

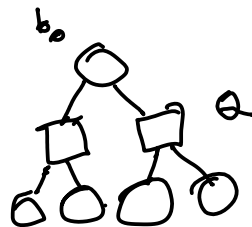
Last Time: Offline POMDP solutions,

Point Based VI

How to choose B

Today: Online POMDP solutions

		S	A	O	T	O
2007	Online Planning Algs for POMDPs AEMS	D	D	D	E	E
2010	MCTS/POMCP	E	D	D	G	G
2013	DESPOT	C	D	D	G	G
2018	POMCPow	C	val/D	C	G	E
2019	DESPOT-α	C	D	C	G	E



belief
action
belief

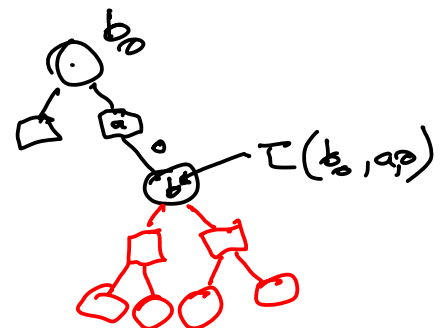
AEMS Anytime Error Minimizing Search

while time remains

$$b^* = \underset{b \in \text{Fringe}(G)}{\text{argmax}} E(b)$$

expand(b^*)

backup(b^*)



$$E(b) = \gamma^d P(b) \hat{E}(b)$$

$$\hat{E}(b) = U(b) - L(b)$$

$$P(b) = \prod_{i=0}^{d-1} P(o^i | b^i, a^i) P(a^i | b^i)$$

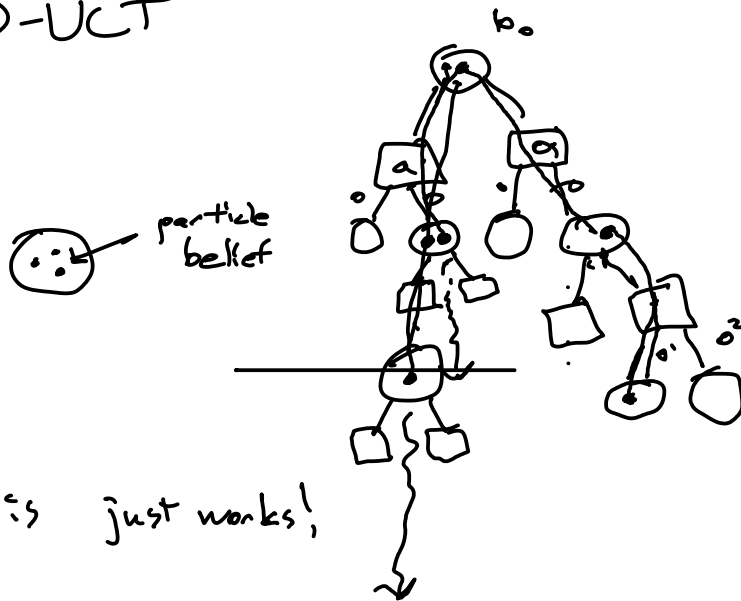
$$\underline{P(a|b)} = \frac{U(a,b) - L(b)}{U(b) - L(b)} \quad \text{AEMS1}$$

$$\underline{P(a|b)} = \begin{cases} 1 & \text{if } a = \text{argmax } U(b,a) \\ 0 & \text{otherwise} \end{cases} \quad \text{AEMS2}$$

Problem belief updates are expensive

MCTS for POMDPs

PO-UCT



Problem: we need
a history-based
simulator

$$o = G(h, a)$$

$$s', o, r = G(s, a, w)$$

This just works!

POMCP

PO-UCT
+ re-using
particles for
belief



Determinized Sparse

K scenarios

each scenario is a fixed random seed

$$s', \phi, r = G(s, a, \phi, t)$$

$$\rightarrow G(s, a, w) = s + a + w$$

$$G(1, 1, 0, 1) = 2 + 0, 1$$

$$G(1, 2, \phi_{1,1}) = 3 + \phi_{1,1}$$

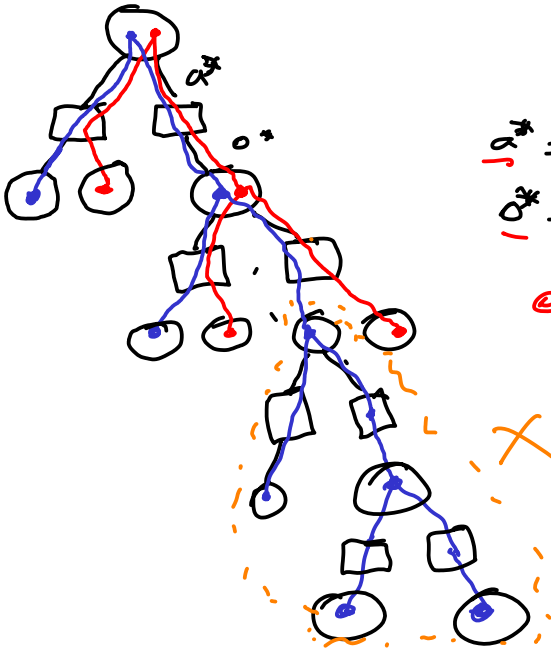
reduces variance

$$\underline{G(s, a, w)} = \begin{cases} s+a+w & \text{if } a=1 \\ s+a-w & \text{if } a=2 \end{cases}$$

$$K = 500 -$$

① = max depth

Not MCTS \rightarrow Heuristic Search



$$\frac{V}{L}$$

$\mu \leftarrow \text{regularized weighted}$

$$\underline{a^*} = \operatorname{argmax} \mu(b, a)$$

$$\underline{\theta^*} = \arg \max_{\theta} E(\tau(\theta, a, o))$$

expand

$$\mu \approx U - \lambda \frac{\text{number of nodes in tree}}{rd}$$

Continuous \bigcirc