

Topics in Machine Learning Machine Learning for Healthcare

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Slide credits: David Sontag, Clinical Machine Learning Lab, MIT



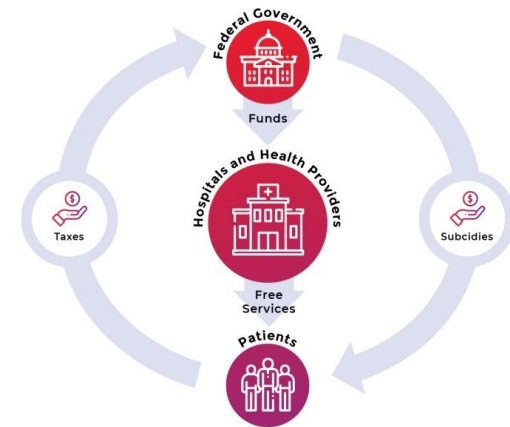
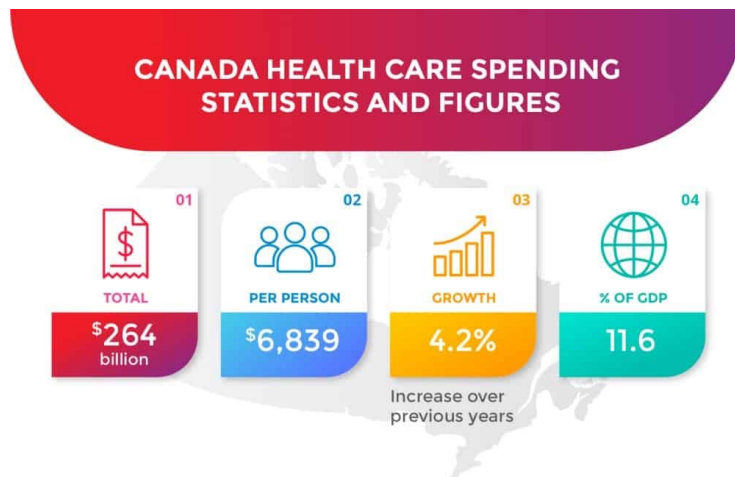
Outline

- Introduction to Machine Learning for Healthcare [MLHC]
 - Why should we care
 - Why do we have data
 - A brief history of MLHC
 - What does the future hold?
 - A word of caution
 - Key challenges in MLHC
- Logistics
 - Course staff
 - Course structure
 - Grading
 - Mandatory quiz
 - Lecture schedule

What is the problem with healthcare?

- Healthcare costs around the world are rising
 - People are living longer,
 - Chronic diseases are consuming clinician time,
- Canada:
 - [Canadian Institute for Health Information \(CIHI\)](#) publishes reports on healthcare costs
 - In 2019, Canada spent ~\$264 billion on healthcare
- United States:
 - >65yo: Medicare
 - <65yo: Private/ public health insurance/ Medicare
 - Health expenditures exceed \$3 trillion

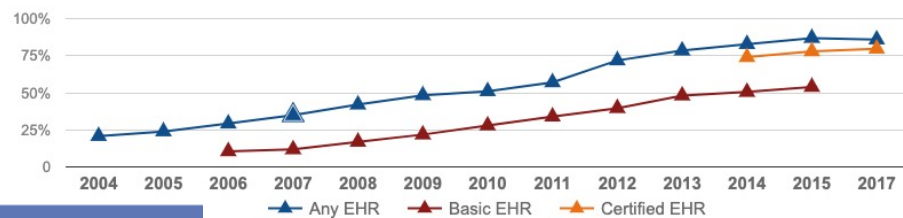
Why should we care about costs?



We're paying more on healthcare and its increasing!

The opportunity with electronic medical records

The adoption of electronic medical records has dramatically increased in the last two decades!



Electronic medical records give us a view into a patient's underlying physiological state.

Source: <https://www.healthit.gov/data/quickstats/office-based-physician-electronic-health-record-adoption>

Hospitals, registries and clinics have an abundance of data



Machine learning

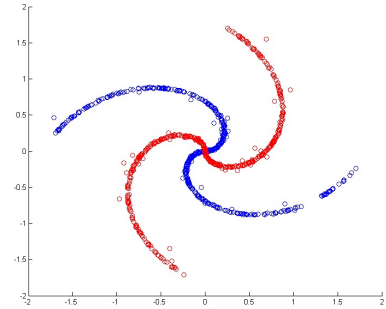
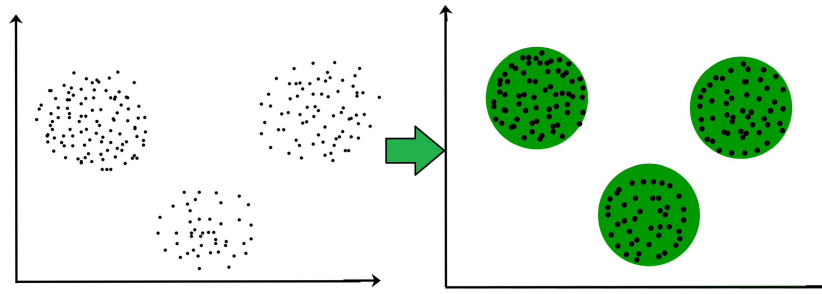
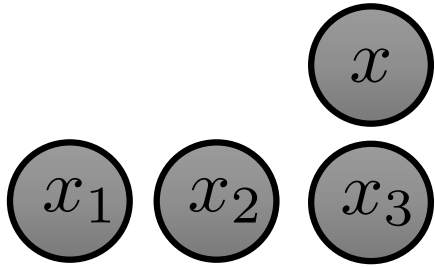
- **For the right tasks**, we could use the data to train machine learning algorithms.
- General recipe:
 - Identify a problem, which if automated, can reduce the cost of a process or help clinicians complete a task better/faster/with less error.
 - Program a model to automatically learn patterns from data
 - Use the model to automate task
- Different kinds of machine learning strategies we can make use of

Supervised learning



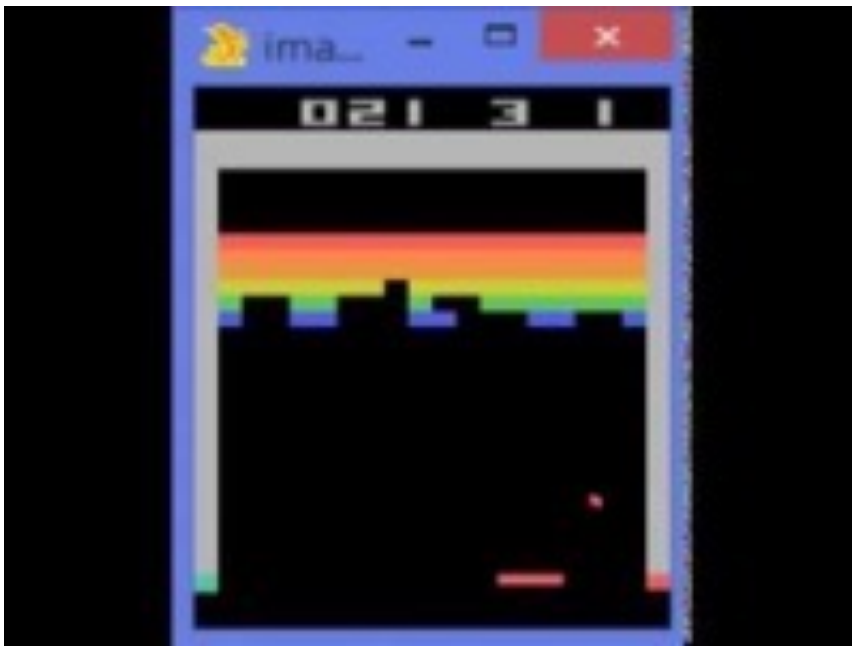
- Step 1: Collect a dataset or curate a subset of data with labels from an existing dataset
- Step 2: Learn the model using the dataset
- Step 3: Use the output of the model to build software to help clinicians reach better decisions, faster.
- **Examples:** Logistic regression, random forests, XGBoost, Deep neural networks

Unsupervised learning



- Step 1: Collect a dataset or curate a subset of data with labels from an existing dataset
- Step 2: Learn the model using the dataset
- Step 3: Use parameters of the model uncover insights about the data and validate with domain experts
- **Examples:** Nearest neighbors, latent factor models, hidden markov models, variational autoencoders

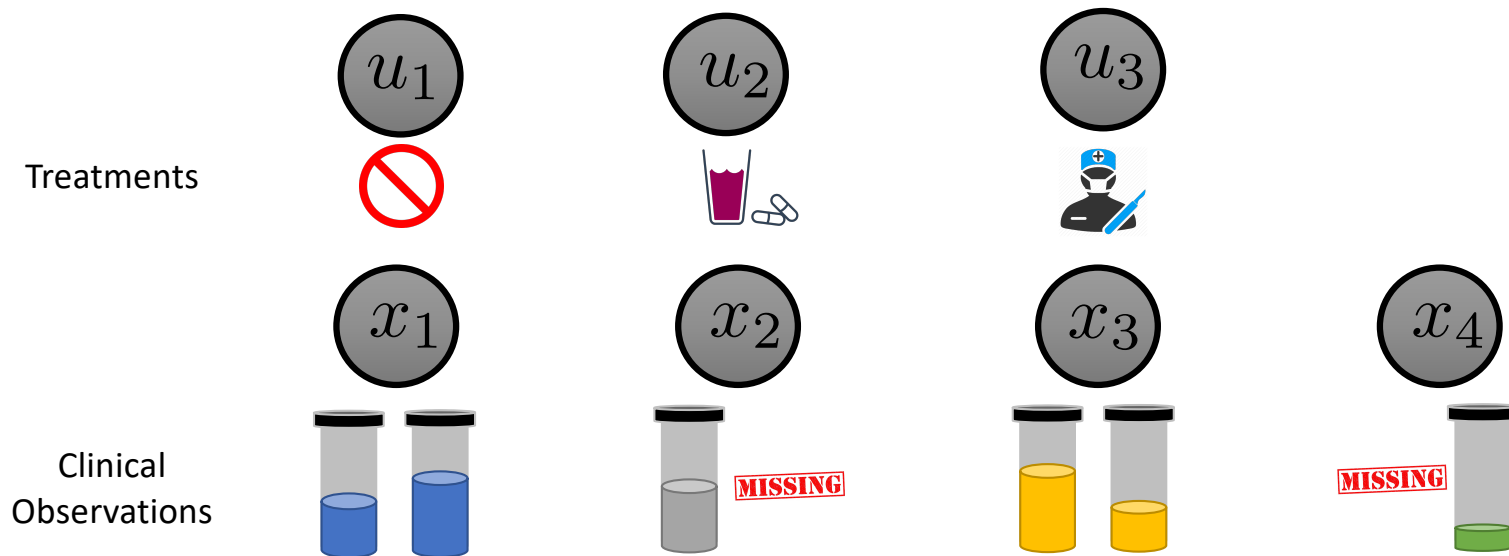
RL in healthcare



- On the left is an example of Deepmind's ATARI RL agent that learns to move the paddle at the bottom
- Can we use similar techniques for problems in healthcare such as developing strategies to treat people?

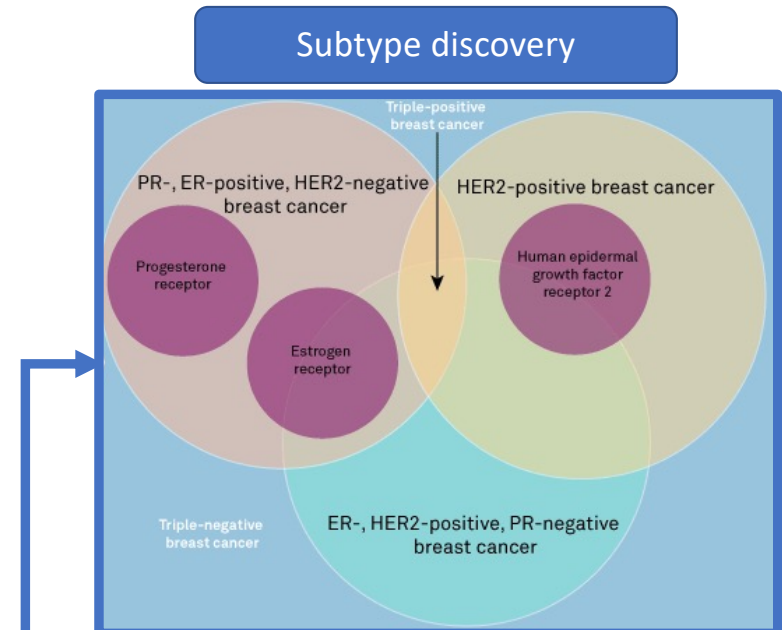
Challenge: Difficult to build good simulators of how the human body will react to drugs

Reinforcement learning from observational data



- Step 1: Collect a longitudinal dataset of patient states and clinician actions
- Step 2: Learn an off-policy model using the observational dataset
- Step 3: Use the model to suggest what action to take for a new patient state
- **Examples:** [Marginalized Off-Policy Evaluation](#)

What can we do with data?



Build clinical tools

A brief history of machine learning/AI and medicine

This seems like an obvious idea – hasn't this been done before?



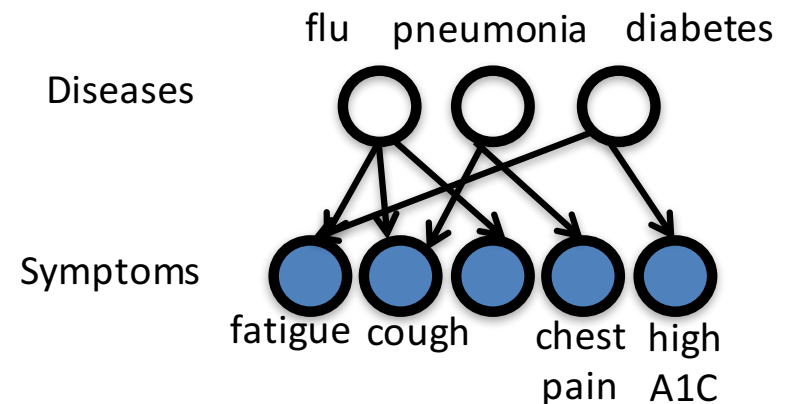
1978: Mycin expert system at Stanford

- Early expert system/AI to diagnose patients based on symptoms and test results
- Used >500 prediction rules:
 - If A & B then predict pneumonia
- Worked better than specialists in blood infections and better than general practitioners

1986 : INTERNIST-1/QUICK MEDICAL REFERENCE (QMR) Project

- Automated diagnosis for internal medicine
- Probabilistic model:
 - hundreds of disease variables,
 - thousands of symptom variables
 - >40000 directed edges between them

The creation of this model led to several advancements in probabilistic inference!



1990s: Neural networks in clinical medicine

- Used very few features to make predictions with
- Data collected by chart review

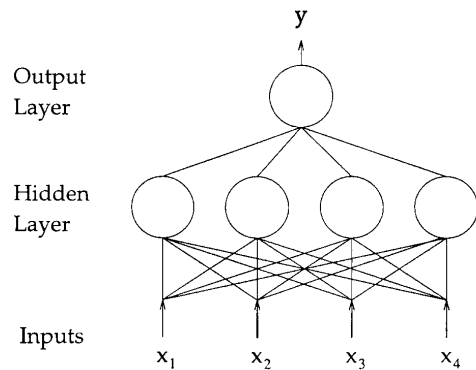


FIGURE 2. A multilayer perceptron. This is a two-layer perceptron with four inputs, four hidden units, and one output unit.

Did not generalize well to new places and difficult to fit into clinical workflow

So why now – better data?

- Large datasets
 - Truven [bought by IBM] has data collected on 230 million patients since 1995
 - All of Us precision medicine initiative: deep phenotyping of 1 million people in the US
 - [GEMINI dataset](#)
- Data standardization
 - FHIR, OHDSI
- Digital health funding
 - ~7B in venture funding in 2018
- Industry interest from Microsoft, Google, IBM

So why now – advances in machine learning!

- 1990s – AI winter, but a productive one!
 - Markov Chain Monte Carlo
 - Variational Inference
 - Convolutional neural networks
 - Reinforcement learning
- 2000s – Vision and NLP started adopting ML models
- 2013: Imagenet – watershed moment for deep learning
- 2018-now:
 - Photorealistic GANs
 - GPT-3 can simulate text indistinguishable from text written by humans

Staging diseases

Using machine learning to uncover stages of disease progression

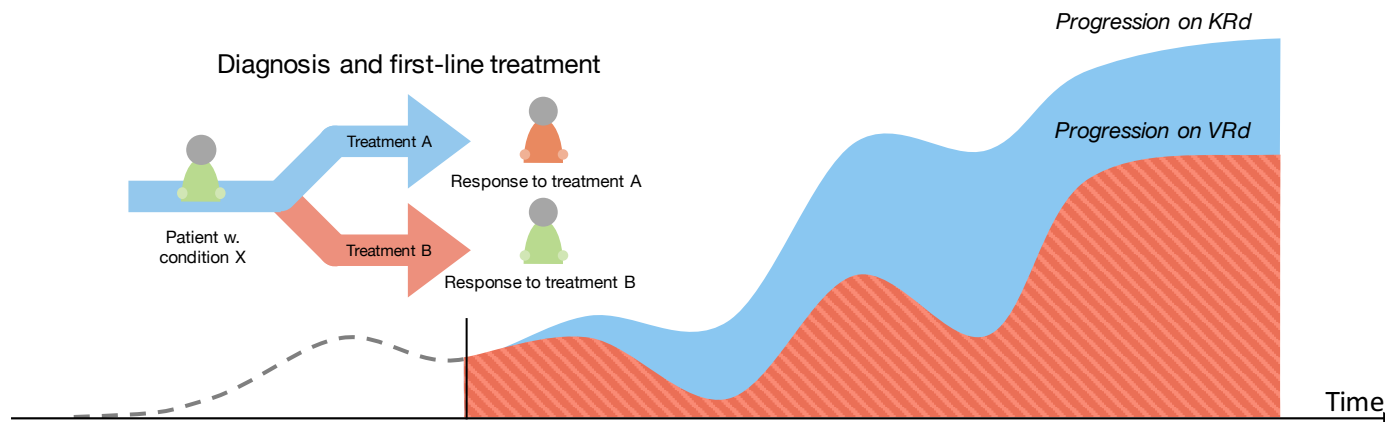
PROGRESSION OF CHRONIC KIDNEY DISEASE (CKD)



Precision oncology

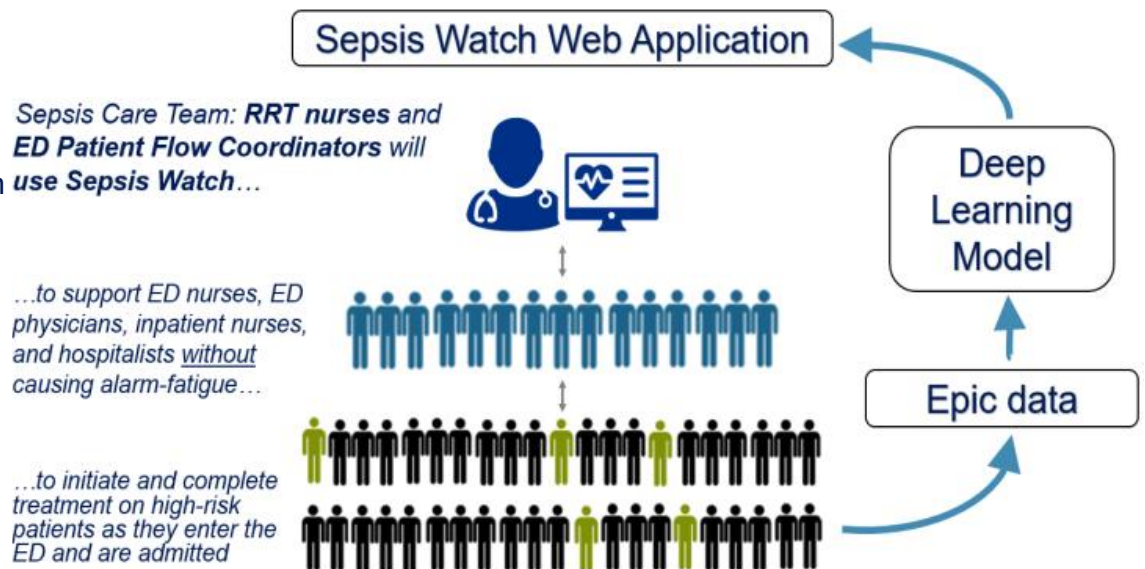
Using machine learning to guide treatment decisions for cancers therapy

A) KRd: carfilzomib-lenalidomide-dexamethasone, **B) VRd:** bortezomib-lenalidomide-dexamethasone



Predicting sepsis in patients admitted to the hospital

- **42,000+ inpatient encounters analyzed** at Duke Hospital over 14 months, **21.3%** with a sepsis event.
- **32+ million data points incorporated:** 25 million vital sign measurements, 2 million med admins, 5.2 million labs.
- **34 physiological variables** (5 vitals, 29 labs).
 - At least one value for each vital in 99% of encounters.
 - Some labs rarely measured (2-4%), most measured 20-80% of the time.
- **35 baseline covariates** (e.g. age, transfer status, comorbidities).
- **10 medication classes** (antibiotics, opioids, heparins).



Source: <https://dihi.org/wp-content/uploads/2020/02/Sepsis-Watch-One-Pager.pdf>

A smart EHR system

The Burden and Burnout in Documenting Patient Care: An Integrative Literature Review
The surge of EHRs has had an unintended consequence : an increase in physician administrative load

KERMIT,F [69 / M]

Temp 99 HR 102 BP 150/70 RR 24 O2sat 99%

69 y/o M Patient with severe intermittent RUQ pain. Began soon after eating. Also is a heavy drinker.

Chief Complaints:

RUQ abdominal pain
Allergic reaction
L Knee pain
Rectal pain
Right sided abdominal pain

Transfer
MCI

Enter Cancel

Triage note

Predicted chief complaints

KERMIT,F [69 / M]

Temp 99 HR 102 BP 150/70 RR 24 O2sat 99%

69 y/o M Patient with severe intermittent RUQ pain. Began soon after eating. Also is a heavy drinker.

Chief Complaints:

RIGHT UPPER QUADRANT PAIN
RUQ ABDOMINAL PAIN
RUQ PAIN
ALLERGIC REACTION
L KNEE PAIN
RECTAL PAIN
RIGHT SIDED ABD PAIN
RIGHT SIDED ABDOMINAL PAIN
L WRIST PAIN
RIGHT SIDED CHEST PAIN
TESTICULAR PAIN
KNEE PAIN
ELBOW PAIN
RIB PAIN
L ELBOW PAIN
HAND PAIN

Enter Cancel

Contextual auto-complete

Many more applications

- Drug discovery for faster, cheaper drug development pipelines
- Automating polyp detection in gastrointestinal diseases



- New and upcoming places for machine learning to have an impact in healthcare:
 - Microbiome
 - Liquid biopsies for cancer detection and tracking

Should we all be doing this?



HOLD YOUR HORSES

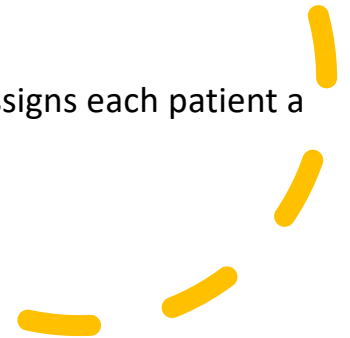
SLOW DOWN AND THINK



The Pain Was Unbearable. So Why Did Doctors Turn Her Away?

A sweeping drug addiction risk algorithm has become central to how the US handles the opioid crisis. It may only be making the crisis worse.

- “NarxCare also offers states access to a complex machine-learning product that automatically assigns each patient a unique, comprehensive Overdose Risk Score”
- Source: <https://www.wired.com/story/opioid-drug-addiction-algorithm-chronic-pain/>



HEALTH

AI-Driven Dermatology Could Leave Dark-Skinned Patients Behind

Machine learning has the potential to save thousands of people from skin cancer each year—while putting others at greater risk.

By Angela Lashbrook

Source: <https://www.theatlantic.com/health/archive/2018/08/machine-learning-dermatology-skin-color/567619/>

Challenges for machine learning in healthcare

- Challenging risk/reward ratios
 - Why: In healthcare, clinicians make life or death decisions
 - What do we need:
 - Algorithm development should proceed with caution and care
 - Need **robust** algorithms with checks and balances
 - Algorithms need to be **fair** and **accountable**
- Labelled data is scarce
 - Why: Clinician time is expensive
 - What do we need:
 - New methods for unsupervised and semi-supervised learning

Challenges for machine learning in healthcare

- Patient populations are different:
 - **Why:** Each individual is unique and people from Mumbai display different clinical phenotypes than those in Toronto
 - What do we need:
 - New methods for transfer learning so that models generalize well across different hospitals
- Missingness
 - **Why:** We only go to the doctor/clinician/hospital when we are sick; hospital administrators may forget to annotate data, records can go missing
 - What do we need:
 - Machine learning models that can make robust predictions even when data is missing

Challenges for machine learning in healthcare

- Data silos
 - **Why:** Countries have regulations (such as HIPAA) that require patient data to be kept private
 - What do we need:
 - New ideas in federated learning for institutions not comfortable with data-sharing
 - Automated methods for de-identification
- Deploying ML software in the clinic
 - **Why:** Machine learning models can stop working after a period of time
 - What do we need:
 - New techniques for lifelong learning
 - Ways to handle domain shift/covariate shift

Course goals

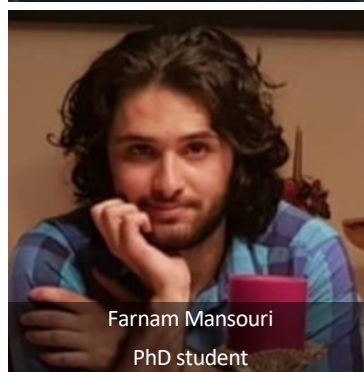
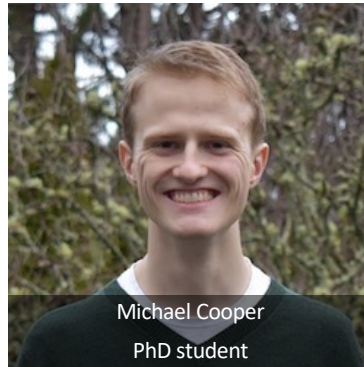
- Intuition for working with healthcare data
- Understand what problems are useful to solve, and what choices of models/learning algorithms to work with
- Appreciate subtleties in applying ML to healthcare problems
- Have fun working (and, if the course project goes well, publishing) in this space!



Course map

Course staff

Office hours
forthcoming



A thematic review of machine learning for healthcare

- Week 2: Supervised learning and survival analysis
- Week 3: Time series modeling
- Week 4: Disease progression
- Week 5: Clinical Natural Language Processing
- Week 6: Medical Imaging
- Week 7: Interpretability
- Week 8: Fairness
- Week 9: Clinical trials
- Week 11: Missingness and causality

Thematic readings

- Each week will have several readings in the course schedule for methodological and applied papers
- **Prerequisite:** Strong foundation in probability, statistics, probabilistic graphical models and machine learning.
 - Unless you have gotten prior approval from me, please **make sure you are comfortable with advanced topics**
 - Do the readings early in the week, they will make your life easier
- **TODO:** There is a pre-requisite quiz for everyone to complete ASAP. If you find the quiz challenging, you will have a lot of additional reading to do for the course

Course announcements

- The course announcements will be posted to Quercus
- The course website will be your one-stop shop for information on the course: <https://csc2541hf-2021.github.io/>

Grades

- Individual
 - 5% class participation (attendance and engagement)
 - 15% assignment
 - Paper deconstruction: Summarize four papers of your choosing: highlight the key ideas, what makes them tick, why you think they work and how they could be improved
 - 15% paper presentation:
 - Present (in pairs) one of the papers from the theme of the week,
 - Sign up for papers on a first come first serve basis,
- Groups
 - 10% project proposal
 - 15% project presentation
 - 40% course project report

Course project

- Undertake a course project where the goal is to create a workshop abstract by the end of the semester
- You are free to use your own healthcare data (should you have access to it). In the next few weeks we will go through and describe several different publicly available datasets that you can apply for access to for your project.
- **IMPORTANT: Form groups and apply for access to projects early! Getting access to healthcare data can take a few weeks and it is important to get started on this now!**

Ethics training

- It is vital to understand and respect clinical data!
- This is data that may look like numbers and figures to you, but always remember that behind them is a real human being, respect their choice to share it and treat the data with care,
- Do not share the data with anyone who is not credentialed to have access to it.
- Never try to re-identify de-identified data
- **CITI training:** <https://physionet.org/about/citi-course/>

Course project

- Groups of **at least two** and **no more than four** people
- The grading rubric will not depend on the number of people contributing to a project
- Friday lectures in the next two weeks will introduce you to freely available clinical datasets that you can use to brainstorm projects
- The goal is to tackle a meaningful problem using healthcare data:

TA hours

- Help brainstorm questions about the course project
- **Mandatory:**
 - Prior to your group/individual presentations, schedule time with one of the TAs for a practice presentation
 - This is part of your grade for the course
 - This will ensure:
 - That your presentation covers the right set of information
 - That your presentation runs on time

Course timeline

- Week 1-3
 - Lectures
- Week 4-8
 - Guest lectures from researchers working on a diverse array of applications of machine learning to healthcare
 - Student presentations
- Week 9, 11, 12, 13, 14
 - Student presentations, project presentations

TODOs (for now and during the course)

- **TODO:**
 - Complete [CITI training for Physionet](#)
 - Complete [prerequisite quiz](#)
 - Starting reaching out to form project groups and partners for paper presentations [Piazza link forthcoming]
 - Start brainstorming ideas of problems you may want to explore
- Week 4: Project proposal due
- Week 8: Paper assignment due
- Week 13: Group presentations begin
- Week 14: Project report due