TEACHING SOFTWARE ENGINEERING FOR AI-ENABLED SYSTEMS

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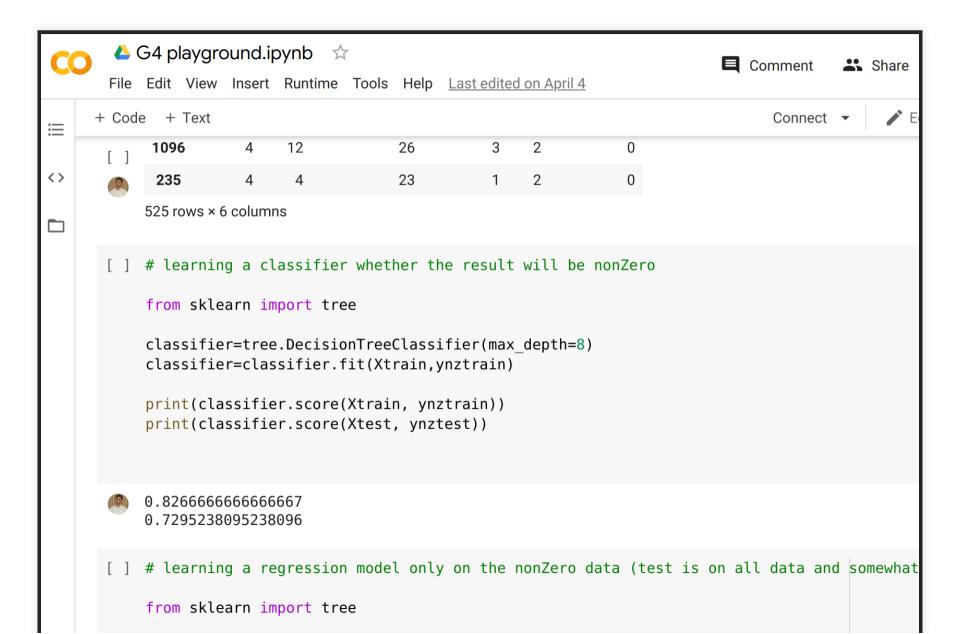
https://ckaestne.github.io/seai/

ICSE-SEET 2020

SOFTWARE ENGINEERING FOR ML-ENABLED SYSTEMS

Building, operating, and maintaining software systems with machine-learned components

SE 4 ML-SYSTEMS != TRAINING MODELS



```
predictor=tree.DecisionTreeRegressor(max_depth=8)
predictor=predictor.fit(XnzTrain,YnzTrain)

print(predictor.score(XnzTrain, YnzTrain))
print(predictor.score(Xtest, ytest))
```



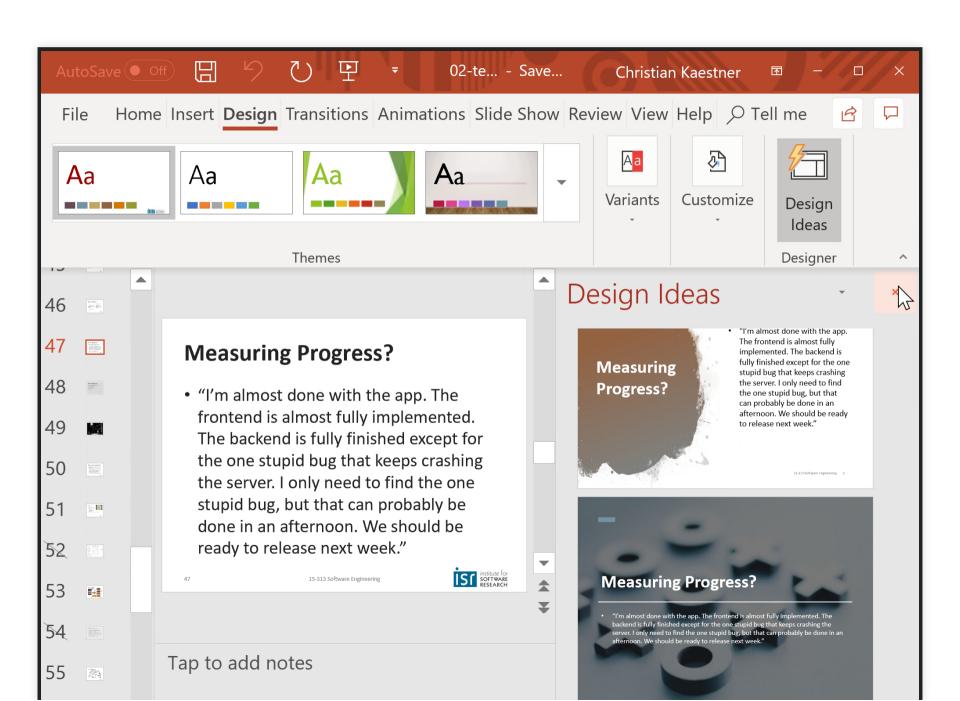
0.9376379365613154
-2.437397740412892

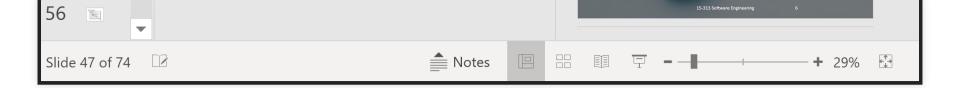
SE 4 ML-SYSTEMS != ML 4 SE

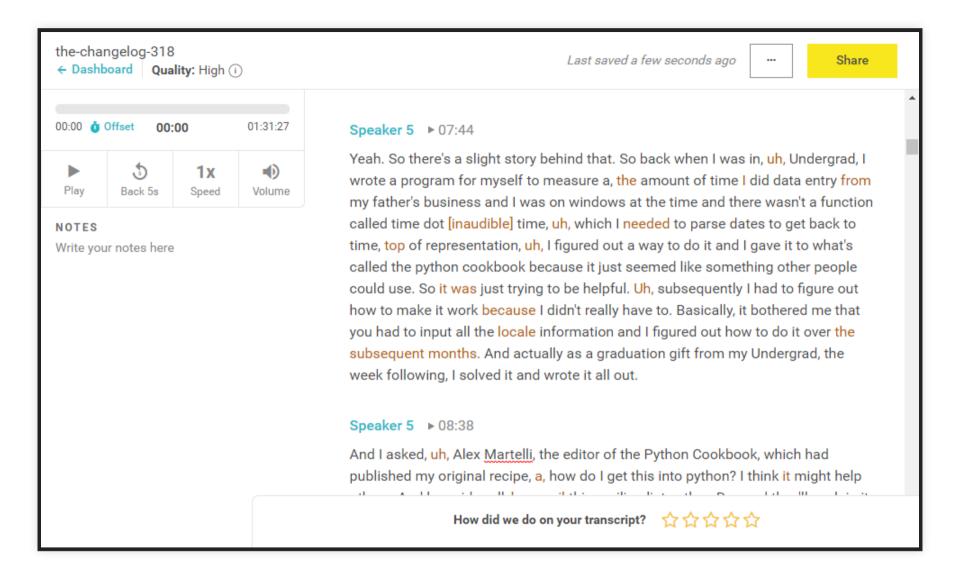
```
import numpy as np

start = -1
stop = 1

flinspace
flinspace(start, stop)
function
flinspace(start, stop, stom function
flinspace(start, stop, stom function)
flinspace(start, stop, stom function)
```







Data Scientists

Software Engineers



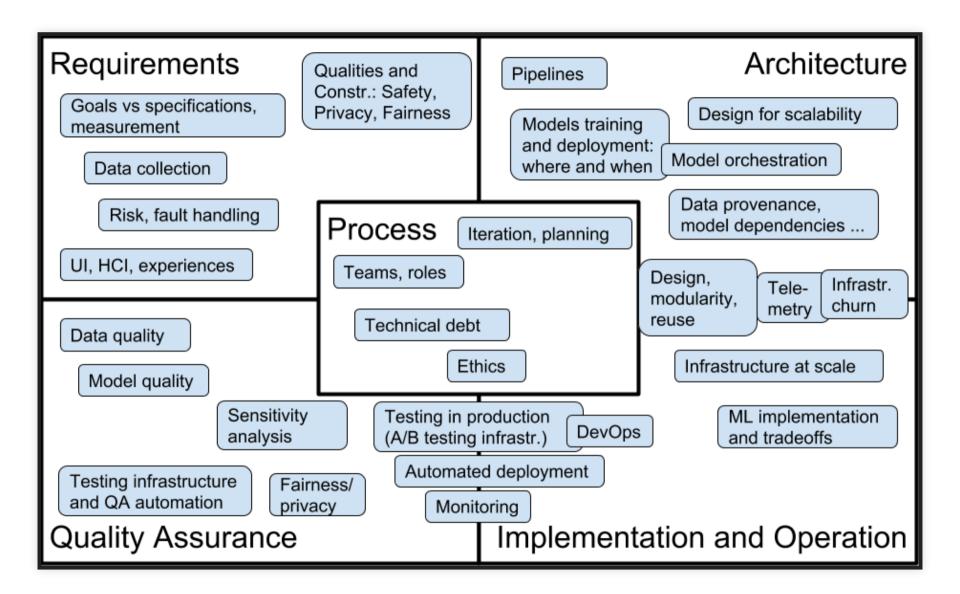
Software Engineers

MANY CHALLENGES

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

SOFTWARE ENGINEERS CAN CONTRIBUTE

- Missing specifications -- *implicit*, *vague specs very common*; *safe systems from unreliable components*, *risk analysis* ("ML is requirements engineering")
- Environment is important -- the world vs the machine (paper)
- 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
- Fairness, robustness, interpretability -- traditional requirements engineering questions



OUR VIEW

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

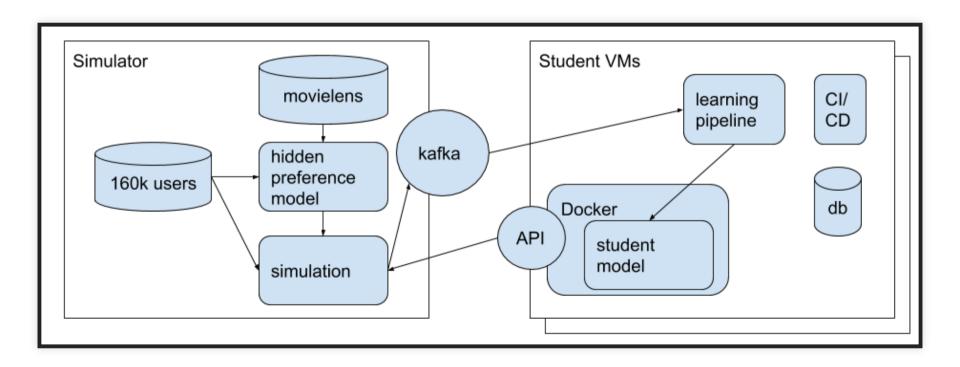
This is an education problem, more than a research problem.

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 recommendations for 1 million simulated users in real time



SUMMARY: SOFTWARE ENGINEERING FOR ML-ENABLED SYSTEMS

- Building, operating, and maintaining systems with ML component
- Data scientists and software engineers have different expertise, both needed
- Software engineering view on intelligent systems:
 - User interaction design
 - Model qualities and deployment tradeoffs
 - Risk analysis and safety
 - Architecture, deployment, telemetry design
 - Quality assurance, fairness, robustness, interpretability
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