Software Engineering for Machine Learning (SE4ML)

17313 - Foundations of Software Engineering

Nadia Nahar

Software Engineering Ph.D. Student, Carnegie Mellon University

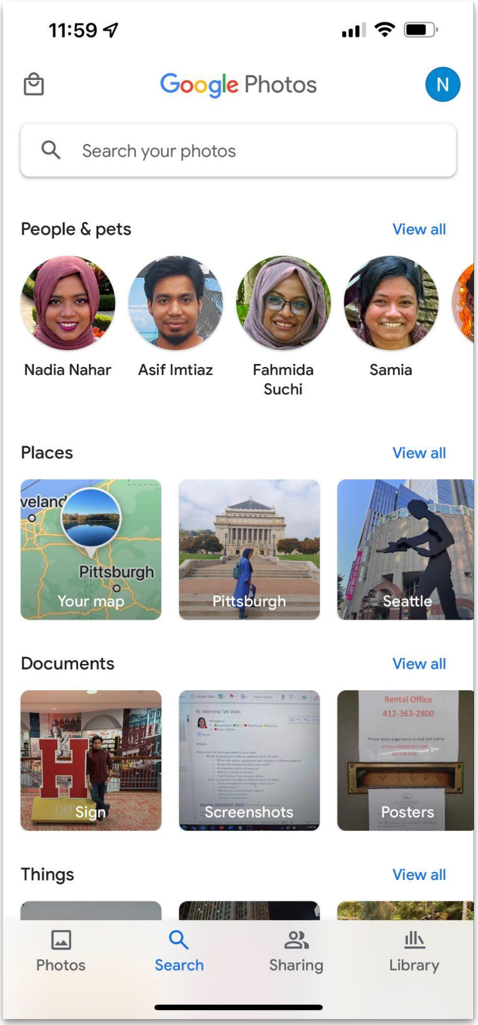
Research on Software Engineering for Machine Learning (SE4ML)

Worked on Deep Learning Inference Service (DLIS) at Microsoft

Machine Learning in Software Products

Can you think of a product you use,
that has one/more ML component(s)?

Google Photos



11:59

Google Photos

N

Search your photos

People & pets — View all

Nadia Nahar
Asif Imtiaz
Fahmida Suchi
Samia

Places — View all

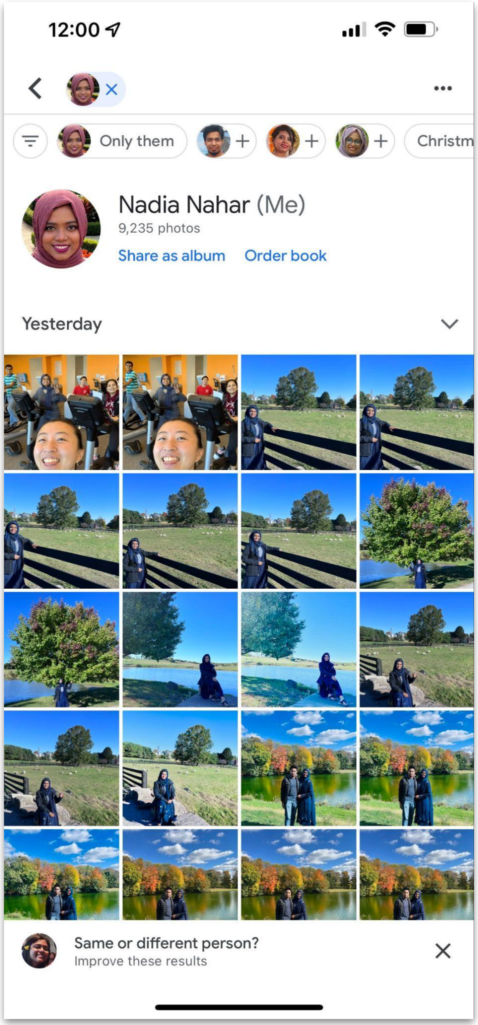
Your map
Pittsburgh
Seattle

Documents — View all

Sign
Screenshots
Posters

Things — View all

Photos
Search
Sharing
Library



12:00

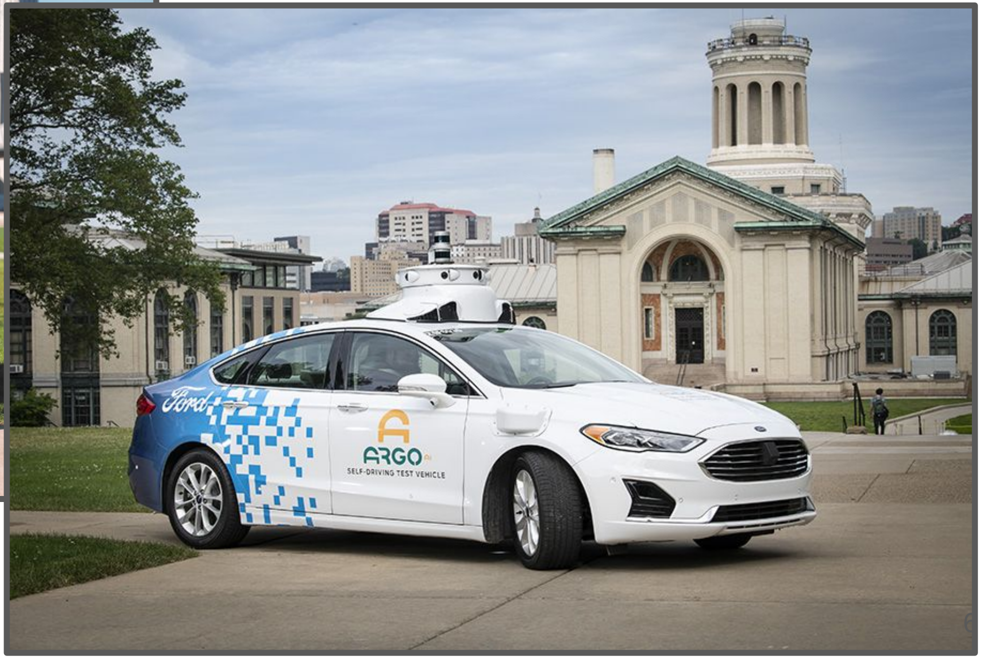
Only them
Christm

Nadia Nahar (Me)
9,235 photos
Share as album
Order book

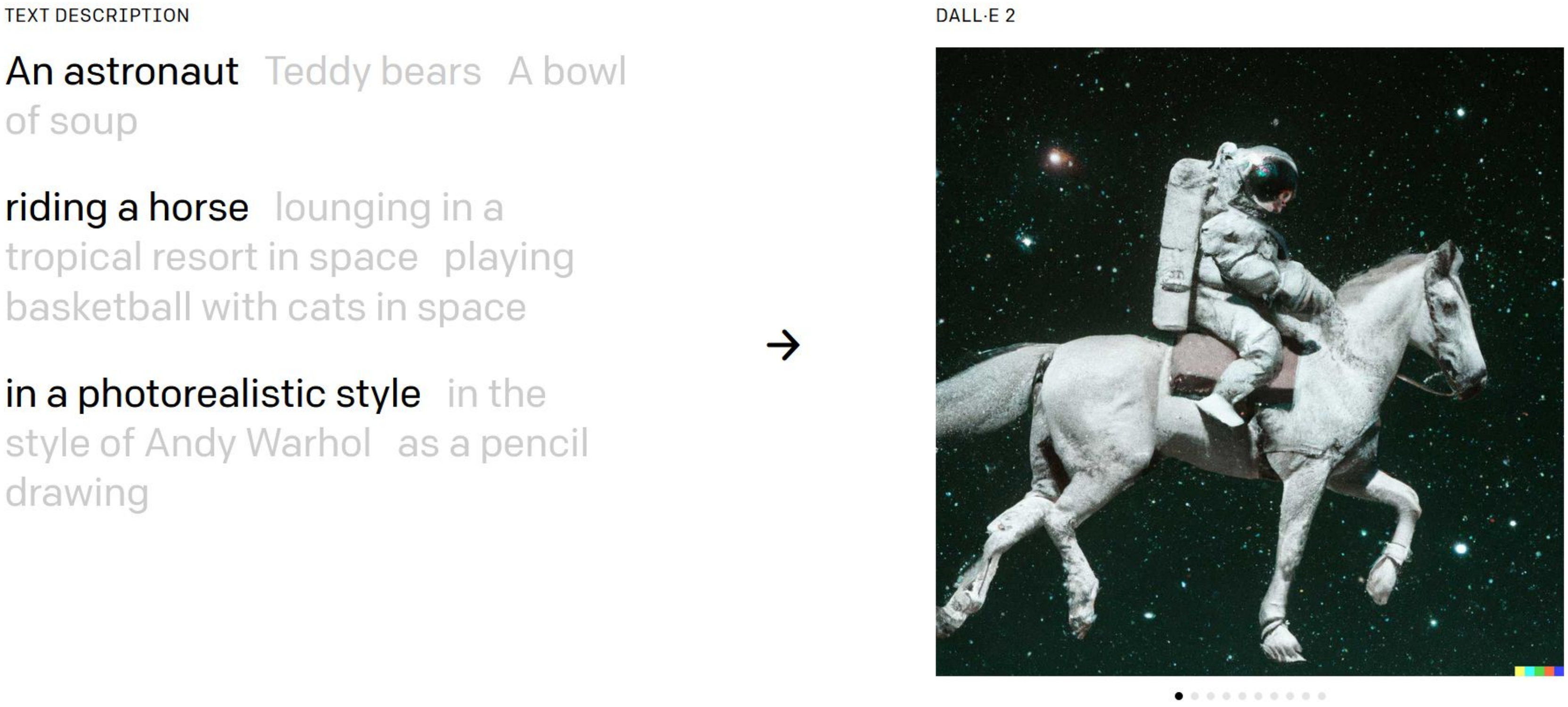
Yesterday

Same or different person?
Improve these results

Autonomous Car



DALL-E



TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

riding a horse lounging in a tropical resort in space playing basketball with cats in space

in a photorealistic style in the style of Andy Warhol as a pencil drawing

→

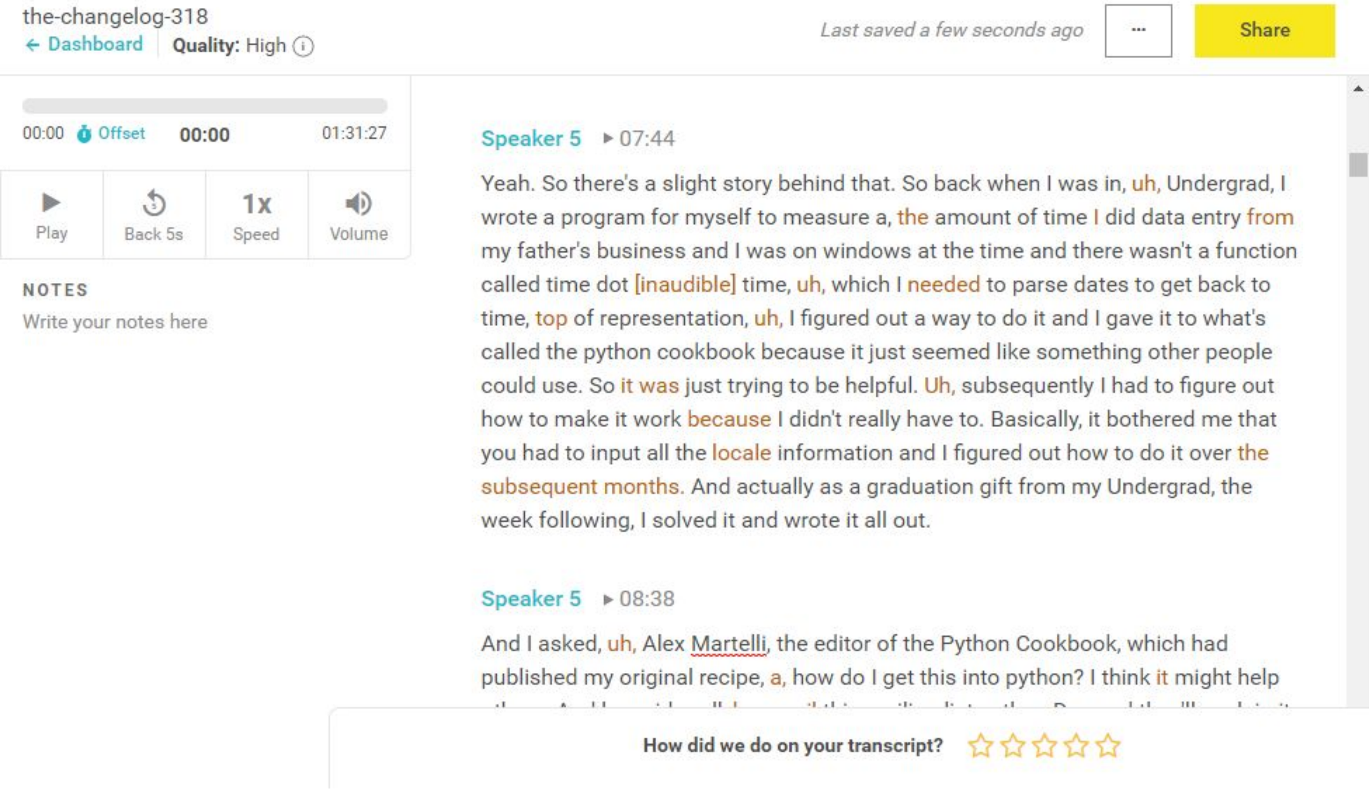
DALL·E 2

Case Study: Transcription Service

Participation Activity

What functionalities do you need to provide, to sell a model for transcription as a product?

Case Study: Transcription Service



Speaker 5 ▸ 07:44

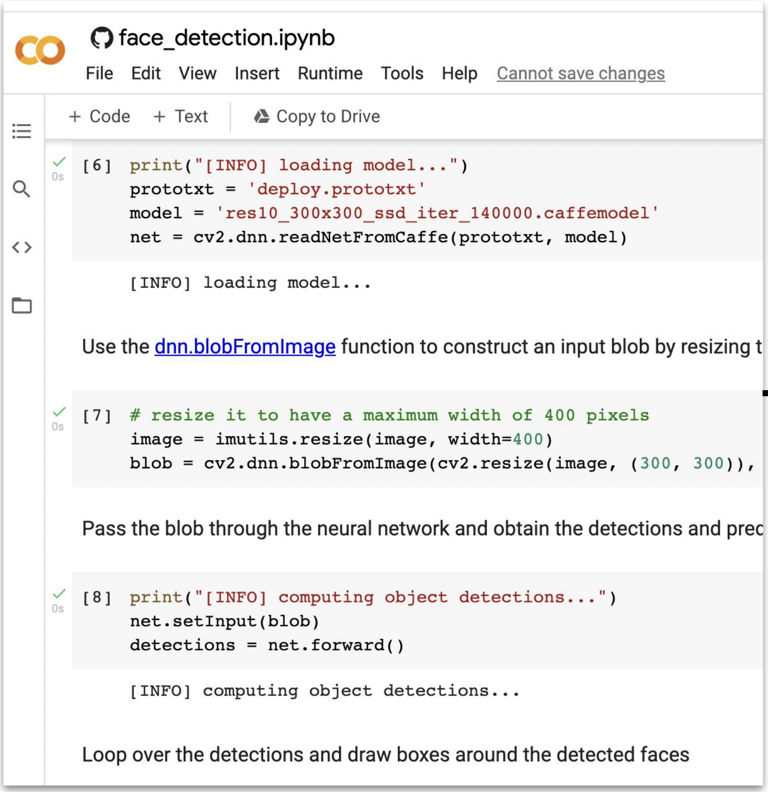
Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed 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

From Models to Systems

Data Science is Model Centric



```
[6]  print("[INFO] loading model...")
     prototxt = 'deploy.prototxt'
     model = 'res10_300x300_ssd_iter_140000.caffemodel'
     net = cv2.dnn.readNetFromCaffe(prototxt, model)

     [INFO] loading model...
```

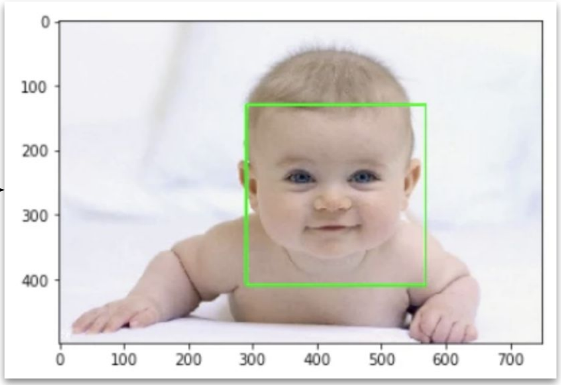
Use the dnn.blobFromImage function to construct an input blob by resizing t

```
[7]  # resize it to have a maximum width of 400 pixels
     image = imutils.resize(image, width=400)
     blob = cv2.dnn.blobFromImage(cv2.resize(image, (300, 300)),
```

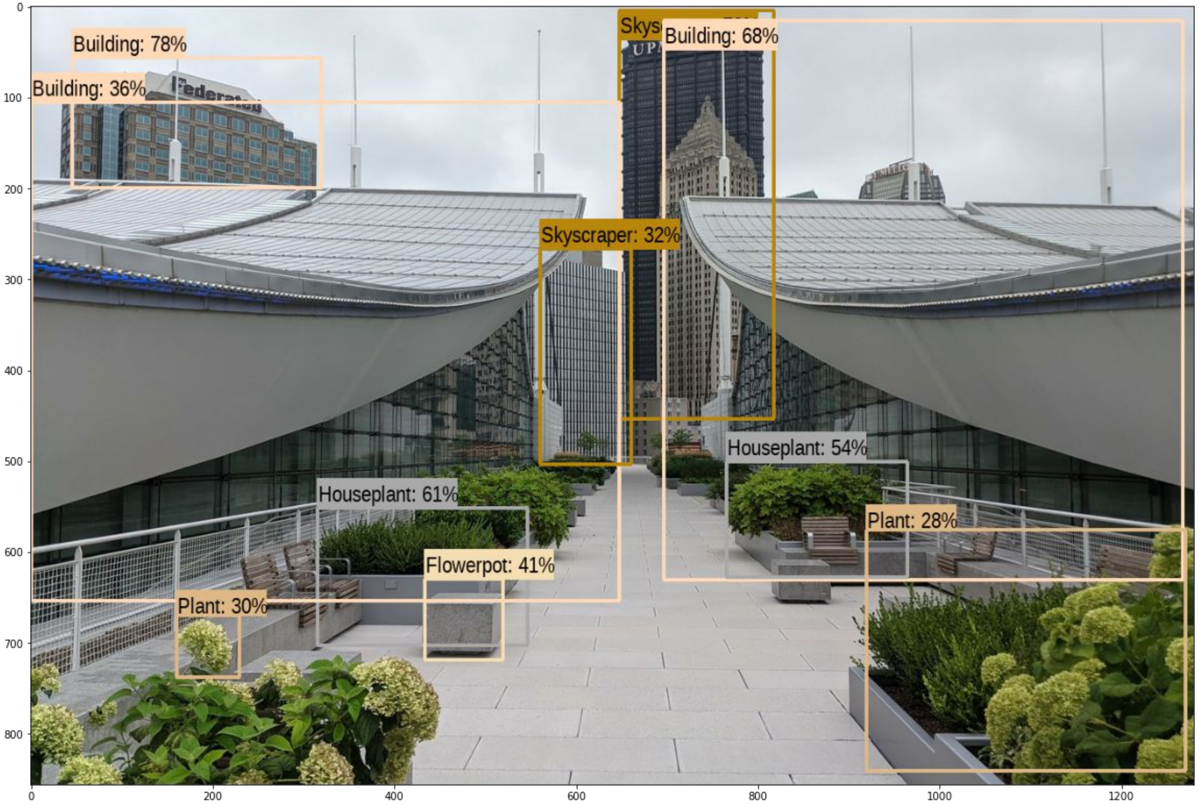
Pass the blob through the neural network and obtain the detections and prec

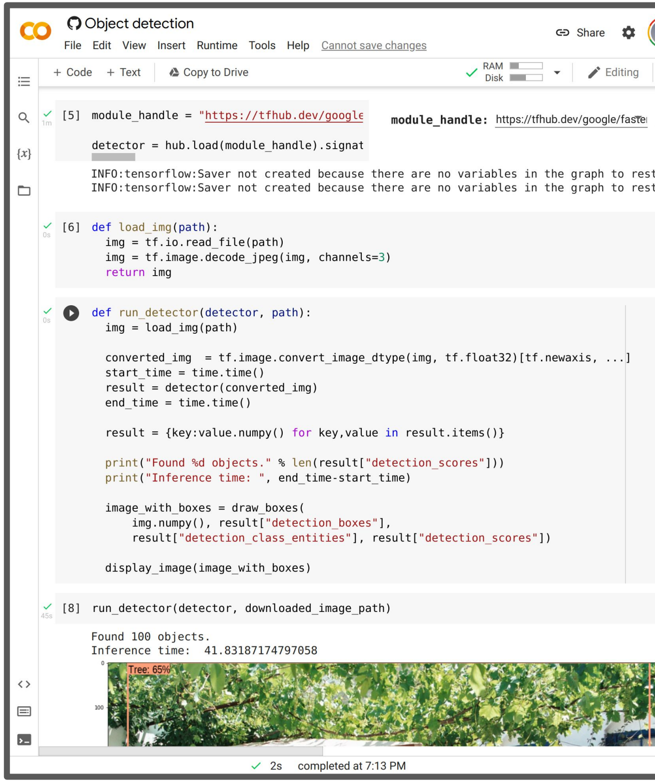
```
[8]  print("[INFO] computing object detections...")
     net.setInput(blob)
     detections = net.forward()

     [INFO] computing object detections...
```

Loop over the detections and draw boxes around the detected faces



Data Science is Model Centric





Object detection
File Edit View Insert Runtime Tools Help Cannot save changes
Share
+ Code + Text
Copy to Drive
RAM
Disk
Editing
module_handle: https://tfhub.dev/google/faste

```
[5]  module_handle = "https://tfhub.dev/google

     detector = hub.load(module_handle).signat

     INFO:tensorflow:Saver not created because there are no variables in the graph to rest
     INFO:tensorflow:Saver not created because there are no variables in the graph to rest
```

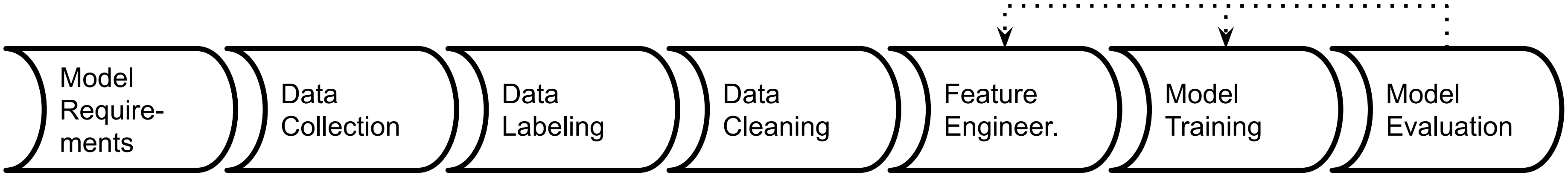
```
[6]  def load_img(path):
       img = tf.io.read_file(path)
       img = tf.image.decode_jpeg(img, channels=3)
       return img
```

```
     def run_detector(detector, path):
       img = load_img(path)

       converted_img  = tf.image.convert_image_dtype(img, tf.float32)[tf.newaxis, ...]
       start_time = time.time()
       result = detector(converted_img)
       end_time = time.time()

       result = {key:value.numpy() for key,value in result.items()}

       print("Found %d objects." % len(result["detection_scores"]))
       print("Inference time: ", end_time-start_time)

       image_with_boxes = draw_boxes(
           img.numpy(), result["detection_boxes"],
           result["detection_class_entities"], result["detection_scores"])

       display_image(image_with_boxes)
```

```
[8]  run_detector(detector, downloaded_image_path)

     Found 100 objects.
     Inference time:  41.83187174797058
```

✓ 2s completed at 7:13 PM

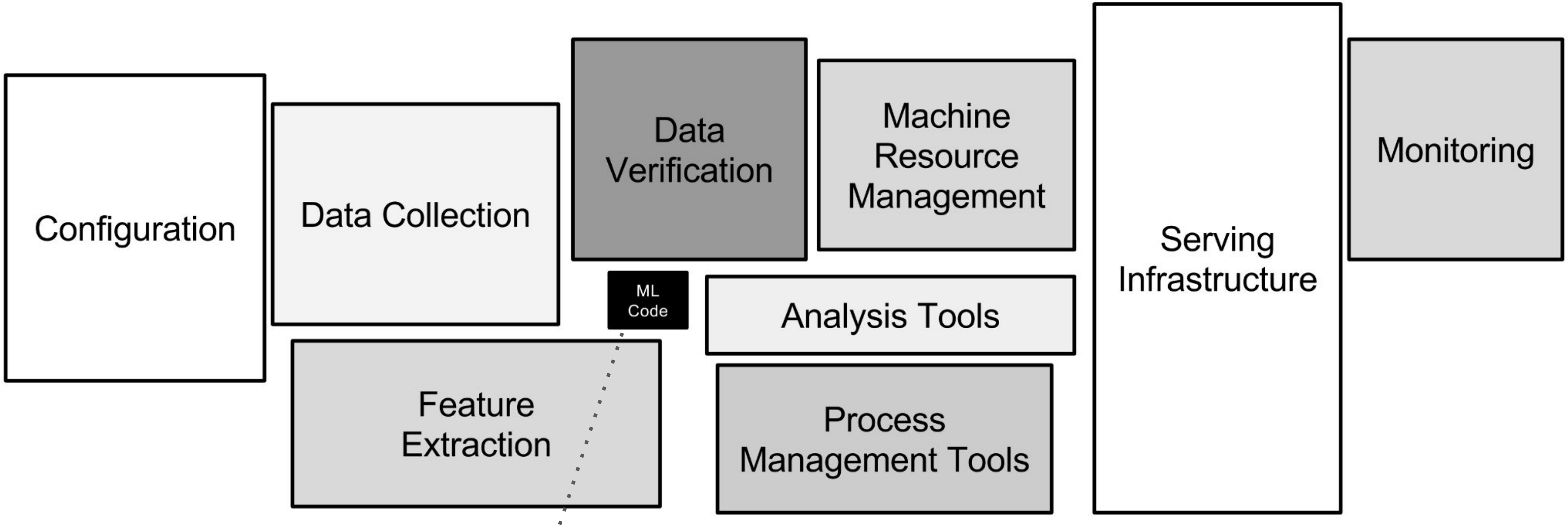
Data Science Pipelines



Typical Machine Learning Book / Course

Focus: building models from given data, evaluating accuracy

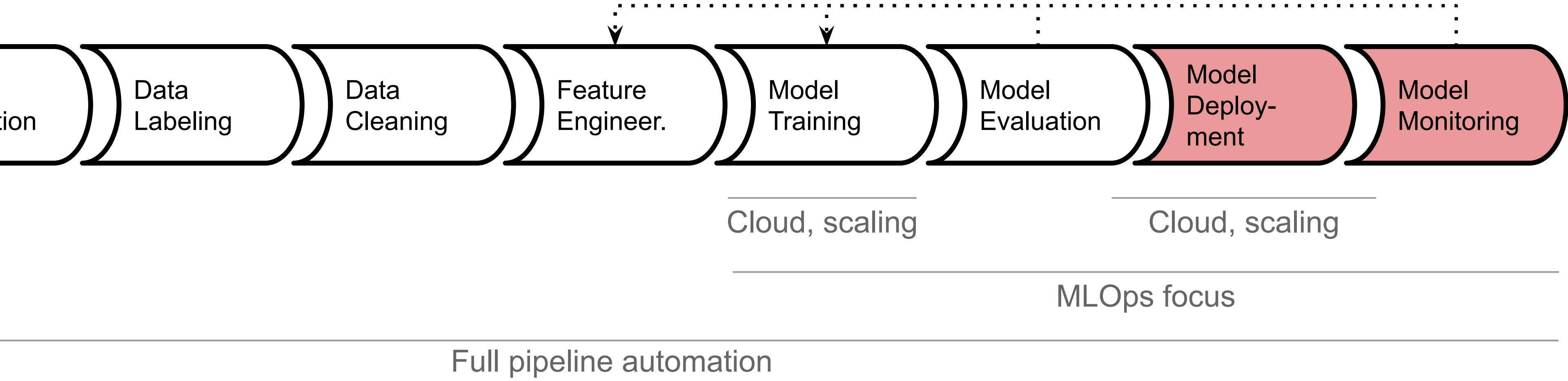
Model Deployment is Complex



ML Code

Sculley, et al. *"Hidden technical debt in machine learning systems."* NeurIPS 28 (2015): 2503-2511.

Pipeline Automation and MLOps



ion

Data Labeling

Data Cleaning

Feature Engineer.

Model Training

Model Evaluation

Model Deploy-ment

Model Monitoring

Cloud, scaling

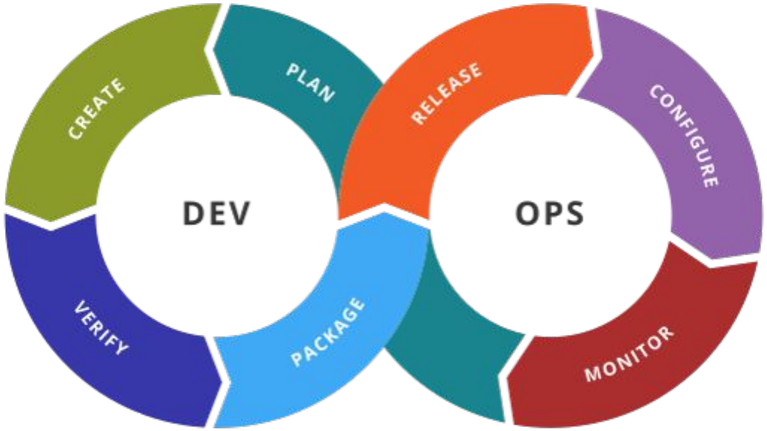
Cloud, scaling

MLOps focus

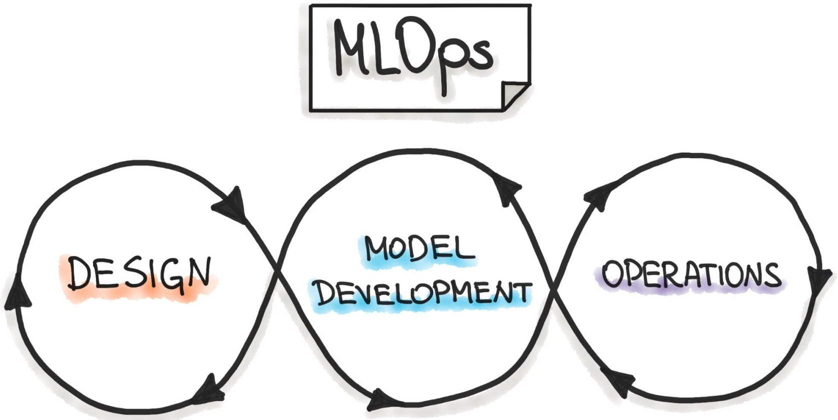
Full pipeline automation

Focus: experimenting, deploying, scaling training and serving, model monitoring and updating

DevOps and MLOps



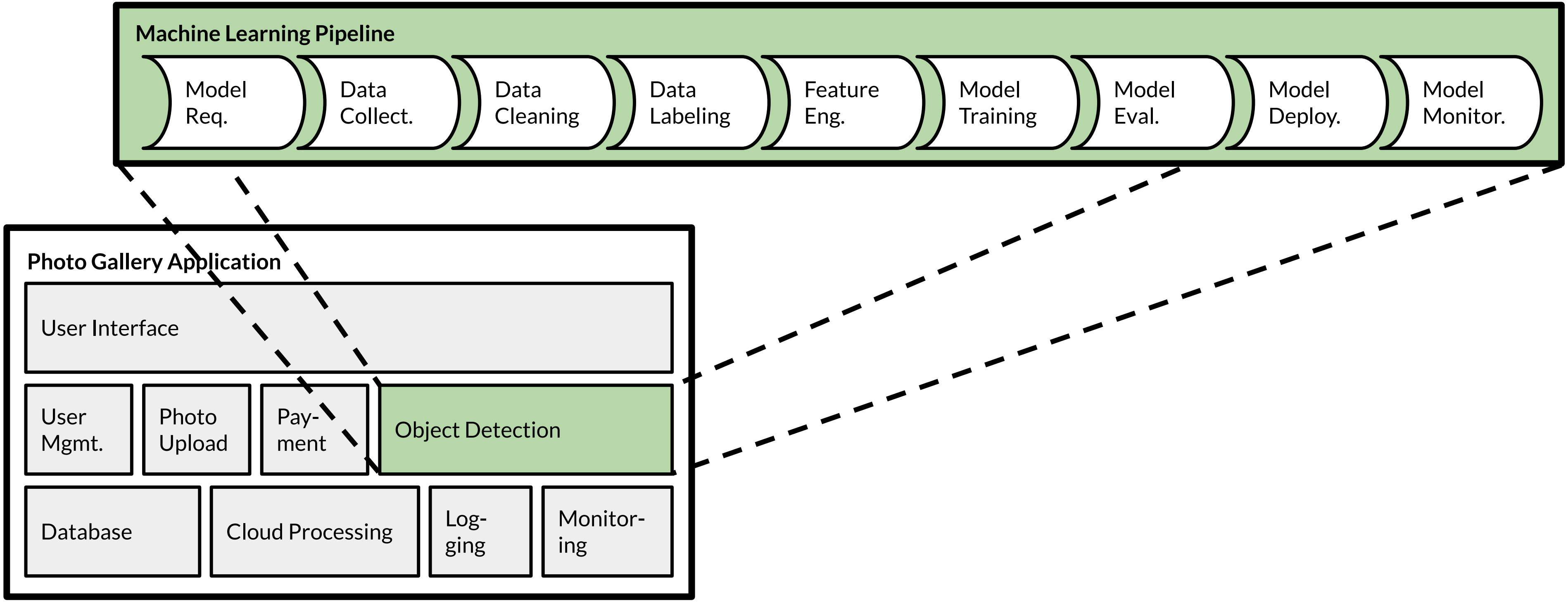
Set of practices for continuous delivery; relies on heavy automation, e.g., continuous delivery, monitoring



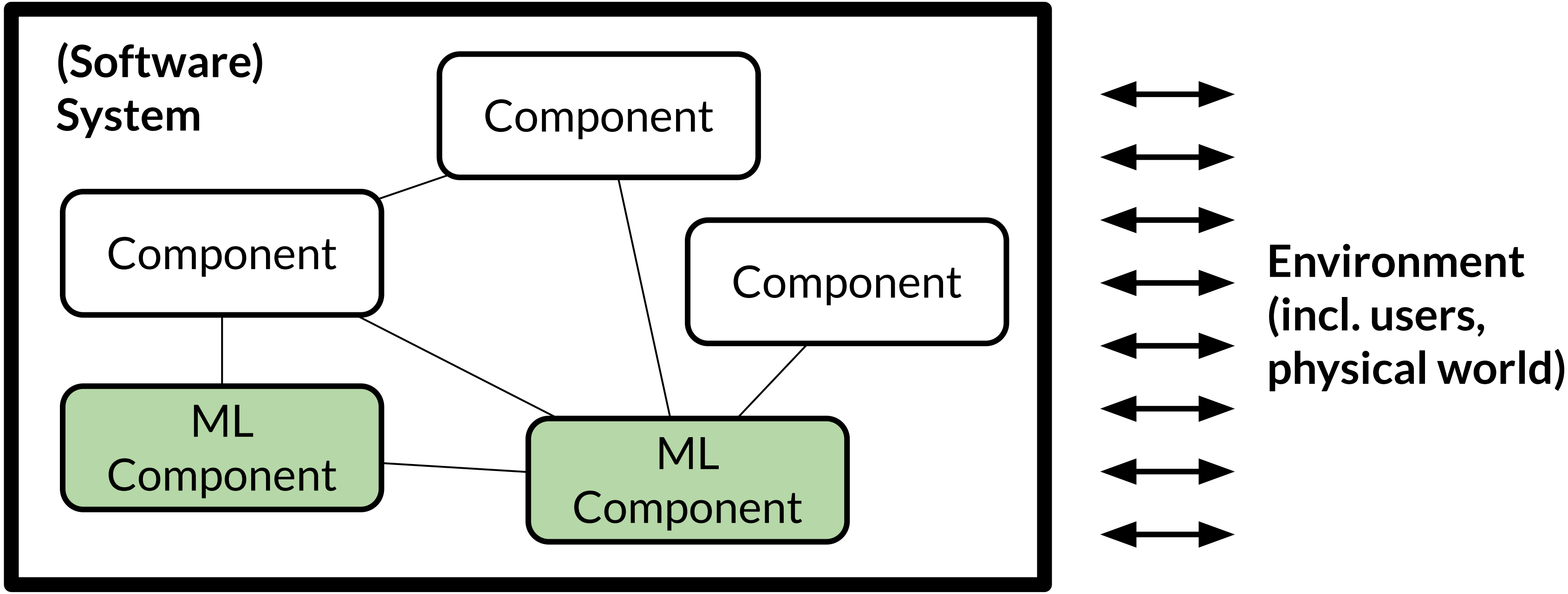
Automation around Machine Learning pipeline, including training, evaluation, versioning, and deployment

Think about MLOps as a specialized subset of DevOps for machine learning applications

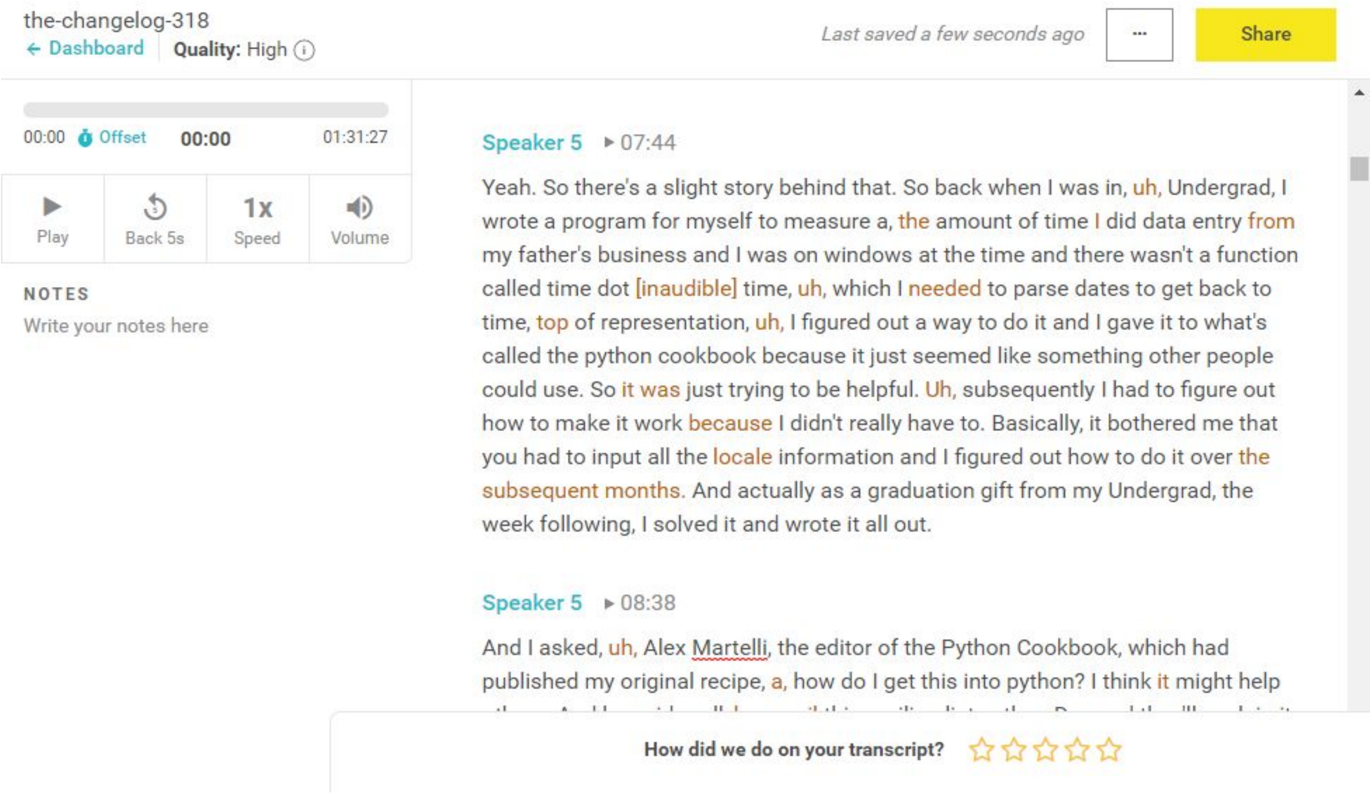
ML is a Component in a System



Systems Thinking



Case Study: Transcription Service



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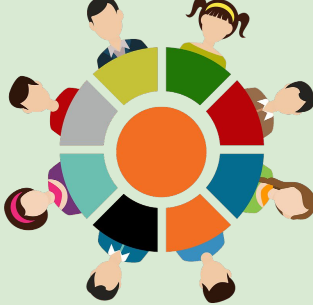
And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help

Can you point out some ML vs non-ML components in the transcription product?

Can you point out some ML vs non-ML components in the apps, you mentioned?



Team Activity

Draw a diagram like this, for the app you mentioned before.

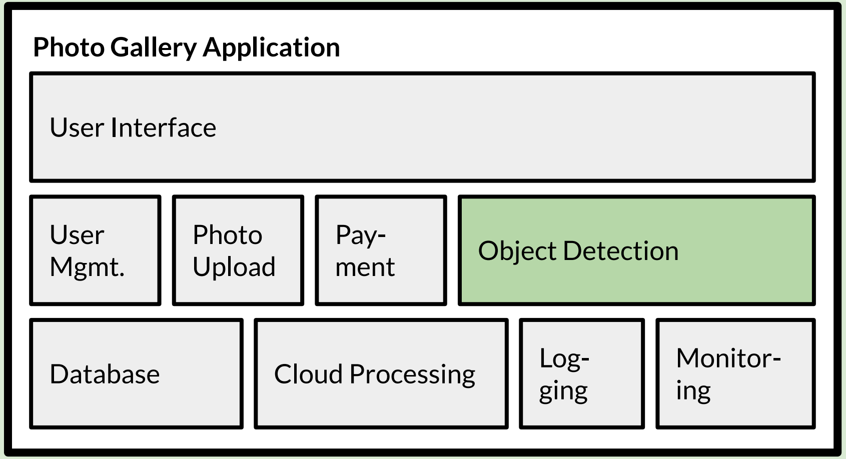


Photo Gallery Application

User Interface

User Mgmt.

Photo Upload

Pay-ment

Object Detection

Database

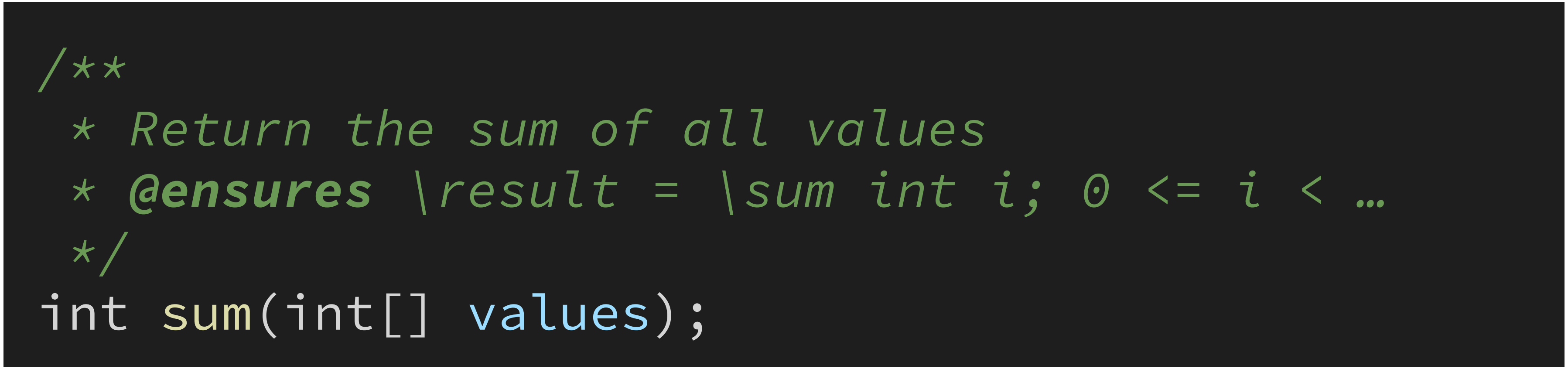
Cloud Processing

Log-ging

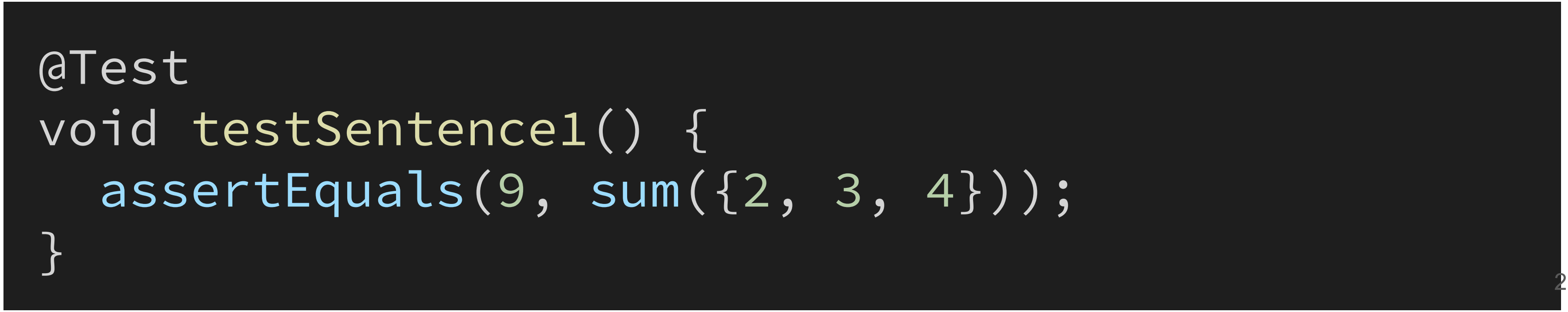
Monitor-ing

What Changes with Machine Learning?

Specifications & Testing in SE



```
/**
 * Return the sum of all values
 * @ensures \result = \sum int i; 0 <= i < …
 */
int sum(int[] values);
```



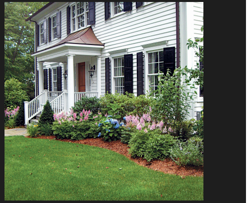
```
@Test
void testSentence1() {
  assertEquals(9, sum({2, 3, 4}));
}
```

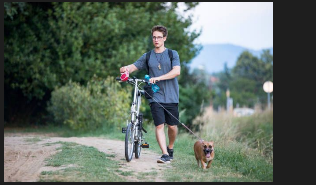
Lack of Specifications in ML

```
/**
 * Detect objects visible in image
 * ????
 */
ObjectId[] detectObjects(File image);
```

Lack of Specifications in ML

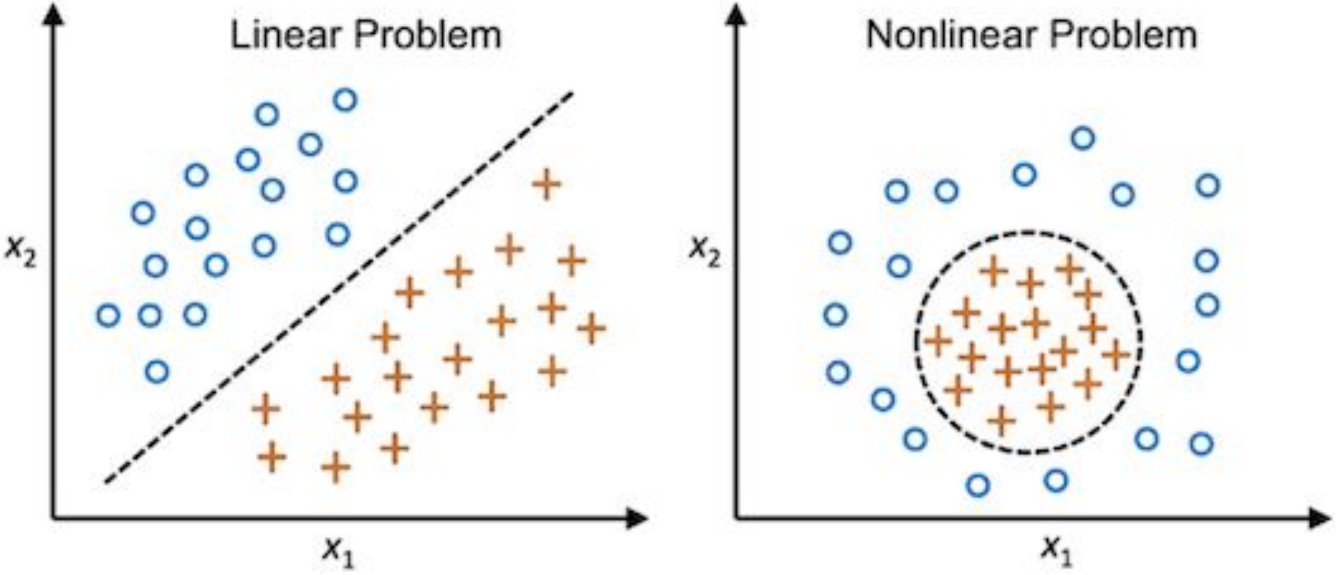
```
@Test
void testHomePhoto() {
  assertEquals({HOUSE, PLANT},
               detectObjects("img1.jpg"));
}
@Test
void testStreetPhoto() {
  assertEquals({PERSON, DOG, BICYCLE},
               detectObjects("img2.jpg"));
}
```



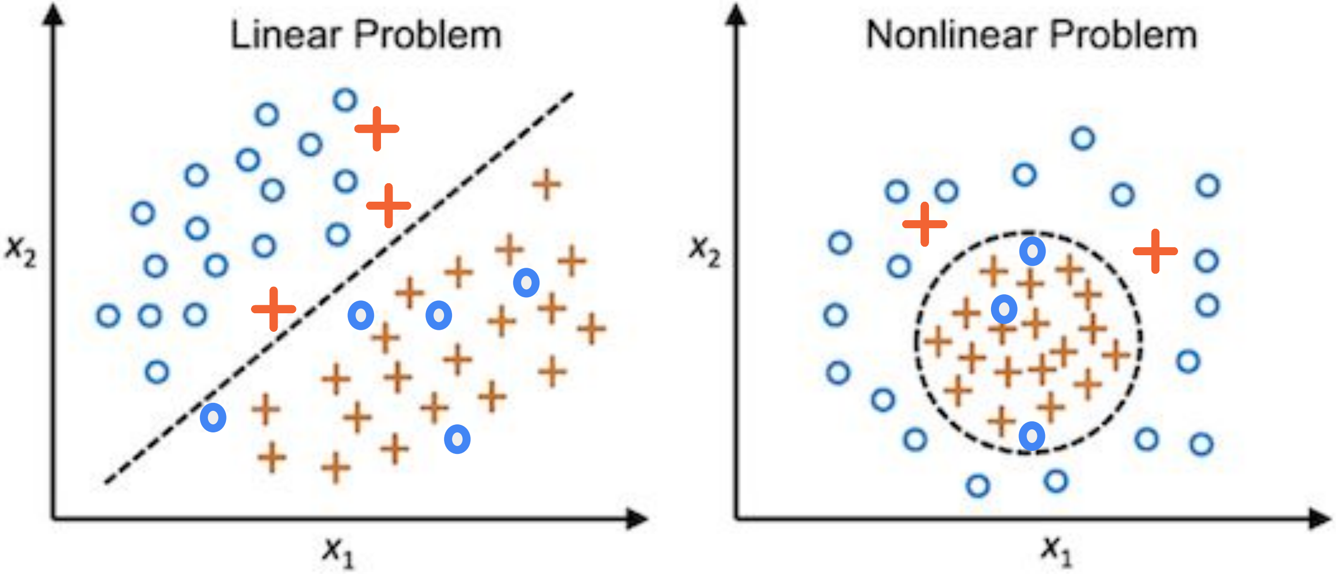


We Cannot Define Rules for Machine Learning Models!

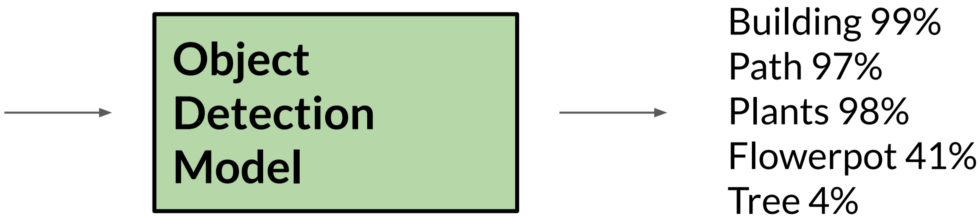
ML Models Learn from Data



Real World Data is not Ideal



ML Model = Unreliable Function



Object Detection Model

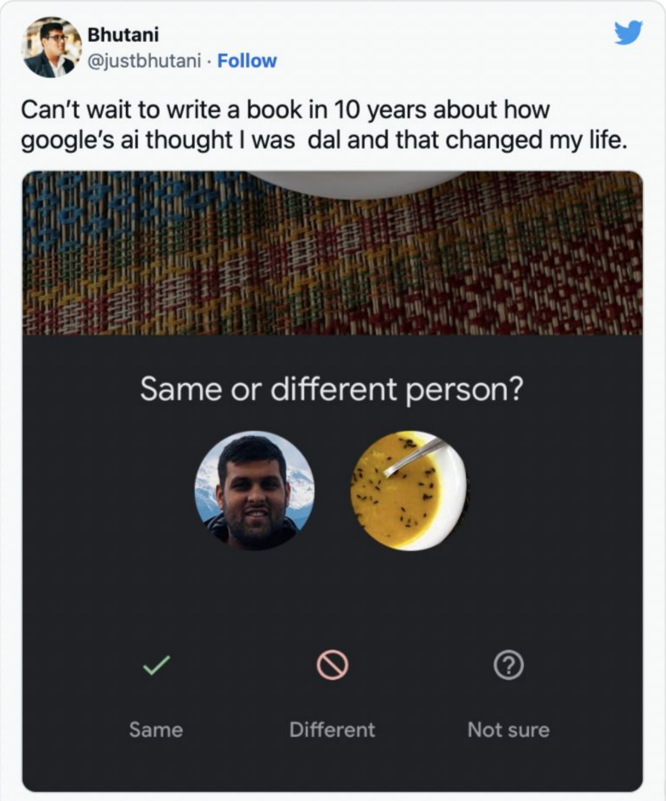
Building 99%
Path 97%
Plants 98%
Flowerpot 41%
Tree 4%

No guarantees, may make mistakes, confidence unreliable

Model often inscrutable, opaque

Evaluated in terms of accuracy, not correctness

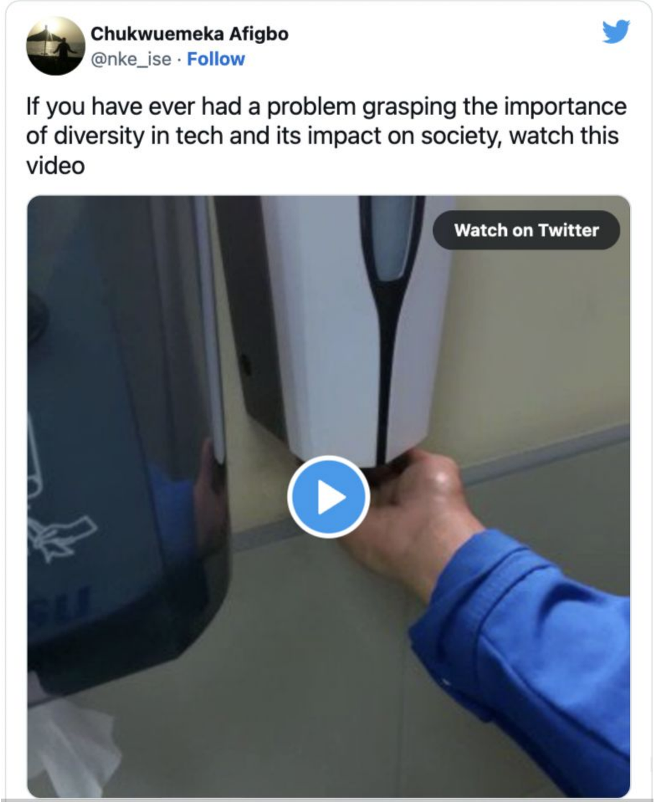
Model Makes Mistake



Bhutani
@justbhutani · Follow

Can't wait to write a book in 10 years about how google's ai thought I was dal and that changed my life.

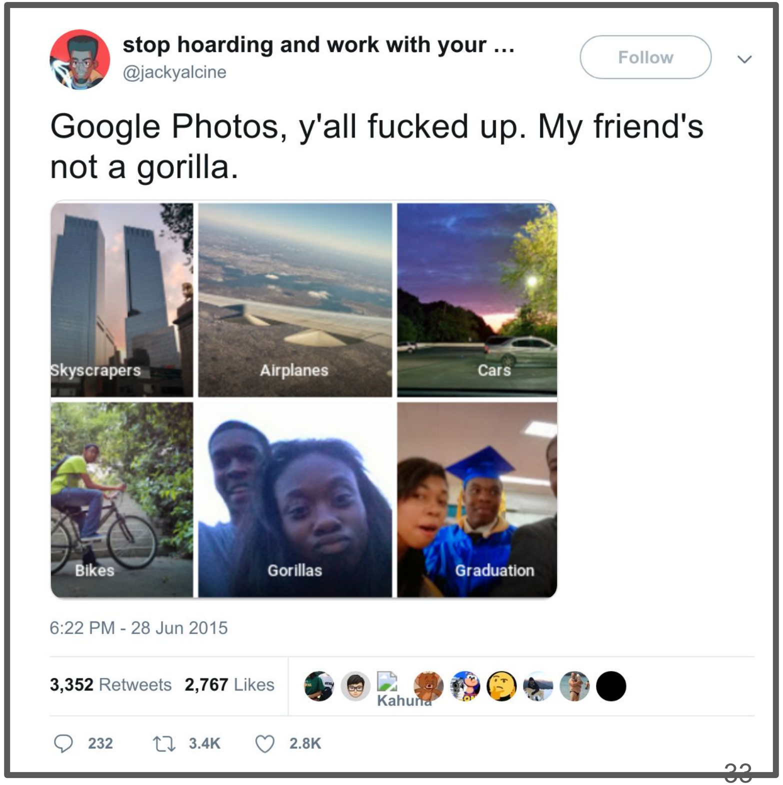
Same or different person?



Chukwuemeka Afigbo
@nke_ise · Follow

If you have ever had a problem grasping the importance of diversity in tech and its impact on society, watch this video

Mistakes Cause Harms



stop hoarding and work with your ...

@jackyalcine

Google Photos, y'all fucked up. My friend's not a gorilla.

6:22 PM - 28 Jun 2015

3,352 Retweets 2,767 Likes

All Models are Wrong!

All models are approximations. Assumptions, whether implied or clearly stated, are never exactly true.
All models are wrong, but some models are useful.
So the question you need to ask is not "Is the model true?" (it never is) but "Is the model good enough for this particular application?"

George Box

Lack of Specifications…

… breaks modular reasoning

… challenges quality assurance

… inhibits safety and fairness reasoning

… hinders coordination across teams

(though, we didn’t need ML to build low quality, harmful, and unethical software)

Building ML-Enabled Systems

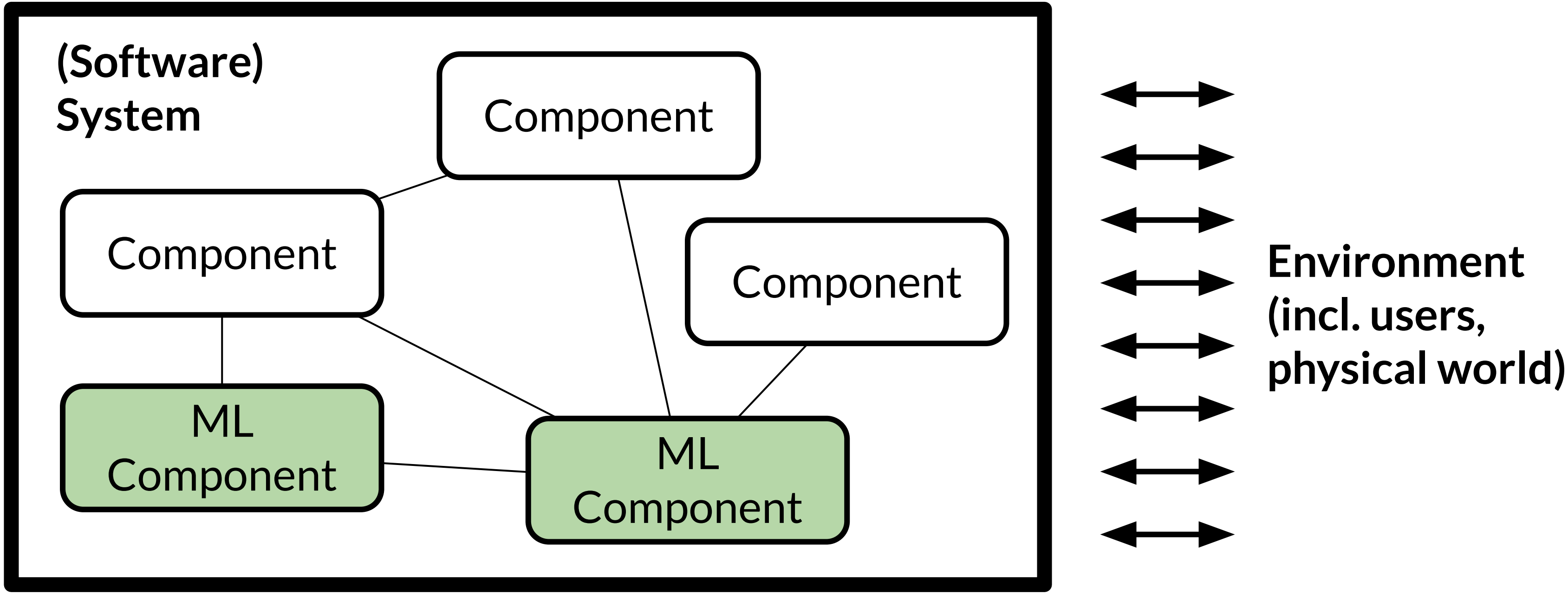
Building ML-Enabled Systems

Understand *system* needs and goals and interactions with environment

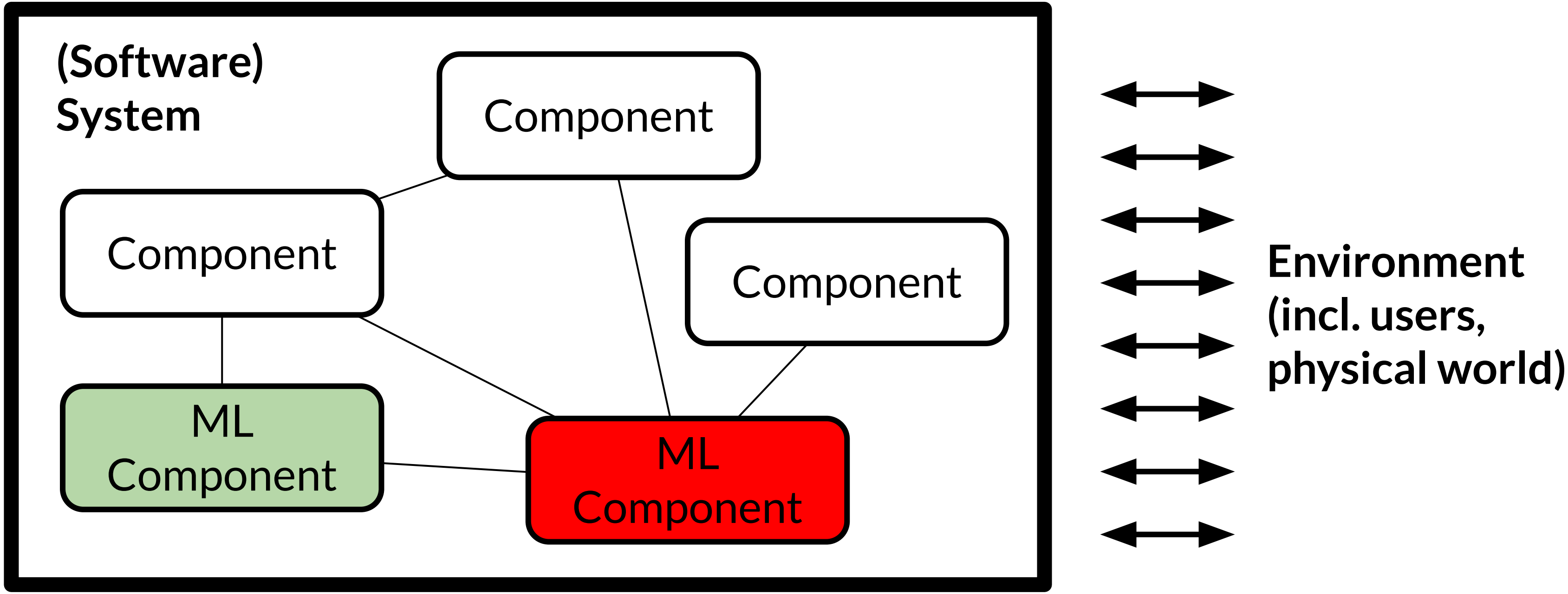
Designing components and integrating ML and non-ML parts into a *system*

Many roles and stakeholders, interdisciplinary endeavour

Systems Thinking



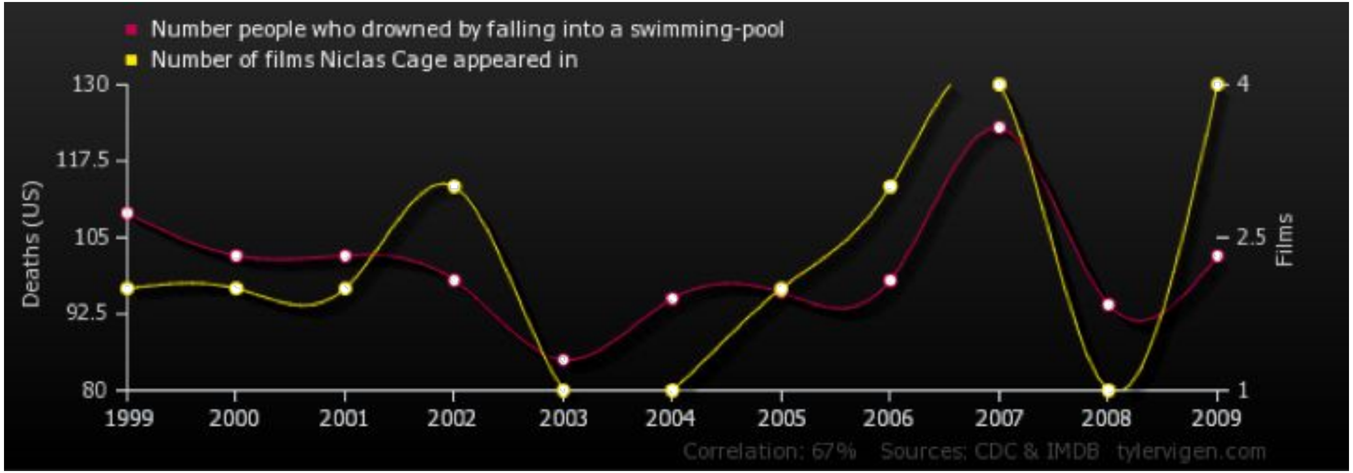
What to do when the ML component makes mistake?

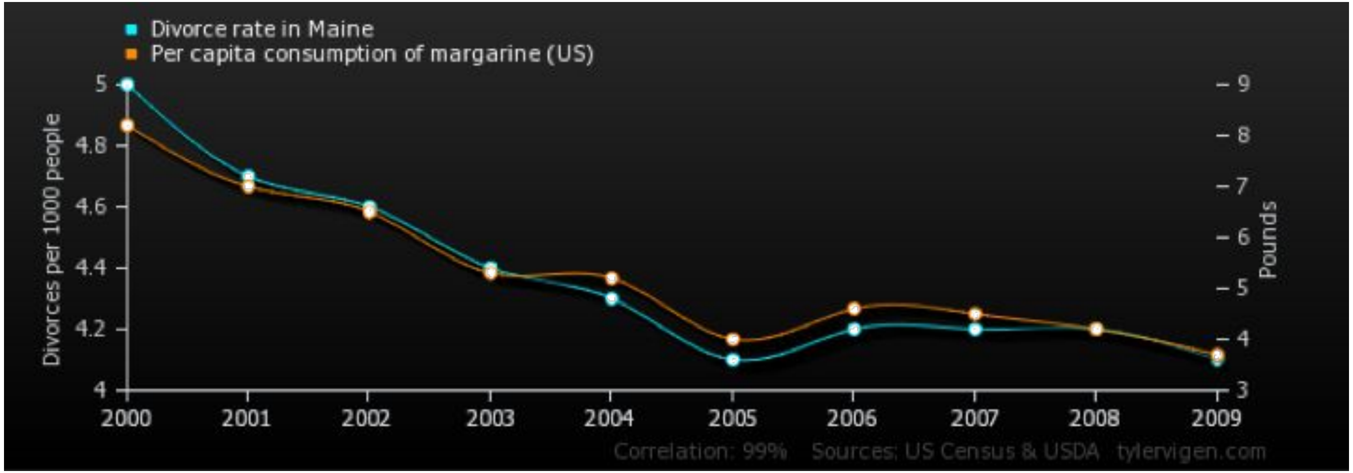


Commons Sources of Wrong Prediction

- Insufficient training data
- Noisy training data
- Biased training data
- Overfitting
- Poor model fit, poor model selection, poor hyperparameters
- Missing context, missing important features
- Noisy inputs
- "Out of distribution" inputs

Correlation vs Causation





Reasons Barely Matter

- No model is always "correct". Some mistakes are unavoidable
- Anticipate the eventual mistake
- Make the system safe despite mistakes

Consider the rest of the system…

Example: Smart Toaster

Safety is a System Property

Code/models are not unsafe, cannot harm people

Systems can interact with the environment in ways that are unsafe

How can you ensure that smart toaster does not burn the kitchen?

Safety Assurance in/outside the Model

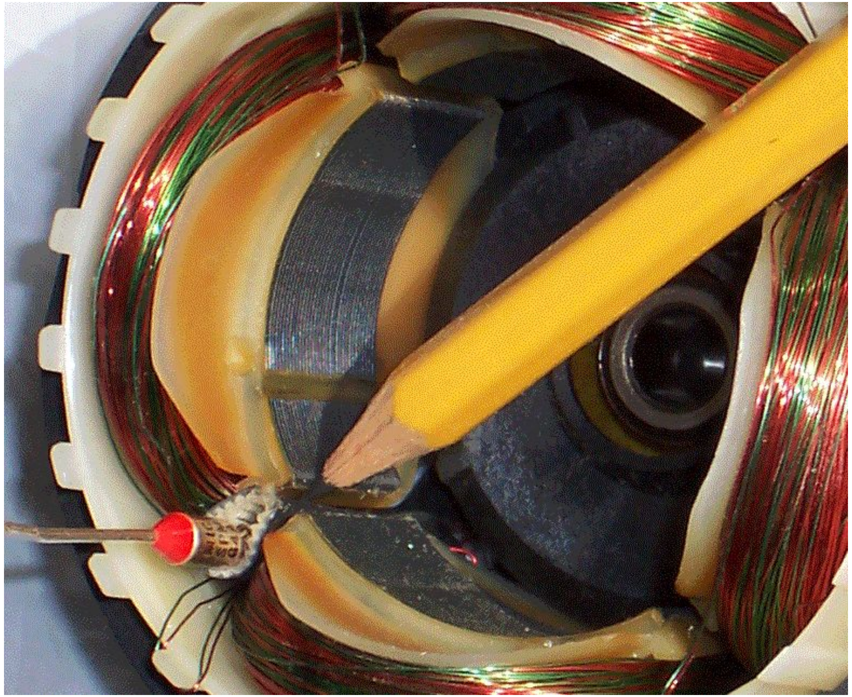
In the model

- Ensure maximum toasting time
- Use heat sensor and past outputs for prediction

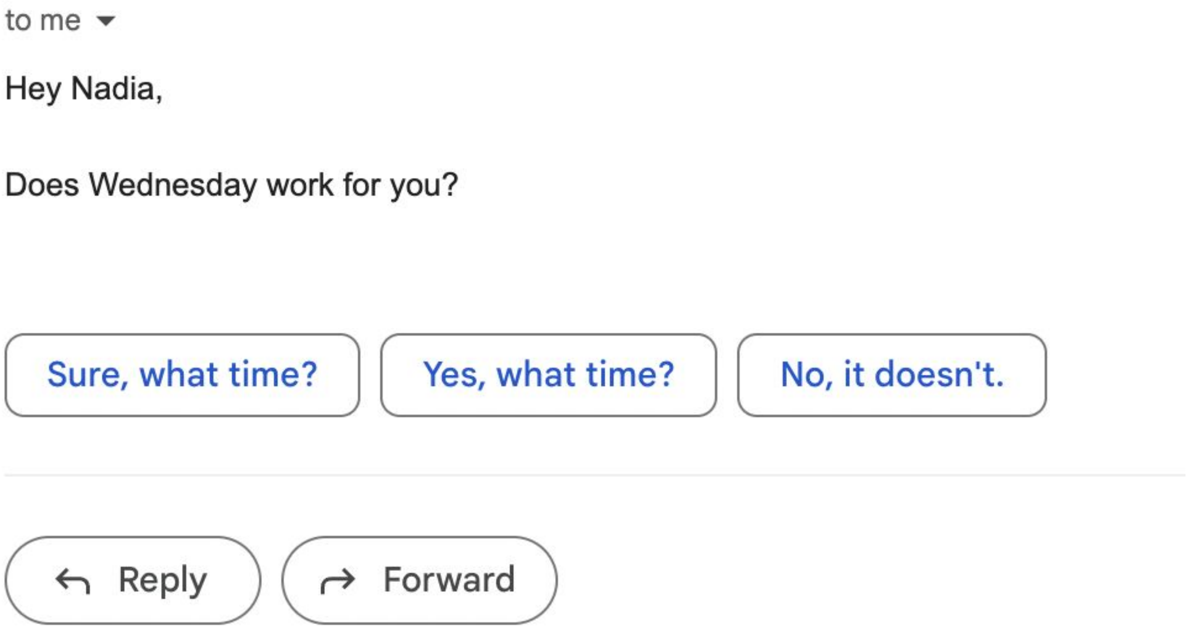
Hard to make guarantees

Outside the model

- Simple code check for max toasting time
- Non-ML rule to shut down if too hot
- Hardware solution: thermal fuse

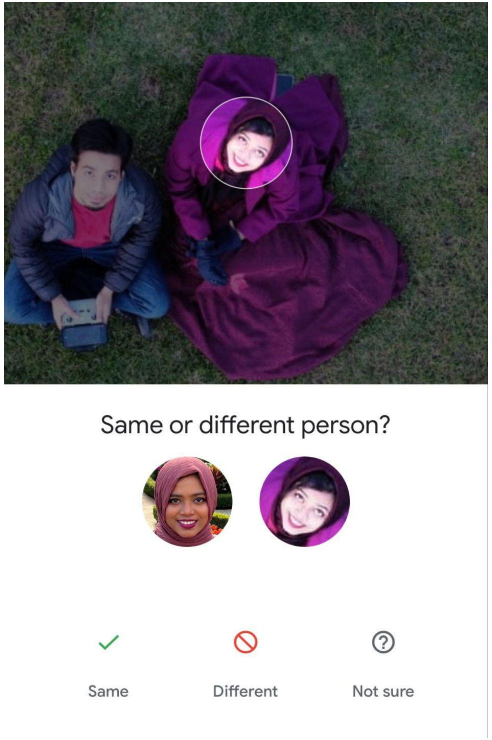


Human in the Loop



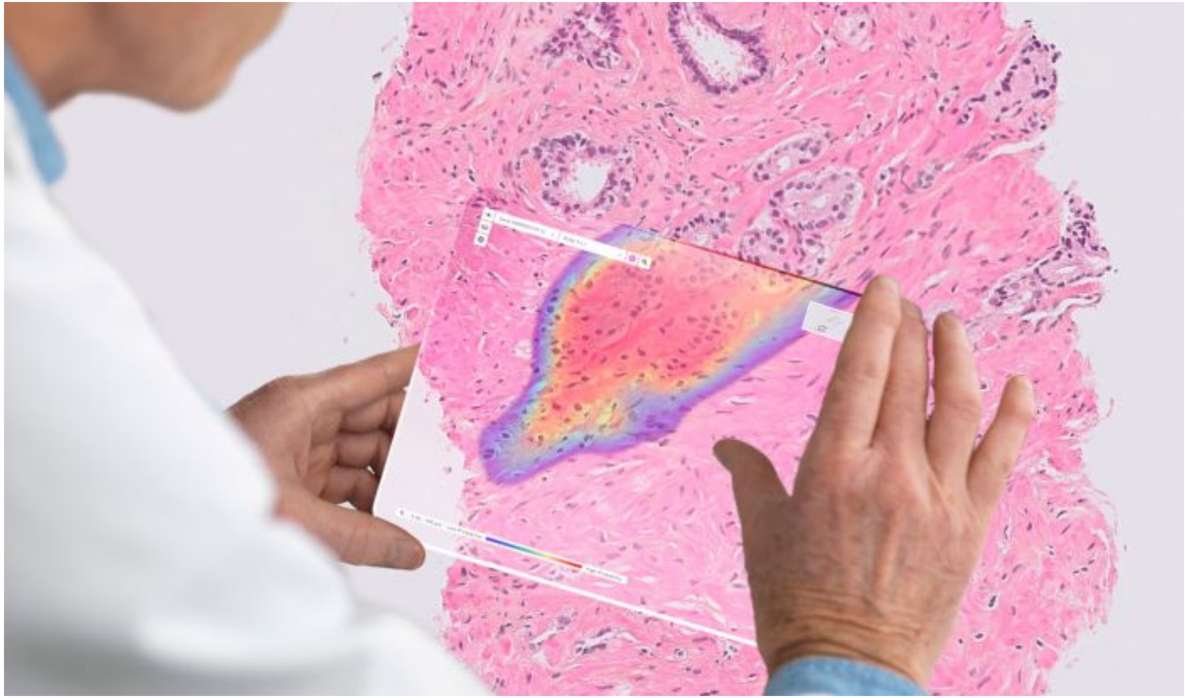
Hey Nadia,

Does Wednesday work for you?



Same or different person?

Human in the Loop



AI powered diagnostic systems for cancer does not replace pathologists

Human in the Loop

Food delivery robot pauses operations after Monday incident

Emily Ackerman relies on a wheelchair for mobility and was trapped on Forbes Avenue when robot wouldn't move

Many different strategies

Based on fault-tolerant design, assuming that there will be software/ML mistakes or environment changes violating assumptions

- Human in the loop
- Undoable actions
- Guardrails
- Mistake detection and recovery (monitoring, doer-checker, fail-over, redundancy)
- Containment and isolation

Actions to Consider While Presenting Intelligence

Automate: Take action on user's behalf

Prompt: Ask the user if an action should be taken

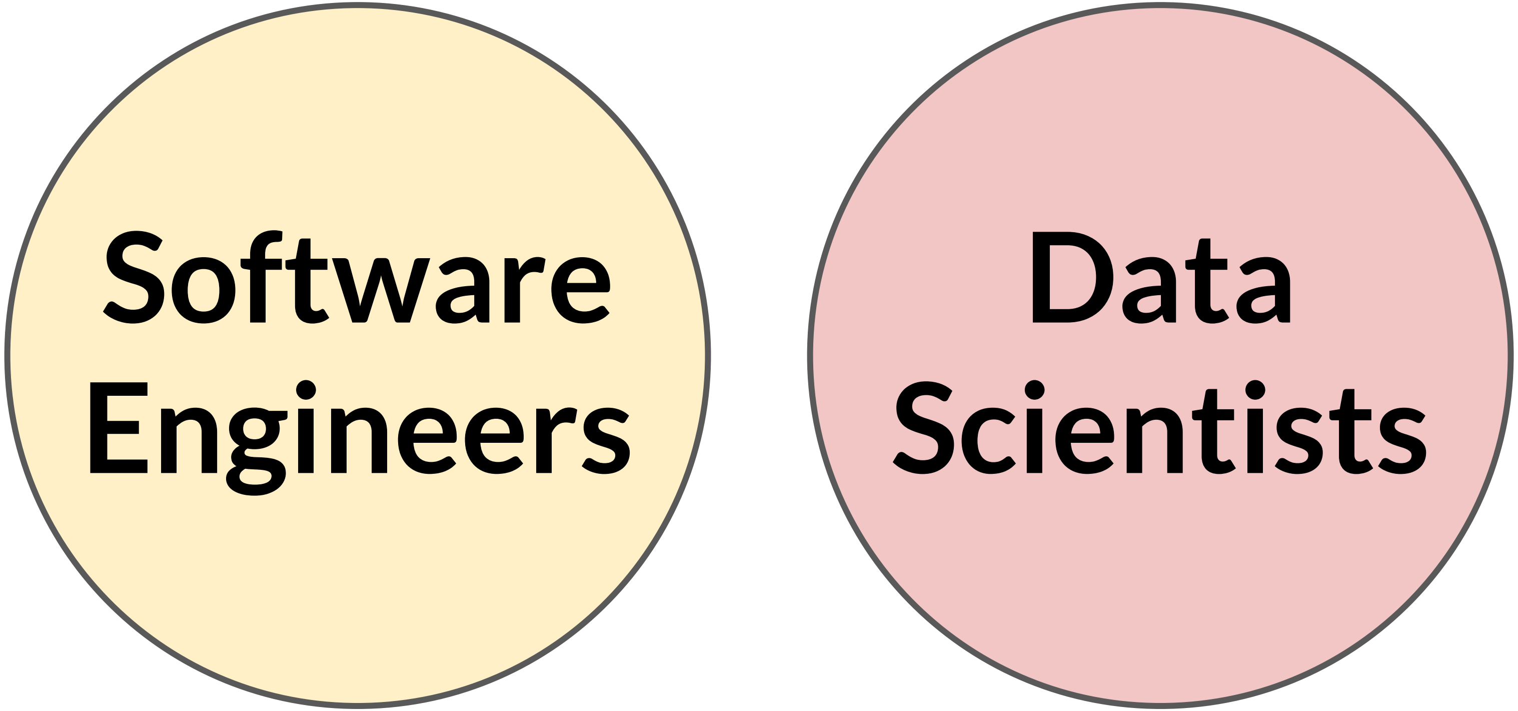
Organize/Annotate/Augment: Add information to a display

Hybrids of these

For your mentioned apps, which of the **Automate**, **Prompt**, or **Augment** would you use, and how?

Building ML-Enabled Systems Need Team Effort

We cannot do it alone

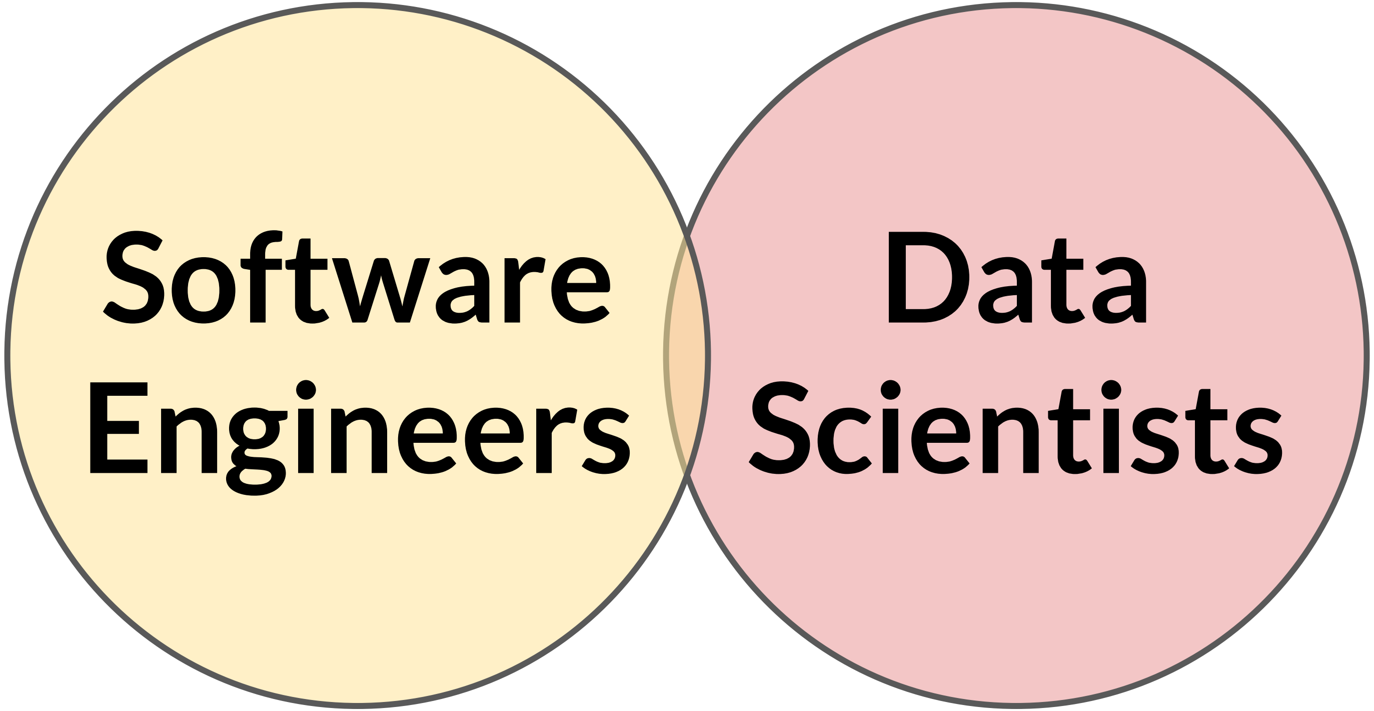


Software Engineers

Data Scientists

and data engineers + domain specialists + operators + business team +
project managers + designers, UI experts + safety, security specialists + lawyers + ...

Interdisciplinary Teams



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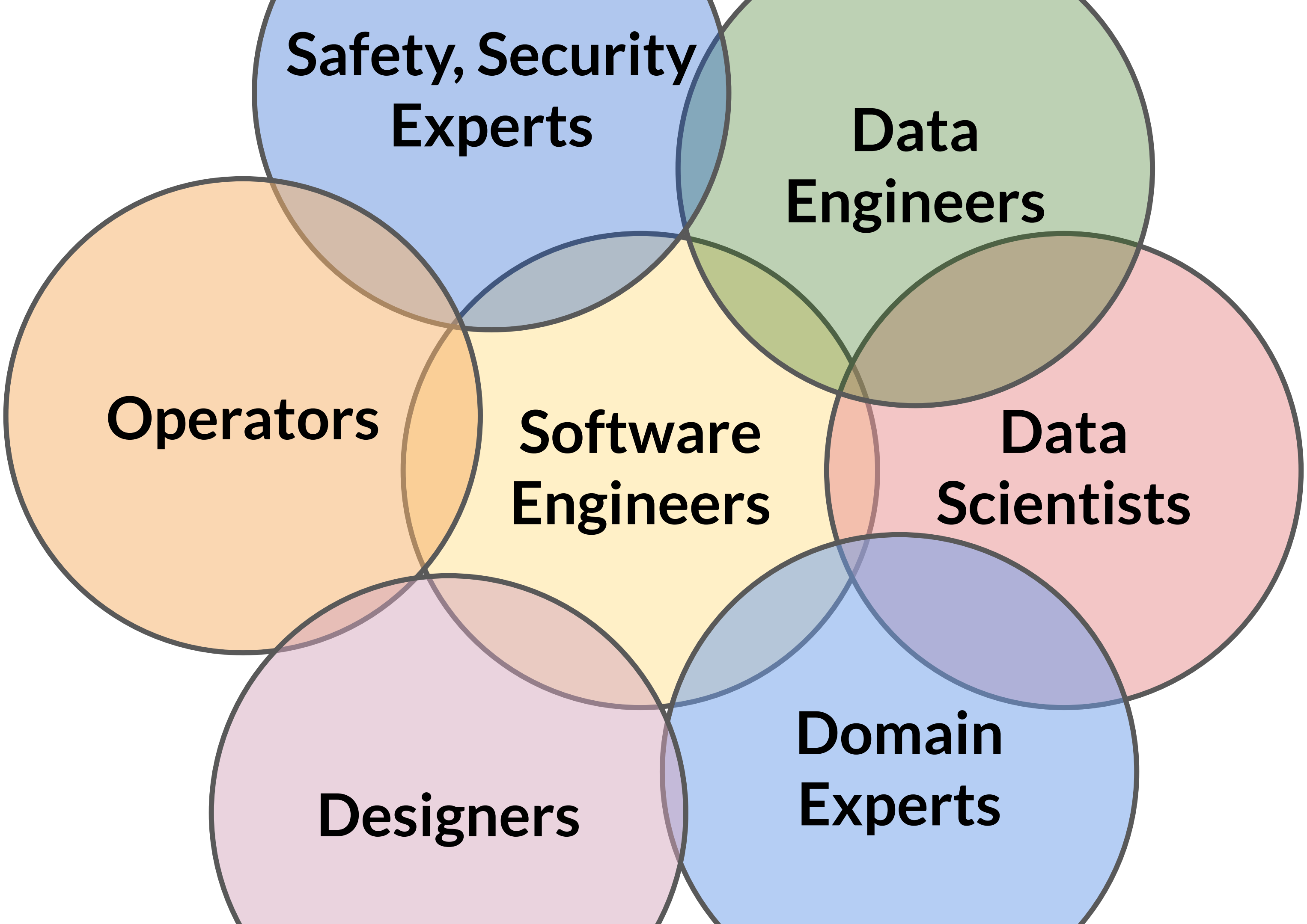


Safety, Security Experts

Data Engineers

Operators

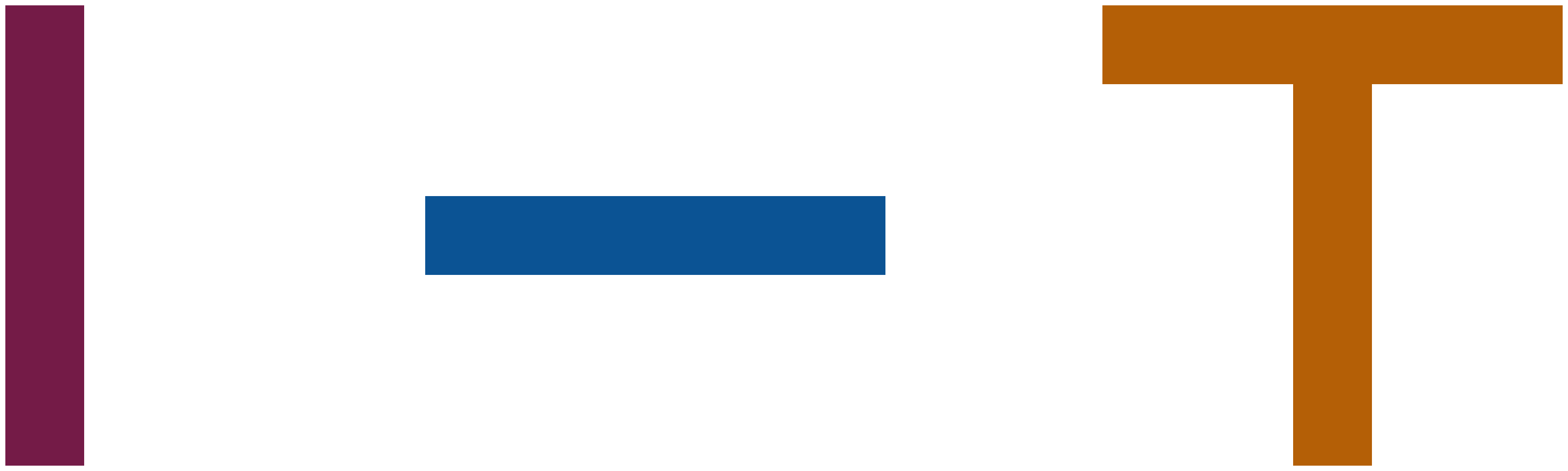
Software Engineers

Data Scientists

Designers

Domain Experts

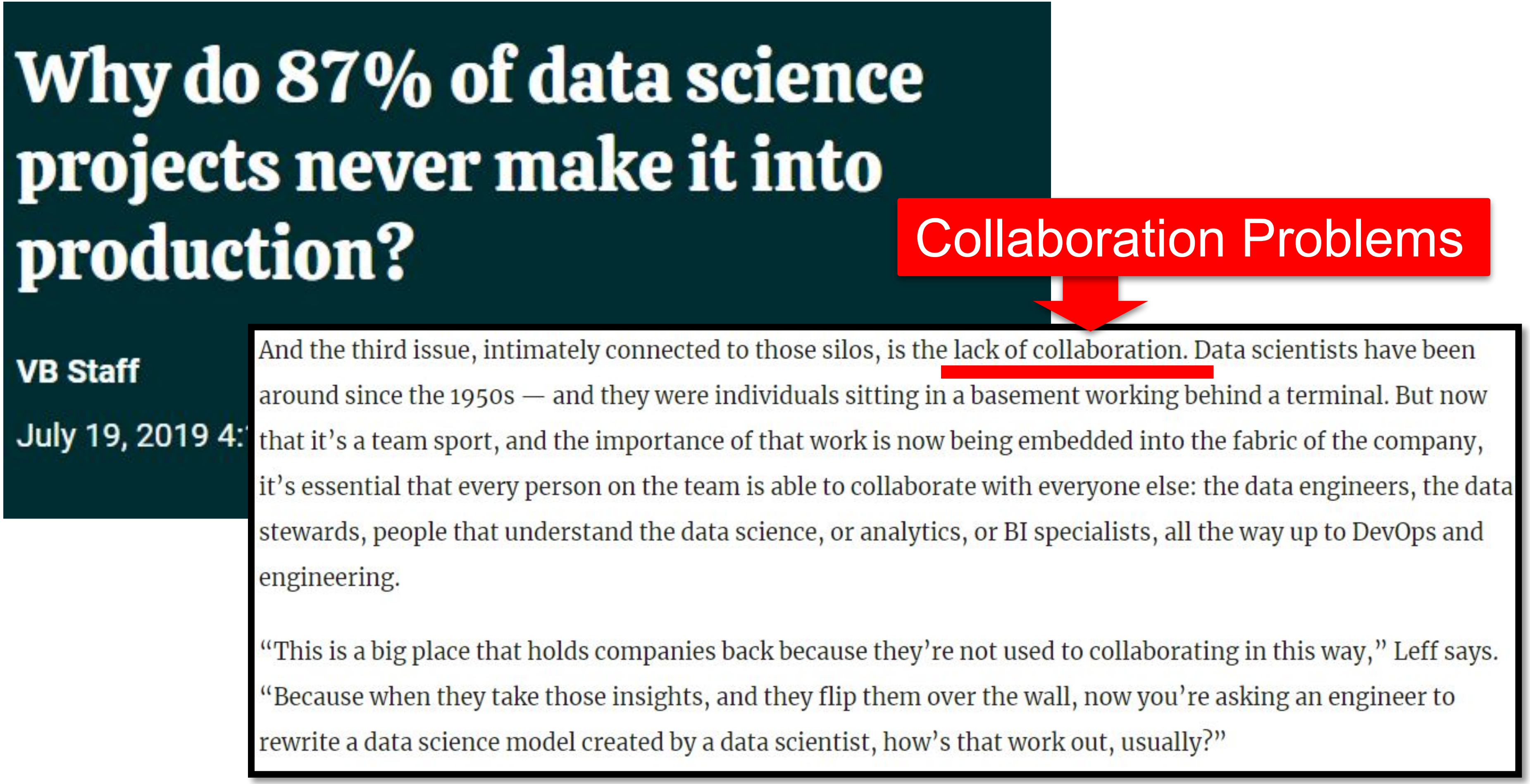
T-Shaped Professionals



I-Shaped
Deep expertise in one topic

Generalist
Broad knowledge of many topics, but not expert in any

T-Shaped
Expert in one topic and broad knowledge of other topics



Why do 87% of data science projects never make it into production?

VB Staff

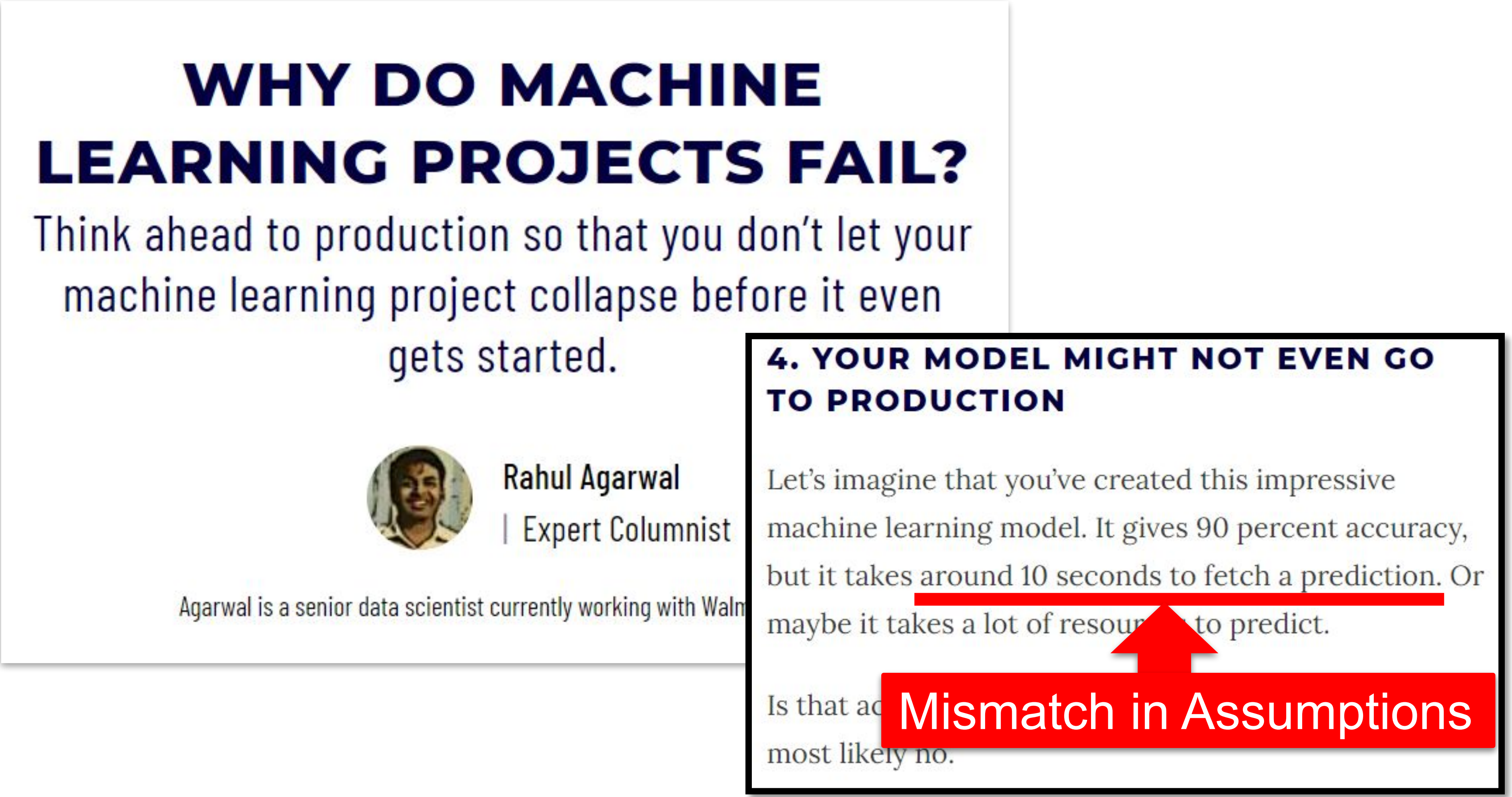
July 19, 2019 4:

Collaboration Problems

And the third issue, intimately connected to those silos, is the lack of collaboration. Data scientists have been around since the 1950s — and they were individuals sitting in a basement working behind a terminal. But now that it's a team sport, and the importance of that work is now being embedded into the fabric of the company, it's essential that every person on the team is able to collaborate with everyone else: the data engineers, the data stewards, people that understand the data science, or analytics, or BI specialists, all the way up to DevOps and engineering.

"This is a big place that holds companies back because they're not used to collaborating in this way," Leff says. "Because when they take those insights, and they flip them over the wall, now you're asking an engineer to rewrite a data science model created by a data scientist, how's that work out, usually?"

https://venturebeat.com/2019/07/19/why-do-87-of-data-science-projects-never-make-it-into-production/



WHY DO MACHINE LEARNING PROJECTS FAIL?

Think ahead to production so that you don't let your machine learning project collapse before it even gets started.

Rahul Agarwal

| Expert Columnist

Agarwal is a senior data scientist currently working with Walm

4. YOUR MODEL MIGHT NOT EVEN GO TO PRODUCTION

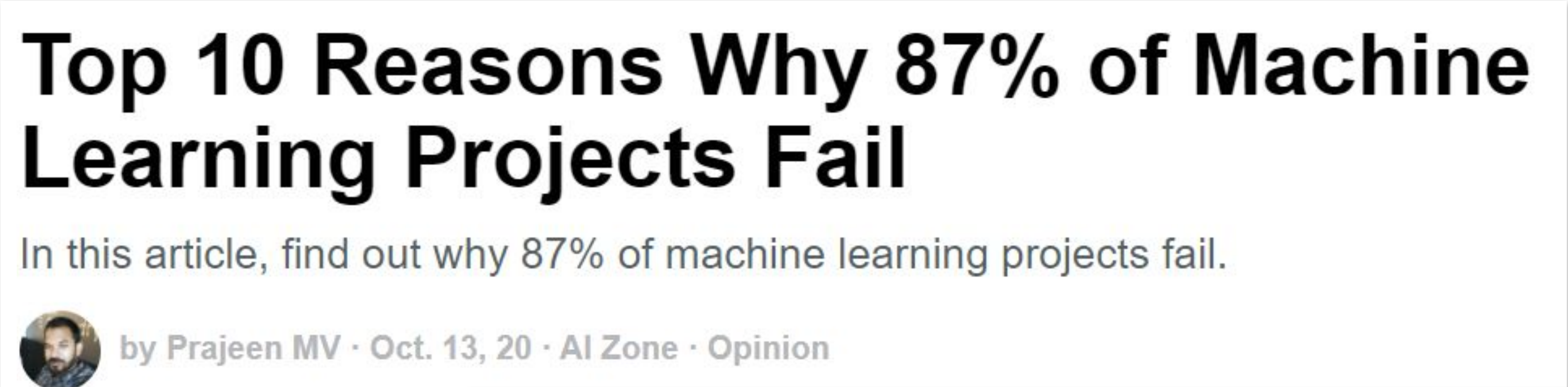
Let's imagine that you've created this impressive machine learning model. It gives 90 percent accuracy, but it takes around 10 seconds to fetch a prediction. Or maybe it takes a lot of resour to predict.

Is that ac

most likely no.

Mismatch in Assumptions

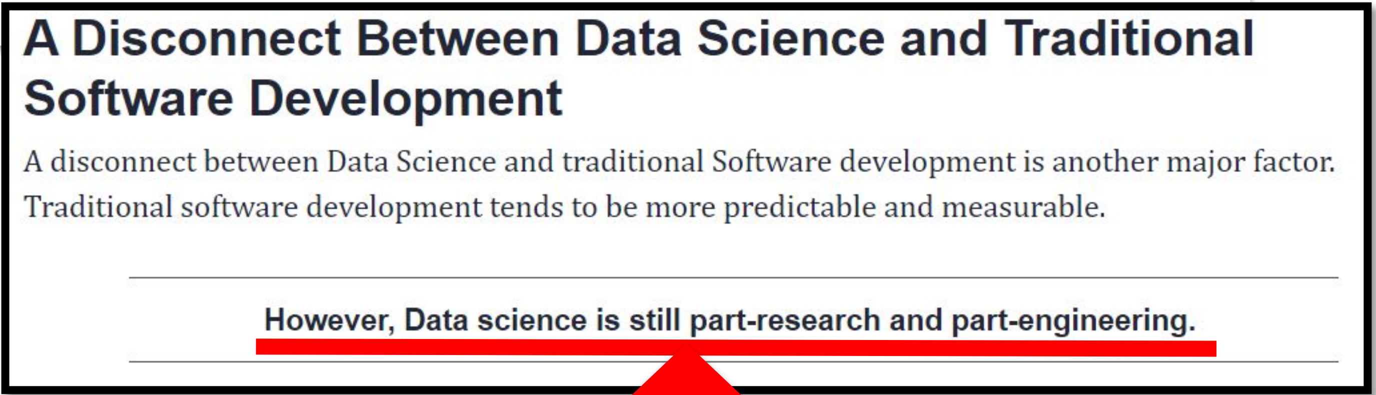
https://builtin.com/machine-learning/why-do-machine-learning-projects-fail



Top 10 Reasons Why 87% of Machine Learning Projects Fail

In this article, find out why 87% of machine learning projects fail.

by Prajeen MV · Oct. 13, 20 · AI Zone · Opinion



A Disconnect Between Data Science and Traditional Software Development

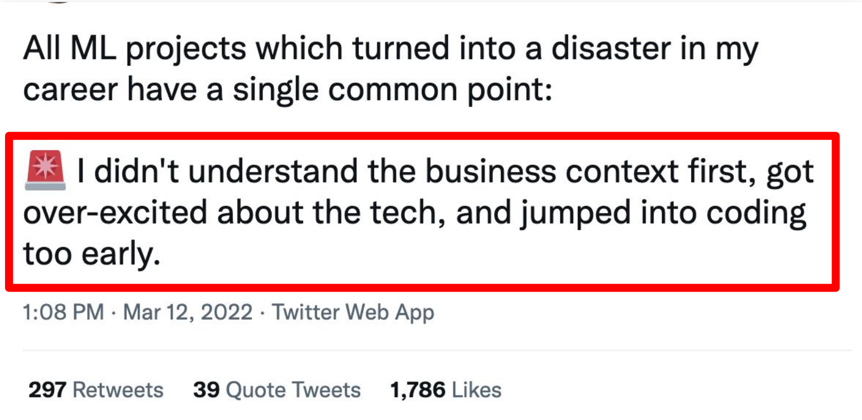
A disconnect between Data Science and traditional Software development is another major factor. Traditional software development tends to be more predictable and measurable.

However, Data science is still part-research and part-engineering.

Different Ways of Working

https://dzone.com/articles/top-10-reasons-why-87-of-the-machine-learning-proj

Frustrations shared in Twitter…

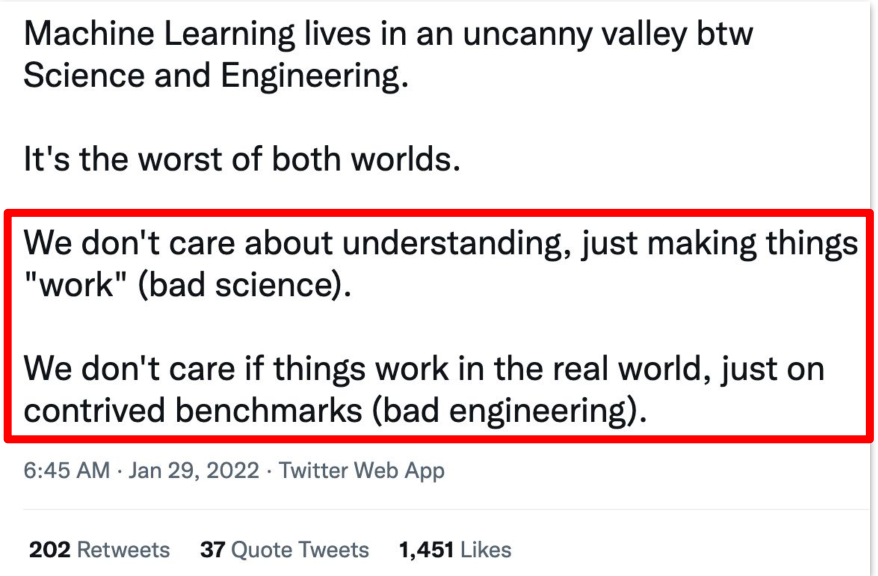


All ML projects which turned into a disaster in my career have a single common point:

🚨 I didn't understand the business context first, got over-excited about the tech, and jumped into coding too early.

1:08 PM · Mar 12, 2022 · Twitter Web App

297 Retweets **39** Quote Tweets **1,786** Likes



Machine Learning lives in an uncanny valley btw Science and Engineering.

It's the worst of both worlds.

We don't care about understanding, just making things "work" (bad science).

We don't care if things work in the real world, just on contrived benchmarks (bad engineering).

6:45 AM · Jan 29, 2022 · Twitter Web App

202 Retweets **37** Quote Tweets **1,451** Likes

We need better collaboration practices, learnings for SE itself

Decades of SE Experience

Development lifecycles

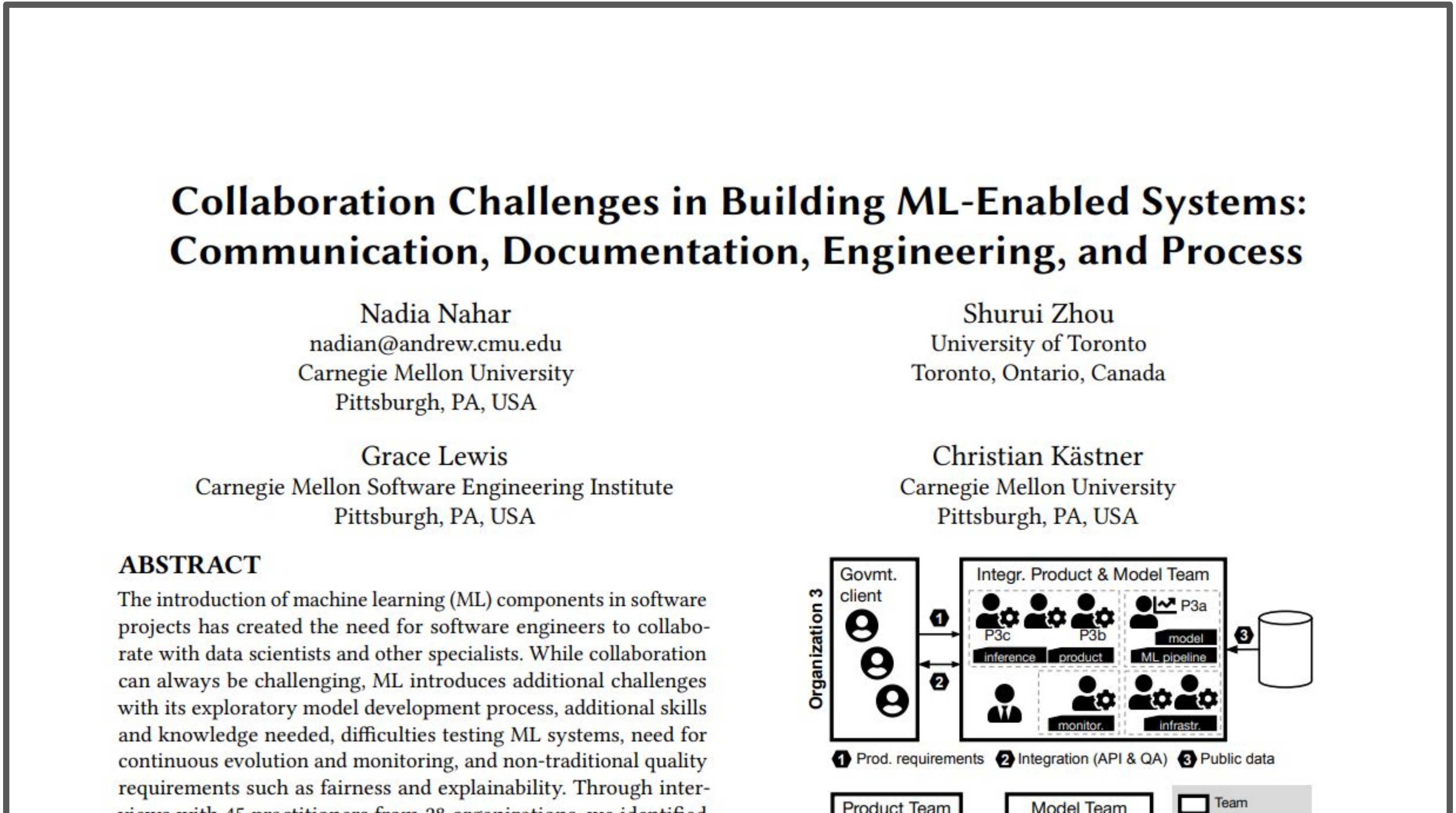
Requirements engineering

Safety engineering

Big-data architectures

Integration & system testing, testing in production

ICSE 2022



Collaboration Challenges in Building ML-Enabled Systems: Communication, Documentation, Engineering, and Process

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ABSTRACT

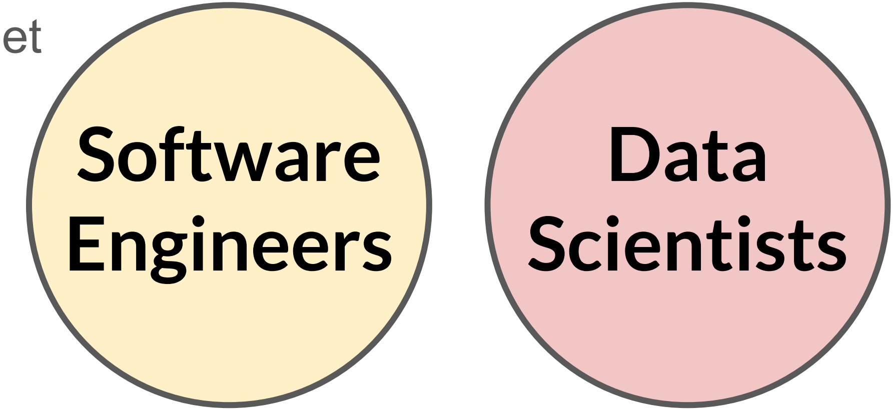
The introduction of machine learning (ML) components in software projects has created the need for software engineers to collaborate with data scientists and other specialists. While collaboration can always be challenging, ML introduces additional challenges with its exploratory model development process, additional skills and knowledge needed, difficulties testing ML systems, need for continuous evolution and monitoring, and non-traditional quality requirements such as fairness and explainability. Through interviews with 45 practitioners from 28 organizations, we identified

Collaboration Challenges at Interfaces between Roles & Teams

Business vs. engineering vs. science mindset

Inconsistent vocabulary

Different priorities, conflicting goals



Software Engineers

Data Scientists

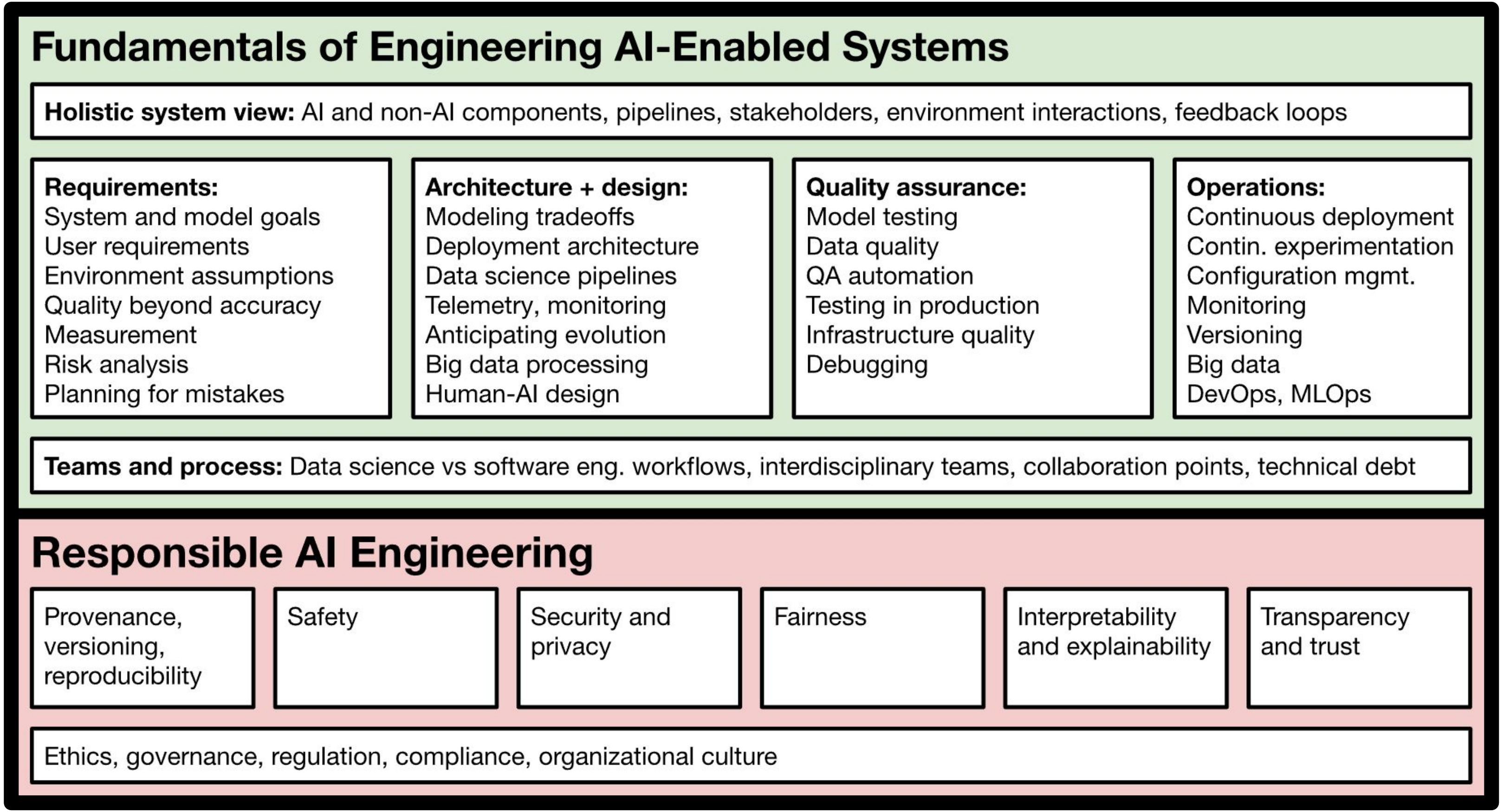
Collaboration Points	*Themes*			
Requirements and Planning				
- Product and Model Requirements	👥	📄	⚙	📅
- Project Planning	👥	–	–	📅
Training Data				
- Negotiating Data Quality and Quantity	👥	📄	⚙	📅
Product-Model Integration				
- Responsibility and Cultural Clashes	👥	–	⚙	📅
- Quality Assurance for Model and Product	👥	📄	⚙	📅

👥 Communication   📄 Documentation   ⚙ Engineering   📅 Process

Summary

- Consider ML as an unreliable component of the System
- All ML models make mistakes
- Safeguard ML models considering the system view
- Building ML systems need team efforts
- Collaborative culture among software engineers, data scientists, and other stakeholders are necessary
- The role of Software Engineering is important in ML

CMU 17-645: Machine Learning in Production



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

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

Further Readings

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