Markov Decision Processes

Last Time

- What does "Markov" mean in "Markov Process"?

Guiding Questions

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- What is a **Markov decision process**?

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- What is a **Markov decision process**?
- What is a **policy**?

Guiding Questions

- What is a **Markov decision process**?
- What is a **policy**?
- How do we **evaluate** policies?

Decision Networks and MDPs

Decision Networks and MDPs

Decision Network

 Chance node

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 Utility node

Decision Networks and MDPs

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MDP Decision Network

Decision Networks and MDPs

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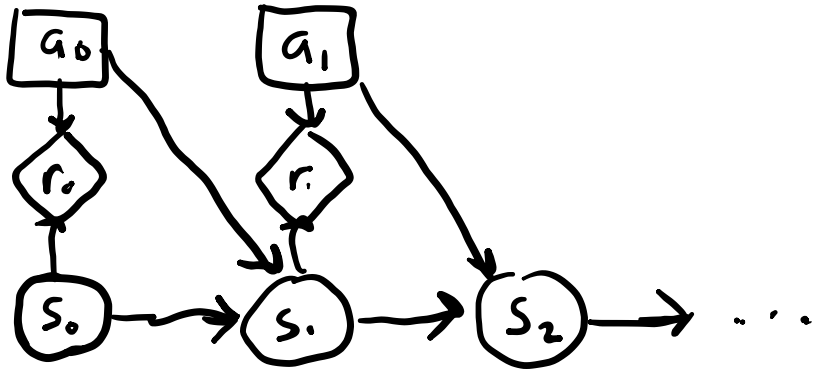
MDP Decision Network



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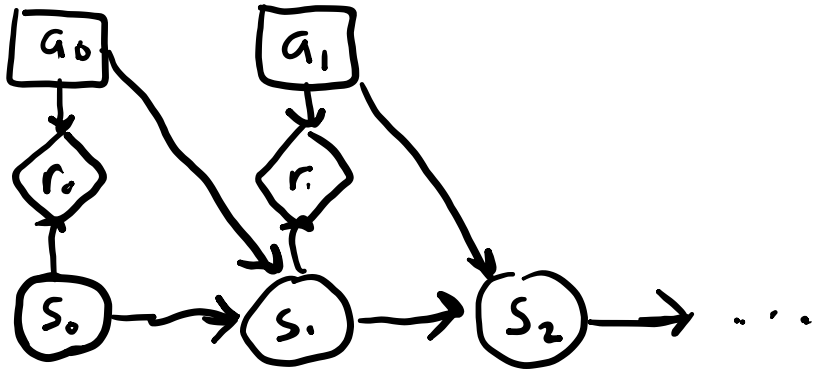

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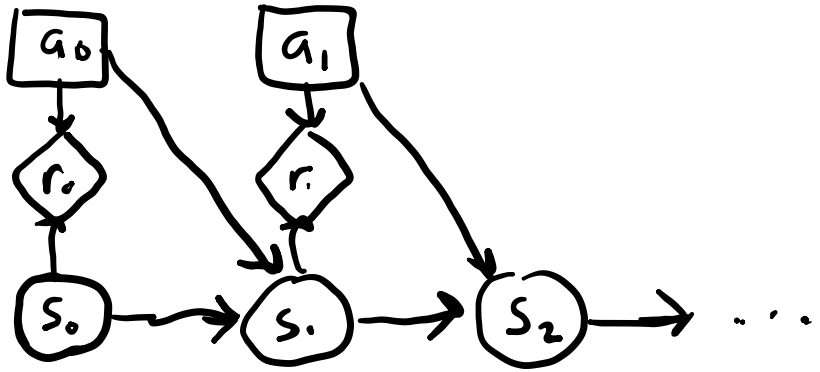

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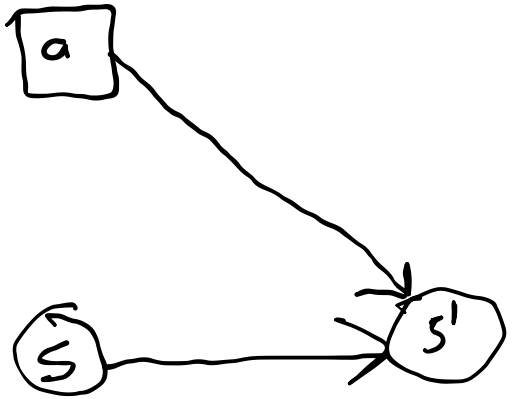

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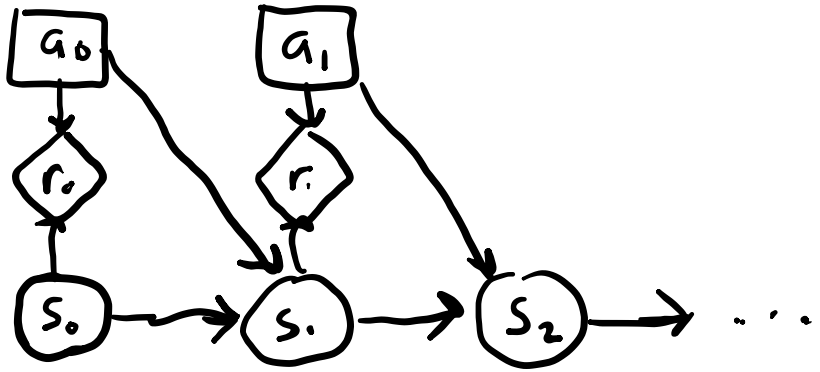

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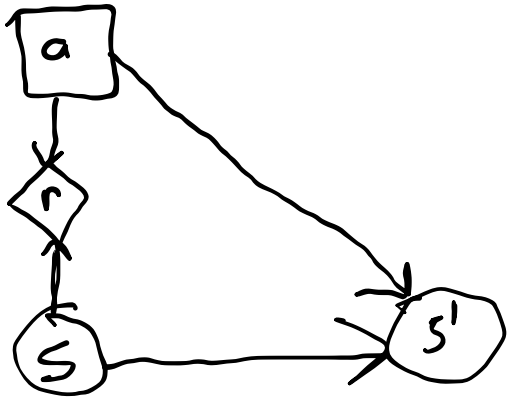

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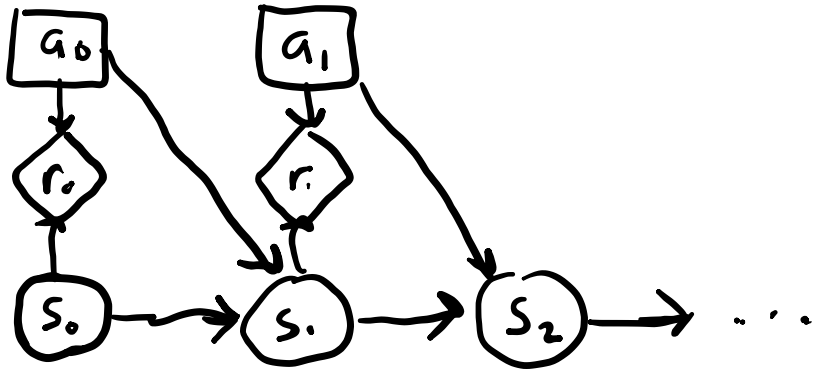

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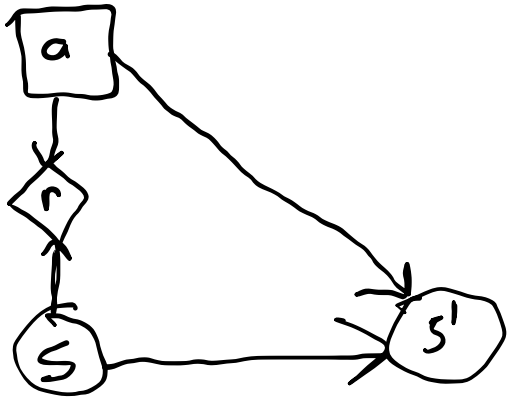

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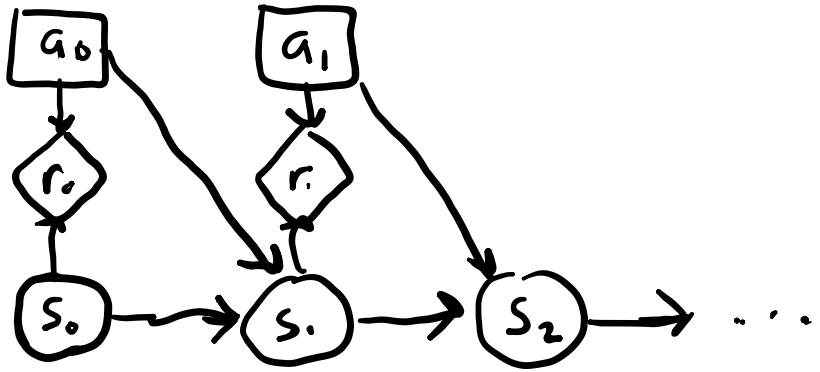

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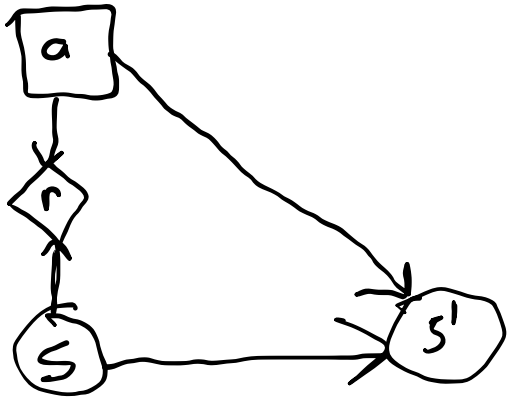

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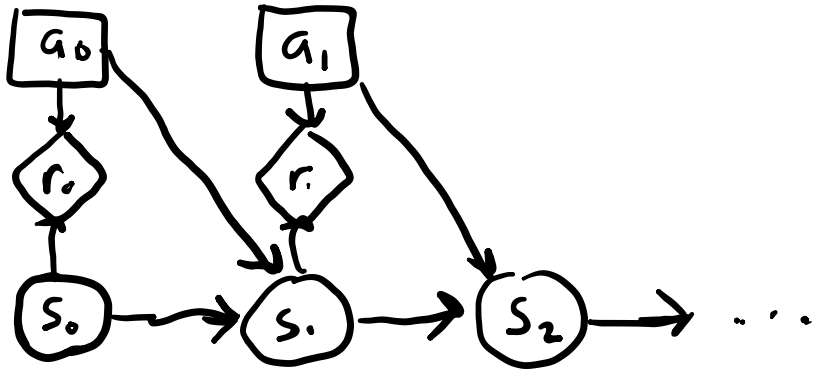

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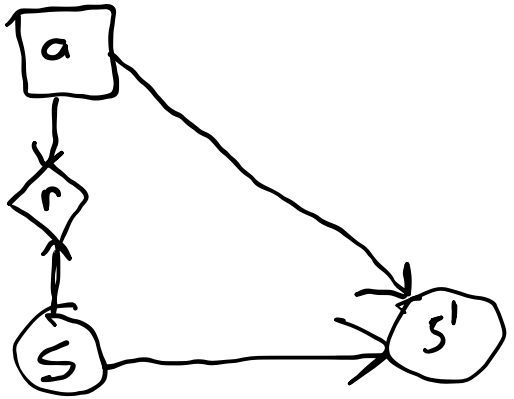

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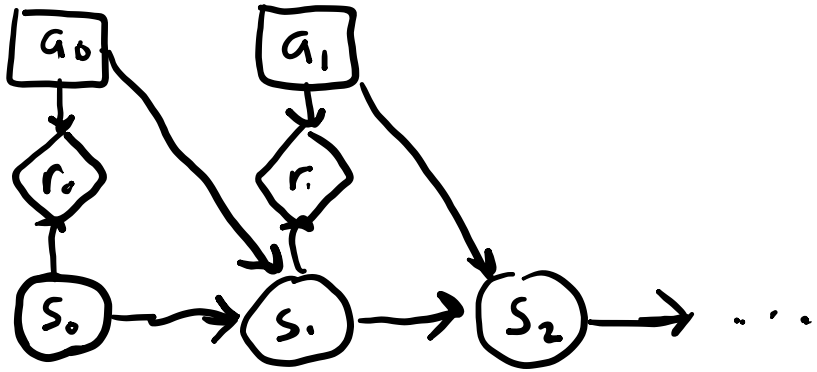

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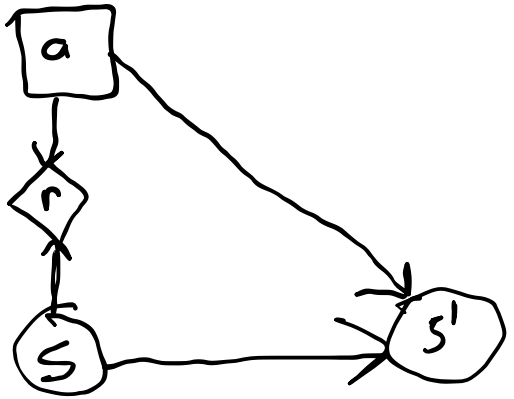

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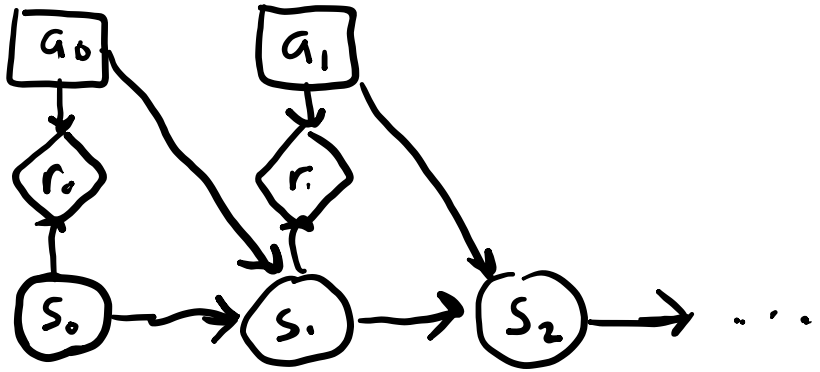

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- γ: discount factor
- b: initial state distribution
- S_t: set of terminal states

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MDP Example

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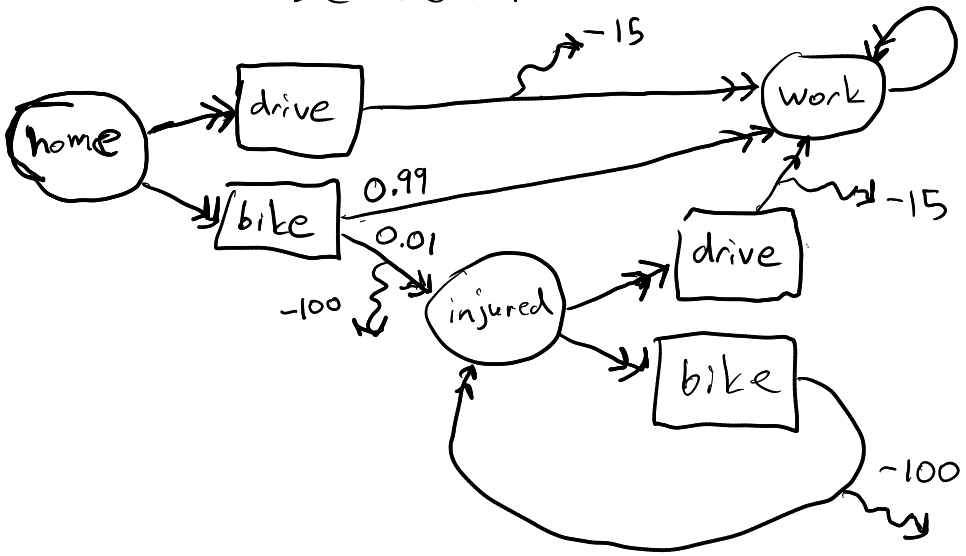
- If you drive, you will have to pay $15 for parking; biking is free.
- On 1% of cold days, the ground is covered in ice and you will crash if you bike, but you can't discover this until you start riding. After your crash, you limp home with pain equivalent to losing $100.

State transition diagram
Not a Decision Network



$S = \{home, injured, work\}$

$A = \{drive, bike\}$

$$T^{drive} = \begin{array}{c} \\ h \\ i \\ w \end{array} \begin{array}{c} \begin{array}{ccc} h & i & w \end{array} \\ \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \quad (s \text{ rows}, s' \text{ columns})$$

$$T^{bike} = \begin{array}{c} \\ h \\ i \\ w \end{array} \begin{array}{c} \begin{array}{ccc} h & i & w \end{array} \\ \begin{bmatrix} 0 & 0.01 & 0.99 \\ 0 & 1.0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{array}$$

$$R(s,a,s') = \begin{cases} -15 & \text{if } a = drive \\ -100 & \text{if } s' = injured \\ 0 & \text{o.w.} \end{cases} \qquad \gamma = 0.99$$

$S_T = \{work\}$ $\qquad b(s) = \begin{cases} 1 & \text{if } s = home \\ 0 & \text{o.w.} \end{cases}$

Policies and Simulation

cf. Alg. 9.1, p. 184

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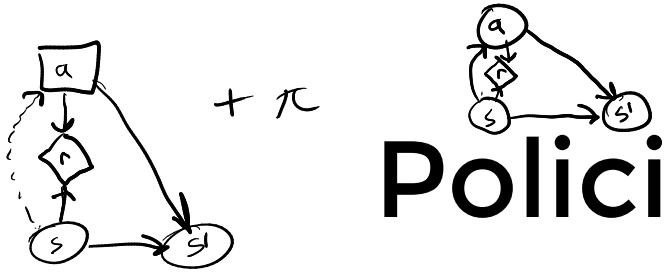

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$$P(s' \mid s) = \sum_a T(s' \mid s, a)\, \pi(a \mid s)$$

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MDP Objective:

$$\text{maximize } U(\pi) = \mathrm{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \mid \pi\right]$$

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Algorithm: Rollout Simulation

Inputs: MDP (S, A, R, T, γ, b) (only need generative model, G), Policy π, horizon H

Outputs: Utility estimate $\hat{u}$

$s \leftarrow \text{sample}(b)$

$\hat{u} \leftarrow 0$

for t in $0 \ldots H-1$

  $a \leftarrow \text{sample}(\pi(a \mid s))$

  $s', r \leftarrow G(s, a)$

  $\hat{u} \leftarrow \hat{u} + \gamma^t r$

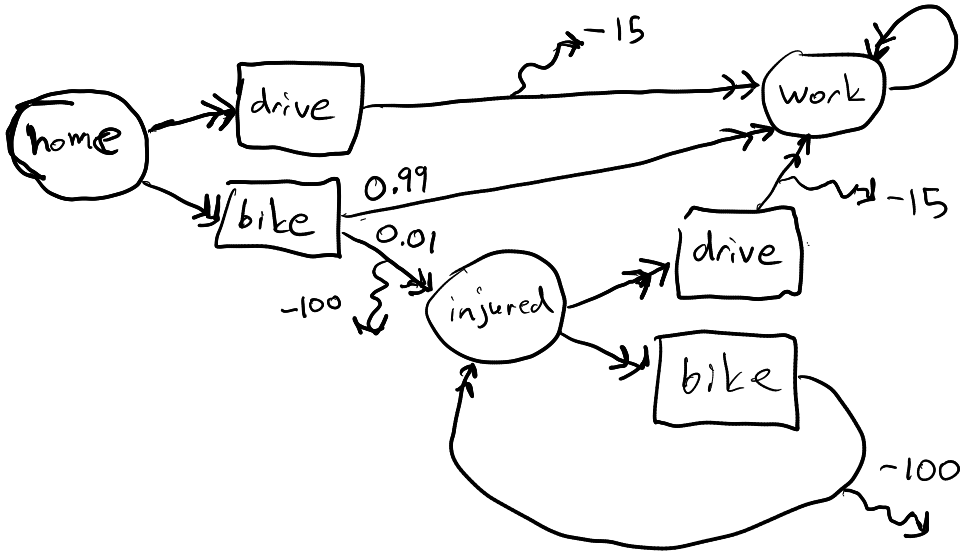
  $s \leftarrow s'$

return $\hat{u}$

cf. Alg. 9.1, p. 184

Break

- Suggest a policy that you think is optimal for the icy day problem



$$\pi(s) = \begin{cases} \text{bike} & \text{if } s = \text{home} \\ \text{drive} & \text{if } s = \text{injured} \end{cases}$$

$$U(\text{bike from home}) = 0.99 \times 0 + 0.01(-100 + -15) = -1.15$$

$$U(\text{drive from home}) = -15$$

Naive Policy Evaluation

Naive Policy Evaluation not on Exam

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Let $\tau = (s_0, a_0, r_0, s_1, \ldots, s_T)$ be a *trajectory* of the MDP, and $R(\tau) = \sum_{t=0}^{\infty} \gamma^t r_t$

Naive Policy Evaluation not on Exam

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$$P(\tau \mid \pi) = b(s_0) \prod_{t=0}^{\infty} T(s_{t+1} \mid s_t, \pi(t))$$

Naive Policy Evaluation not on Exam

Monte Carlo Policy Evaluation

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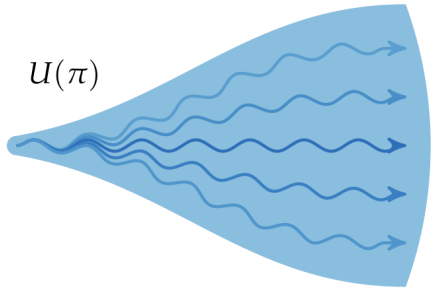

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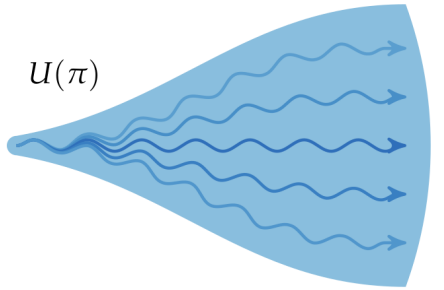

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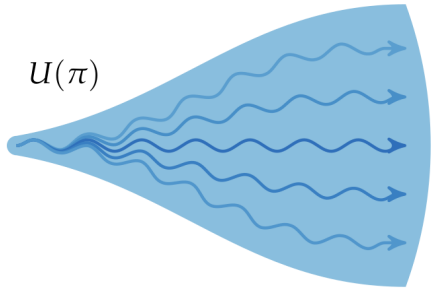

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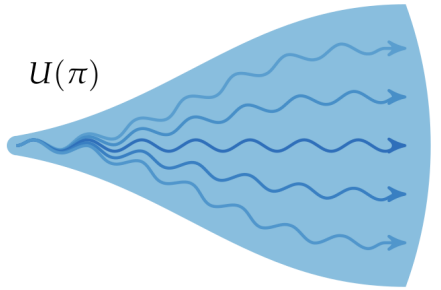

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where $\hat{u}^{(i)}$ is generated by a rollout simulation

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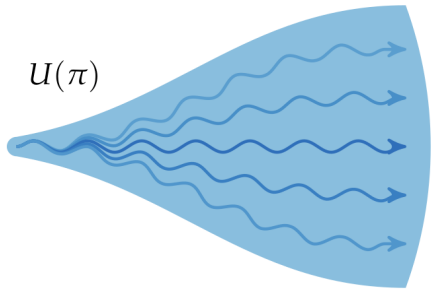

How can we quantify the accuracy of $\bar{u}_m$?

$$\mathrm{Var}(\bar{u}_m) = \mathrm{Var}\left(\frac{1}{m}\sum_i \hat{u}^{(i)}\right)$$

$$= \frac{1}{m^2}\mathrm{Var}\left(\sum_i \hat{u}^{(i)}\right)$$

$$= \frac{1}{m^2}\sum_{i=1}^{m} \mathrm{Var}(\hat{u}^{(i)})$$

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Standard Error of Mean $\quad SEM \equiv \frac{1}{\sqrt{m}}\, std(\hat{u})$

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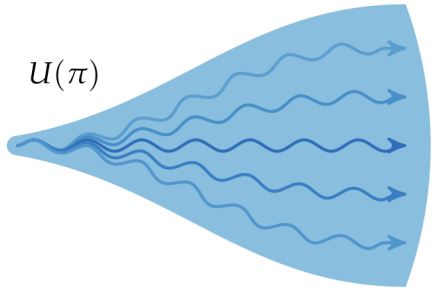

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Value Function-Based Policy Evaluation

Guiding Questions

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- What is a **Markov decision process**?
- What is a **policy**?
- How do we **evaluate** policies?