ORIE 4741: Learning with Big Messy Data

Introduction

Professor Udell
Operations Research and Information Engineering
Cornell

August 26, 2021
Outline

Logistics

Stories

Definitions

Kinds of learning

Syllabus
want to take this class?

▶ ASAP:
  ▶ enroll (or drop) (or get on wait list)
  ▶ fill out course survey
  ▶ sign up for discussion forum
  ▶ sign up for iClicker

▶ Thursday 9/2/2021: homework 0

links on course website:
https://people.orie.cornell.edu/mru8/orie4741/
Prof. Madeleine Udell
TA: Richard Phillips (CS PhD)
TA: Tao Jiang (ORIE PhD)
TA: Connor Lawless (ORIE PhD)
TA: Yuanping Du (ORIE MEng)
TA: Max de Ledebrur (ORIE MEng)
TA: Jody Zhu (ORIE+CS Undergraduate)
TA: Tara Khanna (ORIE Undergraduate)
TA: Kevin Jiang (CS Undergraduate)
Tech stack

- In person or Zoom for lectures, section, and office hours
- Course website for course materials (syllabus, schedule, homework, project, etc)
- iClicker for polls
- Zulip for Q&A
- Gradescope for quizzes, submitting homework, grades, solutions
- Github for code (demos, projects, and hw starter code)
Course requirements and grading

course website:
(grading, course requirements, lectures, homework, etc)
https://people.orie.cornell.edu/mru8/orie4741/

▶ (15%) Participation: for every lecture (after this one), use
  ▶ iClicker for sync lectures
  ▶ participation form for async lectures
▶ (30%) Homework
  ▶ due every two weeks or so
  ▶ first one due next Thursday
▶ (15%) Quizzes
  ▶ 30 min quiz every week or so
▶ (40%) Project
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FAQ:
▶ yes, you can take the class online (even async)
▶ yes, you can take section online (even async), or not take the section
ORIE 5741 vs 4741

- 5741 has same course material as 4741
- Expectations and rubric for course project differ
- More business-oriented project
- More detailed problem formulation
- Project presentation required (in addition to report)
- Rubric will reflect MEng learning outcomes:
  1. Mastery and Application of Core Disciplinary Knowledge
  2. Problem Formulation and Organization and Planning of the Solution Process
  3. Collaborative Problem Solving and Issue Resolution
  4. Communication of Knowledge, Ideas, and Decision Justification
  5. Self-Directed Learning and Professional Development
- Everyone in a project group with 5741 students will be graded according to 5741 rubric.
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Questions

during lecture:
  ▶ ask out loud
  ▶ zoom chat (to everyone, or to a TA)

outside of lecture:
  ▶ ask at office hours
  ▶ ask on discussion forum
  ▶ don’t send email
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Syllabus
Oh, you work with big messy data? Maybe you could help us out...?
My career in big data

academic

▸ B.S. in Mathematics and Physics at Yale
▸ Ph.D. in Computational and Mathematical Engineering at Stanford
▸ postdoctoral fellow at the Center for the Mathematics of Information at Caltech
▸ professor in ORIE at Cornell
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applied work

- finance: Goldman Sachs, BlackRock, Capital One, Schonfeld, Two Sigma, ...
- tech: Google, Retina.ai, Marketing Attribution
- cybersecurity: DARPA, Expanse (formerly Qadium)
- healthcare: Apixio, Ontario
- clean energy: Aurora
- politics: Obama 2012
## Data table: politics

<table>
<thead>
<tr>
<th>age</th>
<th>gender</th>
<th>state</th>
<th>income</th>
<th>education</th>
<th>voted?</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>F</td>
<td>CT</td>
<td>$53,000</td>
<td>college</td>
<td>yes</td>
<td>Biden</td>
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<tr>
<td>57</td>
<td>?</td>
<td>NY</td>
<td>$19,000</td>
<td>high school</td>
<td>yes</td>
<td>?</td>
</tr>
<tr>
<td>?</td>
<td>M</td>
<td>CA</td>
<td>$102,000</td>
<td>masters</td>
<td>no</td>
<td>Trump</td>
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<tr>
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<td>F</td>
<td>NV</td>
<td>$23,000</td>
<td>?</td>
<td>yes</td>
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</tr>
<tr>
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<td>NV</td>
<td>$23,000</td>
<td>?</td>
<td>yes</td>
<td>Trump</td>
</tr>
</tbody>
</table>

goals:

- detect demographic groups?
- find typical responses?
- identify related features?
- impute missing entries?
Medicine
### Data table: medicine

<table>
<thead>
<tr>
<th>age</th>
<th>gender</th>
<th>heart disease</th>
<th>statins?</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>F</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>57</td>
<td>?</td>
<td>no</td>
<td>no</td>
</tr>
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<td>no</td>
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<td>41</td>
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<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- ▶ find similar patients?
- ▶ understand systemic healthcare needs?
- ▶ use symptoms to detect which patients have COVID-19?
- ▶ detect patients who had series of mini-strokes?
Pollution

[Snow, 1854]
# Pollution

<table>
<thead>
<tr>
<th>location</th>
<th>time</th>
<th>CO2</th>
<th>O2</th>
<th>O3</th>
<th>⋯</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>.7</td>
<td>.9</td>
<td>?</td>
<td>⋯</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>.5</td>
<td>.7</td>
<td>?</td>
<td>⋯</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>.4</td>
<td>.5</td>
<td>1.4</td>
<td>⋯</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>⋯</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>⋯</td>
</tr>
</tbody>
</table>
Marketing
## Marketing

<table>
<thead>
<tr>
<th>customer</th>
<th>product 1</th>
<th>product 2</th>
<th>product 3</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>yes</td>
<td>?</td>
<td>yes</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>yes</td>
<td>yes</td>
<td>?</td>
<td>...</td>
</tr>
<tr>
<td>3</td>
<td>?</td>
<td>?</td>
<td>yes</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Finance

GameStop Corp. $206.59 +$201.61 ↑4,048.39%

AMC Entertainment... $45.71 +$40.17 ↑725.09%
## Finance

<table>
<thead>
<tr>
<th>ticker</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>( \ldots )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAPL</td>
<td>0.05</td>
<td>-0.21</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>GOOG</td>
<td>-0.11</td>
<td>0.24</td>
<td>( \ldots )</td>
</tr>
<tr>
<td>FB</td>
<td>0.07</td>
<td>-0.18</td>
<td>( \ldots )</td>
</tr>
</tbody>
</table>

\[ \vdots \]
Environmental, social and governance (ESG) data

- one row for each asset at each time
- one column per key performance indicator (KPI)
  - carbon emissions
  - e-waste management
  - climate change risk
  - worker safety
  - ...
- values: numerical ratings 1, ..., 10 or boolean \{0, 1\}
- triangular missing pattern: KPI/asset coverage increases with time

Goals for ESG analysis:

- impute missing items?
- audit/improve on vendor data quality?
- predict long term returns?
Fraud detection

KPIs
- Average Loss Recovered: 18.4 MWh
- Average MWh: 120
- Lost MWh: 120 Last 12 Months
- Loss Recovered: 24 GWh
- Loss vs Plan: 2.1% Last 12 Months
- Hill Rate: 95% Last 12 Months
- Revs Conducted: 1,403 Last 12 Months
- Revenue Recovered: $1.92 Million Last 12 Months

Total Opportunity by Theft Mode
- Anomalous Activity: 32%
- Large Consumption Drop: 22%
- Tampering: 17%
- Unexplained Outage: 12%
- Unreachable Customer: 9%
- Other: 8%

$200 Million

Geospatial Analysis

Watch List Feed

My Highest Priority AI Cases

Risk Drivers

High-Risk AI Suggestions

J. Franklin paid bill Nov 1, 2020 9:00am EST

Danielle Young commented on your Case KW-4 Sept 21, 2019 11:06 EST

“After looking through several of the AI risk drivers, I have concluded...”
Autocomplete

Your AI pair programmer

With GitHub Copilot, get suggestions for whole lines or entire functions right inside your editor.

Sign up >

```javascript
#!/usr/bin/env ts-node

import { fetch } from "fetch-h2";

// Determine whether the sentiment of text is positive
// Use a web service
async function isPositive(text: string): Promise<boolean> {
  const response = await fetch('http://text-processing.com/api/sentiment/', {
    method: "POST",
    body: `text=${text}`,
    headers: {
      "Content-Type": "application/x-www-form-urlencoded",
    },
  });
  const json = await response.json();
  return json.label === "pos";
}
Application areas

- health
- politics
- governance
- advertising
- retail
- ecommerce
- finance
- ...

...
Outline

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Kinds of learning

Syllabus
Big

- NASA, 1997: “taxing the capacities of main memory, local disk, and even remote disk”

¹Image courtesy of Kim Minor © IBM
Big

- NASA, 1997: “taxing the capacities of main memory, local disk, and even remote disk”
- OED, 2015: “data of a very large size, typically to the extent that its manipulation and management present significant logistical challenges”

\[\text{image courtesy of Kim Minor @ IBM}\]
Big

- NASA, 1997: “taxing the capacities of main memory, local disk, and even remote disk”
- OED, 2015: “data of a very large size, typically to the extent that its manipulation and management present significant logistical challenges”
- 4 Vs:

<table>
<thead>
<tr>
<th>Volume</th>
<th>Velocity</th>
<th>Variety</th>
<th>Veracity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data at rest</td>
<td>Data in motion</td>
<td>Data in many forms</td>
<td>Data in doubt</td>
</tr>
<tr>
<td>Terabytes to exabytes of existing data to process</td>
<td>Streaming data, milliseconds to seconds to respond</td>
<td>Structured, unstructured, text and multimedia</td>
<td>Uncertainty due to data inconsistency and incompleteness, ambiguities, latency, deception and model approximations</td>
</tr>
</tbody>
</table>

1 image courtesy of Kim Minor @ IBM
Big

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- 5th V: value

1 image courtesy of Kim Minor @ IBM
An algorithm for big data is one with computational and memory requirements that scale linearly (or nearly linearly) in the size of the data.
Definition

An algorithm for **big data** is one with computational and memory requirements that scale **linearly** (or nearly linearly) in the size of the data.

why this definition? independent of

- hardware
- business
**Big: our definition**

**Definition**

An algorithm for **big data** is one with computational and memory requirements that scale **linearly** (or nearly linearly) in the size of the data.

why this definition? independent of

- hardware
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if you use only algorithms for **big data**, then you’re working with **big data**
Messy

- noisy: some (or all) values suffer errors, inaccuracies, or malicious corruption
Messy

- noisy: some (or all) values suffer errors, inaccuracies, or malicious corruption
- missing: some values are missing, inconsistent, not recorded, or lost
Messy

- noisy: some (or all) values suffer errors, inaccuracies, or malicious corruption
- missing: some values are missing, inconsistent, not recorded, or lost
- heterogeneous: values of many different types
  - continuous values (e.g., 4.2, \(\pi\))
  - discrete values (e.g., 0, 4, 994)
  - nominal values (e.g., apple, banana, pear)
  - ordinal values (e.g., rarely, sometimes, often)
  - graphs or networks (e.g., person 1 is friends with person 2)
  - text (e.g., doctor’s note describing symptoms)
  - sets (e.g., items purchased)
Learning

▶ machine learning?
▶ human learning?
▶ when data is big and messy, machine help is essential for human learning!
Learning

- machine learning?
Learning

- machine learning?
- human learning?
Learning

- machine learning?
- human learning?
- when data is **big** and **messy**, machine help is essential for human learning!
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Syllabus
Data table

$n$ examples (patients, respondents, households, assets)
$d$ features (tests, questions, sensors, times)

\[
A = \begin{bmatrix}
a_{11} & \cdots & a_{1d} \\
\vdots & \ddots & \vdots \\
a_{n1} & \cdots & a_{nd}
\end{bmatrix}
\]

- $a_i$ is $i$th row of $A$: feature vector for $i$th example
- $a_{\cdot j}$ is $j$th column of $A$: values for $j$th feature across all examples
- $a_{ij}$ is $j$th feature of $i$th example
Supervised learning

- Identify one column of data that we want to predict

\[
A = \begin{bmatrix}
x_{11} & \cdots & x_{1,d-1} & y_1 \\
\vdots & \ddots & \vdots & \vdots \\
x_{n1} & \cdots & x_{n,d-1} & y_n
\end{bmatrix} = \begin{bmatrix} X & y \end{bmatrix}
\]

- \( x_i \in \mathcal{X} \) for \( i = 1, \ldots, n \) are rows of \( X \)
- \( y_i \in \mathcal{Y} \) for \( i = 1, \ldots, n \) are entries of \( y \)
Supervised learning

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  \[
  \begin{bmatrix}
  A \\
  \end{bmatrix}
  =
  \begin{bmatrix}
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- \(y_i \in \mathcal{Y}\) for \(i = 1, \ldots, n\) are entries of \(y\)
- We believe there is a mapping \(f : \mathcal{X} \to \mathcal{Y}\)
  
  \[y_i \approx f(x_i)\]

- Our goal is to learn \(f\)
Example: supervised learning for credit decisioning

- goal: decide which credit card applicants should be approved
- input space: entries of $\mathcal{X} \in \mathbb{R}^d$ correspond to fields in credit application
  - e.g., salary, years in residence, outstanding debt, number of credit lines, ...
- output space: $\mathcal{Y} = \{+1, -1\}$
  - $+1$ means approve
  - $-1$ means reject
- data: $\mathcal{D} = (x_1, y_1), \ldots, (x_n, y_n)$ applications of previous customers, and credit approval decisions made by humans

Q: what are potential problems with using a model built with this data?
A: wrong objective: human decision may not be correct decision; covariate shift: future data may look unlike past data; ...
Example: supervised learning for credit decisioning

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Q: what are potential problems with using a model built with this data?
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Exercise: formalizing real problems

- identify a prediction goal
- identify the input space \( X \)
- identify the output space \( Y \)
- identify the data \( D = (x_1, y_1), \ldots, (x_n, y_n) \) you’d like to use
- what kinds of noise do you expect in the data?
Outline

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Syllabus
Course objectives (I)

- plot
- predict
- cluster
- impute
- denoise
- recommend
- understand
Course objectives (II)

this course is about

▶ algorithms for big messy data
▶ learning to ask the right questions

at the end of the course, you should have learned

▶ at least one method to solve any problem
▶ machine learning is not magic; it’s math
▶ when not to trust your solution
Course objectives (II)

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the rest you can learn online. . .
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