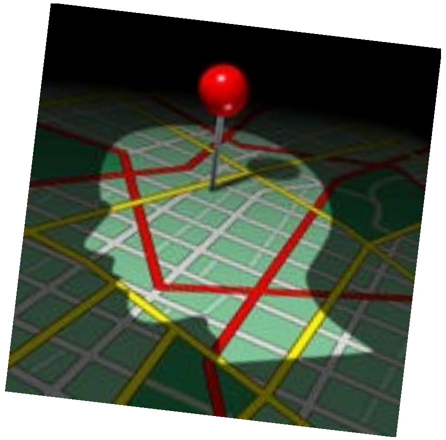
Computational Psychiatry Course – Zürich 2015

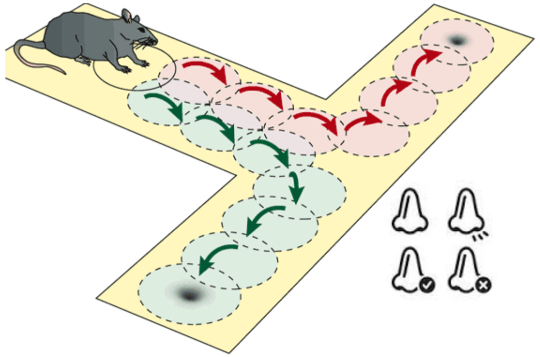
Partially Observable Markov Decision Processes

Lionel Rigoux & Frederike Petzschner

Introduction

- MDP >> Full observability: the agent always knows the state of the world
- This might often not be true in real life
  - *Imperfect memory*
    // navigation: “turn left on the seventh street”
    > what if you loose track of the number of streets already passed?
  - *Changing environment*
    // reward selection in a T-maze
    > reward location changes every trials, as cued by a smell





leave

leave

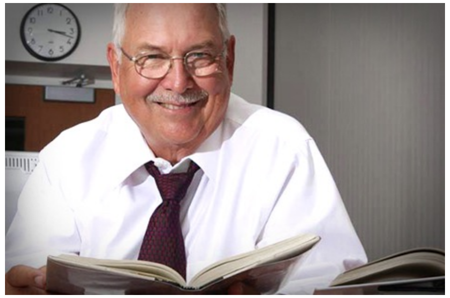
stay

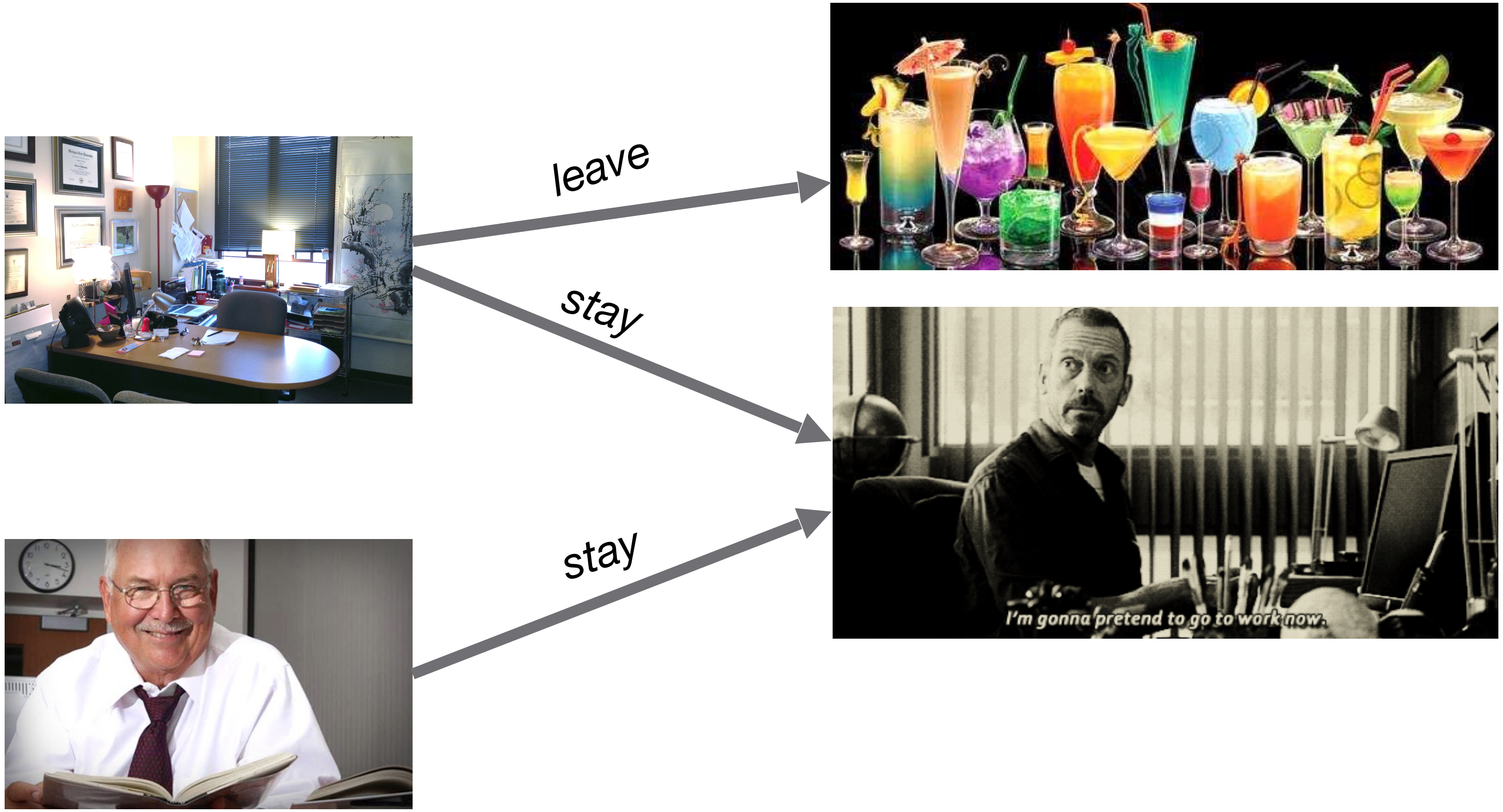
leave

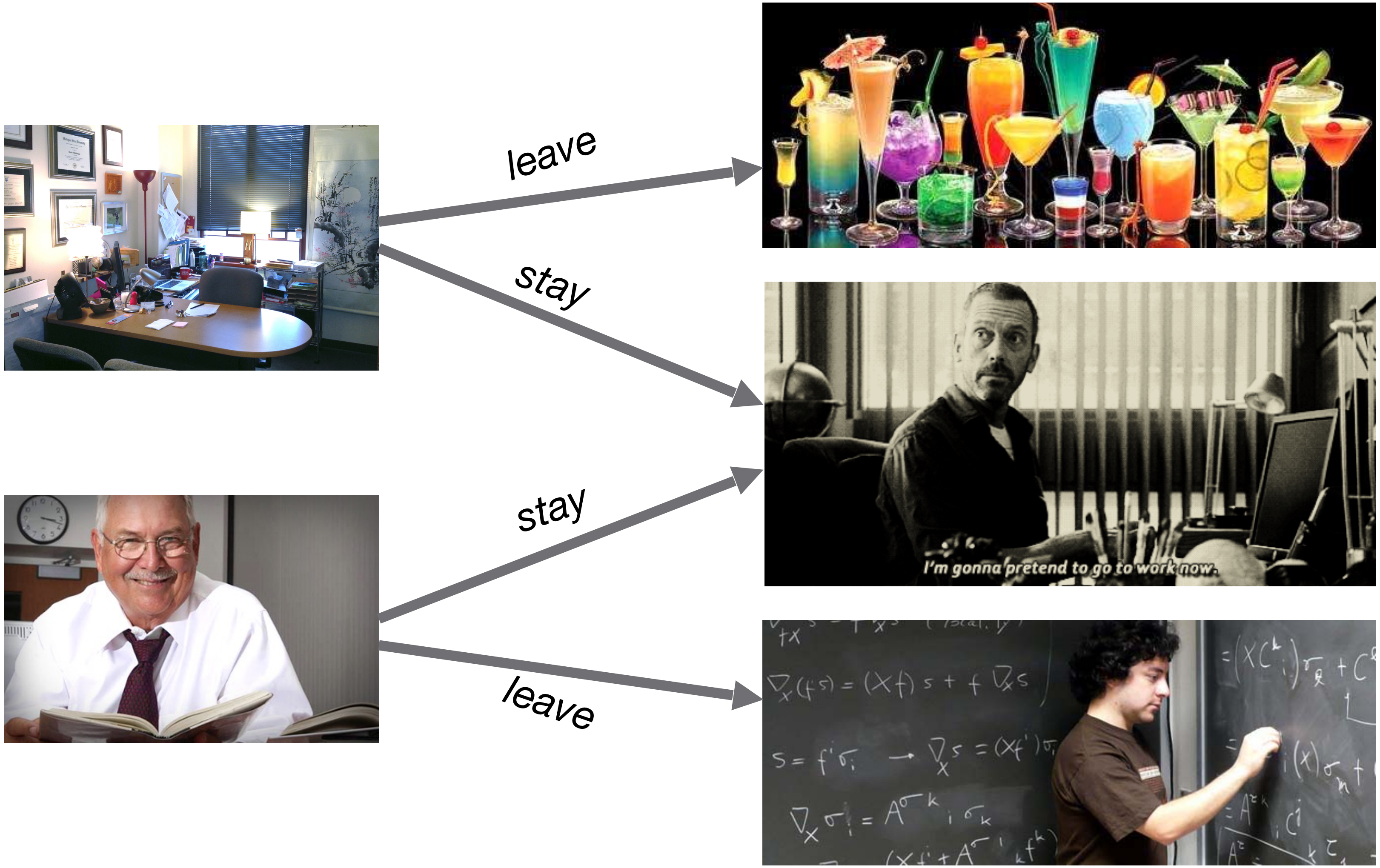
stay

leave

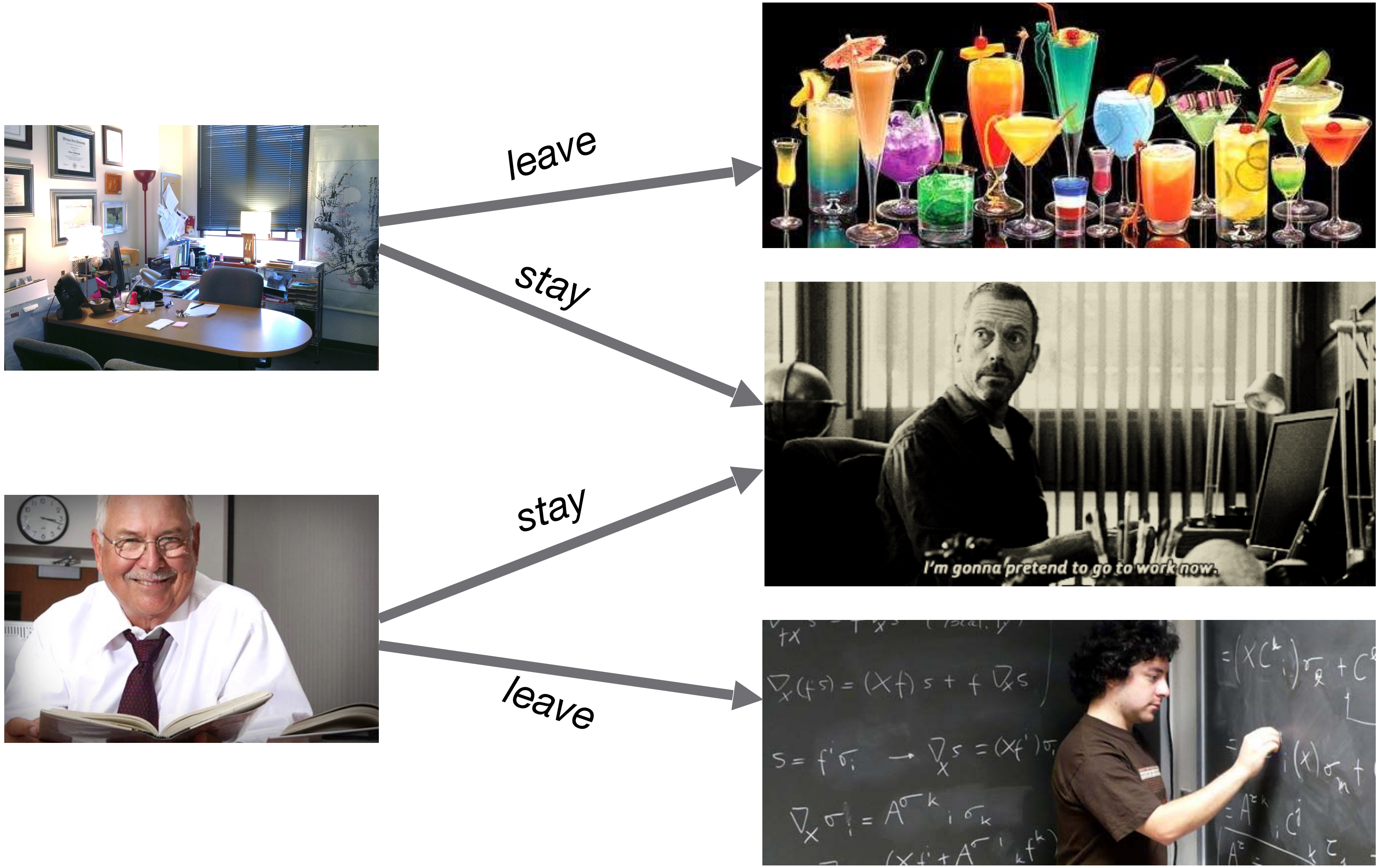
stay



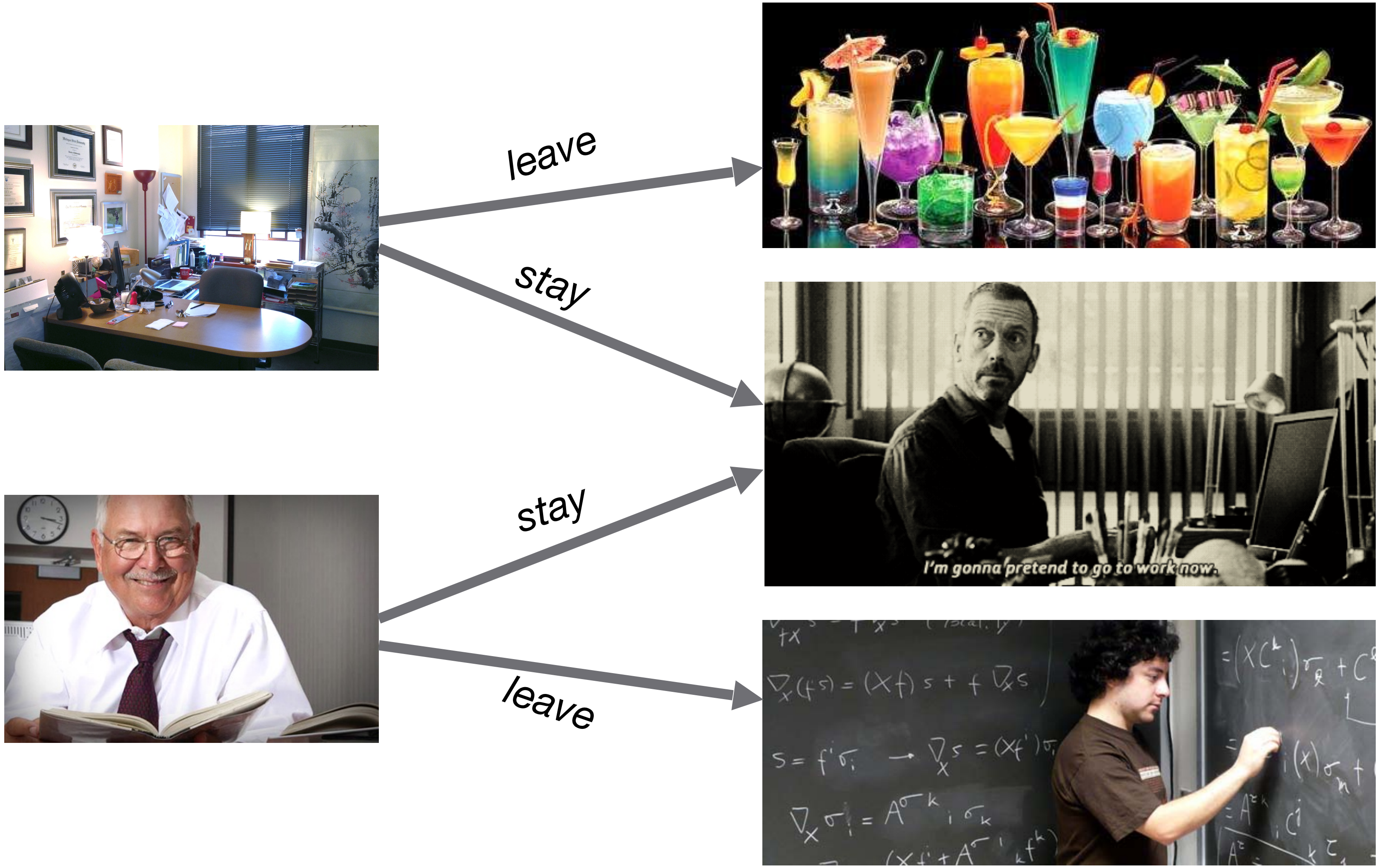

leave
stay
stay
I'm gonna pretend to go to work now.


leave
stay
stay
leave
I'm gonna pretend to go to work now.

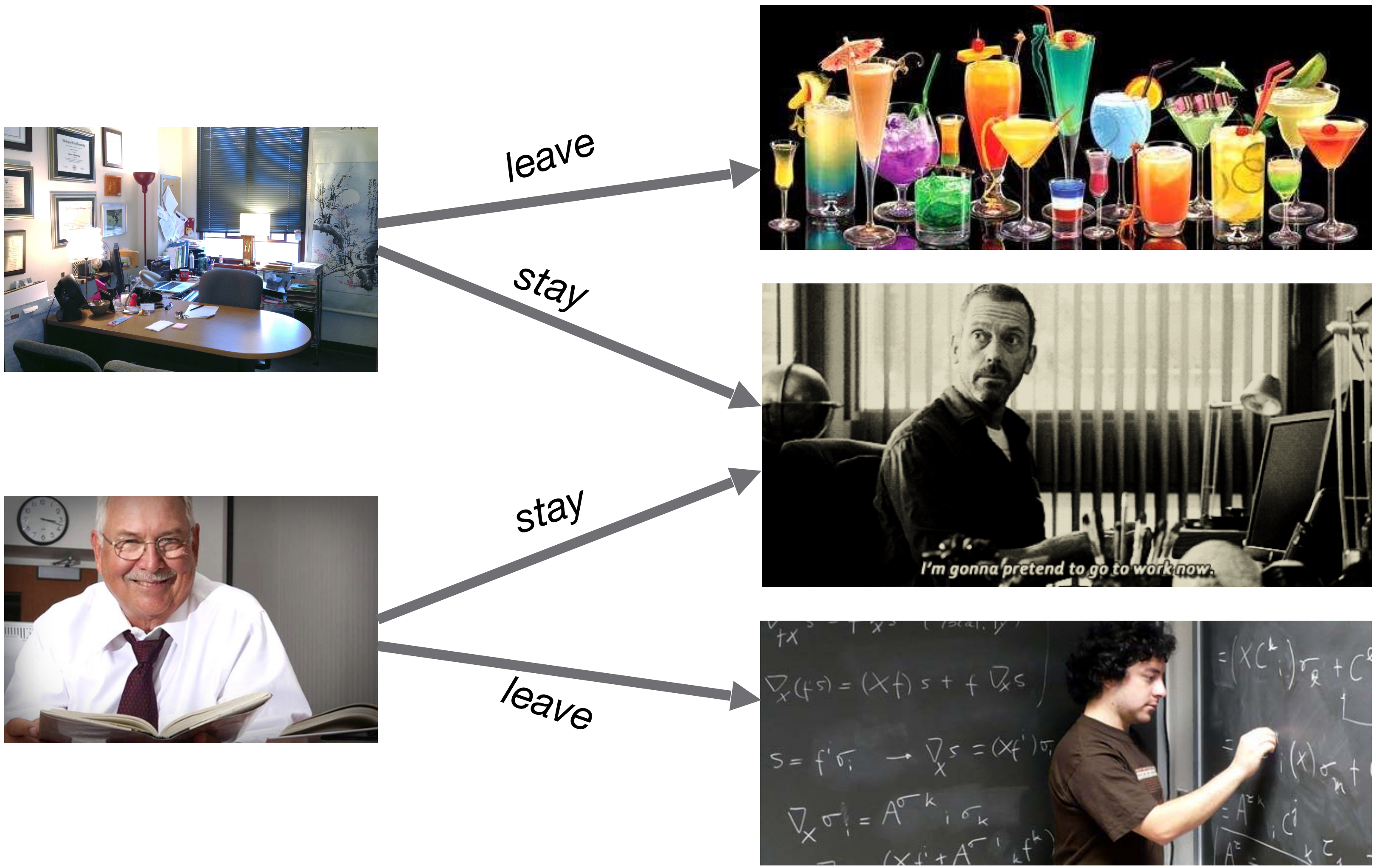
state

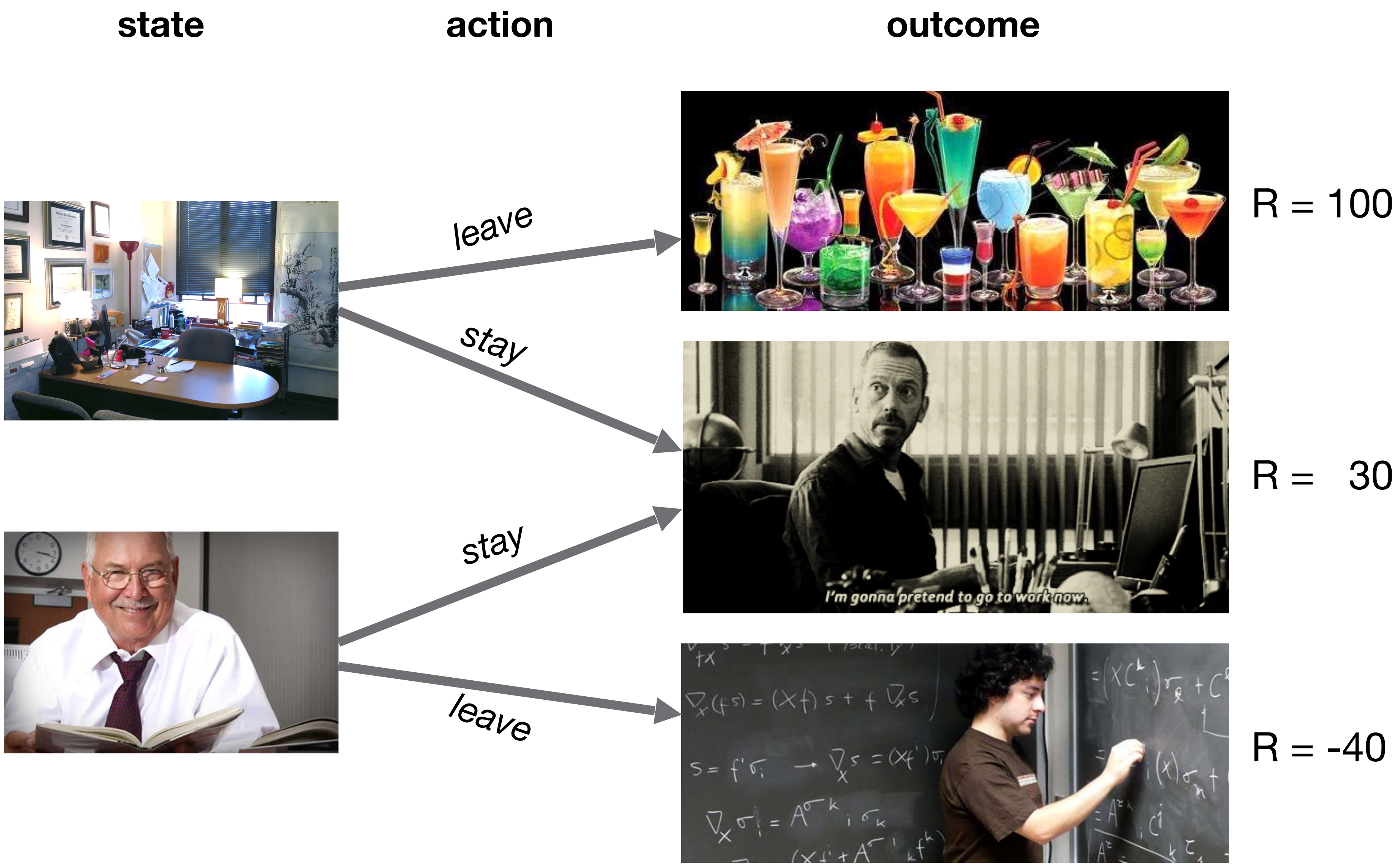


state **action**

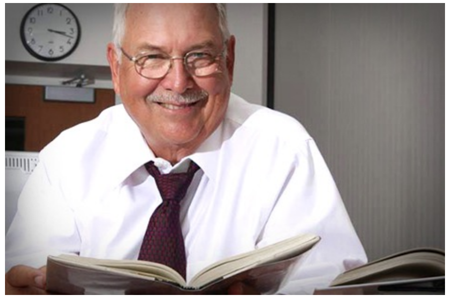


state **action** **outcome**




state
action
outcome
leave
stay
stay
leave
R = 100
R = 30
R = -40
I'm gonna pretend to go to work now.

state **action** **outcome**



R = 100

R = 30

R = -40

state **action** **outcome**

R = 100

R = 30

R = -40

state **action** **outcome**

R = 100

stay

R = 30

R = -40

state **action** **outcome**

R = 100

stay

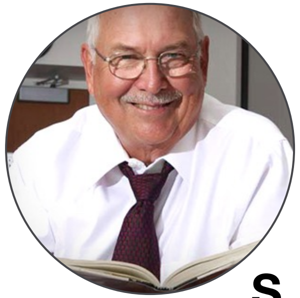
R = 30

R = -40

leave

state

S_0



S_1

state

not known

S_0

S_1

state

not known

belief

$b=p(s=S_1)$

S_0

$p(s=S_1) = 0$

$p(s=S_1) = 1$

S_1

state

not known

S_0

S_1

belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function

state

not known

belief

$b=p(s=S_1)$

actions and payoff function

$p(s=S_1) = 0$

S_0

S_1

$p(s=S_1) = 1$

$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

S_0

S_1

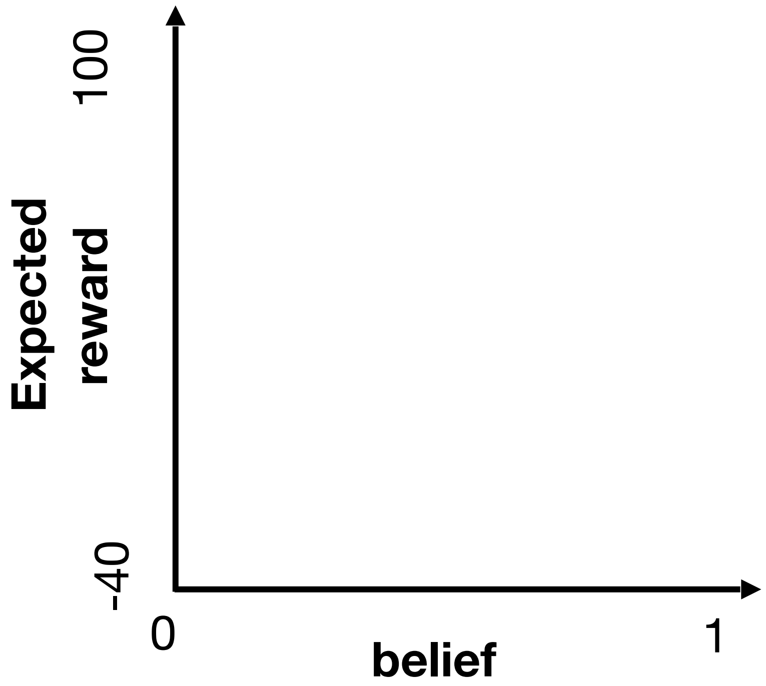
belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

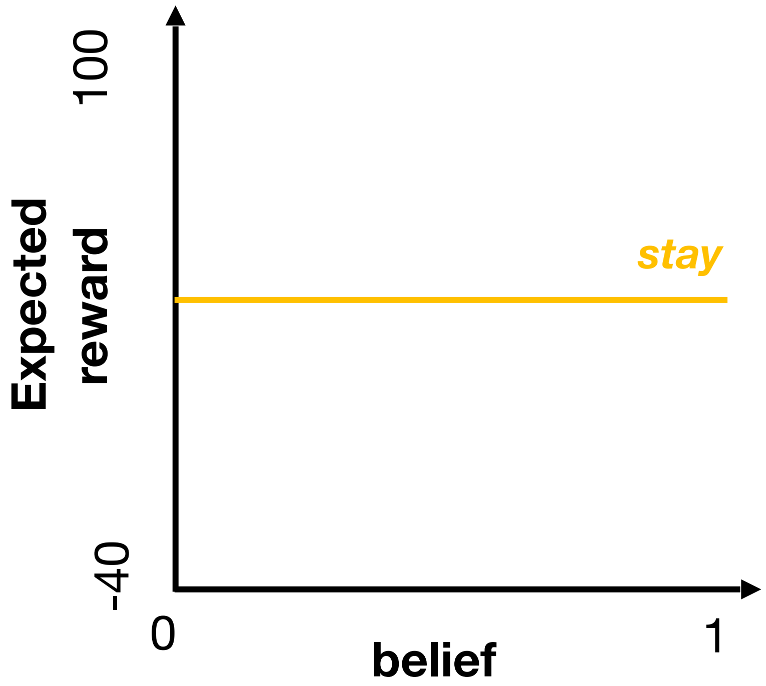
belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\,R_0(a) + p(x=1)\,R_1(a)$$

state

not known

S_0

S_1

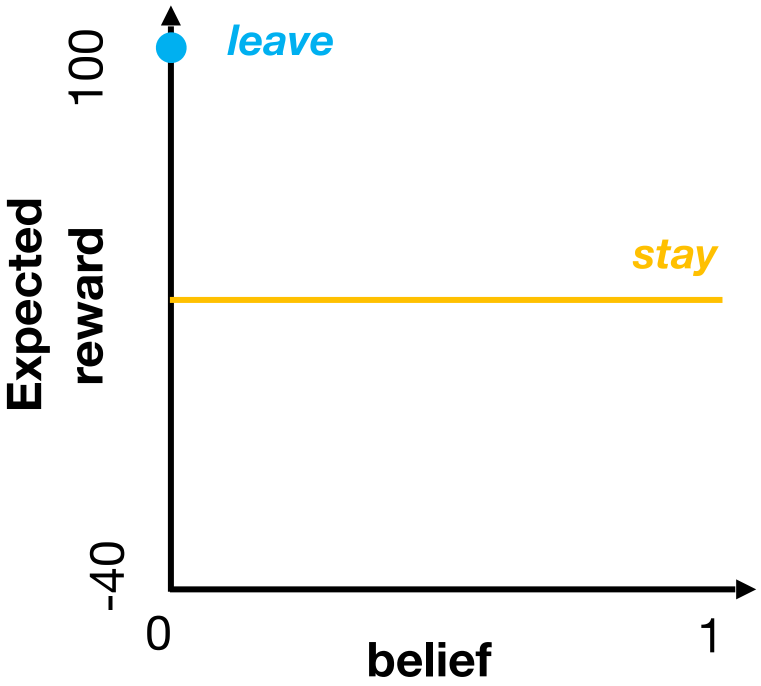
belief

$b = p(s = S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

S_0

S_1

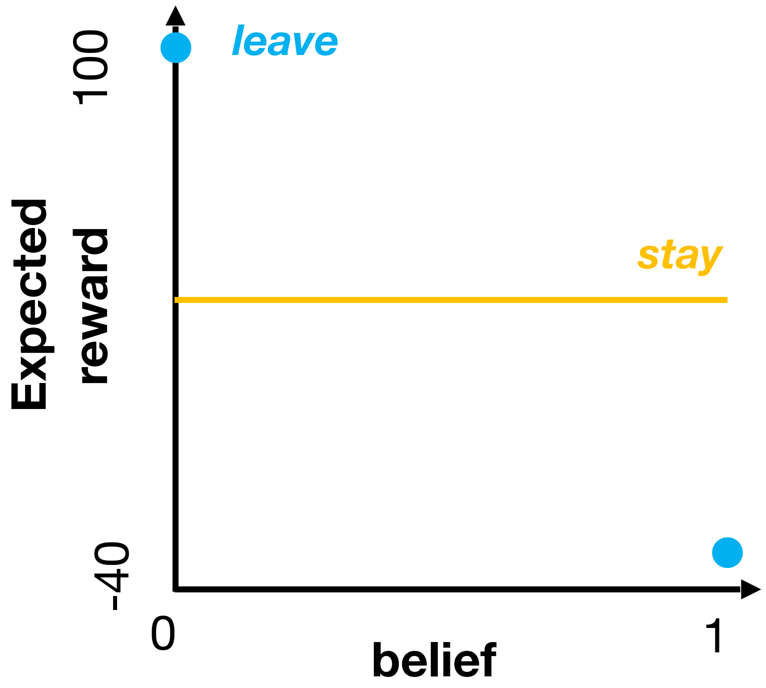
belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

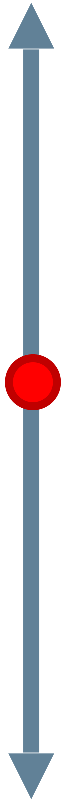
S_0

S_1

belief

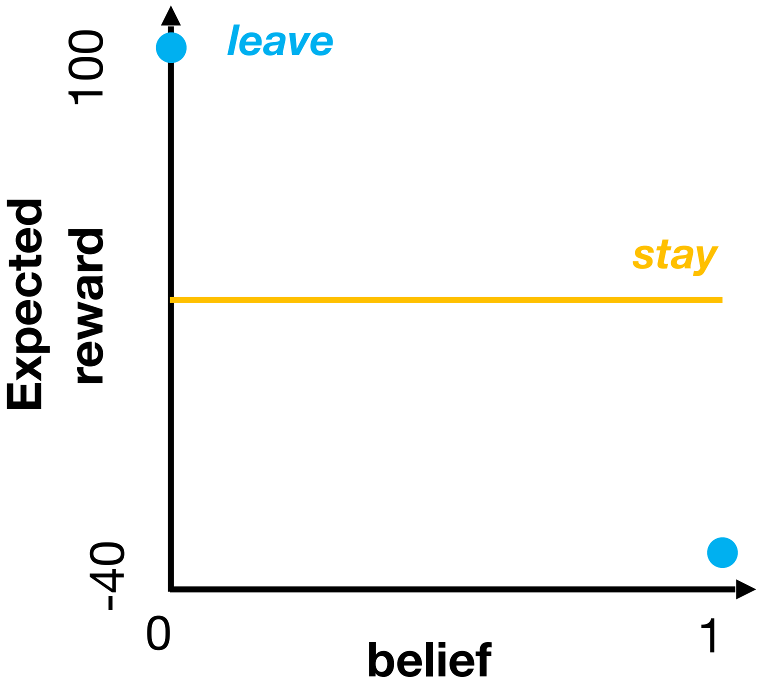
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

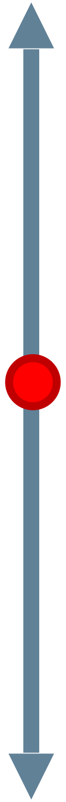
S_0

S_1

belief

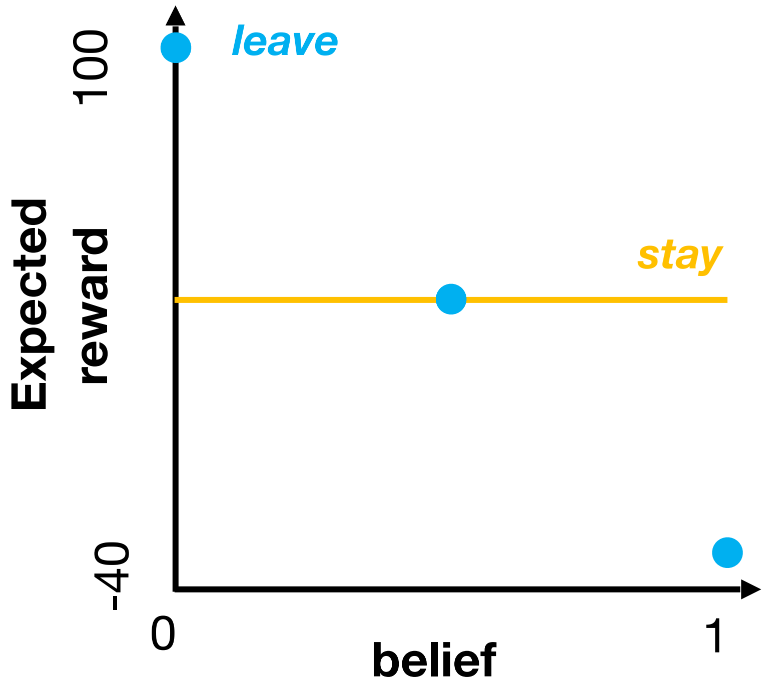
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

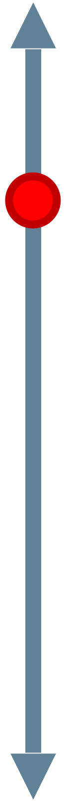
S_0

S_1

belief

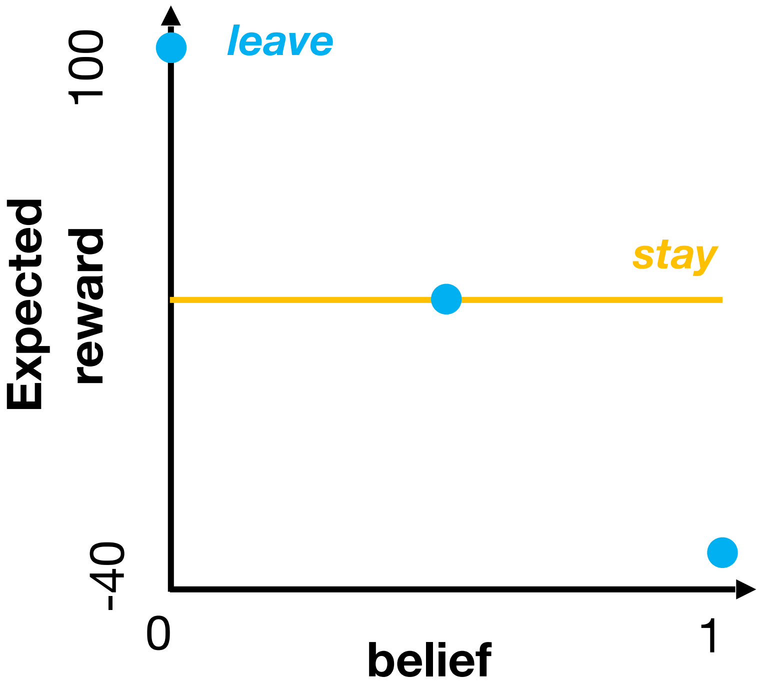
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

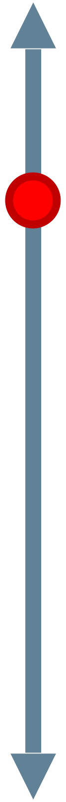
S_0

S_1

belief

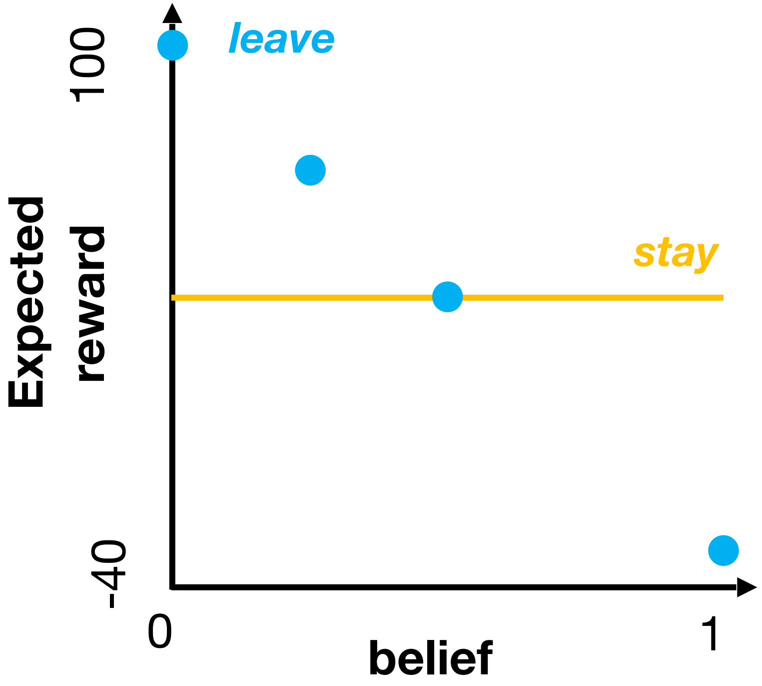
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\,R_0(a) + p(x=1)\,R_1(a)$$

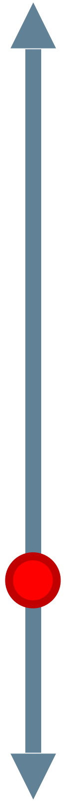
state

not known

belief

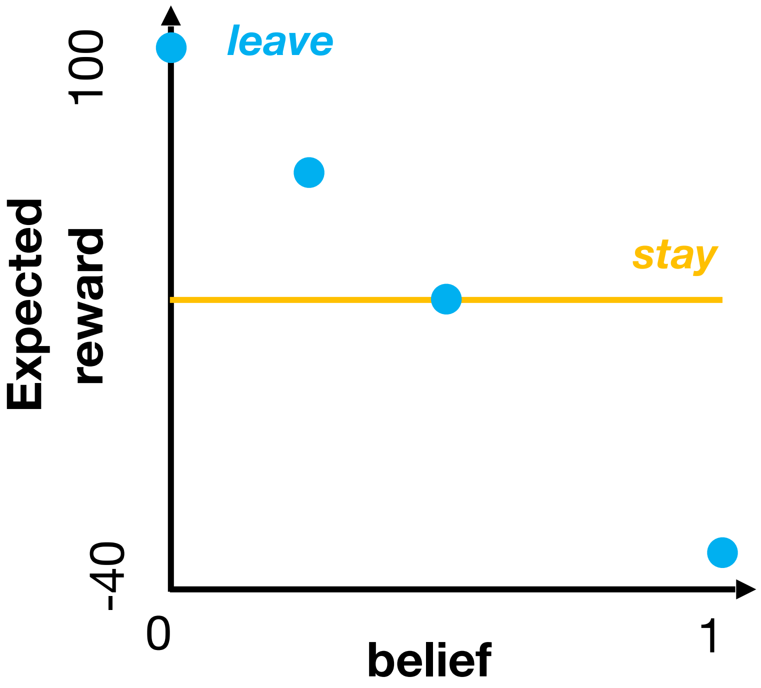
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

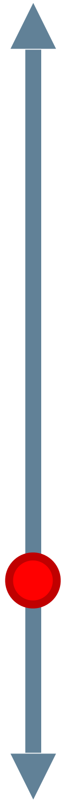
S_0

S_1

belief

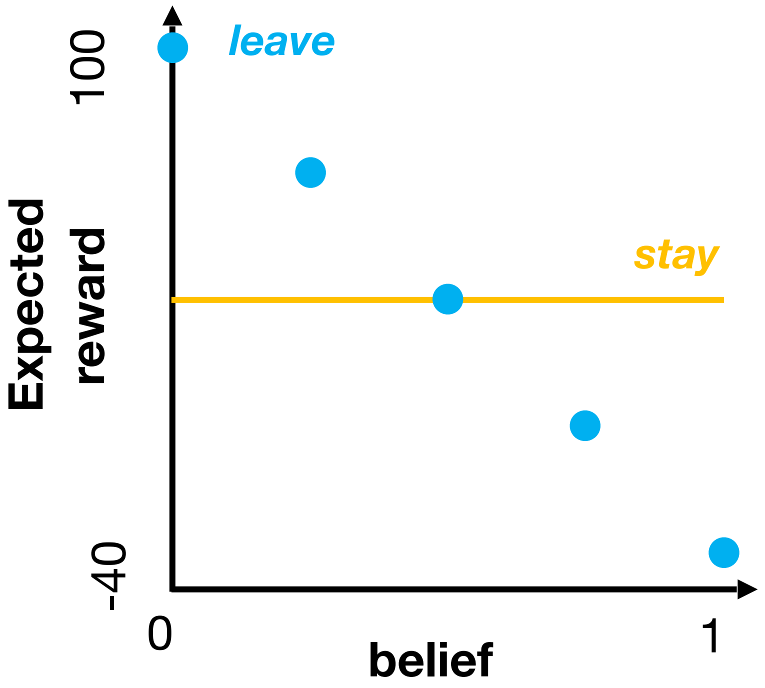
$b=p(s=S_1)$

$p(s=S_1) = 0$



$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

S_0

S_1

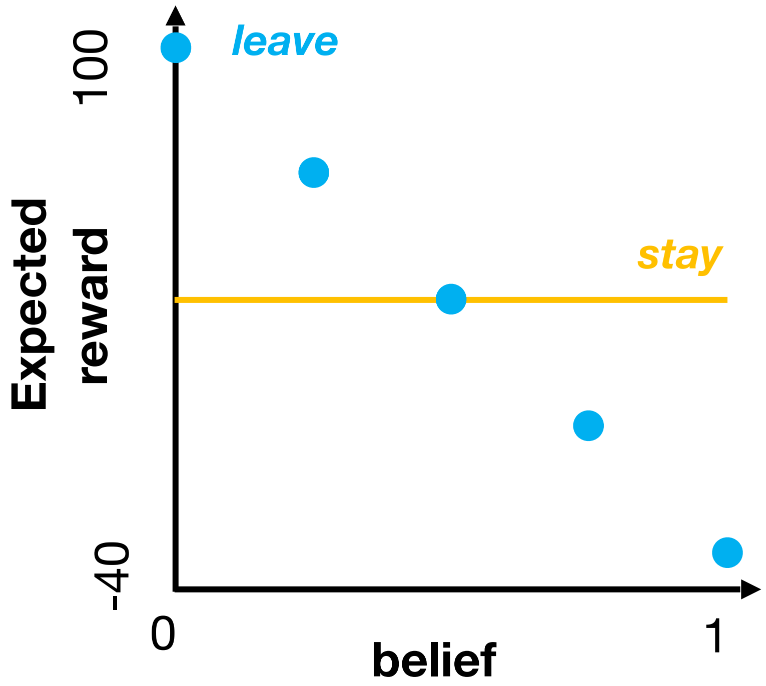
belief

b=p(s=S₁)

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

not known

S_0

S_1

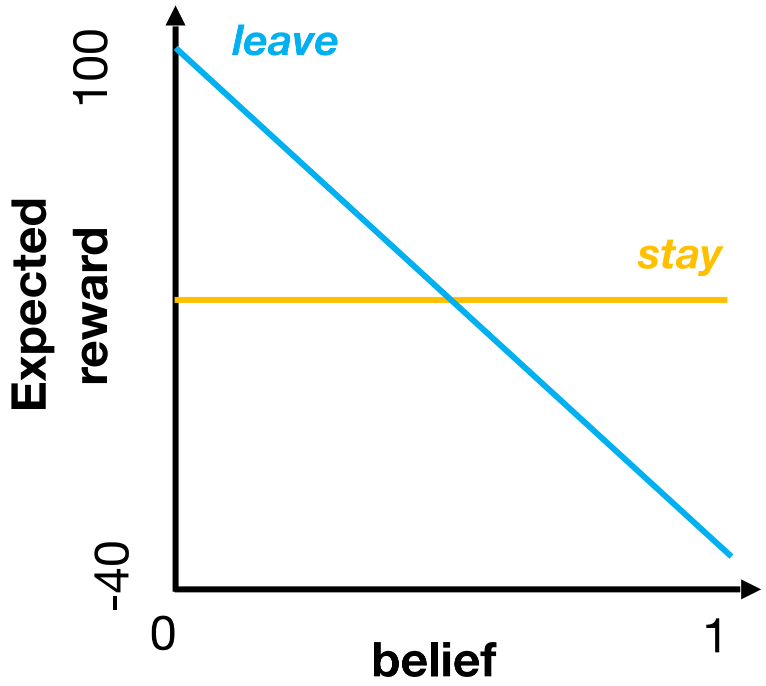
belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function



$$E[R](a) = p(x=0)\ R_0(a) + p(x=1)\ R_1(a)$$

state

not known

S_0

S_1

belief

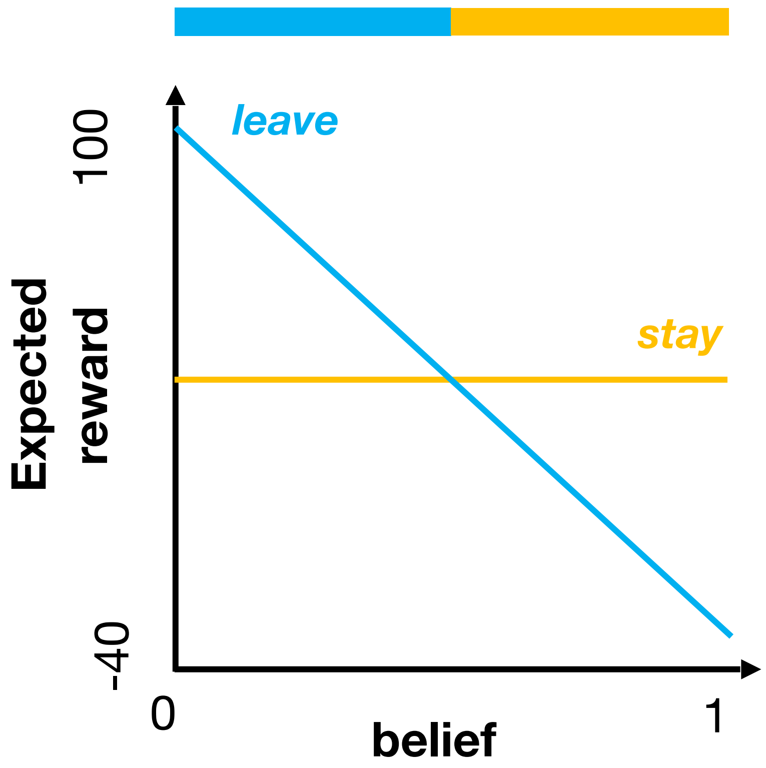
$b = p(s = S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function

optimal policy



$$E[R](a) = p(x=0)\,R_0(a) + p(x=1)\,R_1(a)$$

state

not known

S_0

S_1

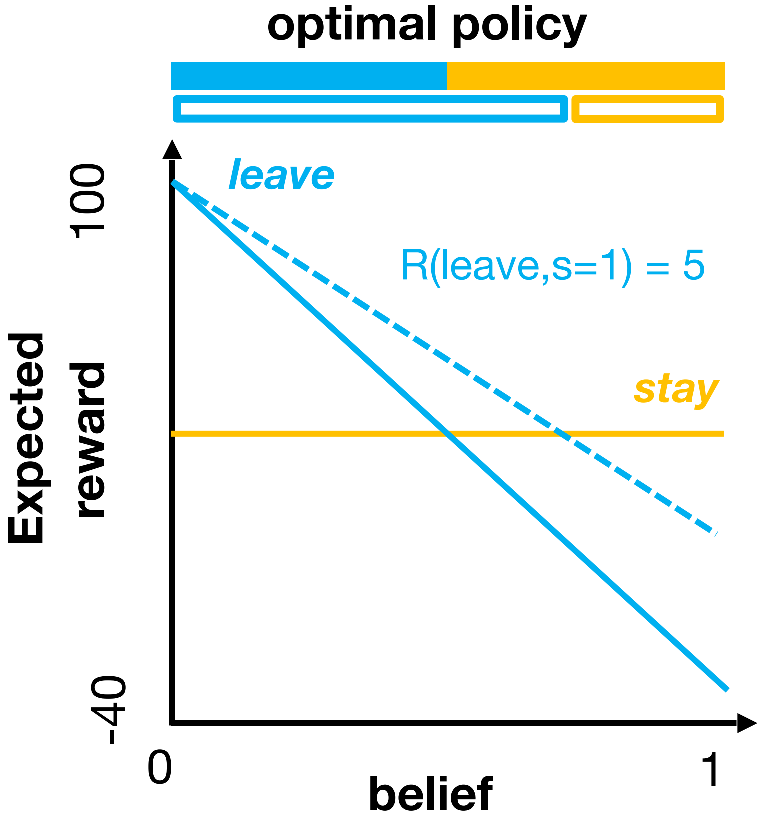
belief

$b=p(s=S_1)$

$p(s=S_1) = 0$

$p(s=S_1) = 1$

actions and payoff function

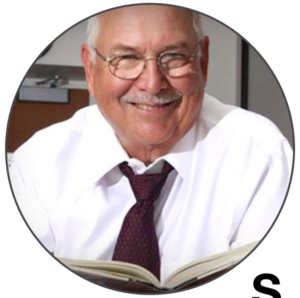


$$E[R](a) = p(x=0)\, R_0(a) + p(x=1)\, R_1(a)$$

state

S_0

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

belief

$p(s=S_1) = 0$

$p(s=S_1) = 1$

state

observation function

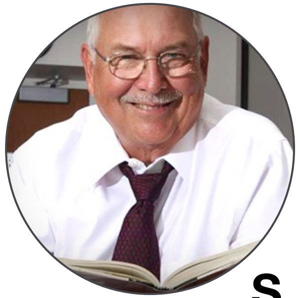
provide information about state

belief

$p(s=S_1) = 0$

S_0

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$

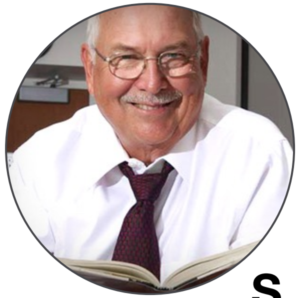


S_1

$p(s=S_1) = 1$

state

S_0



S_1

observation function

provide information about state

	leave	stay	listen
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$

belief

$p(s=S_1) = 0$

$p(s=S_1) = 1$

state

observation function

provide information about state

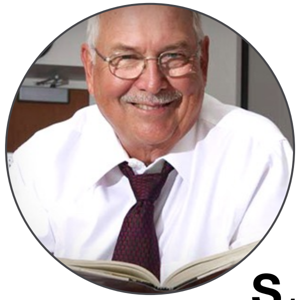
belief

p(s=S_1) = 0

S_0

	leave	*stay*	*listen*
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

	leave	*stay*	*listen*
noises	1	0.5	0.85
no one	0	0.5	0.15

p(s=S_1) = 1

state

observation function

provide information about state

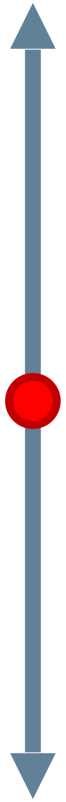
belief

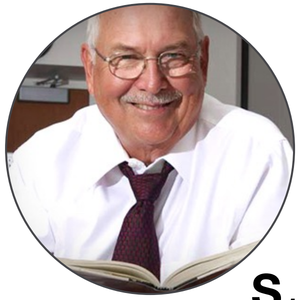
$p(s=S_1) = 0$

S_0

	leave	*stay*	*listen*
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$





S_1

	leave	*stay*	*listen*
noises	1	0.5	0.85
no one	0	0.5	0.15

$p(s=S_1) = 1$

state

observation function

provide information about state

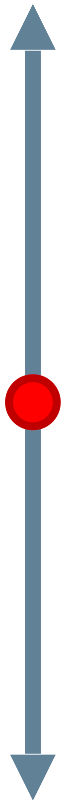
belief

p(s=S_1) = 0

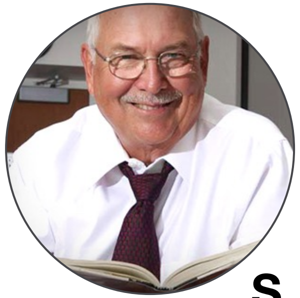
S_0

	leave	stay	listen
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



listen
no one



S_1

	leave	stay	listen
noises	1	0.5	0.85
no one	0	0.5	0.15

p(s=S_1) = 1

state

observation function

provide information about state

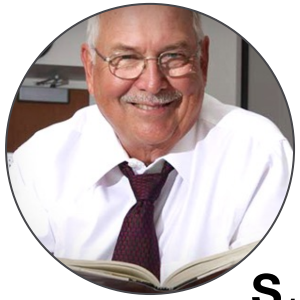
belief

p(s=S_1) = 0

S_0

	leave	stay	listen
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

	leave	stay	listen
noises	1	0.5	0.85
no one	0	0.5	0.15

p(s=S_1) = 1

state

observation function

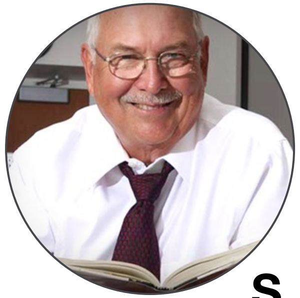
provide information about state

belief

S_0

	leave	*stay*	*listen*
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

	leave	*stay*	*listen*
noises	1	0.5	0.85
no one	0	0.5	0.15

$p(s=S_1) = 0$

$p(s=S_1) = 1$

state

observation function

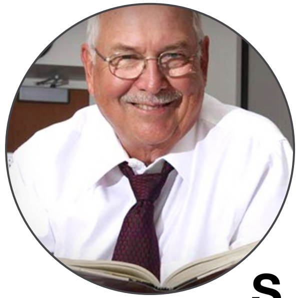
provide information about state

belief

S_0

	leave	*stay*	*listen*
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

	leave	*stay*	*listen*
noises	1	0.5	0.85
no one	0	0.5	0.15

$p(s{=}S_1) = 0$

$p(s{=}S_1) = 1$

state

observation function

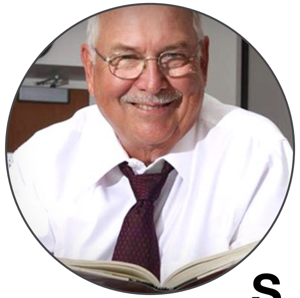
provide information about state

belief

S_0

	leave	*stay*	*listen*
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$



S_1

	leave	*stay*	*listen*
noises	1	0.5	0.85
no one	0	0.5	0.15

$p(s=S_1) = 0$

$p(s=S_1) = 1$

state

observation function

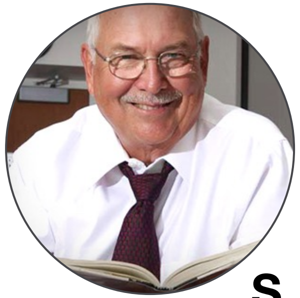
provide information about state

belief


S_0

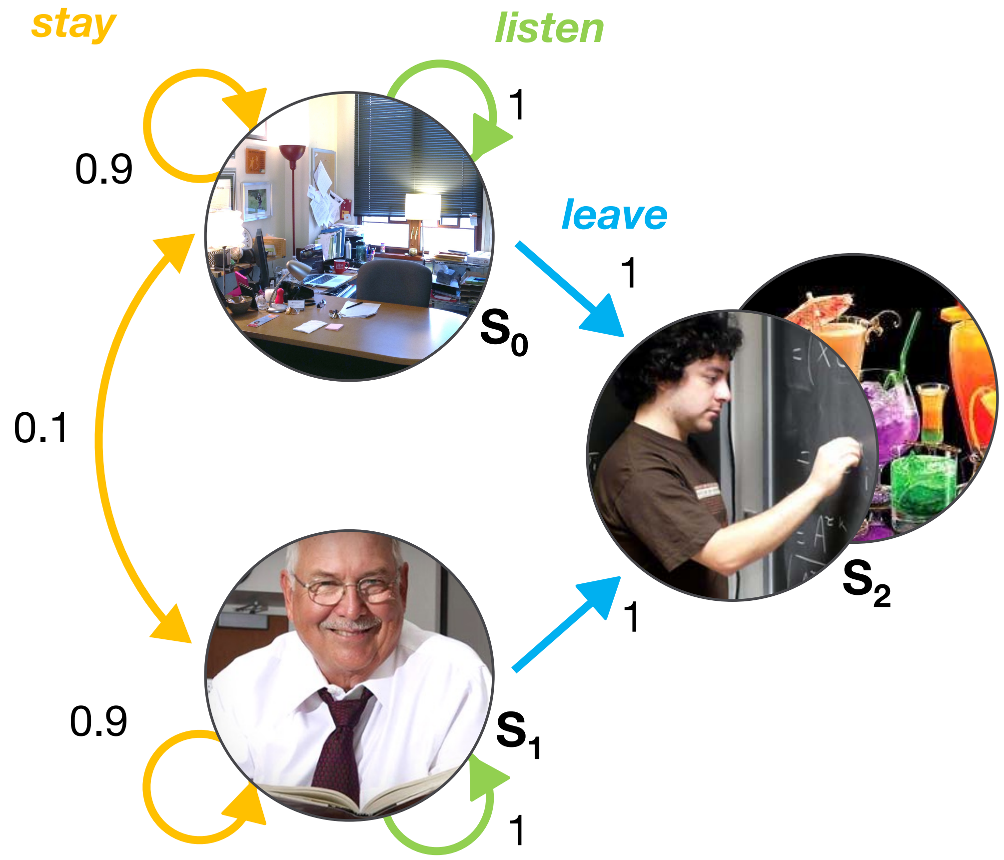
	leave	stay	listen
noises	0	0.5	0.15
no one	1	0.5	0.85

$$b' = \frac{p(o|s',a)\sum_s p(s'|s,a)b(s)}{\sum_{s'} p(o|s',a)\sum_s p(s'|s,a)b(s)}$$

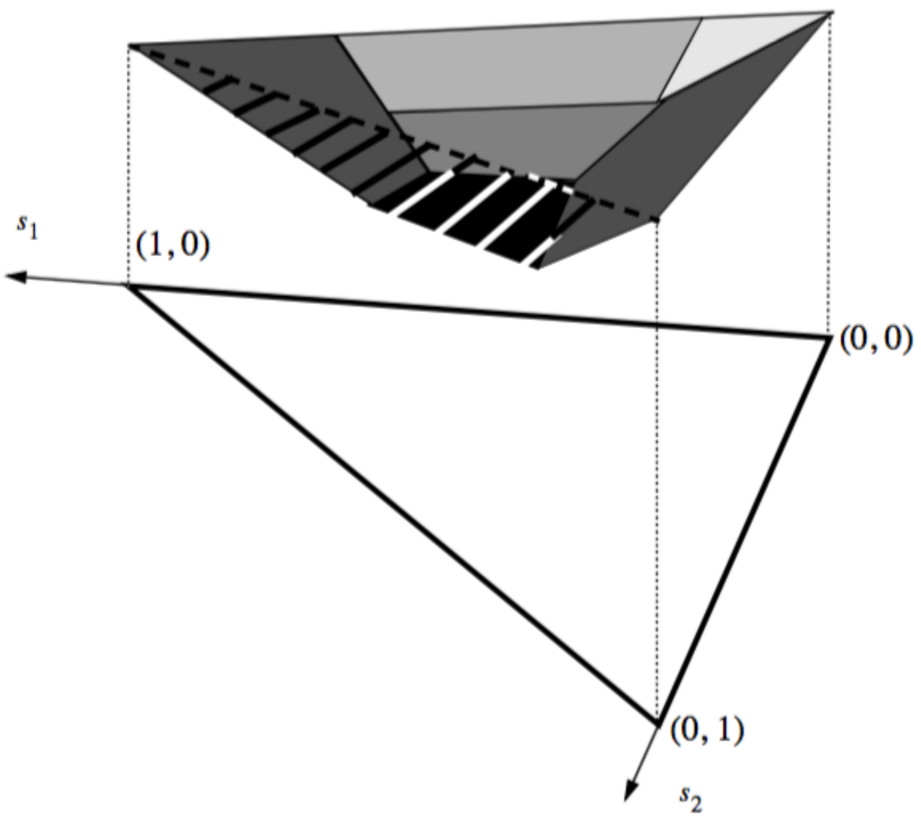

S_1

	leave	stay	listen
noises	1	0.5	0.85
no one	0	0.5	0.15

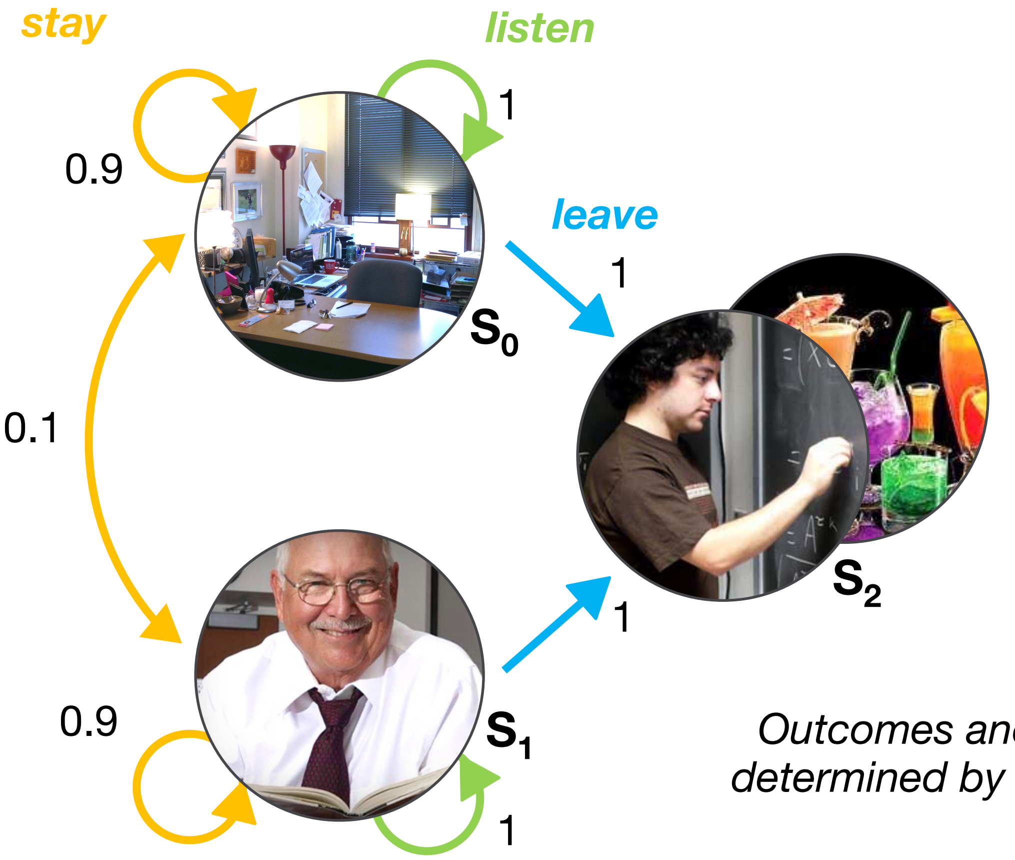
state space



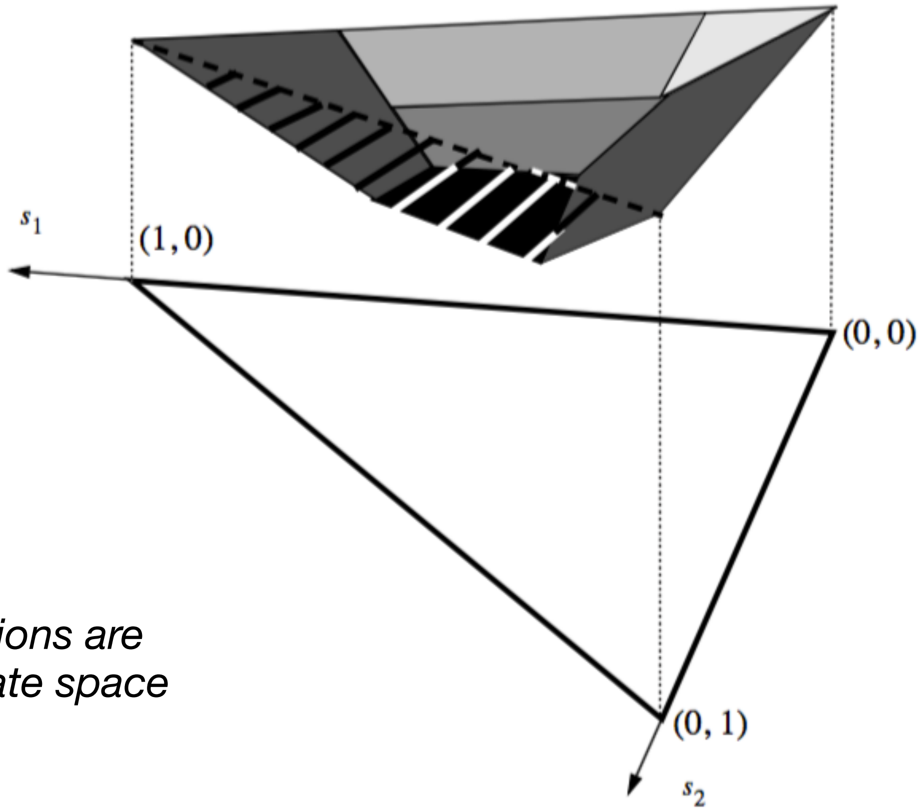
belief space



state space



belief space



Outcomes and observations are determined by the real state space

Policy relies on the belief state

POMDP Formalism

- *MDP*
  - S set of states
  - A set of actions
  - T transition matrix $S \times A \rightarrow S$
  - R reward function $S \times A \rightarrow \mathbb{R}$
  - γ discount factor

POMDP extension

  - Ω set of observations
  - O observation probabilities $S \times A \times \Omega \rightarrow [0,1]$
  - B belief space
  - r reward function $B \times A \rightarrow \mathbb{R}$
  - τ belief update function $B \times A \times \Omega \rightarrow B$

Simulation workflow

Initial state (s, b)

- Select action $a = \pi(b)$
- Update state $s' = T(s, a)$
- Receive outcome $R(s, a)$
- Get observation o $= O(s', a)$
- Update belief $b' = \tau(b, a, o)$
- Start over

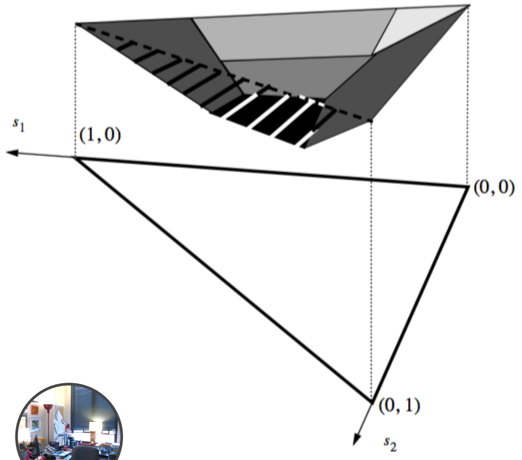
$$V^{\pi}(b) = \sum_{t=0}^{\infty} \gamma^t \, r(b_t, a_t)$$

$$\pi^{\star} = \underset{\pi}{\operatorname{argmax}} \, V^{\pi}$$

Resolution

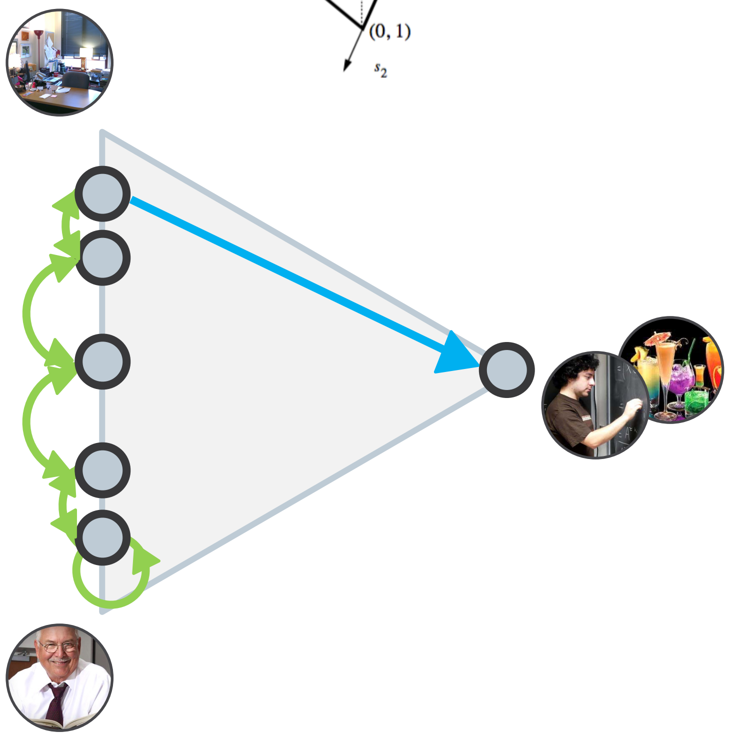
The value function is always convex

- Certainty is preferable to uncertainty
- Gathering information is valuable



The solution can be discretized

- Optimal solution often visit a finite number of belief states
- The POMDP can then be reformulated as a (fully observable) MDP



Take home message

POMDPs allow to model:

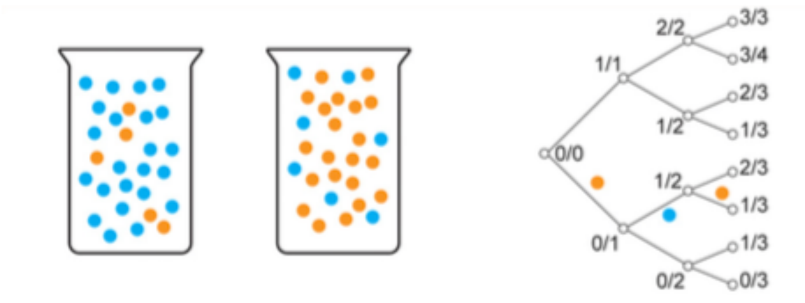
- sequential decision making in a complex environment (MDP)
- subjectivity about the state of the world (PO)

POMDPs can capture:

- information gathering as an economic decision
- irrational behaviour as an optimal policy based on wrong representations

Perspectives

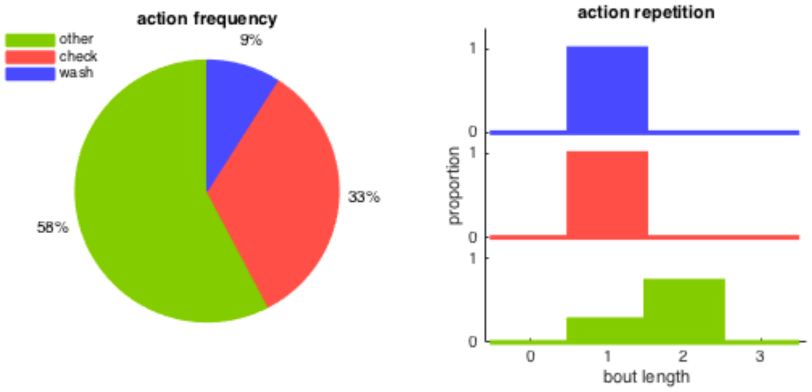
Information sequential sampling with varying payoffs



[Averbeck 2015, PCB]

Errors as exploratory behaviour in reversal learning tasks

Checking behaviours in OCD



Questions?

Thank you for your attention