CSCE 585: Machine Learning Systems

Sustainable AI Systems Deployment, Large Language Models: Serving & Alignment, Multi-Modal Learning in Robotics

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What do you expect to learn in this course?

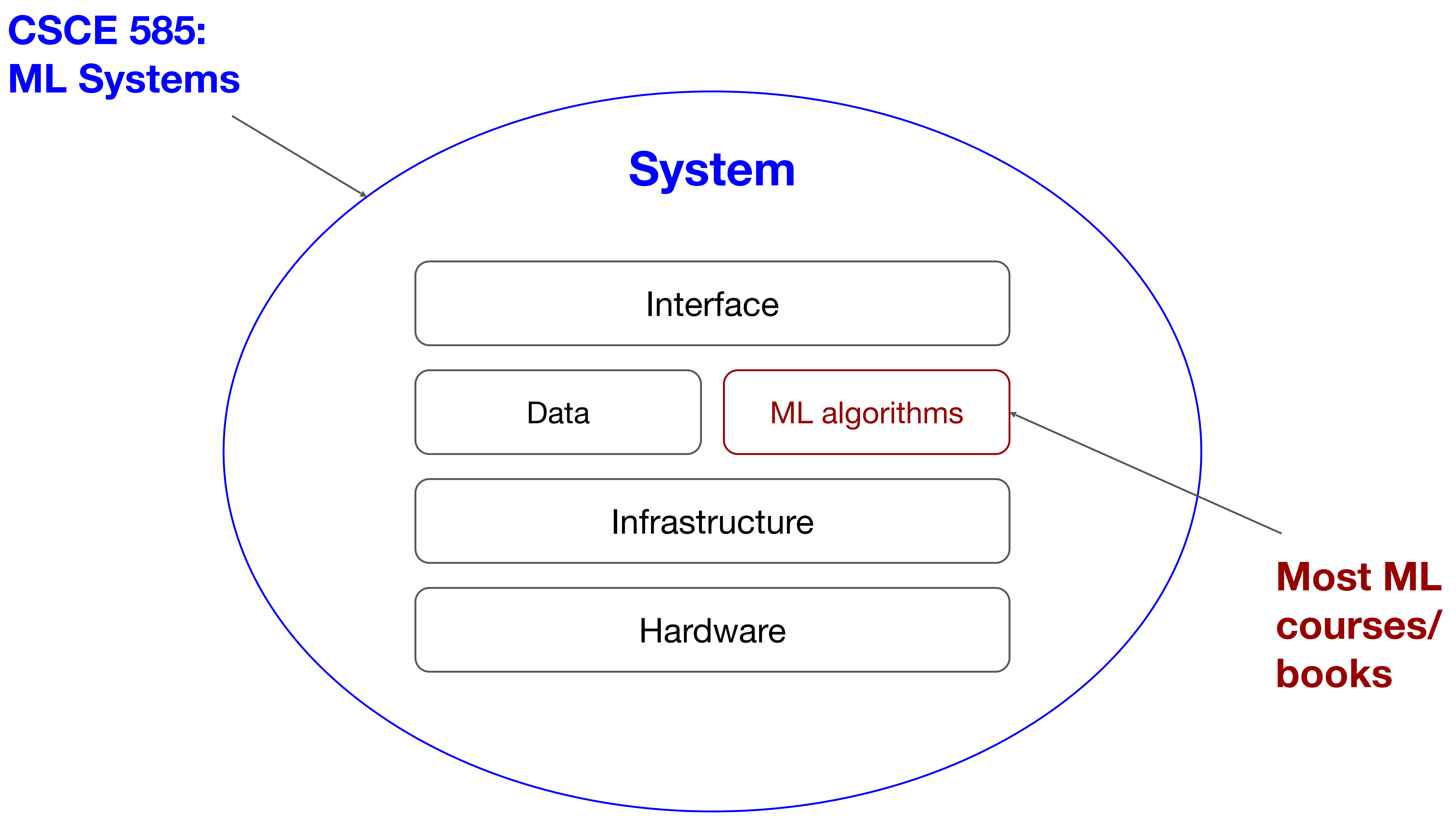
Course Overview

Why ML Systems instead of ML algorithms?

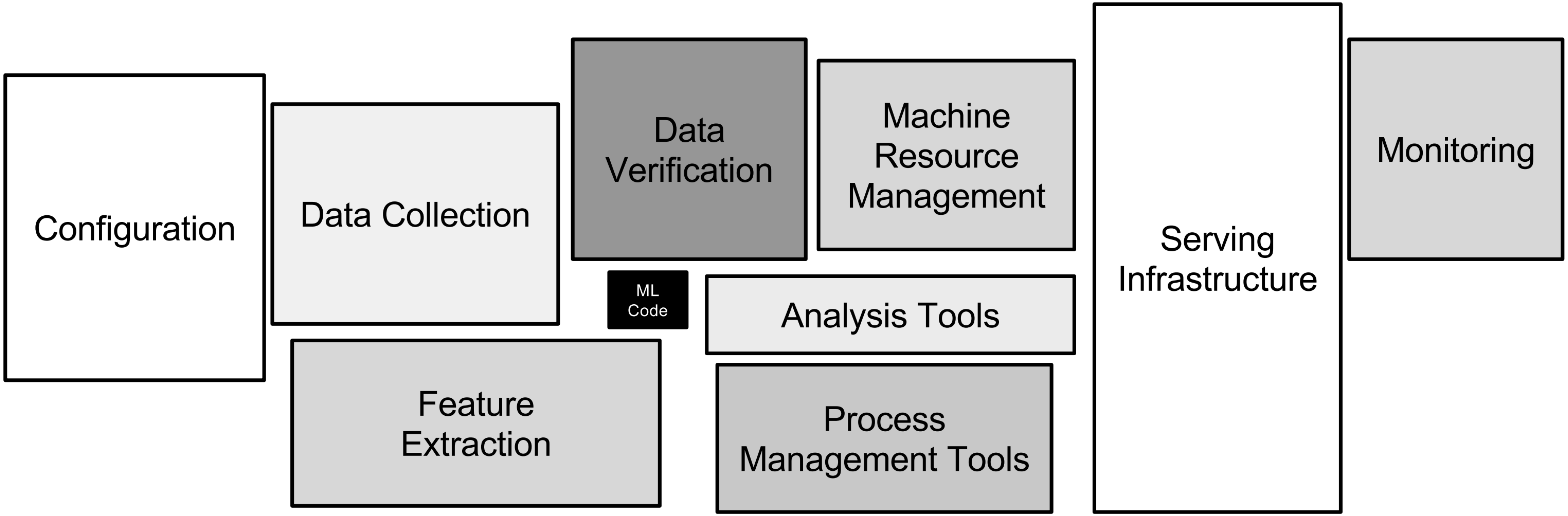
- ML algorithms is the less problematic part.
- The hard part is to **how to make algorithms work with other parts to solve real-world problems**.

Why ML Systems instead of ML algorithms?

- ML algorithms is the less problematic part.
- The hard part is to **how to make algorithms work with other parts to solve real-world problems.**
- 60/96 failures caused by non-ML components


CSCE 585:
ML Systems
System
Interface
Data
ML algorithms
Infrastructure
Hardware
Most ML
courses/
books

ML in Production



How are ML systems designed and implemented?

The process of defining the **interface, algorithms, data**, **infrastructure**, and **hardware** for a machine learning system to satisfy **specified requirements**.

What is machine learning systems design?

The process of defining the **interface, algorithms, data, infrastructure**, and **hardware** for a machine learning system to satisfy **specified requirements**.

reliable, scalable, maintainable, adaptable

The questions this class will help answer …

- You’ve trained a model, now what?
- What are different components of an ML system?
- How to do data engineering?
- How to engineer features?
- How to evaluate your models, both offline and online?
- What’s the difference between online prediction and batch prediction?
- How to serve a model on the cloud? On the edge?
- How to continually monitor and deploy changes to ML systems?
- …

This class will cover ...

- ML production in the real world from software, hardware, and business perspectives
- Iterative process for building ML systems at scale
    - project scoping, data management, developing, deploying, monitoring & maintenance, infrastructure & hardware, business analysis
- Challenges and solutions of ML engineering

Prerequisites

- Knowledge of CS principles and skills
- Understanding of ML algorithms
- Familiar with at least one framework such as TensorFlow, PyTorch, JAX
- Familiarity with basic statistics, linear algebra, and calculus.

You will be fine if you are eager to learn!

Evaluations

ML Systems course is project-based

- Must work in groups of 2-3
- Demo + report + code + experimental results

Grading

- Milestones 1: 20%
- Milestone 2: 30%
- Project Demonstration: 30%
- Final Deliverables: 20%

Important Dates

- Project assignments and proposals: due September 5
- Project milestone 1: due September 28
- Project milestone 2: due October 26
- Project demos: November 28th, 30th, Dec 5th, Dec 7th
- Final report and all deliverables: due December 7th

Piazza

- Piazza: you have already been added!
- Ask questions
- Answer others’ questions
- Learn from others’ questions and answers
- Find teammates

How projects will be evaluated

- You can work in teams of up to 2 or 3 people.

- Every team member should be able to demonstrate her/his contribution(s).

- The outcome will be evaluated based on the quality of the deliverables (code, results, report) and presentations/demonstrations.

- The final report contains motivation, positioning in existing literature, technical details, details about the experimental setup, results regarding ablation analyses, comparisons, and conclusions.

- It is essential to write why you designed the experiments in any specific way and how such a design of the experiment would answer any question of hypothesis.

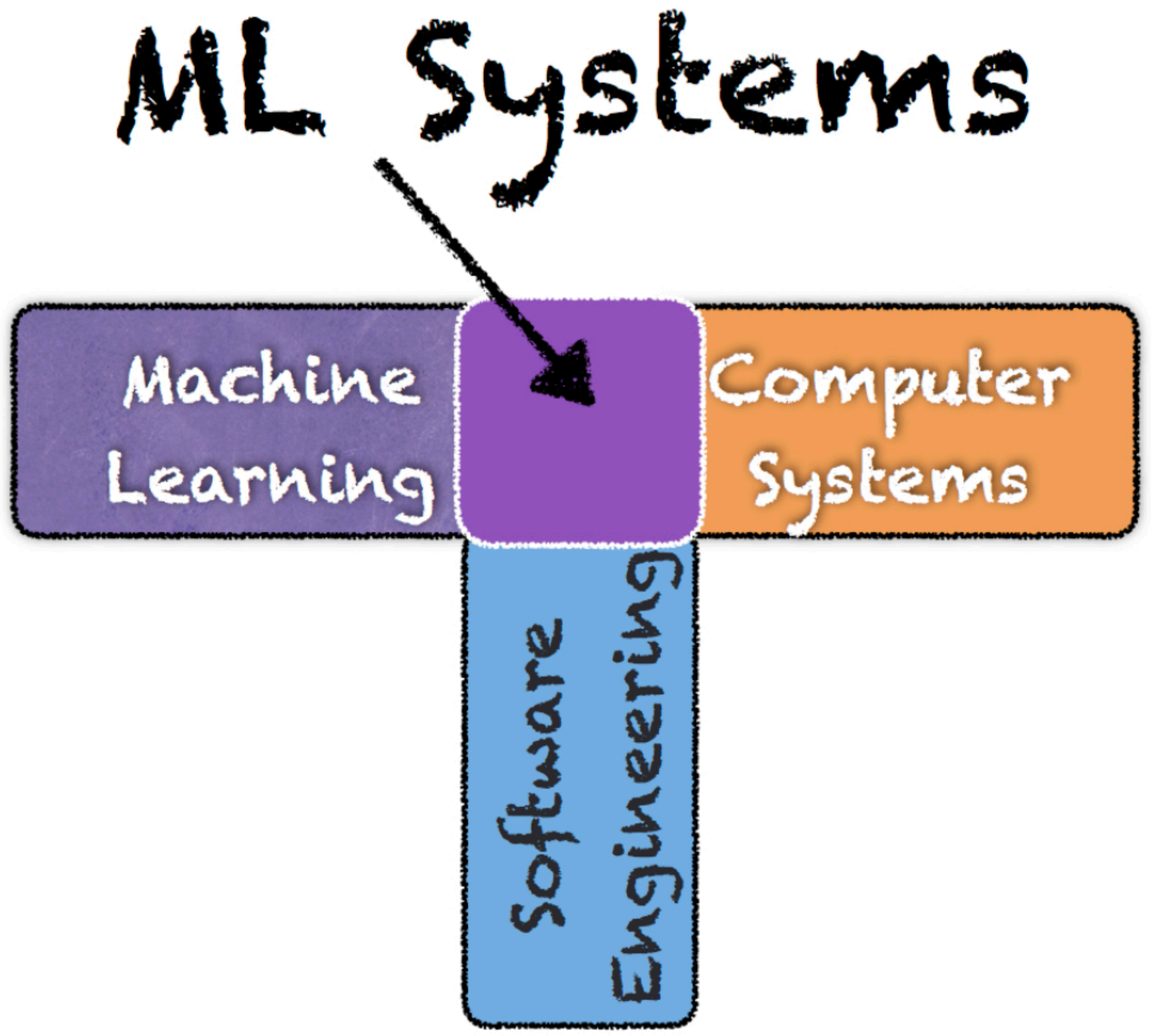
Honor code: permissive but strict - don’t test us ;)

- OK to search about the systems we’re studying.
- Cite all the resources you reference.
    - E.g., if you read it in a paper, cite it.
- NOT OK to ask someone to do assignments/projects for you.
- OK to discuss questions with classmates.
- NOT OK to copy solutions from classmates.
- OK to use existing solutions as part of your projects/assignments. Clarify your contributions.
- NOT OK to pretend that someone’s solution is yours.
- OK to publish your final project after the course is over (we encourage that!)

Important Dates?

CSCE 585 LECTURES PROJECTS RESOURCES POLICIES PIAZZA

Machine Learning Systems



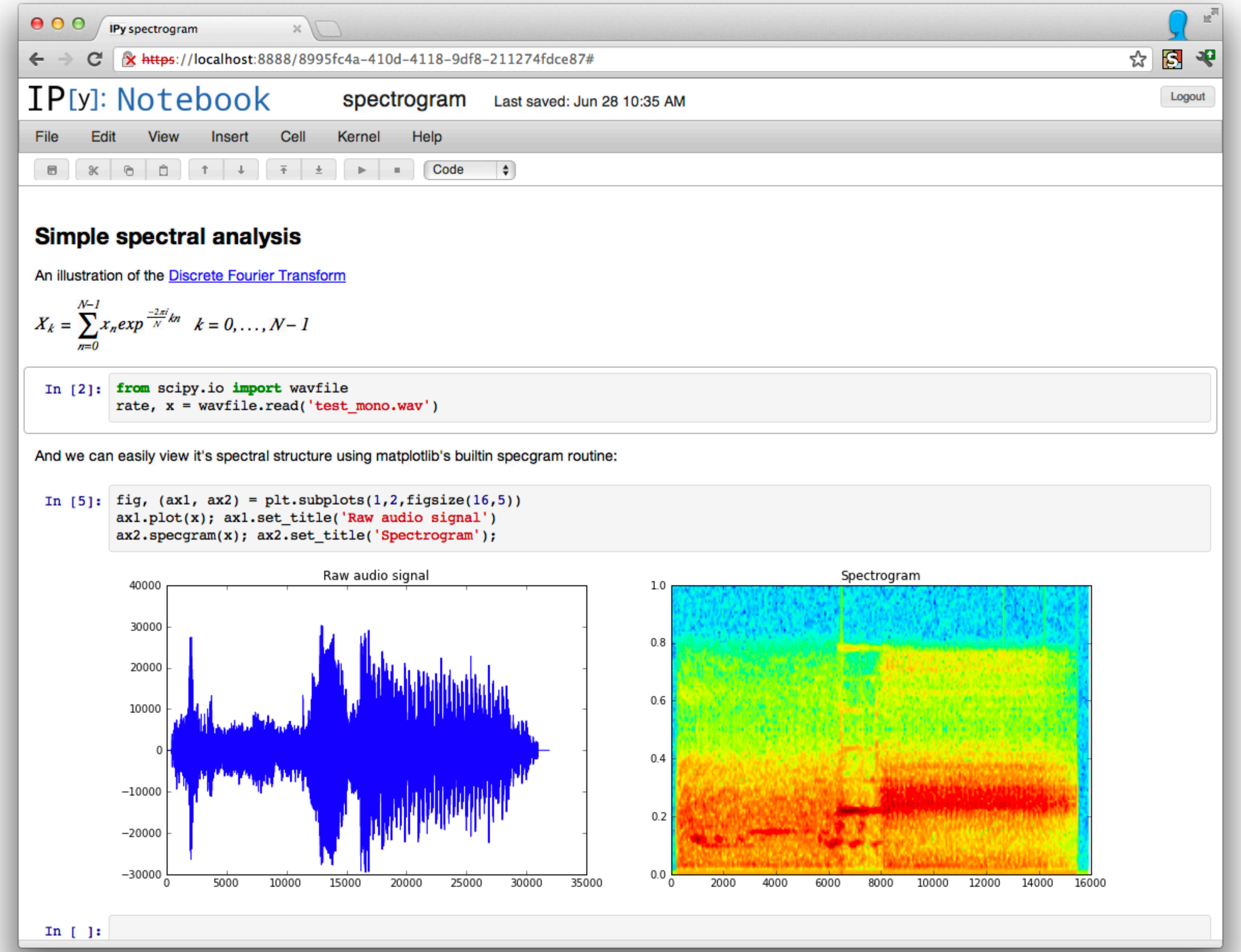
New to machine learning? Not sure how ML works in production? Interested to get involved in advanced ML+Systems research? This class is designed for you!

When we talk about Artificial Intelligence (AI) or Machine Learning (ML), we typically refer to a technique, a model, or an algorithm that gives the computer systems the ability to learn and to reason with data. However, there is a lot more to ML than just implementing an algorithm or a technique. In this course, we will learn the fundamental differences between AI/ML as a model versus AI/ML as a system in production.

https://pooyanjamshidi.github.io/mls/

Examples, Tips, Suggestions

How the project report should looks like?



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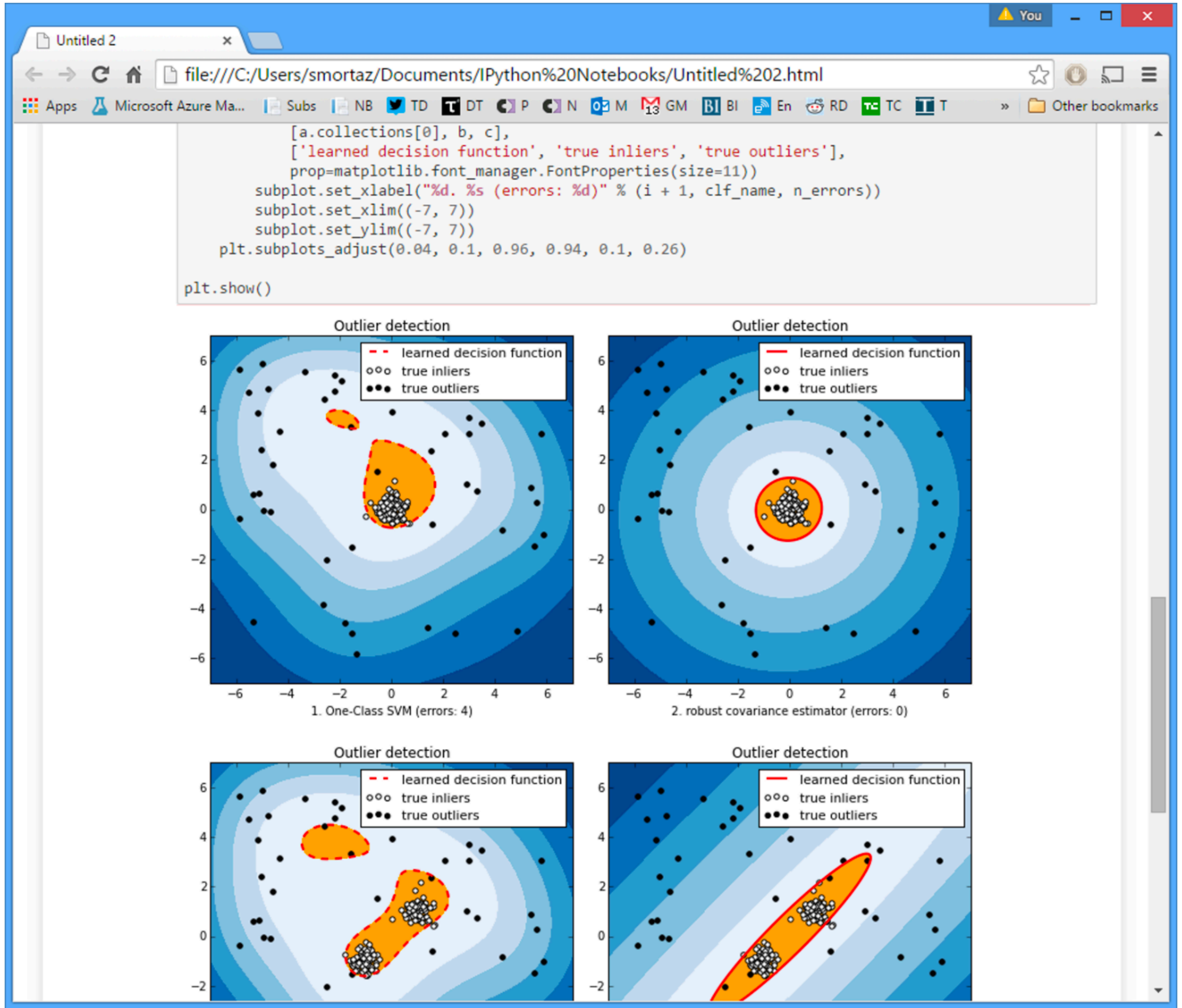

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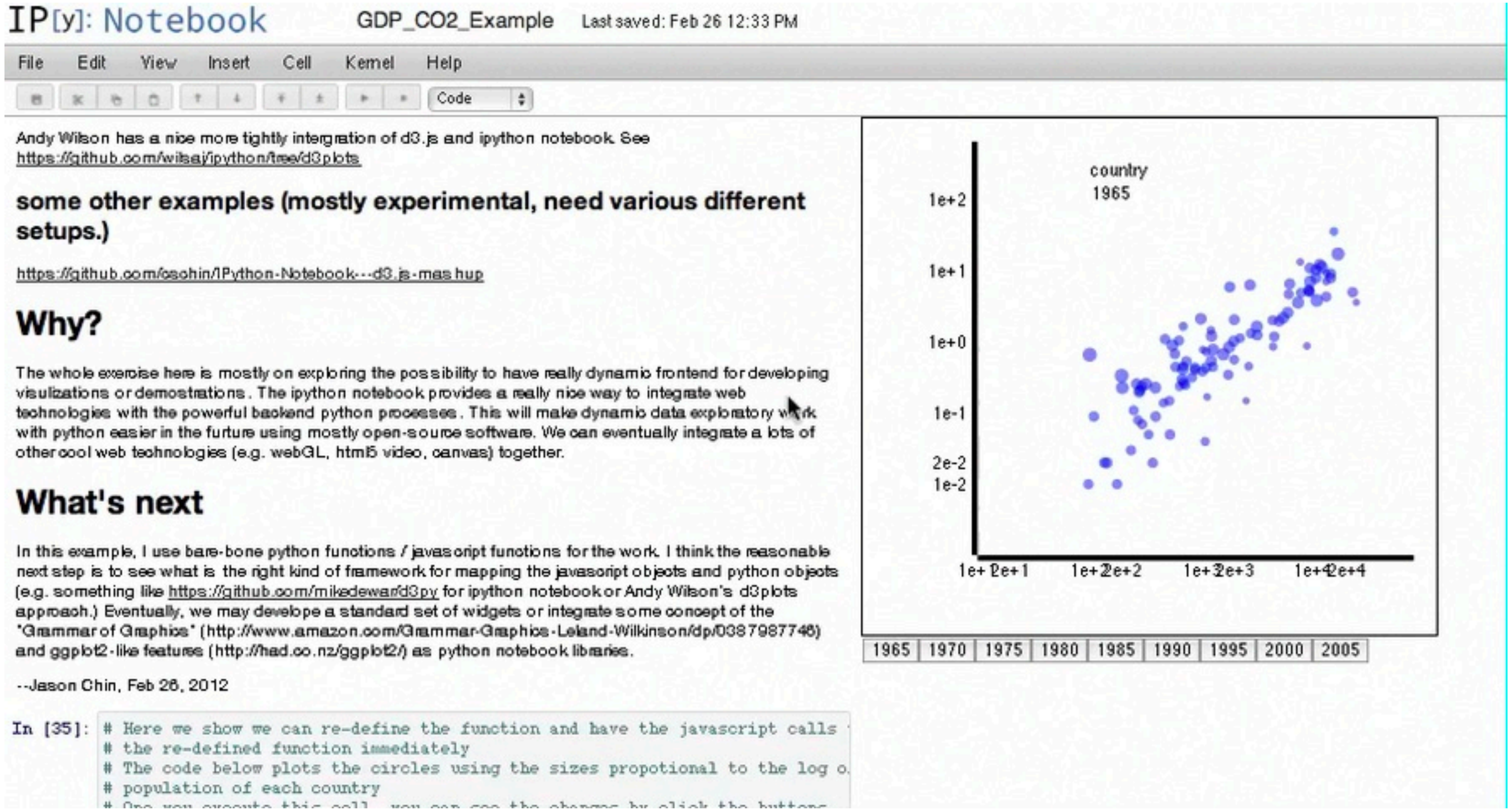


ML Systems Projects

Course Projects

- **Project 1: LLM Serving**: Batching, Scheduling, Eviction Policy, Prefetching
- **Project 2: ML Pipelines**: Configuration Tuning, Runtime Resource Adaptation
- **Project 3: Robotics:** Multi-Modal Learning and Navigation
- **Project 4:** Any Relevant Topic to ML Systems

Project Proposal

- What is the **problem** that you will be investigating? Why is it interesting?
- What **reading** will you examine to provide context and background?
- What **data** will you use? If you are collecting new data, how will you do it?
- What **method** or algorithm are you proposing? If there are existing implementations, will you use them and how? How do you plan to improve or modify such implementations? You don't have to have an exact answer at this point, but you should have a general sense of how you will approach the problem you are working on.
- How will you **evaluate** your results? Qualitatively, what kind of results do you expect (e.g. plots or figures)? Quantitatively, what kind of analysis will you use to evaluate and/or compare your results (e.g. what performance metrics or statistical tests)?

Checkout

Projects

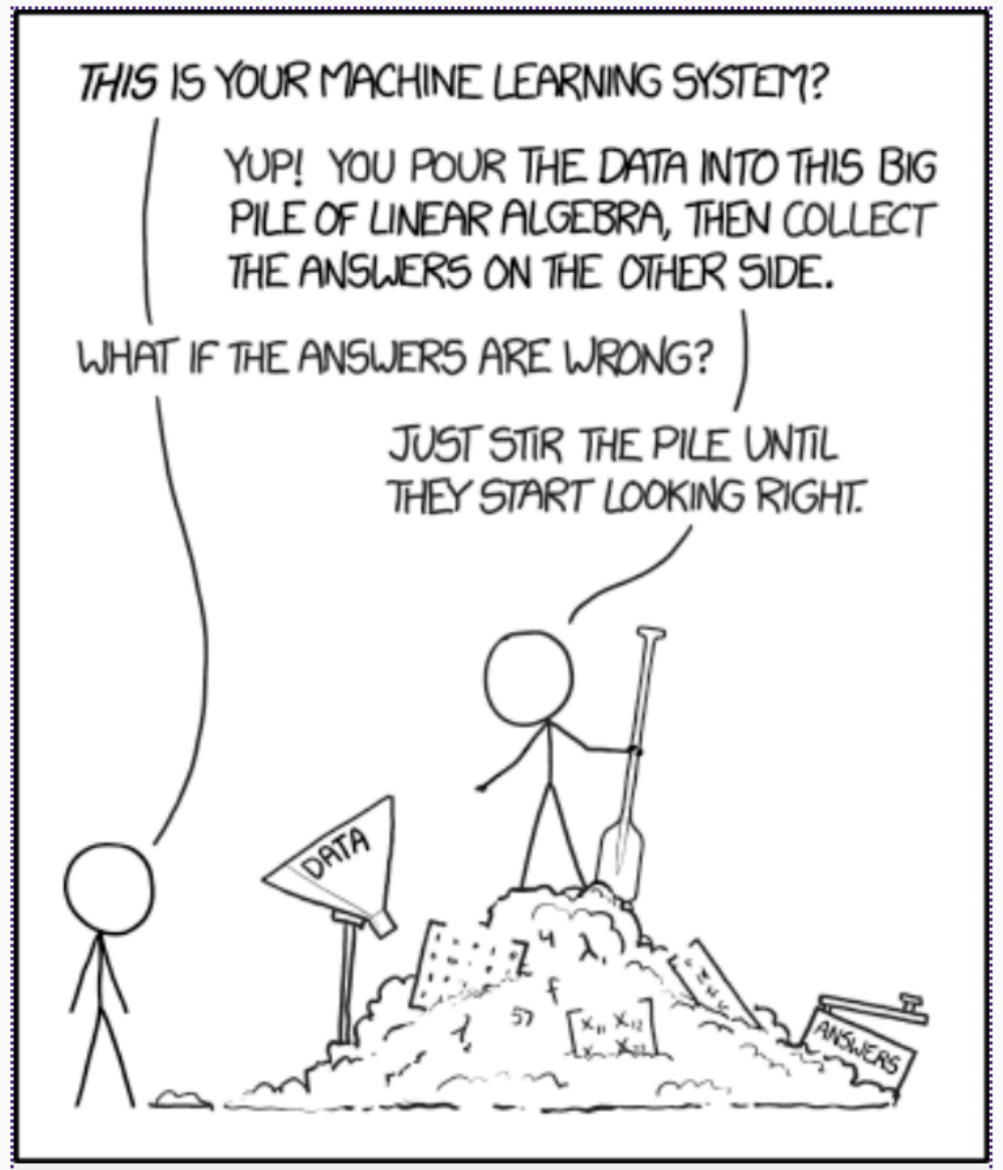
Submission

For submitting your homework and project deliverables, please use the instructions and template in the course resources repository.

Topics

The course project is an opportunity to apply what you have learned in class to a problem of your interest. Potential projects must have these two components:

- `Machine Learning` algorithm: Any ML model class including neural networks or any good old-fashioned ML/AI.
- `Computer Systems`: The project should have at least one computer systems component: (i) Platform: Embedded, Realtime, Cloud, IoT, Edge; (ii) Systems issues such as scalability, performance, reliability; (iii) On-device ML: e.g., TinyML, AI on Edge; (iv) Trustworthy AI: Bias, Fairness, Robustness, Privacy, Security, Explainability, Interpretability, Interoperability; (v) Robot Learning, any project that makes robots more intelligent!



Machine learning systems, explained!

The following categories also fit within the scope, and I highly encourage students to consider such projects:

- There are lots of resources that you can read, review, and study to find a specific project idea with a clear scope. For example, you can use `blog posts` from engineering teams at high-tech companies: Uber Engineering, The Netflix Tech Blog, Spotify Labs, Meta, and many more.
- Topics related to `AI in Robotics` or `Autonomy in Robotics` are great for this course. You can use simulators such as Gazebo or Bullet or use cloud services such as Amazon RoboMaker for your project and do not need to have it on a physical robot, but if you want to do a project with physical robots, you can do it in our robotics lab, come and talk with me. I have several project ideas related to Autonomy and Robotics. We have also a robotics team, called Gamecock Robotics. You can define your project to make the robot autonomous. You can also read blog posts to formulate a well-scoped project.
- Building on top of an `open source ML system` that you can find on GitHub, e.g., you can develop a tracking algorithm and develop a plugin for DeepStream

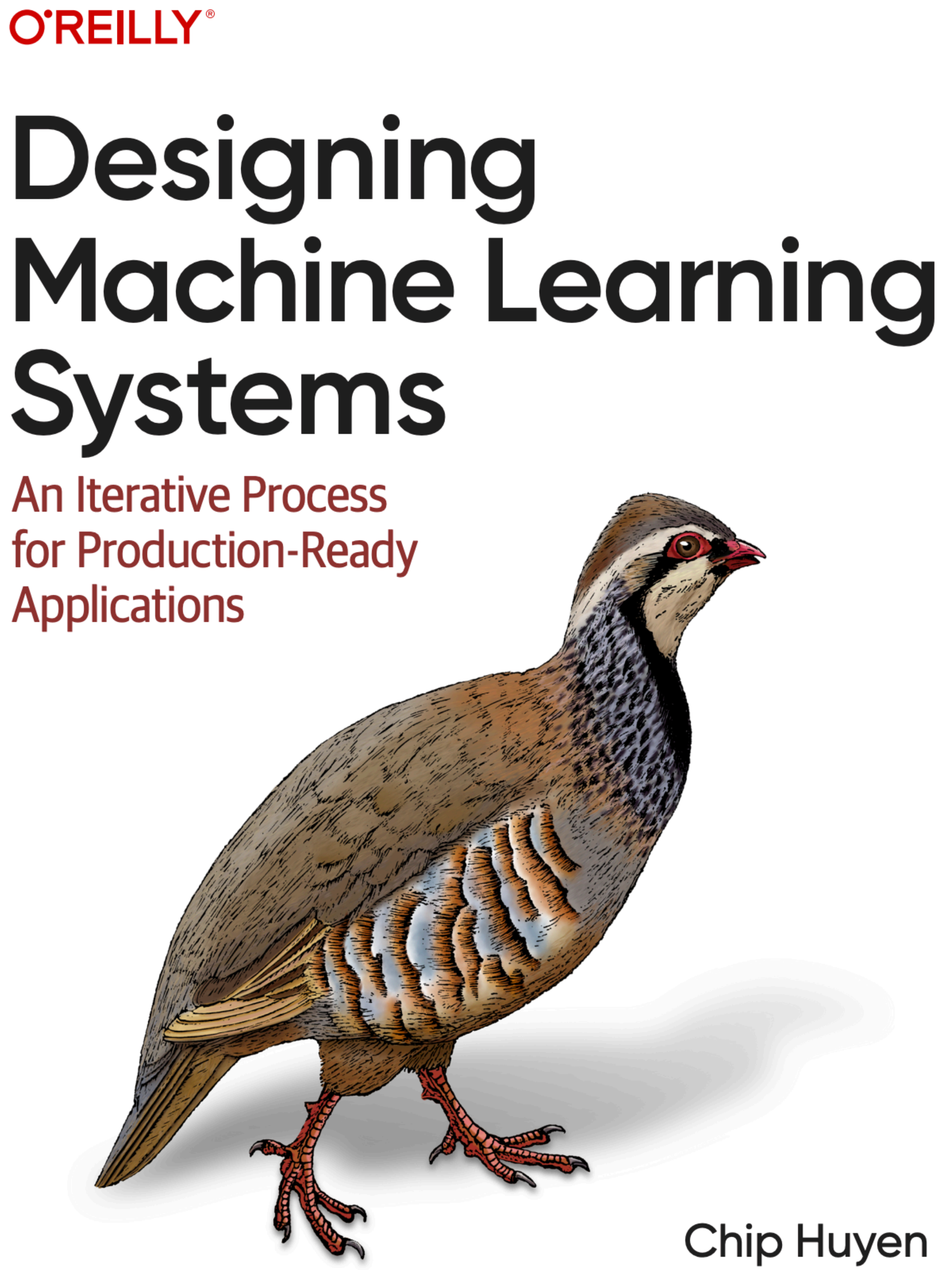
Checkout

- `AI competitions` are great project ideas for non-CS students, e.g., EvalAI hosts many interesting competitions with prizes suitable for students from all backgrounds, e.g., (i) Open Catalyst Challenge for Chemical Engineering students; (ii) Neural Latents Benchmark for Neuroscience students; (iii) The Robotic Vision Challenges for students interested in robotics.
- `Hackathons`: e.g., PyTorch Annual Hackathon 2021, AWS BugBust, Kaggle
- `Systematic study of open source ML Systems` via (i) interview study (please make sure you design the interview study correctly before conducting the interviews) and/or (ii) Formulating interesting research questions about building ML systems, for example, contrasting testing practices for ML systems vs. traditional software systems, collecting data from software repositories, and systematically extracting info from these repositories that answers your research questions.
- `TinyML` projects: You can find many ideas on GitHub and TinyML community forum
- `AI for Social Good`: There are massive opportunities to define your project on AI for Social Good, just google it and listen to podcasts for ideas, e.g., In Machines We Trust or The TWIML AI Podcast.
- Topics related to `Systems for ML` or `ML for Systems`: There are many opportunities to develop an infrastructure to make the ML workflow faster, more efficient, reliable, dependable, etc. Please check out some of the work at AISys lab.
- `AI and Music`: Topics related to music synthesis, music perception, music ranking, music experience, and many more. Please check out some cool works: (i) OpenAI Jukebox, (ii) Deep Learning Could Bring the Concert Experience Home.
- And, in general, for any interesting ML systems project ideas, try GitHub, or Reddit.

If you are unsure whether the project you have defined fits within the scope, please talk with me after class. If you believe that might be helpful for other students, please ask your question on Piazza or during class hours.

Learning Materials

Course Textbook



Learning Materials

- Learn one of these frameworks: TensorFlow, PyTorch, JAX
    - There are many good tutorials for each framework on their website
- Try to build some very simple models with available benchmarks
    - Search for the LeNet model and train it with the MNIST dataset
    - Try to feed some input data and get the prediction and print it on the console
    - Then try to measure basic performance metrics such as Accuracy or Inference time

Case I

Using Machine Learning to Predict Value of Homes On Airbnb

by Robert Chang

Amazing view from a Airbnb Home in Imerovigli, Egeo, Greece

Using Machine Learning to Predict Value of Homes On Airbnb

- Airbnb used machine learning to predict a vital business metric: the value of homes on Airbnb.
- It walks you through the entire workflow: feature engineering, model selection, prototyping, and moving prototypes to production.
- It's completed with lessons learned, tools used, and code snippets too.

Case II

Netflix Technology Blog

Mar 22, 2018 · 7 min read · Listen

Using Machine Learning to Improve Streaming Quality at Netflix

by Chaitanya Ekanadham

One of the common questions we get asked is: "Why do we need machine learning to improve streaming quality?" This is a really important question, especially given the recent hype around machine learning and AI which can lead to instances where we have a "solution in search of a problem." In this blog post, we describe some of the technical challenges we face for video streaming at Netflix and how statistical models and machine learning techniques can help overcome these challenges.

Using Machine Learning to Improve Streaming Quality at Netflix

- As of 2018, Netflix streams to over 117M members worldwide, half of those living outside the US.
- This blog post describes some of their technical challenges and how they use machine learning to overcome these challenges, including:
    - predicting the network quality,
    - detect device anomaly,
    - and allocate resources for predictive caching.

Case III

150 successful machine learning models: 6 lessons learned at Booking.com

OCTOBER 7, 2019 ~ ADRIAN COLYER

150 successful machine learning models: 6 lessons learned at Booking.com
Bernadi et al., *KDD'19*

Here's a paper that will reward careful study for many organisations. We've previously looked at the deep penetration of machine learning models in the product stacks of leading companies, and also some of the pre-requisites for being successful with it. Today's paper choice is a wonderful summary of lessons learned integrating around 150 successful customer facing applications of machine learning at Booking.com. Oddly enough given the paper title, the six lessons are never explicitly listed or enumerated in the body of the paper, but they can be inferred from the division into sections. My interpretation of them is as follows:

150 Successful Machine Learning Models: 6 Lessons Learned at booking.com

- As of 2019, Booking.com has around 150 machine learning models in production.
  - Predicting users’ travel preferences and how many people they travel with
  - Optimizing the background images and reviews to show for each user.
- Lessons Learned:
  - Machine-learned models deliver strong business value.
  - Model performance is not the same as business performance.
  - Be clear about the problem you’re trying to solve.
  - Prediction serving latency matters.
  - Get early feedback on model quality.
  - Test the business impact of your models using randomized controlled trials.