# DADS7305: MLOPs

## Northeastern University

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If you believe any material has been inadequately cited or requires correction, please contact me at:

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*Thank you for your understanding and collaboration.*

## Collecting, Labeling, and Validating Data

# Overview

# 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

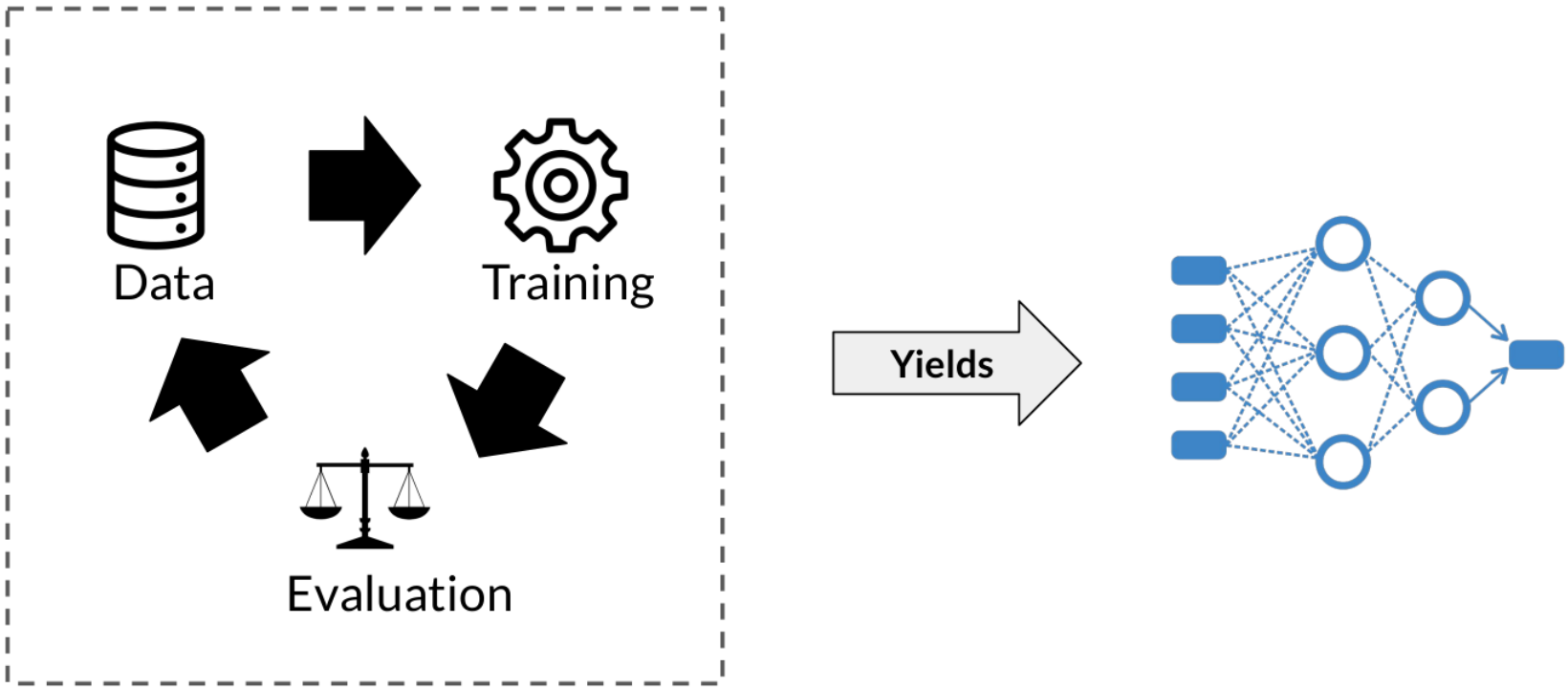
# Introduction to Machine Learning Engineering for Production

## Overview

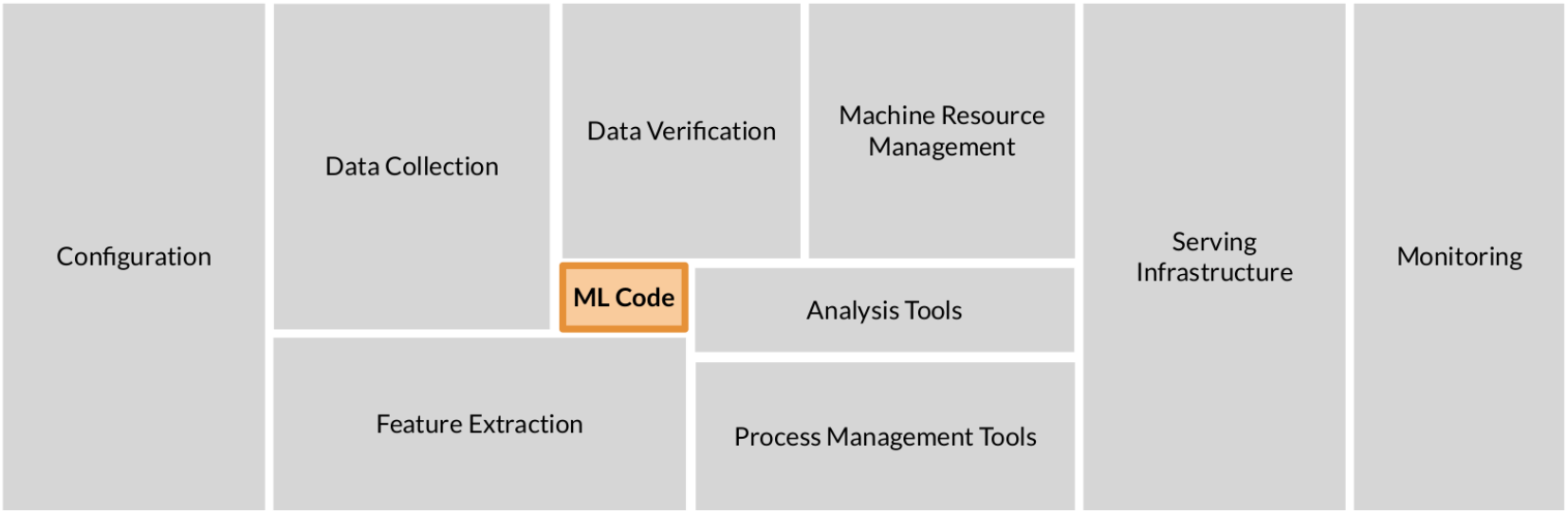
# Outline

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

# Data iteration loop



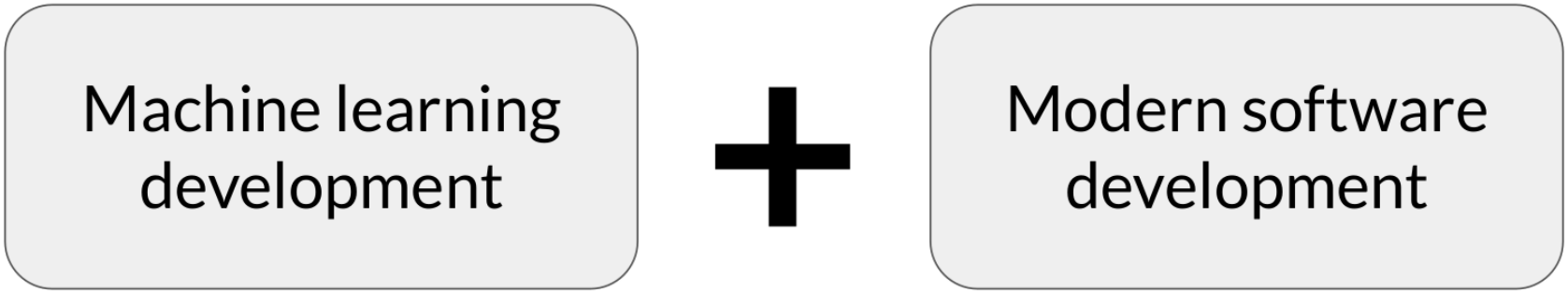
# Production ML systems require so much more



# 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



# 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

# Challenges in production grade ML

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

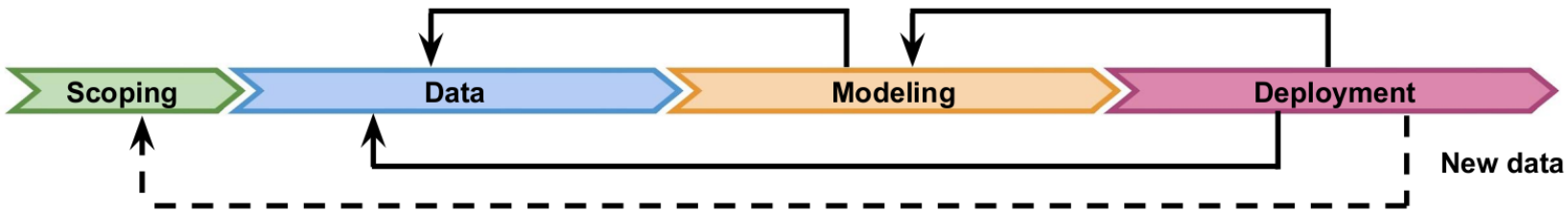
Introduction to Machine Learning Engineering for Production

# ML Pipelines

# Outline

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

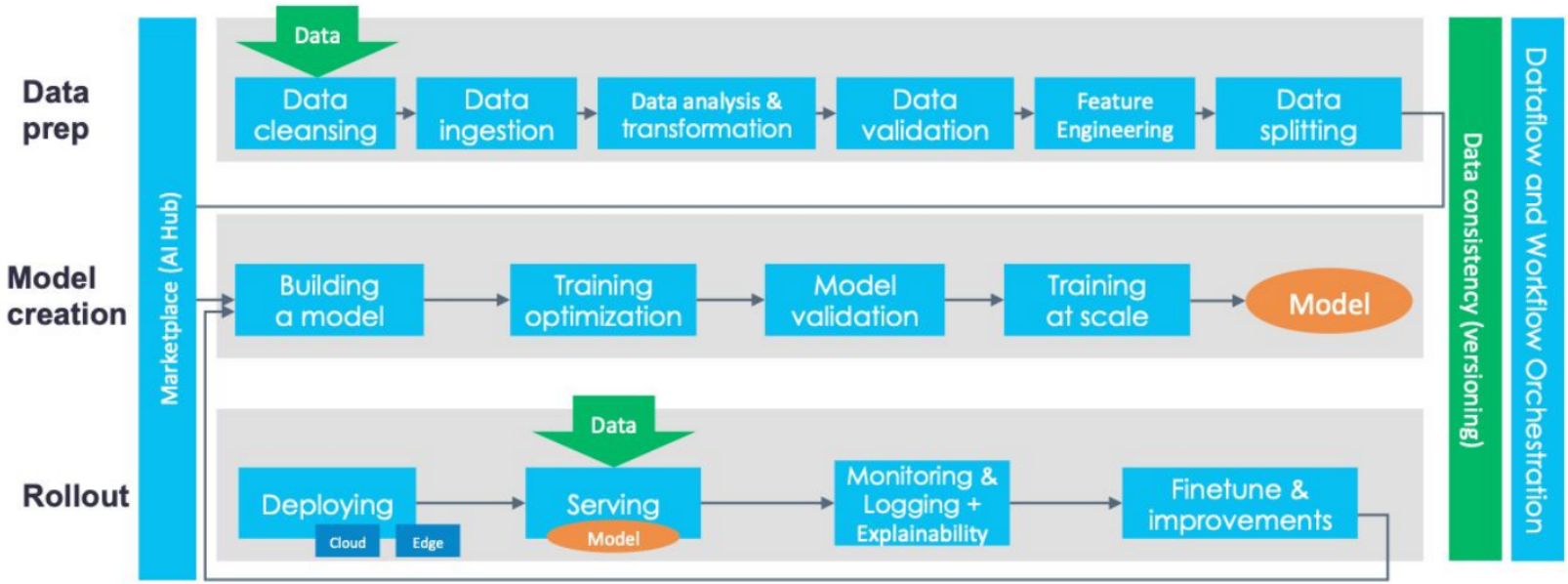
# ML pipelines




Infrastructure for
automating, monitoring, and maintaining
model training and deployment

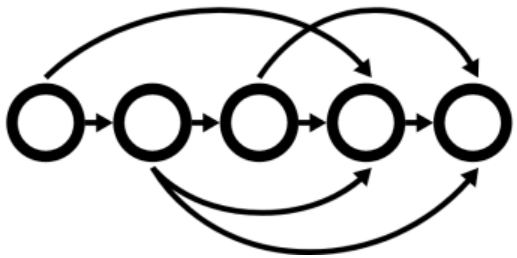
# Production ML infrastructure

CD Foundation MLOps reference architecture

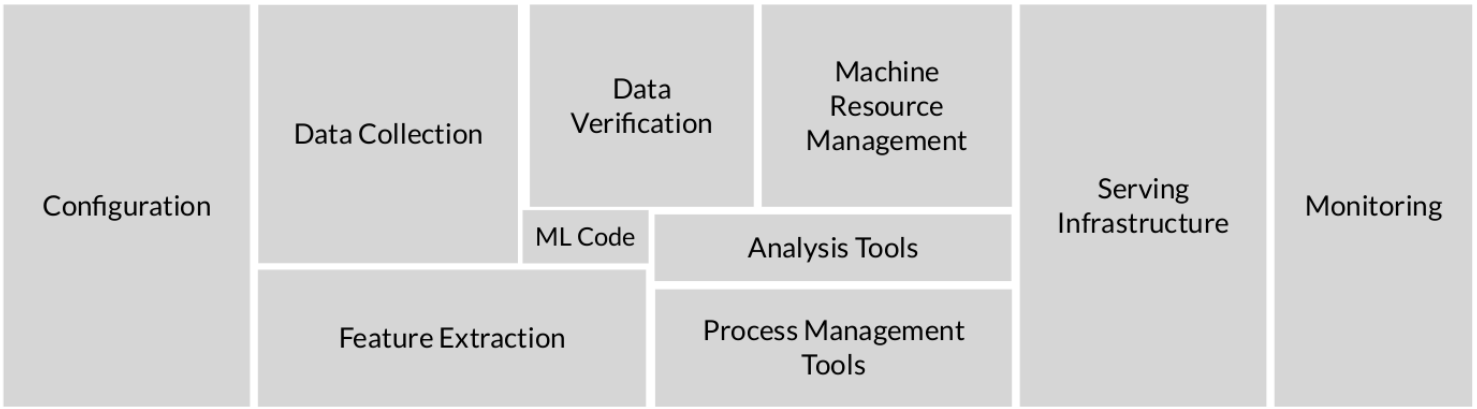


# Directed acyclic graphs


- 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

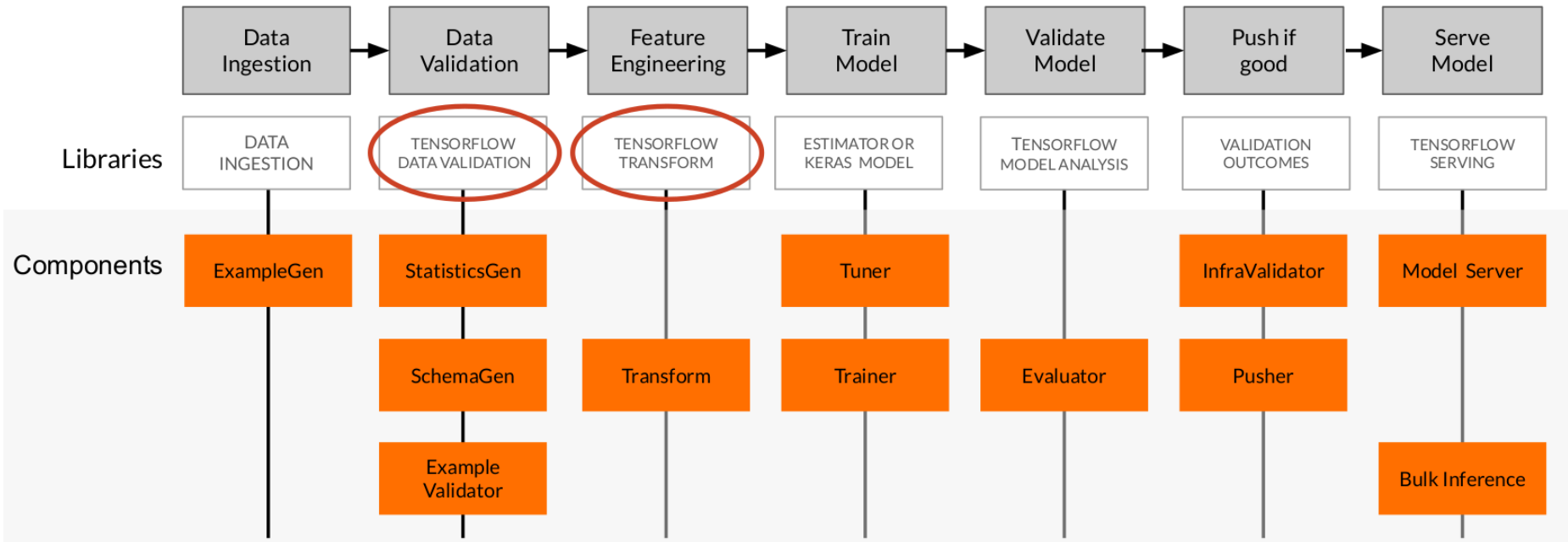
# MLOps orchestration tools

| Tool | Description | Strengths |
|---|---|---|
| **Kubeflow Pipelines** | Based on Kubernetes, great for orchestration of ML workflows | Cloud-native, powerful with Vertex AI & K8s |
| **MLflow (Databricks)** | Tracking, packaging, model registry | Widely adopted in industry, model versioning |
| **Metaflow (Netflix)** | Human-centric, Pythonic MLOps | Great for quick iteration and reproducibility |
| **ZenML** | MLOps framework with modern plugins (e.g., LangChain, HuggingFace, etc.) | Focused on modern use cases like GenAI, easy plugin system |
| **Airflow + Custom DAGs** | Used to manually build MLOps pipelines | Flexible, integrates with everything, not ML-specific |

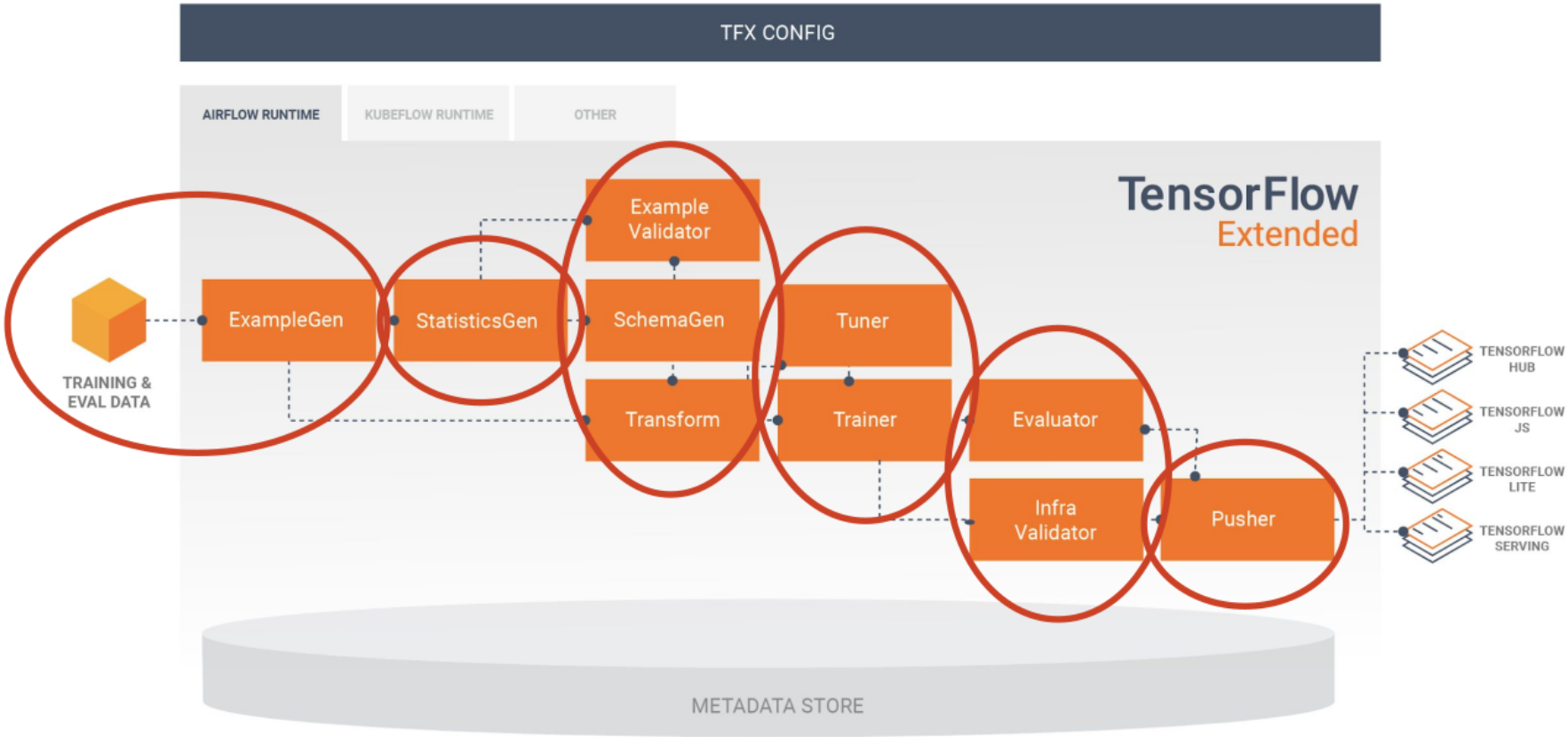
# LLM/RAG tooling overview

| Tool | Description | Use Cases |
|---|---|---|
| **LangChain** | Framework for building agents and RAG pipelines | Agent orchestration, tool use, chains |
| **LangGraph** | State-machine based orchestration for agents (built on LangChain) | Long-lived agents, memory, branching logic |
| **LlamaIndex** | Data indexing and retrieval for LLM pipelines | Data preprocessing, vector stores |
| **Haystack** | NLP/QA pipeline builder, now LLM-compatible | Modular components, good for RAG |
| **Guardrails AI** | Validates and controls LLM outputs using schemas and prompts | Alignment, output control, RAG + eval |
| **DSPy** | Programmatic prompt compiler and optimization framework | LLM pipeline optimization, output structure |

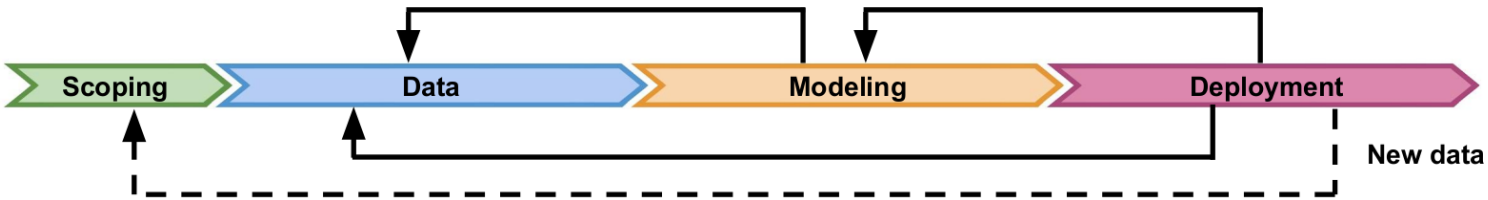
# TFX production components



# TFX Hello World



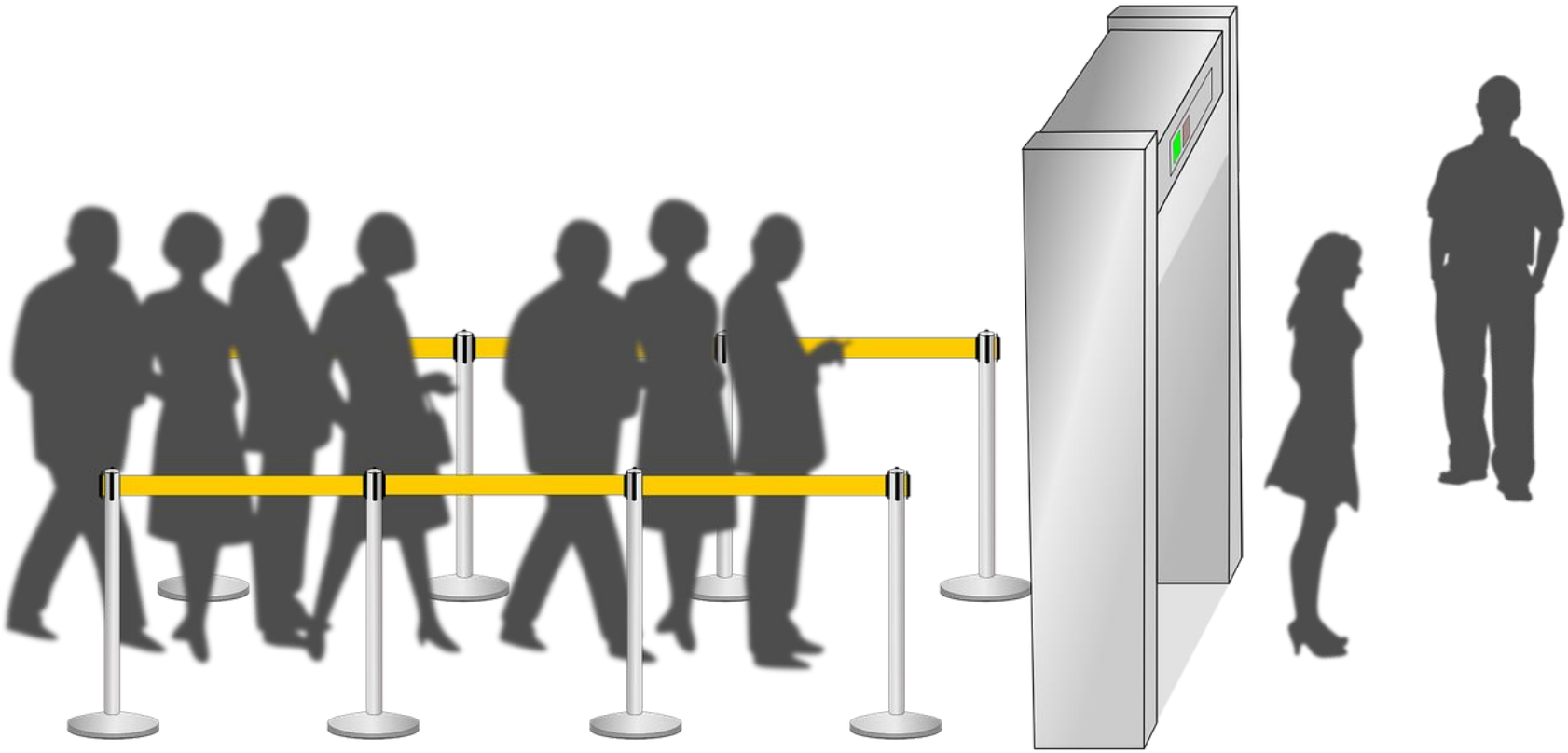
# Key points




- 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

Collecting Data

# Importance of Data

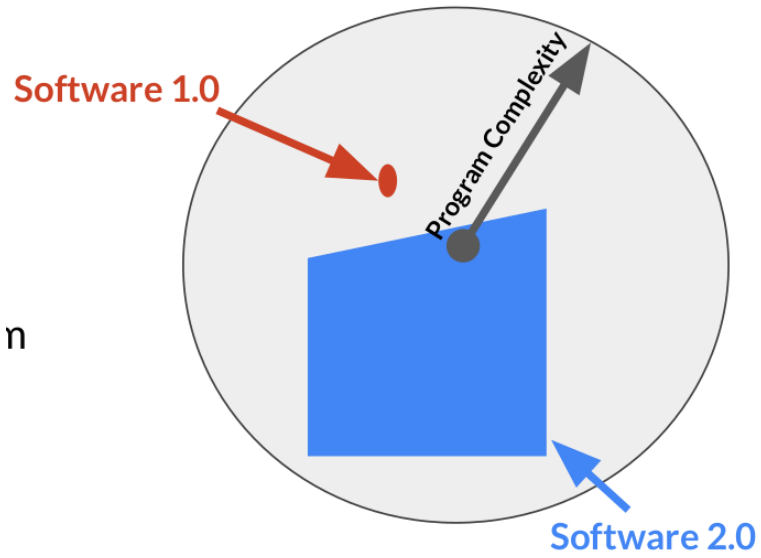


# Outline

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

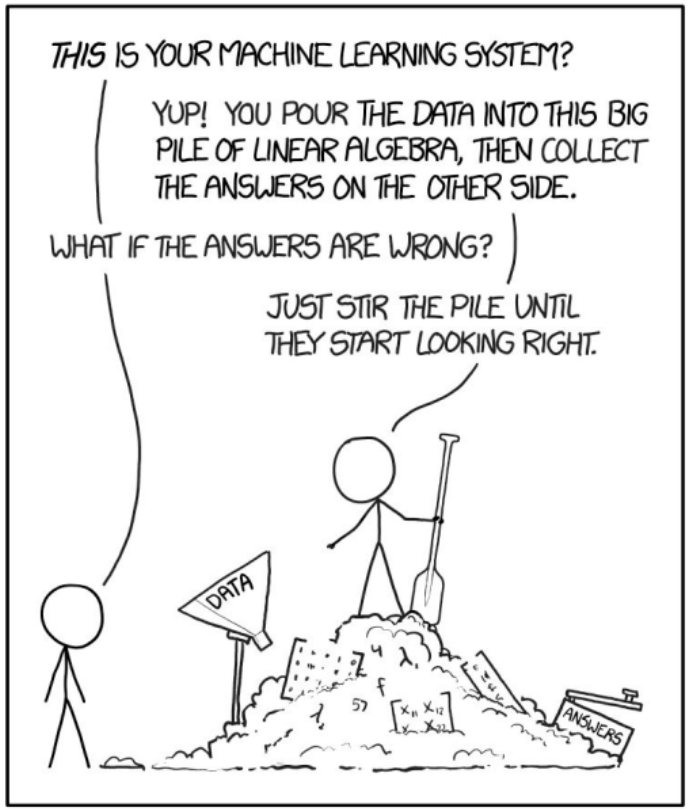
# ML: Data is a first class citizen

- **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

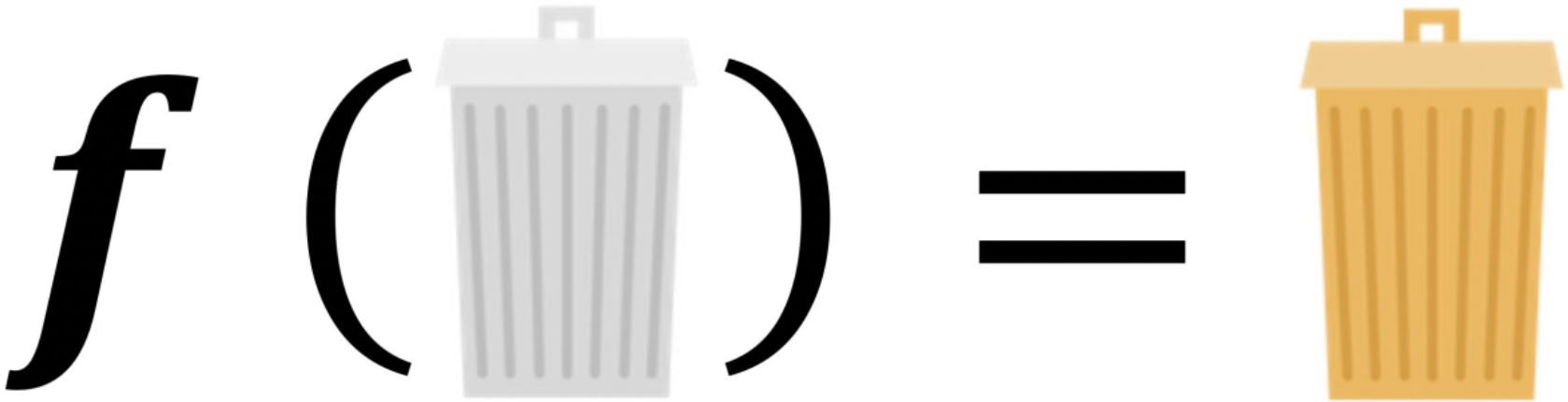


# Everything starts with data

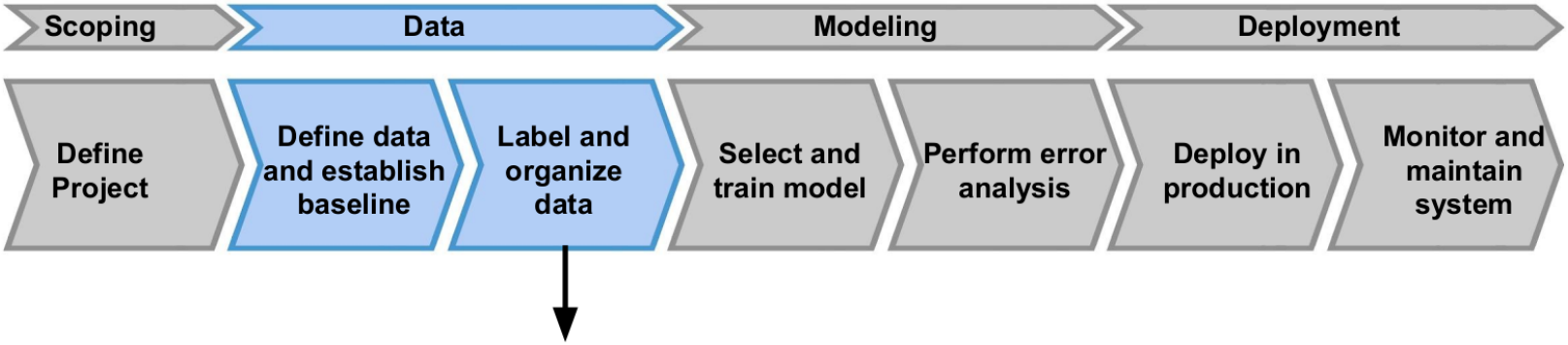
- Models aren't magic
- Meaningful data:
  - maximize predictive content
  - remove non-informative data
  - feature space coverage



# Garbage in, garbage out

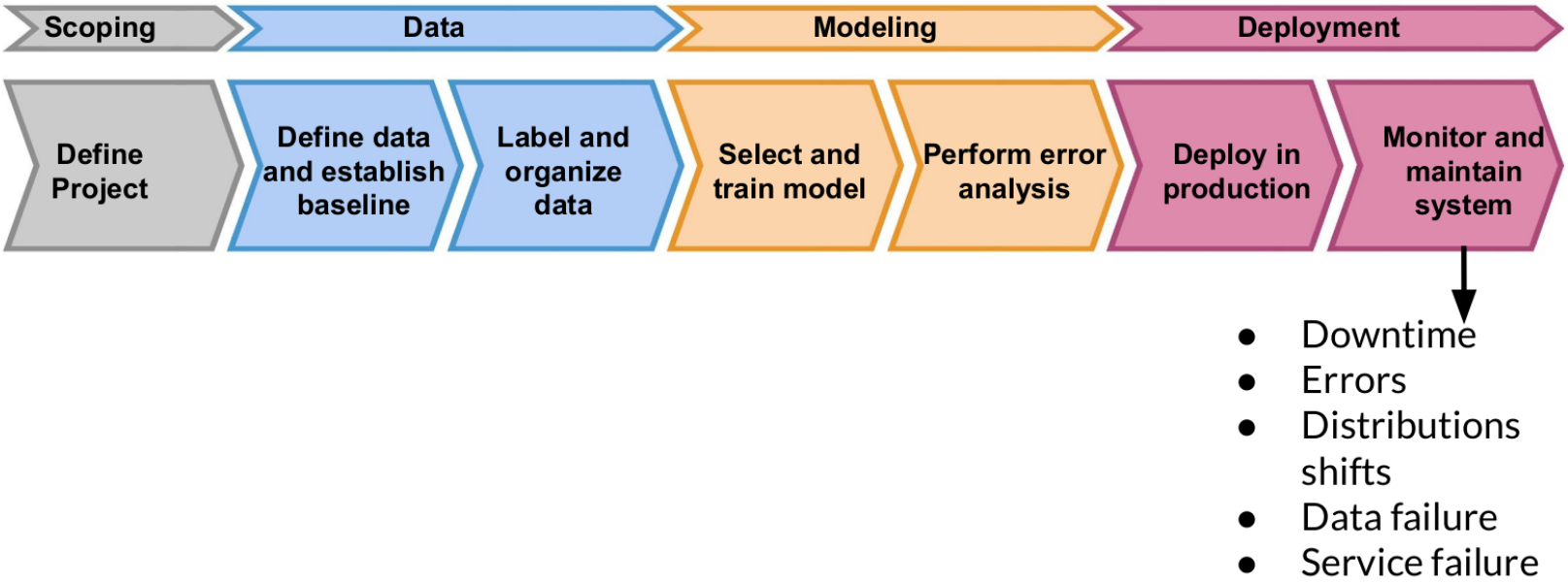


# Data pipeline




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

# Data collection and monitoring



# Key Points

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

# Example Application: Suggesting Runs

# Key considerations

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

# Example dataset

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

## 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<br>▶ Demographic data<br>▶ Local geographic data |

# Translate user needs into data needs

| **Features Needed** | ▶ Runner demographics<br>▶ Time of day<br>▶ Run completion rate<br>▶ Pace<br>▶ Distance ran<br>▶ Elevation gained<br>▶ Heart rate |
|---|---|

# Translate user needs into data needs

| | |
|---|---|
| **Labels Needed** | ▶ Runner acceptance or rejection of app suggestions<br>▶ User generated feedback regarding why suggestion was rejected<br>▶ 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

Collecting Data

# Data for Your LLM Work

## Before using an LLM

- Identify and collect the right data for your task (fine-tuning dataset or domain-specific documents/context for prompting).
- Considerations include domain relevance, sources, and quality vs. quantity.

## Domain Relevance

- Use data that is relevant to your use-case.
- Example: if building an assistant for legal questions, gather legal text documents.
- High-quality, domain-specific data will yield more accurate and useful model outputs.

# Data Sources

- Plain text files, PDFs, websites, databases, APIs, etc.
- LLM applications often involve unstructured data (free-form text) that may require extraction from various formats (PDFs, Word docs, HTML pages).

# Quantity vs Quality

- It's not just about having a lot of data—quality matters more.
- A smaller high-quality dataset often outperforms a larger noisy dataset. Invest time in cleaning and curating the data.

# Synthetic Data

- You might generate data (e.g., using an LLM to create Q&A pairs) to augment your dataset.
- Validate carefully; synthetic data can introduce biases or errors.

# After Data Collection: Preprocessing

- Clean and convert raw data into a format suitable for the model.
- Typical tasks: remove unwanted content, split text into segments, transform formats (e.g., PDF to text).

- If data is already plain text (`.txt`), preprocess by:
  - Cleaning whitespace, correcting encoding issues.
  - Normalizing text (lowercasing, removing special symbols) as appropriate for the use case.

# PDFs and Documents

- PDFs contain layout-oriented text and can be tricky to extract.
- Use libraries like PyMuPDF or `pdfminer.six`; or higher-level tools.
- LangChain provides convenient document loaders (e.g., `PyPDFLoader`) to extract text into a standard format.

# Example: Extract PDF Pages with LangChain

```
from langchain.document_loaders import PyPDFLoader
loader = PyPDFLoader("path/to/document.pdf")
pages = loader.load()  # splits PDF into pages of text

print(f"Loaded {len(pages)} pages from PDF.")
text_content = " ".join(page.page_content for page in pages)
```

# LangChain Documents and Loaders

- In LangChain, a `Document` includes text and metadata (e.g., page number).
- Under the hood, loaders use PDF parsing libraries.
- LangChain supports many loaders (HTML, Notion, Word docs, YouTube transcripts, CSVs, etc.), simplifying ingestion from diverse sources.

## Structured Data

- For tables (CSV, SQL), convert to text suitable for LLMs (e.g., Markdown tables or JSON in prompts).
- LangChain offers structured data loaders (CSV, SQL queries) to integrate tabular data (often by turning rows/cells into text snippets).

# Web Pages and APIs

- Pull data from the web using loaders or general tools (e.g., `requests`, Scrapy).
- Strip HTML to text; respect legality and ethics (robots.txt, API usage terms).

# Multilingual Considerations

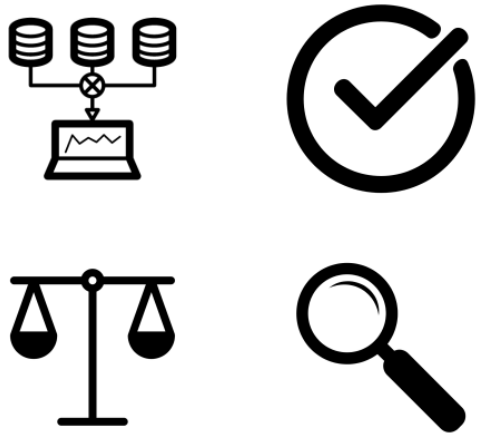
- Ensure correct encodings (UTF-8) and model language support for multilingual data.
- Many modern LLMs (e.g., PaLM/Gemini, LLaMA2) cover multiple languages, but tokenization and performance can vary (we'll discuss tokenization soon).

Collecting Data

# Responsible Data: Security, Privacy and Fairness

# Outline

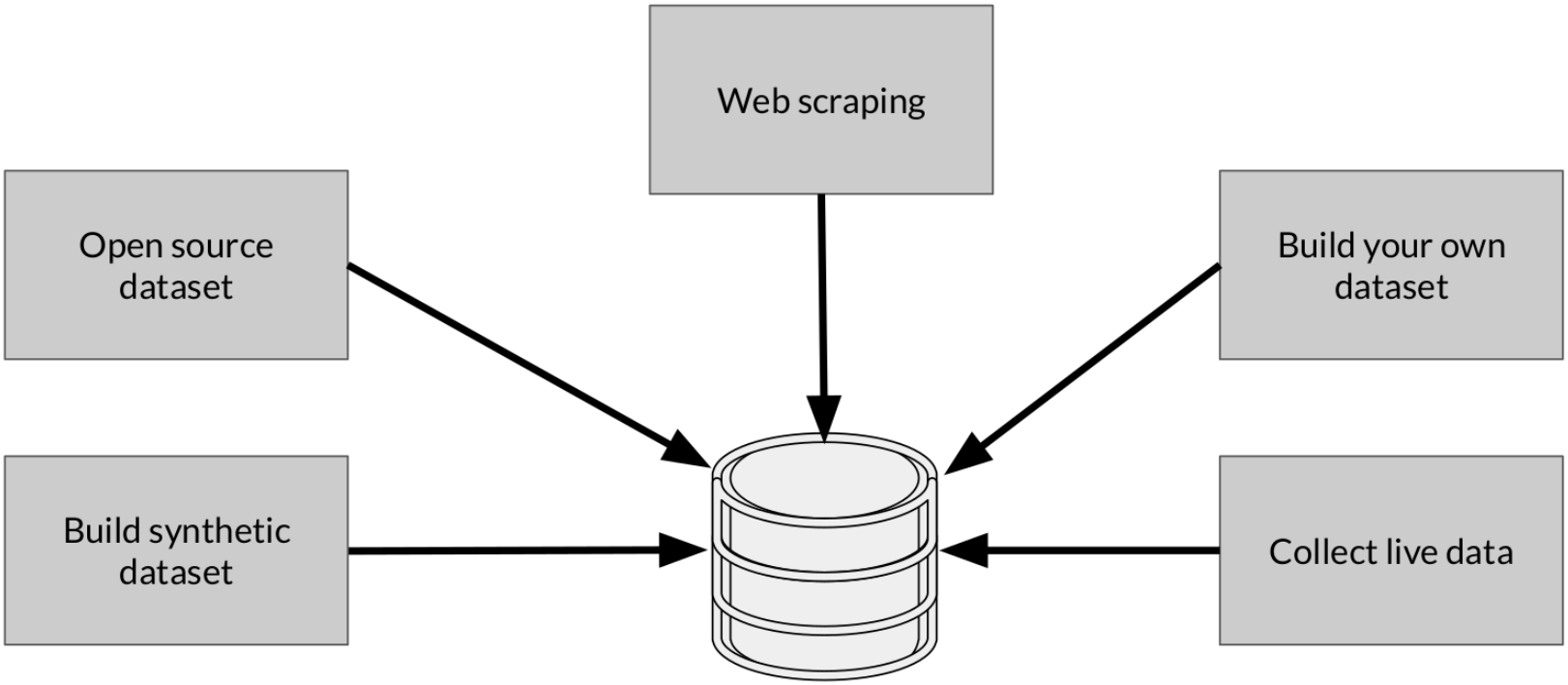
- Data Sourcing
- Data Security and User Privacy
- Bias and Fairness



# Avoiding problematic biases in datasets

## Example: classifier trained on the Open Images dataset

# Avoiding problematic biases in datasets



# Data security and privacy

- Data collection and management isn't just about your model
  - Give users 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 a 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

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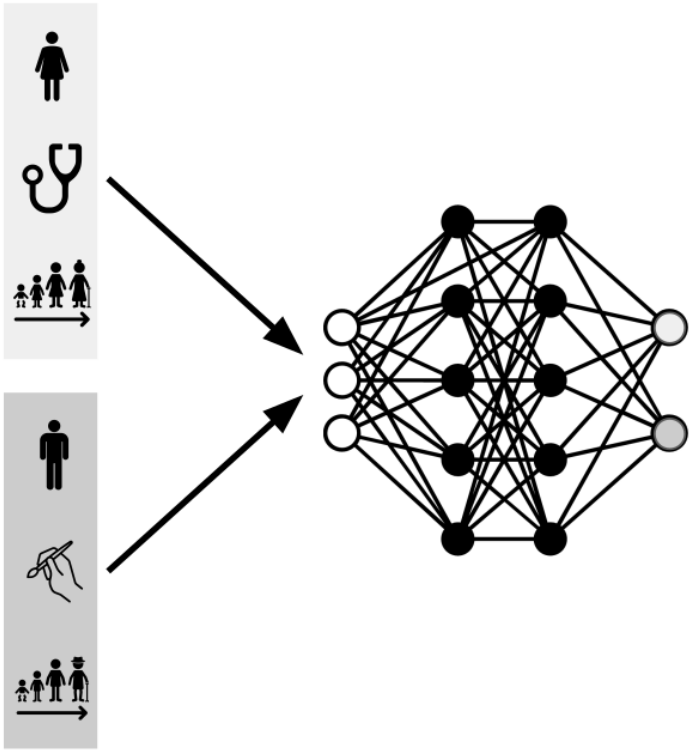
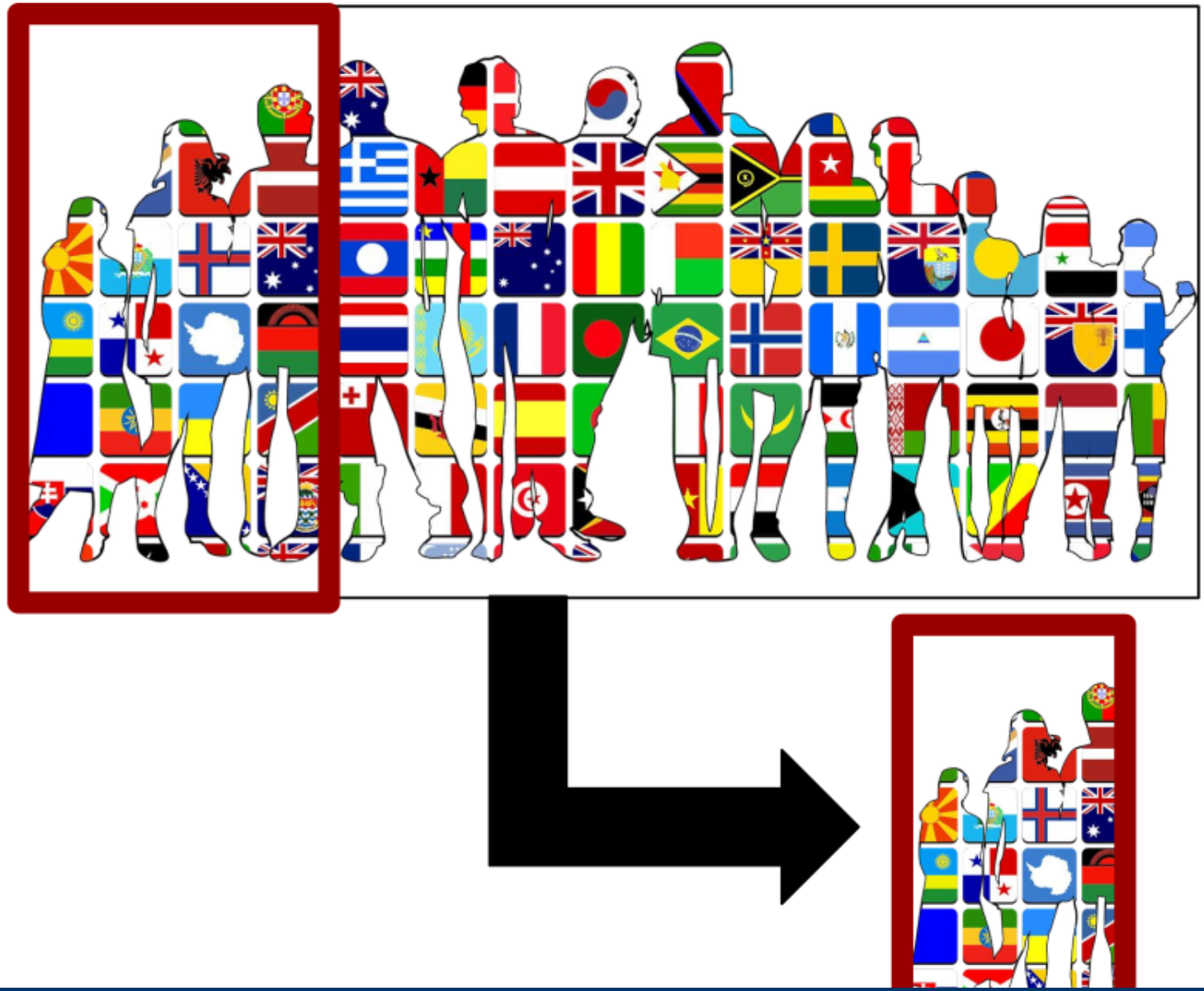


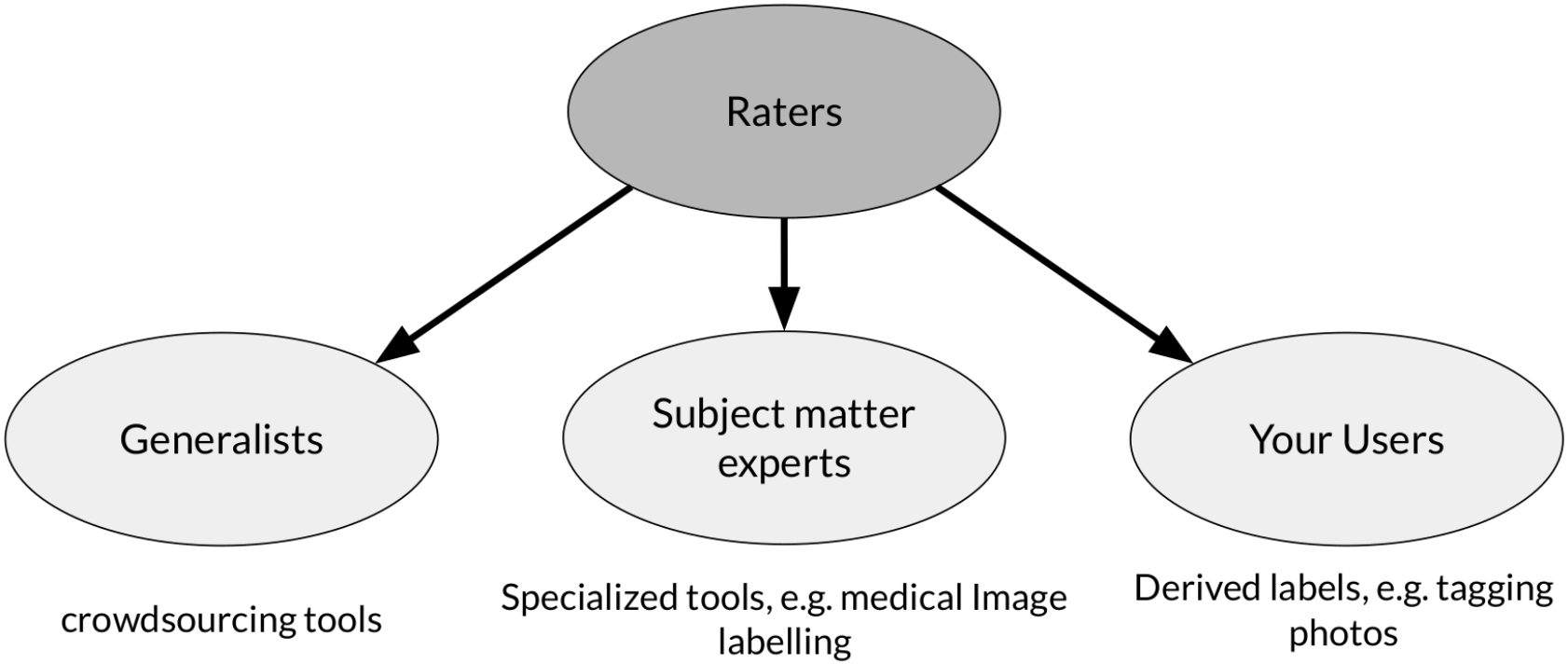
# Biased data representation



# 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



# Key points

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

# Labs for This Week

**Objective**

Briefly describe the learning goal for this week's lab(s).

**Lab Activities:**

- Lab 1: [Snorkel] — [Snorkel Tutorial]
- Lab 2: [AirFlow] — [AirFlow Tutorial 2]

**Submission Deadline:** [Before the next class]

- Assignment 3: [Snorkel] — [Create a labeling pipeline of your choice]

# Reading Materials

**This Week's Theme**

Topic focus: [People + AI Guidebook - Data Collection + Evaluation.pdf]
You should use the worksheet related to this pdf to your project and submit it when its requested.

**Required Readings:**

- [What is Weak Supervision and How Does Weak Supervision Work?]

*Be prepared to discuss highlights and open questions in class.*

# Sources


 DeepLearning.AI

 The People + AI Guidebook