SPARK SUMMIT 2017

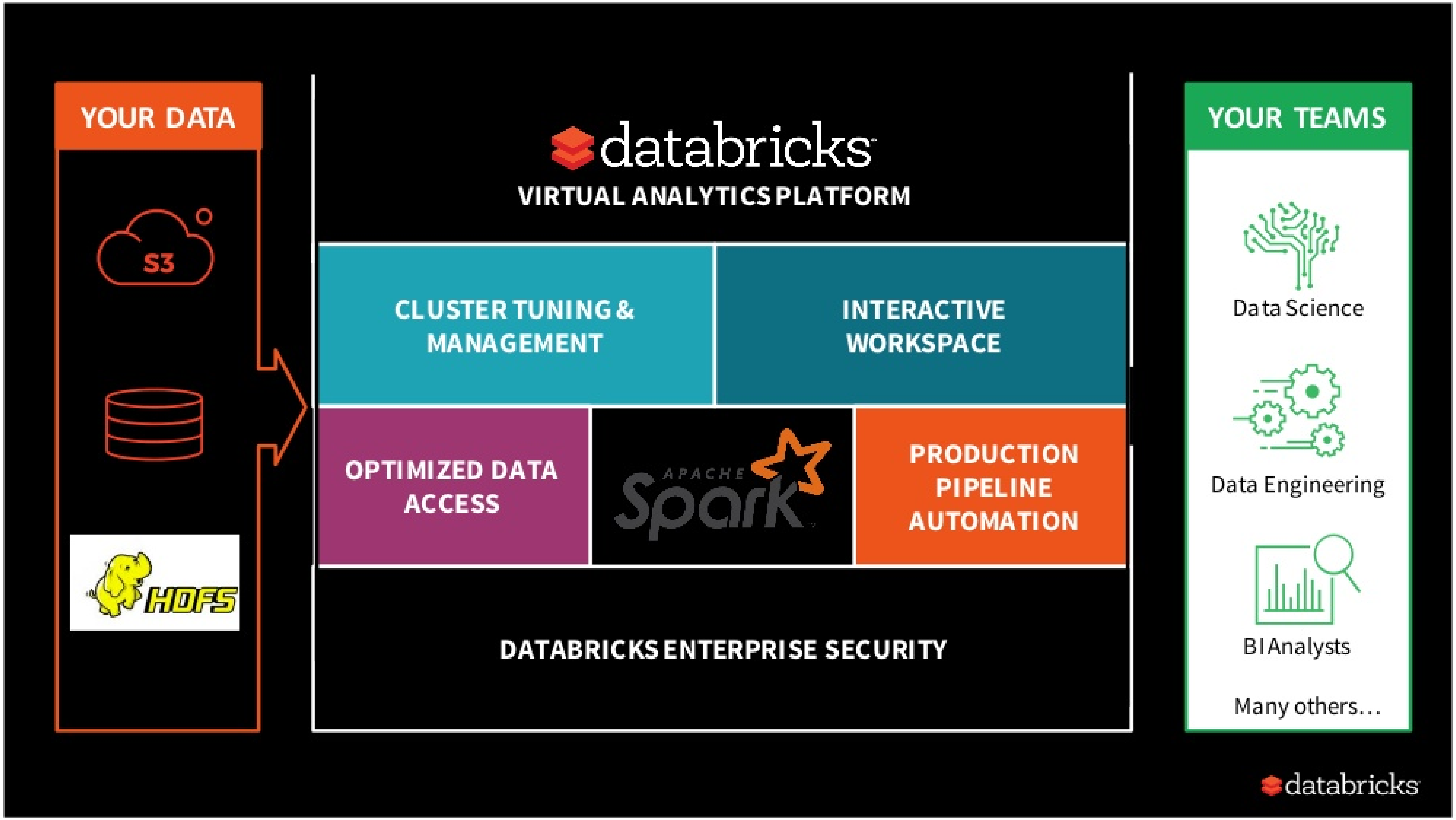
Apache Spark™ MLlib 2.x: How to Productionize your Machine Learning Models

Richard Garris (Principal Solutions Architect)

VISION
Empower anyone to innovate faster with big data.

PRODUCT
A fully-managed data processing platform for the enterprise, powered by Apache Spark.

WHO WE ARE
Founded by the creators of Apache Spark. Contributes **75%** of the open source code, **10x** more than any other company.



YOUR DATA
S3
HDFS
databricks
VIRTUAL ANALYTICS PLATFORM
CLUSTER TUNING & MANAGEMENT
INTERACTIVE WORKSPACE
OPTIMIZED DATA ACCESS
APACHE Spark
PRODUCTION PIPELINE AUTOMATION
DATABRICKS ENTERPRISE SECURITY
YOUR TEAMS
Data Science
Data Engineering
BI Analysts
Many others…
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About Me

- Richard L Garris
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  - Twitter @rlgarris
- Principal Data Solutions Architect @ Databricks
- 12+ years designing Enterprise Data Solutions for everyone from startups to Global 2000
- Prior Work Experience PwC, Google and Skytree – the Machine Learning Company
- Ohio State Buckeye and Masters from CMU

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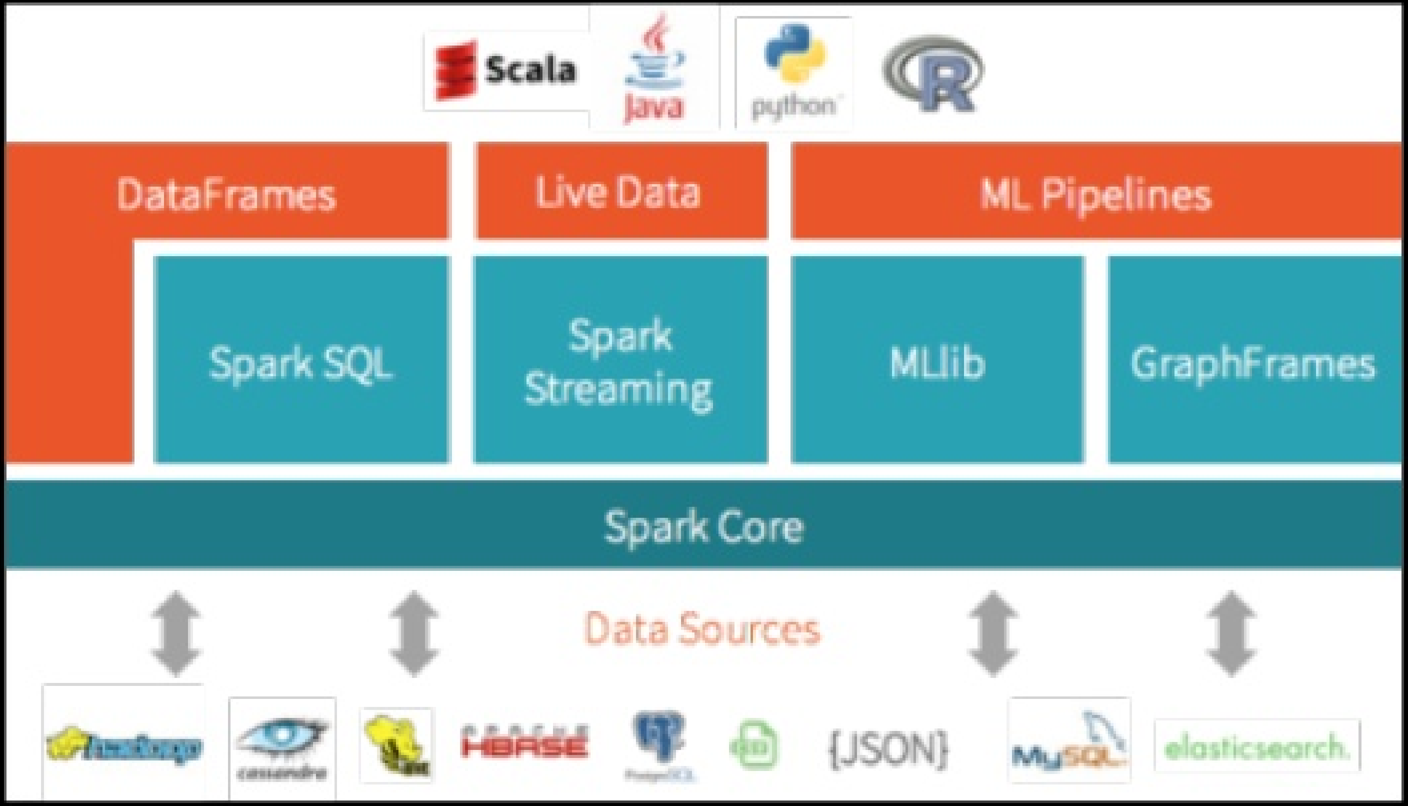
Outline

- Spark Mllib 2.X
- Model Serialization
- Model Scoring System Requirements
- Model Scoring Architectures
- Databricks Model Scoring

About Apache Spark™ MLlib

- Started with Spark 0.8 in the AMPLab in 2014
- Migration to Spark DataFrames started with Spark 1.3 with feature parity within 2.X
- Contributions by 75+ orgs, ~250 individuals
- Distributed algorithms that scale linearly with the data



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MLlib’s Goals

- General purpose machine learning library optimized for big data
  - Linearly scalable = 2x more machines , runtime theoretically cut in half
  - Fault tolerant = resilient to the failure of nodes
  - Covers the most common algorithms with distributed implementations
- Built around the concept of a Data Science Pipeline (scikit-learn)
- Written entirely using Apache Spark™
- Integrates well with the Agile Modeling Process

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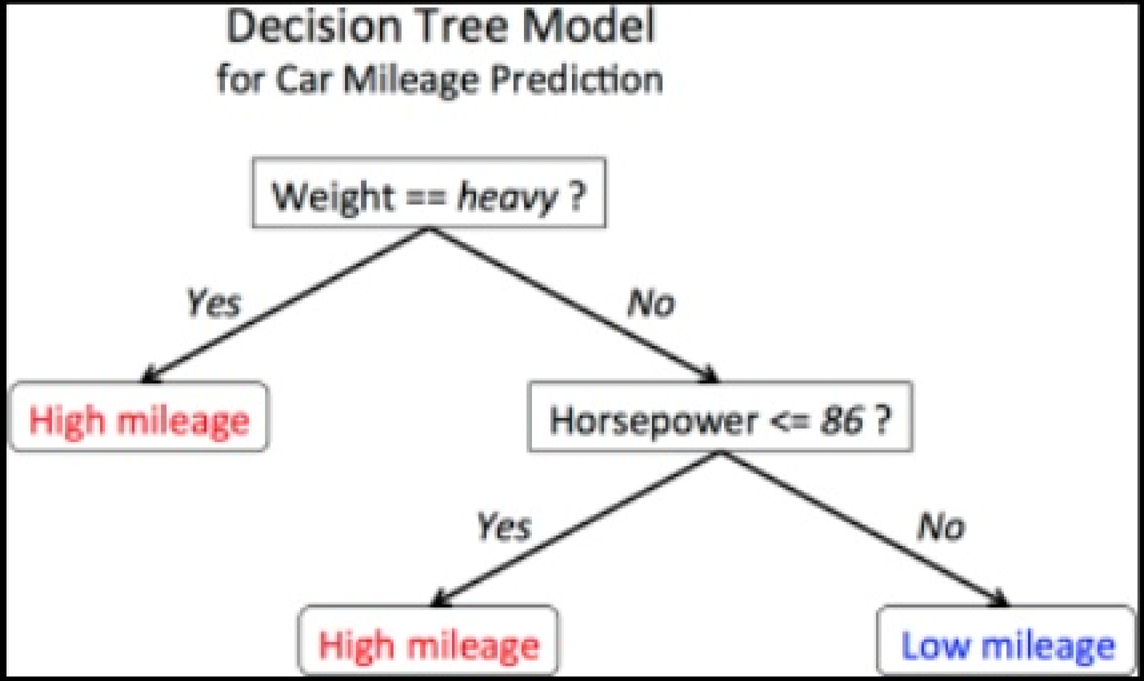
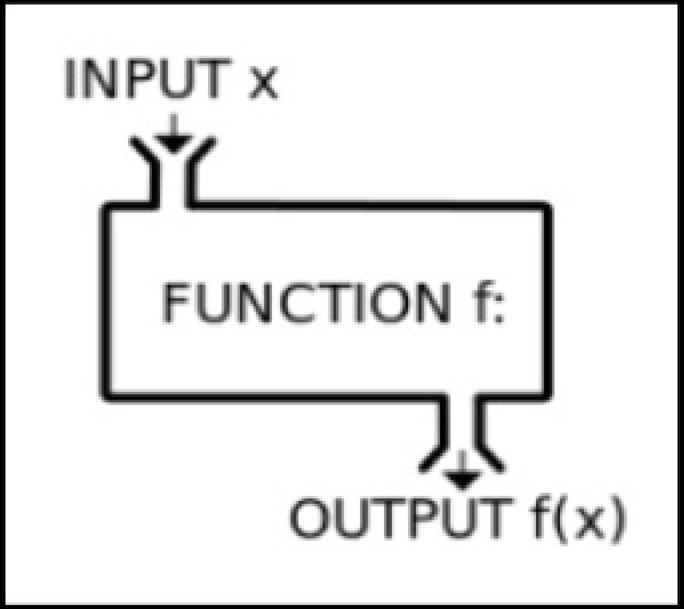
A Model is a Mathematical Function

- A model is a function: $f(x)$
- Linear regression $y = b_0 + b_1 x_1 + b_2 x_2$





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ML Pipelines

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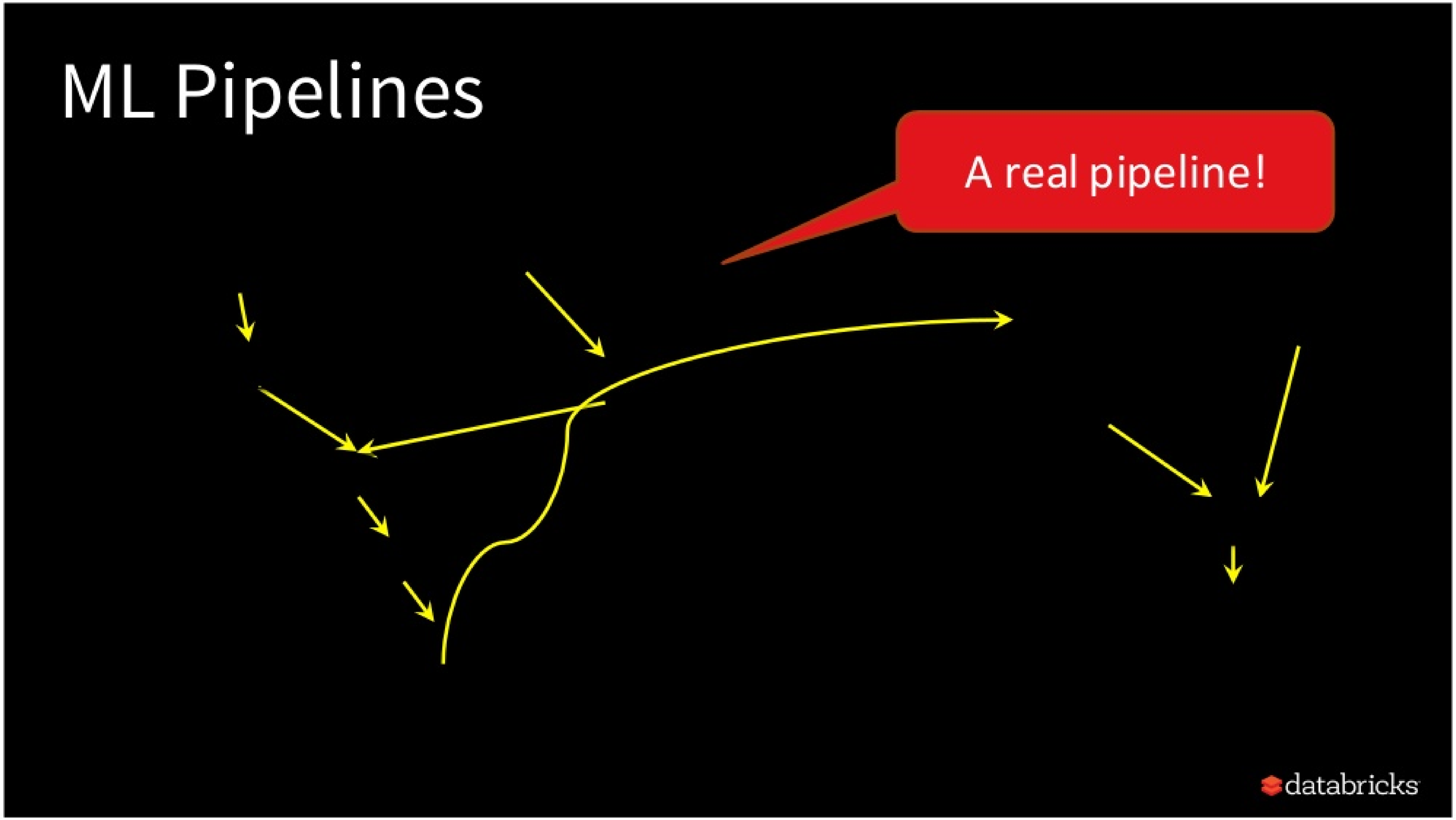
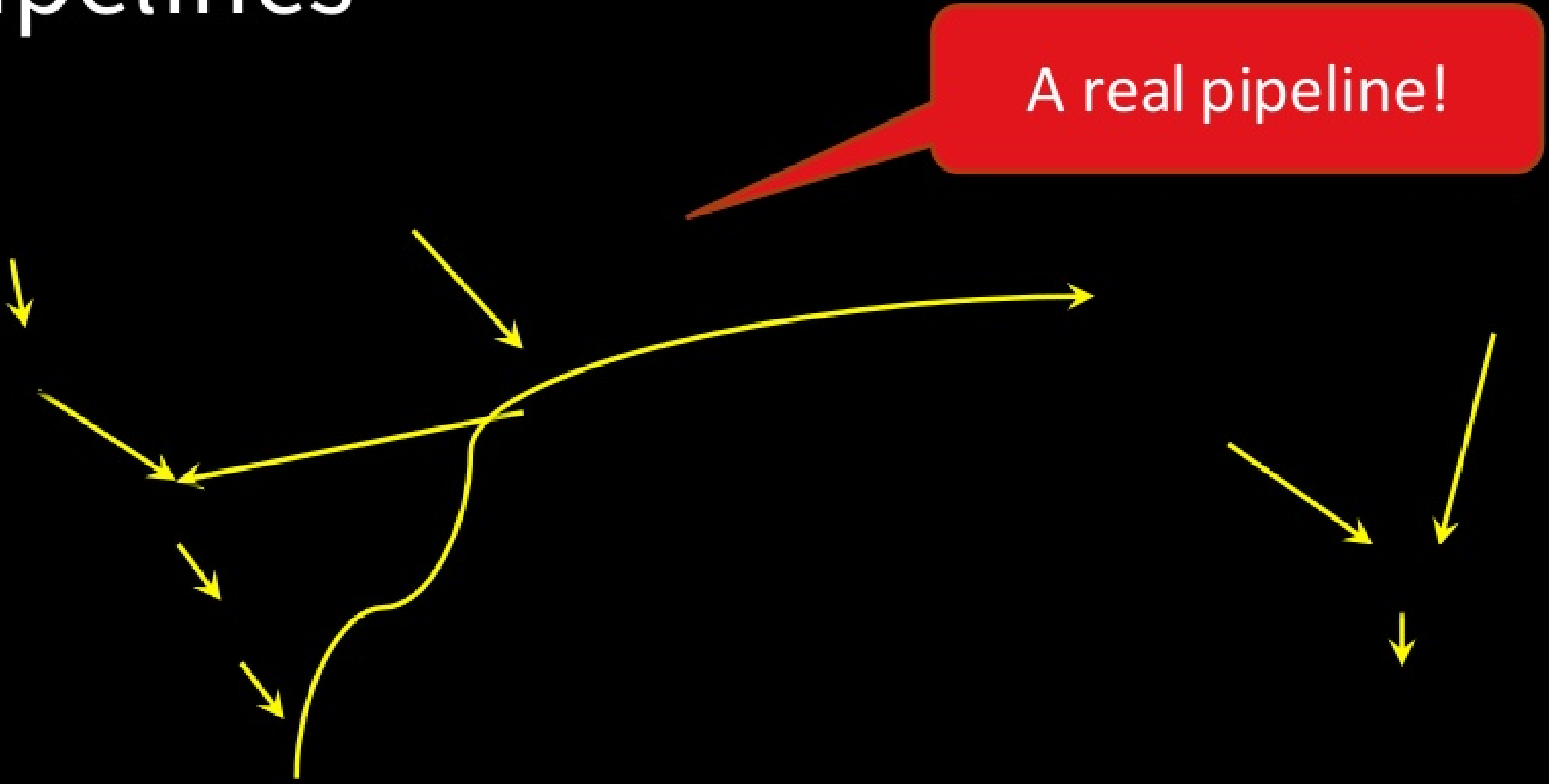


ML Pipelines



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Productionizing Models Today

Data Science

Develop Prototype Model using Python/R

Data Engineering

Re-implement model for production (Java)

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Problems with Productionizing Models

Data Science

Develop Prototype Model using Python/R

Data Engineering

Re-implement model for production (Java)

- Extra work
- Different code paths
- Data science does not translate to production
- Slow to update models

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MLlib 2.X Model Serialization

Data Science

Develop Prototype
Model using Python/R

Persist model or Pipeline:

```
model.save("s3n://...")
```

Data Engineering

Load Pipeline (Scala/Java)

```
Model.load("s3n://...")
```

Deploy in production

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MLlib 2.X Model Serialization Snippet

Scala

```scala
val lrModel = lrPipeline.fit(dataset)

// Save the Model
lrModel.write.save("/models/lr")
```

Python

```python
lrModel = lrPipeline.fit(dataset)

# Save the Model
lrModel.write.save("/models/lr")
```

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Model Serialization Output

Code

```
// List Contents of the Model Dir
dbutils.fs.ls("/models/lr")
```

Output

```
+-------------------------+---------+
|path                     |name     |
+-------------------------+---------+
|dbfs:/models/lr/metadata/|metadata/|
|dbfs:/models/lr/stages/  |stages/  |
+-------------------------+---------+
```

Remember this is a pipeline model and these are the stages!

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Transformer Stage (StringIndexer)

Code

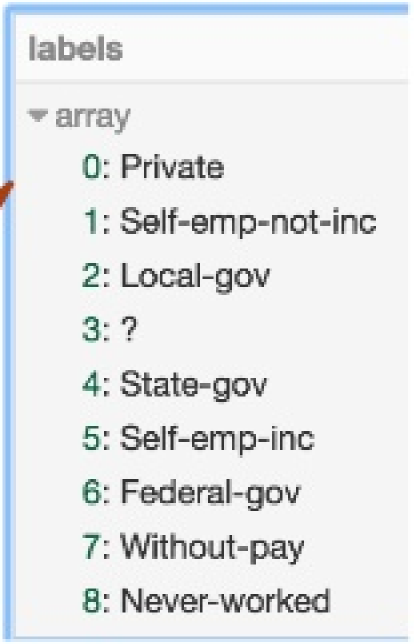
```
// Cat the contents of the Metadata dir
dbutils.fs.head(”/models/lr/stages/00_strIdx_bb9728f85745/metadata/part-00000")

// Display the Parquet File in the Data dir
display(spark.read.parquet(”/models/lr/stages/00_strIdx_bb9728f85745/data/"))
```

Output

Metadata and params

```
{
  "class":"org.apache.spark.ml.feature.StringIndexerModel",
  "timestamp":1488120411719,
  "sparkVersion":"2.1.0",
  "uid":"strIdx_bb9728f85745",
  "paramMap":{
    "outputCol":"workclassIdx",
    "inputCol":"workclass",
    "handleInvalid":"error"
  }
}
```



```
labels
▾ array
    0: Private
    1: Self-emp-not-inc
    2: Local-gov
    3: ?
    4: State-gov
    5: Self-emp-inc
    6: Federal-gov
    7: Without-pay
    8: Never-worked
```

Data (Hashmap)

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Estimator Stage (LogisticRegression)

Code

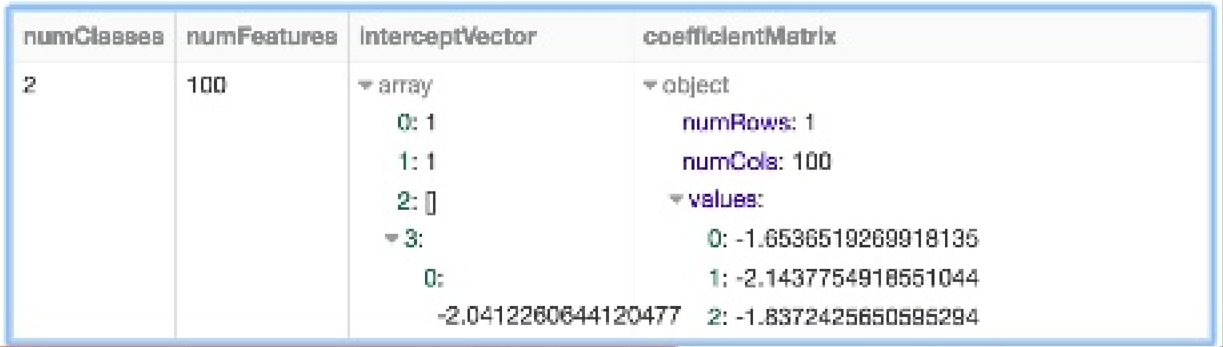
```
// Cat the contents of the Metadata dir
dbutils.fs.head(”/models/lr/stages/18_logreg_325fa760f925/metadata/part-00000")

// Display the Parquet File in the Data dir
display(spark.read.parquet("/models/lr/stages/18_logreg_325fa760f925/data/"))
```

Model params

Output

```
{"class":"org.apache.spark.ml.classification.LogisticRegressionModel",
  "timestamp":1488120446324,                      "maxIter":100,
  "sparkVersion":"2.1.0",                         "elasticNetParam":0.0,
  "uid":"logreg_325fa760f925",                     "family":"auto",
  "paramMap":{                                     "regParam":0.0,
    "predictionCol":"prediction",                 "threshold":0.5,
    "standardization":true,                          "fitIntercept":true,
    "probabilityCol":"probability",                  "labelCol":"label” }}
```



numClasses	numFeatures	interceptVector	coefficientMatrix
2	100	array 0: 1 1: 1 2: [] 3: 0: -2.0412260644120477	object numRows: 1 numCols: 100 values: 0: -1.6536519269918135 1: -2.1437754918551044 2: -1.8372425650595294

Intercept + Coefficients

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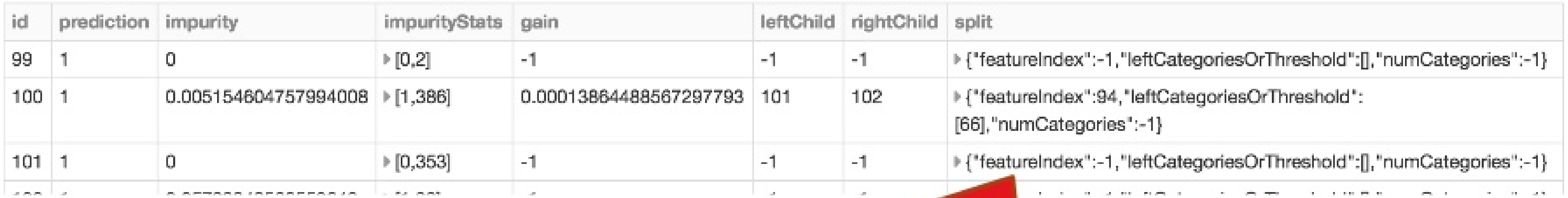
Estimator Stage (DecisionTree)

Code

```
// Display the Parquet File in the Data dir
display(spark.read.parquet("/models/dt/stages/18_dtc_3d614bcb3ff825/data/"))

// Re-save as JSON
spark.read.parquet("/models/dt/stages/18_dtc_3d614bcb3ff825/data/").json(("/models/json/dt").
```

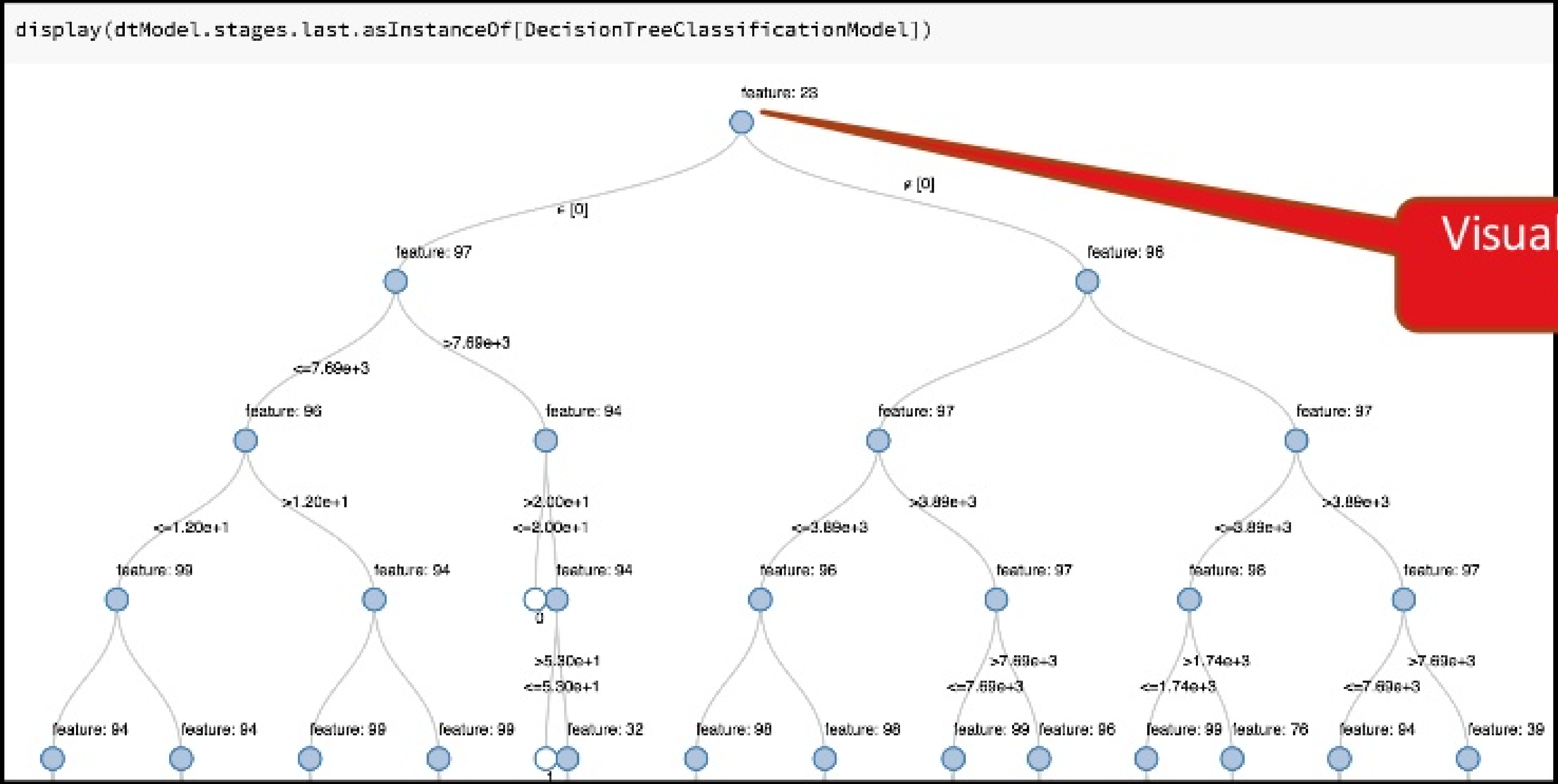
Output



id	prediction	impurity	impurityStats	gain	leftChild	rightChild	split
99	1	0	[0,2]	-1	-1	-1	{"featureIndex":-1,"leftCategoriesOrThreshold":[],"numCategories":-1}
100	1	0.005154604757994008	[1,386]	0.00013864488567297793	101	102	{"featureIndex":94,"leftCategoriesOrThreshold":[66],"numCategories":-1}
101	1	0	[0,353]	-1	-1	-1	{"featureIndex":-1,"leftCategoriesOrThreshold":[],"numCategories":-1}

Decision Tree Splits

Visualize Stage (DecisionTree)



```
display(dtModel.stages.last.asInstanceOf[DecisionTreeClassificationModel])
```

Visualization of the Tree In Databricks

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What are the Requirements for a Robust Model Deployment System?

Model Scoring Environment Examples

- In Web Applications / Ecommerce Portals
- Mainframe / Batch Processing Systems
- Real-Time Processing Systems / Middleware
- Via API / Microservice
- Embedded in Devices (Mobile Phones, Medical Devices, Autos)

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Hidden Technical Debt in ML Systems

"Hidden Technical Debt in Machine Learning Systems ", Google NIPS 2015

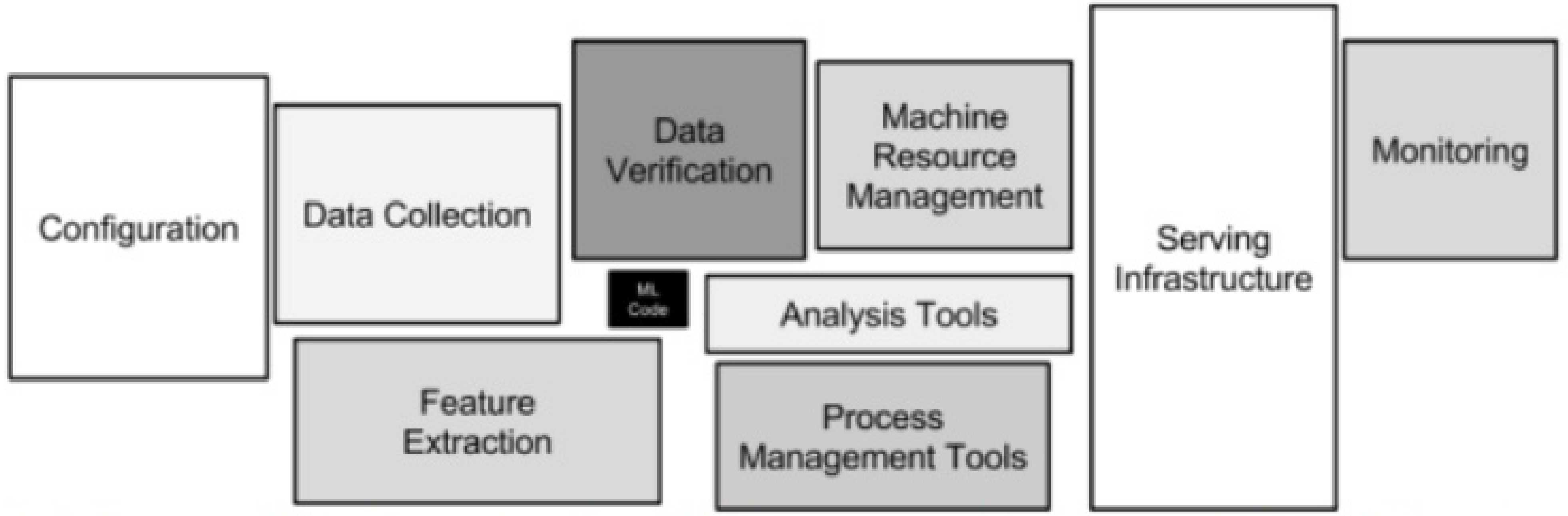

Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

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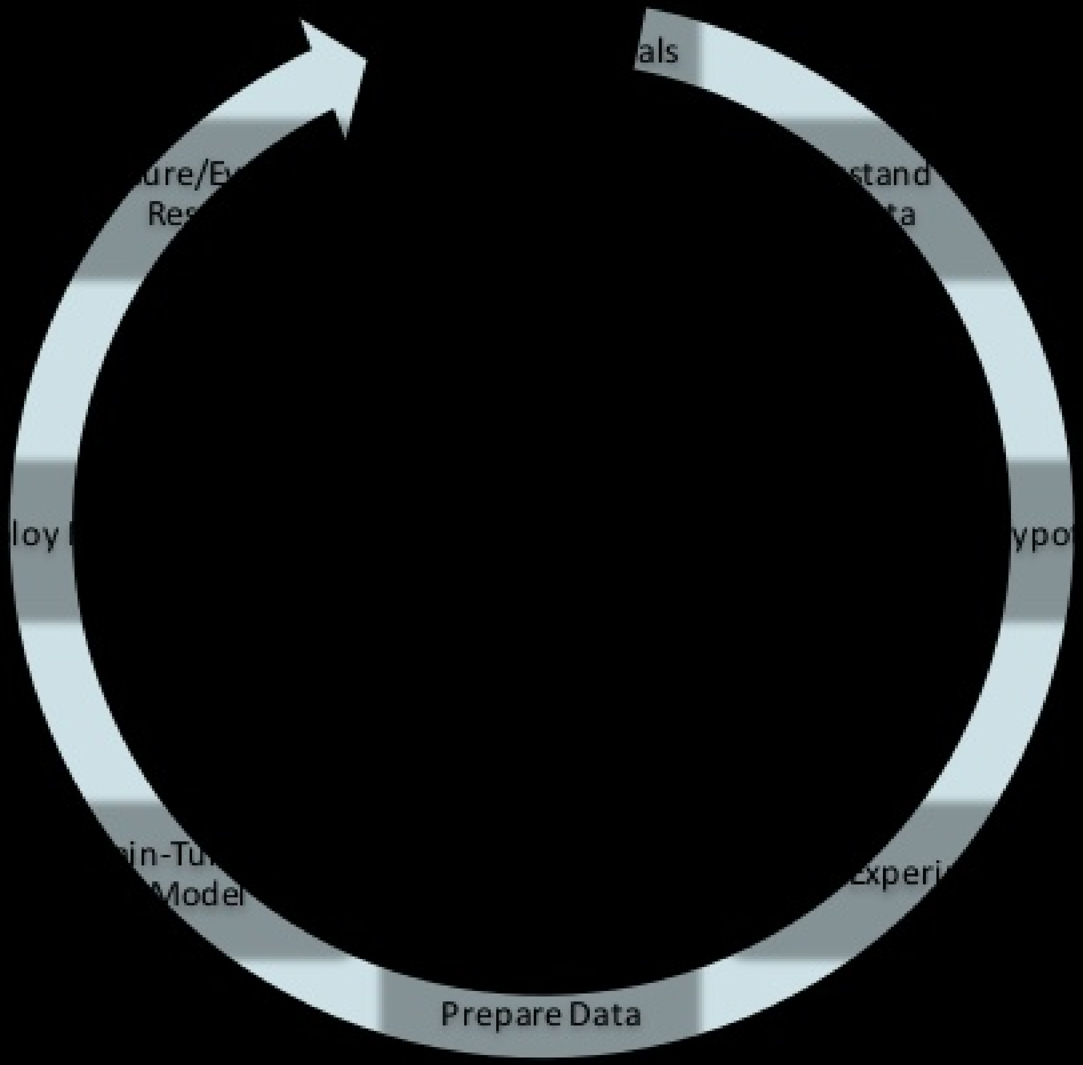
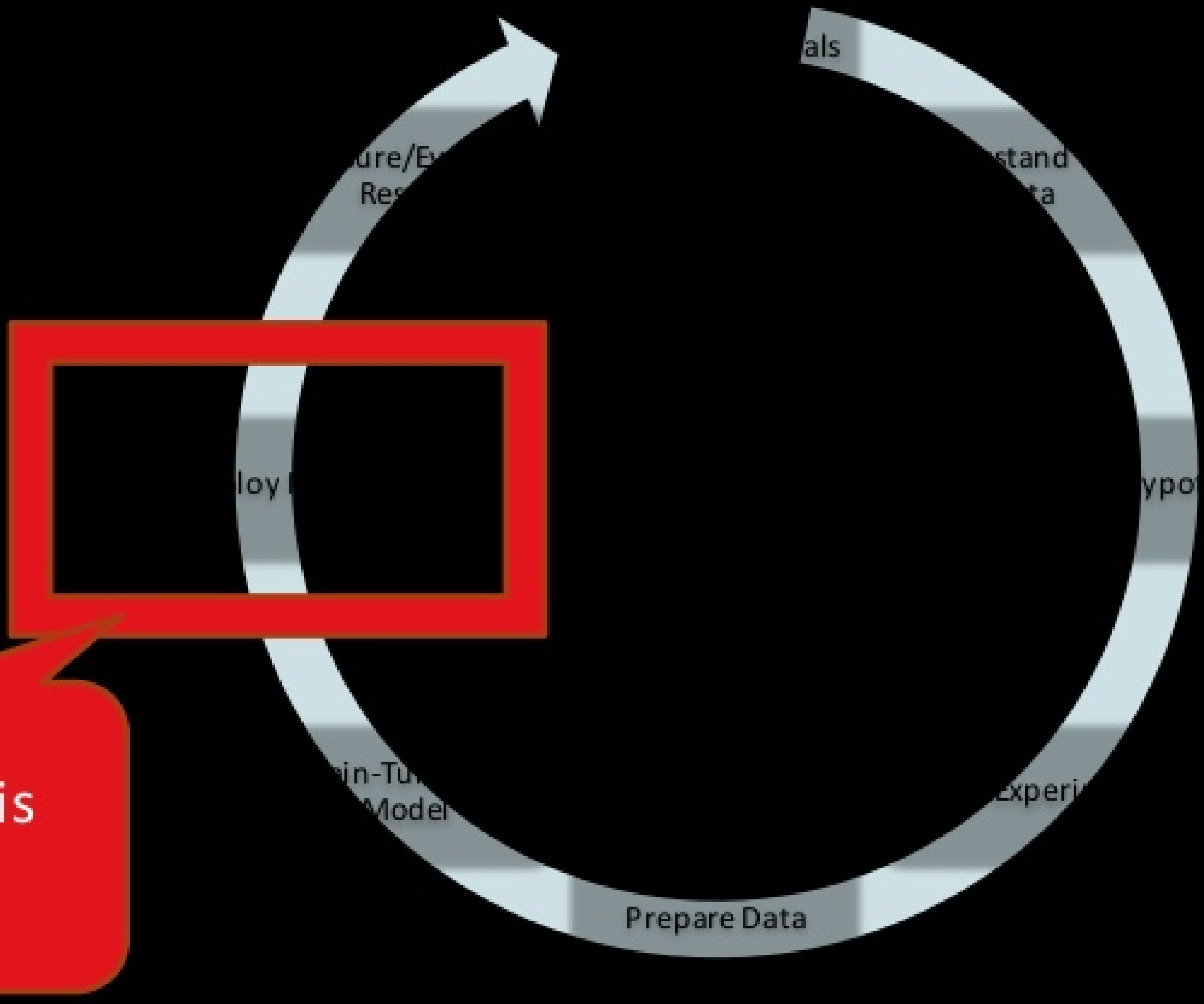
Agile Modeling Process

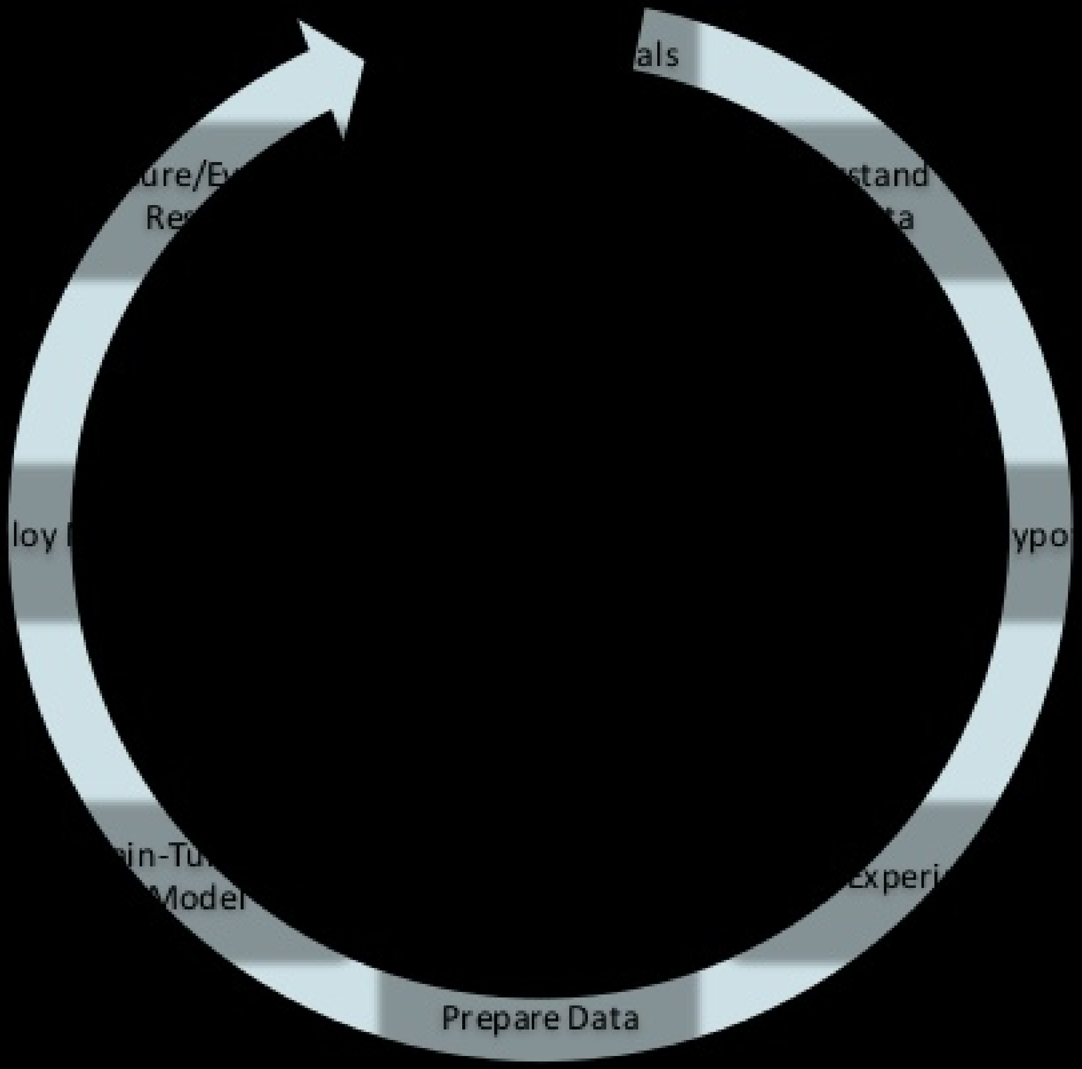


Agile Modeling Process



Focus of this talk

Deployment Should be Agile



- Deployment needs to support A/B testing and experiments
- Deployment should support measuring and evaluating model performance
- Deployment should be fast and adaptive to business needs

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Model A/B Testing, Monitoring, Updates

- A/B testing – comparing two versions to see what performs better
- Monitoring is the process of observing the model's performance, logging it's behavior and alerting when the model degrades
- Logging should log exactly the data feed into the model at the time of scoring
- Model update process
  - Benchmark (or Shadow Models)
  - Phase-In (20% traffic)
  - Avoid Big Bang

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Consider the Scoring Environment

Customer SLAs

- Response time
- Throughput (predictions per second)
- Uptime / Reliability

Tech Stack

- C / C++
- Legacy (mainframe)
- Java

Scoring in Batch vs Real-Time

Batch

- Asynchronous
- Internal Use
- Triggers can be event based on time based
- Used for Email Campaigns, Notifications

Real-Time

- Synchronous
- Could be Seconds:
  - Customer is waiting (human real-time)
- Subsecond:
  - High Frequency Trading
  - Fraud Detection on the Swipe

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Online Learning and Open / Closed Loop

Open / Closed Loop

Open Loop – human being involved

Closed Loop – no human involved

- Model Scoring – almost always closed loop, some open loop e.g. alert agents or customer service
- Model Training – usually open loop with a data scientist in the loop to update the model

Online Learning

- Online is closed loop, entirely machine driven but modeling is risky
- need to have proper model monitoring and safeguards to prevent abuse / sensitivity to noise
- MLlib supports online through streaming models (k-means, logistic regression support online)
- Alternative – use a more complex model to better fit new data rather than using online learning

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Model Scoring – Bot Detection

Not All Models Return Boolean – e.g. a Yes / No

Example: Login Bot Detector

Different behavior depending on probability that use is a bot

0.0-0.4 ☞ Allow login

0.4-0.6 ☞ Send Challenge Question

0.6 to 0.75 ☞ Send SMS Code

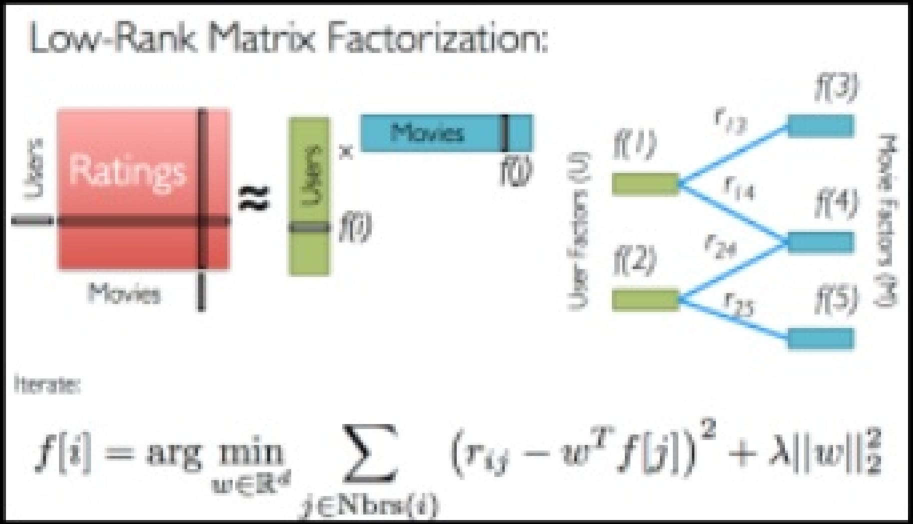
0.75 to 0.9 ☞ Refer to Agent

0.9 - 1.0 ☞ Block

Model Scoring – Recommendations

<u>Output is a ranking of the top n items</u>

API – send user ID + number of items
Return sorted set of items to recommend



$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \text{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

Optional –
pass context sensitive information to tailor results

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Model Scoring Architectures

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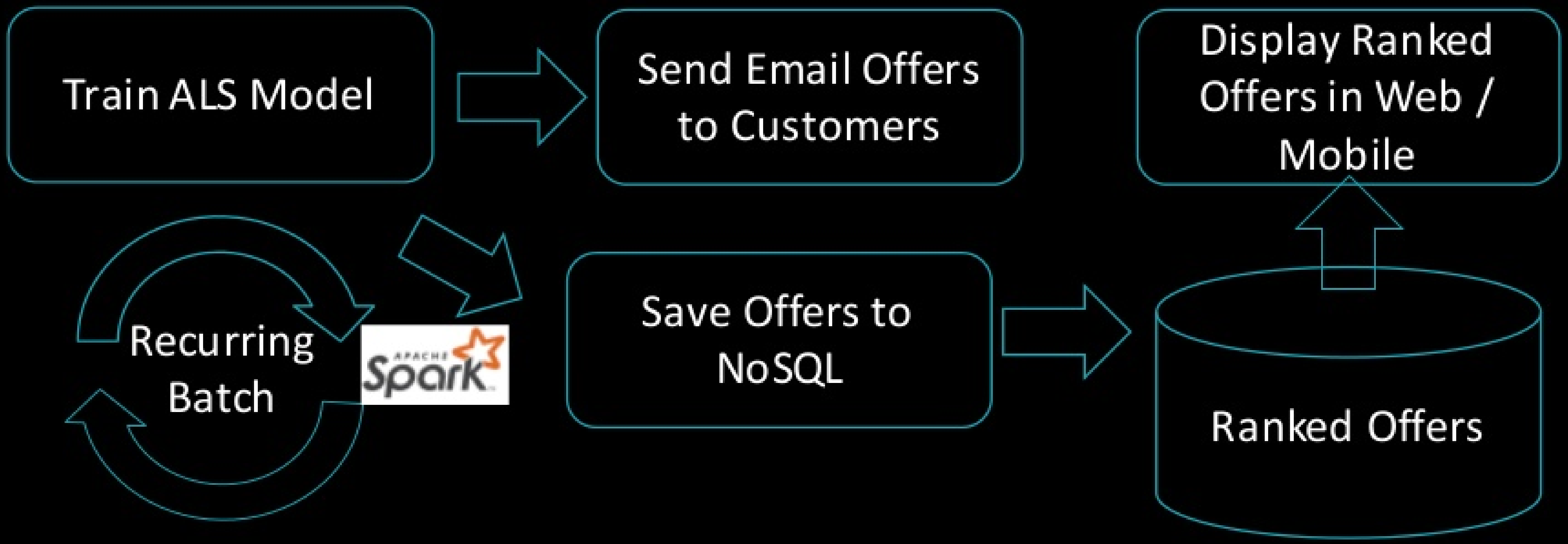
Architecture Option A

Precompute Predictions using Spark and Serve from Database



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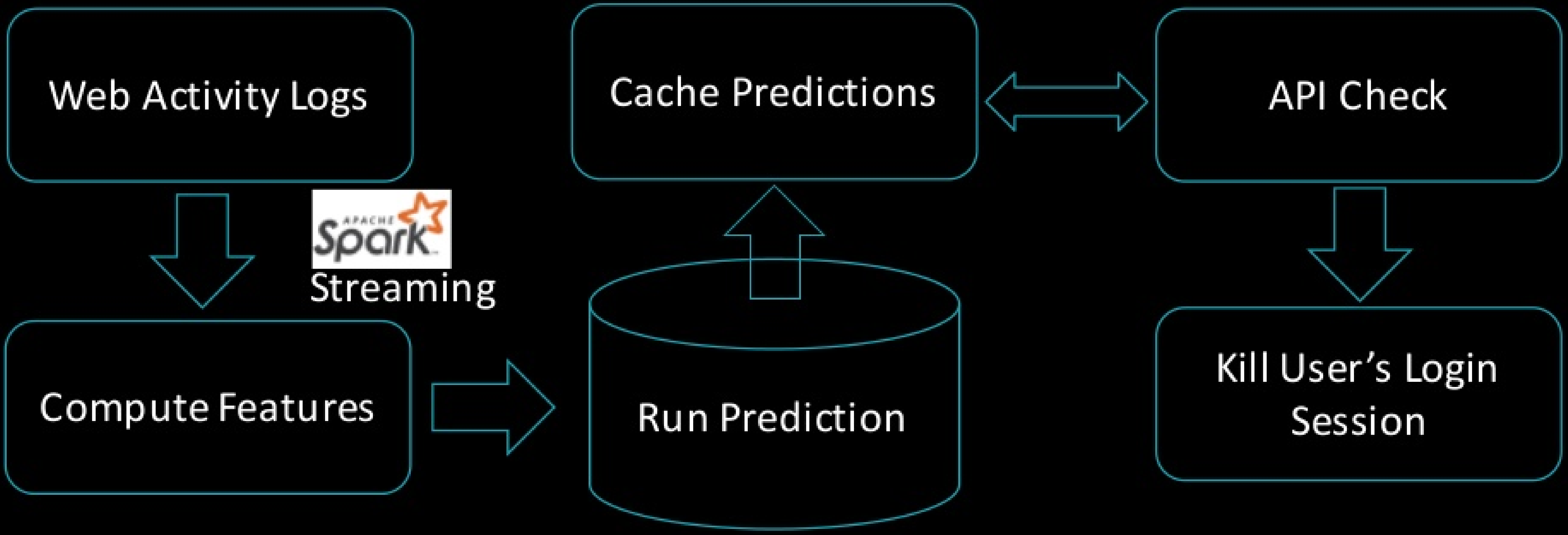
Architecture Option B

Spark Stream and Score using an API with Cached Predictions



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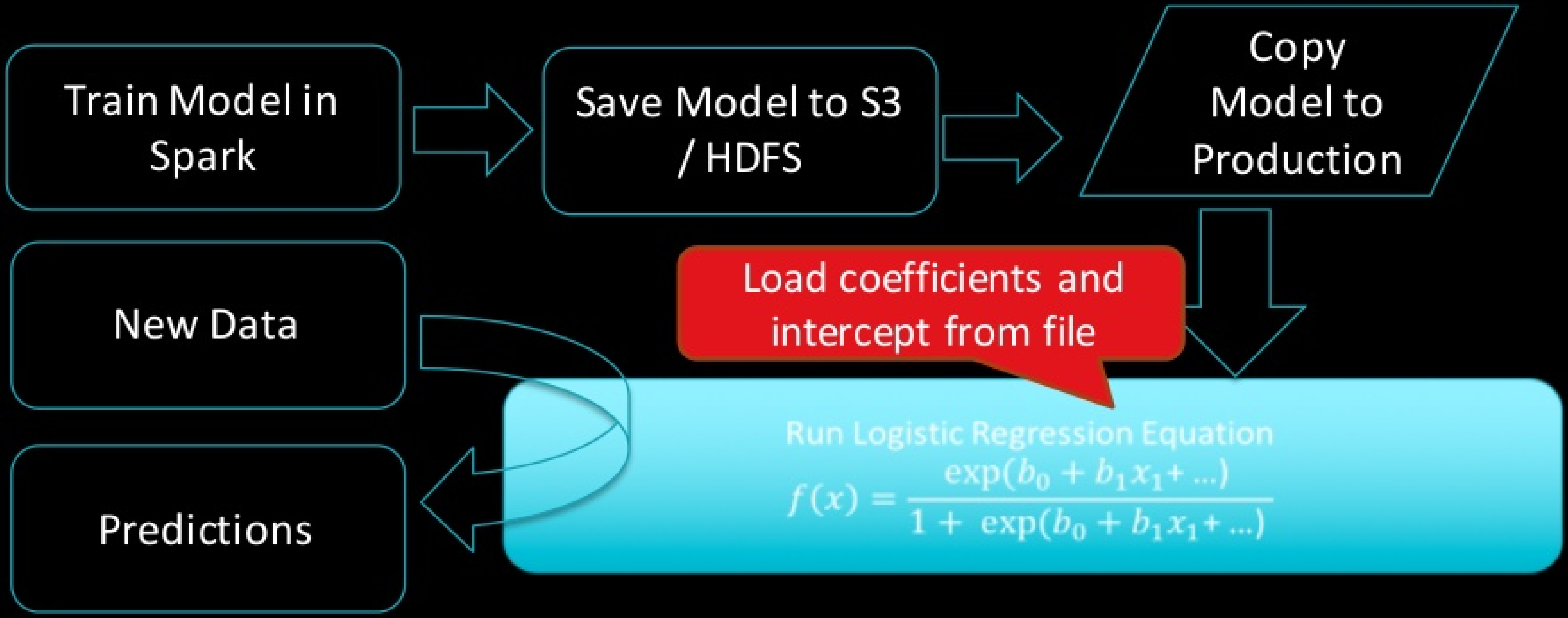
Architecture Option C

Train with Spark and Score Outside of Spark



$$f(x) = \frac{\exp(b_0 + b_1x_1 + \ldots)}{1 + \exp(b_0 + b_1x_1 + \ldots)}$$

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Databricks Model Scoring

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Databricks Model Scoring

- Based on Architecture Option C
- Goal: Deploy MLlib model outside of Apache Spark and Databricks.
  - Easy to Embed in Existing Environments
  - Low Latency and Complexity
  - Low Overhead

Databricks Model Scoring

- Train Model in Databricks
  - Call Fit on Pipeline
  - Save Model as JSON
- Deploy model in external system
  - Add dependency on "dbml-local" package (without Spark)
  - Load model from JSON at startup
  - Make predictions in real time

Code

```
// Fit and Export the Model in Databricks
val lrModel = lrPipeline.fit(dataset)
ModelExporter.export(lrModel, " /models/db ")


// In Your Application (Scala)
import com.databricks.ml.local.ModelImport

val lrModel = ModelImport.import("s3a:/...")
val jsonInput = ...
val jsonOutput = lrModel.transform(jsonInput)
```

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Databricks Model Scoring Private Beta

- Private Beta Available for Databricks Customers
- Available on Databricks using Apache Spark 2.1
- Only logistic regression available now
- Additional Estimators and Transformers in Progress

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Demo Model Scoring

https://community.cloud.databricks.com/?o=1526931011080774#notebook/1904316851197504

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Thank You.

Questions?

Happy Sparking

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