6.7900: Machine Learning
Lecture 24

Lecture start: Tues/Thurs 2:35pm
Who's speaking today? Prof. Tamara Broderick
Course website: gradml.mit.edu
Questions? Ask here or on piazza.com/mit/fall2024/67900/
Materials: Slides, video, etc linked from gradml.mit.edu after the lecture (but there is no livestream)

Last Times

I. Lots of methods and algorithms for machine learning
II. Some insight into when they work and when they don't work

Today's Plan

I. What's left in this class
II. A broader perspective on using ML to make decisions
    A. Some (more) ways to do ML wrong

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- Subject evaluations are open!
  - We take your ideas and opinions very seriously, and they will shape the experience for next year's students.

When can I trust decisions from data?

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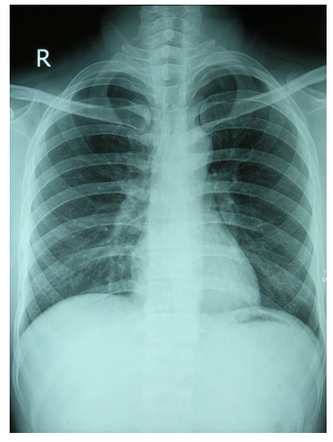
- More data & better computation ➔ data analyses increasingly drive life-changing decisions



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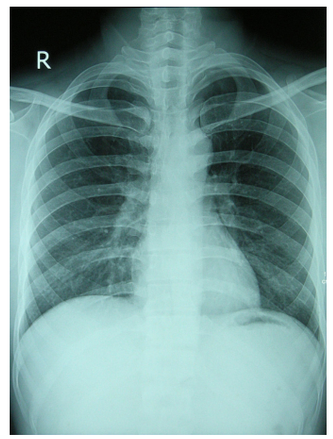

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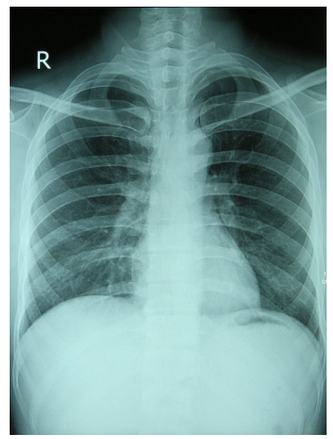

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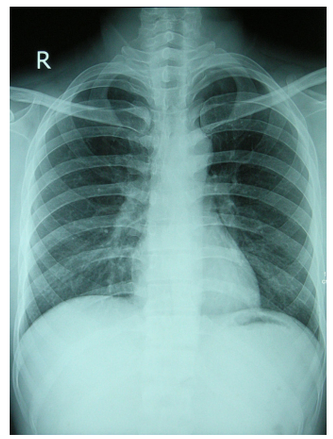

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[Open Science Collaboration, 2015]

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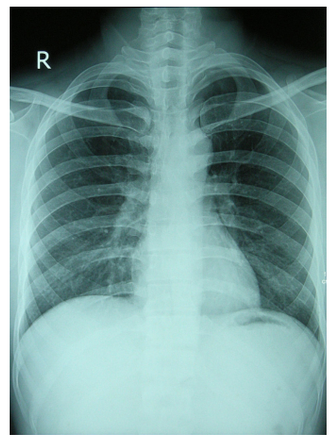

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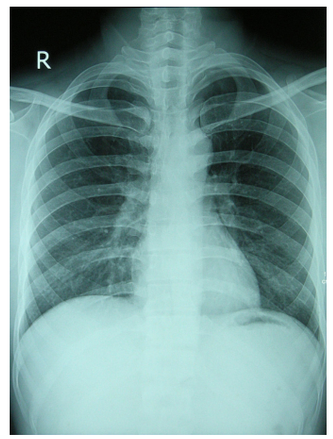

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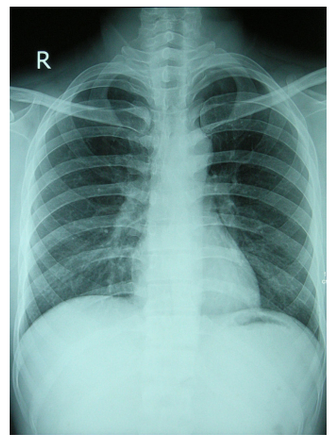

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- **Today**: how generalization could fail when everyone is well-meaning & mastered all their coursework

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  - 2006: Computer science graduate Mark Kelly wrote his own code to check, identified the bug, reported the bug

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- Bugs (e.g. off-by-one errors) in data analyses have led to unjustified treatment of patients in oncology clinical trials [Baggerly, Coombes 2009]
- British Post Office scandal [Flinders 2022; Computer Weekly 2009–2022]
  - Horizon: accounting software from Fujitsu
  - Bug sometimes showed two items as sold though only one was sold → left cash in till short
  - "Between 2000 and 2015, 736 subpostmasters were prosecuted by the Post Office, with many convicted and sent to prison" [Flinders 2022] "Linked to at least four suicides" [Sweney 2024]
  - 2006: Computer science graduate Mark Kelly wrote his own code to check, identified the bug, reported the bug
  - For a decade, Post Office said no errors
  - Finally changed story after High Court litigation in 2019

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  - Tools to support tracking models/packages/pipelines.

[Stodden et al 2014, 2016; Vartak et al 2016; Gebru et al 2021; Heil et al 2021; wandb.ai]

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  - When there's no code, other groups can't check the results/algorithm/method (and can't build on the work)

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- In real life, we start with high-level goals (E.g. "does microcredit help people?")
  - But we have to make a lot of subjective choices before we can formalize a mathematical problem as a proxy for the high-level goal (e.g. what to measure, what counts as helping, should we control for certain features and how)

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  - "All models are wrong," so expect p-value to get small with enough data (but that's not necessarily meaningful) [Box, 1976; Wang, Long 2022]

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- Demand (of yourself) to really understand <u>why</u> the results are the way they are. Don't settle for an absence of observed issues (and the resulting perverse incentives)

So what can we do?

- We've learned about some amazing, useful ML tools
- But we still have to decide which tools to use and how to use them responsibly
- Run unit tests. Run sense checks. Visualize.
- Meaningful results should be stable/robust

[Yu, 2013, 2020; Yu, Kumbier 2020]

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  - Recognize that classes (including this one) are a biased sample: questions are usually chosen for an achievable solution, and examples are chosen to be illustrative
- Gaps are opportunities for engineering solutions

6.7900: Machine Learning

Staff

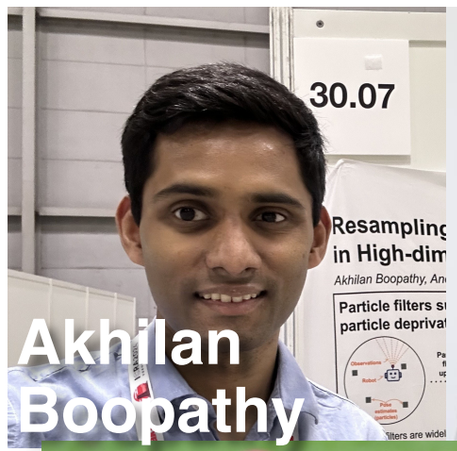
Instructors:

Leslie Kaelbling

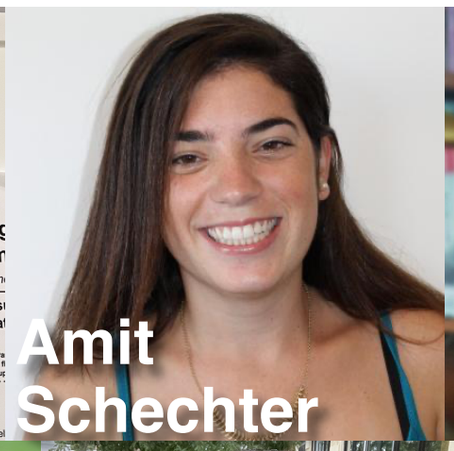
Tamara Broderick

Tommi Jaakkola

Teaching Assistants:

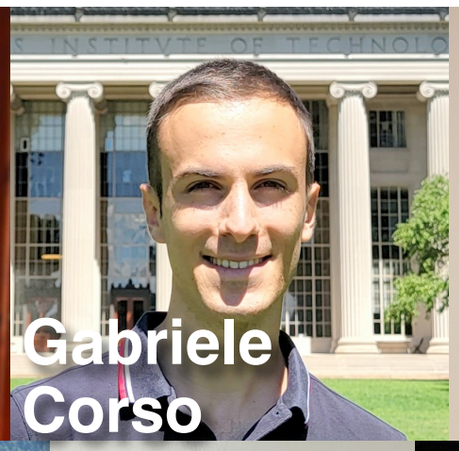


Akhilan Boopathy



Amit Schechter

Feng Zhu



Gabriele Corso

Greg Pylypovych

Jagdeep Bhatia

Morris Yao

Ray Wang

Timmy Qian

Tom Wang

6.7900: Machine Learning

Thank you!

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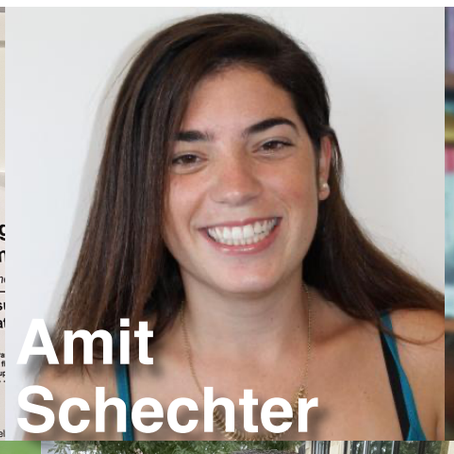

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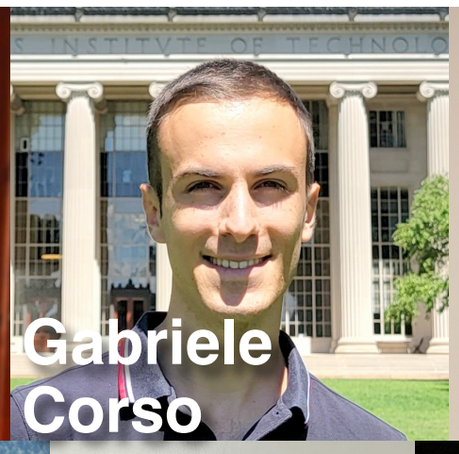

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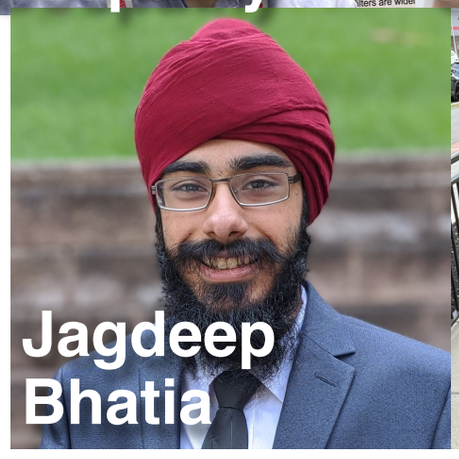
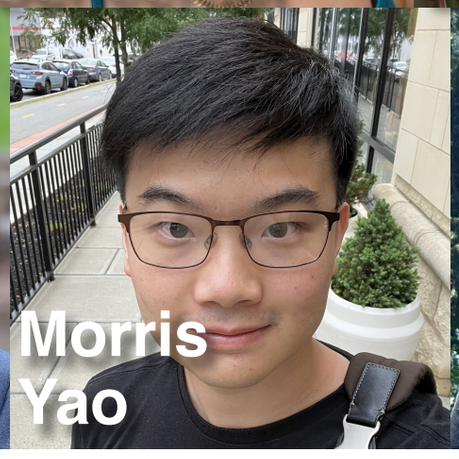


Jagdeep Bhatia



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