Online POMDP Methods

Approximate POMDP Solutions

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Offline

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

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Online

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Offline

Online

Previously

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Offline

Previously

Online

Formulation Approximations

(solve a slightly different problem)

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Offline

Previously

Online

Formulation Approximations

(solve a slightly different problem)

Last Time

QMDP $\pi_{QMDP}(b) = \underset{a}{\text{argmax}} \; E_{s \sim b}[Q_{MDP}(s,a)]$

C.E. $\pi_{CE}(b) = \pi_s(\text{mode}(b))$

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Offline

Previously

Online

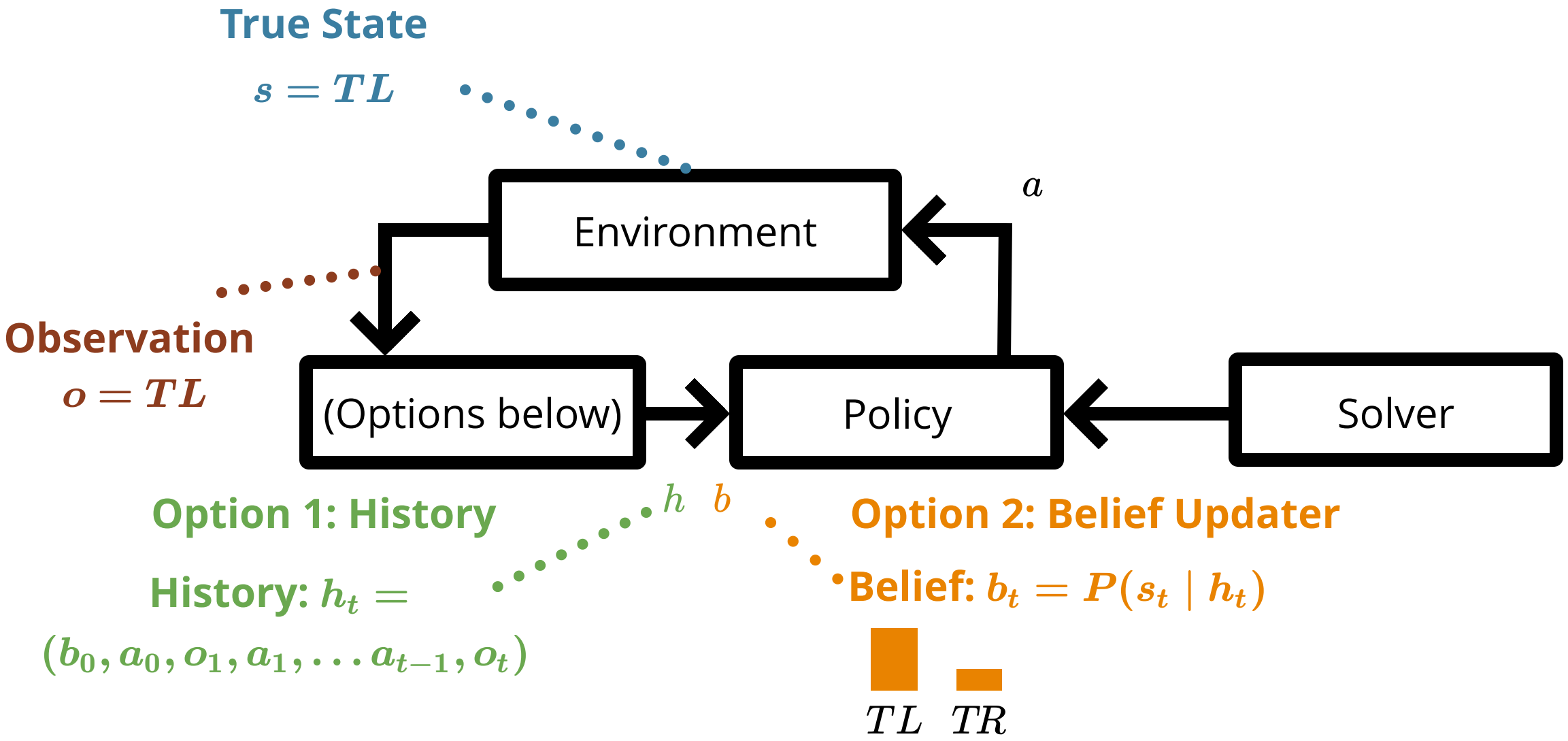
Today!

Formulation Approximations

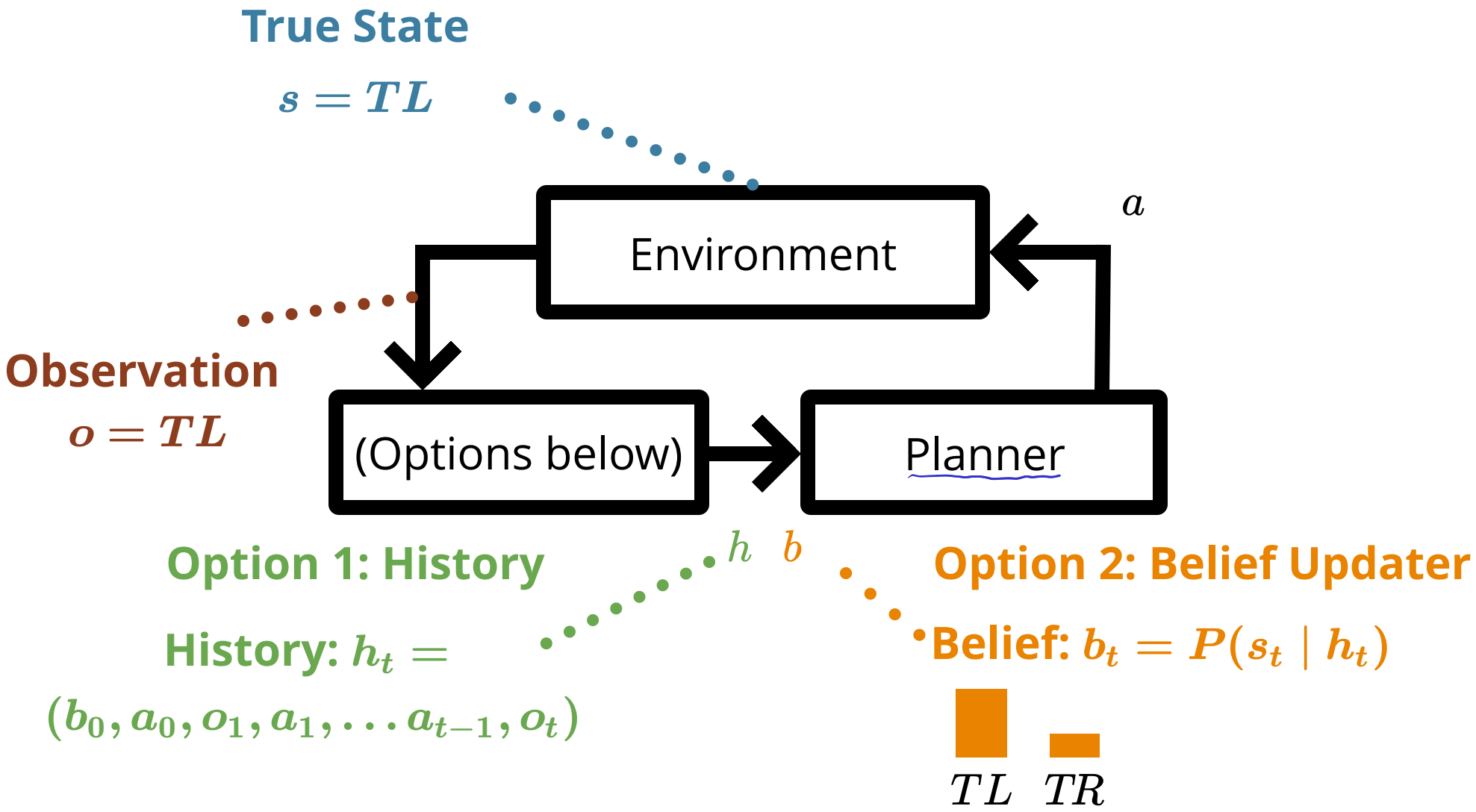
(solve a slightly different problem)

Last Time

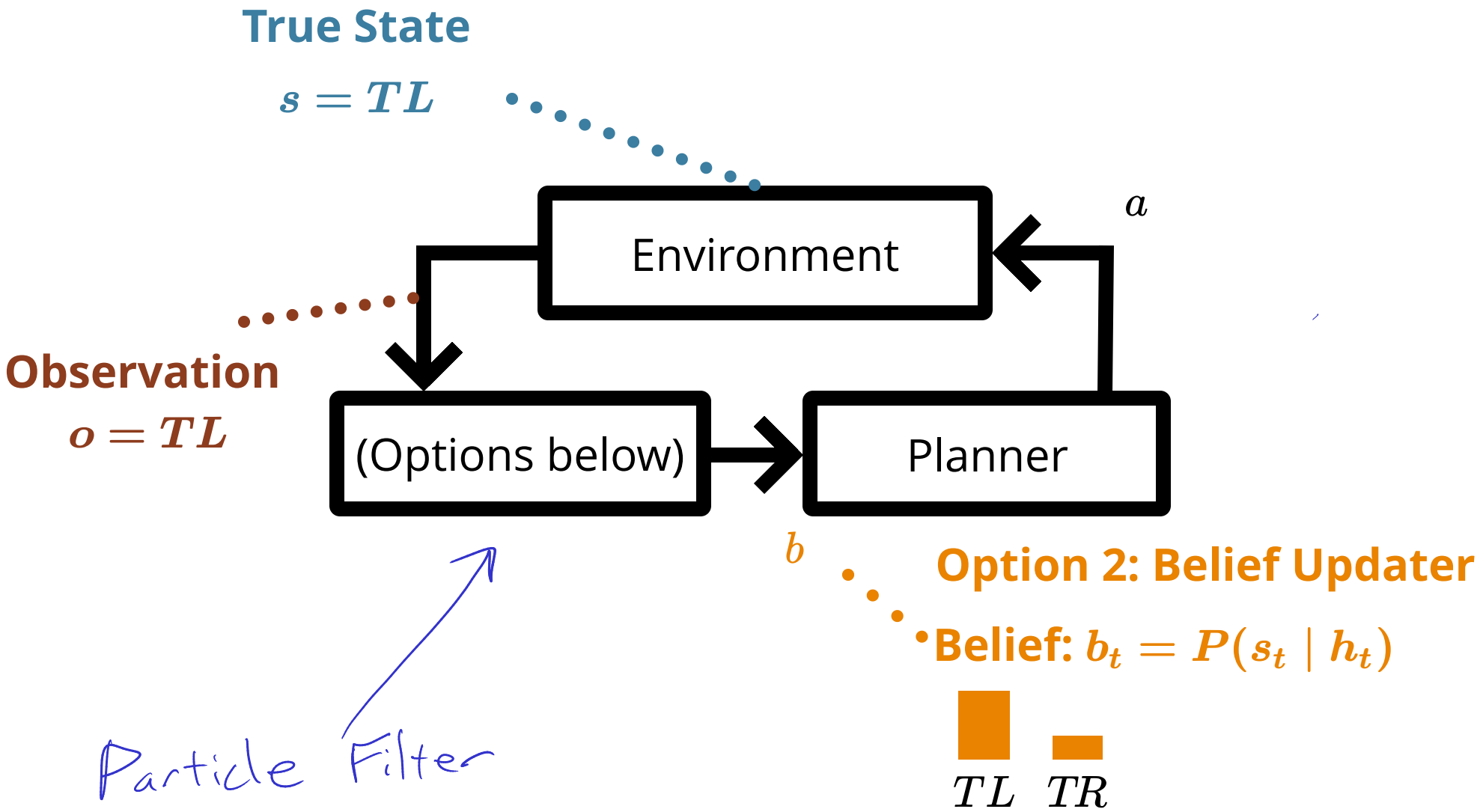
POMDP Sense-Plan-Act Loop



POMDP Sense-Plan-Act Loop

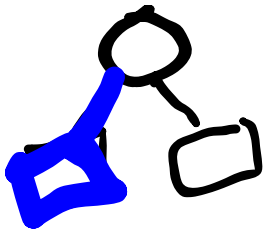


POMDP Sense-Plan-Act Loop

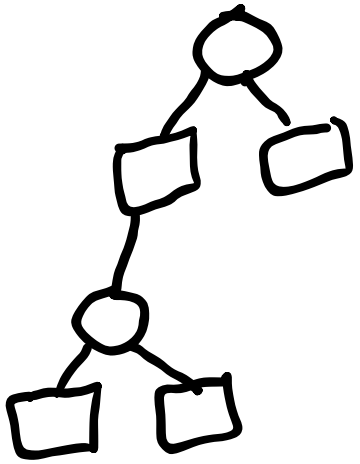


Monte Carlo Tree Search (MCTS/UCT)

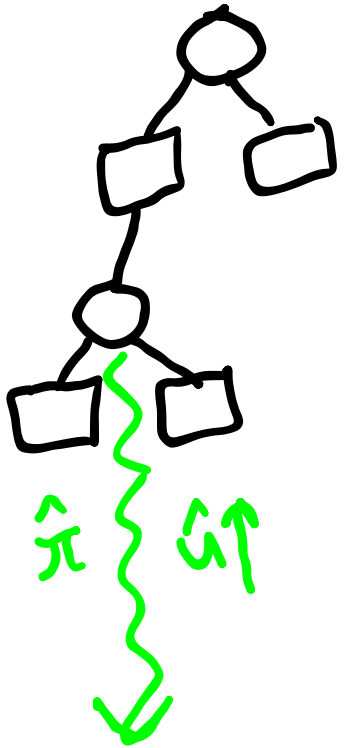
Search



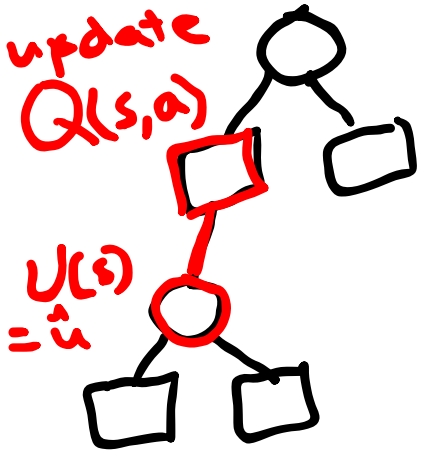
Expansion



Rollout



Backup



$$Q(s,a) + c\sqrt{\frac{\log N(s)}{N(s,a)}}$$

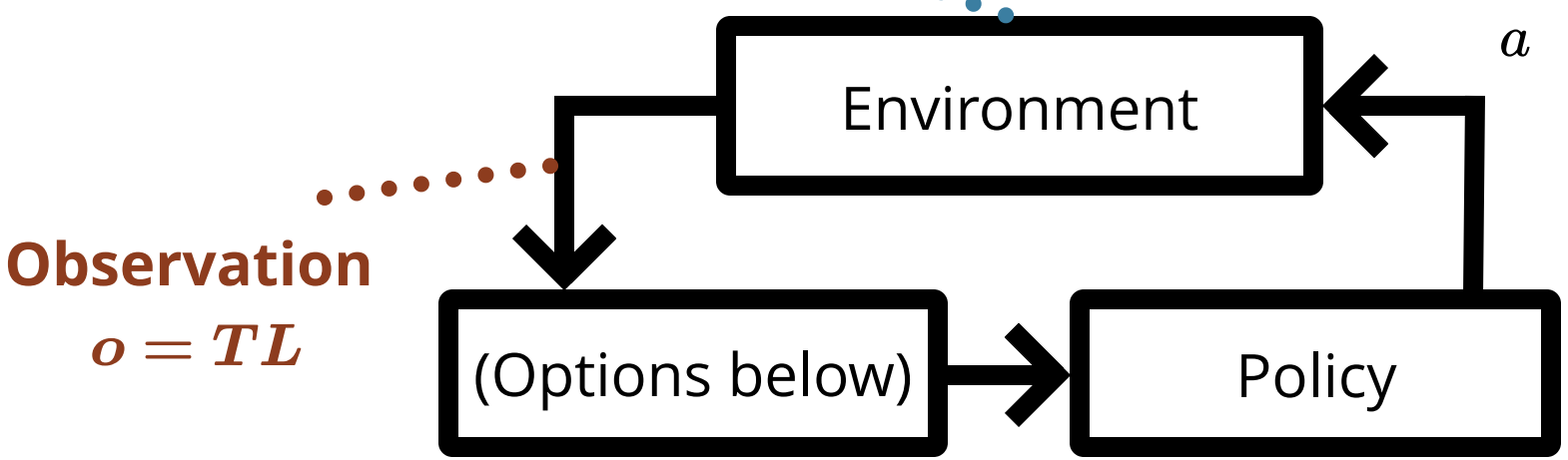
low $N(s,a)/N(s)$ = high bonus

start with $c = 2(\bar{V} - \underline{V})$

How should we adapt MCTS for POMDPs?

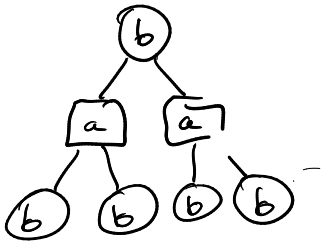
True State

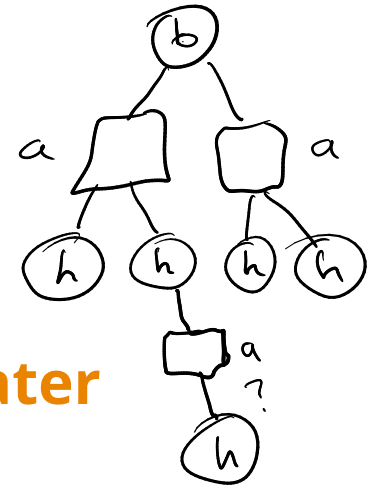
$s = TL$



Observation

$o = TL$





Option 1: History

h

History: $h_t =$

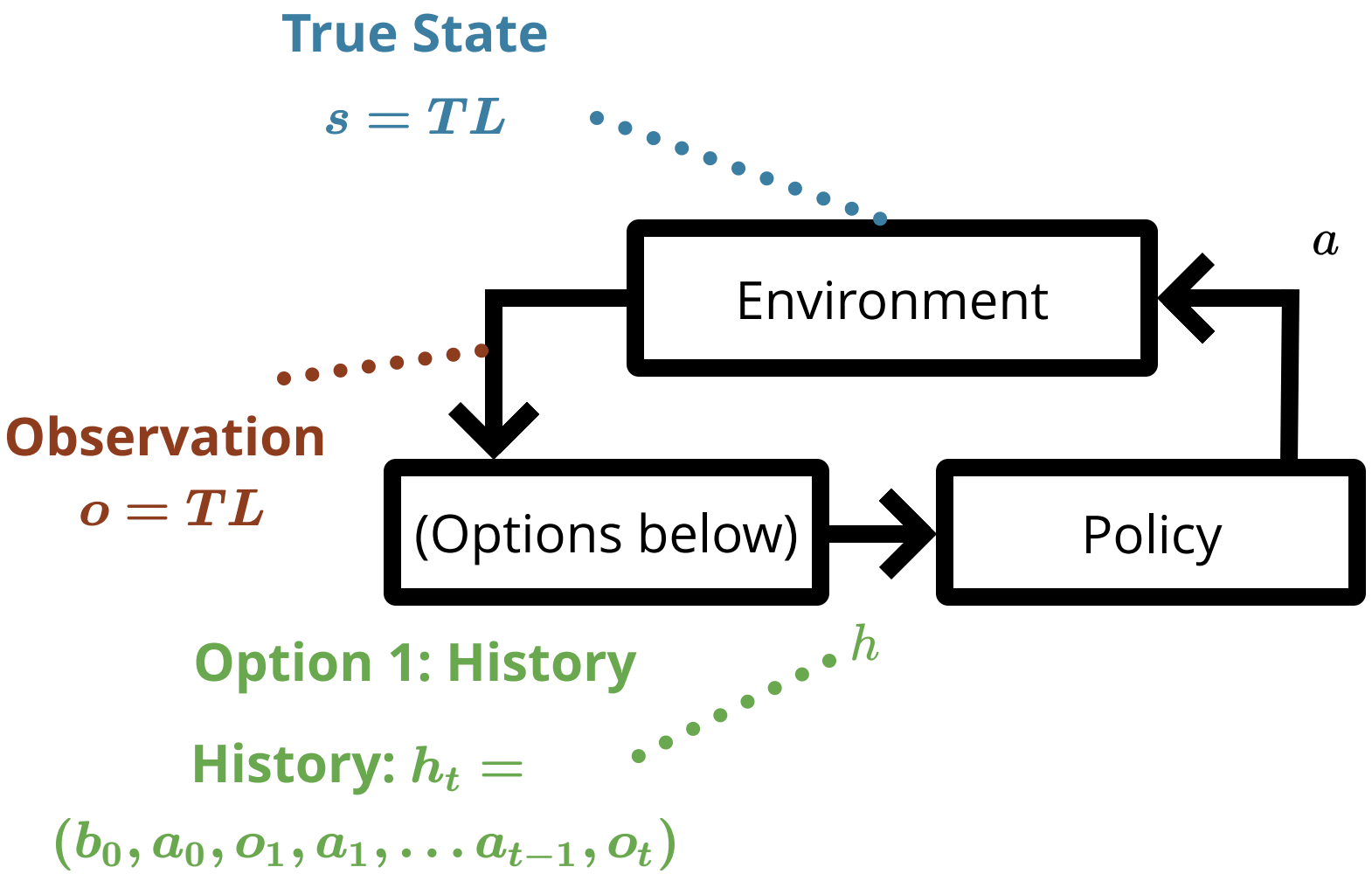
$(b_0, a_0, o_1, a_1, \ldots a_{t-1}, o_t)$

b

Option 2: Belief Updater

Belief: $b_t = P(s_t \mid h_t)$

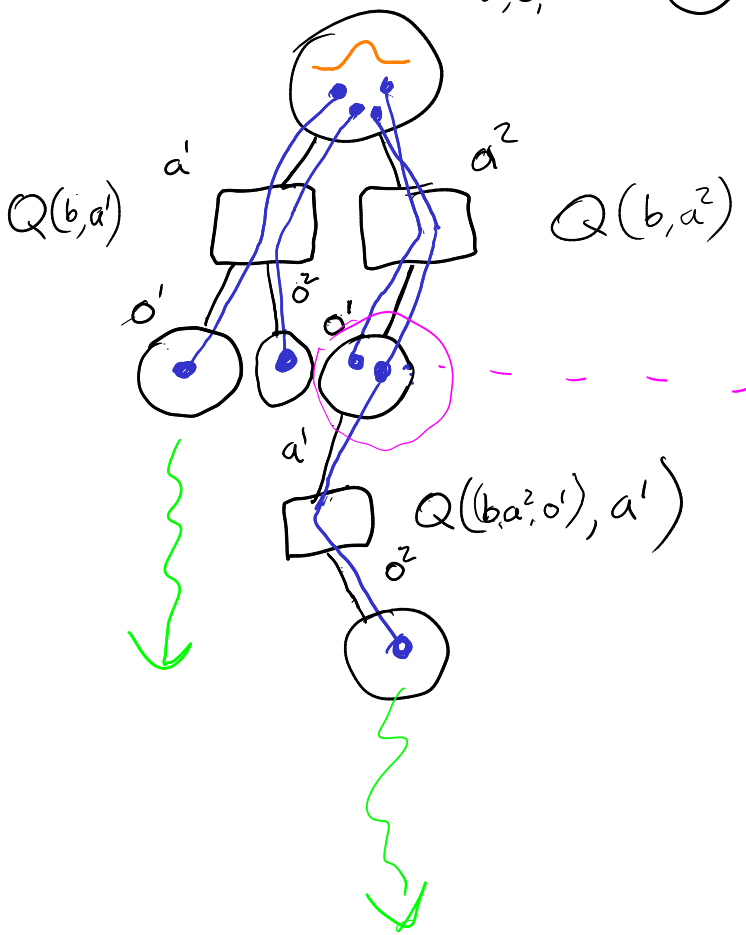
How should we adapt MCTS for POMDPs?



MCTS on Histories

$h_t = (b_0, a_1, o_1, \ldots a_t, o_t) \longrightarrow h_{t+1}$

$s', o, r \leftarrow G(s, a)$

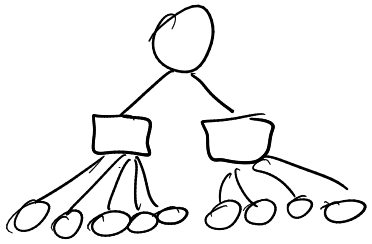


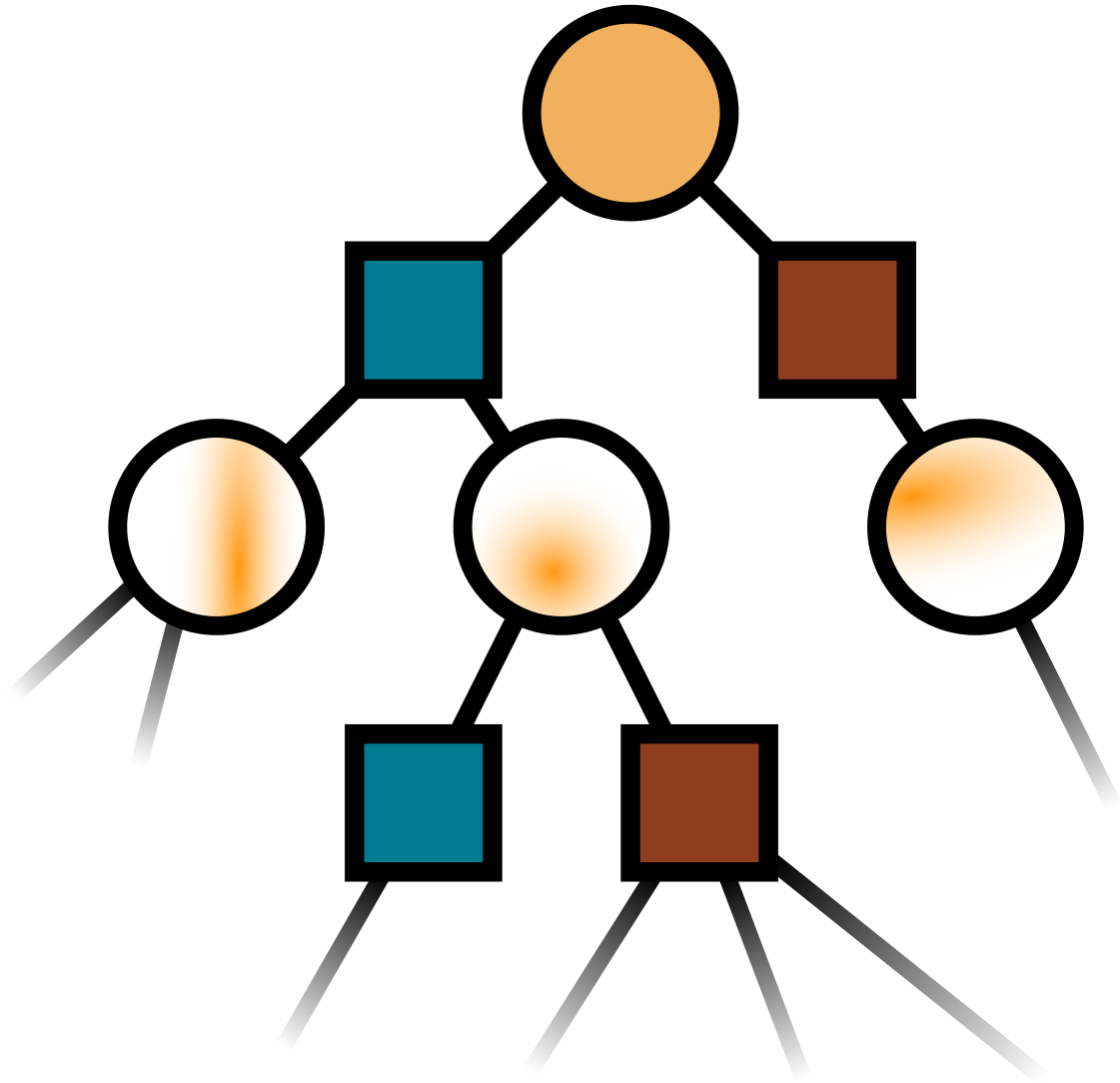
MCTS on histories

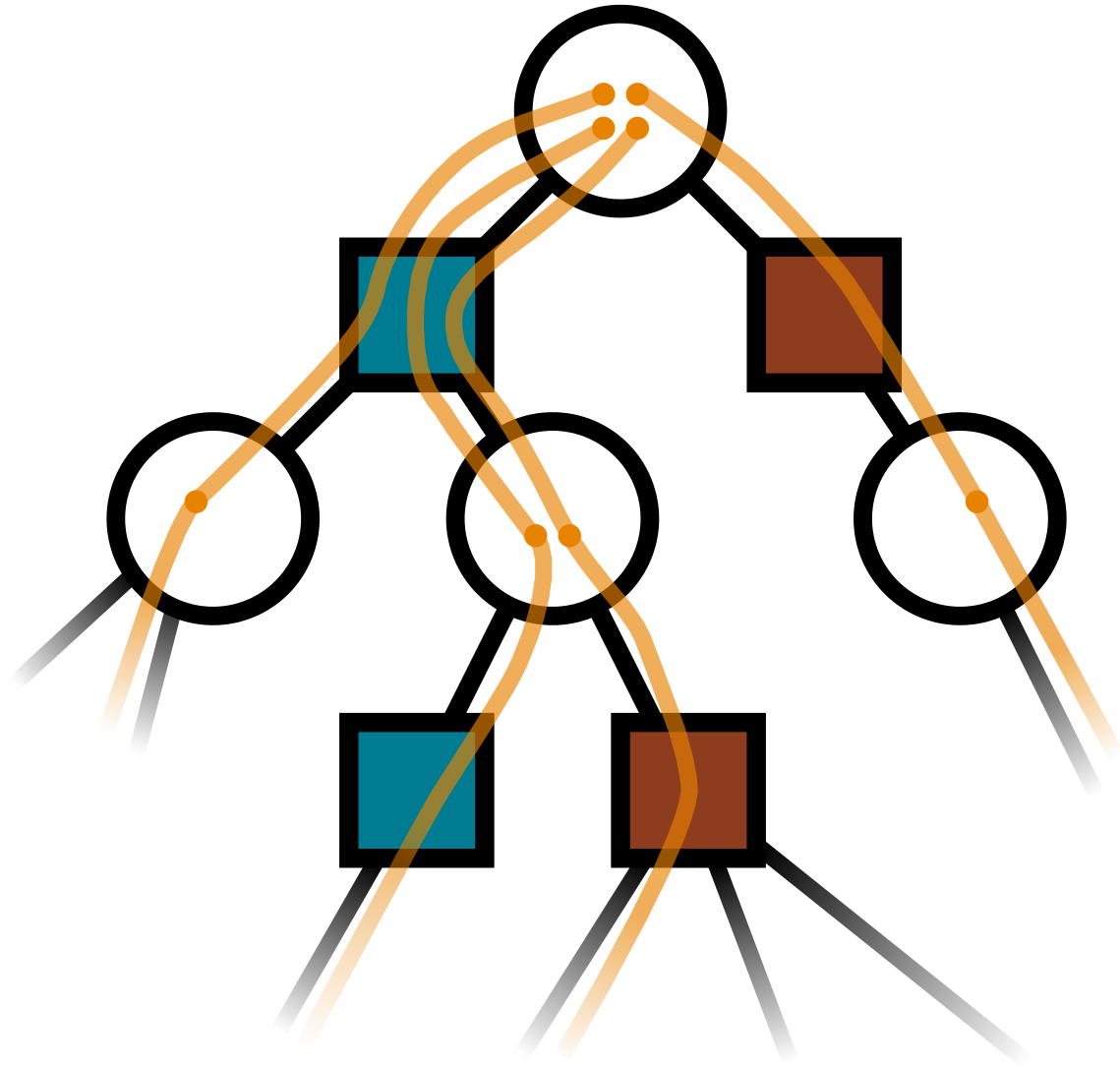
PO-UCT

POMCP technically wrong

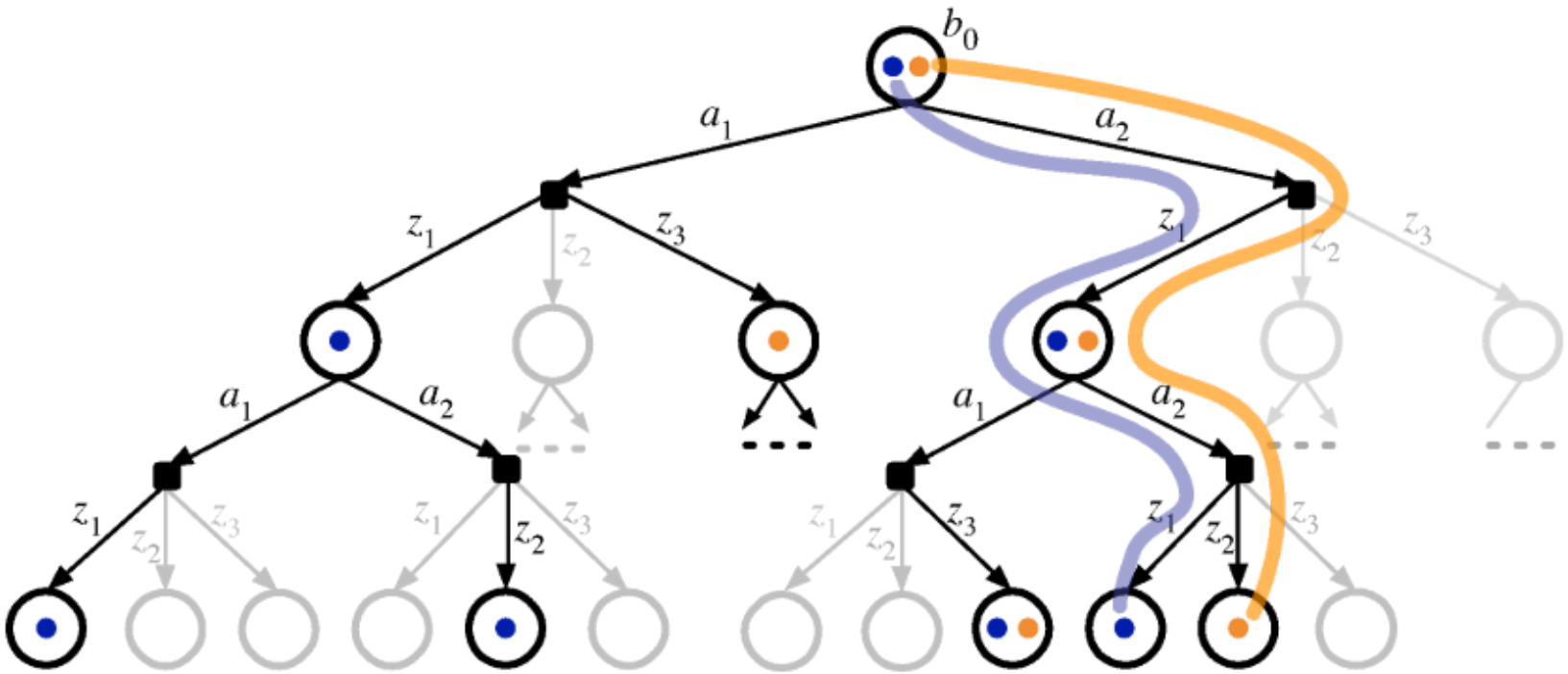
technically you recycle particles from planning





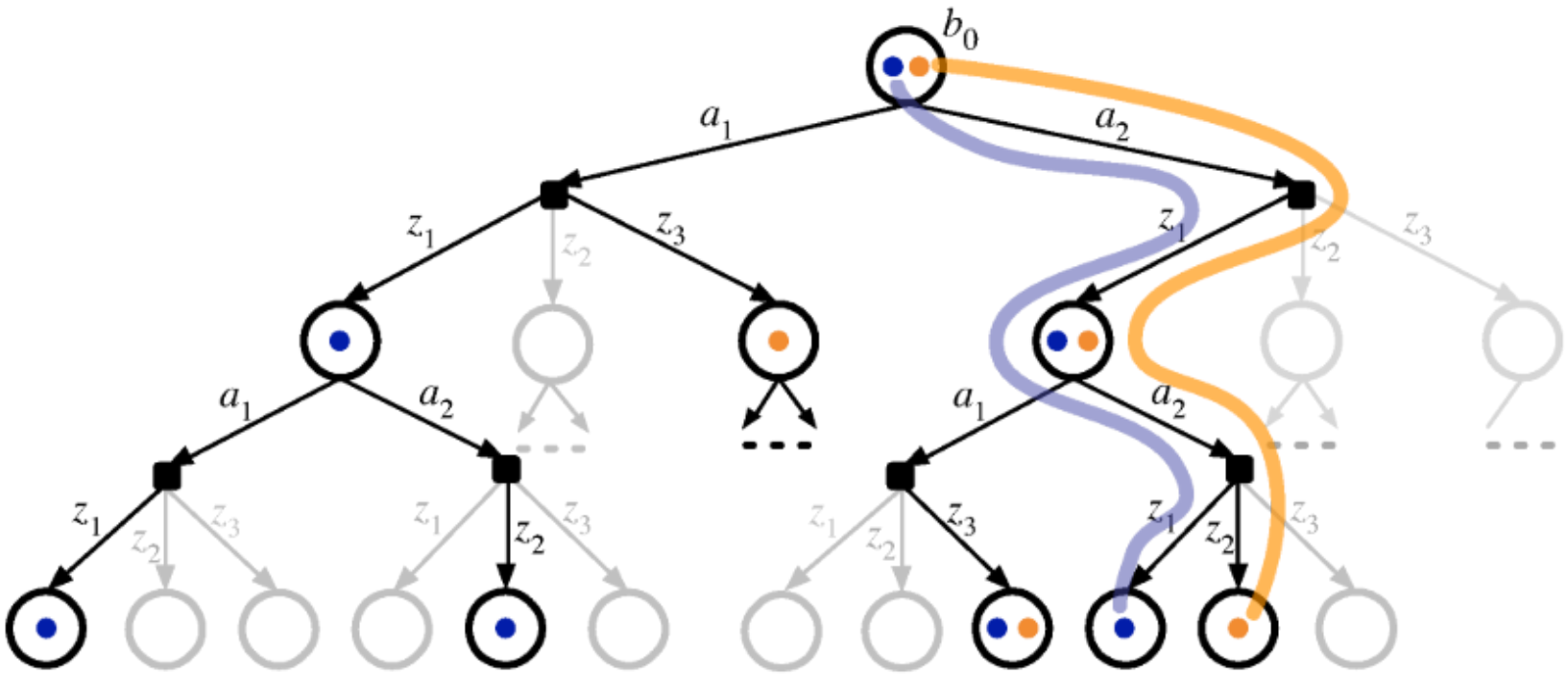


DESPOT



Somani, A., Ye, N., Hsu, D., & Lee, W. "DESPOT : Online POMDP Planning with Regularization." *Journal of Artificial Intelligence Research*, 2017

DESPOT



- Determinized Scenarios

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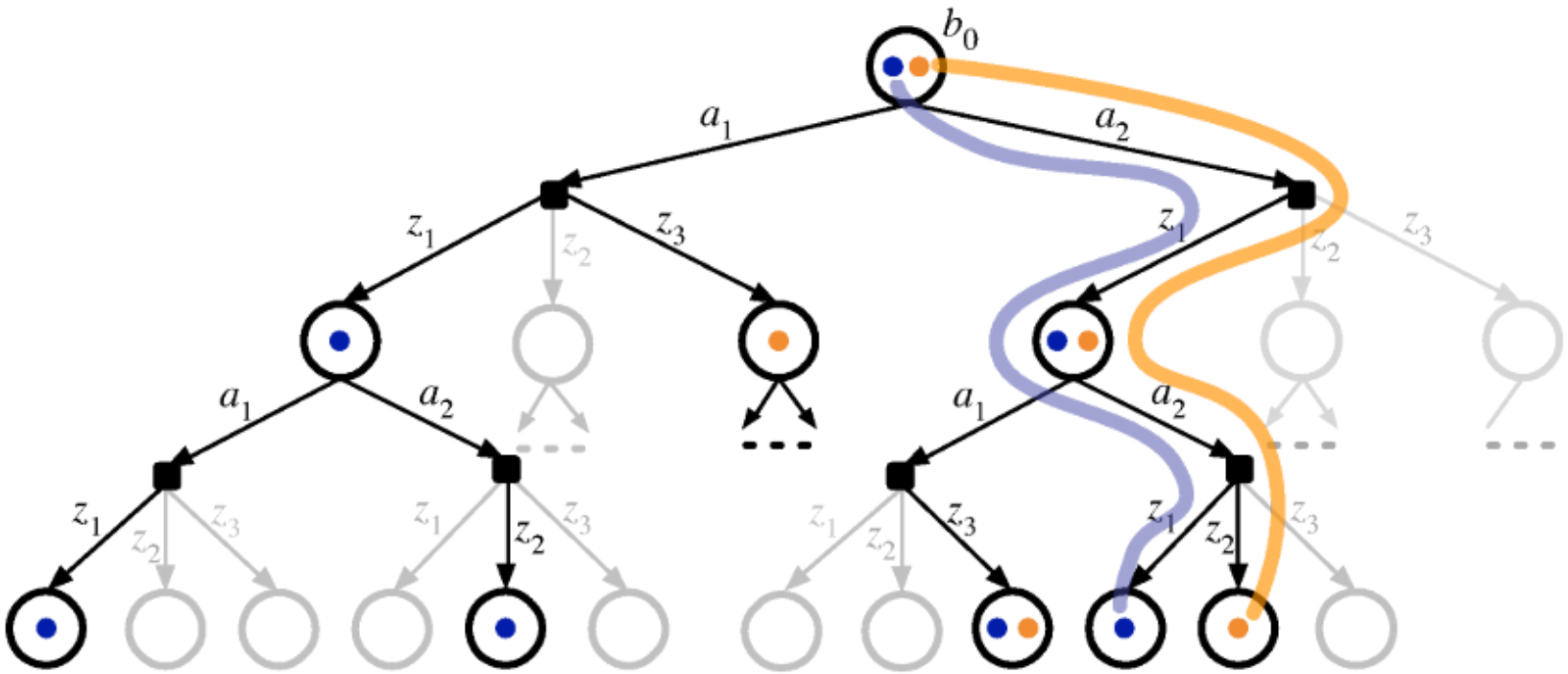
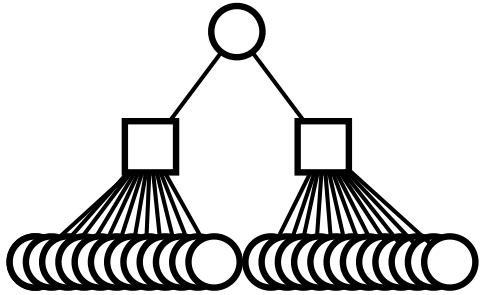


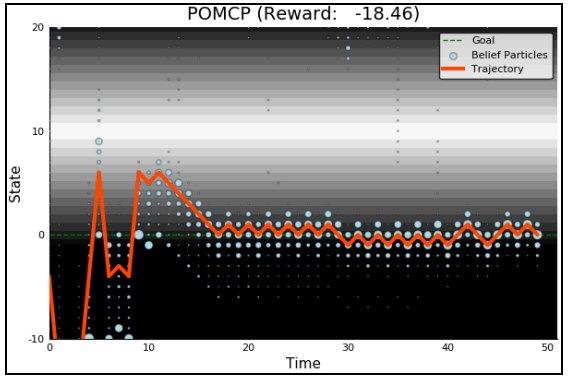
- Determinized Scenarios
- Guided by Lower and Upper Bounds

Somani, A., Ye, N., Hsu, D., & Lee, W. "DESPOT : Online POMDP Planning with Regularization." *Journal of Artificial Intelligence Research*, 2017

Continuous Observation Spaces

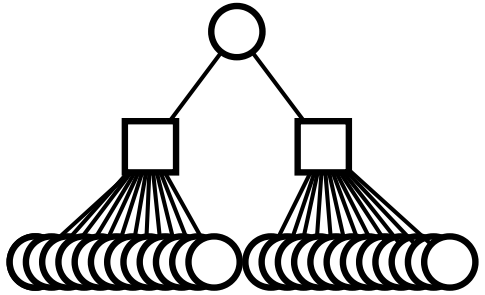
POMCP

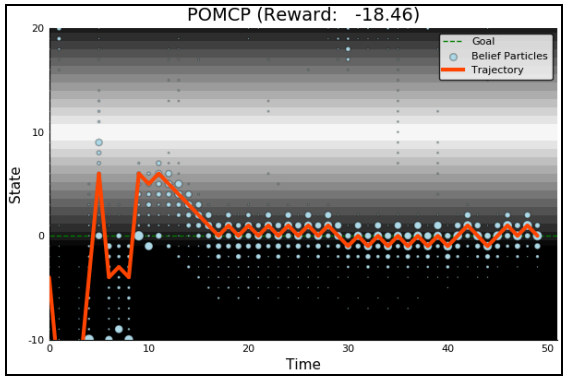




Continuous Observation Spaces

POMCP

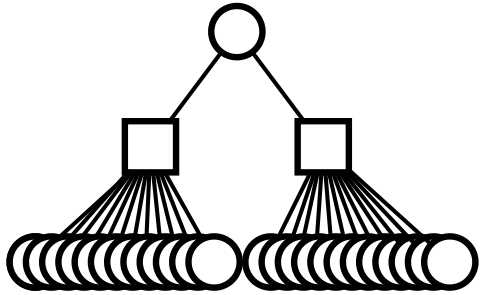


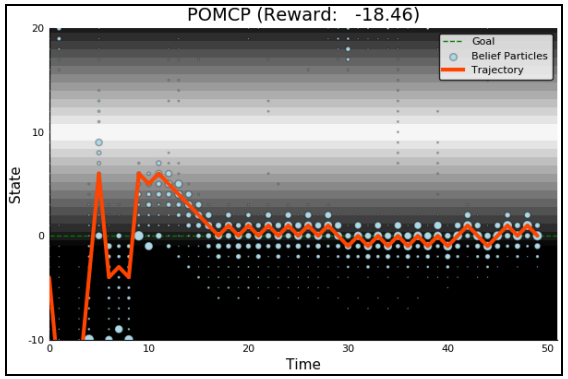


POMCPOW

Continuous Observation Spaces

POMCP





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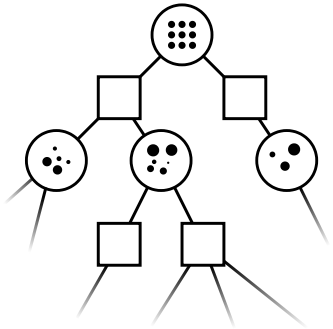

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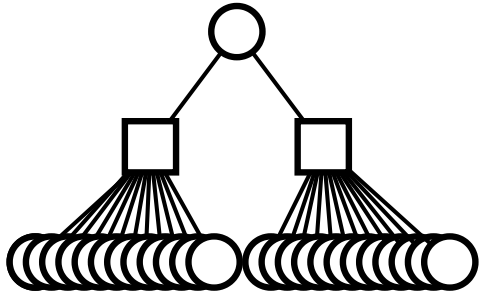

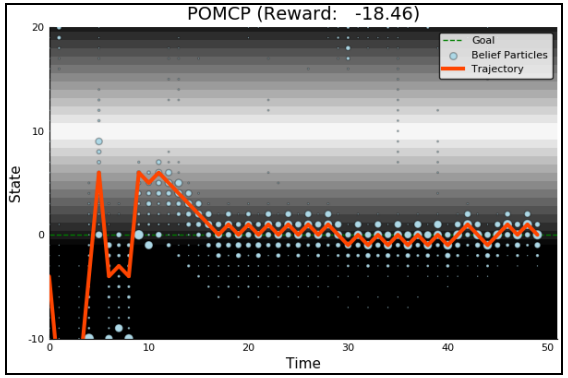

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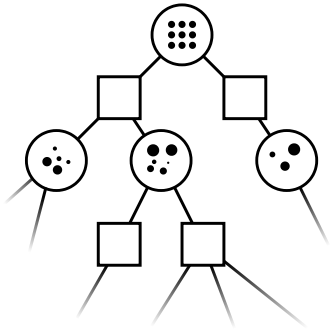

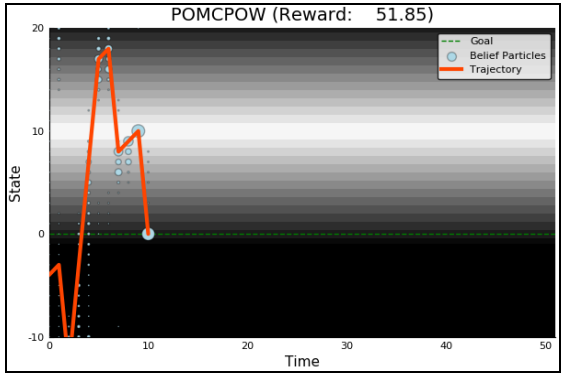

PF Approximation Accuracy

[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

PF Approximation Accuracy

$\mathbf{M_P}$ = Particle belief MDP approximation of POMDP $\mathbf{P}$

[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

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For any $\epsilon > 0$ and $\delta > 0$, if C (number of particles) is high enough,

[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

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For any $\epsilon > 0$ and $\delta > 0$, if C (number of particles) is high enough,

$$|Q^*_{\mathbf{P}}(b, a) - Q^*_{\mathbf{M_P}}(\bar{b}, a)| \leq \epsilon \quad \text{w.p. } 1 - \delta$$

[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

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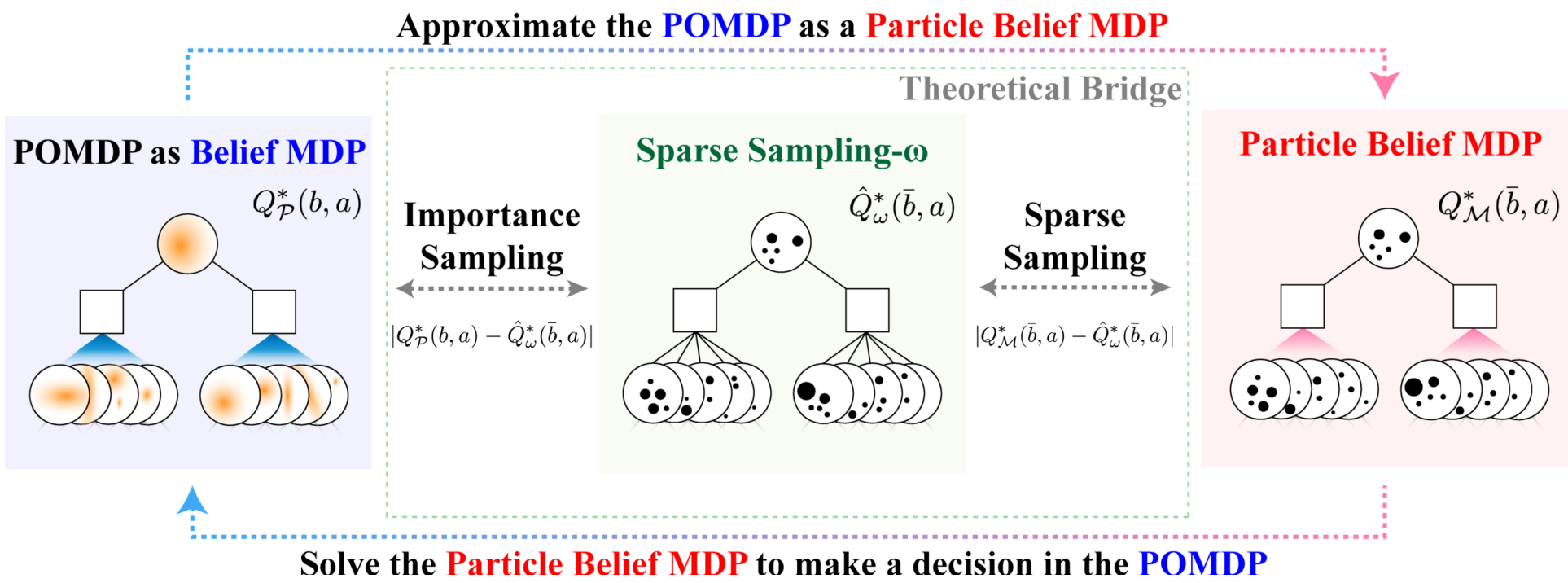

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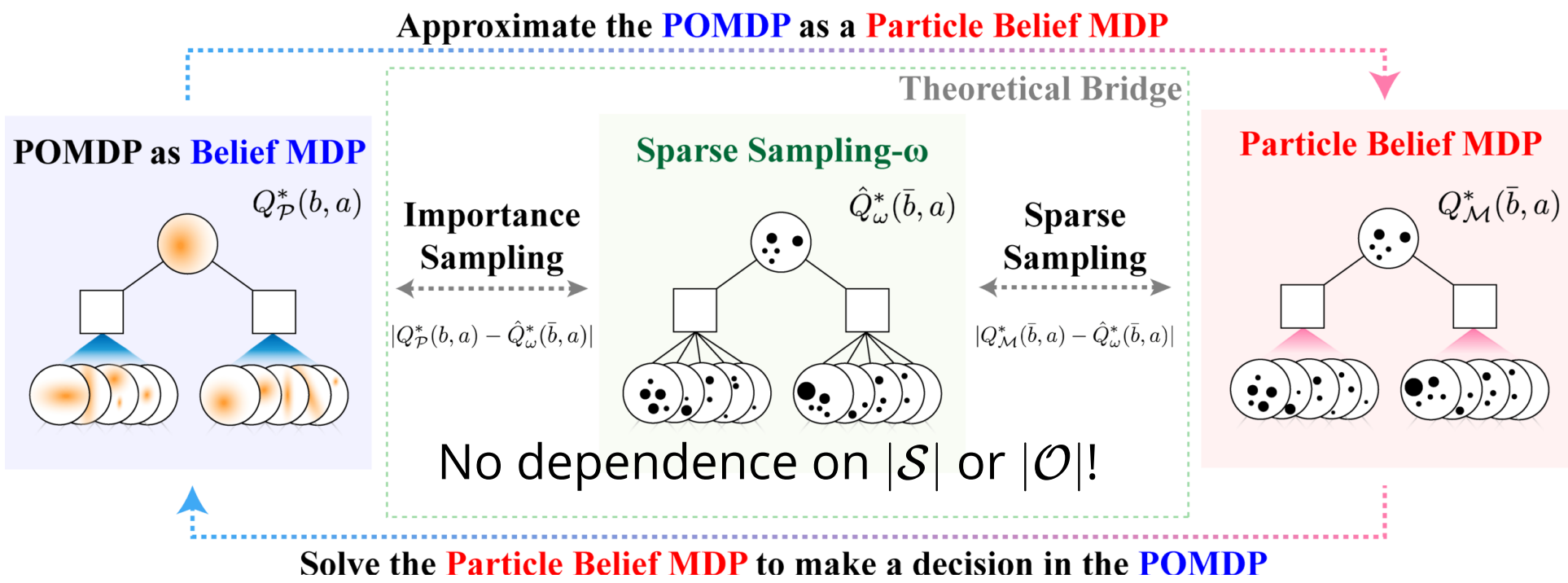


[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

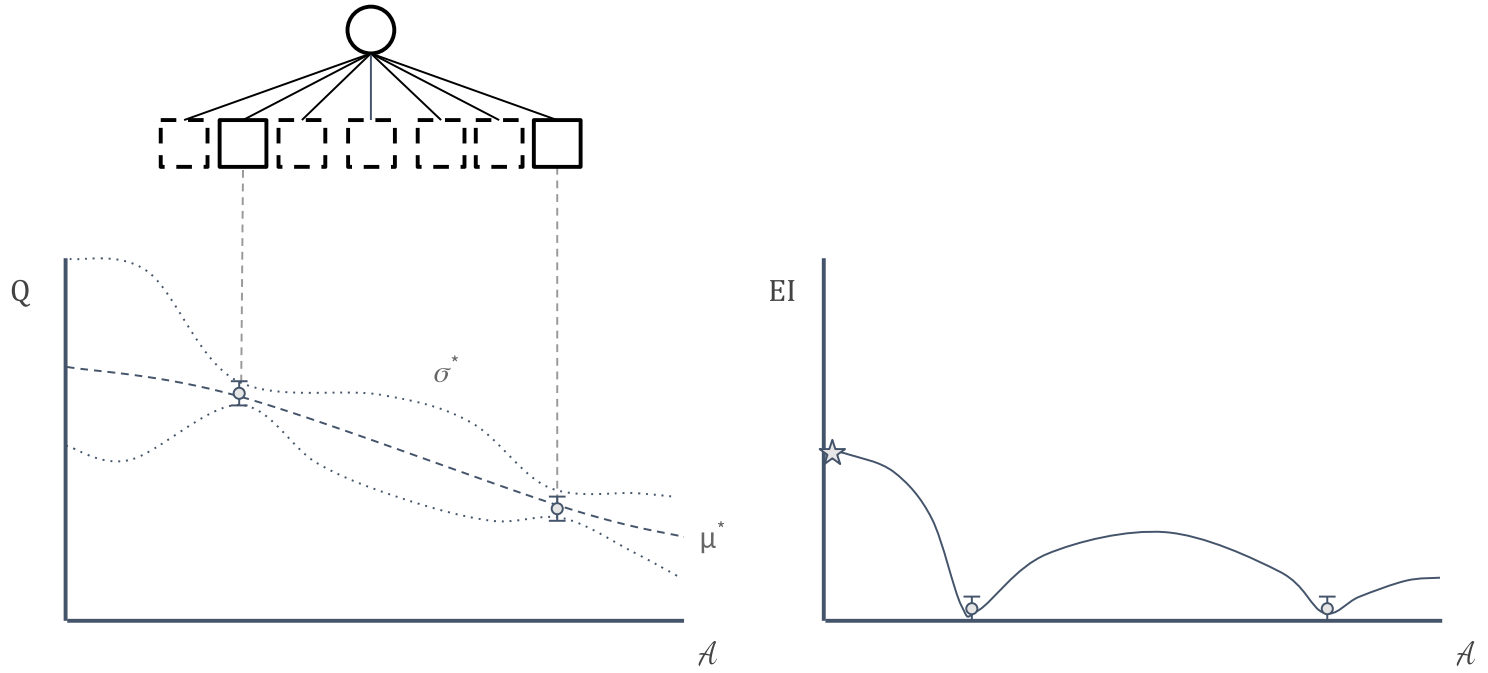
DESPOT-α

Continuous Action Spaces

Continuous Action Spaces

BOMCP

Bayesian Optimized Action Branching



Continuous Action Spaces

BOMCP

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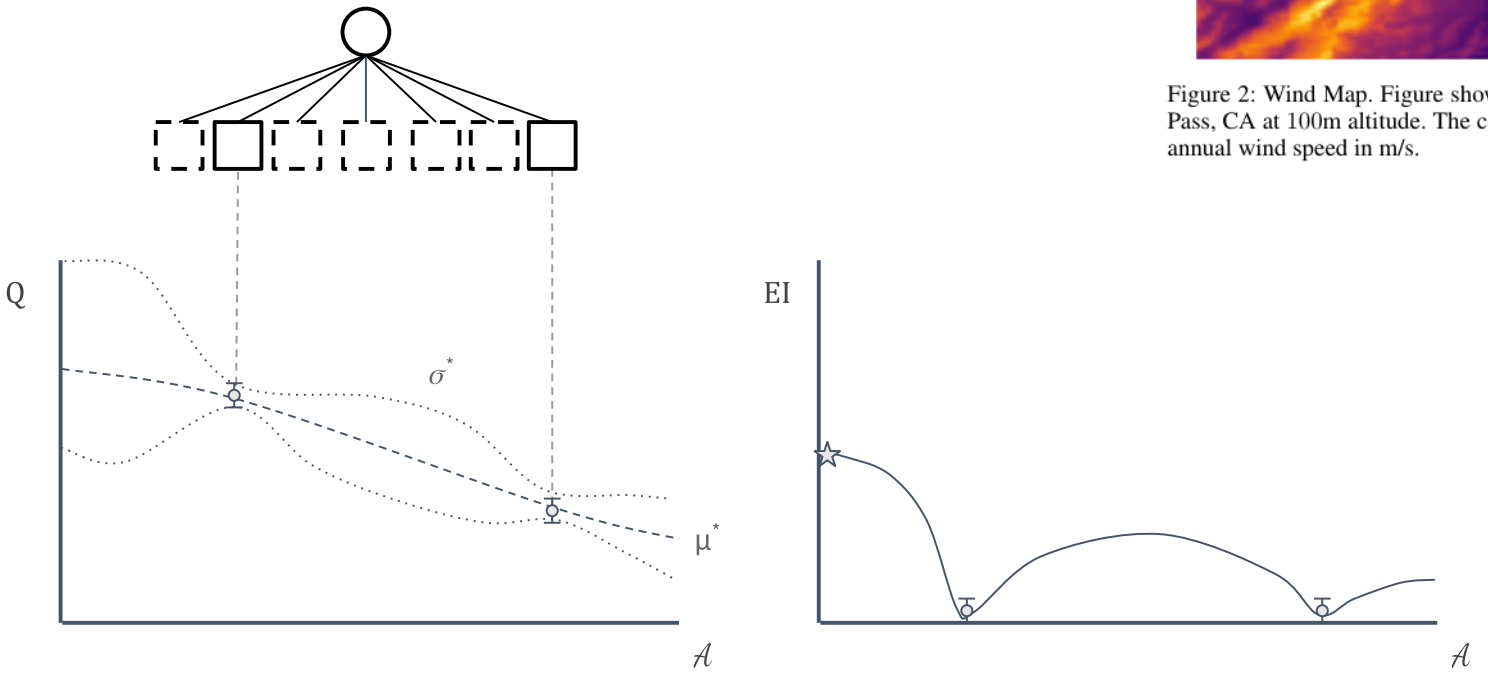


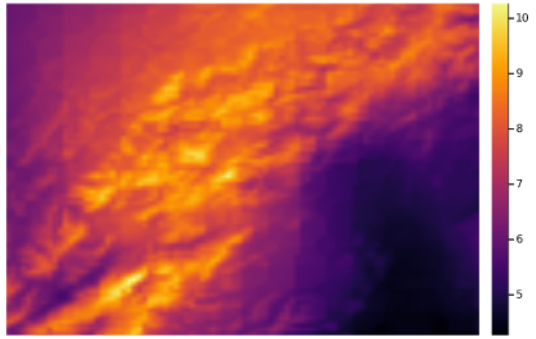
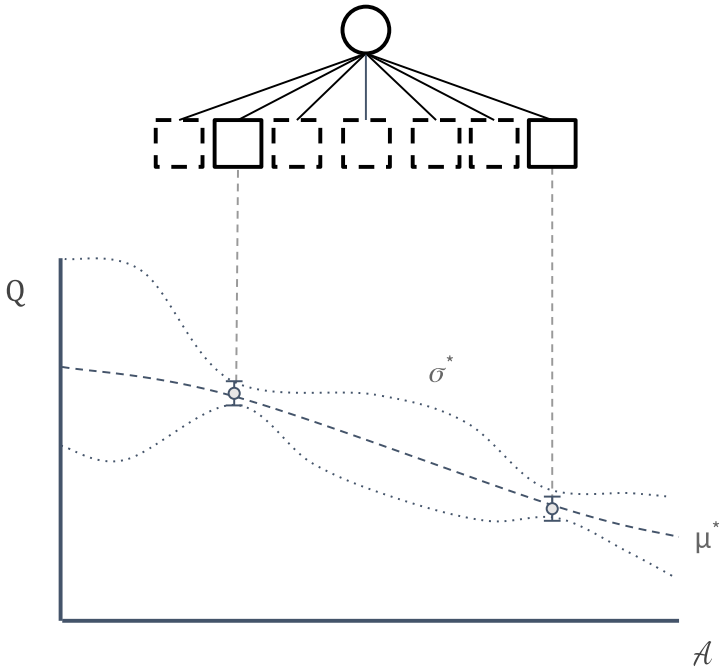


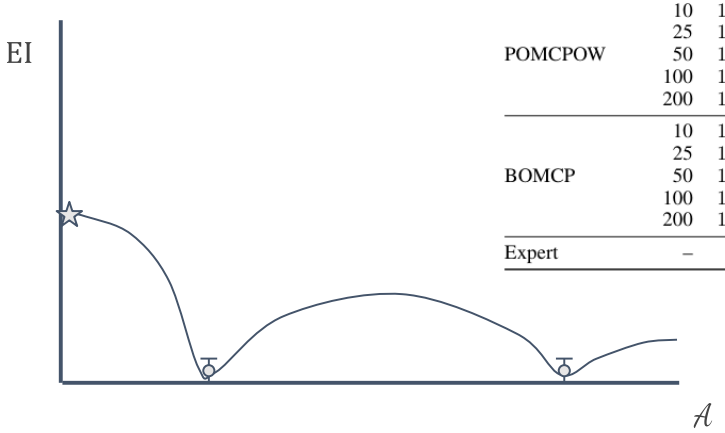
Figure 2: Wind Map. Figure shows wind map for Altamont Pass, CA at 100m altitude. The colors represent the average annual wind speed in m/s.

Continuous Action Spaces

BOMCP

Bayesian Optimized Action Branching





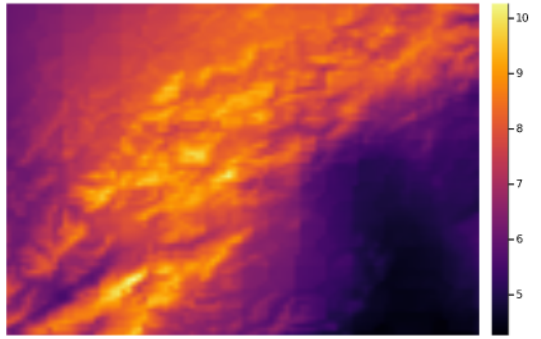
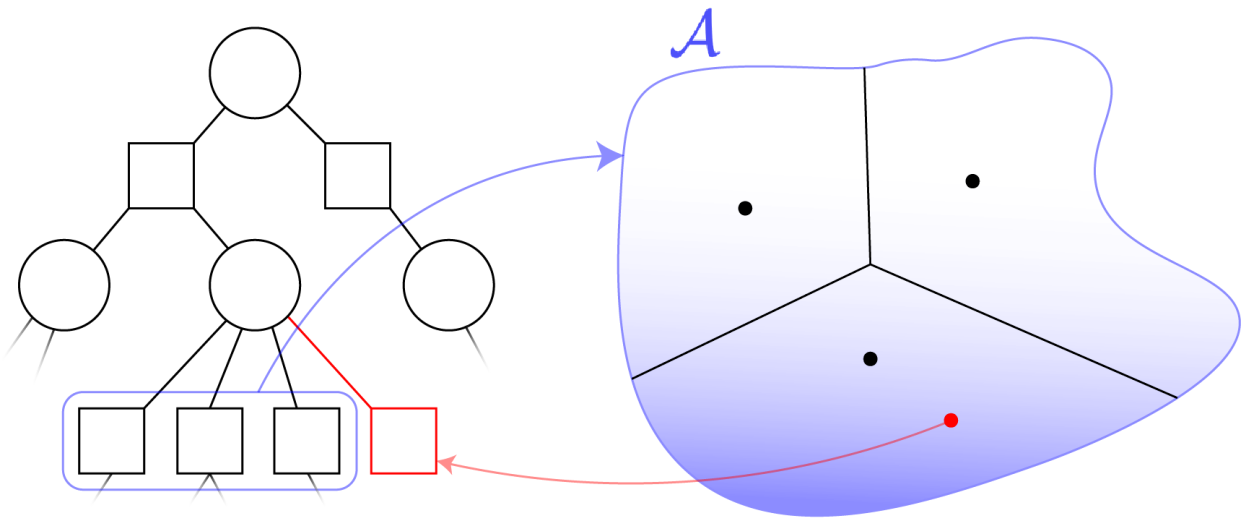


Figure 2: Wind Map. Figure shows wind map for Altamont Pass, CA at 100m altitude. The colors represent the average annual wind speed in m/s.

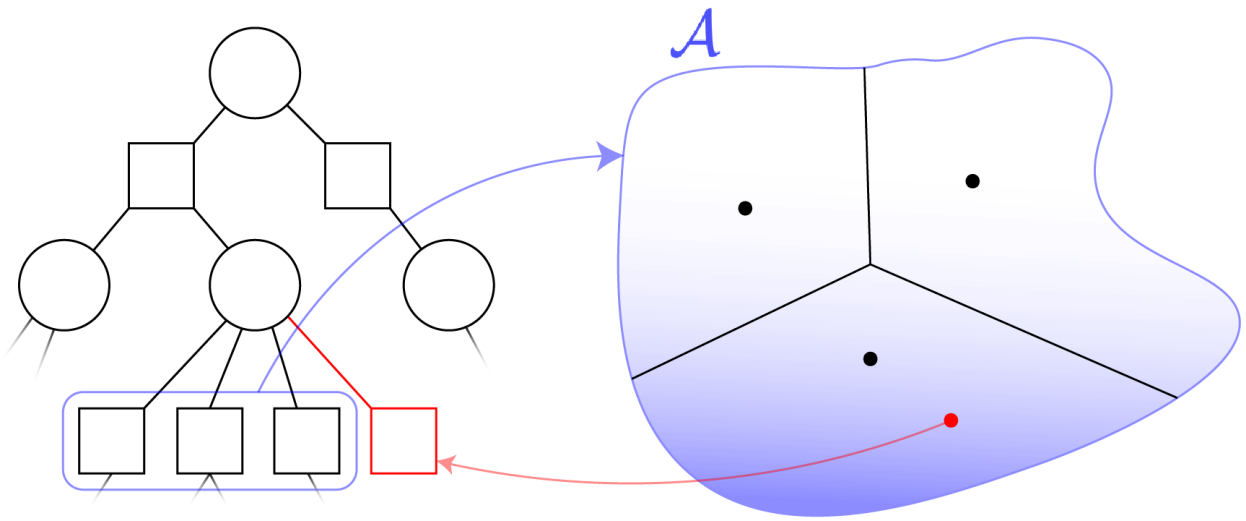
Algorithm	Queries	Score	Time (seconds)
POMCPOW	10	15708 ± 229	2.25 ± 0.07
	25	16234 ± 217	4.80 ± 0.07
	50	16374 ± 212	6.27 ± 0.08
	100	16018 ± 262	11.98 ± 0.07
	200	15787 ± 233	20.67 ± 0.09
BOMCP	10	18095 ± 183	2.55 ± 0.08
	25	18154 ± 158	5.21 ± 0.07
	50	18015 ± 163	6.71 ± 0.06
	100	18225 ± 119	13.39 ± 0.07
	200	18113 ± 157	25.14 ± 0.08
Expert	–	8130 ± 51	–

Voronoi Progressive Widening



Online Tree Search Planner Voronoi Progressive Widening

Voronoi Progressive Widening



Online Tree Search Planner Voronoi Progressive Widening