

# CMPT 419 E200: HDCAI Spring 2024

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## Human- and Data-centered AI

- Special Topics

## Agenda

- Discuss readings for this week
- I'll give some of my thoughts, then we'll discuss
- Intro to readings for next week

## HCML

### Good and bad uses of AI – some go to examples

- auto complete
- predict malignant tumor
- deep fake
- discrimination (skin tone, gender, more)

### Progress? in AI

- Deep learning “gains” don't always hold up to scrutiny

## **People as “objects of prediction”**

- How to counter this?
- Fairness, equality, justice

## **Political concerns**

Why is it important to “refine HCML into a unifying and interdisciplinary force across CS rather than risk fracture with each sub-field of CS taking ownership of an independent vision of HCML”

## **A bit of behind the scenes into CS research**

- Subcommunities often run their own conference
- Drives a lot of the incentives of researchers
- This might matter for research-related jobs in industry too
- e.g., some ML jobs list NeurIPS papers as a requirement, some Responsible AI jobs list FAccT,

## **Early HCML**

- Chancellor highlights some of the history – the “HCI” community and “FAccT” community played major roles
- Information Science and STS
- CSCW

## **Acronym Cheatsheet thus far**

- HCI: human-computer interaction. Main conference is “CHI”, confusingly.
- FAccT: Fairness, Accountability, and Transparency
- CSCW: computer supported cooperative work and social computing
- STS:

## What Counts as HCML?

### Focusing on Practices

Four suggestions are given, i.e. what can you do when you're a software engineer, manager, research scientist, professor, etc.

- should I use ML?
- what's my "position"?
- users vs. humans
- credit other domains
- iterate on failure

### Institutional actions

- new norms at conference, e.g. negative impact statements (NeurIPS)
- institutional support for interdisciplinary research
- computing (broad) vs. computer science
- support students who want to do interdisciplinary research!

## Over to DCAI

### Problems with data

- "Differences in labeling": do you and I agree if a pill is "scratched"? Does my hospital notes system have a different coding system than yours?
- "Emphasis on big data": what about a rare medical condition?
- "Ad hoc data curation": need to systemize?

### Finding label disputes

- We might use tools to find subsets of a dataset with high label dispute
- Influence estimation provides one approach we'll see

### Domain Expertise

- get the biologists to label the cells!
- get former players to provide "labels" for sports analytics
- many more examples
- this is where the DCAI argument really starts to merge with the HCAI argument

## What is DataPerf

- a so-called “benchmark suite”
- focused on data tasks
- meant to be community run and led

## What’s a “ML benchmark?”

Conventional model-centric ML definition: “a standard, fixed dataset for model accuracy comparisons and performance measurement” (p2, Mazumber et al)

## Some terms

- from “Probabilistic Machine Learning: An Introduction”, Murphy 2022 (<https://probml.github.io/pml-book/book1.html>)
- task  $T$  to learn mapping  $f$  from inputs  $x \in X$  to outputs  $y \in Y$
- $x$  called features (or covariates, or predictors)
- $y$  is label (or target, or response)
- we have  $N$  input-output pairs  $D = (x_n, y_n)$  for  $n \in (1, N)$ .  $D$  is the training set,  $N$  is the sample size.

## Comparing model-centric benchmark and data-centric benchmark

- in model-centric, we have a fixed dataset  $D$  and we try a bunch of different ways to find  $f$
- change model architecture, change training hyperparameters, change task metrics
- in data-centric, we keep all these fixed and just change  $D$

## Testable concept: is a benchmark data centric

- you might imagine a test question that describes several different tasks and asks you to identify which one is “data-centric”