

TOWARD A SYSTEM-WIDE AND INTERDISCIPLINARY PERSPECTIVE ON ML SYSTEM PERFORMANCE

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Carnegie Mellon University

@ FASTPATH 2021

A portrait photograph of Christian Kästner, a man with light brown hair, wearing a red button-down shirt, standing outdoors in front of a large, light-colored building with a tower.

CHRISTIAN KÄSTNER

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Associate Professor @ CMU

Interests:

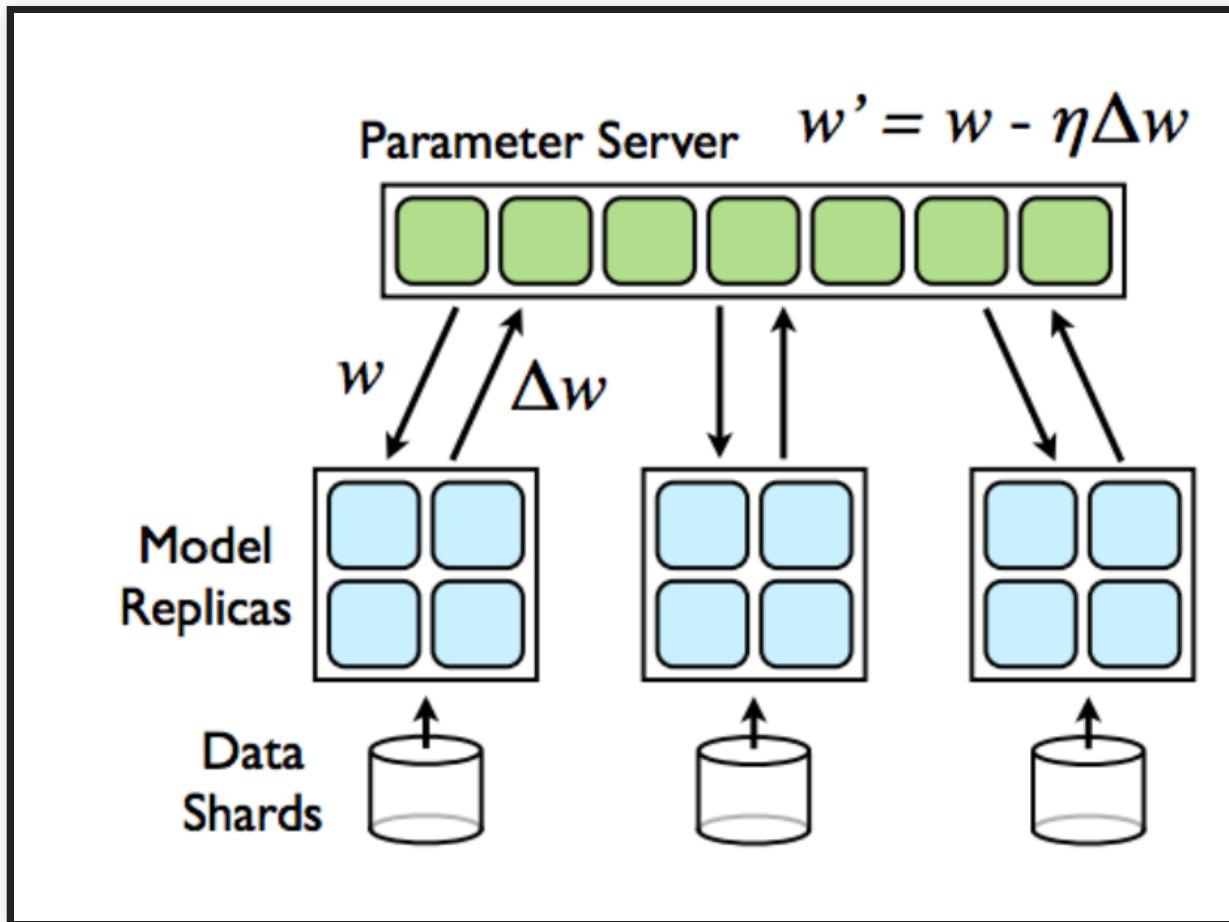
- Software Engineering for ML-Enabled Systems
- Highly-Configurable Systems (incl. performance analysis)
- Sustainability and Stress in Open Source

SOFTWARE ENGINEERING FOR ML-ENABLED SYSTEMS

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

*with interdisciplinary collaborative teams of **data
scientists, software engineers, operators, ...***

SE FOR ML-ENABLED SYSTEMS != DEVELOPING ML FRAMEWORKS



SE FOR ML-ENABLED SYSTEMS

AutoSave (● Off) H ↺ ⏪ ⏴ 02-te... - Save... Christian Kaestner

File Home Insert **Design** Transitions Animations Slide Show Review View Help Tell me

Themes

Design Ideas

Design Ideas

Measuring Progress?

- “I’m almost done with the app. The frontend is almost fully implemented. The backend is fully finished except for the one stupid bug that keeps crashing the server. I only need to find the one stupid bug, but that can probably be done in an afternoon. We should be ready to release next week.”

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46

47 Measuring Progress?

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15-313 Software Engineering 5

isr institute for SOFTWARE RESEARCH

55



Tap to add notes

56



Slide 47 of 74



Notes



6

15-313 Software Engineering

7

29%



SE FOR ML-ENABLED SYSTEMS

the-changelog-318 Last saved a few seconds ago ... Share

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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.

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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

How did we do on your transcript? ☆☆☆☆☆

SYSTEM = ML + NON-ML COMPONENTS

User Interface

Payment

User Accounts

Results &
Editor

Audio
Upload

Speech Recognition

Database, Hadoop, Kafka

SYSTEM DESIGN MATTERS

MOST ML COURSES

Focus narrowly on modeling techniques or building models

Using notebooks, static datasets, evaluating accuracy

The screenshot shows a Jupyter Notebook interface with the following details:

- Title:** G4 playground.ipynb
- File Menu:** File, Edit, View, Insert, Runtime, Tools, Help
- Last edited:** April 4
- Comment and Share buttons:** Comment, Share
- Code Cell Output:** Displays two rows of data and the notebook's structure.

	1096	4	12	26	3	2	0
[]	235	4	4	23	1	2	0

525 rows × 6 columns
- Code Block:**

```
[ ] # learning a classifier whether the result will be nonZero
from sklearn import tree

classifier=tree.DecisionTreeClassifier(max_depth=8)
classifier=classifier.fit(Xtrain, ynztrain)

print(classifier.score(Xtrain, ynztrain))
print(classifier.score(Xtest, ynztest))
```
- Output:** Shows the classifier's score on the training and test sets.

```
[ ] # 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))
```



0.9376379365613154
-2.437397740412892

SE FOR ML-ENABLED SYSTEMS

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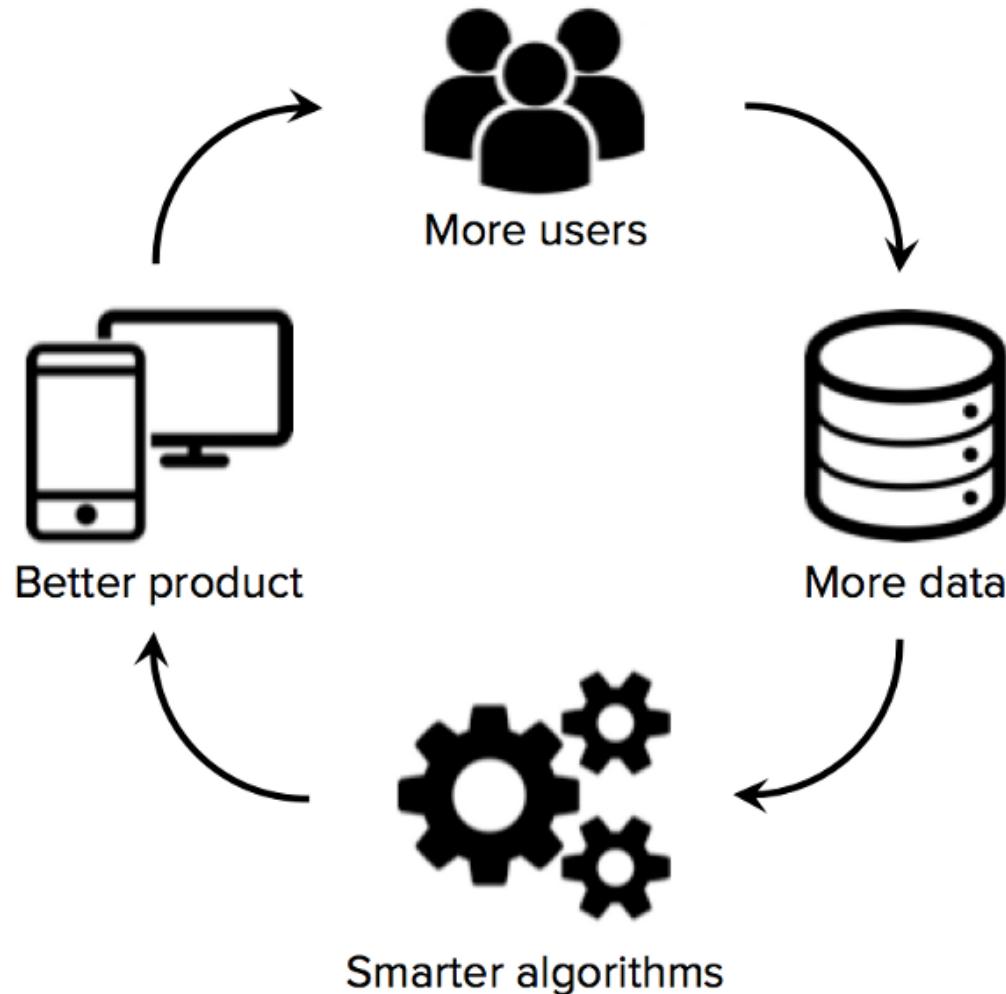
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THE FLYWHEEL



TELEMETRY DESIGN

the-changelog-318
← Dashboard | Quality: High ⓘ

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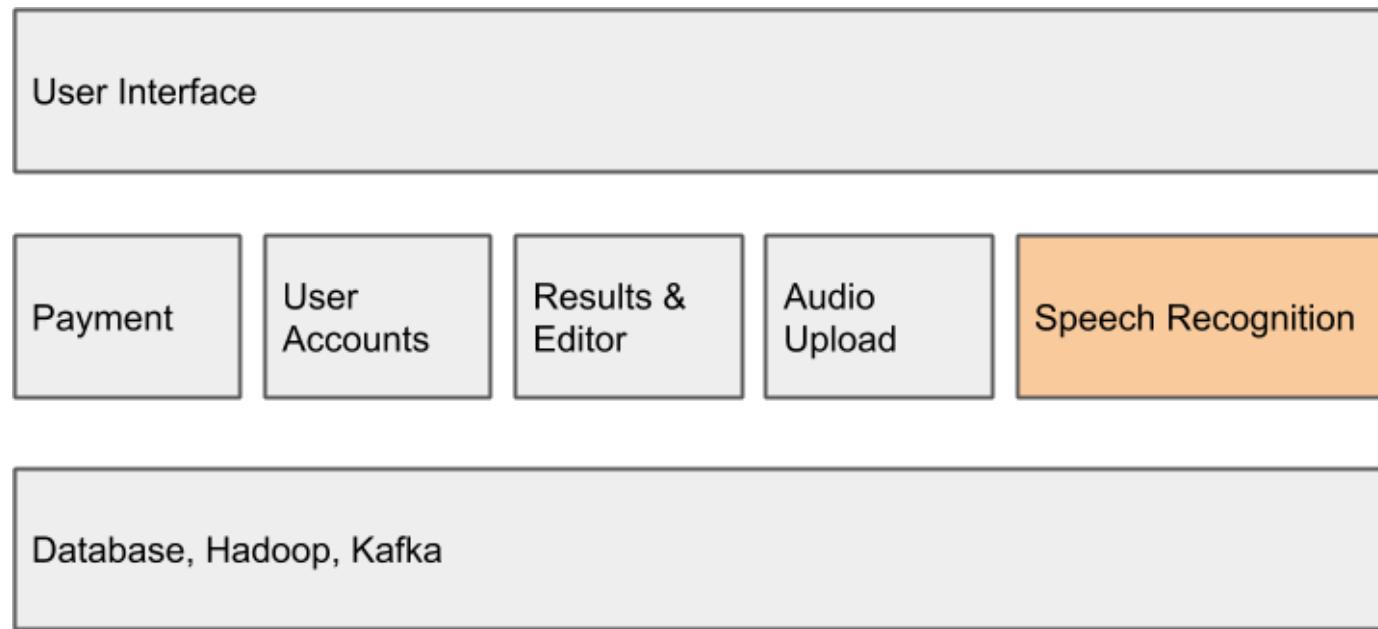
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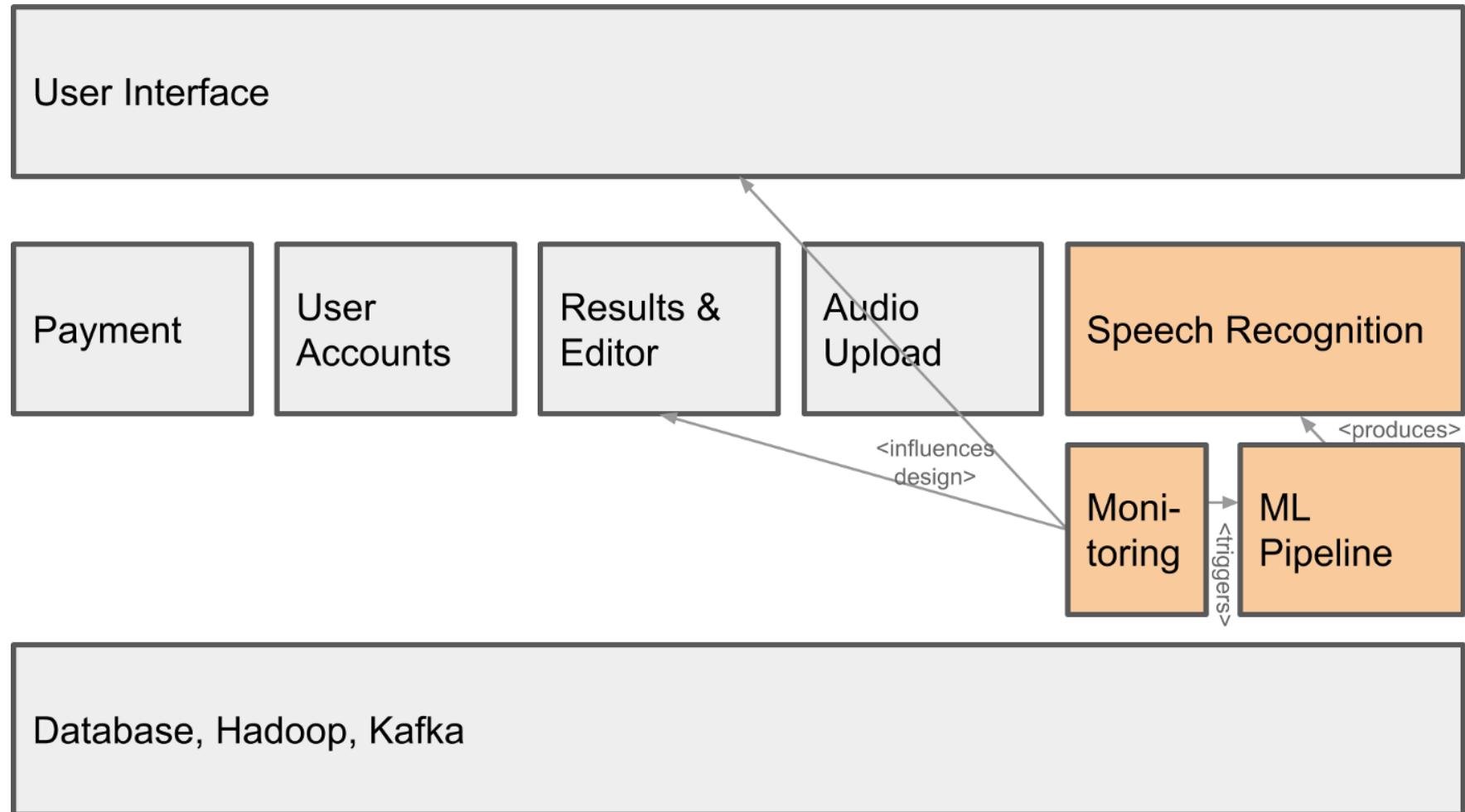
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ML IS A COMPONENT IN A SYSTEM



SYSTEM DESIGN TO SUPPORT ML



EVERYTHING IS A TRADEOFF

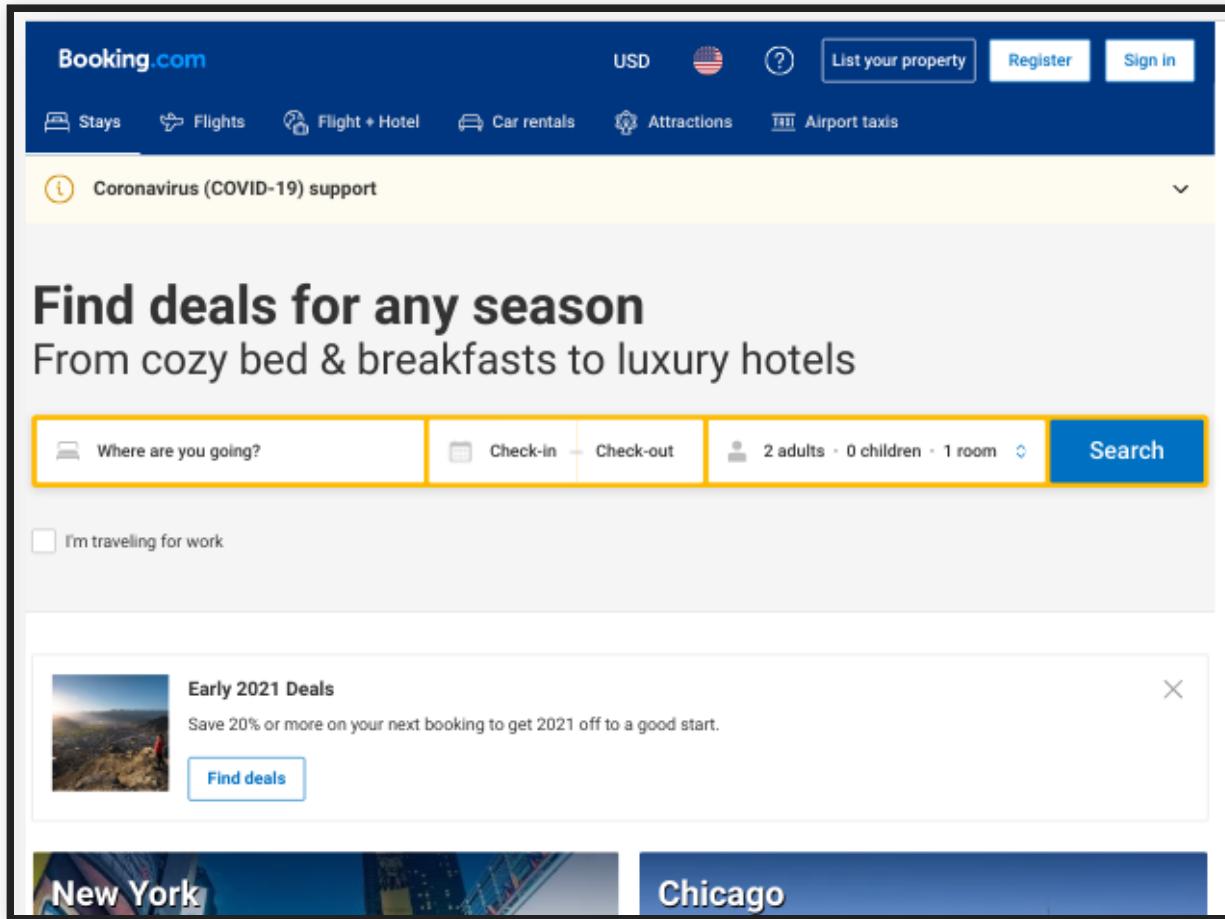
“It Depends.”

MANY QUALITIES OF INTEREST

- Accuracy
- Inference latency, throughput, energy consumption
- Learning time, incremental learning, scalability, resources needed
- Simplicity, maintainability, extensibility,
- Interpretability/explainability, fairness
- Robustness, reproducibility, stability

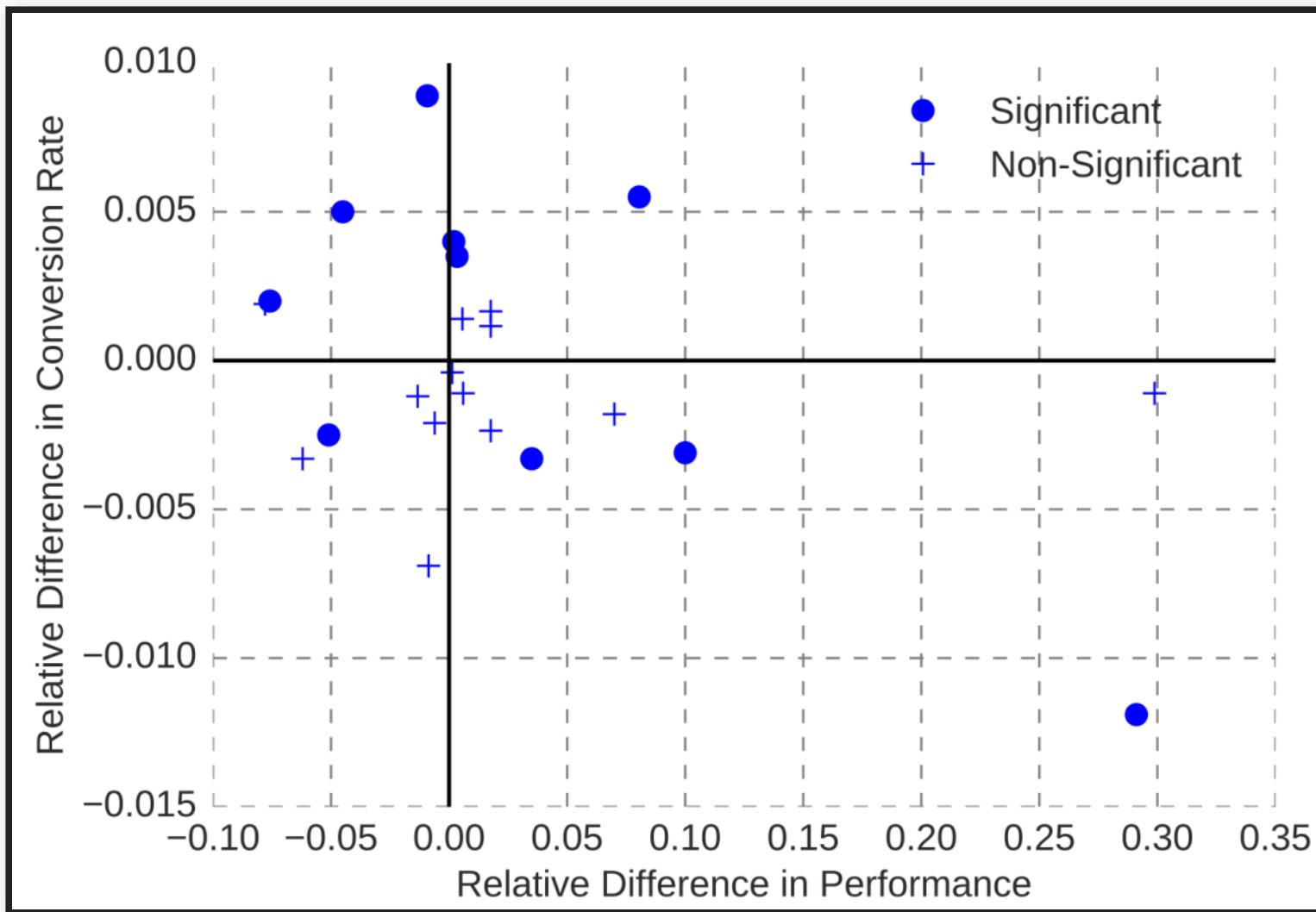
- Usability, trust, accountability
- User satisfaction
- Dealing with mistakes
- Safety, security, privacy
- Development velocity, predictability
- Profit
- ...

MODEL QUALITY VS SYSTEM QUALITY



Bernardi, Lucas, Themistoklis Mavridis, and Pablo Estevez. "150 successful machine learning models: 6 lessons learned at Booking.com." In Proc. International Conference on Knowledge Discovery & Data Mining, 2019.

MODEL QUALITY VS SYSTEM QUALITY



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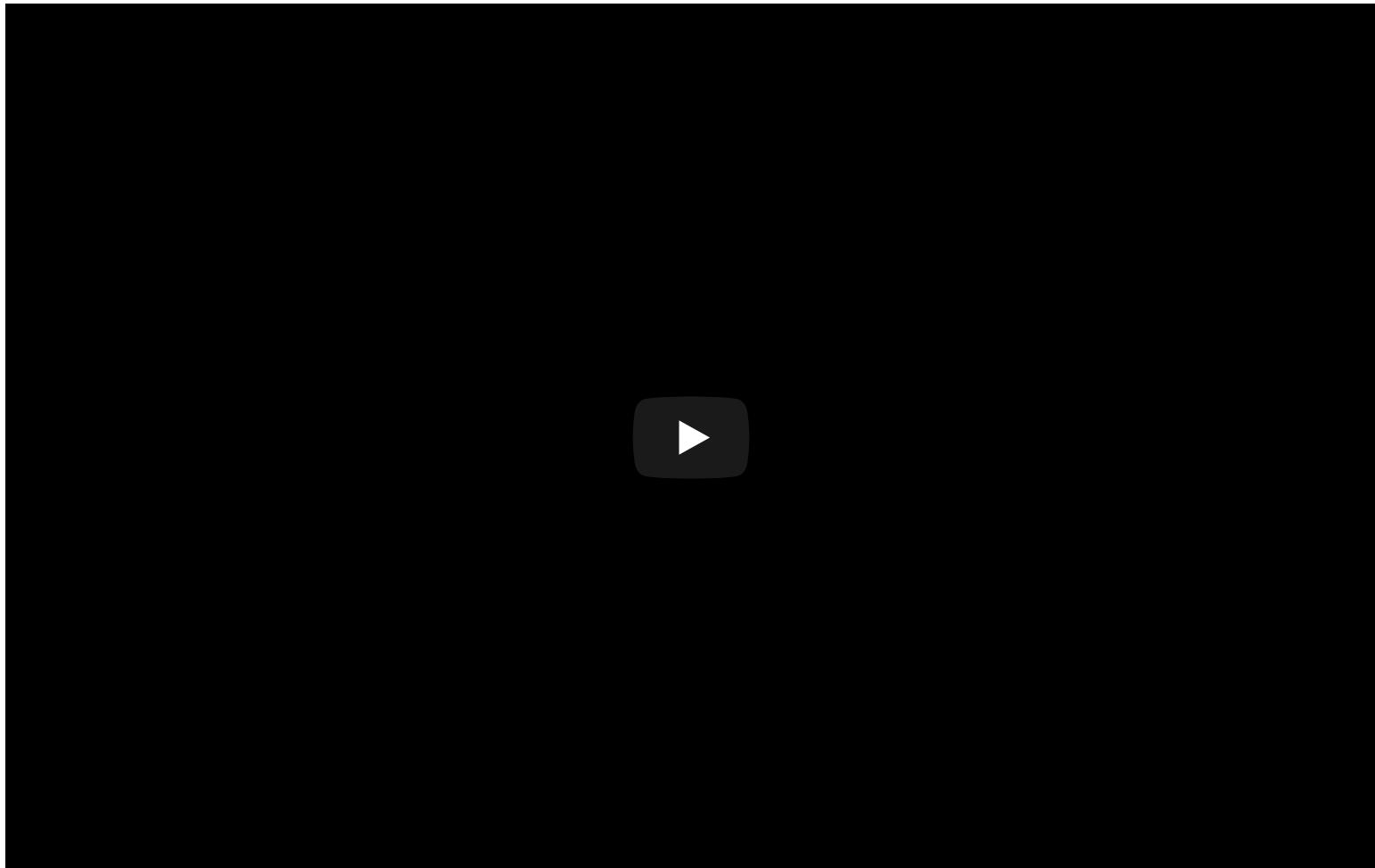
EXAMPLE: AR INSTANT TRANSLATION



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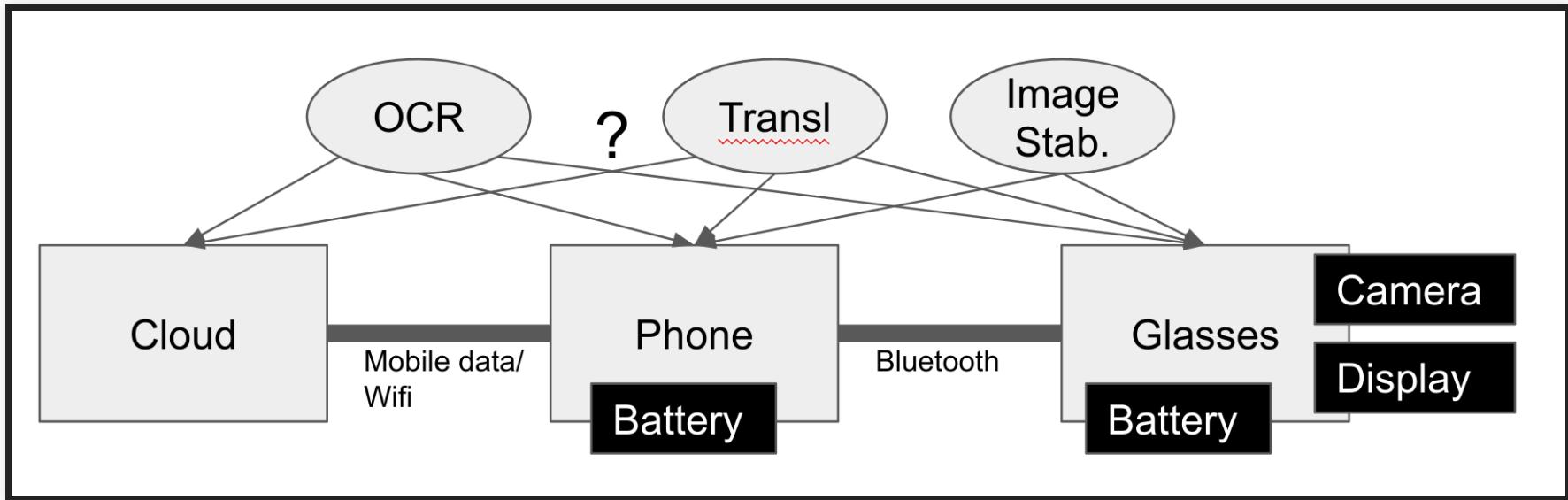
EXAMPLE: AR INSTANT TRANSLATION



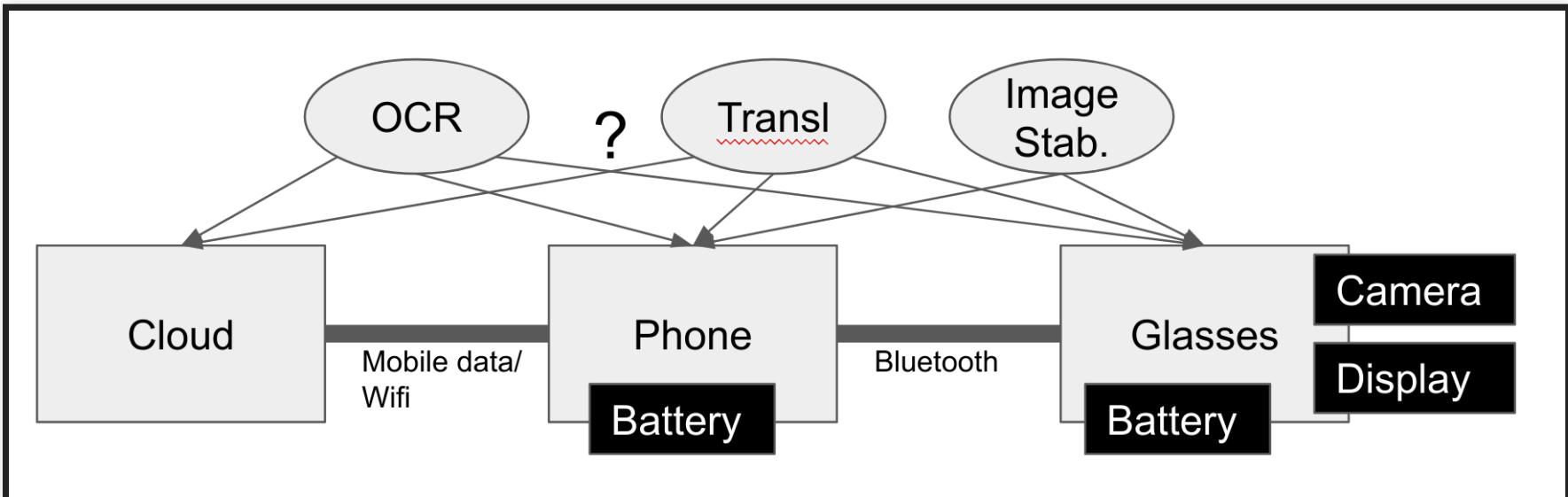
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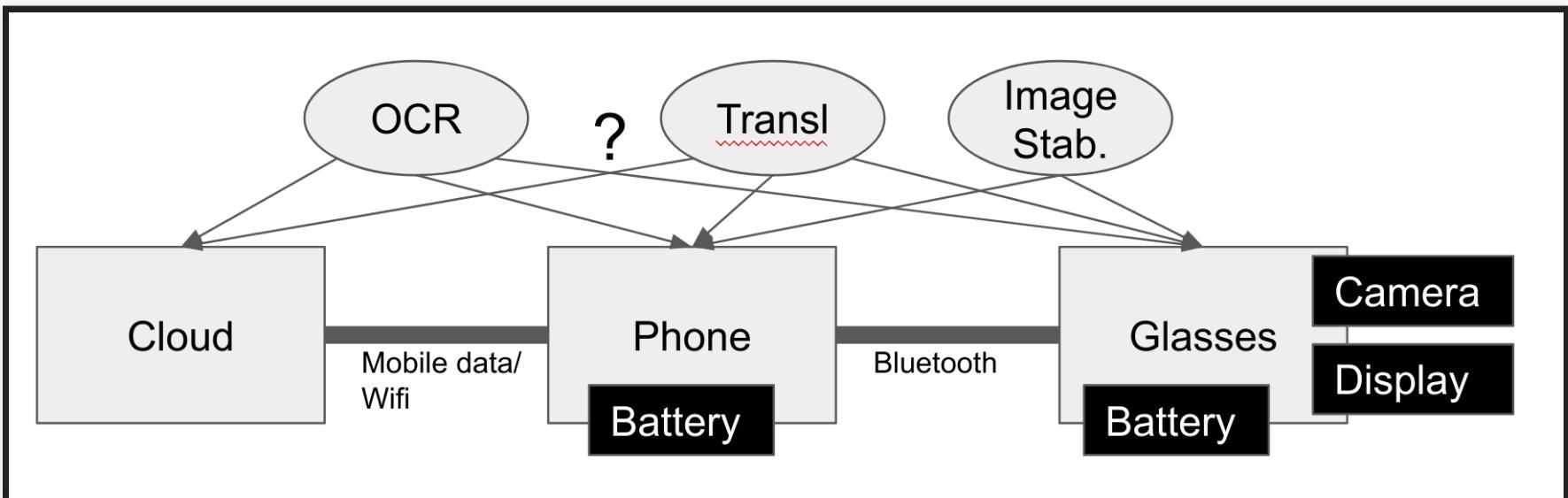
EXAMPLE: AR INSTANT TRANSLATION



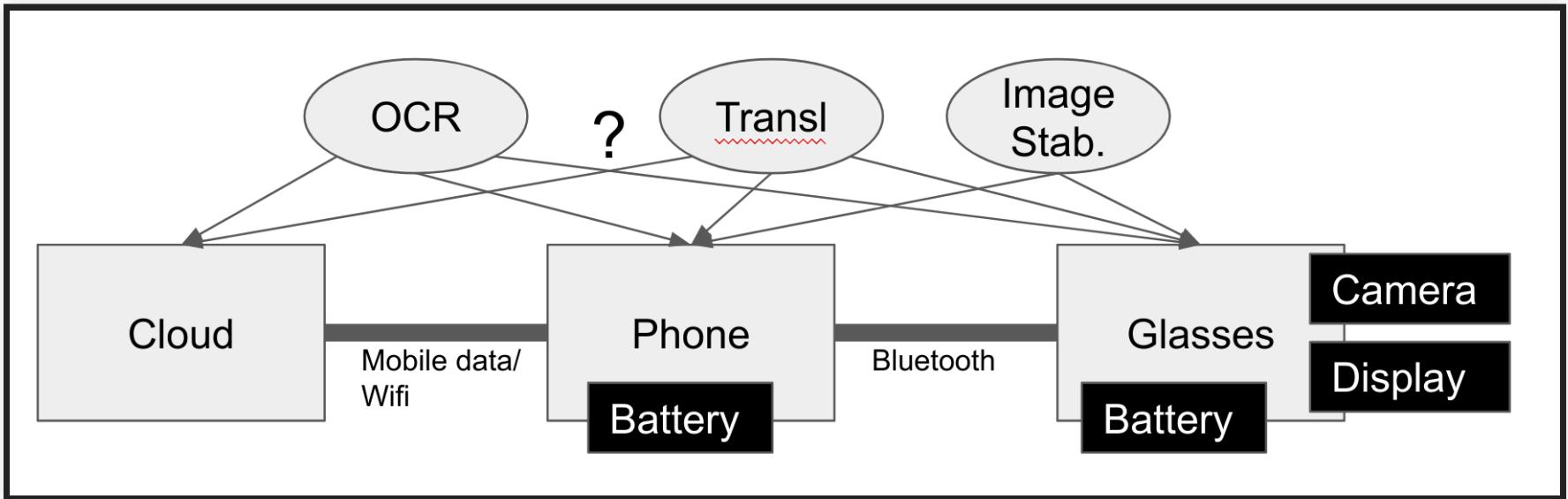
TRADEOFF: ACCURACY VS LATENCY + ENERGY + MODEL SIZE



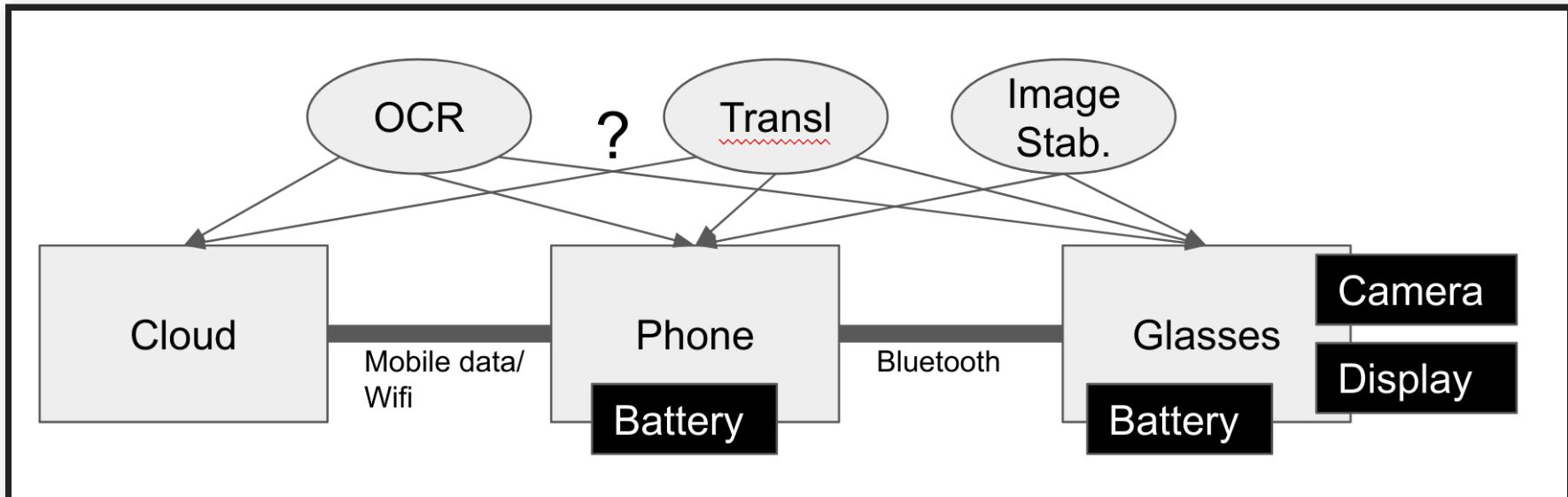
TRADEOFF: LATENCY VS ENERGY CONSUMPTION VS BANDWIDTH



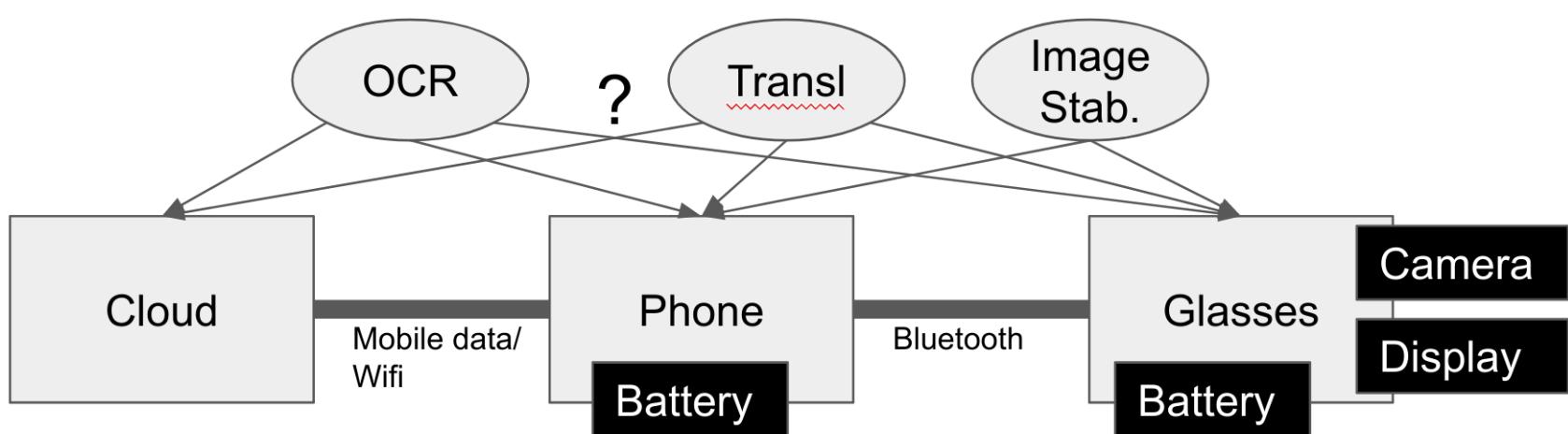
TRADEOFF: PRIVACY VS TELEMETRY



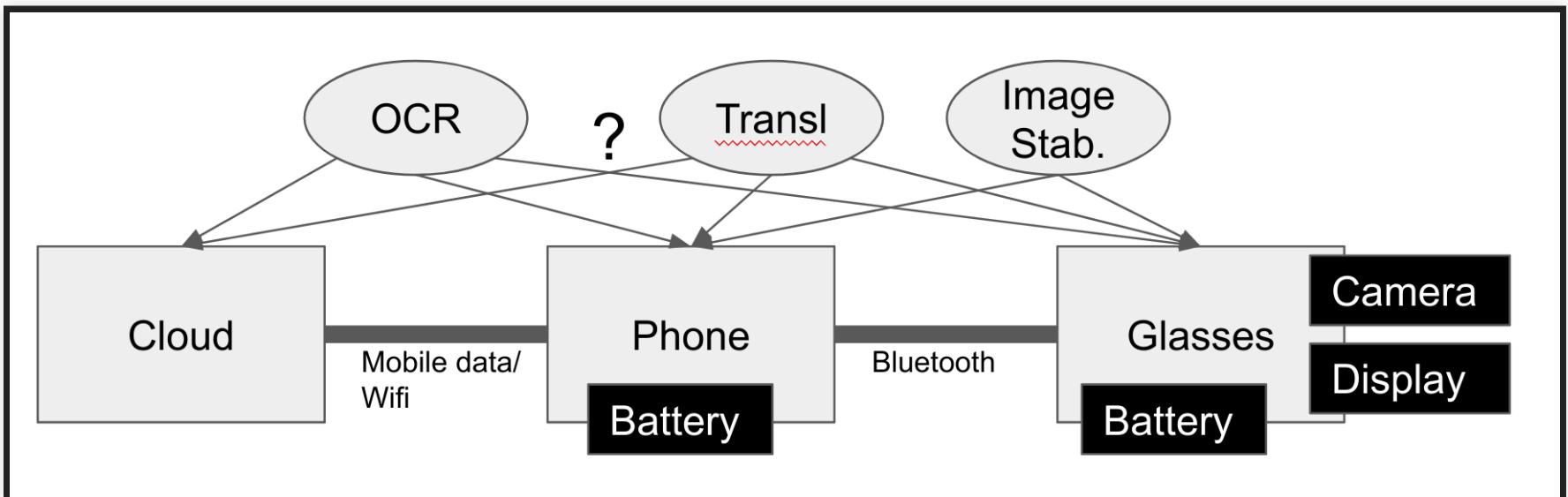
TRADEOFF: TELEMETRY BENEFITS VS TELEMETRY COSTS



TRADEOFF: UPDATE LATENCY VS OFFLINE USE

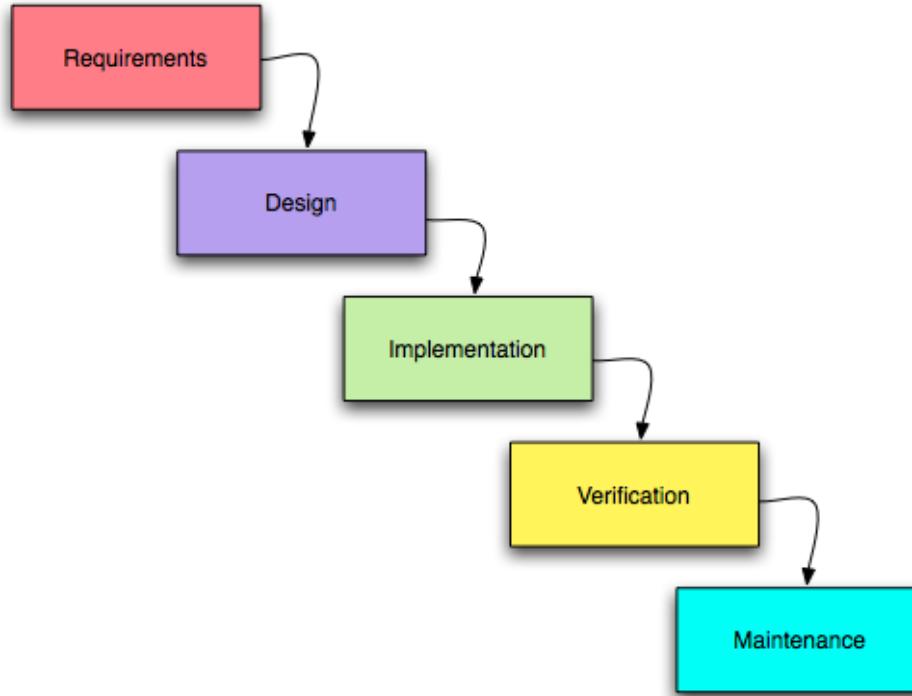


TRADEOFF: TRAINING COST VS UPDATE FREQUENCY



“It Depends.”

THINK LIKE A SOFTWARE ARCHITECT

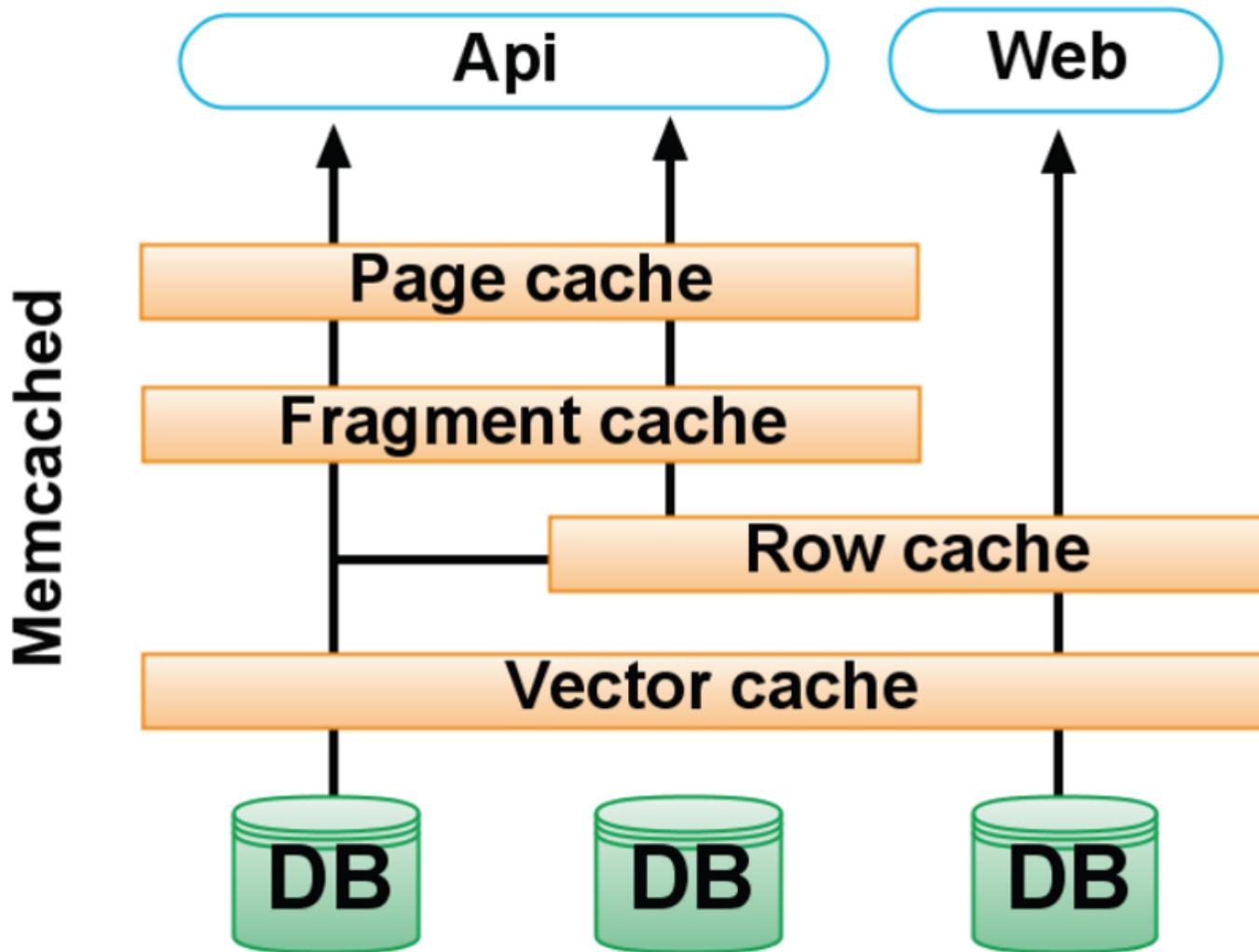


EXCURSION: TWITTER



Raffi. [New Tweets per second record, and how!](#) Twitter Blog, 2013

TWITTER - CACHING ARCHITECTURE



Speaker notes

- Running one of the world's largest Ruby on Rails installations
- 200 engineers
- Monolithic: managing raw database, memcache, rendering the site, and * presenting the public APIs in one codebase
- Increasingly difficult to understand system; organizationally challenging to manage and parallelize engineering teams
- Reached the limit of throughput on our storage systems (MySQL); read and write hot spots throughout our databases
- Throwing machines at the problem; low throughput per machine (CPU + RAM limit, network not saturated)
- Optimization corner: trading off code readability vs performance

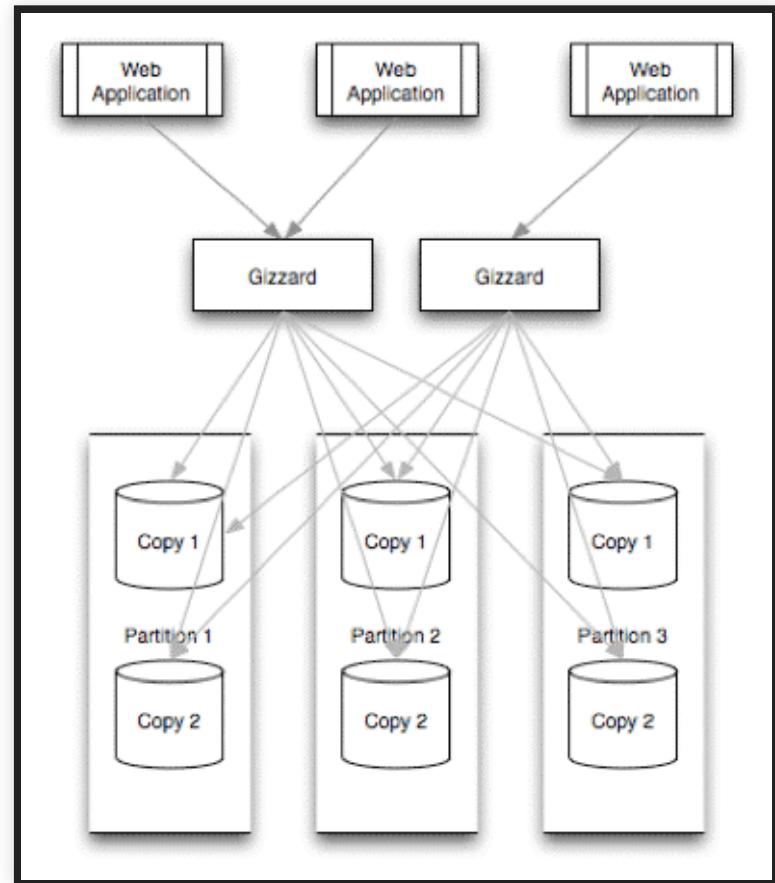
TWITTER'S REDESIGN GOALS

- Performance
 - Improve median latency; lower outliers
 - Reduce number of machines 10x
- Reliability
 - Isolate failures
- Maintainability
 - "We wanted cleaner boundaries with “related” logic being in one place": encapsulation and modularity at the systems level (rather than at the class, module, or package level)
- Modifiability
 - Quicker release of new features: "run small and empowered engineering teams that could make local decisions and ship user-facing changes, independent of other teams"

Raffi. [New Tweets per second record, and how!](#) Twitter Blog, 2013

TWITTER: REDESIGN DECISIONS

- Ruby on Rails -> JVM/Scala
- Monolith -> Microservices
- RPC framework with monitoring, connection pooling, failover strategies, loadbalancing, ... built in
- New storage solution, temporal clustering, "roughly sortable ids"
- Data driven decision making

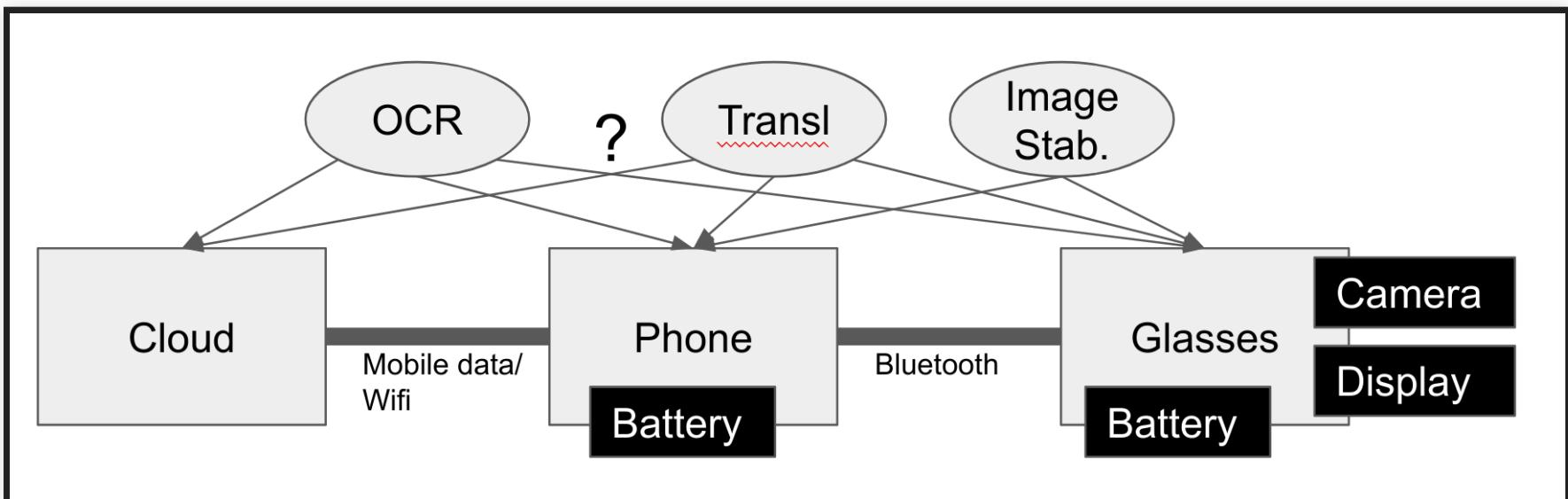


TWITTER CASE STUDY: KEY INSIGHTS

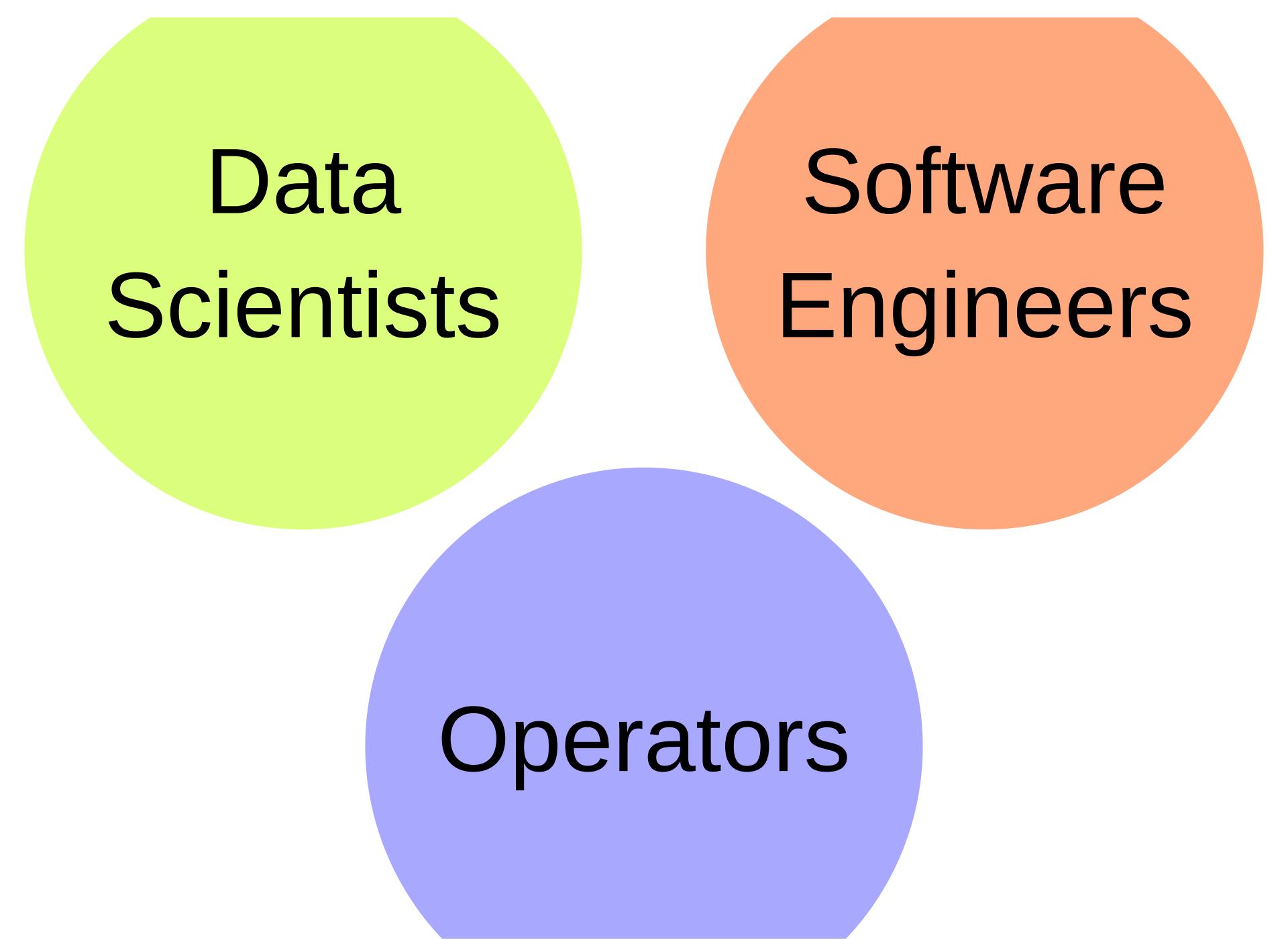
- Architectural decisions affect entire systems, not only individual modules
- Abstract, different abstractions for different scenarios
- Reason about quality attributes early
- Make architectural decisions explicit

ARCHITECTURAL PLANNING

- Identify and prioritize relevant qualities
- Identify system structure and relevant interactions
- Understand constraints and tradeoffs
- Conduct research into requirements and constraints
- Explore alternatives
- Set obligations for components



TEAMS AND PROCESS



A diagram consisting of three overlapping circles. The top-left circle is light green and contains the text "Data Scientists". The top-right circle is light orange and contains the text "Software Engineers". The bottom circle is light blue and contains the text "Operators". The circles overlap in the center, suggesting a shared or interconnected nature of the roles.

**Data
Scientists**

**Software
Engineers**

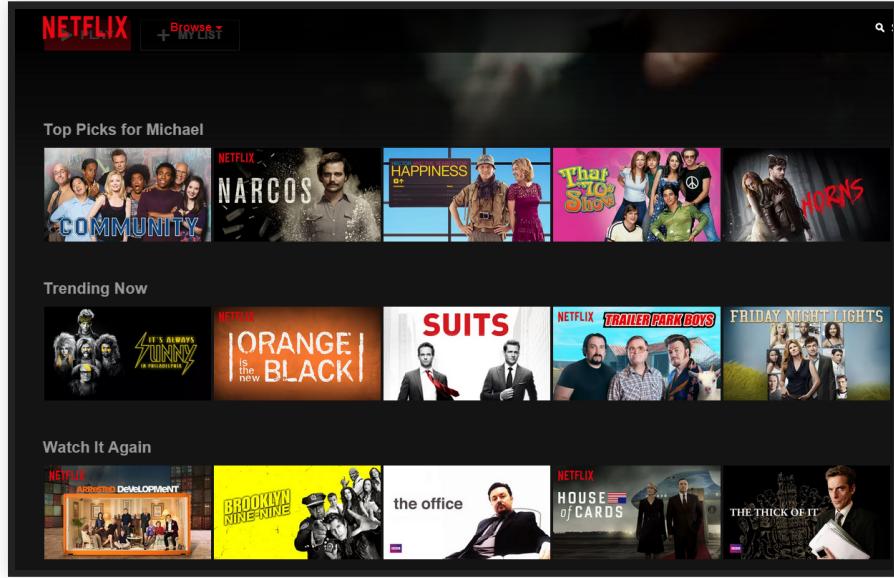
Operators

DATA SCIENTIST

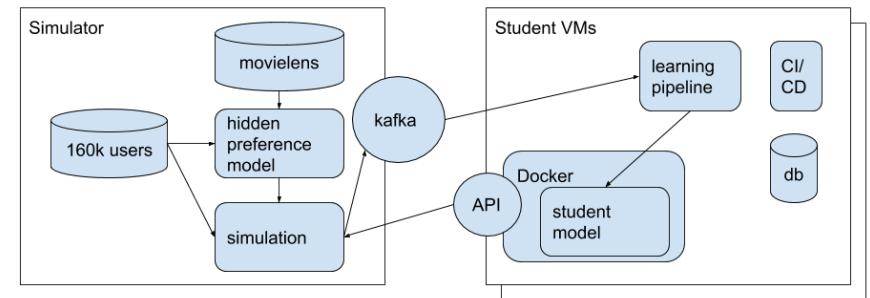
- Often fixed dataset for training and evaluation (e.g., PBS interviews)
- Focused on accuracy
- Prototyping, often Jupyter notebooks or similar
- Expert in modeling techniques and feature engineering
- Model size, updateability, implementation stability typically does not matter
- Starting to worry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



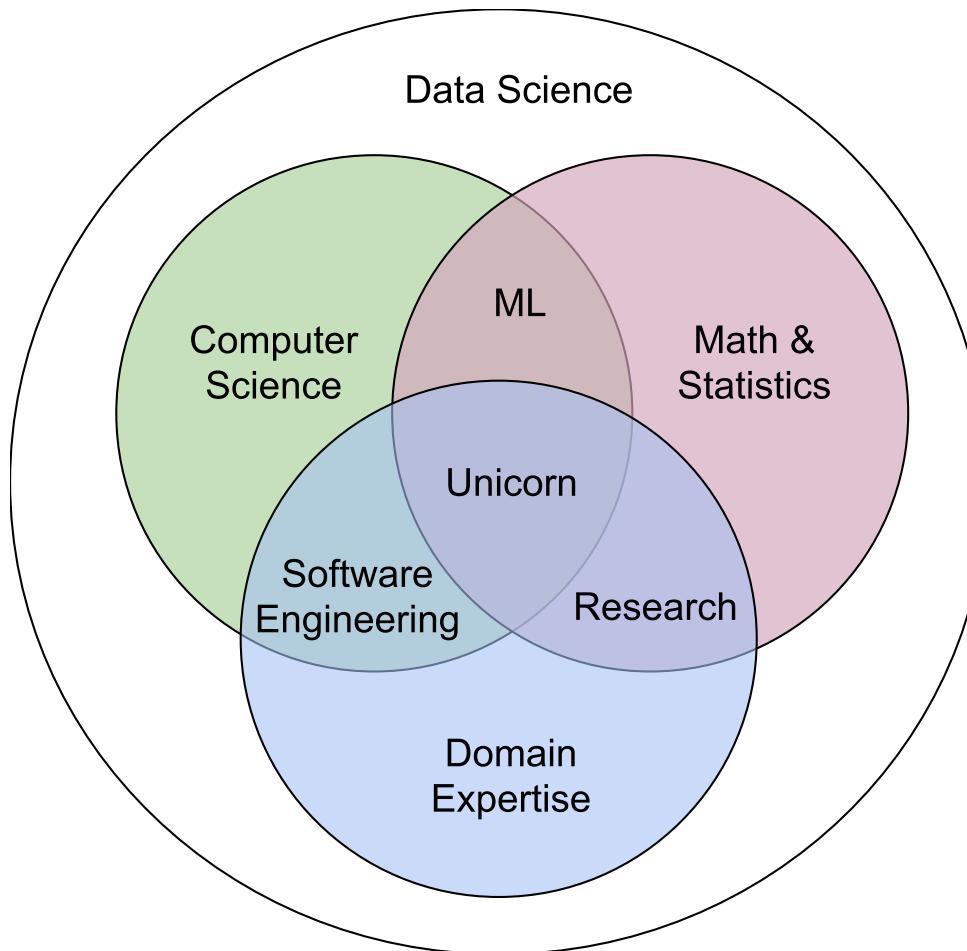
CMU 17-445 Class Project



DATA SCIENCE PRACTICES BY SOFTWARE ENGINEERS

- Many software engineers get involved in data science without explicit training
- Copying from public examples, little reading of documentation
- Lack of data visualization/exploration/understanding, no focus on data quality
- Strong preference for code editors, non-GUI tools
- Try improving model by adding more data or using deep learning, rarely feature engineering or debugging
- Lack of awareness about overfitting/bias problems, single focus on accuracy, no monitoring





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

T-SHAPED PEOPLE

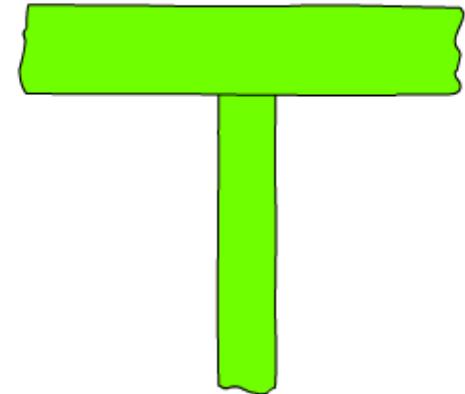
Broad-range generalist + Deep expertise



"I-shaped"
Expert at one thing



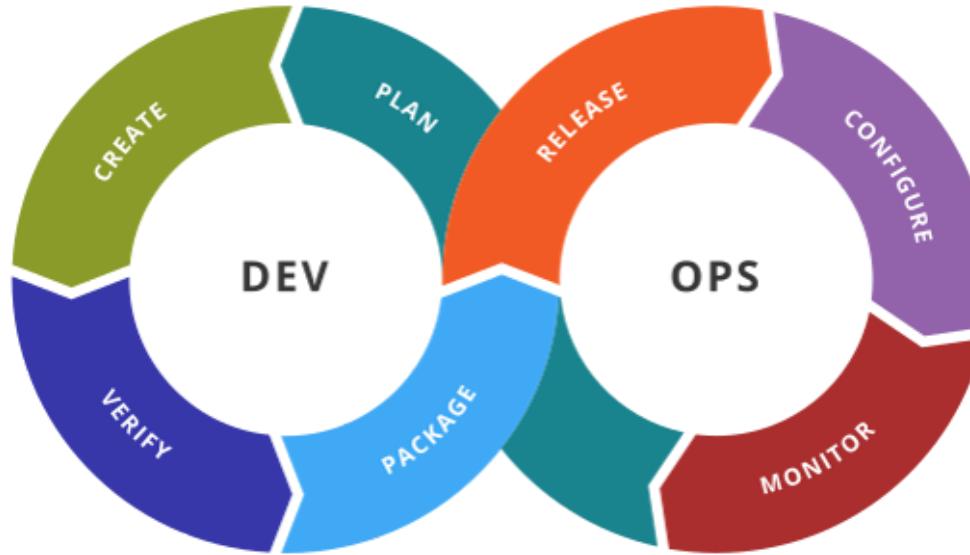
Generalist
Capable in a lot of things
but not expert in any



"T-shaped"
Capable in a lot of things
and expert in one of them

Figure: Jason Yip. [Why T-shaped people?](#). 2018

DEVOPS AS INSPIRATION



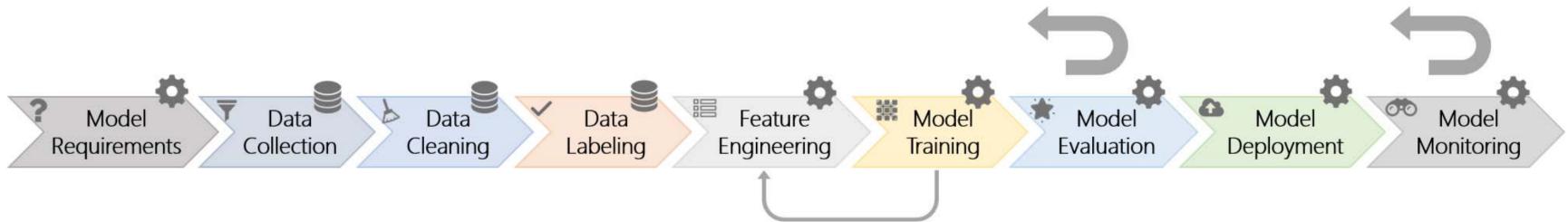
Distinct roles and expertise, but joint responsibilities, joint tooling

Interdisciplinary teams, split expertise, but joint responsibilities

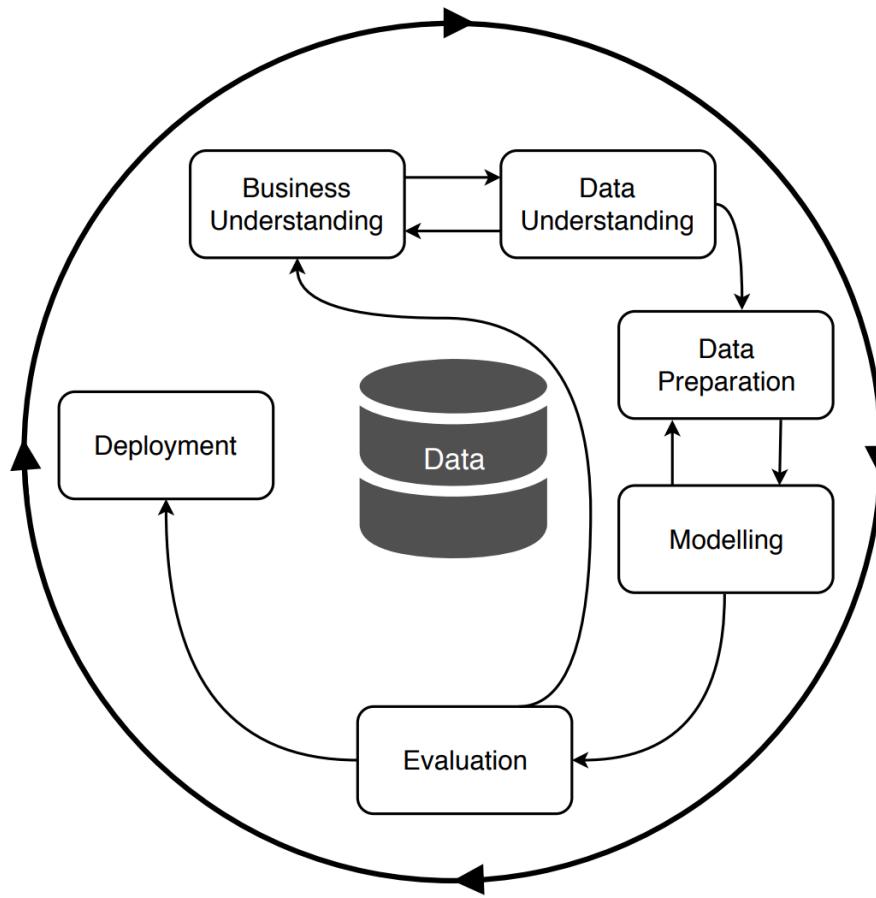
Joint vocabulary and tools

Foster system thinking

PROCESS MODELS

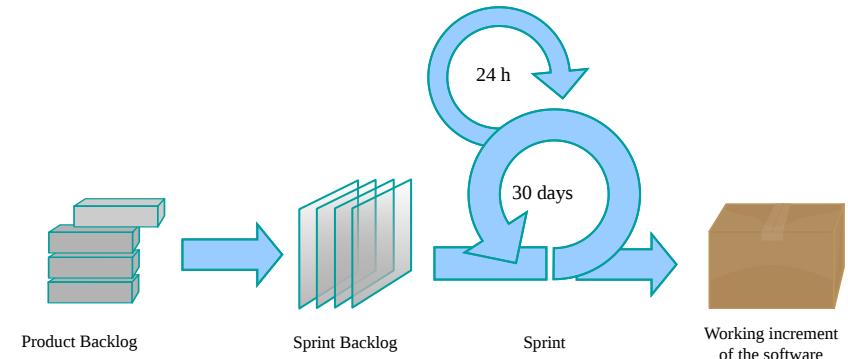
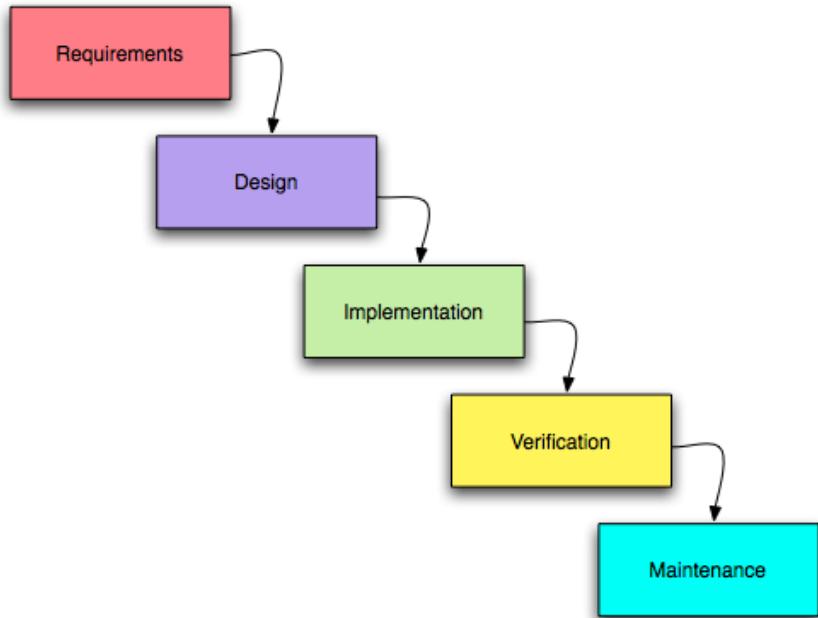


PROCESS MODELS

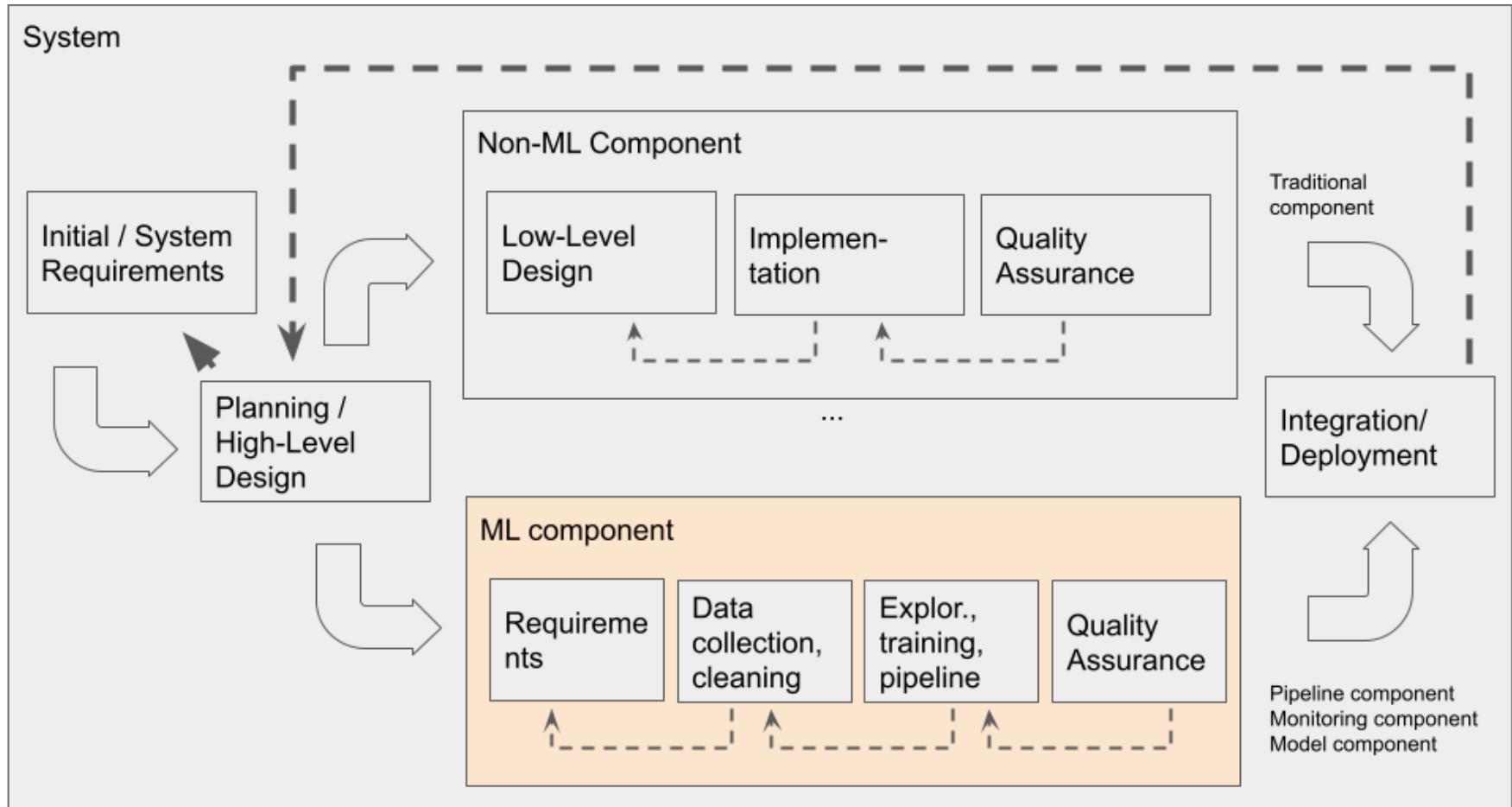


(CRISP-DM)

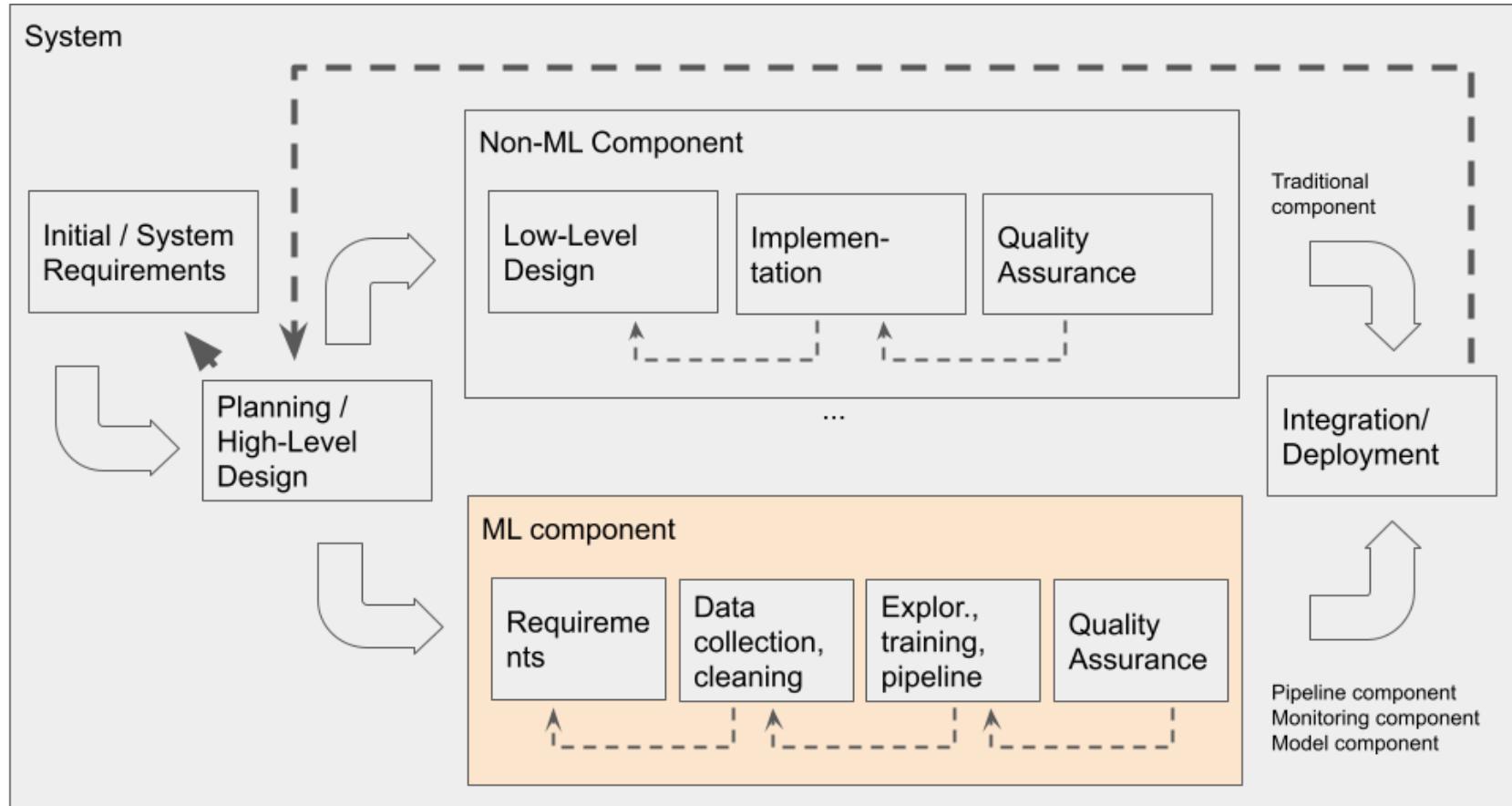
PROCESS MODELS



INTEGRATED ML/NON-ML PROCESS



DEVELOPMENT TRAJECTORIES



Upfront design? ML first? Non-ML system first? Incremental refinement?

SUMMARY

- Adopt a whole-system perspective on ML in production
- Design for quality, don't patch it in later
- Understand qualities and tradeoffs, including performance
- Consider implications of qualities on non-ML components
- Build interdisciplinary teams, integrative process

Interested in talking about your experiences in interdisciplinary ML teams? Contact us.

TRADEOFF: MODEL IMPROVEMENT VS SYSTEM SAFEGUARDS

