Last Time

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

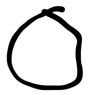
Decision Networks and MDPs

Decision Networks and MDPs

Decision Network

Decision Networks and MDPs

Decision Network



Decision Networks and MDPs

Decision Network

Chance node

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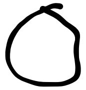
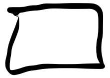
 Chance node

 Decision node

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Utility node

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MDP Dynamic Decision Network

Decision Networks and MDPs

Decision Network

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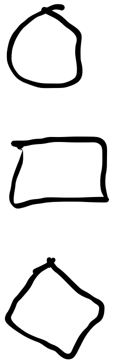
- Decision node
- Utility node

MDP Dynamic Decision Network

$$s \longrightarrow s'$$

Decision Networks and MDPs

Decision Network



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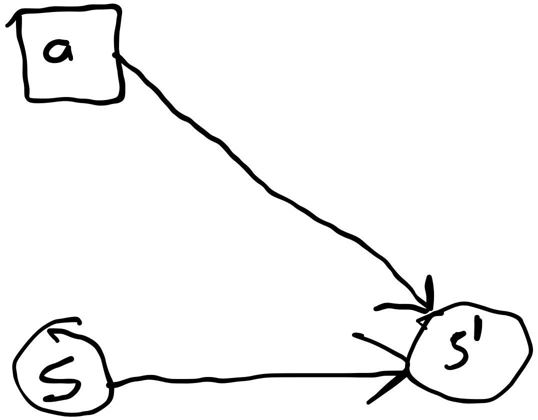

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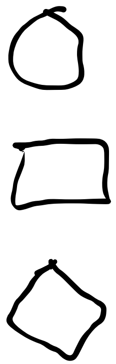

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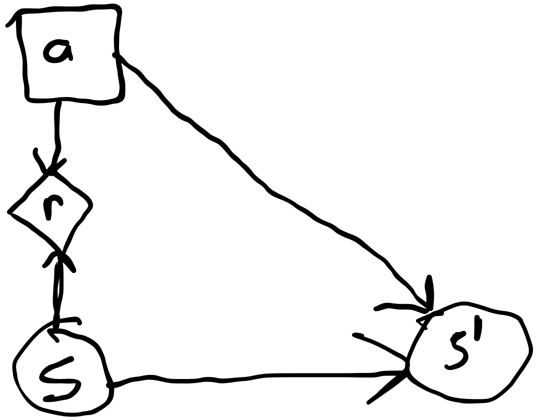

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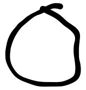
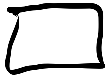
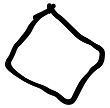
 Chance node

 Decision node

 Utility node

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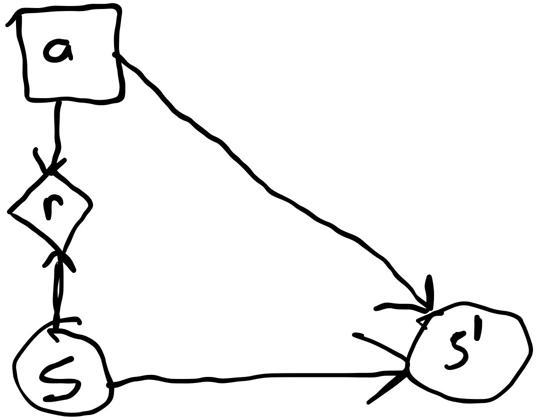

MDP Optimization problem

Decision Networks and MDPs

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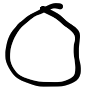
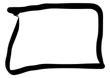
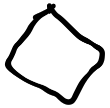
 Chance node

 Decision node

 Utility node

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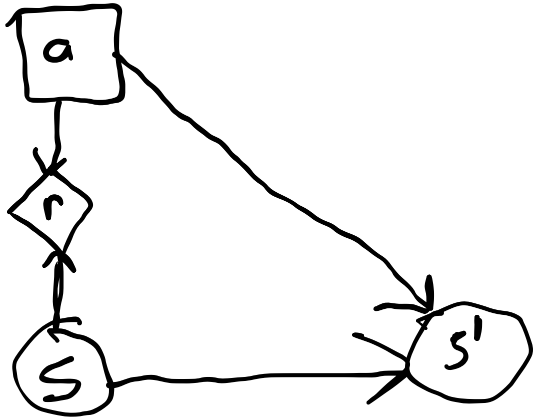

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$$\text{maximize} \quad \mathrm{E}\left[\sum_{t=1}^{\infty} r_t\right]$$

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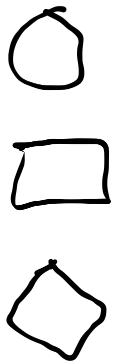

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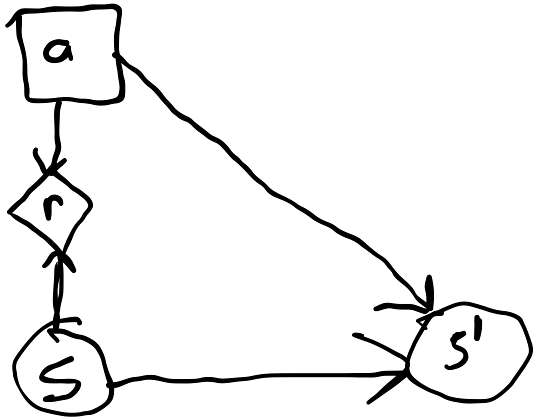

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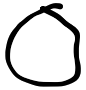
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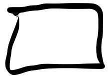
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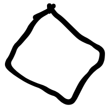
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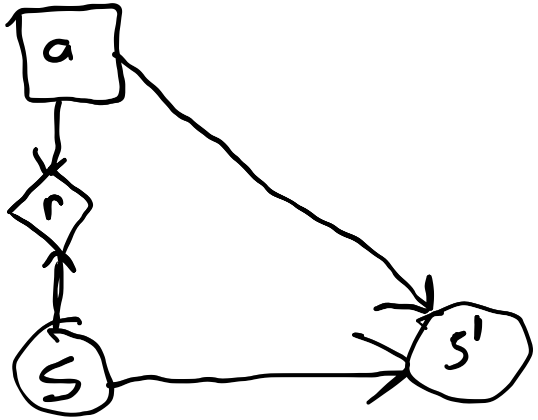

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Infinite time, but a terminal state (no reward, no leaving) is always reached with probability 1.

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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.

Policies and Simulation

Policies and Simulation

- A *policy*, denoted with π, as in $a_t = \pi(s_t)$ is a function mapping every state to an action.

Break

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

Utility

Slide not on Exam

Policy Evaluation

Naive Policy Evaluation not on Exam

Value Function-Based Policy Evaluation

Monte Carlo Policy Evaluation

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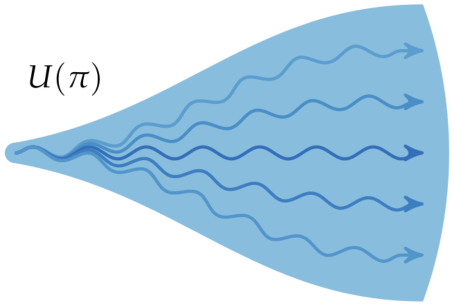

Monte Carlo Policy Evaluation

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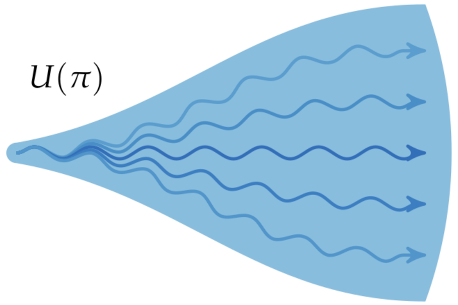

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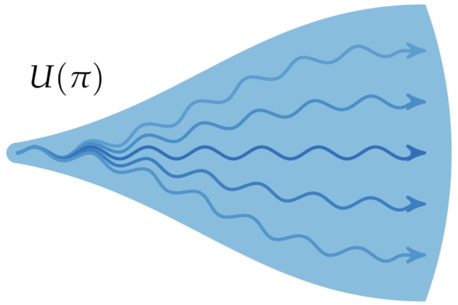

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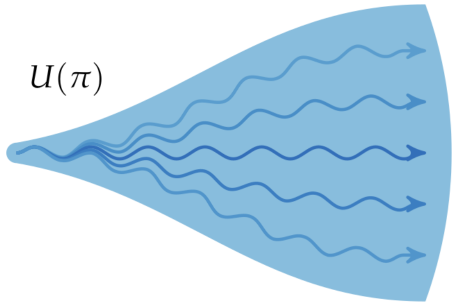

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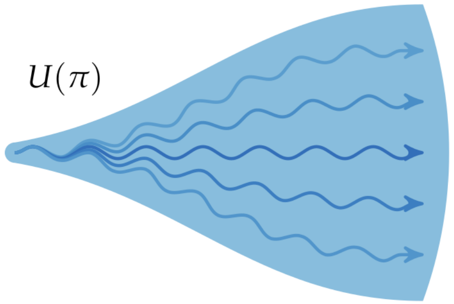

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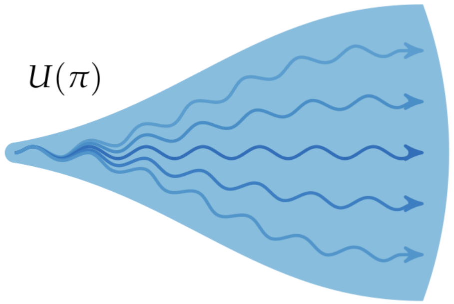

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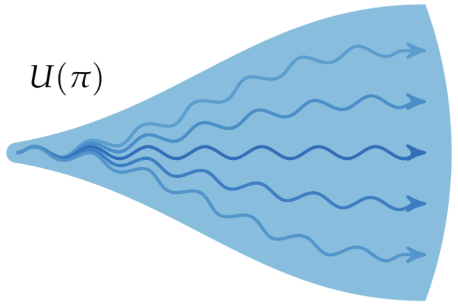

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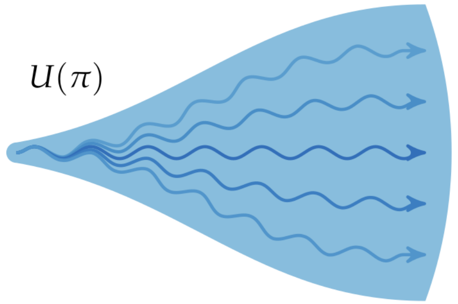

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CLT not on exam

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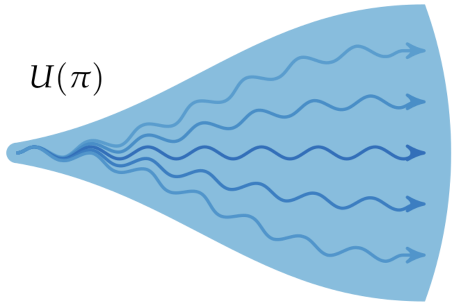

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Standard Error of the Mean

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