# TEACHING SOFTWARE ENGINEERING FOR AI-ENABLED SYSTEMS

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https://github.com/ckaestne/seai

## SOFTWARE ENGINEERING FOR AI-ENABLED SYSTEMS

## SOFTWARE ENGINEERING FOR AI-ENABLED SYSTEMS!= CODING ML FRAMEWORKS



## SOFTWARE ENGINEERING FOR AI-ENABLED SYSTEMS!= ML4SE

```
import numpy as np

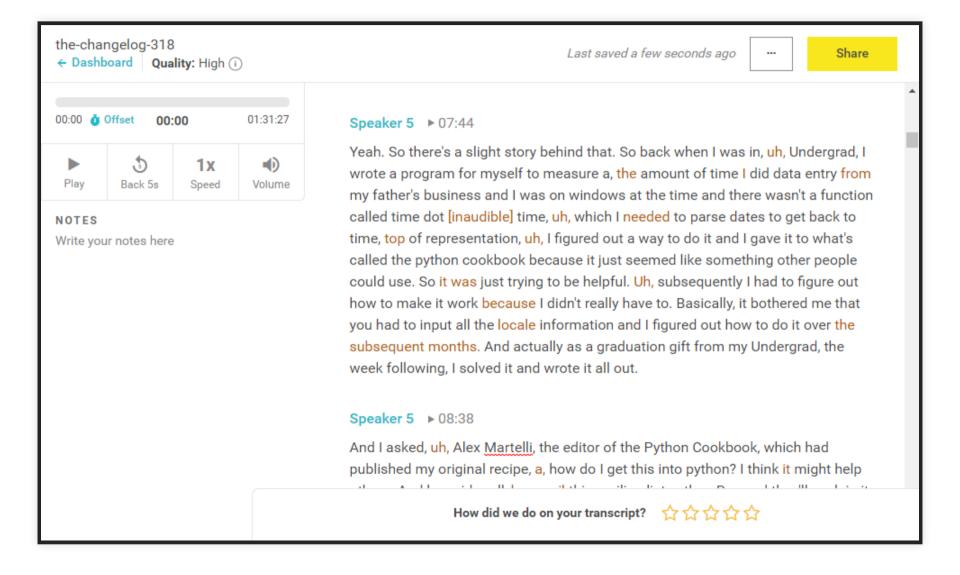
start = -1
stop = 1

import numpy as np

start = -1
stop = 1

flinspace
function
flinspace(start, stop)
function
flinspace(stop, start)
function
flinspace(start, stop, sto... function
flinspace(start, stop, sto... function)
```

# SOFTWARE ENGINEERING FOR AI-ENABLED (AI-ML-BASED, ML-INFUSED) SYSTEMS



(SE 4 ML-enabled systems)

#### **SOFTWARE ENGINEERING**

Software engineering is the branch of computer science that creates practical, cost-effective solutions to computing and information processing problems, preferentially by applying scientific knowledge, developing software systems in the service of mankind.

Engineering judgements under limited information and resources

A focus on design, tradeoffs, and the messiness of the real world

Many qualities of concern: cost, correctness, performance, scalability, security, maintainability, ...

"it depends..."

Mary Shaw. ed. Software Engineering for the 21st Century: A basis for rethinking the curriculum. 2005.

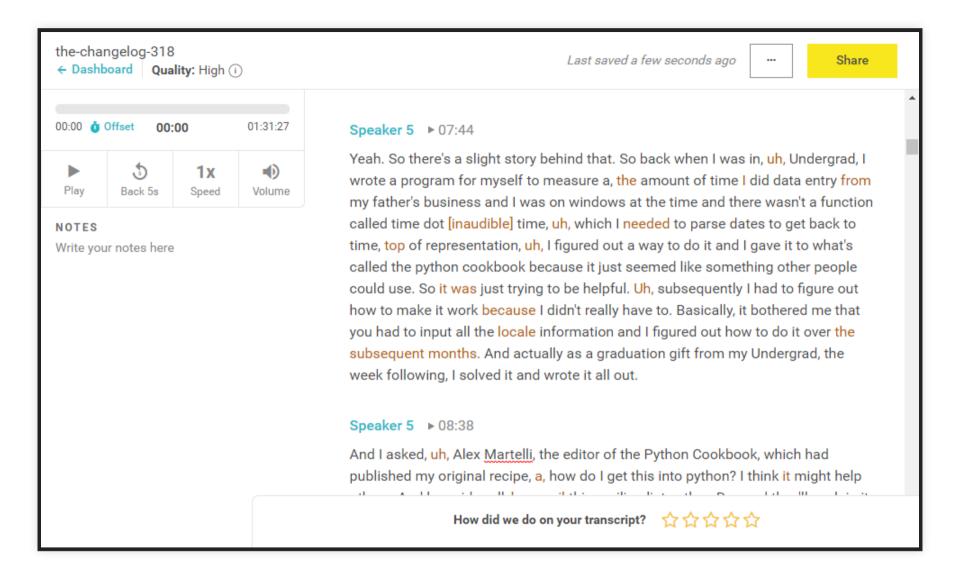
## MOST AI/ML COURSES

Focus narrowly on modeling techniques or building models

Using notebooks, static datasets, evaluating accuracy

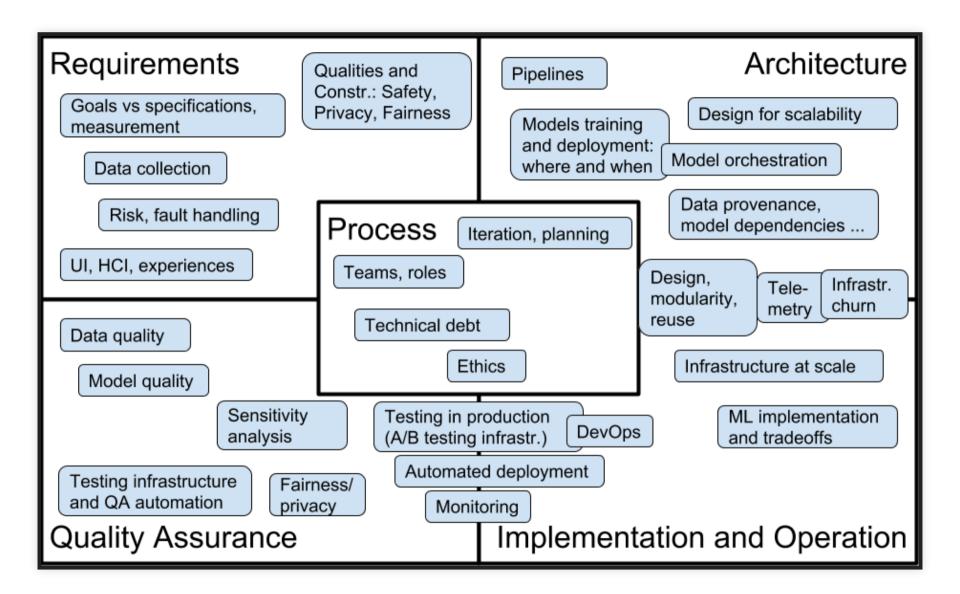
Little attention to software engineering aspects of building complete systems

(see Antonio's talk)



#### **EXAMPLE SOFTWARE ENGINEERING CONCERNS**

- How to build robust AI pipelines and facilitate regular model updates?
- How to deploy and update models in production?
- How to evaluate data and model quality in production?
- How to deal with mistakes that the model makes and manage associated risk?
- How to trade off between various qualities, including learning cost, inference time, updatability, and interpretability?
- How to design a system that scales to large amounts of data?
- How to version models and data?
- How to manage interdisciplinary teams with data scientists, software engineers, and operators?

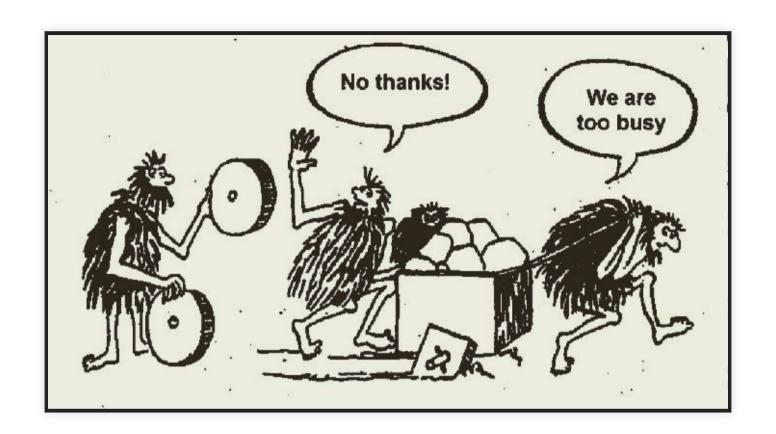


#### WHAT'S DIFFERENT?

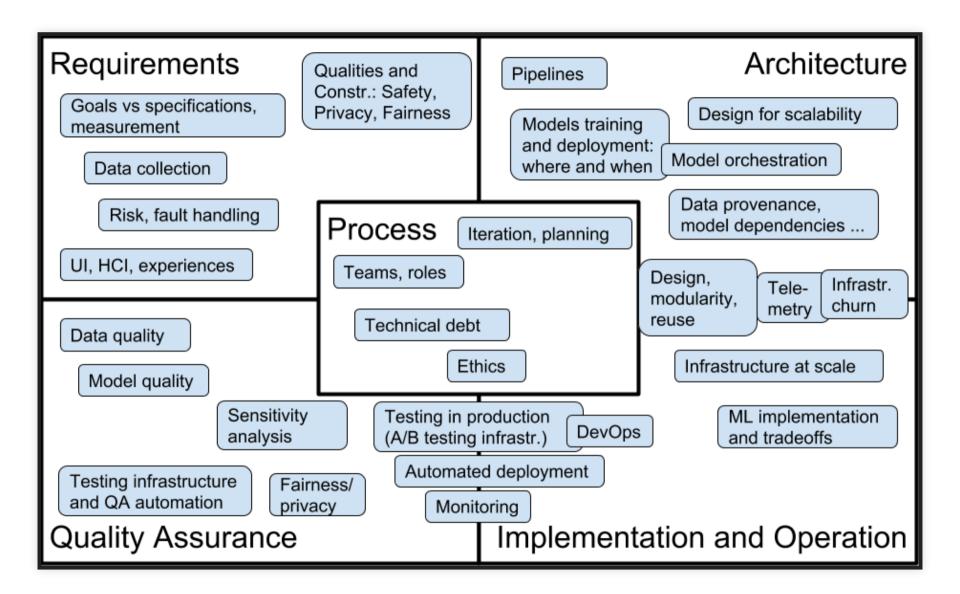
- Missing specifications
- Environment is important (feedback loops, data drift)
- Nonlocal and nonmonotonic effects
- Testing in production
- Data management, versioning, and provenance

#### **REALLY DIFFERENT?**

- Missing specifications -- implicit, vague specs very common; safe systems from unreliable components
- Environment is important -- the world vs the machine
- Nonlocal and nonmonotonic effects -- feature interactions, system testing
- Testing in production -- continuous deployment, A/B testing
- Data management, versioning, and provenance -- stream processing, event sourcing, data modeling



While developers of simple traditional systems may get away with poor practices, most developers of AI-enabled systems will not.

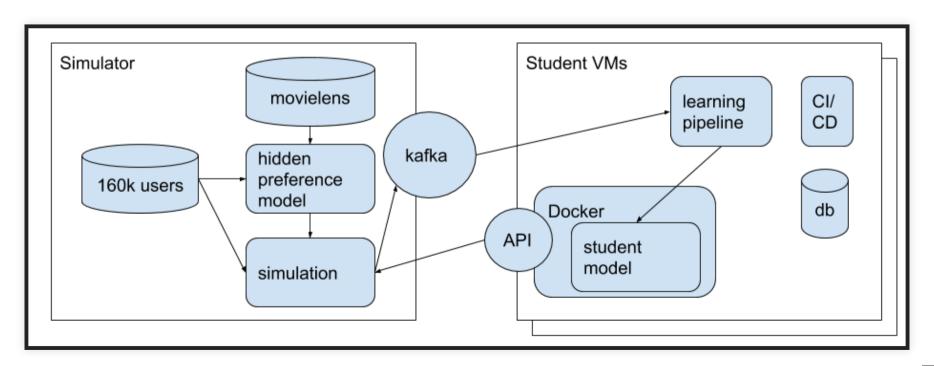


#### **ASSIGNMENTS**

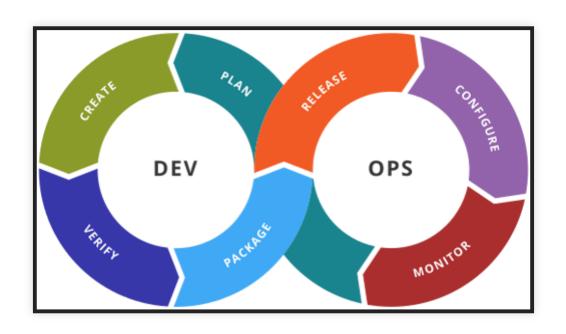
Break the habit of modeling in notebooks on static datasets

Design for realistic "production" setting: deployment, experimentation in production, data drift and feedback loops

Movie recommendation scenario, simulating 160k users watching movies in real time



### **ASIDE: DEVOPS**



#### **READINGS**

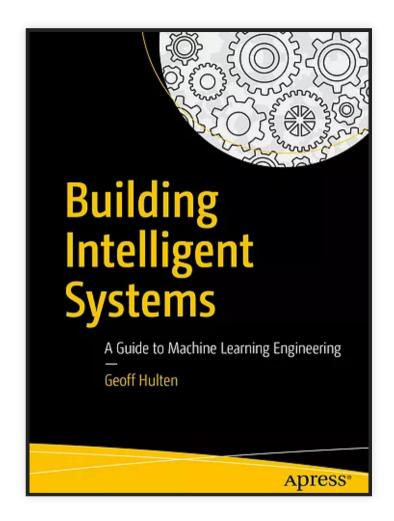
All lecture material (except simulator):

https://github.com/ckaestne/seai

Annotated bibliography:

https://github.com/ckaestne/seaibib

ICSE SEET'20 paper



#### SUGGESTED TOPICS

- Identifying the right requirements for fairness, robustness, privacy, security, usefulness, ...
- Supporting exploratory programming
- Modularity, nonmodularity, and feature interactions
- Versioning of data and models; provenance
- Designing telemetry
- Testing and experimenting in production
- Architectural reasoning and deployment
- Ensuring safety: Designing fallback strategies, railguards, ...
- Designing interactions with users (forcefulness of experience)
- Monitoring, data drift, feedback loops, data quality
- Quality assurance of ML pipeline



