

# Recap

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

- POMDP

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$$(S, A, \underbrace{O}_{\gamma}, R, T, \underbrace{Z}_{\gamma}, \gamma)$$

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- POMDP  $(S, A, O, R, T, Z, \gamma)$
- Belief Updates

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$$b_t(s) = P(s_t = s \mid h_t)$$

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

# Recap

- POMDP  $(S, A, O, R, T, Z, \gamma)$
- Belief Updates

$$b_t(s) = P(s_t = s \mid h_t)$$

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

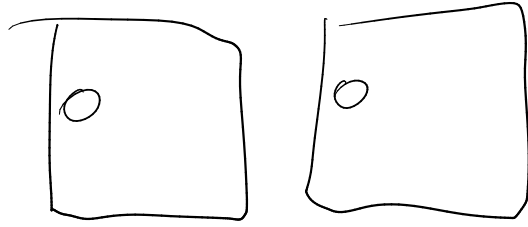
$$b'(s') \propto Z(o \mid a, s') \sum_s T(s' \mid s, a) b(s)$$

# Guiding Quesiton

How do we calculate the optimal action in  
a POMDP?



# Solving the Tiger POMDP

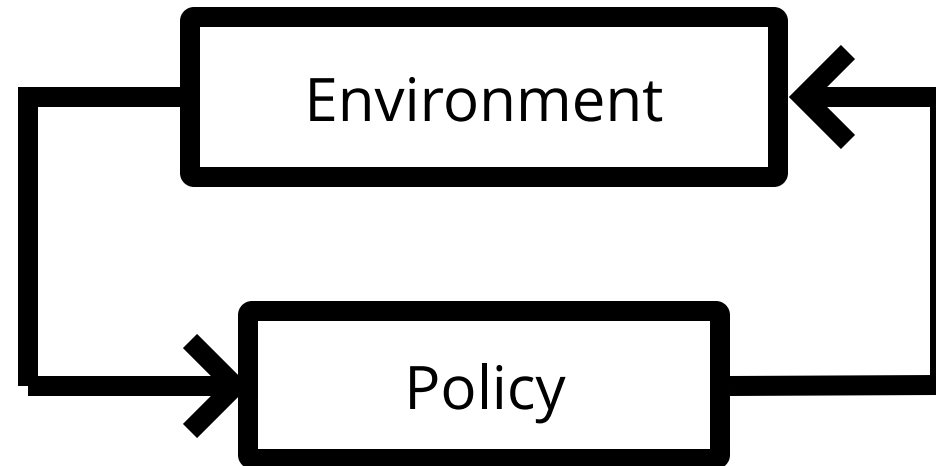


Step 1 = calculate  $Q$

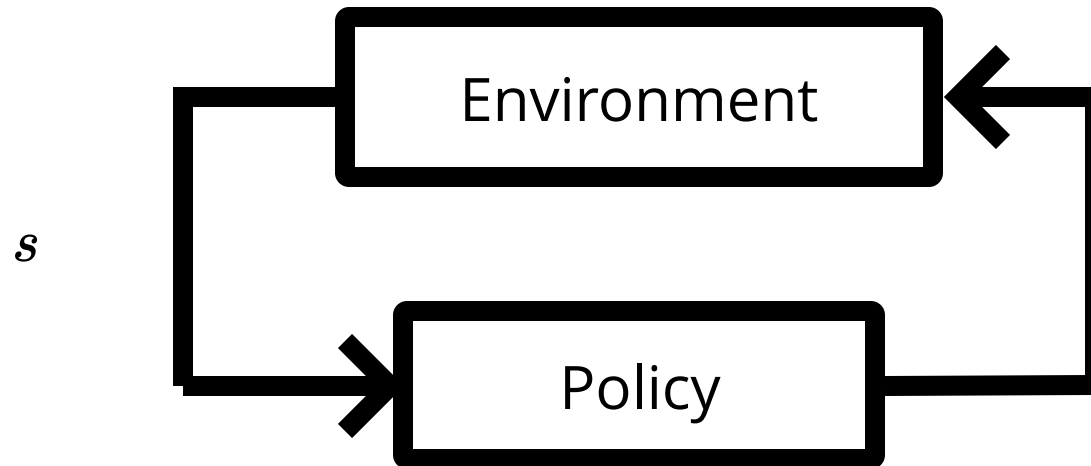
Step 2 = take action with highest value



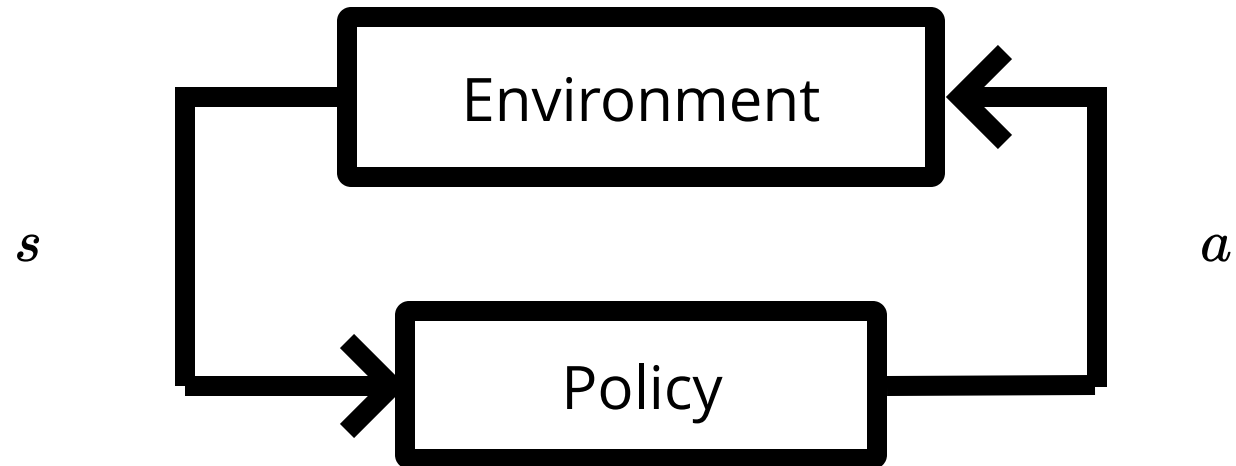
# MDP Sense-Plan-Act Loop



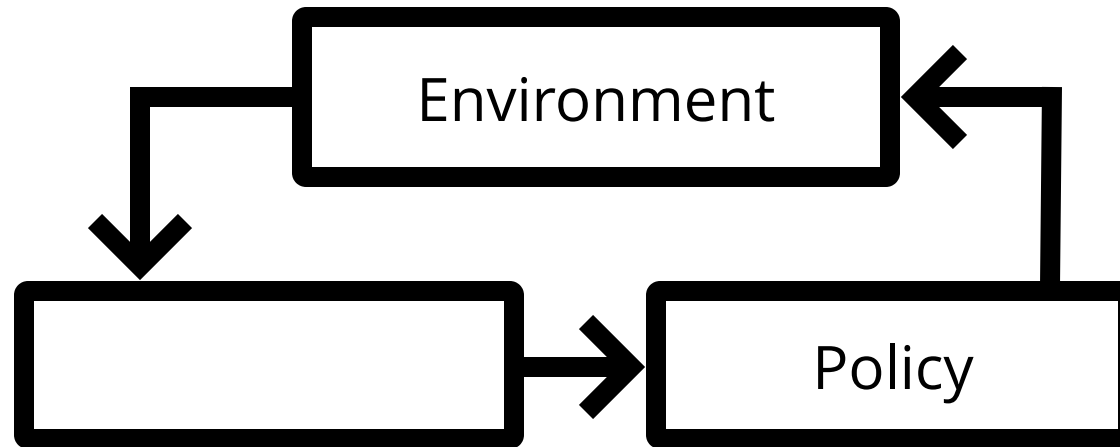
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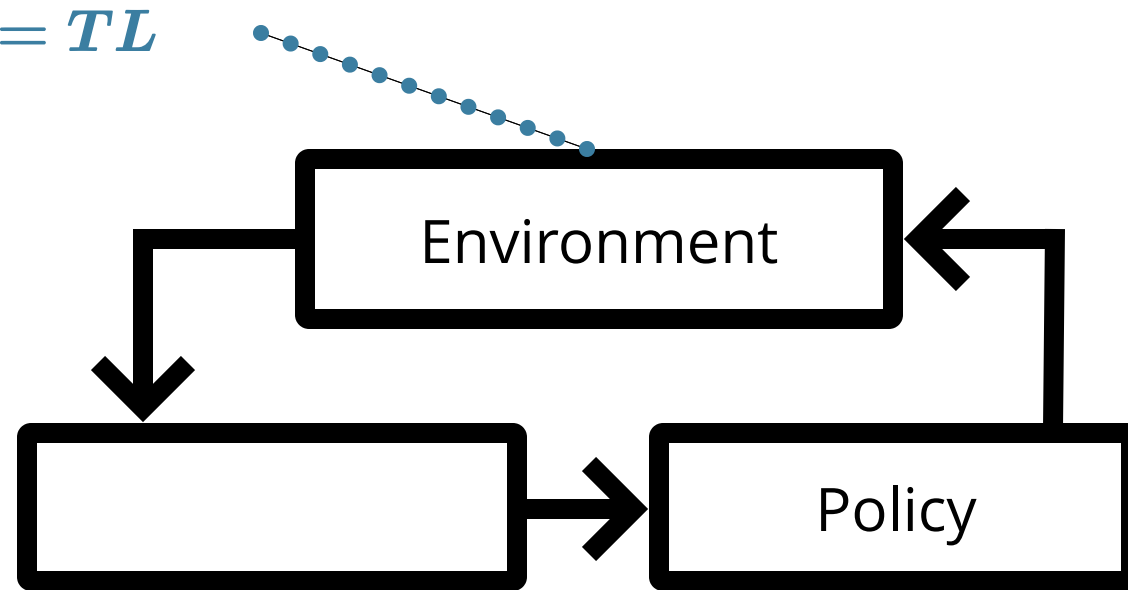
# POMDP Sense-Plan-Act Loop



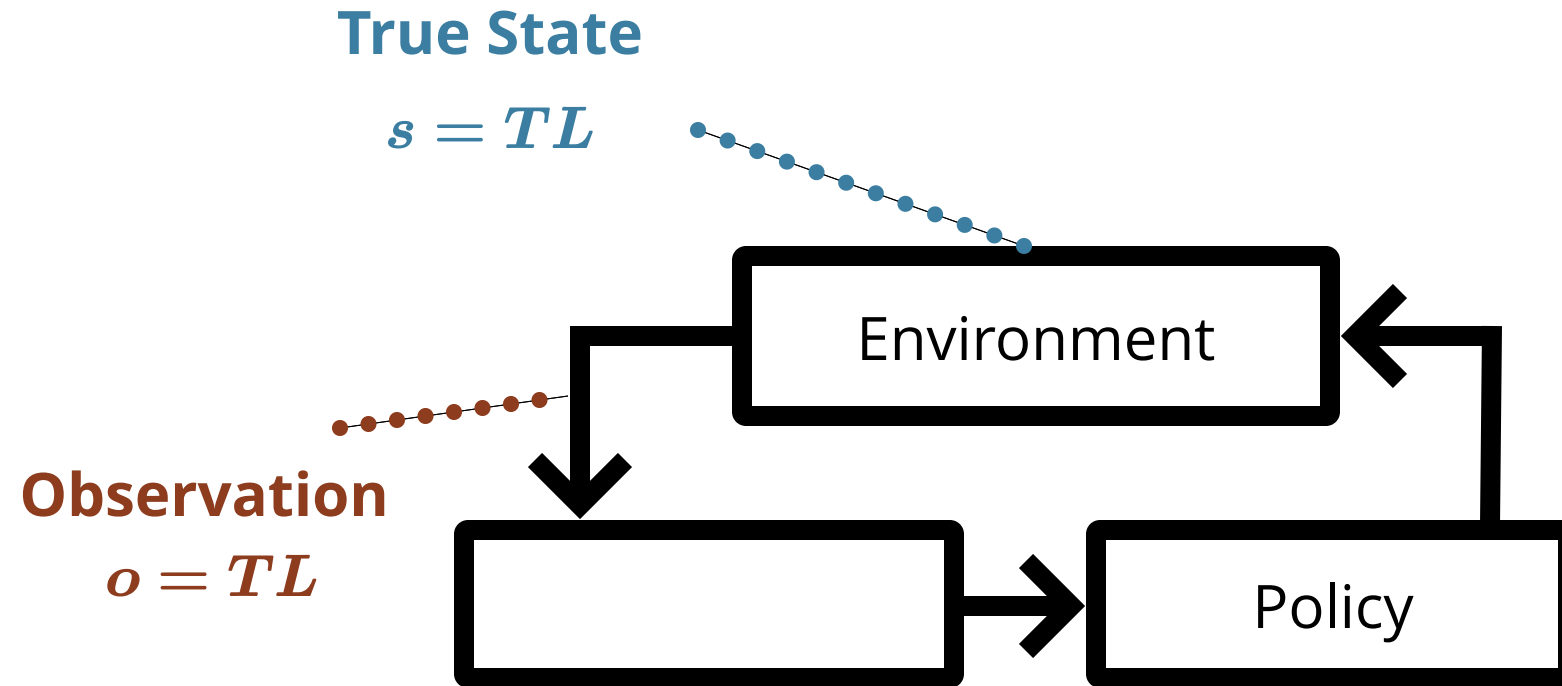
# POMDP Sense-Plan-Act Loop

True State

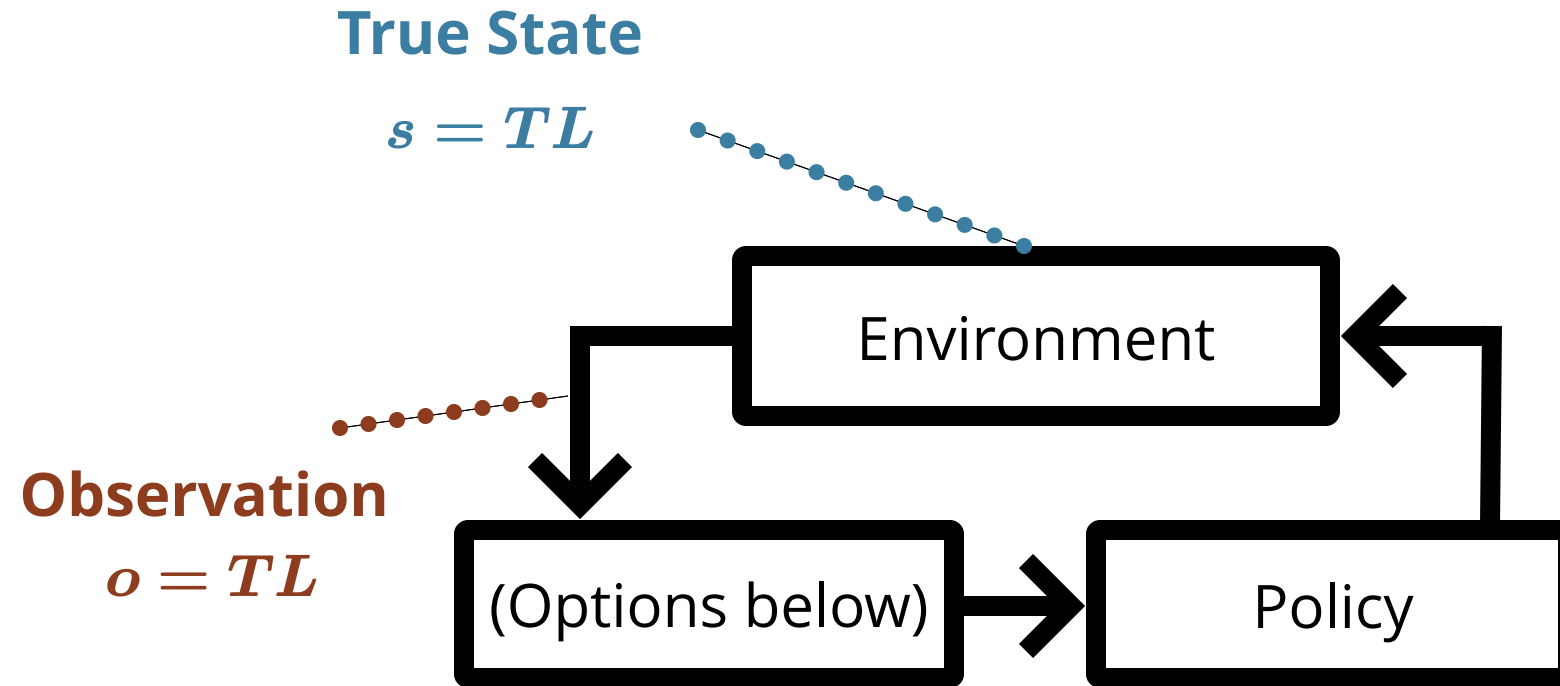
$$s = TL$$



# POMDP Sense-Plan-Act Loop

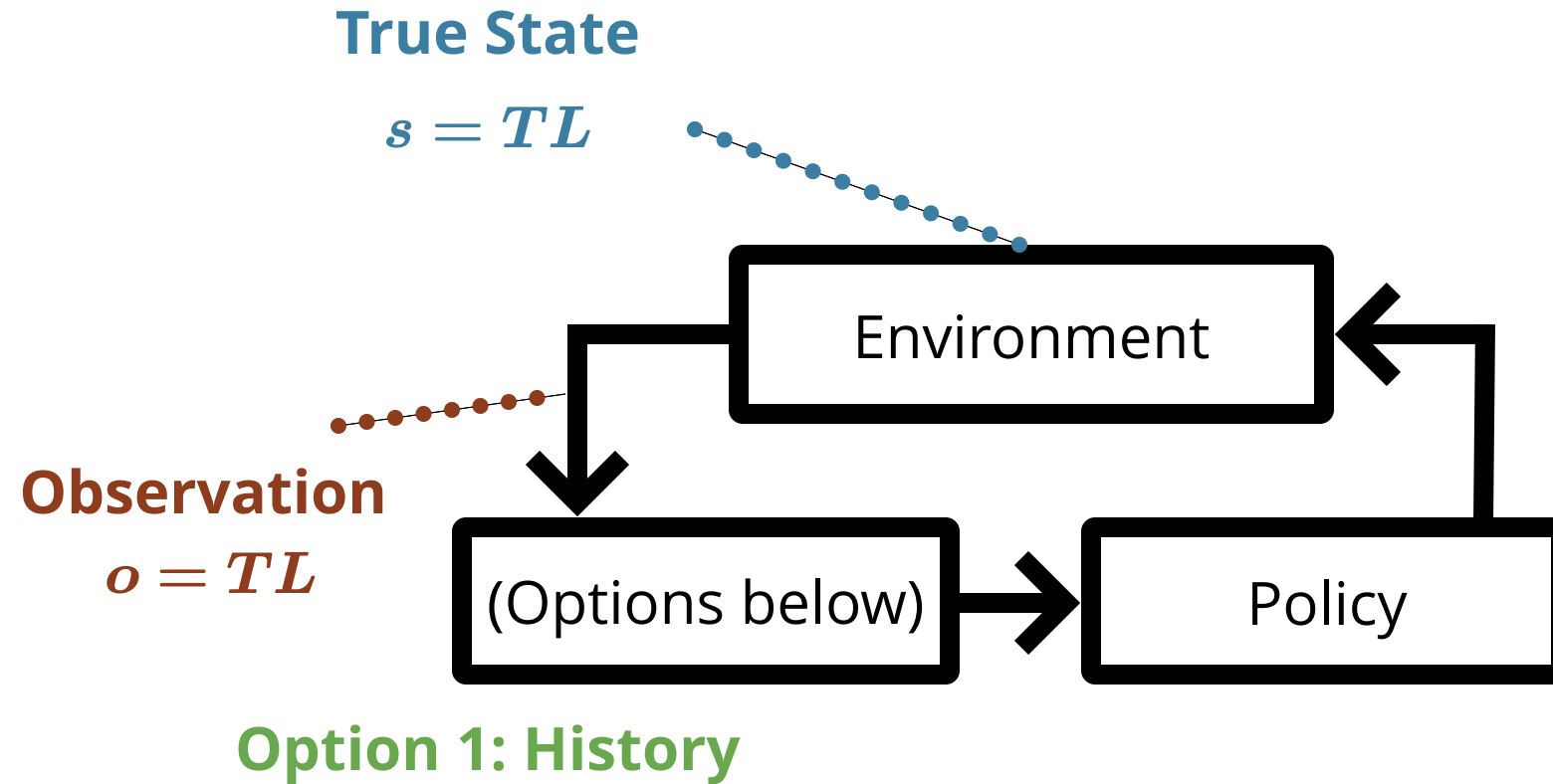


# POMDP Sense-Plan-Act Loop

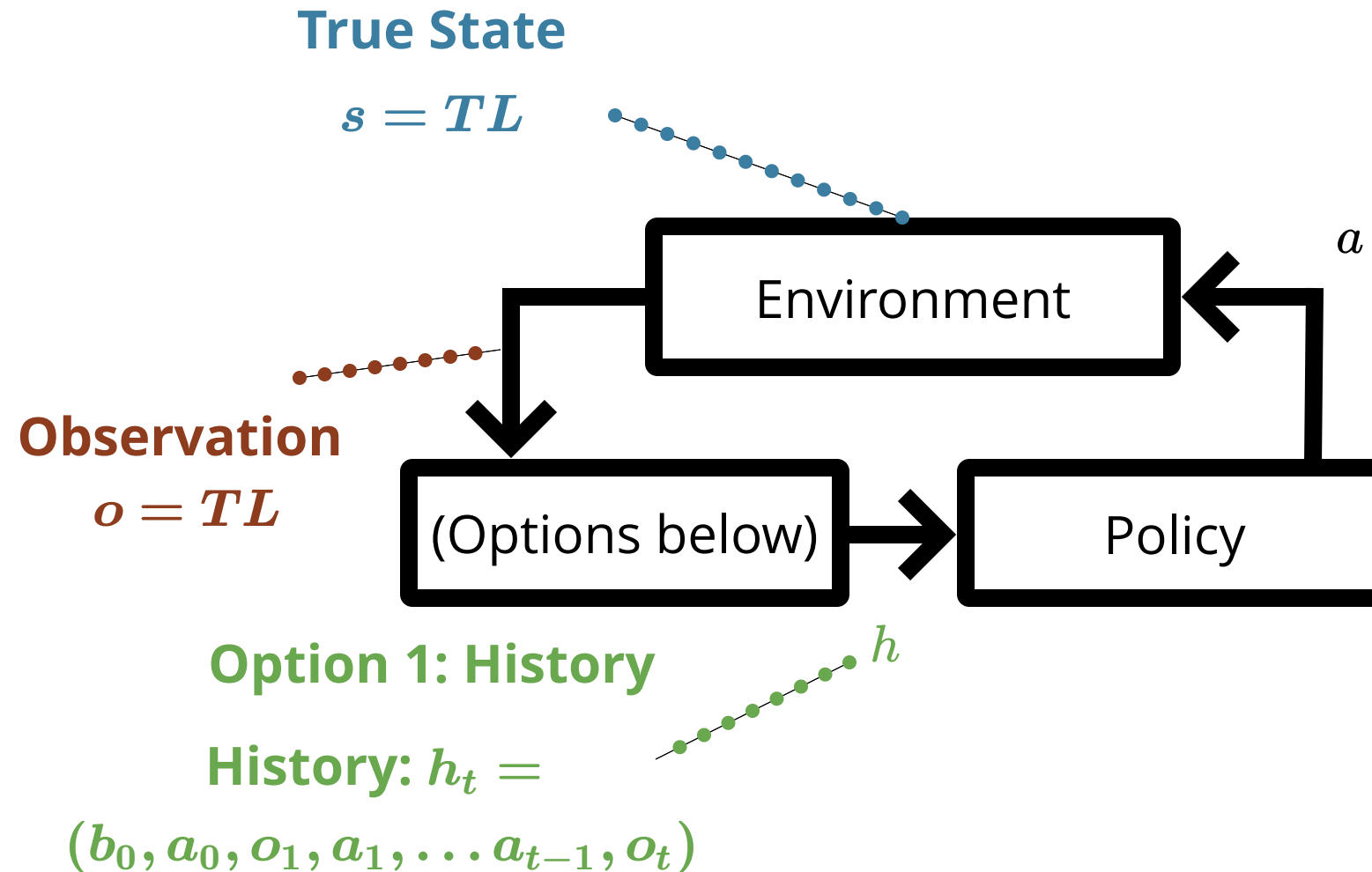




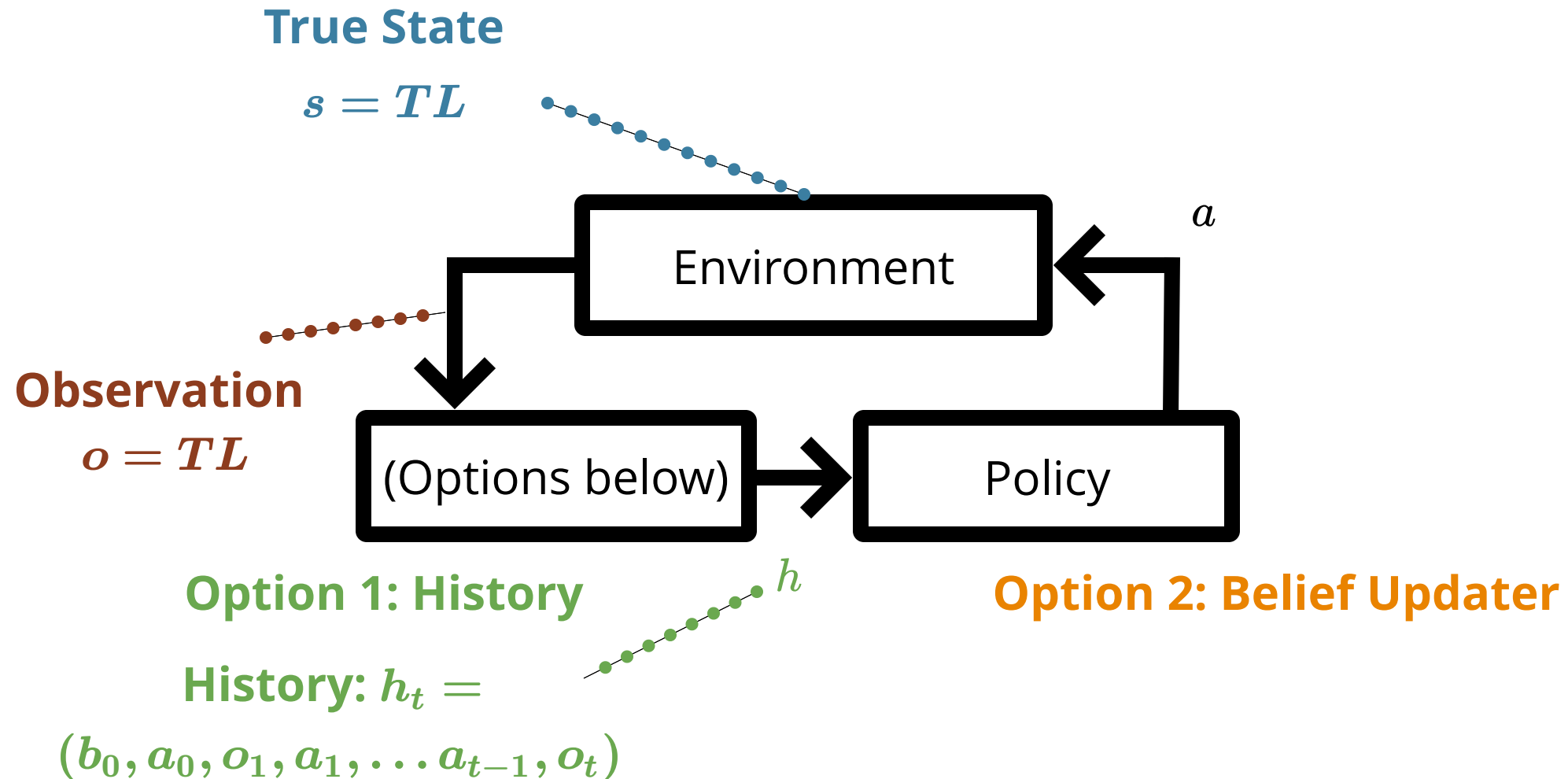
# POMDP Sense-Plan-Act Loop



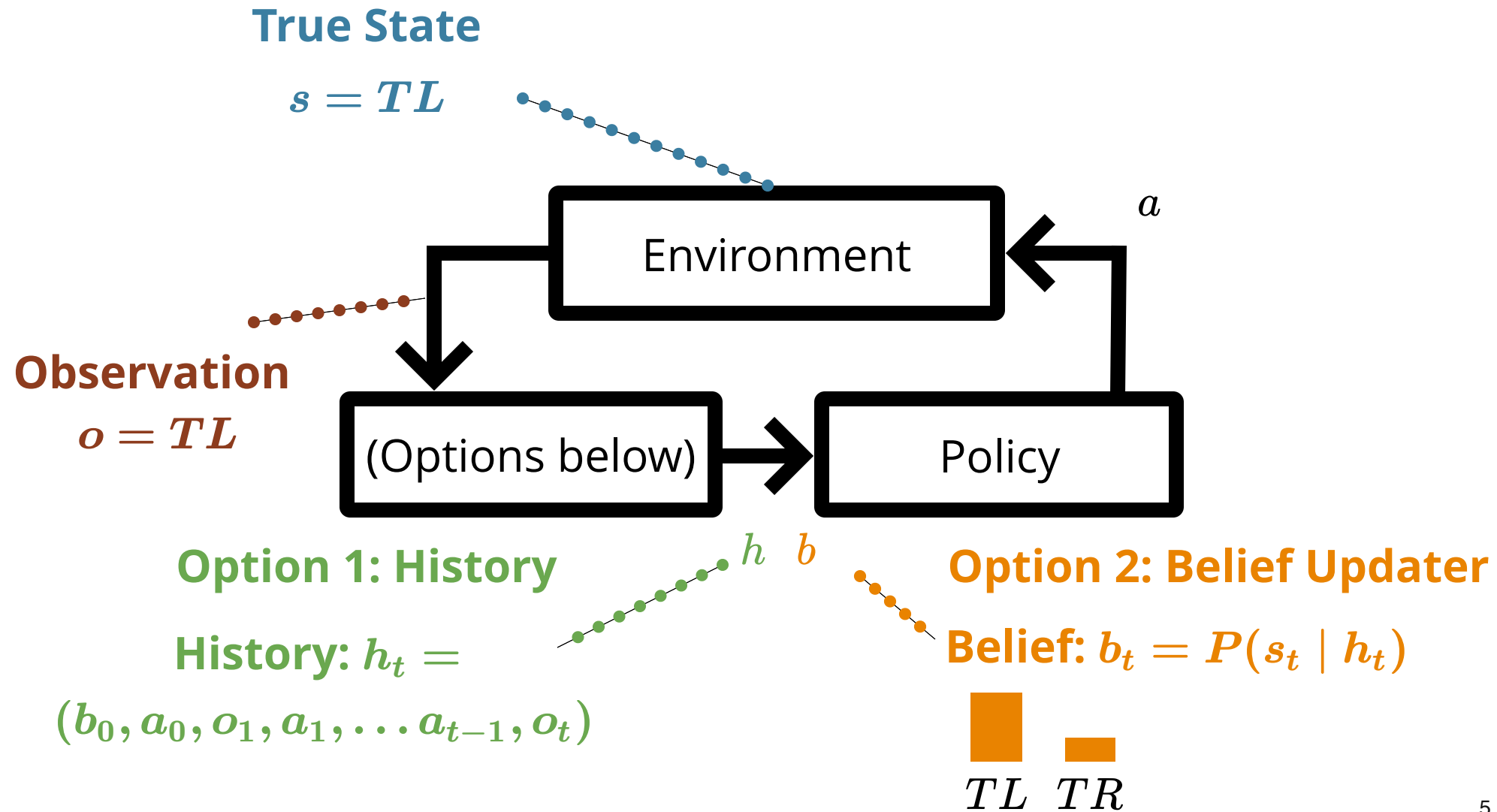
# POMDP Sense-Plan-Act Loop



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# Belief Dynamics

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$$b'(s') \propto Z(o \mid a, s') \sum_s T(s' \mid s, a) b(s)$$

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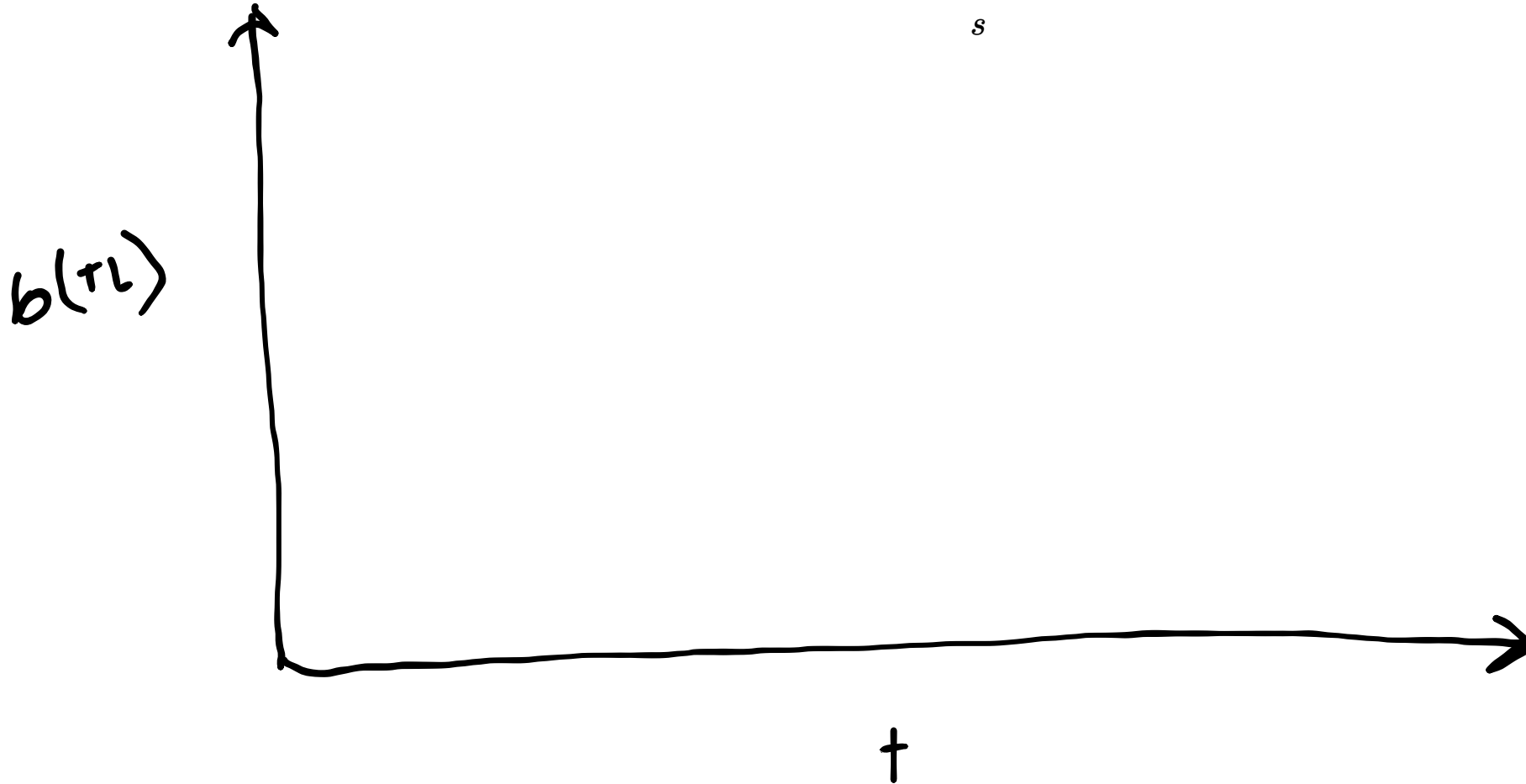
$$b'(s') \propto Z(o \mid a, s') \sum_s T(s' \mid s, a) b(s)$$

$b(\tau_L)$

†

# Belief Dynamics

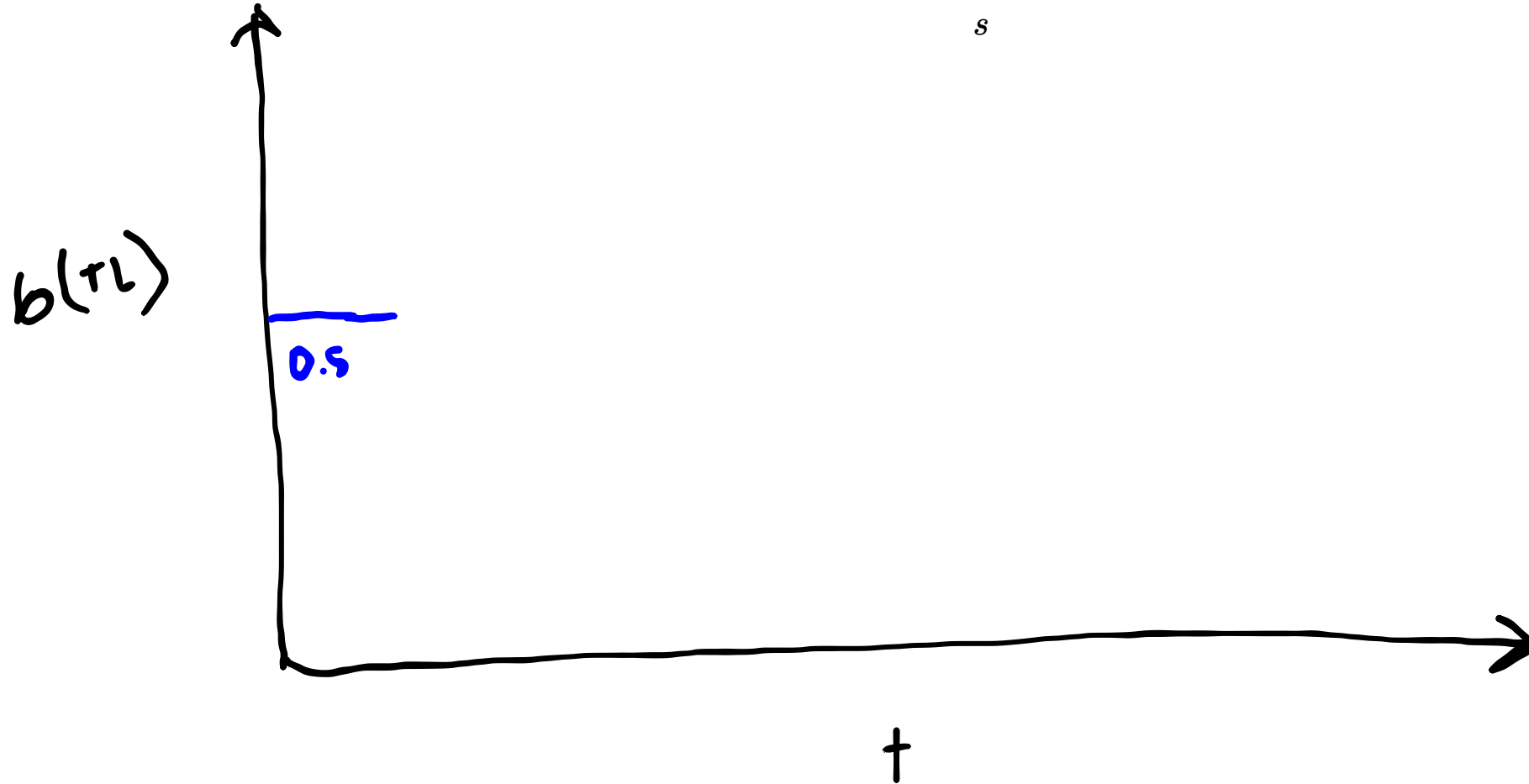
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# Belief Dynamics

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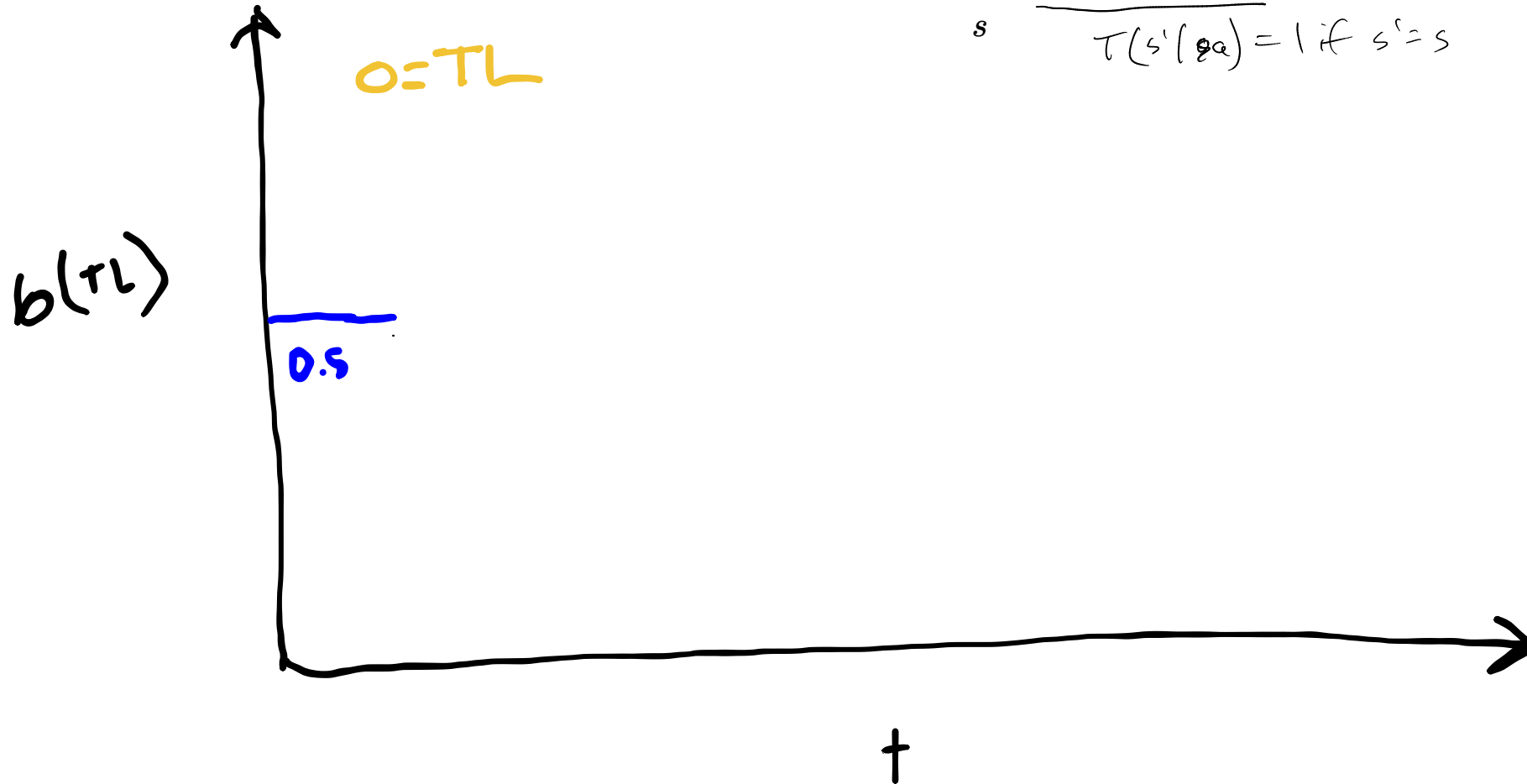
# Belief Dynamics

$$b'(s') \propto Z(o | a, s') \sum_s \underbrace{T(s' | s, a)}_{T(s' | s, a) = 1 \text{ if } s' = s} b(s)$$

$$b'(TL) \propto 0.85 \cdot 0.5$$

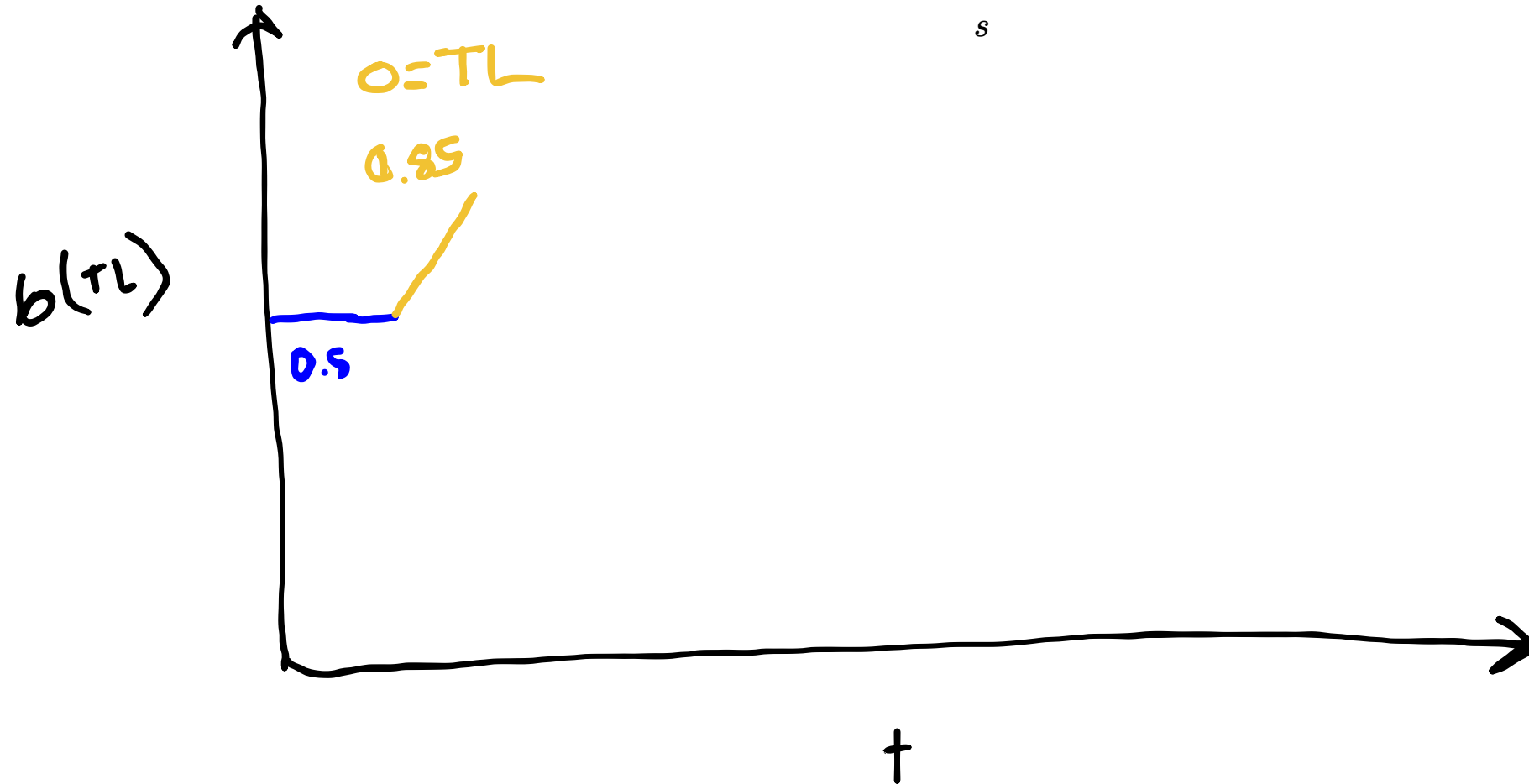
$$b'(TR) \propto 0.15 \cdot 0.5$$

0



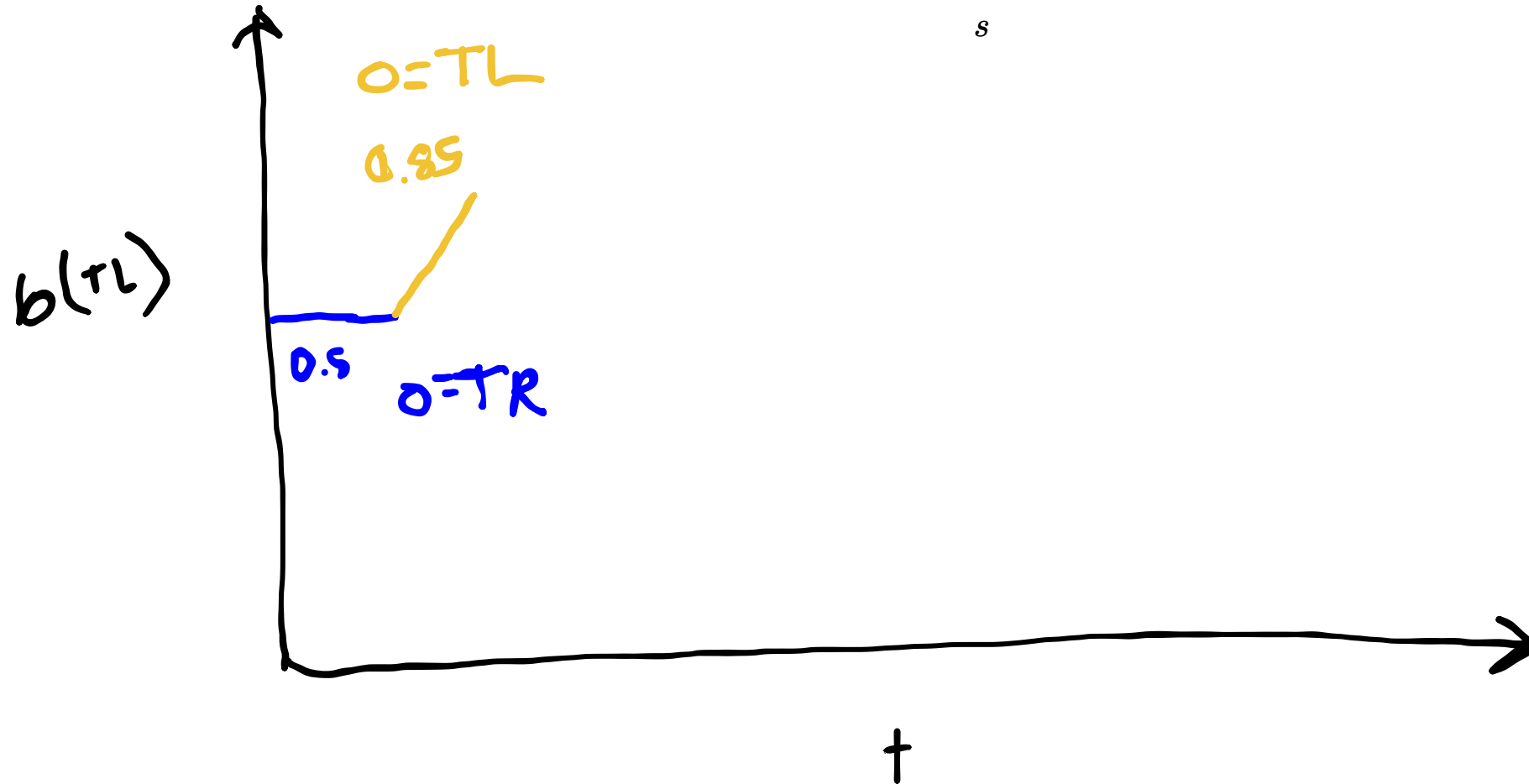
# Belief Dynamics

$$b'(s') \propto Z(o \mid a, s') \sum_s T(s' \mid s, a) b(s)$$



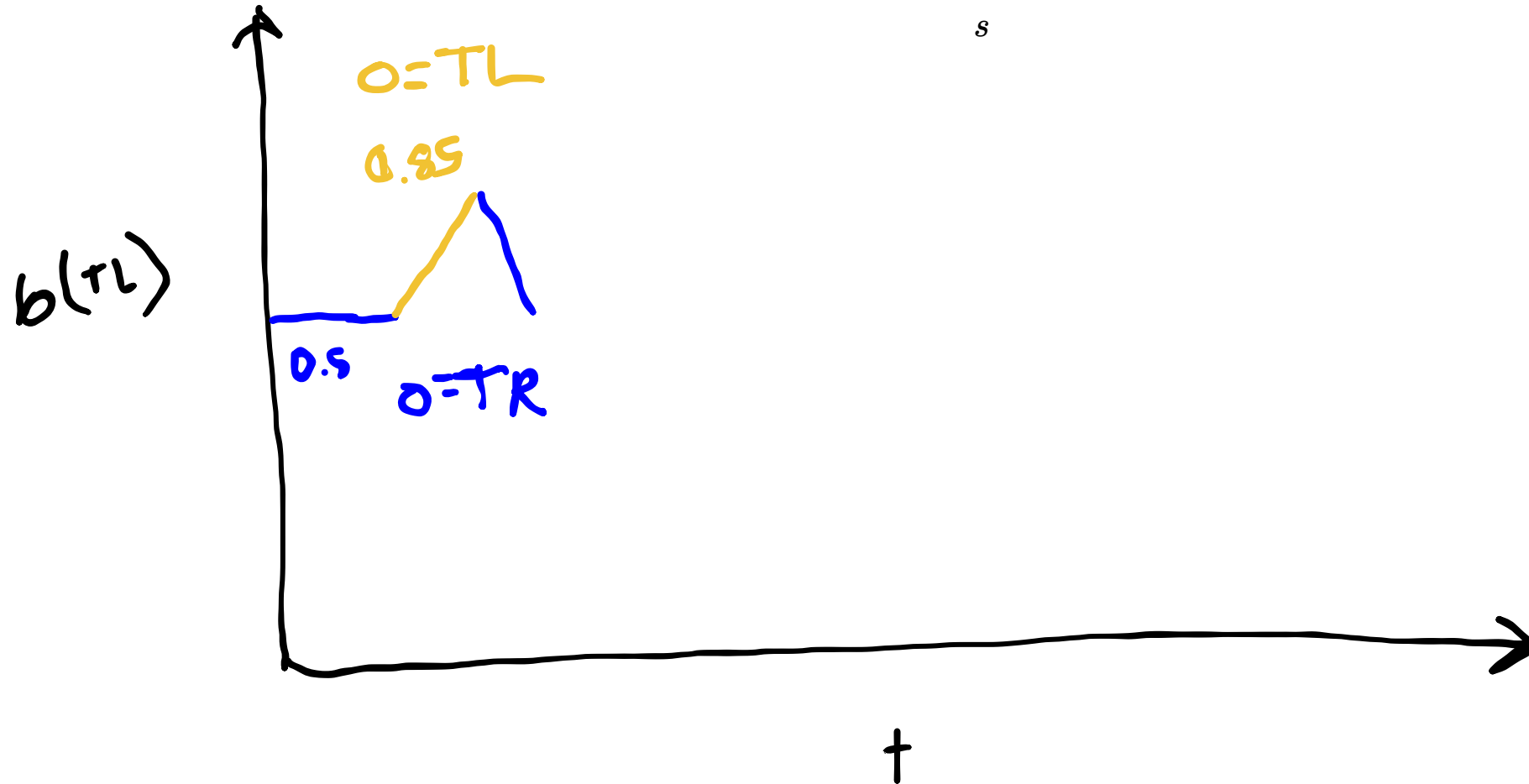
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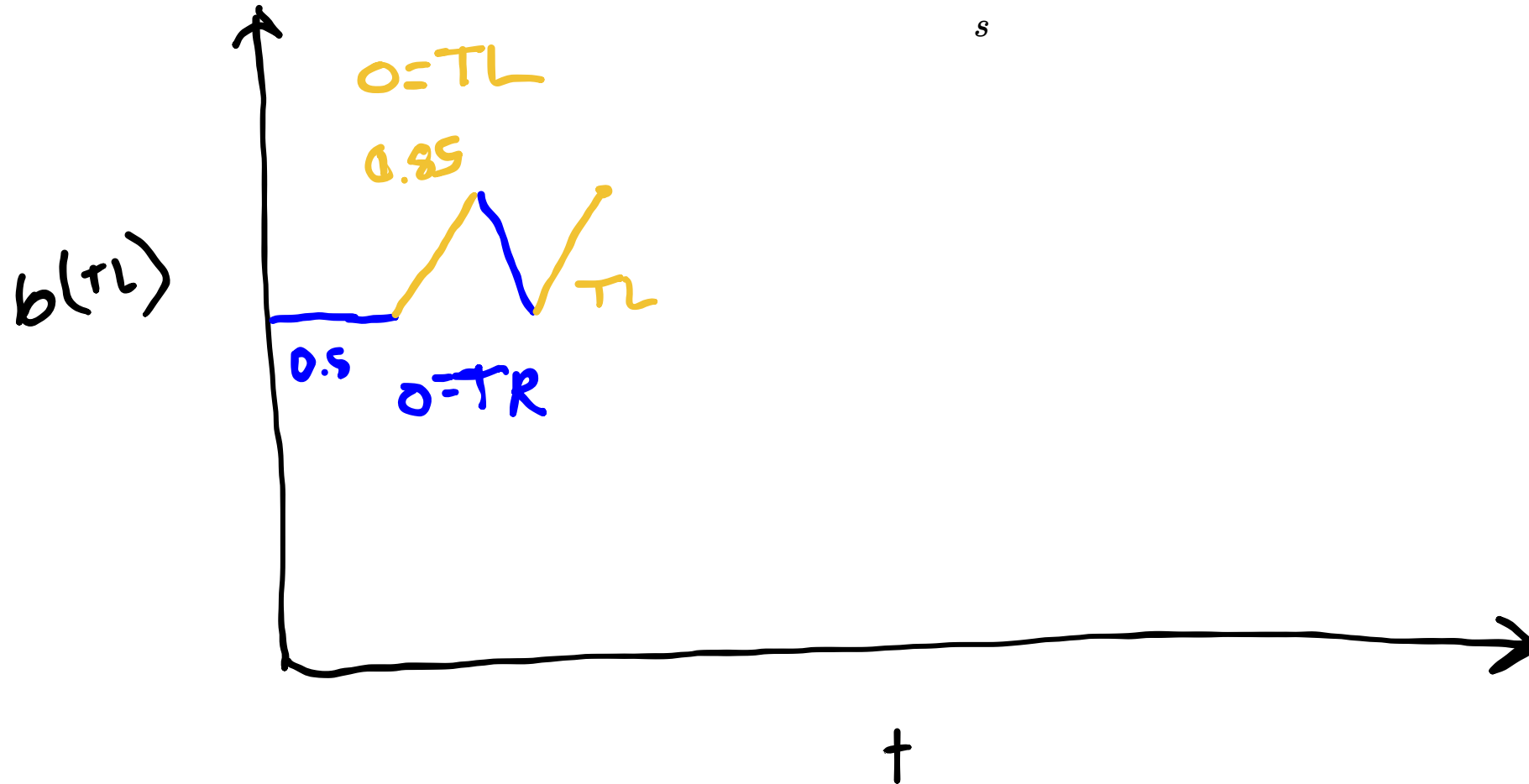
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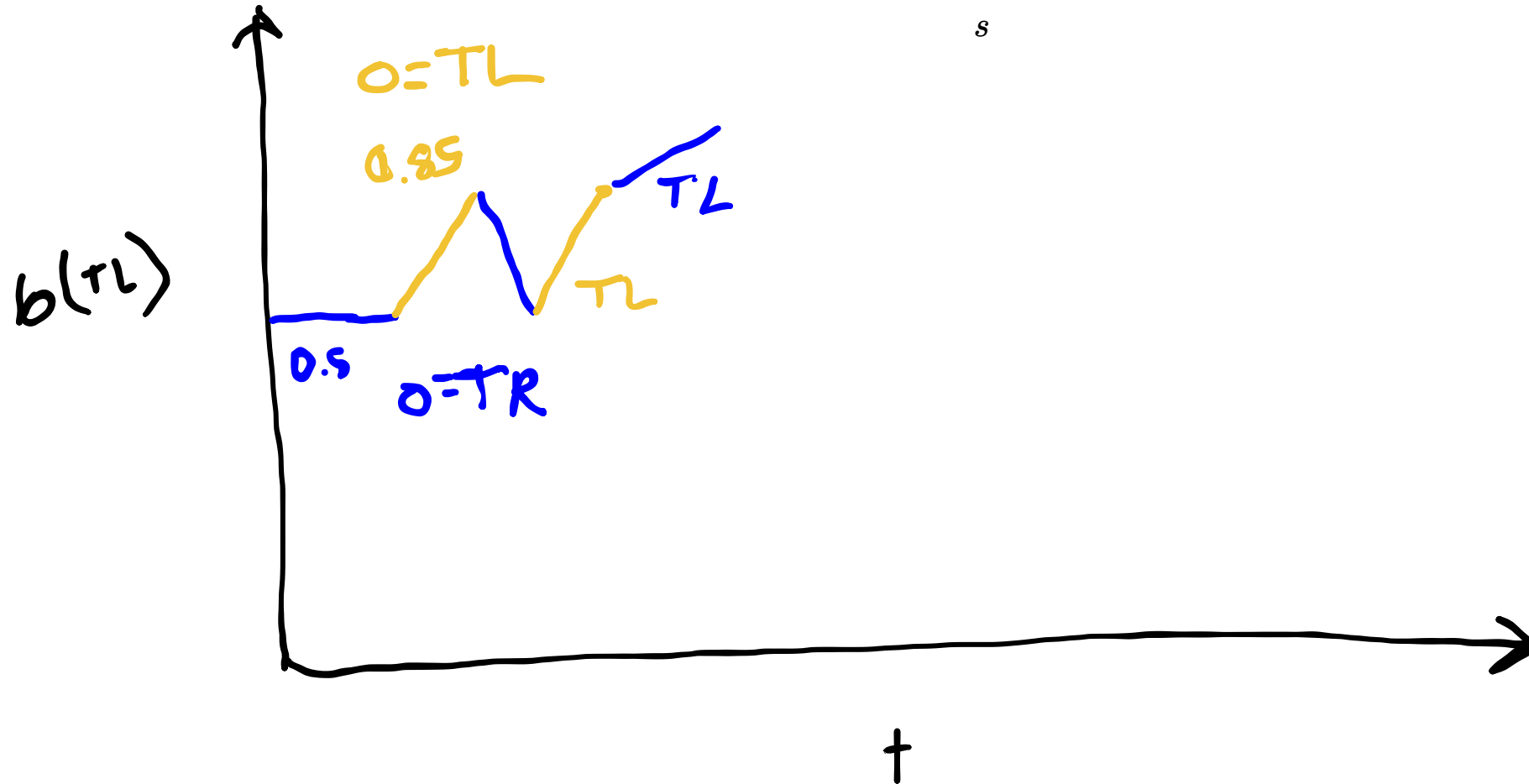
# Belief Dynamics

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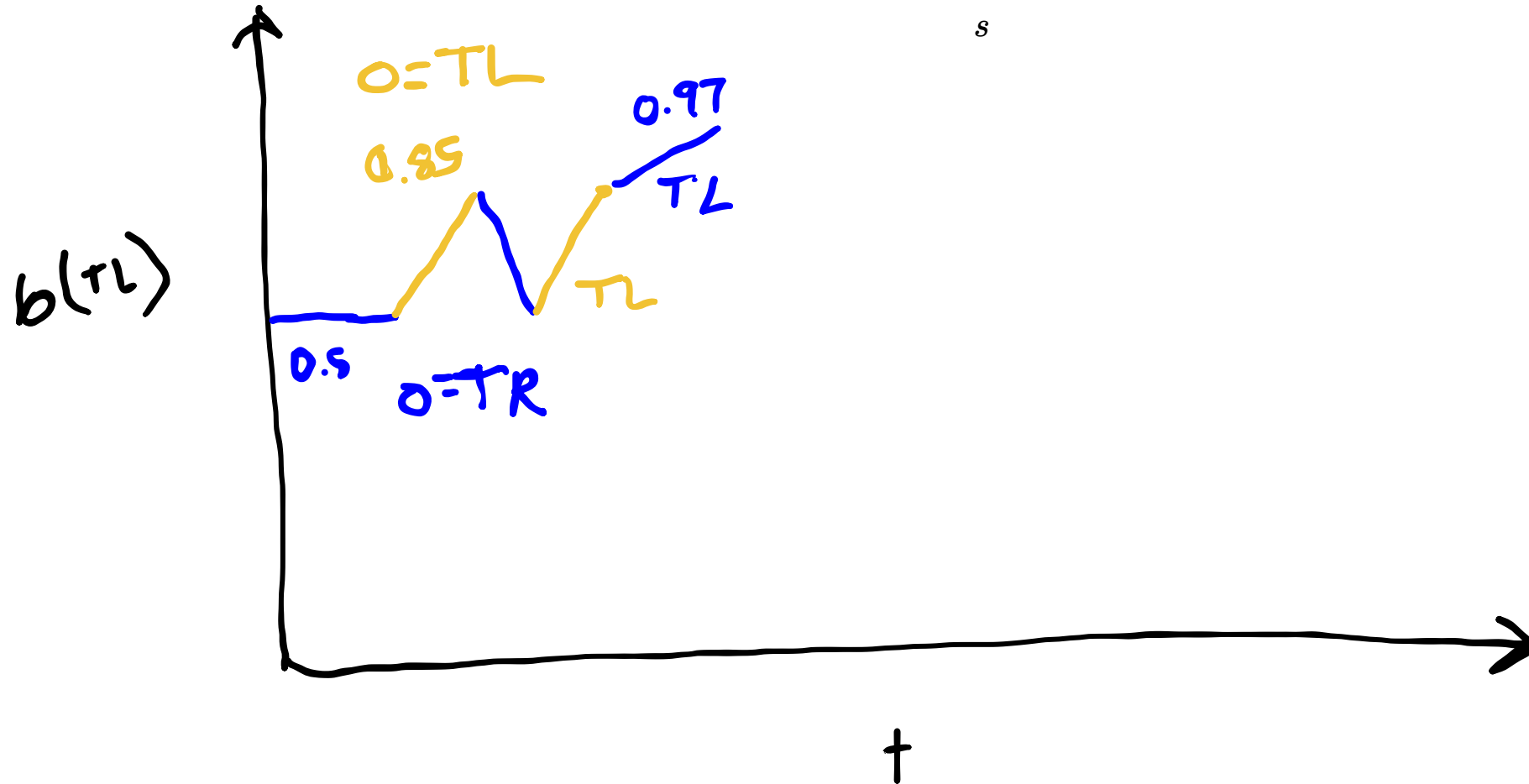
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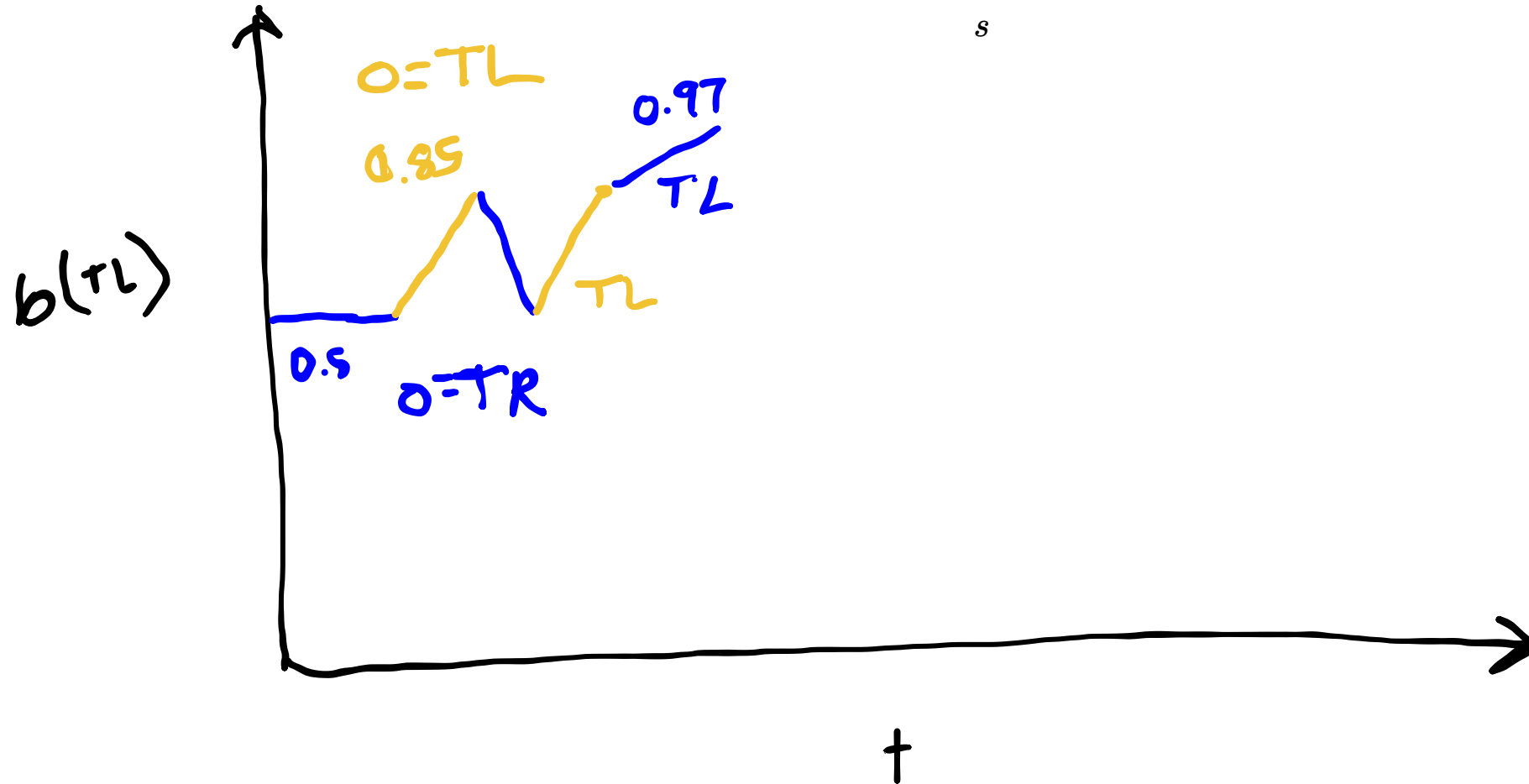
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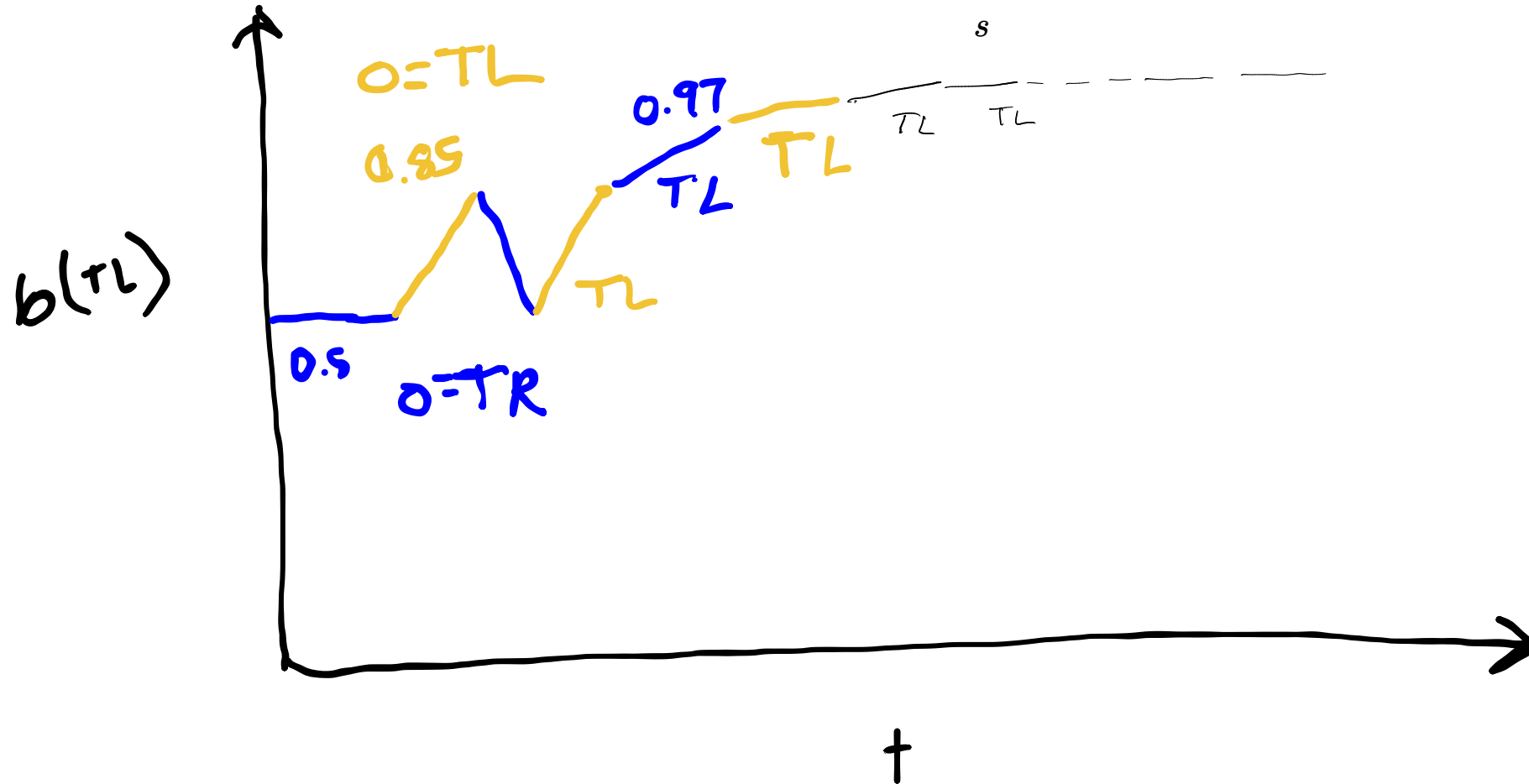
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$$b'(s') \propto Z(o \mid a, s') \sum_s T(s' \mid s, a) b(s)$$

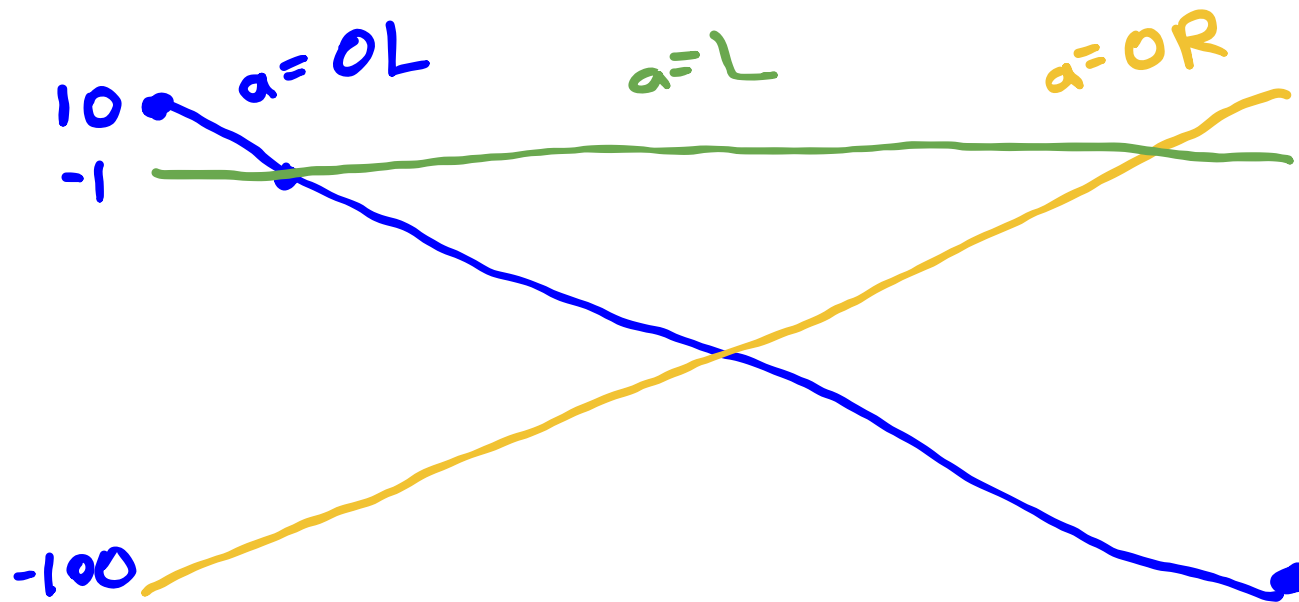


# Belief Dynamics

$$b'(s') \propto Z(o | a, s') \sum_s T(s' | s, a) b(s)$$



# One-step utility



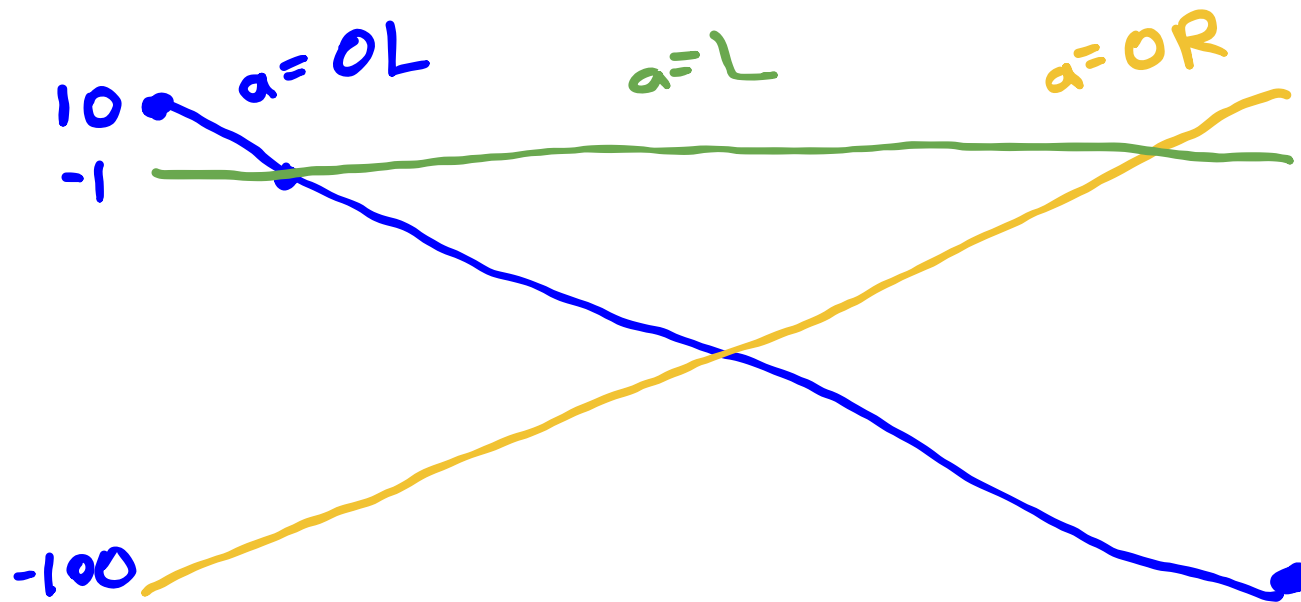
$$R(b, a) = \bar{r}_a \cdot b$$

↑  
 $\alpha$ -vector

$$R(b, a) = 10 \cdot (1 - b(\tau_L)) - 100 b(\tau_L) = -110b + 10$$

# One-step utility

Reward: +10 empty door  
-1 Listen  
-100 Tiger



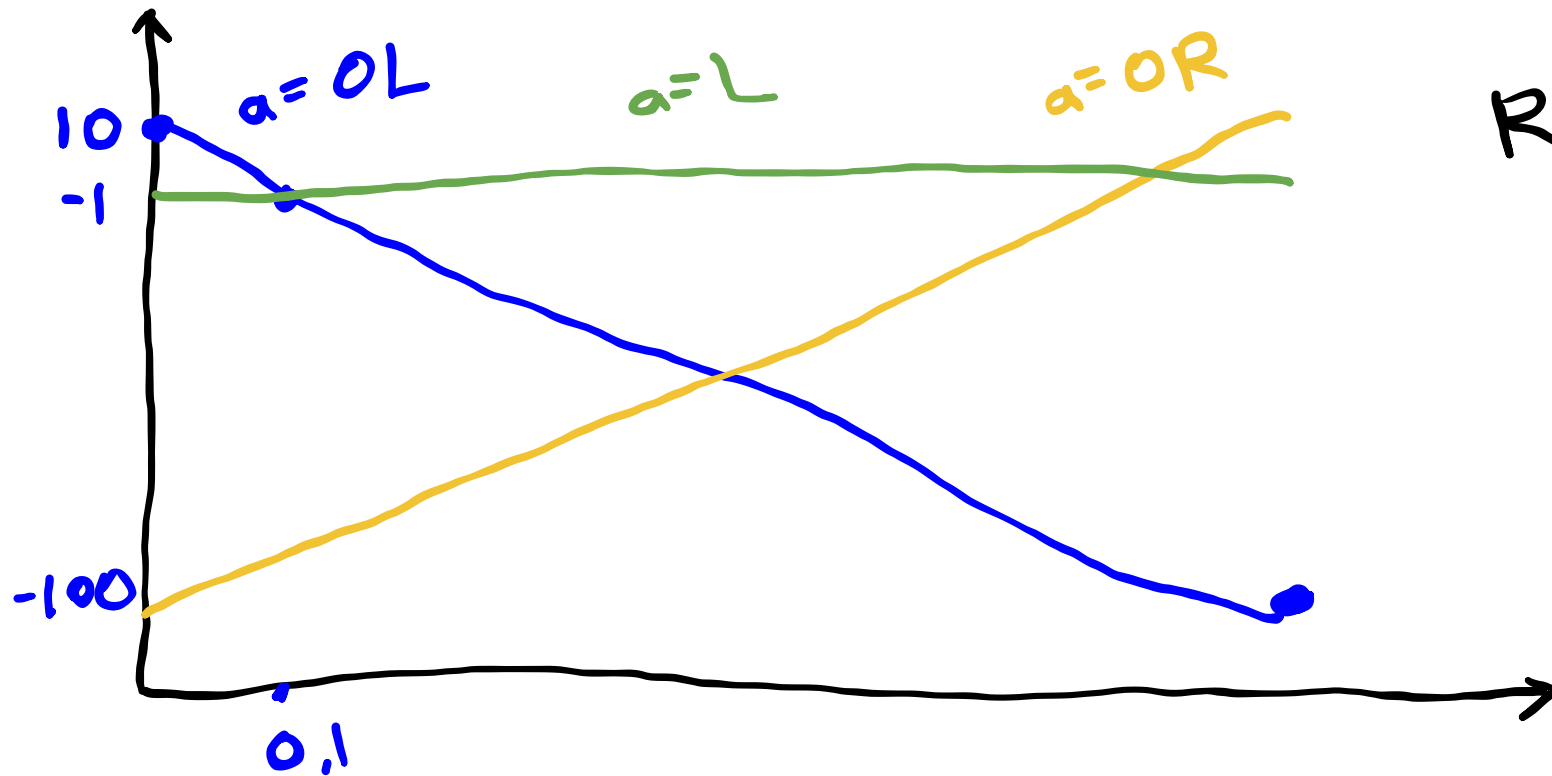
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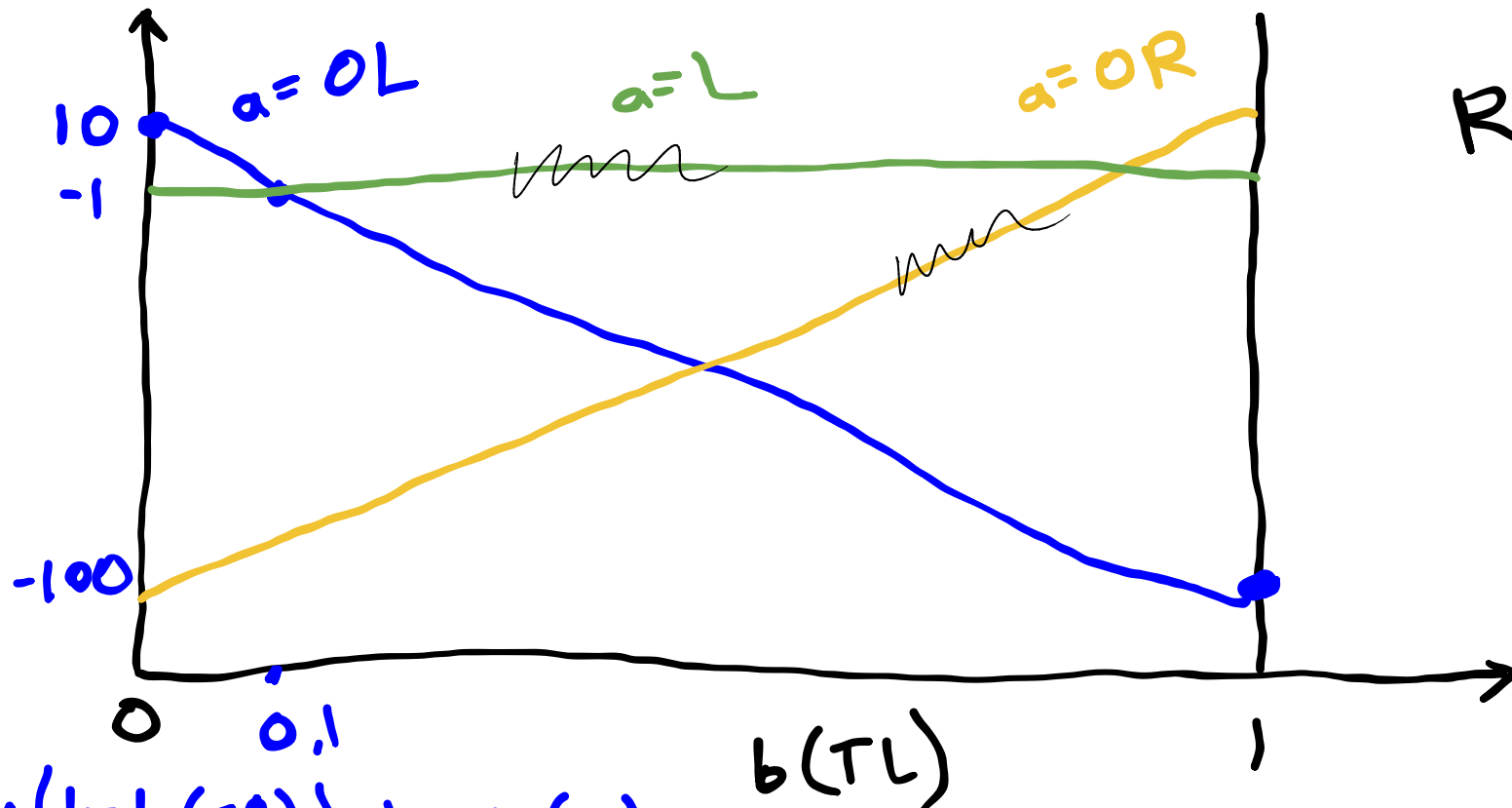
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# One-step utility

Reward: +10 empty door  
-1 Listen  
-100 Tiger

1 step utility for  $a = OL$  for any belief



$$R(b, a) = \bar{r}_a \cdot b$$

↑  
 $\alpha$ -vector

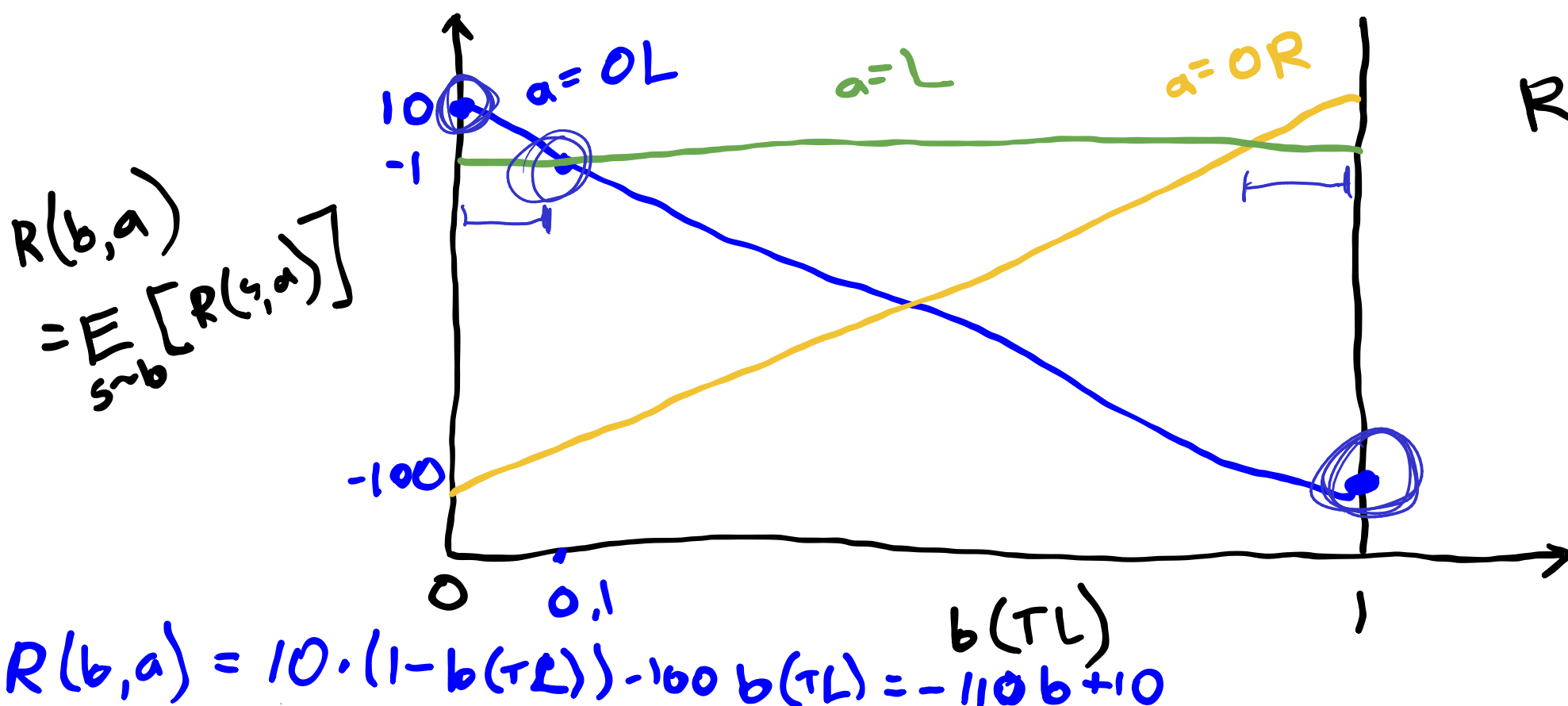
$$R(b, a) = 10 \cdot (1 - b(TL)) - 100 b(TL) = -110b + 10$$

# One-step utility

Reward: +10 empty door  
-1 Listen  
-100 Tiger

$$\begin{aligned} a = OL \\ b(TL) = 0 \\ R(b, a) &= \begin{pmatrix} 0.0 & -100 \end{pmatrix} \begin{pmatrix} b(TL) & R(TL, OL) \end{pmatrix} + \begin{pmatrix} 1.0 & +10 \end{pmatrix} \begin{pmatrix} 1-b(TL) & R(TR, OL) \end{pmatrix} \\ &= 10 \end{aligned}$$

$$\begin{aligned} a = OL \\ b(TL) = 1.0 \\ R(b, a) &= -100 \\ b(TL) &= 0.1 \end{aligned}$$



$$R(b, a) = \bar{r}_a \cdot b$$

↑  
 $\alpha$ -vector

$$R(b, a) = 10 \cdot (1 - b(TL)) - 100 b(TL) = -110b + 10$$

# Alpha Vectors for Conditional Plans



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Conditional Plans: fixed-depth history-based policies

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1 Step:

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Conditional Plans: fixed-depth history-based policies

1 Step:            

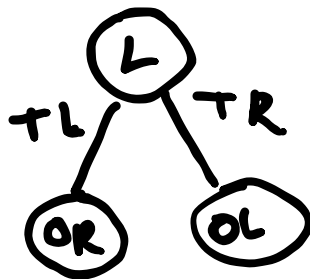
2 Step:

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step:     (L)     (OL)     (OR)

2 Step:

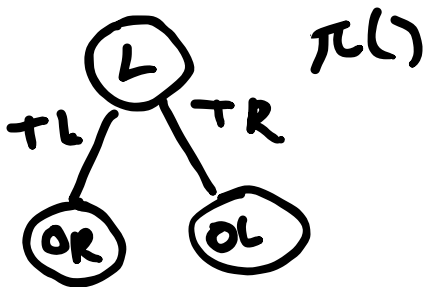


```
graph TD; L((L)) -- TL --> OR1((OR)); L -- TR --> OL((OL))
```

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step: 

2 Step: 

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step: (L) (OL) (OR)

2 Step:

```
graph TD; L((L)) -- TL --> OR((OR)); L -- TR --> OL((OL));
```

$\pi(L)$

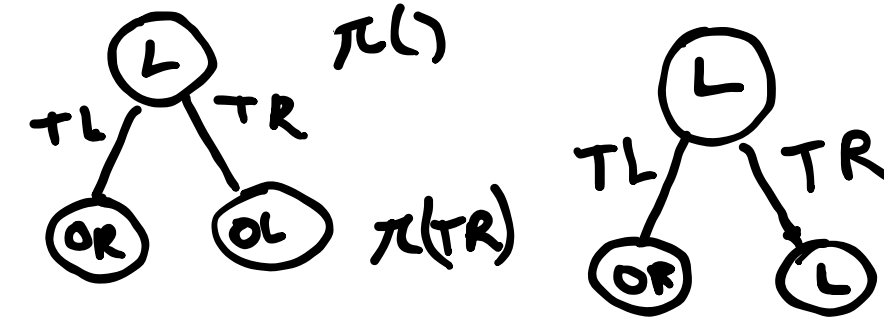
$\pi(TR) = OL$

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step:  $(L)$   $(OL)$   $(OR)$

2 Step:



The first 2-step plan has root  $(L)$ . It has two children:  $(OR)$  via edge  $TL$  and  $(OL)$  via edge  $TR$ . The label  $\pi(L)$  is above the root, and  $\pi(TR)$  is to the right of the  $(OL)$  node.

The second 2-step plan has root  $(L)$ . It has two children:  $(OR)$  via edge  $TL$  and  $(L)$  via edge  $TR$ .



# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step:  $(L)$   $(OL)$   $(OR)$

2 Step:

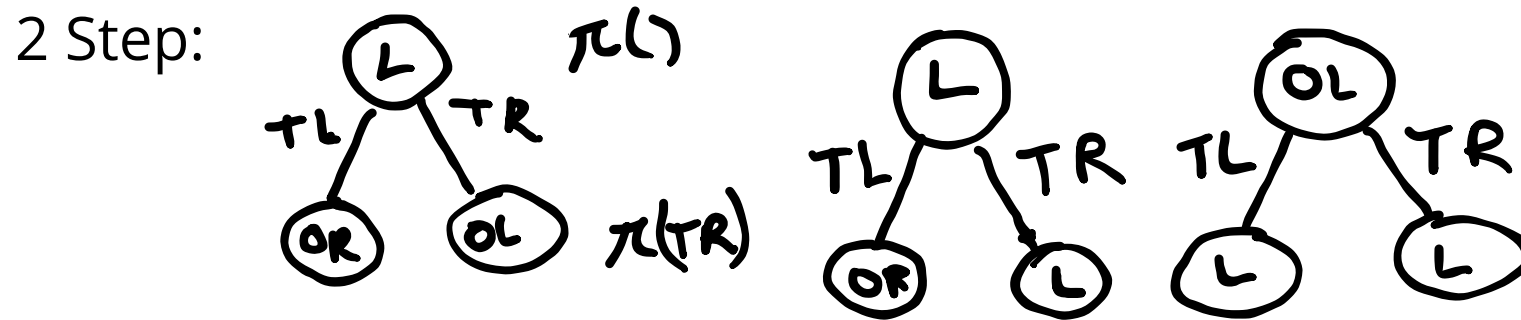
The diagrams show three conditional plans for 2 steps:

- Plan 1: Root node  $(L)$  with children  $(OR)$  (labeled  $TL$ ) and  $(OL)$  (labeled  $TR$ ). The label  $\pi(L)$  is next to the root, and  $\pi(TR)$  is next to the  $(OL)$  node.
- Plan 2: Root node  $(L)$  with children  $(OR)$  (labeled  $TL$ ) and  $(L)$  (labeled  $TR$ ).
- Plan 3: Root node  $(OL)$  with children  $(L)$  (labeled  $TL$ ) and  $(L)$  (labeled  $TR$ ).

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step: (L) (OL) (OR)

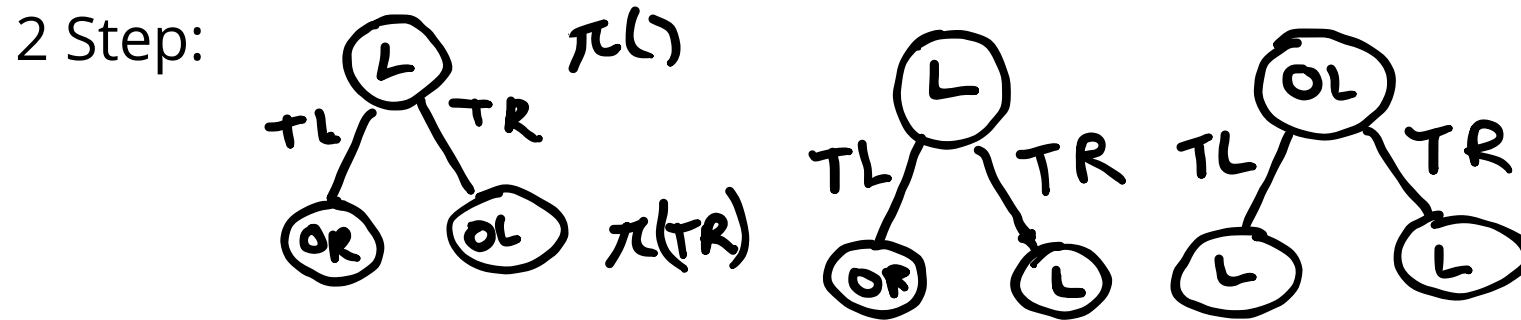


$$|A| \frac{(|O|^h - 1)}{(|O| - 1)}$$

# Alpha Vectors for Conditional Plans

Conditional Plans: fixed-depth history-based policies

1 Step: (L) (OL) (OR)



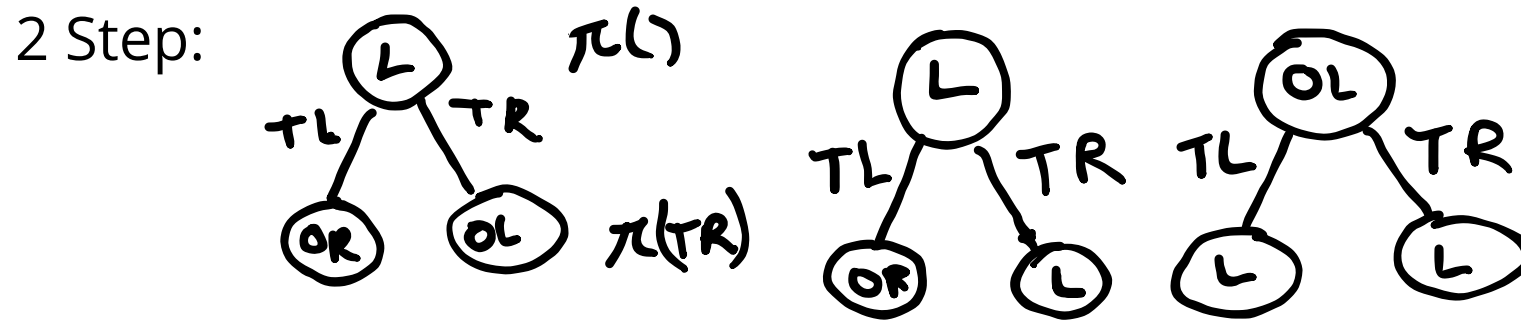
$$|A| \frac{(|O|^h - 1)}{(|O| - 1)}$$

27 two step plans!

# Alpha Vectors for Conditional Plans

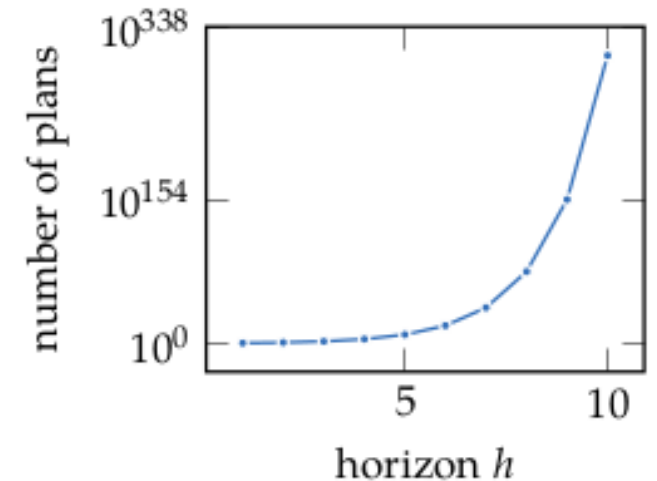
Conditional Plans: fixed-depth history-based policies

1 Step: (L) (OL) (OR)



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27 two step plans!

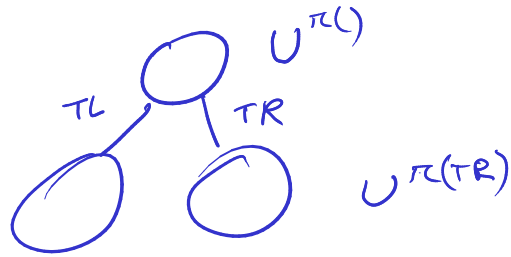


# Alpha Vectors for Conditional Plans

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$$U^\pi(s) = R(s, \pi(s)) + \gamma E(U^\pi(s'))$$

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$



# Alpha Vectors for Conditional Plans

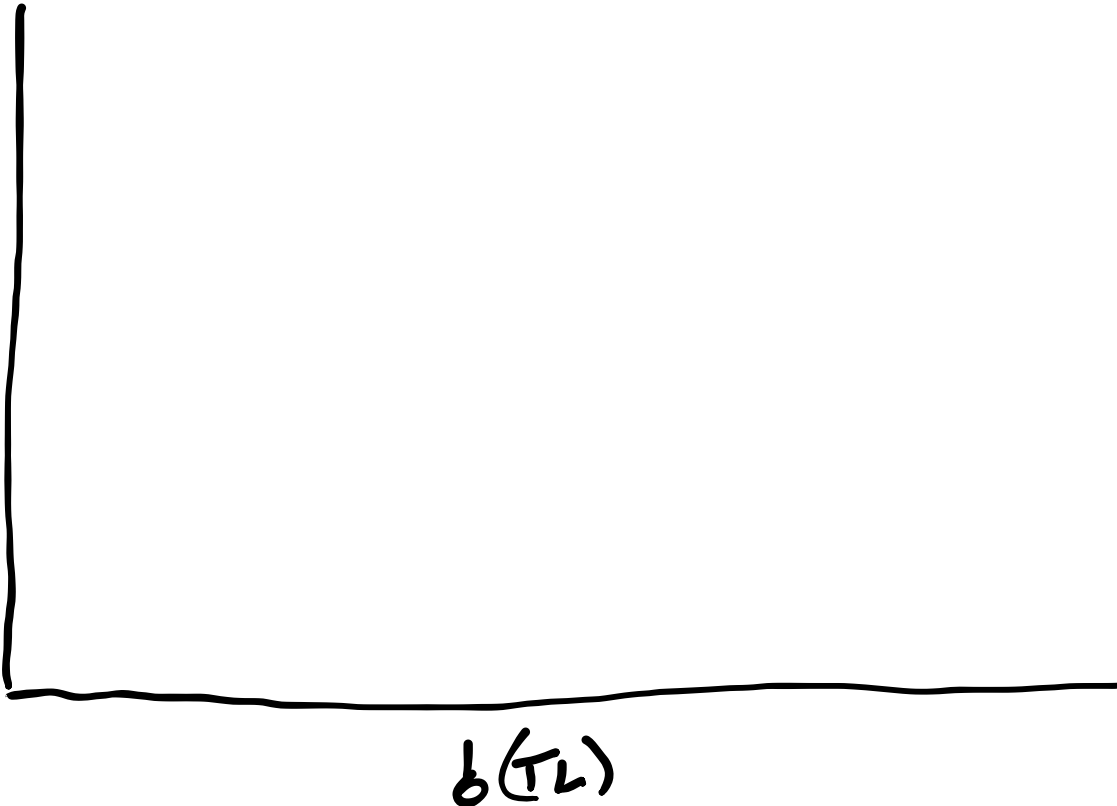
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$

# Alpha Vectors for Conditional Plans

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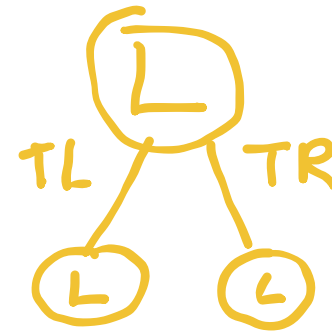




# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$

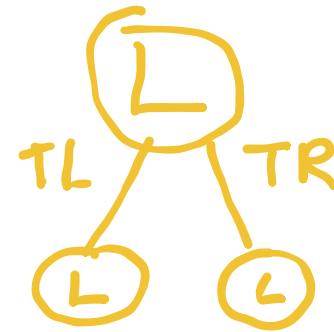


$b(\pi_L)$

# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



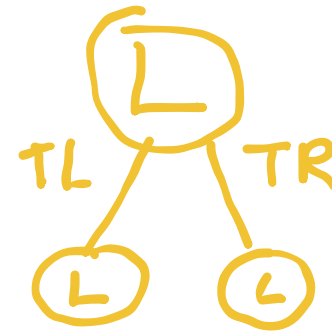
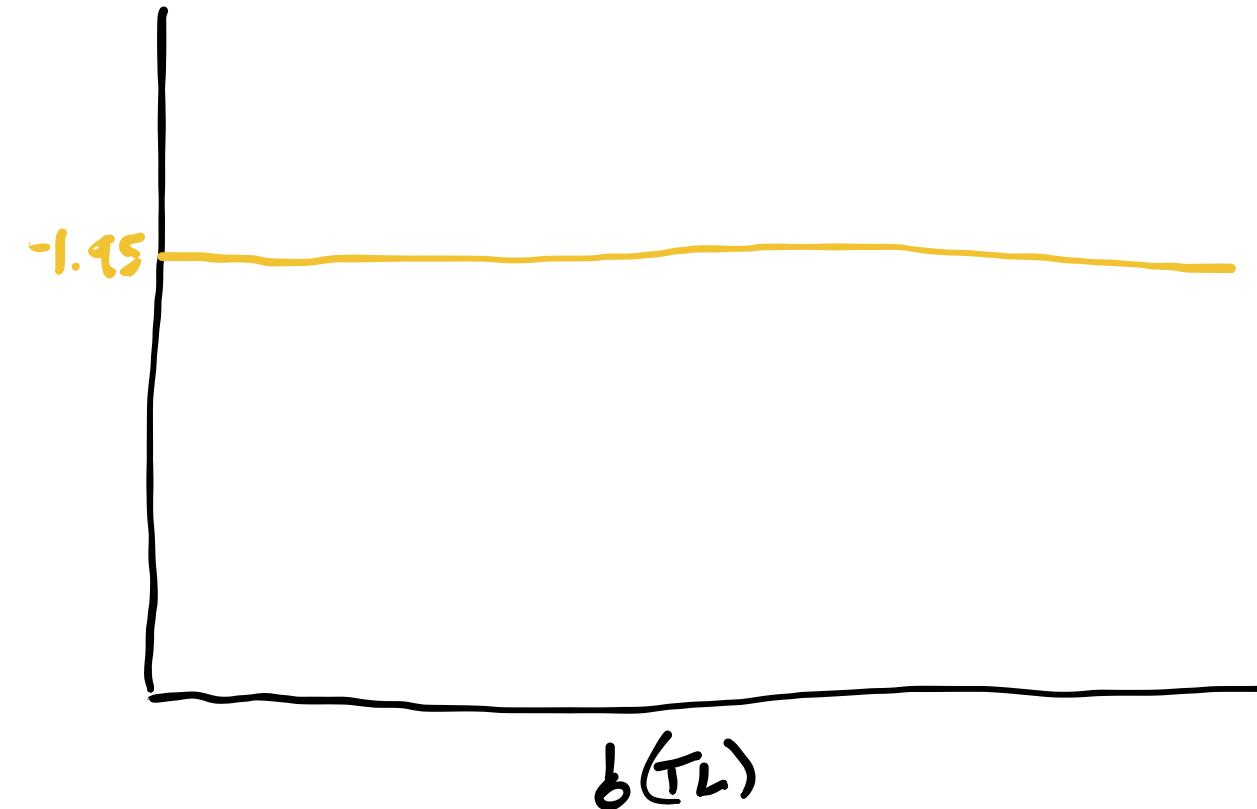
$$U^\pi(s) = -1 + \gamma(-1)$$

$b(\pi_L)$

# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$

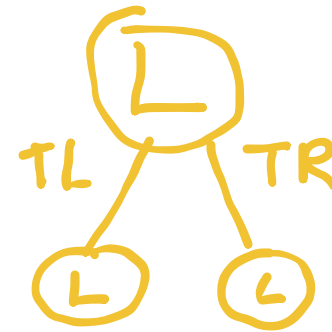
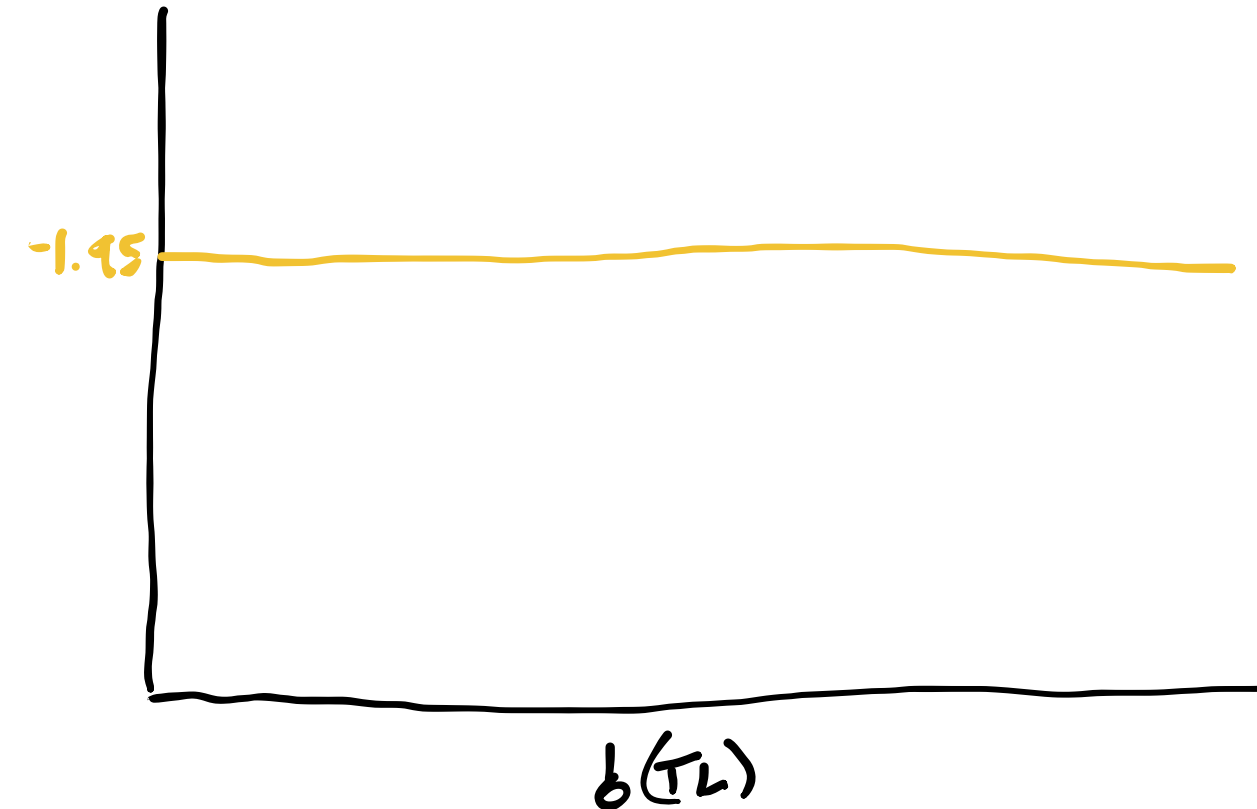


$$U^\pi(s) = -1 + \gamma(-1)$$

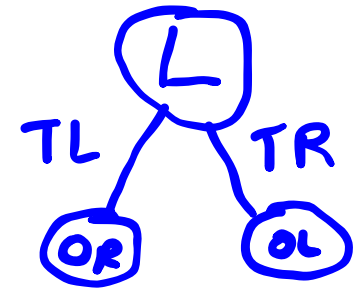
# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



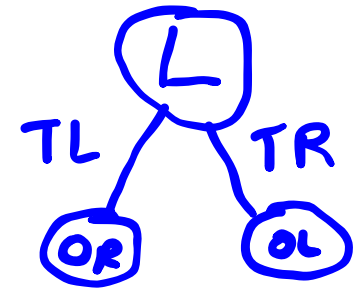
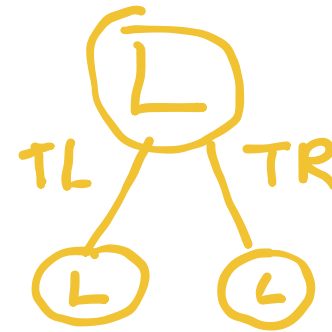
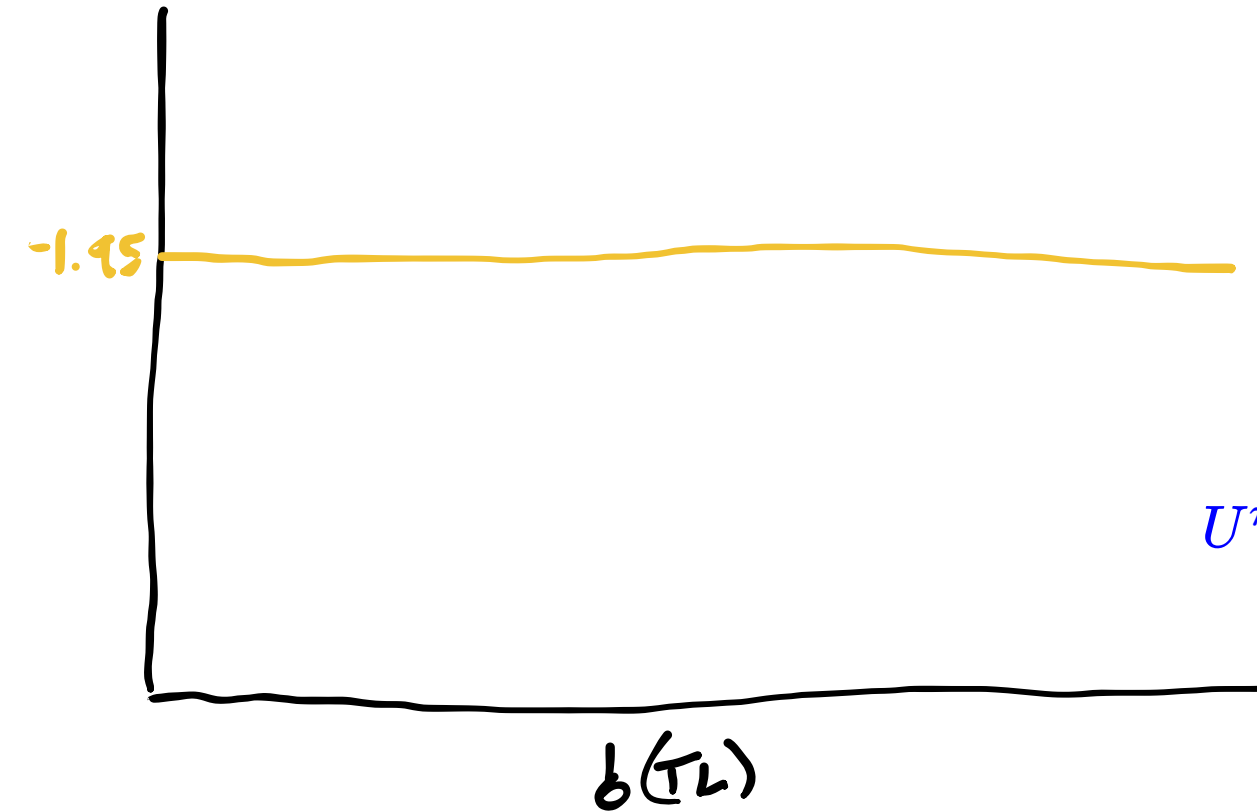
$$U^\pi(s) = -1 + \gamma(-1)$$



# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



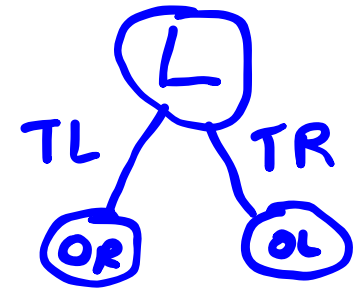
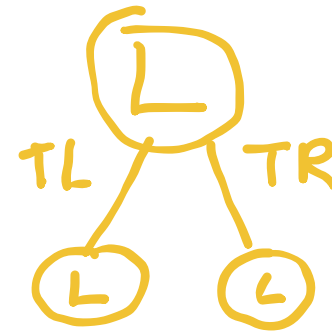
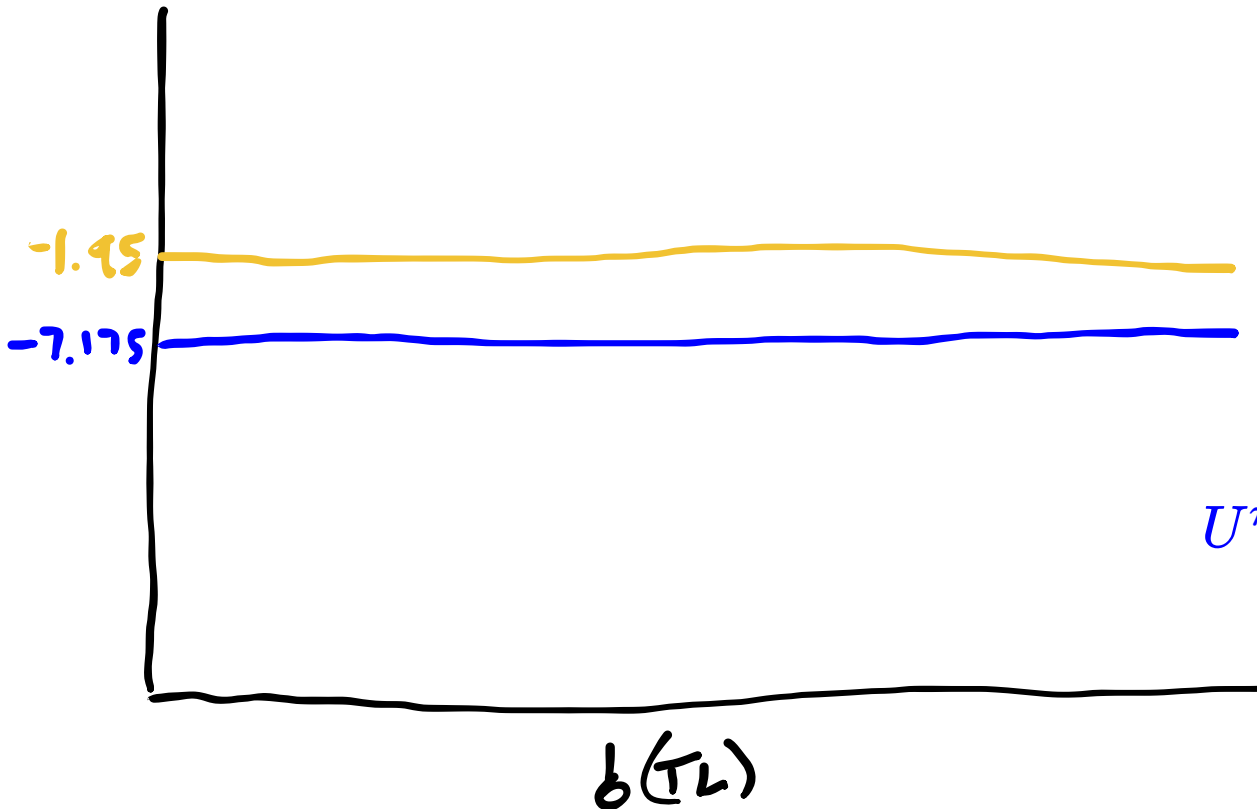
$$U^\pi(s) = -1 + \gamma(-1)$$

$$U^\pi(TL) = -1 + 0.95(1(0.85 \times 10 + 0.15 \times -100))$$

# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



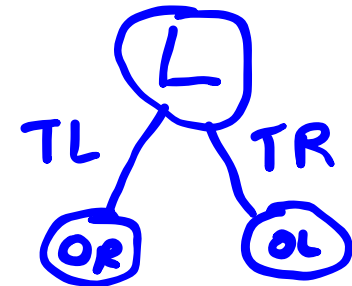
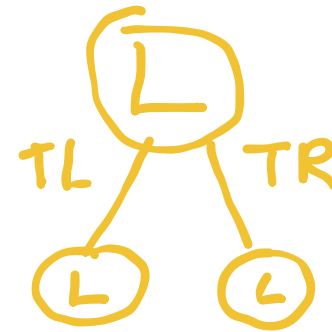
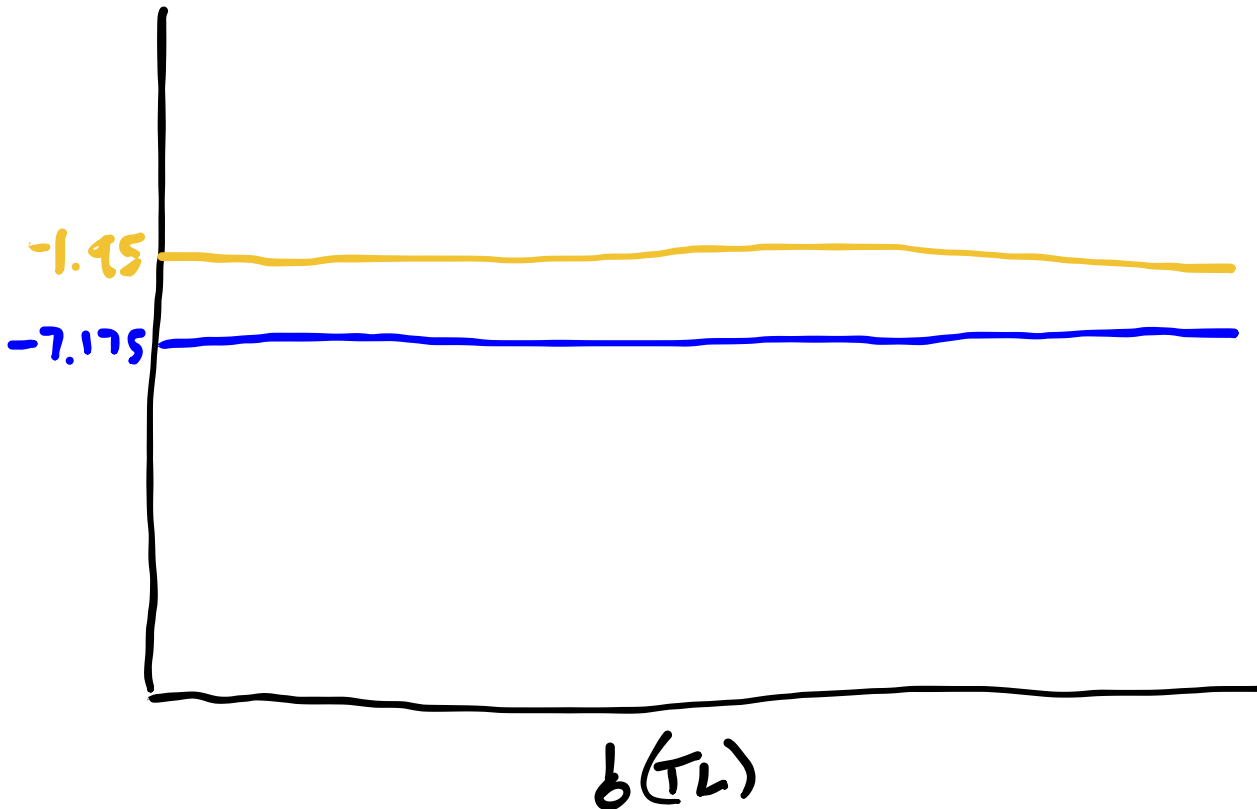
$$U^\pi(s) = -1 + \gamma(-1)$$

$$\begin{aligned} U^\pi(TL) &= -1 + 0.95(1(0.85 \times 10 + 0.15 \times -100)) \\ &= -7.175 \end{aligned}$$

# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

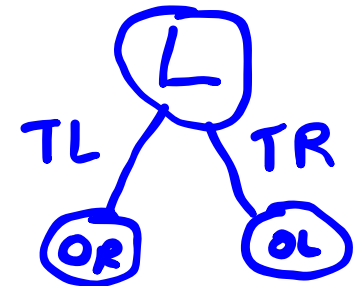
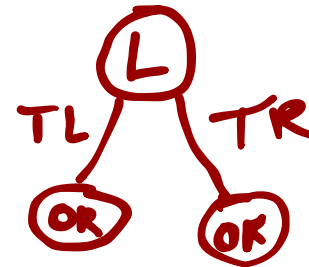
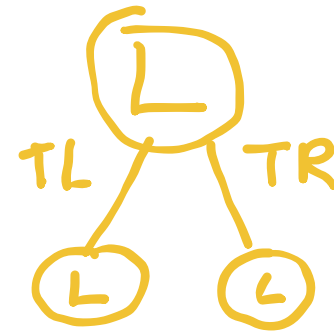
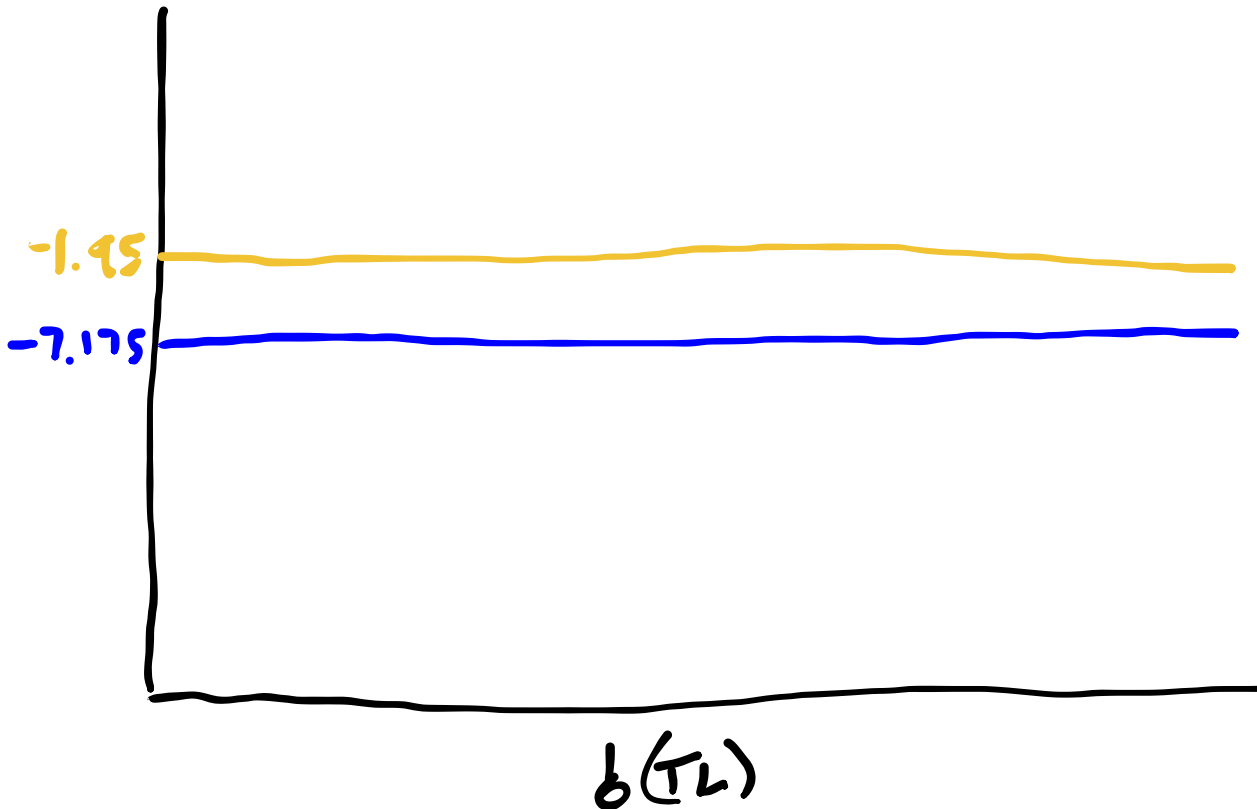
For 1-step:  $U^\pi(s) = R(s, \pi())$



# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

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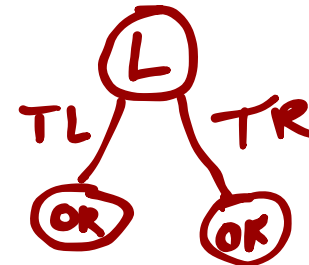
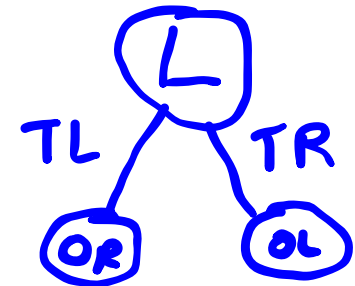
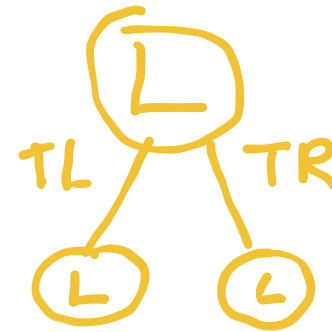
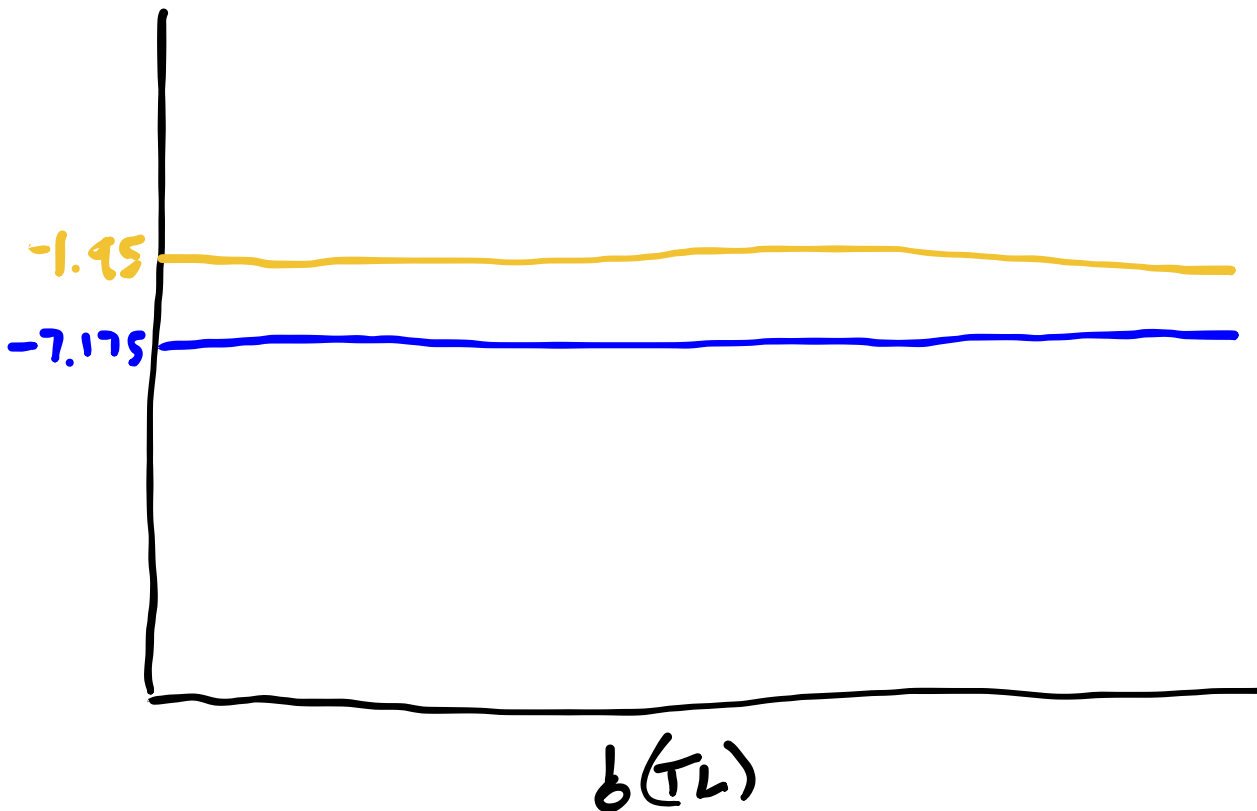




# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

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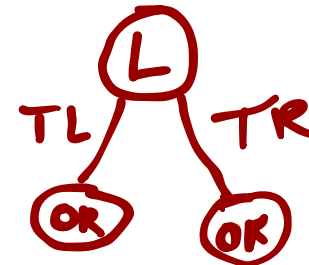
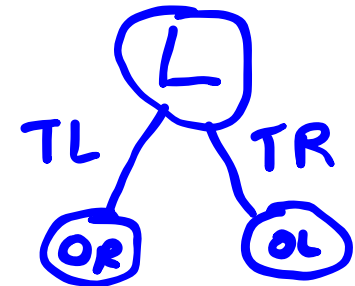
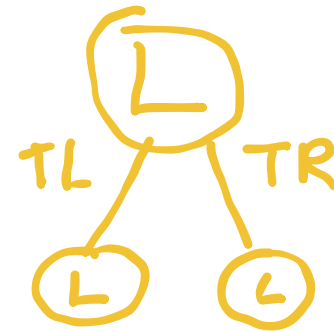
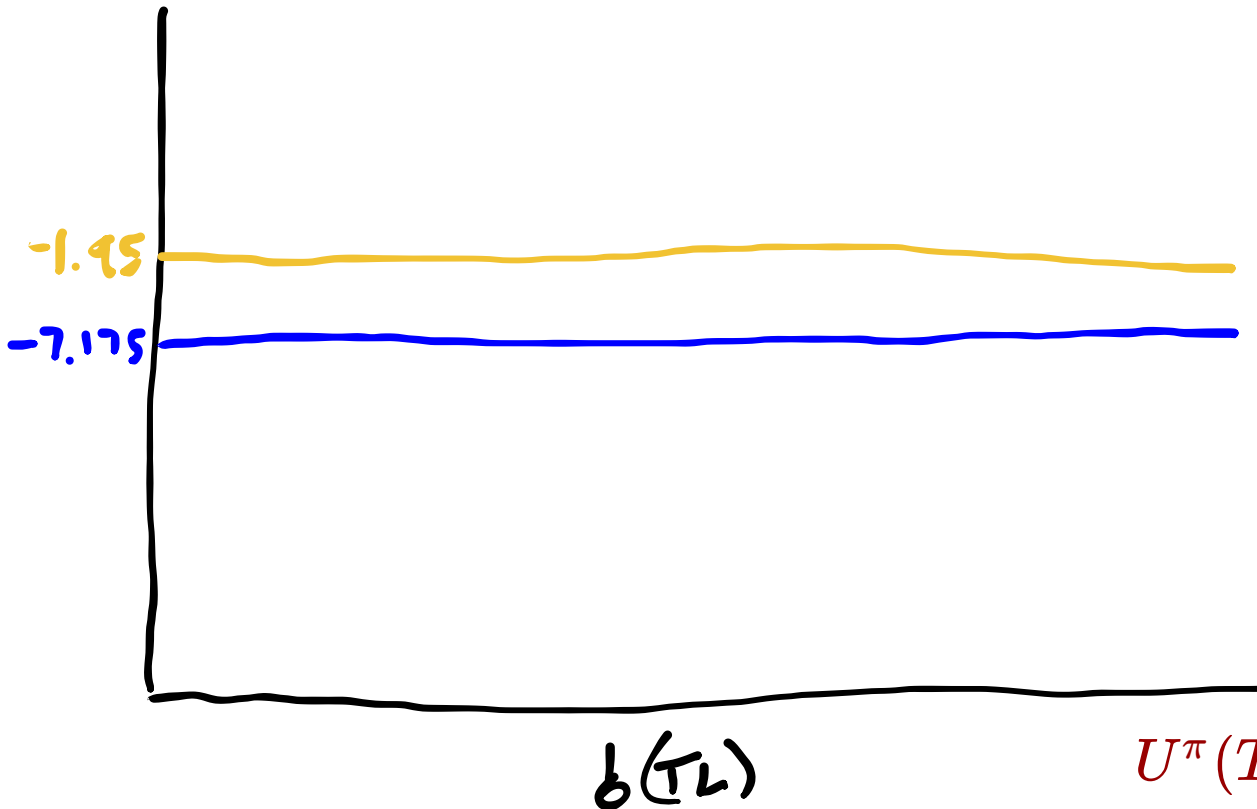


$$U^\pi(TL) = -1 + \gamma 10$$

# Alpha Vectors for Conditional Plans

$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



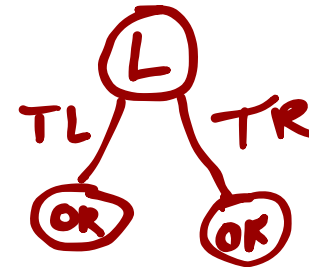
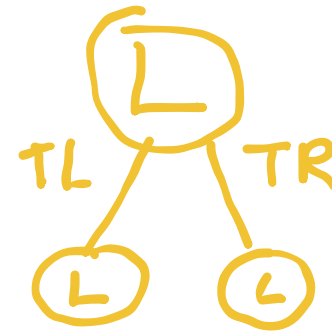
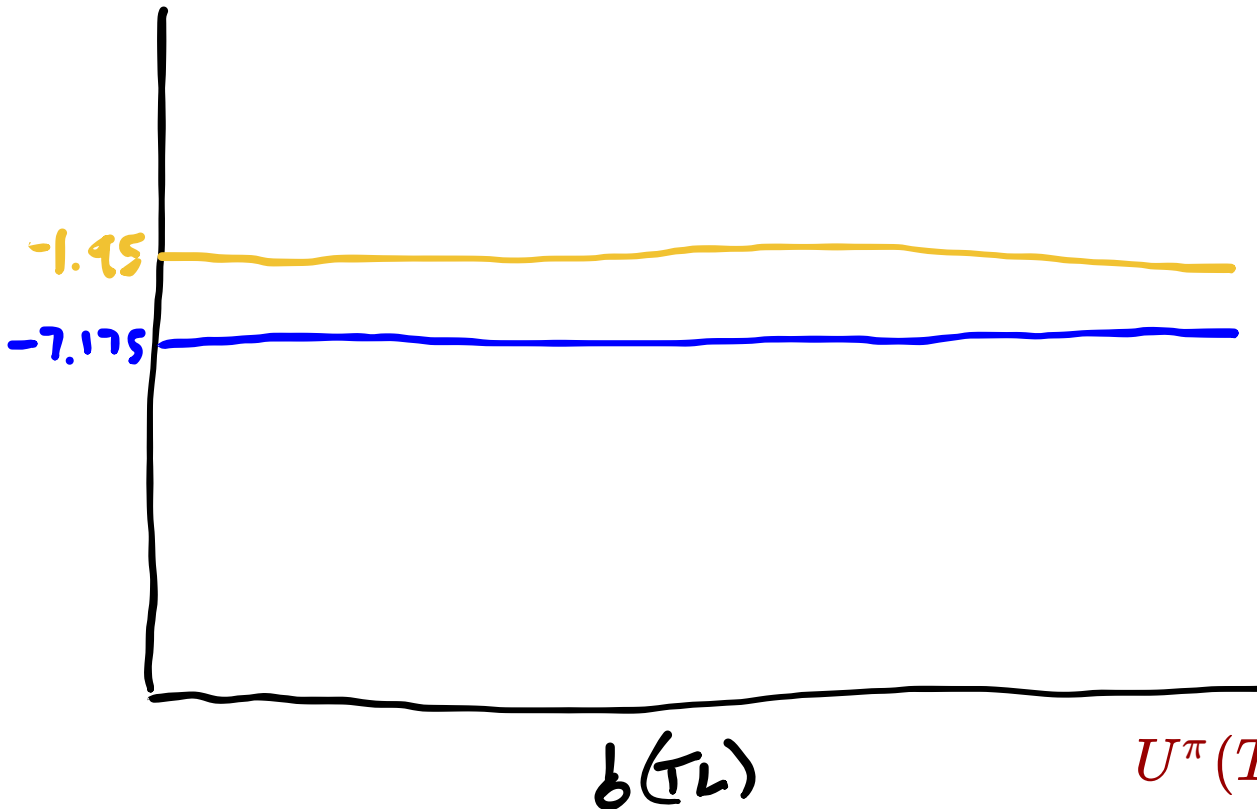
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# Alpha Vectors for Conditional Plans

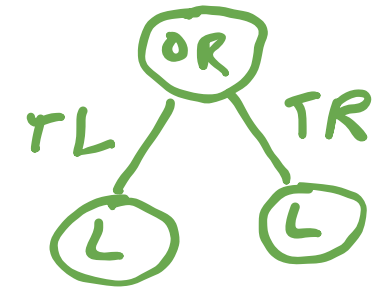
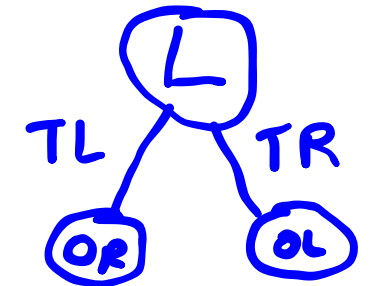
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



$$U^\pi(TL) = -1 + \gamma 10$$

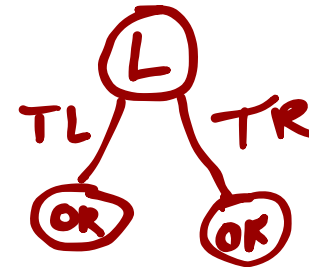
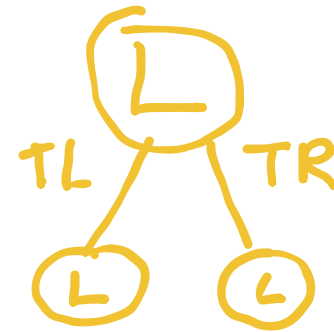
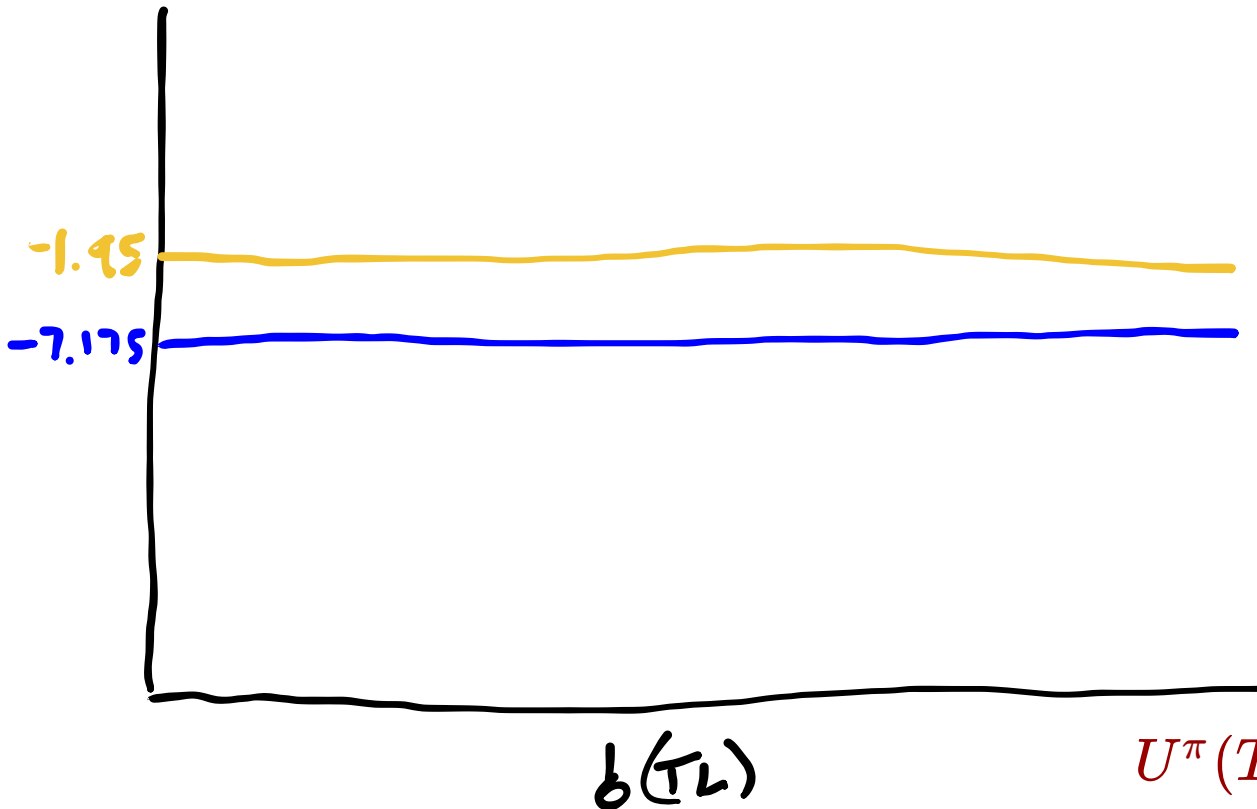
$$U^\pi(TR) = -1 + \gamma(-100)$$



# Alpha Vectors for Conditional Plans

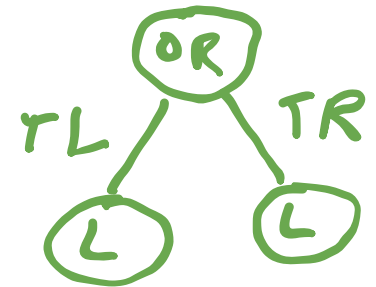
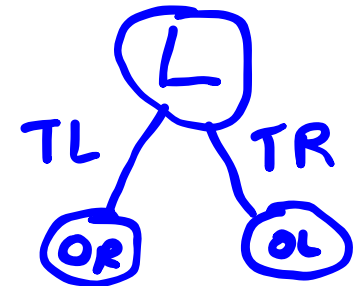
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



$$U^\pi(TL) = -1 + \gamma 10$$

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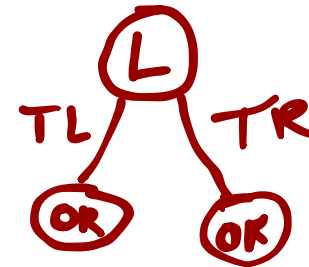
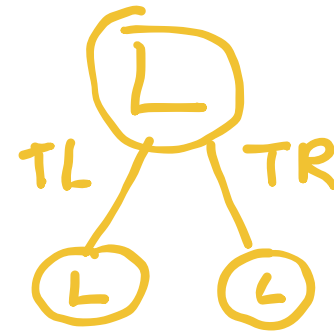
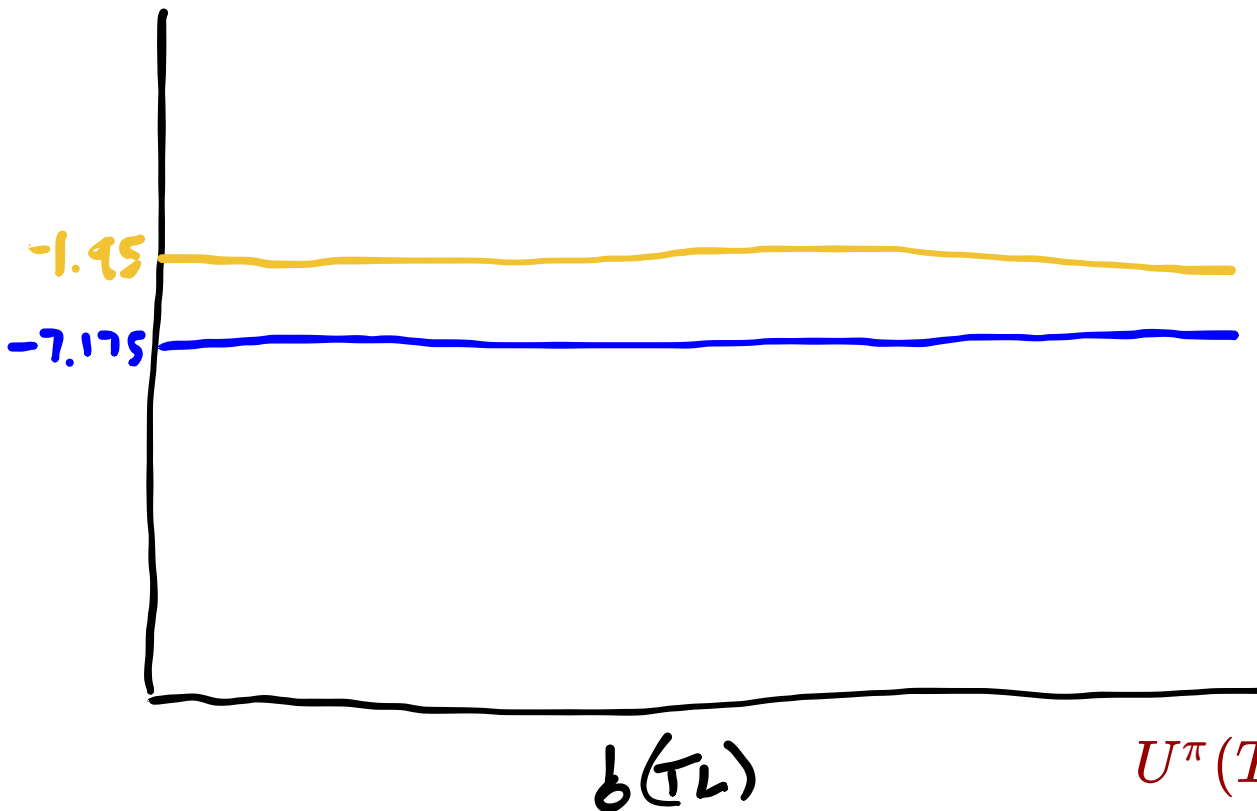


$$U^\pi(TL) = 10 + \gamma(-1)$$

# Alpha Vectors for Conditional Plans

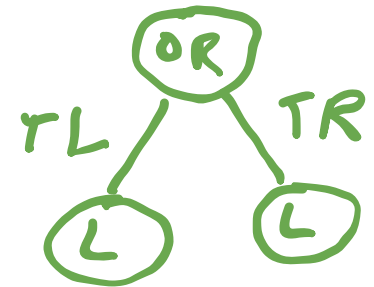
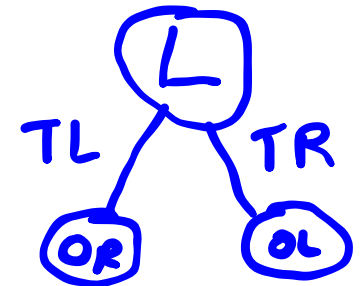
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

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$$U^\pi(TL) = -1 + \gamma 10$$

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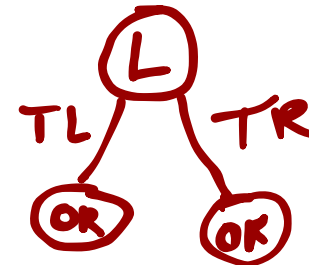
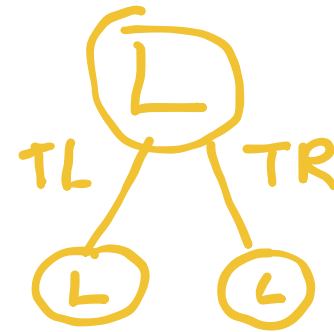
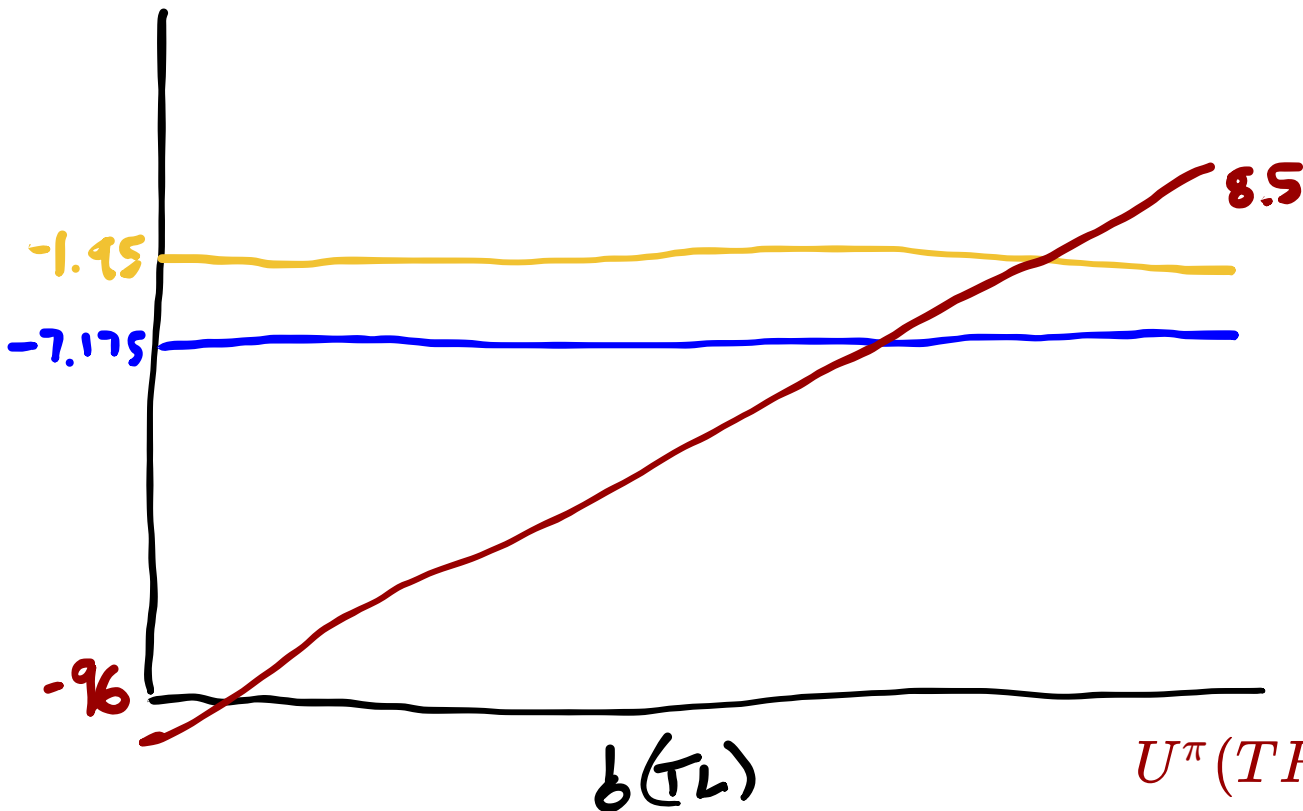
$$U^\pi(TL) = 10 + \gamma(-1)$$

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# Alpha Vectors for Conditional Plans

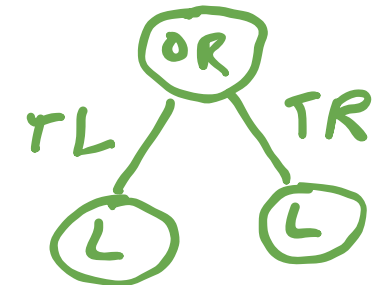
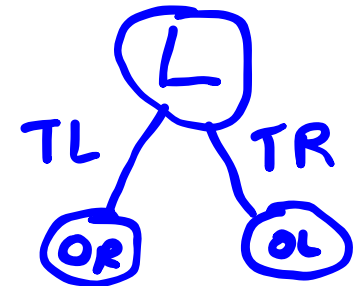
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

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$$U^\pi(TL) = -1 + \gamma 10$$

$$U^\pi(TR) = -1 + \gamma(-100)$$



$$U^\pi(TL) = 10 + \gamma(-1)$$

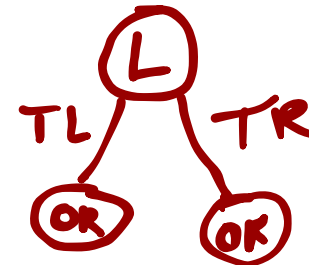
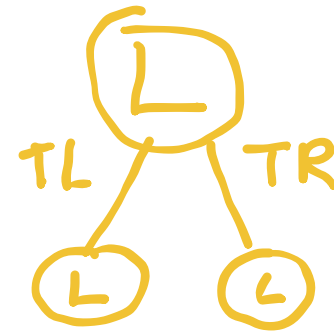
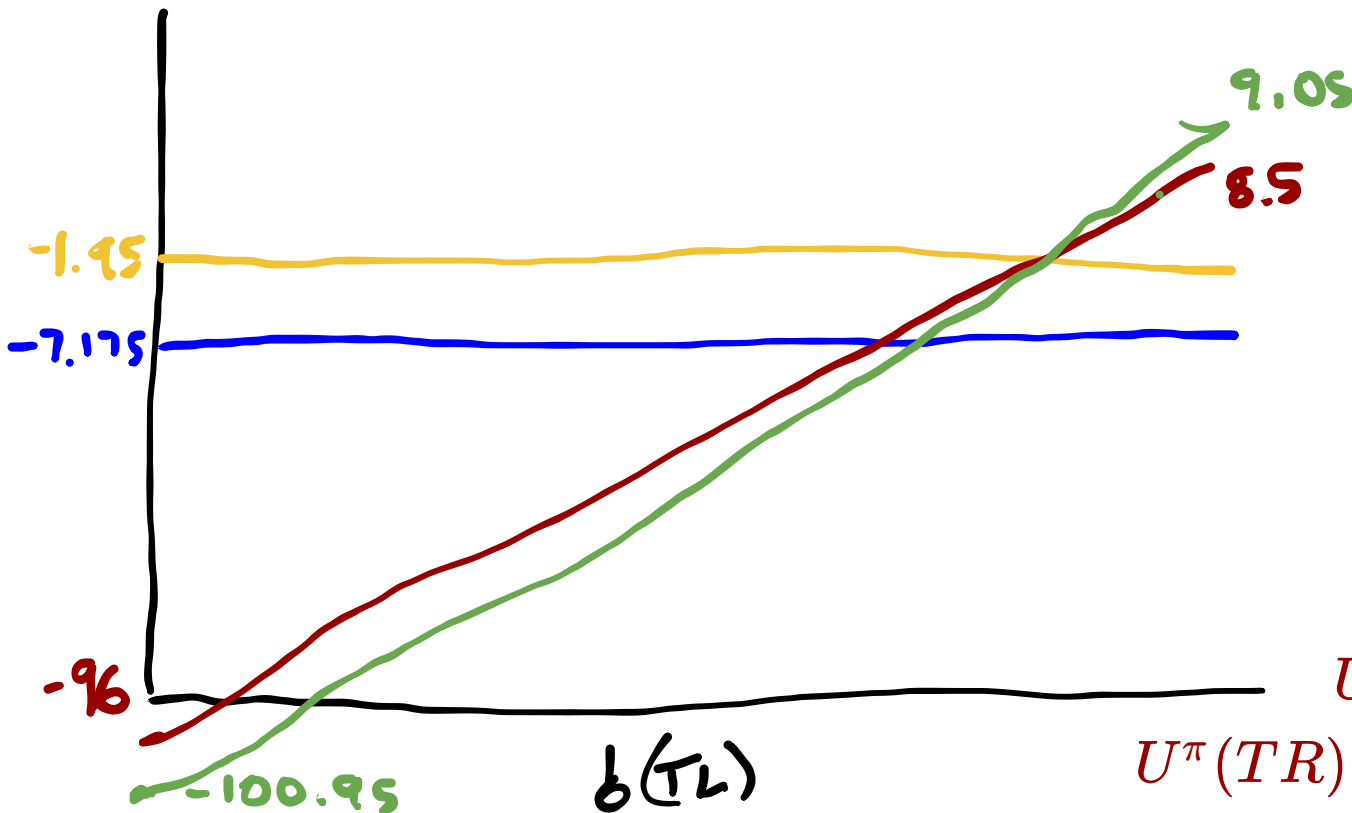
$$U^\pi(TR) = -100 + \gamma(-1)$$

# Alpha Vectors for Conditional Plans

$$U^\pi(b) = \mathbb{E}_{s \sim b} [U^\pi(s)]$$

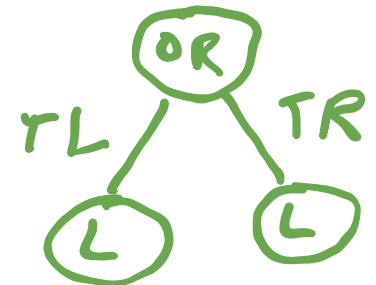
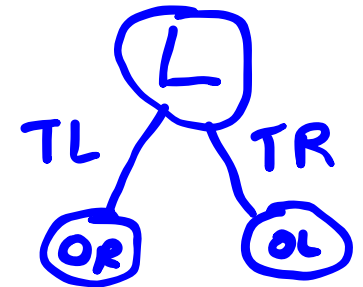
$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' | s, \pi()) \sum_o O(o | \pi(), s') U^{\pi(o)}(s') \right]$$

For 1-step:  $U^\pi(s) = R(s, \pi())$



$$U^\pi(TL) = -1 + \gamma 10$$

$$U^\pi(TR) = -1 + \gamma(-100)$$



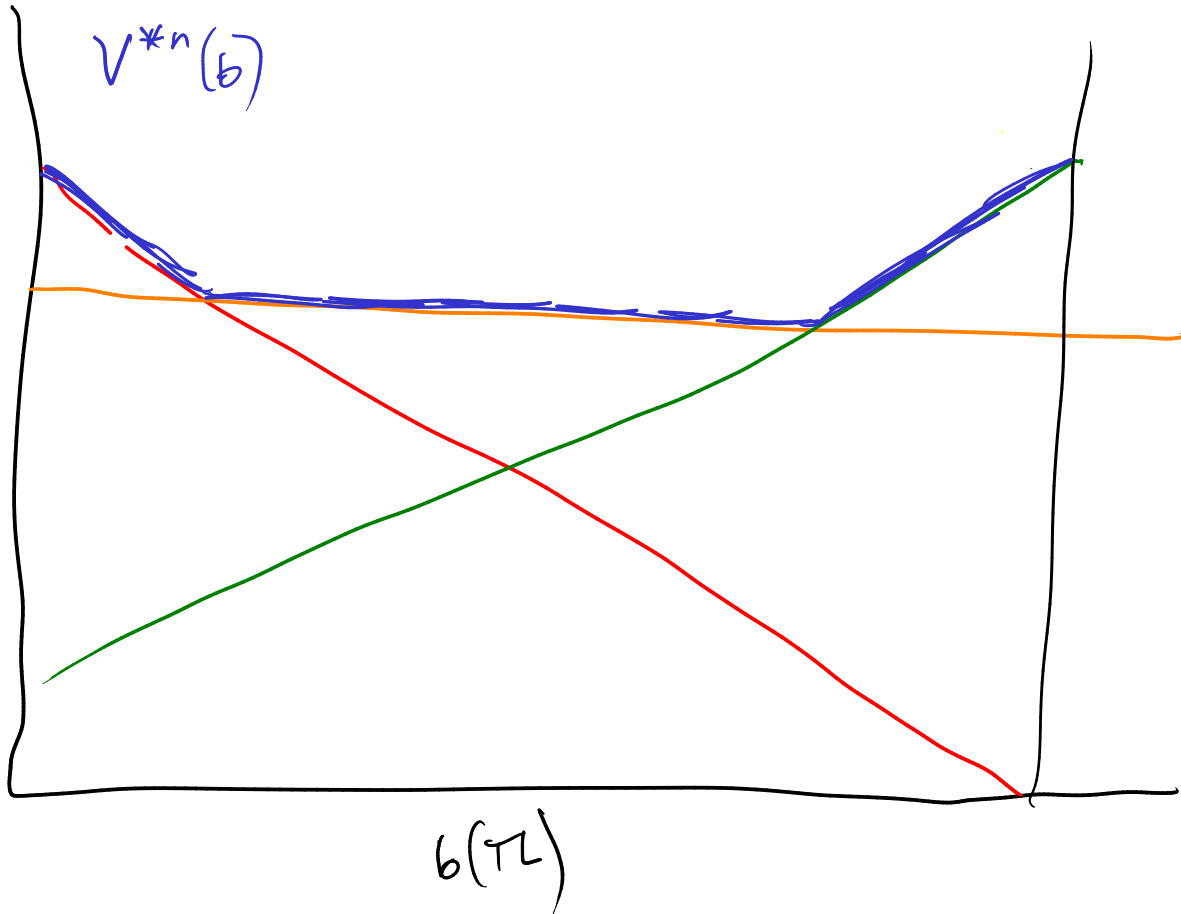
$$U^\pi(TL) = 10 + \gamma(-1)$$

$$U^\pi(TR) = -100 + \gamma(-1)$$

# POMDP Value Functions

Each conditional plan has a corresponding vector

$$\alpha^\pi(s) = U^\pi(s)$$



$n = \text{number of steps}$

$$V^{*n}(b) = \max_{\alpha \in \Gamma} \alpha^\top b$$



# POMDP Value Functions

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

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

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

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

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

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

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

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

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

$$R(s, a) = R(s) + R(a)$$

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

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

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

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

$$R(s, a) = R(s) + R(a)$$

$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

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

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$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

$$R(a) = \begin{cases} -5 & \text{if } a = f \\ 0 & \text{otherwise} \end{cases}$$

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

$$S = \{h, \neg h\} \quad T(h \mid h, \neg f) = 1.0$$

$$A = \{f, \neg f\} \quad T(h \mid \neg h, \neg f) = 0.1$$

$$O = \{c, \neg c\} \quad T(\neg h \mid \cdot, f) = 1.0$$

$$R(s, a) = R(s) + R(a)$$

$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

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$$R(a) = \begin{cases} -5 & \text{if } a = f \\ 0 & \text{otherwise} \end{cases}$$

$$Z(c \mid \cdot, h) = 0.8$$

$$Z(c \mid \cdot, \neg h) = 0.1$$



# Exercise: 2-Step Crying Baby $\alpha$ Vectors

$$S = \{h, \neg h\} \quad T(h \mid h, \neg f) = 1.0$$

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$$R(s, a) = R(s) + R(a)$$

$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

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$$Z(c \mid \cdot, h) = 0.8$$

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$$\gamma = 0.9$$

# Exercise: 2-Step Crying Baby $\alpha$ Vectors

$$S = \{h, \neg h\} \quad T(h \mid h, \neg f) = 1.0$$

$$A = \{f, \neg f\} \quad T(h \mid \neg h, \neg f) = 0.1$$

$$O = \{c, \neg c\} \quad T(\neg h \mid \cdot, f) = 1.0$$

$$R(s, a) = R(s) + R(a)$$

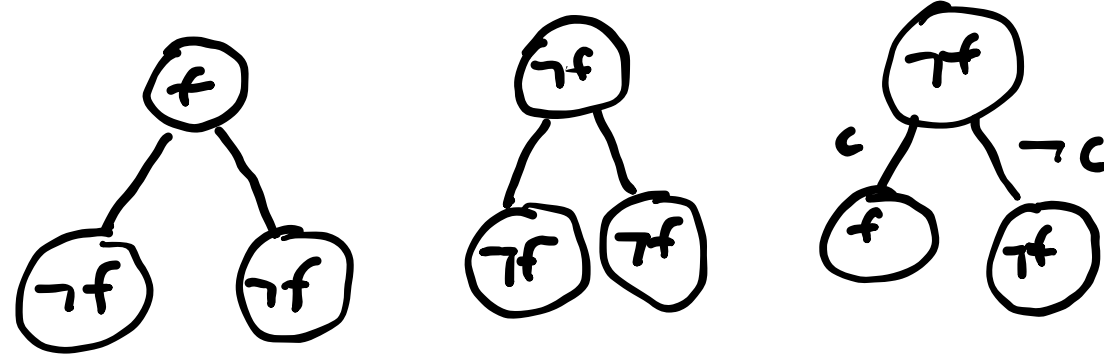
$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

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$$Z(c \mid \cdot, h) = 0.8$$

$$Z(c \mid \cdot, \neg h) = 0.1$$

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# Exercise: 2-Step Crying Baby $\alpha$ Vectors

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

$$T(h \mid h, \neg f) = 1.0$$

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

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$$T(\neg h \mid \cdot, f) = 1.0$$

$$R(s, a) = R(s) + R(a)$$

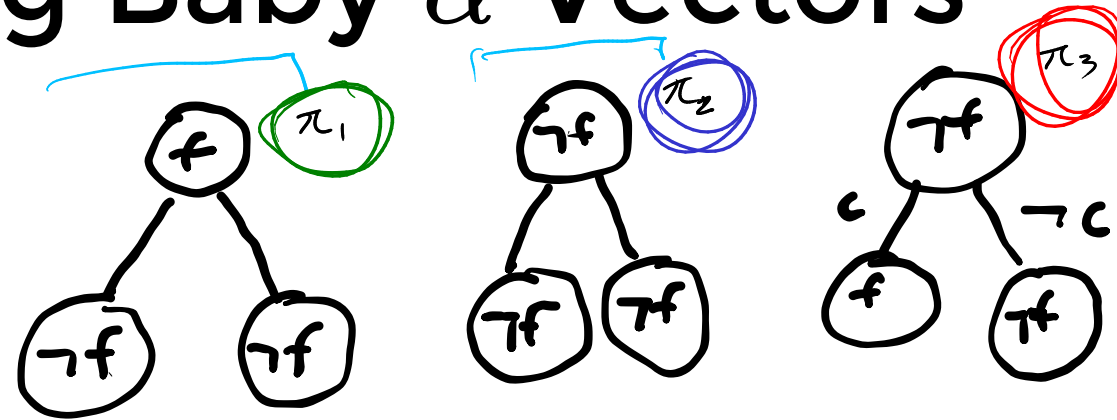
$$R(s) = \begin{cases} -10 & \text{if } s = h \\ 0 & \text{otherwise} \end{cases}$$

$$R(a) = \begin{cases} -5 & \text{if } a = f \\ 0 & \text{otherwise} \end{cases}$$

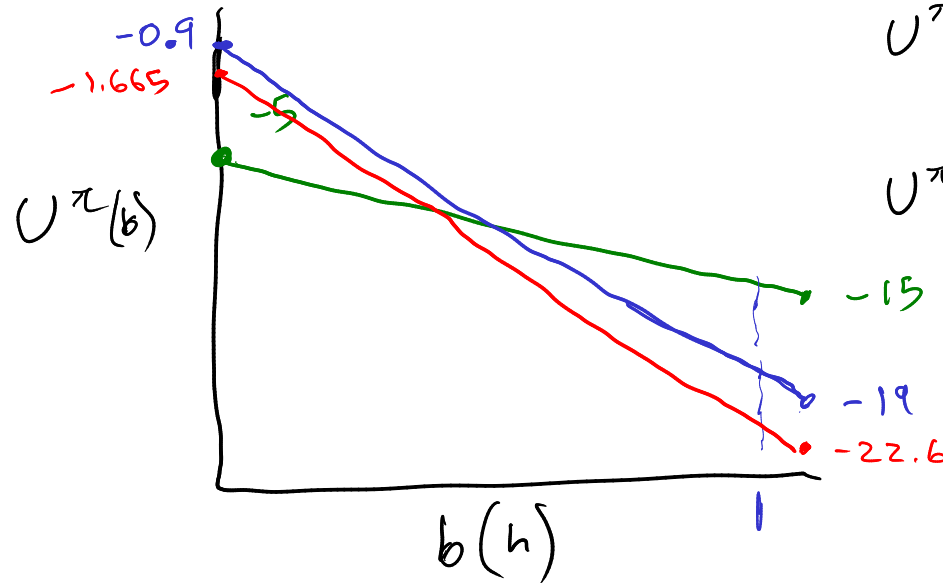
$$Z(c \mid \cdot, h) = 0.8$$

$$Z(c \mid \cdot, \neg h) = 0.1$$

$$\gamma = 0.9$$



$$U^\pi(s) = R(s, \pi()) + \gamma \left[ \sum_{s'} T(s' \mid s, \pi()) \sum_o O(o \mid \pi(), s') U^{\pi(o)}(s') \right]$$

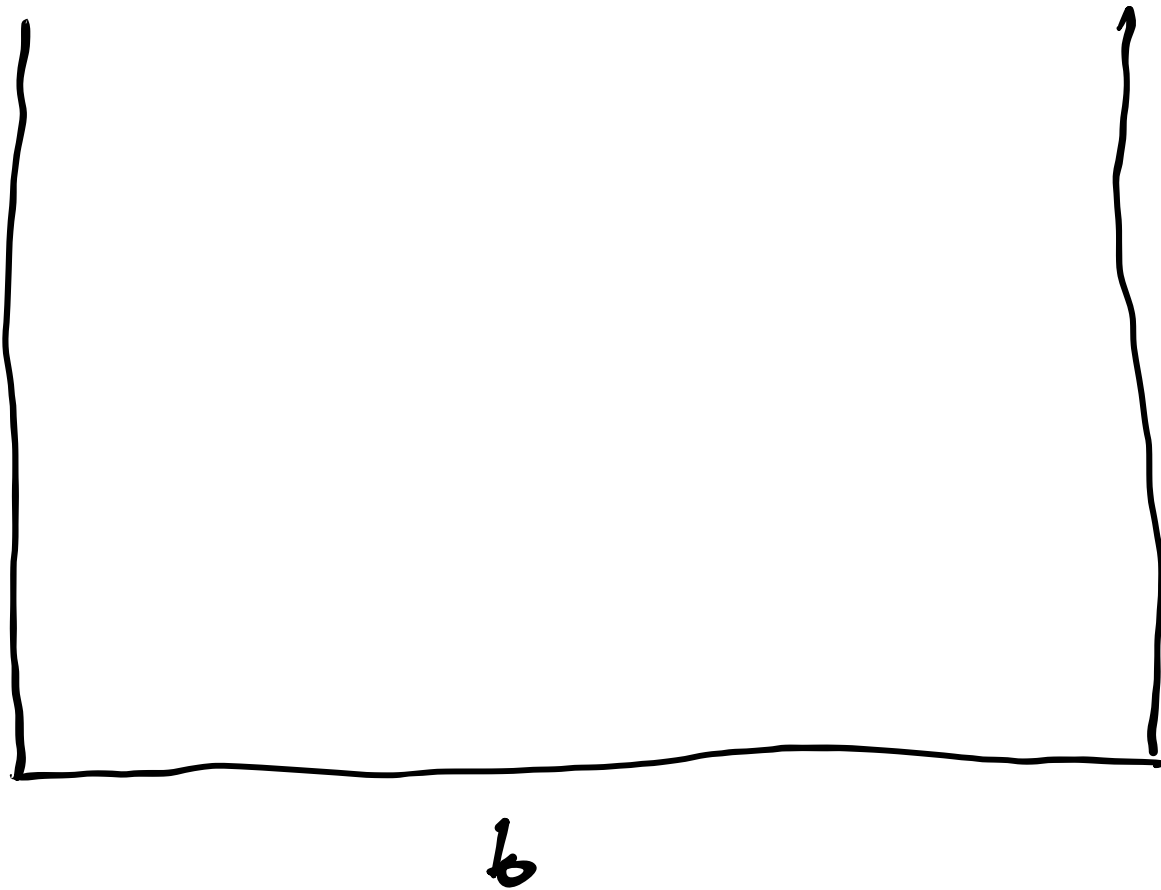


$$U^{\pi_3}(h) = -10 + \gamma(0.8(-15) + 0.2(-10)) = -22.6$$

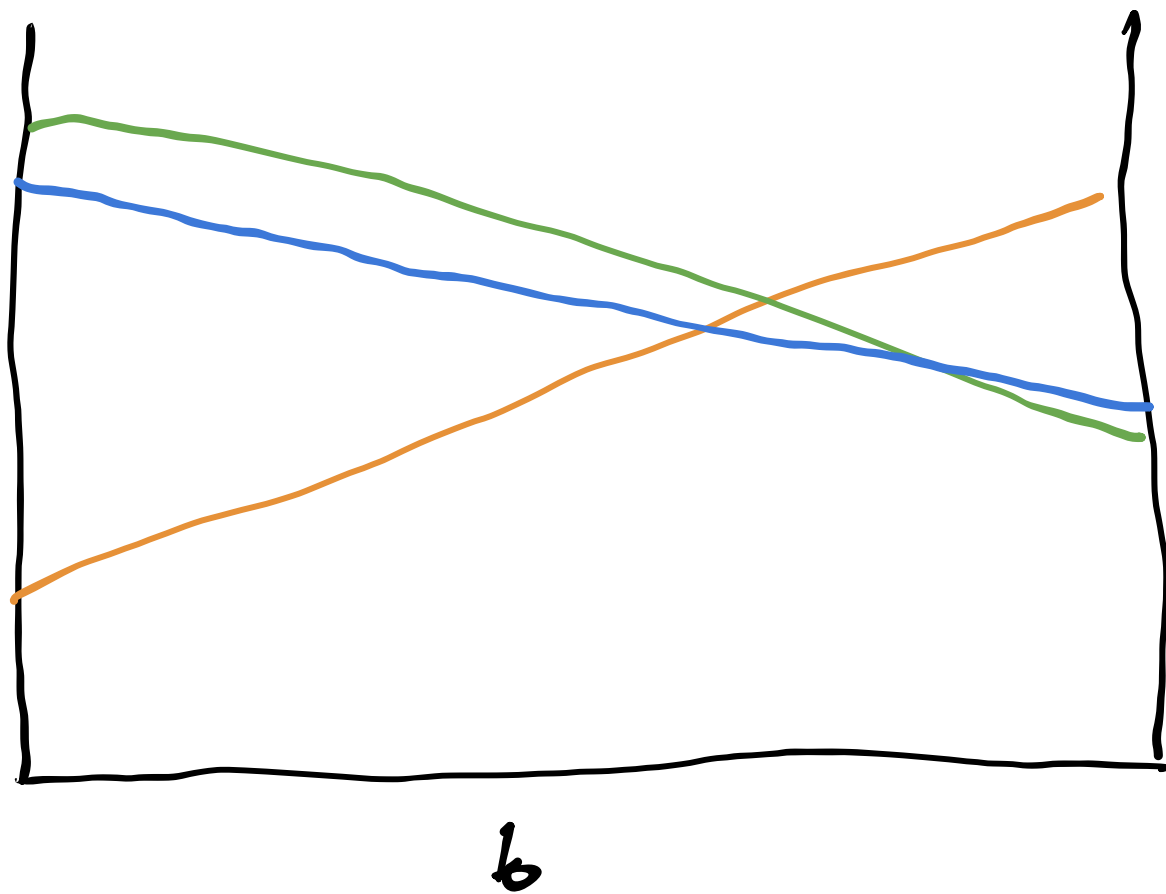
$$U^{\pi_3}(\neg h) = 0 - \gamma(0.1(0.2(-10) + 0.8(-15)) + 0.9(0.9(0) + 0.1(-5))) = -1.665$$

# $\alpha$ -Vector Pruning

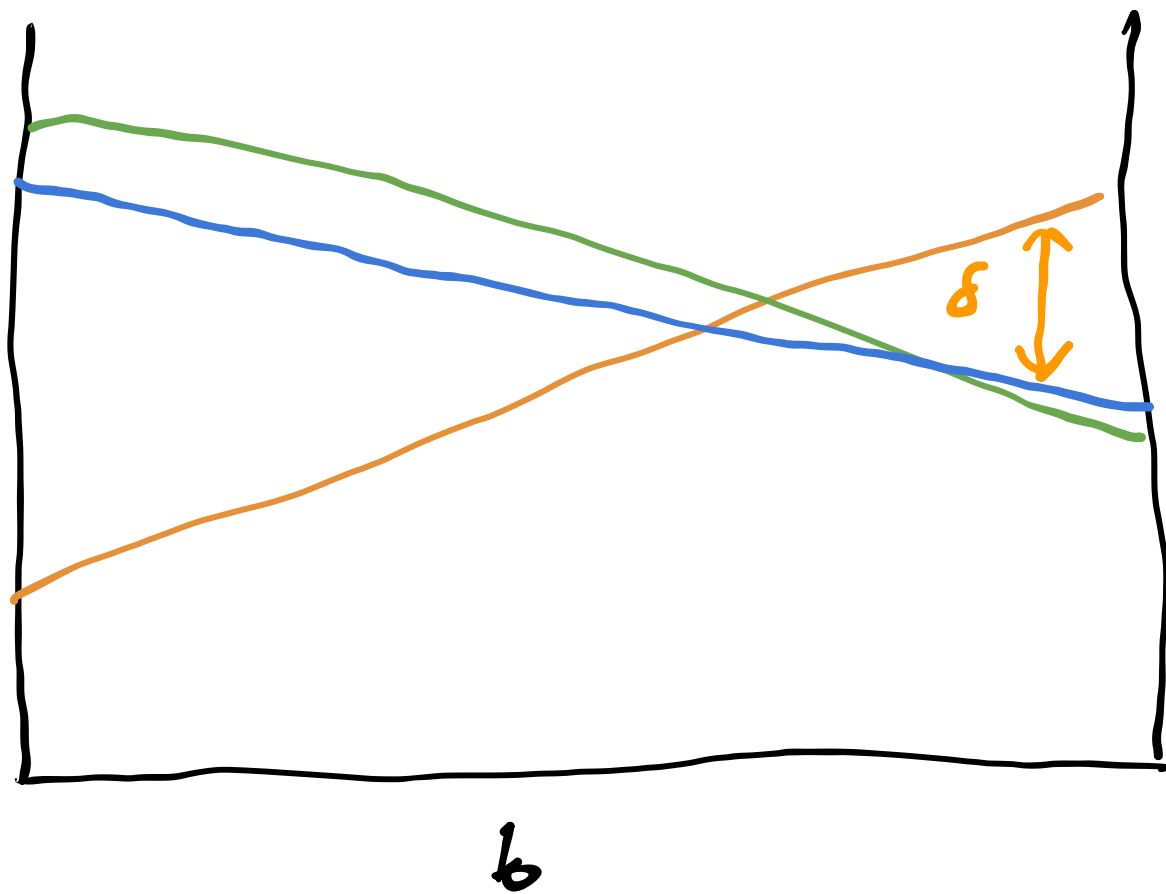
# $\alpha$ -Vector Pruning



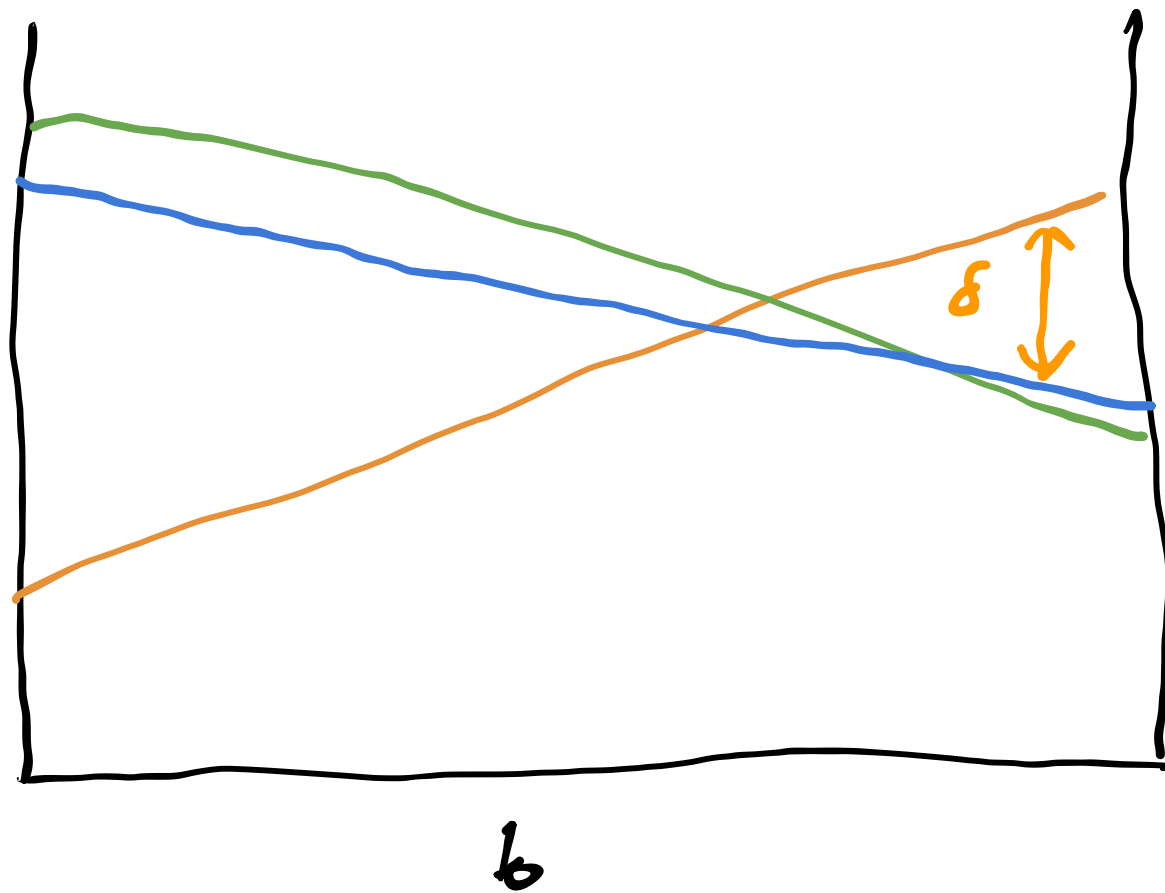
# $\alpha$ -Vector Pruning



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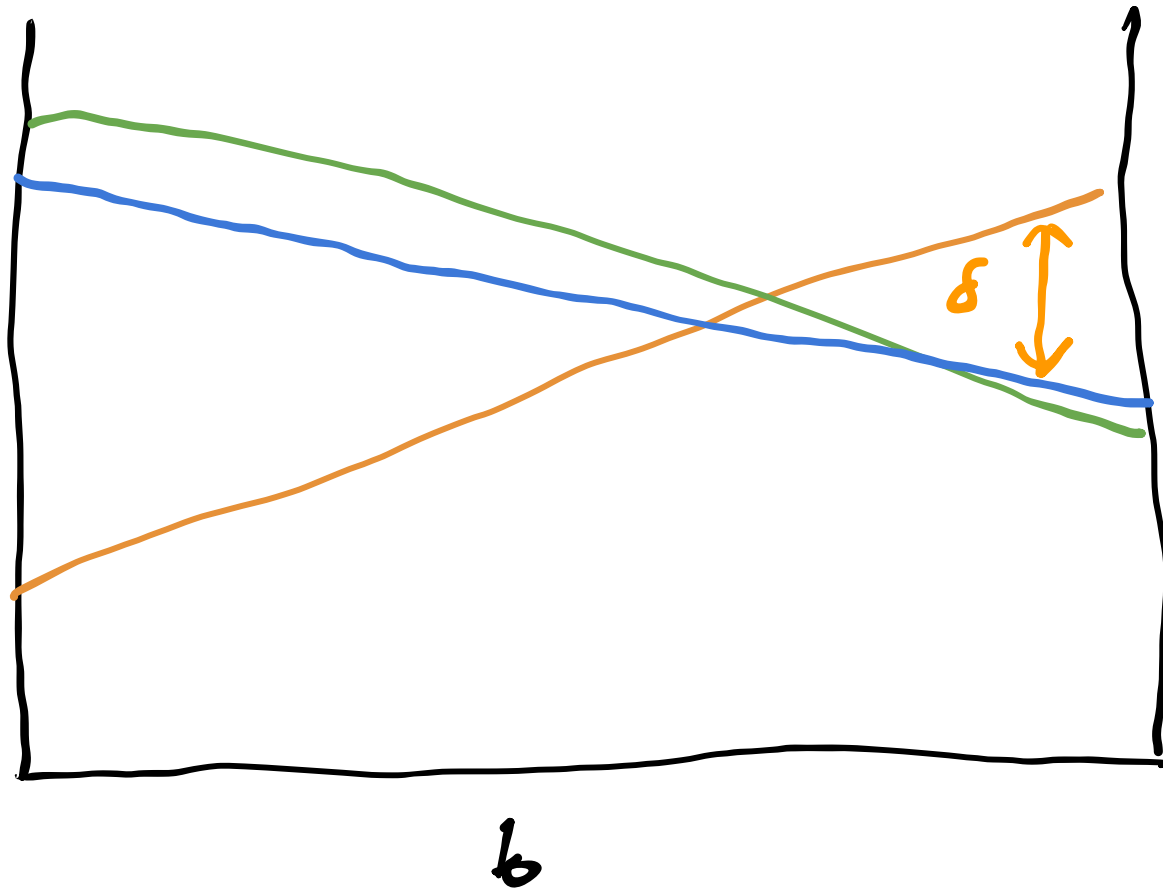
# $\alpha$ -Vector Pruning



maximize  $\delta$   
 $\delta, b$

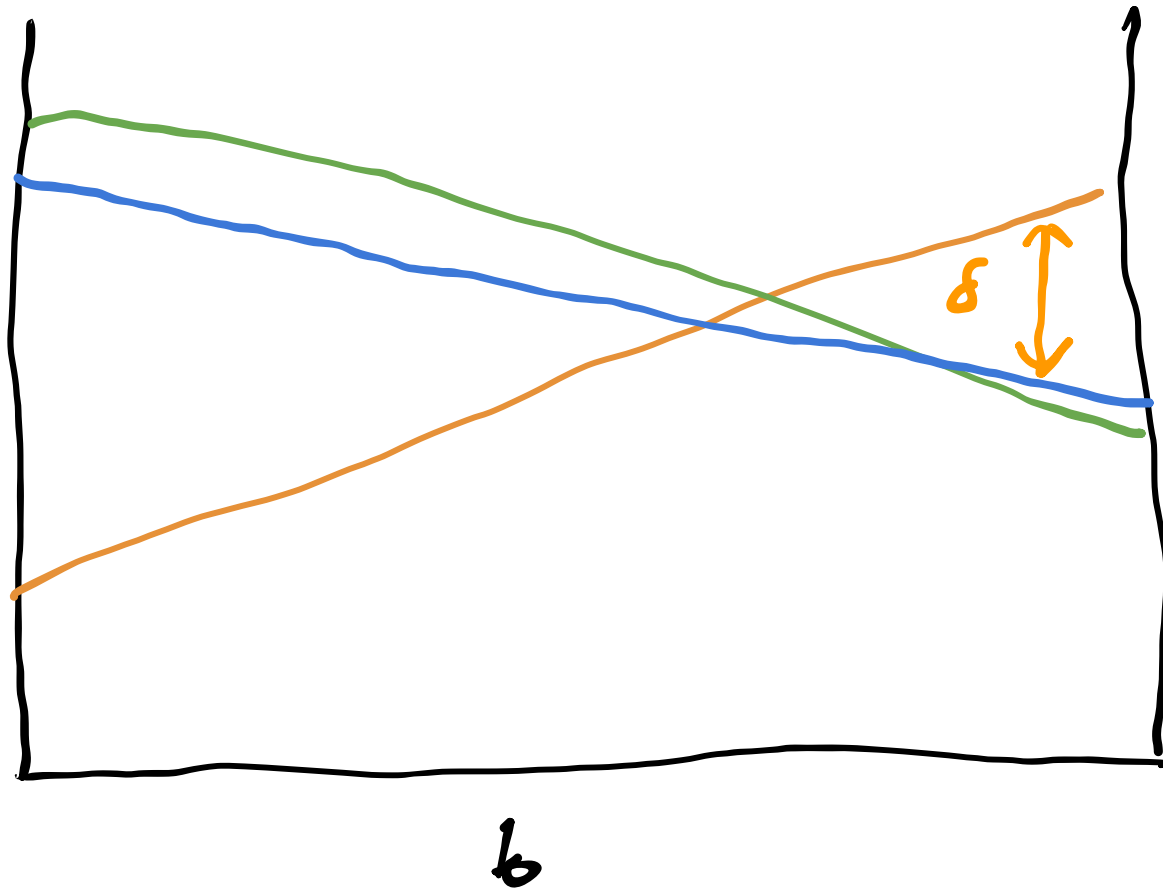


# $\alpha$ -Vector Pruning



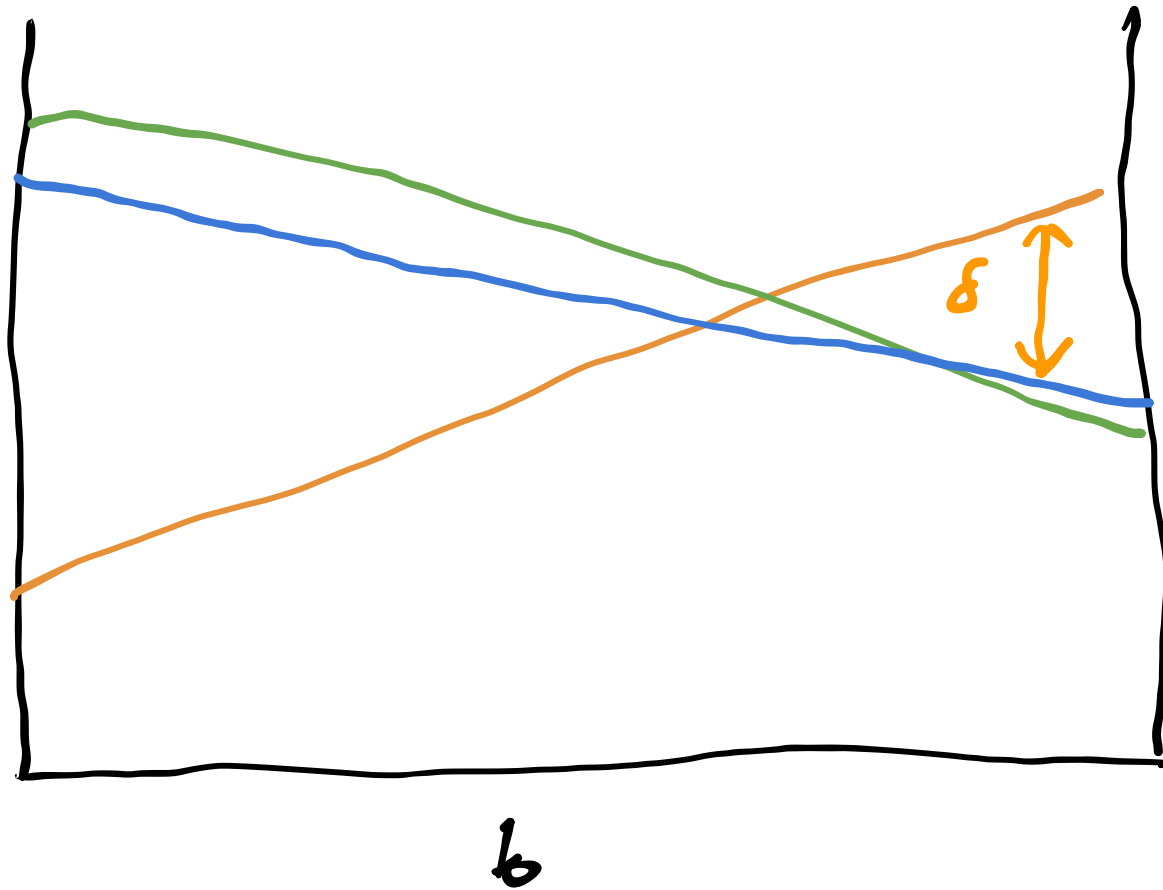
maximize  $\delta$   
subject to  $b \geq 0$

# $\alpha$ -Vector Pruning



$$\begin{aligned} &\underset{\delta, b}{\text{maximize}} && \delta \\ &\text{subject to} && b \geq 0 \\ &&& \mathbf{1}^\top b = 1 \end{aligned}$$

# $\alpha$ -Vector Pruning

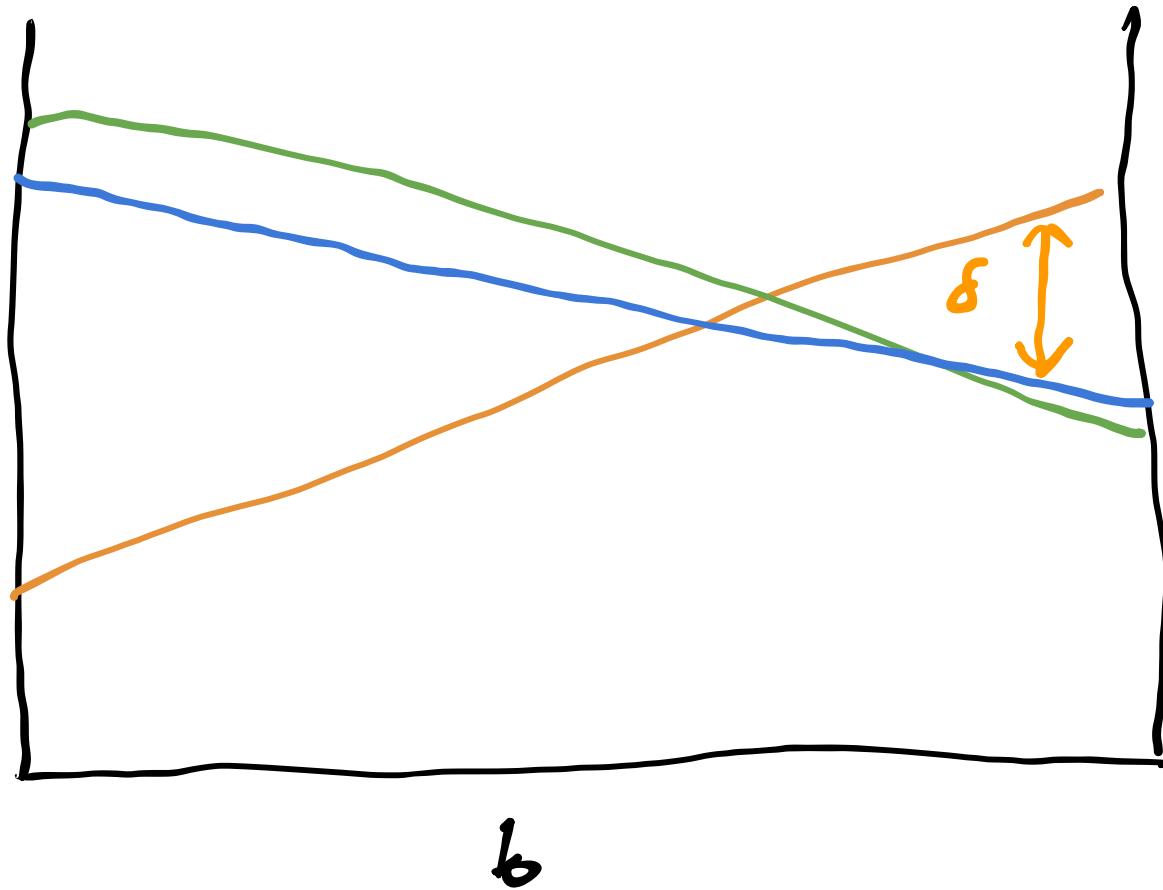


maximize  $\delta$   
subject to  $b \geq 0$

$$\mathbf{1}^\top b = 1$$

$$\alpha^\top b \geq \alpha'^\top b + \delta \quad \forall \alpha' \in \Gamma$$

# $\alpha$ -Vector Pruning



maximize  $\delta$   
 $\delta, b$

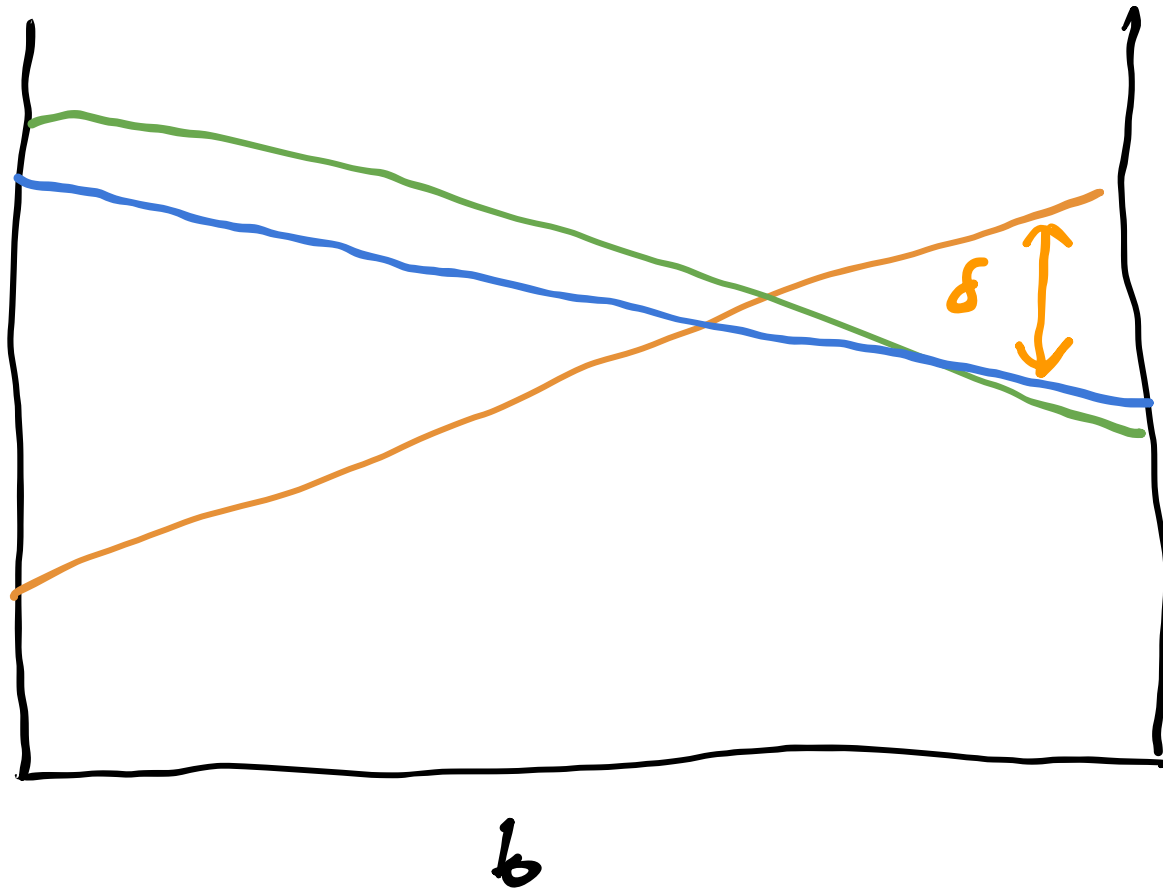
subject to  $b \geq 0$

$$\mathbf{1}^\top b = 1$$

$$\alpha^\top b \geq \alpha'^\top b + \delta \quad \forall \alpha' \in \Gamma$$

"Linear Program"

# $\alpha$ -Vector Pruning



$$\underset{\delta, b}{\text{maximize}} \quad \delta$$

$$\text{subject to} \quad b \geq 0$$

$$\mathbf{1}^\top b = 1$$

$$\alpha^\top b \geq \alpha'^\top b + \delta \quad \forall \alpha' \in \Gamma$$

"Linear Program"

If there is a solution,  $\alpha$  is not dominated;  $b$  solution sometimes called "witness".

# Alpha Vector Expansion



# POMDP Value Iteration

$$\Gamma^0 = \emptyset$$

for  $n \in 1 \dots d$

Construct  $\Gamma^n$  by expanding with  $\Gamma^{n-1}$

Prune  $\Gamma^n$

# Recap



# Recap

- A POMDP is an MDP on the \_\_\_\_\_

# Recap

- A POMDP is an MDP on the belief space

# Recap

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