THE MISSING PIECE IN COMPLEX ANALYTICS: *SCALABLE, LOW LATENCY MODEL SERVING AND MANAGEMENT WITH VELOX*

Daniel Crankshaw, **Peter Bailis**, **Joseph Gonzalez**, Haoyuan Li,
Zhao Zhang, Ali Ghodsi, Michael Franklin, and Michael I. Jordan
UC Berkeley AMPLab

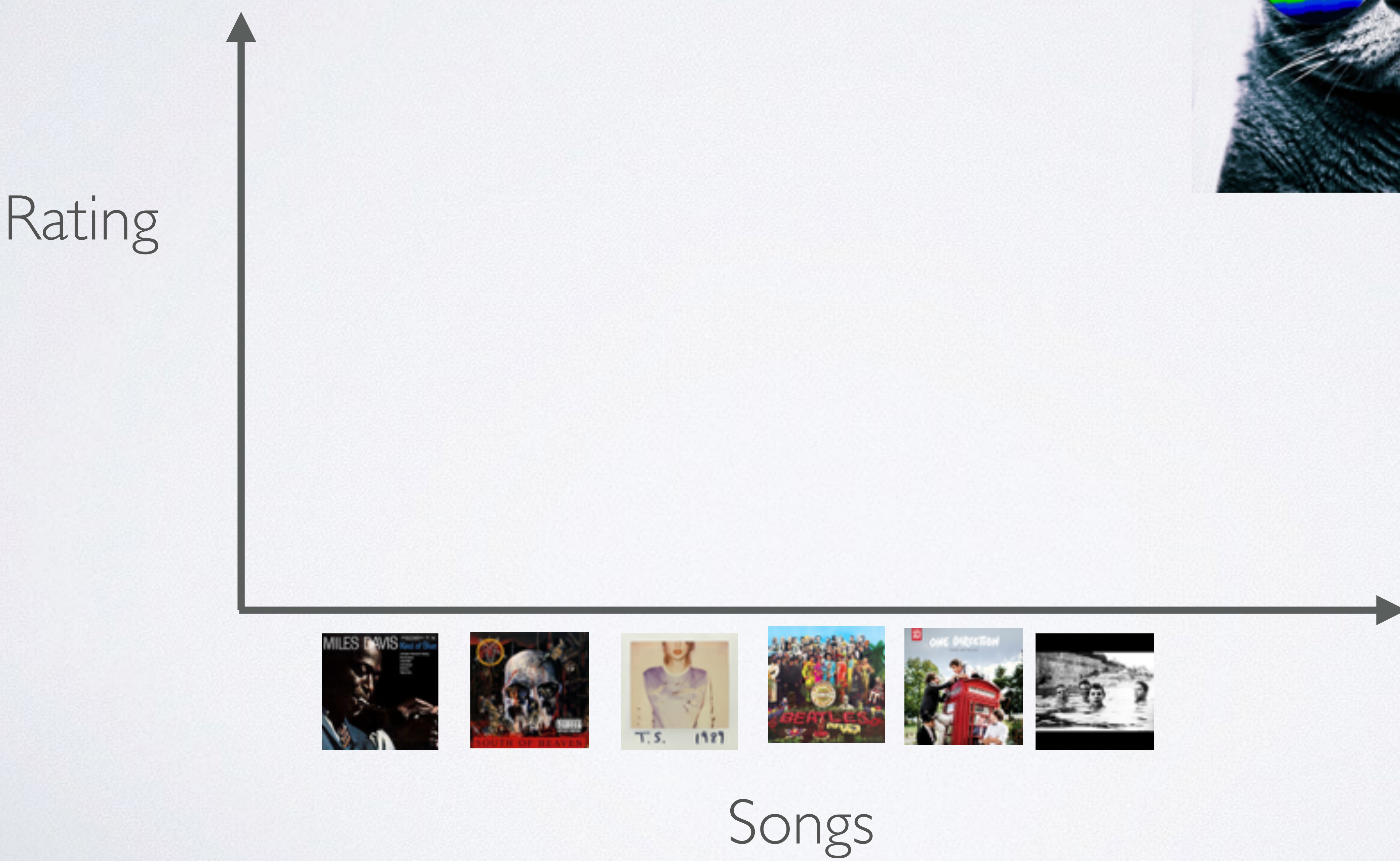
CIDR 2015

Talk Outline

- **ML model management today**
- Velox system architecture
- Key idea: Split model family
- Prediction serving
- Model management
- Next directions

Catify: Music for Cats

MODELING TASK



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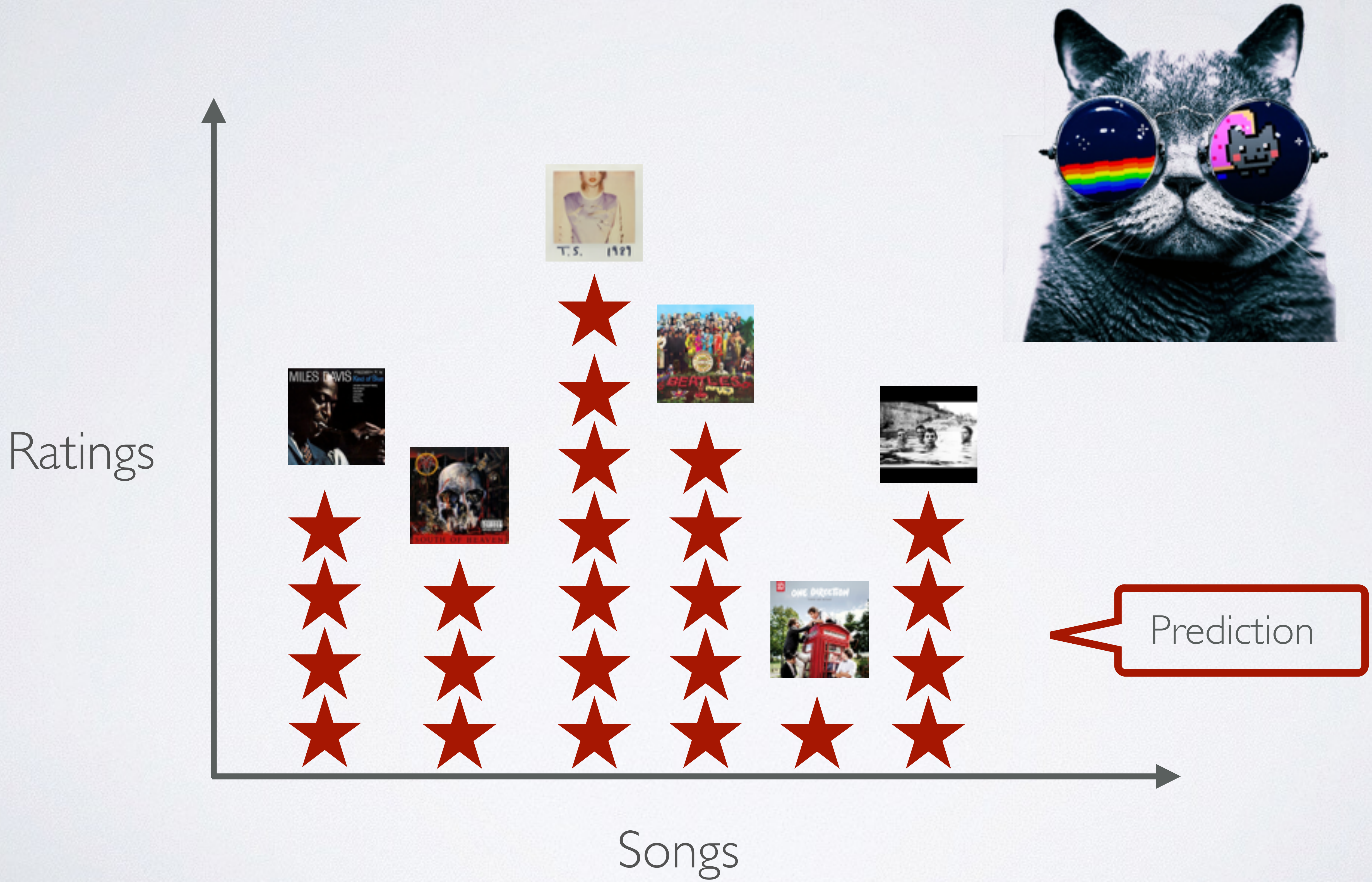
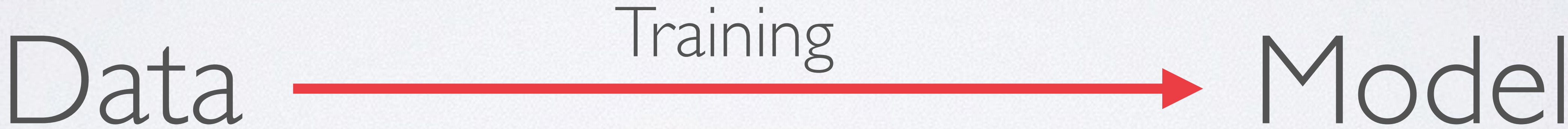
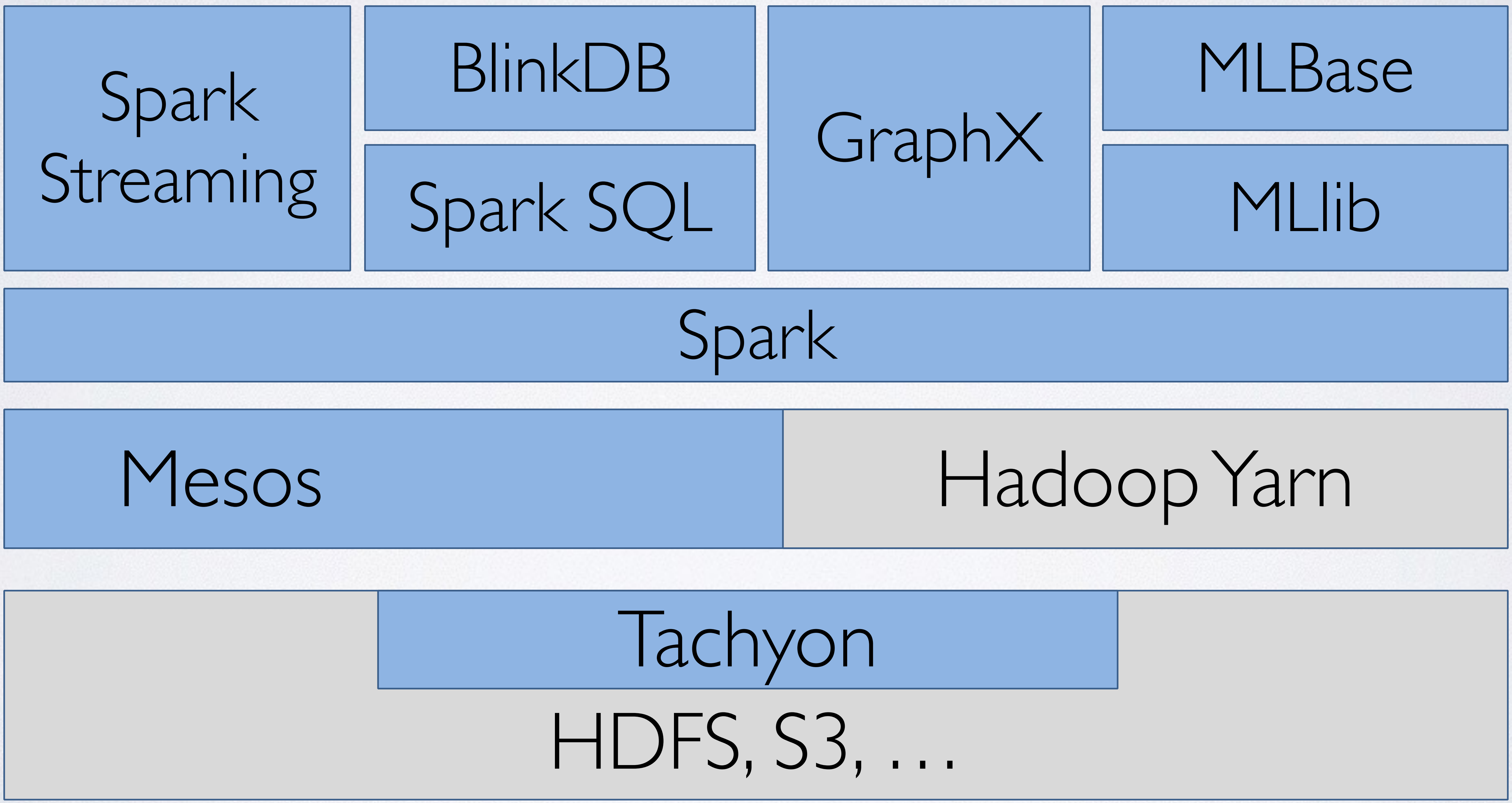


Data

Data → Model


Data
Training
Model

BERKELEY DATA ANALYTICS STACK (BDAS)



Catify: Music for Cats

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CatID	Song	Score
1	16	2.1
1	14	3.7
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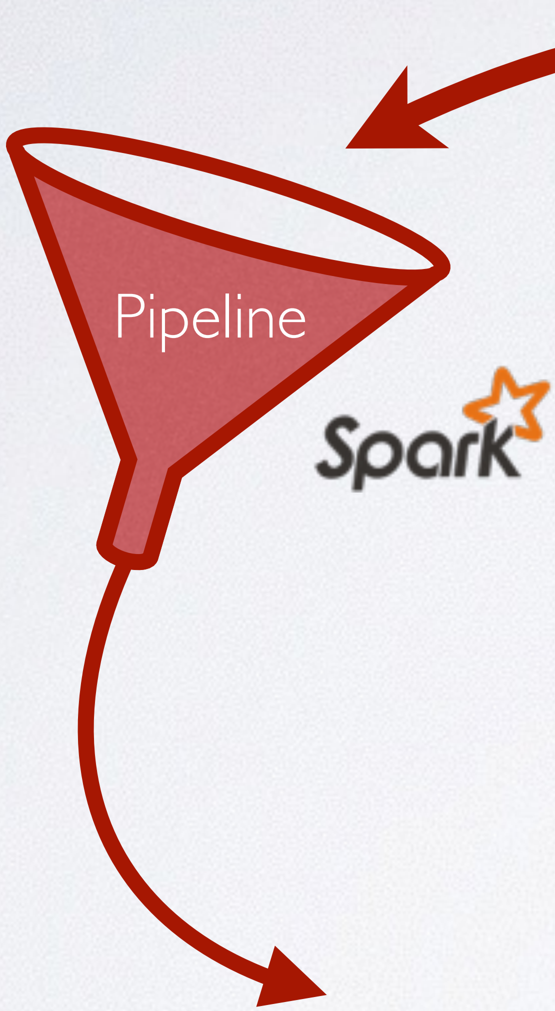

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Tachyon + HDFS

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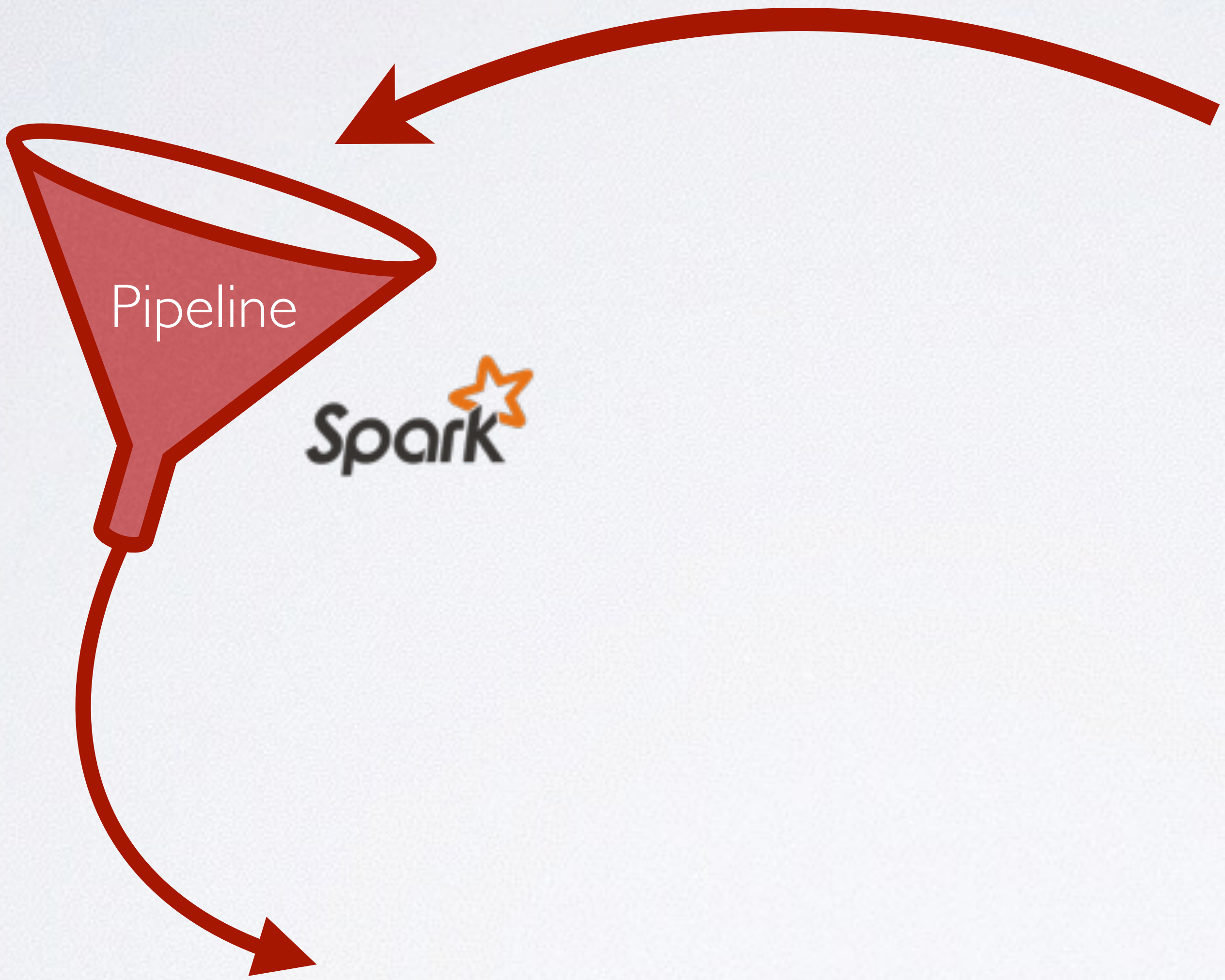

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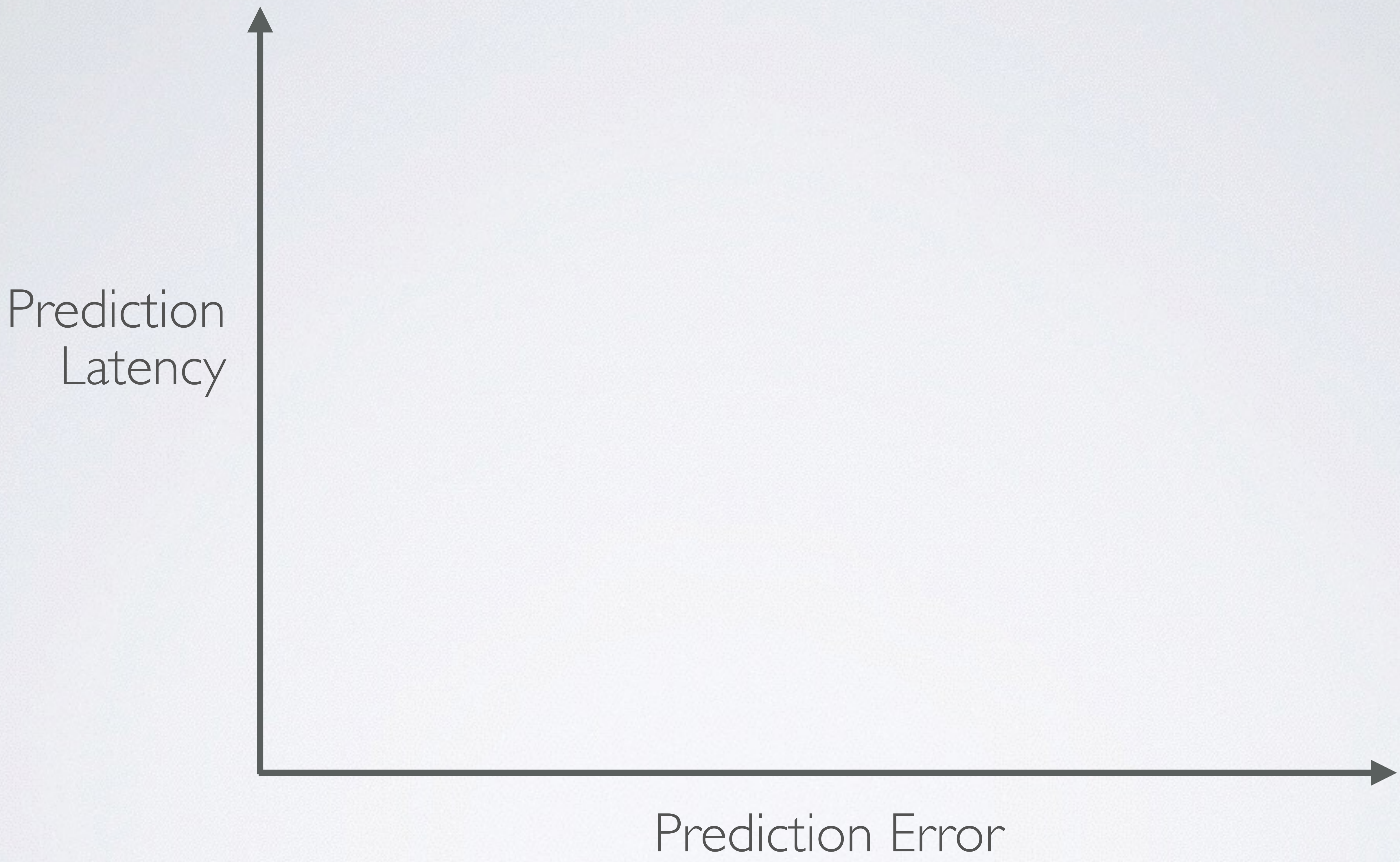
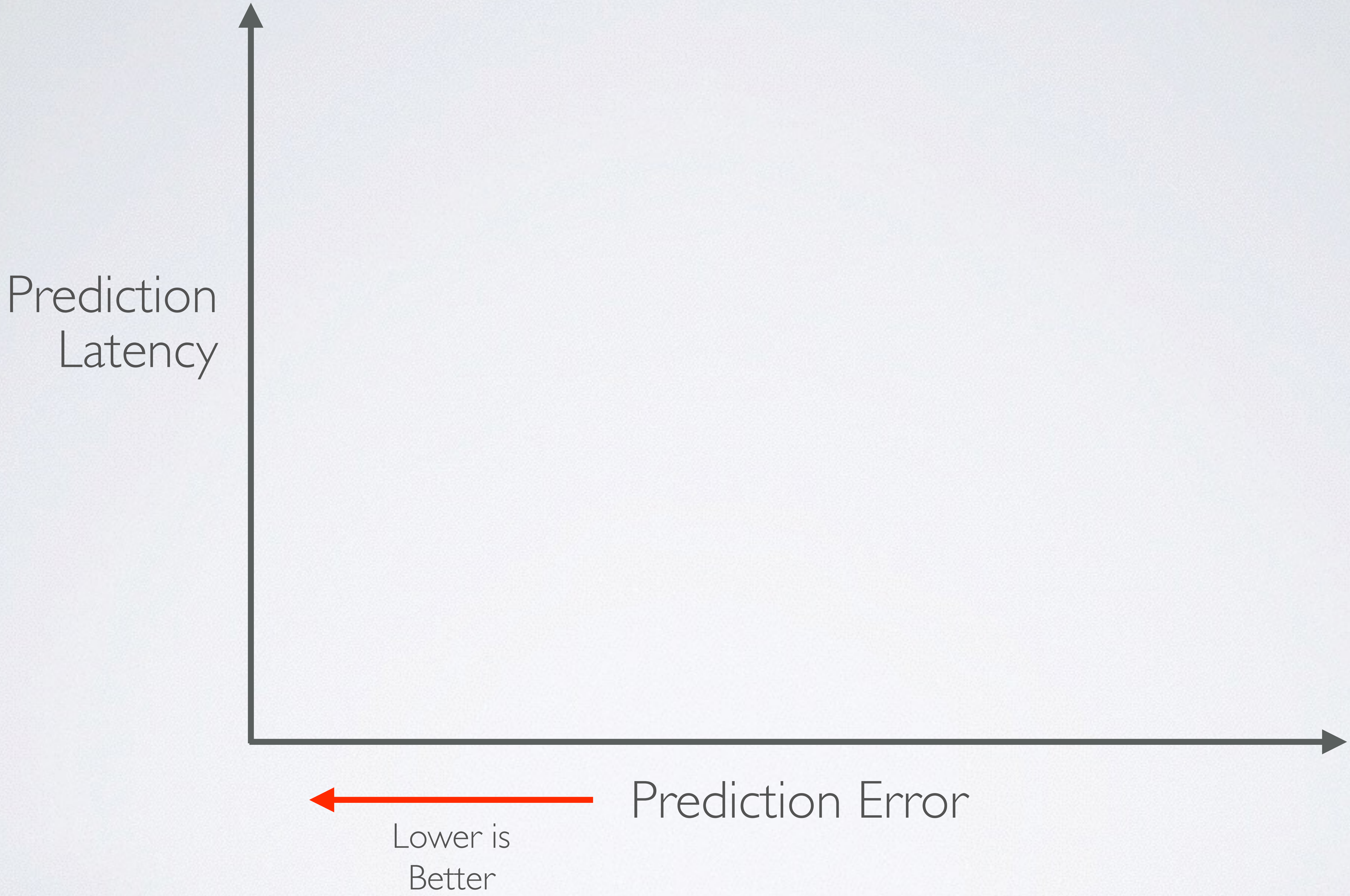
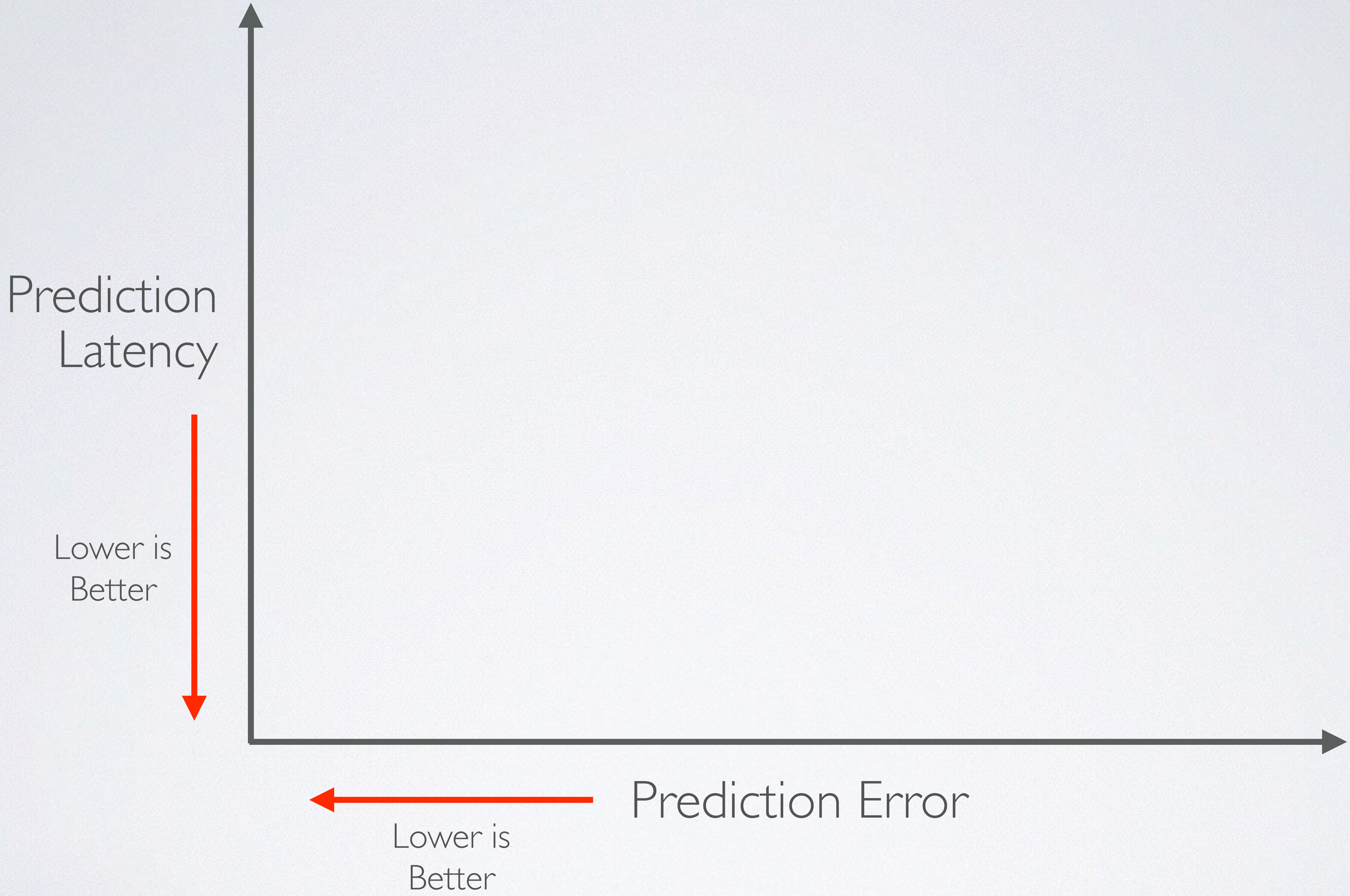
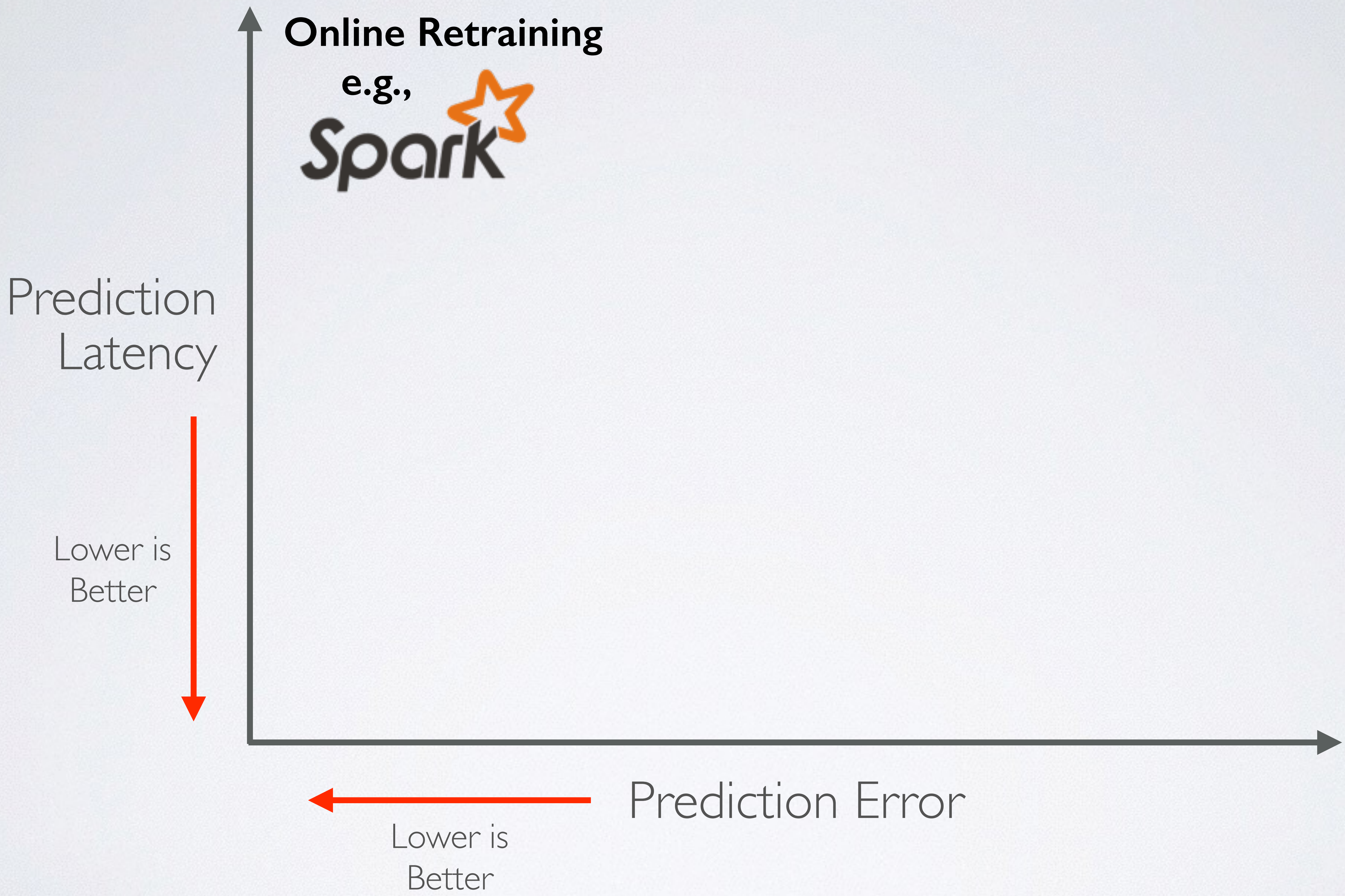


Prediction Latency
Prediction Error


Prediction
Latency
Prediction Error
Lower is
Better


Prediction Latency
Lower is Better
Prediction Error
Lower is Better



Online Retraining
e.g.,
Spark
Prediction Latency
Lower is Better
Prediction Error
Lower is Better

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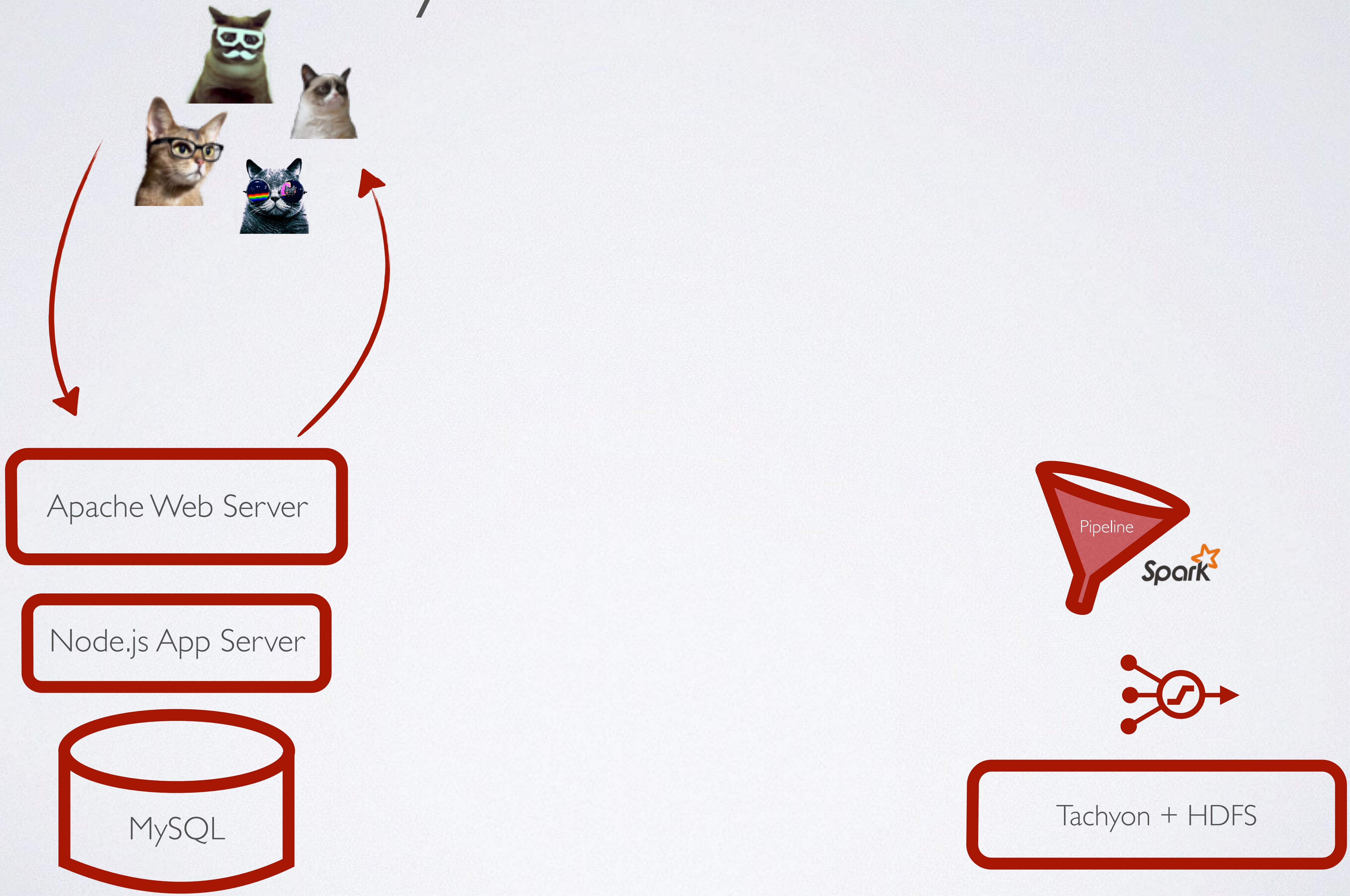

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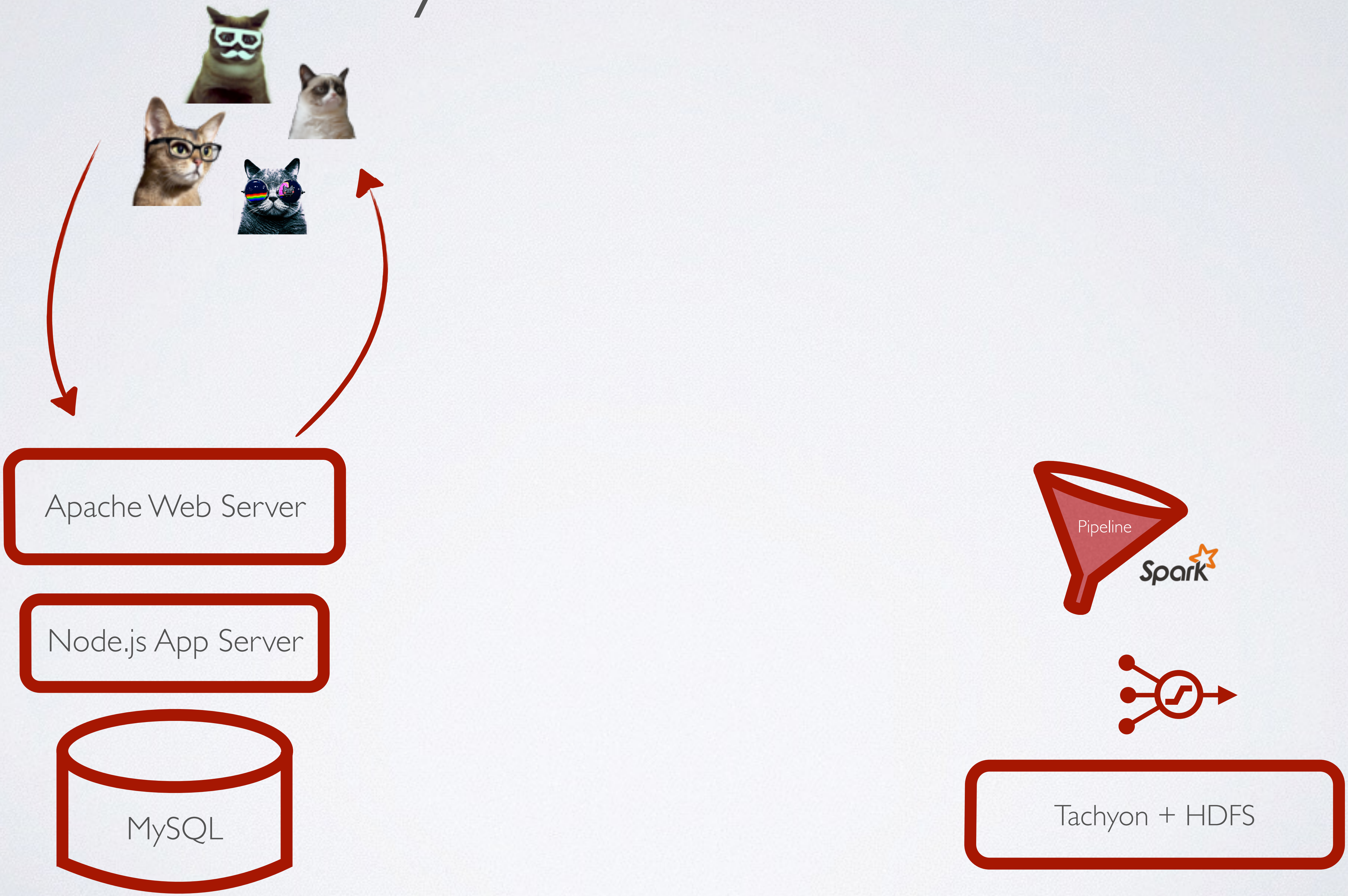

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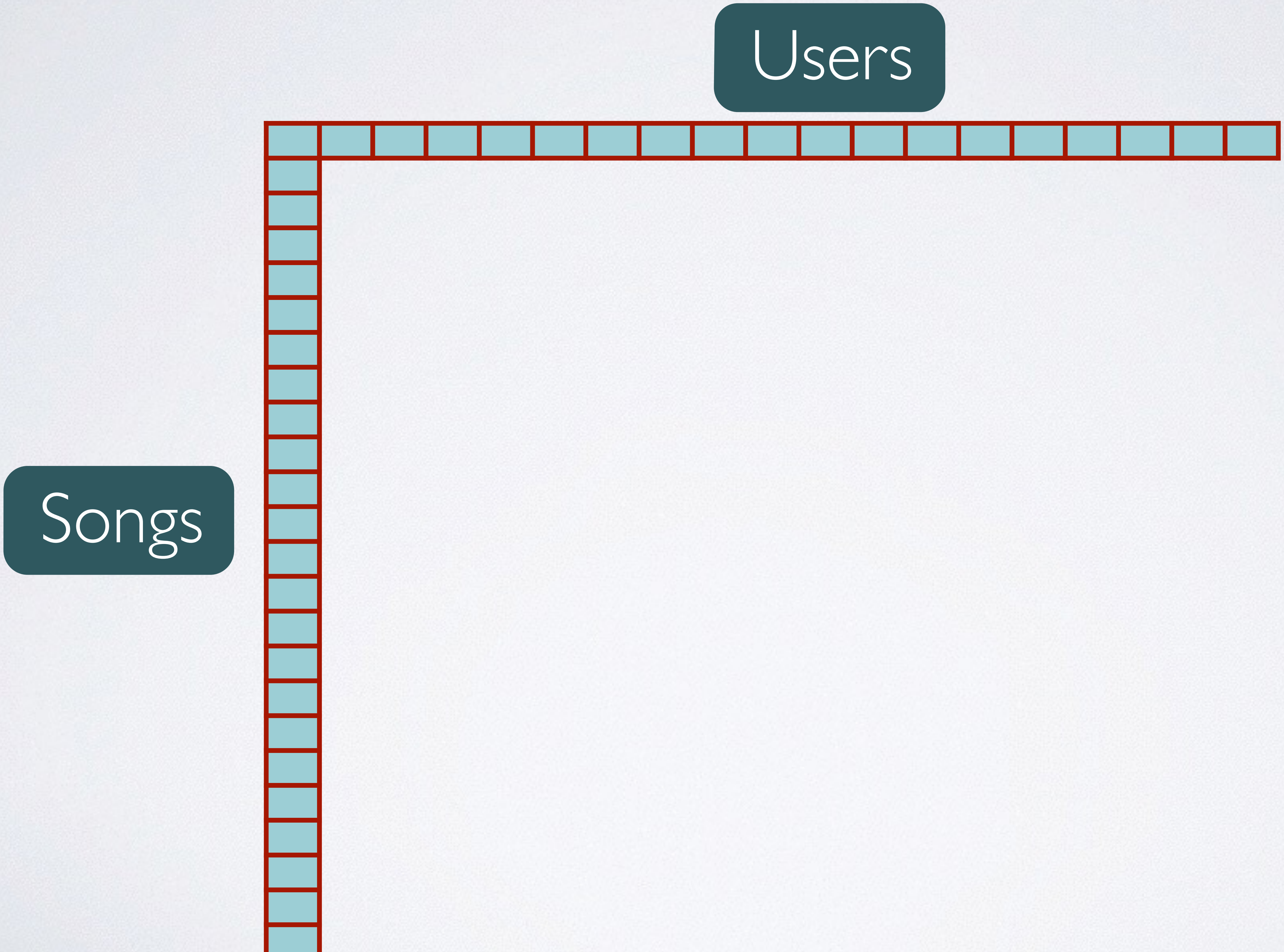

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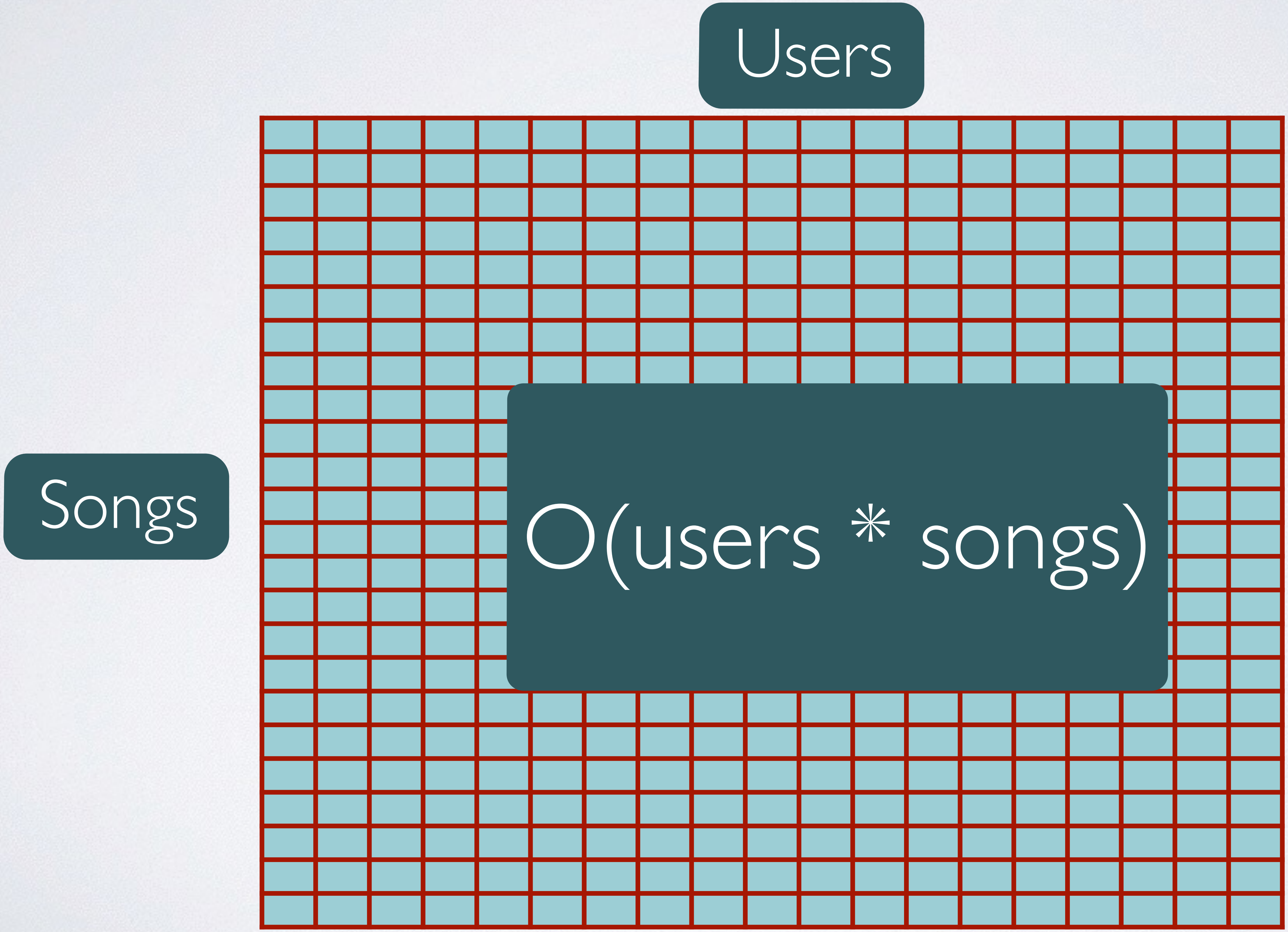

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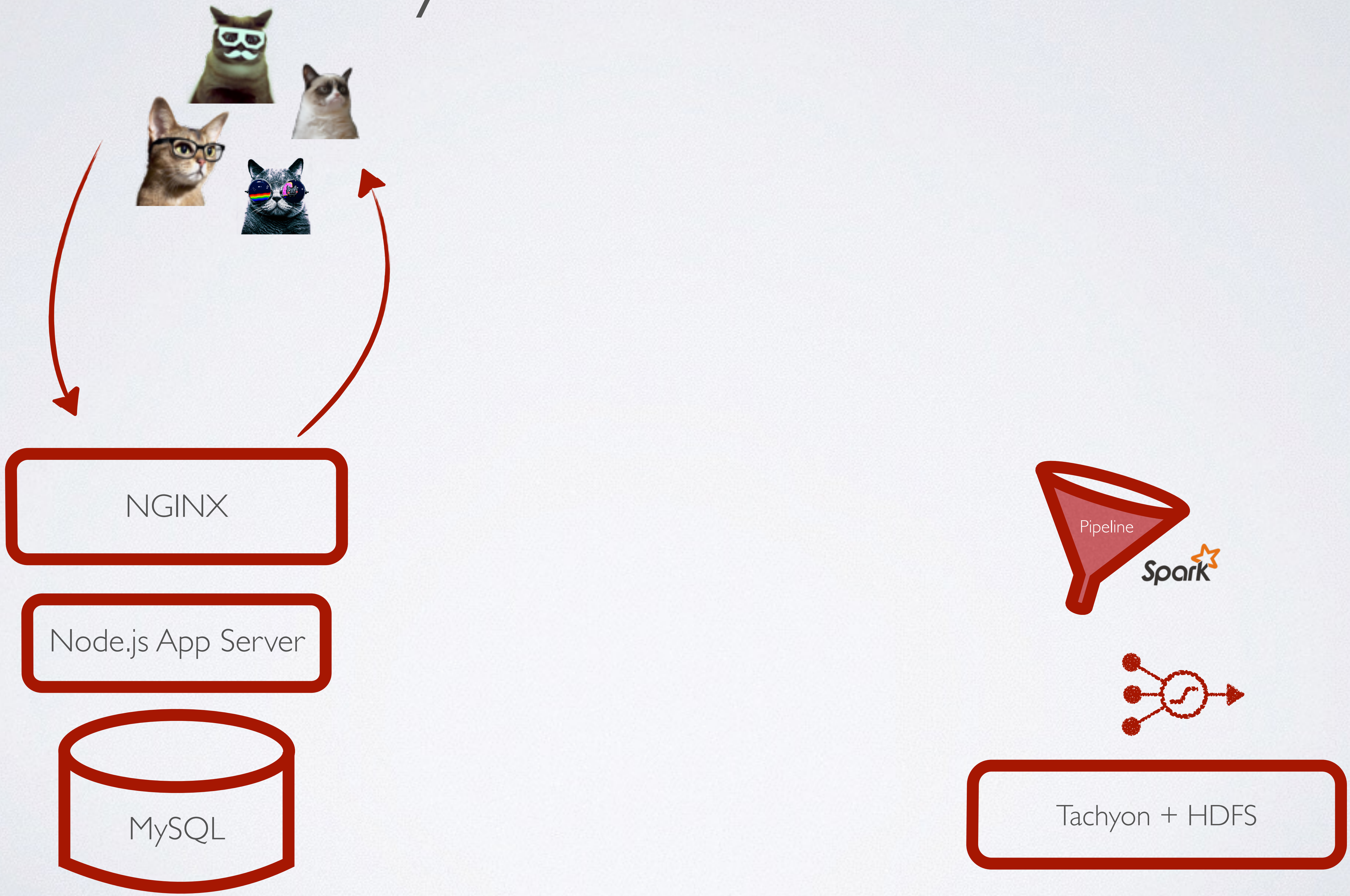

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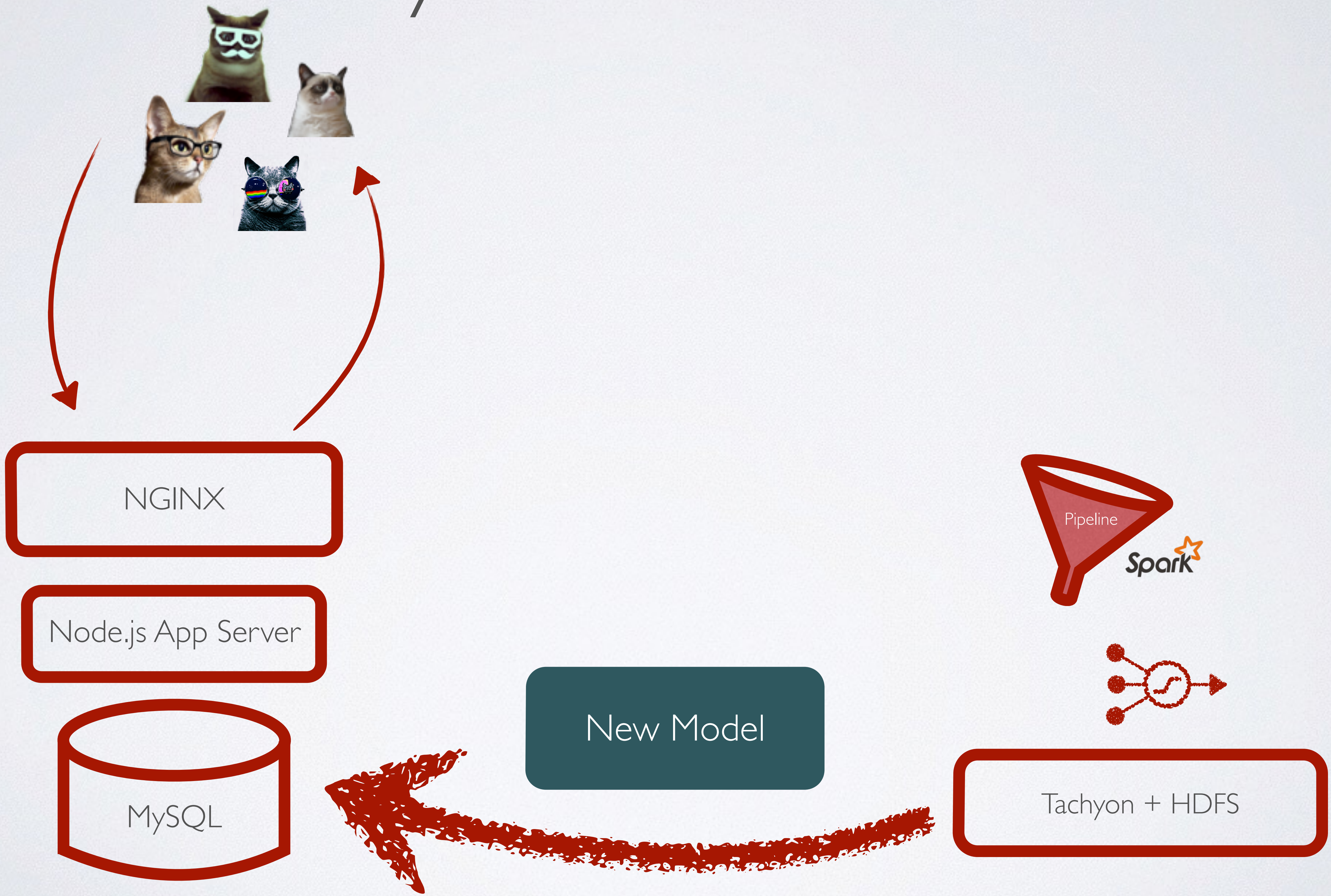

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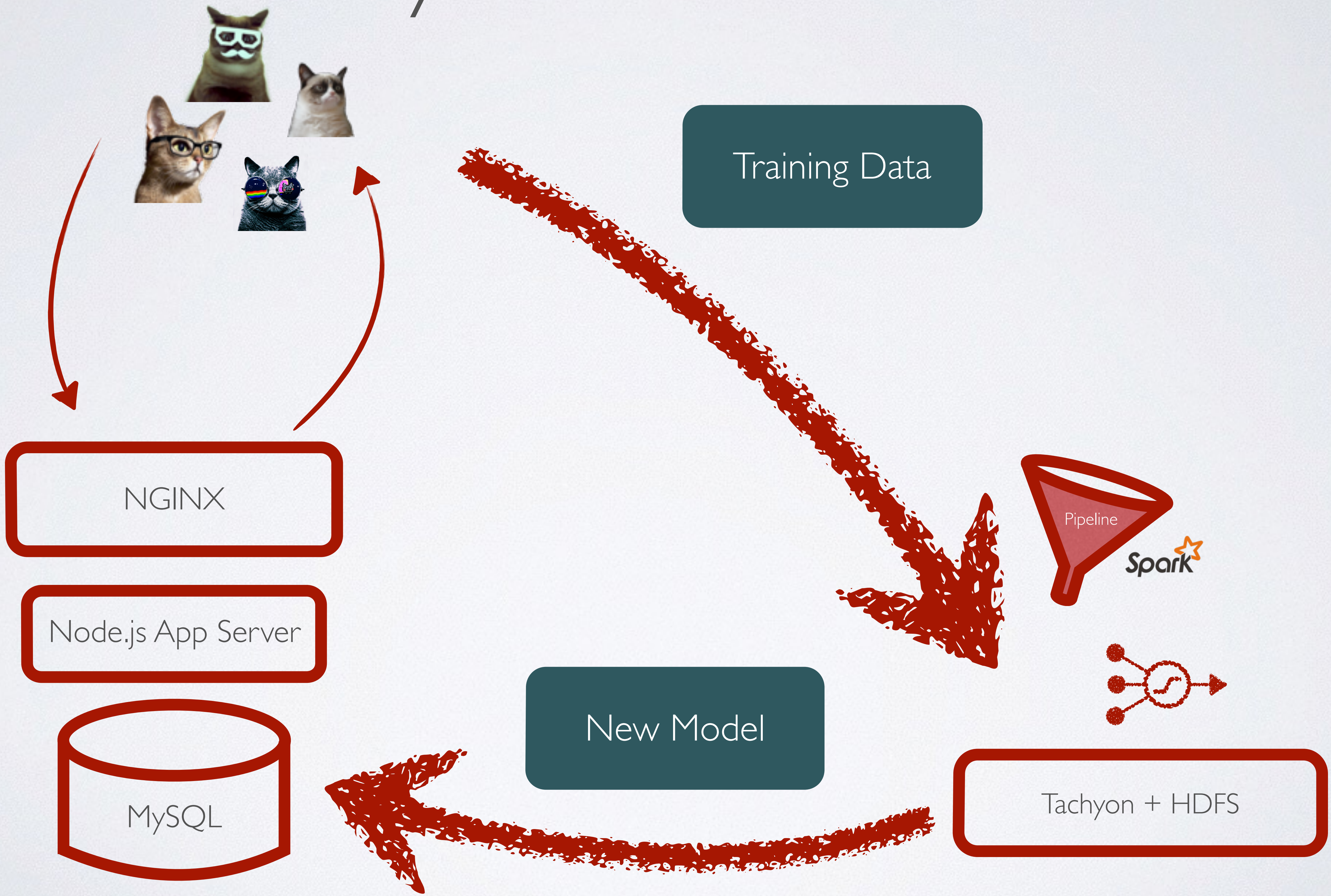

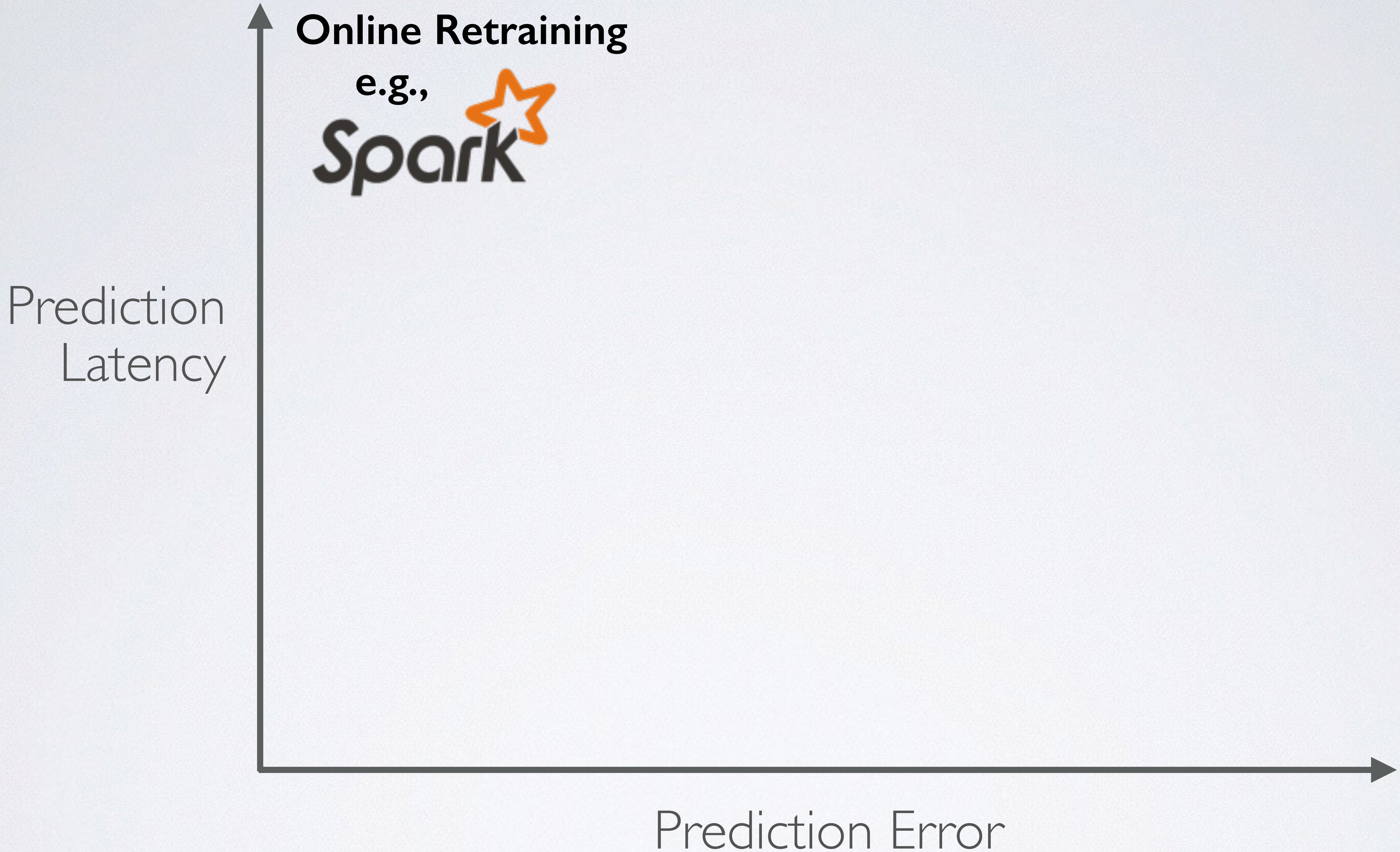
Online Retraining
e.g.,
Spark
Prediction Latency
Prediction Error


Online Retraining
e.g.,
Spark
Prediction Latency
Full pre-materialization
e.g.,
MySQL
Prediction Error

What’s wrong?

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2. Limited optimization of model semantics

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1. Predictions have either:
    a. High latency, low staleness
    b. Low latency, high staleness
2. Limited optimization of model semantics
3. Ad-hoc lifecycle management

Talk Outline

- **ML model management today**
- Velox system architecture
- Split model family
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VELOX GOALS

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2. Cross-cutting model-specific optimizations

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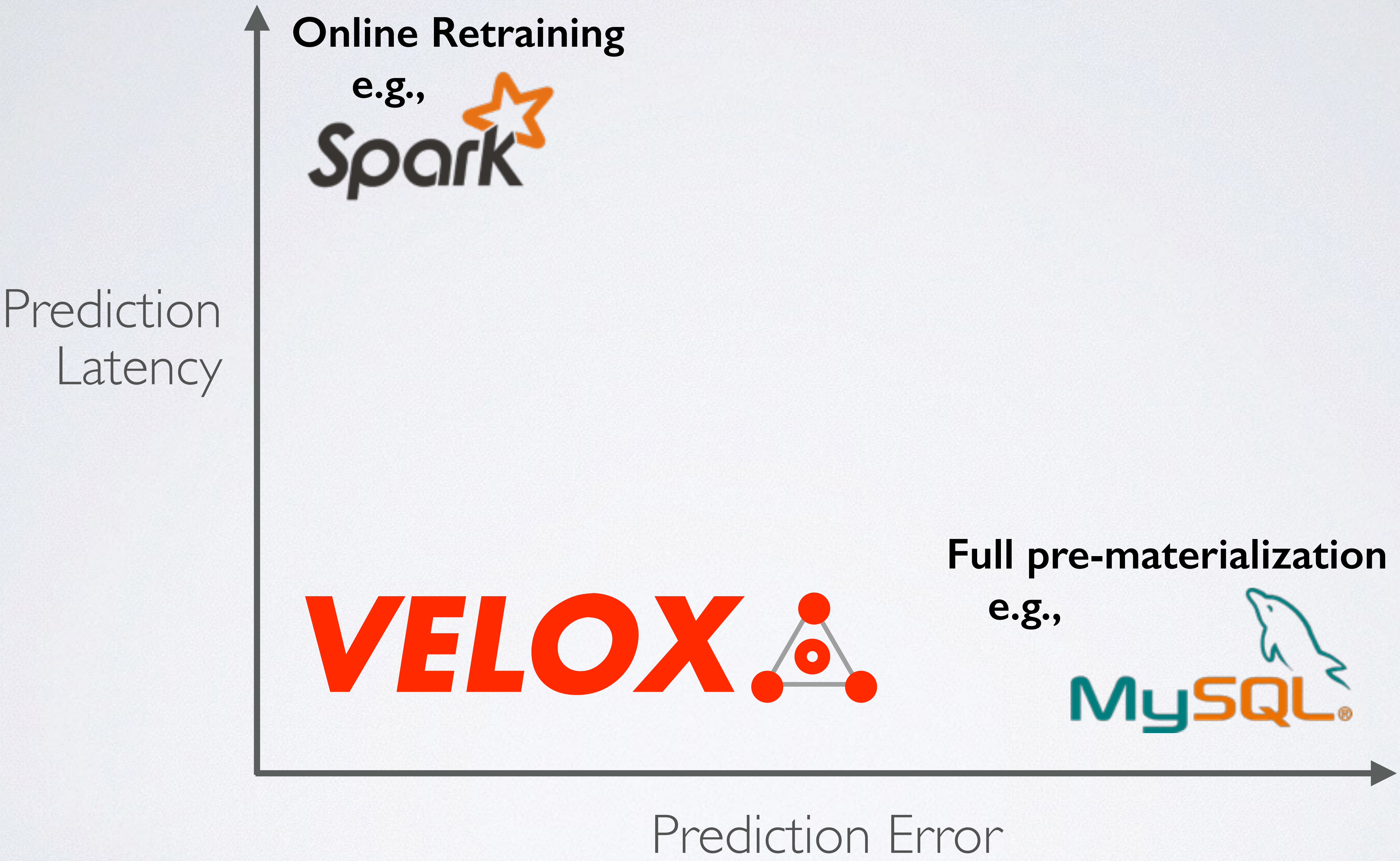
1. Low latency and low error predictions
2. Cross-cutting model-specific optimizations
3. Unified system eases operation



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Online Retraining
e.g.,
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key idea:
split model into
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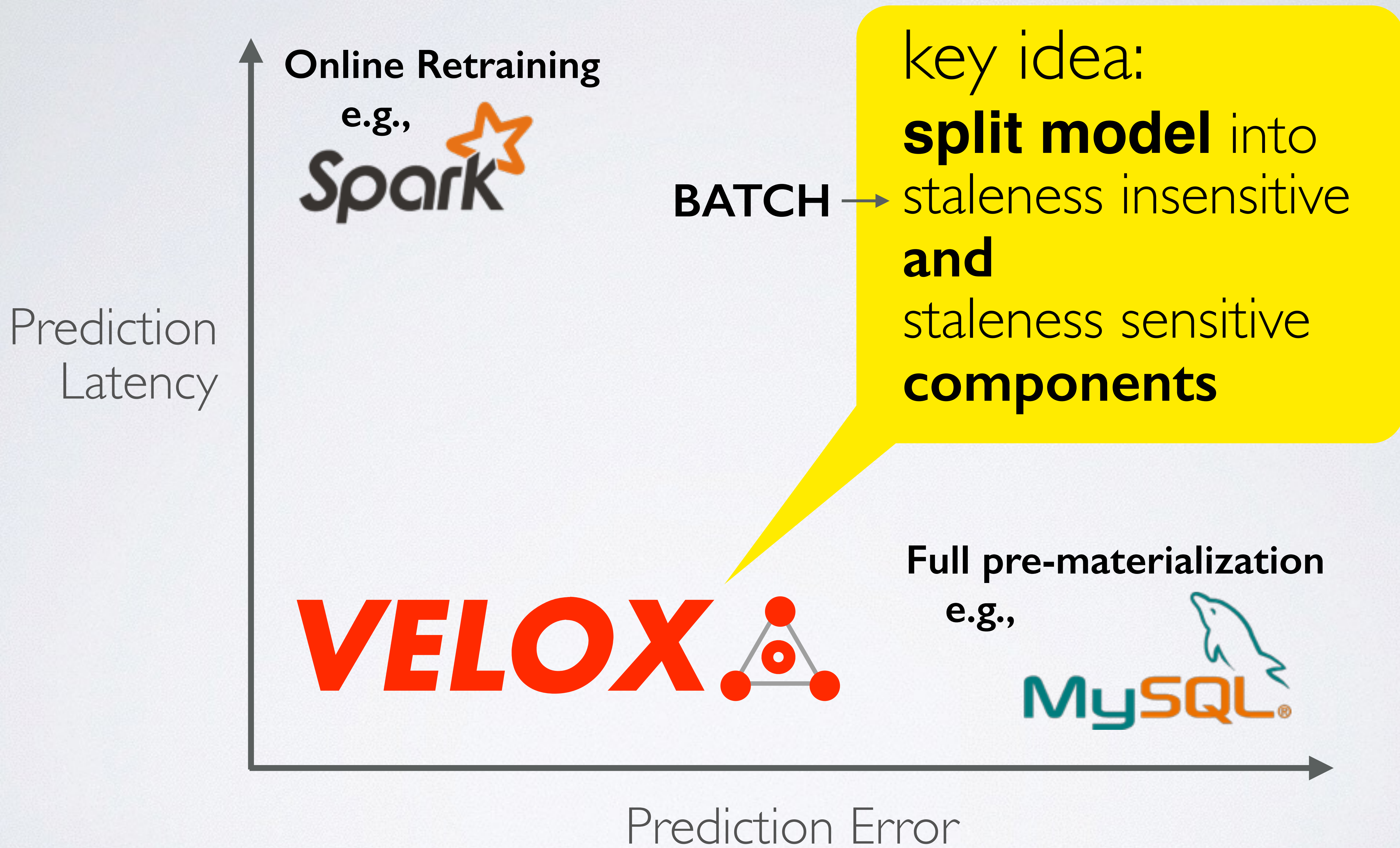
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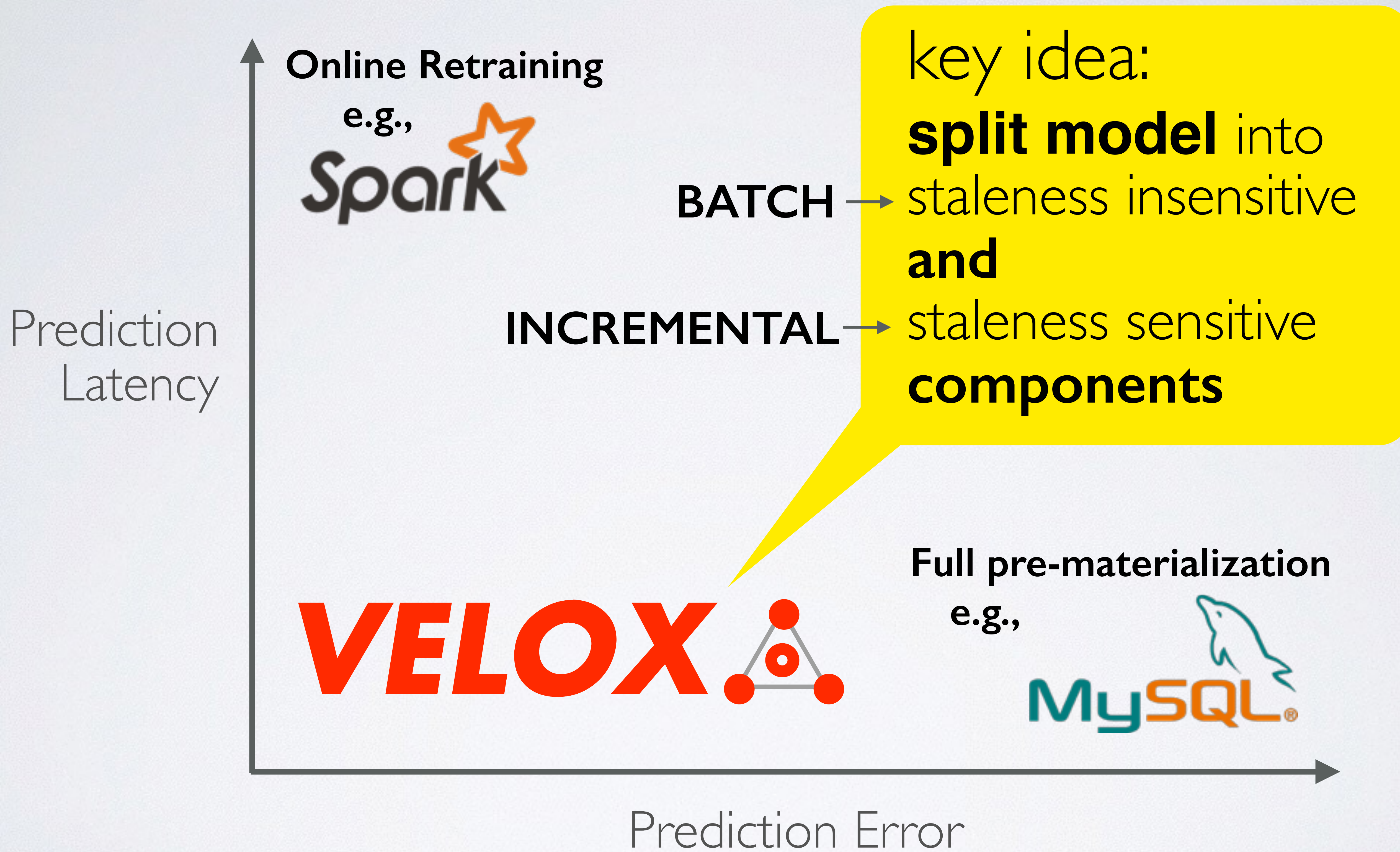
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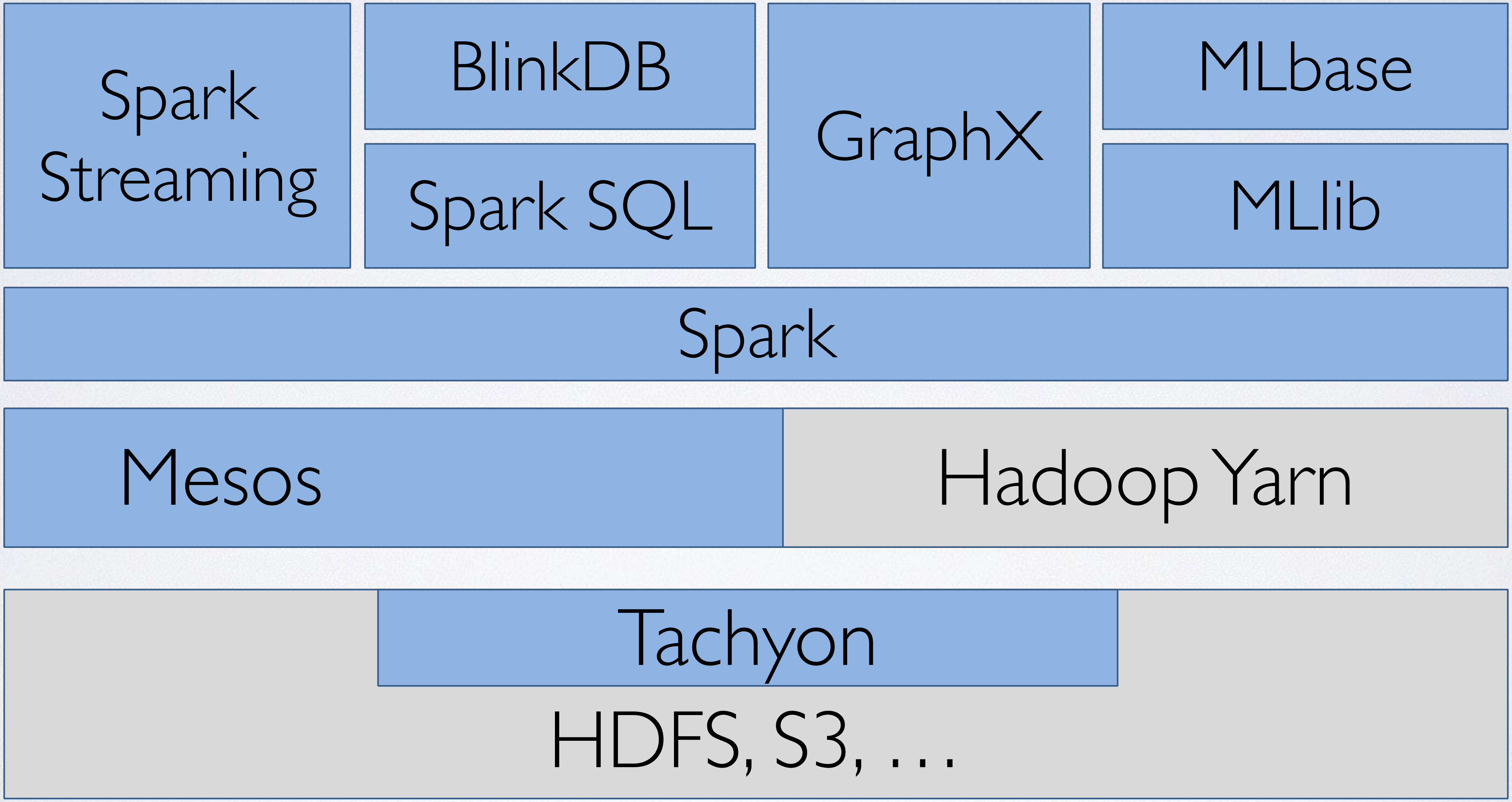
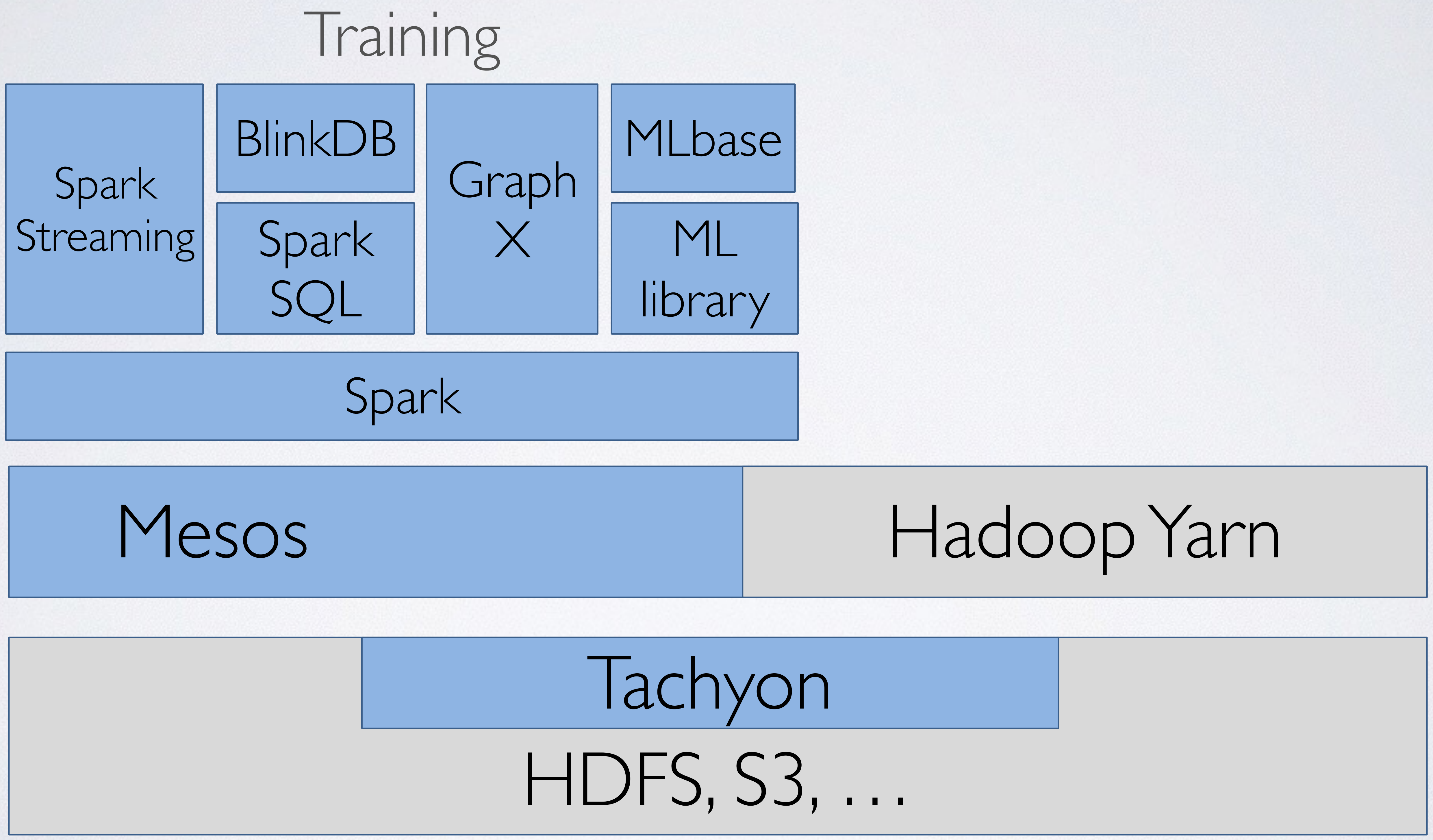


THE MISSING PIECE



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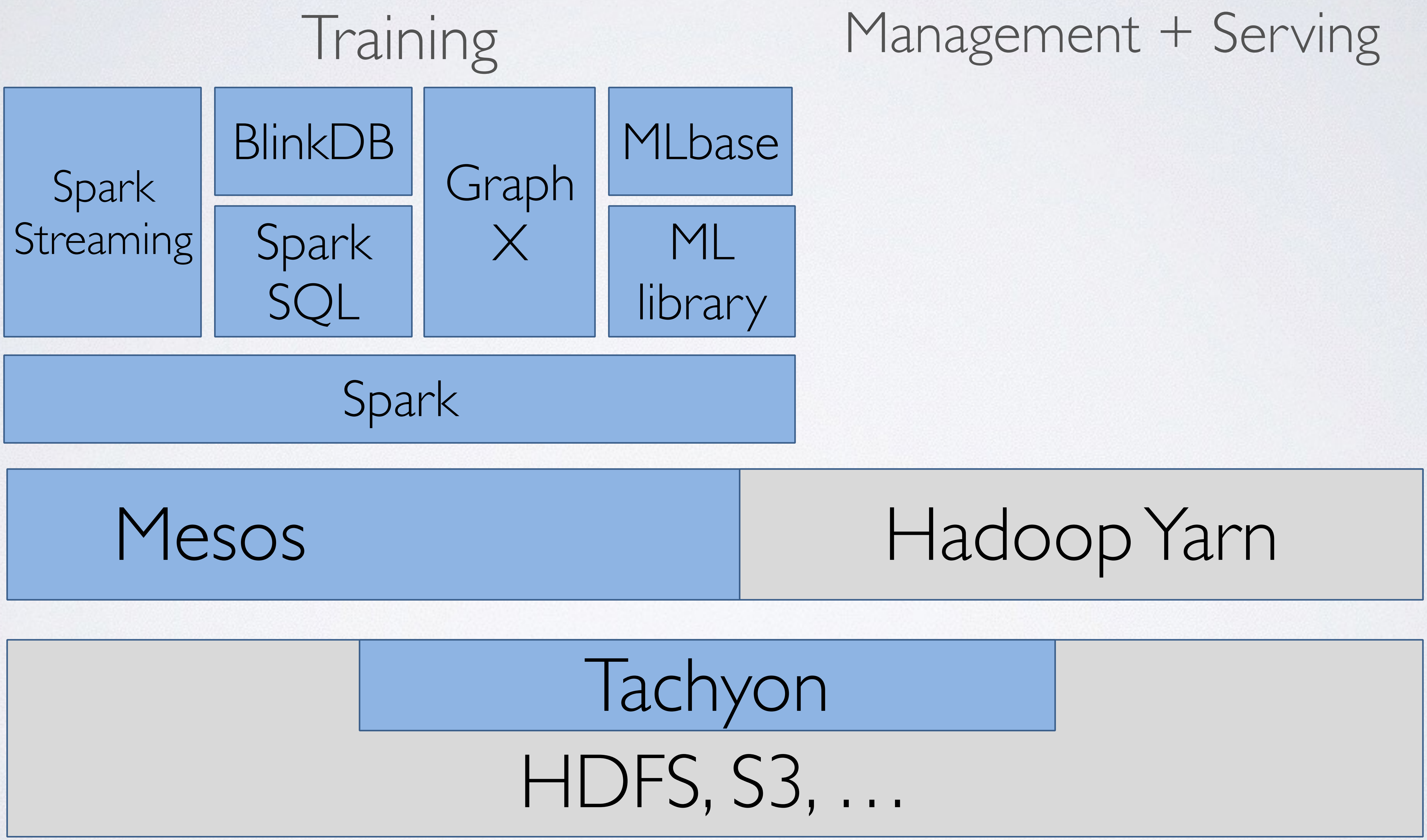

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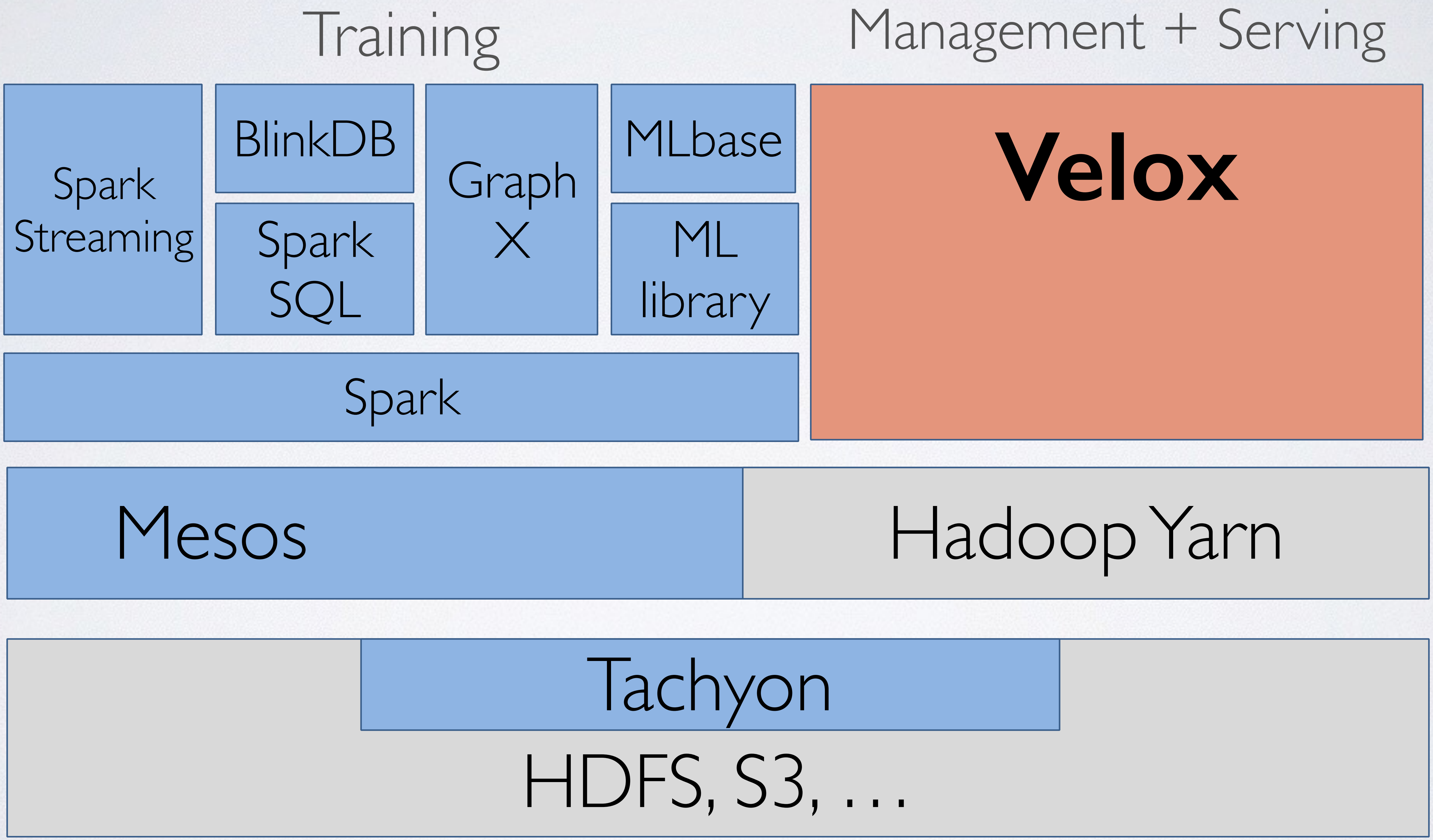

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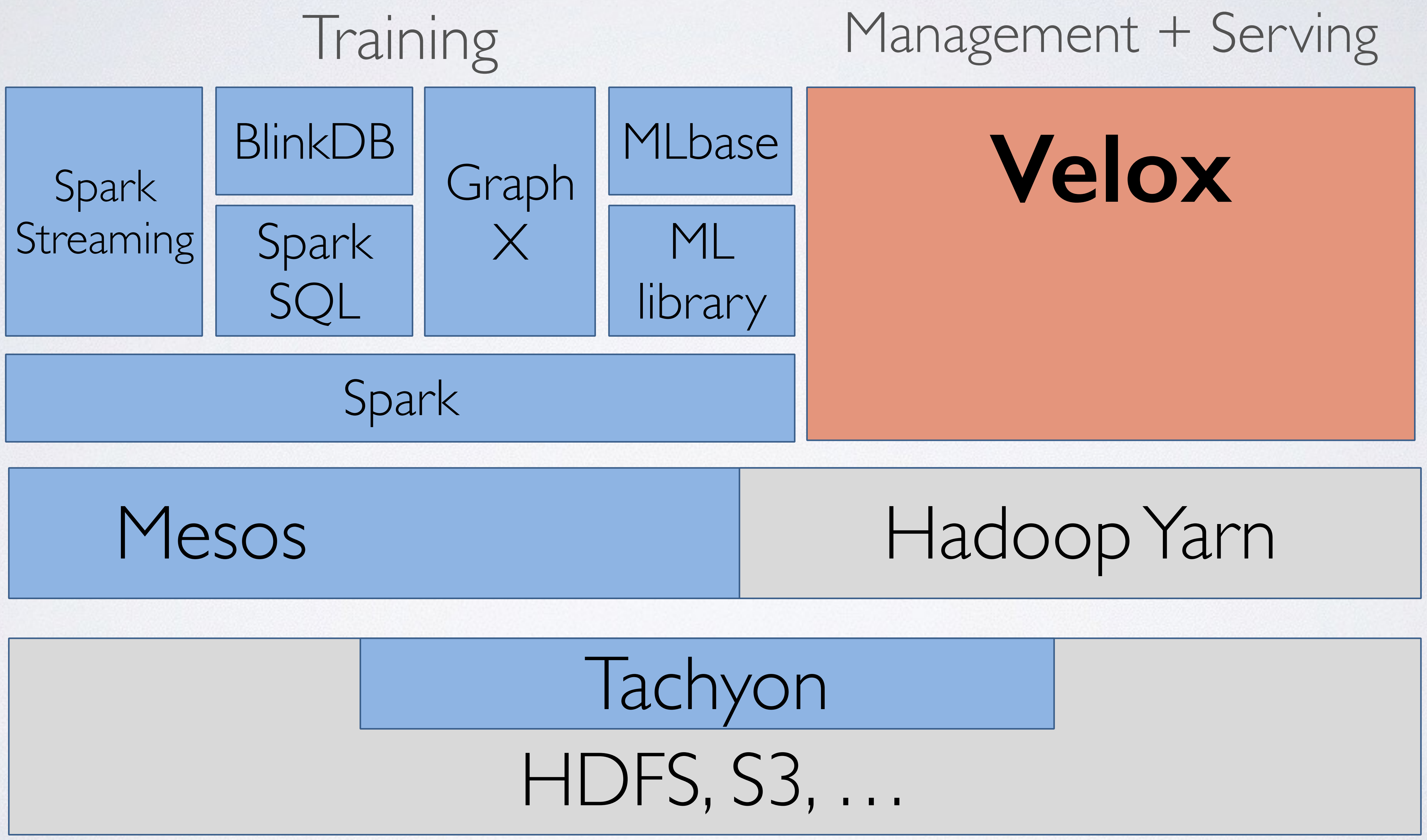

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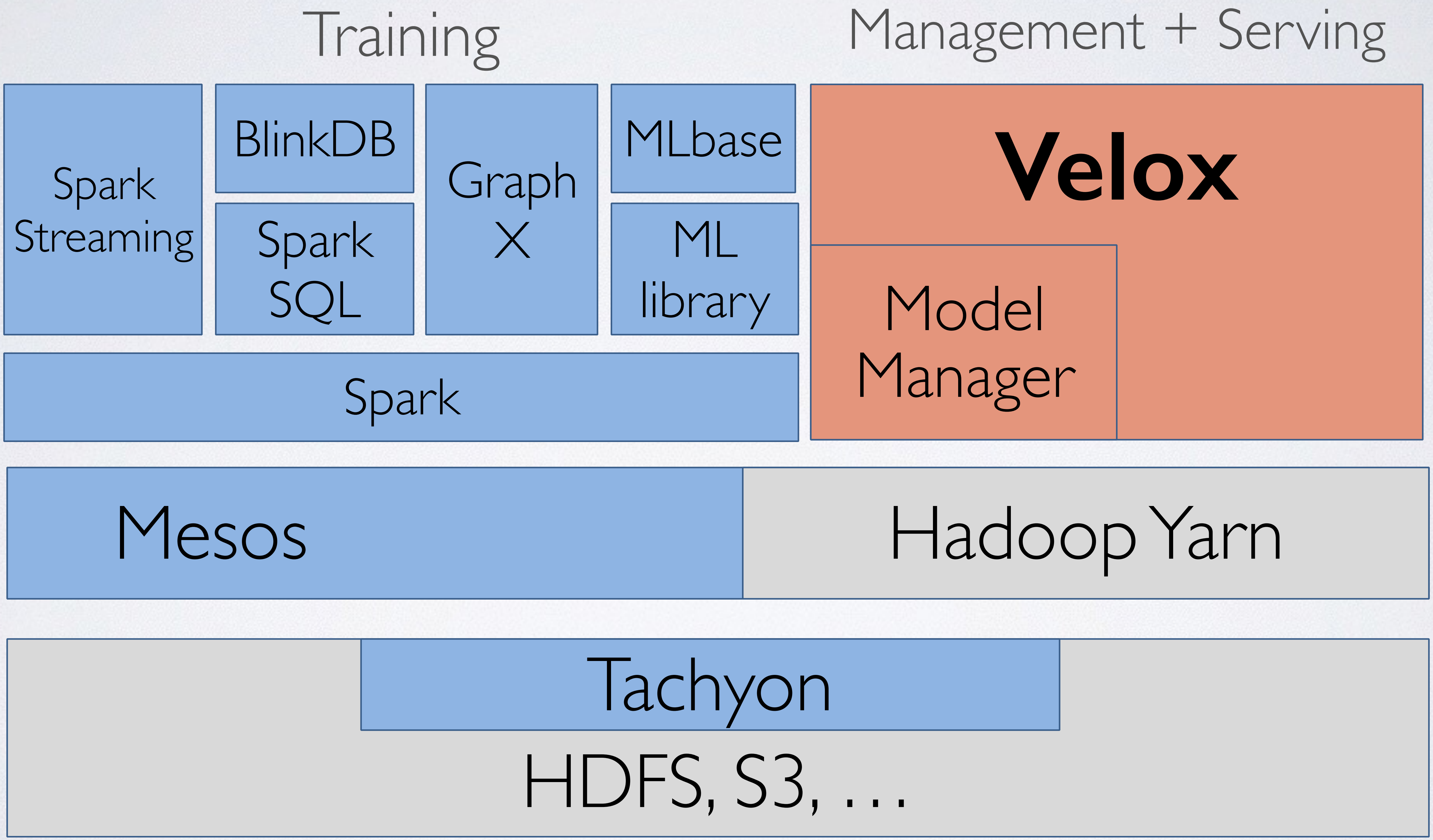

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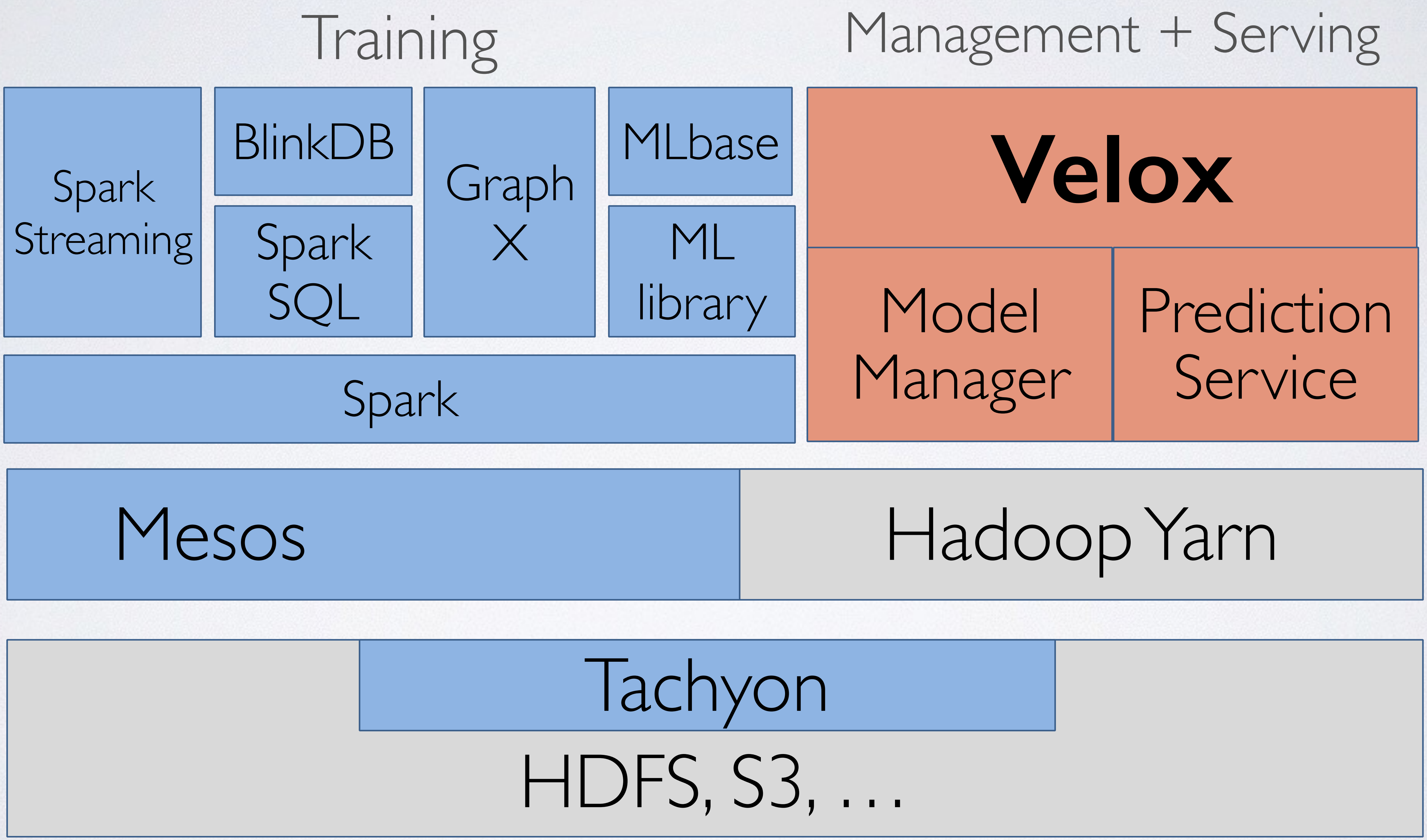

PREDICTION SERVICE

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1. Maintains models via online and batch retraining

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MODEL MANAGER

1. Maintains models via online and batch retraining
2. Stores model catalog, metadata, versioning

PREDICTION SERVICE

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MODEL MANAGER

1. Maintains models via online and batch retraining
2. Stores model catalog, metadata, versioning
3. Contains library of standard models + custom API

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PERSONALIZED MODELING




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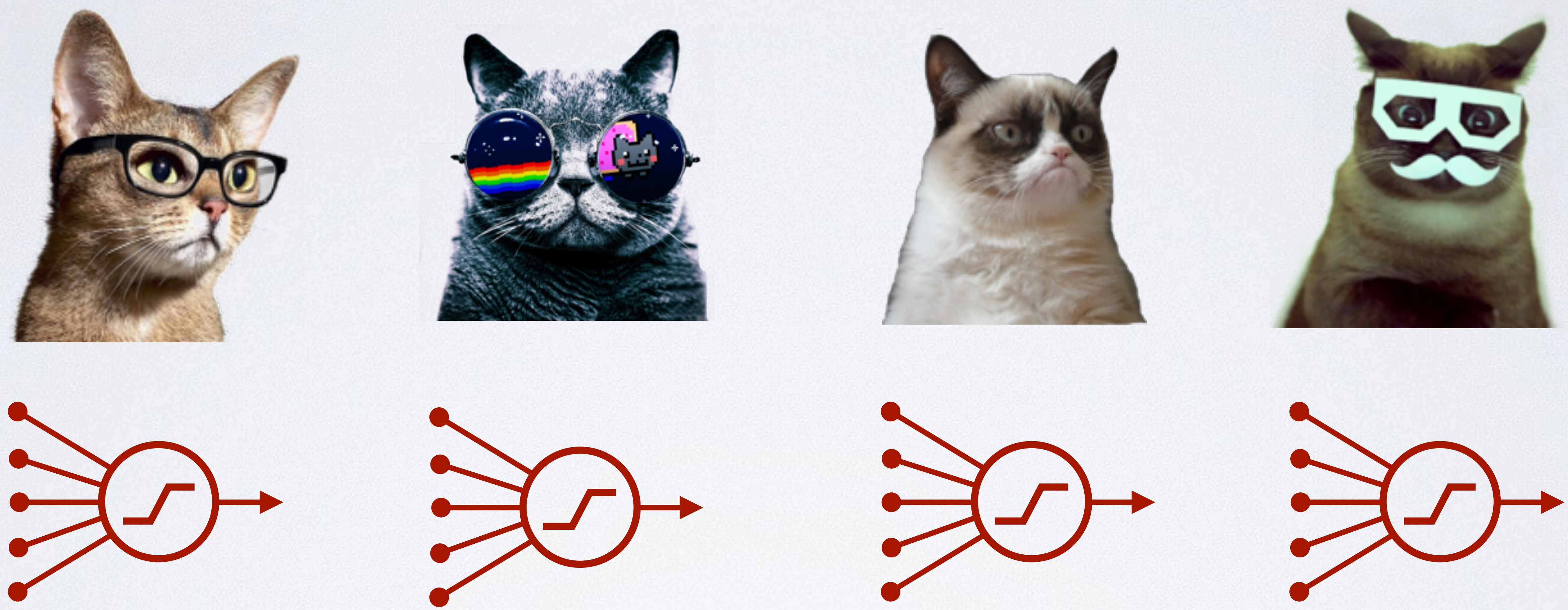

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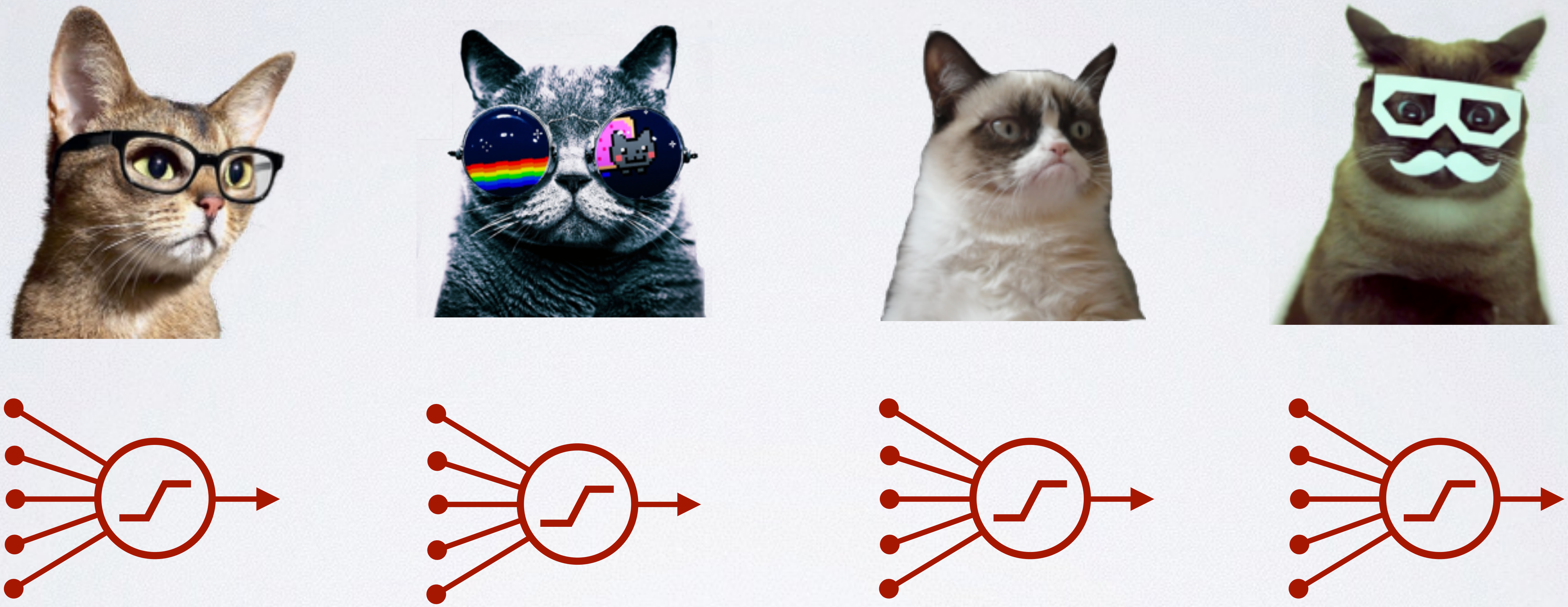
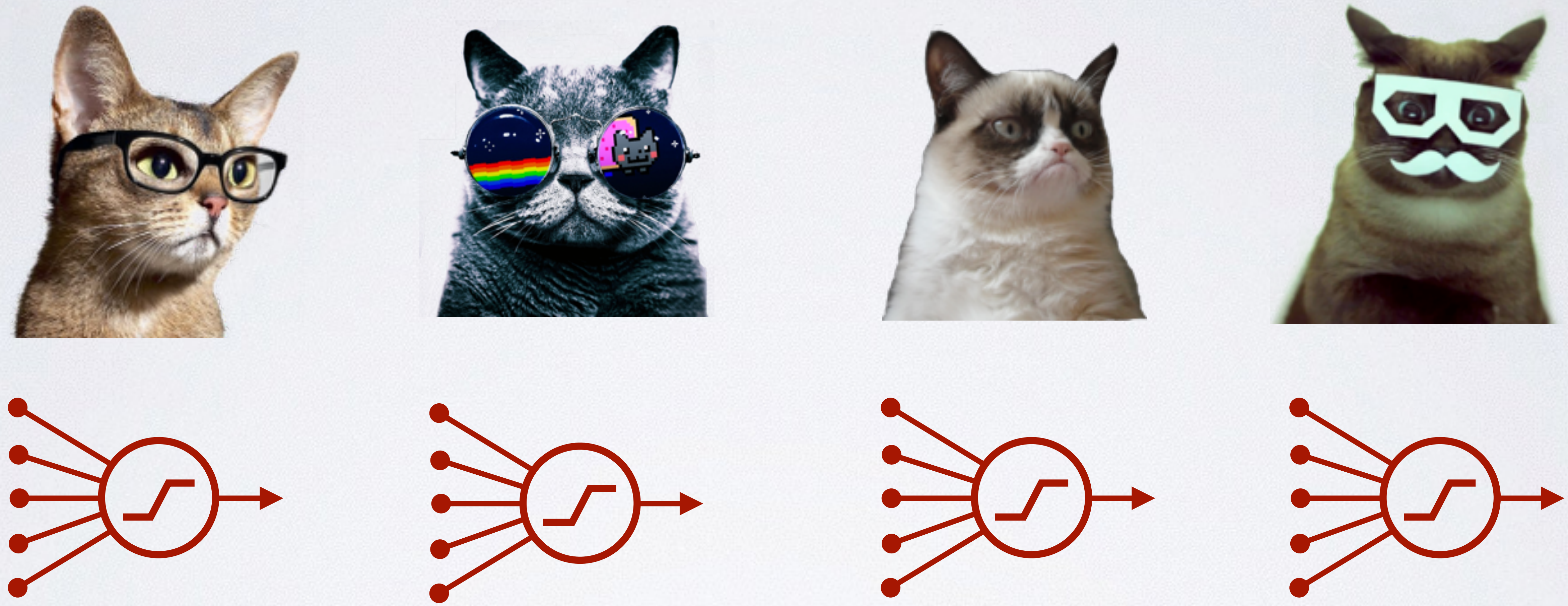


A Separate Model for Each User?

PERSONALIZED MODELING

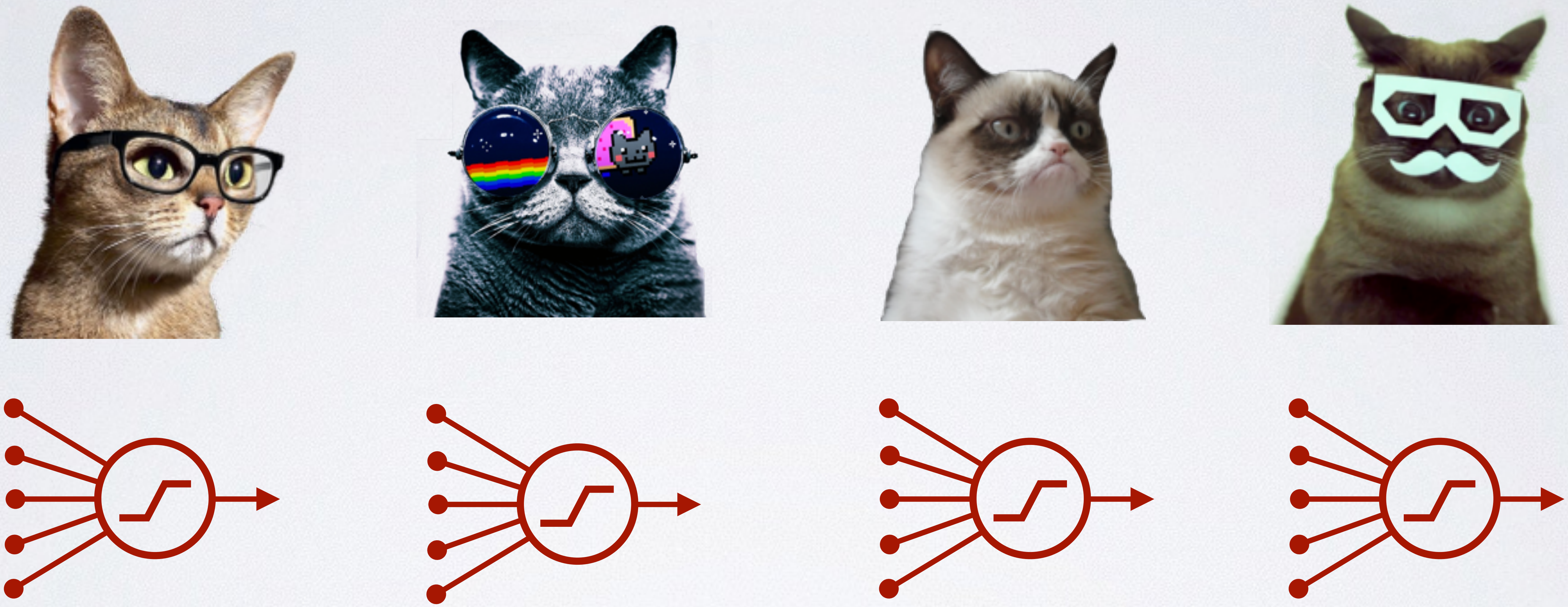


A Separate Model for Each User?

Computationally Inefficient

many complex models

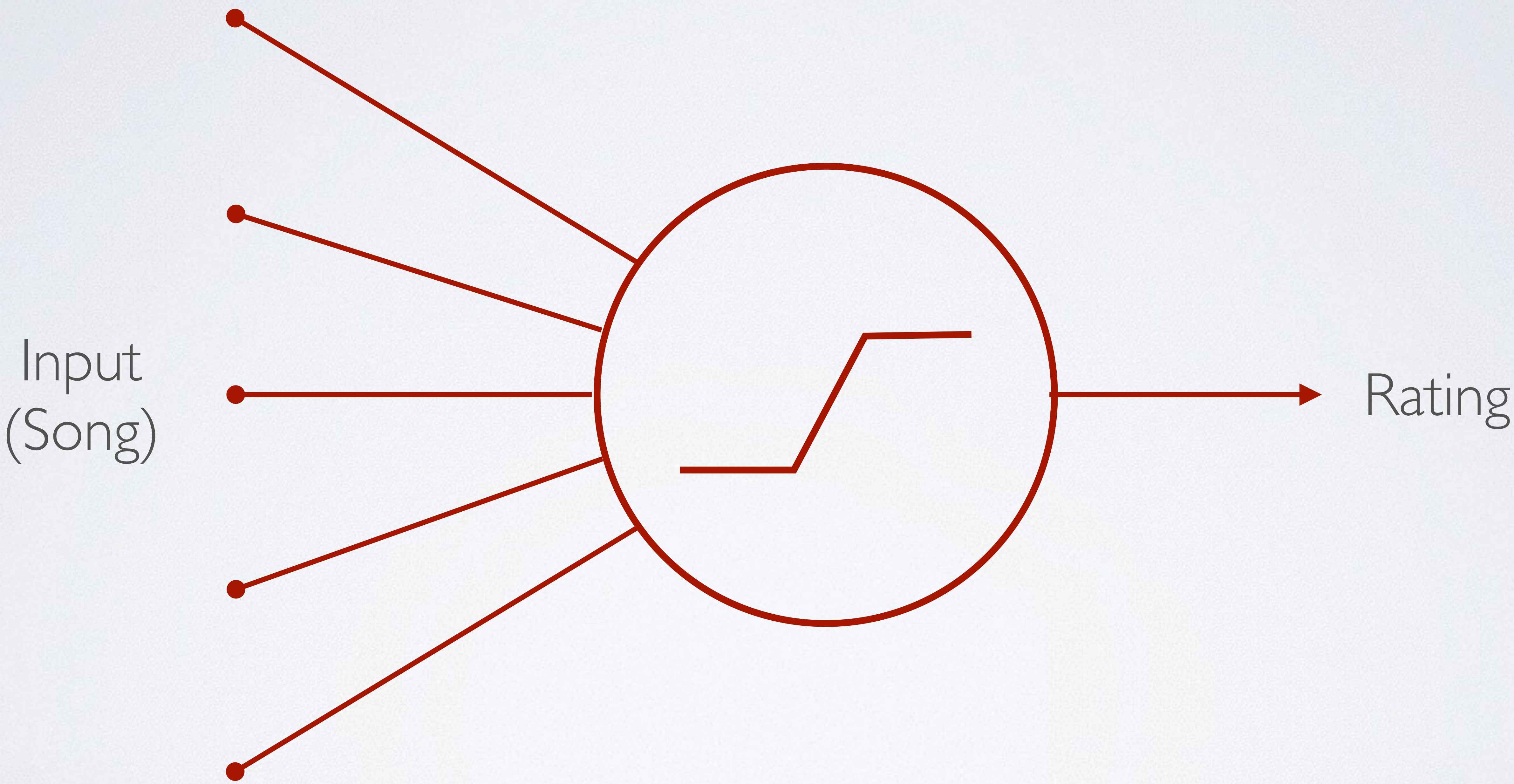
PERSONALIZED MODELING

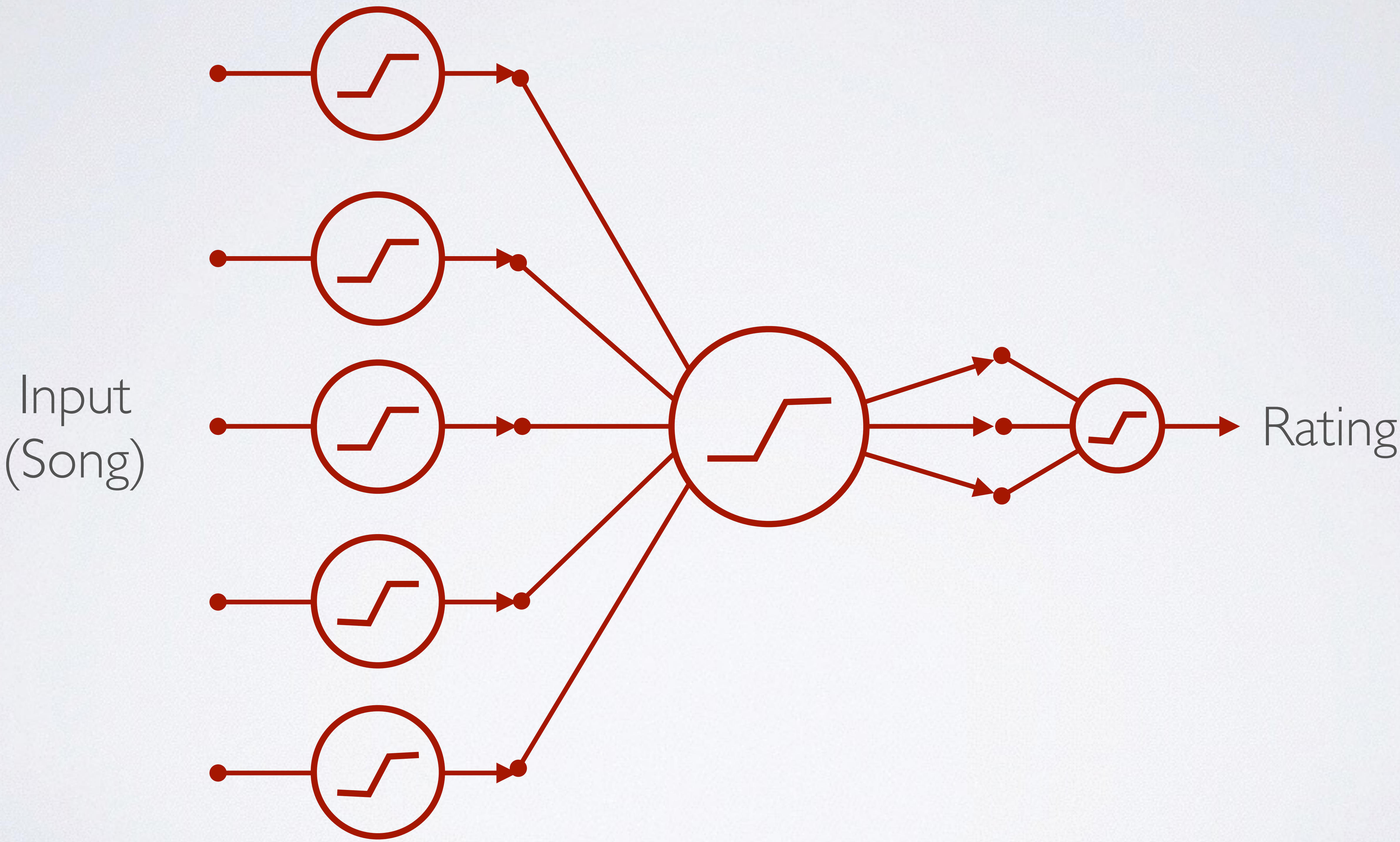


A Separate Model for Each User?

Computationally Inefficient
many complex models

Statistically Inefficient
not enough data per user


Input
(Song)
Rating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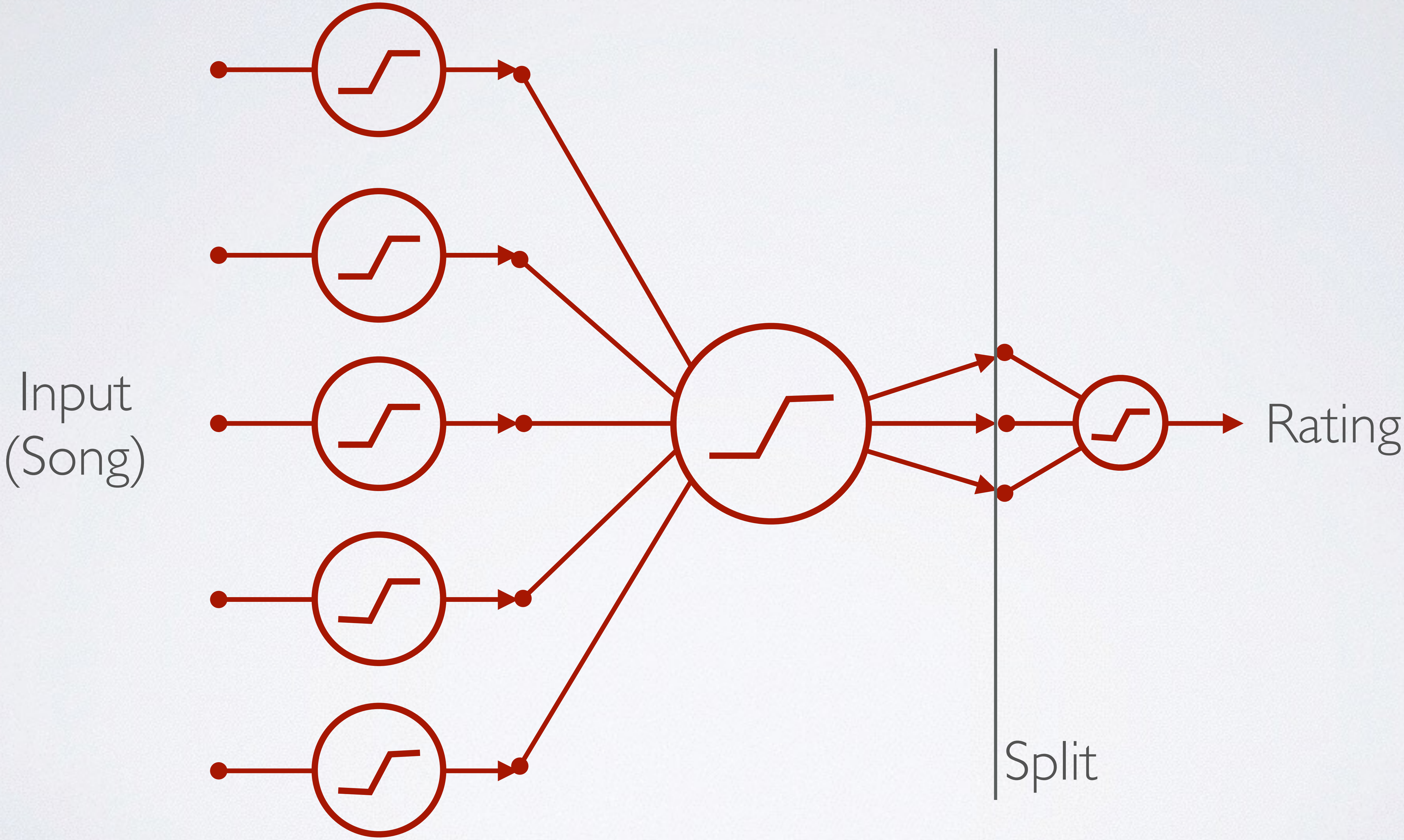
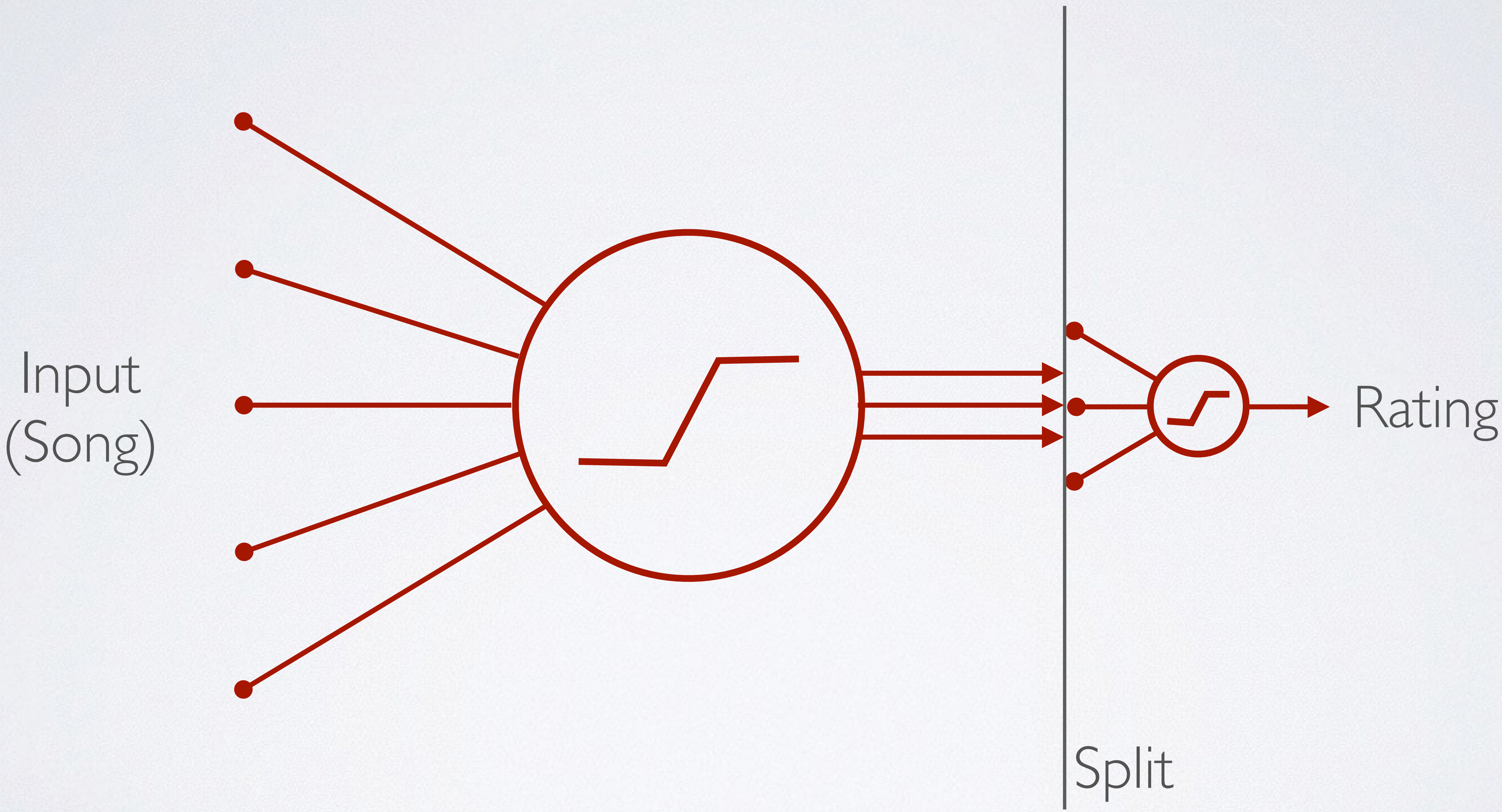

Input
(Song)
Rating
Split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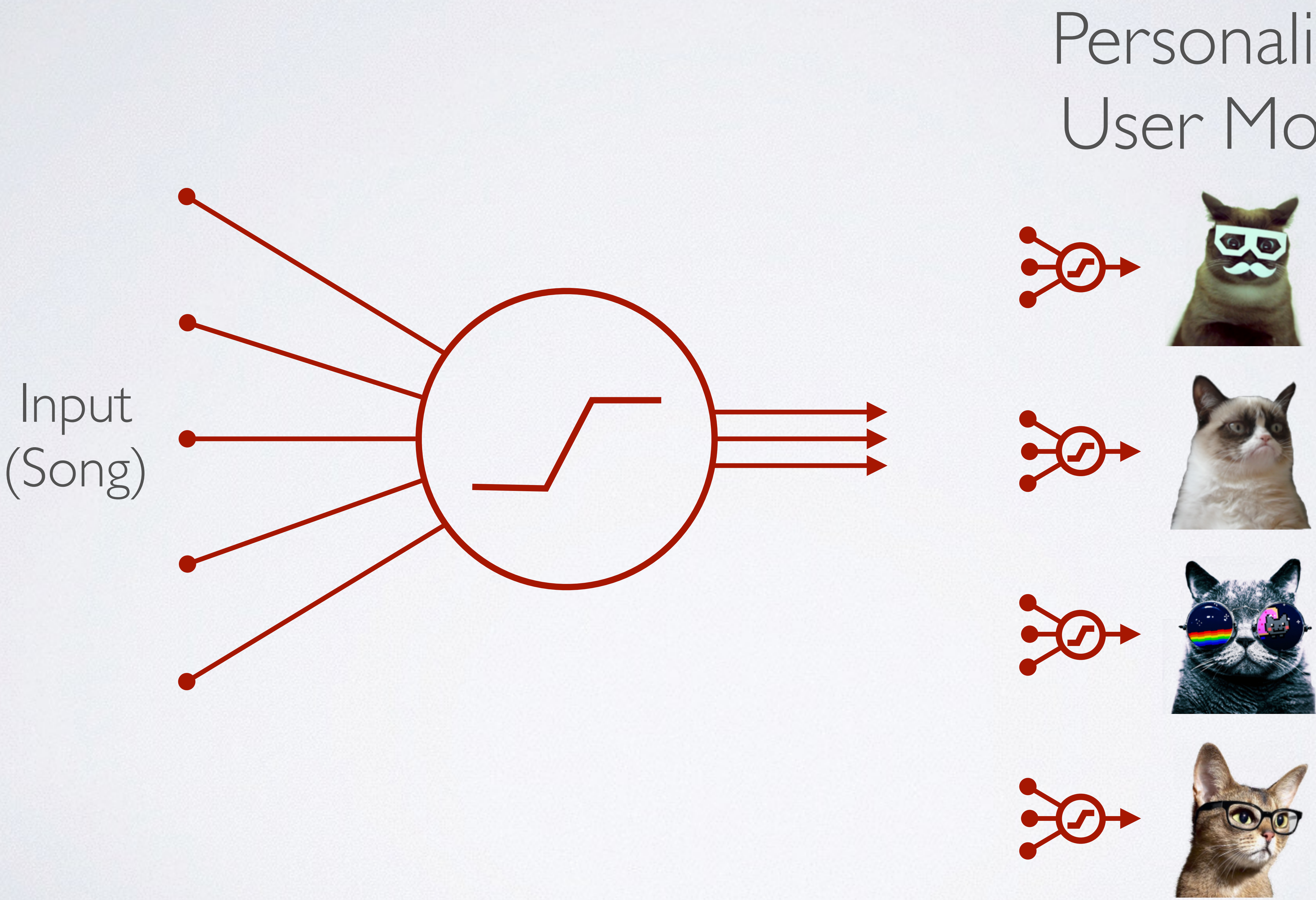

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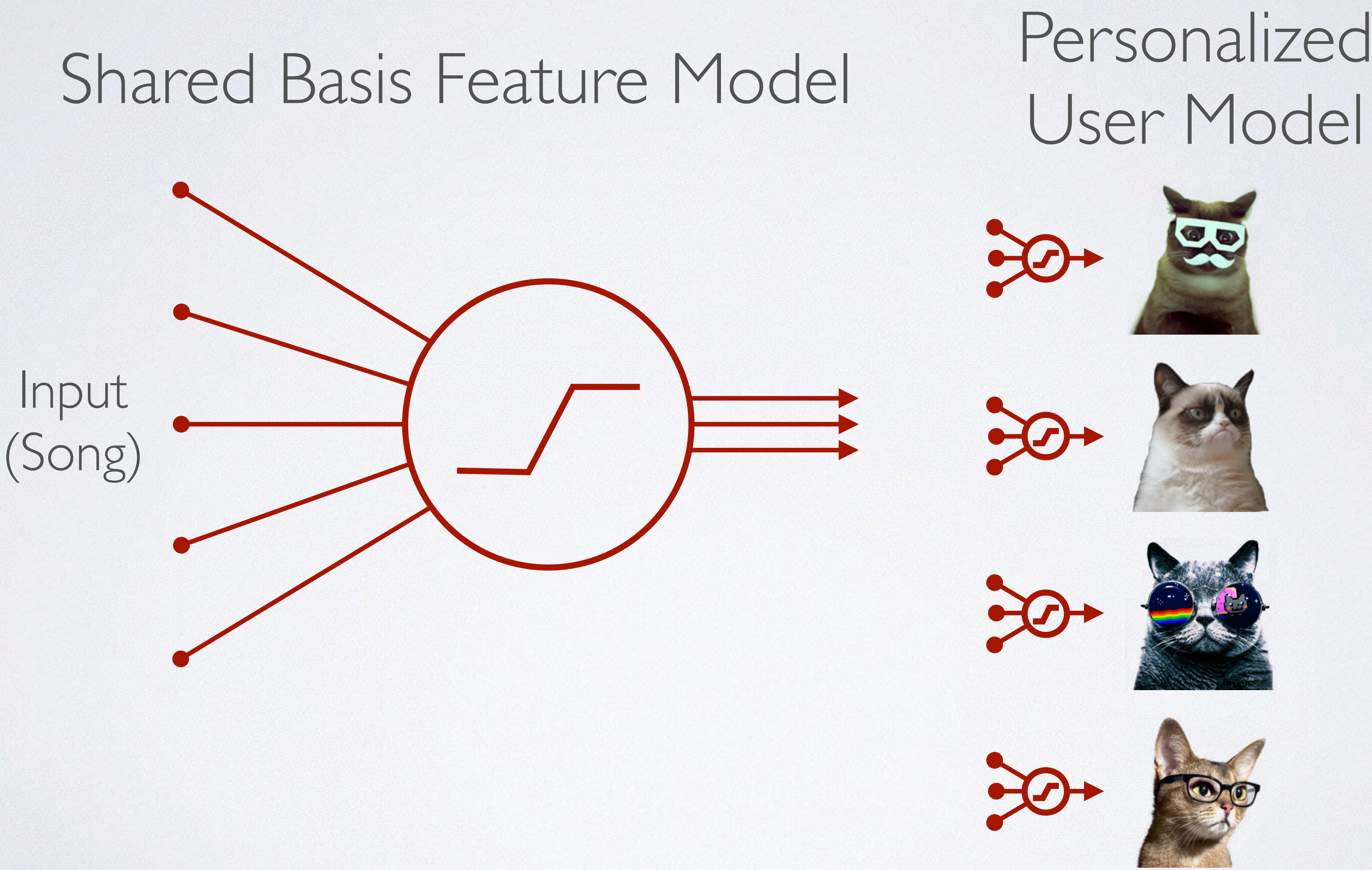


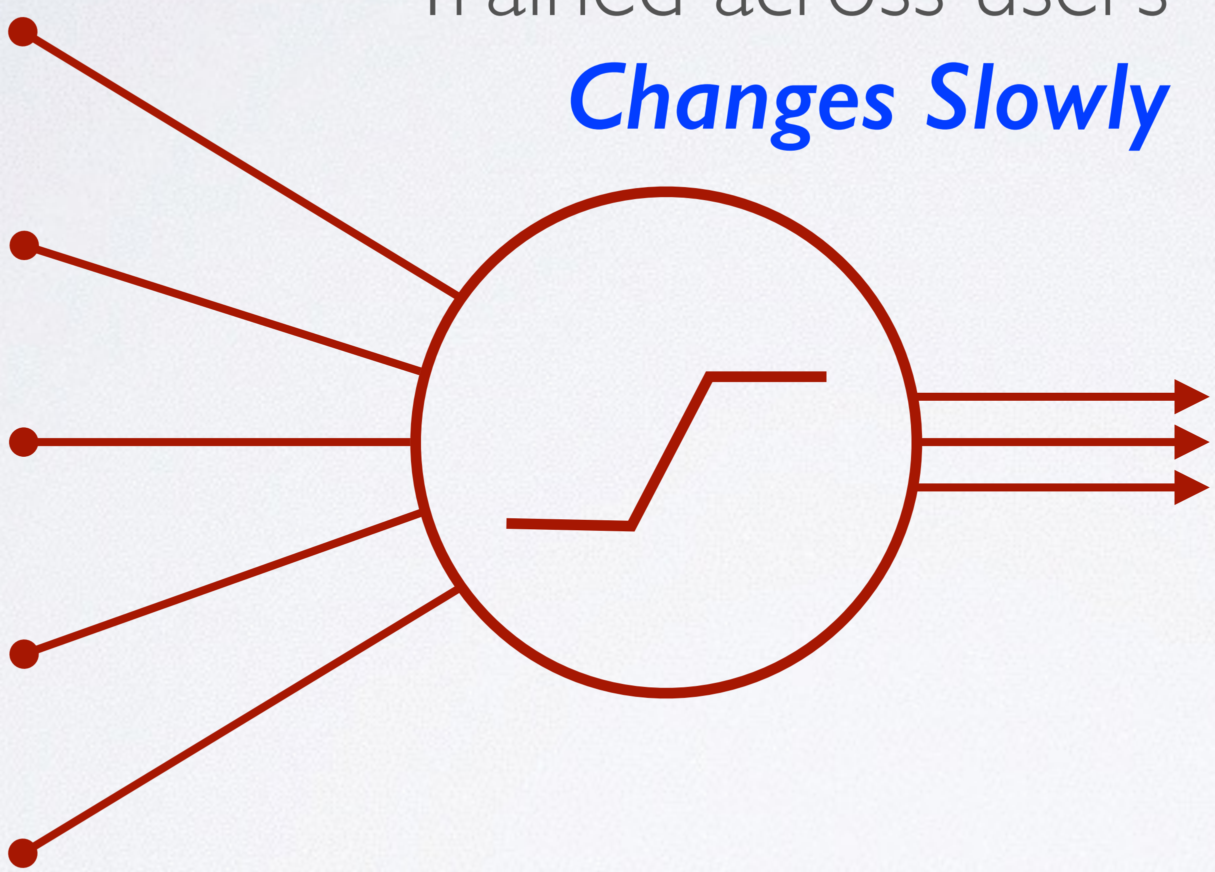
PERSONALIZED MODELING

Shared Basis Feature Model

Trained across users

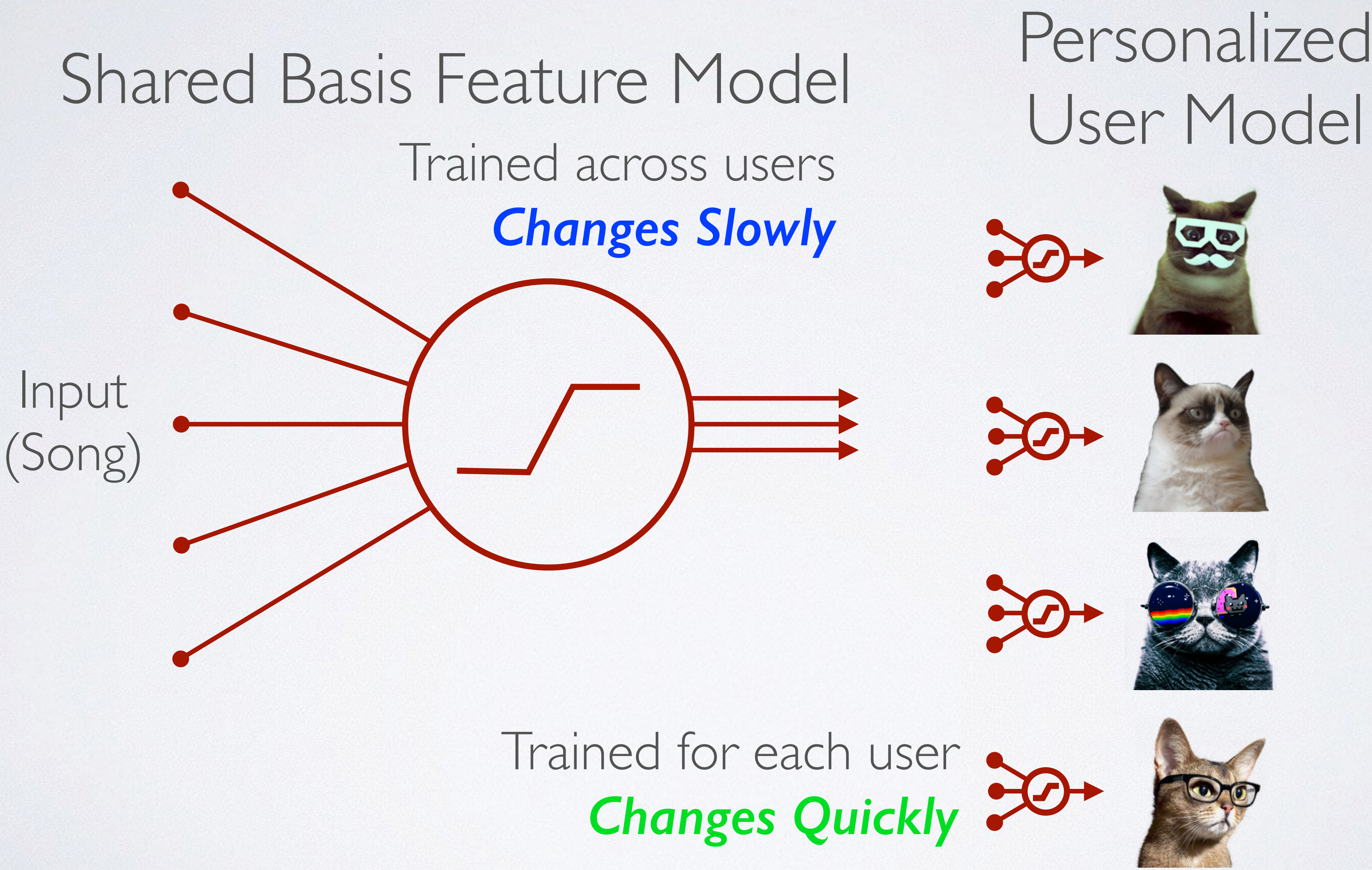
Changes Slowly

Input
(Song)

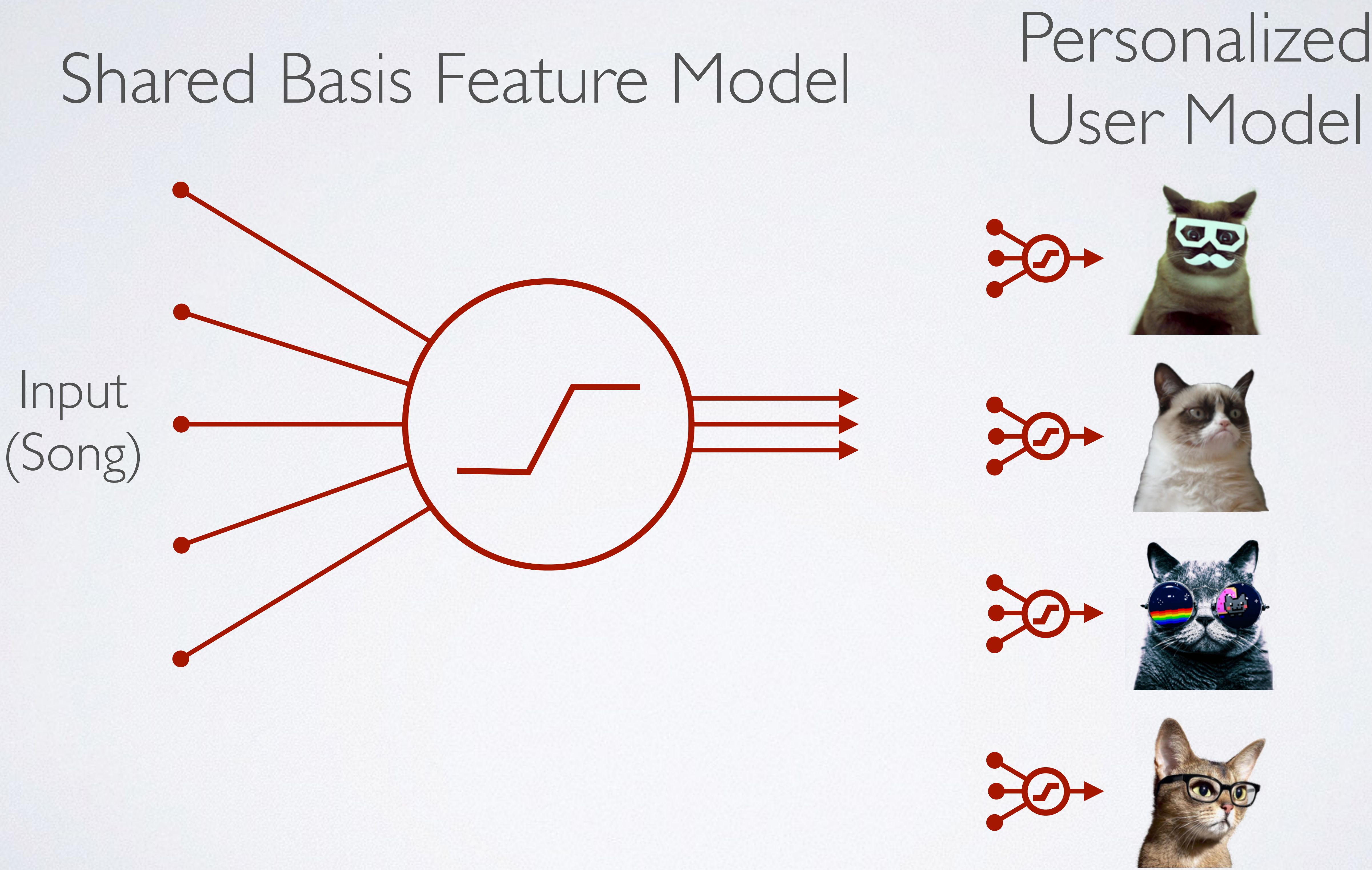


Personalized User Model

PERSONALIZED MODELING



SPLIT MODEL FORMULATION



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Shared Basis Feature Model

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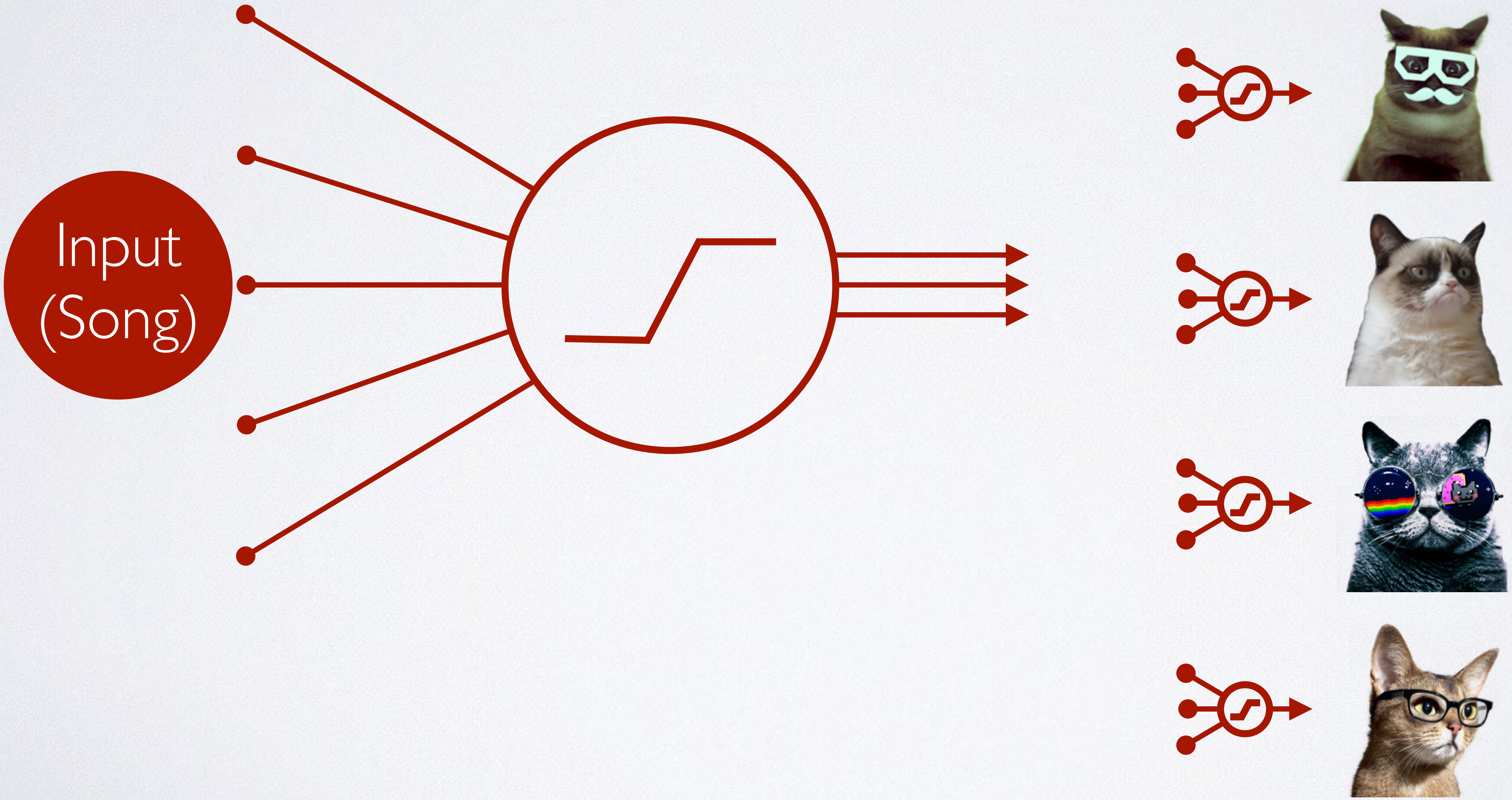

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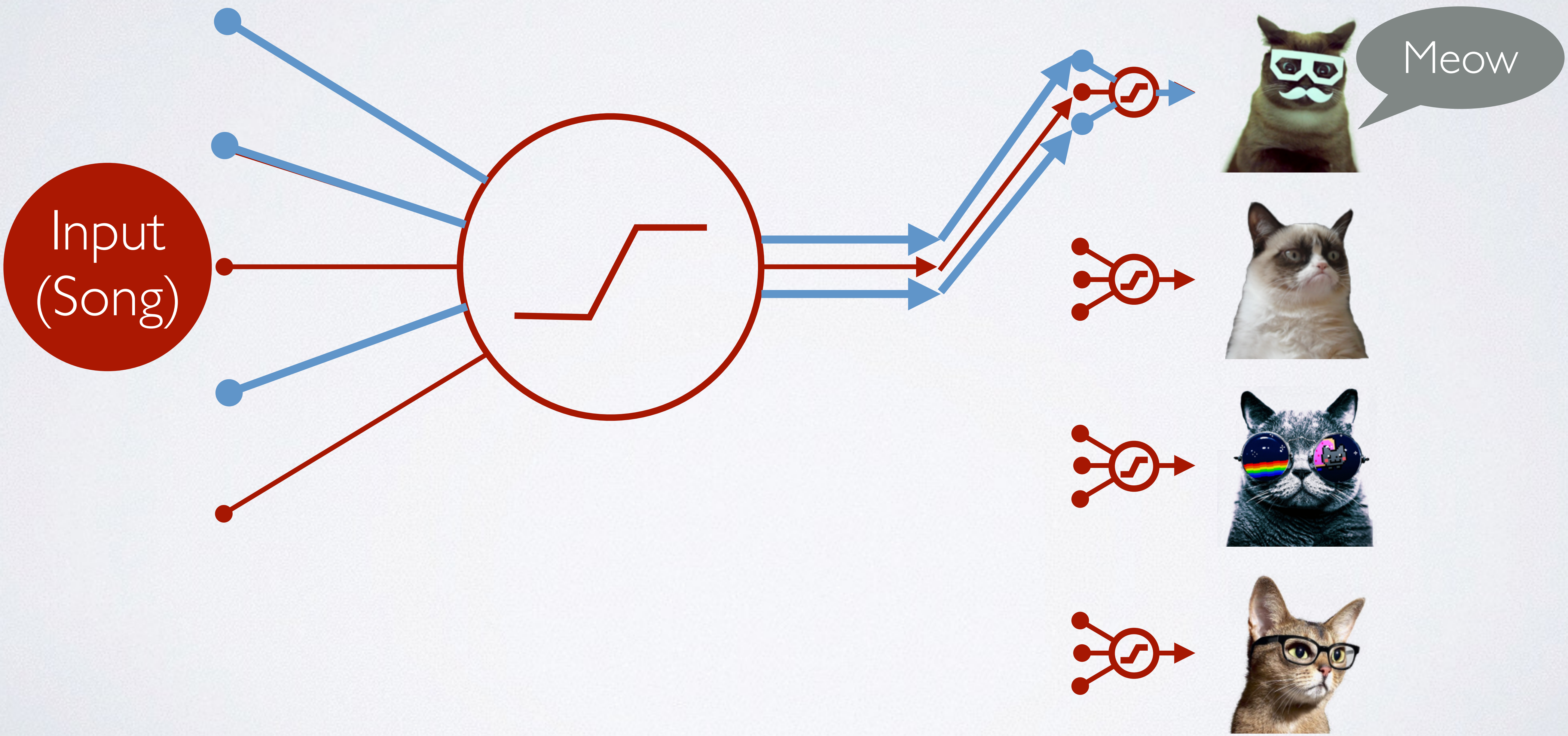

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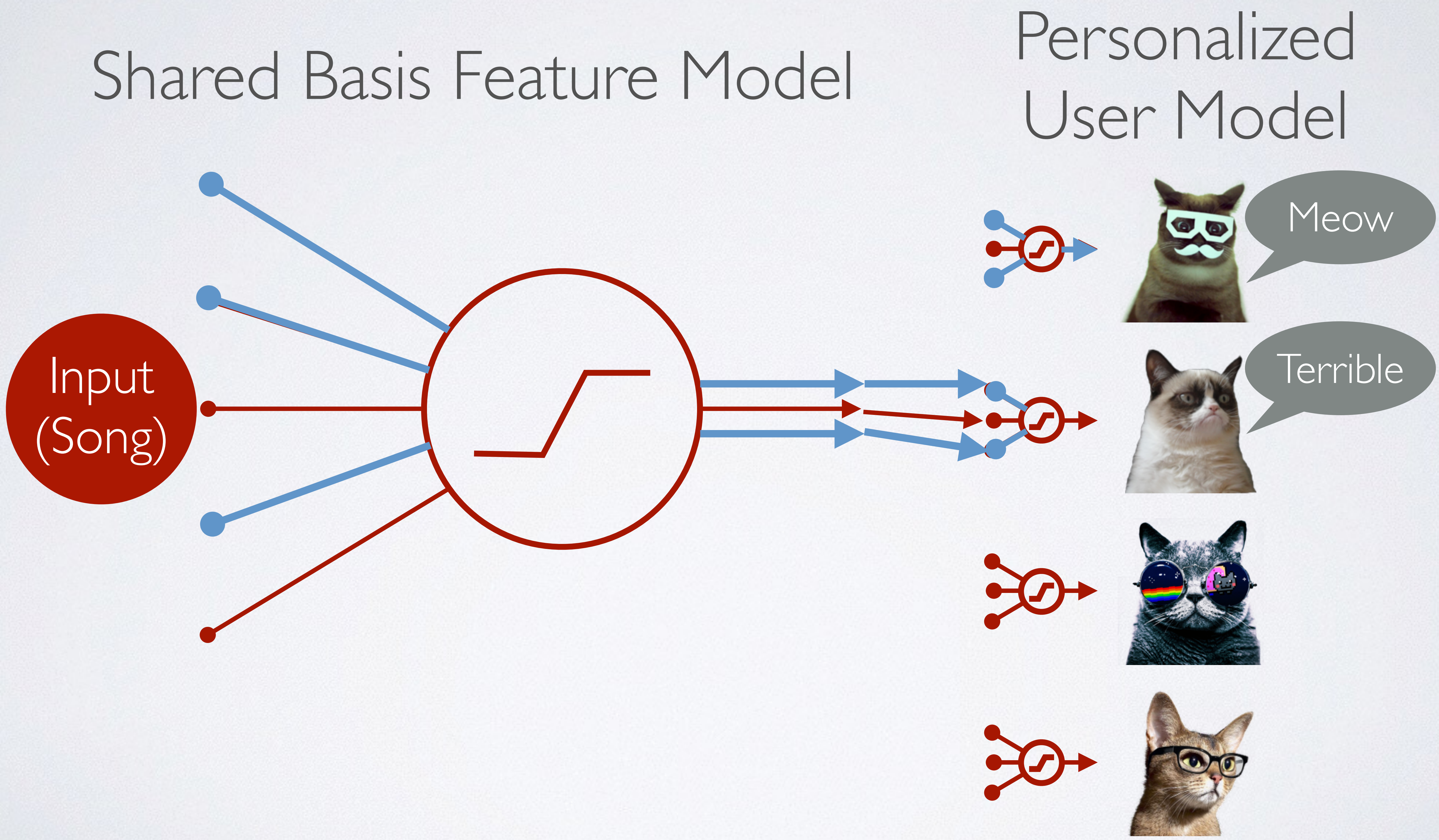
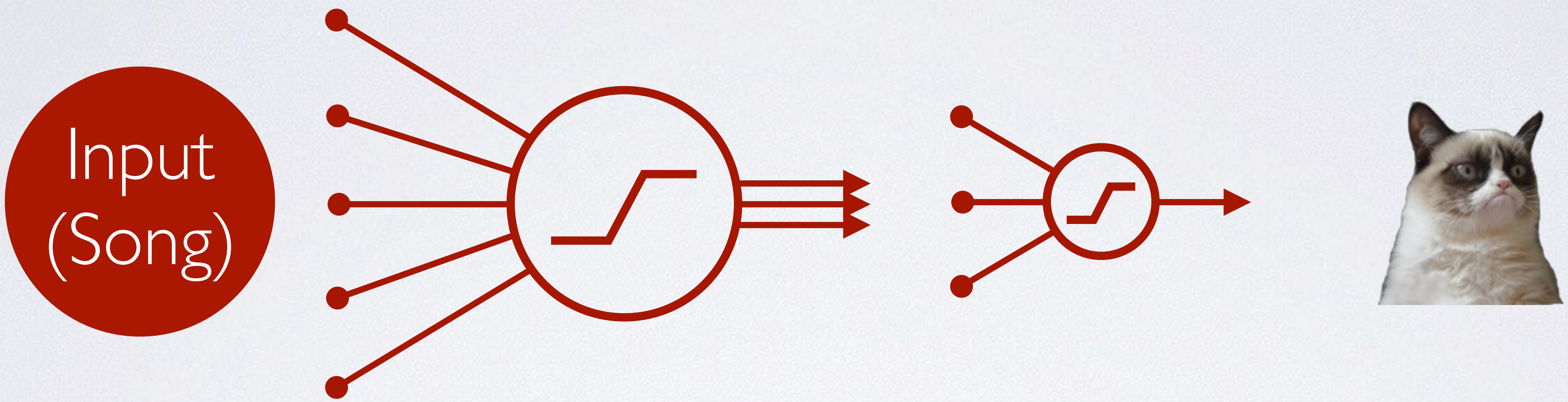


MATHEMATICAL FORMULATION



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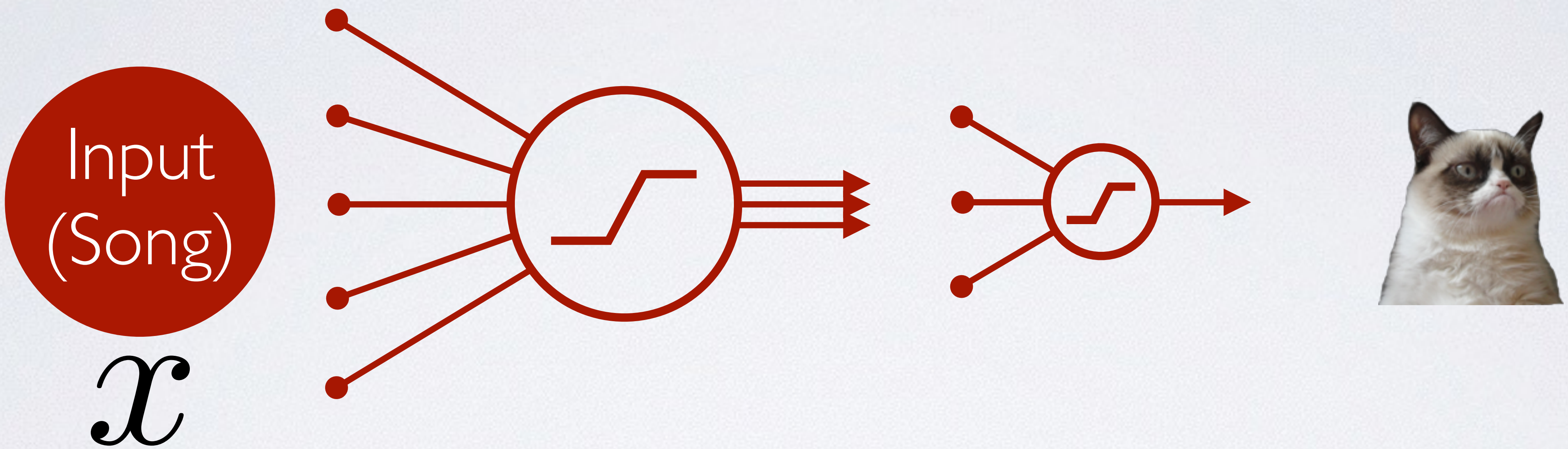

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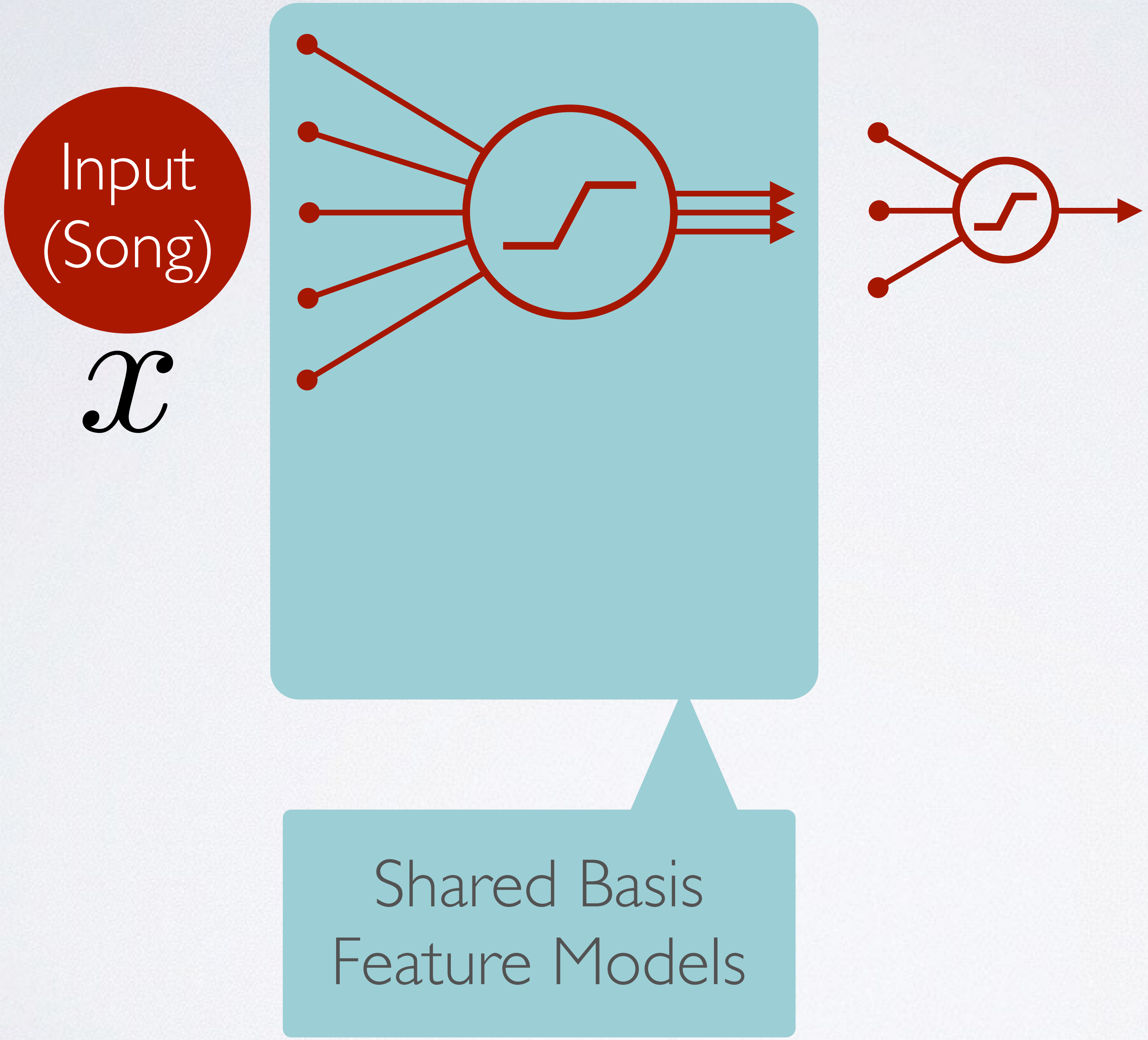

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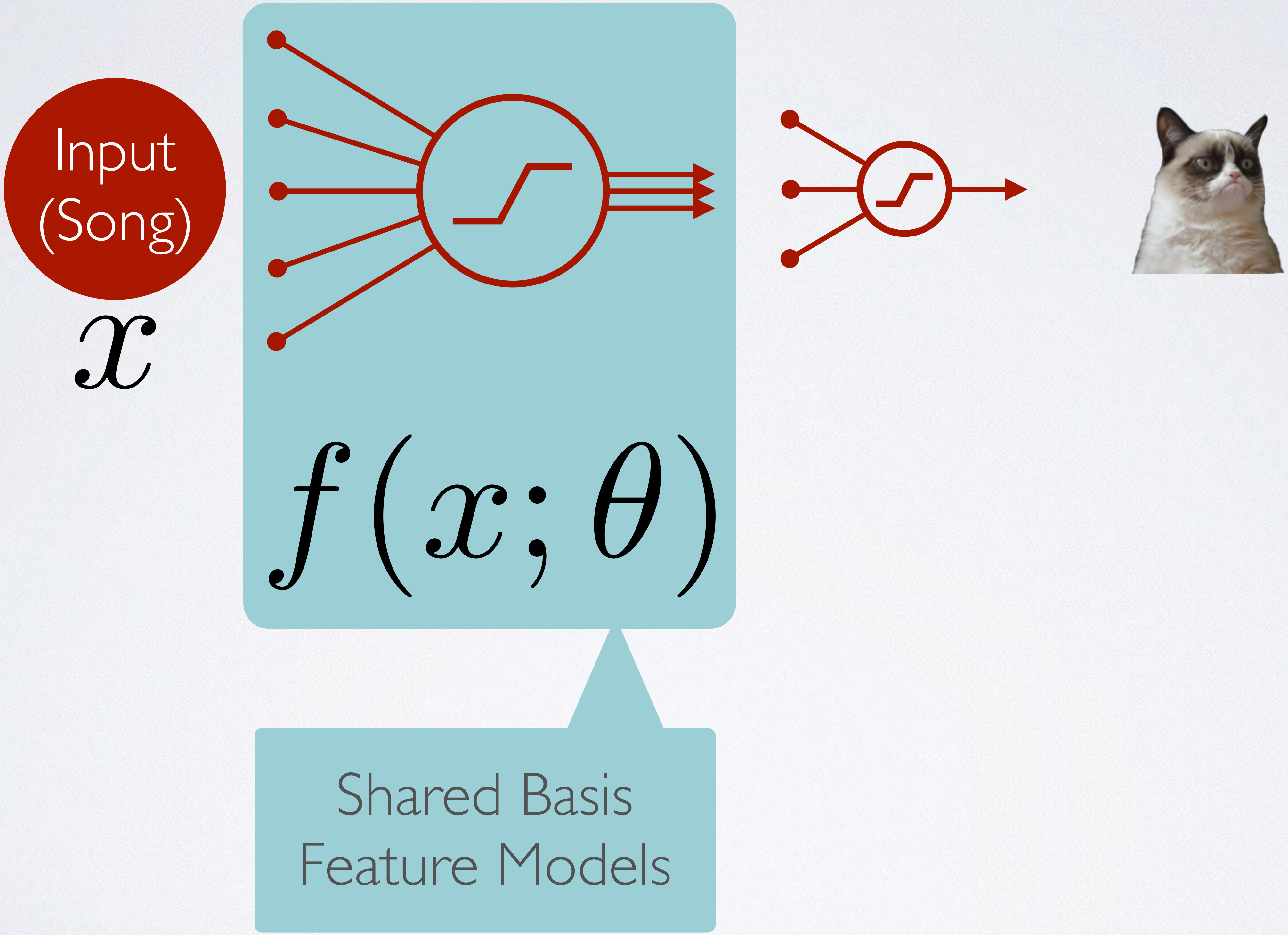

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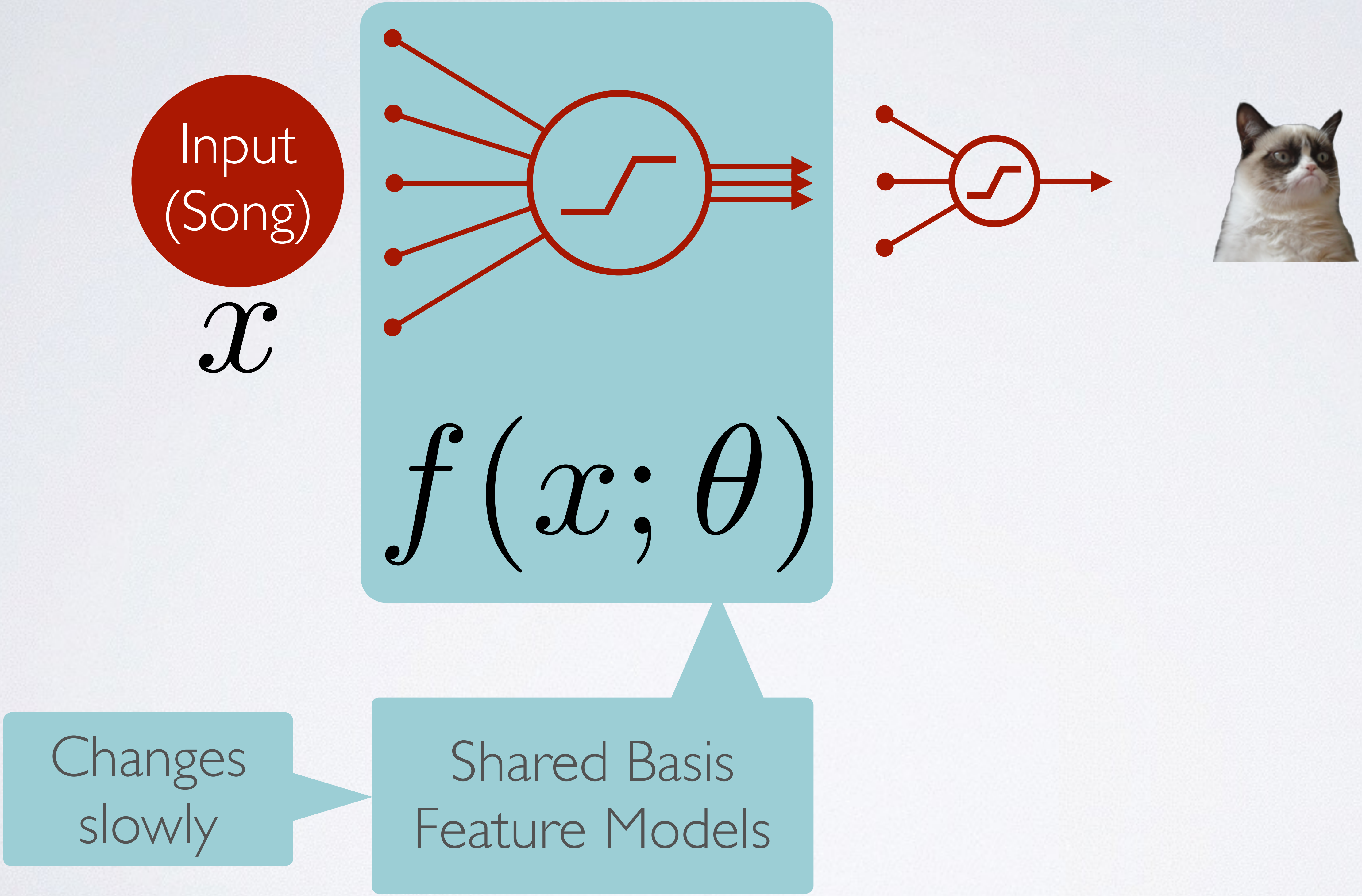

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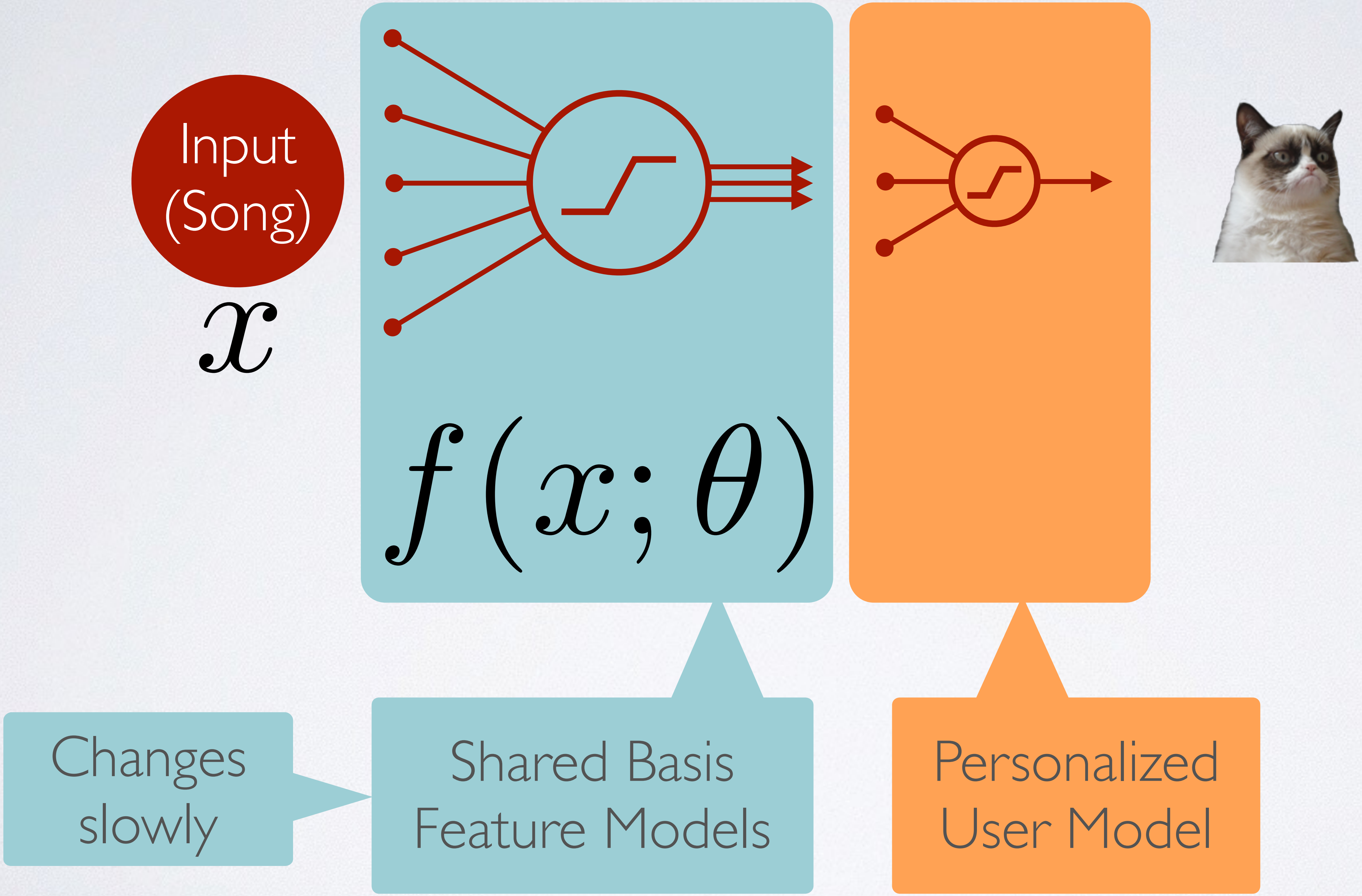

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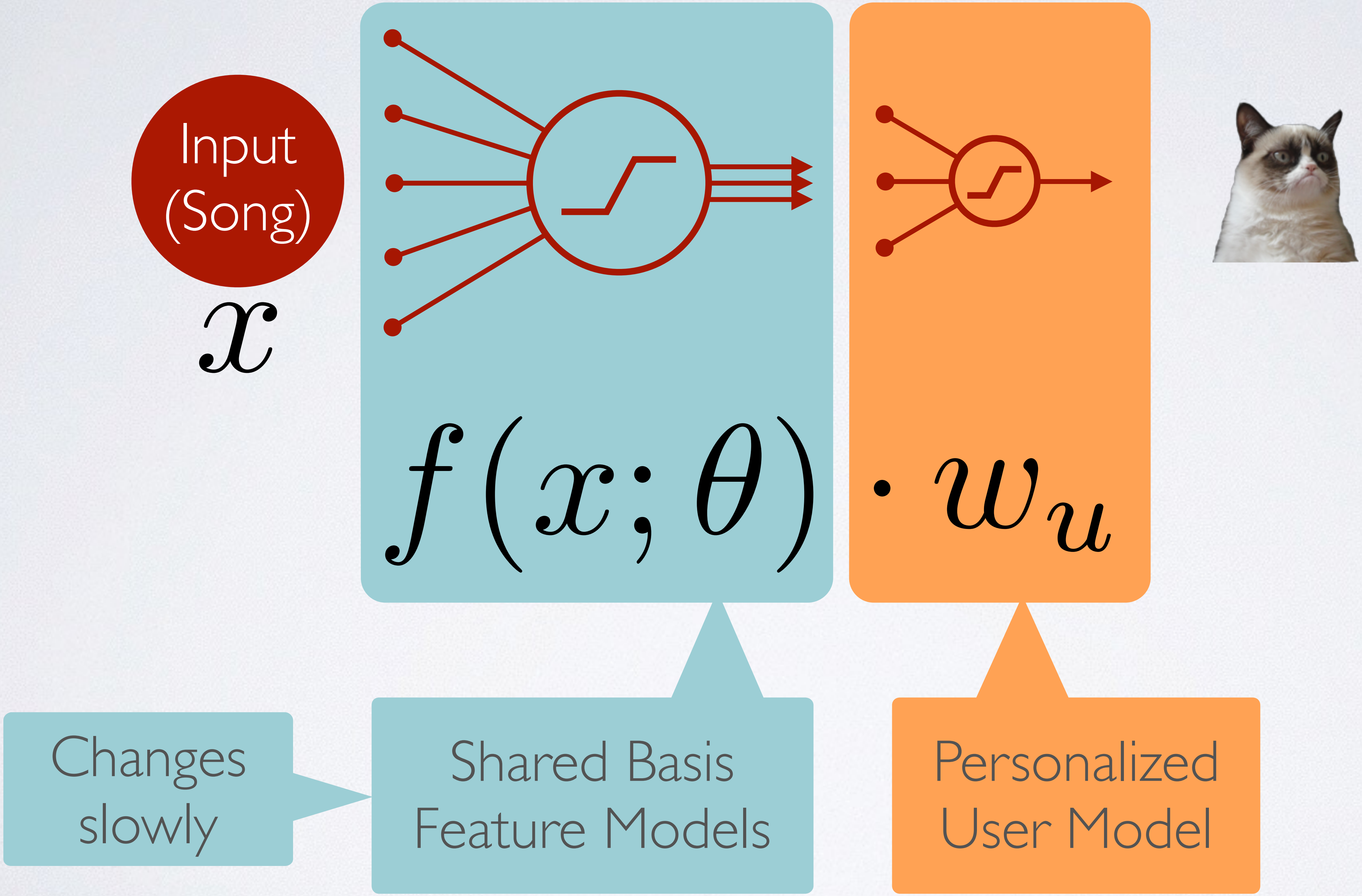

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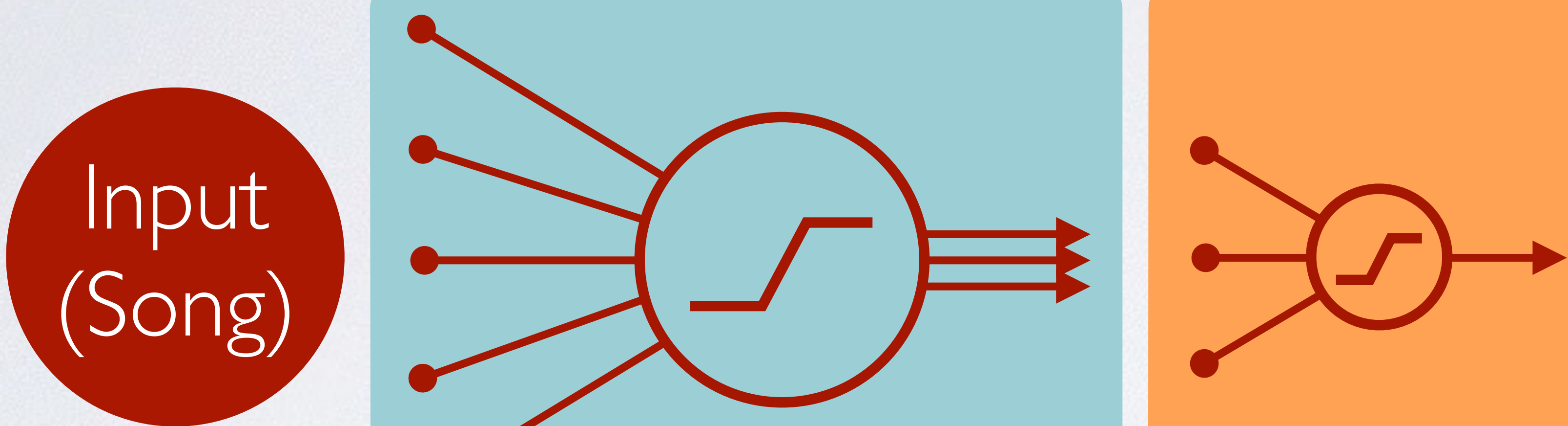
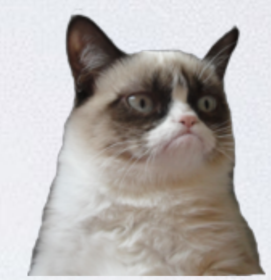


x



$$f(x;\theta) \cdot w_u$$

Changes slowly

Shared Basis Feature Models

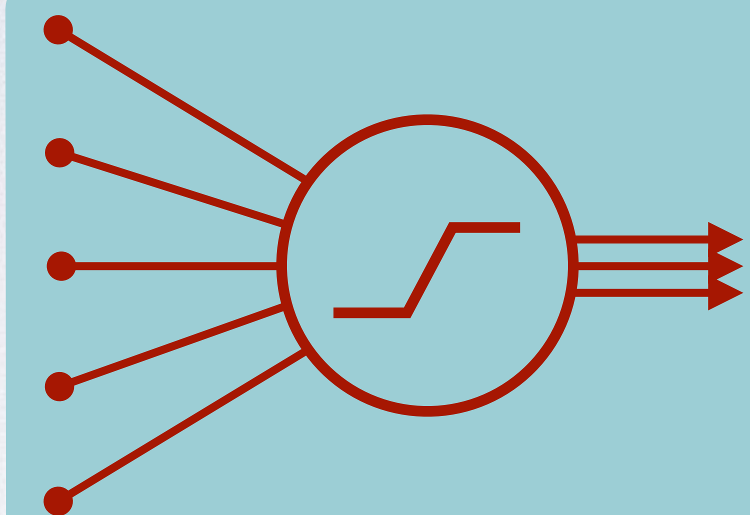
Personalized User Model

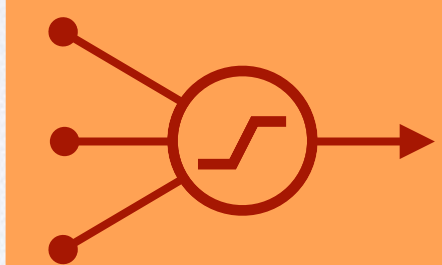
Highly dynamic

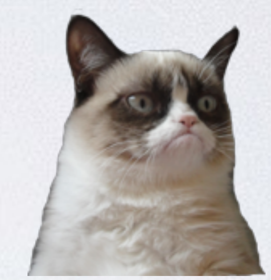
MATHEMATICAL FORMULATION

Input (Song)

x







$$f(x;\theta) \cdot w_u = \text{Rating}$$

Changes slowly

Shared Basis Feature Models

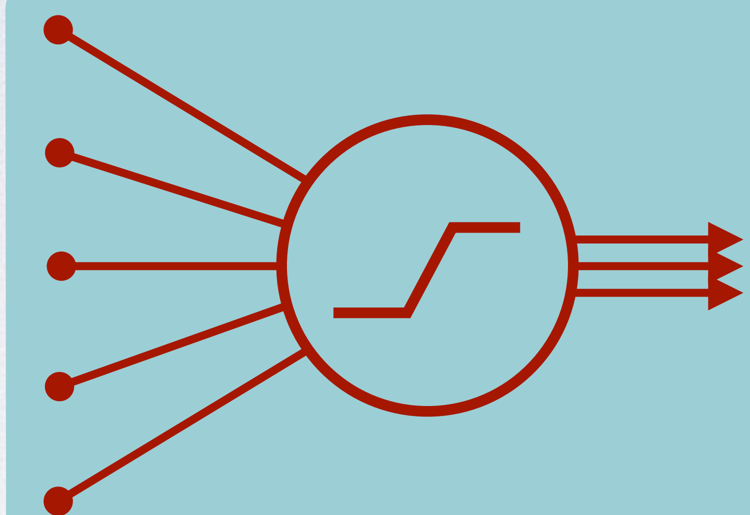
Personalized User Model

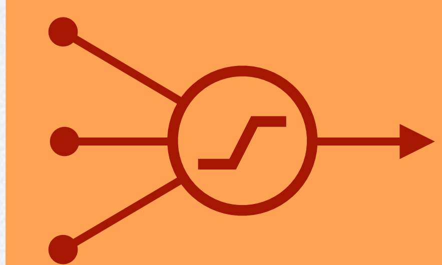
Highly dynamic

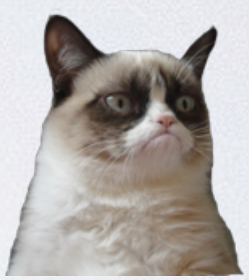
MATHEMATICAL FORMULATION

Input (Song)

x







Terrible

$$f(x;\theta) \cdot w_u = \text{Rating}$$

Changes slowly

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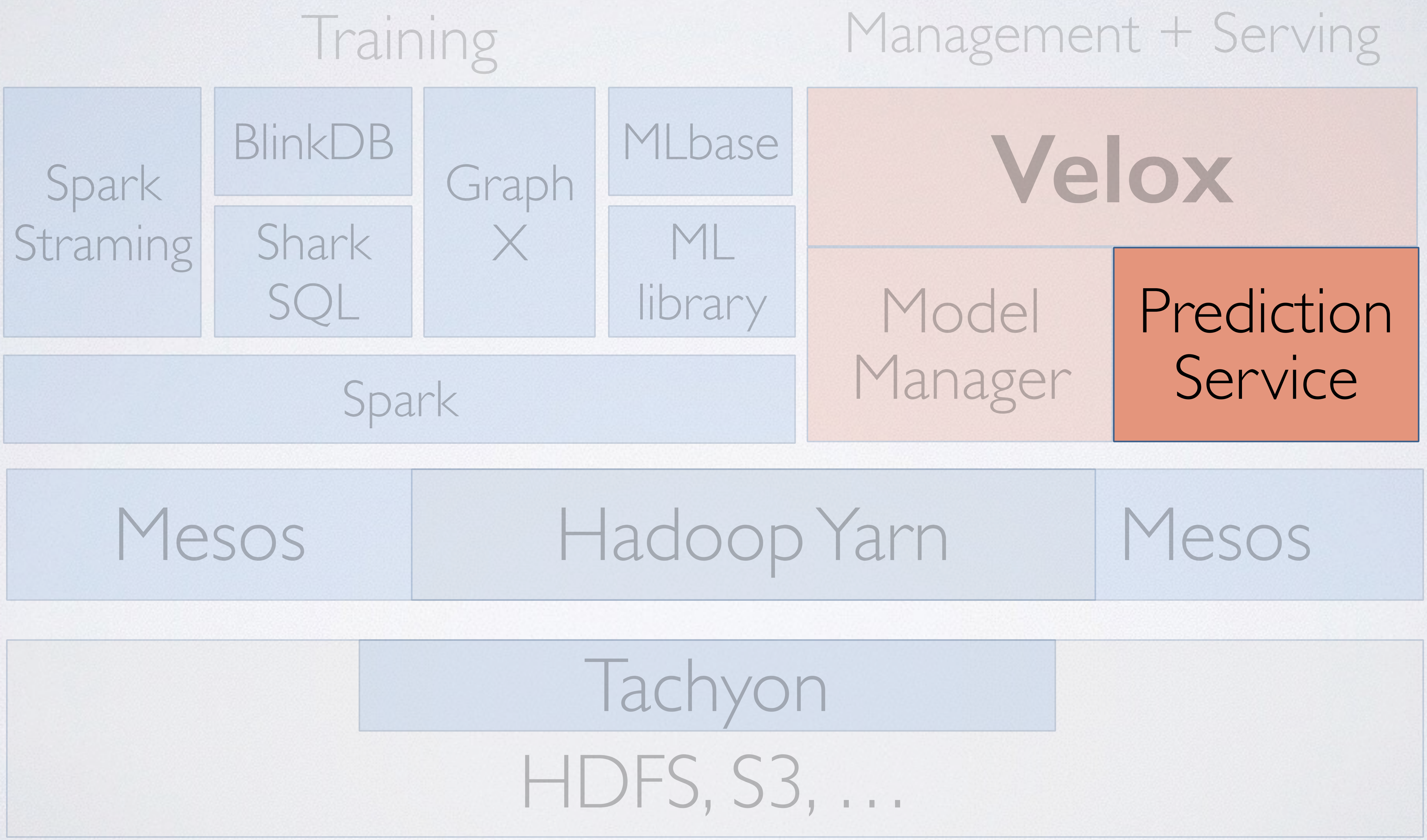
System Architecture



PREDICTION API

Simple point queries:

```
GET /velox/catify/predict?userid=22&song=27632
```

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```
GET /velox/catify/predict?userid=22&song=27632
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More complex ordering queries:

```
GET /velox/catify/predict_top_k?userid=22&k=100
```

PREDICTIONS

```
def predict( u: UUID, x: Context )
```

$$w_u \cdot f(x;\theta)$$

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Look up user weight

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Primary key lookup

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Look up user weight

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Partition query by user: *always local*

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Compute Features

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user independent

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Feature computation could be costly

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def predict( u: UUID, x: Context )
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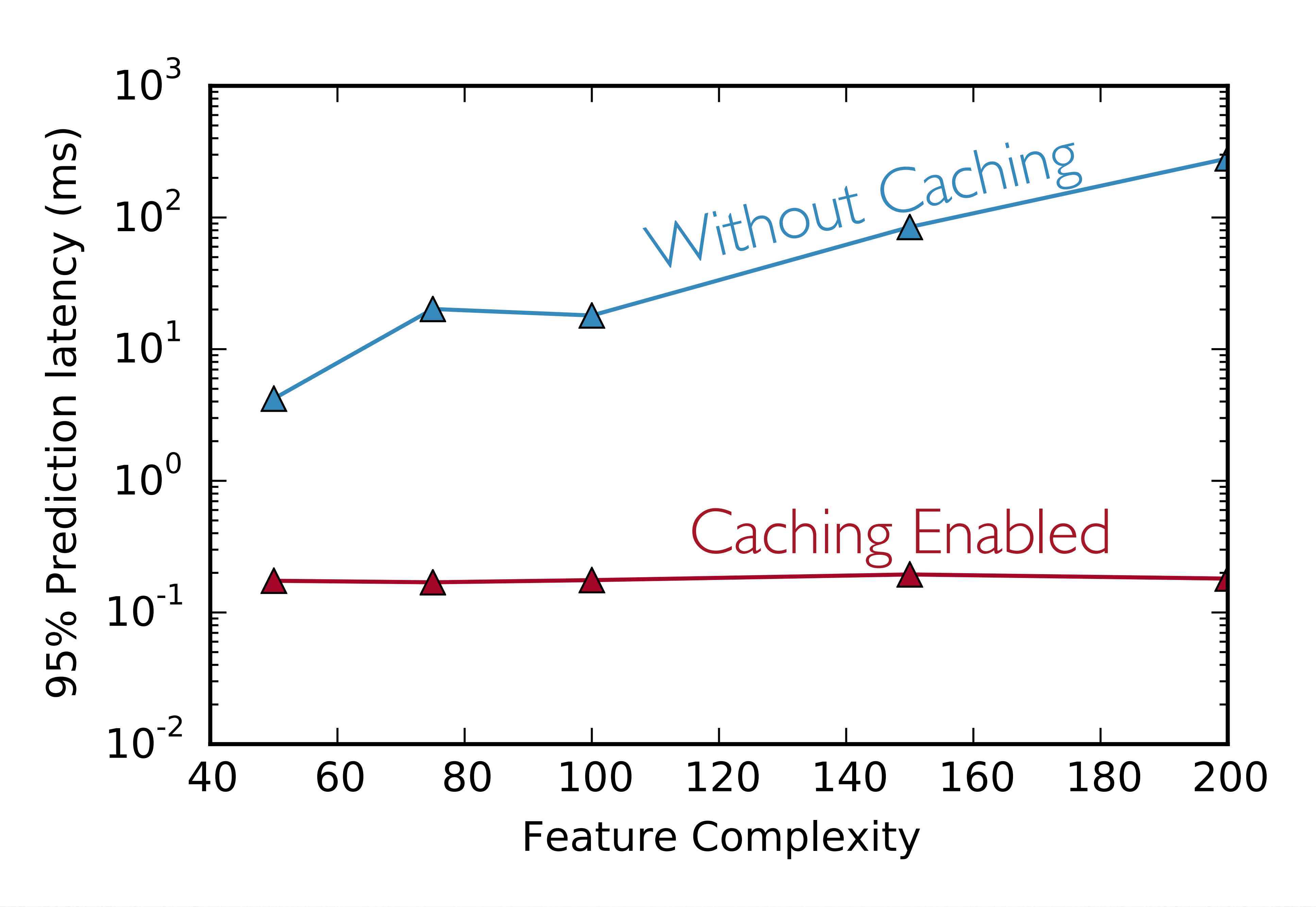
Feature computation could be costly

Compute Features

Cache features for reuse across users

$$w_u \cdot \underbrace{f(x;\theta)}_{\text{user independent}}$$

FEATURE CACHING GAINS



Feature caching leads to order-of-magnitude reduction in latency.

TOP-K QUERIES

Query predicate to pre-filter candidate set

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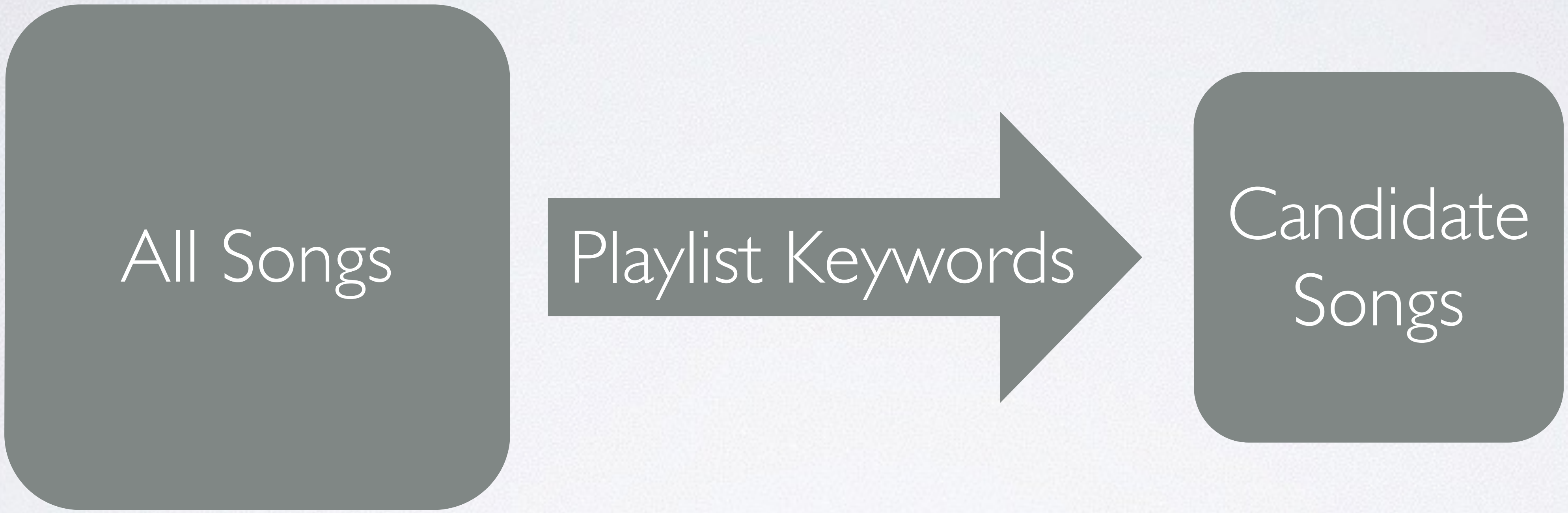

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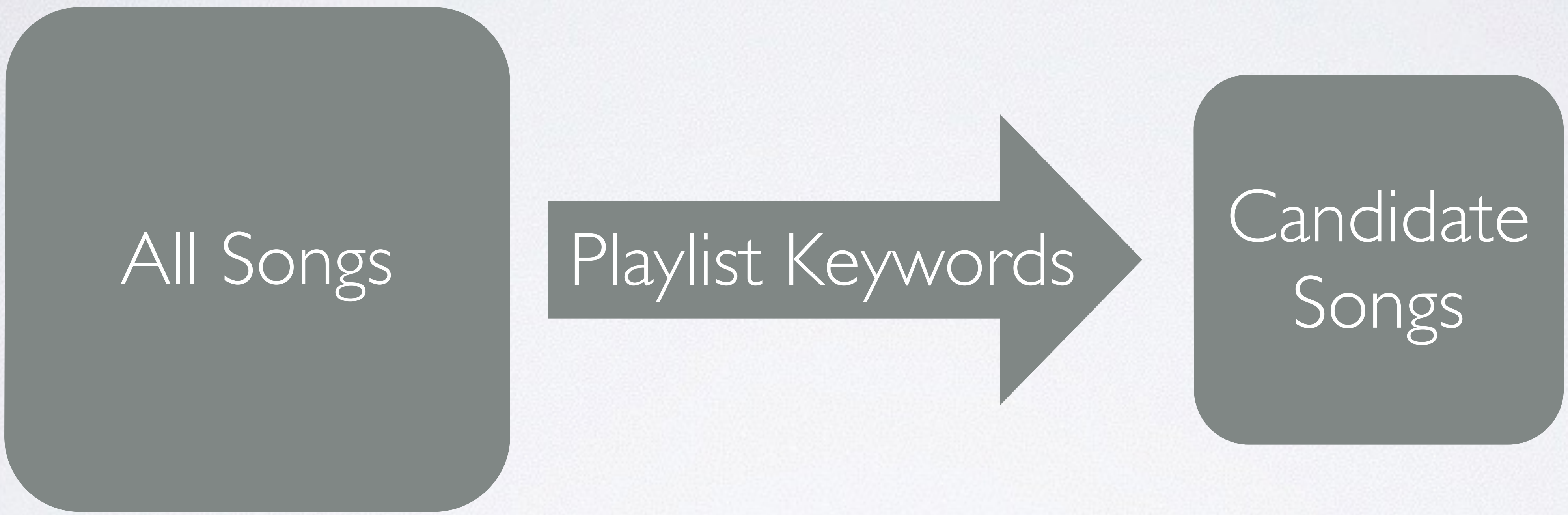
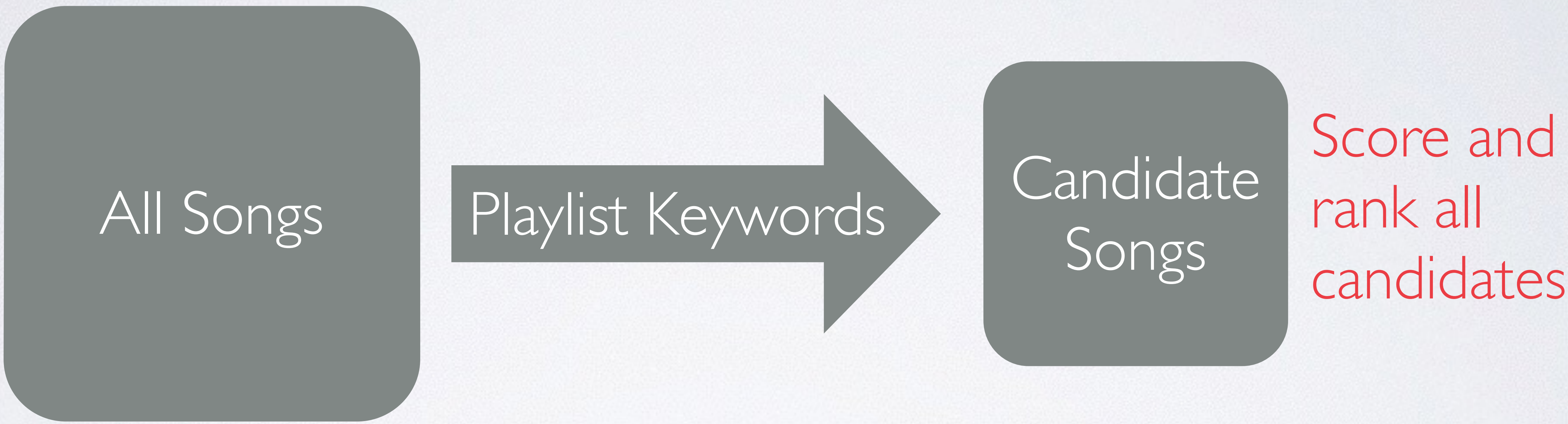


Score and rank all candidates

TOP-K QUERIES

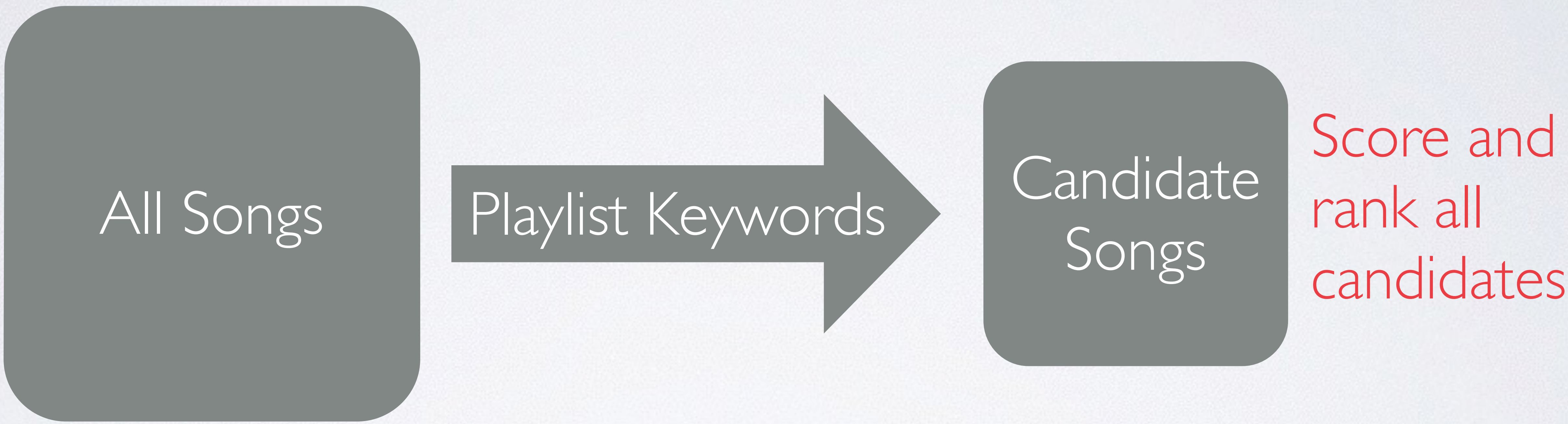
Query predicate to pre-filter candidate set



By exploiting split model design we can leverage:

TOP-K QUERIES

Query predicate to pre-filter candidate set



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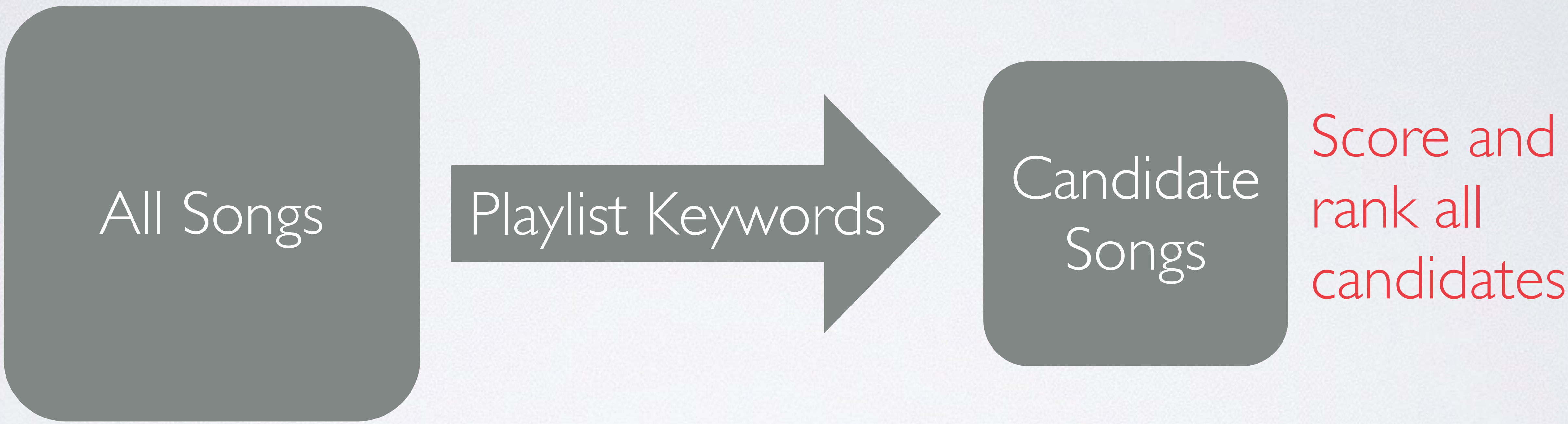

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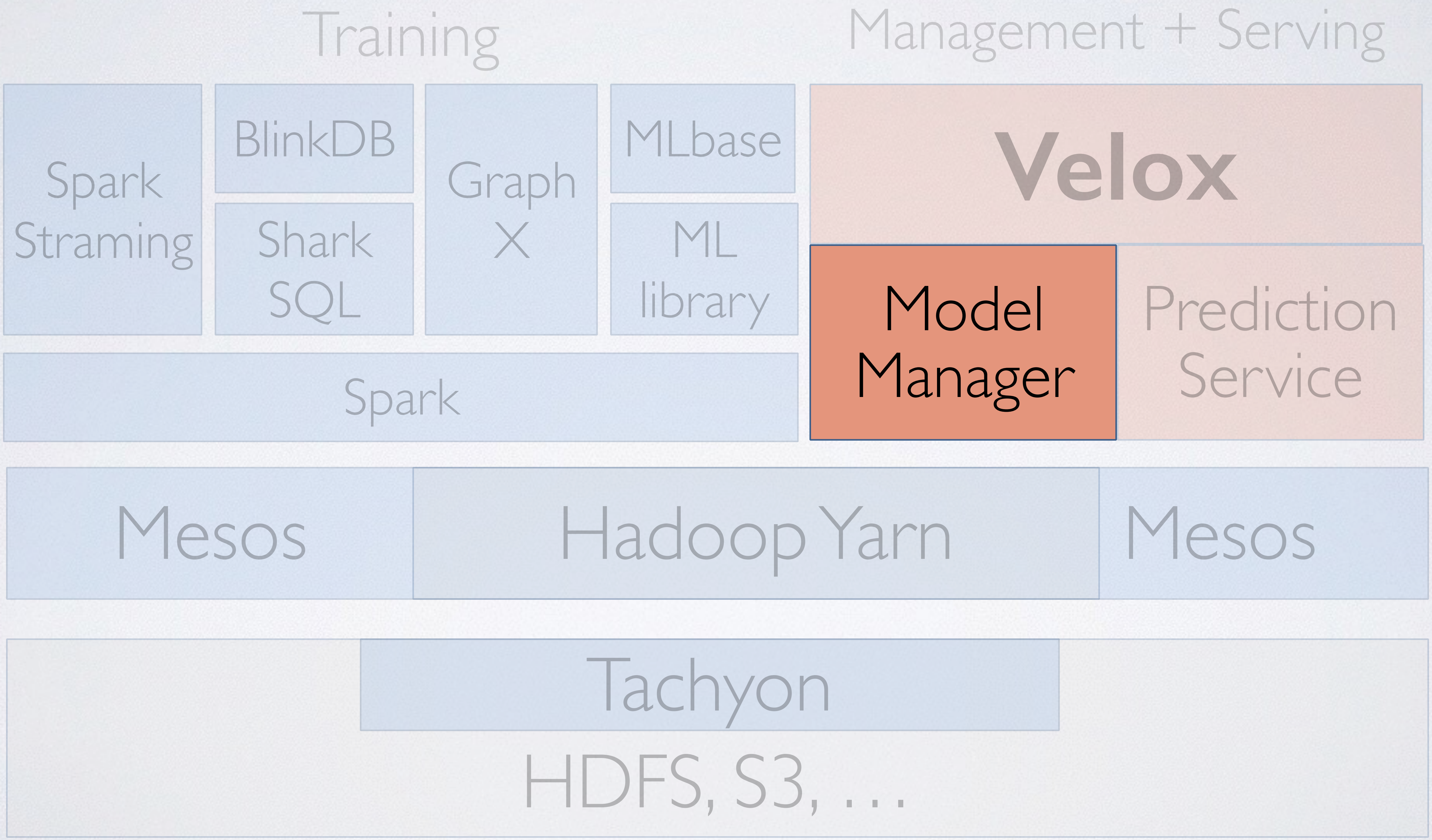

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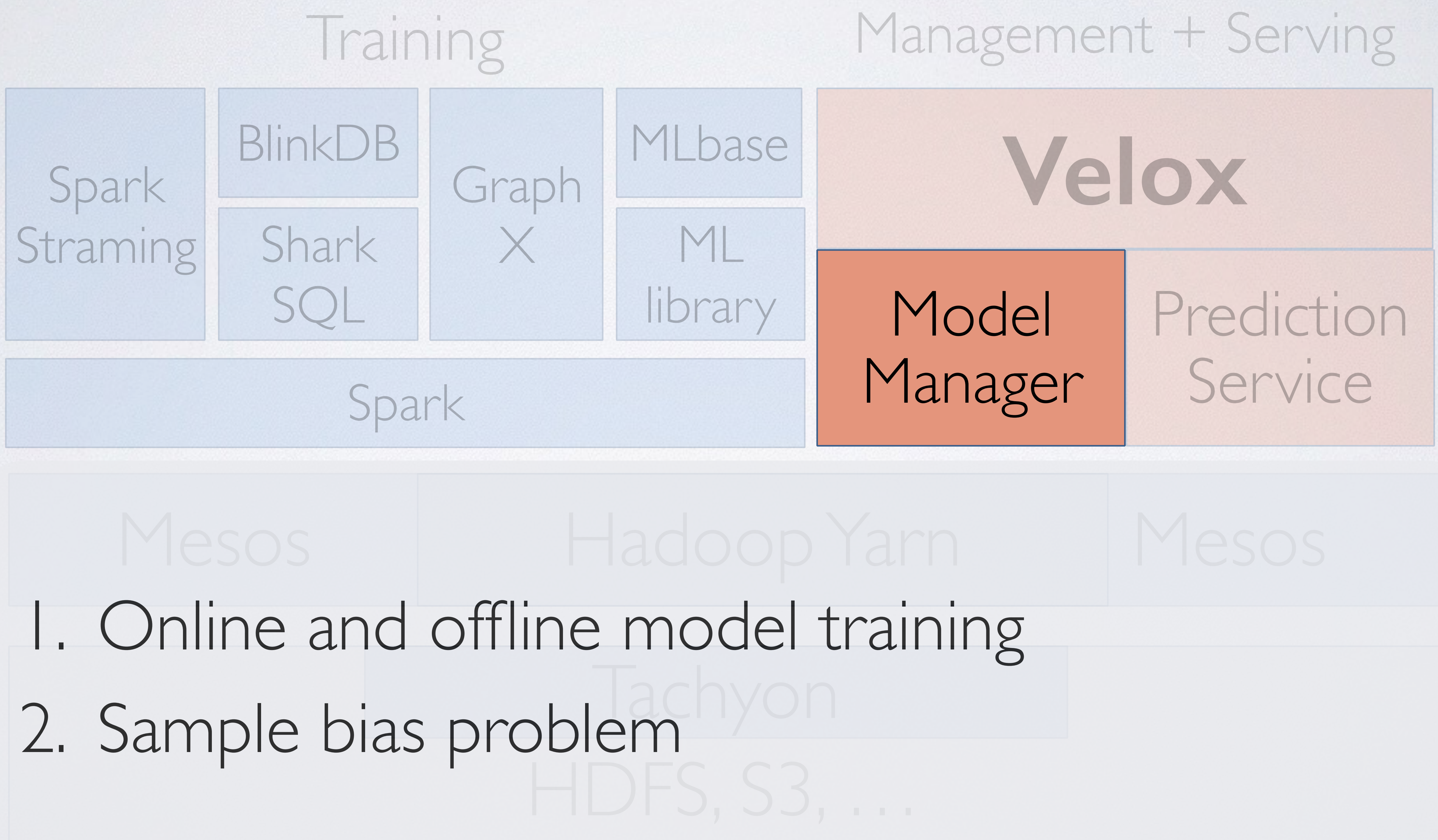

1. Online and offline model training
2. Sample bias problem

FEEDBACK API

Simple direct value feedback:

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Continuously update
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Continuously update user models in Velox

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Evaluation

Continuously assess model performance

ONLINE LEARNING

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def observe(u: UUID, x: Context, y: Score)
```

$$w_u \cdot f(x;\theta)$$

ONLINE LEARNING

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def observe(u: UUID, x: Context, y: Score)
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Update w_u with new training point

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Stochastic gradient descent

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Stochastic gradient descent
Incremental linear algebra

$$w_u \cdot f(x; \theta)$$

OFFLINE LEARNING

```
def retrain(trainingData: RDD)
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Spark Based Training Algs.

Efficient batch training using Spark

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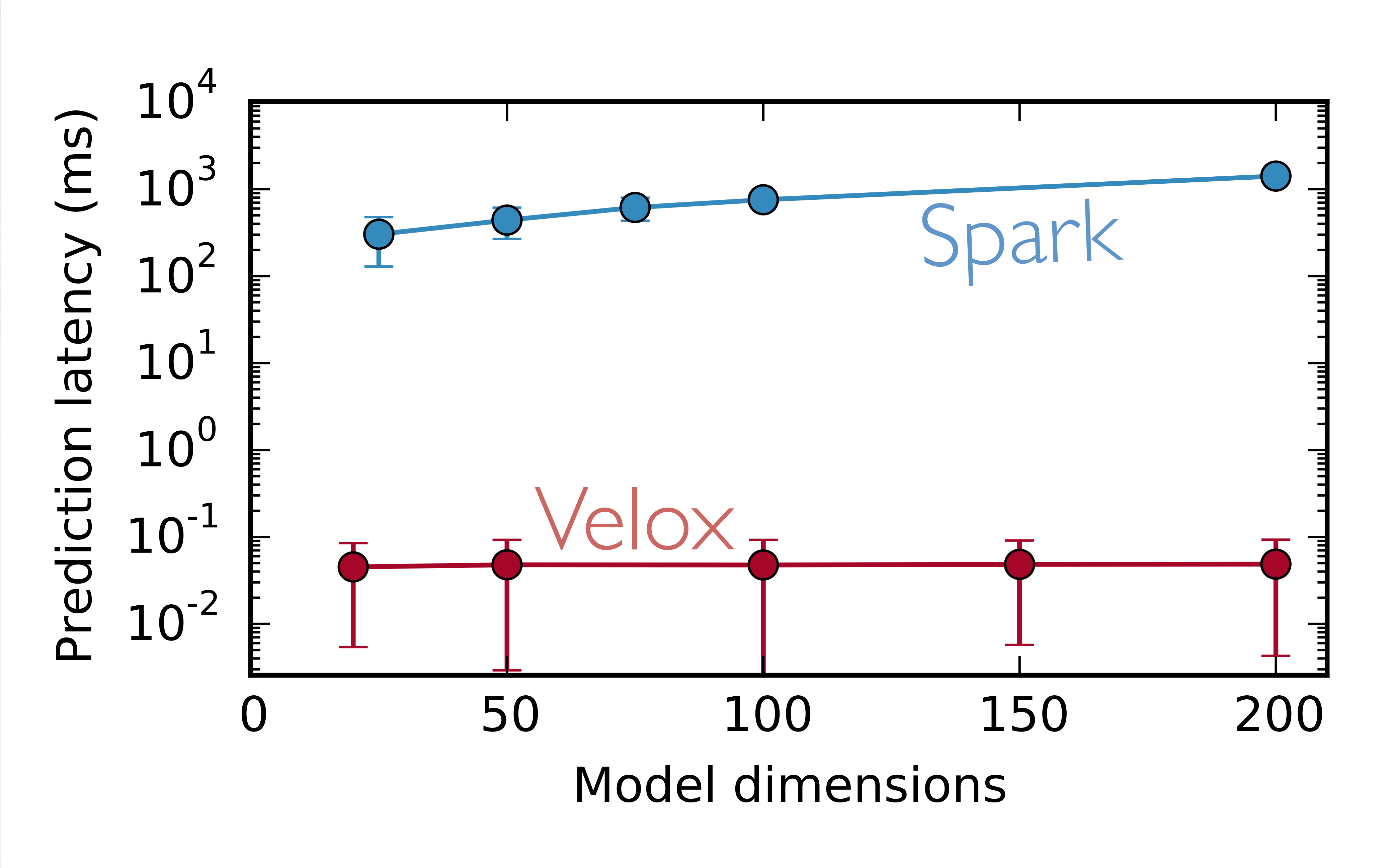
When do we retrain?

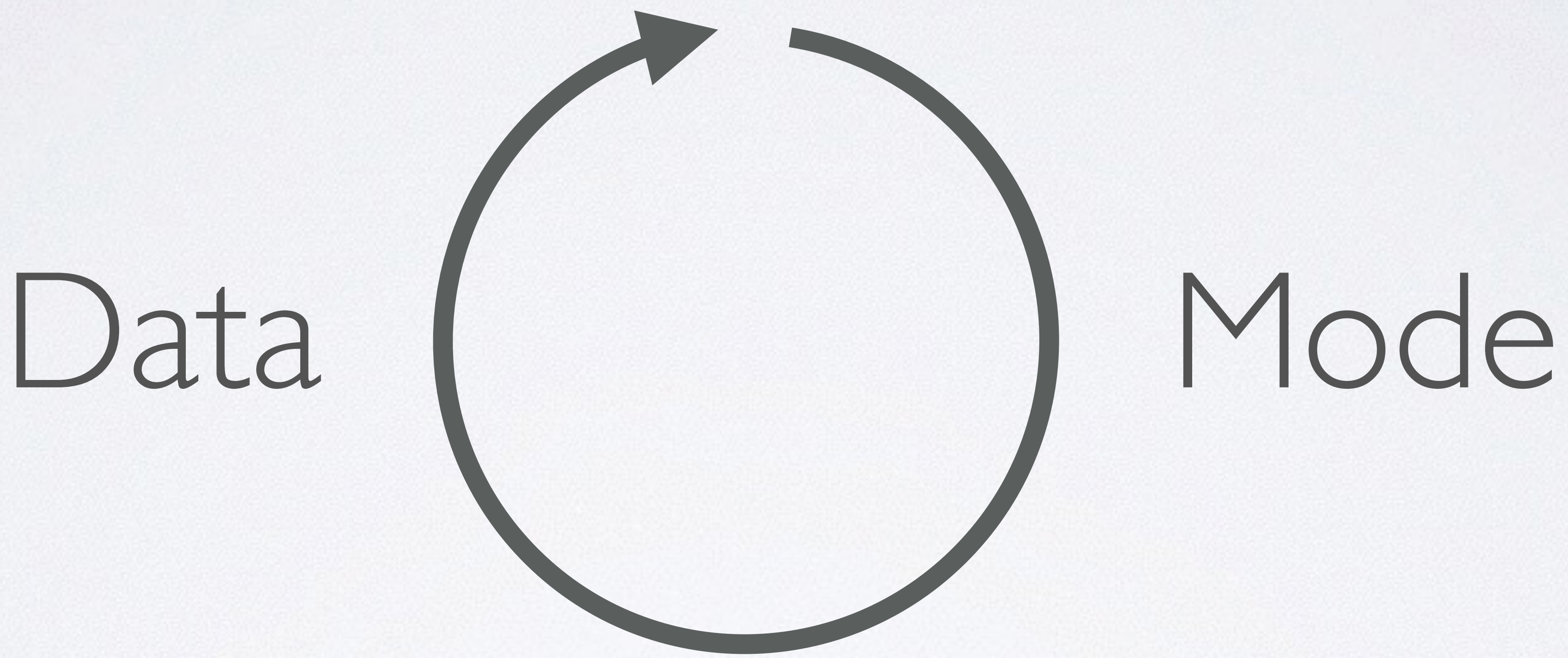
Periodically

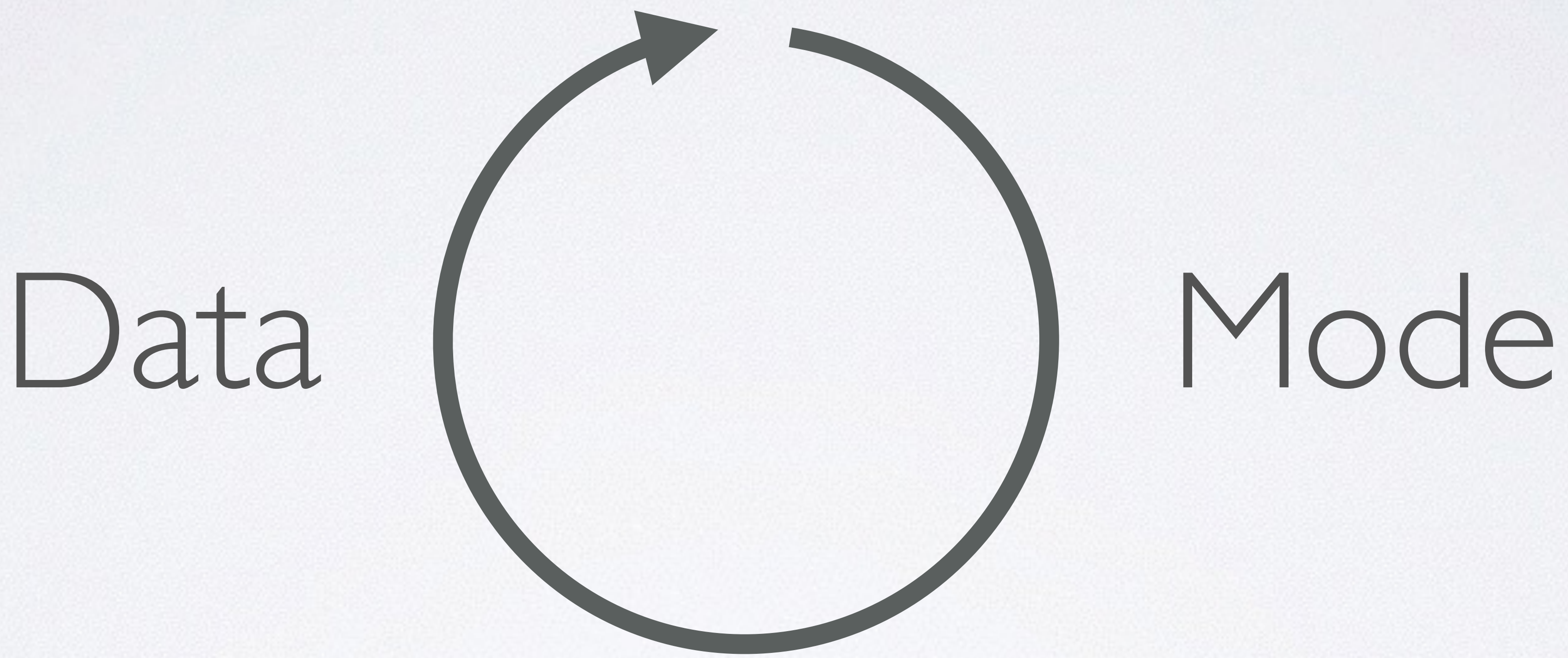
Trigger by the evaluation system

PREDICTION LATENCY
WITH ONLINE TRAINING



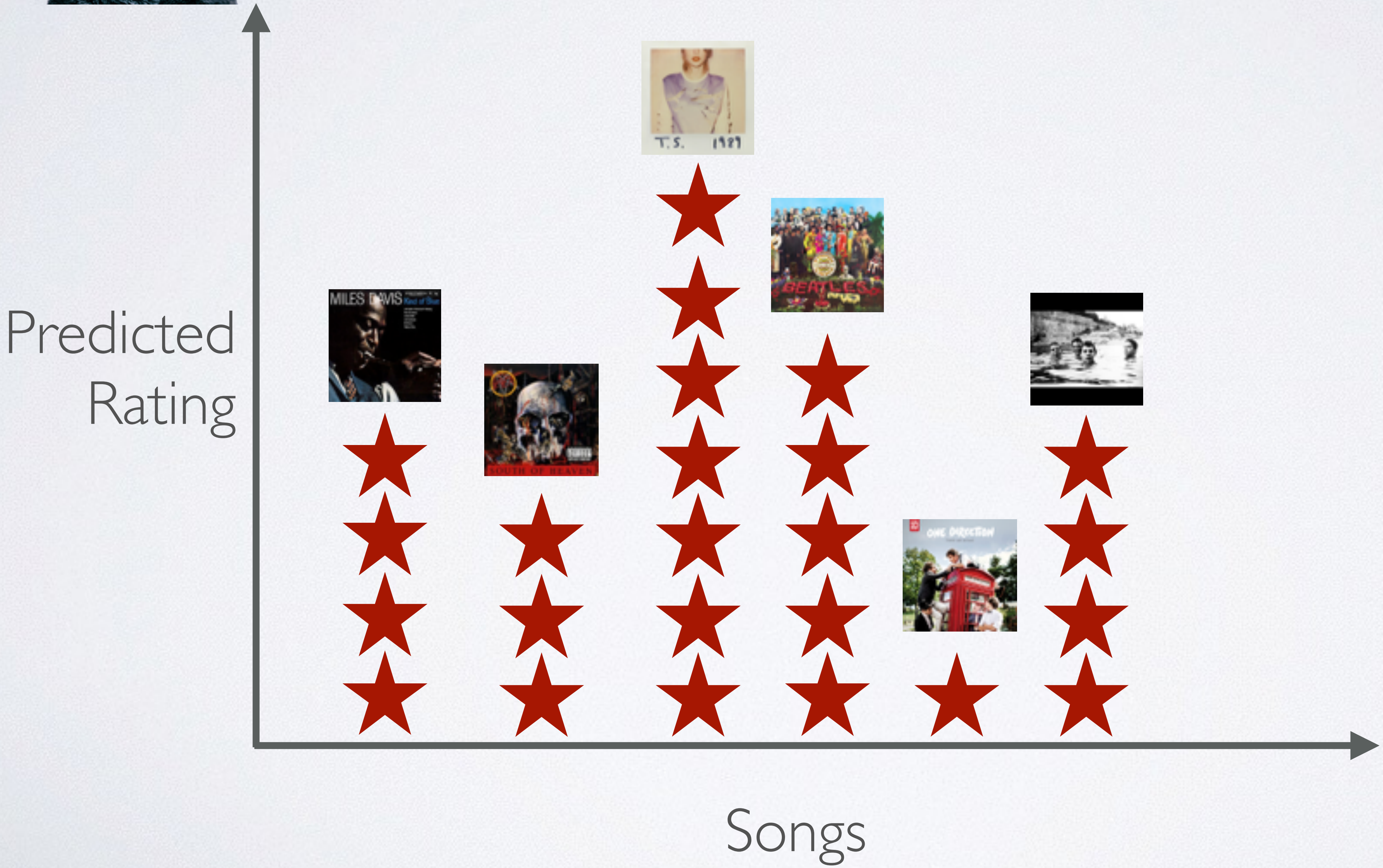
Velox keeps models updated at low latency


Data
Model

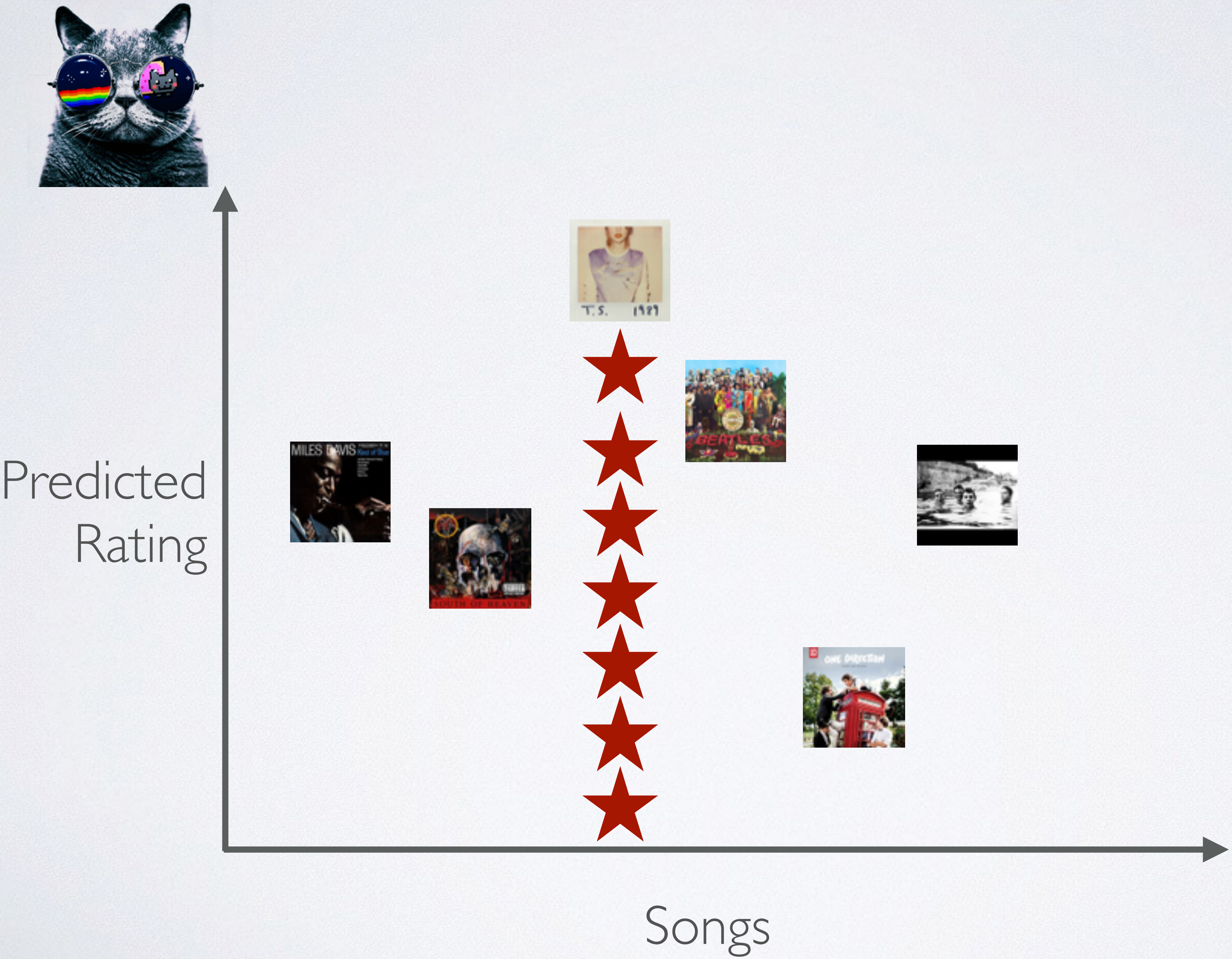


Sample Bias: *model affects the training data*.

ALWAYS SERVE THE BEST SONG?



ALWAYS SERVE THE BEST SONG?



VELOX SOLUTION

With prob. 1- ϵ serve the best predicted song

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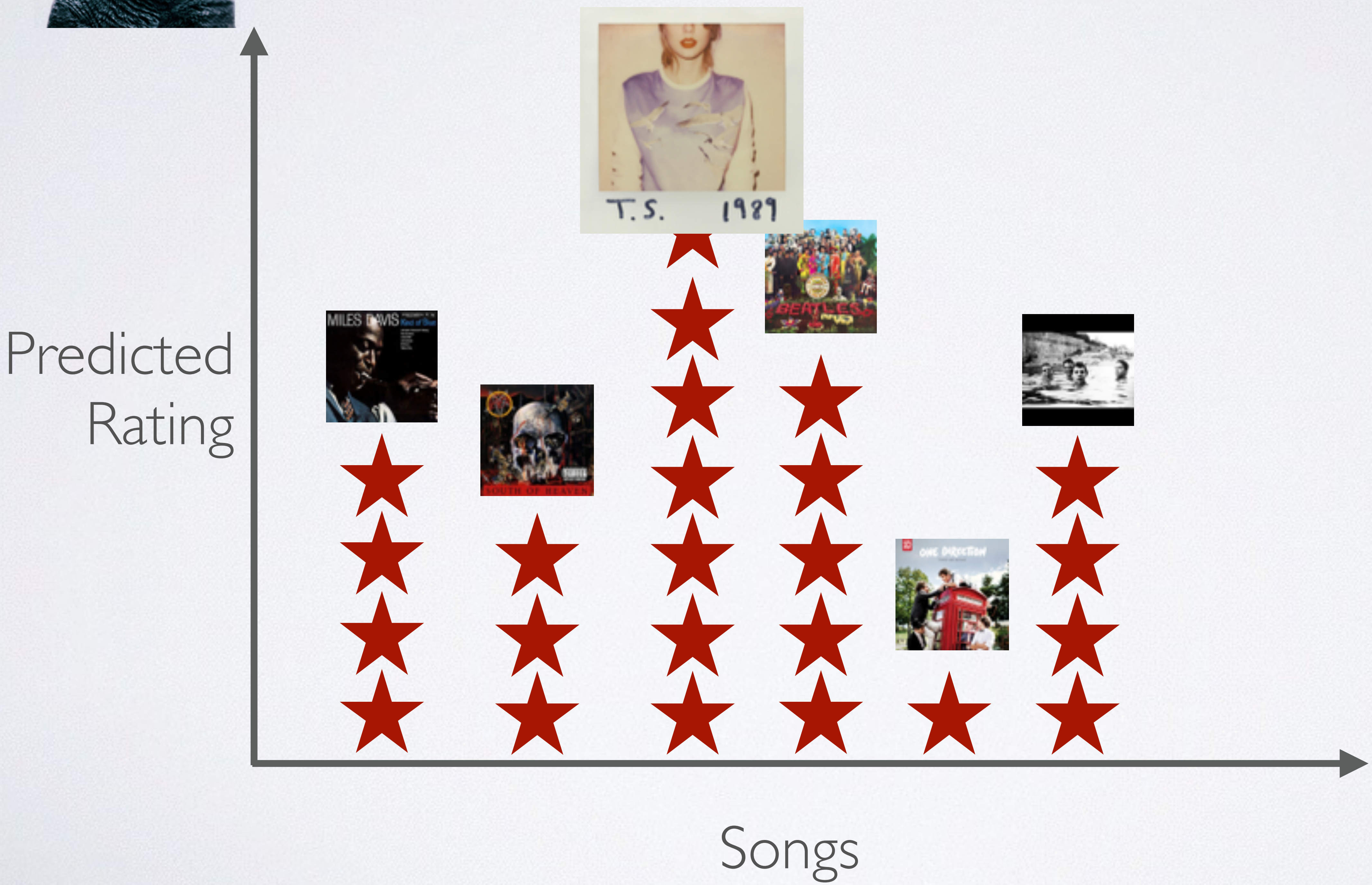

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Epsilon Greedy

Active Learning

Opportunity to explore new systems for this emerging analytics workload

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OPEN CHALLENGES FOR DATABASE SYSTEMS

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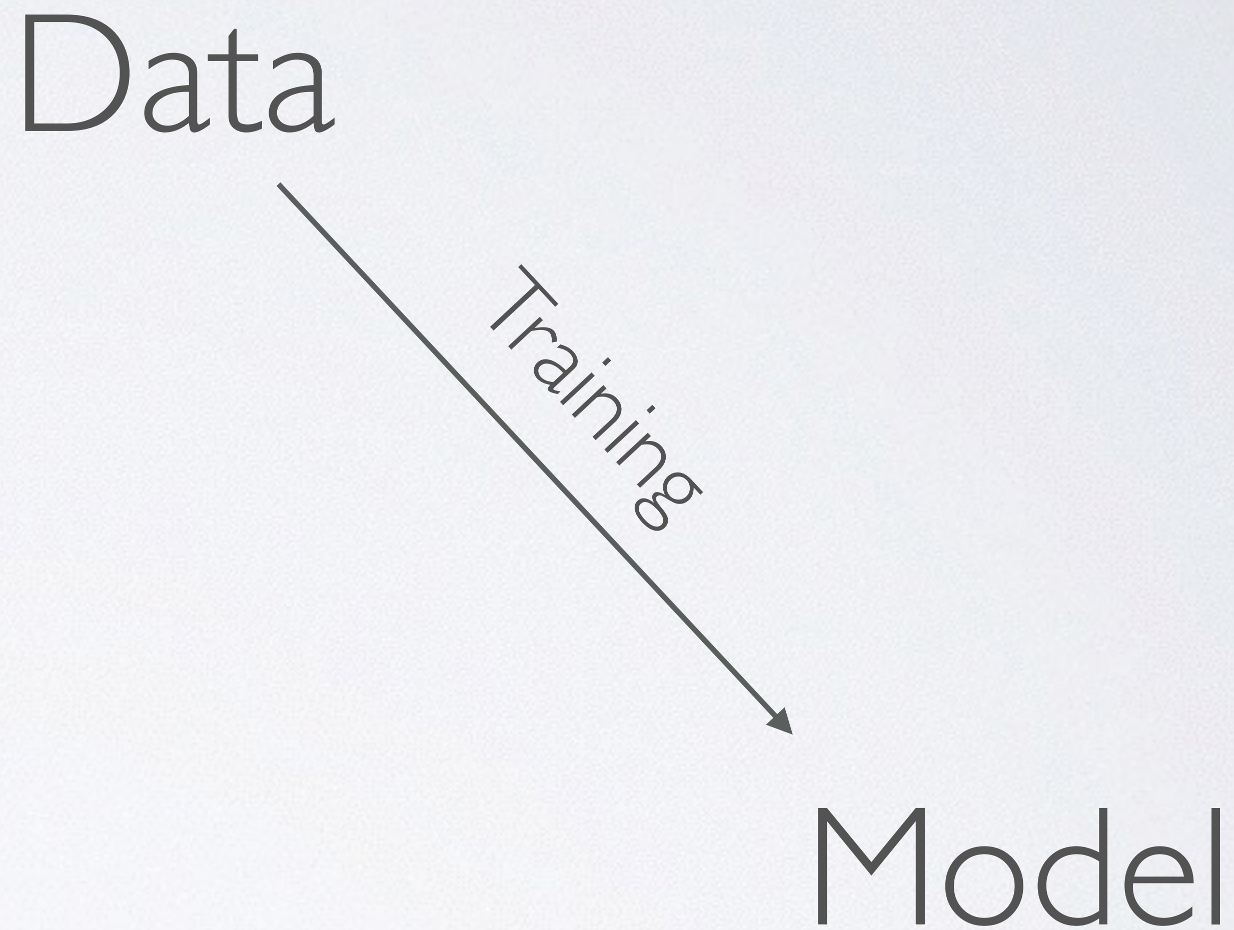
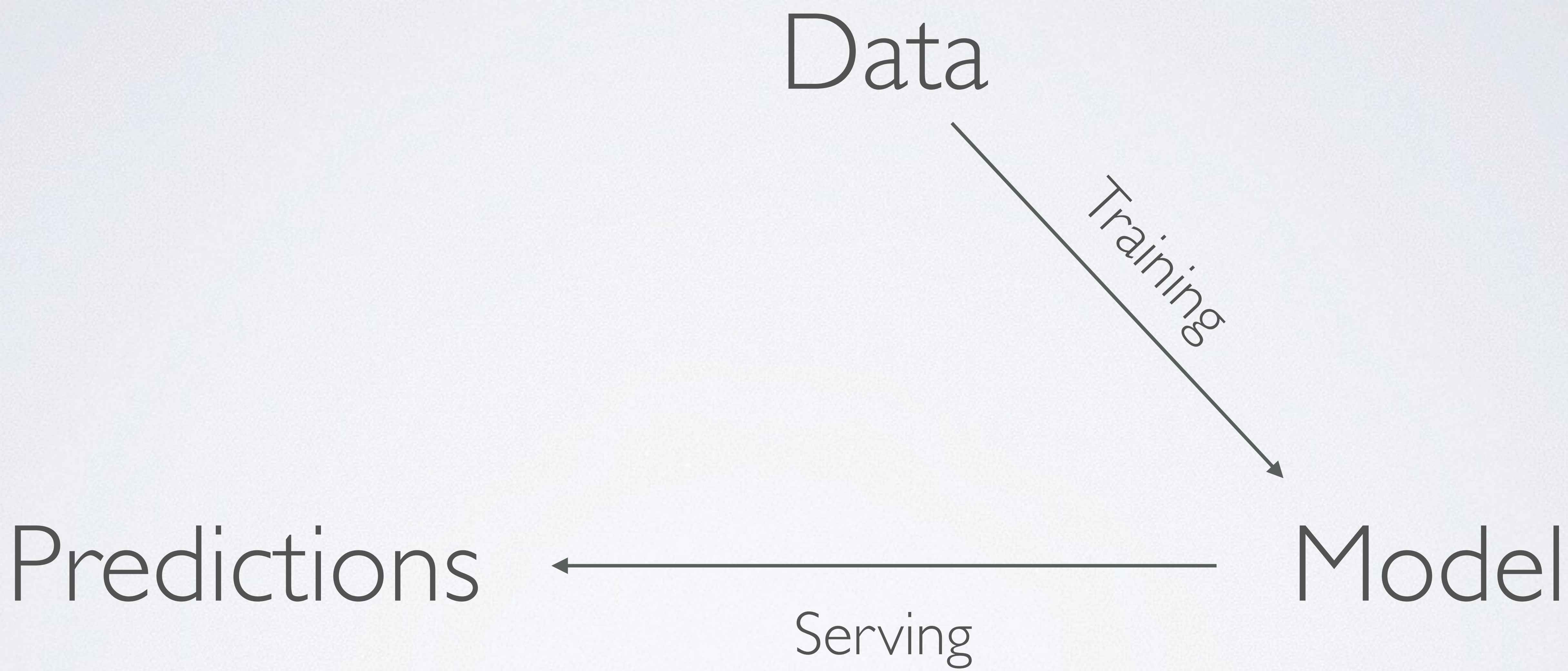
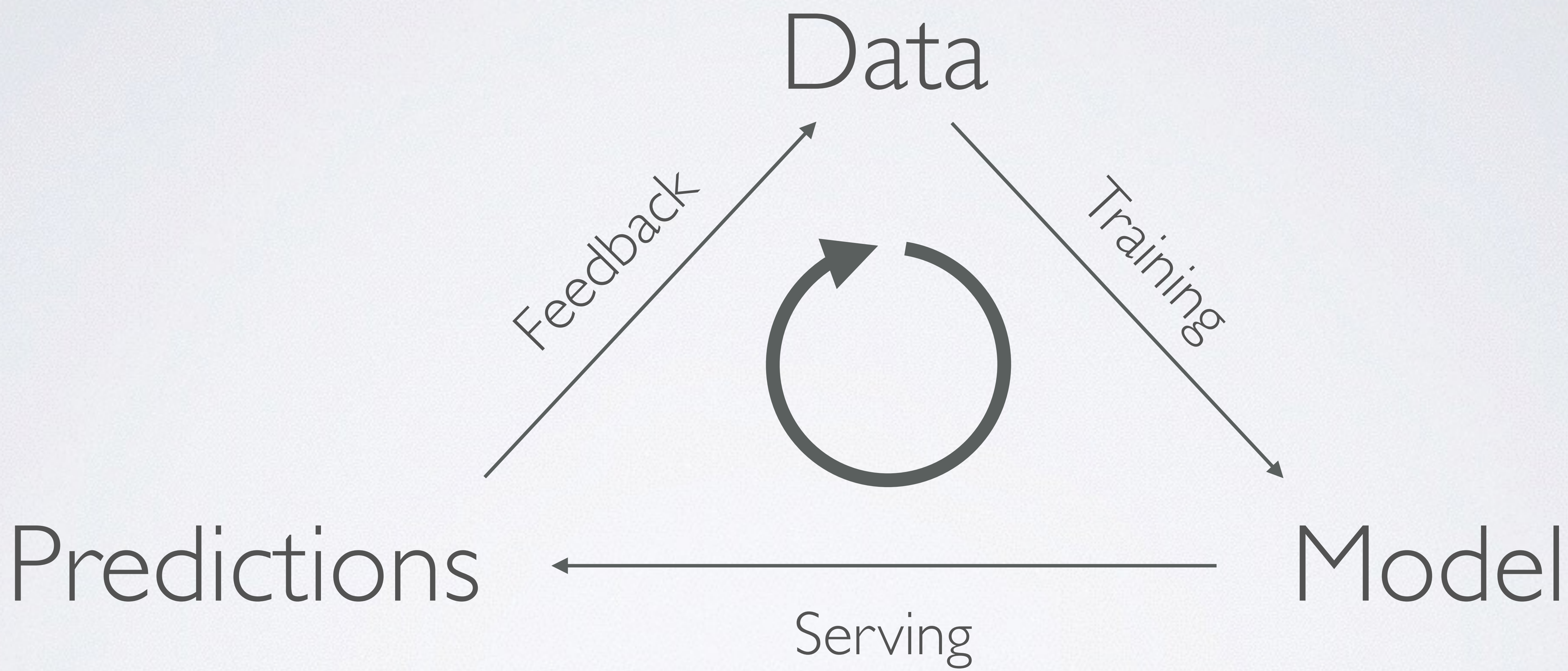
- Ensure user privacy
  - **Privacy-Preserving DBMS**

Data

Data → Model


Data
Training
Model


Data
Training
Predictions
Model
Serving


Data
Feedback
Training
Predictions
Model
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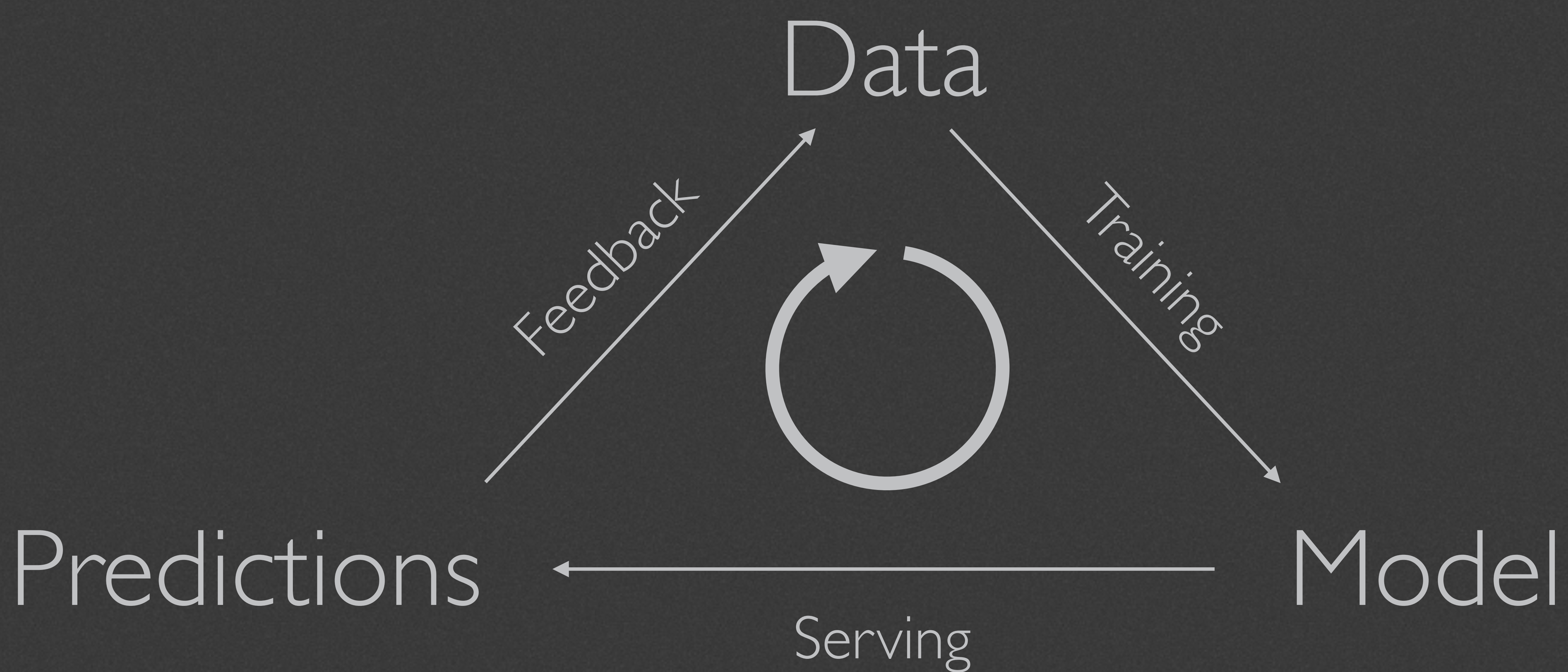
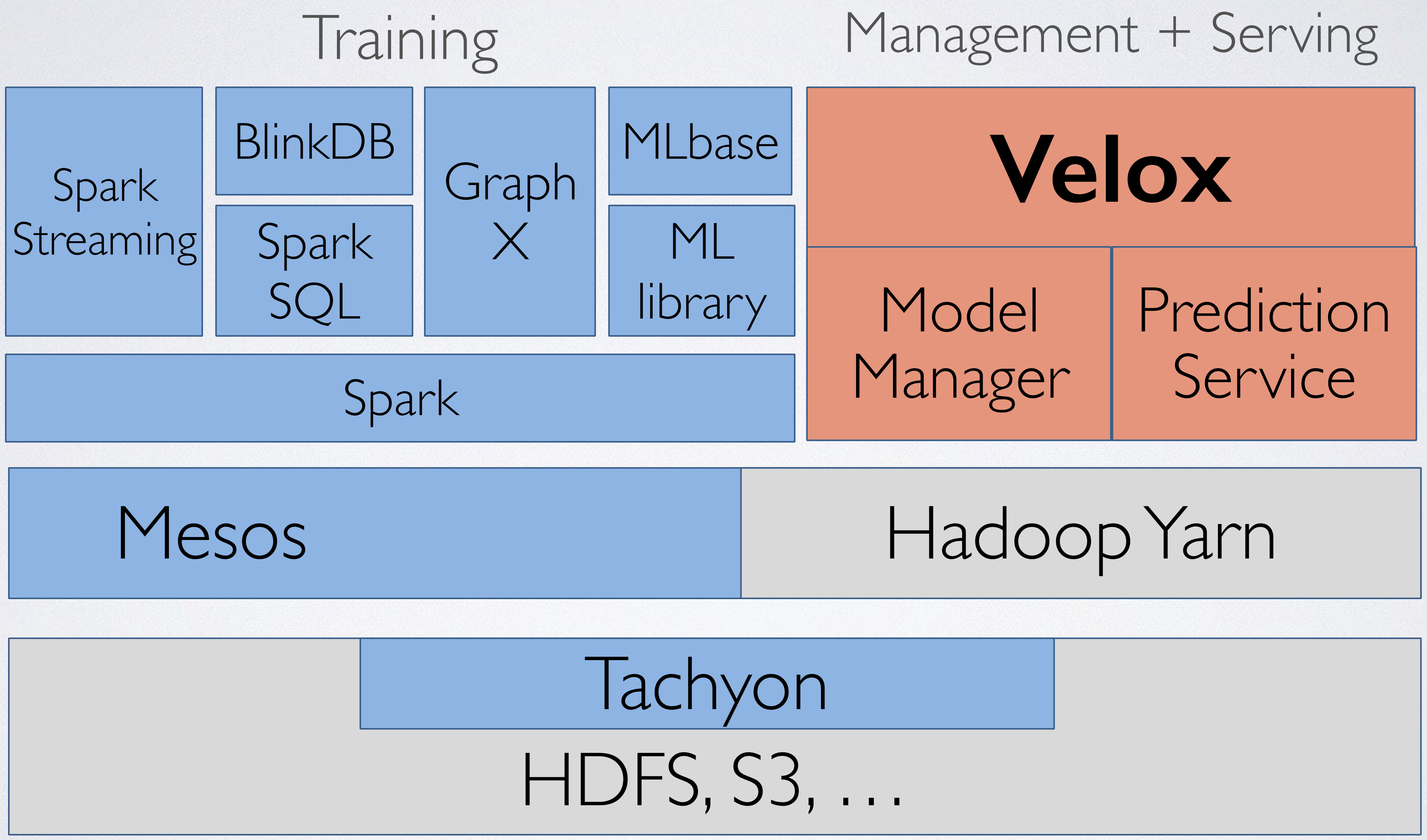
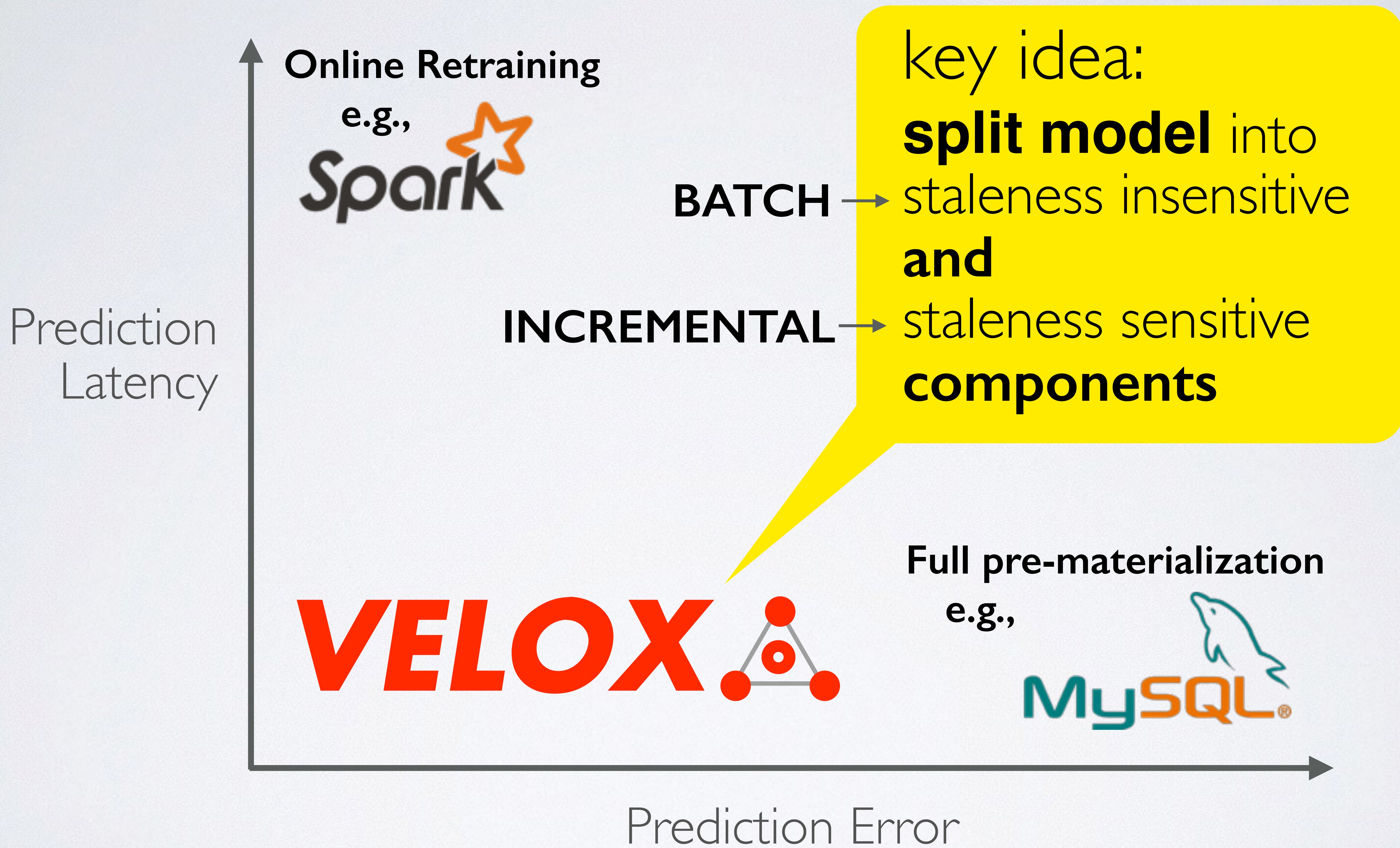
The future of research in scalable learning systems will be in the integration of the learning lifecycle:



THE MISSING PIECE




Prediction Latency
Online Retraining
e.g.,
Spark
BATCH
INCREMENTAL
key idea:
split model into
staleness insensitive
and
staleness sensitive
components
VELOX
Full pre-materialization
e.g.,
MySQL
Prediction Error

SUMMARY

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Today: model training and serving relies on **ad-hoc**, **manual** processes spread across **multiple systems**

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Velox is coming soon as part of BDAS

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https://amplab.cs.berkeley.edu/projects/velox/

QUESTIONS?