Online POMDP Methods

Approximate POMDP Solutions

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

Approximate POMDP Solutions

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(approximately solve original problem)

Offline

Approximate POMDP Solutions

Numerical Approximations

(approximately solve original problem)

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Online

Approximate POMDP Solutions

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(approximately solve original problem)

Offline

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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

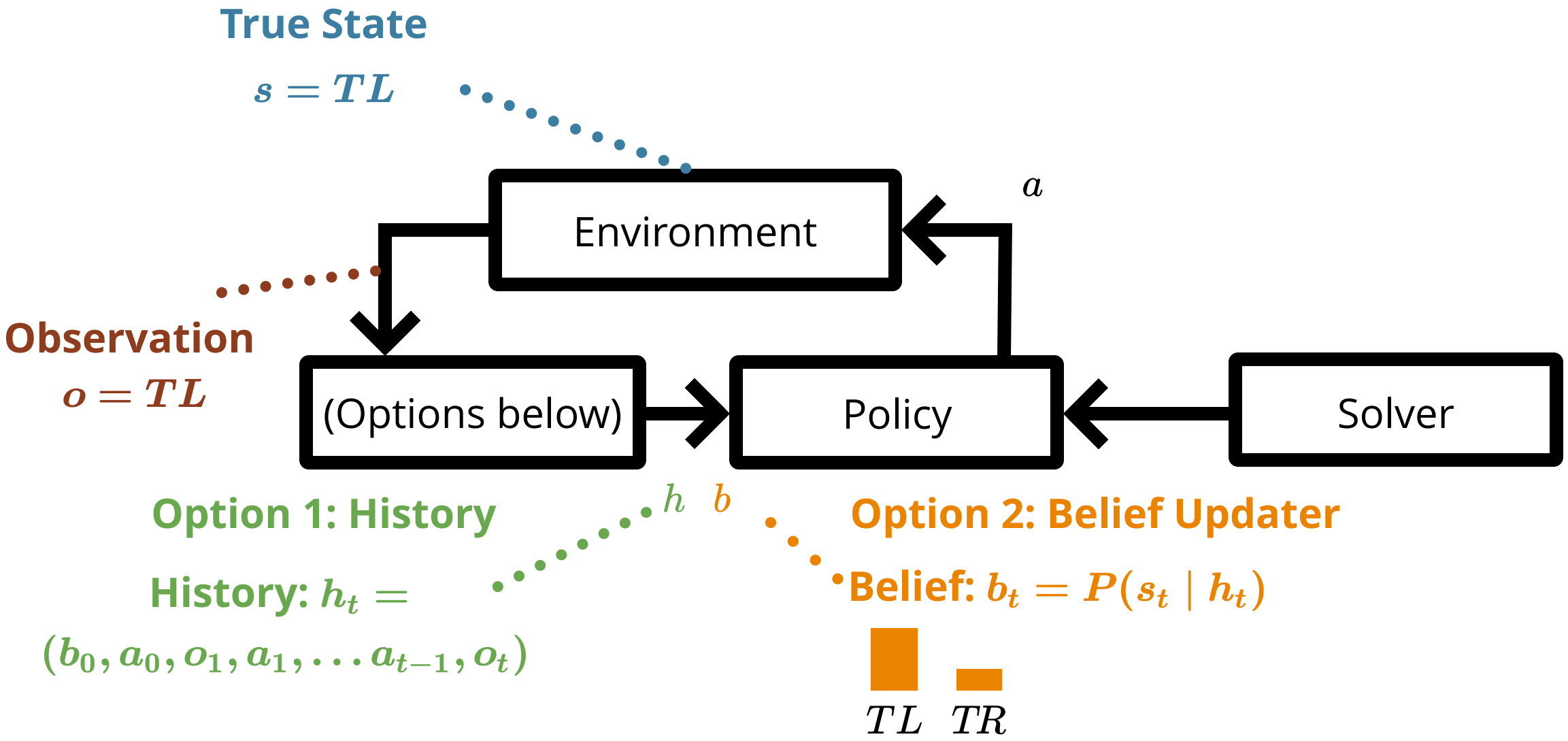
Today!

Formulation Approximations

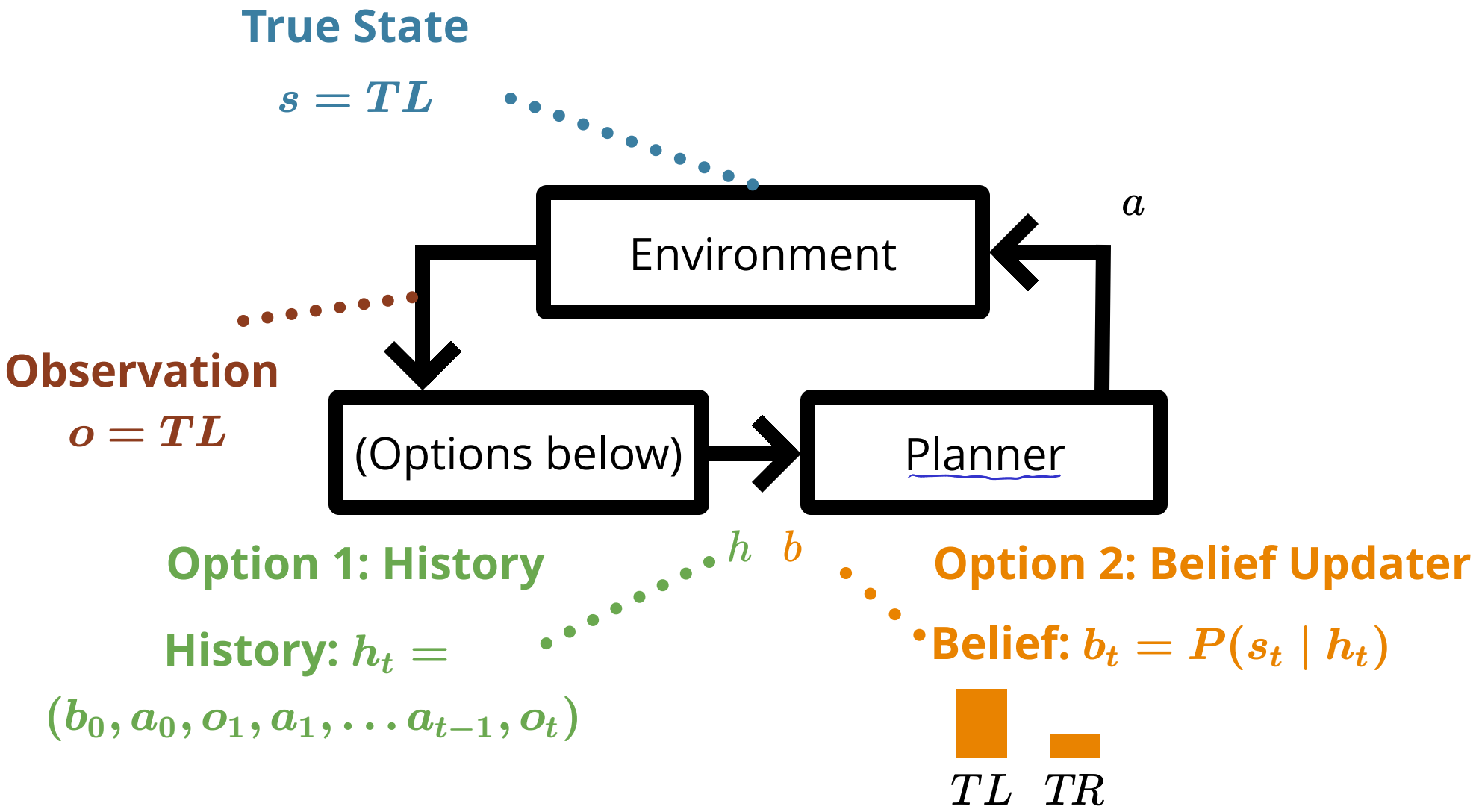
(solve a slightly different problem)

Last Time

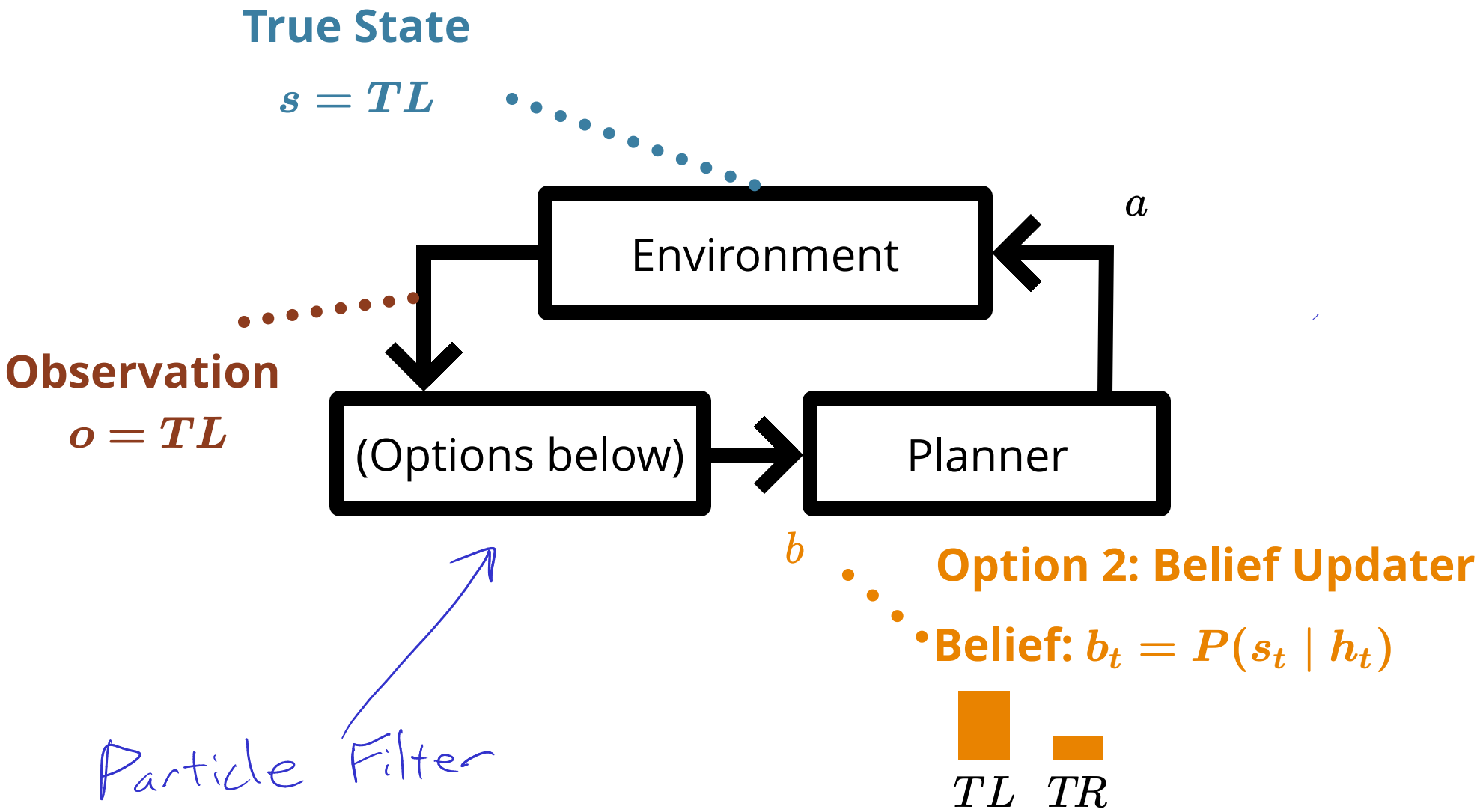
POMDP Sense-Plan-Act Loop



POMDP Sense-Plan-Act Loop

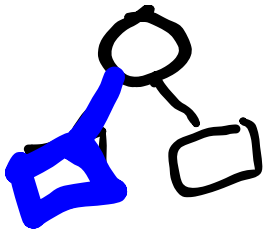


POMDP Sense-Plan-Act Loop

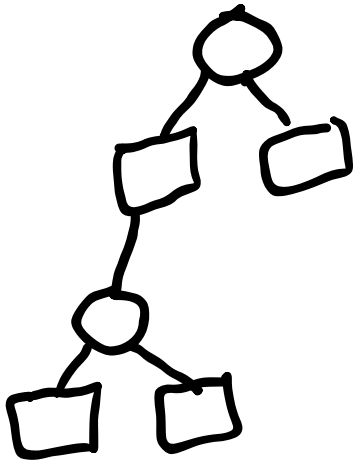


Monte Carlo Tree Search (MCTS/UCT)

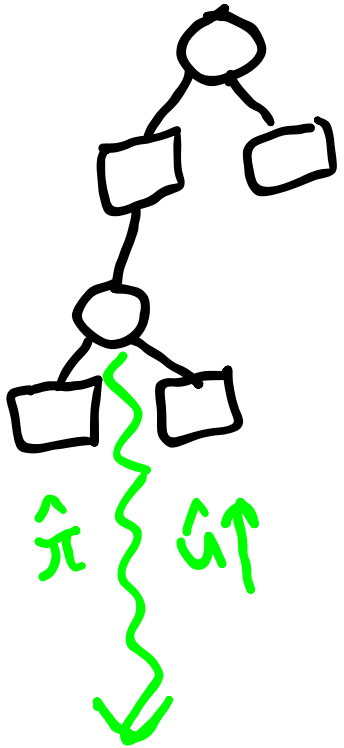
Search



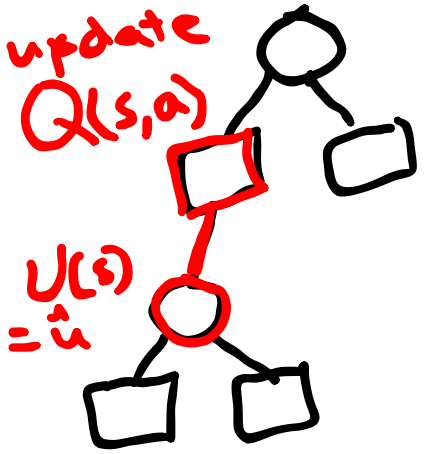
Expansion



Rollout



Backup



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

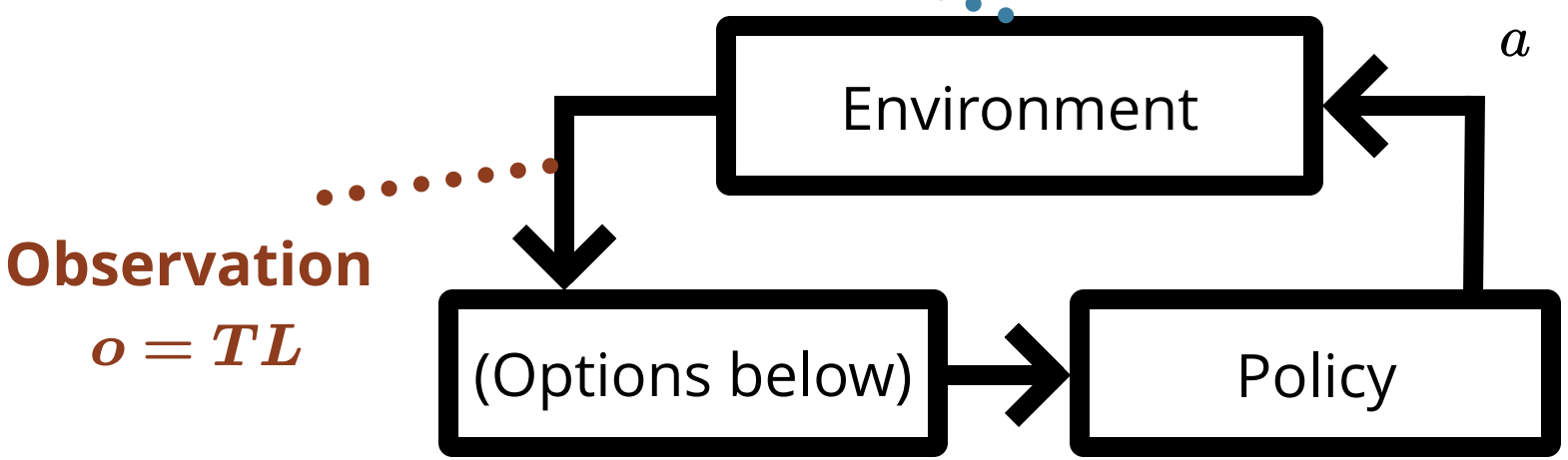
low $N(s,a)/N(s)$ = high bonus

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

How should we adapt MCTS for POMDPs?

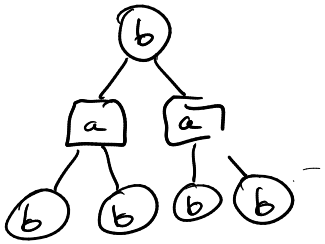
True State

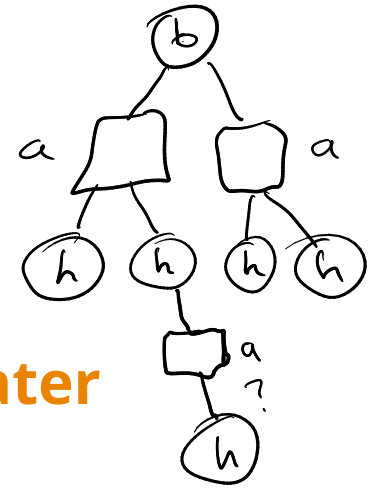
$s = TL$



Observation

$o = TL$





Option 1: History

h

History: $h_t =$

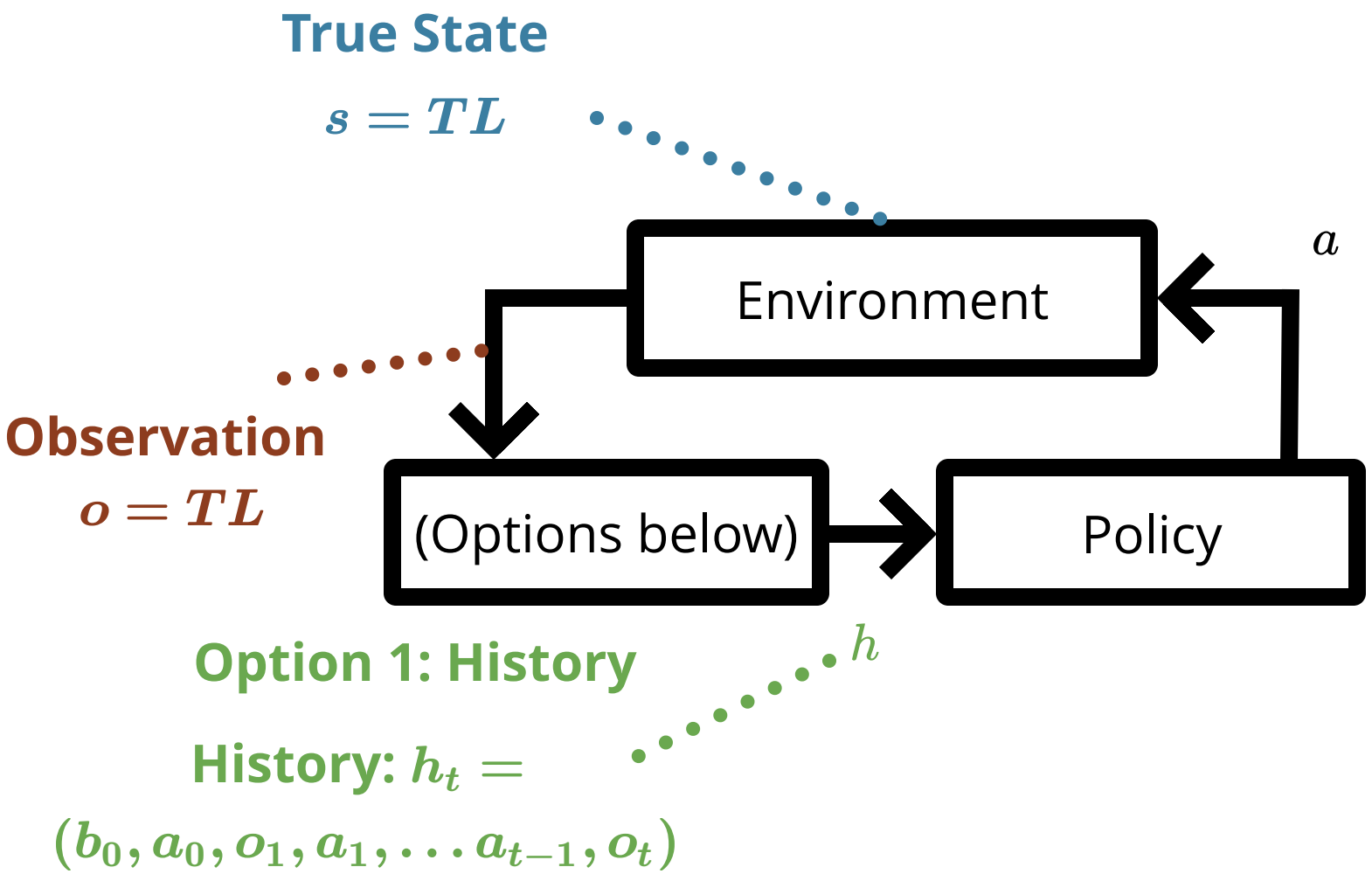
$(b_0, a_0, o_1, a_1, \ldots a_{t-1}, o_t)$

b

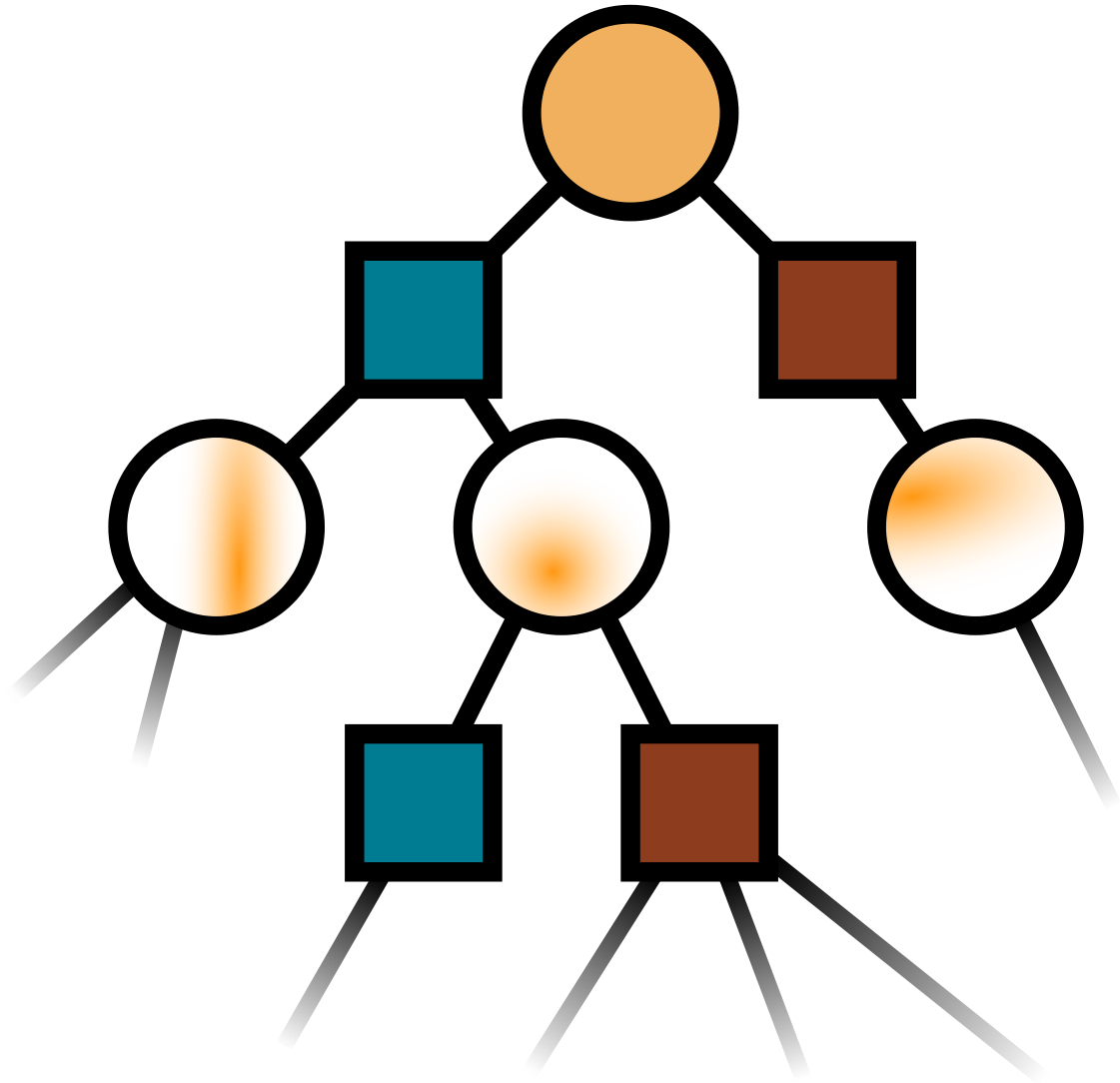
Option 2: Belief Updater

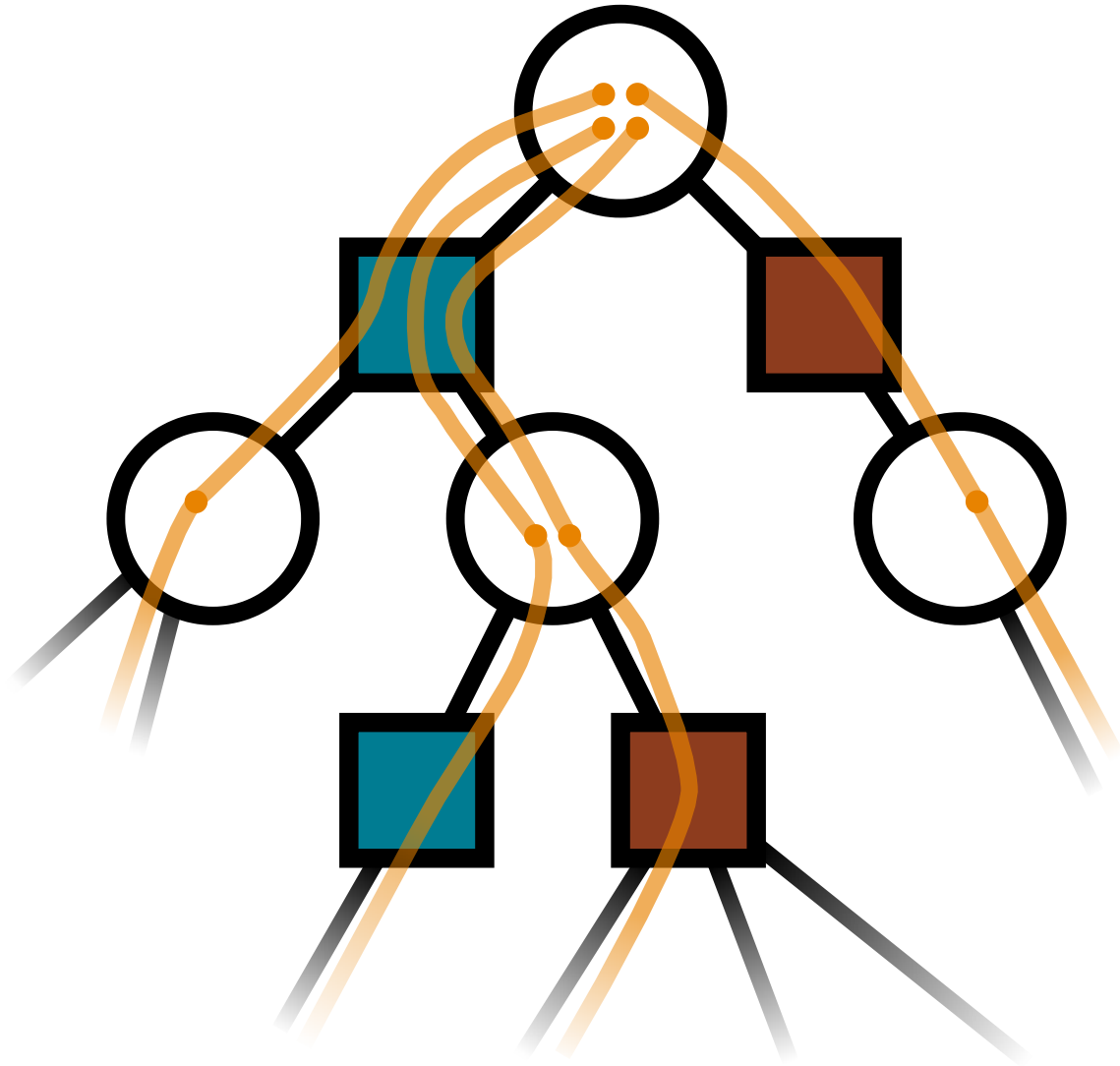
Belief: $b_t = P(s_t \mid h_t)$

How should we adapt MCTS for POMDPs?

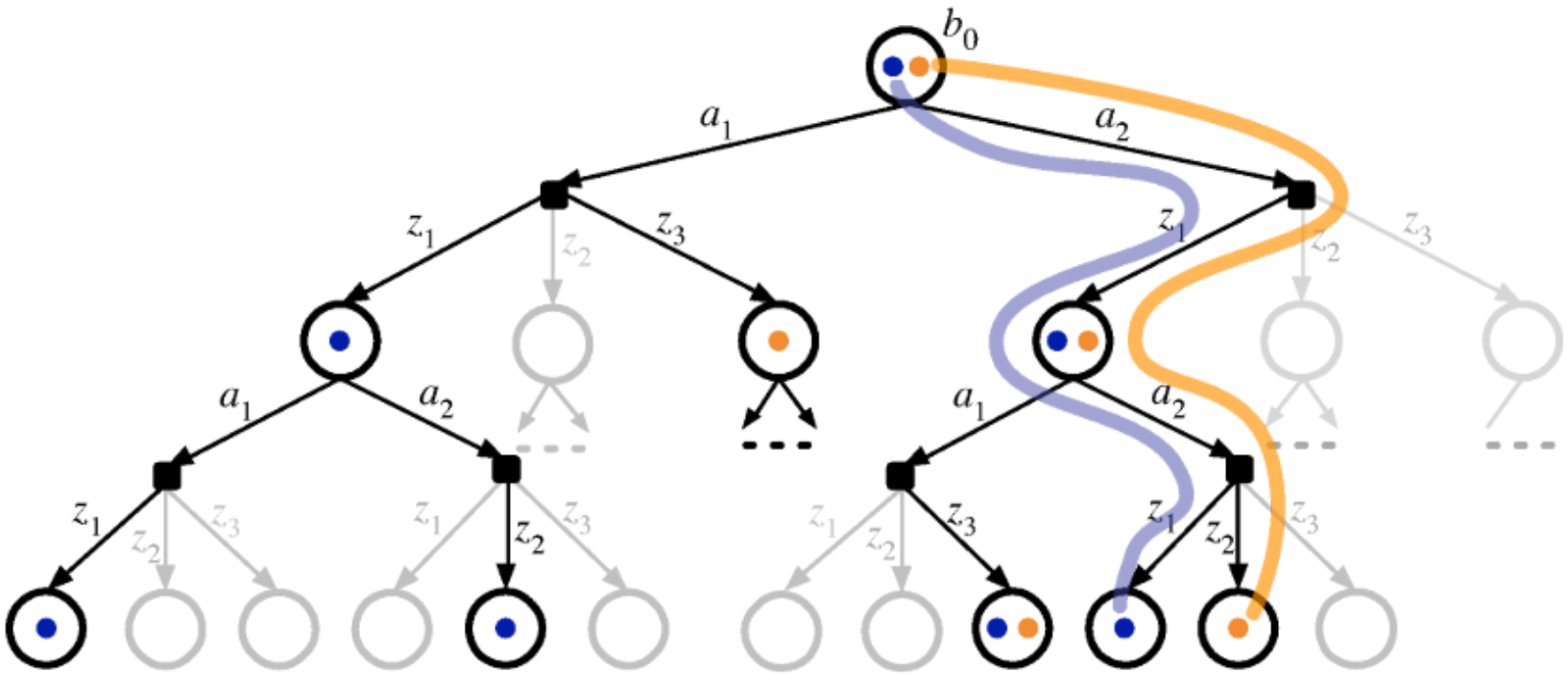


MCTS on Histories



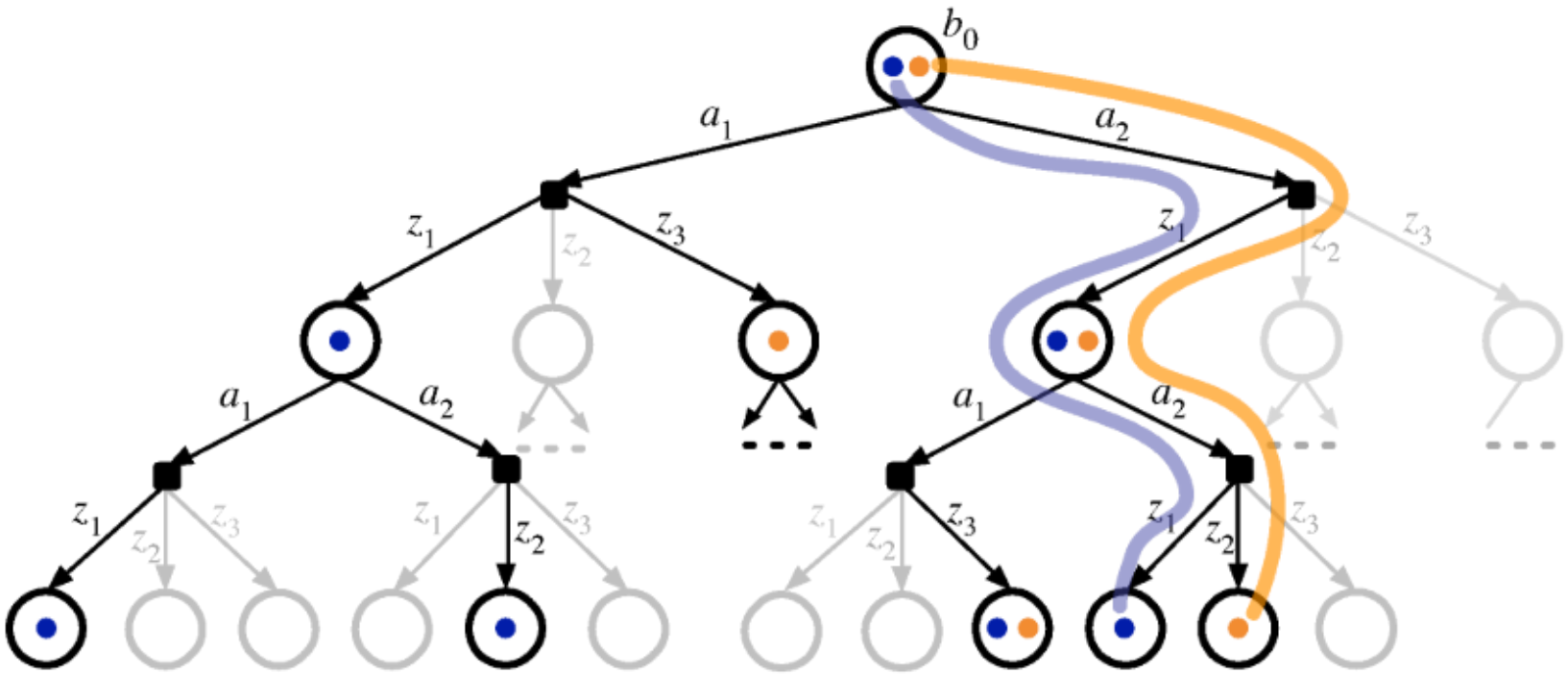


DESPOT



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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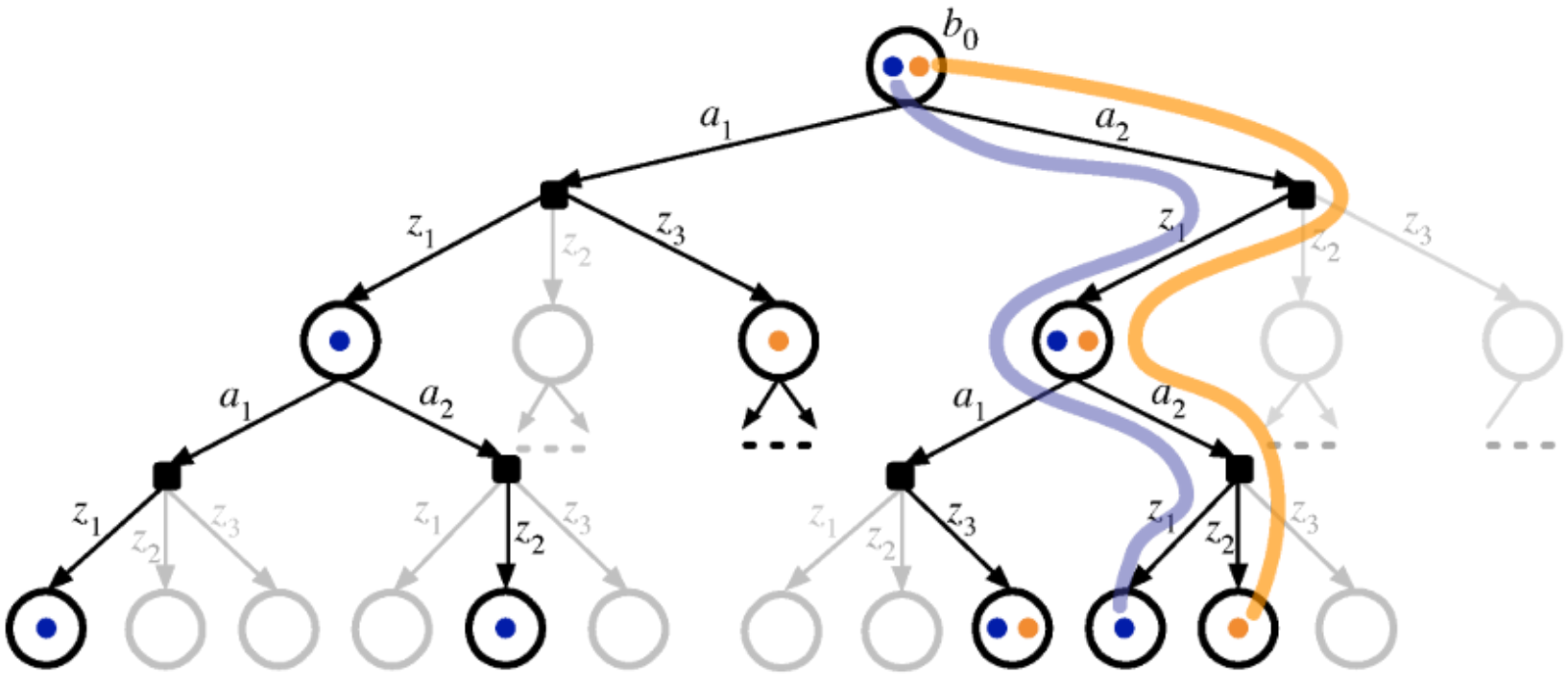
DESPOT



- Determinized Scenarios
- Guided by Lower and Upper Bounds

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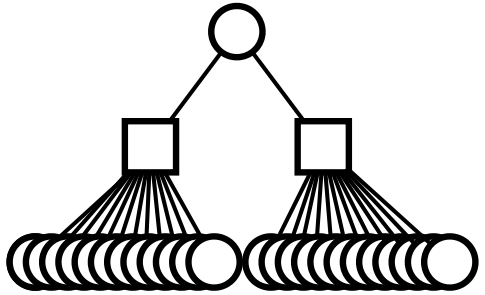
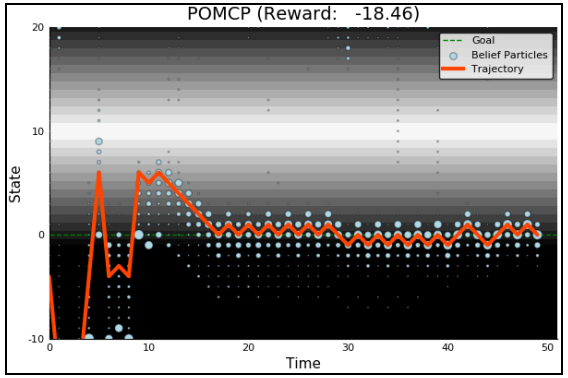
Continuous Observation Spaces

POMCP





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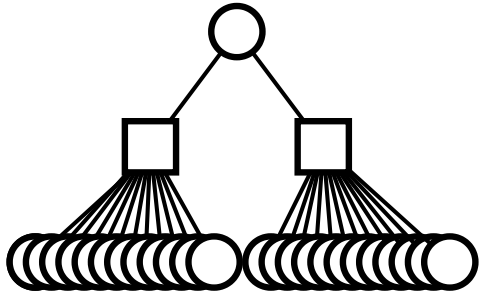
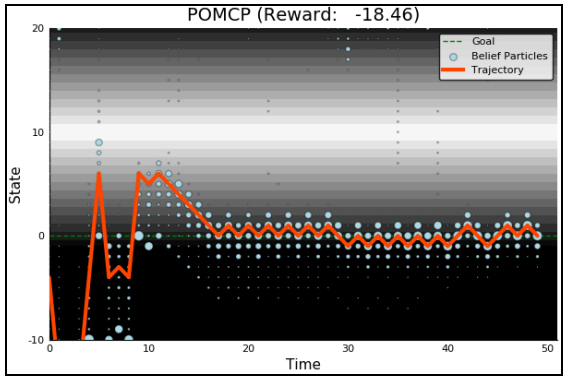
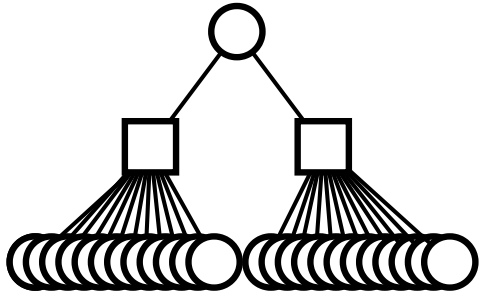


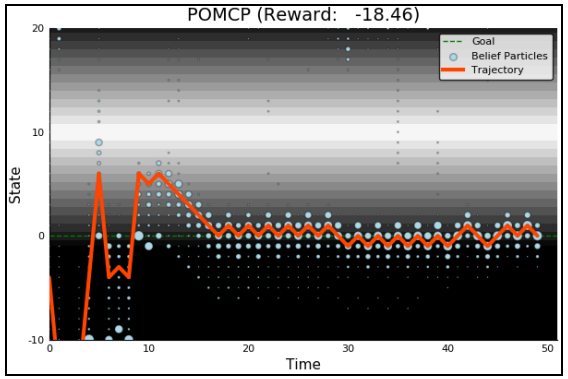


POMCPOW

Continuous Observation Spaces

POMCP





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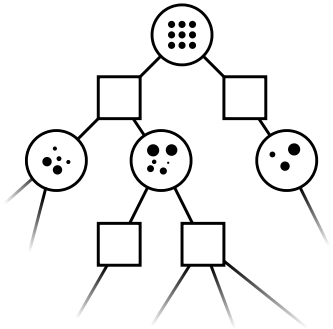

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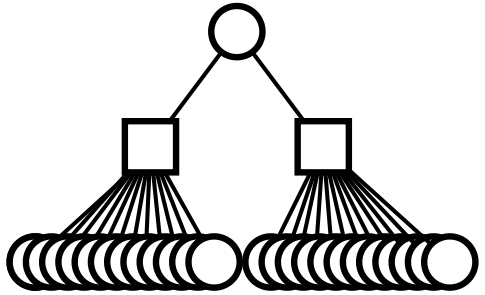

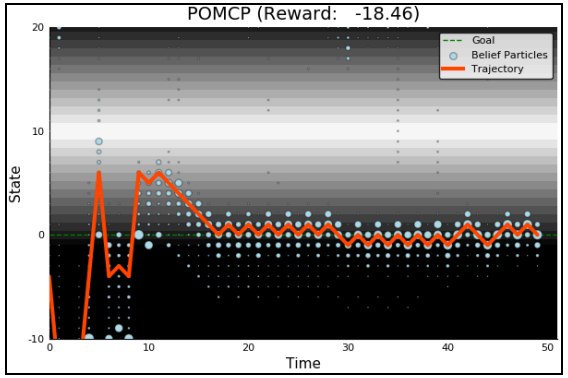

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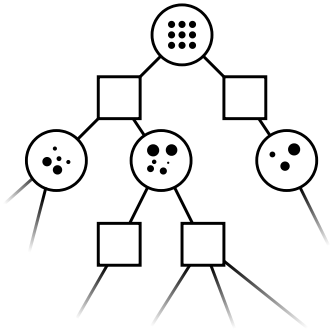

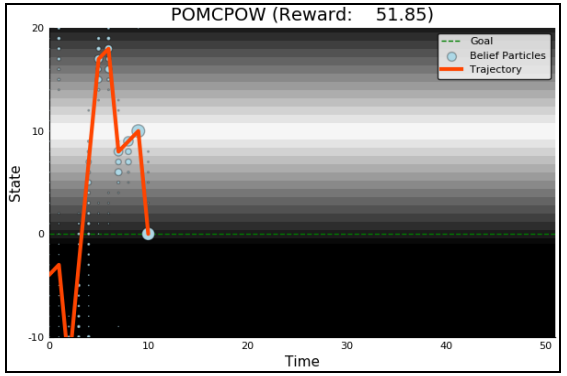

PF Approximation Accuracy

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

PF Approximation Accuracy

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

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

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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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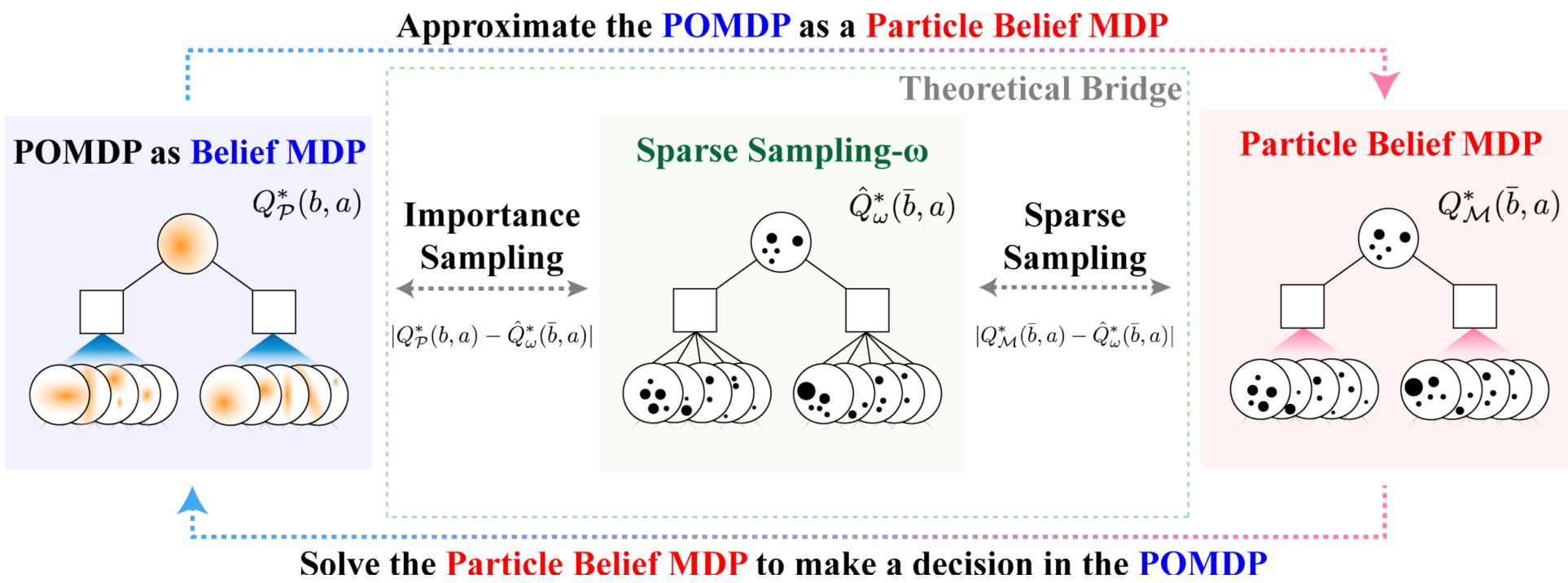

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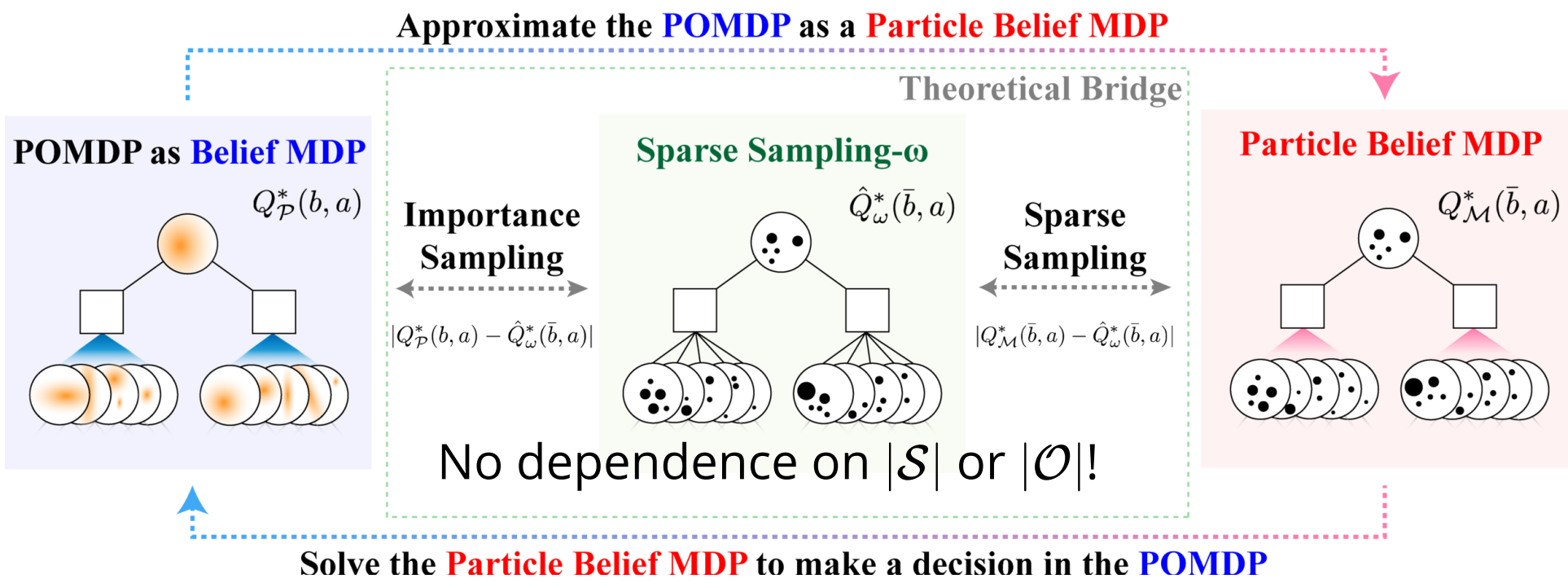


[Lim, Becker, Kochenderfer, Tomlin, & Sunberg, 2023]

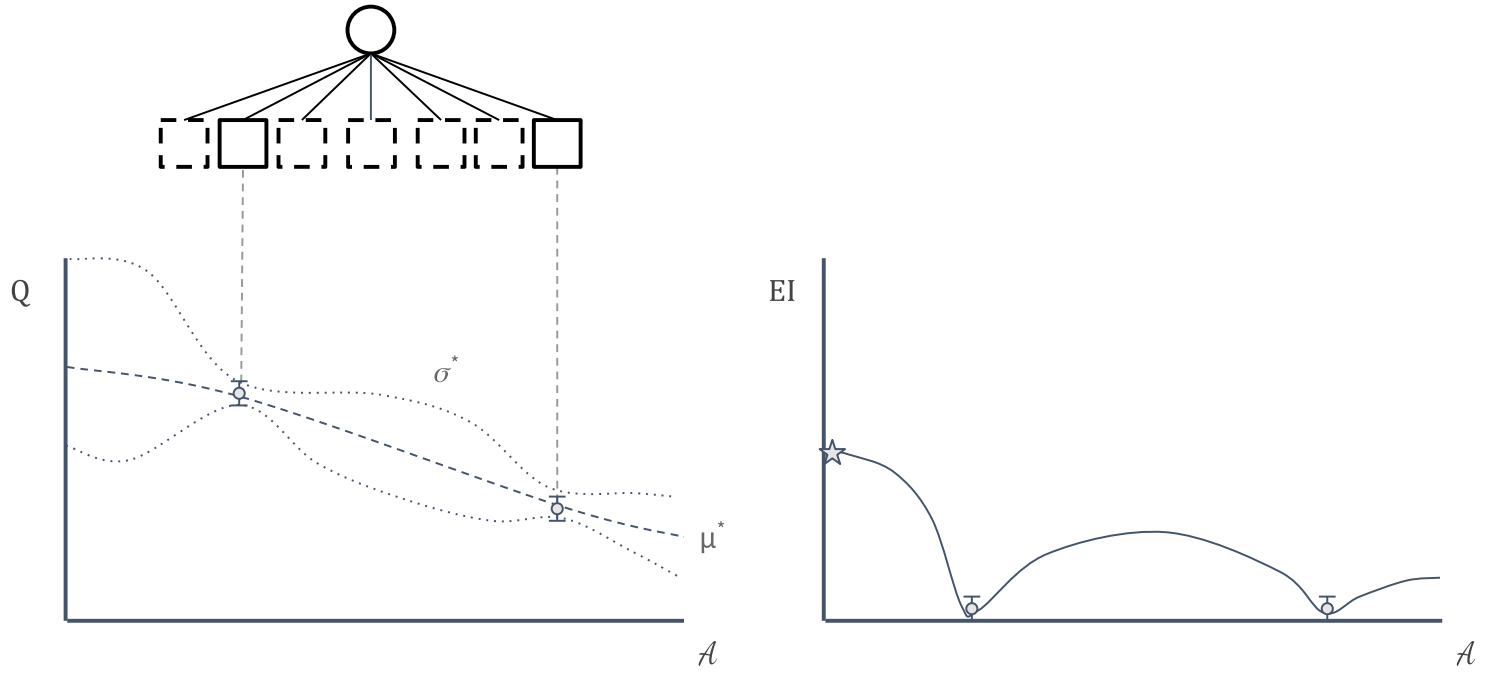
DESPOT-α

Continuous Action Spaces

Continuous Action Spaces

BOMCP

Bayesian Optimized Action Branching



Continuous Action Spaces

BOMCP

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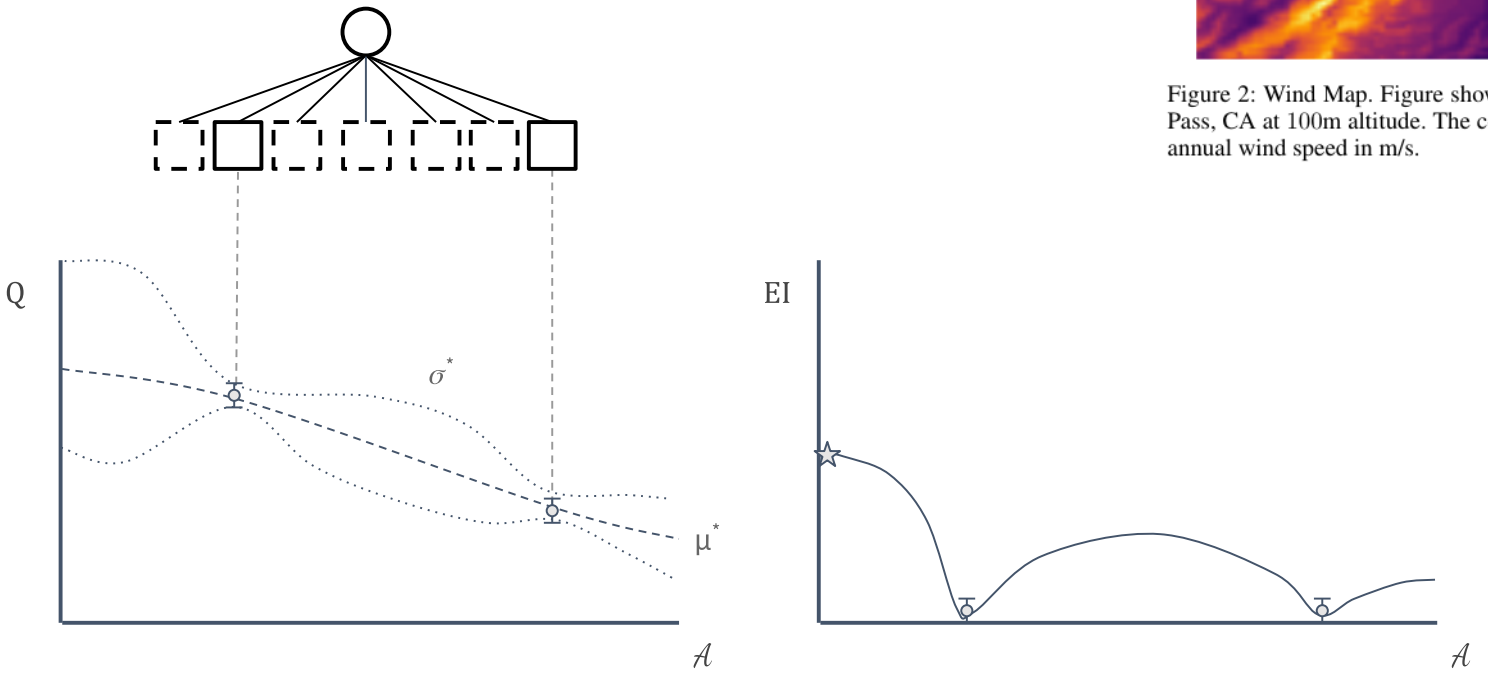


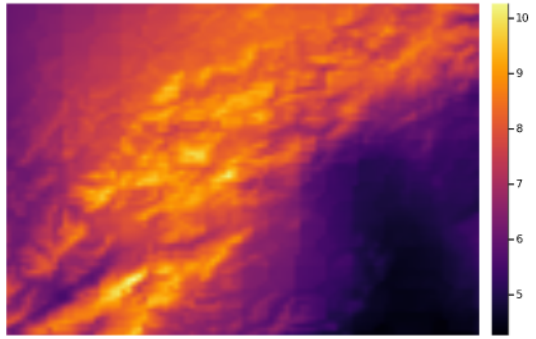
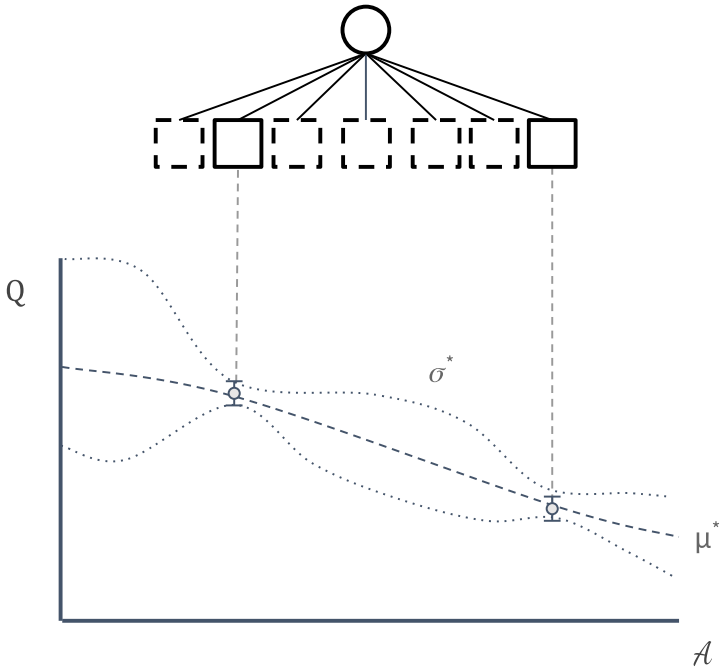


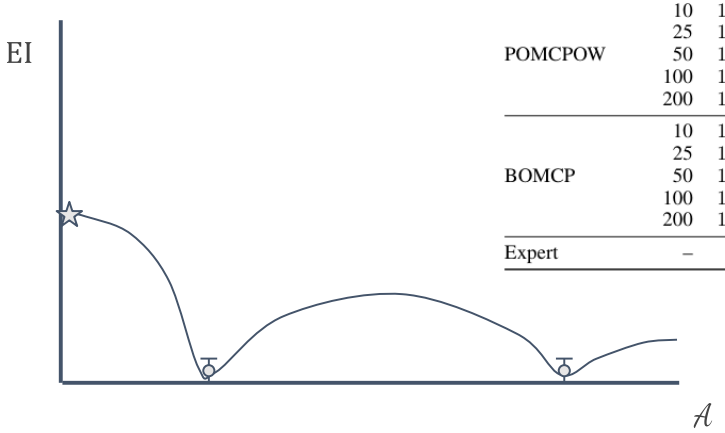
Figure 2: Wind Map. Figure shows wind map for Altamont Pass, CA at 100m altitude. The colors represent the average annual wind speed in m/s.

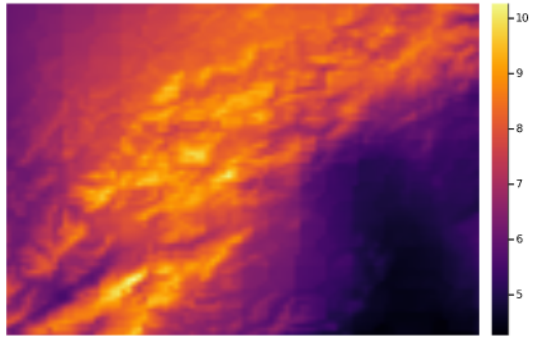
Continuous Action Spaces

BOMCP

Bayesian Optimized Action Branching







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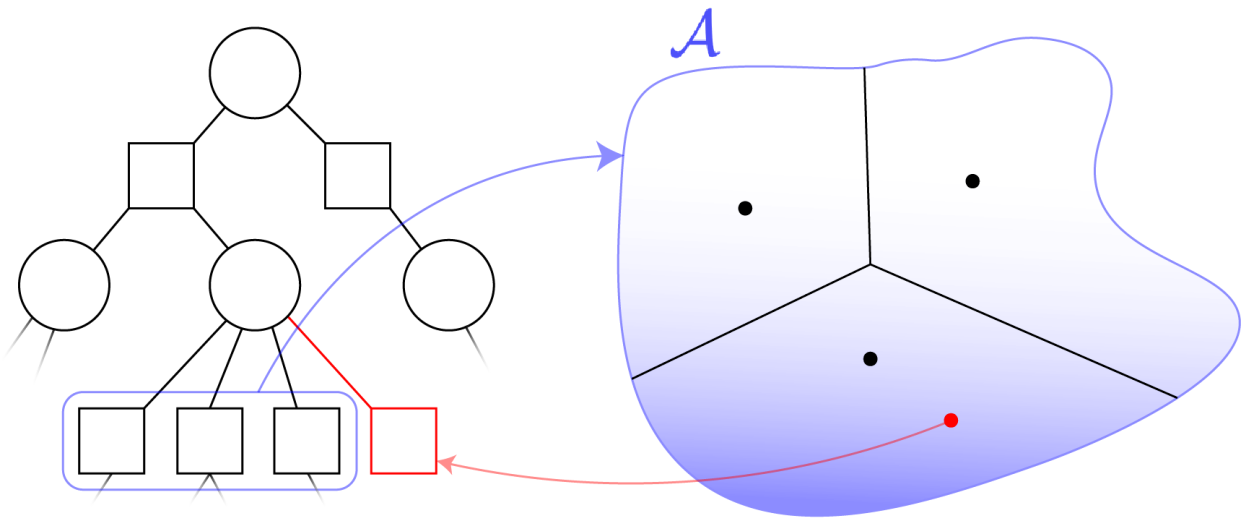
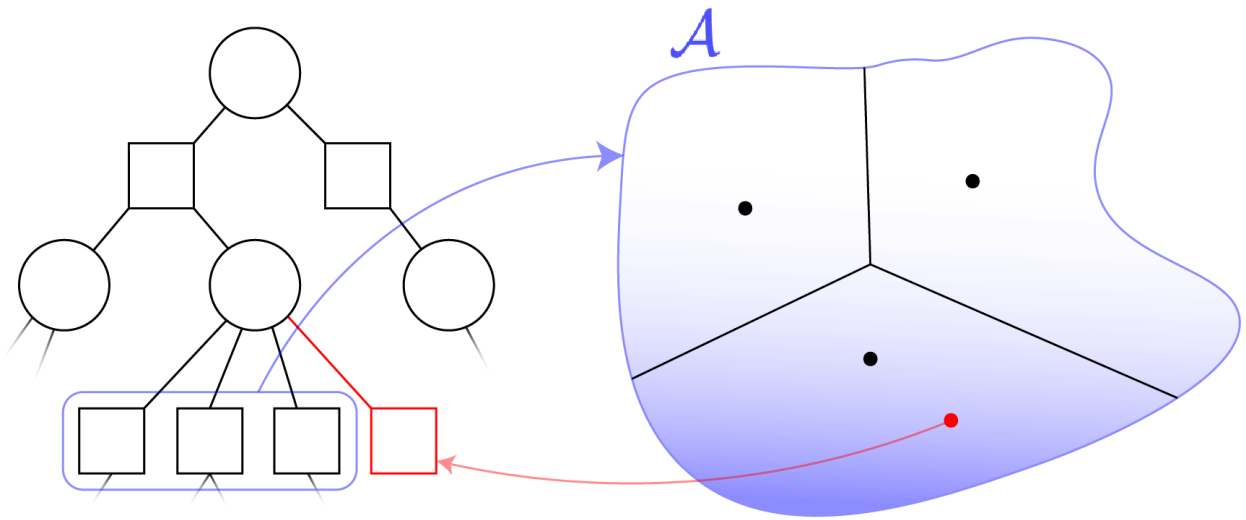
Algorithm	Queries	Score	Time (seconds)
POMCPOW	10	15708 ± 229	2.25 ± 0.07
	25	16234 ± 217	4.80 ± 0.07
	50	16374 ± 212	6.27 ± 0.08
	100	16018 ± 262	11.98 ± 0.07
	200	15787 ± 233	20.67 ± 0.09
BOMCP	10	18095 ± 183	2.55 ± 0.08
	25	18154 ± 158	5.21 ± 0.07
	50	18015 ± 163	6.71 ± 0.06
	100	18225 ± 119	13.39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