AI-Systems

Machine Learning Lifecycle

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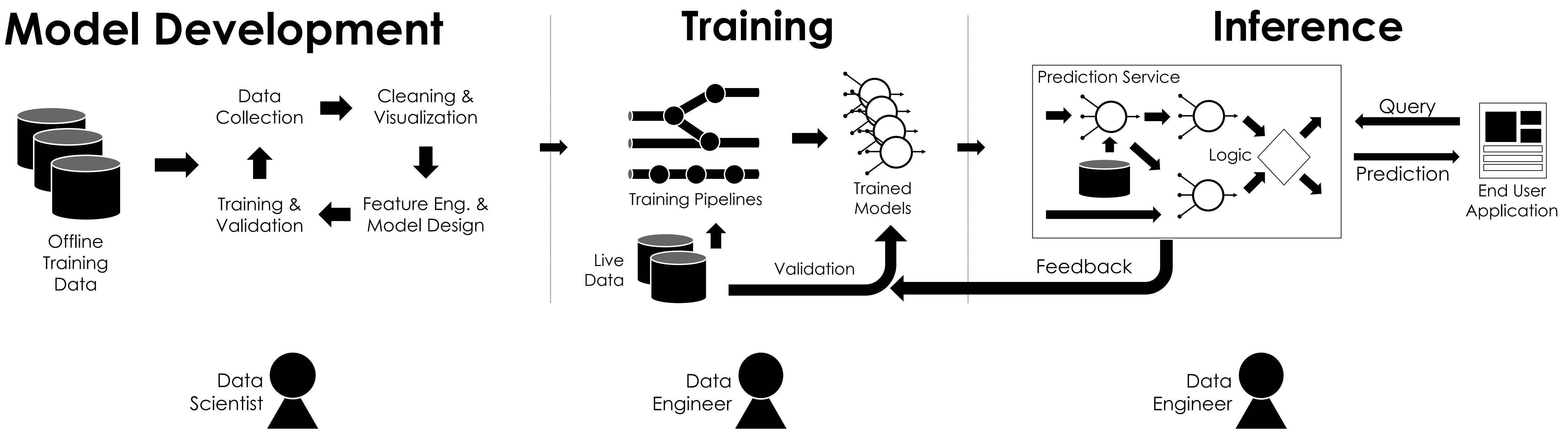
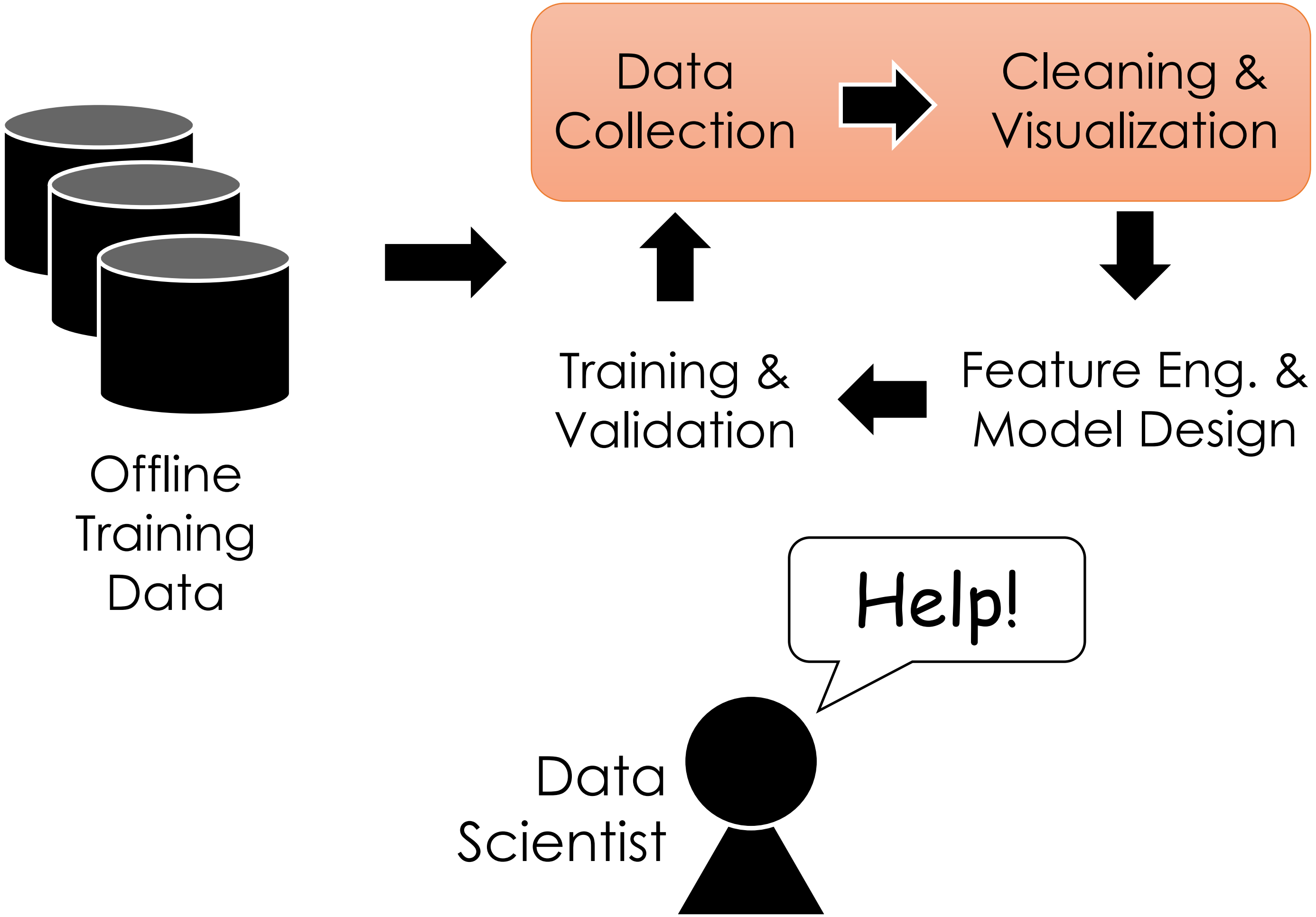
Objectives For Today

- Introduce the machine learning lifecycle
  - Challenges and Opportunities
  - Science vs Engineering
- Review Key Concepts in Readings
  - Hyperparameters
  - Model Pipelines, Features, and Feature Engineering
  - Warm Starting and Fine Tuning
  - Feedback Loops, Retraining and Continuous Training
- Important context for papers and what to expect

What is the
***Machine Learning Lifecycle*?**



Model Development



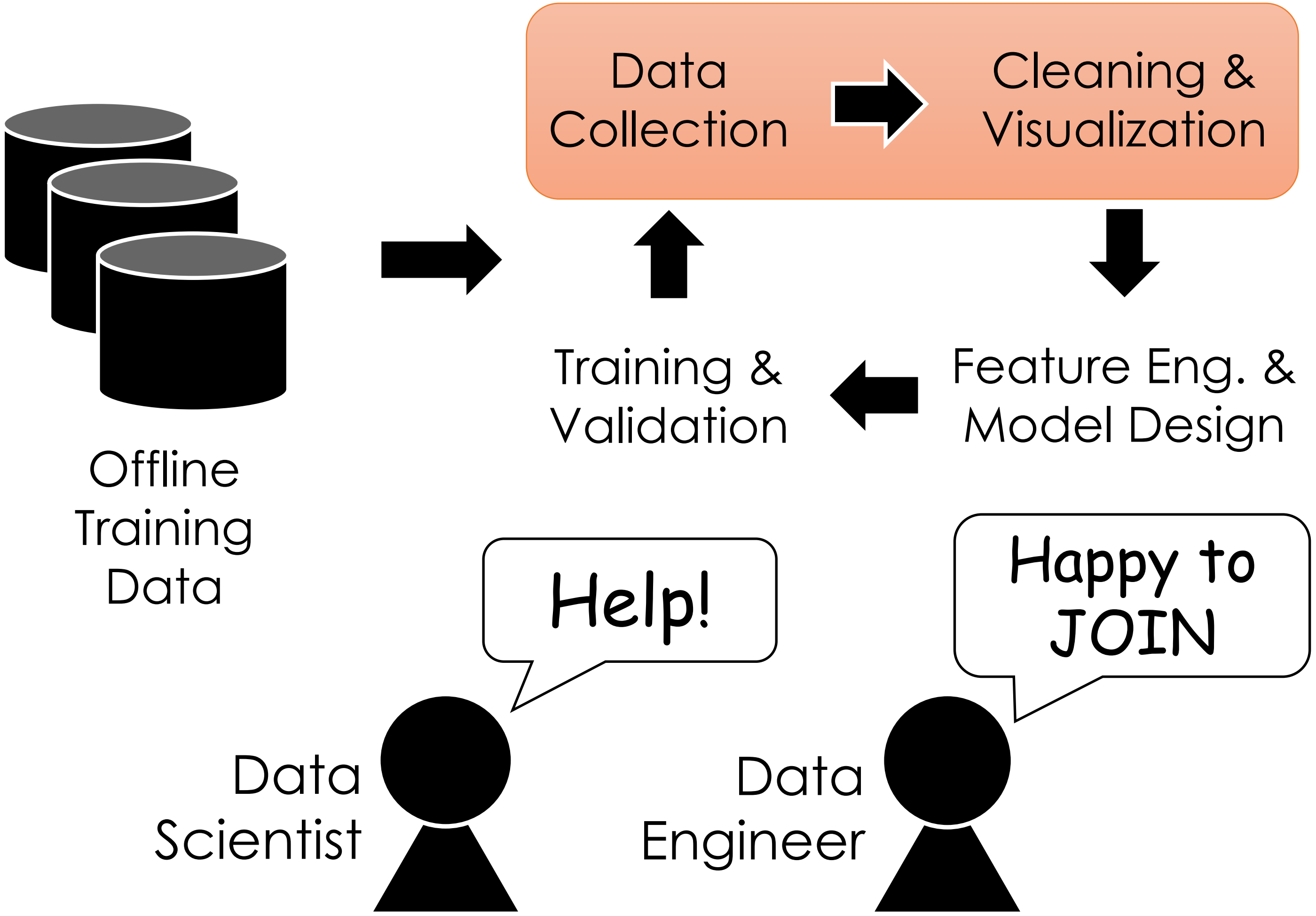
Identifying potential sources of data

Joining data from multiple sources

Addressing **missing values** and **outliers**

Plotting trends to identify **anomalies**

Model Development



Identifying potential sources of data

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Big Data Borat
@BigDataBorat

Follow

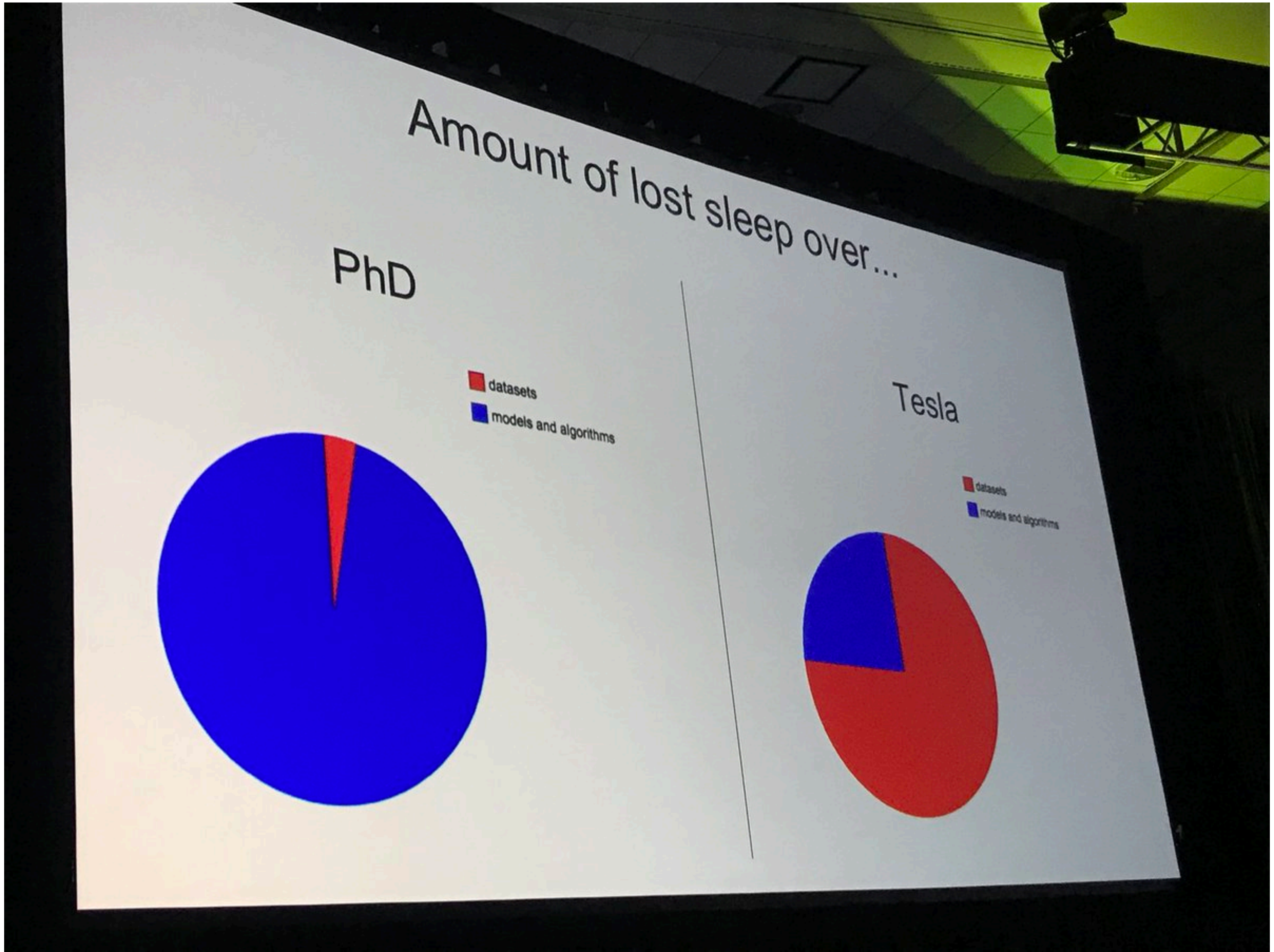
In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

6:47 PM - 26 Feb 2013

533 Retweets **330** Likes

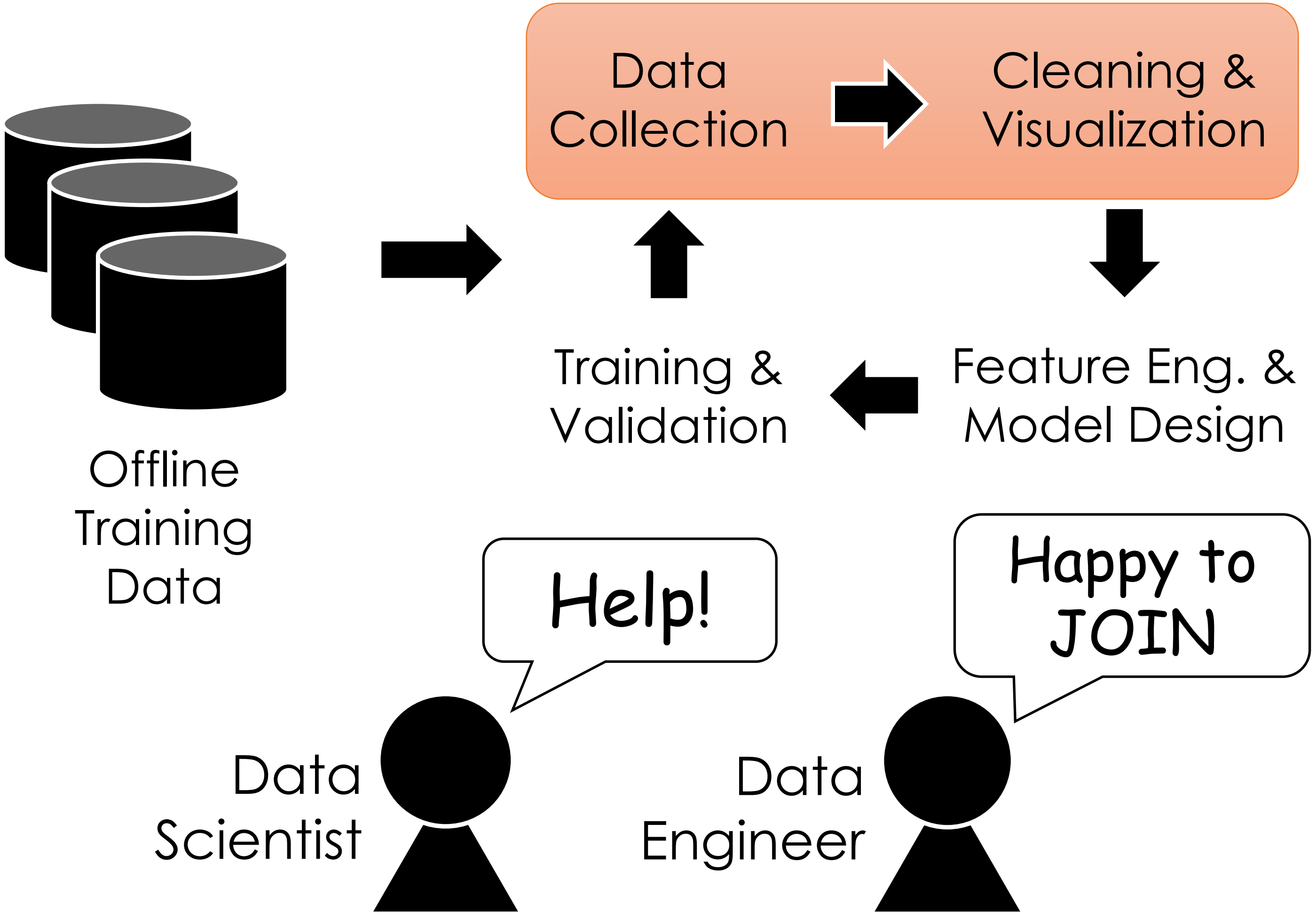
12 533 330

Andrej Karpathy (Tesla Auto Pilot Team)



How many of you have ever worked with real data?

Model Development



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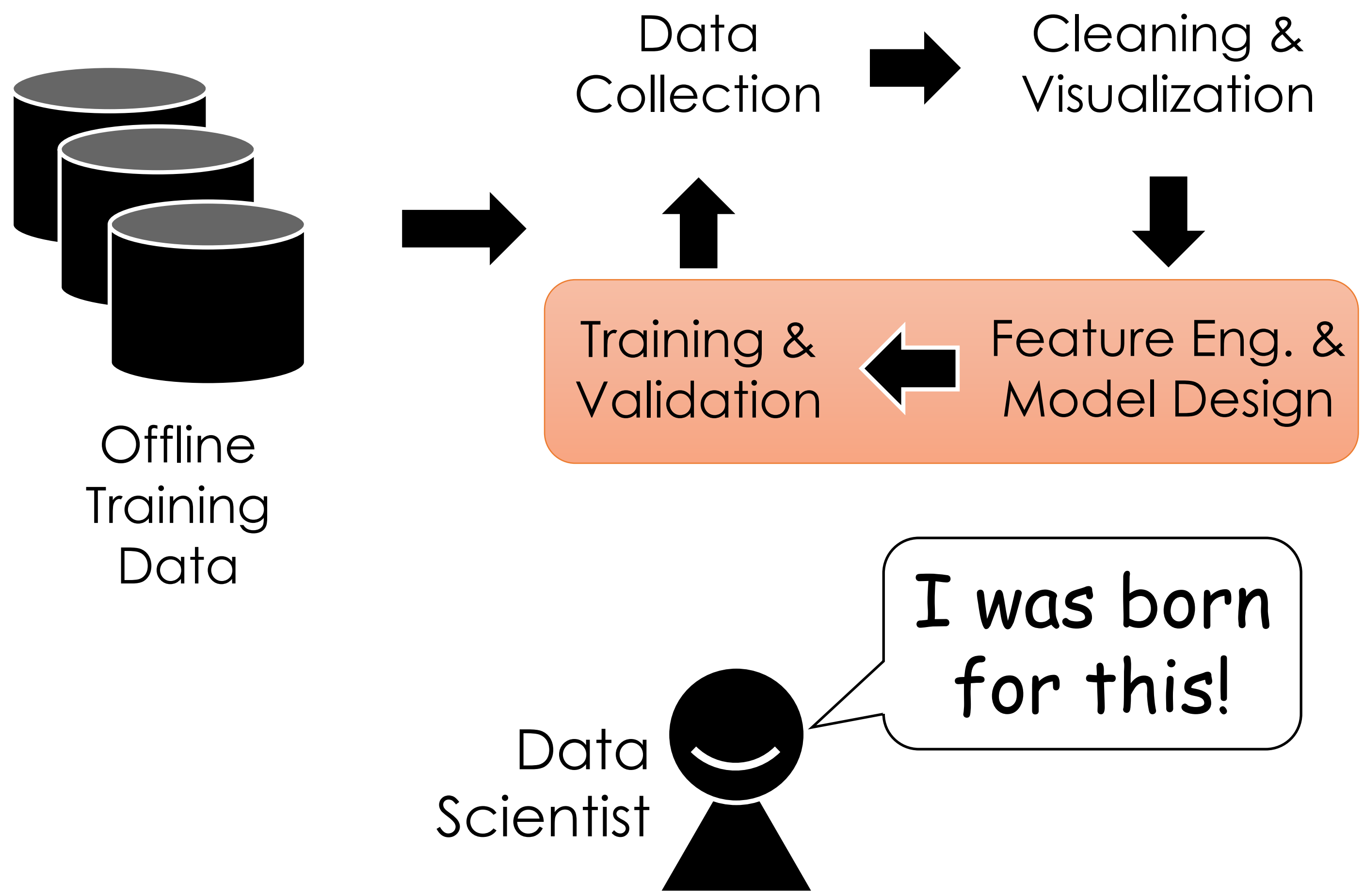


Building informative **features functions**

Designing new **model architectures**

Tuning hyperparameters

Validating prediction accuracy

Features and Feature Engineering

- **Features:** properties or characteristic of the input
- **Click Prediction Example:**

Information about User and Content

Model:

$$f_\theta(x) \rightarrow y$$

Probability user will click on the content

Simple Logistic Model:
("Perceptron")*

$$f_\theta(x) = \sigma\left(\sum_{k=1}^{d} \theta_k \phi_k(x)\right), \quad \sigma(t) = \frac{1}{1+e^{-t}}$$

Features function extract numeric properties from x

Useful features?

- User Features:
  - age, gender, and click history
- Product Features:
  - Price, popularity, and description…
- Combined (Cross) features:
  - I(20 < age < 30, male, "xbox" in desc)…

e.g., Recurrent NN output..

e.g., Language Model Embedding

Hand coded features

* Technically the original perceptron used a 0/1 non-linearity but this is a common abuse of terminology.

Additional Notes on Features

- **Feature Joins:** combine multiple data source in a feature
- **Feature Reuse**: good features can aid in many tasks
  - *Example:* product embeddings, user tags, …
- **Predictions as Features:** predictions for one task (e.g., products in an image) can be useful features for another (e.g., ad targeting)
- **Feature Tables/Caches:** features are often pre-computed and cached
  - Requires tracking data and compute and feature versions
- **Dynamic Features:** features can often be modified faster than models
  - Useful for addressing fast changing dynamics (e.g., user preferences can be encoded in click history features).
  - **Issue:** resulting potential covariate shift can be problematic

Hyperparameters

- the **parameters** and more generally **configuration details** that are not directly determined through training
  - set by hand or tuned using cross validation
  - why not learn directly?
- Find the Hyperparameters:

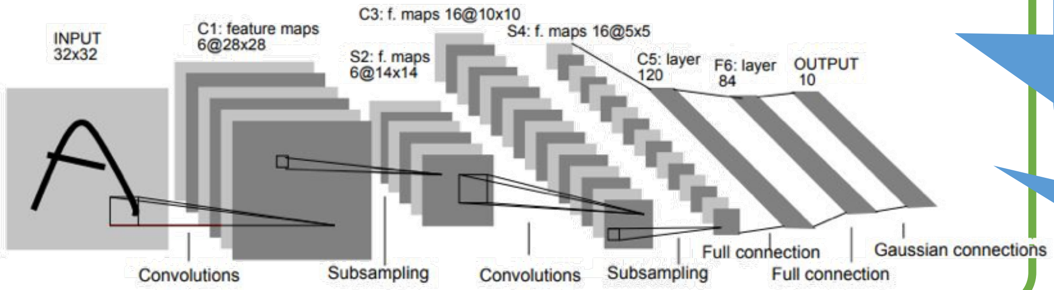
Objective:

$$\arg\min_{\theta} \frac{1}{n}\sum_{i=1}^{n} L_{\alpha}\left(f_{\theta}(x_i), y_i\right) + \lambda R(\theta)$$

Training Algorithm

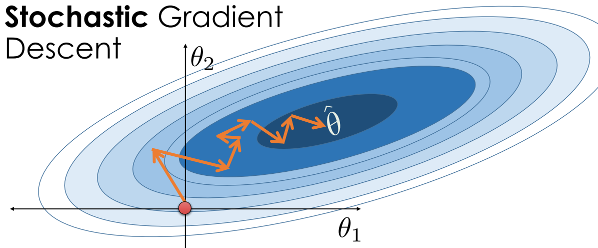
$$u^{(t)} \leftarrow \beta u^{(t-1)} + \eta \sum_{i\in\mathcal{B}} \nabla_{\theta}\left(L_{\alpha}(f_{\theta}(x_i), y_i)\right)\Big|_{\theta^{(t)}}$$

Architecture:

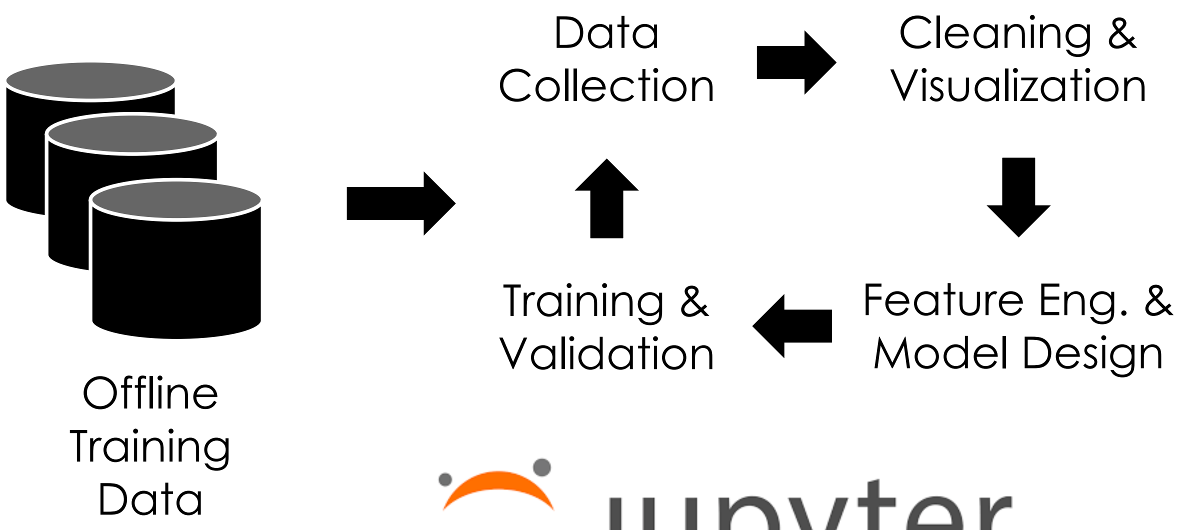


Architecture is sometimes treated as separate from hyperparameters

Can be learned…



Model Development *Technologies*



scikit learn
TensorFlow
R
PYTORCH
Keras
jupyter
mxnet
dmlc XGBoost
matplotlib
Caffe2
pandas $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$
NumPy
APACHE Spark™
DASK
HIVE

What is the output of Model Development

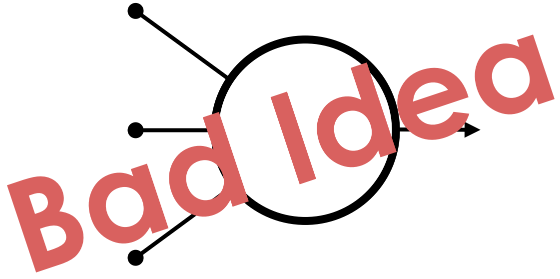
Offline Training Data

Data Collection → Cleaning & Visualization → Feature Eng. & Model Design → Training & Validation → Data Collection

Reports & Dashboards

(insights …)

Trained Model

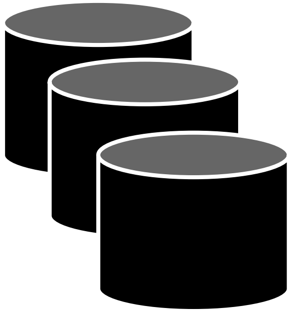


Why is it a **Bad Idea** to directly produce **trained models** from **model development**?

With just a trained model we are **unable to**

1. **retrain** models with new data
2. track data and code for **debugging**
3. capture **dependencies** for deployment
4. audit training for **compliance** (e.g., GDPR)

What is the output of Model Development



Offline Training Data

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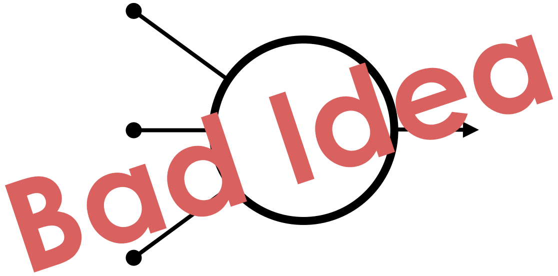
(insights …)

Trained Models



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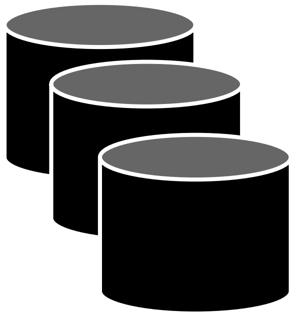

Offline Training Data

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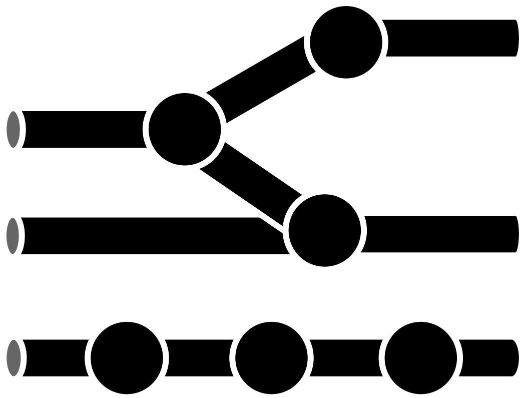
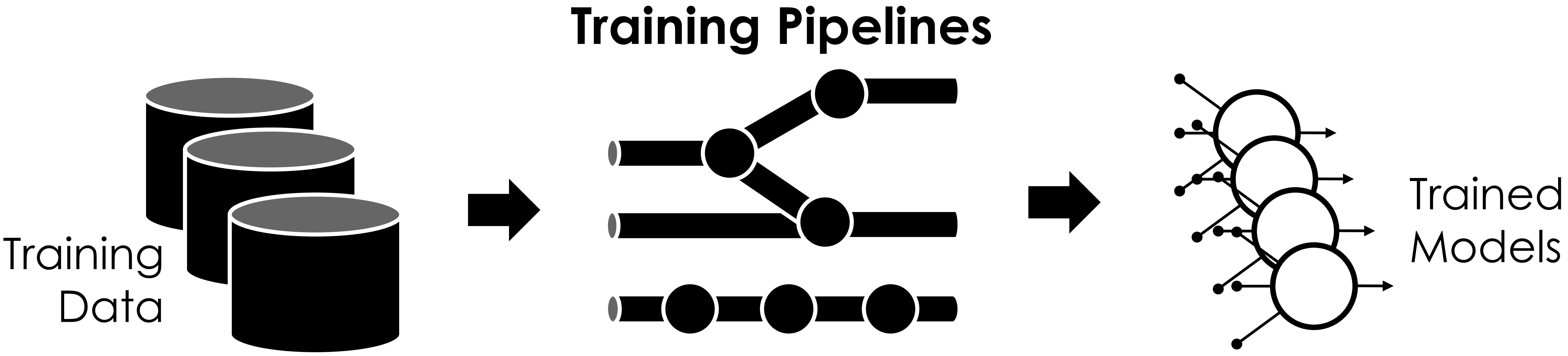
Training Pipelines



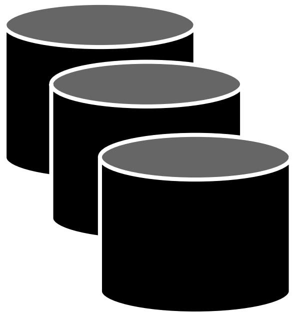
Training Pipelines Capture the **Code** and **Data Dependencies**

- Description of how to train the model from data sources



Software Engineering Analogy	Training Pipelines → Code Trained Models → Binaries

What is the output of Model Development



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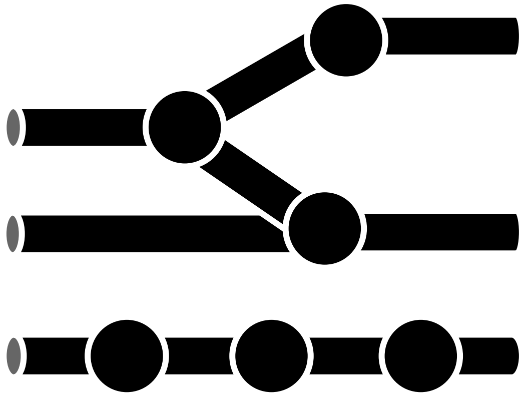
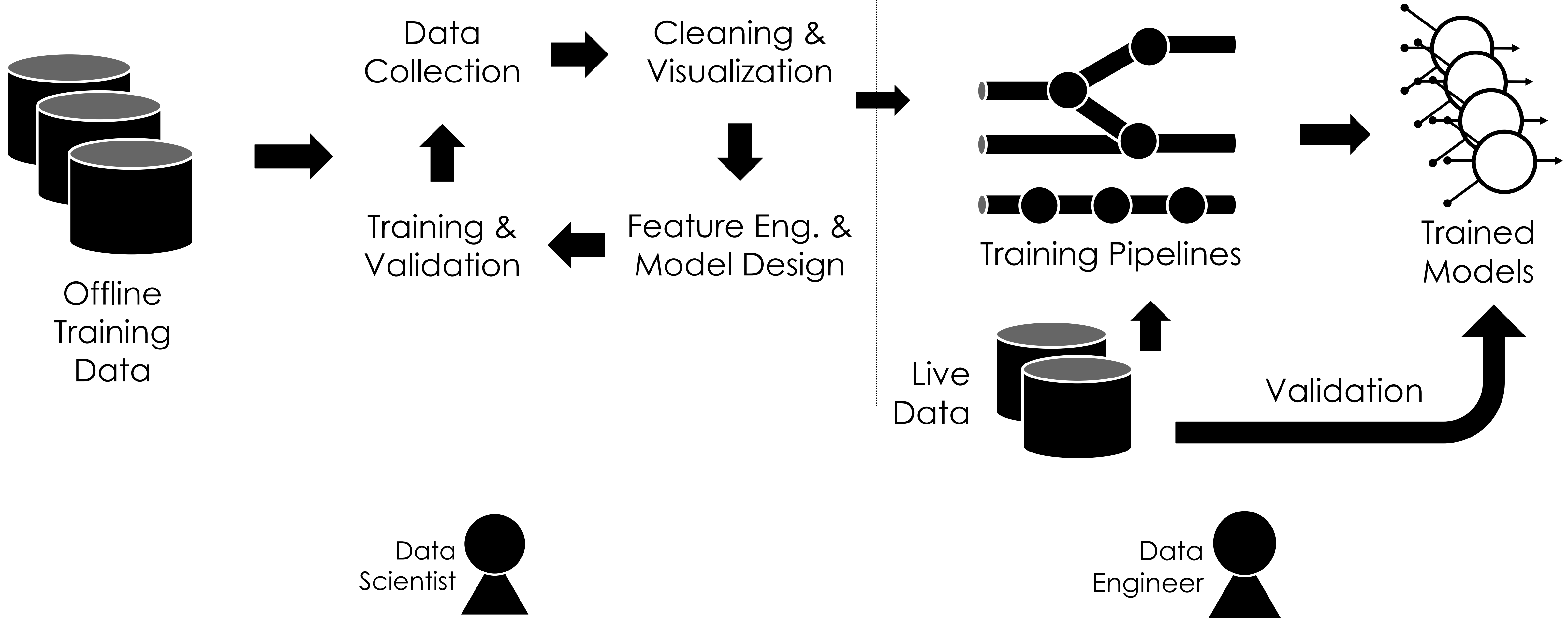
Training Pipelines

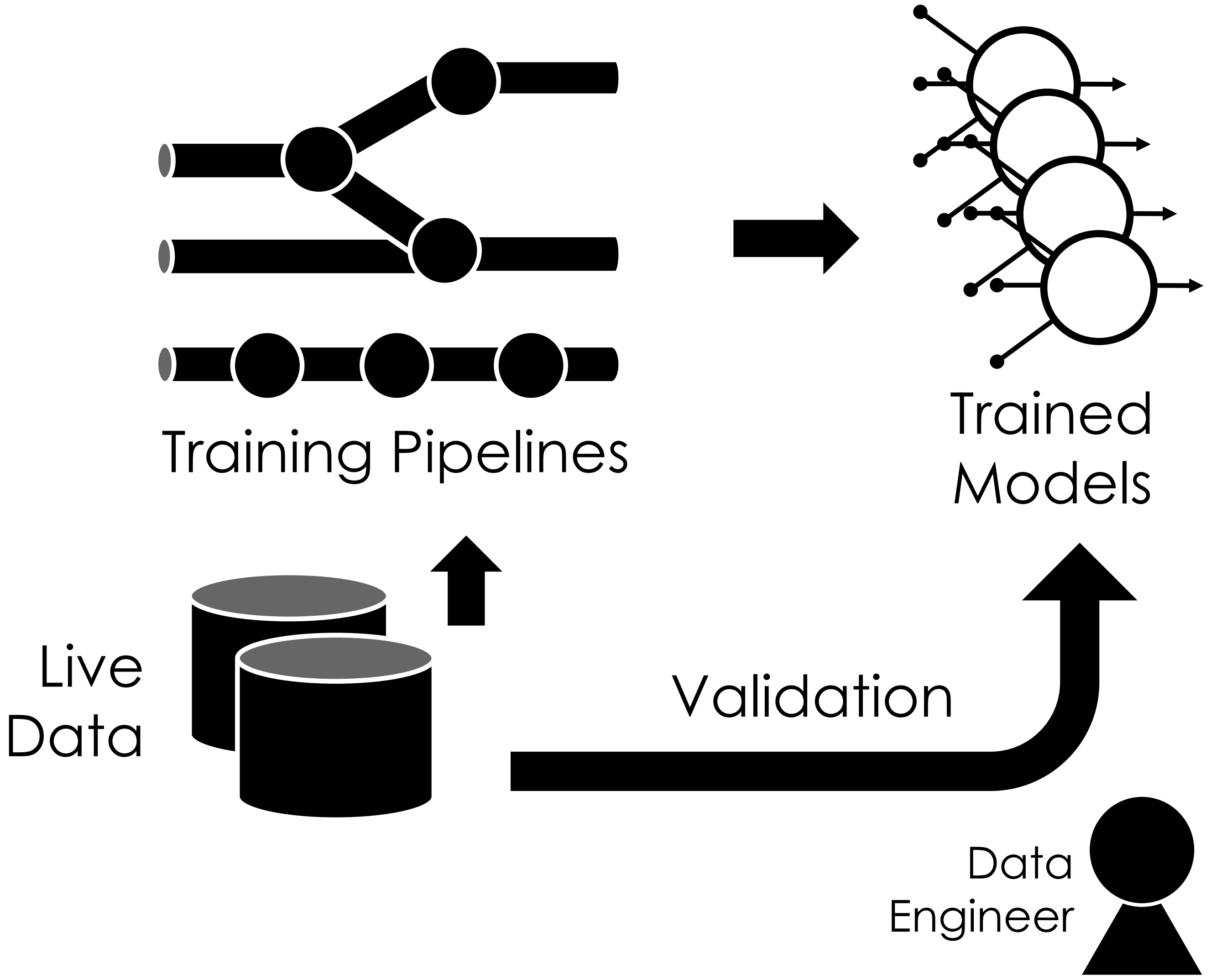


Model Development

Training



Training



Training models **at scale** on **live data**

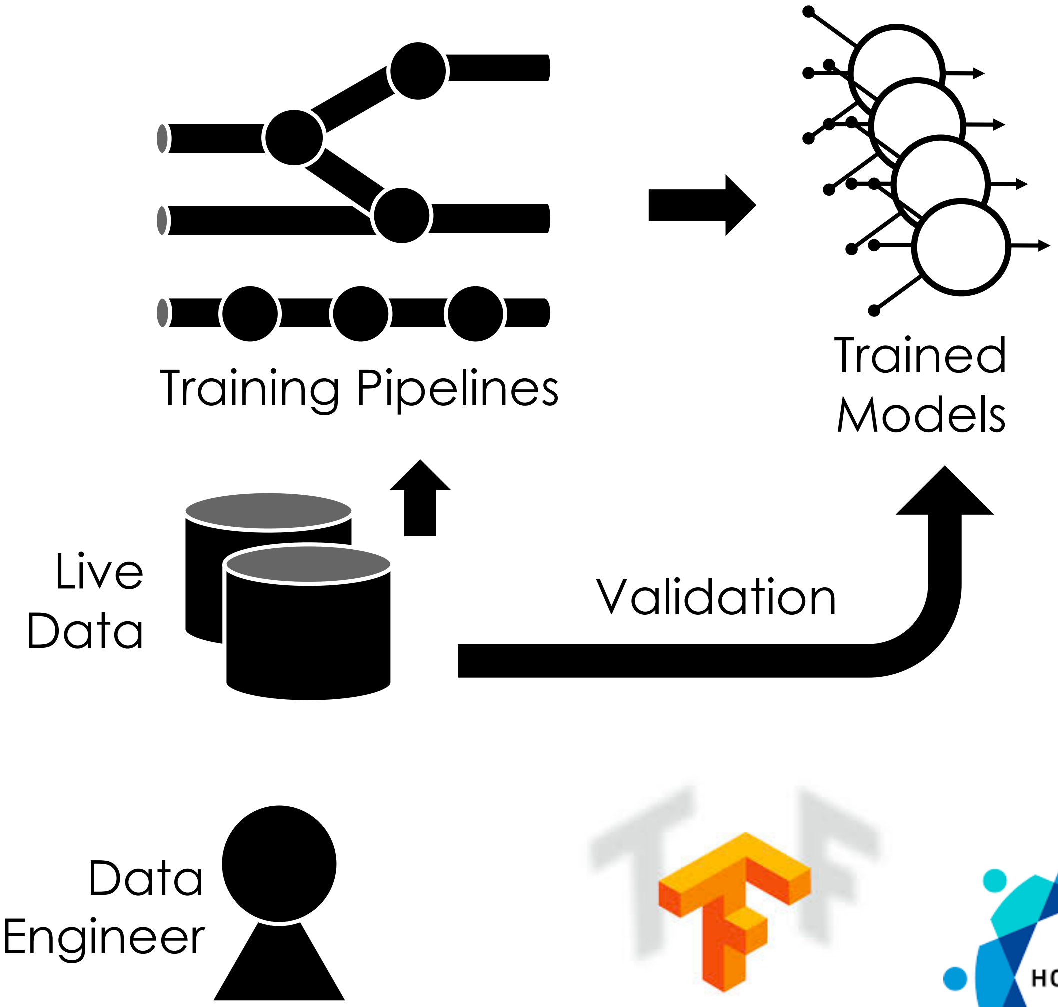
Retraining on new data

Automatically **validate** prediction accuracy

Manage model **versioning**

Requires **minimal expertise** in machine learning

Training *Technologies*



Workflow Management:

Apache Airflow

Luigi

Azkaban
Open-source Workflow Manager

OOZIE

Scalable Training:

PYTORCH

mxnet

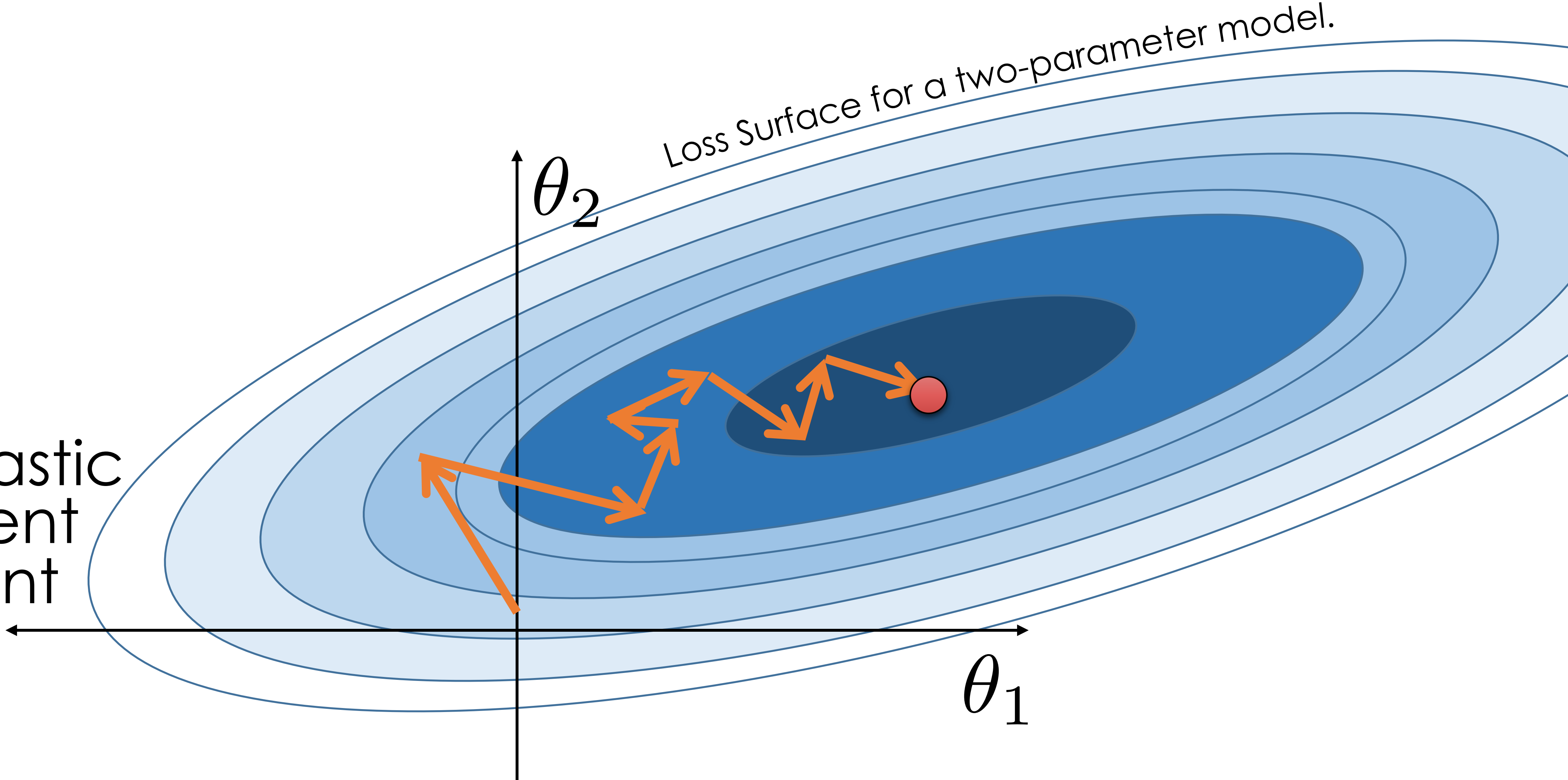
TensorFlow

HOROVOD

APACHE Spark™

dmlc XGBoost

Warm Start Training



Stochastic
Gradient
Descent

Warm Starts Training

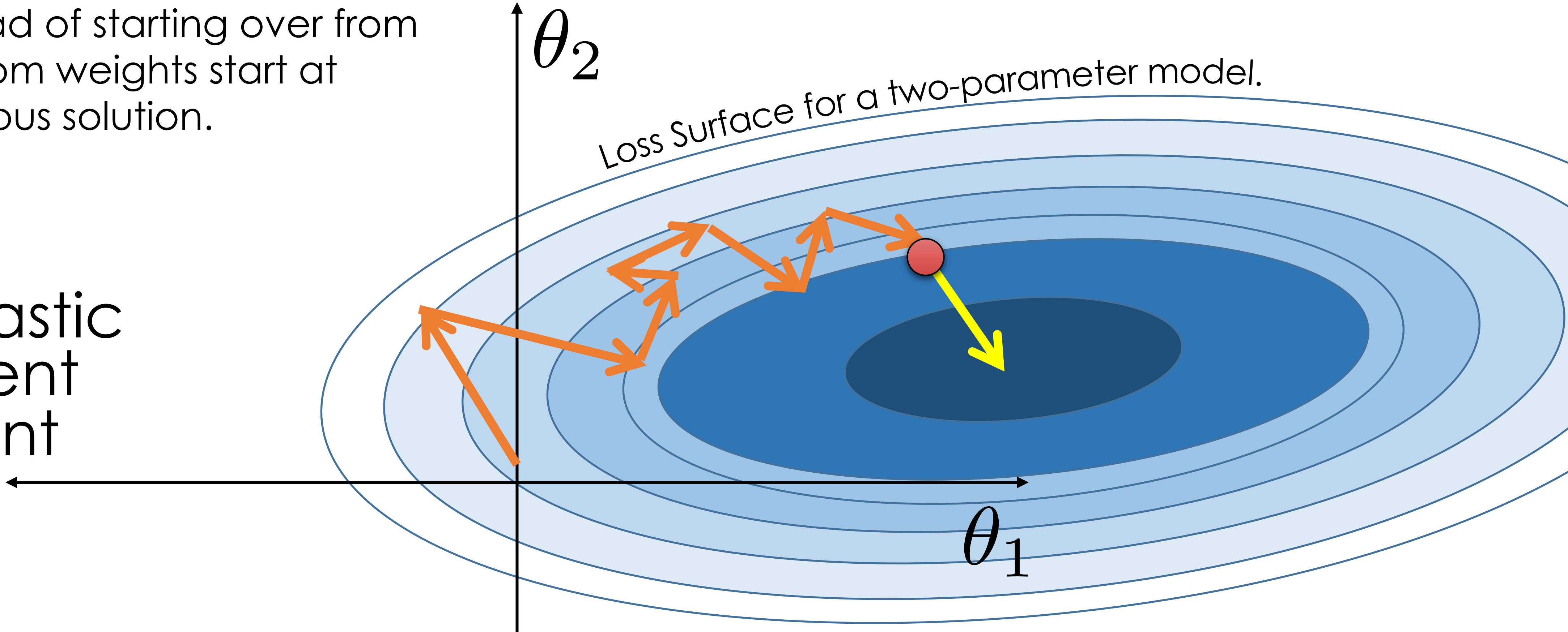
Works well if data is changing slowly.

More challenging for model changes.

1) New training data arrives and changes the loss surface.

2) Instead of starting over from random weights start at previous solution.

Stochastic
Gradient
Descent

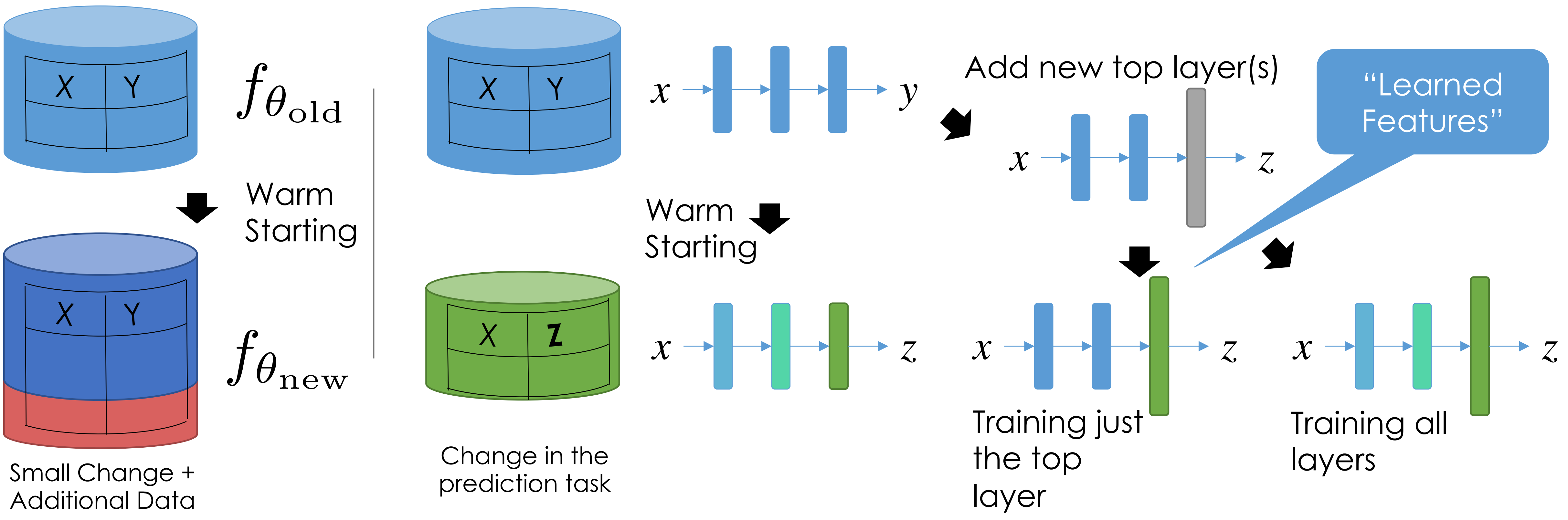


Additional Thoughts on Warm Starting

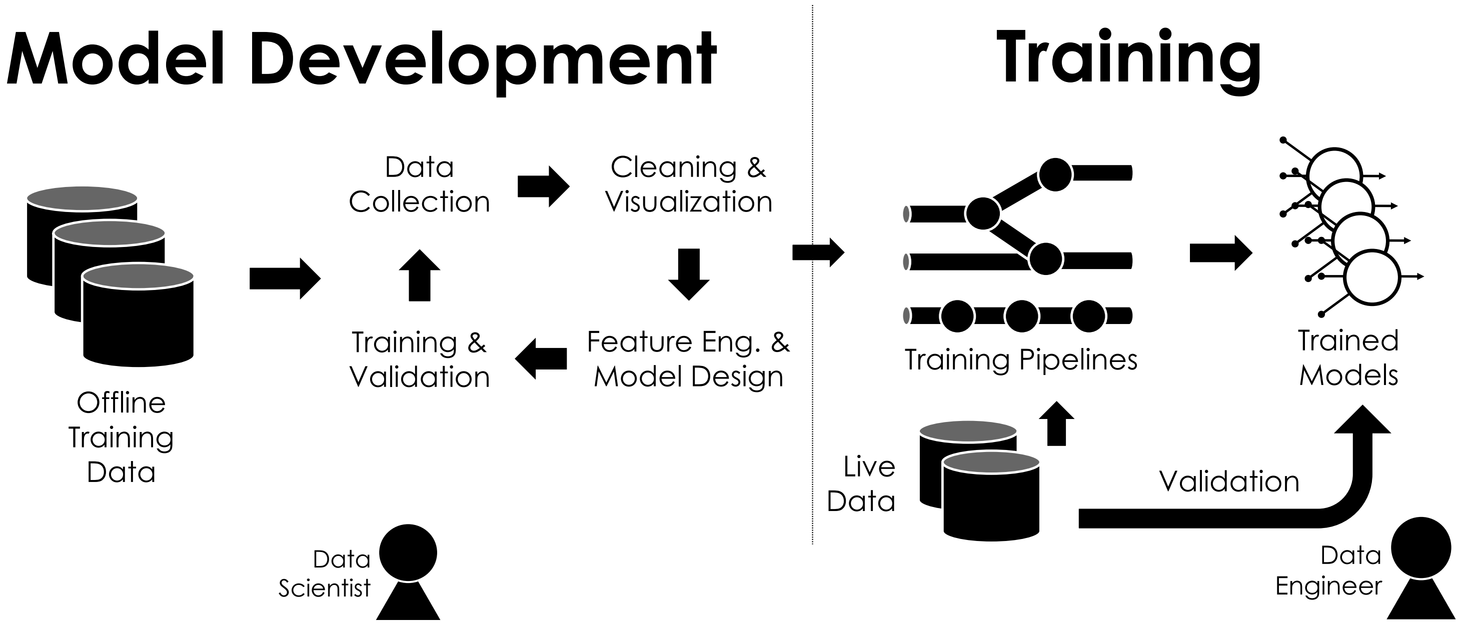
- A form of **transfer learning** across time.
- Useful for situations where **new data** is arriving
  - Data distribution is not changing rapidly (but changing…)
- Issues:
  - Need a mechanism to set learning rates appropriately
    - Typically start much smaller
  - Could get stuck in suboptimal solution for non-convex settings
    - Though this is true in general
  - **Catastrophic forgetting:** if you only train on new data may degrade model on old data
    - Can address by continuing to train on old data

Fine Tuning

- Using small learning rates to train **pre-trained** or **partially pre-trained** model for a **new dataset** or **prediction task**.
  - enables both **faster training** and **improved accuracy**



Open Problems

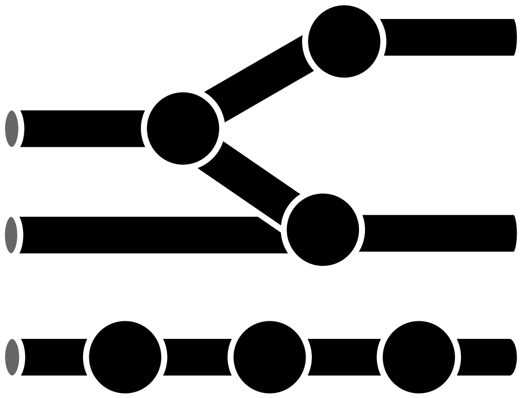


Context & Composition

Context How, What, & Who?

- **How** was the model or data created?
- **What** is the latest or best version?
- **Who** is responsible? (blame...)

Partial Solution



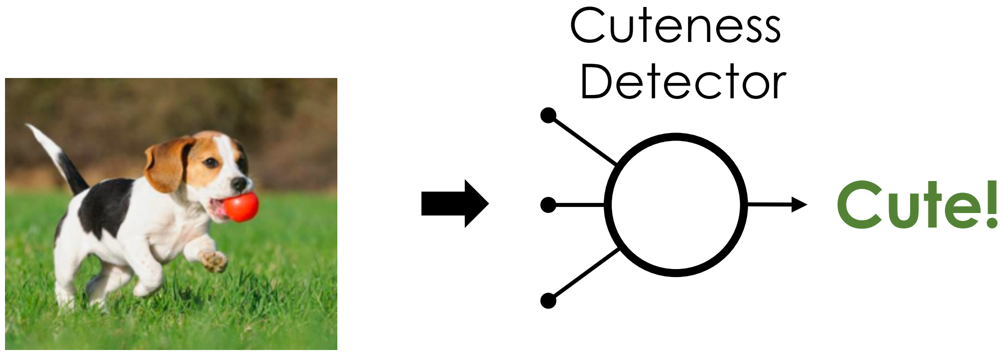
Training Pipelines

Track relationships between

1. **Code** versions ✓ git
2. **Model & Data** versions
3. **People** (versions?)

Composition

Models are being composed to solve new problems



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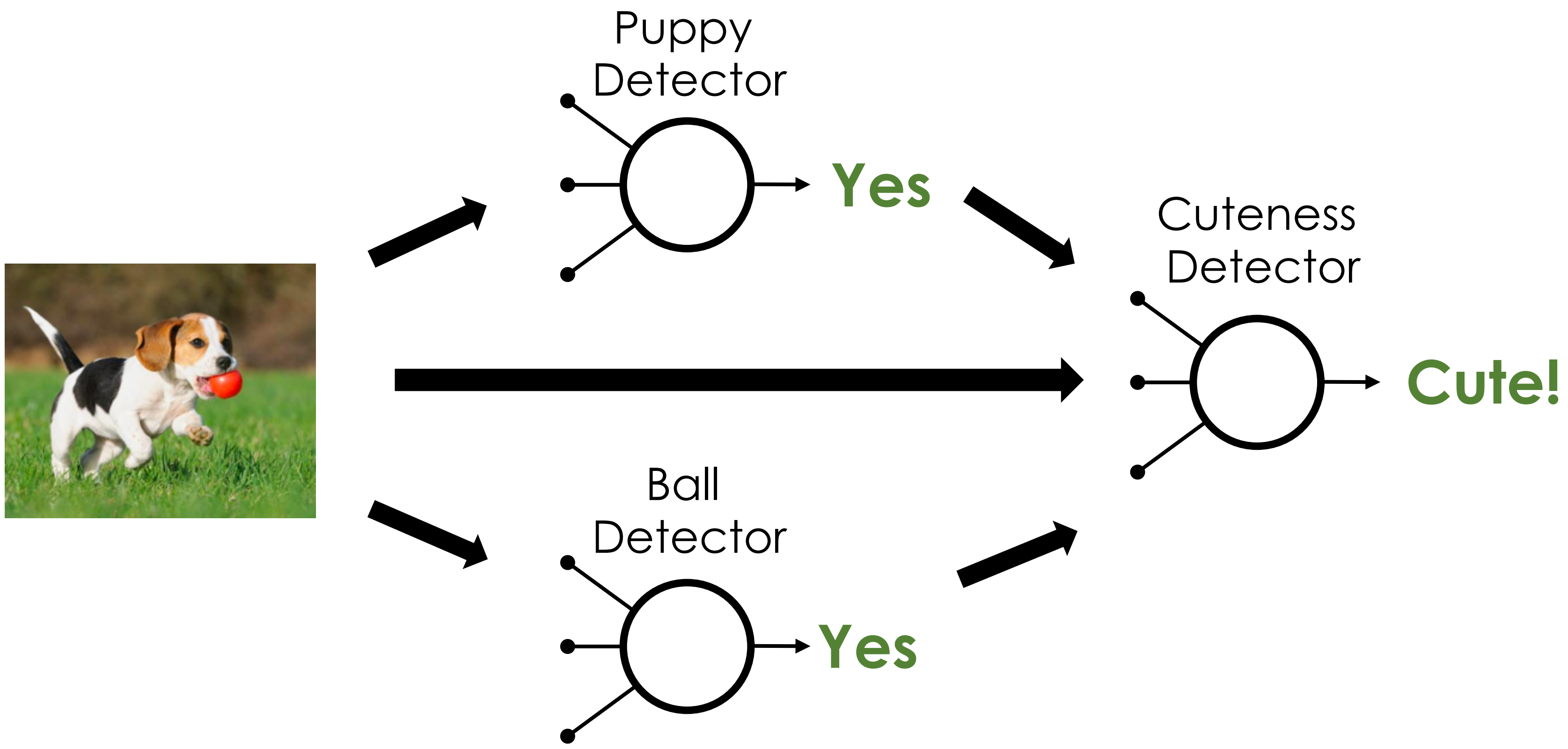

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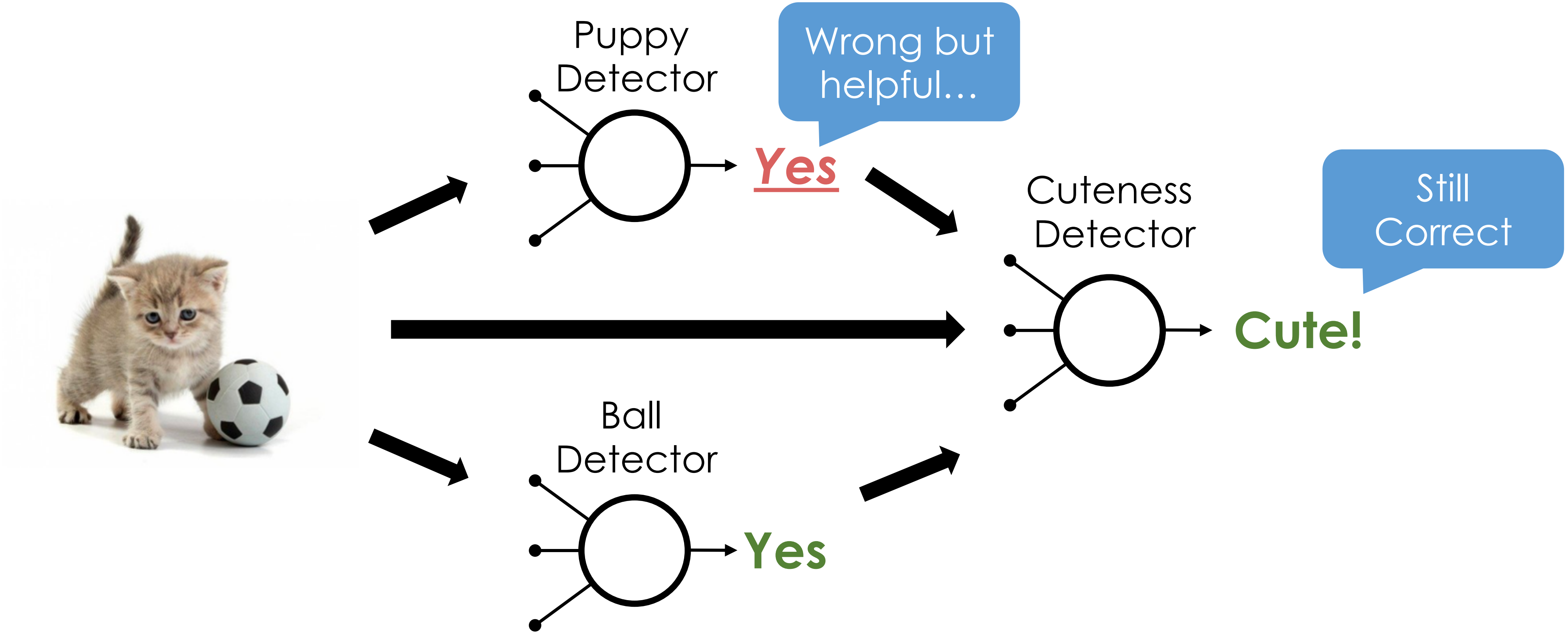

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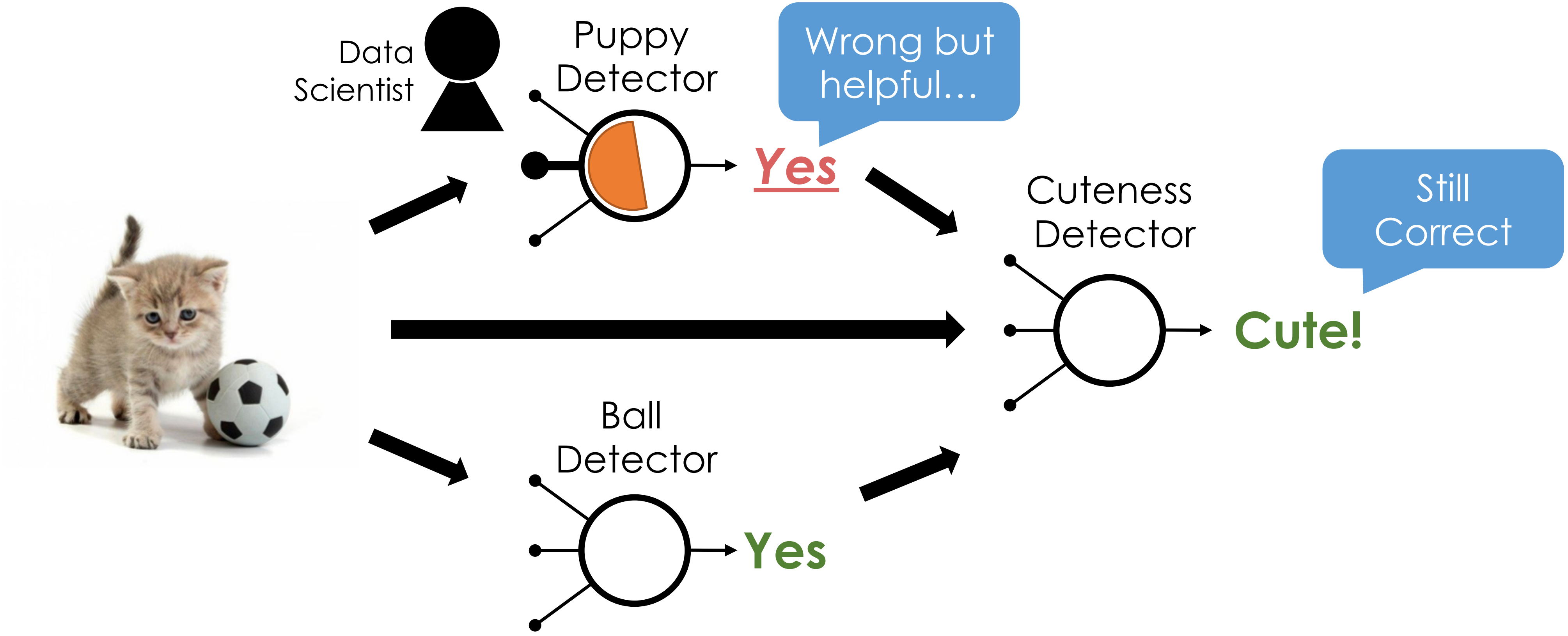

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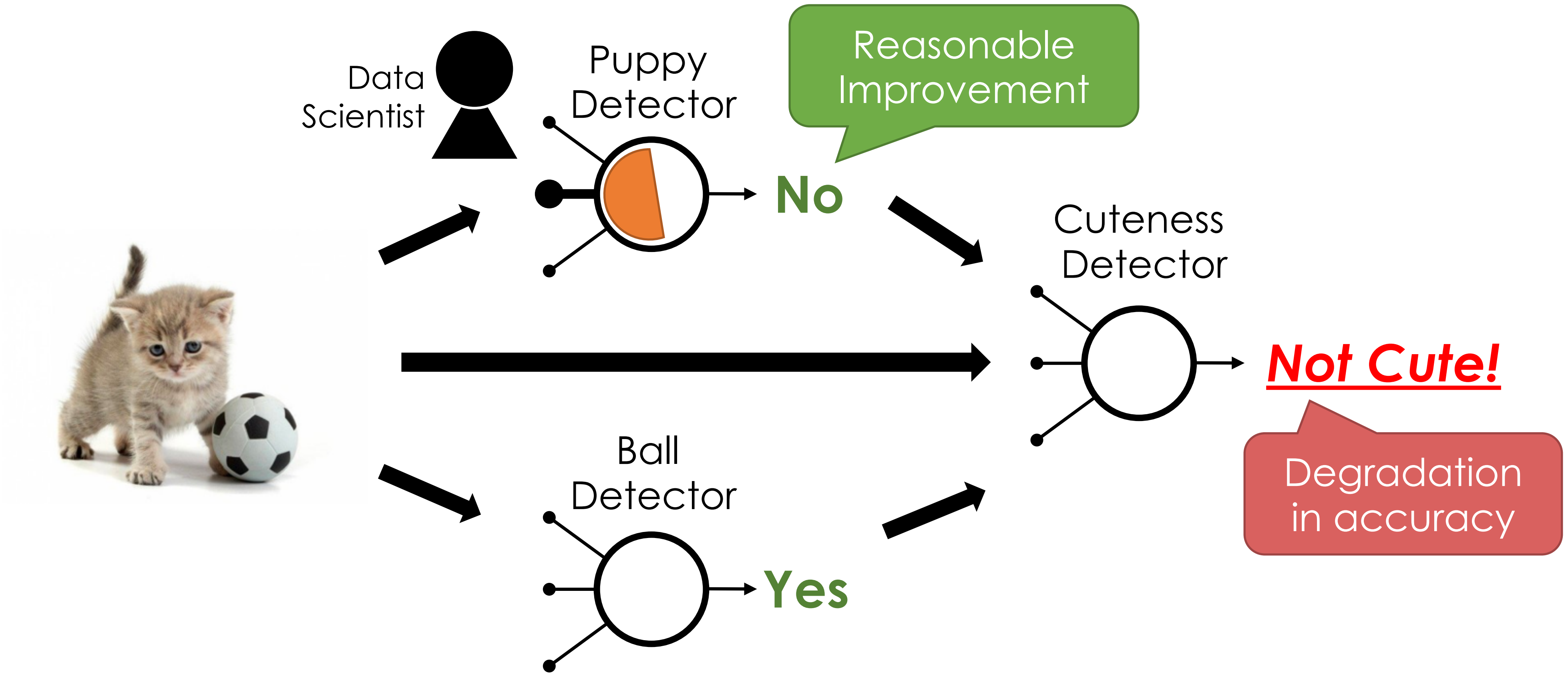

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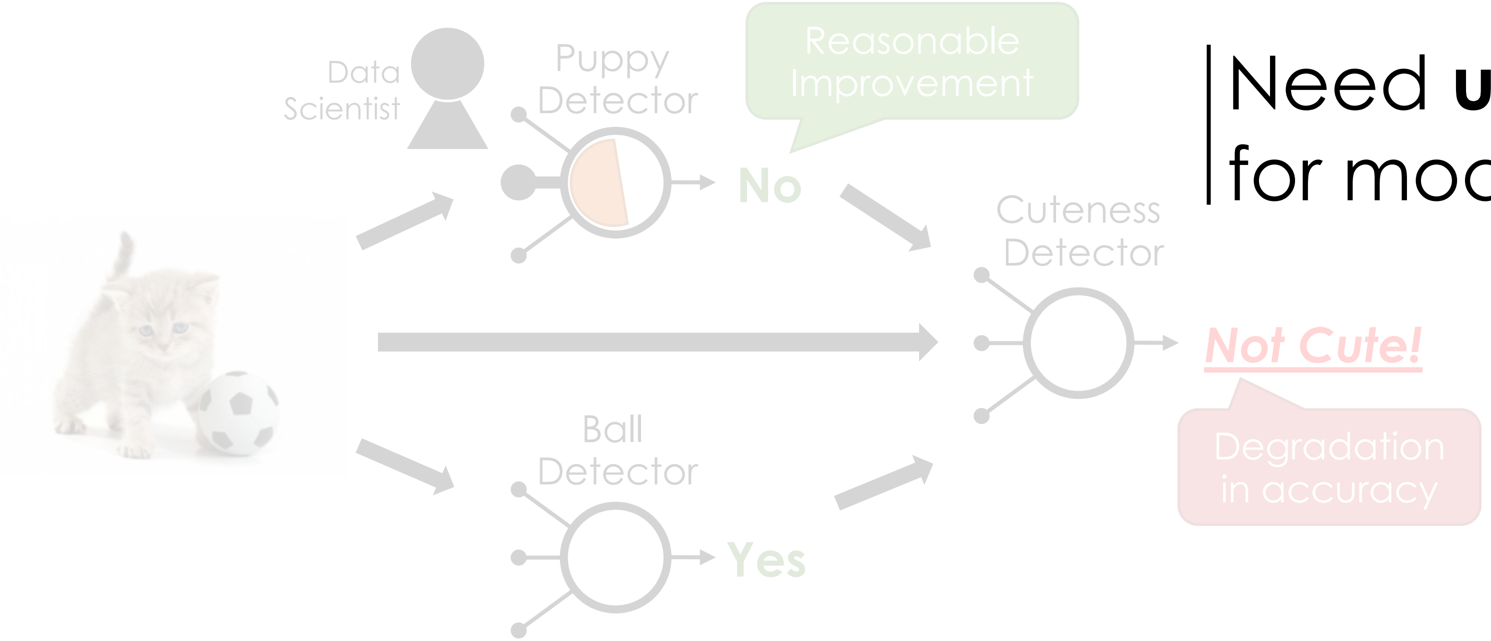
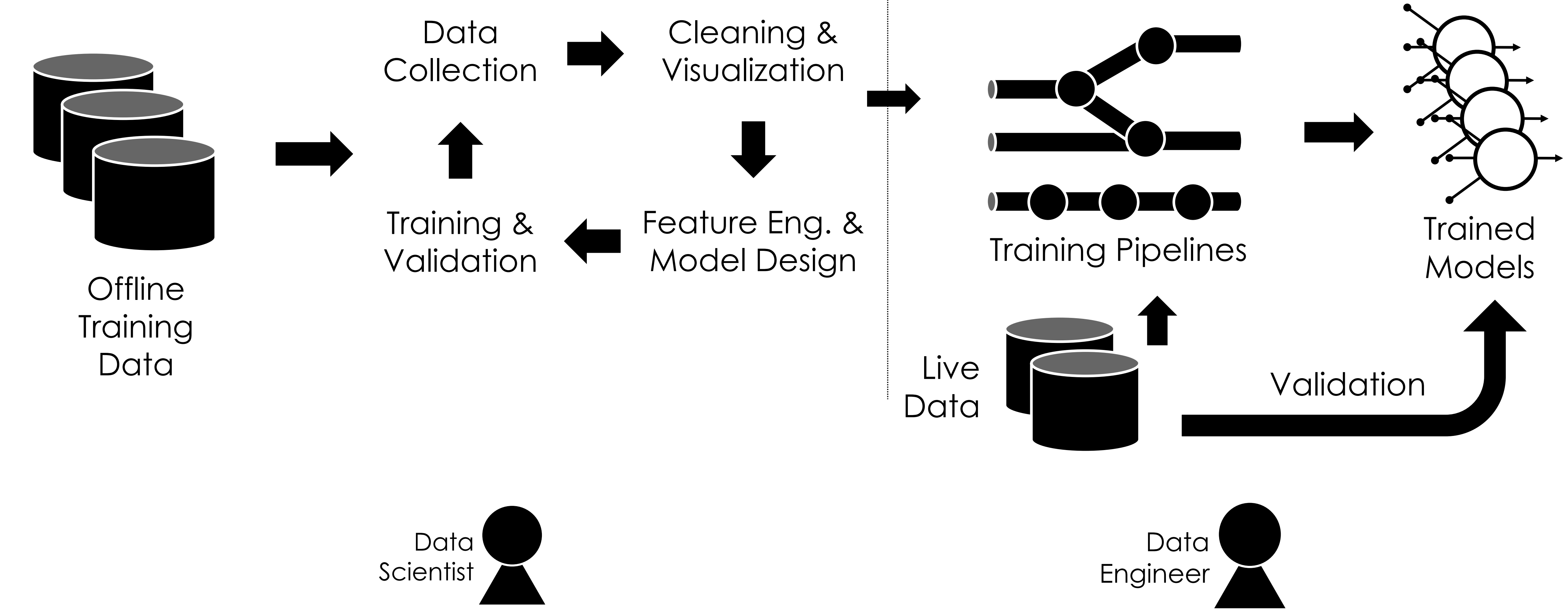


Need to track composition and validate **end-to-end accuracy**.

Need **unit** and **integration** testing for models.

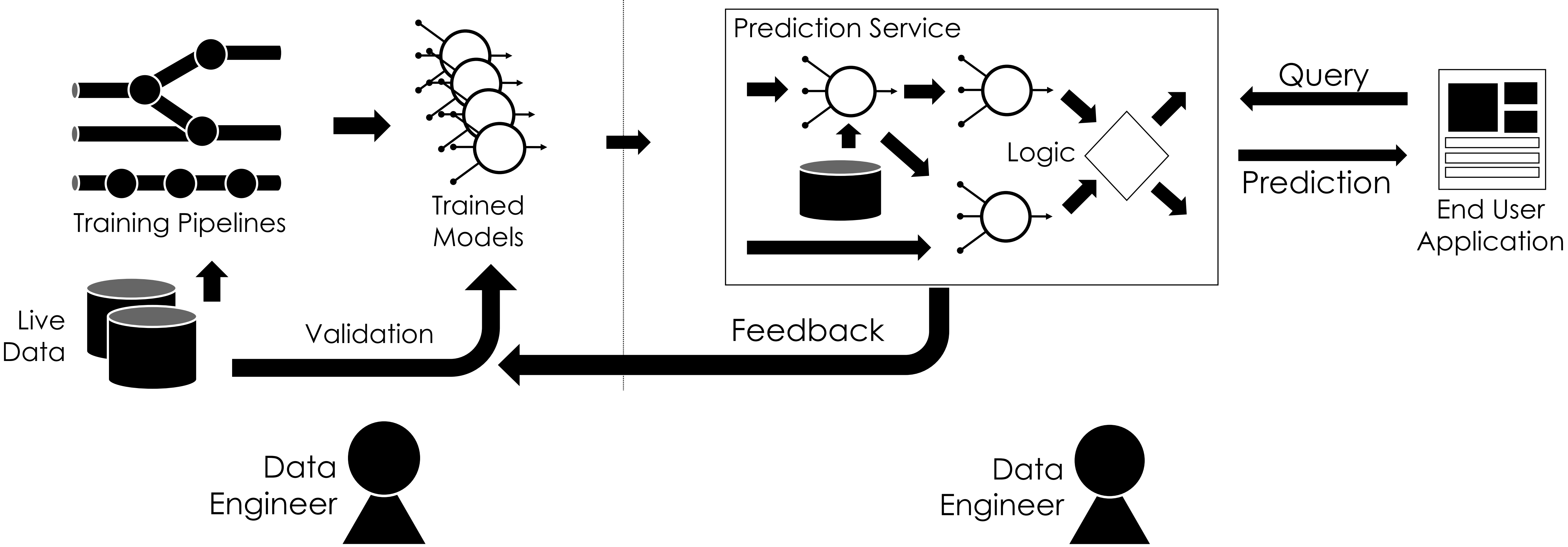
Model Development

Training

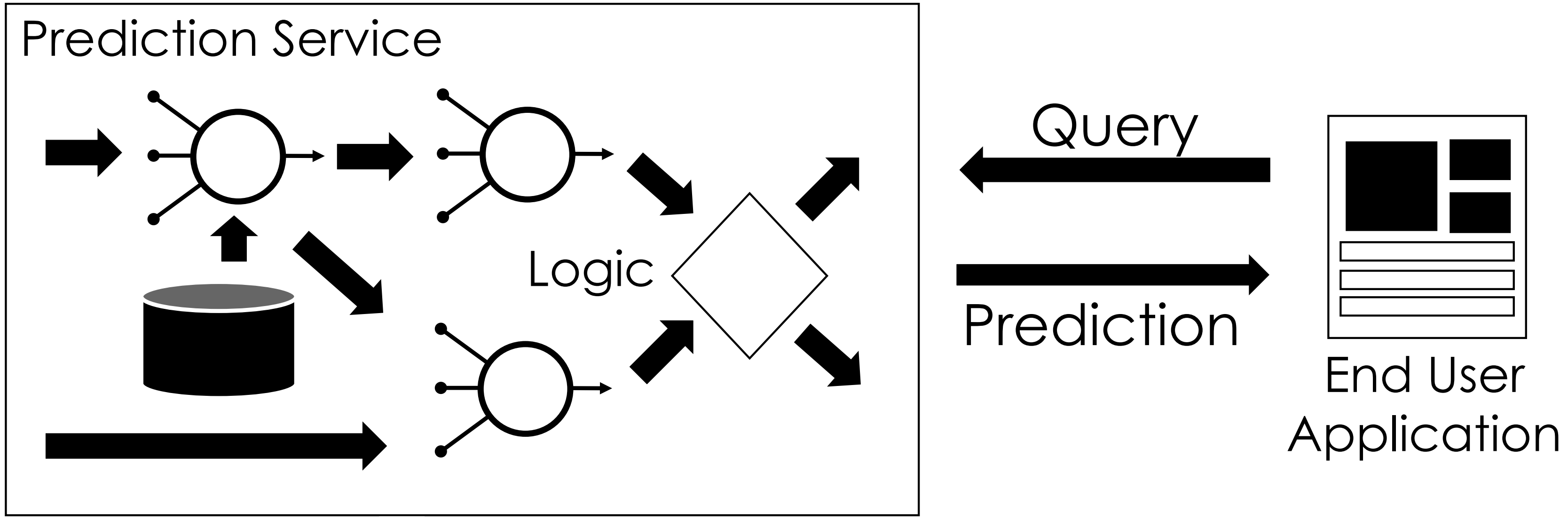


Training

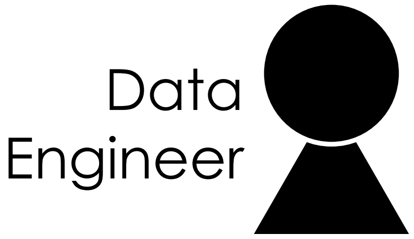
Inference



Inference

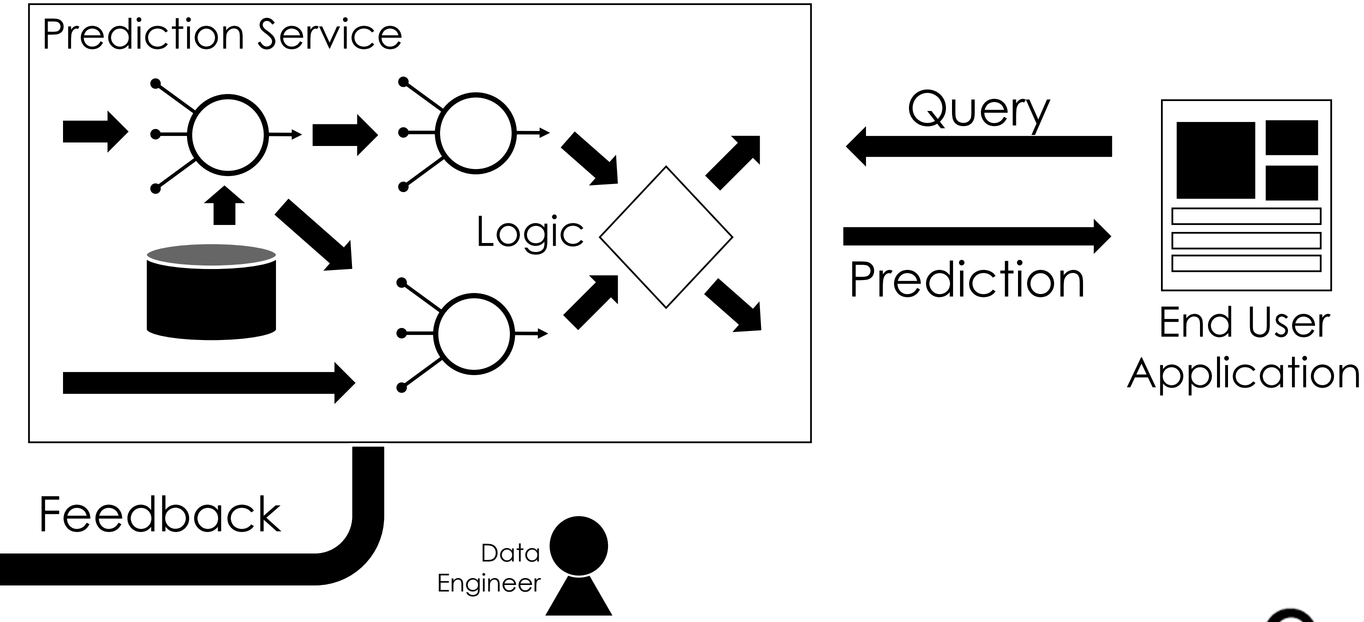


Goal: make predictions in ~10ms under **bursty** load



Complicated by **Deep Neural Networks**
→ New **ML Algorithms** and **Systems**

Inference *Technologies*



Clipper

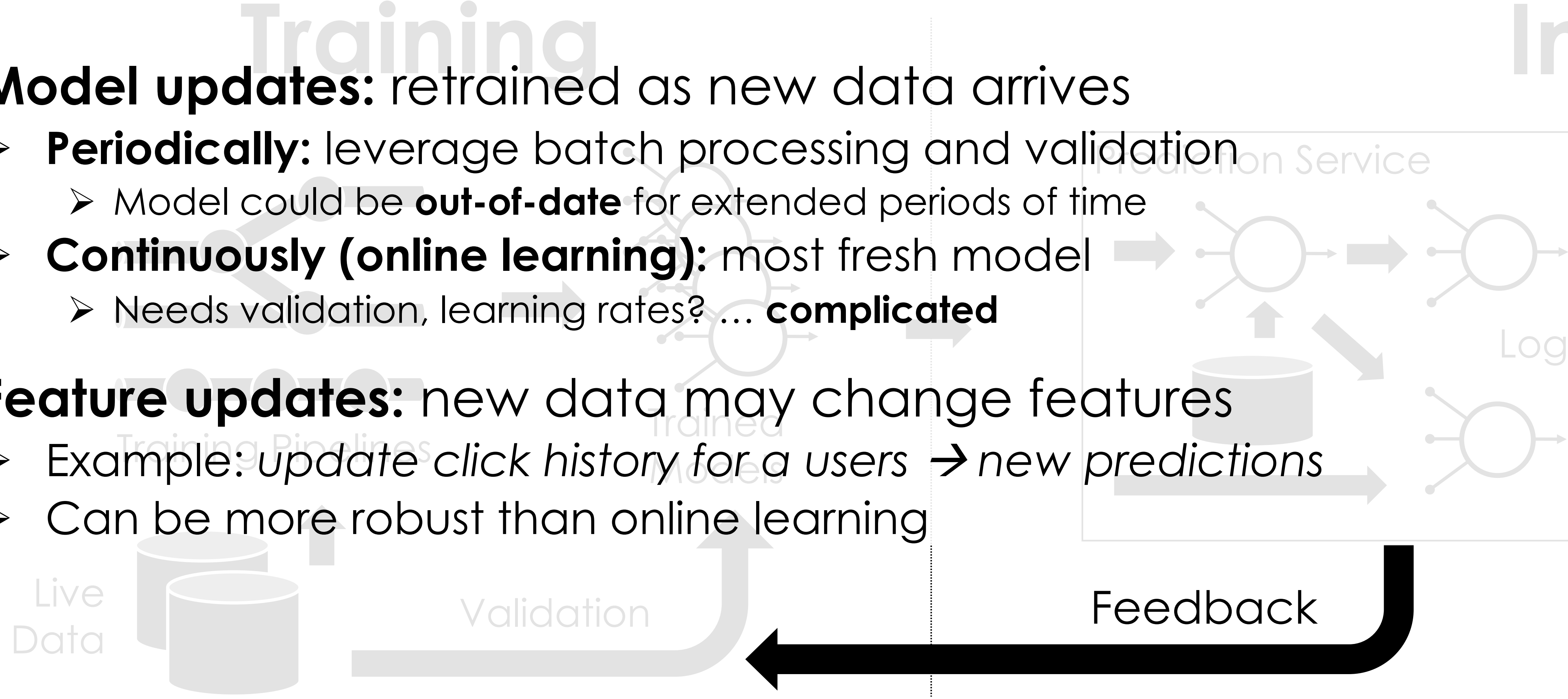
PredictionIO

mxnet

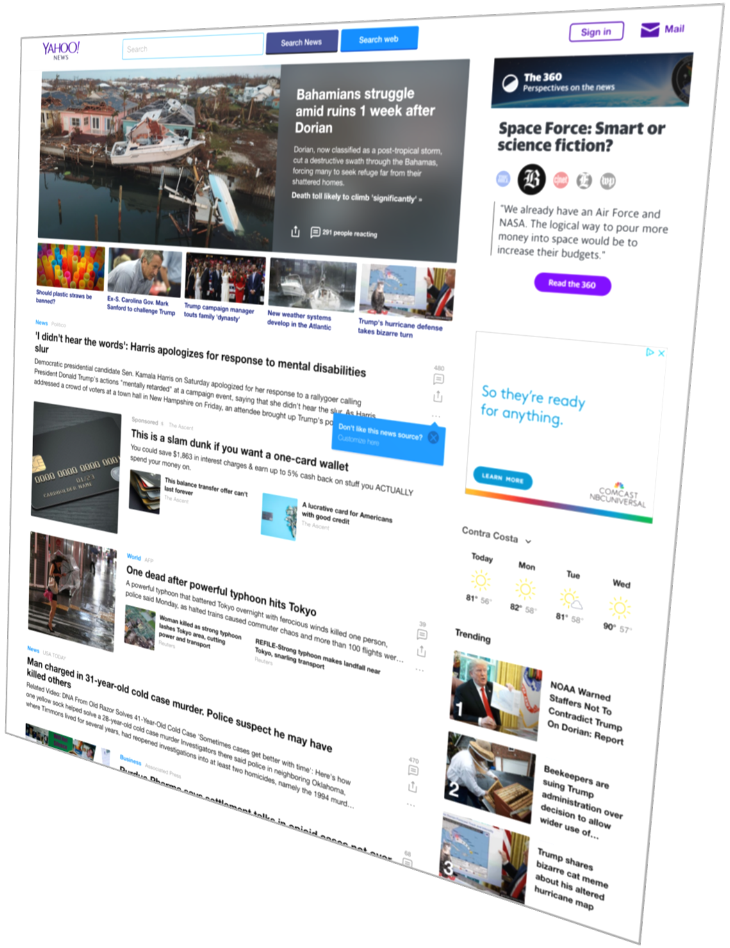
TensorFlow

Incorporating Feedback

- **Model updates:** retrained as new data arrives
  - **Periodically:** leverage batch processing and validation
    - Model could be **out-of-date** for extended periods of time
  - **Continuously (online learning):** most fresh model
    - Needs validation, learning rates? … **complicated**
- **Feature updates:** new data may change features
  - Example: *update click history for a users → new predictions*
  - Can be more robust than online learning

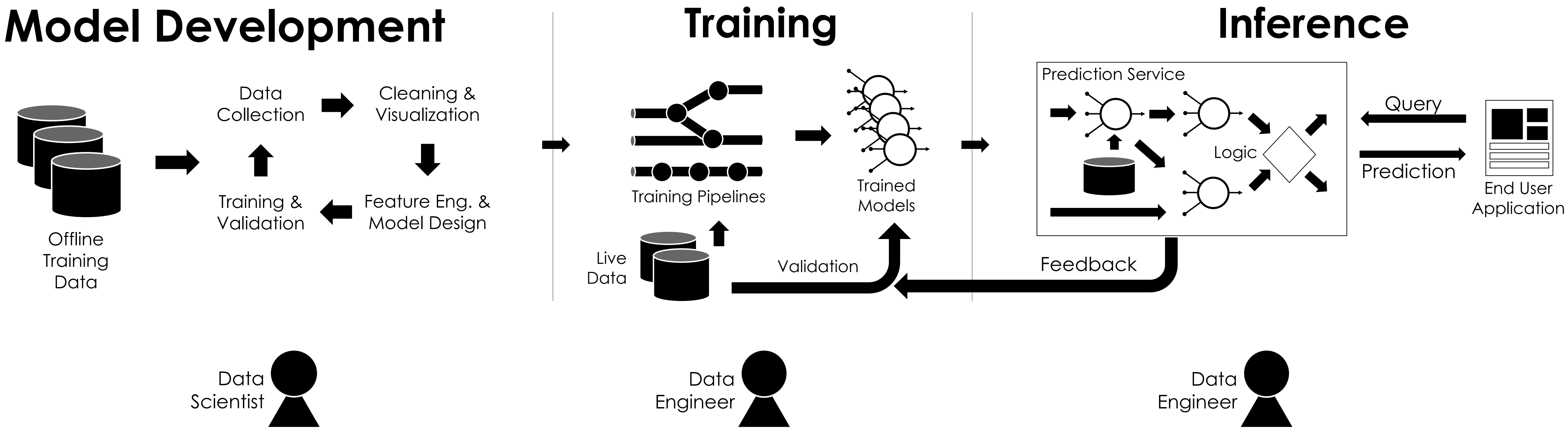


Feedback Cycles



- Models can **bias the data** they collect
  - Example: *content recommendation*
  - Future models may reflect earlier model bias
- **Exploration – Exploitation Trade-off**
  - **Exploration:** observe diverse outcomes
  - **Exploitation:** leverage model to take predicted best action
- **Solutions**
  - **Randomization (ε-greedy):** occasionally ignore the model
  - **Bandit Algorithms/Thompson Sampling:** optimally balance exploration and exploitation → active area of research

Machine Learning Lifecycle



We will cover each phase in more detail throughout the semester but this week we focus on **managing the entire process**.

Objectives For Today

- Introduce the machine learning lifecycle
  - Challenges and Opportunities
  - Science vs Engineering
- Review Key Concepts in Readings
  - Hyperparameters
  - Model Pipelines, Features, and Feature Engineering
  - Warm Starting and Fine Tuning
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- Important Context for Papers and what to expect.

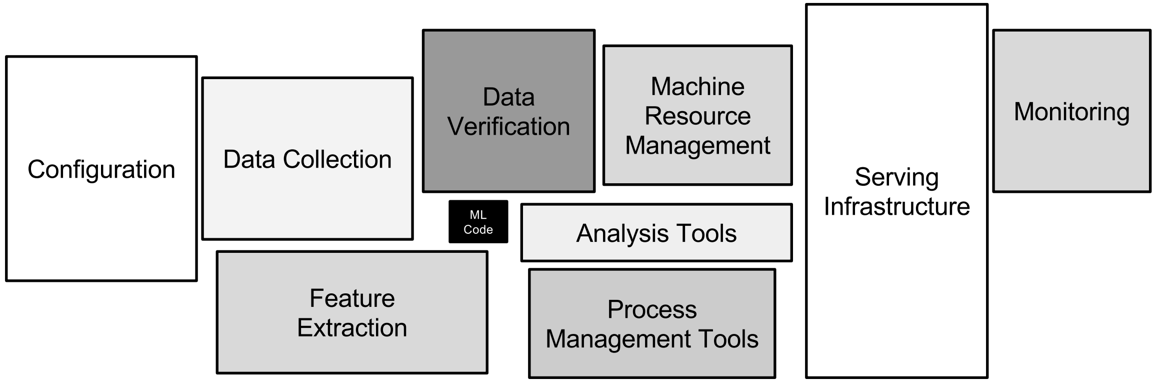
Reading for the Week

- Hidden Technical Debt in Machine Learning Systems
  - NeurIPS'15, widely cited
  - Provides an overview of the challenges from Google
- TFX: A TensorFlow-Based Production-Scale Machine Learning Platform
  - KDD'17, now part of https://www.tensorflow.org/tfx (sort of)
  - Googles solution to the challenges in the first paper
- Towards Unified Data and Lifecycle Management for Deep Learning
  - ICDE'17, Video Demo
  - An alternative database community solution

Related Systems Efforts

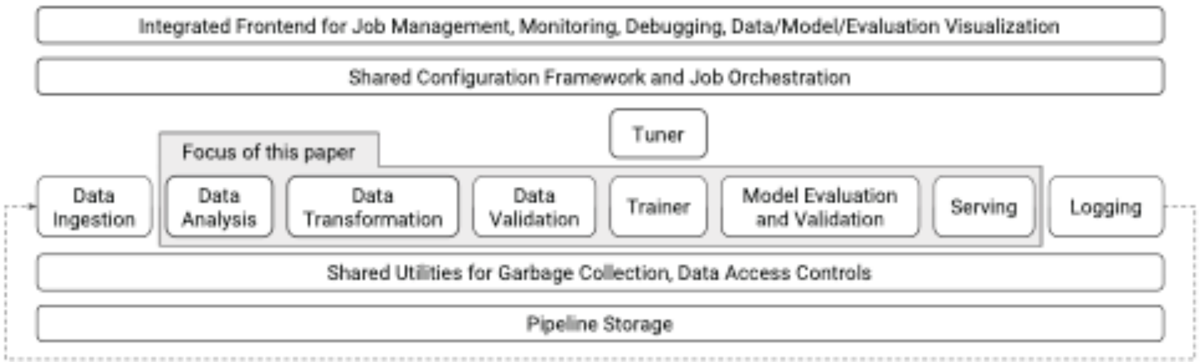
- Doing Machine Learning the Uber Way: Five Lessons From the First Three Years of Michelangelo
- Introducing FBLearner Flow: Facebook's AI backbone
- KubeFlow: Kubernetes Pipeline Orchestration Framework
- DeepBird: Twitters ML Deployment Framework
- Mlflow: A System to Accelerate the Machine Learning Lifecycle
- Data Engineering Bulletin on the Machine Learning Lifecycle
  - Full disclosure: I was the editor

Hidden Technical Debt in Machine Learning Systems



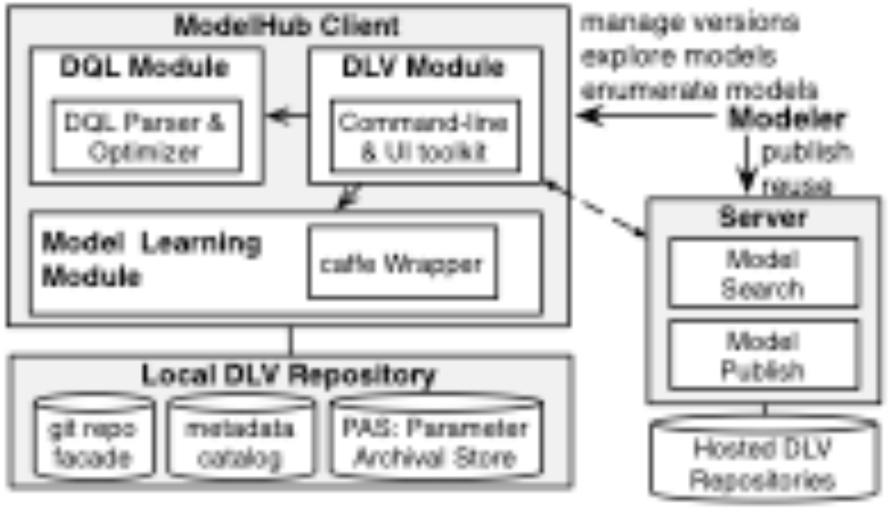
- **Technical Debt:** long term development and maintenance costs incurred by expedient design decisions
- **Key Idea:** machine learning deployments often incur substantial technical debt (compared to traditional software)
- **Contribution:** this paper characterizes the forms of technical debt and alludes to possible compensating actions

TFX: A TensorFlow-Based Production-Scale Machine Learning Platform



- Describes solutions to many of the problem outlined in the technical debt paper.
- **Key Idea:** Adapt best practices for software development to address machine learning lifecycle
  - empathetic to the *reality* of "machine learning developers"
- **Contributions:** actual system, interesting ideas around data and model validation, schema enforcement, and meaningful errors.

Towards Unified Data and Lifecycle Management for Deep Learning



- Describes a system (ModelHub) for managing, querying, and manipulating models and their related metadata.
- **Key Idea(?):** Model lifecycle management combines code and data (parameters) → a natural API would then combine version control commands with SQL-like querying.
- **Solution:** Combines a git-like client API with a SQL-like querying interface to enable basic actions and more complex queries.
  - Leverages optimizations to store model weights more efficiently.
    - (necessary?)

What to think about when reading

- How does the work differentiate between engineering and research challenges?
- What innovations in machine learning are needed?
- What are the key research challenges proposed and addressed?
- Are the proposed solutions too opinionated
  - Would they require top down mandates for adoption?
  - Would you use these systems?
  - Are they sufficiently flexible to support innovation

Done!