ECE276B: Planning & Learning in Robotics
Lecture 3: Markov Decision Processes

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Outline

Markov Decision Processes

Open-Loop vs Closed-Loop Control

Partially Observable Models

Markov Chain

Markov Chain

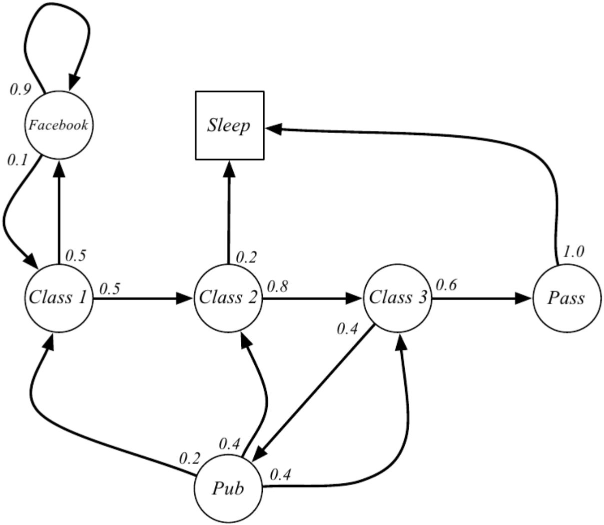
Stochastic process defined by a tuple $(\mathcal{X}, p_0, p_f)$:

- $\mathcal{X}$ is a discrete or continuous space
- p_0 is a prior pdf defined on $\mathcal{X}$
- $p_f(\cdot \mid \mathbf{x})$ is a conditional pdf defined on $\mathcal{X}$ for given $\mathbf{x} \in \mathcal{X}$ that specifies the stochastic process transitions

- When the state space is finite, $\mathcal{X} := \{1, \ldots, N\}$, the pdf p_f can be represented by an $N \times N$ transition matrix with elements:

$$P_{ij} := \mathbb{P}(x_{t+1} = j \mid x_t = i) = p_f(j \mid x_t = i)$$

Example: Student Markov Chain



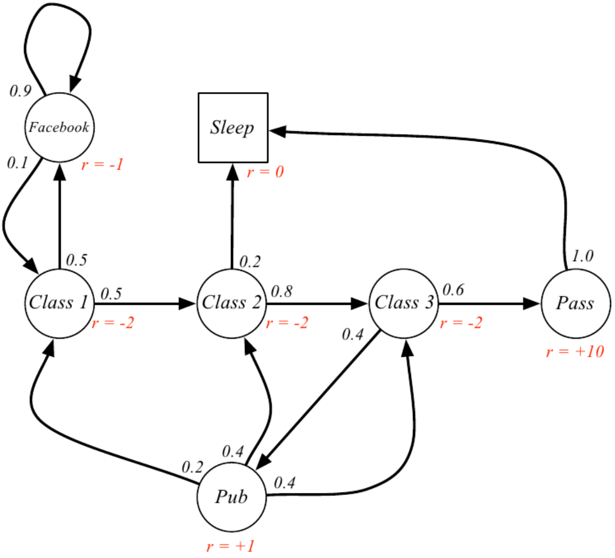
Markov Reward Process

Markov Reward Process

Markov chain with costs defined by a tuple $(\mathcal{X}, p_0, p_f, T, \ell, \mathfrak{q}, \gamma)$:

- $\mathcal{X}$ is a discrete or continuous space
- p_0 is a prior pdf defined on $\mathcal{X}$
- $p_f(\cdot \mid \mathbf{x})$ is a conditional pdf defined on $\mathcal{X}$ for given $\mathbf{x} \in \mathcal{X}$ that specifies the stochastic process transitions
- T is a finite/infinite time horizon
- $\ell(\mathbf{x})$ is stage cost of state $\mathbf{x} \in \mathcal{X}$
- $\mathfrak{q}(\mathbf{x})$ is terminal cost of being in state $\mathbf{x}$ at time T
- $\gamma \in [0, 1]$ is a discount factor

Example: Student Markov Reward Process



MRP Value Function

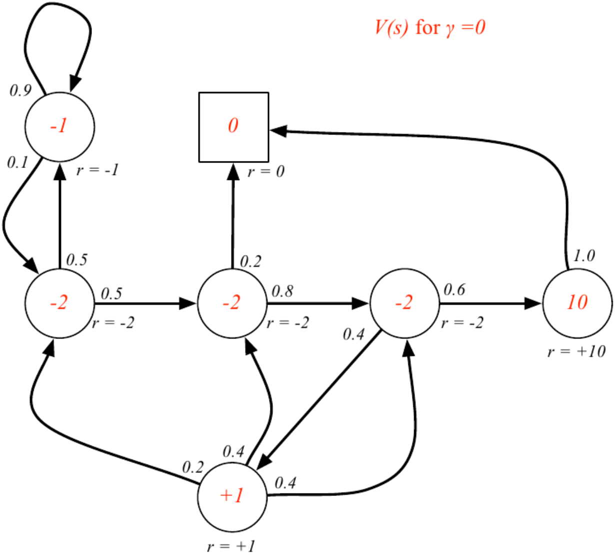
- **Value function**: the expected cumulative cost of an MRP starting from state $\mathbf{x} \in \mathcal{X}$ at time t

- **Finite-horizon MRP**: trajectories terminate at fixed $T < \infty$

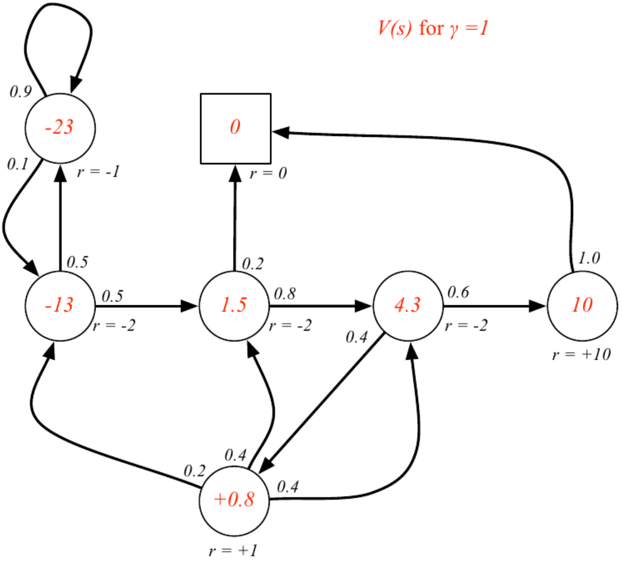
$$V_t(\mathbf{x}) := \mathbb{E}\left[\mathfrak{q}(\mathbf{x}_T) + \sum_{\tau=t}^{T-1} \ell(\mathbf{x}_\tau) \mid \mathbf{x}_t = \mathbf{x}\right]$$

- **Infinite-horizon MRP**:
  - **First-exit MRP**: trajectories terminate at the first passage time $T = \min\{t \in \mathbb{N} | \mathbf{x}_t \in \mathcal{T}\}$ to a terminal state $\mathbf{x}_t \in \mathcal{T} \subseteq \mathcal{X}$
  - **Discounted MRP**: trajectories continue forever but stage costs are discounted by **discount factor** $\gamma \in [0, 1)$:
    - γ close to 0 leads to myopic/greedy evaluation
    - γ close to 1 leads to nonmyopic/far-sighted evaluation
    - Mathematically convenient since discounting avoids infinite costs as $T \to \infty$
  - **Average-cost MRP**: trajectories continue forever and the value function is the expected average stage cost

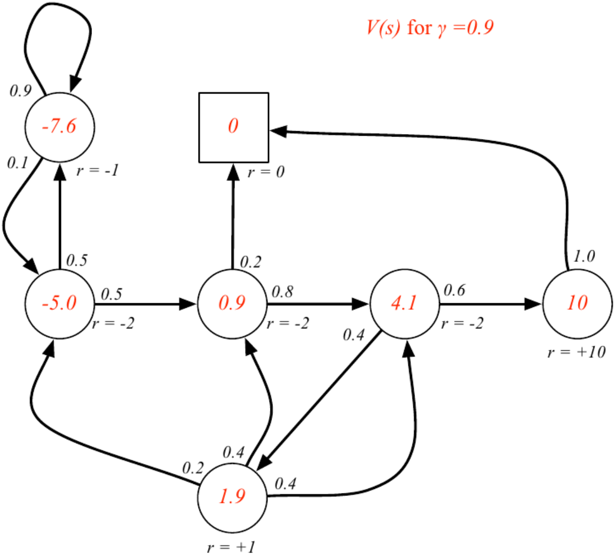
Example: Student MRP Value Function



Example: Student MRP Value Function



Example: Student MRP Value Function



Markov Decision Process

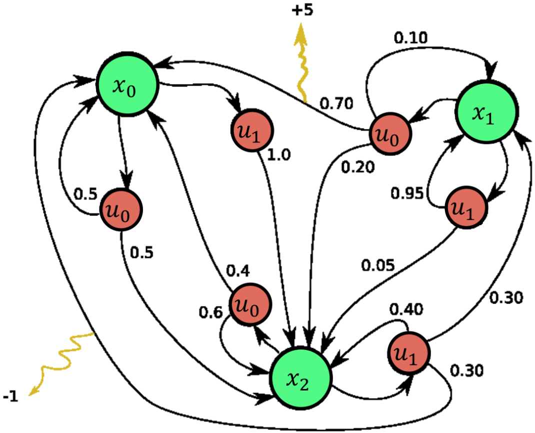
Markov Decision Process

Markov Reward Process with controlled transitions defined by a tuple $(\mathcal{X}, \mathcal{U}, p_0, p_f, T, \ell, \mathfrak{q}, \gamma)$

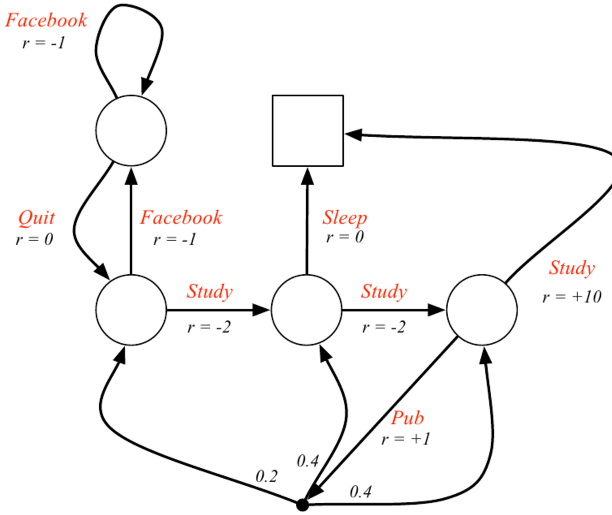
- $\mathcal{X}$ is a discrete or continuous state space
- $\mathcal{U}$ is a discrete or continuous control space
- p_0 is a prior pdf defined on $\mathcal{X}$
- $p_f(\cdot \mid \mathbf{x}_t, \mathbf{u}_t)$ is a conditional pdf defined on $\mathcal{X}$ for given $\mathbf{x}_t \in \mathcal{X}$ and $\mathbf{u}_t \in \mathcal{U}$ (matrices P^u with elements $P^u_{ij} := p_f(j \mid x_t = i, u_t = u)$ in the finite-dimensional case)
- T is a finite or infinite time horizon
- $\ell(\mathbf{x}, \mathbf{u})$ is stage cost of applying control $\mathbf{u} \in \mathcal{U}$ in state $\mathbf{x} \in \mathcal{X}$
- $\mathfrak{q}(\mathbf{x})$ is terminal cost of being in state $\mathbf{x}$ at time T
- $\gamma \in [0, 1]$ is a discount factor

Example: Markov Decision Process

- A control $\mathbf{u}_t$ applied in state $\mathbf{x}_t$ determines the next state $\mathbf{x}_{t+1}$ and the stage cost $\ell(\mathbf{x}_t, \mathbf{u}_t)$



Example: Student Markov Decision Process



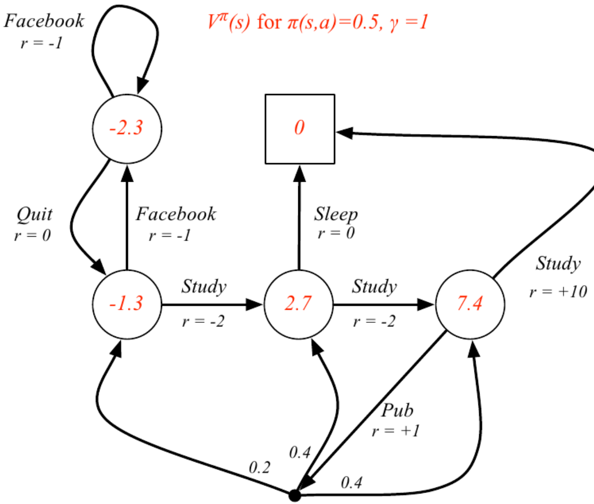
MDP Control Policy and Value Function

- **Control policy**: a function π that maps a time step $t \in \mathbb{N}$ and a state $\mathbf{x} \in \mathcal{X}$ to a feasible control input $\mathbf{u} \in \mathcal{U}$
- **Value function**: expected cumulative cost of a policy π applied to an MDP with initial state $\mathbf{x} \in \mathcal{X}$ at time t:
- **Finite-horizon MDP**: trajectories terminate at fixed $T < \infty$:

$$V_t^\pi(\mathbf{x}) := \mathbb{E}\left[\mathfrak{q}(\mathbf{x}_T) + \sum_{\tau=t}^{T-1} \ell(\mathbf{x}_\tau, \pi_\tau(\mathbf{x}_\tau)) \mid \mathbf{x}_t = \mathbf{x}\right]$$

- **Infinite-horizon MDP**: as $T \to \infty$, optimal policies become stationary, i.e., $\pi := \pi_0 \equiv \pi_1 \equiv \cdots$
  - **First-exit MDP**: trajectories terminate at the first passage time $T = \min\{t \in \mathbb{N} | \mathbf{x}_t \in \mathcal{T}\}$ to a terminal state $\mathbf{x}_t \in \mathcal{T} \subseteq \mathcal{X}$
  - **Discounted MDP**: trajectories continue forever but stage costs are discounted by a factor $\gamma \in [0, 1)$
  - **Average-cost MDP**: trajectories continue forever and the value function is the expected average stage cost

Example: Value Function of Student MDP



Alternative Cost Formulations

- **Noise-dependent costs**: stage costs ℓ' depend on motion noise $\mathbf{w}_t$:

$$V_0^\pi(\mathbf{x}) := \mathbb{E}_{\mathbf{w}_{0:T},\mathbf{x}_{1:T}}\left[\mathfrak{q}(\mathbf{x}_T) + \sum_{t=0}^{T-1} \ell'(\mathbf{x}_t, \pi_t(\mathbf{x}_t), \mathbf{w}_t) \mid \mathbf{x}_0 = \mathbf{x}\right]$$

- Using the pdf $p_w(\cdot \mid \mathbf{x}_t, \mathbf{u}_t)$ of $\mathbf{w}_t$, this is equivalent to our formulation:

$$\ell(\mathbf{x}_t, \mathbf{u}_t) := \mathbb{E}_{\mathbf{w}_t|\mathbf{x}_t,\mathbf{u}_t}\left[\ell'(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t)\right] = \int \ell(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) p_w(\mathbf{w}_t \mid \mathbf{x}_t, \mathbf{u}_t) d\mathbf{w}_t$$

  The expectation can be computed if p_w is known or approximated.

- **Joint cost-state pdf**: allow random costs ℓ' with joint pdf $p(\mathbf{x}', \ell' \mid \mathbf{x}, \mathbf{u})$. This is equivalent to our formulation as follows:

$$p_f(\mathbf{x}' \mid \mathbf{x}, \mathbf{u}) := \int p(\mathbf{x}', \ell' \mid \mathbf{x}, \mathbf{u}) d\ell'$$

$$\ell(\mathbf{x}, \mathbf{u}) := \mathbb{E}\left[\ell' \mid \mathbf{x}, \mathbf{u}\right] = \int\int \ell' p(\mathbf{x}', \ell' \mid, \mathbf{x}, \mathbf{u}) d\mathbf{x}' d\ell'$$

Alternative Motion-Model Formulations

- **Time-lag motion model**: $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{x}_{t-1}, \mathbf{u}_t, \mathbf{u}_{t-1}, \mathbf{w}_t)$
- Can be converted to the standard form via **state augmentation**
- Let $\mathbf{y}_t := \mathbf{x}_{t-1}$ and $\mathbf{s}_t := \mathbf{u}_{t-1}$ and define the augmented dynamics:

$$\tilde{\mathbf{x}}_{t+1} := \begin{bmatrix} \mathbf{x}_{t+1} \\ \mathbf{y}_{t+1} \\ \mathbf{s}_{t+1} \end{bmatrix} = \begin{bmatrix} f_t(\mathbf{x}_t, \mathbf{y}_t, \mathbf{u}_t, \mathbf{s}_t, \mathbf{w}_t) \\ \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} =: \tilde{f}_t(\tilde{\mathbf{x}}_t, \mathbf{u}_t, \mathbf{w}_t)$$

- This procedure works for an arbitrary number of time lags but the dimension of the state space grows and increases the computational burden exponentially ("curse of dimensionality")

Alternative Motion-Model Formulations

- System dynamics: $\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t)$
- **Correlated Disturbance**: $\mathbf{w}_t$ correlated across time (colored noise):

$$\begin{aligned}\mathbf{y}_{t+1} &= A_t \mathbf{y}_t + \boldsymbol{\xi}_t \\ \mathbf{w}_t &= C_t \mathbf{y}_{t+1}\end{aligned}$$

  where A_t, C_t are known and $\boldsymbol{\xi}_t$ are independent random variables

- **Augmented state**: $\tilde{\mathbf{x}}_t := (\mathbf{x}_t, \mathbf{y}_t)$ with dynamics:

$$\tilde{\mathbf{x}}_{t+1} = \begin{bmatrix}\mathbf{x}_{t+1} \\ \mathbf{y}_{t+1}\end{bmatrix} = \begin{bmatrix} f_t(\mathbf{x}_t, \mathbf{u}_t, C_t(A_t \mathbf{y}_t + \boldsymbol{\xi}_t)) \\ A_t \mathbf{y}_t + \boldsymbol{\xi}_t \end{bmatrix} =: \tilde{f}_t(\tilde{\mathbf{x}}_t, \mathbf{u}_t, \boldsymbol{\xi}_t)$$

- **State estimator**: $\mathbf{y}_t$ must be observed at time t, which can be done using a state estimator

MDP Notation and Terminology (Summary)

$t \in \{0, \ldots, T\}$	discrete time
$\mathbf{x} \in \mathcal{X}$	discrete/continuous state
$\mathbf{u} \in \mathcal{U}$	discrete/continuous control
$p_0(\mathbf{x})$	prior probability density function defined on $\mathcal{X}$
$p_f(\mathbf{x}' \mid \mathbf{x}, \mathbf{u})$	transition/motion model
$\ell(\mathbf{x}, \mathbf{u})$	stage cost of choosing control $\mathbf{u}$ in state $\mathbf{x}$
$\mathfrak{q}(\mathbf{x})$	terminal cost at state $\mathbf{x}$
$\pi_t(\mathbf{x})$	control policy: **function** from state $\mathbf{x}$ at time t to control $\mathbf{u}$
$V_t^{\pi}(\mathbf{x})$	value function: **expected cumulative cost** of starting at state $\mathbf{x}$ at time t and acting according to π
$\pi_t^*(\mathbf{x})$	optimal control policy
$V_t^*(\mathbf{x})$	optimal value function

MDP Finite-horizon Optimal Control (Summary)

Finite-horizon Optimal Control

The finite-horizon optimal control problem in an MDP $(\mathcal{X}, \mathcal{U}, p_0, p_f, T, \ell, \mathfrak{q}, \gamma)$ with initial state $\mathbf{x}$ at time t is:

$$\min_{\pi_{t:T-1}} V_t^{\pi}(\mathbf{x}) := \mathbb{E}_{\mathbf{x}_{t+1:T}} \left[\gamma^{T-t} \mathfrak{q}(\mathbf{x}_T) + \sum_{\tau=t}^{T-1} \gamma^{\tau-t} \ell(\mathbf{x}_\tau, \pi_\tau(\mathbf{x}_\tau)) \,\middle|\, \mathbf{x}_t = \mathbf{x} \right]$$

$$\text{s.t.} \;\; \mathbf{x}_{\tau+1} \sim p_f(\cdot \mid \mathbf{x}_\tau, \pi_\tau(\mathbf{x}_\tau)), \qquad \tau = t, \ldots, T-1$$

$$\mathbf{x}_\tau \in \mathcal{X}, \;\; \pi_\tau(\mathbf{x}_\tau) \in \mathcal{U}$$

Outline

Markov Decision Processes

Open-Loop vs Closed-Loop Control

Partially Observable Models

Open-Loop vs Closed-Loop Control

- **Open-loop policy**: control inputs $\mathbf{u}_{0:T-1}$ are determined at once at time 0 as a function of $\mathbf{x}_0$ and do not change online depending on $\mathbf{x}_t$
- **Closed-loop policy**: control inputs are determined "just-in-time" as a function π_t of the current state $\mathbf{x}_t$
- Open-loop control is a special case of closed-loop control that disregards the state $\mathbf{x}_t$ and, hence, never gives better performance
- In the absence of motion noise and in a special linear quadratic Gaussian (LQG) case, open-loop and closed-loop control have the same performance
- Open-loop control is computationally much cheaper than closed-loop control. Consider a discrete-space example with $|\mathcal{X}| = 10$ states, $|\mathcal{U}| = 10$ control inputs, planning horizon $T = 4$, and given x_0:
  - There are $|\mathcal{U}|^T = 10^4$ open-loop strategies
  - There are $|\mathcal{U}|(|\mathcal{U}|^{|\mathcal{X}|})^{T-1} = |\mathcal{U}|^{|\mathcal{X}|(T-1)+1} = 10^{31}$ closed-loop strategies
- **Open-loop feedback control** (OLFC) recomputes a new open-loop sequence $\mathbf{u}_{t:T-1}$ online, whenever a new state $\mathbf{x}_t$ is available. OLFC is guaranteed to perform better than open-loop control and is computationally more efficient than closed-loop control.

Example: Chess Strategy Optimization

- **Objective**: come up with a strategy that maximizes the chances of winning a 2 game chess match
- Possible outcomes:
  - Win/Lose: 1 point for the winner, 0 for the loser
  - Draw: 0.5 points for each player
  - If the score is equal after 2 games, the players continue playing until one wins (sudden death)
- Playing styles:
  - **Timid**: draw with probability p_d and lose with probability $(1 - p_d)$
  - **Bold**: win with probability p_w and lose with probability $(1 - p_w)$
  - **Assumption**: $p_d > p_w$

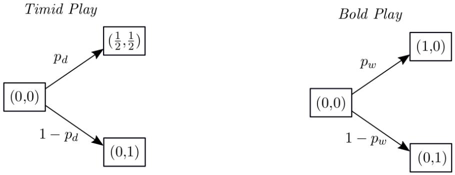
Chess Match Model

- **State** $\mathbf{x}_t$: 2-D vector with our and the opponent's score after the t-th game
- **Control** $u_t \in \mathcal{U} = \{\text{timid, bold}\}$
- **Noise** w_t: score of the next game
- Since timid play does not make sense during the sudden death stage, the planning horizon is $T = 2$
- We can construct a **time-dependent motion model** P^u_{ijt} for $t \in \{0, 1\}$ (shown on the next slide)
- **Cost**: minimize loss probability: $-P_{win} = \mathbb{E}_{\mathbf{x}_{1:2}}\left[\mathfrak{q}(\mathbf{x}_2) + \sum_{t=0}^{1} \ell(\mathbf{x}_t, u_t)\right]$, where

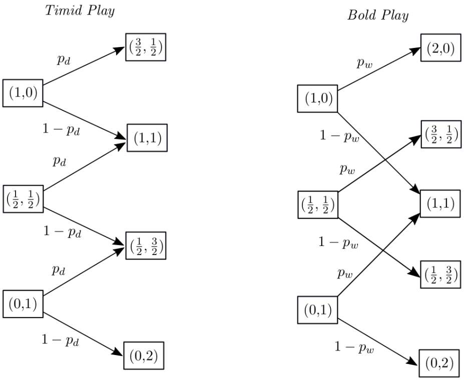
$$\ell(\mathbf{x}, u) = 0 \quad \text{and} \quad \mathfrak{q}(\mathbf{x}) = \begin{cases} -1 & \text{if } \mathbf{x} = \left(\frac{3}{2}, \frac{1}{2}\right) \text{ or } (2, 0) \\ -p_w & \text{if } \mathbf{x} = (1, 1) \\ 0 & \text{if } \mathbf{x} = \left(\frac{1}{2}, \frac{3}{2}\right) \text{ or } (0, 2) \end{cases}$$

Chess Transition Probabilities

Game 1:



Game 2:



Open-Loop Chess Strategy

- There are 4 possible open-loop policies:
  1. timid-timid: $P_{win} = p_d^2 p_w$
  2. bold-bold: $P_{win} = p_w^2 + p_w(1 - p_w)p_w + (1 - p_w)p_w p_w = p_w^2(3 - 2p_w)$
  3. bold-timid: $P_{win} = p_w p_d + p_w(1 - p_d)p_w$
  4. timid-bold: $P_{win} = p_d p_w + (1 - p_d)p_w^2$

- Since $p_d^2 p_w \le p_d p_w \le p_d p_w + (1 - p_d)p_w^2$, timid-timid is not optimal

- The best achievable winning probability is:

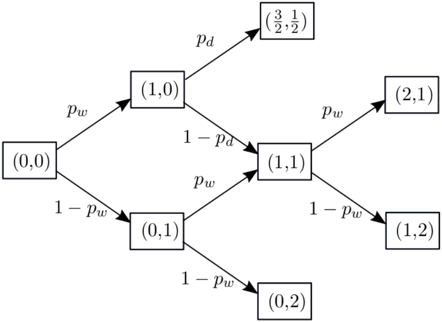
$$\begin{aligned} P_{win}^* &= \max\{\overbrace{p_w^2(3 - 2p_w)}^{\text{bold-bold}}, \overbrace{p_d p_w + (1 - p_d)p_w^2}^{\text{3. or 4.}}\} \\ &= p_w^2 + p_w(1 - p_w)\max\{2p_w, p_d\} \end{aligned}$$

- If $p_w \le 0.5$, then $P_{win}^* \le 0.5$
  - For $p_w = 0.45$ and $p_d = 0.9$, $P_{win}^* = 0.43$
  - For $p_w = 0.5$ and $p_d = 1.0$, $P_{win}^* = 0.5$

- If $p_d > 2p_w$, bold-timid and timid-bold are optimal open-loop policies; otherwise bold-bold is optimal

Closed-Loop Chess Strategy

- There are 16 closed-loop policies
- Consider one option: play timid if and only if ahead (it will turn out that this is optimal)



- The probability of winning is:
  $P_{win} = p_d p_w + p_w((1-p_d)p_w + p_w(1-p_w)) = p_w^2(2-p_w) + p_w(1-p_w)p_d$
- In the closed-loop case, we can achieve P_{win} larger than 0.5 even when p_w is less than 0.5:
  - For $p_w = 0.45$ and $p_d = 0.9$, $P_{win} = 0.5$
  - For $p_w = 0.5$ and $p_d = 1.0$, $P_{win} = 0.625$

Outline

Markov Decision Processes

Open-Loop vs Closed-Loop Control

Partially Observable Models

Hidden Markov Model

Hidden Markov Model

Markov Chain with partially observable states defined by tuple $(\mathcal{X}, \mathcal{Z}, p_0, p_f, p_h)$

- $\mathcal{X}$ is a discrete or continuous state space
- $\mathcal{Z}$ is a discrete or continuous observation space
- p_0 is a prior pdf defined on $\mathcal{X}$
- $p_f(\cdot \mid \mathbf{x}_t)$ is a conditional pdf defined on $\mathcal{X}$ for given $\mathbf{x}_t \in \mathcal{X}$ (summarized by matrix P with $P_{ij} = p_f(j \mid x_t = i)$ in finite-dim case)
- $p_h(\cdot \mid \mathbf{x}_t)$ is a conditional pdf defined on $\mathcal{Z}$ for given $\mathbf{x}_t \in \mathcal{X}$ (summarized by matrix O with $O_{ij} := p_h(j \mid x_t = i)$ in finite-dim case)

Partially Observable Markov Decision Process

Partially Observable Markov Decision Process

Markov Decision Process with partially observable states defined by tuple $(\mathcal{X}, \mathcal{U}, \mathcal{Z}, p_0, p_f, p_h, T, \ell, \mathfrak{q}, \gamma)$

- $\mathcal{X}$ is a discrete or continuous state space
- $\mathcal{U}$ is a discrete or continuous control space
- $\mathcal{Z}$ is a discrete or continuous observation space
- p_0 is a prior pdf defined on $\mathcal{X}$
- $p_f(\cdot \mid \mathbf{x}_t, \mathbf{u}_t)$ is a conditional pdf defined on $\mathcal{X}$ for given $\mathbf{x}_t \in \mathcal{X}$ and $\mathbf{u}_t \in \mathcal{U}$ (summarized by matrices P^u with elements $P^u_{ij} = p_f(j \mid x_t = i, u_t = u)$ in finite-dim case)
- $p_h(\cdot \mid \mathbf{x}_t)$ is a conditional pdf defined on $\mathcal{Z}$ for given $\mathbf{x}_t \in \mathcal{X}$ (summarized by matrix O with $O_{ij} := p_h(j \mid x_t = i)$ in finite-dim case)
- T is a finite/infinite time horizon
- $\ell(\mathbf{x}, \mathbf{u})$ is stage cost of applying control $\mathbf{u} \in \mathcal{U}$ in state $\mathbf{x} \in \mathcal{X}$
- $\mathfrak{q}(\mathbf{x})$ is terminal cost of being in state $\mathbf{x}$ at time T
- $\gamma \in [0, 1]$ is a discount factor

Comparison of Markov Models

	observed	partially observed
uncontrolled	**Markov Chain/MRP**	**HMM**
controlled	**MDP**	**POMDP**

- Markov Chain + Partial Observability = HMM
- Markov Chain + Control = MDP
- Markov Chain + Partial Observability + Control = HMM + Control = MDP + Partial Observability = POMDP

Bayes Filter

- A probabilistic inference technique for summarizing information $\mathbf{i}_t := (\mathbf{z}_{0:t}, \mathbf{u}_{0:t-1})$ about a partially observable state $\mathbf{x}_t$

- The Bayes filter keeps track of: $$p_{t|t}(\mathbf{x}_t) := p(\mathbf{x}_t \mid \mathbf{z}_{0:t}, \mathbf{u}_{0:t-1})$$ $$p_{t+1|t}(\mathbf{x}_{t+1}) := p(\mathbf{x}_{t+1} \mid \mathbf{z}_{0:t}, \mathbf{u}_{0:t})$$

- Derived using total probability, conditional probability, and Bayes rule based on the motion and observation models of the system

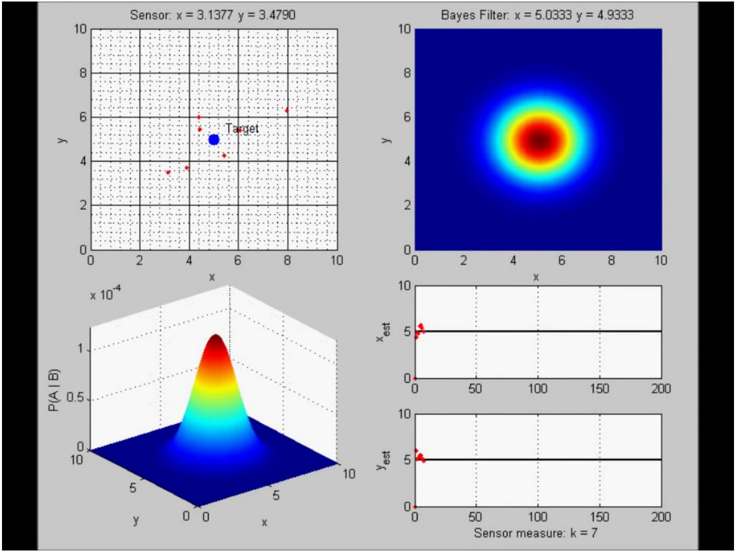
- **Motion model**: $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t, \mathbf{w}_t) \sim p_f(\cdot \mid \mathbf{x}_t, \mathbf{u}_t)$

- **Observation model**: $\mathbf{z}_t = h(\mathbf{x}_t, \mathbf{v}_t) \sim p_h(\cdot \mid \mathbf{x}_t)$

- **Bayes filter**: consists of **predict** and **update** steps:

$$p_{t+1|t+1}(\mathbf{x}_{t+1}) = \underbrace{\frac{1}{p(\mathbf{z}_{t+1}|\mathbf{z}_{0:t}, \mathbf{u}_{0:t})} p_h(\mathbf{z}_{t+1} \mid \mathbf{x}_{t+1}) \overbrace{\int p_f(\mathbf{x}_{t+1} \mid \mathbf{x}_t, \mathbf{u}_t) p_{t|t}(\mathbf{x}_t) d\mathbf{x}_t}^{\textbf{Predict: } p_{t+1|t}(\mathbf{x}_{t+1})}}_{\textbf{Update}}$$

Bayes Filter Example



Equivalence of POMDPs and MDPs

- A POMDP $(\mathcal{X}, \mathcal{U}, \mathcal{Z}, p_0, p_f, p_h, T, \ell, \mathfrak{q}, \gamma)$ is equivalent to an MDP $(\mathcal{P}(\mathcal{X}), \mathcal{U}, p_0, p_\psi, T, \bar{\ell}, \bar{\mathfrak{q}}, \gamma)$ such that:
  - **State space**: $\mathcal{P}(\mathcal{X})$ is the **continuous** space of pdfs over $\mathcal{X}$
    - If $\mathcal{X}$ is continuous, then $\mathcal{P}(\mathcal{X}) := \{p : \mathcal{X} \to \mathbb{R}_{\geq 0} \mid \int p(\mathbf{x}) d\mathbf{x} = 1\}$
    - If $|\mathcal{X}| = N$, then $\mathcal{P}(\mathcal{X}) := \{\mathbf{p} \in [0,1]^N \mid \mathbf{1}^\top \mathbf{p} = 1\}$
  - **Initial state**: $p_0 \in \mathcal{P}(\mathcal{X})$
  - **Motion model**: the Bayes filter $p_{t+1|t+1} = \psi(p_{t|t}, \mathbf{u}_t, \mathbf{z}_{t+1})$ acts as a motion model for $p_{t|t}$ with motion noise given by the observations $\mathbf{z}_{t+1}$ with density:

$$\eta(\mathbf{z} \mid p_{t|t}, \mathbf{u}_t) := \int \int p_h(\mathbf{z} \mid \mathbf{x}_{t+1}) p_f(\mathbf{x}_{t+1} \mid \mathbf{x}_t, \mathbf{u}_t) p_{t|t}(\mathbf{x}_t) d\mathbf{x}_t d\mathbf{x}_{t+1}$$

  - **Cost**: the equivalent MDP stage and terminal cost functions are the expected values of the POMDP stage and terminal costs:

$$\bar{\ell}(p, \mathbf{u}) := \int \ell(\mathbf{x}, \mathbf{u}) p(\mathbf{x}) d\mathbf{x} \qquad \bar{\mathfrak{q}}(p) := \int \mathfrak{q}(\mathbf{x}) p(\mathbf{x}) d\mathbf{x}$$

POMDP Finite-horizon Optimal Control

- POMDP $(\mathcal{X}, \mathcal{U}, \mathcal{Z}, p_0, p_f, p_h, T, \ell, \mathfrak{q}, \gamma)$:

$$\begin{aligned}
\min_{\pi_{0:T-1}} \quad & \mathbb{E}\left[\gamma^T \mathfrak{q}(\mathbf{x}_T) + \sum_{t=0}^{T-1} \gamma^t \ell(\mathbf{x}_t, \mathbf{u}_t)\right] \\
\text{s.t.} \quad & \mathbf{x}_{t+1} \sim p_f(\cdot \mid \mathbf{x}_t, \mathbf{u}_t), \qquad t = 0, \ldots, T-1 \\
& \mathbf{z}_{t+1} \sim p_h(\cdot \mid \mathbf{x}_t), \qquad t = 0, \ldots, T-1 \\
& \mathbf{u}_t \sim \pi_t(\cdot \mid \mathbf{i}_t), \qquad t = 0, \ldots, T-1 \\
& \mathbf{x}_0 \sim p_0(\cdot)
\end{aligned}$$

- Equivalent MDP $(\mathcal{P}(\mathcal{X}), \mathcal{U}, p_0, p_\psi, T, \bar{\ell}, \bar{\mathfrak{q}}, \gamma)$ with state $p_{t|t}$:

$$\begin{aligned}
\min_{\pi_{0:T-1}} \quad & V_0^\pi(p_0) = \mathbb{E}\left[\gamma^T \bar{\mathfrak{q}}(p_{T|T}) + \sum_{t=0}^{T-1} \gamma^t \bar{\ell}(p_{t|t}, \mathbf{u}_t)\right] \\
\text{s.t.} \quad & p_{t+1|t+1} = \psi(p_{t|t}, \mathbf{u}_t, \mathbf{z}_{t+1}), \quad t = 0, \ldots, T-1 \\
& \mathbf{z}_{t+1} \sim \eta(\cdot \mid p_{t|t}, \mathbf{u}_t), \qquad t = 0, \ldots, T-1 \\
& u_t \sim \pi_t(\cdot \mid p_{t|t}), \qquad t = 0, \ldots, T-1
\end{aligned}$$

- Due to the equivalence between POMDPs and MDPs, we will focus exclusively on MDPs