Machine Learning in Production

Motivation, Syllabus, and Introductions

Catastrophic Success

The Waitlist Situation

Waitlist unlikely to fully clear

For those joining late:

- Record early lectures
- Extension for Homework 1

Finalizing enrollment on Sep 7 (start of group projects)

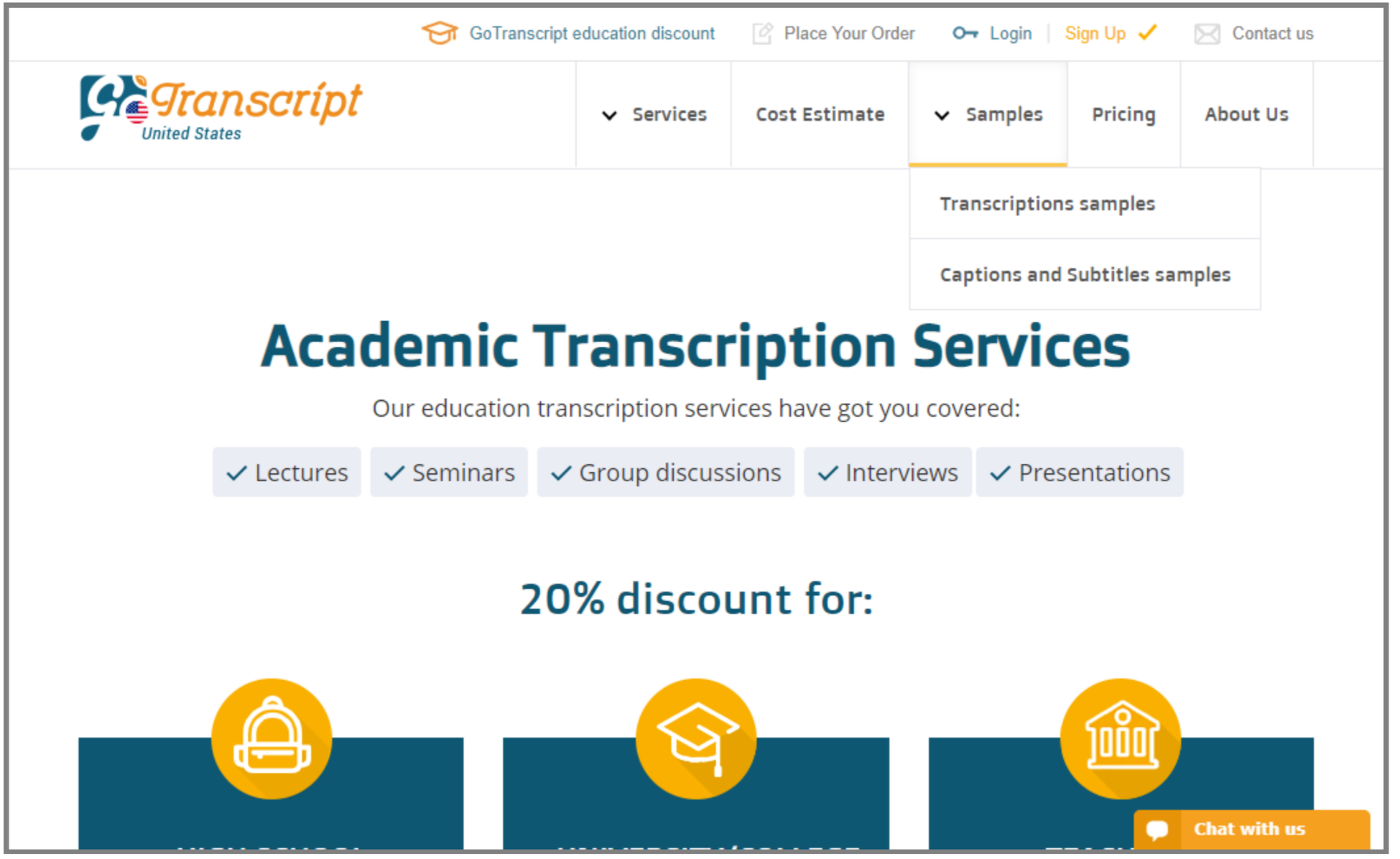
Learning Goals

- Understand how ML components are parts of larger systems
- Illustrate the challenges in engineering an ML-enabled system beyond accuracy
- Explain the role of specifications and their lack in machine learning and the relationship to deductive and inductive reasoning
- Summarize the respective goals and challenges of software engineers vs data scientists
- Explain the concept and relevance of "T-shaped people"

Agenda Today

1. Preliminaries (just done)
2. Case Study
3. Syllabus
4. Introductions

Case Study: A Transcription Service Startup


GoTranscript education discount
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Our education transcription services have got you covered:
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Transcription services

Take audio or video files and produce text.

- Used by academics to analyze interview text
- Podcast show notes
- Subtitles for videos

State of the art a few years ago: Manual transcription, often mechanical turk (1.5 $/min)

Recently: Many ML models for transcription (e.g., in Youtube, Alexa, Siri, Zoom)

The startup idea

PhD research on domain-specific speech recognition, that can detect technical jargon

DNN trained on public PBS interviews + transfer learning on smaller manually annotated domain-specific corpus

Research has shown amazing accuracy for talks in medicine, poverty and inequality research, and talks at Ruby programming conferences; published at top conferences

Idea: Let's commercialize the software and sell to academics and conference organizers

Breakout: Likely challenges in building commercial product?

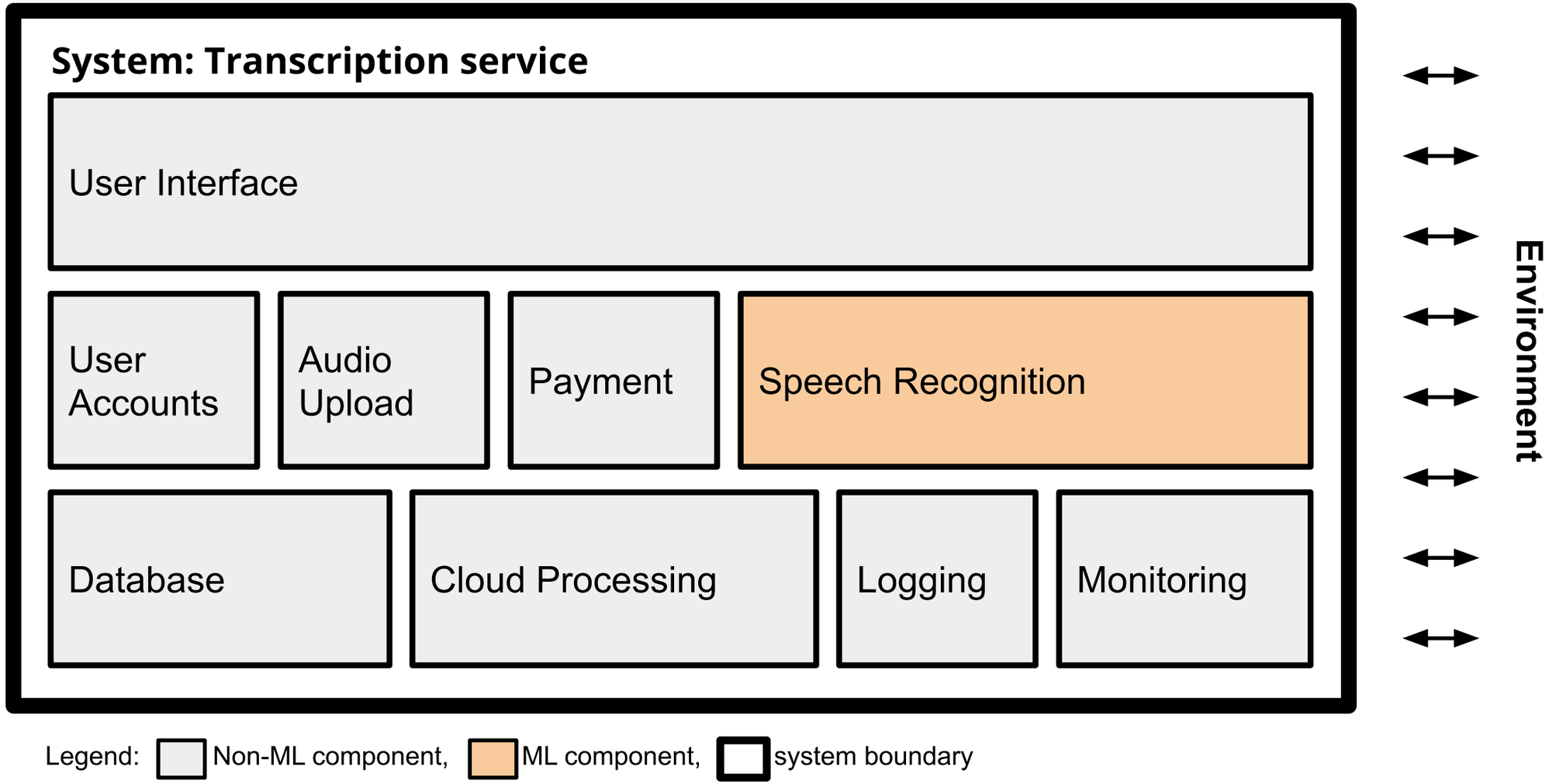
As a group, think about challenges that the team will likely focus when turning their research into *a product*:

- One machine-learning challenge
- One engineering challenge in building the product
- One challenge from operating and updating the product
- One team or management challenge
- One business challenge
- One safety or ethics challenge

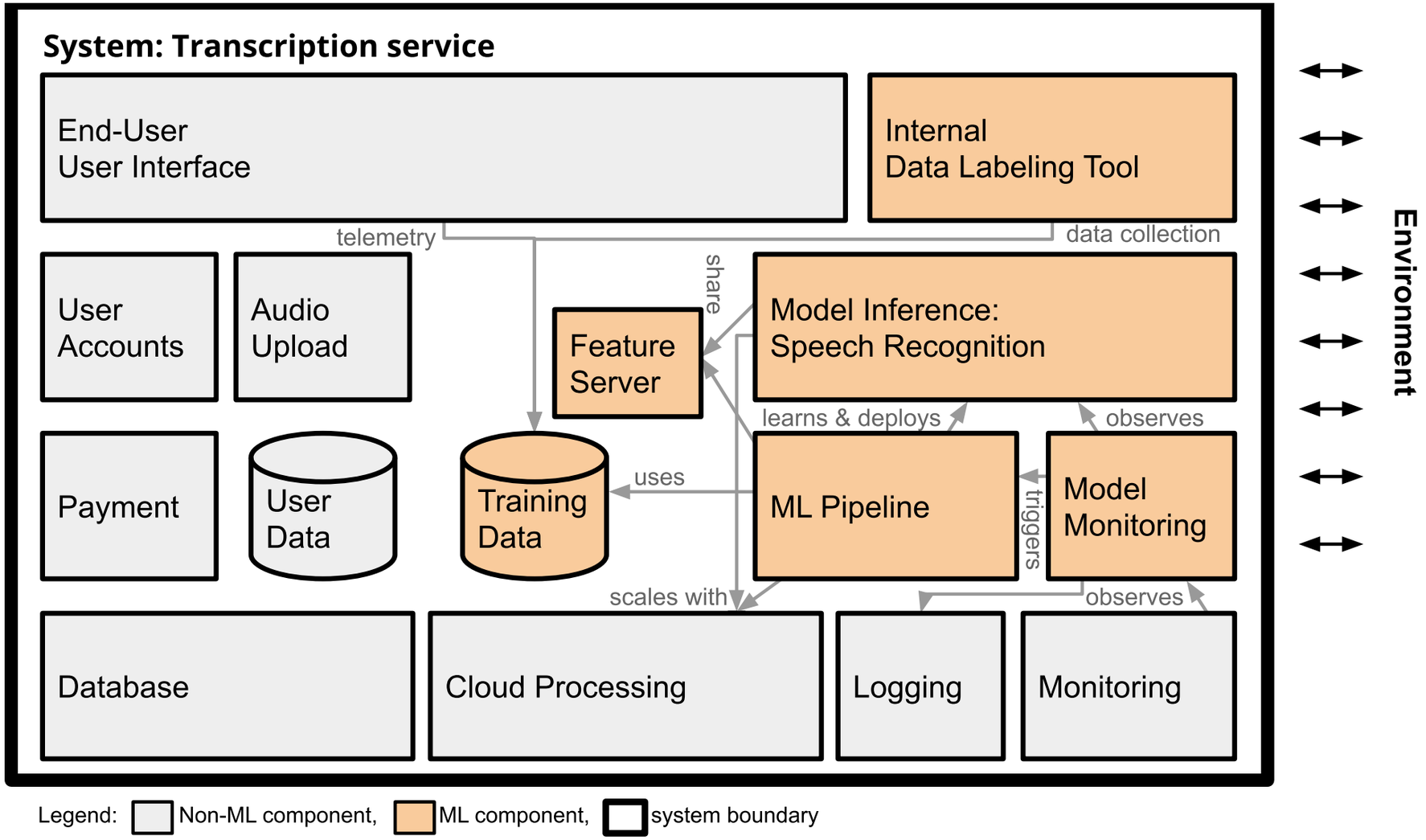
Post answer to `#lecture` on Slack and tag all group members

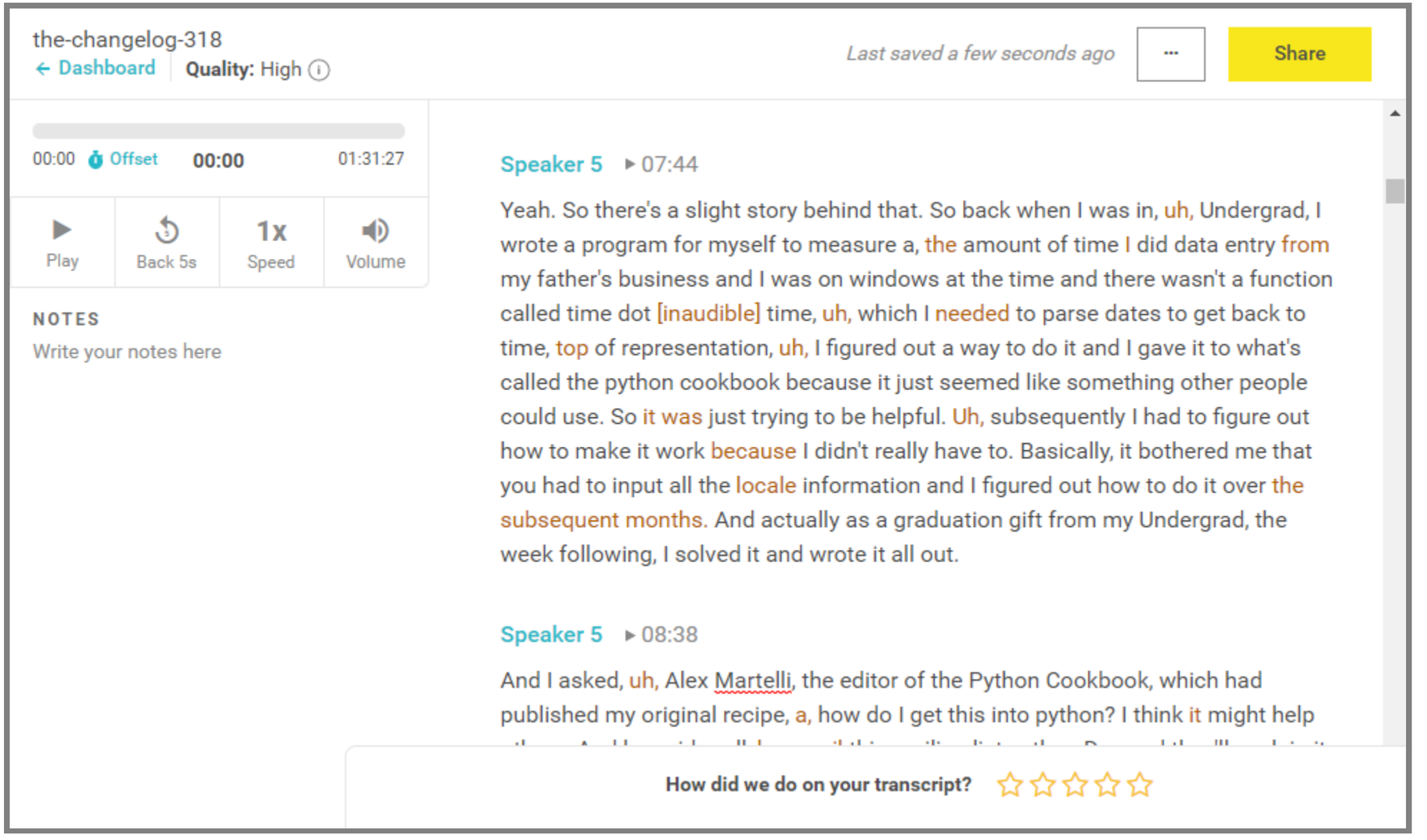
What qualities are important for a good commercial transcription product?

ML in a Production System



ML in a Production System




the-changelog-318
← Dashboard
Quality: High
Last saved a few seconds ago
Share
00:00
Offset
00:00
01:31:27
Play
Back 5s
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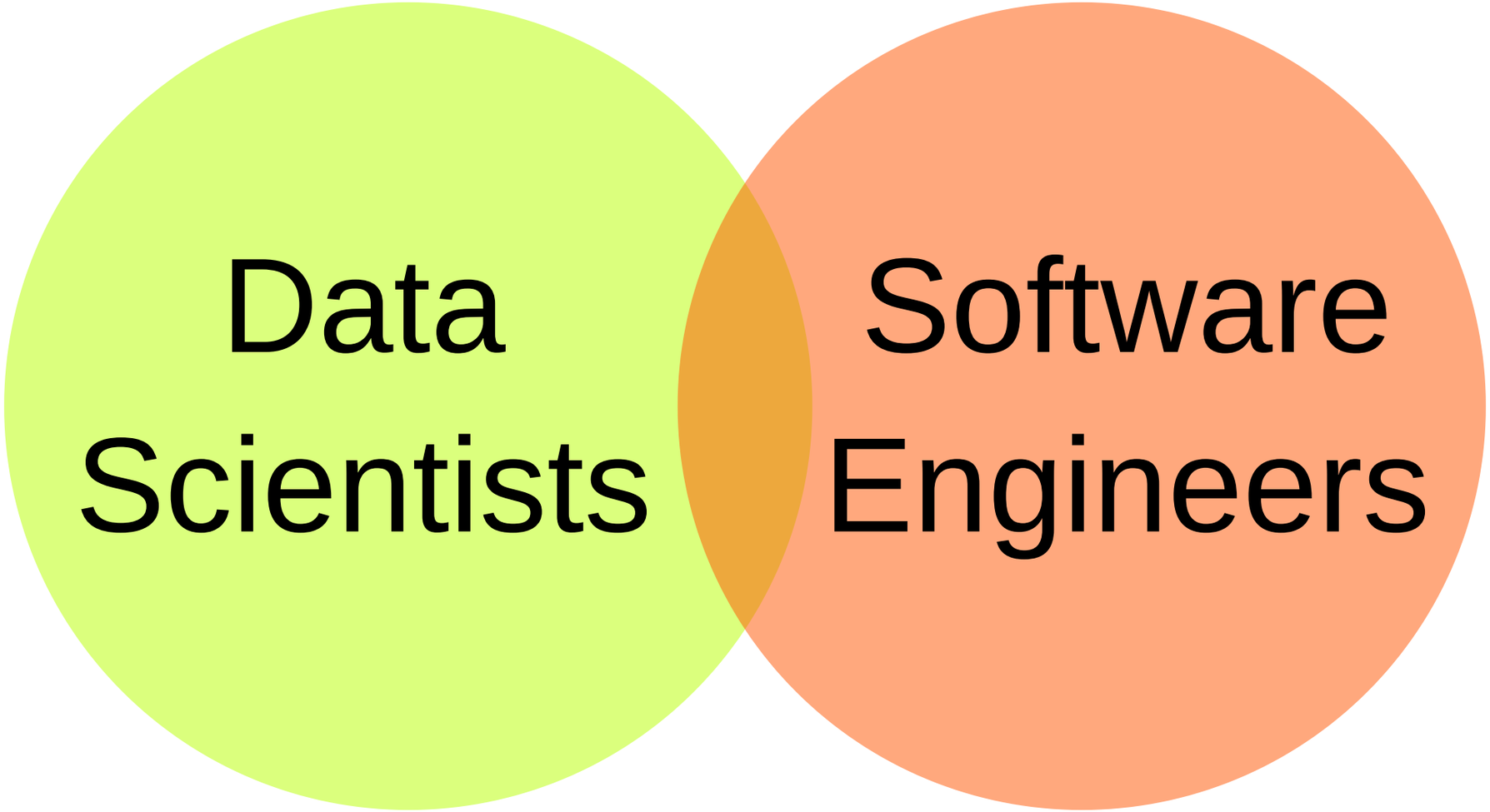
NOTES
Write your notes here
Speaker 5 ▸ 07:44
Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed to parse dates to get back to time, top of representation, uh, I figured out a way to do it and I gave it to what's called the python cookbook because it just seemed like something other people could use. So it was just trying to be helpful. Uh, subsequently I had to figure out how to make it work because I didn't really have to. Basically, it bothered me that you had to input all the locale information and I figured out how to do it over the subsequent months. And actually as a graduation gift from my Undergrad, the week following, I solved it and wrote it all out.
Speaker 5 ▸ 08:38
And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help
How did we do on your transcript?

Speaker notes

Highlights challenging fragments. Can see what users fix inplace to correct. Star rating for feedback.



and Data engineers + Domain specialists + Operators + Business team + Project managers + Designers, UI Experts + Safety, security specialists + Lawyers + Social scientists + ...

Data scientist

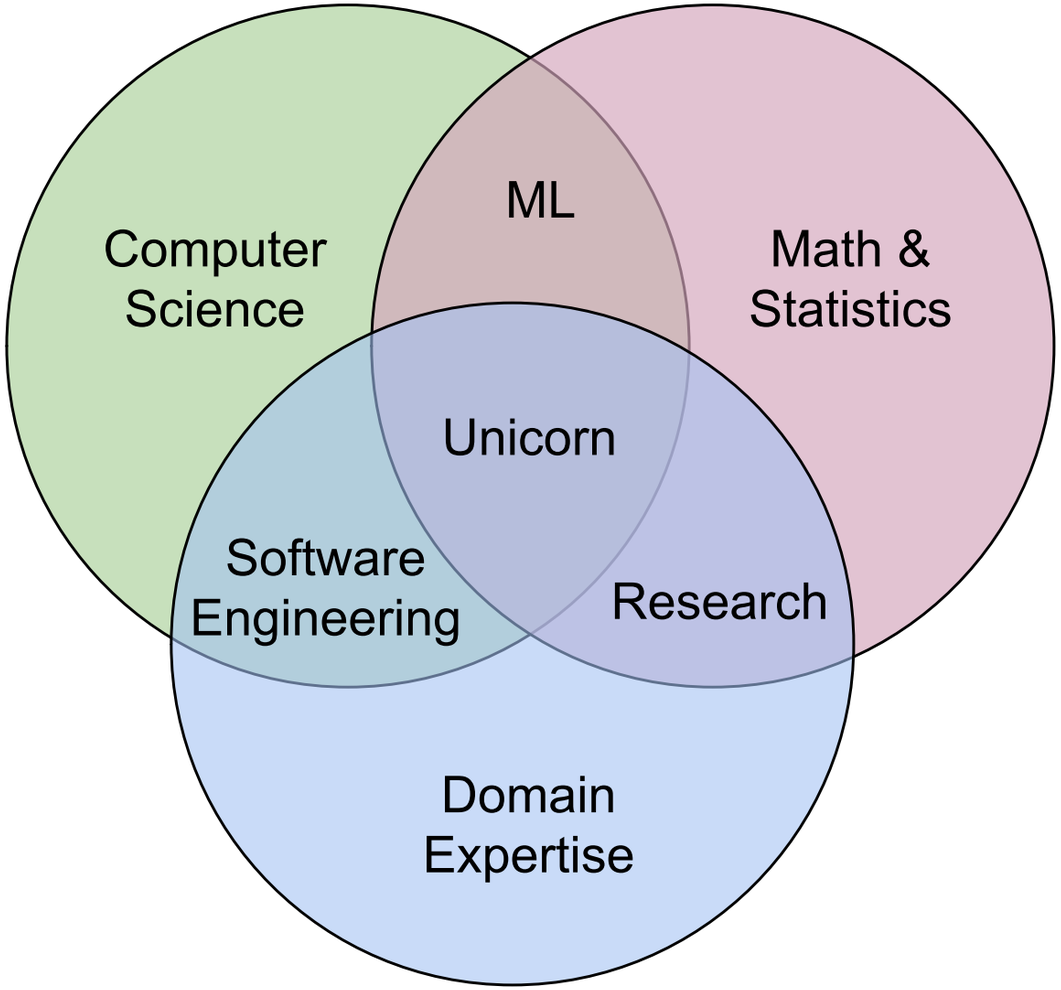
- Often fixed dataset for training and evaluation (e.g., PBS interviews)
- Focused on accuracy
- Prototyping, often Jupyter notebooks or similar
- Expert in modeling techniques and feature engineering
- Model size, updateability, implementation stability typically does not matter

Software engineer

- Builds a product
- Concerned about cost, performance, stability, release time
- Identify quality through customer satisfaction
- Must scale solution, handle large amounts of data
- Detect and handle mistakes, preferably automatically
- Maintain, evolve, and extend the product over long periods
- Consider requirements for security, safety, fairness

Likely collaboration challenges?

What might Software Engineers and Data Scientists Focus on?



By Steven Geringer, via Ryan Orban. Bridging the Gap Between Data Science & Engineer: Building High-Performance Teams. 2016

T-Shaped People

Broad-range generalist + Deep expertise

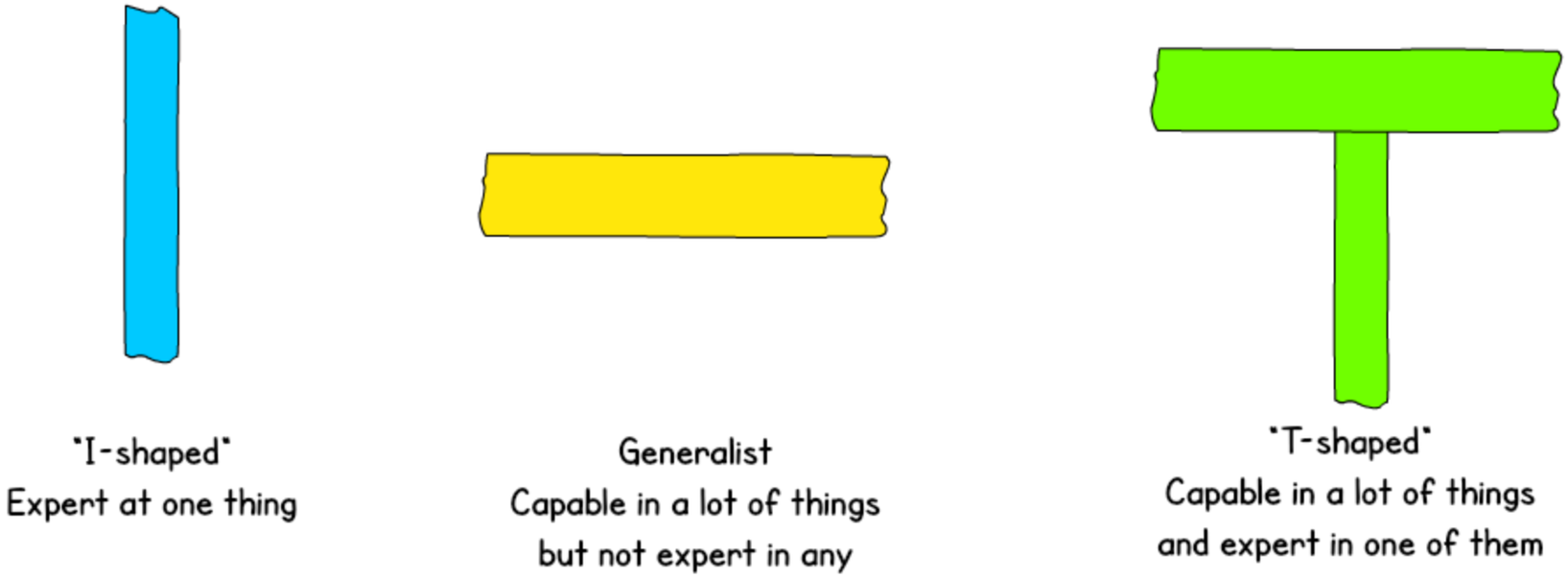


Figure: Jason Yip. Why T-shaped people?. 2018

T-Shaped People

Broad-range generalist + Deep expertise

Example:

- Basic skills of software engineering, business, distributed computing, and communication
- Deep skills in deep neural networks (technique) and medical systems (domain)

Examples for discussion

- What does correctness or accuracy really mean? What accuracy do customers care about?
- How can we see how well we are doing in practice? How much feedback are customers going to give us before they leave?
- Can we estimate how good our transcriptions are? How are we doing for different customers or different topics?
- How to present results to the customers (including confidence)?
- When customers complain about poor transcriptions, how to prioritize and what to do?

- What are unacceptable mistakes and how can they be avoided? Is there a safety risk?
- Can we cope with an influx of customers?
- Will transcribing the same audio twice produce the same result? Does it matter?
- How can we debug and fix problems? How quickly?

Examples for discussion 2

- With more customers, transcriptions are taking longer and longer -- what can we do?
- Transcriptions sometimes crash. What to do?
- How do we achieve high availability?
- How can we see that everything is going fine and page somebody if it is not?
- We improve our entity detection model but somehow system behavior degrades... Why?
- Tensorflow update; does our infrastructure still work?
- Once somewhat successful, how to handle large amounts of data per day?
- Buy more machines or move to the cloud?

- Models are continuously improved. When to deploy? Can we roll back?
- Can we offer live transcription as an app? As a web service?
- Can we get better the longer a person talks? Should we then go back and reanalyze the beginning? Will this benefit the next upload as well?

Examples for discussion 3

- How many domains can be supported? Do we have the server capacity?
- How specific should domains be? Medical vs "International Conference on Allergy & Immunology"?
- How to make it easy to support new domains?

- Can we handle accents?
- Better recognition of male than female speakers?

- Can and should we learn from customer data?
- How can we debug problems on audio files we are not allowed to see?
- Any chance we might private leak customer data?
- Can competitors or bad actors attack our system?

Syllabus and Class Structure

17-445/17-645/17-745, Fall 2022, 12 units

Monday/Wednesdays 1:25-2:45pm

Recitation Fridays 10:10-11:00am / 1:25-2:45pm

Instructors

Christian Kaestner

Priyank Bhandia

Ranadeep Singh

Tianye Song

Communication

- Email us or ping us on Slack (invite link on Canvas)
- Class announcements made through Canvas
- Weekly office hours (see Canvas for schedule)
- Post questions on Slack
  - Please use `#general` or `#assignments` and post publicly if possible; your classmates will benefit from your Q&A!
- All course materials (lectures, assignments, etc.,) available on GitHub and course website. Pull requests encouraged!

Class with software engineering flavor

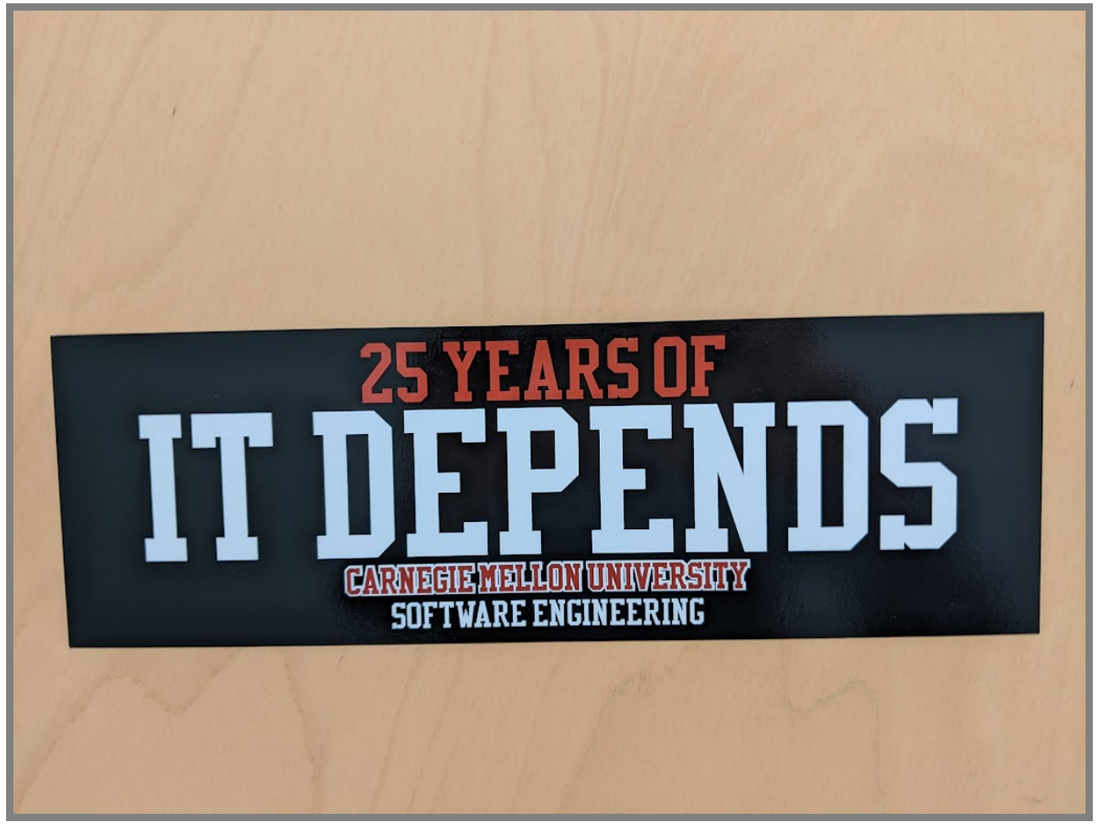
Focused on engineering judgment

Arguments, tradeoffs, and justification, rather than single correct answer

Practical engagement, building systems, testing, automation

Strong teamwork component

Both text-based and code-based homework assignments



Prerequisites

Some machine-learning experience required

- Basic understanding of data science process, incl. data cleaning, feature engineering, using ML libraries
- High level understand of machine-learning approaches
  - supervised learning
  - regression, decision trees, neural networks
  - accuracy, recall, precision, ROC curve
- Ideally, some experience with notebooks, sklearn or other frameworks

Basic programming and command-line skills will be needed

No further software-engineering knowledge required

- Teamwork experience in product team is useful but not required
- No required exposure to requirements, software testing, software design, continuous integration, containers, process management, etc
  - If you are familiar with these, there will be some redundancy -- sorry!

First Homework Assignment

"Coding warmup assignment"

Out now, due Sep 7

Enhance simple web *application* with ML-based feature: Automated image captioning

Open ended coding assignment, change existing code, learn new APIs

Active lecture

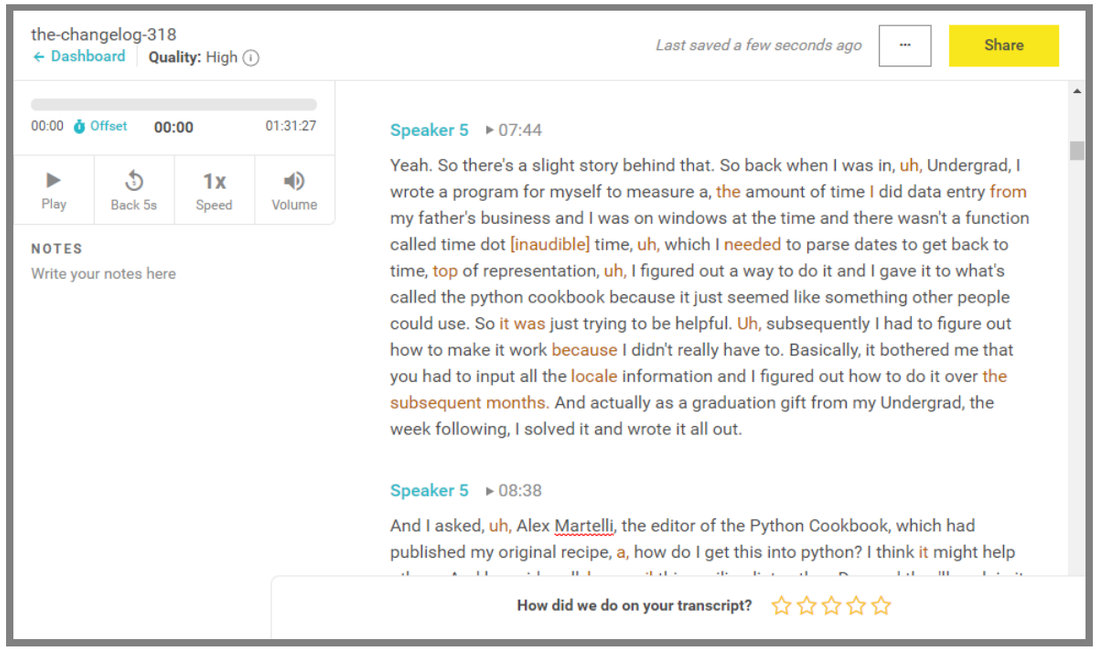
Case study driven

Discussions highly encouraged

Regular in-class activities, breakouts

Contribute your own experience!

Discussions over definitions



Recordings and Attendance

Try to attend lecture -- discussions are important to learning

Participation is part of your grade

No lecture recordings, textbook and slides available

Contact us for accommodations (illness, interview travel, unforseen events) or have your advisor reach out. We try to be flexible

Participation

Participation != Attendance

Grading:

- 100%: Participates at least once in most lectures by (1) asking or responding to questions or (2) contributing to breakout discussions
- 100%: Participates in 25% of lectures and actively contributes to discussions in most recitations
- 90%: Participates at least once in over half of the lectures
- 70%: Participates at least once in 25% of the lectures
- 40%: Participates at least once in at least 3 lectures or recitations.
- 0%: No participation in the entire semester.

Fundamentals of Engineering AI-Enabled Systems

Holistic system view: AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

Requirements:
System and model goals
User requirements
Environment assumptions
Quality beyond accuracy
Measurement
Risk analysis
Planning for mistakes

Architecture + design:
Modeling tradeoffs
Deployment architecture
Data science pipelines
Telemetry, monitoring
Anticipating evolution
Big data processing
Human-AI design

Quality assurance:
Model testing
Data quality
QA automation
Testing in production
Infrastructure quality
Debugging

Operations:
Continuous deployment
Contin. experimentation
Configuration mgmt.
Monitoring
Versioning
Big data
DevOps, MLOps

Teams and process: Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

Responsible AI Engineering

Provenance, versioning, reproducibility

Safety

Security and privacy

Fairness

Interpretability and explainability

Transparency and trust

Ethics, governance, regulation, compliance, organizational culture

Reading Assignments & Quizzes

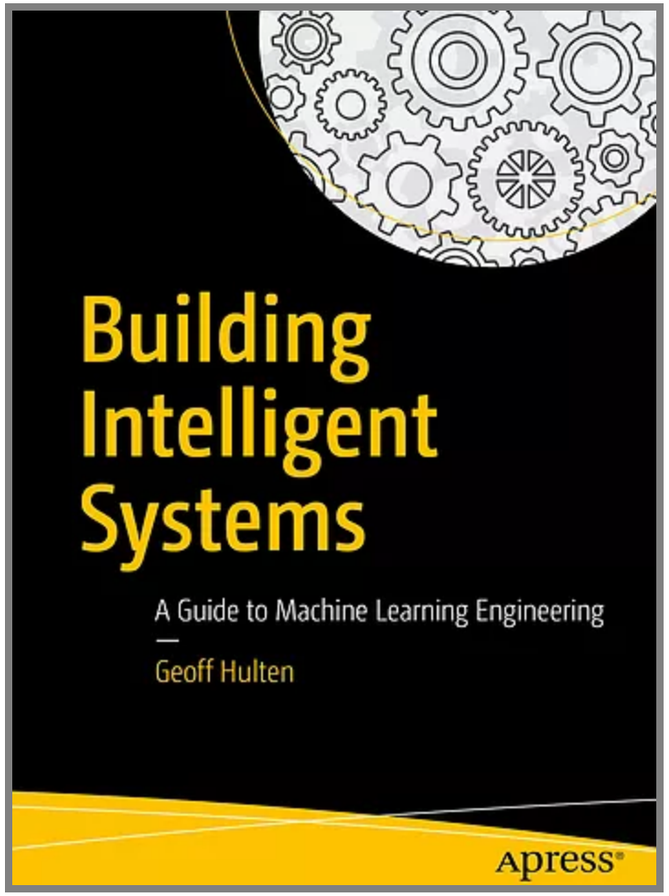
Building Intelligent Systems by Geoff Hulten

https://www.buildingintelligentsystems.com/

Most chapters assigned at some point in the semester

Supplemented with research articles, blog posts, videos, podcasts, …

Electronic version in the library



Reading Quizzes

Short essay questions on readings, due before start of lecture (Canvas quiz)

Planned for: about 30-45 min for reading, 15 min for discussing and answering quiz

Can be done with changing partner (optional)

- Not the same partner for more than 2 weeks
- Suggested partners on Canvas or find your own
- Both submit same answer, name partner in answer

Book for the Class

> *"Machine Learning in Production: From Models to Products"*

Mostly similar coverage to lecture

Not required, use as supplementary reading

Still editing, not all chapters final

Feedback appreciated!

Published online

Assignments

All assignments available on GitHub now

Series of 4 small to medium-sized **individual assignments**:

- Engage with practical challenges
- Analyze risks, fairness
- Reason about tradeoffs and justify your decisions
- Mostly written reports, a little modeling, some coding

Large **team project** with 4 milestones:

- Build and deploy a prediction (movie recommendation) service
- Testing in production, monitoring
- Final presentation

- Usually due Wednesday night; see schedule

17-745 PhD Research Project

Research project instead of individual assignments 3 and 4

Design your own research project and write a report

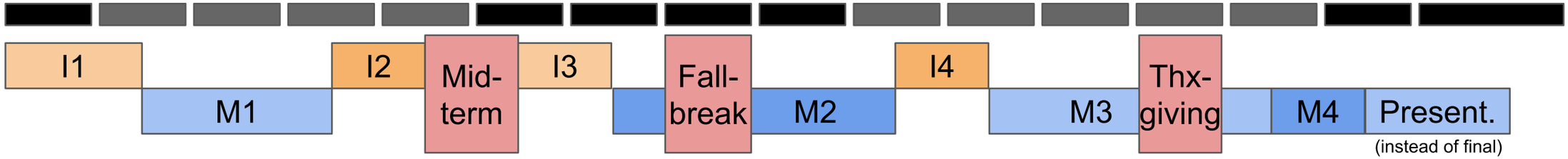
- A case study, empiricial study, literature survey, etc.,

Very open ended: Align with own research interests and existing projects

See the project description and talk to us

Timeline

17-445/17-645



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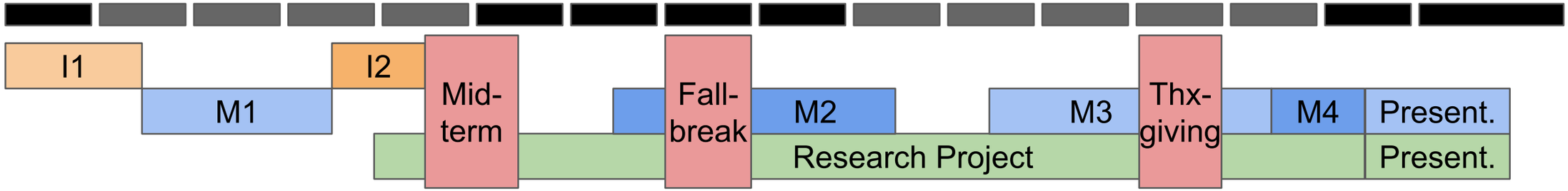


Recitations

Typically hands on exercises, use tools, analyze cases -- bring a laptop

Designed to introduce tools and discuss material relevant for assignments

First recitation on **this Friday**: Git and calling model APIs

Grading

- 40% individual assignment
- 30% group project with final presentation
- 10% midterm
- 10% participation
- 10% reading quizzes
- No final exam (final presentations will take place in that timeslot)

Expected grade cutoffs in syllabus (>82% B, >93 A-, >96% A, >99% A+)

Grading Philosophy

Specification grading, based in adult learning theory

Giving you choices in what to work on or how to prioritize your work

We are making every effort to be clear about expectations (specifications), will clarify if you have questions

Assignments broken down into expectations with point values, each graded **pass/fail**

Opportunities to resubmit work until last day of class

≡ [Example]

Token System for Flexibility

7 individual tokens per student:

- Submit individual assignment 1 day late for 1 token (after running out of tokens 15% penalty per late day)
- Redo individual assignment for 3 token
- Resubmit or submit reading quiz late for 1 token
- Remaining tokens count toward participation

7 team tokens per team:

- Submit milestone 1 day late for 1 token (no late submissions accepted when out of tokens)
- Redo milestone for 3 token

Group project

Instructor-assigned teams

Teams stay together for project throughout semester, starting next week

Fill out Catme Team survey before Sep 6 11:59pm

Some advice in lectures; we'll help with debugging team issues

Peer grading on all milestones (based on citizenship on team)

Bonus points for social interaction in project teams

Academic honesty

See web page

In a nutshell: do not copy from other students, do not lie, do not share or publicly release your solutions

In group work, be honest about contributions of team members, do not cover for others

If you feel overwhelmed or stressed, please come and talk to us (see syllabus for other support opportunities)

What makes software with ML challenging?

ML Models Make Mistakes

NeuralTalk2: A flock of birds flying in the air

Microsoft Azure: A group of giraffe standing next to a tree

Image: Fred Dunn, https://www.flickr.com/photos/gratapictures - CC-BY-NC

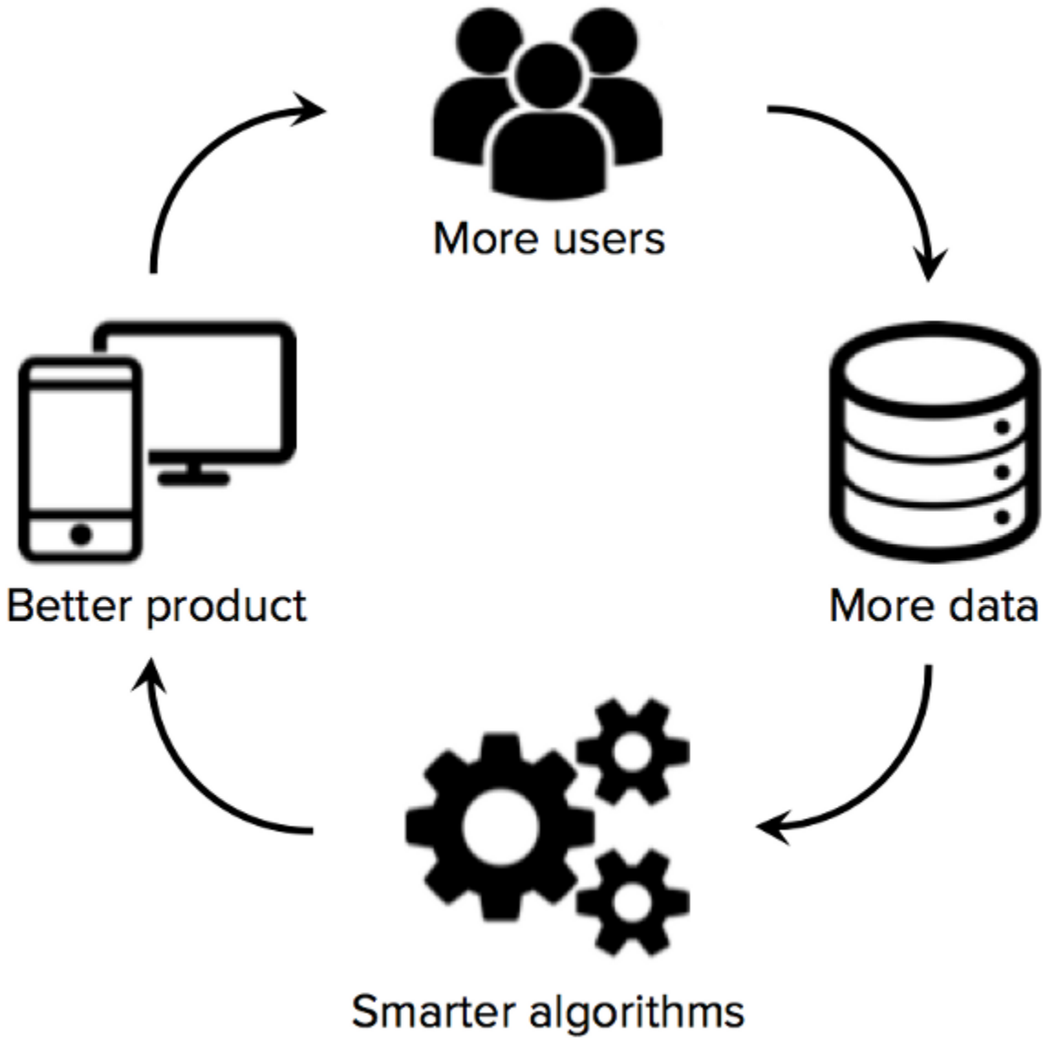
Speaker notes

Source: https://www.aiweirdness.com/do-neural-nets-dream-of-electric-18-03-02/

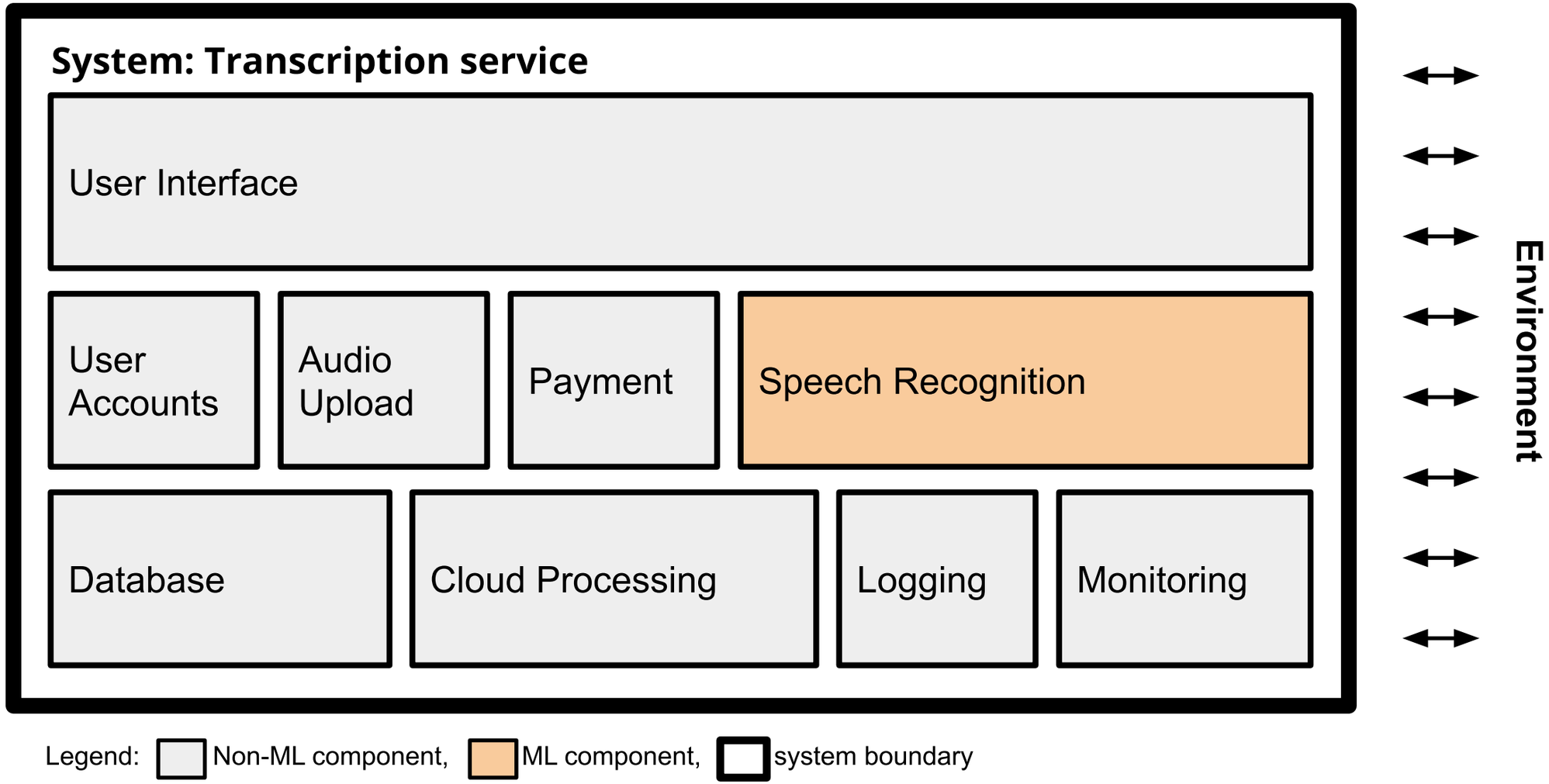
Lack of Specifications

```
/**
  Return the text spoken within the audio file
  ????
*/
String transcribe(File audioFile);
```

Data Focused and Scalable



Interaction with the environment



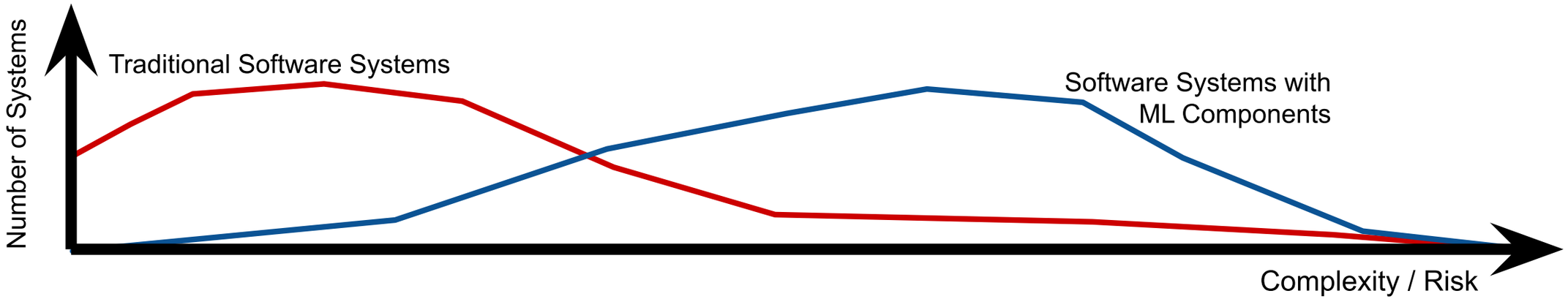
It's not all new

We routinely build:

- Safe software with unreliable components
- Cyberphysical systems
- Non-ML big data systems, cloud systems
- "Good enough" and "fit for purpose" not "correct"

ML intensifies our challenges

Complexity


Number of Systems
Traditional Software Systems
Software Systems with
ML Components
Complexity / Risk

Introductions

Before the next lecture, introduce yourself in Slack channel `#social`:

- Your (preferred) name
- In 1~2 sentences, your data science background and goals (e.g., coursework, internships, work experience)
- In 1~2 sentences, your software engineering background, if any, and goals (e.g., coursework, internships, work experience)
- One topic you are particularly interested in learning during this course?
- A hobby or a favorite activity outside school

Summary

Machine learning components are part of larger systems

Data scientists and *software engineers* have different goals and focuses

- Building systems requires both
- Various qualities are relevant, beyond just accuracy

Machine learning brings new challenges and intensifies old ones