ORIE 4741: Learning with Big Messy Data

Introduction

Professor Udell
Operations Research and Information Engineering
Cornell

October 16, 2021
Outline

Logistics

Stories

Definitions

Kinds of learning

Syllabus
ORIE 4741/5741: Learning with Big Messy Data

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/
Course staff

- 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 Ledebur (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
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

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.
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.
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
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.
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
Outline

Logistics

Stories

Definitions

Kinds of learning

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

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
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

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>
</tr>
<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>
</tr>
<tr>
<td>41</td>
<td>F</td>
<td>NV</td>
<td>$23,000</td>
<td>?</td>
<td>yes</td>
<td>Trump</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## 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>
</tr>
<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>
</tr>
<tr>
<td>41</td>
<td>F</td>
<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?
<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>
<tr>
<td>?</td>
<td>M</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>41</td>
<td>F</td>
<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

<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
<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 $40.17 ↑725.09% ×
<table>
<thead>
<tr>
<th>ticker</th>
<th>$t_1$</th>
<th>$t_2$</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAPL</td>
<td>.05</td>
<td>-.21</td>
<td>...</td>
</tr>
<tr>
<td>GOOG</td>
<td>-.11</td>
<td>.24</td>
<td>...</td>
</tr>
<tr>
<td>FB</td>
<td>.07</td>
<td>-.18</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
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

C3 AI Fraud Detection

KPIs
- Avg. Loss Recovered: 19.4 MWh
- Verified Opportunities: 1,305
- Loss Recovered: 24 GWh
- HILL Rate: 93%
- Reviews Conducted: 1,403
- Revenue Recovered: $1.92 Million

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

My Highest Priority AI Cases

<table>
<thead>
<tr>
<th>ID</th>
<th>Status</th>
<th>Customer</th>
<th>Risk Score</th>
<th>Consumption</th>
<th>Days Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>KW-4</td>
<td>Pending</td>
<td>K. Wilson</td>
<td>92</td>
<td>High</td>
<td>19</td>
</tr>
<tr>
<td>MD-2</td>
<td>Pending</td>
<td>M. Davis</td>
<td>96</td>
<td>High</td>
<td>9</td>
</tr>
<tr>
<td>RP-4</td>
<td>Unactioned</td>
<td>R. Patterson</td>
<td>91</td>
<td>High</td>
<td>2</td>
</tr>
<tr>
<td>GB-3</td>
<td>Unactioned</td>
<td>G. Brad</td>
<td>88</td>
<td>High</td>
<td>7</td>
</tr>
</tbody>
</table>

Watch List Feed

Report
- J. Franklin paid bill
  Nov 1, 2020 9:00am EST
- Danielle Young commented on your Case KW-4
  Sept 23, 2019 1:00pm EST

Risk Score
- 92
  High  
  8
  Last 30 Days

Risk Drivers
- Suspicious
- Not Suspicious

Consumption
- Account # 003783313
- Type Residential
- Years Active 4.7

Overview
- Customer Profile
- Comments

About
- Sarah Johnson
- Team Lead
- Danielle Young
- Status Pending
- Days Open 19

Global
- All Alerts
- X

High Risk
- K. Wilson
- 92
- Identified by C3 AI as a High Risk customer
- Mar 23, 2021 9:00AM EST
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

Logistics

Stories

Definitions

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”

\[^1\text{image courtesy of Kim Minor @ IBM}\]
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:

- **Volume**: Data at rest
  - Terabytes to exabytes of existing data to process

- **Velocity**: Data in motion
  - Streaming data, milliseconds to seconds to respond

- **Variety**: Data in many forms
  - Structured, unstructured, text and multimedia

- **Veracity**: Data in doubt
  - Uncertainty due to data inconsistency and incompleteness, ambiguities, latency, deception and model approximations

---

1 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>

• 5th V: value

1^image courtesy of Kim Minor @ IBM
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.
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
- 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
- business

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

When data is big and messy, machine help is essential for human learning!
Learning

- machine learning?

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

- machine learning?
- human learning?
Learning

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

$n$ examples (patients, respondents, households, assets)

$d$ features (tests, questions, sensors, times)

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

- $a_i$ is $i$th row of $A$: feature vector for $i$th example
- $a_{ij}$ 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

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

- \( x_i \in \mathcal{X} \) 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

- Identify one column of data that we want to predict

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

- \(x_i \in \mathcal{X}\) for \(i = 1, \ldots, n\) are rows of \(X\)

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

- We believe there is a mapping \(f : \mathcal{X} \rightarrow \mathcal{Y}\)

\[
y_i \approx f(x_i)
\]

- 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

▷ 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?
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; …
Exercise: formalizing real problems

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

Logistics

Stories

Definitions

Kinds of learning

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)

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

the rest you can learn online. . .
ORIE 4741: Learning with Big Messy Data

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/