

# ECSE 506: Stochastic Control and Decision Theory

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# Learning objectives

Develop ability to read and understand research papers in stochastic control.

Emphasis on understanding proofs. We will prove **every** result that we state in class.

Study examples from different application domains: communications, operations research, control systems, and power systems. Focus on being able to establish qualitative properties of optimal policies

Understand the role and limitations of models.

# Course content

## Stochastic optimization

Single decision made by single decision maker.

## MDPs (Markov decision processes)

Multiple decisions made by single DM with perfect information

## POMDPs (Partially observable MDPs)

Multiple decisions made by a single DM with imperfect information.

## Decentralized control (also called Dec-POMDPs)

Multiple decisions made by multiple DMs with imperfect info.

# Background

## Graduate probability

Conceptual understanding of random variables and conditional expectation

## Real analysis

Basic understanding of limits and convergence, metric spaces, and completeness.

## Optimization

Basic understanding of convexity and first and second order conditions for optimality.

# Logistics

## Assignments (20%)

- ▶ Weekly assignments; posted on the course website.
- ▶ Only one randomly selected question will be graded. Lowest assignment dropped.
- ▶ Solutions posted on myCourses and only accessible to registered students.
- ▶ If you are auditing and need access, send me a message.

## Mid Term (40%)

- ▶ **If classes are online: Week of 28th March**

Online exam. Available for 72hrs. Once you start, you'll have 2.5hrs to finish the exam.

- ▶ **If classes are in-person: 29th March**

In person, 1.5 hr exam, during class time.

## Term Project (20%)

- ▶ To be done either alone or in groups of two. Due end of term
- ▶ Critique one or two papers related to the course. Deliverables: project report and presentation.

# Course Notes

Partial course notes available on the course website:

<https://adityam.github.io/stochastic-control>

While classes are online, the zoom recording will be available on myCourses.

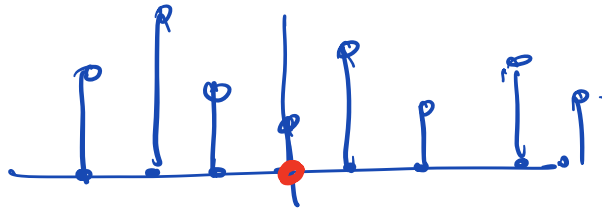
If/when in-person classes resume, video recordings may not be available. (Most rooms don't have video recording infrastructure).

# Communication

Announcements and solutions posted on myCourses. Please check regularly.

All communication with the instruction should be via the discussion board on myCoures.

## OPTIMIZATION



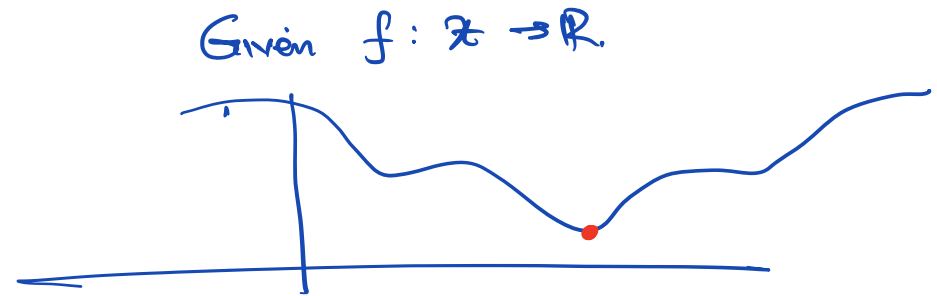
Brute force search

for  $x \in X$

if  $f(\text{argmin}) > f(x)$

$\text{argmin} = x$

end  
end



Find  $x^* = \text{argmin}_{x \in X} f(x)$

$X$ : Is cts. Calculus

Regularity cond.: convexity

$X$ : Is discrete

## Decision prob vs optimization

INFORMATION / UNCERTAINTY.



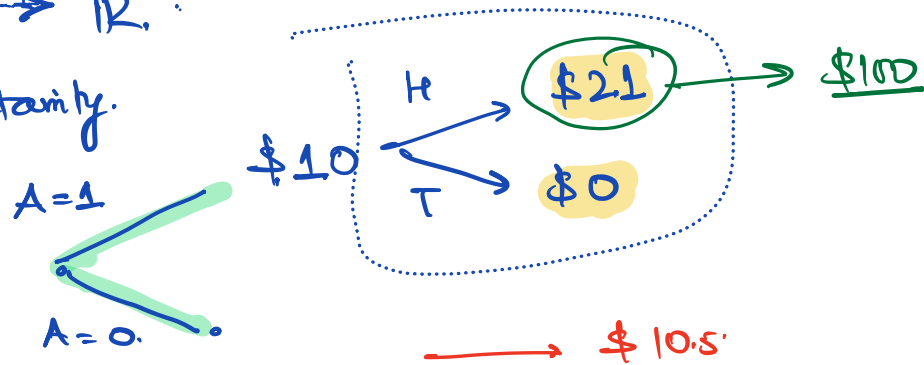
# Deterministic optimization

$$\min_{a \in A} \underline{c(a)}$$

$c: A \rightarrow \mathbb{R}$   
 ↙ ↘ ↘  
 cost fn Action space Real #

②  $\mathcal{W} \times A \rightarrow \mathbb{R}$

Set of uncertainty.



Assuming:  $P_W$  is known

\$10 · 1

✓

\$30 · 0.6

\$0 · 0.4

✓

~~\$20~~ \$21 · 0.5

\$0 · 0.5

✓

\$21 · 0.5

\$0 · 0.5

✓

$$a_1 > a_2$$

$$a_2 > a_3$$

$$a_1 > a_3$$

⇒ Consistent

Utility maximizers

If a DM has consistent pref over a random outcomes.

$\Rightarrow \exists$  a utility fn. st.

DM is a utility maximizer

Unique up to  
additive and multiplicative  
const.

$$\arg \max_{a \in A} \mathbb{E}[\underline{10} \underline{u}(\underline{c}(w, a))] + 3$$

==

$$c: W \times A \rightarrow \mathbb{R}$$

$$\arg \min_{a \in A} \mathbb{E}[c(w, a)] \quad \arg \max_{a \in A} \mathbb{E}[r(w, a)]$$

—

	\$21 (0.5)		\$210 (0.5)
\$10	\$0 (0.5)	\$100	\$0 (0.5)
$A=1$		$A_1=1$	\$5 <u>10</u>
$A=0$		$A=0$	\$0
	<div style="border: 1px solid red; padding: 5px; display: inline-block;"> <math>10.5 - 10 = 0.5 \cdot \\$</math>  <math>= 0</math> </div>		

$$\arg \max \{ \underline{0.5}, 0 \}$$

$$\arg \max \{ \underline{5}, 0 \}$$

$$\begin{array}{ll} A=1 & -0.5 \\ A=0 & 0 \end{array} \quad \arg \max \{ -0.5, \underline{0} \}$$

$$\arg \max \{ 0_1, 0_2, \dots, 0_k \} \equiv \arg \max \{ \alpha 0_1, \alpha 0_2, \dots, \alpha 0_k \}$$

if  $\underline{\alpha > 0}$

$$\equiv \arg \max \{ \alpha 0_1 + \beta, \alpha 0_2 + \beta, \dots \}$$

Deterministic optimization

$$\min_{a \in A} \underline{c(a)}$$

Stochastic optimization

$$\min_{a \in A} \underbrace{\mathbb{E}[c(w, a)]}_{\underline{c(a)}}$$

Example



$A=1$

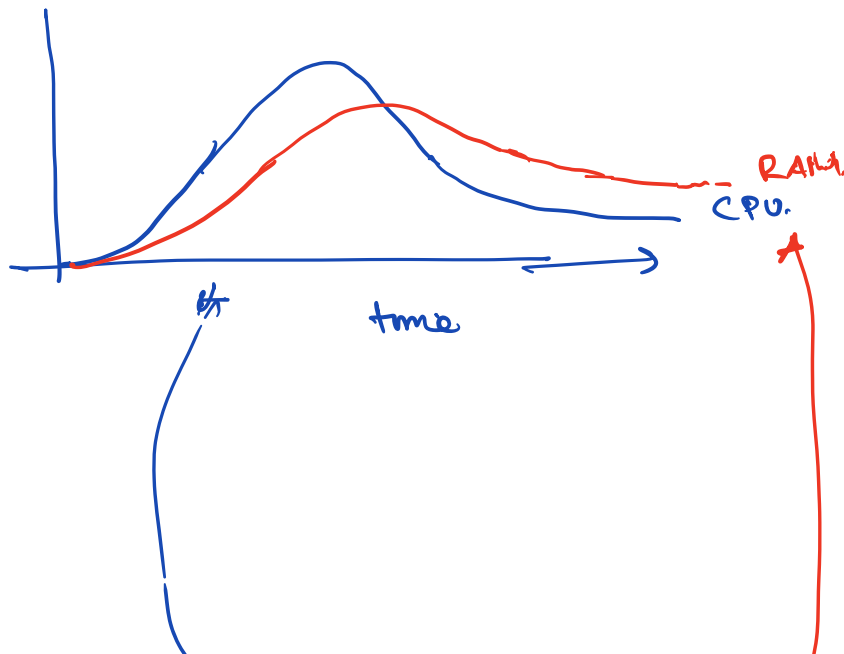
CPU/RAM



$A=2$

Max the time to failure

density



$w_{CPU}$

$w_{CPU_1}$

$w_{CPU_2}$

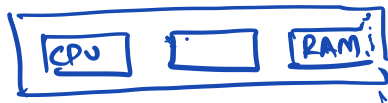
$w_{RAM}$  ✓

$w_{RAM_1}$

$w_{RAM_2}$

$W = \{w_{CPU_1}, w_{CPU_2}, w_{RAM_1}, w_{RAM_2}\}$

$$\begin{aligned} \mathbb{E}[r(W, \underline{A=1})] &= \mathbb{E}[\min\{\max\{w_{CPU_1}, w_{CPU_2}\}, w_{RAM_1}\}] \\ \mathbb{E}[r(W, \underline{A=2})] &= \mathbb{E}[\min\{w_{CPU_1}, \max\{w_{RAM_1}, w_{RAM_2}\}\}] \end{aligned}$$



CPU  $\leftarrow$  Manf 1  
 Manf 2

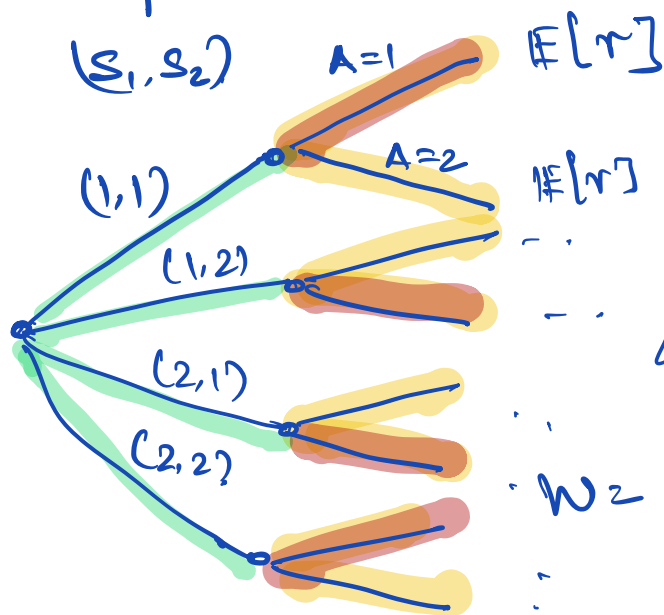
$s_1 \in \{1, 2\}$

RAM  $\rightarrow$  M1  
 M2

$s_2 \in \{1, 2\}$



State  $S = (s_1, s_2)$



$r: S \times W \times A \rightarrow \mathbb{R}$

$w_{CPU,1}$   
 1

$w_{CPU,1}$   
 2

$w_{CPU,2}$   
 1

$w_{CPU,2}$   
 2

$w_{RAM,1}$   
 1

$w_{RAM,1}$   
 2

$w_{RAM,2}$   
 1

$w_{RAM,2}$   
 2

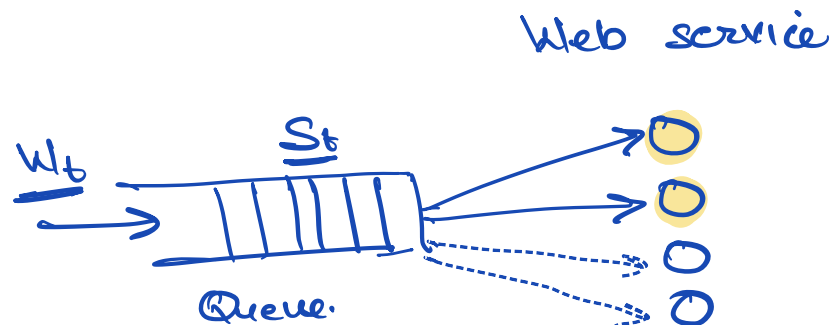
$$r(s_1, s_2, W, \underline{1}) = \min \left\{ \max \{ w_1^{\text{CPU}, s_1}, w_2^{\text{CPU}, s_1} \}, w_1^{\text{RAM}, s_2} \right\}$$

Policy  $\pi: S \rightarrow A$

$$\max_{\pi: S \rightarrow A} \mathbb{E}[r(\underline{s}, W, \underline{\pi(s)})] \Rightarrow$$

functional opt.

Converted to  
a sequence  
of pars. opt.  
prob.



1 - CPU  
2 - CPU  
3 - CPU  
4 CPU

$P$

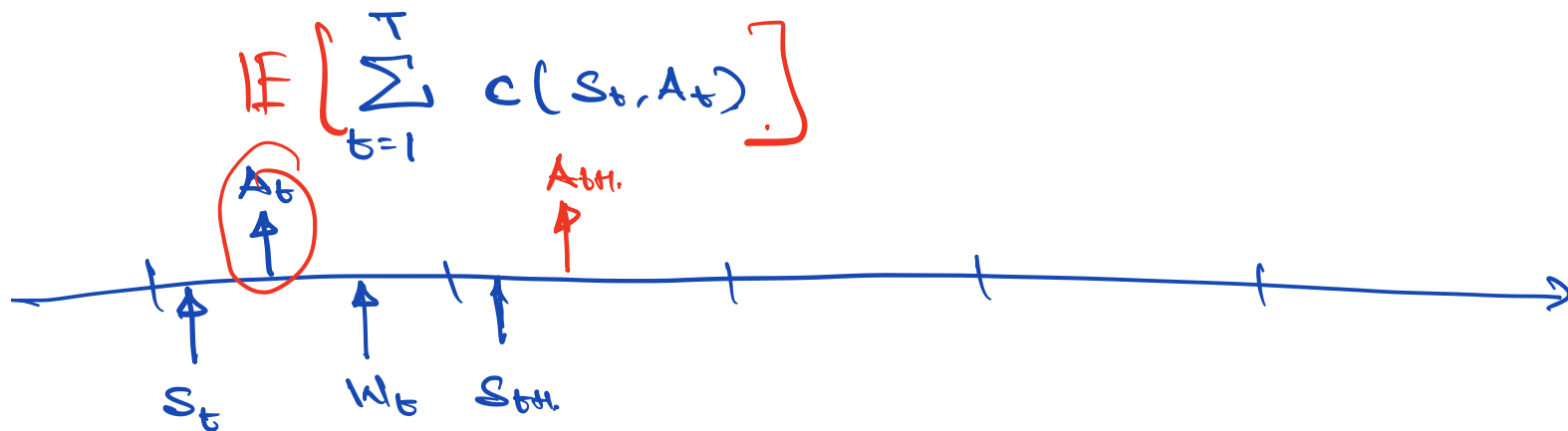
$A_t \in \{1, 2, 3, 4\}$

$$S_{t+1} = S_t - \min\{A_t, S_t\} + W_t$$

Random new jobs

$$c(S_t, A_t) = h(S_t) + p A_t$$

Holding cost



Info  $I_t$  available at time  $t$

Full info MDP

$A_t = \pi_t(I_t)$

Partial | POMDP



$$\min_{\pi_1, \pi_2 \dots \pi_T} \mathbb{E} \left[ \sum_{t=1}^T c(S_t, A_t) \right]$$

Under some cond.  
 $\Rightarrow$  seq. of para.  
optimization