Lecture 2: September 7

ML Project Design

- Senior Design High Level Timeline
- Github Projects Setup & Sprint Progress Expectations
- ML Project Design
- Tech Lab Overview



- Senior Design High Level Timeline
- Github Projects Setup & Sprint Progress Expectations
- ML Project Design
- Tech Lab Overview



Month	Expected Status	Monthly Focus	Deliverables
September	N/A	- Figure out teams - Brainstorm projects	- Create teams - resume
Mid-September	- Teams selected - Handful of project ideas	- Final project selection - Begin meeting w/ mentors	 Project proposal Hardware/software request Writing: Executive Summary
October	- Project selected & approved	 Begin technical investigations (services, apis, language, etc) Flesh out project functionality & requirements Coding should start (scaffolding, ci/cd, prototyping) 	- Writing: Technical summary - Presentation: Elevator pitch
November	Main technologies selectedproject is well-definedEveryone is actively coding	- Answer all questions needed to complete TDD - Lot's of coding for alpha demo	- Writing: PRD - Presentation: Project Design
December	- Code complete for alpha demo	- more coding for beta demo - Formalize design discussions into proper TDD	- Presentation: Alpha prototype - Writing: TDD
January	- Continued focus on project development	- continued development for beta demo - focus on proper testing & integration	- Website Design
February	- Code complete for beta demo	 Refine code from a prototype into a fleshed out project testing, integration, polishing continued development for prelim prototype (get as close to finished as you can here) 	- Presentation: Beta prototype - Presentation: Elevator pitch/promotional
March	- Code complete for prelim demo	final code polishing to wrap up projectcomplete any necessary integration workadd extra features if possible	- Presentation: Pelim prototype
April	- Code 99% complete for final demo	- finishing touches for final project submission - ideally you are done with coding by this point	- Presentation: Final demo - Promotional video
May			- Final package due

- Senior Design High Level Timeline
- Sprint Progress Expectations
- Github Projects Setup
- ML Project Design (industry vs academia)
- Tech Lab Overview

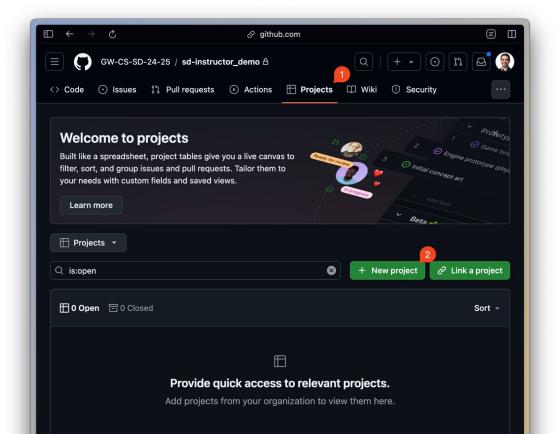


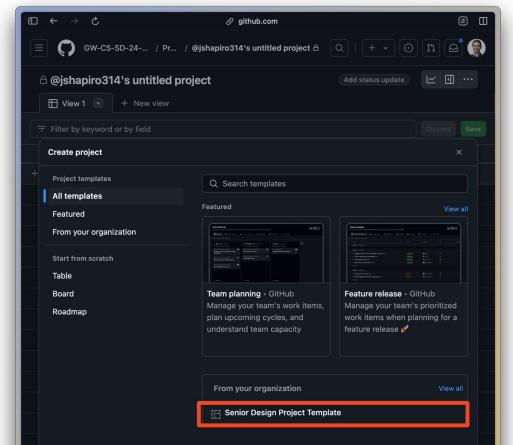
Sprint Progress - Components

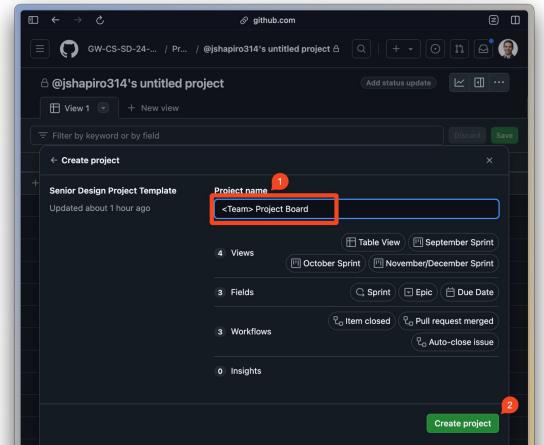
- Sprint Board
- Weekly Updates
- Slack Participation
- Code

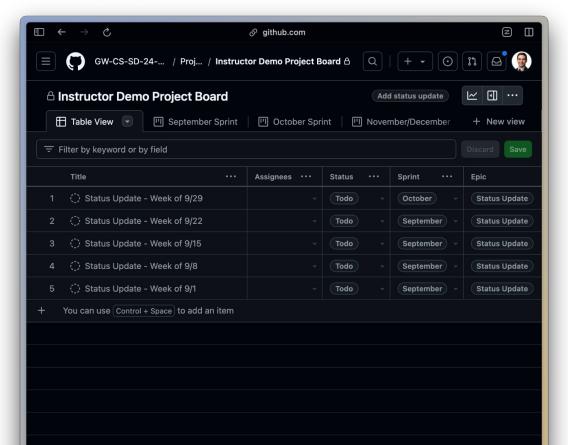
Components - Sprint Board

- Team members should create a backlog of tickets to work on
- At the beginning of each sprint, members should pull tickets from their backlog into their sprint
- Tickets should include the following:
 - Description
 - Assignee
 - Epic
 - Due date
 - Sprint
 - Status
- By the end of a sprint, all tickets should be **done**, **won't do**, or moved to the next sprint
- All senior design work should be accompanied by tickets (including presentations & writings)
- Tickets should be appropriately scoped to single features/prs
- Sprint boards should be created / populated during monthly sprint planning









Create September Tickets

Title	Epic	Due Date	Assignees	Sprint	Status
Submit Resume	Writing	9/8	Individual	September	TODO
Draft Project Proposal	Design	9/15	all	September	TODO
Refined Project Proposal	Design	9/22	all	September	TODO
HW/SW Requests	Design	9/22	all	September	TODO
Writing 1	Writing	10/6	Individual	October	TODO

Components - Status Updates

- Students should post weekly status updates covering:
 - What they completed (can link out to tickets)
 - What they are blocked by
 - What they are currently working on
 - Each student must leave their own comment
 - It is ok for the update to reflect no work
- These updates should be captured on Status Update tickets
 - Move ticket from TODO to DONE as week progresses
 - Leave comment BEFORE DUE DATE to receive credit
- Complete these updates prior to weekly meeting with mentor (used to lead discussion)
- Create new status update tickets as sprints progress
 - Title should be Status Update Week of MM/YY
 - Due date should be following Sunday

Components - Slack / Participation

- Use slack as the main communication method between teammates and:
 - Other teammates
 - Mentors
 - Instructors

Components - Code

- We expect all students to write code for senior design
- Only code pushed to main/master will be evaluated
- Code should be written in branches & PRed into master
- PR reviews are highly encouraged during the fall and required in the spring
- Code PRs should be well-scoped to single features and tied to sprint tickets

Sprint Progress Rubric

Fall Semester

Full credit

- Tickets addressed as either "done", "won't do", or moved to next sprint.
- Weekly standup updates & slack participation
- Code is PRed & merged to master. Branches & PRs are well-scoped.

Partial credit

- Majority of tickets addressed as either "done", "won't do", or moved to next sprint.
- Occasional standup updates & moderate participation
- Code is committed, PRs are sometimes present and sometimes well-scoped

Minimal credit

- Few tickets addressed as either "done", "won't do", or moved to next sprint.
- Minimal standup updates & rare participation
- Minimal code is committed, PRs are missing or not well-scoped.

No credit

- No sprint board activity
- No standup updates
- No slack participation
- No code committed to master/main

Sprint Schedule

Fall Semester Sprints Spring Semester Sprints

September Sprint January / February Sprint

October Sprint March Sprint

November / December Sprint April Sprint (2 weeks!)

- Senior Design High Level Timeline
- Github Projects Setup
- Sprint Progress Expectations
- ML Project Design (industry vs academia)
- Tech Lab Overview



Context

1. We anticipate many teams will explore some form of machine learning as part of their senior design project

2. Implementing ML in a product is not easy. It's also not a skill set typically taught in class.

3. These are the problems I focus on day to day, and I've found success in this approach.

Goals

- Know when to apply ML to a problem
- Know how to build out an ML solution
- Understand what different ML roles in industry entail



Non-Goals

- Explain how to train models
- Explain how to productionize models



- How to tell if a problem is well-suited for an ML solution
- How to approach an ML solution
- Different roles in the ML field



What makes an idea good for ML?

- 1. Can the problem be uniquely solved by ML?
 - a. Can a human solve this task manually?
 - b. Does a rules-based approach work?
 - c. What are the existing bottlenecks to solving this problem?

2. Do you have data / can you get data?

- 3. The IVO test: can the user immediately validate the output?
 - a. Change the user
 - b. Make validation easier
 - c. Change the output format



- How to tell if a problem is well-suited for an ML solution
- How to approach an ML solution (an ML Technical Design Doc)
 - Defining the input/output
 - What is your data
 - What are the metrics
 - Establishing baselines & benchmarks
 - Model training/exploration
 - Approaching ML in Senior Design
- Different roles in the ML field



Approaching an ML Solution: Inputs & Outputs

- 1. Identify the interface of your product user experience
- 2. Identify the interface of your ML model(s)
 - a. What is the input?
 - b. What is the output?

- Adds structure to ambiguity can't just lean on ML for scope creep
- Engineering is easier with interfaces. ML is hard, isolating from the rest of a system is important.
- Your interfaces will dictate the data you need and the training approach you're using (regression, classification, clustering, generation)

Approaching an ML Solution: Data

- 1. Do you have data that matches your input/output interface?
- 2. How costly is it to collect labelled data? Are there other ways of getting "labelled" data?
- 3. Do you have/need unlabeled data?
- 4. What is your training/validation/test set?
- 5. What are the characteristics of your data? (amount, biases, etc)

- If you don't have data, you're going to have a bad time.
- Figure out early if ML is not the right approach
- Data needs can change during experimentation



Approaching an ML Solution: Metrics

- 1. What offline "correctness" metrics do you care about?
- 2. Are there separate online metrics that are important?
- 3. Are there performance metrics that impact your solution?
- 4. What is the one metric that matters most?

- Need a way to objectively measure different approaches
- Need a way to evaluate a system once in production
- Forces you to focus attention on a small number of things to optimize



- How to tell if a problem is well-suited for an ML solution
- How to approach an ML solution (an ML TDD)
 - Defining the input/output
 - What is your data
 - What are the metrics
 - Establishing baselines & benchmarks
 - Model training/exploration
 - Approaching ML in Senior Design
- Different roles in the ML field



Approaching an ML Solution: **Human Performance**

- Using the data & metrics defined previously, how does a human measure on the task?
- What is needed to collect this data?

- Ensures you can evaluate your system
- Sets a bar for performance to aim for (higher precision, higher recall, faster)



Approaching an ML Solution: Quick Baseline

- What is the simplest approach we can take to solve this problem? (Almost always logistic regression, xgboost, non deep learning or ml techniques)
- How does the simple approach measure up?

- Helps build out pipeline for evaluation without focusing on experimentation
- Can be used as a placeholder while building out the engineering system
- Sets a minimum bar for performance
- Identifies the gap between humans & ml



Approaching an ML Solution: Upper Bound Baseline

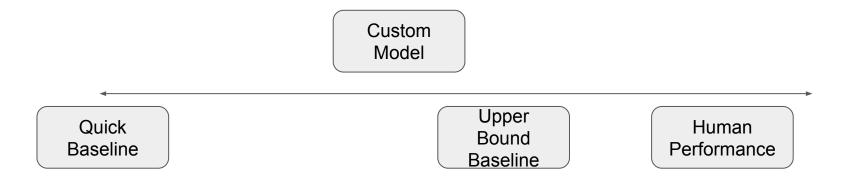
- If compute/money was no object, how would we do? (Throw an LLM at the problem)
- How does zero shot vs few shot affect results?

- Sets a pseudo-upper bound to expected ML performance
- Helps you understand tradeoffs between "accuracy" metrics & performance metrics



Approaching an ML Solution: Experiment!

- You've done your homework, now train your own model



 \equiv

ML in Senior Design

- Identify if ML is the right solution to your problem

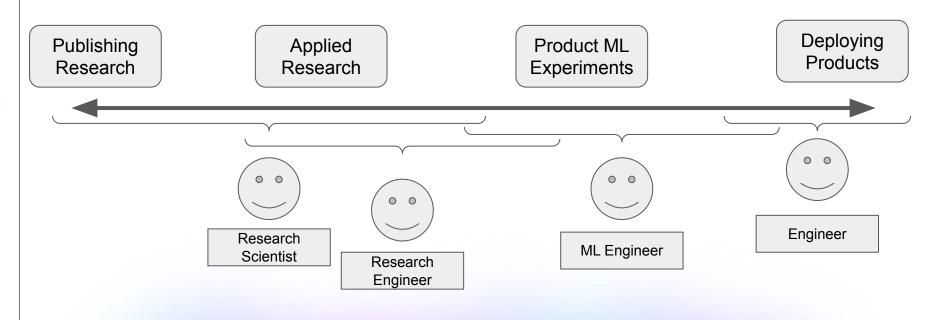
- It is not enough to integrate ML into your solution – you must be able to explain why it is necessary / how much it helps

- Creating a full eval pipeline can be time consuming. Up to your team whether or not this is something worth prioritizing.

- How to tell if a problem is well-suited for an ML solution
- How to approach an ML solution (an ML TDD)
 - Defining the input/output
 - What is your data
 - What are the metrics
 - Establishing baselines & benchmarks
 - Model training/exploration
 - Approaching ML in Senior Design
- Different roles in the ML field



Roles in the ML field





Research Scientist

Expectations:

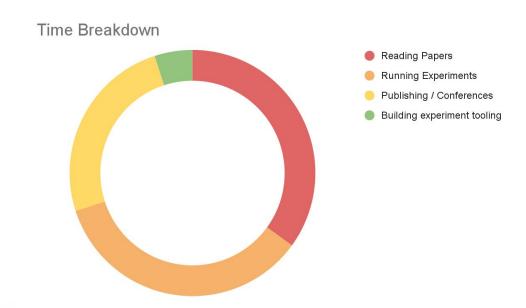
- Publish papers
- Create patents
- Novel ideas 1-2 years out

Challenges:

- Running lots of experiments & analyzing results
- Getting eng / infra help for experimentation
- Compute
- Working with teams to get data

Teams:

- Research engineers
- ML engineers
- Data science





Research Engineer

Expectations:

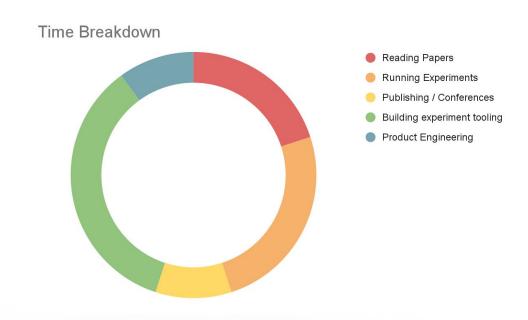
- Make experimentation easier
- Novel ideas 6-12 months out
- Publish papers/patents

Challenges:

- Build infra for research scientists
- Act as liaison between ml & research

Teams:

- Research scientists
- ML engineers
- Data science
- Product





ML Engineer

Expectations:

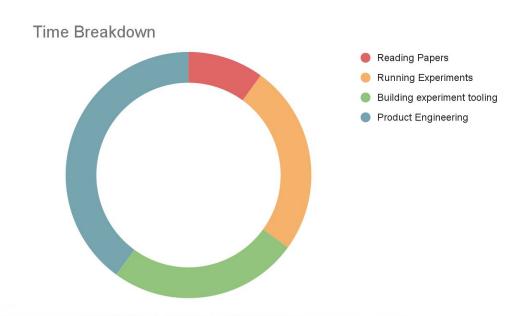
- Productionize applied research
- Build ml services
- Short-term experiments (1-2 months out)
- Monitor ml services

Challenges:

- Convert product ideas to ml problems
- Identify how to safely deploy ml models

Teams:

- Research engineers
- Data science
- Product engineers
- Product





Tools & Technologies used

Programming Languages: Python, C++, Cuda

ML Frameworks: PyTorch, Jax, sklearn

Common Libraries: Hugging Face, Pytorch Lightning, Pandas, Numpy

Experiment Tracking: Weights & Biases, MLFlow, Tensorboard

Other Technologies: Docker, Kubernetes, SQL, Airflow/Prefect

Agenda

- Senior Design High Level Timeline
- Github Projects Setup & Sprint Progress Expectations
- ML Project Design
- Tech Lab Overview



Tech Labs

- You'll likely be using technologies you aren't familiar with to complete your SD project
- It can be difficult knowing where to start and finding time to go through introductory tutorials
- Individuals usually run into similar problems with setup, but hit them at different times during the project.
- Setting up your development environment can take time, this forces you to do so early on in the semester.

You'll spend next week's lab choosing a high-level topic to focus on, and spend a few hours completing a tutorial.



Tech Labs - Requirements

- 1. You can work on these labs together, but each student must submit their own code
- 2. Each team must complete at least 2 different tutorials (not everyone can work on the same thing)
- 3. You can choose one of the suggested topics, or choose your own



Tech Labs - Topics

- 1. Backends:
 - a. Python backend web app (django, flask, fastapi)
 - b. Node.js / Express.js
- 2. Frontends:
 - a. React
 - b. iOS
 - c. Android
- 3. ML
 - a. Google Colab
 - b. Pytorch
 - c. sklearn
- 4. IoT, Raspberry Pi, Arduino

Tech Labs - Python Web Apps

Common python frameworks for creating backends

1. Django

- Full-featured all-in-one web framework. Includes ORM, authentication, admin UI, etc
- Suitable for complex web applications, but comes with a steep learning curve

2. Flask

- Lightweight library good for rapid development
- Lacks a ton of built-in features, relies on additional extension libraries

3. FastAPI

- Modern, asynchronous python framework good for rapid prototyping
- Relies on type annotations for I/O interface, self-documenting
- Relatively new, might lack mature solutions



Tech Labs - Python Web Apps

Choose a framework and complete at least the first tutorial

- 1. Django
 - https://docs.djangoproject.com/en/5.0/intro/tutorial01/ (parts 1-4)
 - https://code.visualstudio.com/docs/python/tutorial-django
- 2. Flask
 - https://flask.palletsprojects.com/en/3.0.x/tutorial/
 - https://code.visualstudio.com/docs/python/tutorial-flask
- 3. FastAPI
 - https://fastapi.tiangolo.com/tutorial/ (basic & advanced tutorial)
 - https://www.tutorialspoint.com/fastapi/index.htm
 - https://code.visualstudio.com/docs/python/tutorial-fastapi



Tech Labs - Node.js / Express.js

If you're familiar with javascript, you can write your backend in javascript as well

Node.js: javascript runtime allowing developers to run javascript server-side

Express.js: a minimal, flexible web app framework for Node.js

Choose one of the following (do both if you have time)

- https://codexam.vercel.app/docs/project/xt/xt1
- https://codexam.vercel.app/docs/project/mernchat (fullstack + db + react)



Tech Labs - Front Ends

- **React**: common front end for web-apps, written in javascript

- **iOS**: mobile operating system in the Apple ecosystem. Defines a framework for developing mobile apps, written in Swift. Used for frontend, can also be used for backend.

- **Android**: mobile operating system from Google. Defines a framework for developing mobile apps. Used for frontend, can also be used for backend.

Tech Labs - Front Ends

- **React**: (choose one, do both if you have time)
 - https://react.dev/learn/tutorial-tic-tac-toe
 - https://www.freecodecamp.org/news/react-tutorial-build-a-project/
 - https://codexam.vercel.app/docs/project/mernchat (fullstack + db + react)
- **iOS**: (complete the first, get as far as you can in the second)
 - https://www.swift.org/getting-started/swiftui/ (focused on swift ui)
 - https://developer.apple.com/tutorials/app-dev-training (thorough but very long, won't finish)
- Android:
 - https://developer.android.com/get-started/overview



Tech Labs - ML

Complete the intro to Google Colab tutorial. Then choose at least one of the pytorch tutorials OR the sklearn tutorials.

- Google Colab: web-based jupyter notebook that provides free access to gpu compute
 - https://colab.research.google.com/# (intro to colab)
- Sklearn: library providing non-deep learning ml algorithms + training utilities
 - https://colab.research.google.com/github/jakevdp/PythonDataScienceHandbook/blob/master/notebooks/05.02-Introducing-Scikit-Learn.ipynb
- **PyTorch**: library for deep learning commonly used in industry
 - https://pytorch.org/tutorials/beginner/basics/intro.html
 - https://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.html
 - https://colab.research.google.com/github/phlippe/uvadlc_notebooks/blob/master/docs/tutorial_notebooks/blob/master/docs/tutorial_notebooks/tutorial_notebooks/blob/master/docs/tutorial_notebooks/blob/ma
- Datascience handbook: useful resource on ml & datascience as a whole
 - https://github.com/jakevdp/PythonDataScienceHandbook/tree/master



Tech Labs - IoT / Raspberry Pi / Arduino / etc

- Any tutorials with a hardware component. Bring your own hardware and we're happy to help!
 - Arduino: https://docs.arduino.cc/built-in-examples/
 - Raspberry Pi: https://tutorials-raspberrypi.com/
- ROS: robotic operating system used as part of the RTX projects
 - https://www.youtube.com/watch?v=979IZWOXC_0&list=PL8MgID9MCju0GMQDTWzYmfiU3w Y_Zdjl5

.

For Next Week

- Complete weekly status update (get into the habit, it's ok if you don't have much to report)
- Create September sprint tasks that would be useful for your project
- Submit Resume (blackboard)
- Continue refining project ideas
- Decide which tech lab(s) you'll focus on next week

