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Reframing Control as an Inference Problem

CS 285

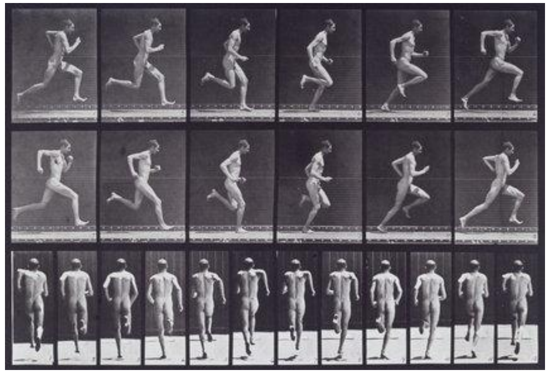
Instructor: Sergey Levine
UC Berkeley

Today's Lecture

1. Does reinforcement learning and optimal control provide a reasonable model of human behavior?
2. Is there a better explanation?
3. Can we derive optimal control, reinforcement learning, and planning as *probabilistic inference*?
4. How does this change our RL algorithms?
5. (next lecture) We'll see this is crucial for *inverse* reinforcement learning

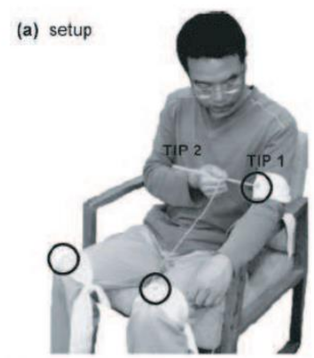
- Goals:
  - Understand the connection between inference and control
  - Understand how specific RL algorithms can be instantiated in this framework
  - Understand why this might be a good idea

Optimal Control as a Model of Human Behavior



Muybridge (c. 1870)

Mombaur et al. ‘09



Li & Todorov ‘06

Ziebart ‘08

$$\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg \max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} \sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)$$

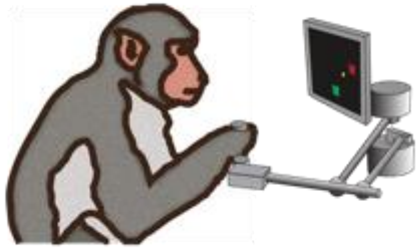
$$\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t)$$

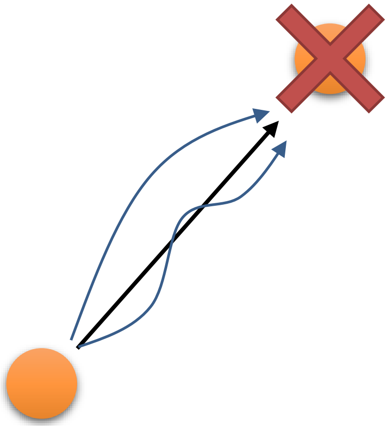
optimize this to explain the data

$$\pi = \arg \max_{\pi} E_{\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t), \mathbf{a}_t \sim \pi(\mathbf{a}_t | \mathbf{s}_t)} [r(\mathbf{s}_t, \mathbf{a}_t)]$$

$$\mathbf{a}_t \sim \pi(\mathbf{a}_t | \mathbf{s}_t)$$

What if the data is **not** optimal?





some mistakes matter more than others!

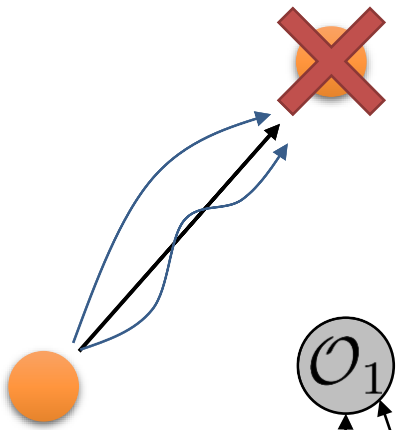
behavior is **stochastic**

but good behavior is still the most likely

A probabilistic graphical model of decision making

$$\cancel{\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg\max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} \sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)}$$

$$\cancel{\mathbf{s}_{t+1} = f(\mathbf{s}_t, \mathbf{a}_t)}$$



$$p(\underbrace{\mathbf{s}_{1:T}, \mathbf{a}_{1:T}}_{\tau}) = ??$$

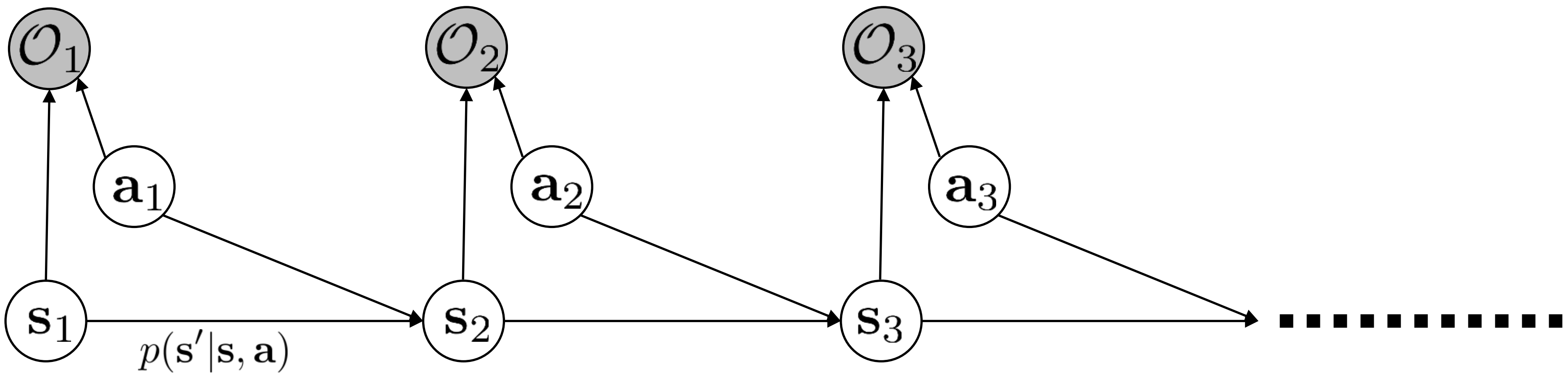
no assumption of optimal behavior!

$$p(\tau | \mathcal{O}_{1:T})$$

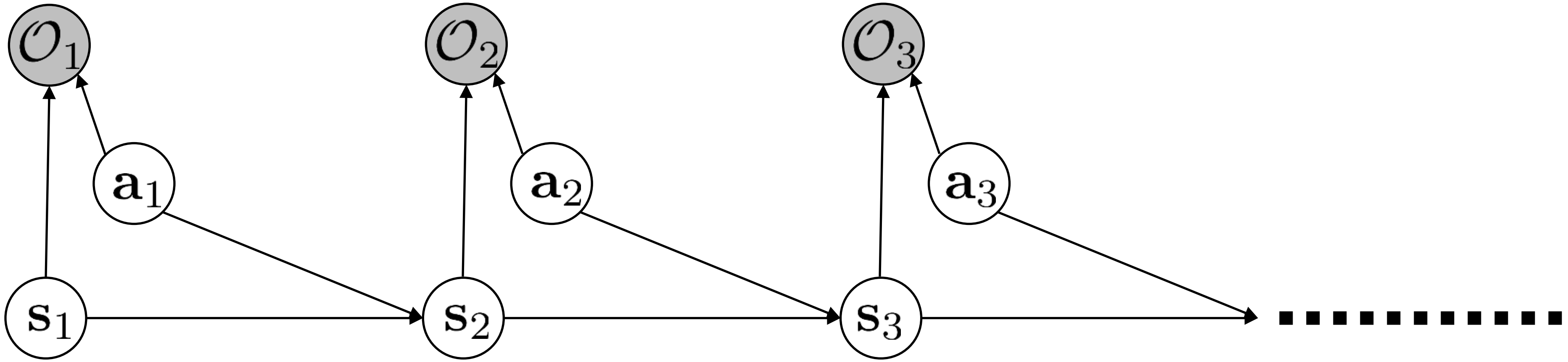
$$p(\mathcal{O}_t | \mathbf{s}_t, \mathbf{a}_t) = \exp(r(\mathbf{s}_t, \mathbf{a}_t))$$

$$p(\tau | \mathcal{O}_{1:T}) = \frac{p(\tau, \mathcal{O}_{1:T})}{p(\mathcal{O}_{1:T})}$$

$$\propto p(\tau) \prod_t \exp(r(\mathbf{s}_t, \mathbf{a}_t)) = p(\tau) \exp\left(\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right)$$



Why is this interesting?

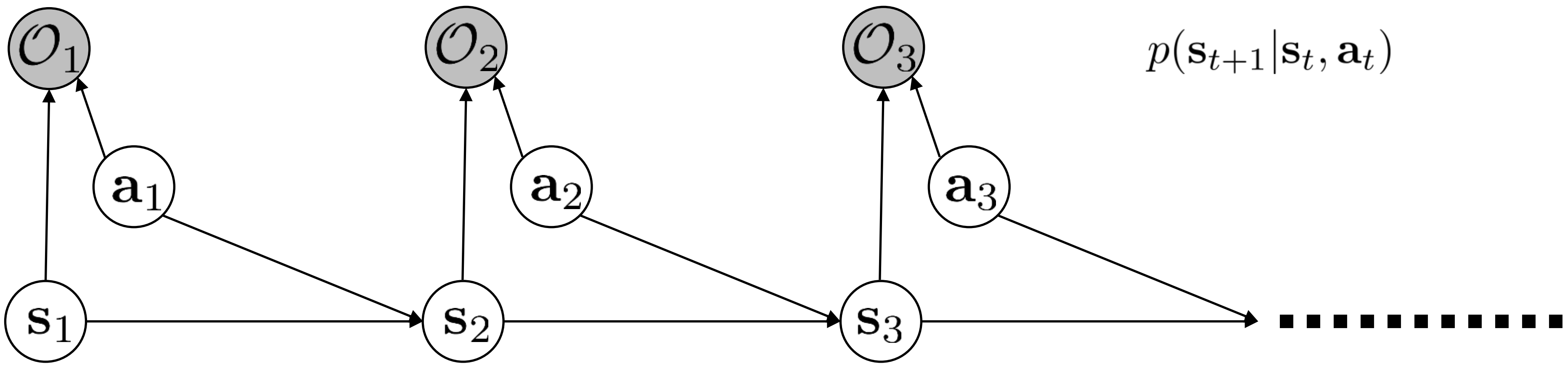


- Can model suboptimal behavior (important for inverse RL)
- Can apply inference algorithms to solve control and planning problems
- Provides an explanation for why stochastic behavior might be preferred (useful for exploration and transfer learning)

Inference = planning

$p(\mathcal{O}_t|\mathbf{s}_t, \mathbf{a}_t) \propto \exp(r(\mathbf{s}_t, \mathbf{a}_t))$

$p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$



how to do inference?

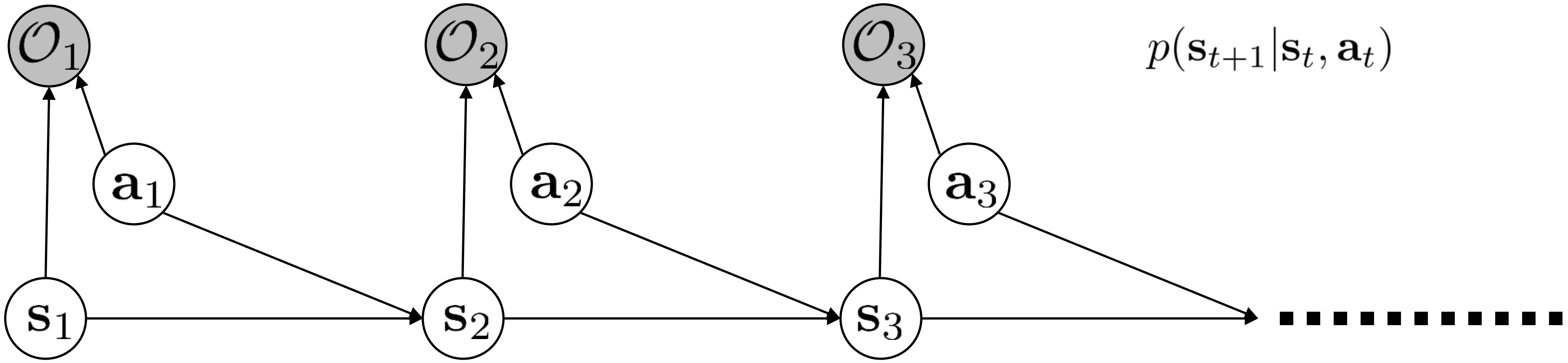
1. compute backward messages $\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_{t:T}|\mathbf{s}_t, \mathbf{a}_t)$
2. compute policy $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T})$
3. compute forward messages $\alpha_t(\mathbf{s}_t) = p(\mathbf{s}_t|\mathcal{O}_{1:t-1})$

Control as Inference

Inference = planning

$p(\mathcal{O}_t|\mathbf{s}_t, \mathbf{a}_t) \propto \exp(r(\mathbf{s}_t, \mathbf{a}_t))$

$p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$



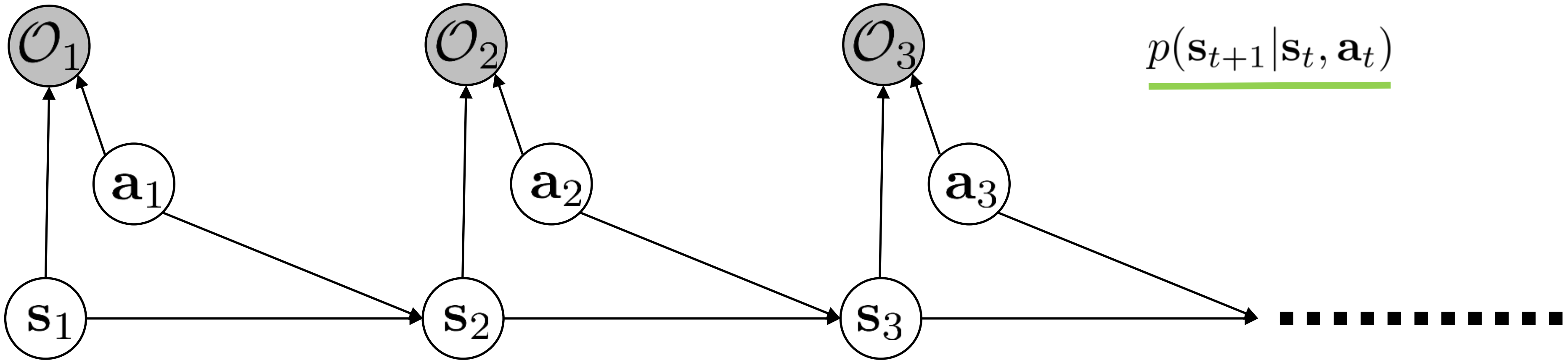
how to do inference?

1. compute backward messages $\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_{t:T}|\mathbf{s}_t, \mathbf{a}_t)$
2. compute policy $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T})$
3. compute forward messages $\alpha_t(\mathbf{s}_t) = p(\mathbf{s}_t|\mathcal{O}_{1:t-1})$

Backward messages

$$p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t) \propto \exp(r(\mathbf{s}_t,\mathbf{a}_t))$$

$$p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)$$



$$\begin{aligned}\beta_t(\mathbf{s}_t,\mathbf{a}_t) &= p(\mathcal{O}_{t:T}|\mathbf{s}_t,\mathbf{a}_t)\\ &= \int p(\mathcal{O}_{t:T},\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)d\mathbf{s}_{t+1}\\ &= \int p(\mathcal{O}_{t+1:T}|\mathbf{s}_{t+1})p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t)d\mathbf{s}_{t+1}\end{aligned}$$

$$p(\mathcal{O}_{t+1:T}|\mathbf{s}_{t+1}) = \int \underbrace{p(\mathcal{O}_{t+1:T}|\mathbf{s}_{t+1},\mathbf{a}_{t+1})}_{\beta_t(\mathbf{s}_{t+1},\mathbf{a}_{t+1})}\cancel{p(\mathbf{a}_{t+1}|\mathbf{s}_{t+1})}d\mathbf{a}_{t+1}$$

which actions are likely *a priori*
(assume uniform for now)

for $t = T-1$ to 1:

$$\beta_t(\mathbf{s}_t,\mathbf{a}_t) = p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t)E_{\mathbf{s}_{t+1}\sim p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}[\beta_{t+1}(\mathbf{s}_{t+1})]$$

$$\beta_t(\mathbf{s}_t) = E_{\mathbf{a}_t\sim p(\mathbf{a}_t|\mathbf{s}_t)}[\beta_t(\mathbf{s}_t,\mathbf{a}_t)]$$

A closer look at the backward pass

for $t = T-1$ to 1:

$$\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_t|\mathbf{s}_t, \mathbf{a}_t) E_{\mathbf{s}_{t+1}\sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}[\beta_{t+1}(\mathbf{s}_{t+1})]$$

$$\beta_t(\mathbf{s}_t) = E_{\mathbf{a}_t\sim p(\mathbf{a}_t|\mathbf{s}_t)}[\beta_t(\mathbf{s}_t, \mathbf{a}_t)]$$

value iteration algorithm:

1. set $Q(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + \gamma E[V(\mathbf{s}')]$
2. set $V(\mathbf{s}) \leftarrow \max_{\mathbf{a}} Q(\mathbf{s}, \mathbf{a})$

let $V_t(\mathbf{s}_t) = \log \beta_t(\mathbf{s}_t)$

let $Q_t(\mathbf{s}_t, \mathbf{a}_t) = \log \beta_t(\mathbf{s}_t, \mathbf{a}_t)$

$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t))d\mathbf{a}_t$$

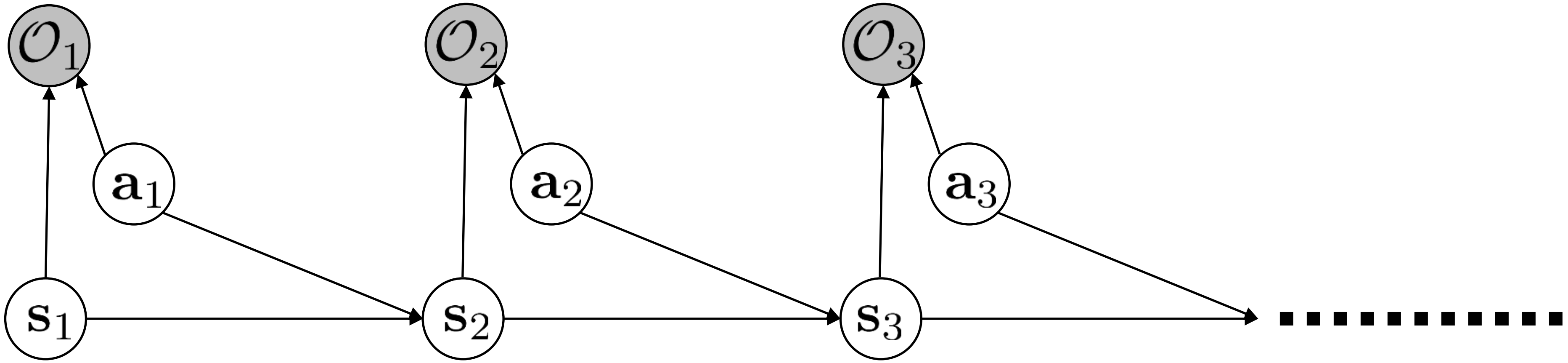
$$V_t(\mathbf{s}_t) \rightarrow \max_{\mathbf{a}_t} Q_t(\mathbf{s}_t, \mathbf{a}_t) \text{ as } Q_t(\mathbf{s}_t, \mathbf{a}_t) \text{ gets bigger!}$$

$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \overbrace{\log E[\exp(V_{t+1}(\mathbf{s}_{t+1}))]}^{\text{“optimistic” transition (not a good idea!)}}$$

deterministic transition: $Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + V_{t+1}(\mathbf{s}_{t+1})$

we'll come back to the stochastic case later!

Backward pass summary



$\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_{t:T} | \mathbf{s}_t, \mathbf{a}_t)$ probability that we can be optimal at steps t through T given that we take action $\mathbf{a}_t$ in state $\mathbf{s}_t$

for $t = T - 1$ to 1:

$\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_t | \mathbf{s}_t, \mathbf{a}_t) E_{\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t)}[\beta_{t+1}(\mathbf{s}_{t+1})]$ compute recursively from $t = T$ to $t = 1$

$\beta_t(\mathbf{s}_t) = E_{\mathbf{a}_t \sim p(\mathbf{a}_t | \mathbf{s}_t)}[\beta_t(\mathbf{s}_t, \mathbf{a}_t)]$

let $V_t(\mathbf{s}_t) = \log \beta_t(\mathbf{s}_t)$

let $Q_t(\mathbf{s}_t, \mathbf{a}_t) = \log \beta_t(\mathbf{s}_t, \mathbf{a}_t)$

log of β_t is "Q-function-like"

The action prior

remember this?

$$p(\mathcal{O}_{t+1:T}|\mathbf{s}_{t+1}) = \int \underbrace{p(\mathcal{O}_{t+1:T}|\mathbf{s}_{t+1},\mathbf{a}_{t+1})}_{\beta_t(\mathbf{s}_{t+1},\mathbf{a}_{t+1})} \cancel{p(\mathbf{a}_{t+1}|\mathbf{s}_{t+1})} d\mathbf{a}_{t+1}$$

(“soft max”)

what if the action prior is not uniform?

$$V(\mathbf{s}_t) = \log \int \exp(Q(\mathbf{s}_t,\mathbf{a}_t) + \log p(\mathbf{a}_t|\mathbf{s}_t))\mathbf{a}_t$$

$$Q(\mathbf{s}_t,\mathbf{a}_t) = r(\mathbf{s}_t,\mathbf{a}_t) + \log E[\exp(V(\mathbf{s}_{t+1}))]$$

$$\text{let } \tilde{Q}(\mathbf{s}_t,\mathbf{a}_t) = r(\mathbf{s}_t,\mathbf{a}_t) + \log p(\mathbf{a}_t|\mathbf{s}_t) + \log E[\exp(V(\mathbf{s}_{t+1}))]$$

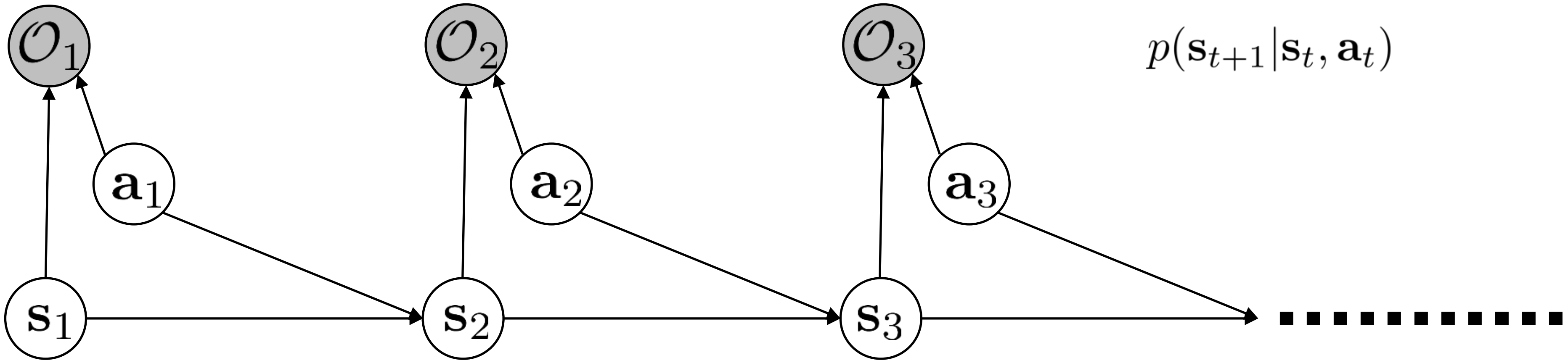
$$V(\mathbf{s}_t) = \log \int \exp(\tilde{Q}(\mathbf{s}_t,\mathbf{a}_t))\mathbf{a}_t \quad \Leftrightarrow \quad V(\mathbf{s}_t) = \log \int \exp(Q(\mathbf{s}_t,\mathbf{a}_t) + \log p(\mathbf{a}_t|\mathbf{s}_t))\mathbf{a}_t$$

can **always** fold the action prior into the reward! uniform action prior can be assumed without loss of generality

Policy computation

$$p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t) \propto \exp(r(\mathbf{s}_t,\mathbf{a}_t))$$

$$p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)$$



2. compute policy $p(\mathbf{a}_t|\mathbf{s}_t,\mathcal{O}_{1:T})$

$$\beta_t(\mathbf{s}_t,\mathbf{a}_t) = p(\mathcal{O}_{t:T}|\mathbf{s}_t,\mathbf{a}_t)$$

$$\beta_t(\mathbf{s}_t) = p(\mathcal{O}_{t:T}|\mathbf{s}_t)$$

$$\begin{aligned}
p(\mathbf{a}_t|\mathbf{s}_t,\mathcal{O}_{1:T}) &= \pi(\mathbf{a}_t|\mathbf{s}_t) \\
&= p(\mathbf{a}_t|\mathbf{s}_t,\mathcal{O}_{t:T}) \\
&= \frac{p(\mathbf{a}_t,\mathbf{s}_t|\mathcal{O}_{t:T})}{p(\mathbf{s}_t|\mathcal{O}_{t:T})} \\
&= \frac{p(\mathcal{O}_{t:T}|\mathbf{a}_t,\mathbf{s}_t)p(\mathbf{a}_t,\mathbf{s}_t)/\cancel{p(\mathcal{O}_{t:T})}}{p(\mathcal{O}_{t:T}|\mathbf{s}_t)p(\mathbf{s}_t)/\cancel{p(\mathcal{O}_{t:T})}} \\
&= \frac{p(\mathcal{O}_{t:T}|\mathbf{a}_t,\mathbf{s}_t)}{p(\mathcal{O}_{t:T}|\mathbf{s}_t)}\frac{p(\mathbf{a}_t,\mathbf{s}_t)}{p(\mathbf{s}_t)} = \frac{\beta_t(\mathbf{s}_t,\mathbf{a}_t)}{\beta_t(\mathbf{s}_t)}\cancel{p(\mathbf{a}_t|\mathbf{s}_t)}
\end{aligned}$$

$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \frac{\beta_t(\mathbf{s}_t,\mathbf{a}_t)}{\beta_t(\mathbf{s}_t)}$$

Policy computation with value functions

for $t = T - 1$ to 1:

$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \log E[\exp(V_{t+1}(\mathbf{s}_{t+1}))]$$

$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t))\mathbf{a}_t$$

$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \frac{\beta_t(\mathbf{s}_t, \mathbf{a}_t)}{\beta_t(\mathbf{s}_t)}$$

$$V_t(\mathbf{s}_t) = \log \beta_t(\mathbf{s}_t)$$

$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = \log \beta_t(\mathbf{s}_t, \mathbf{a}_t)$$

$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t) - V_t(\mathbf{s}_t)) = \exp(A_t(\mathbf{s}_t, \mathbf{a}_t))$$

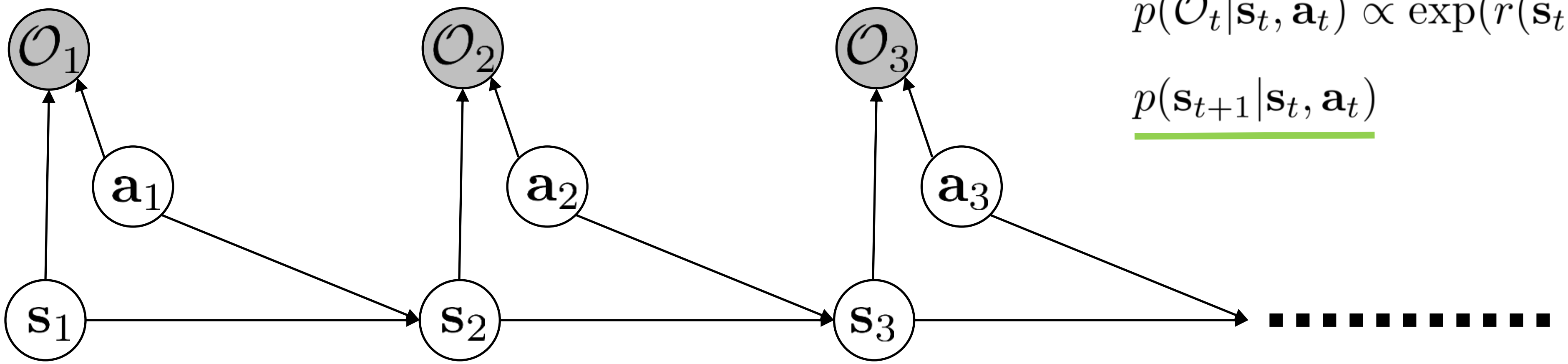
Policy computation summary

$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t) - V_t(\mathbf{s}_t)) = \exp(A_t(\mathbf{s}_t, \mathbf{a}_t))$$

$$\text{with temperature: } \pi(\mathbf{a}_t|\mathbf{s}_t) = \exp(\tfrac{1}{\alpha}Q_t(\mathbf{s}_t, \mathbf{a}_t) - \tfrac{1}{\alpha}V_t(\mathbf{s}_t)) = \exp(\tfrac{1}{\alpha}A_t(\mathbf{s}_t, \mathbf{a}_t))$$

- Natural interpretation: better actions are more probable
- Random tie-breaking
- Analogous to Boltzmann exploration
- Approaches greedy policy as temperature decreases

Forward messages



$$p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t) \propto \exp(r(\mathbf{s}_t,\mathbf{a}_t))$$

$$p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)$$

$\alpha_1(\mathbf{s}_1) = p(\mathbf{s}_1)$ (usually known)

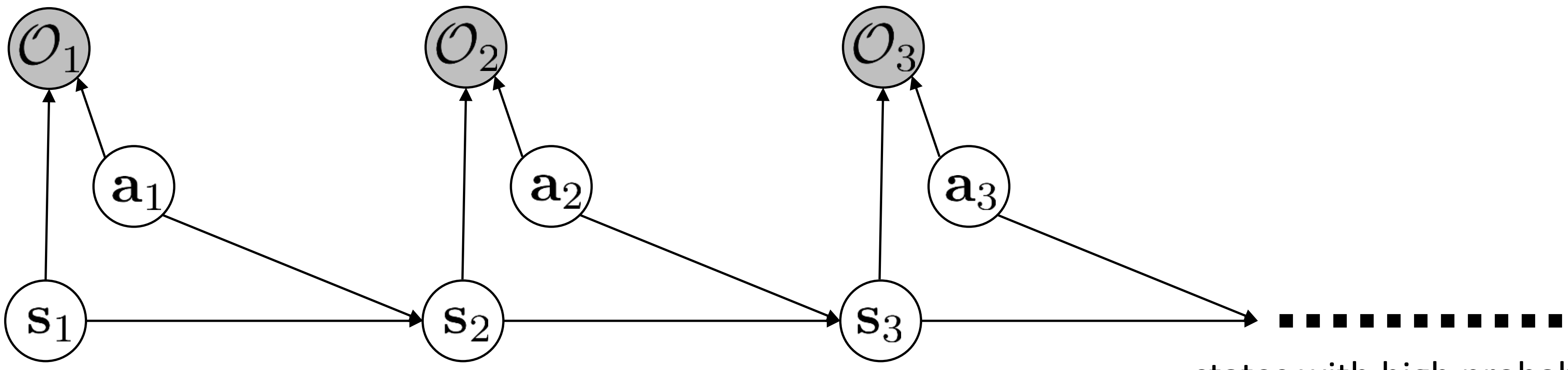
$$\begin{aligned}
\alpha_t(\mathbf{s}_t) &= p(\mathbf{s}_t|\mathcal{O}_{1:t-1}) \\
&= \int p(\mathbf{s}_t,\mathbf{s}_{t-1},\mathbf{a}_{t-1}|\mathcal{O}_{1:t-1})d\mathbf{s}_{t-1}d\mathbf{a}_{t-1} = \int p(\mathbf{s}_t|\mathbf{s}_{t-1},\mathbf{a}_{t-1},\cancel{\mathcal{O}_{1:t-1}})p(\mathbf{a}_{t-1}|\mathbf{s}_{t-1},\mathcal{O}_{1:t-1})p(\mathbf{s}_{t-1}|\mathcal{O}_{1:t-1})d\mathbf{s}_{t-1}d\mathbf{a}_{t-1} \\
&= \int p(\mathbf{s}_t|\mathbf{s}_{t-1},\mathbf{a}_{t-1})p(\mathbf{a}_{t-1}|\mathbf{s}_{t-1},\mathcal{O}_{t-1})p(\mathbf{s}_{t-1}|\mathcal{O}_{1:t-1})d\mathbf{s}_{t-1}d\mathbf{a}_{t-1}
\end{aligned}$$

$$p(\mathbf{a}_{t-1}|\mathbf{s}_{t-1},\mathcal{O}_{t-1})p(s_{t-1}|\mathcal{O}_{1:t-1}) = \frac{p(\mathcal{O}_{t-1}|\mathbf{s}_{t-1},\mathbf{a}_{t-1})p(\mathbf{a}_{t-1}|\mathbf{s}_{t-1})}{\cancel{p(\mathcal{O}_{t-1}|\mathbf{s}_{t-1})}} \frac{\cancel{p(\mathcal{O}_{t-1}|\mathbf{s}_{t-1})}\overbrace{p(\mathbf{s}_{t-1}|\mathcal{O}_{1:t-2})}^{\alpha_{t-1}(\mathbf{s}_{t-1})}}{p(\mathcal{O}_{t-1}|\mathcal{O}_{1:t-2})}$$

what if we want $p(\mathbf{s}_t|\mathcal{O}_{1:T})$?

$$p(\mathbf{s}_t|\mathcal{O}_{1:T}) = \frac{p(\mathbf{s}_t,\mathcal{O}_{1:T})}{p(\mathcal{O}_{1:T})} = \frac{\overbrace{p(\mathcal{O}_{t:T}|\mathbf{s}_t)}^{\beta_t(\mathbf{s}_t)}p(\mathbf{s}_t,\mathcal{O}_{1:t-1})}{p(\mathcal{O}_{1:T})} \propto \beta_t(\mathbf{s}_t)\underbrace{p(\mathbf{s}_t|\mathcal{O}_{1:t-1})}_{\alpha_t(\mathbf{s}_t)}\cancel{p(\mathcal{O}_{1:t-1})} \propto \beta_t(\mathbf{s}_t)\alpha_t(\mathbf{s}_t)$$

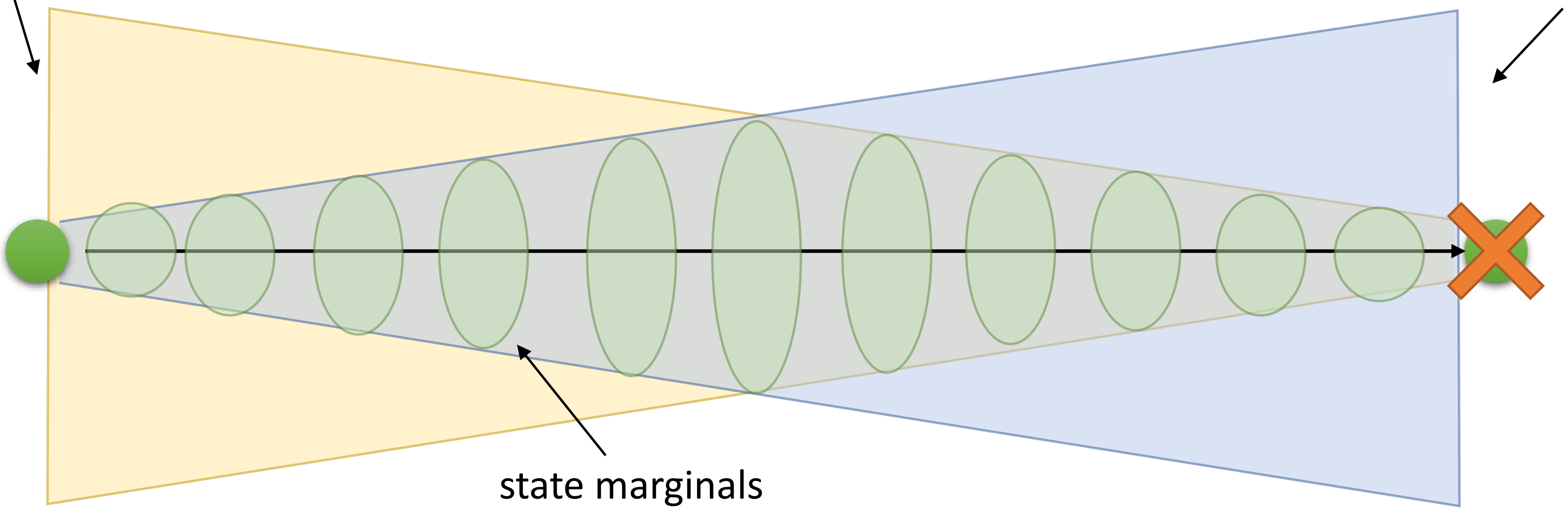
Forward/backward message intersection



states with high probability of reaching goal

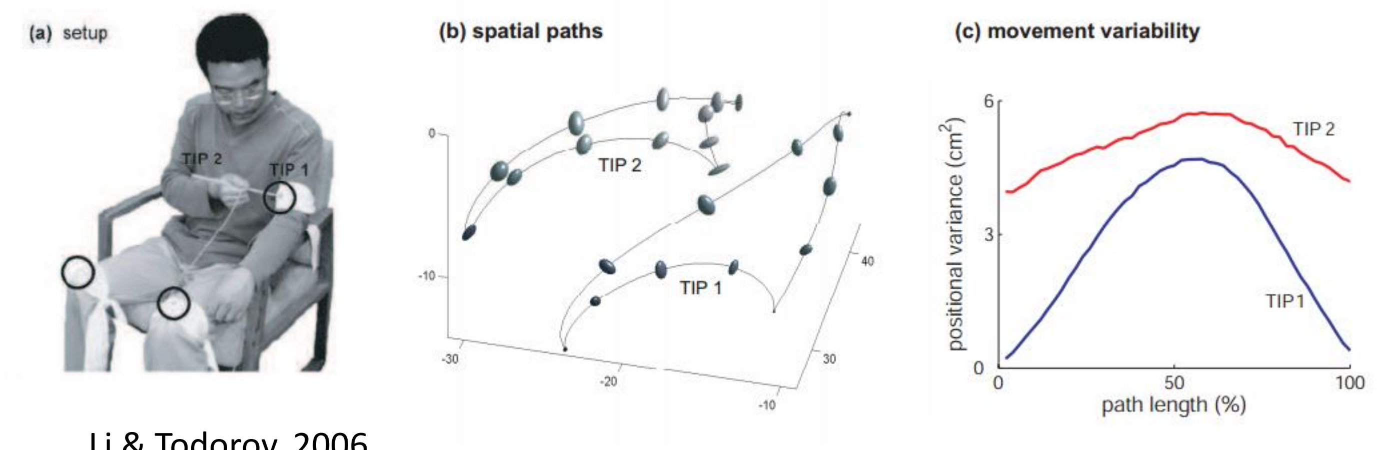
$$p(\mathbf{s}_t) \propto \beta_t(\mathbf{s}_t)\alpha_t(\mathbf{s}_t)$$

states with high probability of being reached from initial state (with high reward)



state marginals

Forward/backward message intersection

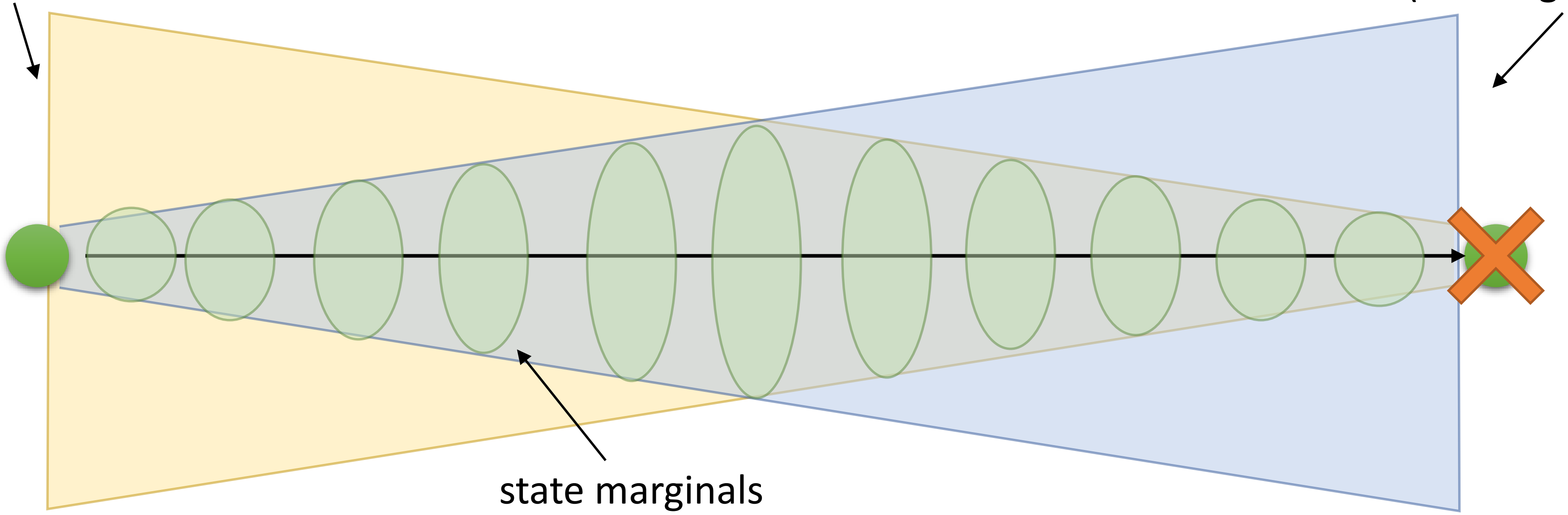


Li & Todorov, 2006

states with high probability of reaching goal

$$p(\mathbf{s}_t) \propto \beta_t(\mathbf{s}_t)\alpha_t(\mathbf{s}_t)$$

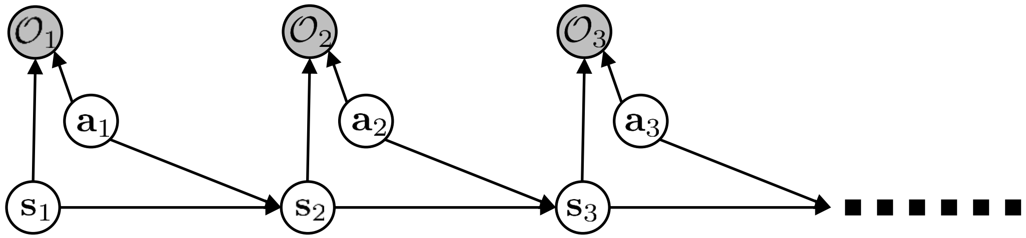
states with high probability of being reached from initial state (with high reward)



state marginals

Summary

1. Probabilistic graphical model for optimal control



2. Control = inference (similar to HMM, EKF, etc.)

3. Very similar to dynamic programming, value iteration, etc. (but “soft”)

Control as **Variational** Inference

The optimism problem

for $t = T-1$ to 1:

$$\beta_t(\mathbf{s}_t, \mathbf{a}_t) = p(\mathcal{O}_t|\mathbf{s}_t, \mathbf{a}_t) E_{\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}[\beta_{t+1}(\mathbf{s}_{t+1})]$$

$$\beta_t(\mathbf{s}_t) = E_{\mathbf{a}_t \sim p(\mathbf{a}_t|\mathbf{s}_t)}[\beta_t(\mathbf{s}_t, \mathbf{a}_t)]$$

let $V_t(\mathbf{s}_t) = \log \beta_t(\mathbf{s}_t)$

let $Q_t(\mathbf{s}_t, \mathbf{a}_t) = \log \beta_t(\mathbf{s}_t, \mathbf{a}_t)$

$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \overbrace{\log E[\exp(V_{t+1}(\mathbf{s}_{t+1}))]}^{\text{"optimistic" transition (not a good idea!)}}$$

why did this happen?

the inference problem: $p(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}|\mathcal{O}_{1:T})$

marginalizing and conditioning, we get: $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T})$ (the policy)

"given that you obtained high reward, what was your action probability?"

marginalizing and conditioning, we get: $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \mathcal{O}_{1:T}) \neq p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$

"given that you obtained high reward, what was your transition probability?"

Addressing the optimism problem

marginalizing and conditioning, we get: $p(\mathbf{a}_t|\mathbf{s}_t, \mathcal{O}_{1:T})$ (the policy) ⟵ we want this

"given that you obtained high reward, what was your action probability?"

marginalizing and conditioning, we get: $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t, \mathcal{O}_{1:T}) \neq p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ ⟵ but not this!

"given that you obtained high reward, what was your transition probability?"

"given that you obtained high reward, what was your action probability, *given that your transition probability did not change*?"

can we find another distribution $q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$ that is close to $p(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}|\mathcal{O}_{1:T})$ but has dynamics $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$

where have we seen this before?

let $\mathbf{x} = \mathcal{O}_{1:T}$ and $\mathbf{z} = (\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$ find $q(\mathbf{z})$ to approximate $p(\mathbf{z}|\mathbf{x})$

let's try variational inference!

Control via variational inference

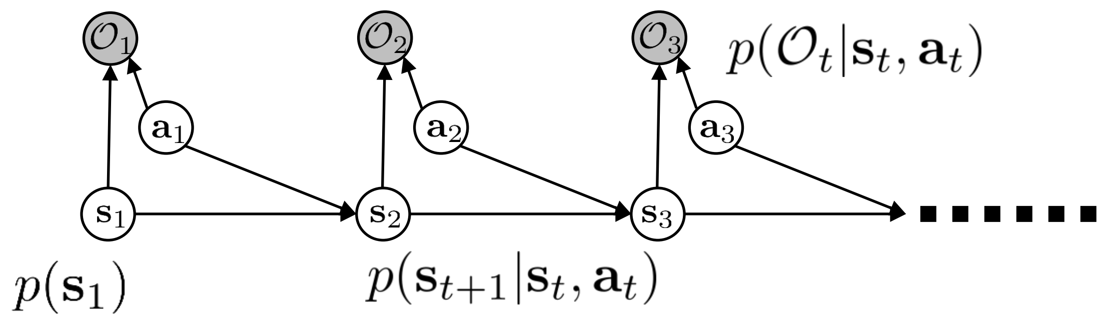
let $q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}) = p(\mathbf{s}_1) \prod_t p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) q(\mathbf{a}_t|\mathbf{s}_t)$

same dynamics and initial state as p

only new thing

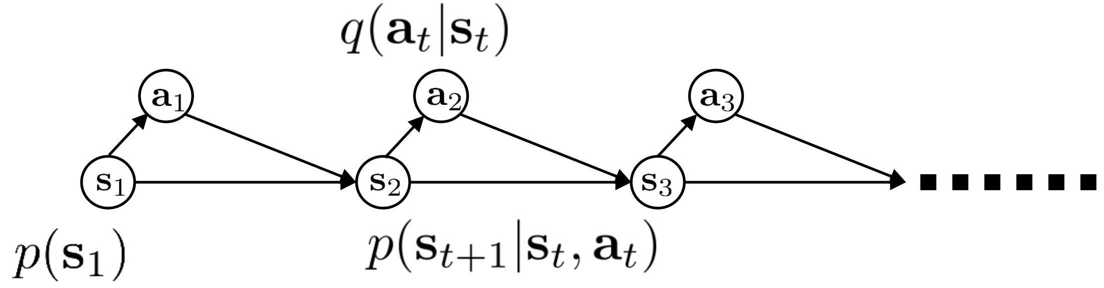
let $\mathbf{x} = \mathcal{O}_{1:T}$ and $\mathbf{z} = (\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$

$p(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}|\mathcal{O}_{1:T})$



$p(\mathbf{z}|\mathbf{x})$

$q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$



$q(\mathbf{z})$

The variational lower bound

$$\log p(\mathbf{x}) \geq E_{\mathbf{z}\sim q(\mathbf{z})}[\log p(\mathbf{x},\mathbf{z}) - \log q(\mathbf{z})]$$

let $\mathbf{x} = \mathcal{O}_{1:T}$ and $\mathbf{z} = (\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$

the entropy $\mathcal{H}(q)$

let $q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}) = \underline{p(\mathbf{s}_1)} \underline{\prod_t p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)} q(\mathbf{a}_t|\mathbf{s}_t)$

$$\log p(\mathcal{O}_{1:T}) \geq E_{(\mathbf{s}_{1:T},\mathbf{a}_{1:T})\sim q}\Big[\cancel{\log p(\mathbf{s}_1)} + \sum_{t=1}^{T} \cancel{\log p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)} + \sum_{t=1}^{T} \log p(\mathcal{O}_t|\mathbf{s}_t,\mathbf{a}_t)$$

$$\underline{- \cancel{\log p(\mathbf{s}_1)}} - \underline{\sum_{t=1}^{T} \cancel{\log p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}} - \sum_{t=1}^{T} \log q(\mathbf{a}_t|\mathbf{s}_t)\Big]$$

$$= E_{(\mathbf{s}_{1:T},\mathbf{a}_{1:T})\sim q}\left[\sum_t r(\mathbf{s}_t,\mathbf{a}_t) - \log q(\mathbf{a}_t|\mathbf{s}_t)\right]$$

$$= \sum_t E_{(\mathbf{s}_t,\mathbf{a}_t)\sim q}[r(\mathbf{s}_t,\mathbf{a}_t) + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t))]$$

maximize reward and maximize action entropy!

Optimizing the variational lower bound

let $q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T}) = p(\mathbf{s}_1) \prod_t p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t) q(\mathbf{a}_t|\mathbf{s}_t)$

$$\log p(\mathcal{O}_{1:T}) \geq \sum_t E_{(\mathbf{s}_t, \mathbf{a}_t) \sim q} \left[r(\mathbf{s}_t, \mathbf{a}_t) + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t)) \right]$$

base case: solve for $q(\mathbf{a}_T|\mathbf{s}_T)$:

$$q(\mathbf{a}_T|\mathbf{s}_T) = \arg\max E_{\mathbf{s}_T \sim q(\mathbf{s}_T)} \left[E_{\mathbf{a}_T \sim q(\mathbf{a}_T|\mathbf{s}_T)} [r(\mathbf{s}_T, \mathbf{a}_T)] + \mathcal{H}(q(\mathbf{a}_T|\mathbf{s}_T)) \right]$$

$$= \arg\max E_{\mathbf{s}_T \sim q(\mathbf{s}_T)} \left[E_{\mathbf{a}_T \sim q(\mathbf{a}_T|\mathbf{s}_T)} [r(\mathbf{s}_T, \mathbf{a}_T) - \log q(\mathbf{a}_T|\mathbf{s}_T)] \right]$$

optimized when $q(\mathbf{a}_T|\mathbf{s}_T) \propto \exp(r(\mathbf{s}_T, \mathbf{a}_T))$

$$q(\mathbf{a}_T|\mathbf{s}_T) = \frac{\exp(r(\mathbf{s}_T, \mathbf{a}_T))}{\int \exp(r(\mathbf{s}_T, \mathbf{a})) d\mathbf{a}} = \exp(Q(\mathbf{s}_T, \mathbf{a}_T) - V(\mathbf{s}_T))$$

$$V(\mathbf{s}_T) = \log \int \exp(Q(\mathbf{s}_T, \mathbf{a}_T)) d\mathbf{a}_T$$

$$E_{\mathbf{s}_T \sim q(\mathbf{s}_T)} \left[E_{\mathbf{a}_T \sim q(\mathbf{a}_T|\mathbf{s}_T)} [r(\mathbf{s}_T, \mathbf{a}_T) - \log q(\mathbf{a}_T|\mathbf{s}_T)] \right] = E_{\mathbf{s}_T \sim q(\mathbf{s}_T)} \left[E_{\mathbf{a}_T \sim q(\mathbf{a}_T|\mathbf{s}_T)} [V(\mathbf{s}_T)] \right]$$

Optimizing the variational lower bound

$$\log p(\mathcal{O}_{1:T}) \geq \sum_t E_{(\mathbf{s}_t,\mathbf{a}_t)\sim q}\left[r(\mathbf{s}_t,\mathbf{a}_t) + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t))\right]$$

$$q(\mathbf{a}_T|\mathbf{s}_T) = \frac{\exp(r(\mathbf{s}_T,\mathbf{a}_T))}{\int \exp(r(\mathbf{s}_T,\mathbf{a}))d\mathbf{a}} = \exp(Q(\mathbf{s}_T,\mathbf{a}_T) - V(\mathbf{s}_T))$$

$$E_{\mathbf{s}_T\sim q(\mathbf{s}_T)}\left[E_{\mathbf{a}_T\sim q(\mathbf{a}_T|\mathbf{s}_T)}[r(\mathbf{s}_T,\mathbf{a}_T) - \log q(\mathbf{a}_T|\mathbf{s}_T)]\right] = E_{\mathbf{s}_T\sim q(\mathbf{s}_T)}\left[E_{\mathbf{a}_T\sim q(\mathbf{a}_T|\mathbf{s}_T)}[V(\mathbf{s}_T)]\right]$$

$$\begin{aligned}
q(\mathbf{a}_t|\mathbf{s}_t) &= \arg\max E_{\mathbf{s}_t\sim q(\mathbf{s}_t)}\left[E_{\mathbf{a}_t\sim q(\mathbf{a}_t|\mathbf{s}_t)}[r(\mathbf{s}_t,\mathbf{a}_t) + E_{\mathbf{s}_{t+1}\sim p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}[V(\mathbf{s}_{t+1})]] + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t))\right] \\
&= \arg\max E_{\mathbf{s}_t\sim q(\mathbf{s}_t)}\left[E_{\mathbf{a}_t\sim q(\mathbf{a}_t|\mathbf{s}_t)}[Q(\mathbf{s}_t,\mathbf{a}_t)] + \mathcal{H}(q(\mathbf{a}_t|\mathbf{s}_t))\right] \\
&= \arg\max E_{\mathbf{s}_t\sim q(\mathbf{s}_t)}\left[E_{\mathbf{a}_t\sim q(\mathbf{a}_t|\mathbf{s}_t)}[Q(\mathbf{s}_t,\mathbf{a}_t) - \log q(\mathbf{a}_t|\mathbf{s}_t)]\right]
\end{aligned}$$

optimized when $q(\mathbf{a}_t|\mathbf{s}_t) \propto \exp(Q(\mathbf{s}_t,\mathbf{a}_t))$

regular Bellman backup

not optimistic

$$Q_t(\mathbf{s}_t,\mathbf{a}_t) = r(\mathbf{s}_t,\mathbf{a}_t) + E[(V_{t+1}(\mathbf{s}_{t+1})]$$

$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t,\mathbf{a}_t))d\mathbf{a}_t$$

$$q(\mathbf{a}_t|\mathbf{s}_t) = \exp(Q(\mathbf{s}_t,\mathbf{a}_t) - V(\mathbf{s}_t))$$

Backward pass summary - variational

for $t = T - 1$ to 1:

$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + E[(V_{t+1}(\mathbf{s}_{t+1})]$$

$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t)) d\mathbf{a}_t$$

value iteration algorithm:

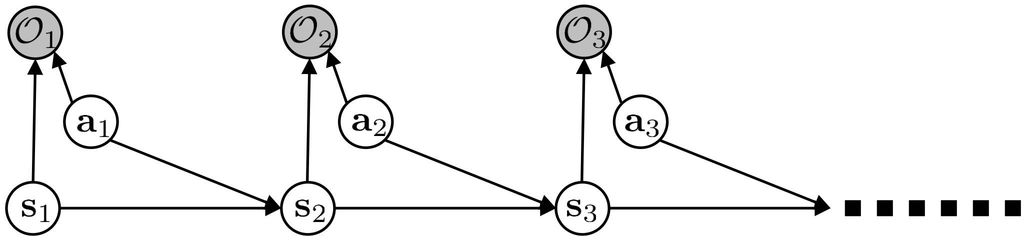
1. set $Q(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + \gamma E[V(\mathbf{s}')]$
2. set $V(\mathbf{s}) \leftarrow \max_{\mathbf{a}} Q(\mathbf{s}, \mathbf{a})$

soft value iteration algorithm:

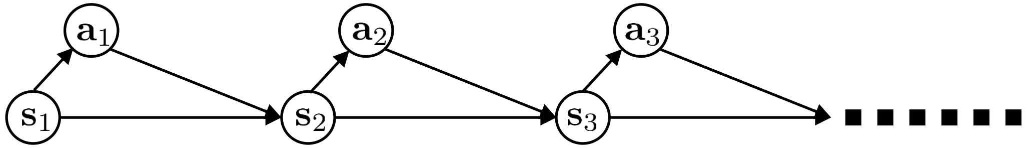
1. set $Q(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + \gamma E[V(\mathbf{s}')]$
2. set $V(\mathbf{s}) \leftarrow \text{soft}\max_{\mathbf{a}} Q(\mathbf{s}, \mathbf{a})$

Summary

$$p(\mathbf{s}_{1:T}, \mathbf{a}_{1:T} | \mathcal{O}_{1:T})$$



$$q(\mathbf{s}_{1:T}, \mathbf{a}_{1:T})$$



$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t)) d\mathbf{a}_t \qquad Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + E[(V_{t+1}(\mathbf{s}_{t+1})]$$

variants:

discounted SOC: $Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \gamma E[V_{t+1}(\mathbf{s}_{t+1})]$

explicit temperature: $V_t(\mathbf{s}_t) = \alpha \log \int \exp\left(\frac{1}{\alpha} Q_t(\mathbf{s}_t, \mathbf{a}_t)\right) d\mathbf{a}_t$

For more details, see: Levine. (2018). Reinforcement Learning and Control as Probabilistic Inference: Tutorial and Review.

Algorithms for RL as Inference

Q-learning with soft optimality

standard Q-learning: $\phi \leftarrow \phi + \alpha \nabla_\phi Q_\phi(\mathbf{s},\mathbf{a})(r(\mathbf{s},\mathbf{a}) + \gamma V(\mathbf{s}') - Q_\phi(\mathbf{s},\mathbf{a}))$

target value: $V(\mathbf{s}') = \max_{\mathbf{a}'} Q_\phi(\mathbf{s}',\mathbf{a}')$

soft Q-learning: $\phi \leftarrow \phi + \alpha \nabla_\phi Q_\phi(\mathbf{s},\mathbf{a})(r(\mathbf{s},\mathbf{a}) + \gamma V(\mathbf{s}') - Q_\phi(\mathbf{s},\mathbf{a}))$

target value: $V(\mathbf{s}') = \text{soft}\max_{\mathbf{a}'} Q_\phi(\mathbf{s}',\mathbf{a}') = \log \int \exp(Q_\phi(\mathbf{s}',\mathbf{a}'))d\mathbf{a}'$

$\pi(\mathbf{a}|\mathbf{s}) = \exp(Q_\phi(\mathbf{s},\mathbf{a}) - V(\mathbf{s})) = \exp(A(\mathbf{s},\mathbf{a}))$

1. take some action $\mathbf{a}_i$ and observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$, add it to $\mathcal{R}$
2. sample mini-batch $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\}$ from $\mathcal{R}$ uniformly
3. compute $y_j = r_j + \gamma \text{soft}\max_{\mathbf{a}'_j} Q_{\phi'}(\mathbf{s}'_j, \mathbf{a}'_j)$ using *target* network $Q_{\phi'}$
4. $\phi \leftarrow \phi - \alpha \sum_j \frac{dQ_\phi}{d\phi}(\mathbf{s}_j, \mathbf{a}_j)(Q_\phi(\mathbf{s}_j, \mathbf{a}_j) - y_j)$
5. update ϕ': copy ϕ every N steps, or Polyak average $\phi' \leftarrow \tau\phi' + (1-\tau)\phi$

Policy gradient with soft optimality

$$\pi(\mathbf{a}|\mathbf{s}) = \exp(Q_\phi(\mathbf{s},\mathbf{a}) - V(\mathbf{s})) \text{ optimizes } \sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t)] + \underbrace{E_{\pi(\mathbf{s}_t)}[\mathcal{H}(\pi(\mathbf{a}_t|\mathbf{s}_t))]}_{\text{policy entropy}}$$

intuition: $\pi(\mathbf{a}|\mathbf{s}) \propto \exp(Q_\phi(\mathbf{s},\mathbf{a}))$ when π minimizes $D_{\mathrm{KL}}(\pi(\mathbf{a}|\mathbf{s}) \| \frac{1}{Z}\exp(Q(\mathbf{s},\mathbf{a})))$

$$D_{\mathrm{KL}}(\pi(\mathbf{a}|\mathbf{s}) \| \tfrac{1}{Z}\exp(Q(\mathbf{s},\mathbf{a}))) = E_{\pi(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] - \mathcal{H}(\pi)$$

often referred to as “entropy regularized” policy gradient

combats premature entropy collapse

turns out to be closely related to soft Q-learning:
see Haarnoja et al. ‘17 and Schulman et al. ‘17

Ziebart et al. ‘10 “Modeling Interaction via the Principle of Maximum Causal Entropy”

Policy gradient vs Q-learning

policy gradient derivation:

$$J(\theta) = \sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t)] + E_{\pi(\mathbf{s}_t)}[\underbrace{\mathcal{H}(\pi(\mathbf{a}|\mathbf{s}_t))}_{E_{\pi(\mathbf{a}_t|\mathbf{s}_t)}[-\log \pi(\mathbf{a}_t|\mathbf{s}_t)]}] = \sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t) - \log \pi(\mathbf{a}_t|\mathbf{s}_t)]$$

$$\nabla_\theta \left[\sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t) - \underline{\log \pi(\mathbf{a}_t|\mathbf{s}_t)}] \right]$$

can ignore (baseline)

$$\approx \frac{1}{N}\sum_i \sum_t \nabla_\theta \log \pi(\mathbf{a}_t|\mathbf{s}_t) \left(r(\mathbf{s}_t,\mathbf{a}_t) + \underbrace{\left(\sum_{t'=t+1}^{T} r(\mathbf{s}_{t'},\mathbf{a}_{t'}) - \log \pi(\mathbf{a}_{t'}|\mathbf{s}_{t'}) \right)}_{\approx Q(\mathbf{s}_{t+1},\mathbf{a}_{t+1})} - \log \pi(\mathbf{a}_t|\mathbf{s}_t) - \cancel{1} \right)$$

recall: $\log \pi(\mathbf{a}_t|\mathbf{s}_t) = Q(\mathbf{s}_t,\mathbf{a}_t) - V(\mathbf{s}_t)$

$$\approx \frac{1}{N}\sum_i \sum_t \underline{(\nabla_\theta Q(\mathbf{a}_t|\mathbf{s}_t) - \nabla_\theta V(\mathbf{s}_t))} \left(r(\mathbf{s}_t,\mathbf{a}_t) + Q(\mathbf{s}_{t+1},\mathbf{a}_{t+1}) - Q(\mathbf{s}_t,\mathbf{a}_t) + \cancel{V(\mathbf{s}_t)} \right)$$

Q-learning $$-\frac{1}{N}\sum_i \sum_t \underline{\nabla_\theta Q(\mathbf{a}_t|\mathbf{s}_t)} \left(r(\mathbf{s}_t,\mathbf{a}_t) + \underline{\operatorname{soft}\max_{\mathbf{a}_{t+1}} Q(\mathbf{s}_{t+1},\mathbf{a}_{t+1})} - Q(\mathbf{s}_t,\mathbf{a}_t) \right)$$

descent (vs ascent)

off-policy correction

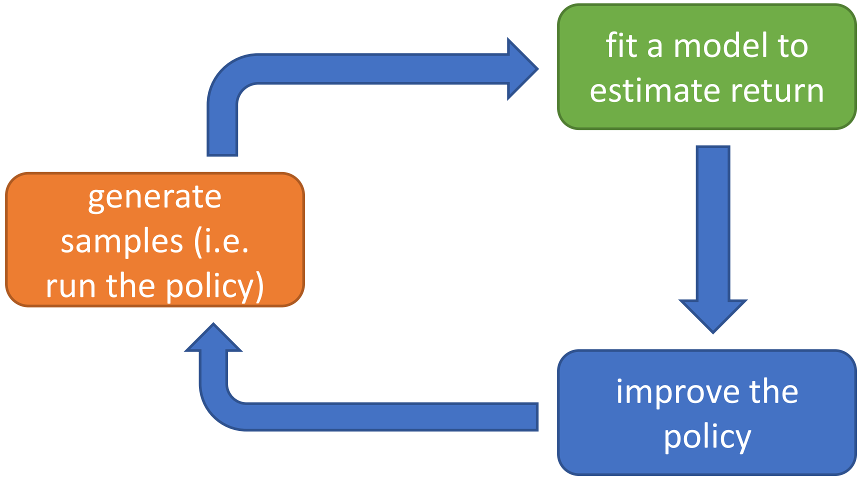
Benefits of soft optimality

- Improve exploration and prevent entropy collapse
- Easier to specialize (finetune) policies for more specific tasks
- Principled approach to break ties
- Better robustness (due to wider coverage of states)
- Can reduce to hard optimality as reward magnitude increases
- Good model for modeling human behavior (more on this later)

Review

- Reinforcement learning can be viewed as inference in a graphical model
    - Value function is a backward message
    - Maximize reward and entropy (the bigger the rewards, the less entropy matters)
    - Variational inference to remove optimism
- Soft Q-learning
- Entropy-regularized policy gradient

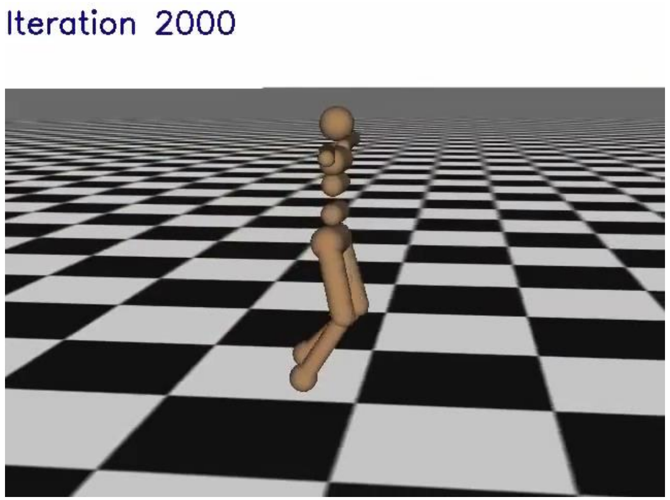
$$Q_\phi(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + \gamma \text{soft max}_{\mathbf{a}'} Q_\phi(\mathbf{s}', \mathbf{a}')$$

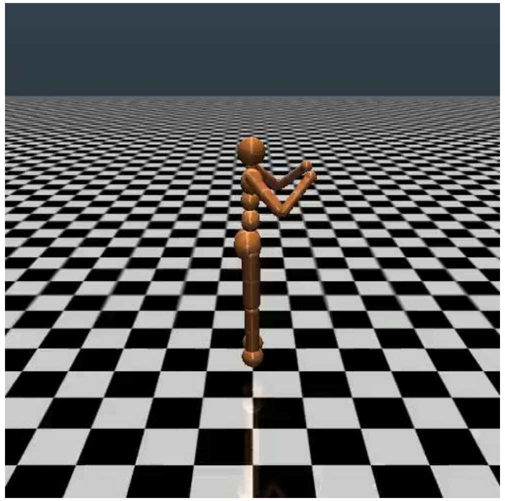


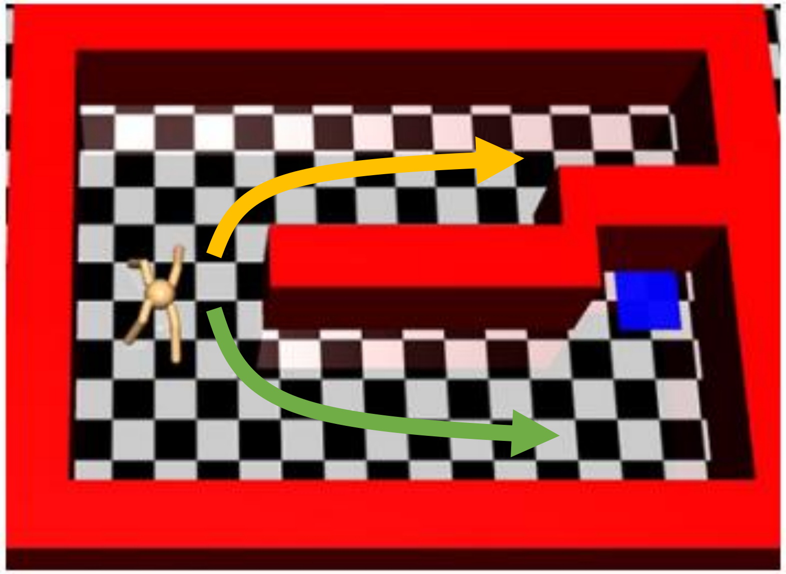
$$\mathbf{a} = \arg\max_{\mathbf{a}} Q_\phi(\mathbf{s}, \mathbf{a})$$

Example Methods

Stochastic models for learning control



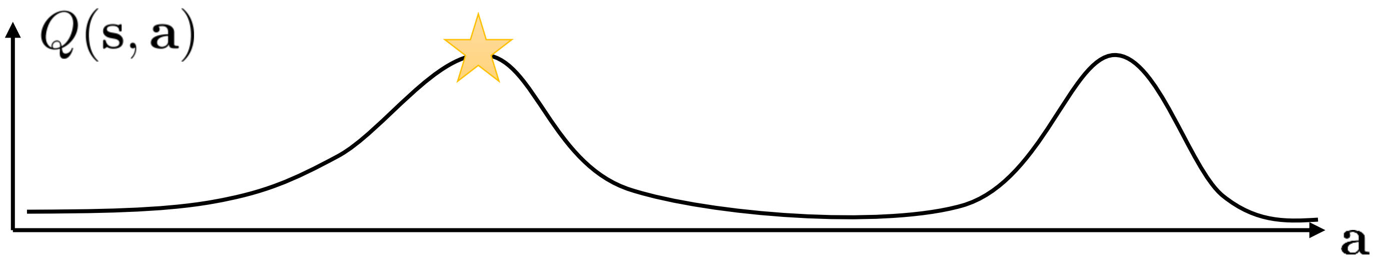


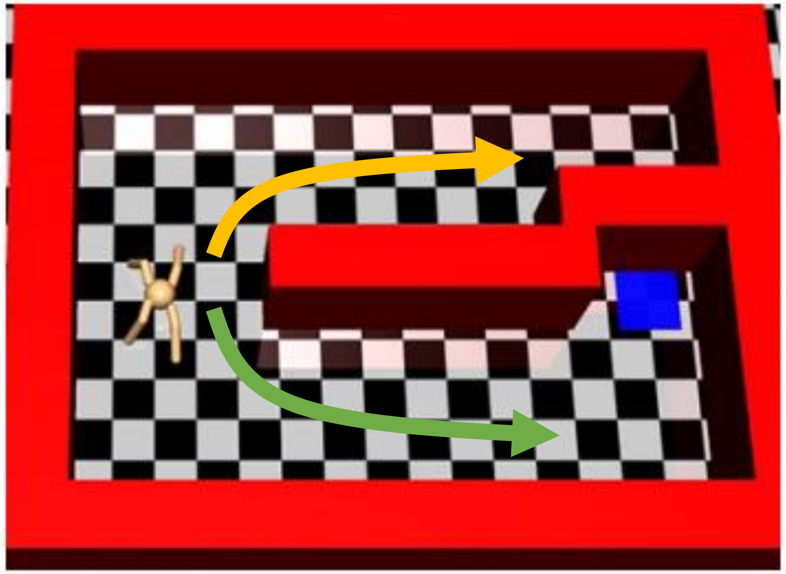


- How can we track *both* hypotheses?

Stochastic energy-based policies

Q-function: $Q(\mathbf{s}, \mathbf{a}) : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$





$$\pi(\mathbf{a}|\mathbf{s}) \propto \exp(Q(\mathbf{s}, \mathbf{a}))$$

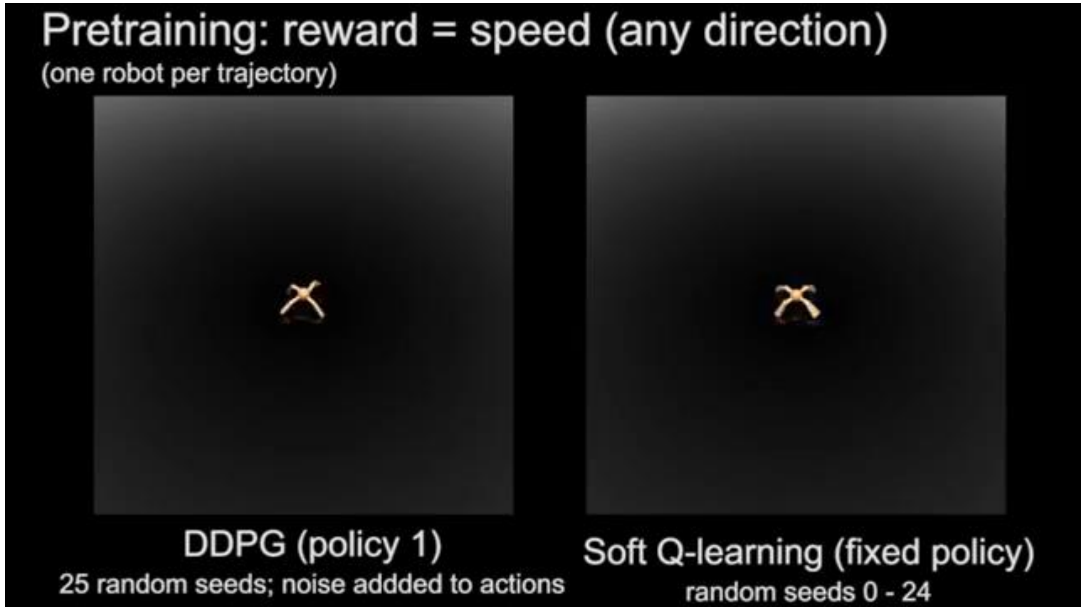
$$\pi(\mathbf{a}_t|\mathbf{s}_t) = \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t) - V_t(\mathbf{s}_t)) = \exp(A_t(\mathbf{s}_t, \mathbf{a}_t))$$

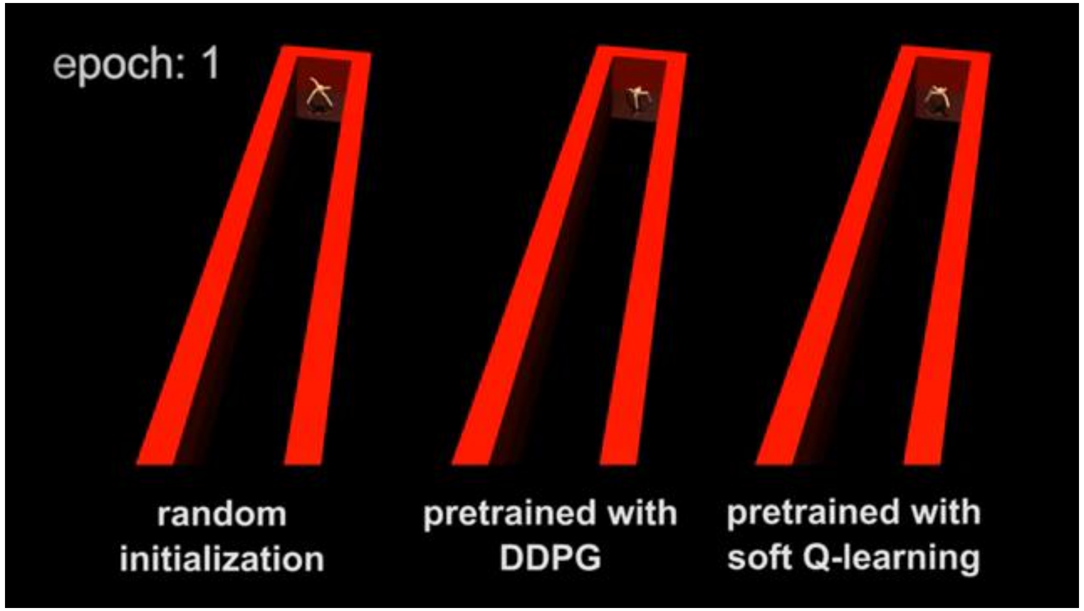
$$Q_t(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + E[V_{t+1}(\mathbf{s}_{t+1})]$$

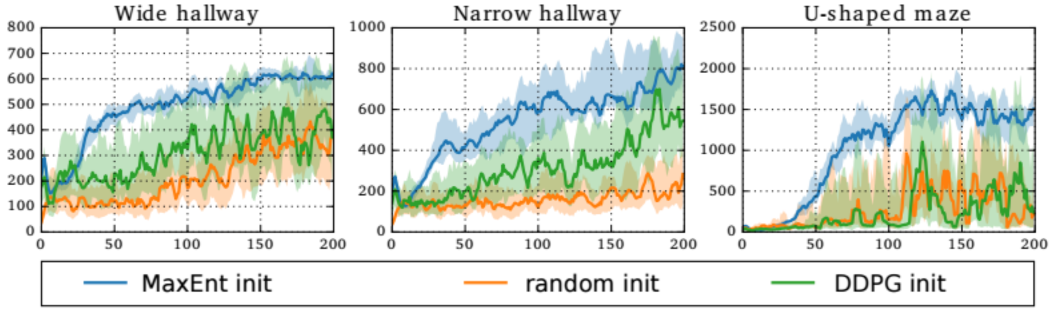
$$V_t(\mathbf{s}_t) = \log \int \exp(Q_t(\mathbf{s}_t, \mathbf{a}_t))\mathbf{a}_t$$

Haarnoja*, Tang*, Abbeel, L., Reinforcement Learning with Deep Energy-Based Policies. ICML 2017

Stochastic energy-based policies provide pretraining







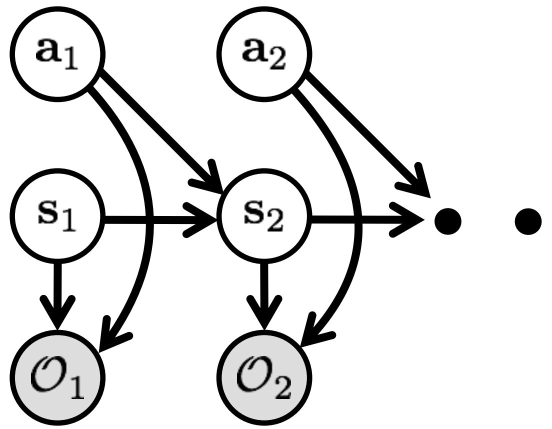
Soft actor-critic

1. Q-function update

Update Q-function to evaluate current policy:

$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + \mathbb{E}_{\mathbf{s}'\sim p_{\mathbf{s}},\ \mathbf{a}'\sim\pi}\left[Q(\mathbf{s}',\mathbf{a}') - \log\pi(\mathbf{a}'|\mathbf{s}')\right]$$

This converges to Q^{π}.



update messages

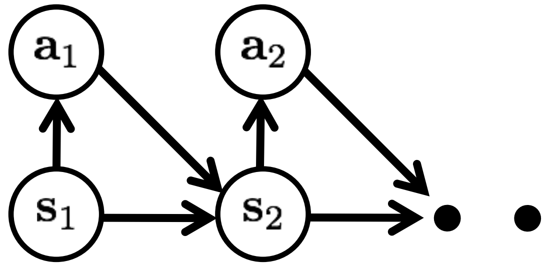
2. Update policy

Update the policy with gradient of information projection:

$$\pi_{\text{new}} = \arg\min_{\pi'} \mathrm{D}_{\mathrm{KL}}\left(\pi'(\,\cdot\,|\mathbf{s})\ \middle\|\ \frac{1}{Z}\exp Q^{\pi_{\text{old}}}(\mathbf{s},\,\cdot\,)\right)$$

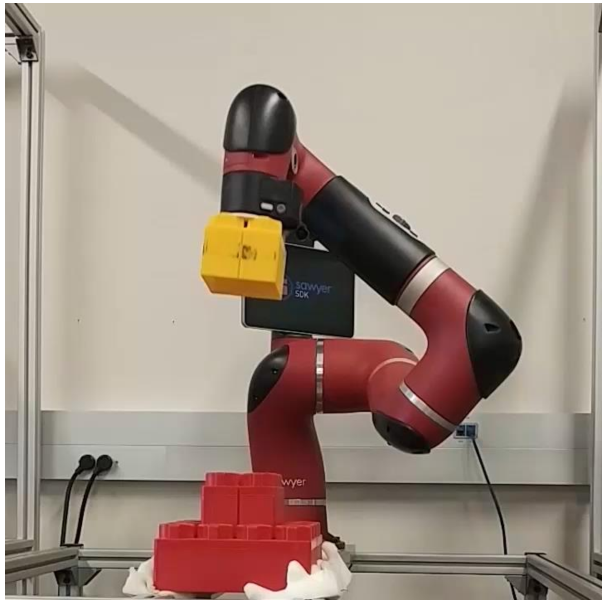
In practice, only take one gradient step on this objective

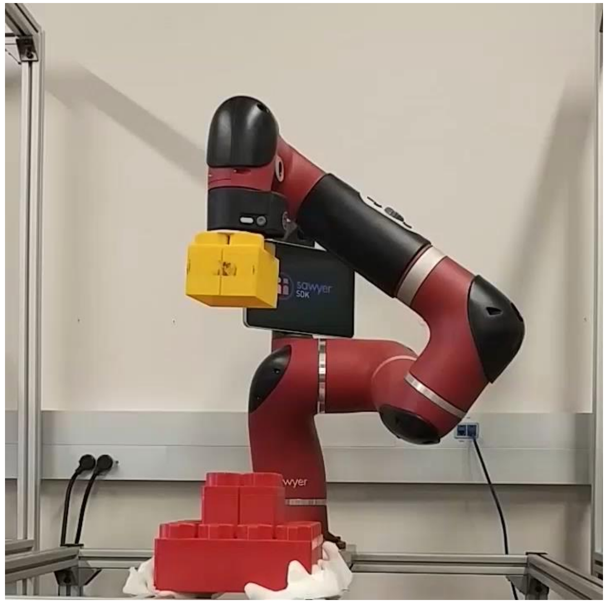
fit variational distribution

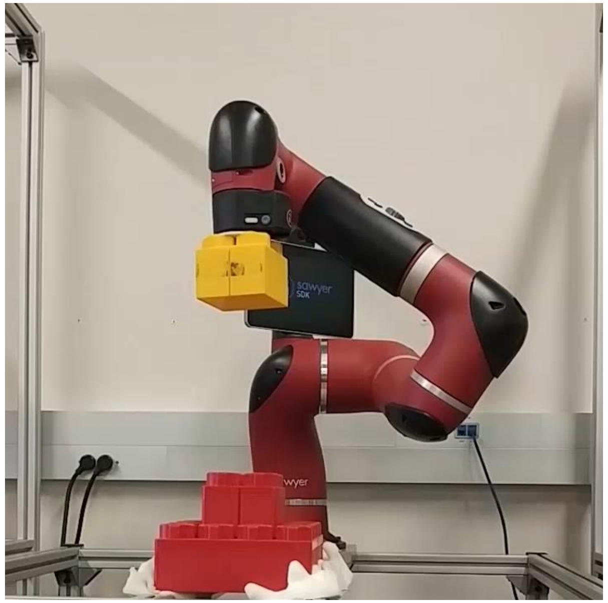


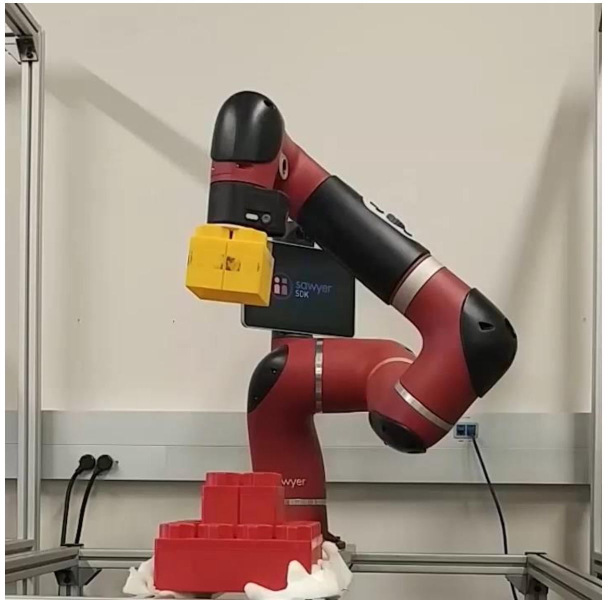
3. Interact with the world, collect more data

Haarnoja, Zhou, Hartikainen, Tucker, Ha, Tan, Kumar, Zhu, Gupta, Abbeel, L. **Soft Actor-Critic Algorithms and Applications**. ‘18









0 min

12 min

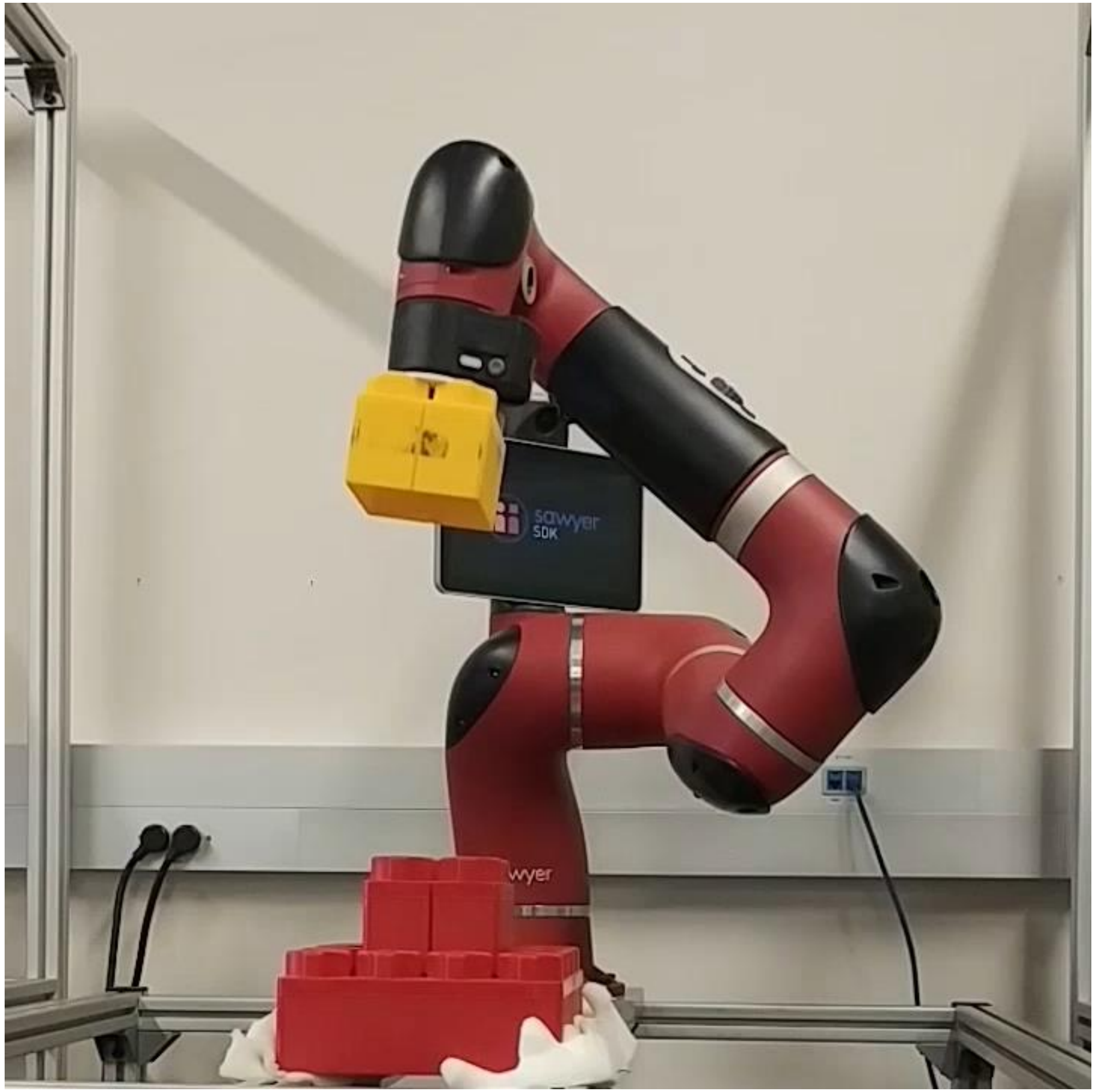
30 min

2 hours

Training time

sites.google.com/view/composing-real-world-policies/

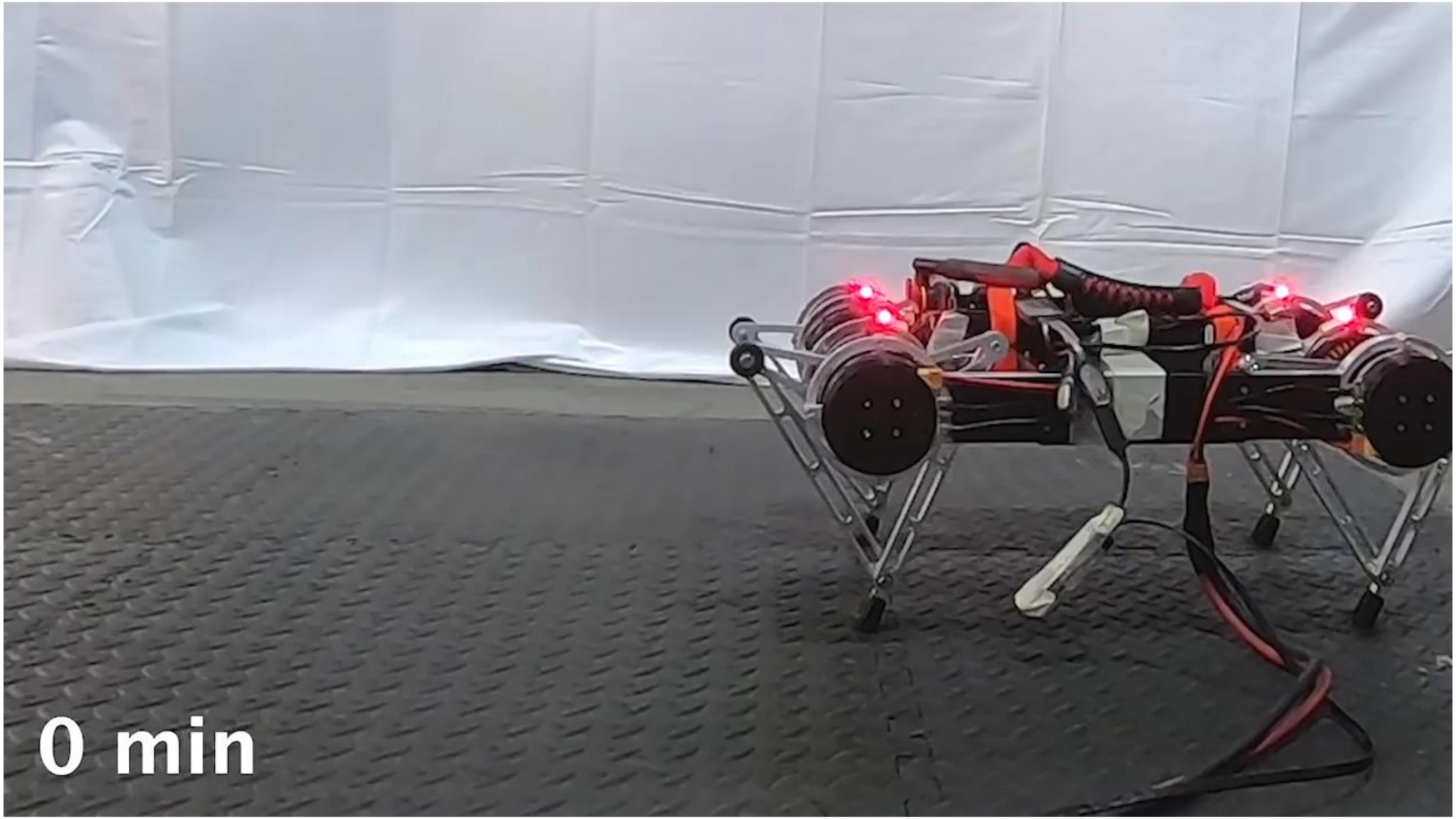
Haarnoja, Pong, Zhou, Dalal, Abbeel, L. **Composable Deep Reinforcement Learning for Robotic Manipulation**. ‘18



After 2 hours of training

sites.google.com/view/composing-real-world-policies/

Haarnoja, Pong, Zhou, Dalal, Abbeel, L. **Composable Deep Reinforcement Learning for Robotic Manipulation**. ‘18



Haarnoja, Zhou, Ha, Tan, Tucker, L. **Learning to Walk via Deep Reinforcement Learning**. ‘19

Haarnoja, Zhou, Ha, Tan, Tucker, L. **Learning to Walk via Deep Reinforcement Learning**. ‘19

Soft optimality suggested readings

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- Kappen. (2009). Optimal control as a graphical model inference problem: frames control as an inference problem in a graphical model.
- Ziebart. (2010). Modeling interaction via the principle of maximal causal entropy: connection between soft optimality and maximum entropy modeling.
- Rawlik, Toussaint, Vijaykumar. (2013). On stochastic optimal control and reinforcement learning by approximate inference: temporal difference style algorithm with soft optimality.
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- Nachum, Norouzi, Xu, Schuurmans. (2017). Bridging the gap between value and policy based reinforcement learning.
- Schulman, Abbeel, Chen. (2017). Equivalence between policy gradients and soft Q-learning.
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- Levine. (2018). Reinforcement Learning and Control as Probabilistic Inference: Tutorial and Review

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