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AI-driven product

path from research to production

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Tech Lead, involved in AI projects last 3 years.
Mostly I’m working with NLP projects:
- Question answering systems
- Text classifiers
- Semantic Search
- Entity Extraction

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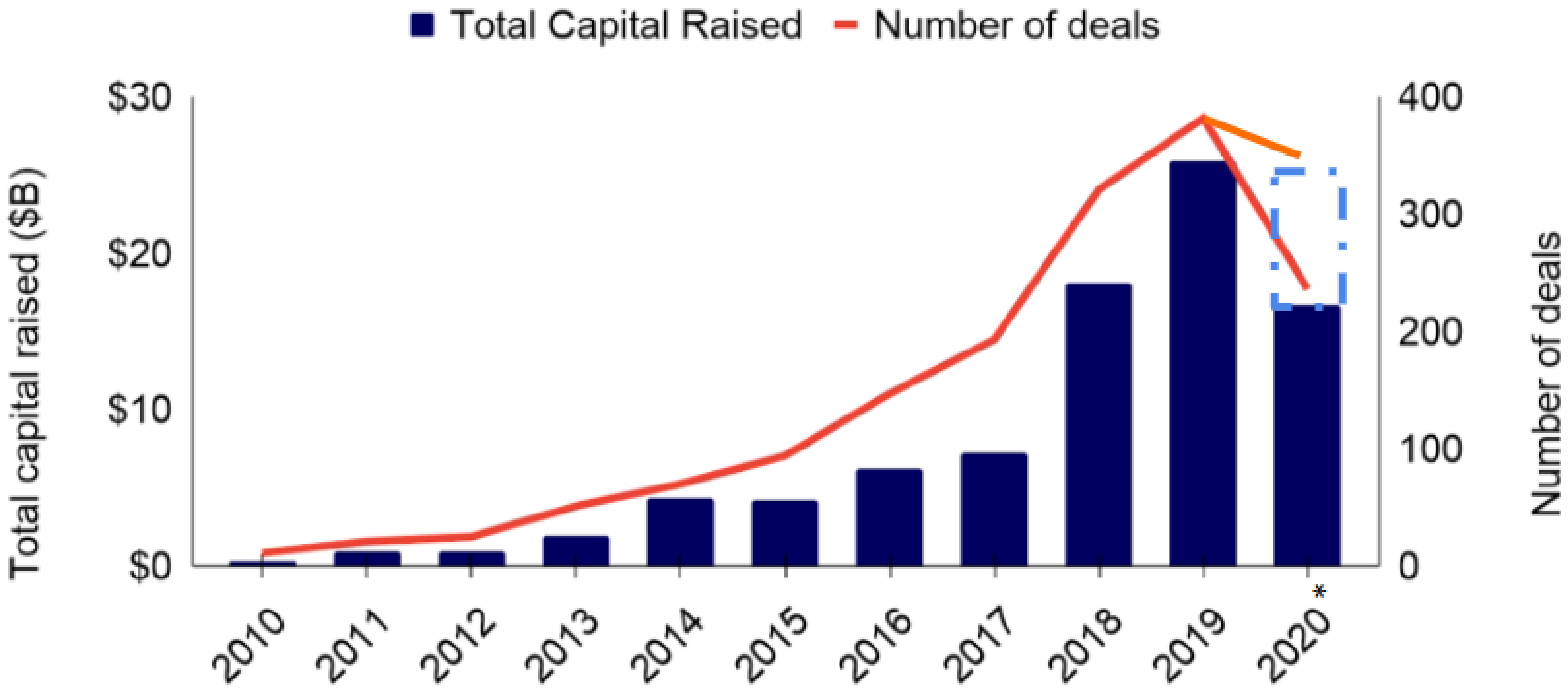
AI industry is growing



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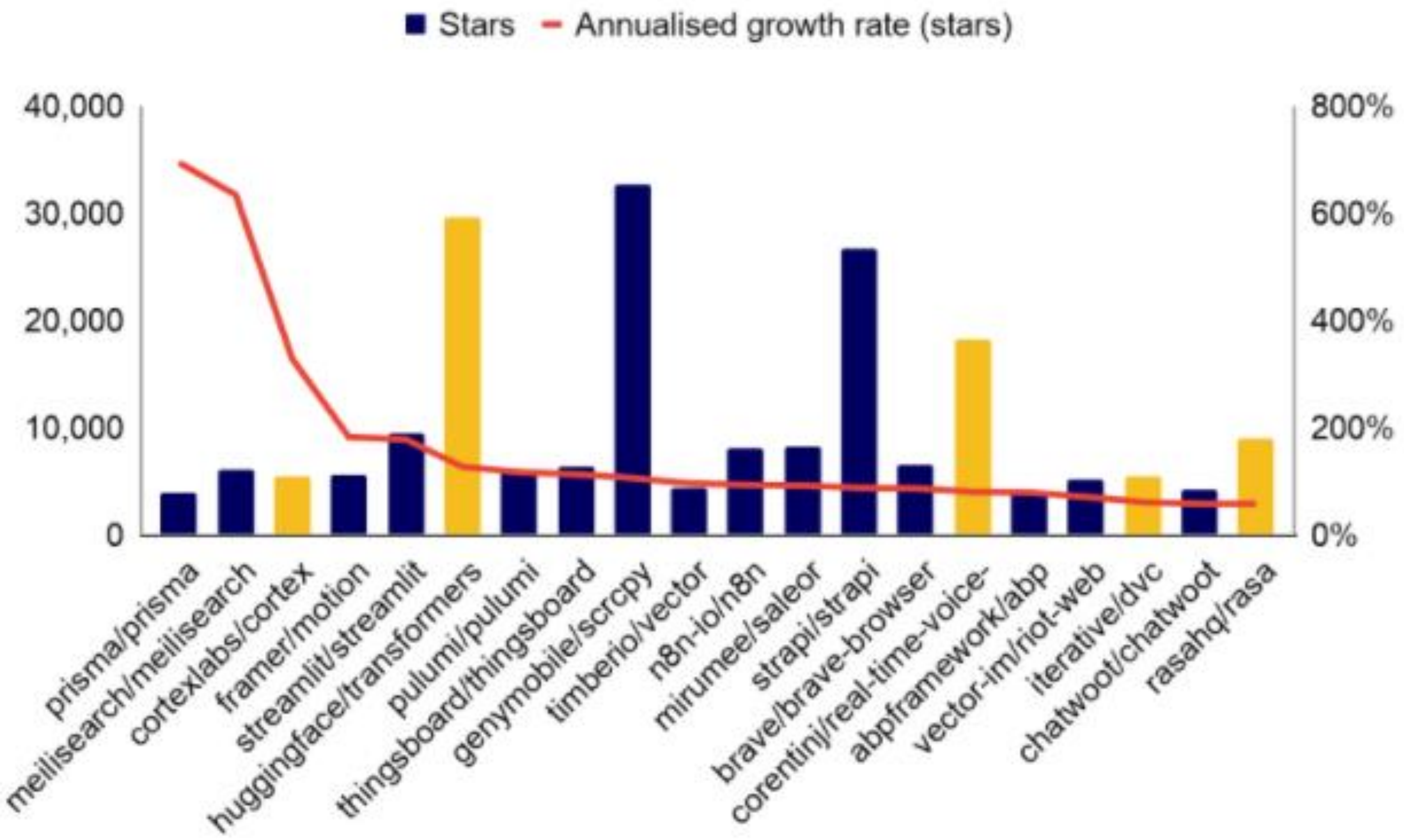
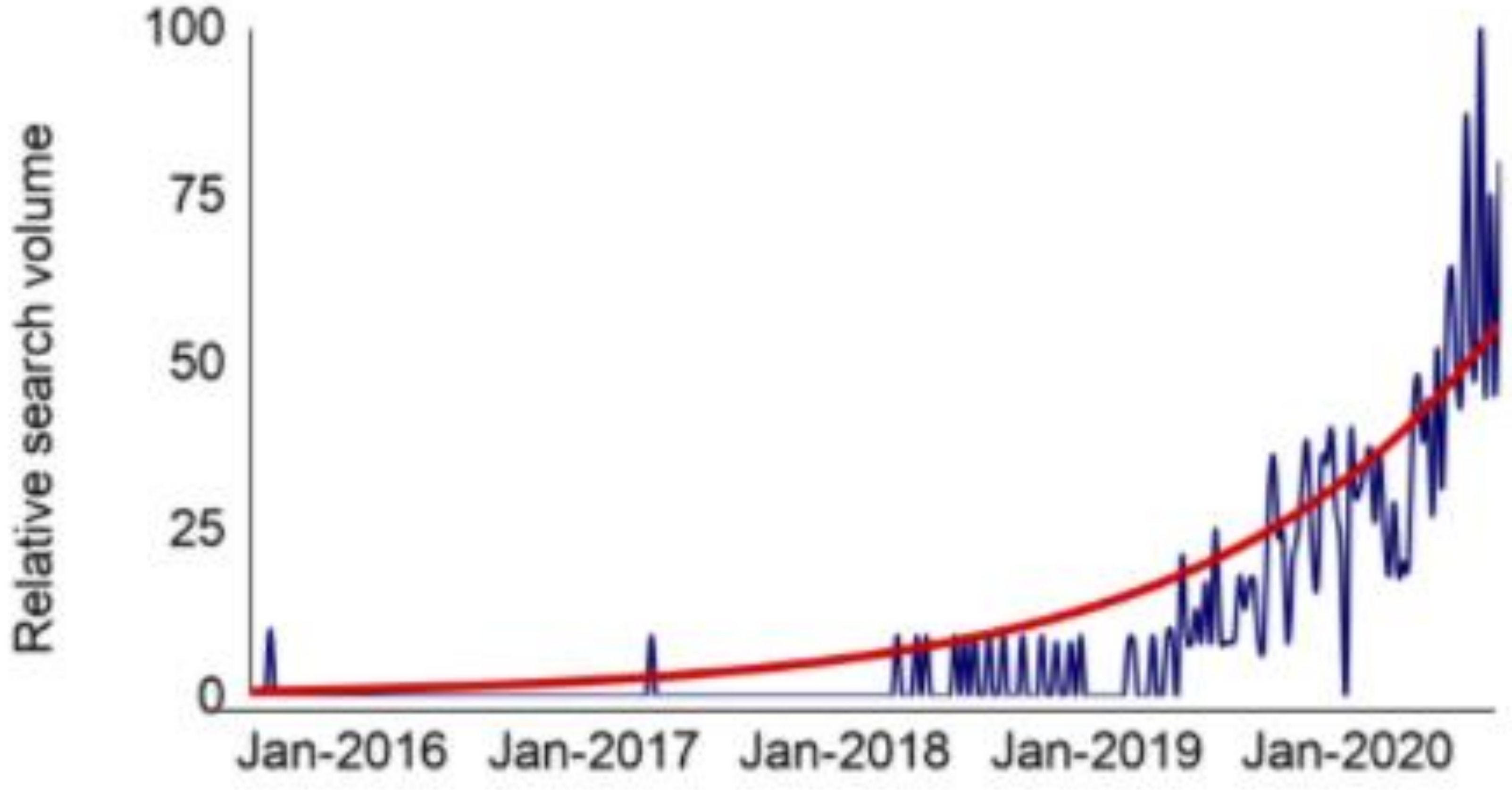
What does it mean for engineers

The rise of MLOps (DevOps for ML) signals an industry shift from technology R&D (how to build models) to operations (how to run models)





25% of the top-20 fastest growing GitHub projects in Q2 2020 concern ML infrastructure, tooling and operations. Google Search traffic for “MLOps” is now on uptick for the first time.

How much time is needed for deployment

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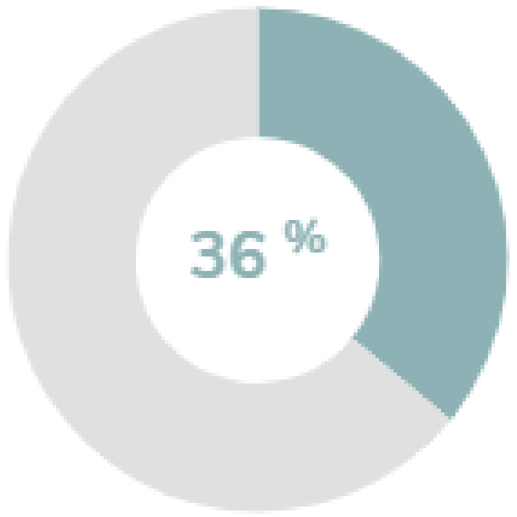
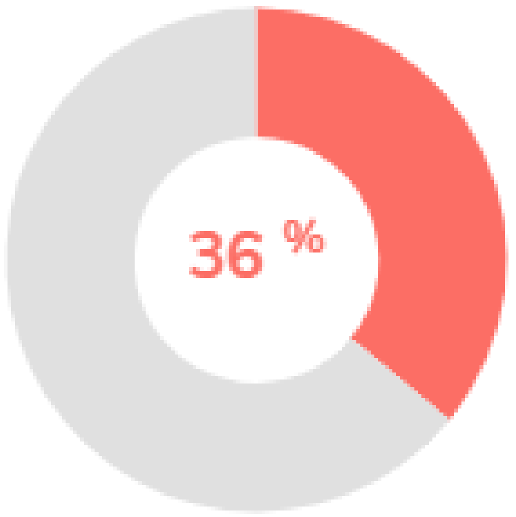
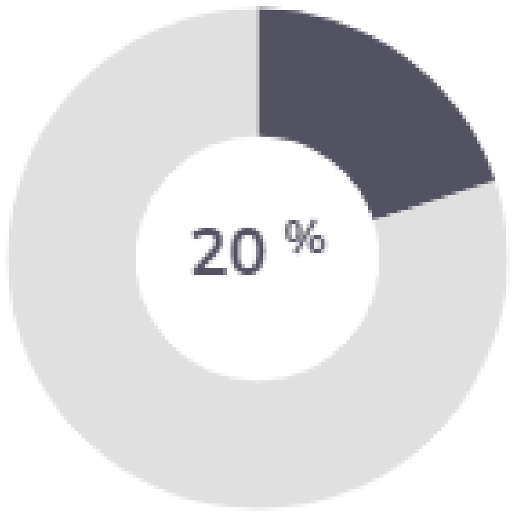


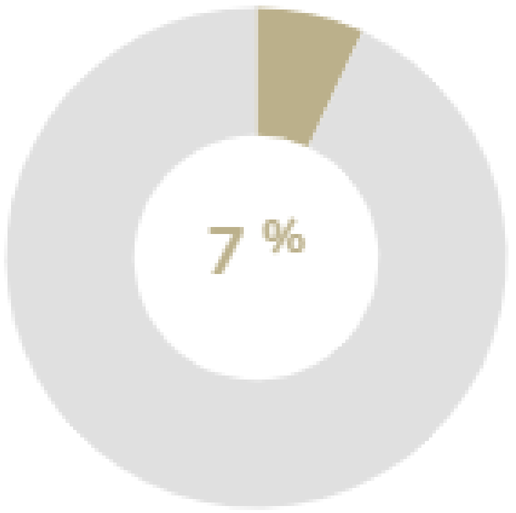
36% of survey participants said their data scientists spend **a quarter** of their time deploying ML models



36% of survey participants said their data scientists spend **a quarter to half** of their time deploying ML models



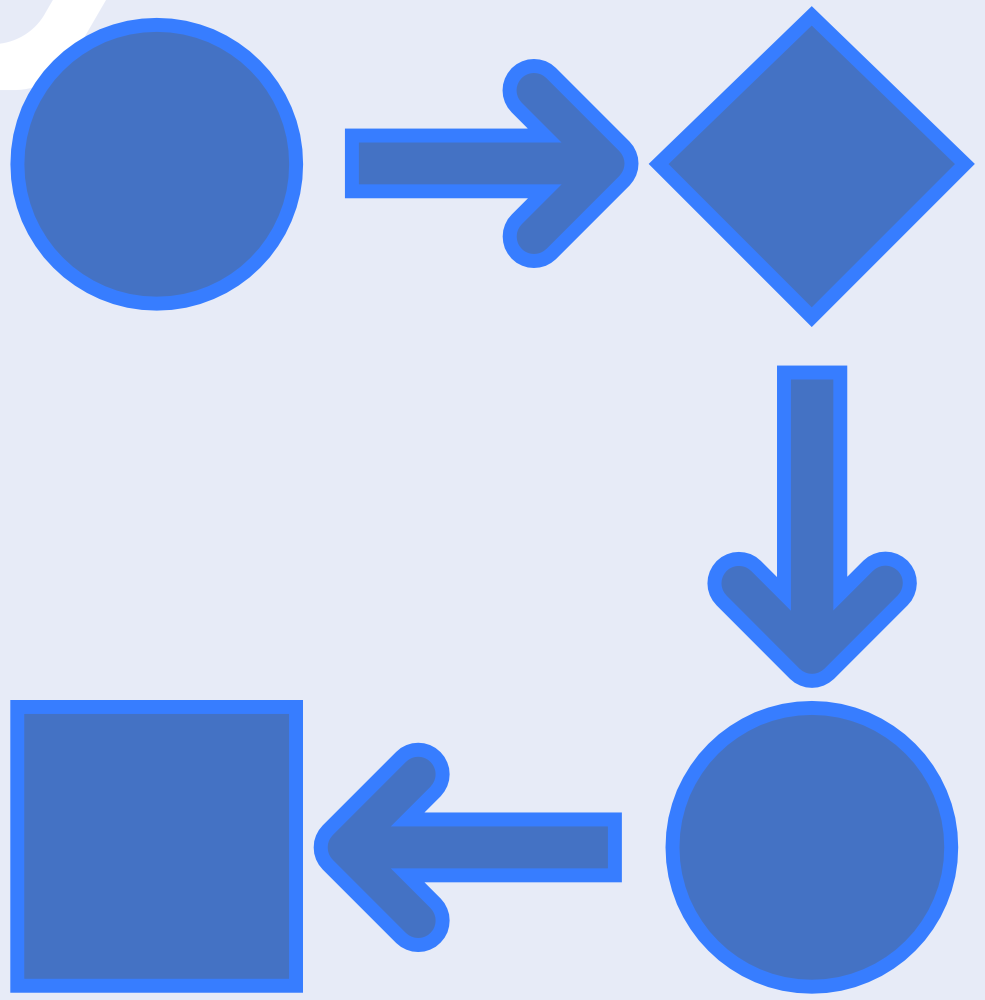
20% of survey participants said their data scientists spend **half to three-quarters** of their time deploying ML models



7% of survey participants said their data scientists spend **more than three-quarters** of their time deploying ML models

https://algorithmia.com/state-of-ml

Why is delivery of AI such a difficult task?



Challenges of AI projects

- Good metrics but **poor product**
- Infinite experiments but **no delivery**
- **Reproducibility** of experiments
- Data, artifacts, code and metrics mess
- **Time to introduce new** ML engineer in a team

Trivial example — Sentiment classification

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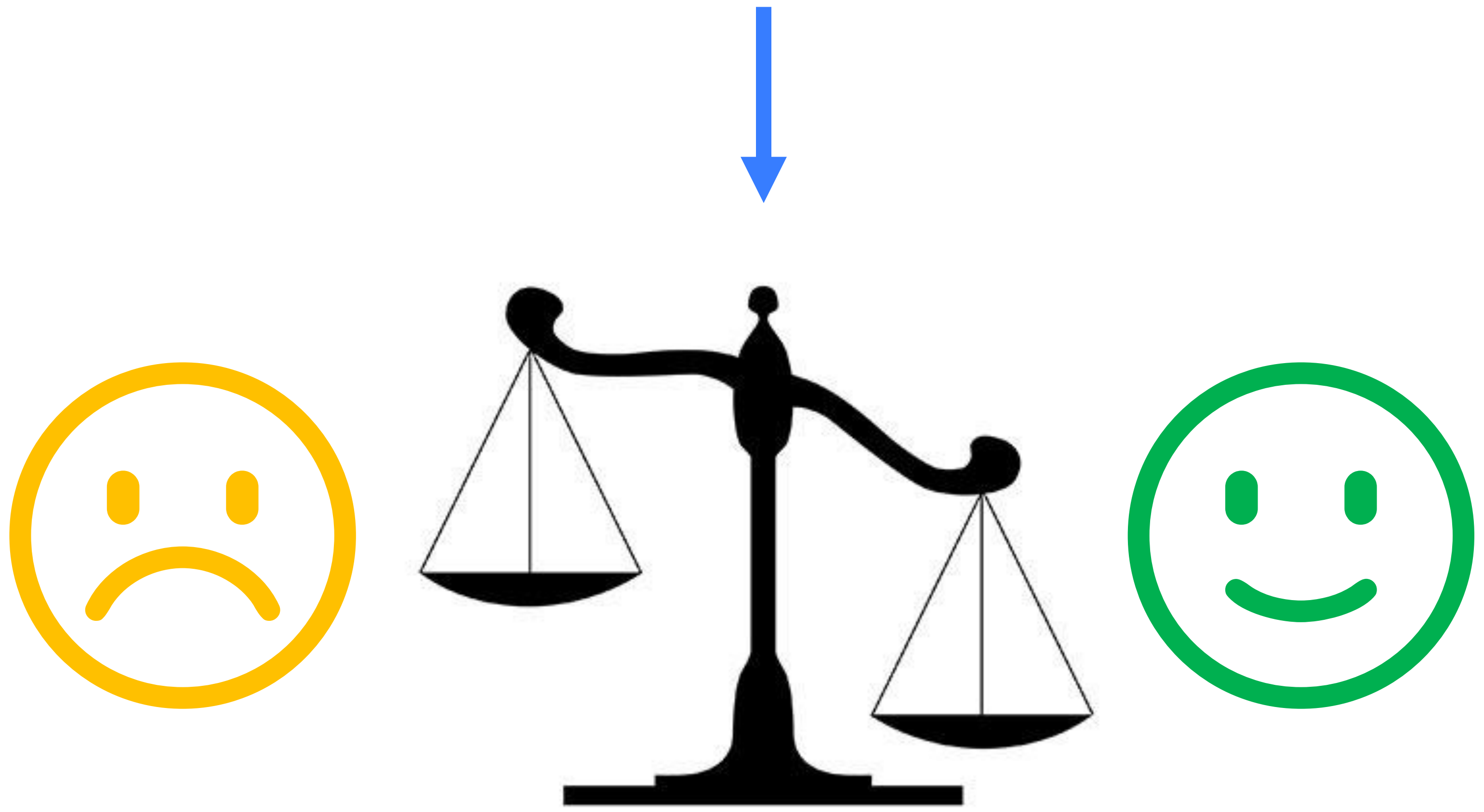
Linux Foundation Training
@LF_Training

"Containers Fundamentals" training from @CloudNativeFdn will teach you how to do container and image operations w/ different runtimes, manage network and storage w/ #containers, build and run multi-container applications with #Docker & more: bit.ly/33IAMyl #learnlinux



Trivial example — Business Objective

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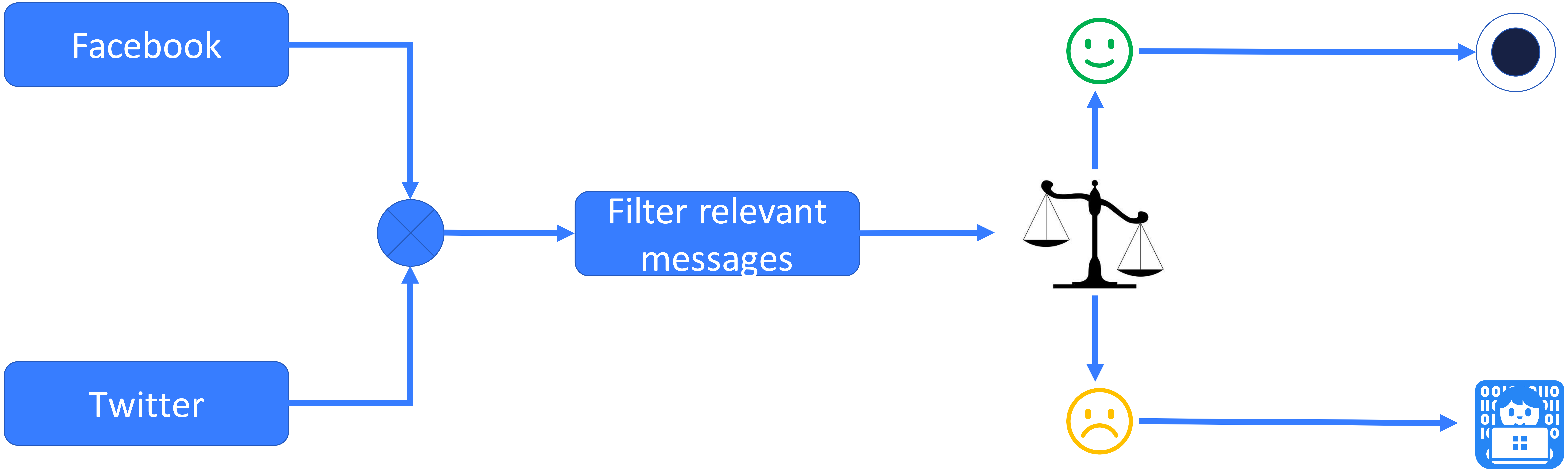

Use this business objective to define metrics and recognize “**what good is good enough**”

Data First — Machine Learning in Nutshell

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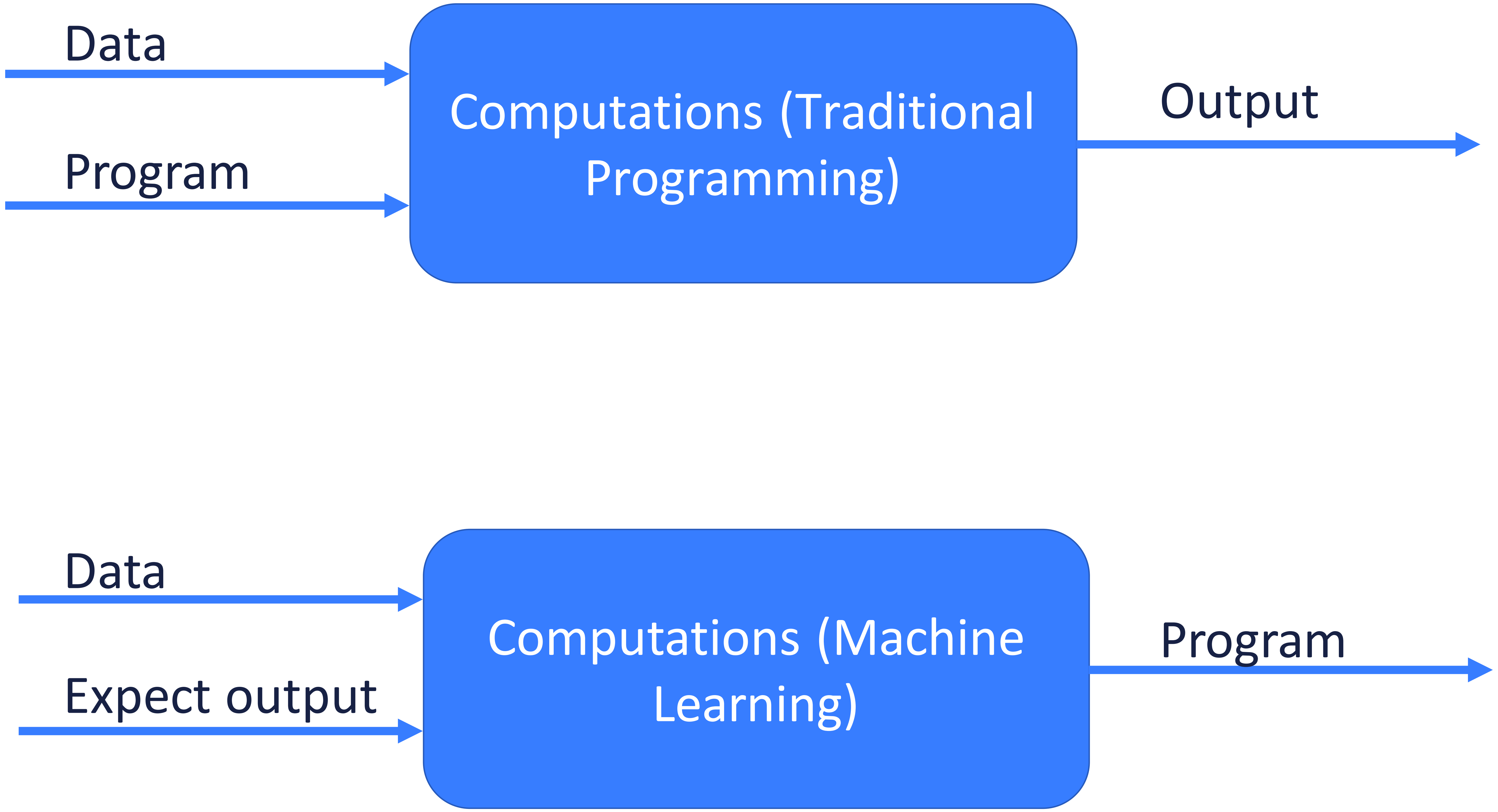

Trivial example — Data annotation

Trivial example — Experiments

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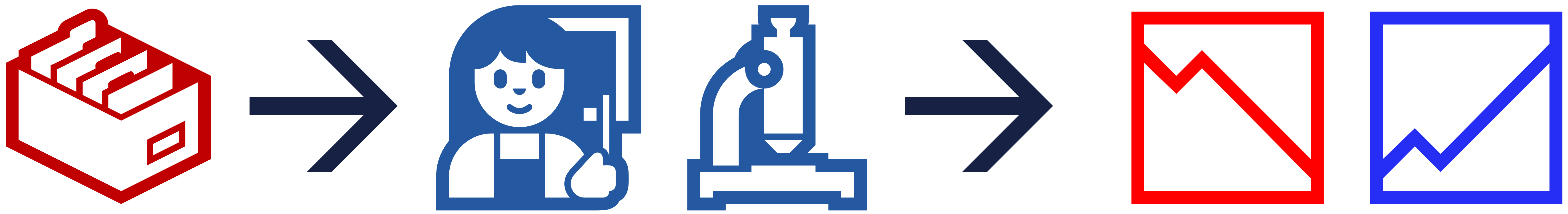
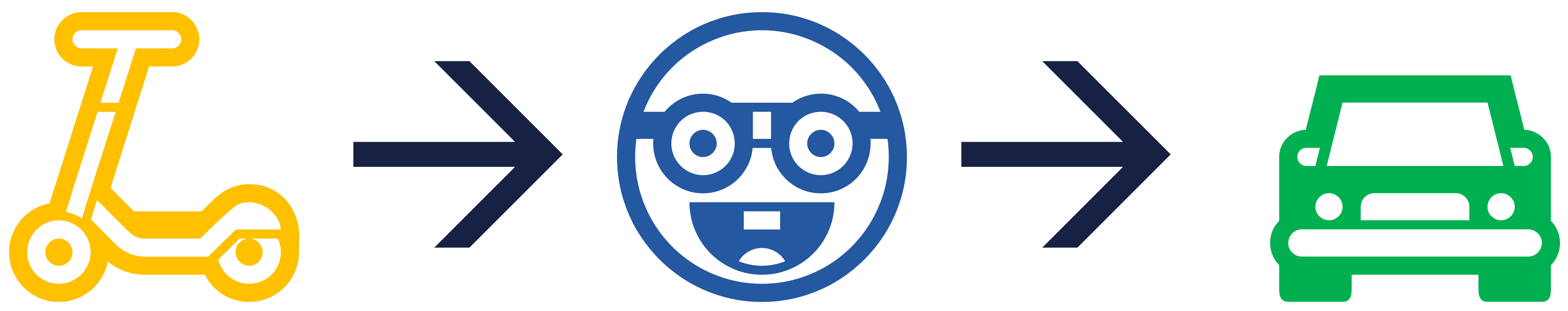


Trivial example — Operationalization



Trivial example — Delivery

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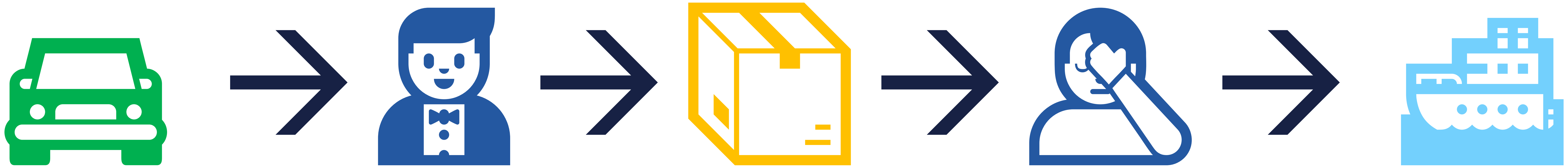
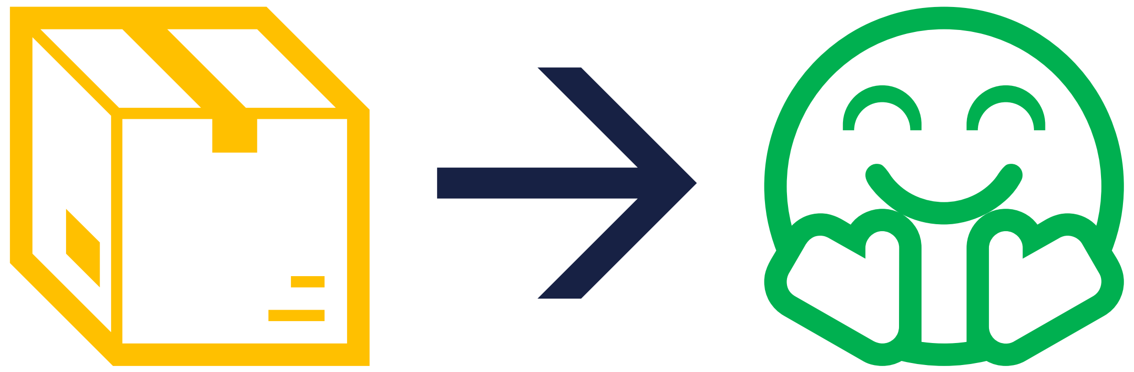


Trivial example

Expectation



Reality

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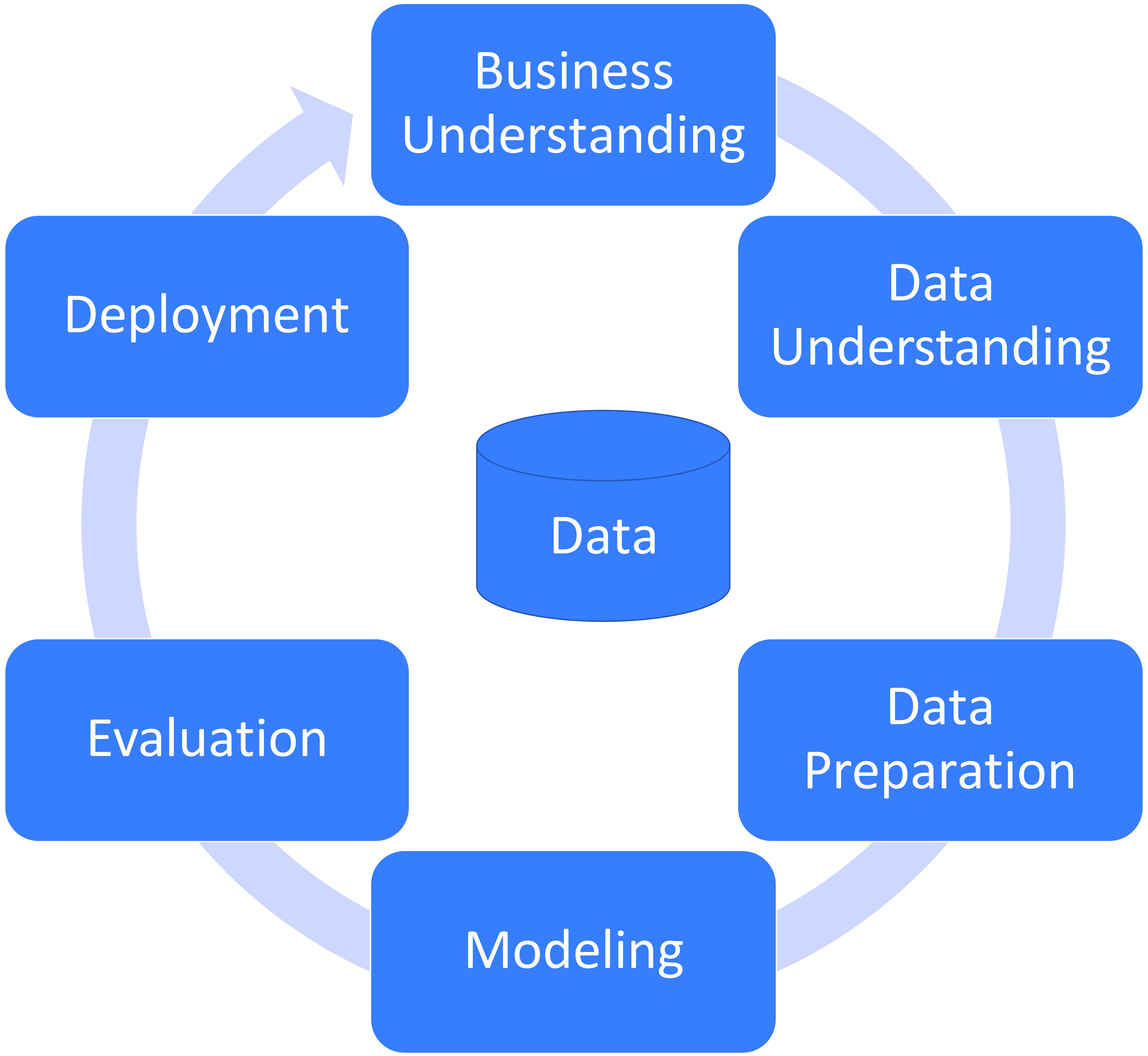
Developing of ML project is **iterative process** with many steps back and forward with artifact on each step.



https://en.wikipedia.org/wiki/Cross-industry_standard_process_for_data_mining

Stages

PREPARATION

MODELING

DELIVERY

Preparation
01
Before experiments

Modeling
02
During experiments

Delivery
03
Integration model

Challenges

DEFINE BUSINESS PROBLEM IN TERMS OF ML

DEFINE CRITERIA OF READINESS

COLLECT AND ANNOTATE DATA

DATA QUALITY

Definition of Business Objectives

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Decisions

How are predictions used to make decisions that provide the proposed value to the end-user?

ML task

Input, output to predict, type of problem.

Value Propositions

What are we trying to do for the end-user(s) of the predictive system? What objectives are we serving?

Data Sources

Which raw data sources can we use (internal and external)?

Collecting Data

How do we get new data to learn from (inputs and outputs)?

Making Predictions

When do we make predictions on new inputs? How long do we have to featurize a new input and make a prediction?

Offline Evaluation

Methods and metrics to evaluate the system before deployment.

Features

Input representations extracted from raw data sources.

Building Models

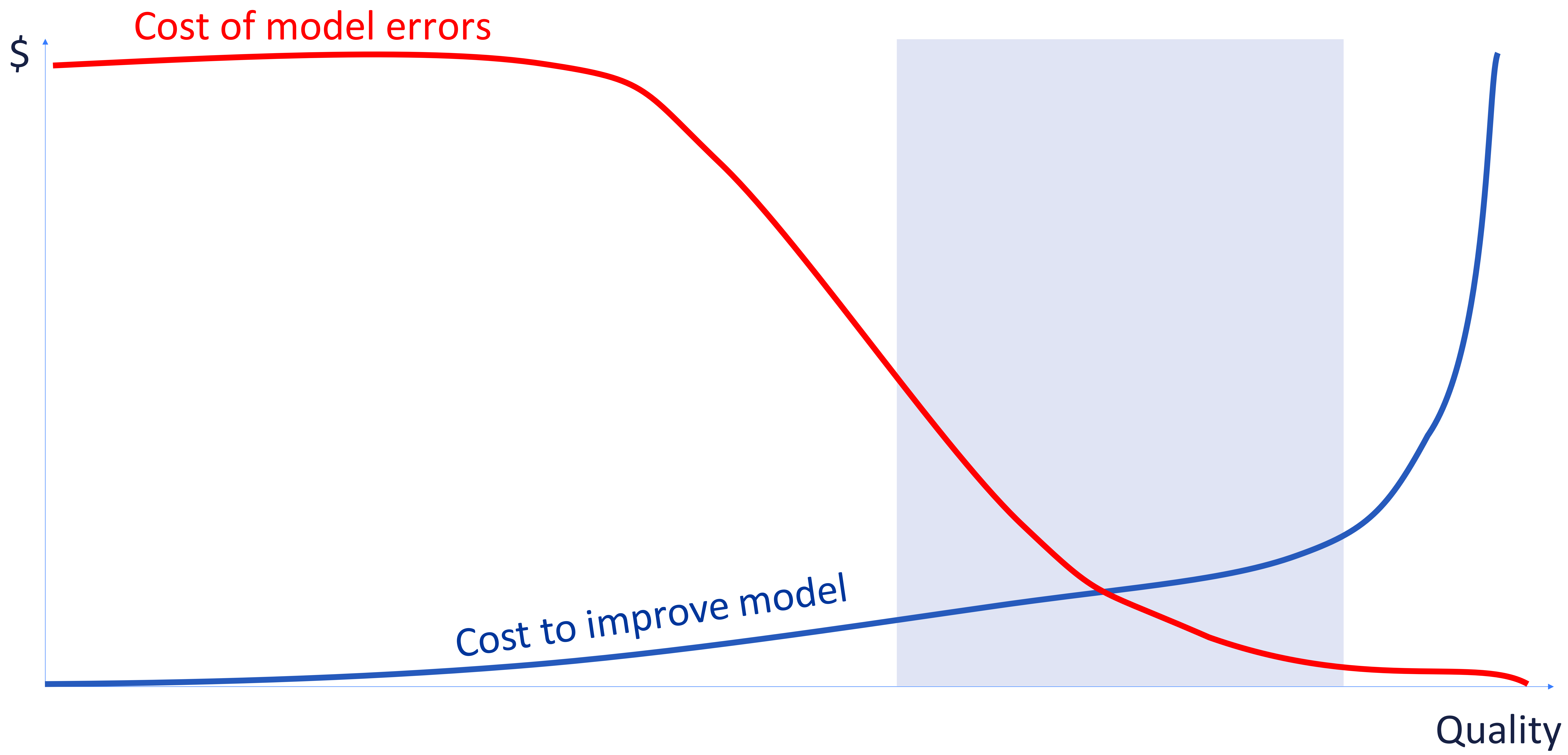
When do we create/update models with new training data? How long do we have to featurize training inputs and create a model?

Live Evaluation and Monitoring

Methods and metrics to evaluate the system after deployment, and to quantify value creation.

http://machinelearningcanvas.com/

How costly are wrong predictions?



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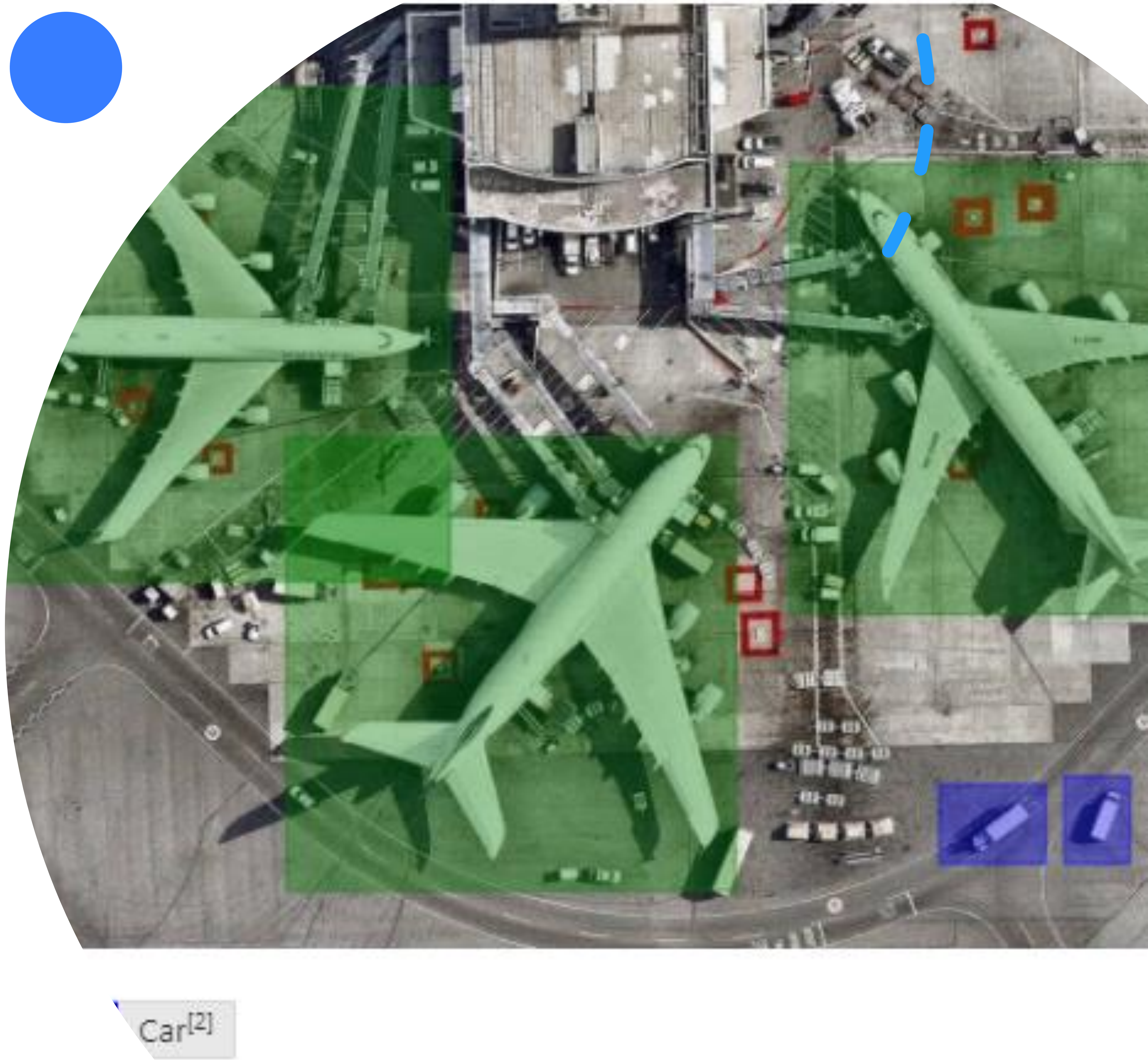
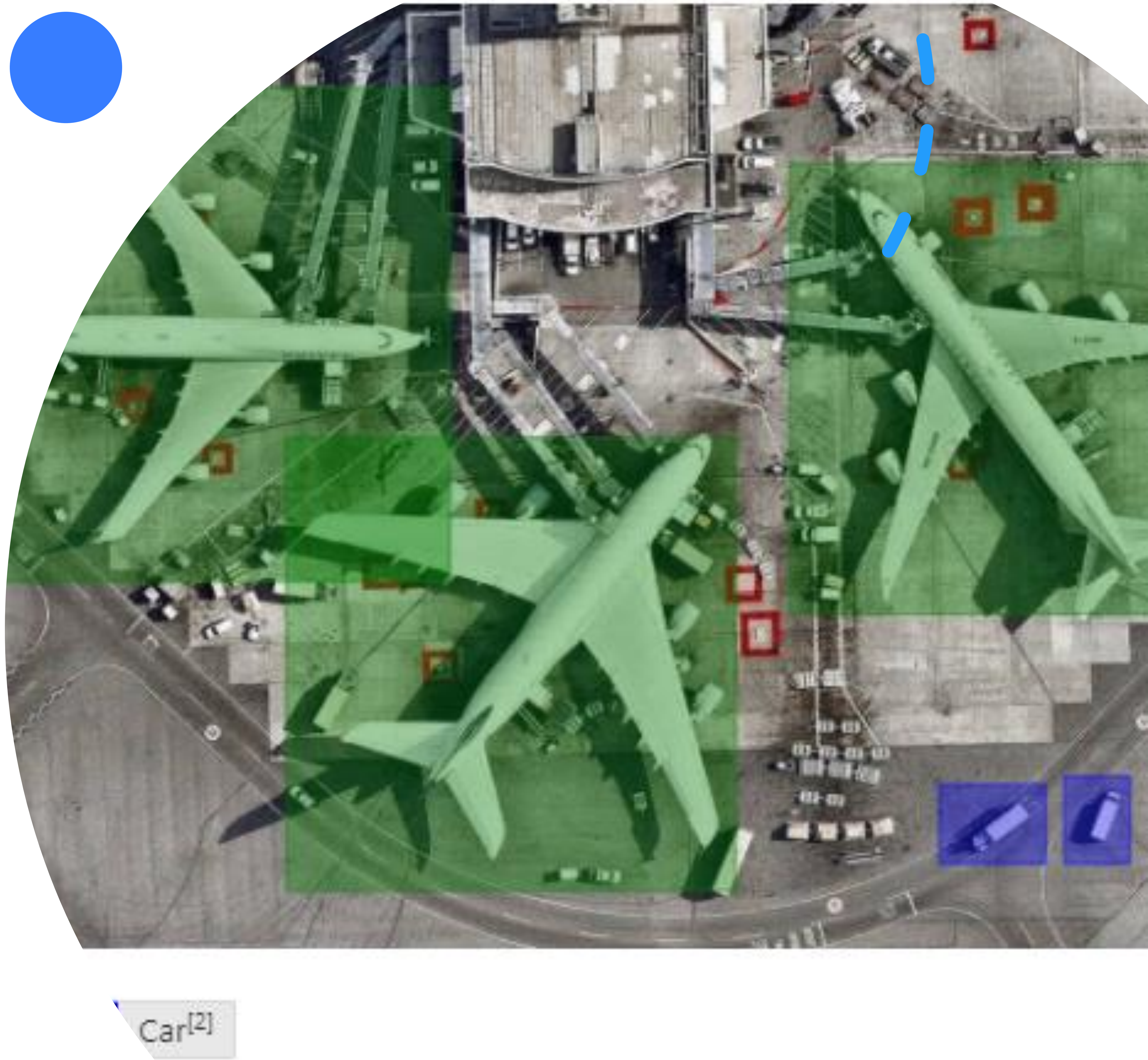
Data Annotation

- Create Guides
- Validate labels with ML team
- Cross-validate labels



Data Annotation

- Label studio (https://labelstud.io)
- Sagemaker Graund truth
- Check github awesome-data-labeling



Garbage in – Garbage out!

Summary

- Think about problem, not a metric
- Select metric connected with business goal
- Define how good is good enough
- No Data — No AI

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01

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03

Integration model

Challenges

ORGANIZE
DATA RENEWAL, TRANSFORMATION AND VERSIONING

ACHIEVE
REPRODUCIBILITY

MANAGE
ARTIFACTS AND REPORTS

Define a Data Flow — DAG

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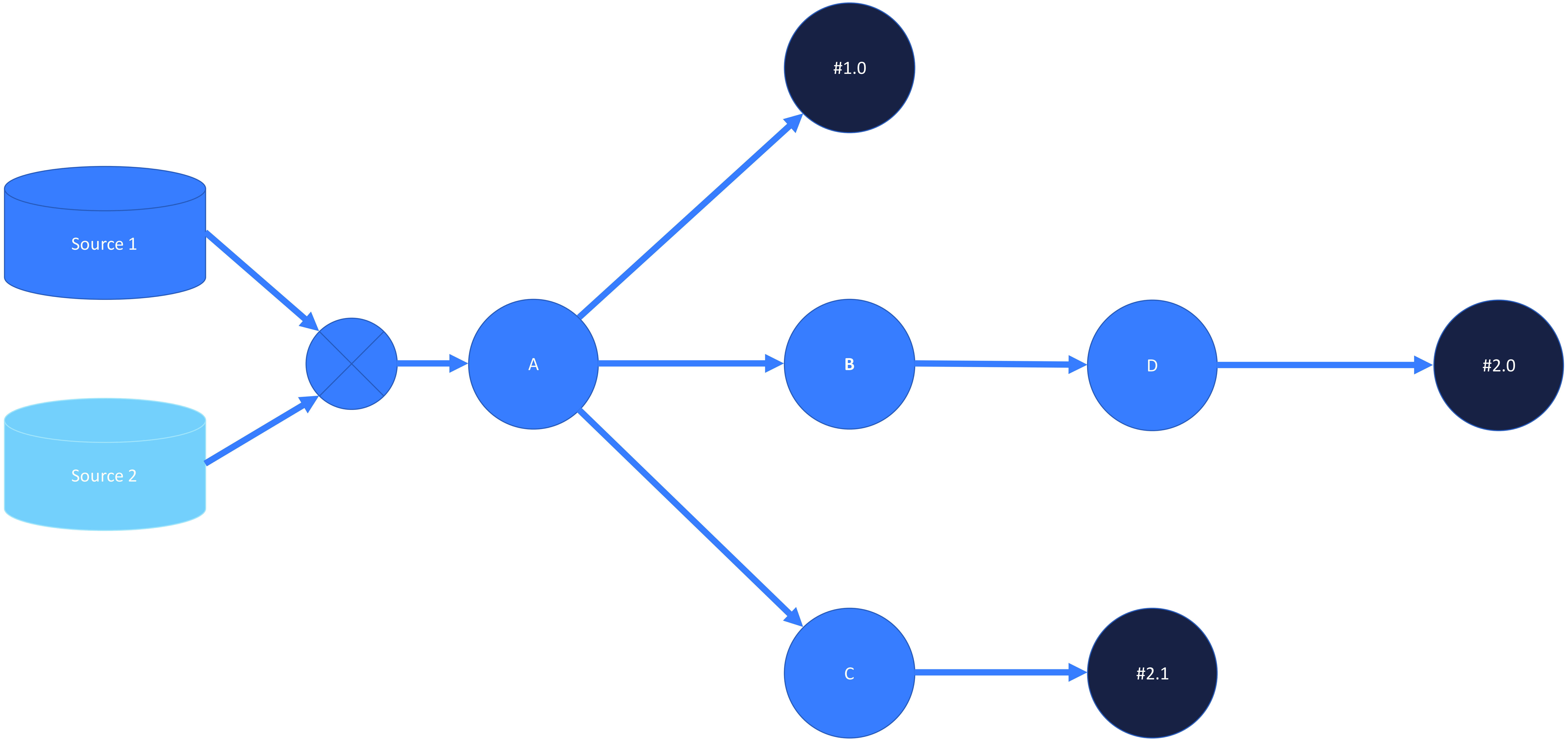
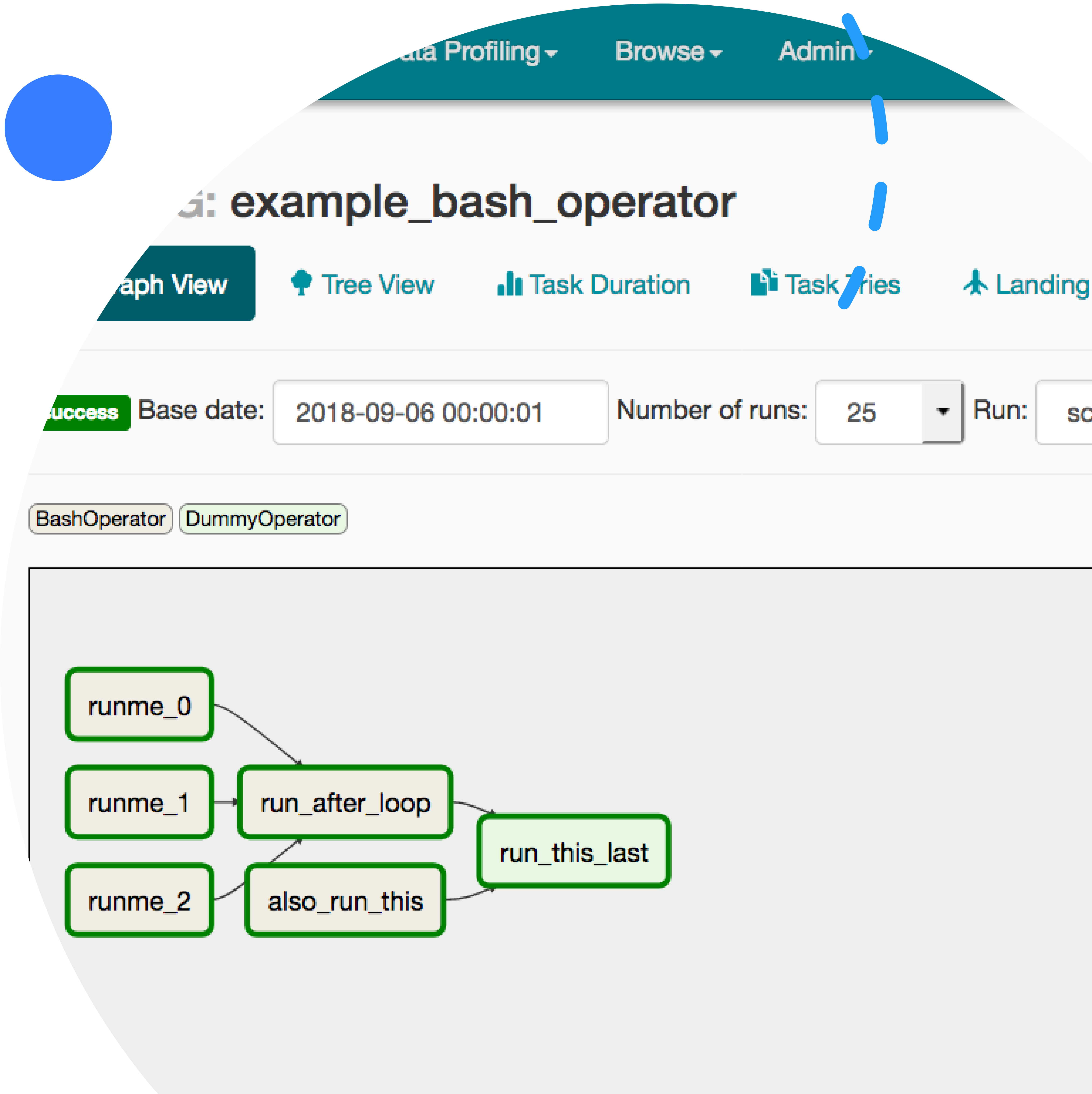


Define a Data Flow — DAG

- Scripts (bash, python…)
- Workflow management systems (Apache Airflow)
- DVC



Date Version Control

- Experiments management
- Tracking models and data
- Deployment and collaboration

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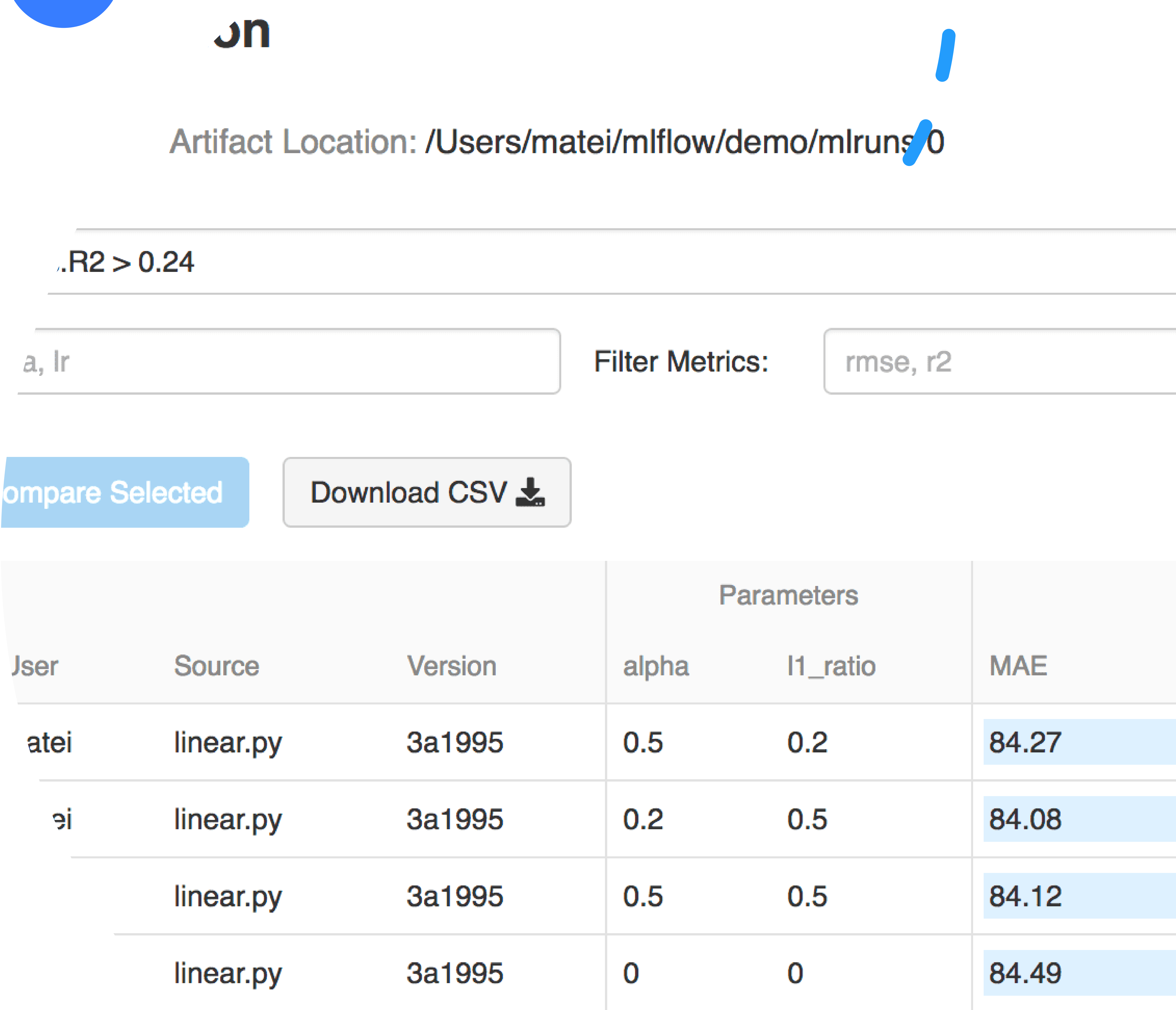
Track experiment runs

- DVC
- MLFlow
- Sagemaker



Summary

- Data it is continuation of you code, treat them like code
- Define Data Flow with DAG
- Keep in mind automation and reproducibility
- Connect model, code and data

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Challenges

MODEL INTEGRATION

MODEL SERVING

CI/CD PIPELINES

MONITORING AND FEEDBACKS

Model Integration Patterns

	Static learning	Dynamic learning	
On-demand	Services (API / Message Queues) Embedded models	Real-time Streaming analytics Online learning	Real-time data
Batch	Forecast Batch Prediction	Automated ML	Historical data

https://ml-ops.org/content/three-levels-of-ml-software

Model Serving Patterns

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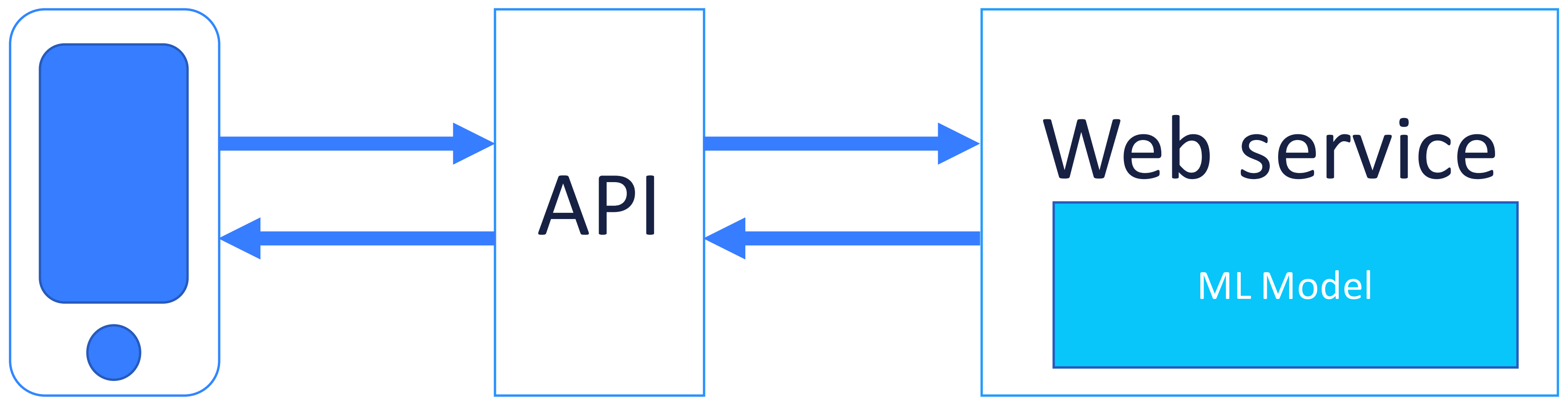
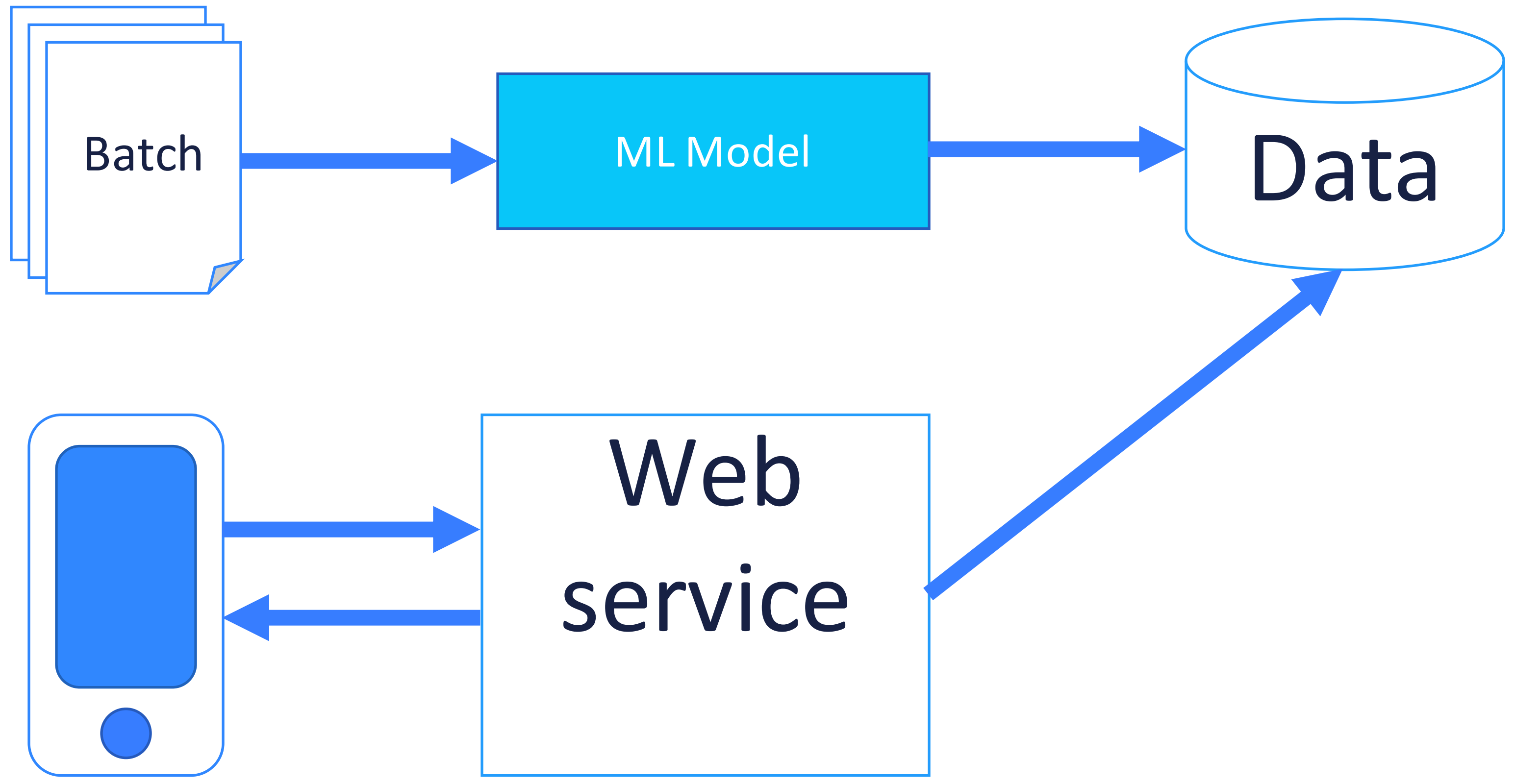
Model-as-Service



Model-as-Dependency

Precompute



Continuous X

Continuous Integration (CI) extends the testing and validating code and components by adding testing and validating data and models.

Continuous Delivery (CD) concerns with delivery of an ML training pipeline that automatically deploys another the ML model prediction service.

Continuous Training (CT) is unique to ML systems property, which automatically retrains ML models for re-deployment.

Continuous Monitoring (CM) concerns with monitoring production data and model performance metrics, which are bound to business metrics.

What to monitor?

- Data distribution
- Measure production predictions
  - Detect model degradations
- Feedback
  - Insights from user, which can help measure or improve model

Summary

- Select integration pattern depending on model use-cases
- Monitor data
- Collect feedback

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Take always

- Wrongly defined problem most popular cause of ML project fail
- Delivery of ML usually takes more then half of time of ML team
- Good machine learning skills is not enough for successful product delivery
- Follow updated about MLOps https://ml-ops.org/

QA

https://t.me/data_driven_community
https://t.me/data_driven_chat
@nesterione