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C1W1 Slides



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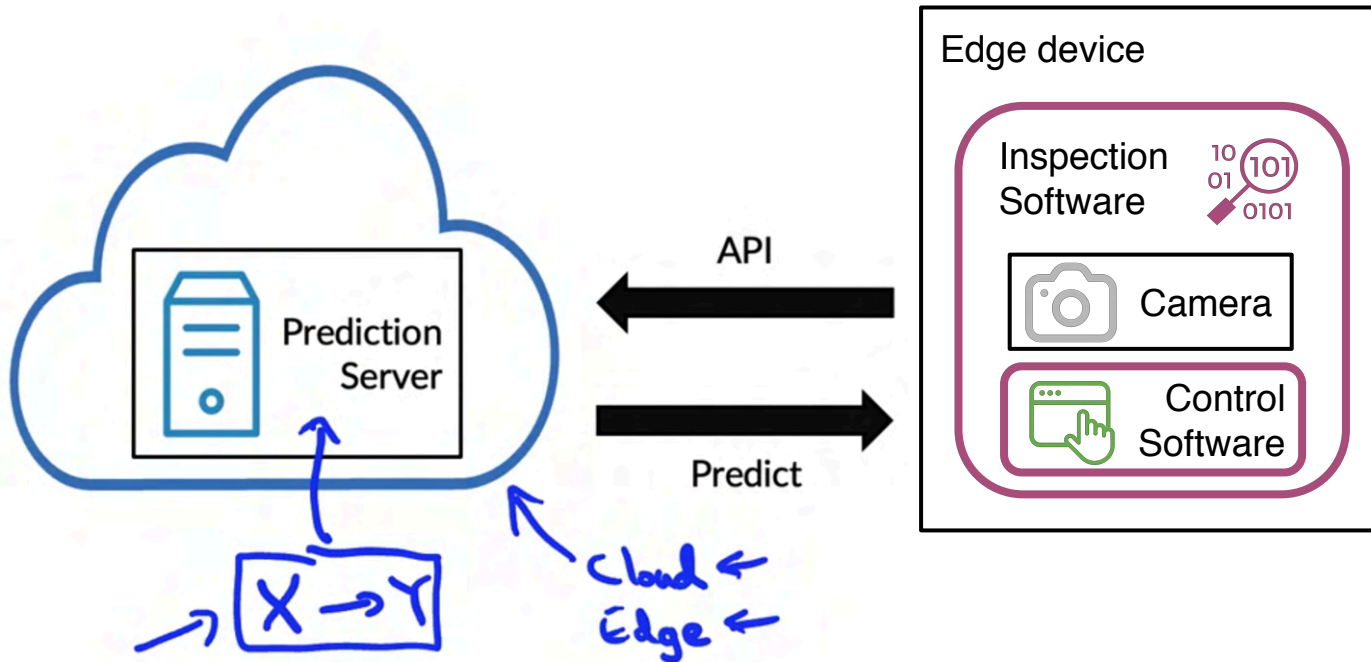
The Machine Learning Project Lifecycle

Welcome

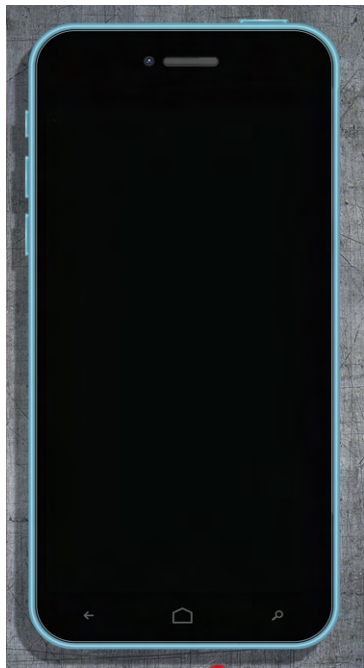
Deployment example



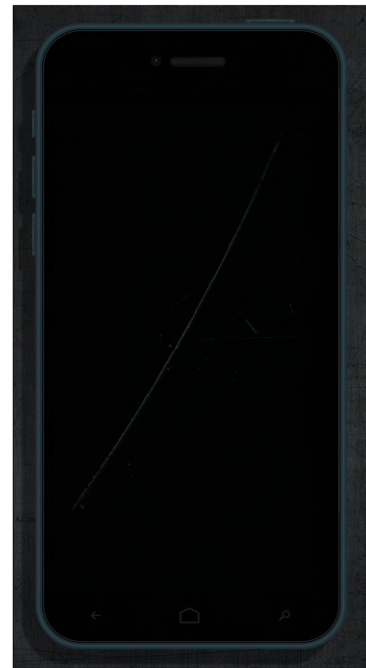
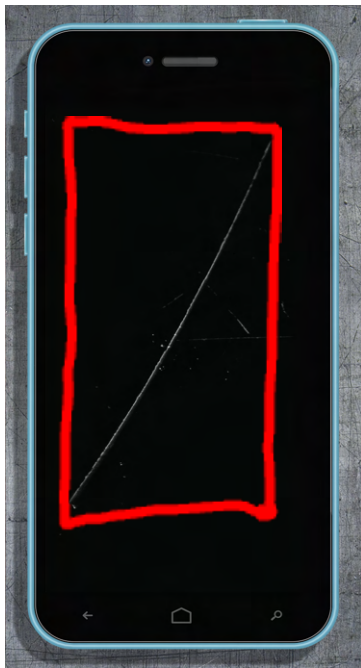
Photo from camera



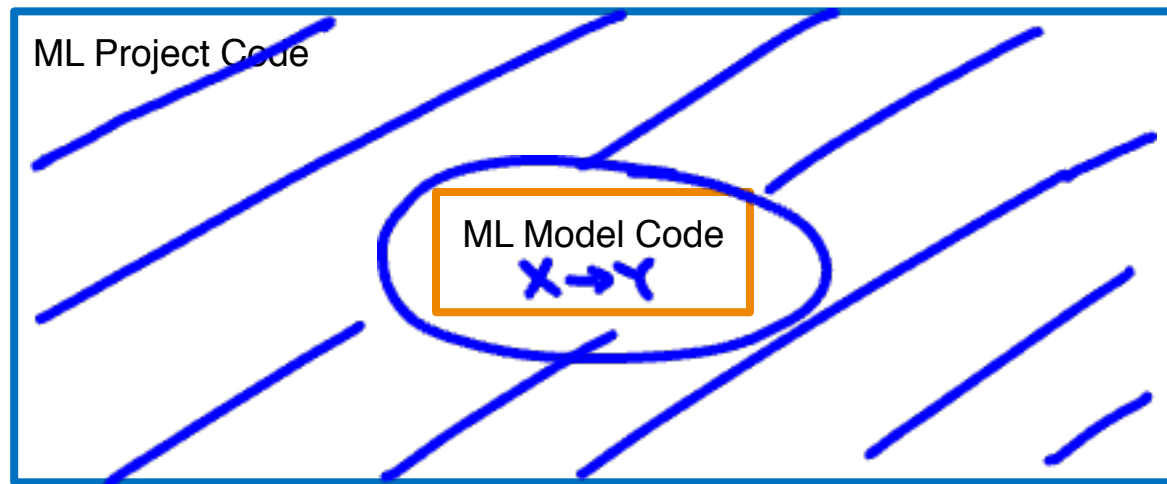
Visual inspection example



OK



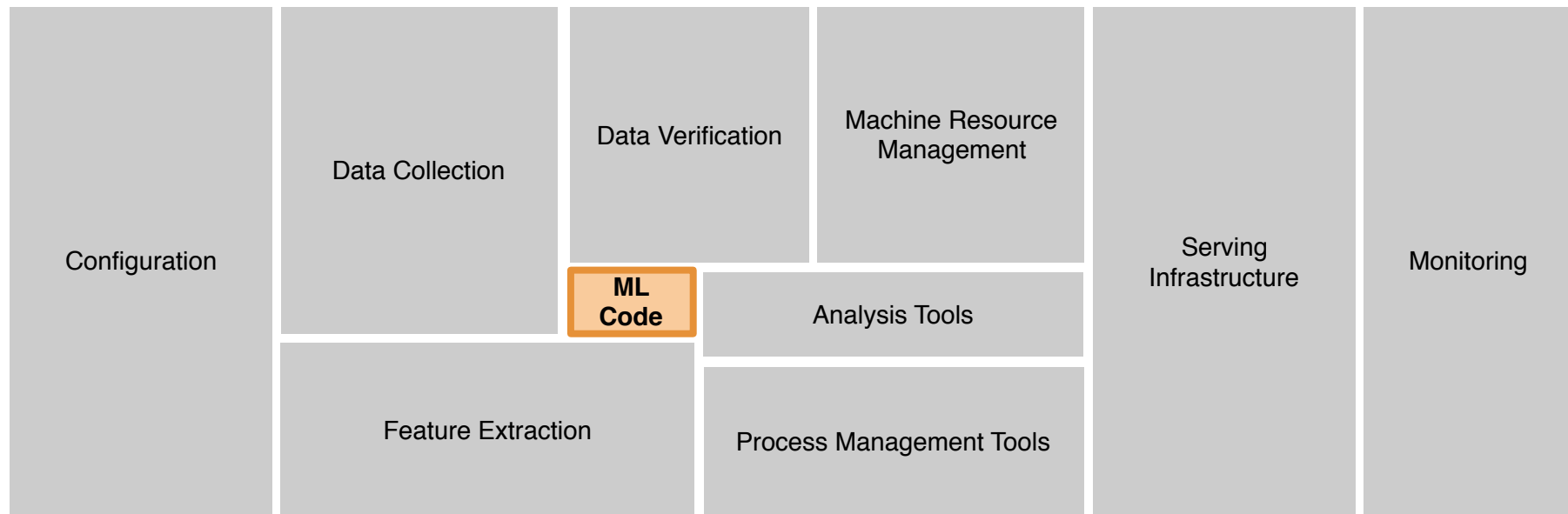
ML in production



5-10%

"POC to Production Gap"

The requirements surrounding ML infrastructure



[D. Sculley et. al. NIPS 2015: Hidden Technical Debt in Machine Learning Systems] ←

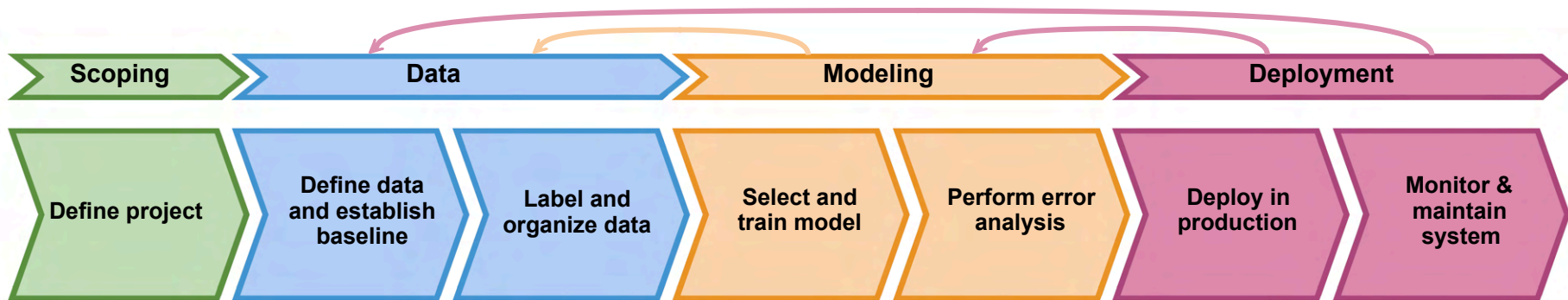


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The Machine Learning Project Lifecycle

Steps of an ML project

The ML project lifecycle



x-y

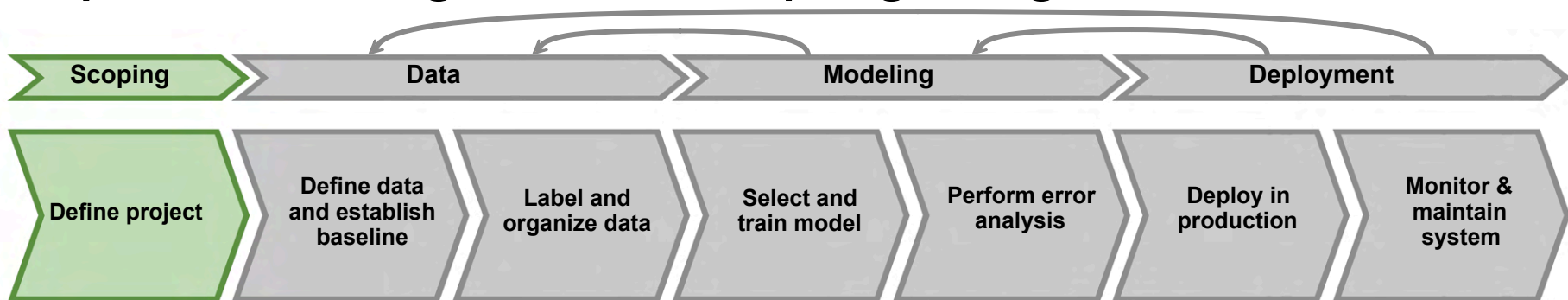


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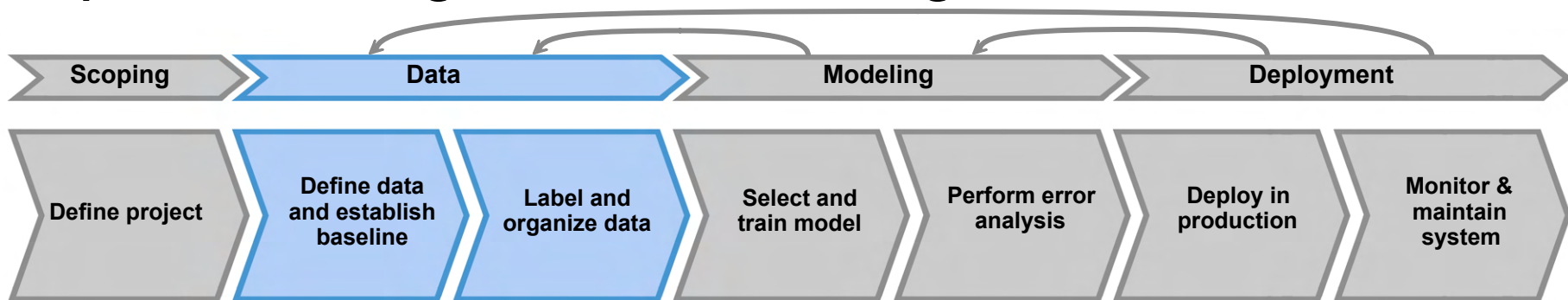
Case study:
speech recognition

Speech recognition: Scoping stage



- Decide to work on speech recognition for voice search.
- Decide on key metrics:
 - Accuracy, latency, throughput
- Estimate resources and timeline

Speech recognition: Data stage



Define data ←

- Is the data labeled consistently?
- How much silence before/after each clip?
- How to perform volume normalization?

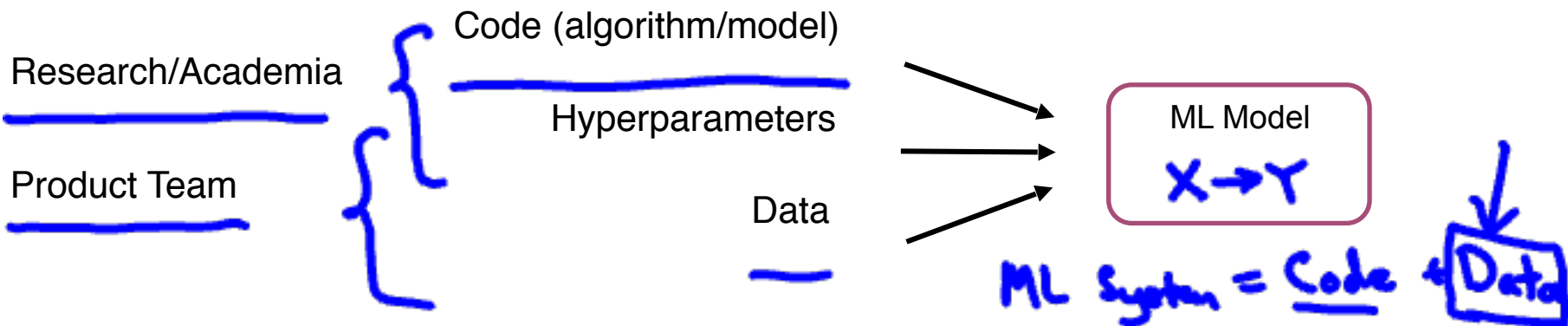
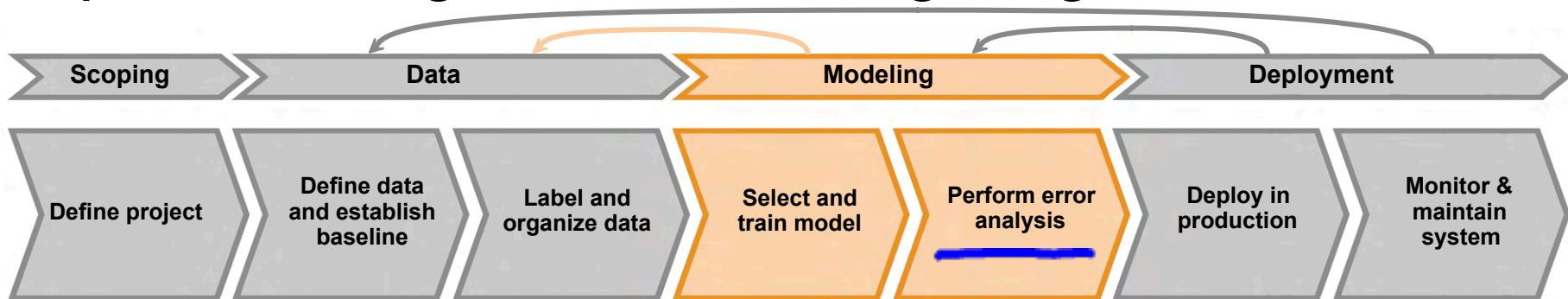
“Um, today’s weather” ←

“Um... today’s weather”

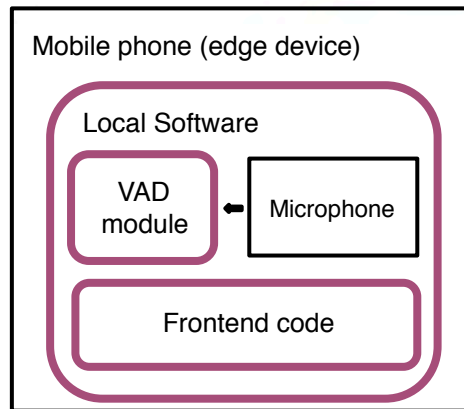
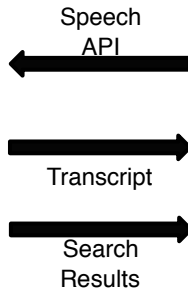
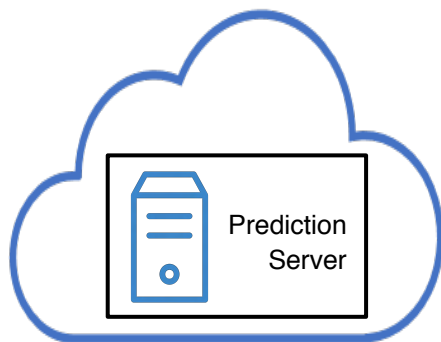
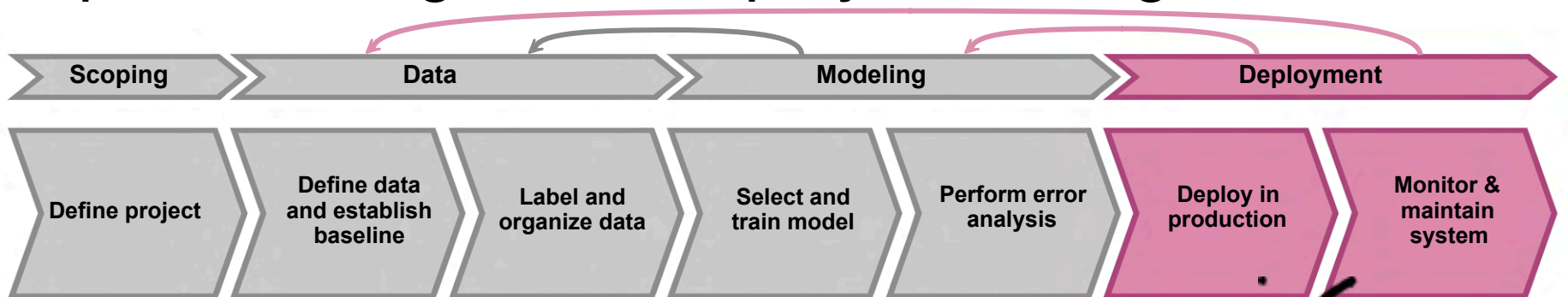
“Today’s weather”

100ms 300ms 500ms

Speech recognition: Modeling stage



Speech recognition: Deployment stage



*Voice activity detection on
→ Concept / Data
data*

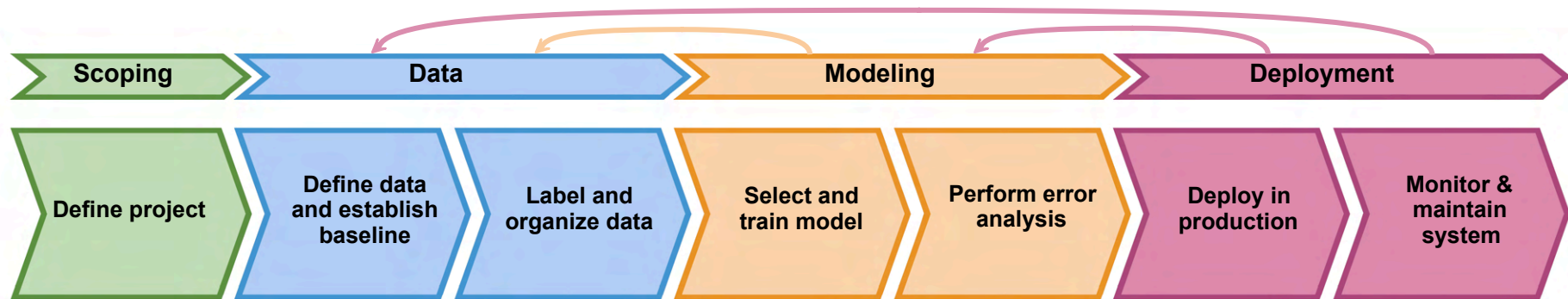


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The Machine Learning Project Lifecycle

Course outline

Course outline



1. Deployment
2. Modeling
3. Data



Optional: Scoping

MLOps (Machine Learning Operations) is an emerging discipline, and comprises a set of tools and principles to support progress through the ML project lifecycle.



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Deployment

Key challenges

Concept drift and Data drift



$x \rightarrow y$
Speech recognition example

Training set:

$x \rightarrow y$

- Purchased data, historical user data with transcripts

Test set:

- Data from a few months ago

Gradual change
Sudden shock

How has the data changed?

Software engineering issues

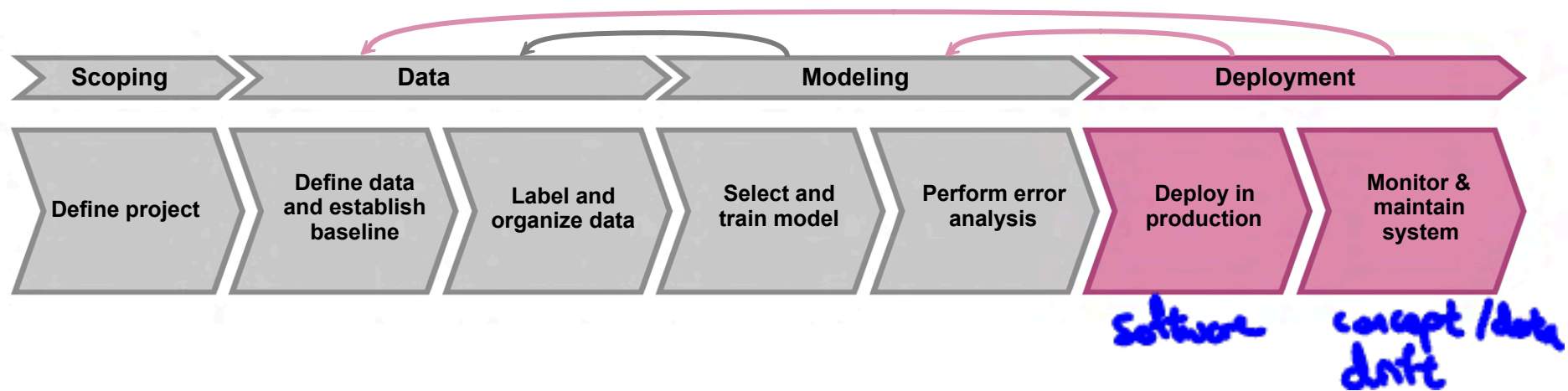
Checklist of questions

- Realtime or Batch
- Cloud vs. Edge/Browser
- Compute resources (CPU/GPU/memory)
- Latency, throughput (QPS)
- Logging
- Security and privacy



500ms, 1000 QPS

First deployment vs. maintenance





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Deployment

Deployment patterns

Common deployment cases

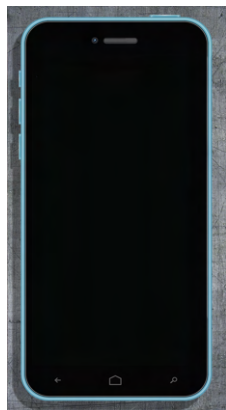
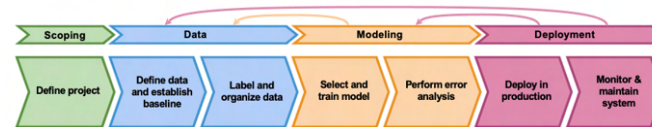
1. New product/capability
2. Automate/assist with manual task
3. Replace previous ML system

Key ideas:

- Gradual ramp up with monitoring
- Rollback

Visual inspection example

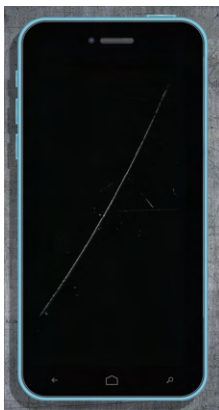
shadow mode



Human



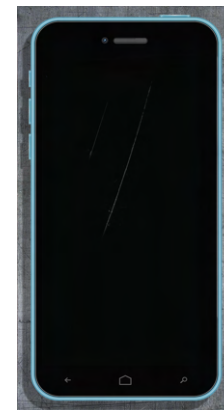
ML



Human



ML



Human



ML

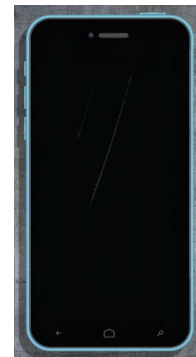
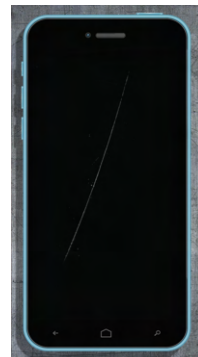
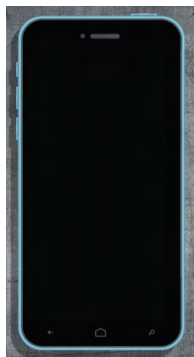
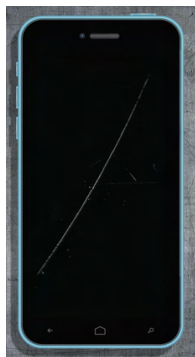
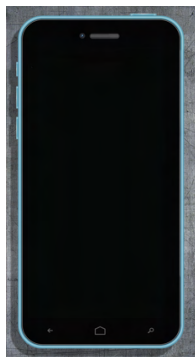
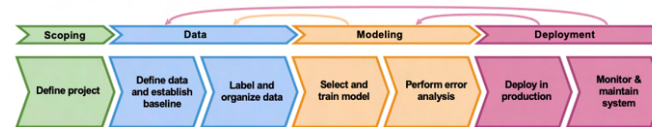


ML system shadows the human and runs in parallel.

ML system's output not used for any decisions during this phase.

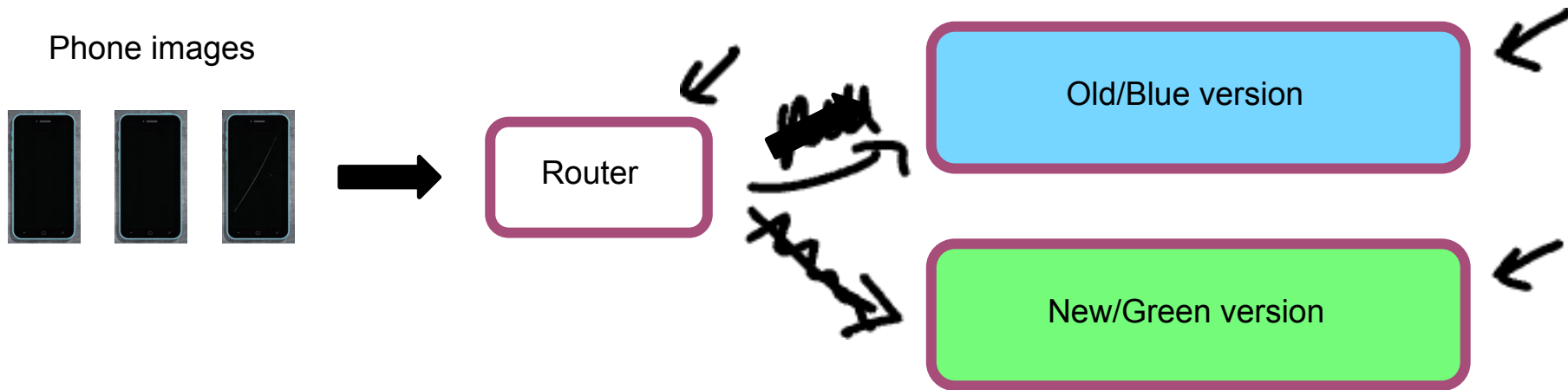
Sample outputs and verify predictions of ML system.

Canary deployment



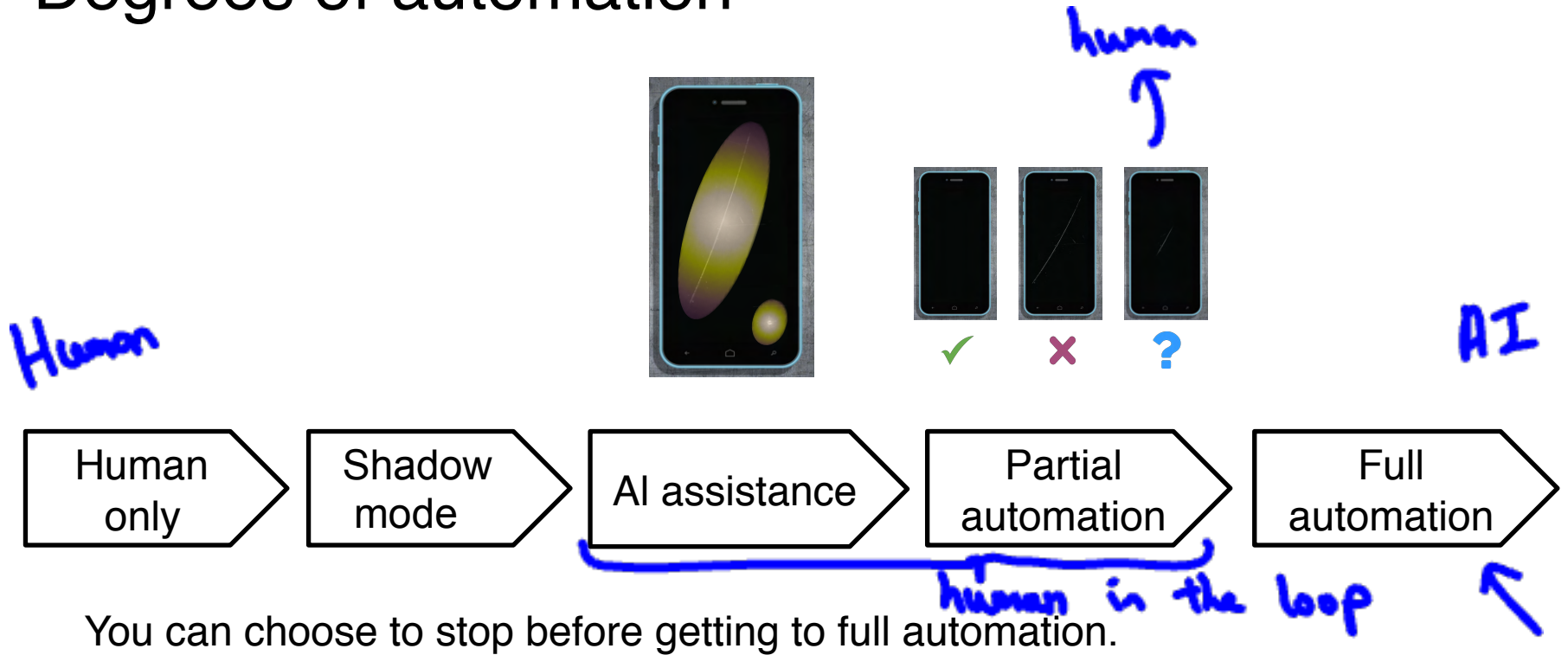
- Roll out to small fraction (say 5%) of traffic initially.
- Monitor system and ramp up traffic gradually.

Blue green deployment



Easy way to enable rollback

Degrees of automation





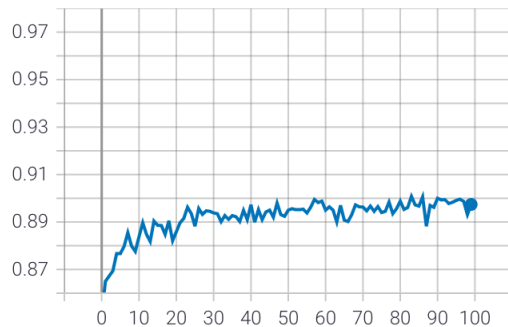
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Deployment

Monitoring

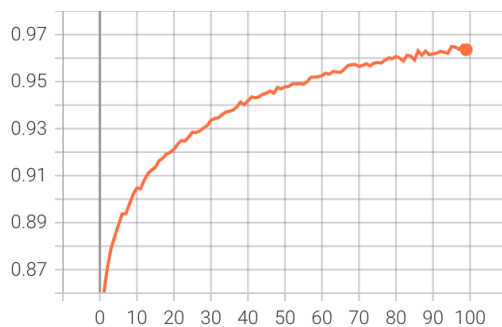
Monitoring dashboard

Server load



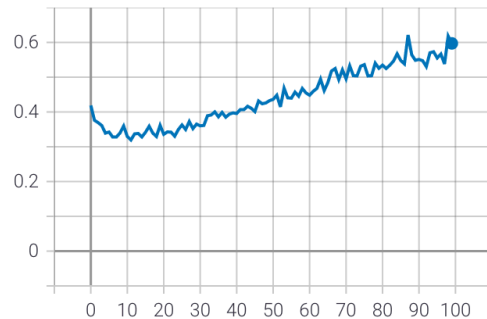
Time

Fraction of non-null outputs



Time

Fraction of missing input values



Time

- Brainstorm the things that could go wrong.
- Brainstorm a few statistics/metrics that will detect the problem.
- It is ok to use many metrics initially and gradually remove the ones you find not useful.

Examples of metrics to track

Software metrics:

Memory, compute, latency, throughput, server load

Input metrics:

x

Avg input length

Avg input volume

Num missing values

Avg image brightness

Output metrics:

y

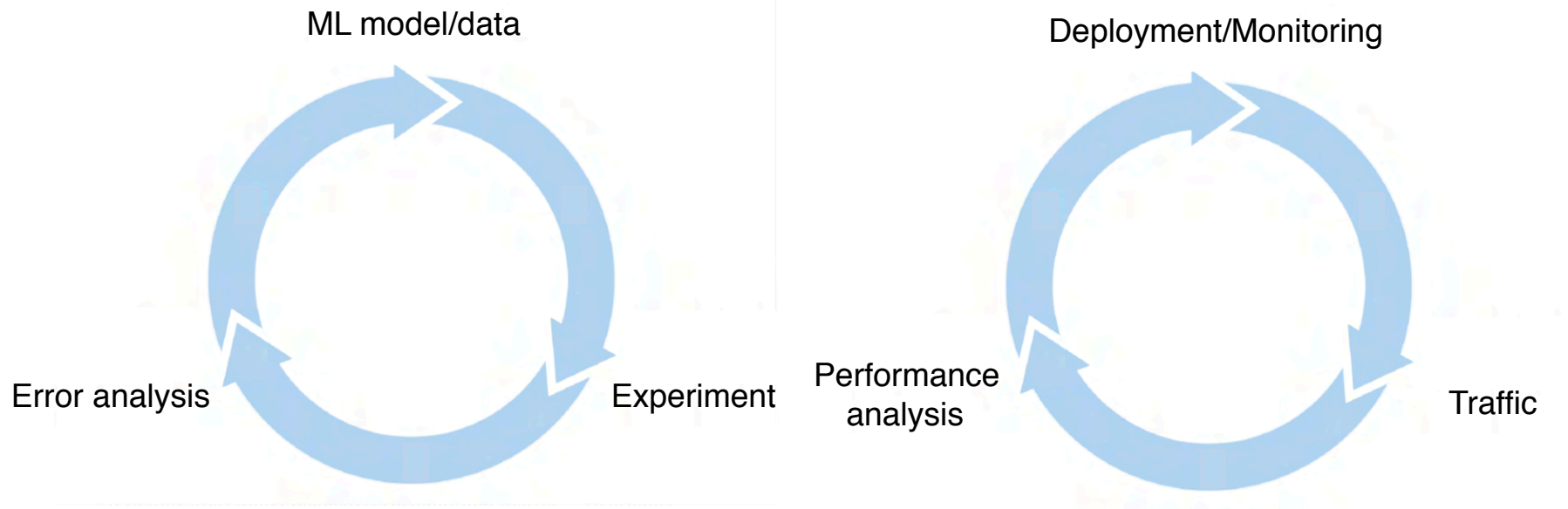
times return " " (null)

times user redoes search

times user switches to typing

CTR

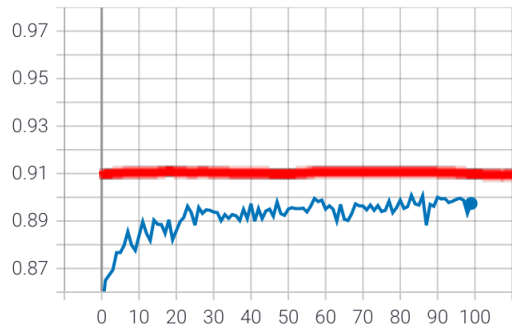
Just as ML modeling is iterative, so is deployment



Iterative process to choose the right set of metrics to monitor.

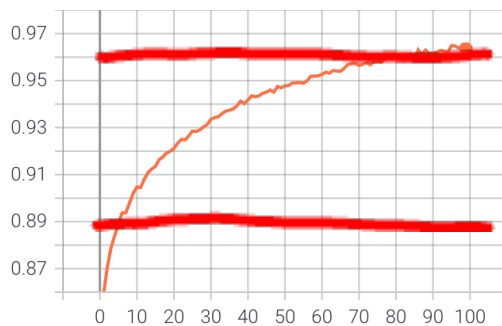
Monitoring dashboard

Server load



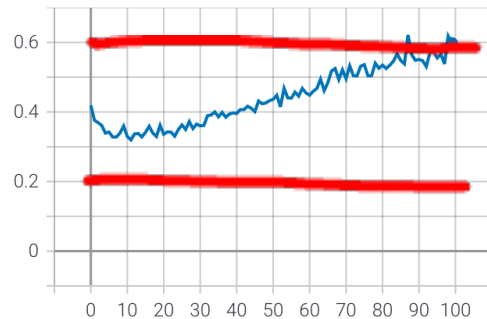
Time

Fraction of non-null outputs



Time

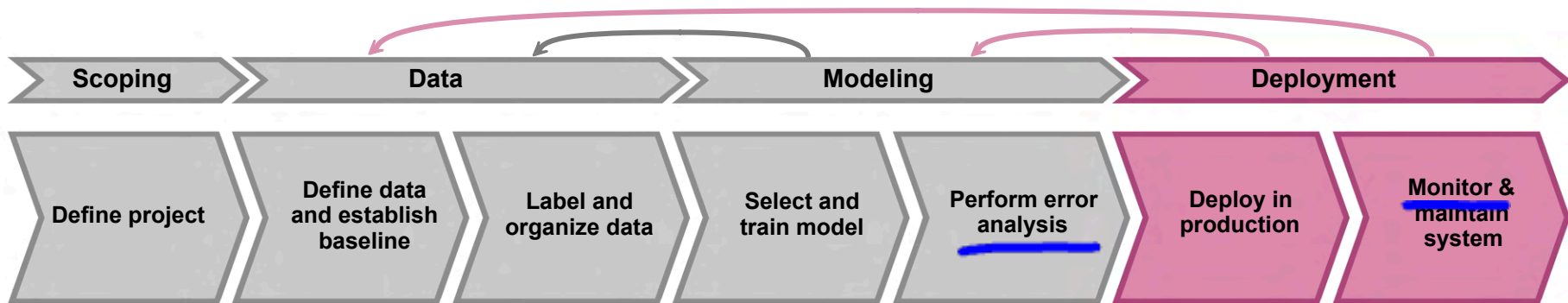
Fraction of missing input values



Time

- Set thresholds for alarms
- Adapt metrics and thresholds over time

Model maintenance



- Manual retraining ←
- Automatic retraining ←

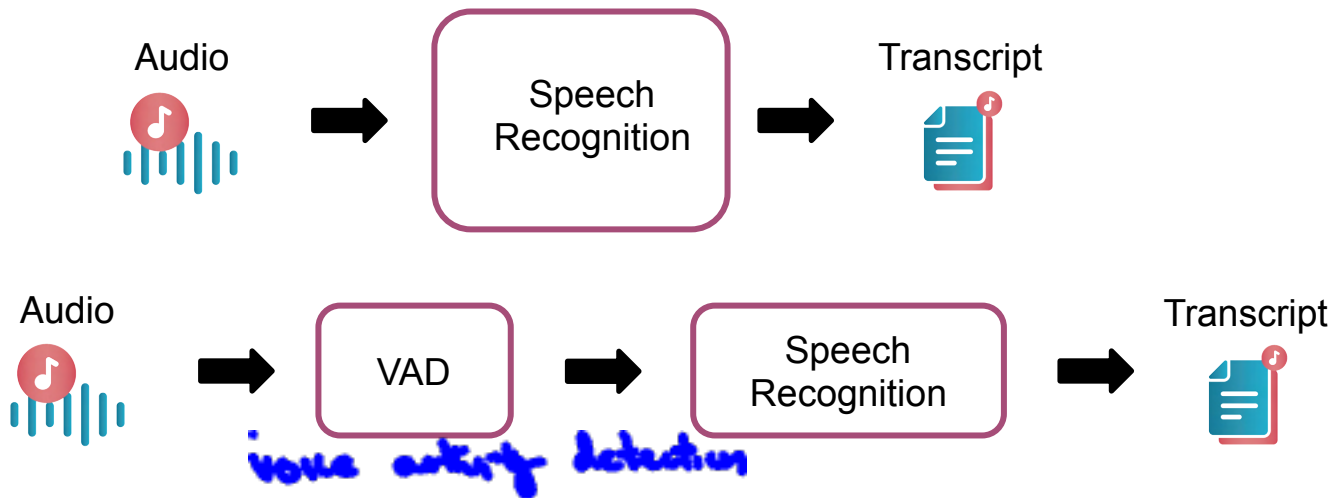


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Deployment

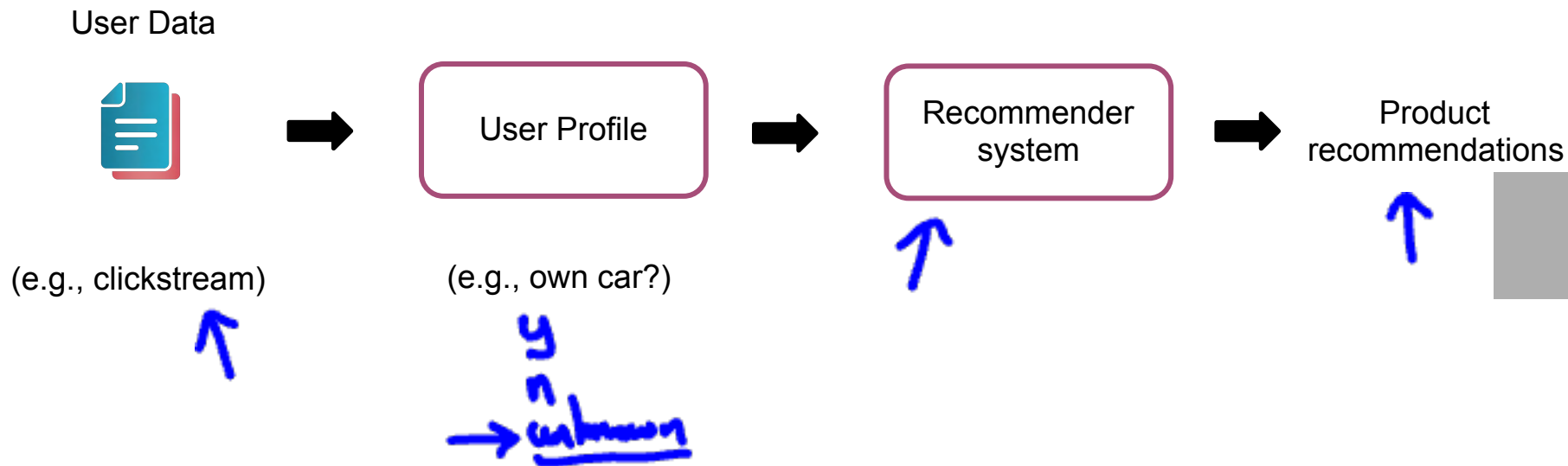
Pipeline monitoring

Speech recognition example



Some cellphones might have VAD clip audio differently, leading to degraded performance

User profile example



Metrics to monitor

Monitor

- Software metrics
- Input metrics
- Output metrics

How quickly do they change?

- User data generally has slower drift.
- Enterprise data (B2B applications) can shift fast.

