Lecture 1: Course Introduction
Welcome

- This is the 3rd offering of BIODS 220 Artificial Intelligence in Healthcare (CS 271, BIOMEDIN 220)

- What we hope you will get out of this course:
  1. Broad knowledge of opportunities for AI in healthcare
  2. Fluency in cutting edge deep learning algorithms, and practical ability to develop models for diverse types of healthcare data
  3. Understanding of real-world considerations and challenges for deploying AI algorithms in healthcare
Today’s agenda

- A brief overview of AI in healthcare
- Course logistics
AI in healthcare: a rapidly exploding field

Google, Verily using AI to screen for diabetic retinopathy in India

The machine learning algorithm can also help with screening for diabetic macular edema, a boon for patients in a country where physicians are in short supply.

By Mike Miilard | February 26, 2019 | 03:17 PM

Hospitals Roll Out AI Systems to Keep Patients From Dying of Sepsis

Septic shock kills 50 percent of people who are affected—Sepsis Watch could save their lives

By Eliza Strickland

In hospitals, doctors and nurses keep vigilant watch over patients'

Serena Yeung

BIODS 220: AI in Healthcare

Lecture 1 - 4
AI in healthcare: a rapidly exploding field

Apple's future healthcare market moves will rely heavily on AI analysis

By Malcolm Owen
Monday, September 16, 2019, 09:03 am PT (12:03 pm ET)

Apple's moves in the healthcare market could involve the tracking of user data for further analysis by artificial intelligence and billing model based on cost-savings, with analysts pointing out areas of the consumer health industry Apple could easily advance by building upon its already-released technology and services.

Google to Store and Analyze Millions of Health Records

The tech company's deal with Ascension is part of a push to use artificial intelligence to aid health services.

Amazon Makes Healthcare Buy As Its Plans Start to Take Shape

The e-commerce giant just bought a telemedicine technology startup to help with its healthcare-related efforts.

In what is its first healthcare-related acquisition since spending $753 million in June 2018 to acquire PillPack, Amazon.com (NASDAQ:AMZN) inked a deal to buy Health Navigator, a start-up that provides digital triage tools and symptom lookup. The value of the deal was not disclosed.

Amazon intends to offer Health Navigator services to its employees, shedding further light on where the e-commerce giant is heading in the healthcare market.

Microsoft Healthcare is a new effort to push doctors to the cloud

Microsoft wants to be a big part of the cloud and AI healthcare race

By Tom Warren | @tomwarren | Jun 27, 2018, 6:59am EDT
AI in healthcare: a rapidly exploding field
A journey back in time… brief history of modern AI

1956: Birth of AI as a modern research discipline

John McCarthy
Early progress in the late 50s and 60s

Perceptron model: Rosenblatt, 1958

ELIZA chatbot: Weizenbaum, 1966
Progress and excitement in the late 50s and 60s

Capabilities of early projects soon reached limitations they could not surpass. Enthusiasm for AI dwindled in the 70s.

Perceptron model: Rosenblatt, 1958

ELIZA chatbot: Weizenbaum, 1966

Welcome to

Eliza is a mock Rogerian psychotherapist. Designed by Joseph Weizenbaum in 1966. Developed further by Christian Stein and Peter Steiner 2005.

Eliza: Can you think of a specific example?
YOU: Well, my boyfriend made me come here.

Eliza: Is it important to you that your boyfriend made you come here?
YOU: Well, he says I'm depressed much of the time.

Eliza: I am sorry to hear that you are depressed.
YOU: It's true. I am unhappy.

Eliza: Can you explain what made you unhappy?
YOU: 
Resurgence in the 80s

Expert systems, 1970s and 80s. Feigenbaum, etc.

First appearances of modern neural networks

LeCun, 1990s.

First appearances of modern neural networks

But limitations reached again… -> AI winter of the 1990s and 2000s

eCun, 1990s.

2012: Deep learning breakthrough

Krizhevsky et al. 2012. 8-layer “AlexNet”.

ImageNet Visual Recognition Challenge results.
Convergence of key ingredients of deep learning

**Algorithms**

- **Compute**
  - Data

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2015: Very deep convnets and challenging vision tasks

He et al. 2015. ResNet.
2018: Breakthroughs in deep learning for natural language processing (sequences)

Transformer architectures and pre-training -> fine-tuning. State-of-the-art on 11 NLP benchmarks.

Devlin et al. 2018. BERT.
2020: Very large scale text and image generation models

OpenAI models for text generation (left), text-to-image generation (right-top), and zero-shot classification tasks (right-bottom)

**SYSTEM PROMPT (HUMAN-WRITTEN)**

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

**MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)**

The scientist named the population, after their distinctive horn, Ovid’s Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

GPT-3 (figure from GPT-2). Brown et al. 2020.

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the exact same cat on the top as a sketch on the bottom


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healthy lymph node tissue (22.8%) Ranked 2 out of 2

* this is a photo of lymph node tumor tissue

✓ this is a photo of healthy lymph node tissue

Deep learning for healthcare: the rise of medical data
Deep learning for healthcare: the rise of medical data

Question: When was x-ray invented?
Deep learning for healthcare: the rise of medical data

X-rays (invented 1895).
Deep learning for healthcare: the rise of medical data

X-rays (invented 1895).

Question: When was CT invented?
Deep learning for healthcare: the rise of medical data

X-rays (invented 1895).

CT (invented 1972).
Deep learning for healthcare: the rise of medical data

X-rays (invented 1895).

CT (invented 1972).

Question: When was MRI invented?
Deep learning for healthcare: the rise of medical data

X-rays (invented 1895).

CT (invented 1972).

MRI (invented 1977).
Deep learning for healthcare: the rise of medical data

Q: What are other examples of medical data?
Electronic health records -- making patient data available

1960s: invention
1980s: increased effort
2009: 51% adoption, HITECH Act
2017: 98% adoption

Clinical notes

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<thead>
<tr>
<th>Test</th>
<th>Value</th>
<th>Reference</th>
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<tr>
<td>Hemoglobin</td>
<td>8.0</td>
<td>8.5–11.0 mmol/L</td>
</tr>
<tr>
<td>C-reactive protein</td>
<td>279</td>
<td>&lt;5.0 mg/L</td>
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<tr>
<td>Red blood cell count</td>
<td>3.86</td>
<td>4.3–6.0 x 10^12/L</td>
</tr>
<tr>
<td>White blood cell count</td>
<td>27.1</td>
<td>4.0–10.0 x 10^9/L</td>
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<tr>
<td>Thrombocytes</td>
<td>462</td>
<td>150–400 x 10^9/L</td>
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<tr>
<td>Glucose</td>
<td>12.9</td>
<td>4.0–7.8 mmol/L</td>
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<tr>
<td>Sodium</td>
<td>127</td>
<td>135–145 mmol/L</td>
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<tr>
<td>Potassium</td>
<td>4.2</td>
<td>3.5–5.0 mmol/L</td>
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<tr>
<td>Creatinine</td>
<td>40</td>
<td>50–110 μmol/L</td>
</tr>
<tr>
<td>Estimated glomerular filtration rate</td>
<td>&gt;90</td>
<td>&gt;60 mL/min</td>
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<tr>
<td>Urea</td>
<td>3.2</td>
<td>2.5–7.3 mmol/L</td>
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<tr>
<td>Lactate dehydrogenase</td>
<td>106</td>
<td>&lt;2500 U/L</td>
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<tr>
<td>Aspartate aminotransferase</td>
<td>14</td>
<td>&lt;400 U/L</td>
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<tr>
<td>Alanine aminotransferase</td>
<td>13</td>
<td>&lt;50 U/L</td>
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<tr>
<td>Alkaline phosphatase</td>
<td>127</td>
<td>&lt;120 U/L</td>
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<tr>
<td>Gamma-glutamyl transferase</td>
<td>96</td>
<td>&lt;50 U/L</td>
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Genomics data

1953 - Watson and Crick discover double helix structures of DNA

1977 - Fred Sanger sequences first full genome of a virus

1990 - 2003: Human Genome Project sequences full human genome

2003: ENCODE project launched to identify and characterize genes in human genome

1000 Genomes Project: 2008 - 2015

UK100,000 Genomes Project: 2012 - 2018
Wearables and other sensor data

First iPhone: 2007

Fitbit: 2009

Apple Watch: 2014
AI in healthcare: biomedical image interpretation

Wu et al. 2019

Liu et al. 2017
AI in healthcare: clinical event prediction

Harutyunyan et al. 2019
AI in healthcare: genomic analysis

Zhou et al. 2015

Poplin et al. 2016
AI in healthcare: drug discovery and drug interaction prediction

Step 1 - Unsupervised Pocket Graph Autoencoder
- Latent Pocket Space
  - Unsupervised PROTEIN POCKET REPRESENTATION
    - DEEP GRAPH AUTOENCODER
    - Protein pocket graph
  - Pocket Graph-CNN Weight Initialization

Step II - Supervised Graph Convolutional Binding Classifier
- BINDING CLASSIFIER
  - PROTEIN POCKET REPRESENTATION
    - DEEP GRAPH CONVOLUTION
    - Protein pocket graph
  - SMALL MOLECULE REPRESENTATION
    - DEEP GRAPH CONVOLUTION
    - 2D molecular graph

Ryu et al. 2018

Torng et al. 2019
AI in healthcare: intelligent healthcare spaces and environments

Yeung et al. 2019

robinhealthcare.com
AI in healthcare: mobile health and wearables

5. Rate the child’s social initiations.
   - Excellent
   - Good
   - Satisfactory
   - Poor
   - N/A

Features run through each classifier:
- ADtreeB
- ADTree7
- SVM5
- LRS
- LR9
- SVM12
- SVM10
- LR10

Features extracted

Raters score video

ASD Sensitivity Specificity
- ADtreeB 100% 22.4%
- ADTree7 94.5% 37.3%
- SVM5 100% 54.9%
- LRS 84.5% 77.4%
- LR9 100% 31.4%
- SVM12 100% 9%
- SVM10 100% 17.4%
- LR10 100% 51.0%

Menictas et al. 2019
Tariq et al. 2018

Phones/wearables
- Phones/wearables are available 24/7
- In the USA, 81% of people own a smartphone and 12% of people own a wearable device
- Low cost of healthcare delivery

Traditional care
- Episodic visits. Each visit lasts 15 minutes on average
- In the USA, <1 doctor for every 330 people, <1 psychiatrist for every 10,000 people
- High cost of healthcare delivery

Serena Yeung
BIODS 220: AI in Healthcare
Lecture 1 - 34
Q: What are ways in which AI can be used to help tackle the COVID-19 crisis?
AI in healthcare: recent applications for COVID-19

Yan et al. 2020

Harmon et al. 2020

Jumper et al. 2020
The promise is great…
but many open challenges
in deployment as well
Uncertainty and AI / human collaboration

WHAT IS THE PROBABILITY THAT THE PATIENT HAS PNEUMONIA?

20-40%

40-60%

60-80%

80-100%

IMAGE 23B:

Rosenberg et al. 2018
Bias and fairness

Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer1,2, Brian Powers3, Christine Vogel3, Sendhil Mullainathan3,4

Health systems rely on commercial prediction algorithms to identify and help patients with complex health needs. We show that a widely used algorithm, typical of this industry-wide approach and affecting millions of patients, exhibits significant racial bias: At a given risk score, Black patients are considerably sicker than White patients, as evidenced by signs of uncontrolled illnese. Remedying this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%. The bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients than for White patients. Thus, despite health care cost appearing to be an effective proxy for health by some measures of predictive accuracy, large racial biases arise. We suggest that the choice of convenient, seemingly effective proxies for ground truth can be an important source of algorithmic bias in many contexts.

There is growing concern that algorithms may reproduce racial and gender disparities via the people building them or through the data used to train them (7–13). Empirical work is increasingly lending support to these concerns. For example, job search ads for highly paid positions are less likely to trigger ads for arrest records (5), and image searches for professions such as CEO produce fewer images of women (6). Facial recognition systems increasingly used in law enforcement perform worse on recognizing faces of women and Black individuals (7, 8), and natural language processing algorithms encode language in gendered ways (9).

researcher-created algorithms (10–12). Without an algorithm’s training data, objective function, and prediction methodology, we can only guess as to the actual mechanisms for the important algorithmic disparities that arise. In this study, we exploit a rich dataset that provides insight into a live, sealed algorithm deployed nationwide today. It is one of the largest and most typical examples of a class of commercial risk-prediction tools that, by industry estimates, are applied to roughly 200 million people in the United States each year. Large health systems and payers rely on this algorithm to target patients for “high-risk care management” programs. These programs seek to improve the care of patients with complex health needs by providing additional that rely on past data to build a predictor of future health care needs. Our dataset describes one such typical algorithm. It contains both the algorithm’s predictions as well as the data needed to understand its inner workings: that is, the underlying ingredients used to form the algorithm (data, objective function, etc.) and links to a rich set of outcome data. Because we have the inputs, outputs, and eventual outcomes, our data allow us a rare opportunity to quantify racial disparities in algorithms and isolate the mechanisms by which they arise. It should be emphasized that this algorithm is not unique. Rather, it is emblematic of a generalized approach to risk prediction in the health sector, widely adopted by a range of for- and non-profit medical centers and governmental agencies (21).

Our analysis has implications beyond what we learn about this particular algorithm. First, the specific problem solved by this algorithm has analogies in many other sectors: The predicted risk of some future outcome (in our case, health care needs) is widely used to target policy interventions under the assumption that the treatment effect is monotonic in that risk, and the methods used to build the algorithm are standard. Mechanisms of bias uncovered in this study likely operate elsewhere. Second, even beyond our particular finding, we hope that this exercise illustrates the importance, and the large opportunity, of studying algorithmic bias in health care, not just as a model system but also in its own right. By any standard—e.g., number of lives affected, life-and-death consequences of the decision—health is one of the most important and widespread social sectors in which algorithms are already used at scale today, unbeknownst to many.
Privacy and security

Price et al. 2019

Figure: https://news.developer.nvidia.com/first-privacy-preserving-federated-learning-system/
In this class

1st part: developing DL algos for health data

2nd part: deploying AI for health
Speed Breakouts

Get to know your classmates

2x 4-minute breakouts (4 students each)

- Name, program, year
- What’s one thing you hope to get out of this class?
- What kind of healthcare tasks or data are you most interested in?
Course Logistics

Lectures: MW 1:30-3:00pm, Alway M106

- Lectures will be recorded and posted afterwards on Canvas

A few review sessions (e.g., Tensorflow, Project Partner Finding): select Fridays 1:30-2:30pm, Alway M112

- First one will be a session for finding project partners, Fri 9/24
- Stay tuned for announcements of future Friday reviews

Course materials will be hosted on website: http://biods220.stanford.edu/
## Teaching team

<table>
<thead>
<tr>
<th>Instructor</th>
<th>Teaching Assistants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Serena Yeung</td>
<td>James Burgess</td>
</tr>
<tr>
<td><a href="mailto:syyeung@stanford.edu">syyeung@stanford.edu</a></td>
<td><a href="mailto:jmhb@stanford.edu">jmhb@stanford.edu</a></td>
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<tr>
<td>OH: Mon 9AM-11AM</td>
<td>OH: Mon 3PM-5PM</td>
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<td>Location: Packard 361</td>
<td>Location: Alway M214</td>
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<td>Sanket Gupte</td>
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<td></td>
<td><a href="mailto:sanketg@stanford.edu">sanketg@stanford.edu</a></td>
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<td>OH: Fri 10AM-12PM</td>
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<td>Location: CCSR 4107</td>
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Office hours will start week 2
Prerequisites

1. Proficiency in Python, or significant experience with a different programming language and ability to self-learn. Python will be used for homework assignments and the course project.

2. Basic familiarity with college calculus (e.g. Math 19 or 41, comfortable taking derivatives), linear algebra (e.g. Math 51 or EE 103 / CME 103, comfortable with common matrix vector operations and notation), and probability and statistics (e.g. CME 106 or CS 109, comfortable with common probability distributions, mean, standard deviation, etc).

3. Familiarity with machine learning, e.g. comfortable with the framework of machine learning and experience training a machine learning model.

4. Familiarity with deep learning is highly recommended, e.g. prior experience training a deep learning model.
Piazza

- Will be used for all course communications.
- Sign up using link on course website “logistics” tab
- If it is a personal matter (e.g., OAE), please make a private post to the teaching team or instructor.
- Note: we will not be using canvas in this course, with the exception of zoom lecture links. Communications will be through Piazza, and grading will be through gradescope.
Grading

- Sign up for Gradescope through the “logistics tab”
- Breakdown:
  - Assignment 1: 15%
  - Assignment 2: 15%
  - Assignment 3: 15%
  - Midterm (in person): 15%
  - Course project: 40%
Assignments

- Main objective to build conceptual and practical foundations in using deep learning for biomedical data
- A0 (Data access prerequisites): Out Tue 9/21, due Tue 9/28. No grade, but required by due date to gain data access required for later assignments.
- A1 (Medical images): Out Tue 9/28, due Tue 10/12.
- A2 (EHR and text data): Out Tue 10/12, due Tue 10/26.
- A3 (Genomics): Out Tue 10/26, due Tue 11/9.

- In this class, all deadlines refer to 11:59pm PST on the stated day.
- A limited amount of Google cloud credits will be provided for the assignments. Should be sufficient, but use wisely.
- Collaboration policy: please read on course website. Study groups are allowed, but each student must produce independent assignment and write names of group on assignment.
Project

- Opportunity to gain in-depth experience developing an AI-based approach to a healthcare problem.
- Worth 40% of grade. Can work in groups of 1-3. (Grades will be calibrated by group size)
- Since large part of course is focused on deep learning, must involve implementation and training of at least one deep learning model on health data. Otherwise, significant flexibility in technical component (compare DL vs. non-DL models, analyze DL model in depth, novel DL architectures, etc.).
- Can use any health-related data of your choice. Options include public datasets and challenges (e.g., start from a published paper!), ongoing projects at Stanford (if applicable), projects suggestions from Stanford Medical School, etc.
- Will release detailed project guidelines and suggestions, and discuss in lecture on Mon 9/27.
Project (cont.)

- Graded components:
  - Proposal: Due Fri 10/15.
  - Milestone: Due Fri 11/5.
  - TA project advising sessions: after the milestone, details TBD.
  - Final project poster session: In person, during the final exam period for this course (Thursday 12/9, 12:15-3:15pm)
  - Final report due: Fri 12/10.
Late days

- Can be used on A1, A2, A3, project proposal, project milestone report.
- Cannot be used on project final presentation, or final project report.
- 6 late days total, 2 max for any assignment.
- Grades will be deducted by 25% for each additional late day.
<table>
<thead>
<tr>
<th>Lecture</th>
<th>Date</th>
<th>Topic</th>
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<tr>
<td>Lecture 1</td>
<td>Sep 20 (Mon)</td>
<td>Course Introduction</td>
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<tr>
<td>Assignment</td>
<td>Sep 21 (Tue)</td>
<td>Assignment 0 Released</td>
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<td>Lecture 2</td>
<td>Sep 22 (Wed)</td>
<td>Deep Learning Fundamentals</td>
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<td>Section</td>
<td>Sep 24 (Fri)</td>
<td>Project Partner Finding Session</td>
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<td>Medical Images: Classification</td>
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<td>Medical Images: Advanced Vision Models (Detection and Segmentation)</td>
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<td>Section</td>
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<td>Numpy/TensorFlow Review Session</td>
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<td>Oct 4 (Mon)</td>
<td>Medical Images: Advanced Vision Models (3D and Video)</td>
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<td>Oct 6 (Wed)</td>
<td>Electronic Health Records: Introduction</td>
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<td>Electronic Health Records: Advanced Topics</td>
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<td>Lecture 8</td>
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<td>More on Text Data and Representations</td>
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<td>Oct 18 (Mon)</td>
<td>Genomics: Introduction</td>
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<td>Lecture 10</td>
<td>Oct 20 (Wed)</td>
<td>Genomics: Advanced Topics</td>
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<td>Guest Lecture</td>
<td>Oct 25 (Mon)</td>
<td>Strategies for Interdisciplinary Projects in AI and Healthcare: Speaker TBD</td>
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<td>Assignment 2 Due; Assignment 3 Released</td>
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<td>Lecture 11</td>
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<td>Multimodal Data, Multimodal Models, and Weakly Supervised Learning</td>
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<td>Midterm</td>
<td>Nov 1 (Mon)</td>
<td>Midterm Exam (in person during class hours)</td>
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<td>Lecture 12</td>
<td>Nov 3 (Wed)</td>
<td>Special Topics: AI for COVID-19</td>
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<td>Lecture 13</td>
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<td>Unsupervised Learning and Reinforcement Learning</td>
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<td>Lecture 14</td>
<td>Nov 10 (Wed)</td>
<td>Interpretability, Fairness, and Ethics</td>
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<td>Conclusion</td>
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<td>Dec 9 (Thu)</td>
<td>Poster Session (in person from 12:15PM to 3:15 PM)</td>
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<tr>
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Next time

- Review of deep learning fundamentals