# SOFTWARE ENGINEERING FOR ML-ENABLED SYSTEMS

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https://github.com/ckaestne/seai



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Interests:

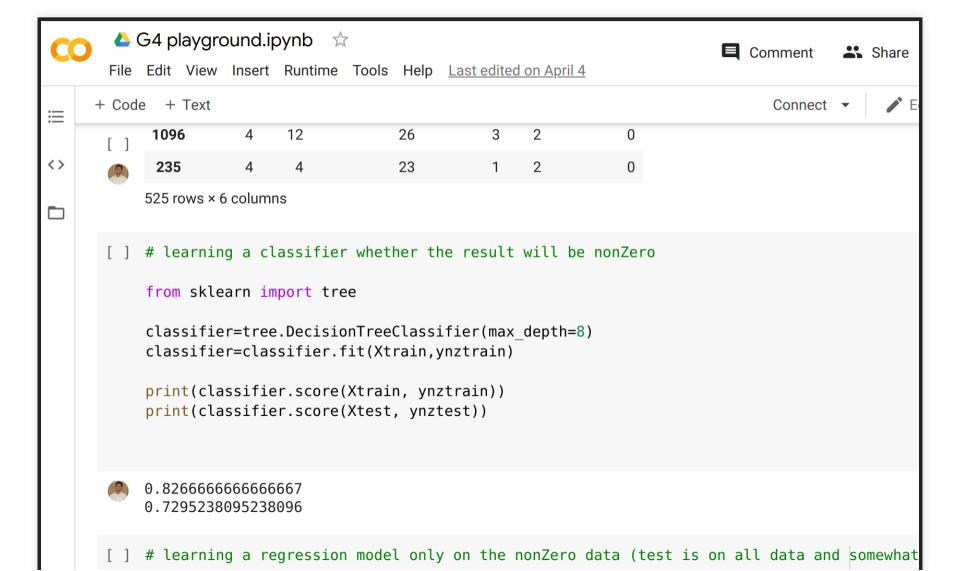
- Software Engineering
- Highly-Configurable Systems & Configuration Engineering
- Sustainability and Stress in Open Source
- Software Engineering for ML-Enabled Systems

## SOFTWARE ENGINEERING FOR ML-ENABLED SYSTEMS

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

with interdisciplinary collaborative teams of data scientists and software engineers

## SE FOR ML-ENABLED SYSTEMS != BUILDING MODELS



```
from sklearn import tree

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 FOR ML-ENABLED SYSTEMS != CODING ML FRAMEWORKS



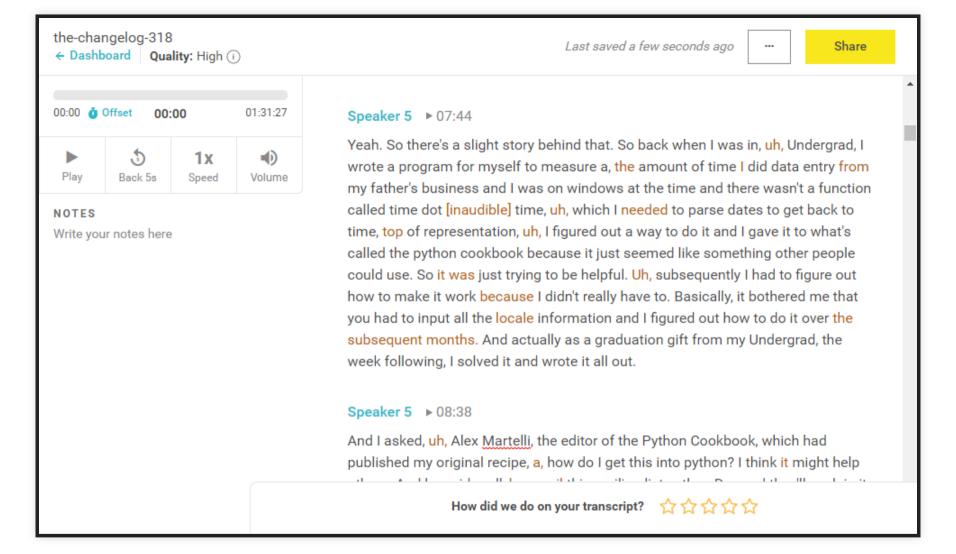
## SE FOR ML-ENABLED SYSTEMS != ML FOR SE TOOLS

```
import numpy as np

start = -1
stop = 1

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

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



temi.com

### Data Scientists

## Software Engineers

#### **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..."

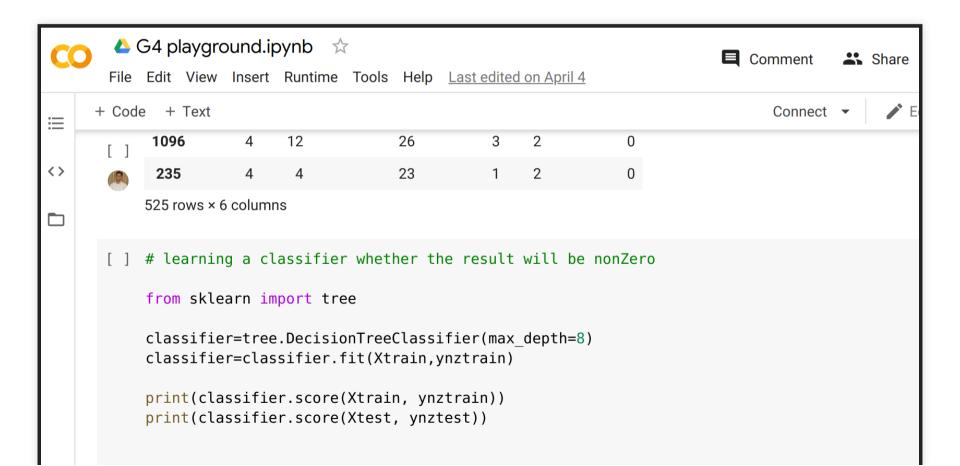
Mary Shaw. ed. Software Engineering for the 21st Century: A basis for rethinking the curriculum. 2005.

#### **MOST ML COURSES/TALKS**

Focus narrowly on modeling techniques or building models

Using notebooks, static datasets, evaluating accuracy

Little attention to software engineering aspects of building complete systems

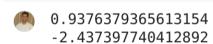


```
0.8266666666666667
0.7295238095238096

[] # learning a regression model only on the nonZero data (test is on all data and somewhat from sklearn import tree

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

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



#### **DATA SCIENTIST**

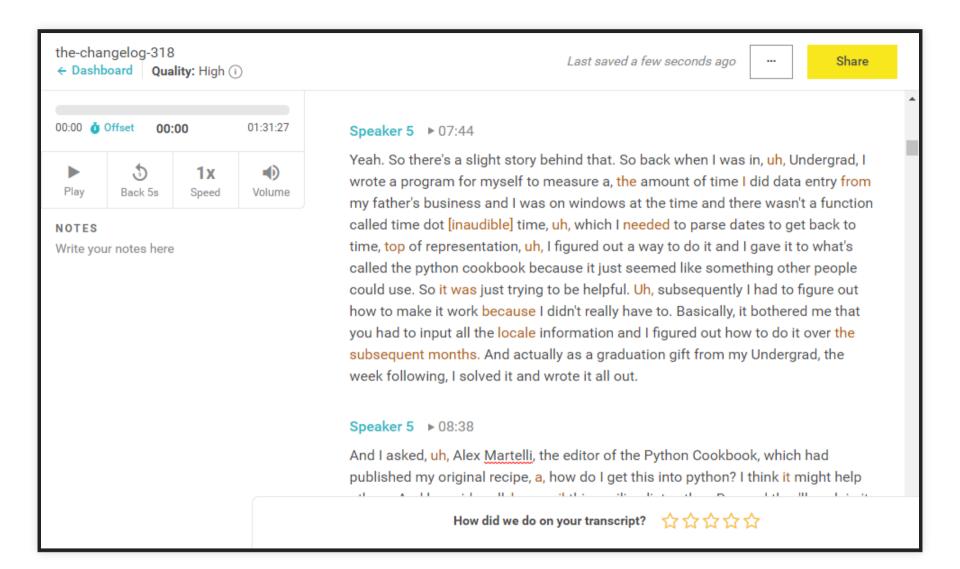
- Often fixed dataset for training and evaluation (e.g., PBS interviews)
- Focused on accuracy
- Prototyping, often Jupyter notebooks or similar
- Expert in modeling techniques and feature engineering
- Model size, updateability, implementation stability typically does not matter
- Starting to worry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

#### **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
- Plan for mistakes and safeguards
- Maintain, evolve, and extend the product over long periods
- Consider requirements for security, safety, fairness

### Data Scientists

## Software Engineers



# A SOFTWARE ENGINEERING PERSPECTIVE ON ML

#### WHAT'S DIFFERENT?

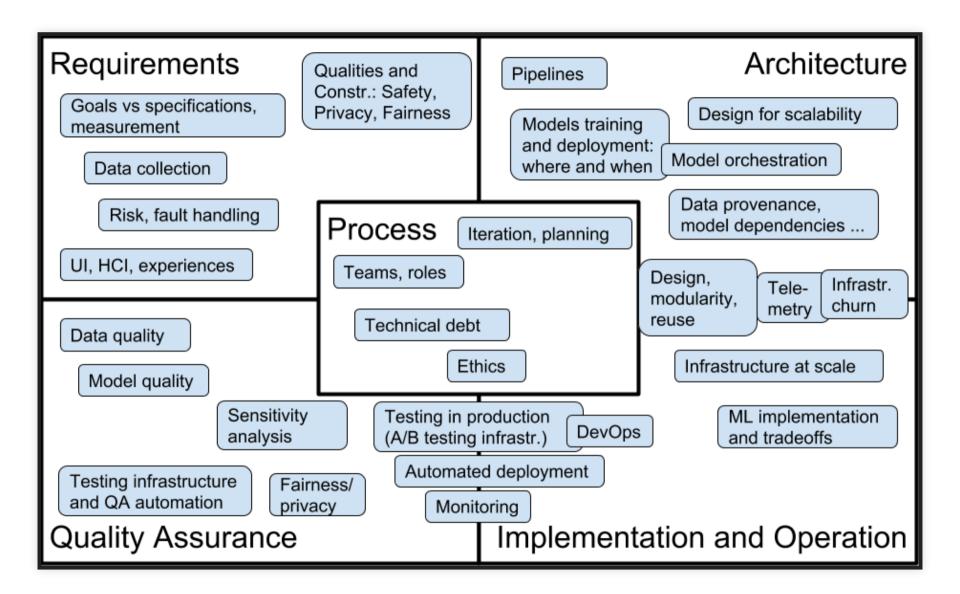
- Missing specifications
- Environment is important (feedback loops, data drift)
- Nonlocal and nonmonotonic effects
- Testing in production
- Data management, versioning, and provenance

#### **REALLY DIFFERENT?**

- Missing specifications -- *implicit*, *vague specs very common*; *safe systems from unreliable components* ("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

### EXAMPLES OF 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?



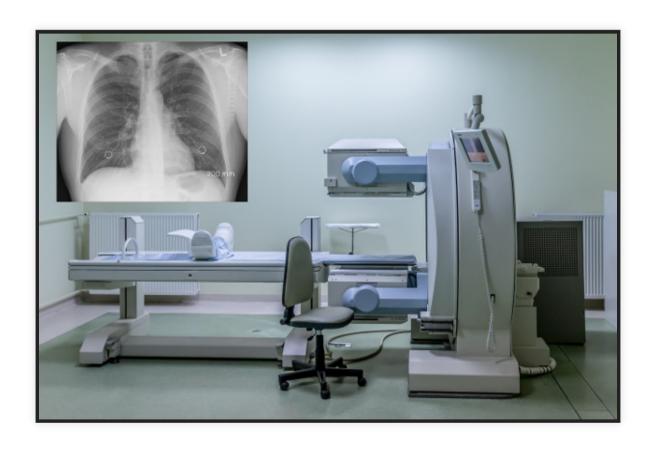
#### **MY VIEW**

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

# QUALITY ASSURANCE FOR ML-ENABLED SYSTEMS

#### TRADITIONAL FOCUS: MODEL ACCURACY

- Train and evaluate model on fixed labled data set
- Compare prediction with labels



#### TRADITIONAL FOCUS: MODEL ACCURACY

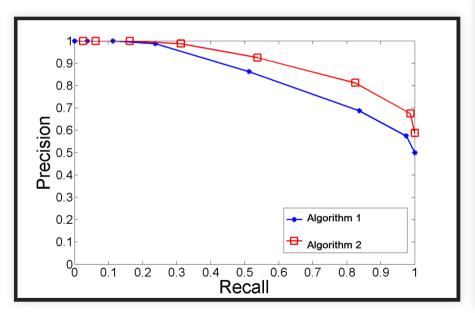
	Actually A	Actually not A
AI predicts A	True Positive (TP)	False Positive (FP)
AI predicts not A	False Negative (FN)	True Negative (TN)

Accuary, Recall, Precision, F1-Score

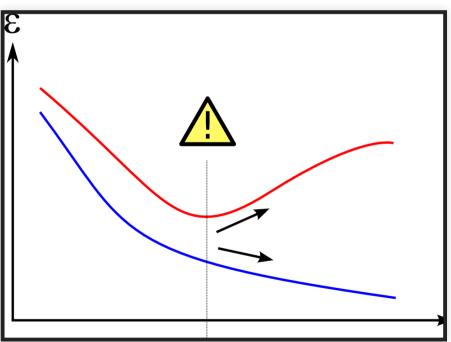
#### MORE TRADITIONAL MODEL QUALITY **DISCUSSIONS**

Many model quality metrics (recall,

MAPE, ROC, log loss, top-k, ...)



Generalization/overfitting (train/test/eval split, crossvalidation)



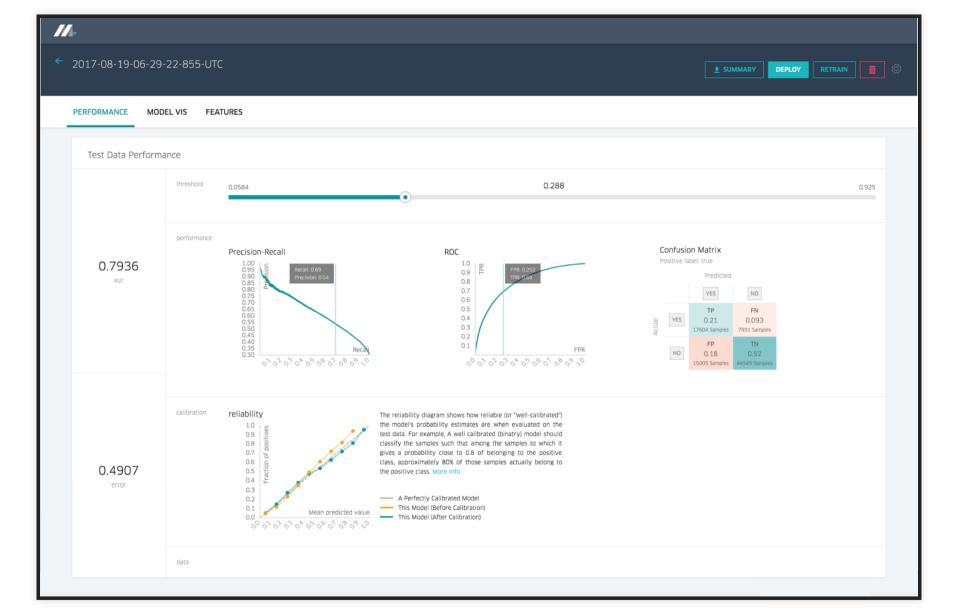
(CC SA 3.0 by Dake)

#### NOT ALL MISTAKES ARE EQUAL

- False positives vs false negatives (e.g., cancer detection)
- Fairness across subpopulations
- Learn from black-box testing:
  - Equivalence classes
  - Boundary conditions
  - Critical test cases ("call mom")
  - Combinatorial testing
  - Fuzzing

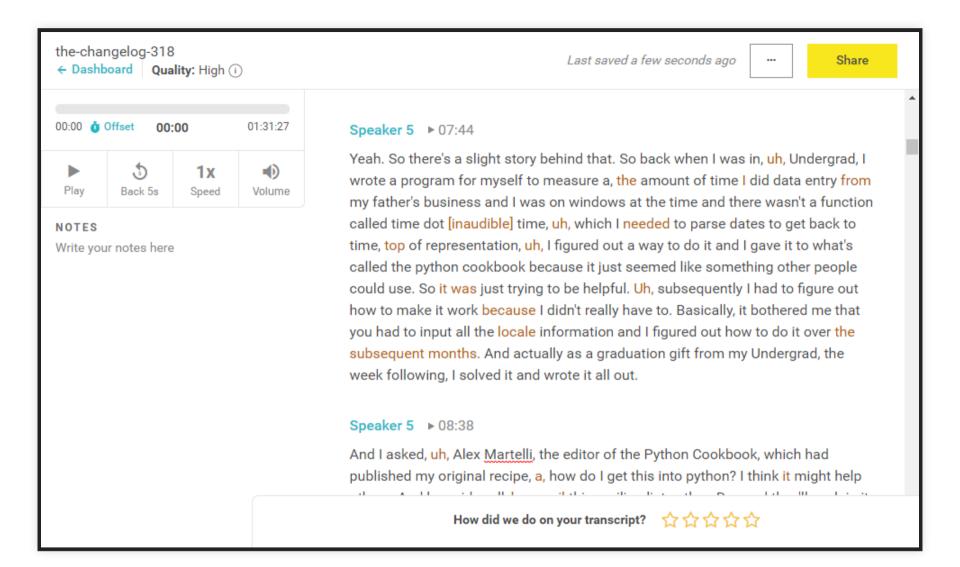
#### **AUTOMATING MODEL EVALUATION**

- Continuous integration, automated measurement, tracking of results
- Data and model versioning, provenance



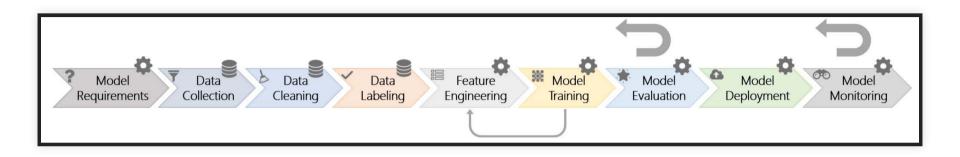
#### **QUALITY CONCERNS FOR ML-ENABLED SYSTEMS**

- Learning time, cost and scalability
- Update cost, incremental learning
- Inference cost
- Size of models learned
- Amount of training data needed
- Fairness
- Robustness
- Safety, security, privacy
- Explainability, reproducibility
- Time to market
- Overall operating cost (cost per prediction)



### INFRASTRUCTURE QUALITY

## THINK OF PIPELINES, NOT MODELS, NOT NOTEBOOKS



Many steps: Data collection, data cleaning, labeling, feature engineering, training, evaluation, deployment, monitoring

Automate each step -- test each step

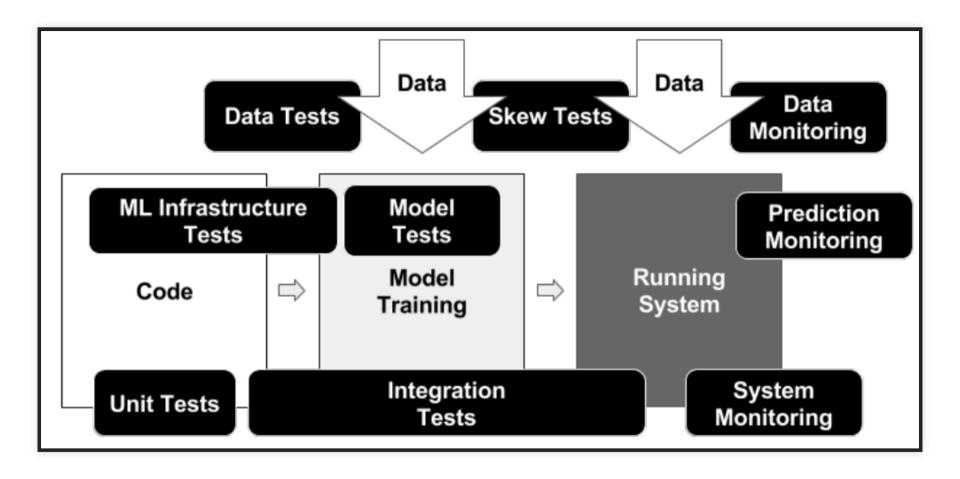
Graphic: Amershi, Saleema, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann. "Software engineering for machine learning: A case study." In 2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP), pp. 291-300. IEEE, 2019.

#### POSSIBLE MISTAKES IN ML PIPELINES

Danger of "silent" mistakes in many phases:

- Dropped data after format changes
- Failure to push updated model into production
- Incorrect feature extraction
- Use of stale dataset, wrong data source
- Data source no longer available (e.g web API)
- Telemetry server overloaded
- Negative feedback (telemtr.) no longer sent from app
- Use of old model learning code, stale hyperparameter
- Data format changes between ML pipeline steps
- ...

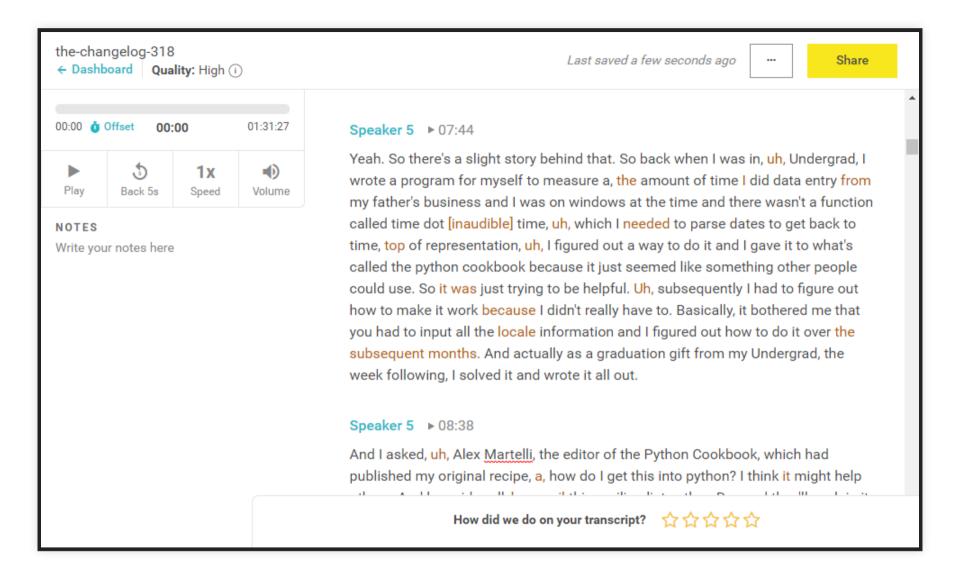
# QUALITY ASSURANCE FOR THE ENTIRE PIPELINE



Source: Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction. Proceedings of IEEE Big Data (2017)

## PIPELINE TESTING

- Unit tests (e.g., data cleaning)
- End to end pipeline tests
- Testing with stubs, test error handling (e.g., test model redeployment after dropped connection)
- Test monitoring infrastructure (e.g., "fire drills")

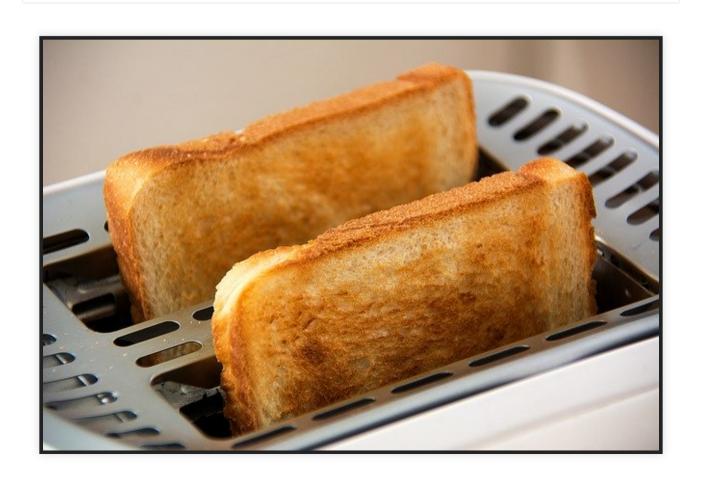


# THINKING OF THE ENTIRE SYSTEM

ML models are "just" one component

# LIVING WITH MISTAKES

The smart toaster may occasionally burn my toast, but it should not burn down my kitchen.



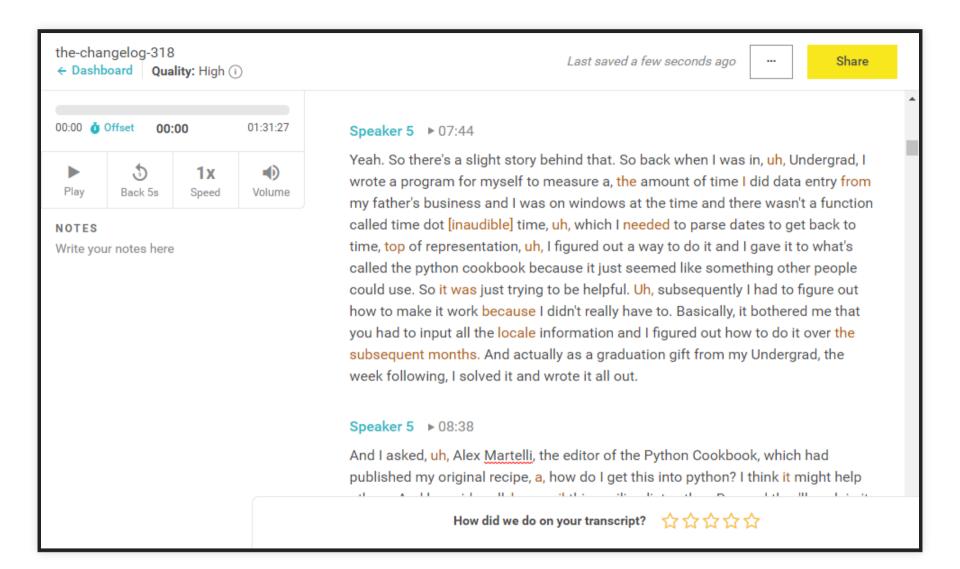
#### Speaker notes

A smart toaster may occasionally burn the toast, but it should never burn down the kitchen. The latter can be achieved without relying on perfect accuarcy of a smart component, just stop it when it's overheating.

Plan for mistakes: User interaction, undo, safeguards

# MODEL ACCURACY VS SYSTEM GOALS

- System goals are supported by AI components, e.g.,
  - maximizing sales
  - minimizing loss
  - maximizing community growth
  - retaining customers
  - maximizing engagement time
- A better model will support system goals better
  - more accurate
  - faster answers
  - fewer bad mistakes
  - more explainable
  - easier to evolve



## **TESTING IN PRODUCTION**

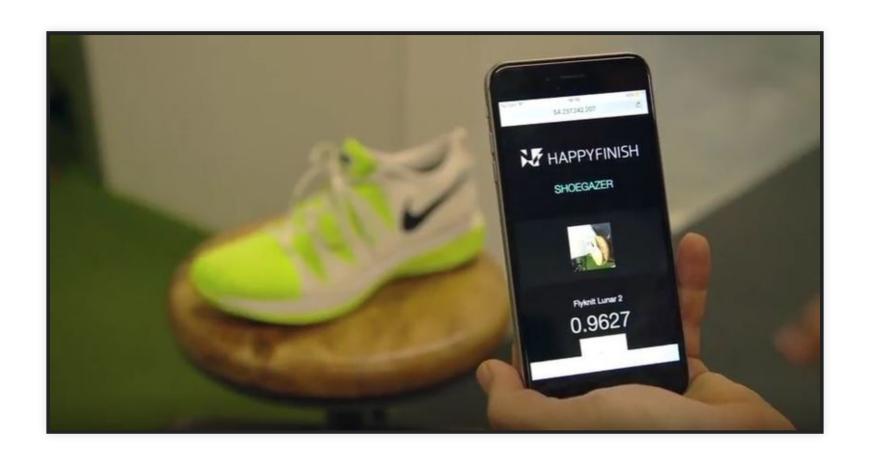
Production data = ultimate unseen data

Focus on system goals, not model accuracy

Monitoring performance over time, canary releases

Finding and debugging common mistakes

Experimentation with A/B tests



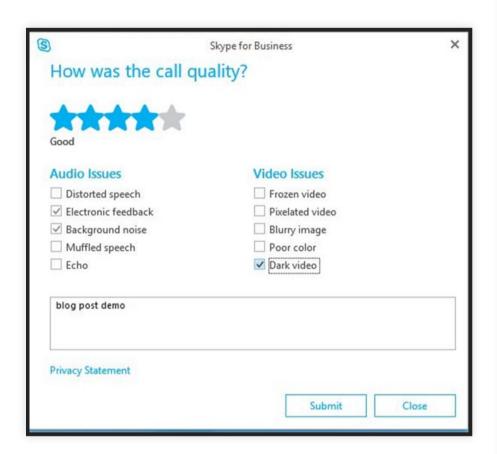
Source: https://www.trendhunter.com/trends/shoegazer

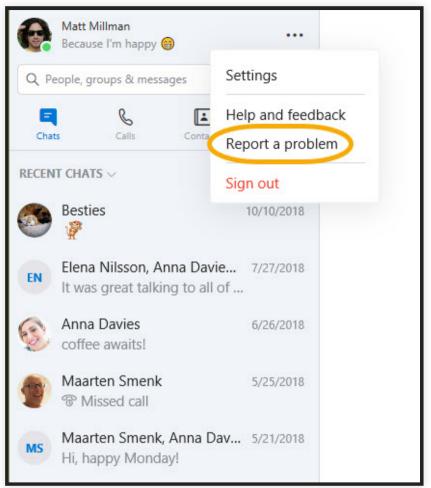
## **KEY DESIGN CHALLENGE: TELEMETRY**

- Identify mistakes in production ("what would have been the right prediction?")
- Many challenges:
  - How can we identify mistakes? Both false positives and false negatives?
  - How can we collect feedback without being intrusive (e.g., asking users about every interactions)?
  - How much data are we collecting? Can we manage telemetry at scale? How to sample properly?
  - How do we isolate telemetry for specific AI components and versions?

#### TELEMETRY DESIGN EXAMPLES

- Was there actually cancer in a scan?
- Did we identify the right soccer player?
- Did we correctly identify tanks?
- Was a Youtube recommendation good?
- Was the ranking of search results good?
- Was the weather prediction good?
- Was the translation correct?
- Did the self-driving car break at the right moment?



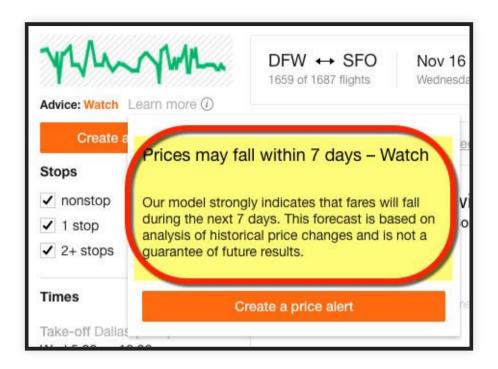


#### Speaker notes

Expect only sparse feedback and expect negative feedback over-proportionally

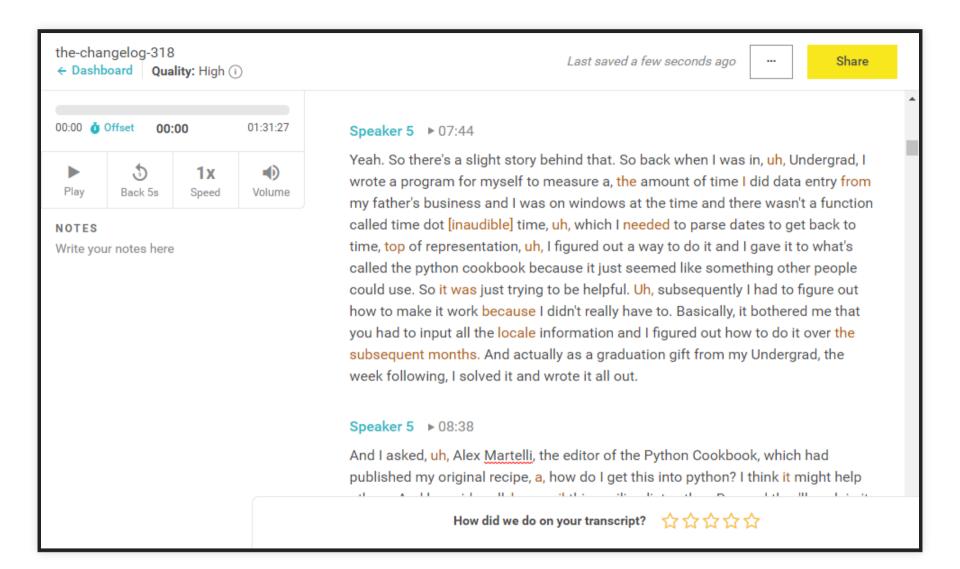
# MANUALLY LABEL PRODUCTION SAMPLES





#### Speaker notes

Can just wait 7 days to see actual outcome for all predictions



#### Speaker notes

Clever UI design allows users to edit transcripts. UI already highlights low-confidence words, can observe changes in editor (UI design encourages use of editor). In addition 5 star rating for telemetry.

# MEASURING MODEL QUALITY WITH TELEMETRY

- Telemetry can provide insights for correctness
  - sometimes very accurate labels for real unseen data
  - sometimes only mistakes
  - sometimes indicates severity of mistakes
  - sometimes delayed
  - often just samples, may be hard to catch rare events
  - often just weak proxies for correctness
- Often sufficient to approximate precision/recall or other measures
- Mismatch to (static) evaluation set may indicate stale or unrepresentative test data
- Trend analysis can provide insights even for inaccurate proxy measures

# MONITORING MODEL QUALITY IN PRODUCTION

- Watch for jumps after releases
  - roll back after negative jump
- Watch for slow degradation
  - Stale models, data drift, feedback loops, adversaries
- Debug common or important problems
  - Mistakes uniform across populations?
  - Challenging problems -> refine training, add regression tests



# **= techradar**





TRENDING

**Buying Guides** 

Note 10

Best Laptops

iOS 13

**Best Phones** 

#### Amazon Alexa stores voice recordings for as long as it likes (and shares them too)

By Olivia Tambini 21 days ago Digital Home

A letter from Amazon reveals all











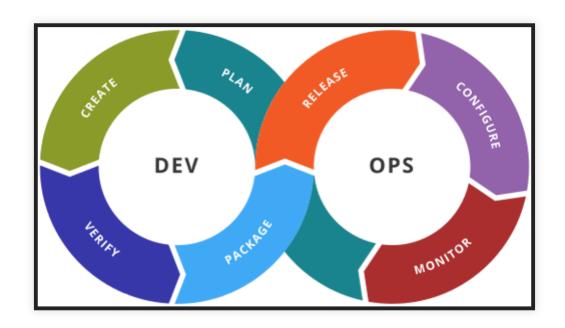


# Software Engineers



# Software Engineers

# **LET'S LEARN FROM DEVOPS**



Distinct roles and expertise, but joint responsibilities, joint tooling

# TOWARD BETTER ML-SYSTEMS ENGINEERING

Interdisciplinary teams, split expertise, but joint responsibilities

Joint vocabulary and tools

Foster system thinking

Awareness of production quality concerns

Perform risk + hazard analysis



# Software Engineers

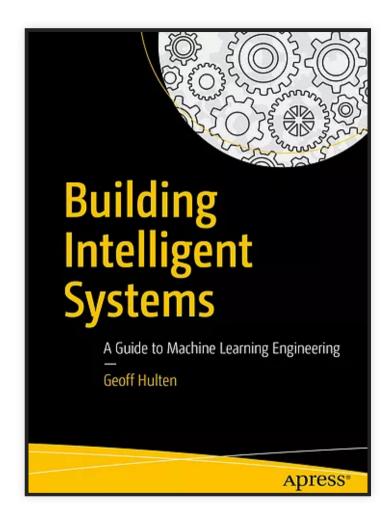
## **READINGS**

All lecture material:

https://github.com/ckaestne/seai

Annotated bibliography:

https://github.com/ckaestne/seaibib



# 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
- Quality assurance beyond model accuracy
  - Blackbox testing, test automation
  - Testing the entire ML pipeline
  - Consider whole system
  - Testing in production with telemetry
- Interdisciplinary teams, joint vocabulary, and awareness

kaestner@cs.cmu.edu -- @p0nk -- https://github.com/ckaestne/seai/



