rather than memorization / numeration

- Expecting offline data has global coverage is too much;
- Learning to compete the best among those covered