Decision Making Under Uncertainty: Lecture 2—Sample Average Approximation

Lecture 2

Ryan Cory-Wright

Spring 2026

Some Housekeeping

- Reminder: Please name the paper you are presenting for critical paper review and the week you are presenting in (by email to me) by Friday.

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- HW1 is now out, due on 2 Feb (see Insendi)—brief discussion of HW questions.
- I'll set aside some time at the end of the Monday Week 4 lecture, in case you have questions on the homework then.

Warm-Up: Solve This Problem

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Conclusion: Terminology matters; should define everything carefully!

Outline of Lecture 2

Motivation: Ordinary Least Squares Regression

Linear Regression Setup—Rearranging

Linear regression: n i.i.d. observations of p-dimensional input vector $\boldsymbol{x}$ and output y, $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n}$. We believe input-output follows model $y = \boldsymbol{x}^\top \boldsymbol{\beta}_{\text{true}} + \epsilon$, where $\boldsymbol{\beta}_{\text{true}}$ fixed vector, ϵ i.i.d. zero-mean noise.

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After some calculus

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where $\boldsymbol{A}^\dagger$ denotes pseudoinverse of $\boldsymbol{A}$.

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where $\boldsymbol{A}^\dagger$ denotes pseudoinverse of $\boldsymbol{A}$. Assume p fixed, $n > p$

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Aside: Matrix Pseudoinverses

If $\boldsymbol{X}$ a matrix with singular value decomposition $\boldsymbol{X} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$
Then $\boldsymbol{X}^\dagger = \boldsymbol{V}\boldsymbol{\Sigma}^\dagger\boldsymbol{U}^\top$ where $\boldsymbol{\Sigma}^\dagger$ is a diagonal matrix where we invert all non-zero diagonal entries, keep zeroes as zeroes.

For a symmetric matrix like $\boldsymbol{X}^\top\boldsymbol{X}$, can define

$$(\boldsymbol{X}^\top\boldsymbol{X})^\dagger := \lim_{\lambda\to 0}(\boldsymbol{X}^\top\boldsymbol{X} + \lambda\mathbb{I})^{-1}\boldsymbol{X}^\top.$$

See the book "Matrix Analysis" by Horn and Johnson.

Reminder: Almost Sure Convergence

Almost Sure Definition

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and let $\{\boldsymbol{X}_i\}_{i\in\mathbb{N}}, \boldsymbol{X}$ be random variables. Suppose that $\boldsymbol{A} \in \mathcal{F}$ is a measurable set such that $\mathbb{P}(\boldsymbol{A}) = 1$ and for all $\omega \in \mathcal{A}$ we have

$$\boldsymbol{X}_i(\omega) \to \boldsymbol{X}(\omega).$$

Then, we say that $\boldsymbol{X}_i \stackrel{a.s.}{\to} \boldsymbol{X}$.

Reminder: Continuous Mapping Theorem

Continuous Mapping Theorem

Let $\boldsymbol{X}_i, \boldsymbol{X}$ be random variables. Suppose that $\boldsymbol{X}_i \overset{a.s.}{\to} \boldsymbol{X}$ and f is continuous almost everywhere. Then

$$f(\boldsymbol{X}_i) \overset{a.s.}{\to} f(\boldsymbol{X})$$

Asymptotics of Linear Regression

Consider our rearranged equation:

$$\hat{\boldsymbol{\beta}} = (\boldsymbol{X}^\top \boldsymbol{X})^\dagger \boldsymbol{X}^\top \boldsymbol{y} = \boldsymbol{\beta}_{\text{true}} + (\boldsymbol{X}^\top \boldsymbol{X})^\dagger \boldsymbol{X}^\top \boldsymbol{\epsilon}$$

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As $n \to \infty$, what happens to $\hat{\beta}$?

- SLLN $\frac{1}{n}\boldsymbol{X}\boldsymbol{X}^\top \xrightarrow{a.s.} \mathbb{E}[\boldsymbol{x}_i \boldsymbol{x}_i^\top]$
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- Therefore $\hat{\boldsymbol{\beta}} \overset{a.s.}{\to} \boldsymbol{\beta}_{\text{true}}$ (under some mild conditions on span of $\mathbb{E}[\boldsymbol{x}_i \boldsymbol{x}_i^\top]$ etc.)

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- Plan for lecture: Show holds more generally, how to solve SAA

Sample Average Approximation: Theory

Let's warm up with a special case

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- Each newspaper costs c, can be sold for q if there is demand
- Unsold newspapers get thrown in the recycling bin
- How to optimally set x?

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That is, a $\frac{(q-c)}{q}$th quantile of D_ω

Insight: setting x equal to $\mathbb{E}[D_\omega]$ could be bad, especially if $q \gg c$

The General Problem

Overall Problem Setting: Two-Stage Stochastic Linear Opt

Consider stochastic optimization problem:

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- A linear optimization problem with random parameters

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  - As hard as counting number of solutions to NP-hard problem
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- Structure of Optimal Solutions: In general, $\boldsymbol{y}$ a function of ω

Sample Average Approximation to the Rescue

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- Who can tell me why we use "arg min" and "a minimizer" here?

Almost Sure Convergence Proof (Sketch)

- Define a sample-average function, redefine expected value

$$\hat{g}_N(\boldsymbol{x}) := \min_{\boldsymbol{y}(\boldsymbol{\omega}^i)} \boldsymbol{c}^\top \boldsymbol{x} + \frac{1}{N}\sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i),$$

$$g(\boldsymbol{x}) := \min_{\boldsymbol{y}(\omega)} \mathbb{E}_\omega[\boldsymbol{c}^\top \boldsymbol{x} + \frac{1}{N}\sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega})]$$

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Pointwise maximum also reveals h is continuous on its domain

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- By SLLN, continuity of g_N, g: $g_N(\boldsymbol{x}) \overset{a.s.}{\to} g(\boldsymbol{x}) \; \forall \boldsymbol{x} : \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b}$

[1] See Corollary 3 of "Monte Carlo Sampling Methods" by Shapiro (2003) for details.

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- Therefore, (under mild conditions[1]), $\inf_{\boldsymbol{x}} g_N(\boldsymbol{x}) \overset{a.s.}{\to} \inf_{\boldsymbol{x}} g(\boldsymbol{x})$

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When Things go Wrong, as They Sometimes Will

Let's look at our sample-average approximation again:

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- $\hat{\boldsymbol{x}}_N$ might be far from $\boldsymbol{x}^\star$, especially if N small relative to dim of $\boldsymbol{x}$
  - A motivation for distributionally robust optimization—see later

Let's break for five minutes.

Then talk about how to solve these problems

Sample Average Approximation: Algorithmics

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- Example: electricity market with random demand at 20 nodes that can independently be "low" or "high" That's $2^{20} = 1048576$ copies of $\boldsymbol{y}$, which is intractable for a real market
- Still, you can sometimes do well by subsampling the scenarios (Shapiro and Homem-de-Mello, 1998)

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What optimizers usually do: use a decomposition scheme called Benders decomposition (sometimes called the “L-shaped” method)

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Consider

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Let $\theta \ge \frac{1}{n} \sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i)$ be an epigraph variable

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\min_{\boldsymbol{x} \in \mathbb{R}^n, \theta} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \theta \\
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(Sketch) We iteratively

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until we converge.

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Remark: About to go through how this works in gory detail. However, I find the best way to understand this method is to code it for yourself.

Benders Decomposition

Suppose we solve

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and obtain some solution $\boldsymbol{x}$. Two cases:

- There is some scenario ω^i for which no $\boldsymbol{y}(\boldsymbol{\omega})$ can make the scenario feasible $\rightarrow$ we need to tell the master problem that this $\boldsymbol{x}$ is infeasible, via a *feasibility cut*

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- Every scenario ω^i is feasible $\rightarrow$ we need to tell the master problem how much $\boldsymbol{x}$ costs via an *optimality cut*

Benders Decomposition: Feasibility Cut

Suppose we solve

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and obtain some solution $\boldsymbol{x}$ such that in scenario i no $\boldsymbol{y}(\boldsymbol{\omega})$ can make the scenario feasible. Then, the dual problem in this scenario is unbounded (why?), so there is some $\boldsymbol{\mu}(\boldsymbol{\omega}^i)$ such that

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Therefore, we fix $\boldsymbol{\mu}(\boldsymbol{\omega}^i)$ and impose the feasibility cut

$$(\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i) \le 0,$$

in the master problem, where everything but $\boldsymbol{x}$ is data

In This Case, The Master Problem Now Looks Like

$$
\begin{aligned}
\min_{\boldsymbol{x}\in\mathbb{R}^n,\theta} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \theta \\
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θ usually underestimates $1/n \sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i)$

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By strong duality

$$\frac{1}{n}\sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i) = 1/n \sum_{i=1}^{n} (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i),$$

where $\boldsymbol{\mu}(\boldsymbol{\omega}^i)$, dual-optimal in scenario i, is data

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$$\frac{1}{n}\sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i) = 1/n \sum_{i=1}^{n} (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i),$$

where $\boldsymbol{\mu}(\boldsymbol{\omega}^i)$, dual-optimal in scenario i, is data

By weak duality, for any $\bar{\boldsymbol{x}}$

$$\frac{1}{n}\sum_{i=1}^{n} h(\bar{\boldsymbol{x}}, \boldsymbol{\omega}^i) \geq \frac{1}{n}\sum_{i=1}^{n} (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\bar{\boldsymbol{x}})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i),$$

where everything but $\bar{\boldsymbol{x}}$ is data

Case Two: Each Scenario Was Feasible

θ usually underestimates $1/n \sum_{i=1}^{n} h(\boldsymbol{x}, \boldsymbol{\omega}^i)$

Need cut involving θ, which tells master problem what $\boldsymbol{x}$ costs

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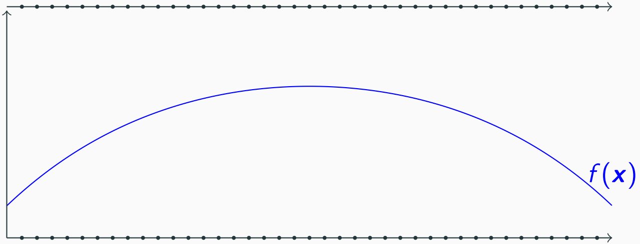
Therefore, we add cut

$$\theta \geq \frac{1}{n}\sum_{i=1}^{n} (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i)$$

The Master Problem Might Now Look Like

$$
\begin{aligned}
\min_{\boldsymbol{x}\in\mathbb{R}^n,\theta} \quad & \boldsymbol{c}^\top \boldsymbol{x} + \theta \\
\text{s.t.} \quad & \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b}, \\
& \theta \geq \frac{1}{n}\sum_{i=1}^{n} (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i), \\
& (\boldsymbol{d}(\boldsymbol{\omega}^i) - \boldsymbol{D}(\boldsymbol{\omega}^i)\boldsymbol{x})^\top \boldsymbol{\mu}(\boldsymbol{\omega}^i) \leq 0.
\end{aligned}
$$

Benders Decomposition, in 1000 words



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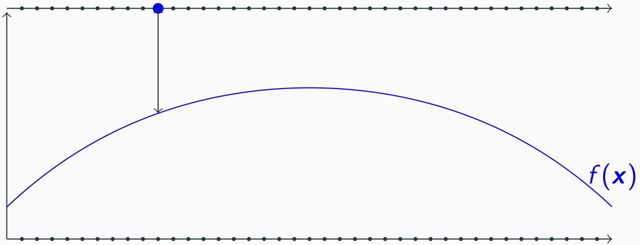

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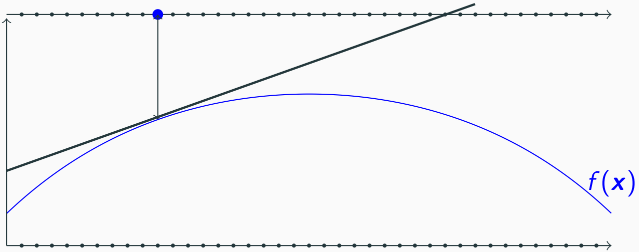

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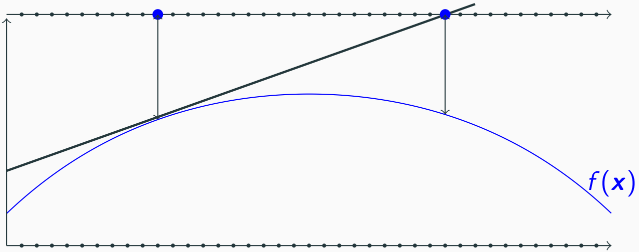

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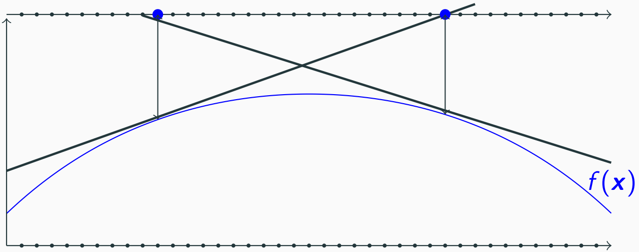

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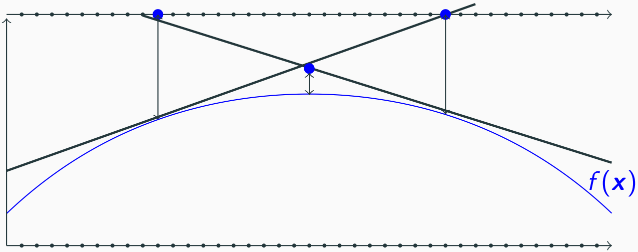

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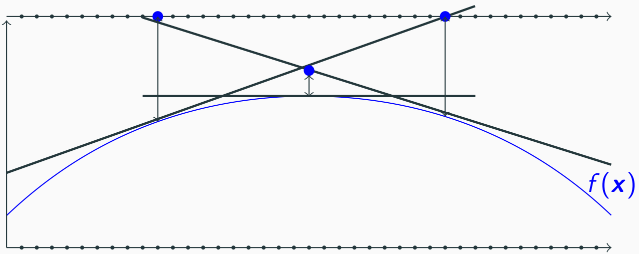

Sample Average Approximation: Code
You will write this yourself in the first assignment :-)

Can we do Better? Ridge Regression and Sample-Average Approximation

Can we do Better Than the Sample-Average Approximation?

Returning to Linear Regression

Statisticians don't solve problems like

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \quad \frac{1}{n} \|\boldsymbol{X}\boldsymbol{\beta} - \boldsymbol{y}\|_2^2$$

to pick $\boldsymbol{\beta}$, despite SAA's properties. Why not?

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where $R(\cdot)$ is a regularization term, e.g., $\frac{1}{2\gamma}\|\boldsymbol{\beta}\|_2^2 + \lambda\|\boldsymbol{\beta}\|_1$ for appropriately chosen λ, γ (elastic net method, Zou and Hastie 2005).

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This usually performs better out-of-sample.

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- For more on this, see: Bertsimas, Dimitris, Vishal Gupta, and Nathan Kallus. "Robust sample average approximation." Mathematical Programming 171.1 (2018): 217-282.

Extension: Benders Decomposition for Facility Location

See slides by Fischetti (2017)

Suggested Readings

Suggested Readings to Accompany Today's Lecture

A friendly reminder:

> *"To get as much out of this class as possible, we suggest that you spend at least as much time on reading the papers and textbooks referenced in the lectures/reviewing the lectures as you spend in class." — The syllabus*

Recommended reading:

- Shapiro, Dentcheva, Ruszczynski *Lectures on Stochastic Programming: Modeling and Theory* (2013), Chapters 1.1 and 2.

Optional further reading:

- Recht *Lecture* 1. In CS294 The Mathematics of Data Science lecture notes, UC Berkeley (2013).
- Kim, Pasupathy, Henderson *A Guide to Sample-Average Approximation*. In: Handbook of simulation optimization (2015).

Thank you, and see you next week!