

1.  $(s, A, T, R)$  MDPs

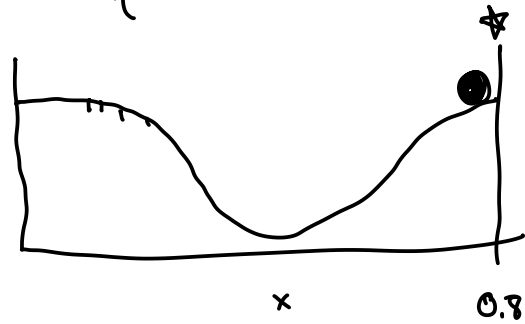
2. reset! RL  
step!  
actions

1. Exploration + Exploitation ←

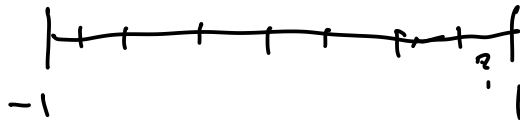
2. Credit Assignment ←

3. Generalization ←

$s', r, done, info = step!(s, a)$   
↑



$s' = [0.76, 0.01]$

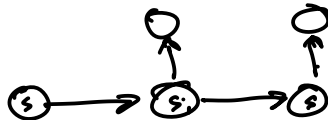


# Review

POMDP - MDP, but only observe  $o$   
make decisions based on  $h_t = (o, \dots, a_t)$

HMM

state dynamics  $T$   
observation model  $Z$



$$b_t(s) = p(s_t = s | h_t)$$

$$b' = \tau(b, o)$$

↑ "Update Belief"

Discrete Bayesian  
Particle Filters ← Discrete Continuous  
↑  $O(n)$

Today:

1. More Efficient belief updates on high-dim continuous spaces
2. How is the POMDP Value function related to beliefs?
3. What do POMDP policies look like

Exact if Linear, Gaussian Noise Dynamics + Observations

$$s' \sim N(As + \underset{z}{b}, V) \quad o \sim (Cs' + \underset{d}{d}, W) \quad s_0 \sim N(\mu_0, \Sigma_0)$$

Kalman Filter

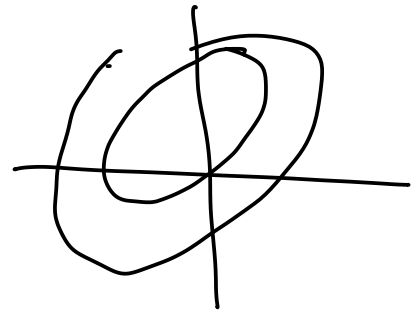
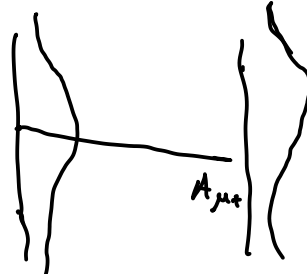
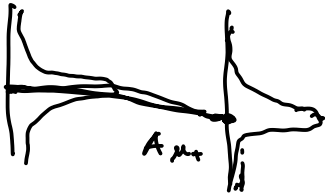
5044

$$b_t = N(\mu_t, \Sigma_t)$$

$$\Sigma_{t+1} = A \Sigma_t ( \Sigma_t C^T (C \Sigma_t C^T + W)^{-1} C \Sigma_t ) A^T + V$$

$$K = A \Sigma_t C^T (C \Sigma_t C^T + W)^{-1}$$

$$\mu_{t+1} = A \mu_t + K(o - C \mu_t)$$



Works for nonlinear? Yes, as long as unimodal



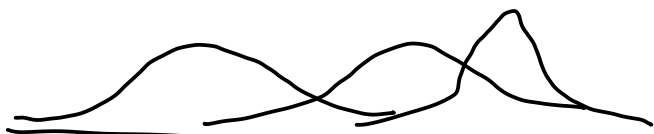
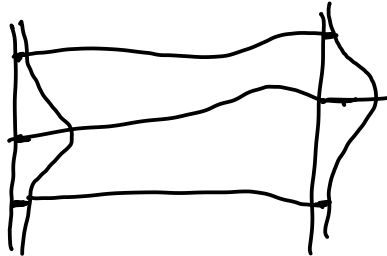
EKF Linearize Dynamics

$$s' = f(s, w) \quad \leftarrow A$$

$$s' \approx f(\hat{s}) + \frac{\partial f}{\partial s} \Big|_{\hat{s}} (s - \hat{s})$$

SSS

UKF



Mixture of Gaussians

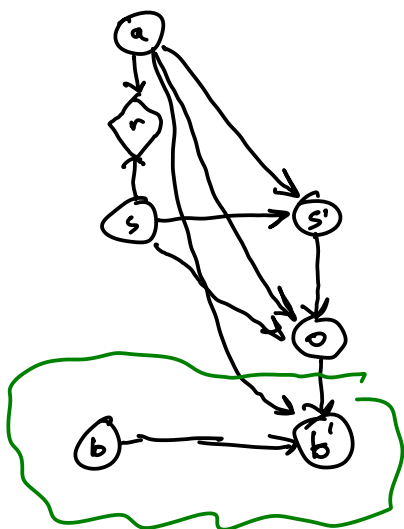
## 2. POMDP

Value Functions? Policies?

MDP  $(S, A, T, R, \gamma)$   $(P_0)$

POMDP  $(S, A, \mathcal{O}, T, R, Z, \gamma)$   
 $\uparrow$  obs space  $\uparrow$  obs dist

$Z(o(a, s'))$  or  
 $Z(o(s, a, s'))$



$$b' = \tau(b, o)$$

$$b' = \tau(b, a, o)$$

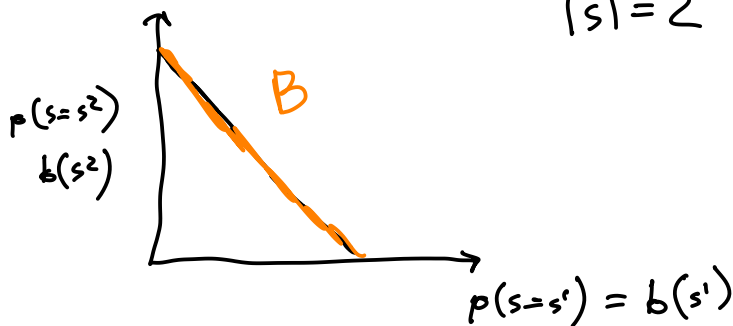
$$\pi: \mathcal{B} \rightarrow A$$

$$\pi: \mathcal{H} \rightarrow A$$

$$b: S \rightarrow [0, 1]$$

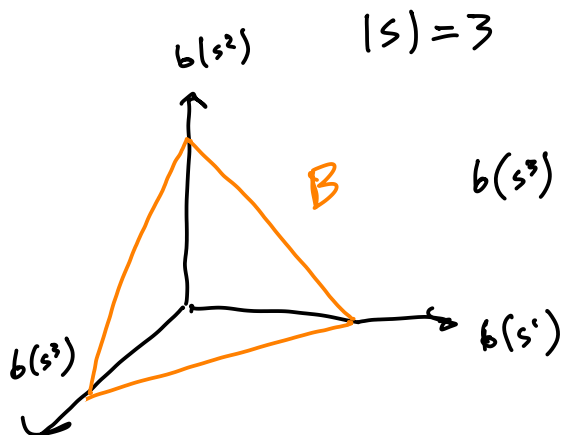
$$b \in [0, 1]^{|S|}$$

$$|S| = 2$$



$$b(s^3) = 1 - b(s') - b(s^2)$$

$$b(s') + b(s^2) + b(s^3) = 1$$



## Tiger POMDP

$$S = \{TL, TR\}$$

$$A = \{OL, OR, L\}$$

$$O = \{TL, TR\}$$

T: static until open, reset

Z: 85%

R: +10 good door -100 open tiger

## Crying Baby

$$S = \{h, \neg h\}$$

$$A = \{f, \neg f\}$$

$$O = \{c, \neg c\}$$

$$T(s' = \neg h | s, f) = 1.0$$

$$T: f \rightarrow \neg h \quad h, \neg f \rightarrow h$$

$$\neg h, f \rightarrow h \quad 10\%$$

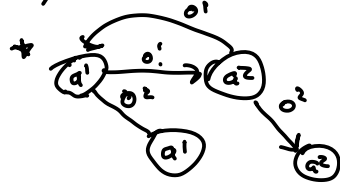
$$Z: h \rightarrow c \quad 80\%$$

$$\neg h \rightarrow c \quad 10\%$$

$$R: f: -5 \quad h: -10$$

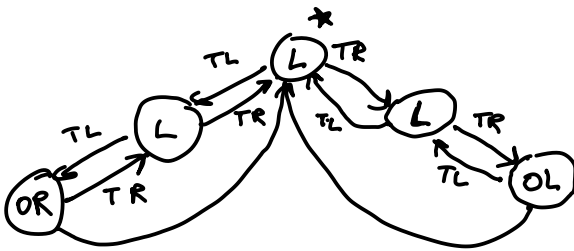
## Policies

### a) Policy Graph

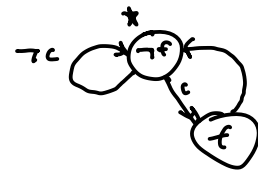


Start at  $\star$   
loop  
take a at current node  
observe o  
traverse graph on edge o

## Tiger



## Feed when crying

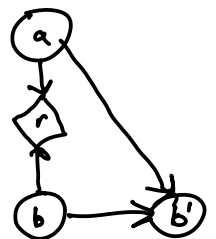
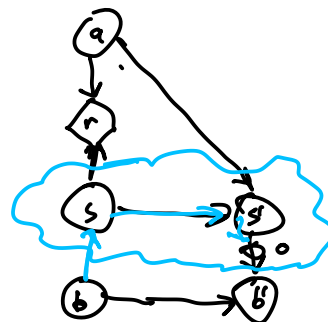


### b) Alpha Vectors

Even if  $S, A, O$  are discrete

$B$  is continuous

Important: A POMDP is an MDP on the belief space



$$b^1 \text{ close } b^2 \rightarrow Q(b^1, a) \text{ close } Q(b^2, a)$$

$\alpha$  vector  $|S|$ -dimensional vector

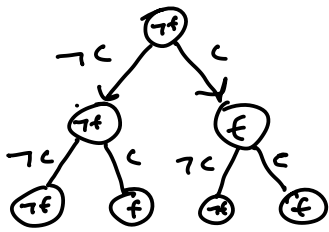
$$\alpha \in \mathbb{R}^{|S|}$$

each entry  $Q^p(\delta_s, p_0)$

$$\alpha^p[s^z] = Q^p(\delta_{s^z}, p_0)$$

Conditional plan: history based policy with fixed steps

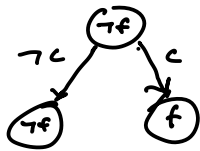
2-step c.p. for crying baby



$$V(b) = \max_{\alpha \in \Gamma} b^T \alpha$$

$\uparrow$   
 $\sum_{s \in S} b(s) \alpha[s]$

1 step c.p.  $\tilde{p}$

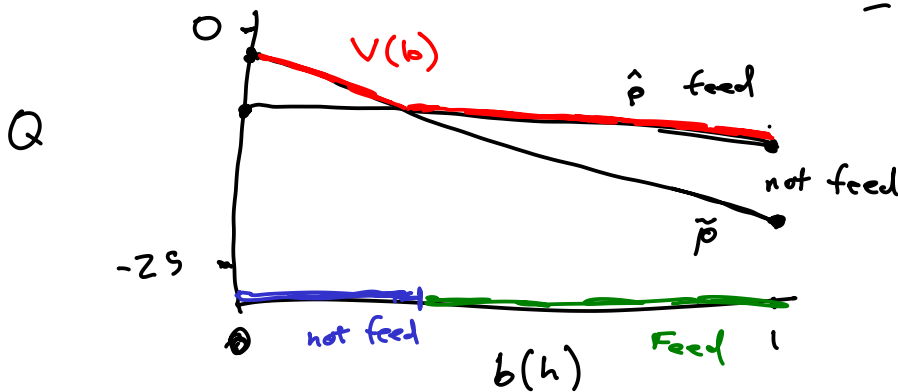


if  $s = h$

$$Q^{\tilde{p}}(h, \tilde{p}) = -10 + \gamma (0.8 \times -15 + 0.2 \times -10) = -22.6$$

if  $s = \neg h$

$$Q^{\tilde{p}}(\neg h, \tilde{p}) = 0 + \gamma \begin{matrix} h & c \\ \neg h & \neg c \end{matrix} = -1$$



1 step

Thursday:

Value Iteration