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Collecting, Labeling, and Validating Data

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Welcome

The importance of data

"Data is the hardest part of ML and the most important piece to get right... Broken data is the most common cause of problems in production ML systems"

- Scaling Machine Learning at Uber with Michelangelo - Uber

"No other activity in the machine learning life cycle has a higher return on investment than improving the data a model has access to."

- Feast: Bridging ML Models and Data - Gojek

Introduction to Machine Learning Engineering for Production

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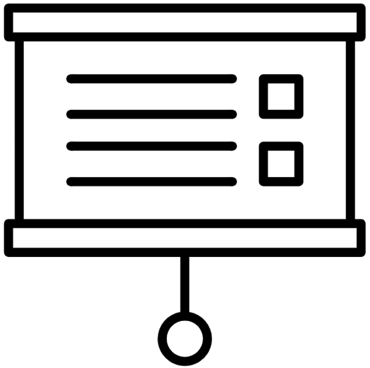
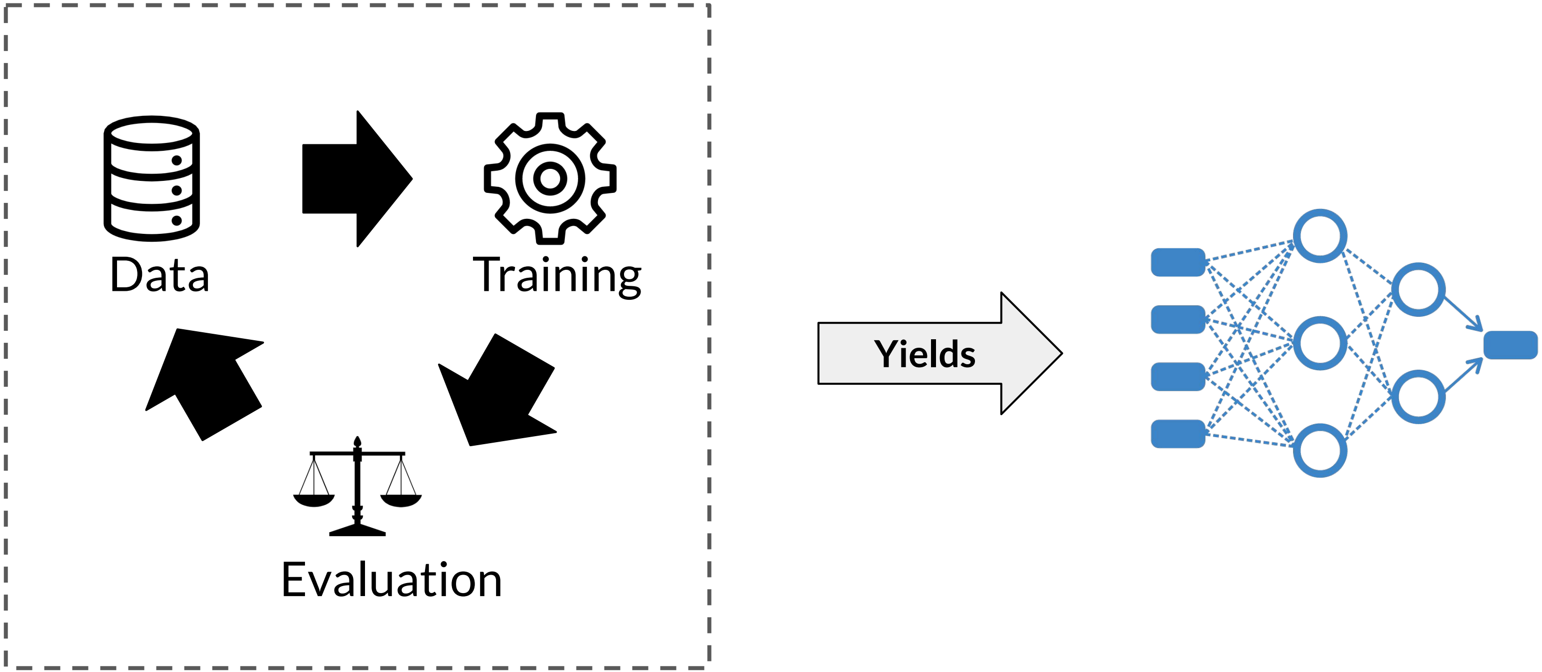
Overview

Outline

- Machine learning (ML) engineering for production: overview
- Production ML = ML development + software development
- Challenges in production ML



Traditional ML modeling



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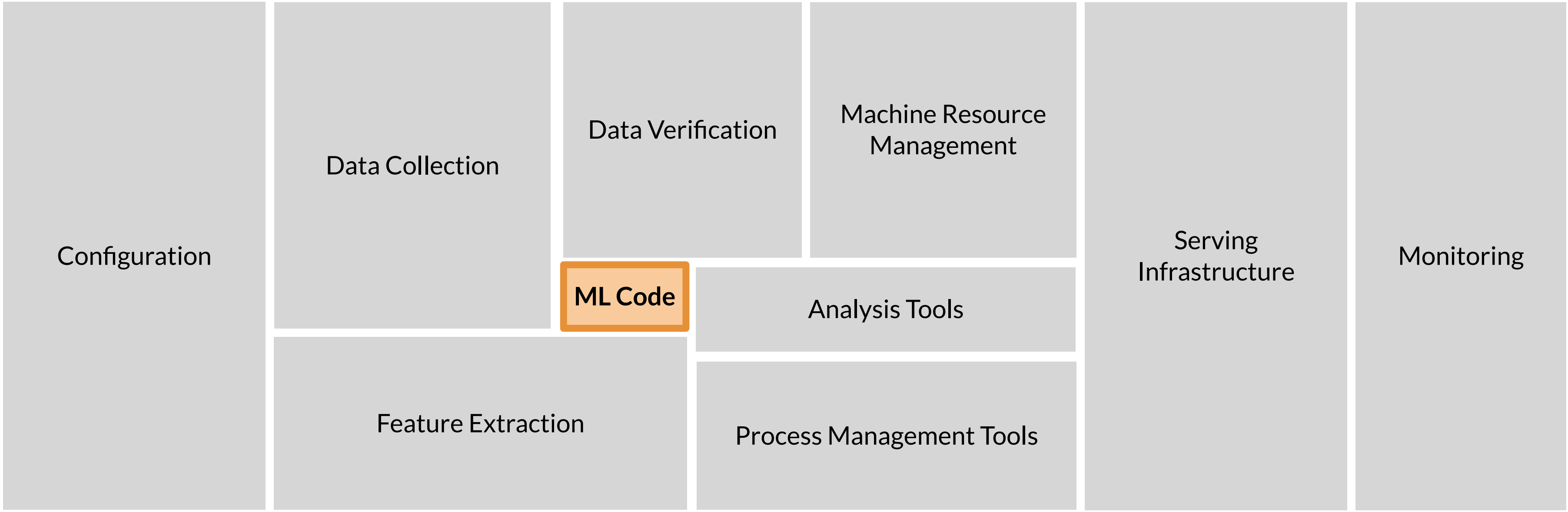
Production ML systems require so much more



ML modeling vs production ML

	Academic/Research ML	Production ML
Data	Static	Dynamic - Shifting
Priority for design	Highest overall accuracy	Fast inference, good interpretability
Model training	Optimal tuning and training	Continuously assess and retrain
Fairness	Very important	Crucial
Challenge	High accuracy algorithm	Entire system

Production machine learning

Machine learning development

+

Modern software development

Managing the entire life cycle of data

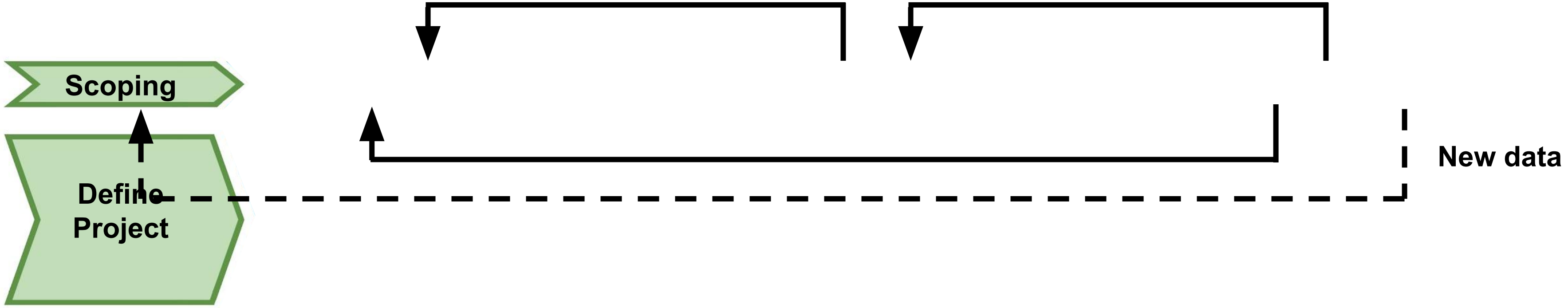
- Labeling
- Feature space coverage
- Minimal dimensionality
- Maximum predictive data
- Fairness
- Rare conditions

Modern software development

Accounts for:

- Scalability
- Extensibility
- Configuration
- Consistency & reproducibility
- Safety & security
- Modularity
- Testability
- Monitoring
- Best practices

Production machine learning system



Challenges in production grade ML

- Build integrated ML systems
- Continuously operate it in production
- Handle continuously changing data
- Optimize compute resource costs

Introduction to Machine Learning Engineering for Production

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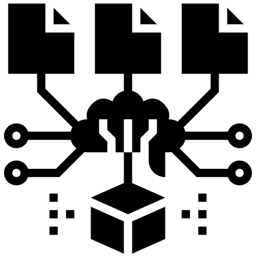
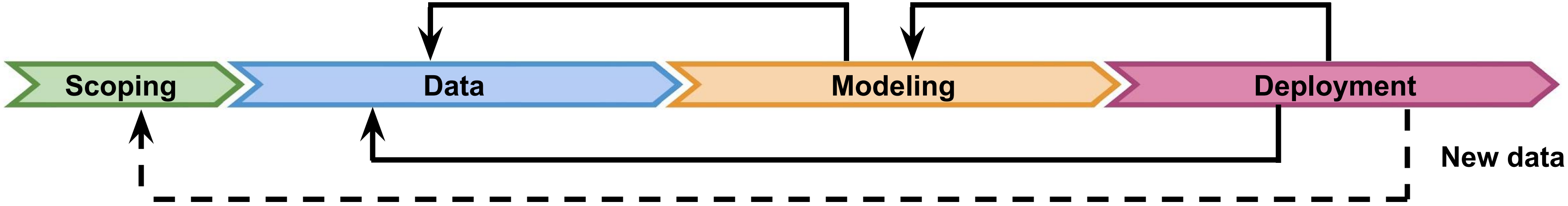
ML Pipelines

Outline

- ML Pipelines
- Directed Acyclic Graphs and Pipeline Orchestration Frameworks
- Intro to TensorFlow Extended (TFX)



ML pipelines



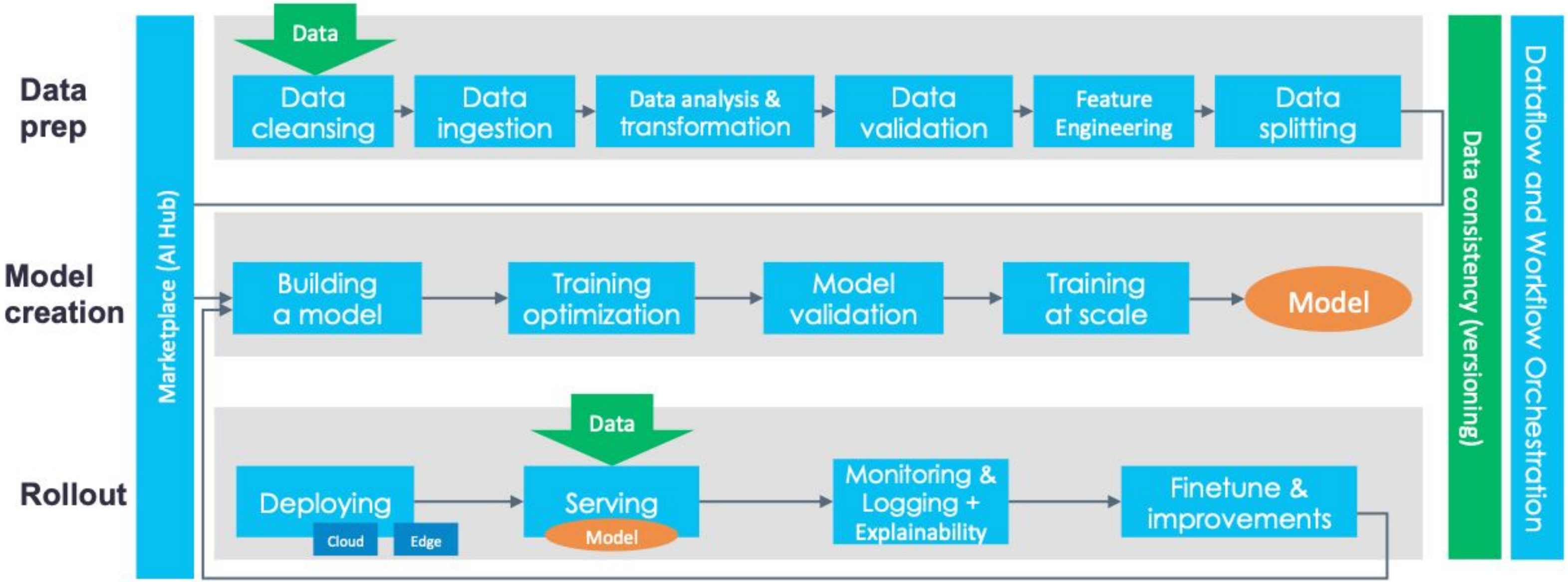
Infrastructure for

automating, monitoring, and maintaining

model training and deployment

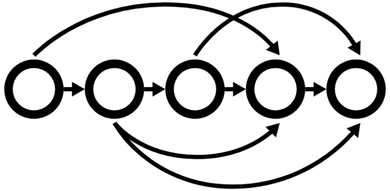
Production ML infrastructure

CD Foundation MLOps reference architecture

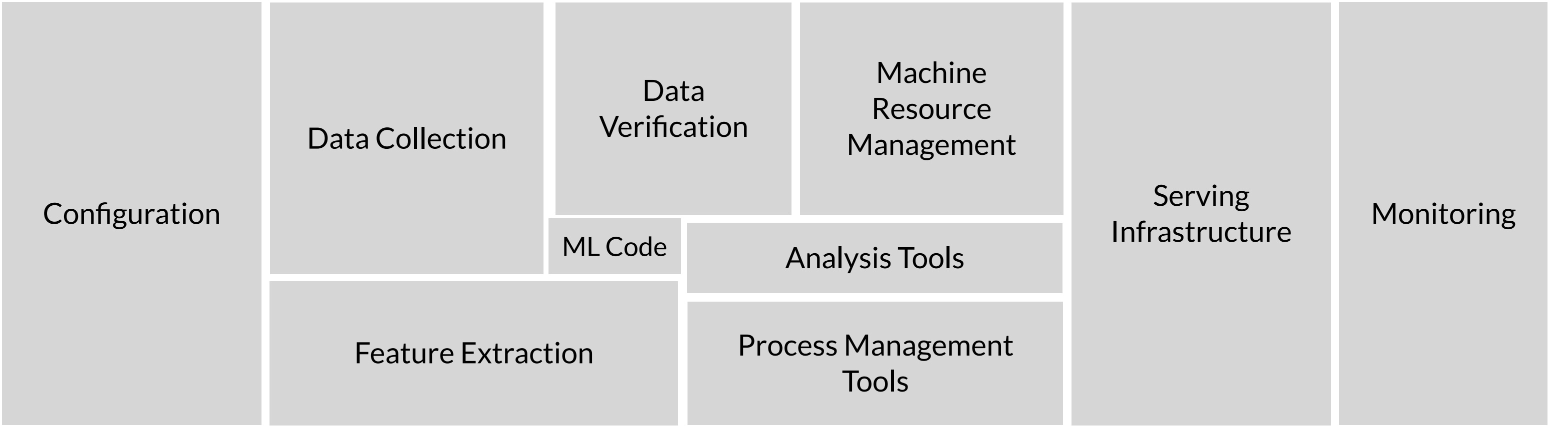


Directed acyclic graphs

- A directed acyclic graph (DAG) is a directed graph that has no cycles
- ML pipeline workflows are usually DAGs
- DAGs define the sequencing of the tasks to be performed, based on their relationships and dependencies.



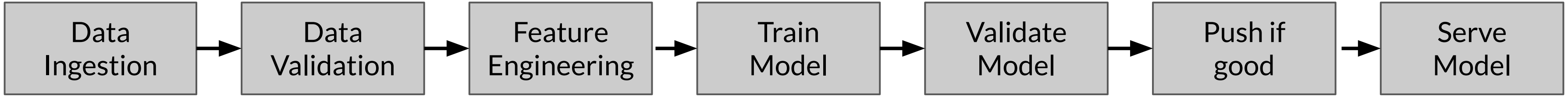
Pipeline orchestration frameworks



- Responsible for scheduling the various components in an ML pipeline DAG dependencies
- Help with pipeline automation
- Examples: Airflow, Argo, Celery, Luigi, Kubeflow

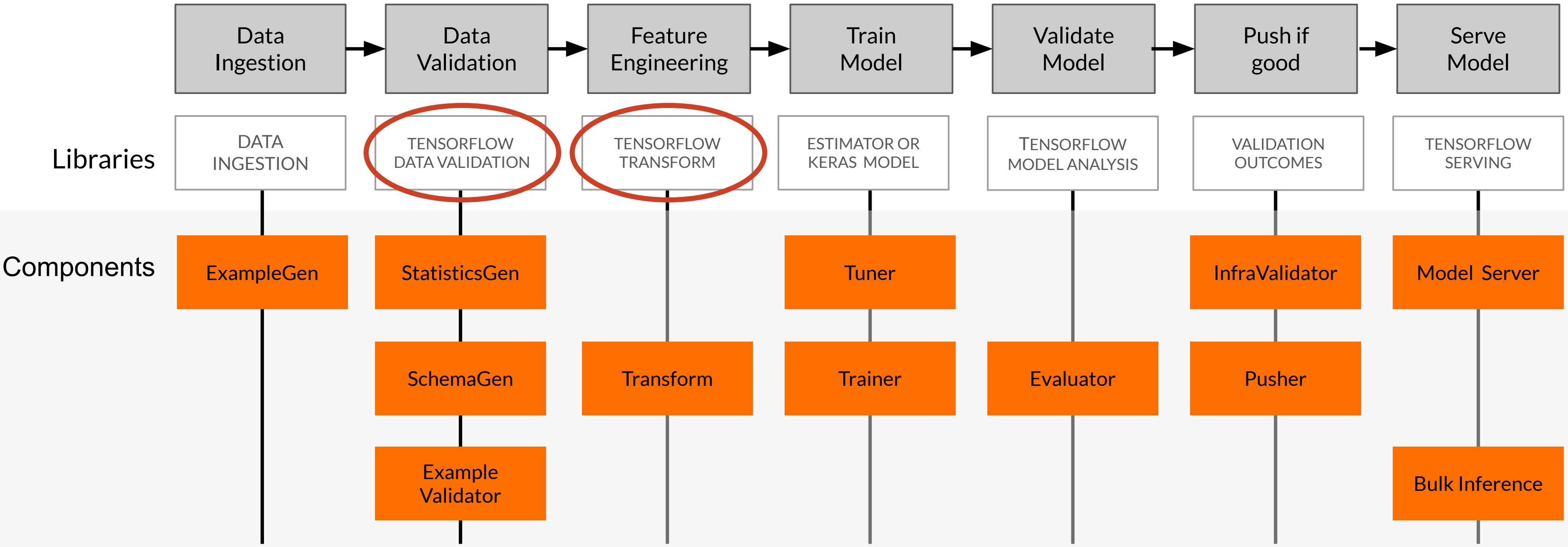
TensorFlow Extended (TFX)

End-to-end platform for deploying production ML pipelines

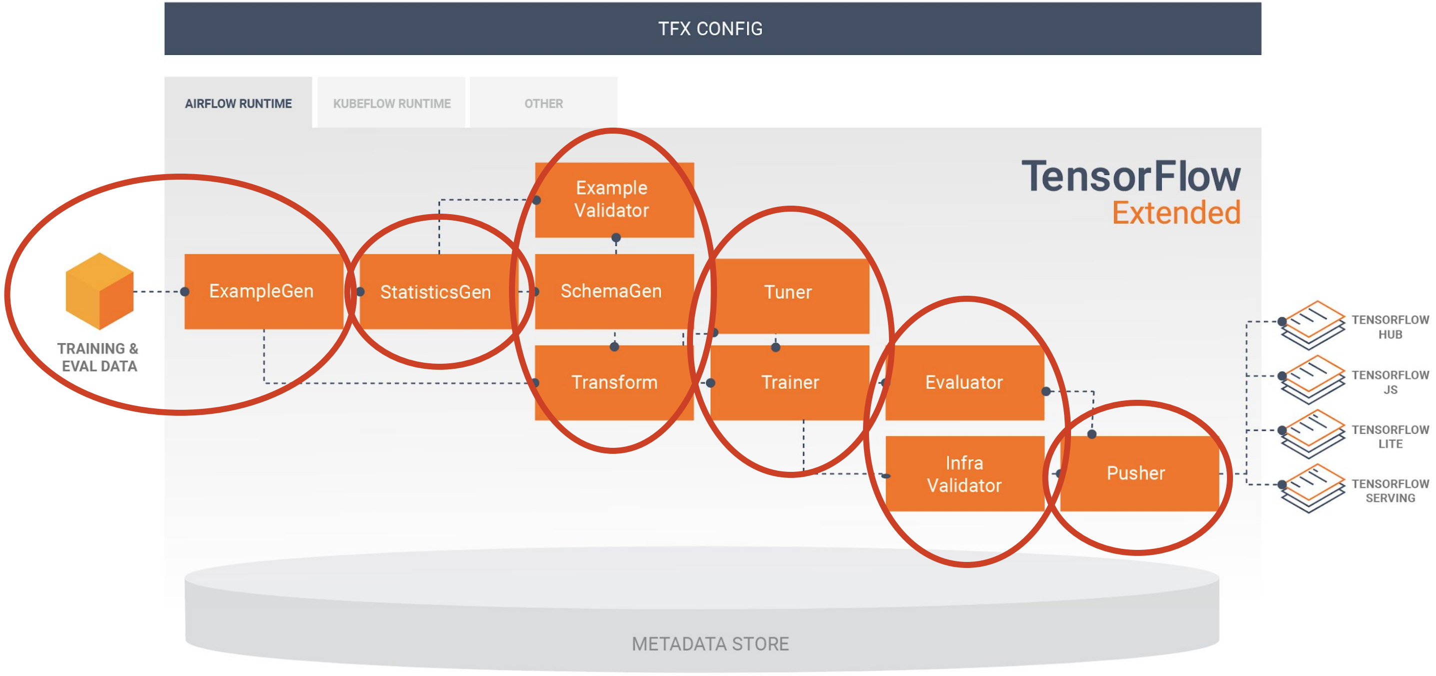


Sequence of components that are designed for scalable, high-performance machine learning tasks

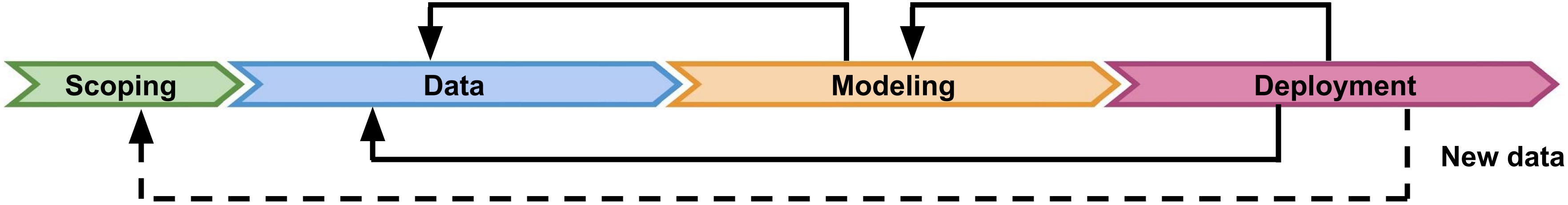
TFX production components



TFX Hello World



Key points



- Production ML pipelines: automating, monitoring, and maintaining end-to-end processes
- Production ML is much more than just ML code
  - ML development + software development
- TFX is an open-source end-to-end ML platform

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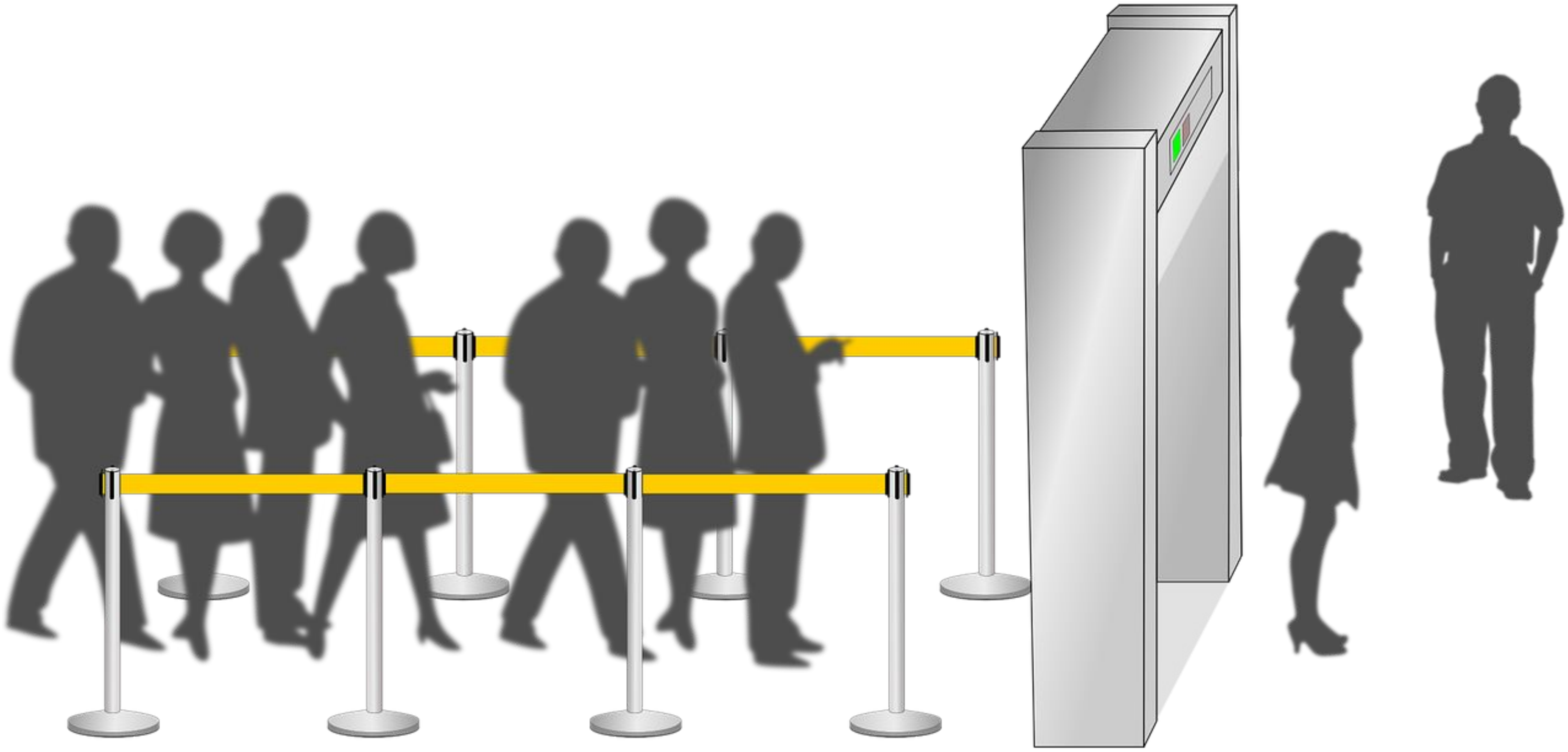
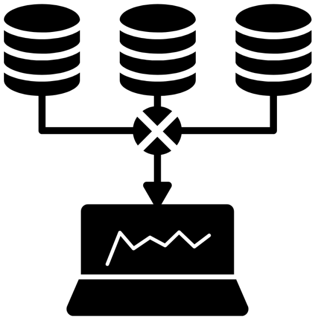
Collecting Data

Importance of Data



Outline

- Importance of data quality
- Data pipeline: data collection, ingestion and preparation
- Data collection and monitoring



The importance of data

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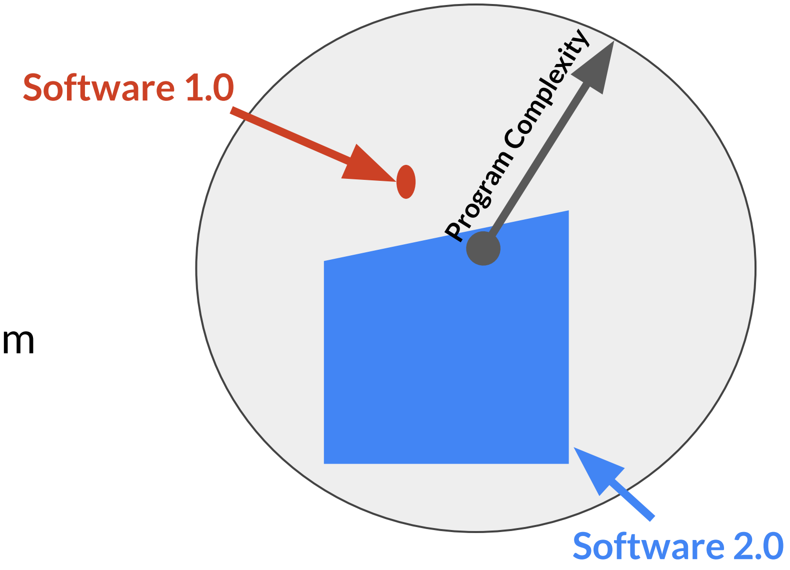
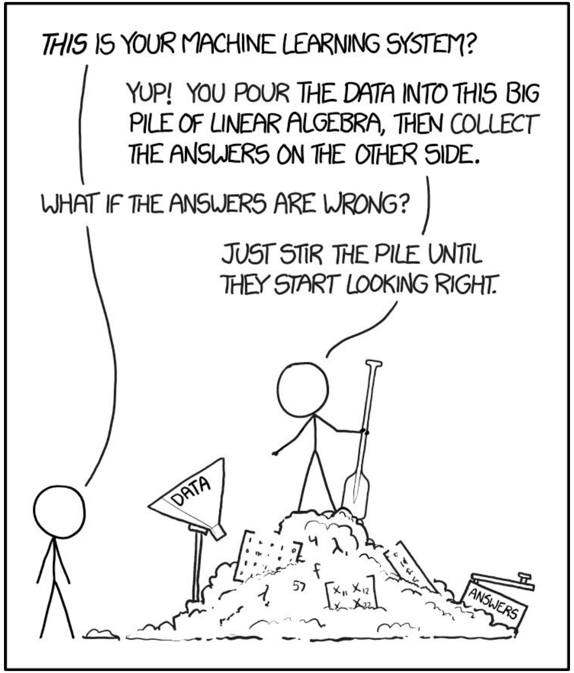
ML: Data is a first class citizen

- Software 1.0
  - Explicit instructions to the computer
- Software 2.0
  - Specify some goal on the behavior of a program
  - Find solution using optimization techniques
  - Good data is key for success
  - Code in Software = Data in ML

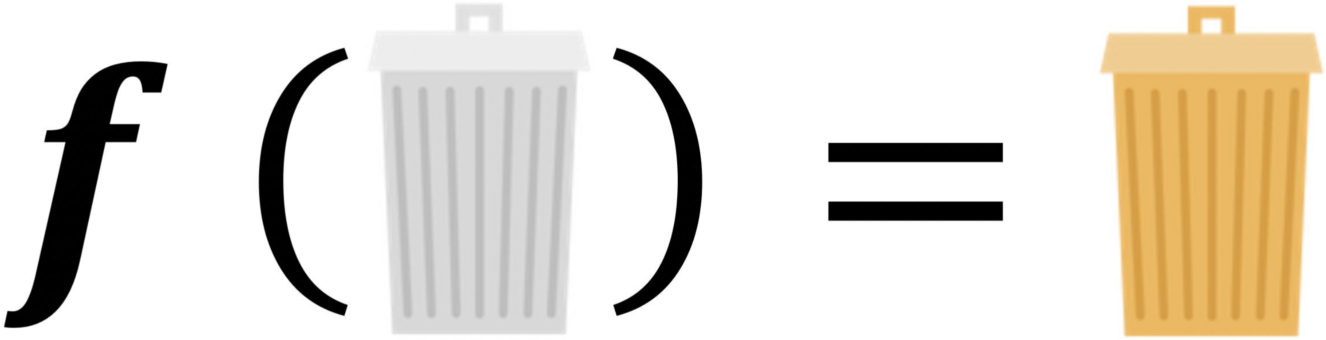


Everything starts with data

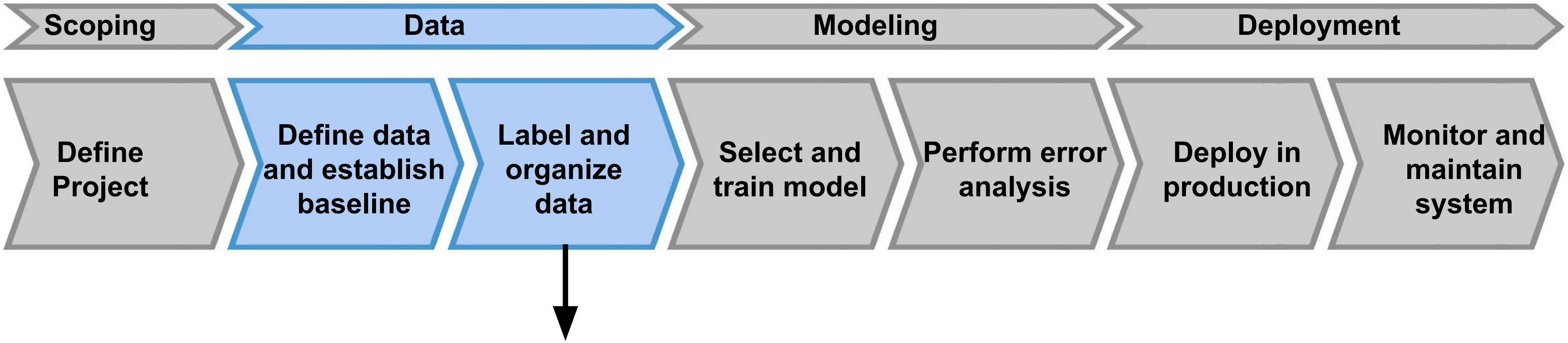
- Models aren't magic
- Meaningful data:
  - maximize predictive content
  - remove non-informative data
  - feature space coverage



Garbage in, garbage out

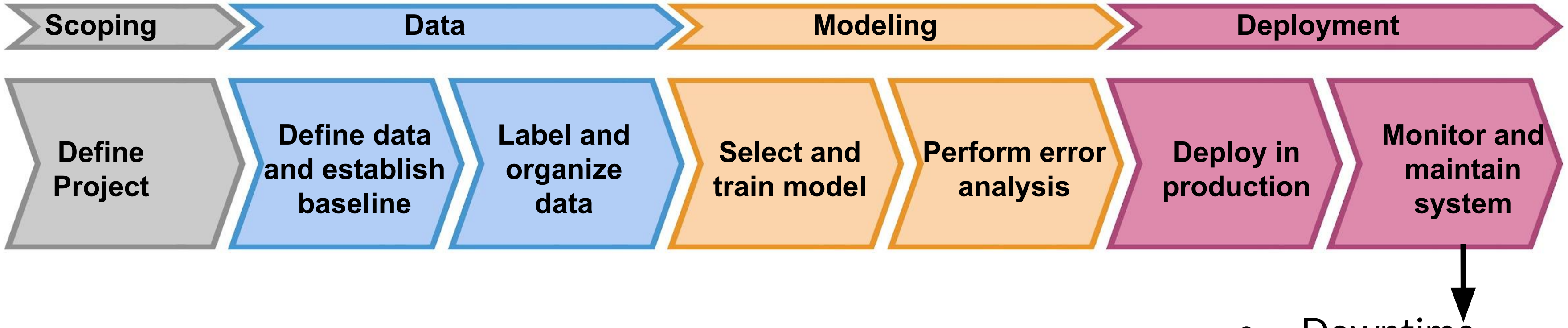


Data pipeline



- Data collection
- Data ingestion
- Data formatting
- Feature engineering
- Feature extraction

Data collection and monitoring



- Downtime
- Errors
- Distributions shifts
- Data failure
- Service failure

Key Points

- Understand users, translate user needs into data problems
- Ensure data coverage and high predictive signal
- Source, store and monitor quality data responsibly

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Collecting Data

Example Application: Suggesting Runs

🏃🏃Example application: Suggesting runs

Users	Runners
User Need	Run more often
User Actions	Complete run using the app
ML System Output	• What routes to suggest • When to suggest them
ML System Learning	• Patterns of behaviour around accepting run prompts • Completing runs • Improving consistency

🏃🏃Key considerations

- Data availability and collection
  - What kind of/how much data is available?
  - How often does the new data come in?
  - Is it annotated?
    - If not, how hard/expensive is it to get it labeled?
- Translate user needs into data needs
  - Data needed
  - Features needed
  - Labels needed

Example dataset

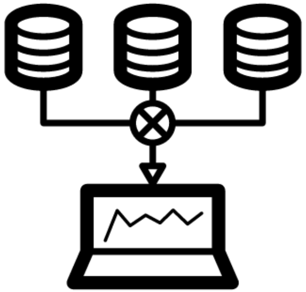
	FEATURES			
Runner ID	**Run**	**Runner Time**	**Elevation**	**Fun**
AV3DE	Boston Marathon	03:40:32	1,300 ft	Low
X8KGF	Seattle Oktoberfest 5k	00:35:40	0 ft	High
BH9IU	Houston Half-marathon	02:01:18	200 ft	Medium

EXAMPLES

LABELS

Get to know your data

- Identify data sources
- Check if they are refreshed
- Consistency for values, units, & data types
- Monitor outliers and errors



Dataset issues

- Inconsistent formatting
  - Is zero “0”, “0.0”, or an indicator of a missing measurement
- Compounding errors from other ML Models
- Monitor data sources for system issues and outages

Measure data effectiveness

- Intuition about data value can be misleading
  - Which features have predictive value and which ones do not?
- Feature engineering helps to maximize the predictive signals
- Feature selection helps to measure the predictive signals

Translate user needs into data needs

Data Needed	• Running data from the app • Demographic data • Local geographic data

Translate user needs into data needs

Features Needed	• Runner demographics • Time of day • Run completion rate • Pace • Distance ran • Elevation gained • Heart rate

Translate user needs into data needs

Labels Needed	- Runner acceptance or rejection of app suggestions - User generated feedback regarding why suggestion was rejected - User rating of enjoyment of recommended runs

Key points

- Understand your user, translate their needs into data problems
    - What kind of/how much data is available
    - What are the details and issues of your data
    - What are your predictive features
    - What are the labels you are tracking
    - What are your metrics

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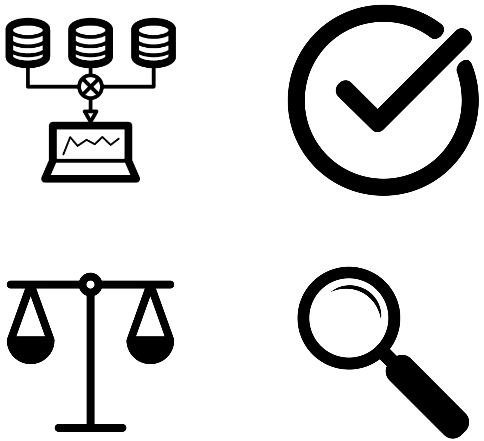
Collecting Data

Responsible Data: Security, Privacy & Fairness

Outline

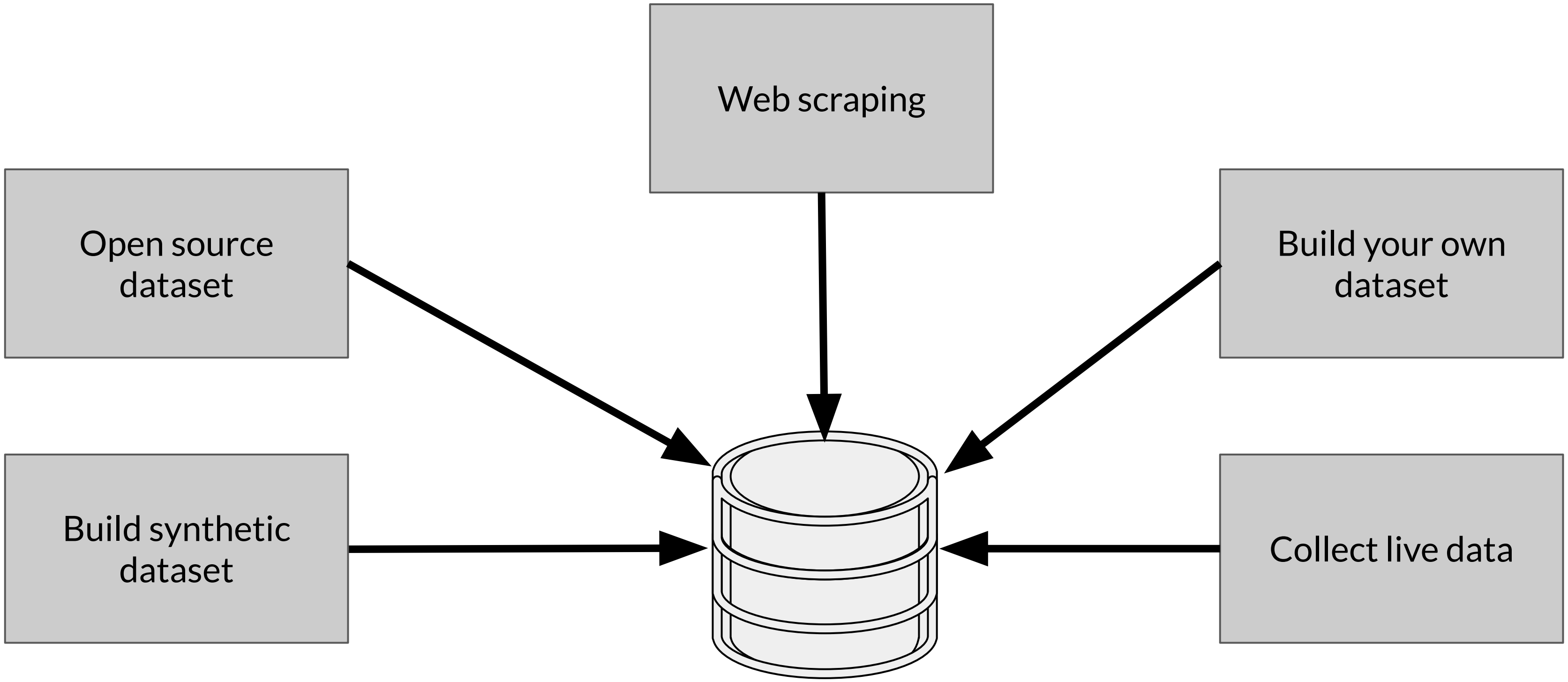
- Data Sourcing
- Data Security and User Privacy
- Bias and Fairness



Avoiding problematic biases in datasets

Example: classifier trained on the Open Images dataset

Source Data Responsibly



Data security and privacy

- Data collection and management isn't just about your model
  - Give user control of what data can be collected
  - Is there a risk of inadvertently revealing user data?
- Compliance with regulations and policies (e.g. GDPR)

Users privacy

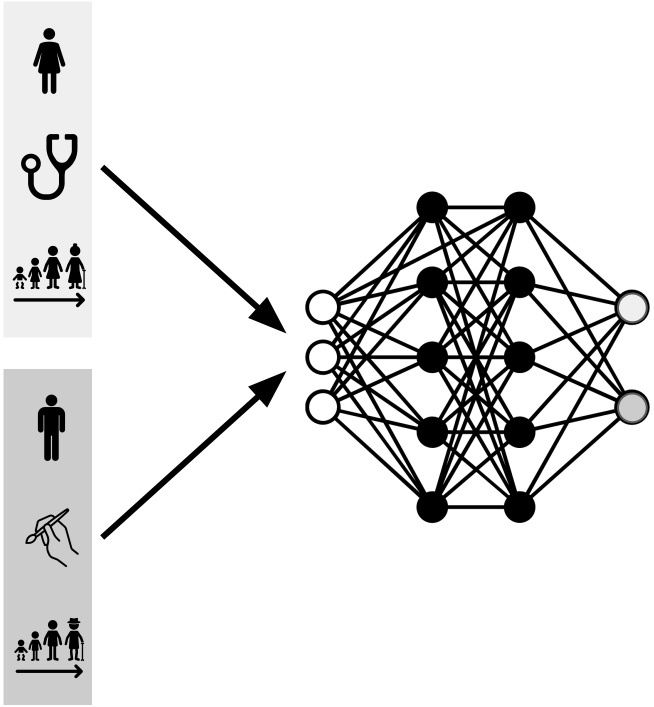
- Protect personally identifiable information
  - Aggregation - replace unique values with summary value
  - Redaction - remove some data to create less complete picture

How ML systems can fail users

Fair | Accountable | Transparent | Explainable

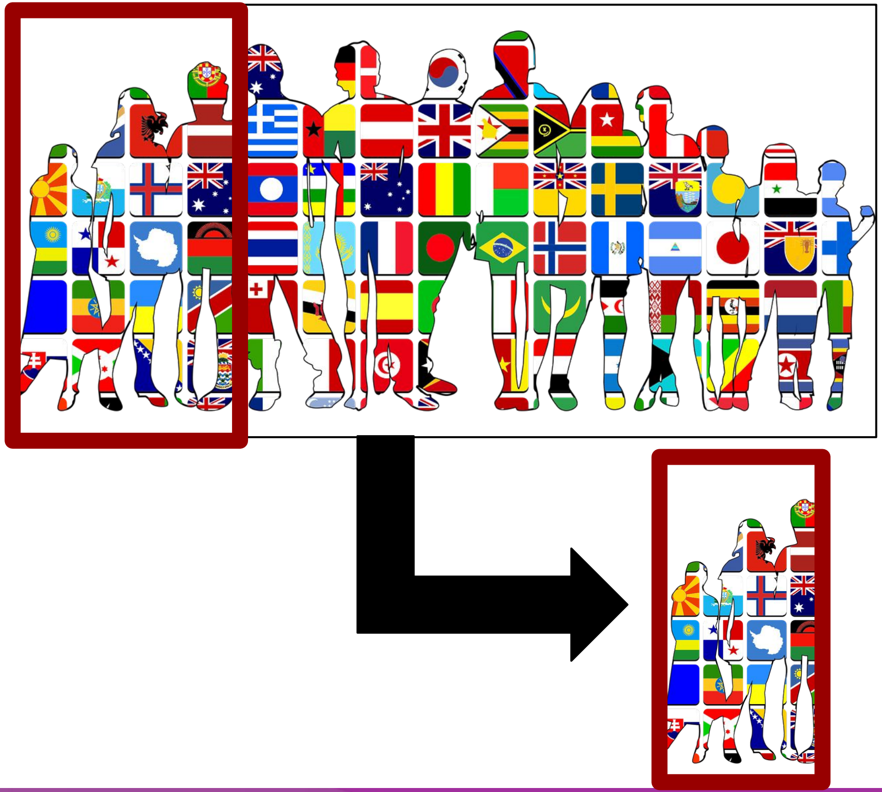
- Representational harm
- Opportunity denial
- Disproportionate product failure
- Harm by disadvantage

Commit to fairness



- Make sure your models are fair
  - Group fairness, equal accuracy
- Bias in human labeled and/or collected data
- ML Models can amplify biases

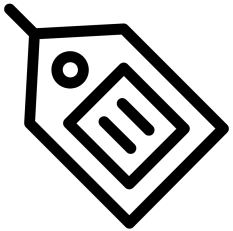
Biased data representation



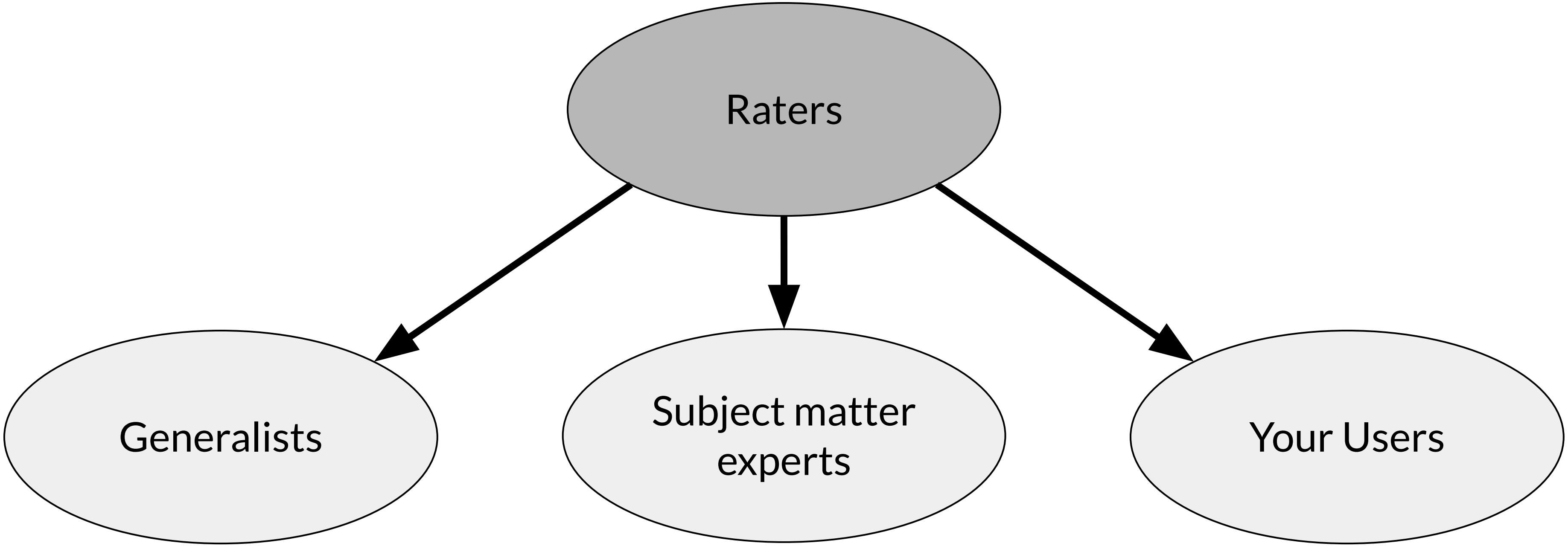
Reducing bias: Design fair labeling systems

- Accurate labels are necessary for supervised learning

- Labeling can be done by:
  - Automation (logging or weak supervision)
  - Humans (aka “Raters”, often semi-supervised)



Types of human raters



crowdsourcing tools

Specialized tools, e.g. medical Image labelling

Derived labels, e.g. tagging photos

Key points

- Ensure rater pool diversity
- Investigate rater context and incentives
- Evaluate rater tools
- Manage cost
- Determine freshness requirements

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Labeling Data

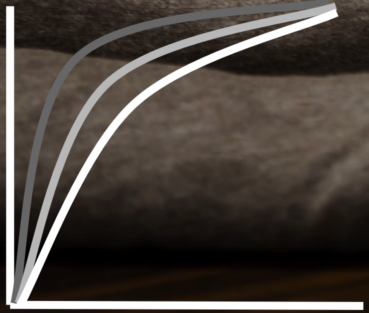
Case Study: Degraded Model Performance

You're an Online Retailer Selling Shoes ...

Your model predicts **click-through rates (CTR)**, helping you decide how much inventory to order

When suddenly

Your AUC and prediction accuracy have **dropped** on men's dress shoes!



Why?

How do we know that we have a problem?

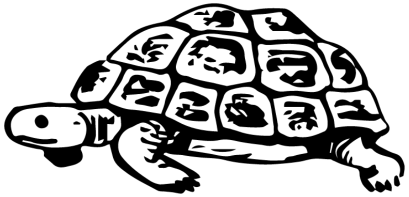
Case study: taking action

- How to detect problems early on?
- What are the possible causes?
- What can be done to solve these?

What causes problems?

Kinds of problems:

- Slow - example: drift
- Fast - example: bad sensor, bad software update



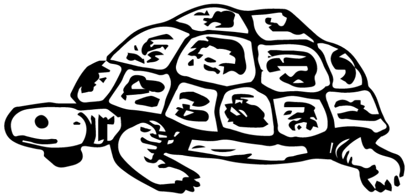
Gradual problems

Data changes

- Trend and seasonality
- Distribution of features changes
- Relative importance of features changes

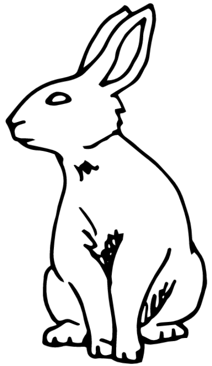
World changes

- Styles change
- Scope and processes change
- Competitors change
- Business expands to other geos



Sudden problems

Data collection problem	Systems problem
• Bad sensor/camera • Bad log data • Moved or disabled sensors/cameras	• Bad software update • Loss of network connectivity • System down • Bad credentials



Why "Understand" the model?

- Mispredictions do not have uniform **cost** to your business
- The **data you have** is rarely the data you wish you had
- Model objective is nearly always a **proxy** for your business objectives
- Some percentage of your customers may have a **bad experience**

The real world does not stand still!

Labeling Data

Data and Concept Change in Production ML

Outline

- Detecting problems with deployed models
    - Data and concept change
- Changing ground truth
    - Easy problems
    - Harder problems
    - Really hard problems

Detecting problems with deployed models

- Data and scope changes
- Monitor models and validate data to find problems early
- Changing ground truth: **label** new training data

Easy problems

- Ground truth changes slowly (months, years)
- Model retraining driven by:
  - Model improvements, better data
  - Changes in software and/or systems
- Labeling
  - Curated datasets
  - Crowd-based

Harder problems

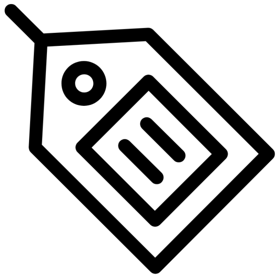
- Ground truth changes faster (weeks)
- Model retraining driven by:
    - **Declining model performance**
    - Model improvements, better data
    - Changes in software and/or system
- Labeling
    - Direct feedback
    - Crowd-based

Really hard problems

- Ground truth changes very fast (days, hours, min)
- Model retraining driven by:
  - **Declining model performance**
  - Model improvements, better data
  - Changes in software and/or system
- Labeling
  - Direct feedback
  - Weak supervision

Key points

- Model performance decays over time
  - Data and Concept Drift
- Model retraining helps to improve performance
  - Data labeling for changing ground truth and scarce labels



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Labeling Data

Process Feedback and Human Labeling

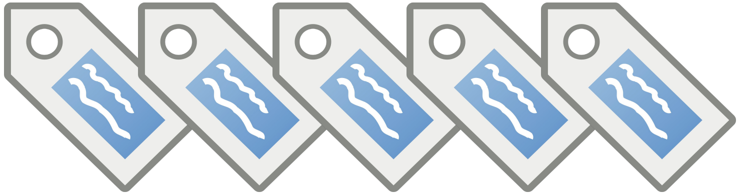
Data labeling

Variety of Methods

- Process Feedback (Direct Labeling)
- Human Labeling
- ~~Semi-Supervised Labeling~~
- ~~Active Learning~~
- ~~Weak Supervision~~

➡ Practice later as advanced labeling methods

Data labeling



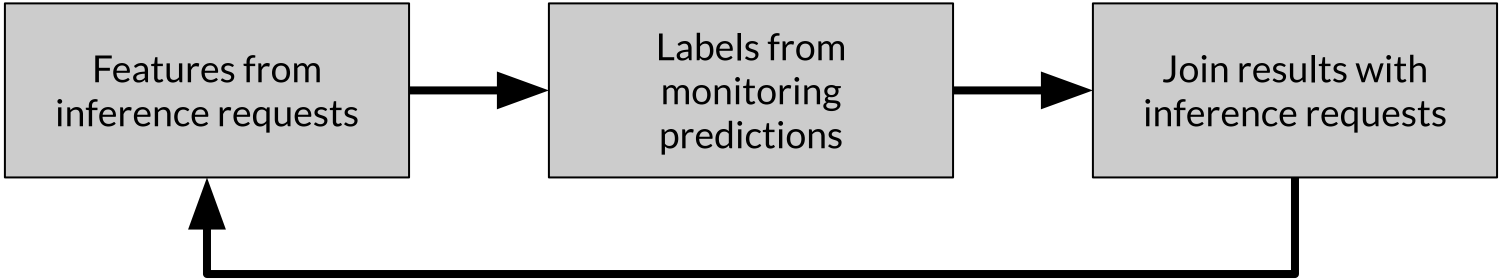
Process Feedback — Example: Actual vs predicted click-through

Human Labeling — Example: Cardiologists labeling MRI images

Why is labeling important in production ML?

- Using business/organisation available data
- Frequent model retraining
- Labeling ongoing and critical process
- Creating a training datasets requires labels

Direct labeling: continuous creation of training dataset



Similar to reinforcement learning rewards

Process feedback - advantages

- Training dataset continuous creation
- Labels evolve quickly
- Captures strong label signals

Process feedback - disadvantages

- Hindered by inherent nature of the problem
- Failure to capture ground truth
- Largely bespoke design

Process feedback - Open-Source log analysis tools

Logstash

Free and open source data processing pipeline

- Ingests data from a multitude of sources
- Transforms it
- Sends it to your favorite "stash."

Fluentd

Open source data collector

Unify the data collection and consumption

Process feedback - Cloud log analytics

Cloud Log Analysis

Google Cloud Logging

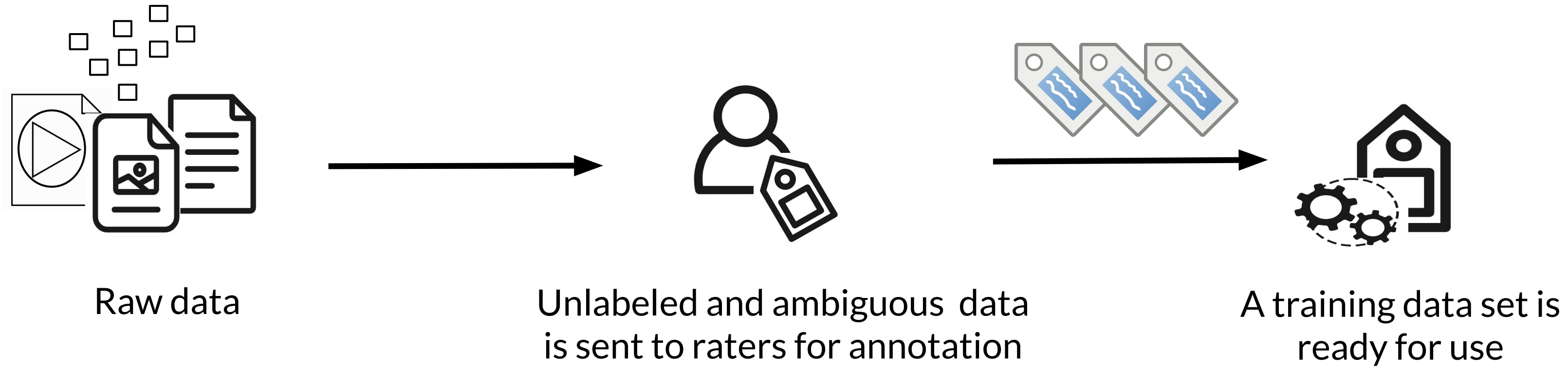
- Data and events from Google Cloud and AWS
- BindPlane. Logging: application components, on-premise and hybrid cloud systems
- Sends it to your favorite "stash"

AWS ElasticSearch

Azure Monitor

Human labeling

People ("raters") to examine data and assign labels manually



Human labeling - Methodology

Unlabeled data is collected

Human “raters” are recruited

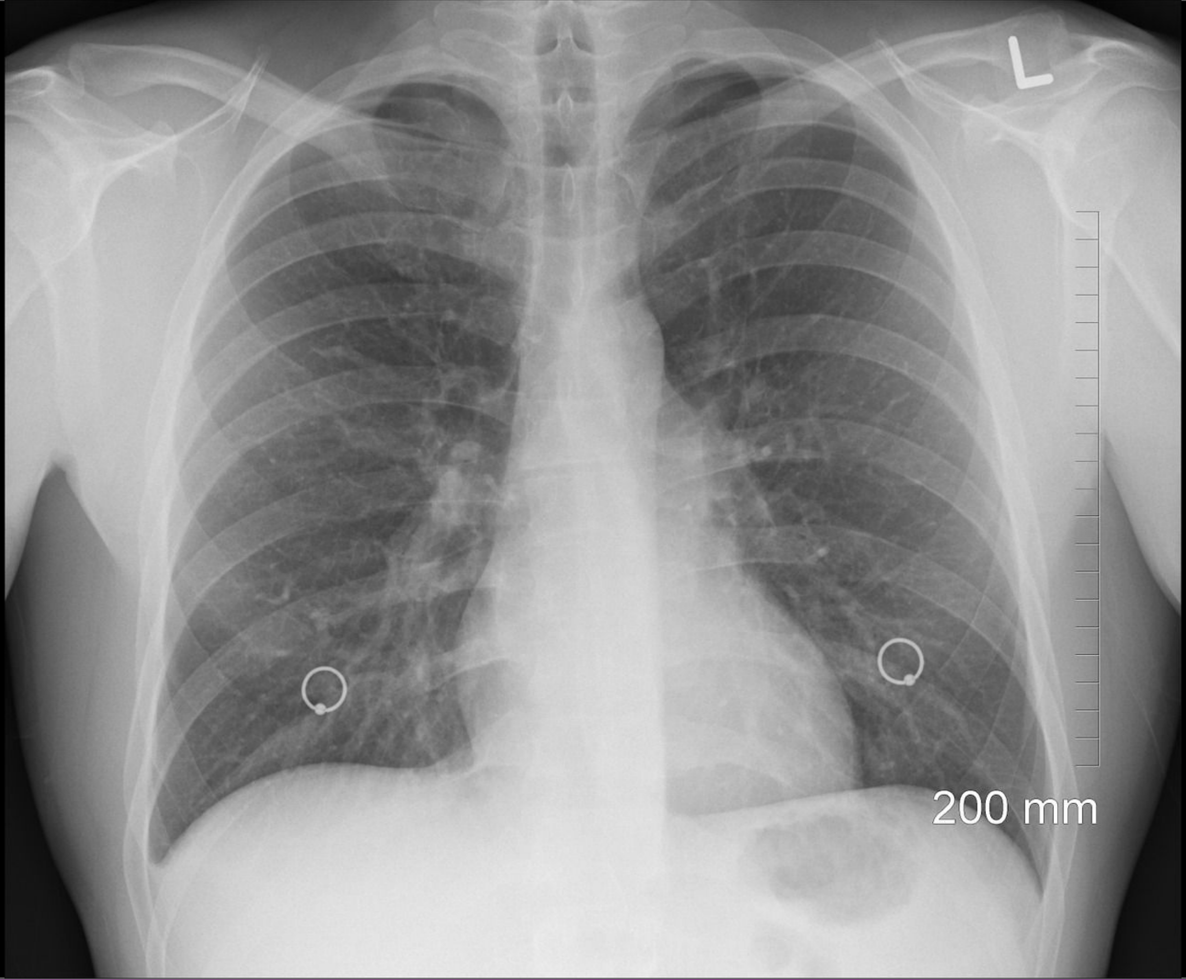
Instructions to guide raters are created

Data is divided and assigned to raters

Labels are collected and conflicts resolved

Human labeling - advantages

- More labels
- Pure supervised learning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Human labeling - Disadvantages

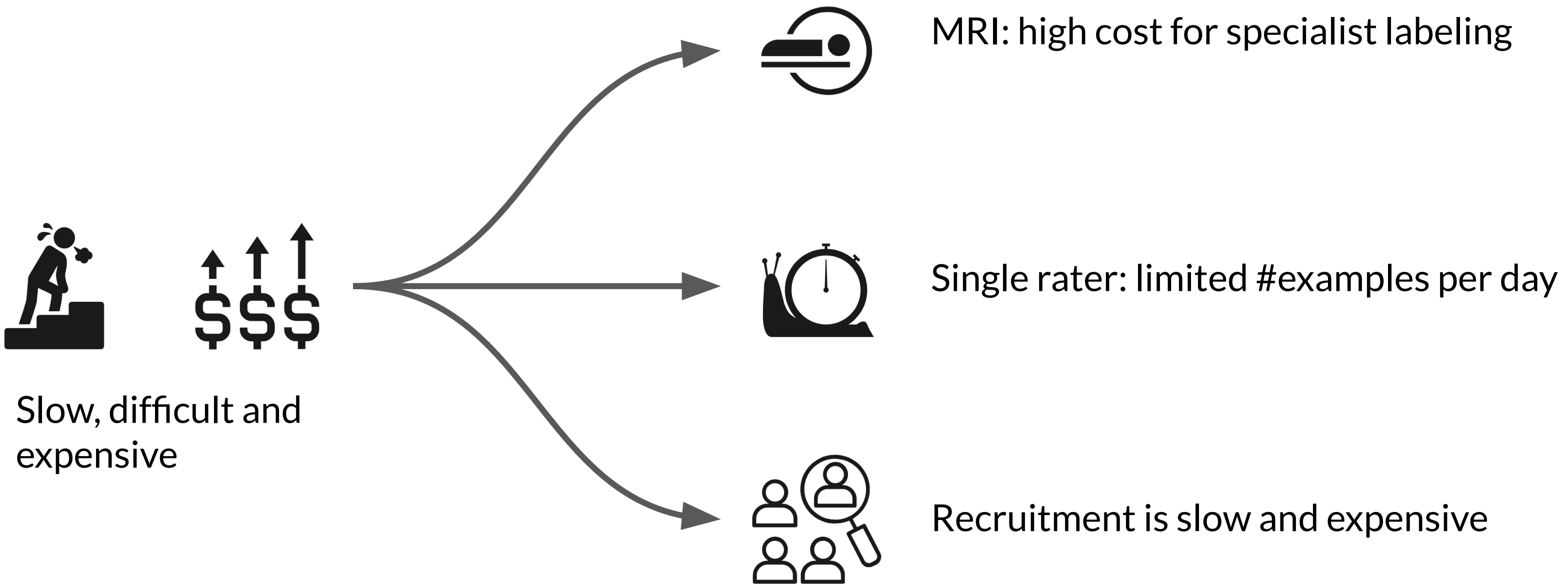
Quality consistency: Many datasets difficult for human labeling

Slow

Expensive

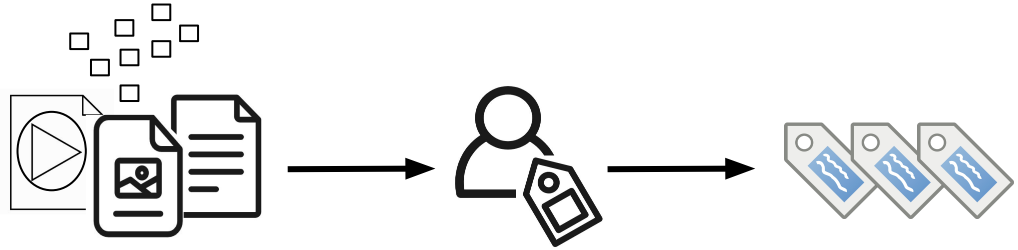
Small dataset curation

Why is human labeling a problem?



Key points

- Various methods of data labeling
    - Process feedback
    - Human labeling



- Advantages and disadvantages of both

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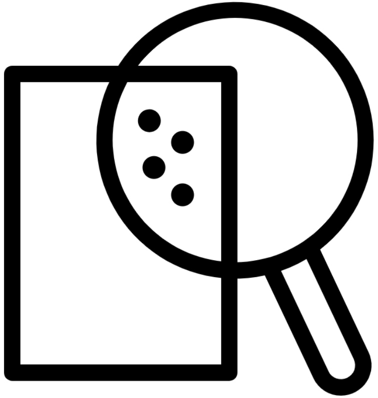
Validating Data

Detecting Data Issues

Outline

- Data issues
  - Drift and skew
    - Data and concept Drift
    - Schema Skew
    - Distribution Skew
- Detecting data issues



Drift and skew

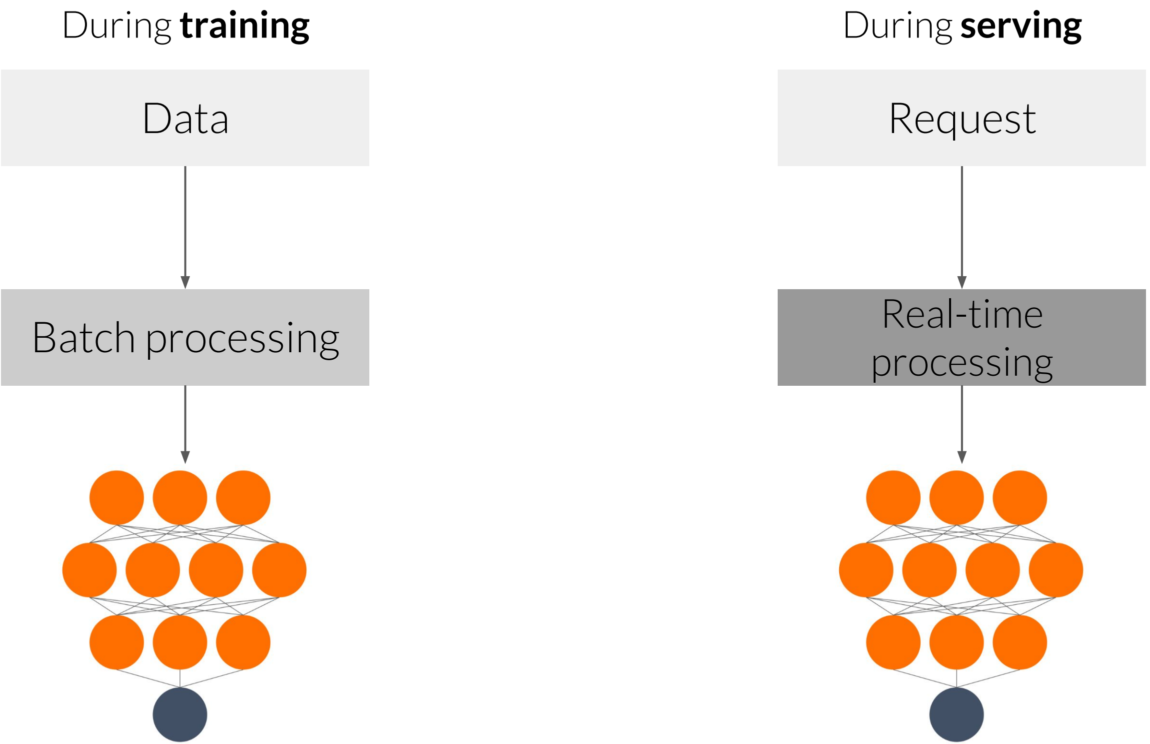
Drift

Changes in data over time, such as data collected once a day

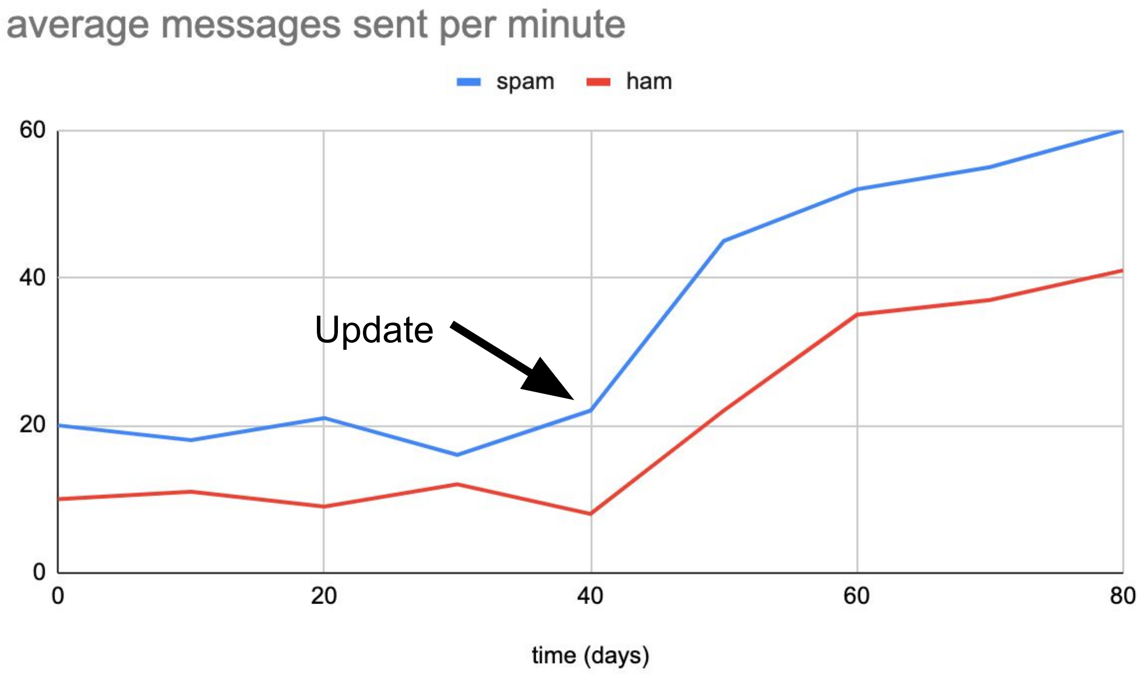
Skew

Difference between two static versions, or different sources, such as training set and serving set

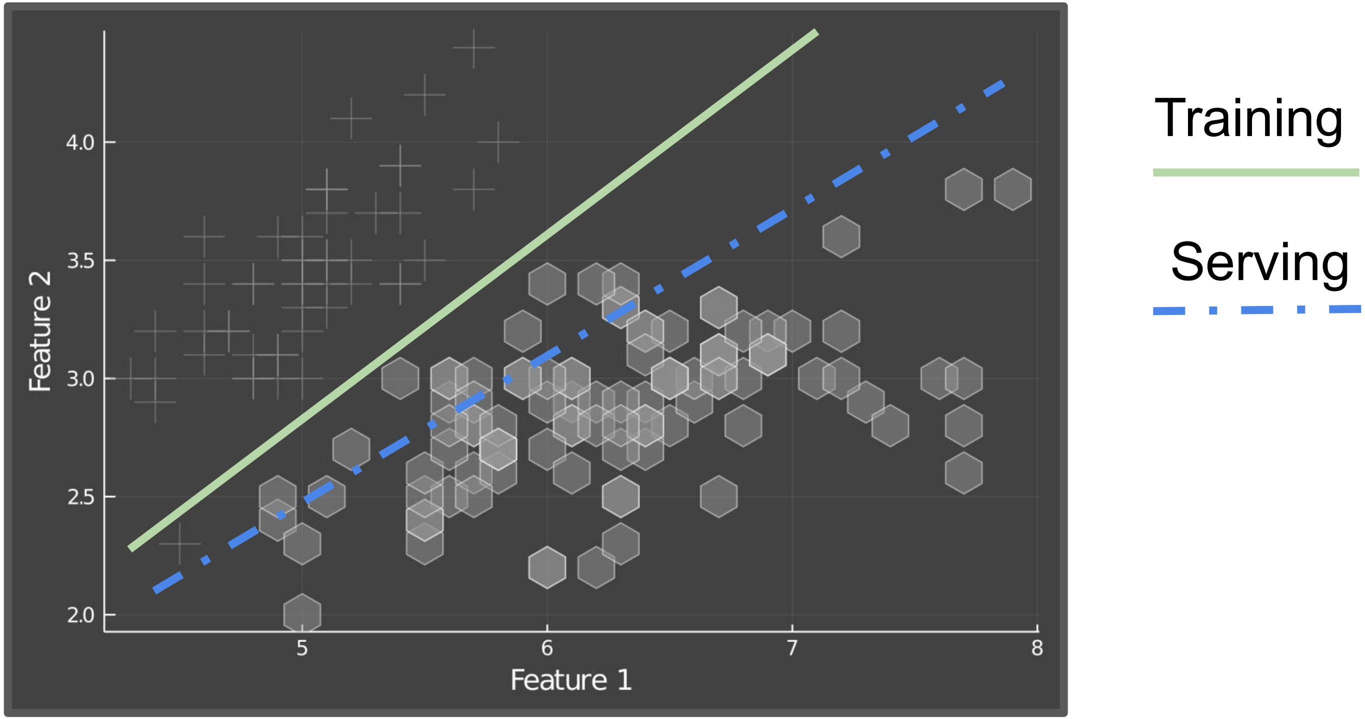
Typical ML pipeline



Model Decay : Data drift



Performance decay : Concept drift



Detecting data issues

- Detecting schema skew
  - Training and serving data do not conform to the same schema
- Detecting distribution skew
  - Dataset shift → covariate or concept shift
- Requires continuous evaluation

Detecting distribution skew

	Training	Serving
Joint	$P_{\text{train}}(y, x)$	$P_{\text{serve}}(y, x)$
Conditional	$P_{\text{train}}(y\|x)$	$P_{\text{serve}}(y\|x)$
Marginal	$P_{\text{train}}(x)$	$P_{\text{serve}}(x)$

Dataset shift $P_{\text{train}}(y, x) \neq P_{\text{serve}}(y, x)$

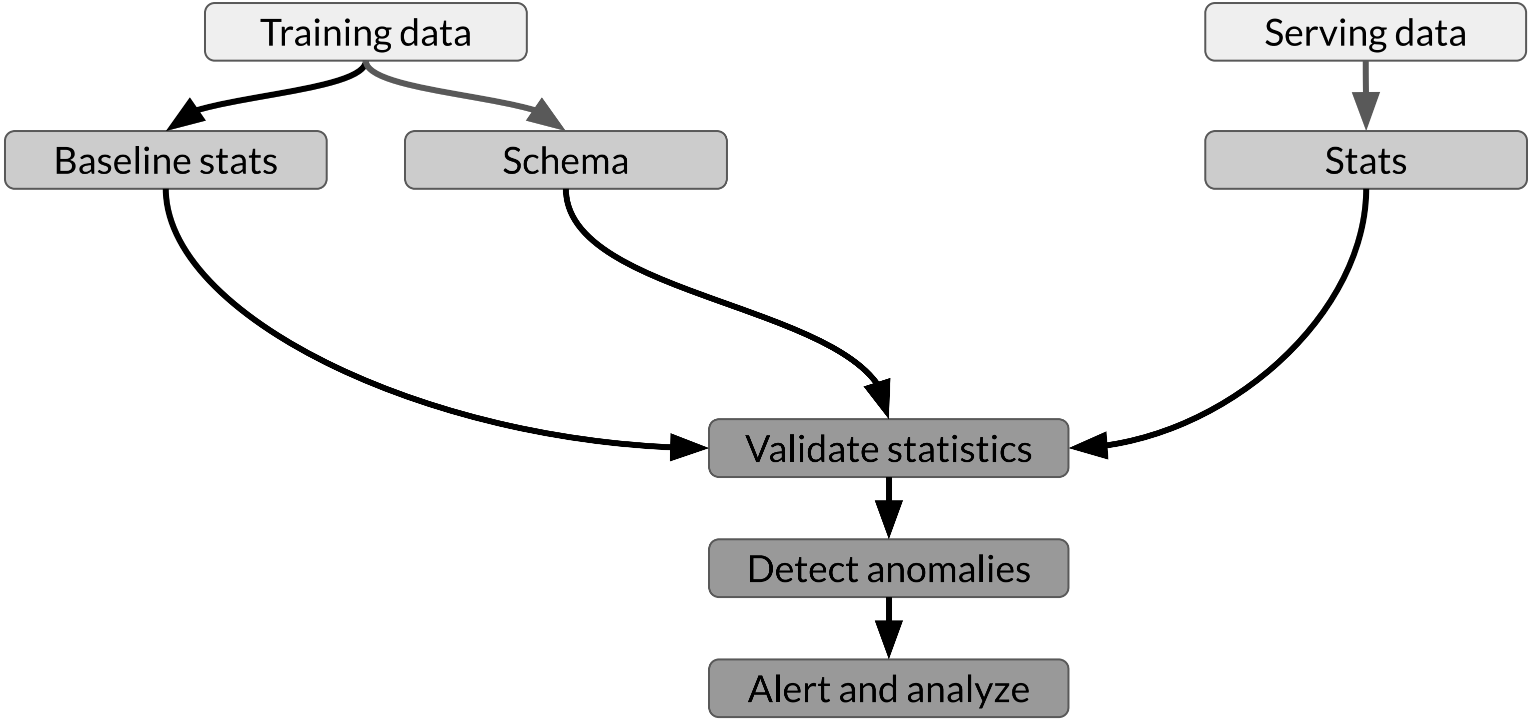
Covariate shift $P_{\text{train}}(y|x) = P_{\text{serve}}(y|x)$

$P_{\text{train}}(x) \neq P_{\text{serve}}(x)$

Concept shift $P_{\text{train}}(y|x) \neq P_{\text{serve}}(y|x)$

$P_{\text{train}}(x) = P_{\text{serve}}(x)$

Skew detection workflow



DeepLearning.AI

Validating Data

TensorFlow Data Validation

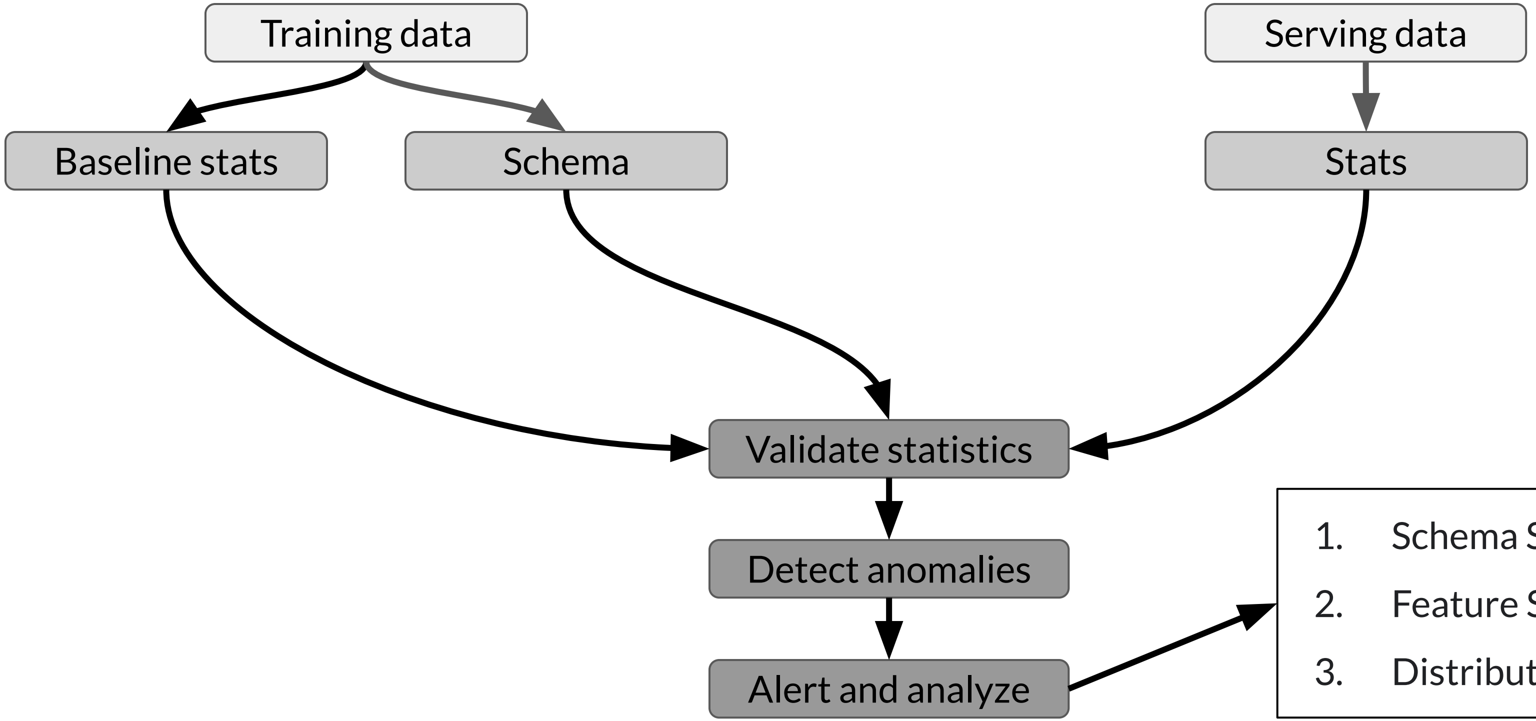
TensorFlow Data Validation (TFDV)

- Understand, validate, and monitor ML data at scale
- Used to analyze and validate petabytes of data at Google every day
- Proven track record in helping TFX users maintain the health of their ML pipelines

TFDV capabilities

- Generates data statistics and browser visualizations
- Infers the data schema
- Performs validity checks against schema
- Detects training/serving skew

Skew detection - TFDV

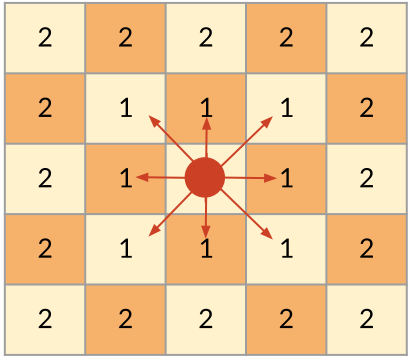


1. Schema Skew
2. Feature Skew
3. Distribution Skew

Skew - TFDV

- Supported for categorical features
- Expressed in terms of L-infinity distance (Chebyshev Distance):

$$D_{\text{Chebyshev}}(x, y) = \max_i(|x_i - y_i|)$$



- Set a threshold to receive warnings

Schema skew

Serving and training data don't conform to same schema:

- For example, `int != float`

Feature skew

Training **feature values** are different than the serving **feature values:**

- Feature values are modified between training and serving time
- Transformation applied only in one of the two instances

Distribution skew

Distribution of serving and training dataset is significantly different:

- Faulty sampling method during training
- Different data sources for training and serving data
- Trend, seasonality, changes in data over time

Key points

- TFDV: Descriptive statistics at scale with the embedded facets visualizations
- It provides insight into:
    - What are the underlying statistics of your data
    - How does your training, evaluation, and serving dataset statistics compare
    - How can you detect and fix data anomalies

Wrap up

- Differences between ML modeling and a production ML system
- Responsible data collection for building a fair production ML system
- Process feedback and human labeling
- Detecting data issues

Practice data validation with TFDV in this week's exercise notebook

Test your skills with the programming assignment