

# Course overview and logistics

## CS861: Theoretical Foundations of Machine Learning

**Kirthi Kandasamy**

University of Wisconsin - Madison

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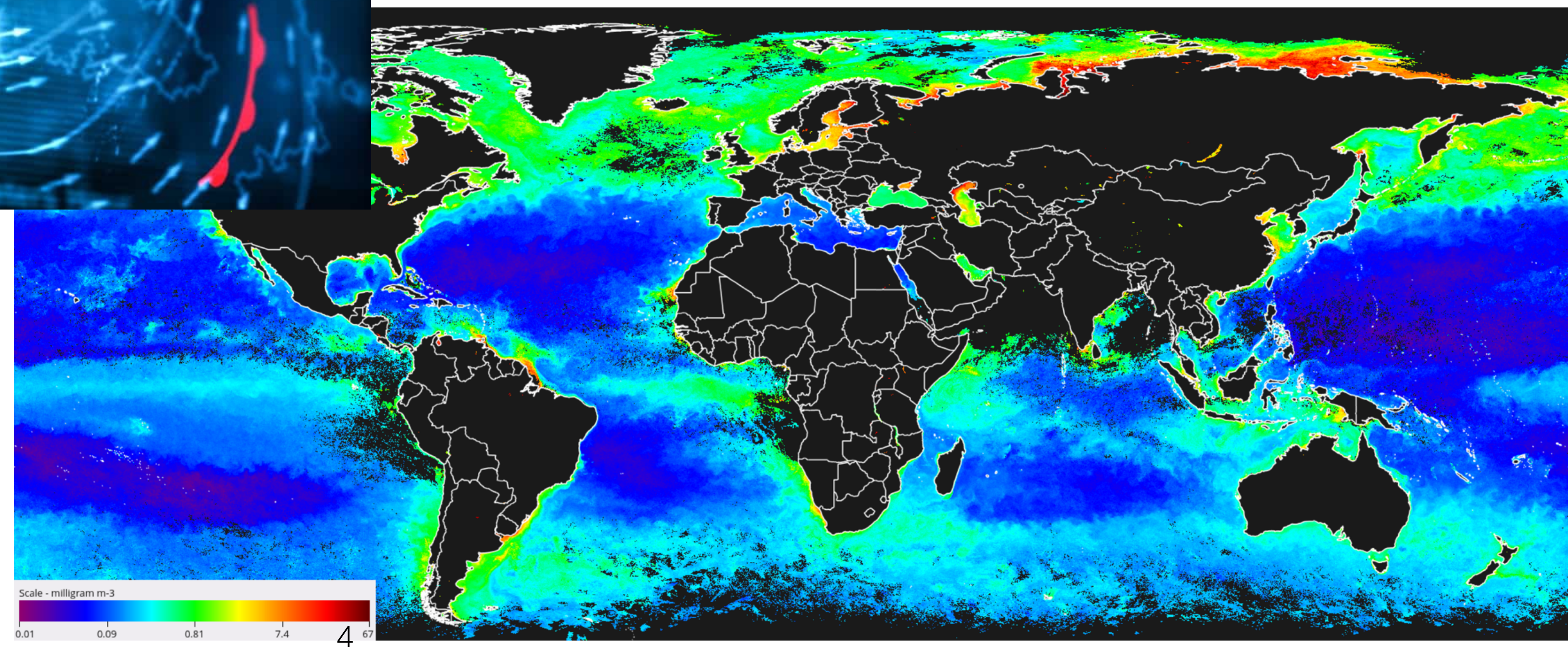
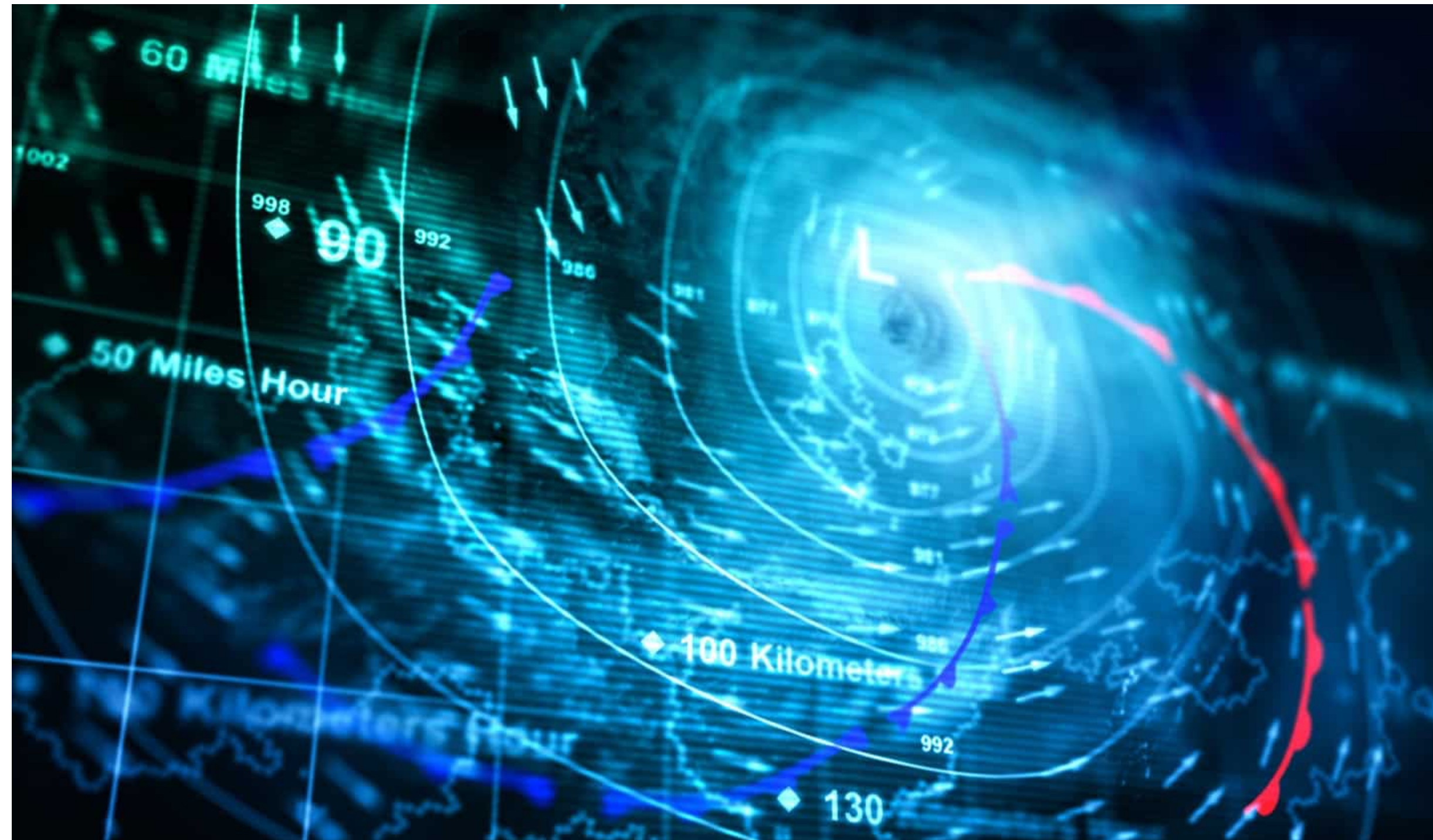
# AI/ML is popular nowadays!

- *“A breakthrough in ML will be worth 10 Microsofts”*  
- Bill Gates
- *“ML is the new internet”*  
- Tony Tether, Director, DARPA
- *“AI will be the best or worst thing ever for humanity”*  
- Elon Musk

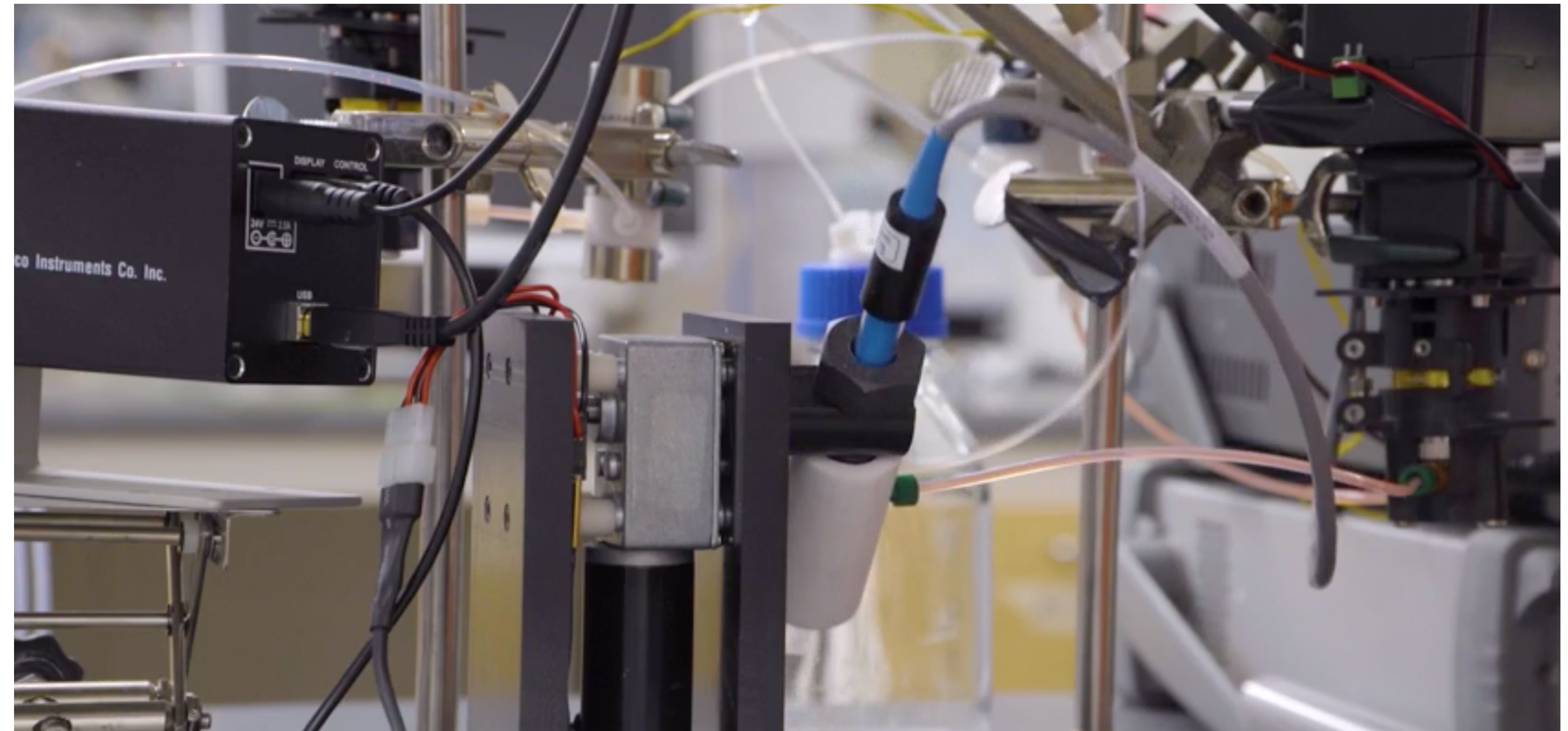
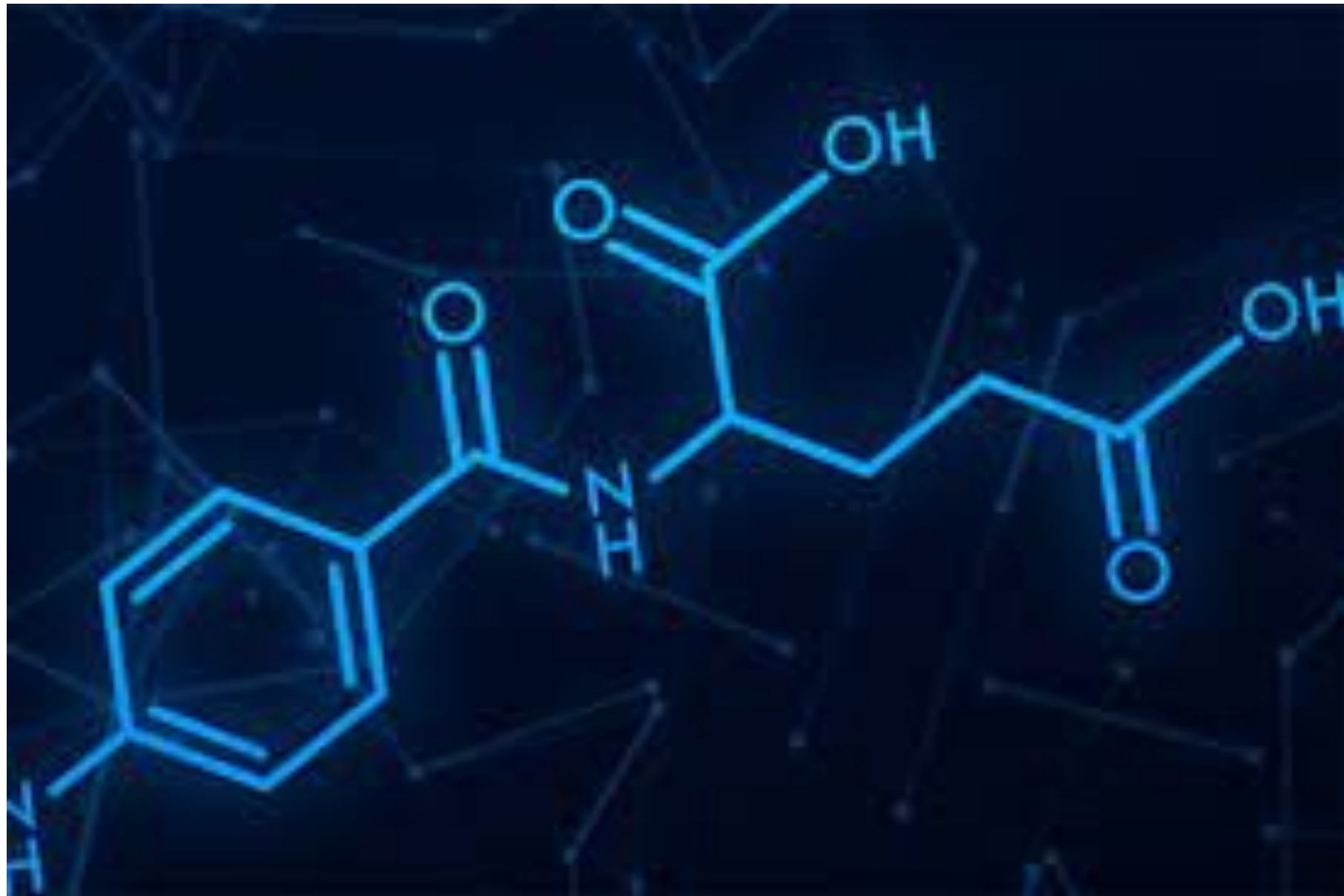
# Object detection & segmentation



# Weather forecasting & Climatology



# Optimizing drugs and materials



# Autonomous vehicles



# Language generation & LLMs

**Q: What is your favorite animal?**

A: My favorite animal is a dog.

**Q: Why?**

A: Because dogs are loyal and friendly.

**Q: What are two reasons that a dog might be in a bad mood?**

A: Two reasons that a dog might be in a bad mood are if it is hungry or if it is hot.

**Q: How many eyes does a giraffe have?**

A: A giraffe has two eyes.

**Q: How many legs does a frog have?**

A: A frog has four legs.

**Q: Are there any animals with three legs?**

A: No, there are no animals with three legs.

**Q: Why don't animals have three legs?**

A: Animals don't have three legs because they would fall over.

# Image generation

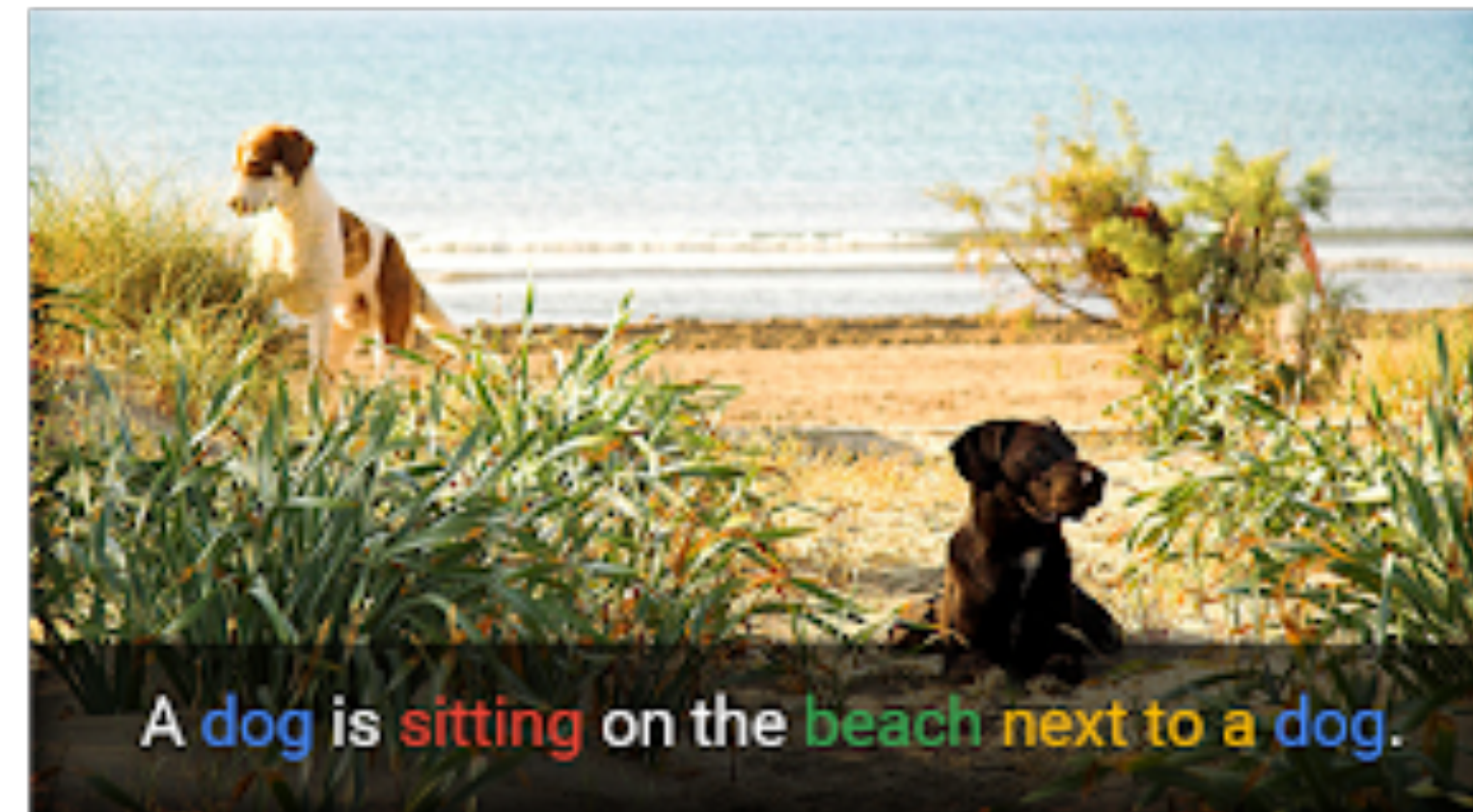


# Image to text generation

Human captions from the training set



Automatically captioned



# This class: *Theoretical Foundations* of ML

## Why take this class? Why study ML theory?

1. Understand fundamental limitations about a learning problem.
  - When is it possible to learn?
  - What are the primary challenges we need to solve?
  - How much data do we need to learn?

# This class: *theoretical foundations* of ML

**Why take this class? Why study ML theory?**

2. Develop fundamental intuitions for designing learning algorithm
  - What is the “correct” way to think about these challenges?
  - How do we trade-off between multiple challenges?

Will focus on simple (as opposed to “*realistic/practical*”) settings

3. It is fun!

# Outline

1. Course logistics
2. Syllabus
3. Who should take this class? Prerequisites and expectations

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# Logistics: Lectures, OHs, Grader, Enrollment

- **Lectures**

- MWF, 11 am - 12.15 pm at ENGR HALL 3534.
- 27-30 lectures. Class will conclude around the first or second week of Nov.
- Slides will be posted ahead of the lecture.
- Lectures will be mainly on I-Pad and Whiteboard.

- **My office hours:** Wed 1.30 - 2.50 pm at MH5066

- **Grader:** Julia Nakhleh

- **Enrollment**

- If you cannot enroll due to pre-requisites, please speak to me.

# Logistics: Webpages

- **Course website**

- <https://pages.cs.wisc.edu/~kandasamy/courses/25fall-cs861>
- Logistics, syllabus, lectures, homeworks, and grading

- **Piazza**

- <https://piazza.com/wisc/fall2025/csece861>
- Ask public questions whenever possible.
- Announcements, peer discussions on lectures, homework clarifications.

- **Canvas**

- Homeworks, exams, and some announcements

# Grading

- **Proofreading lecture notes (slides): 4%**
- **Homeworks: 42%**
- **Take-home Exam: 32%**
- **Course project (setting a homework question): 22%**

# Proofreading lecture notes (slides)

- Each student will proofread ~2 lectures. Two students per lecture. (This may change if enrollment drops.)
  - See course website for sign-up link
- **Instructions (see course website as well)**
  - Proofreaders **must** attend class.
  - After class, carefully read and identify typos, errors, and unclear explanations.
  - Within **2 days**, each student will **email separate submissions**, either marked on downloaded slides or typed up as a separate pdf.
  - If you are unsure about taking the class, sign up for after Oct 6. If you decide to drop, *delete your name **and** email me.*
  - After you sign up, please don't change your slot without informing me.

# Homework

- 5 Homeworks (including homework 0)
- Typically due every other Saturday at 11.59pm on Canvas.
- A total of 3 late days for the entire course. Extensions only for documented emergencies.
- Homeworks will be *difficult*.
  - Expect to spend multiple hours/days on some problems.
  - On starred (\*) problems, you *are allowed* to collaborate with up to 2 classmates. You should attempt other problems on your own.
  - Do not search the internet or use LLM-based tools.

# Take-home Exam

- Take-home exam from Mon 11/17 12.01 AM – Fri 11/21 11.59 PM.
- You have 48 hours to complete the exam.
- No collaboration allowed on the exam.

# Course project (setting a homework problem)

- You will work in groups of size up to 3, to design a homework problem.
- Your peers will attempt and evaluate your question.
- Model depth/difficulty based on starred homework problems in HW 1 - 4 (not HW 0).
- See webpage for guidelines.

## Key dates

- A preliminary draft of the problem (with solutions) due on Sat 10/18.
- Final problems due on Sat 11/15.
- I will assign 1-2 questions to each of you. Solutions and evaluation of the questions due on 12/06.
- If you set a good question, I will include it in future courses and acknowledge your contribution!

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- 2. Syllabus**
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# Syllabus: Overview

0. Background topics
1. Statistical lower bounds
2. Nonparametric methods
3. Statistical learning theory
4. Stochastic bandits
5. Online learning and adversarial bandits
6. Online convex optimization

# 1. Statistical lower bounds (6-9 lectures)

- Lower bounds for point estimation
- Lower bounds for hypothesis testing: Le Cam & Fano methods
- Going from estimation to testing
- Plan: lower bounds for mean estimation in Ch 1, but we will apply the ideas to classification, regression, density estimation, online learning, bandits etc.

## 2. Nonparametric methods (2-3 lectures)

- Nonparametric regression, Nadaraya-Watson estimator
- Kernel density estimation
- Lower bounds for regression and density estimation

### 3. Statistical Learning Theory (7-10 lectures)

- Basic framework: loss, hypothesis classes, excess risk
- Empirical risk minimization
- Uniform convergence
- Rademacher complexity
- VC dimension and Sauer's Lemma
- Dudley entropy integral and chaining
- Lower bounds: binary classification, linear regression

## 4. Stochastic bandits (4-6 lectures)

- Optimism in the face of uncertainty and the Upper Confidence Bound (UCB) algorithm
- Lower bounds for stochastic K-armed bandits
- Linear bandits, martingale concentration
- Best arm identification (if time permits)

## 5. Online learning, Adversarial bandits (5-7 lectures)

- Learning from experts and the Hedge algorithm
- Adversarial bandits and EXP3
- Lower bounds for adversarial bandits and learning from experts
- Contextual bandits and EXP4
- Learning in games (if time permits)
- Regret minimization in non-stationary environments (if time permits)

## 6. Online Convex Optimization (4-5 lectures)

- Follow the leader, Follow the regularized leader
- FTRL with convex regularizers
- Online gradient descent
- Follow the perturbed leader, online shortest paths
- Lower bounds for OCO

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# Target audience for the class

- Ph.D students doing research in theoretical **(statistical)** machine learning.
- **Background knowledge**
  - **Formal prerequisite:** CS761 or equivalent.
  - Strong background (intermediate-level graduate course) in statistics, probability, and mathematics (calculus, linear algebra etc).
- **Who should not take this class.**
  - *“I want to learn about ML/AI”* (Take 540, 532)
  - *“I want to apply ML in an applied area of research”* (Take 760)
  - *“I want to learn take an introductory ML theory class”* (Take 761)

# Homework 0

## Three problems:

1. Normal mean estimation
2. A simple bandit model and algorithm
3. Some questions from Chapter 0

## Three Objectives

- I. A preview of some topics
- II. Lets you assess if you are ready to take this class

# General advice when taking this class

1. Focus on learning, and not on grades.
  - Class will be challenging. But if you are able to keep up, you will get a good grade.
2. Give me feedback about the course.
3. Be good citizens: attend class, ask questions, answer questions, let others answer/ask questions, respond to questions on piazza.