What's New in Apache Spark 2.3?

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About Me

- Software Engineer at Databricks
- Apache Spark Committer and PMC Member
- Previously, IBM Master Inventor
- Spark SQL, Database Replication, Information Integration
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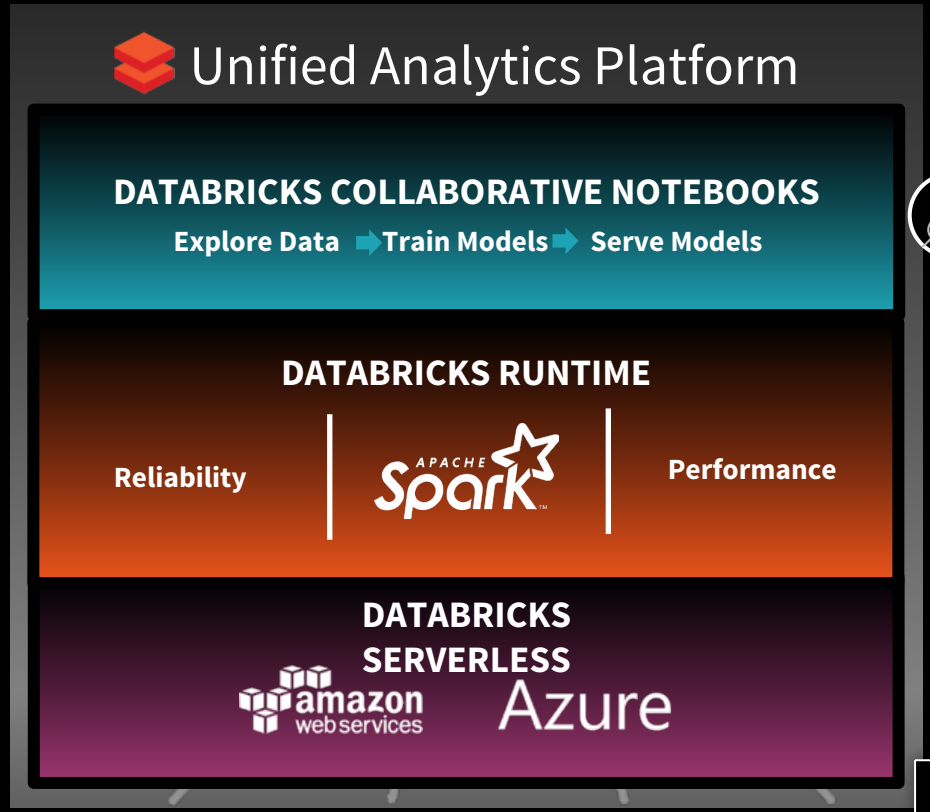
- Github: gatorsmile

Simplify Big Data and AI with Databricks



Increases Data Science Productivity by 5x

Eliminates Disparate Tools with Optimized Spark

Removes Devops & Infrastructure Complexity

Open Extensible API's

+ableau looker

Accelerates & Simplifies Data Prep for Analytics

Databricks Enterprise Security

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IoT / STREAMING DATA

CLOUD STORAGE

DATA WAREHOUSES

HADOOP STORAGE

Databricks Customers Across Industries

Financial Services

Healthcare & Pharma

Media & Entertainment

Data & Analytics Services

Technology

Public Sector

Retail & CPG

Consumer Services

Marketing & AdTech

Energy & Industrial IoT

This Talk

Databricks Runtime 4.0

Continuous Processing

Streaming ML + Image Reader

PySpark Performance

Spark on Kubernetes

Databricks Delta

OSS Apache Spark 2.3

Major Features on Spark 2.3

Continuous Processing

Data Source API V2

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PySpark Performance

ML on Streaming

History Server V2

Stream-stream Join

UDF Enhancements

Image Reader

Native ORC Support

Stable Codegen

Various SQL Features

Over 1300 issues resolved!

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Structured Streaming

stream processing on Spark SQL engine

fast, scalable, fault-tolerant

rich, unified, high level APIs

deal with *complex data* and *complex workloads*

rich ecosystem of data sources

integrate with many *storage systems*

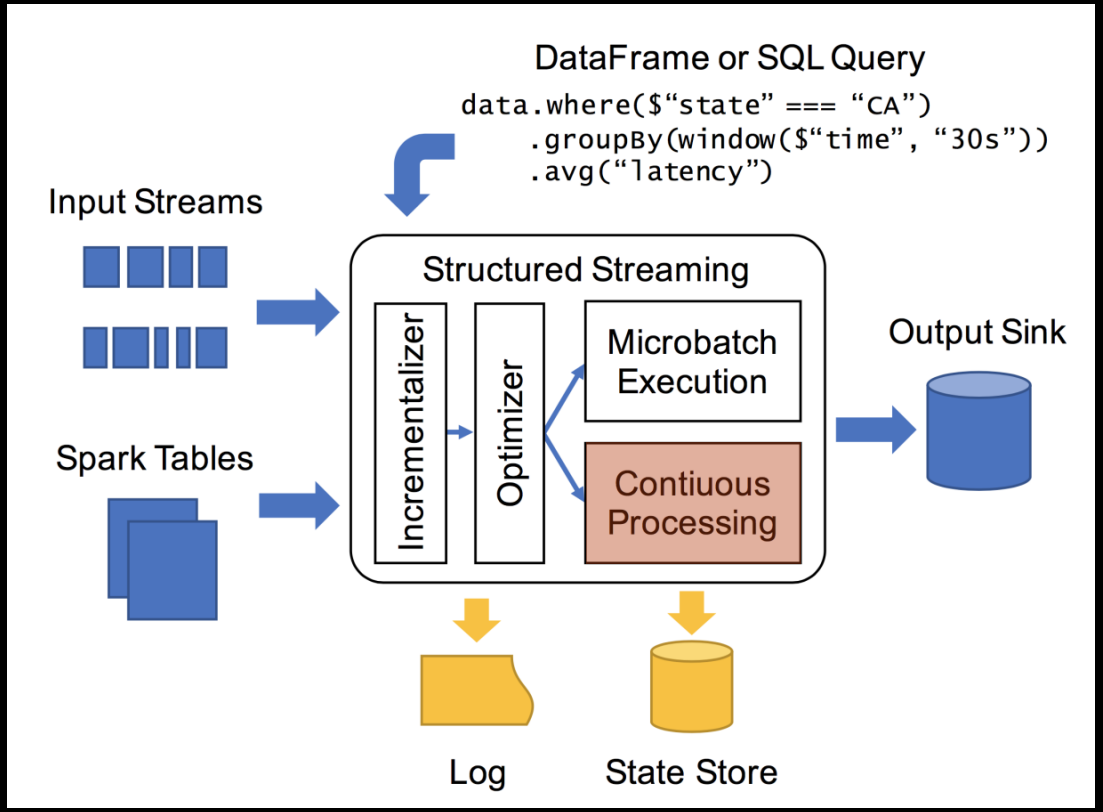
Structured Streaming

Introduced in Spark 2.0

Among Databricks customers:

- 10X more usage than DStream
- Processed 100+ trillion records in production

Structured Streaming



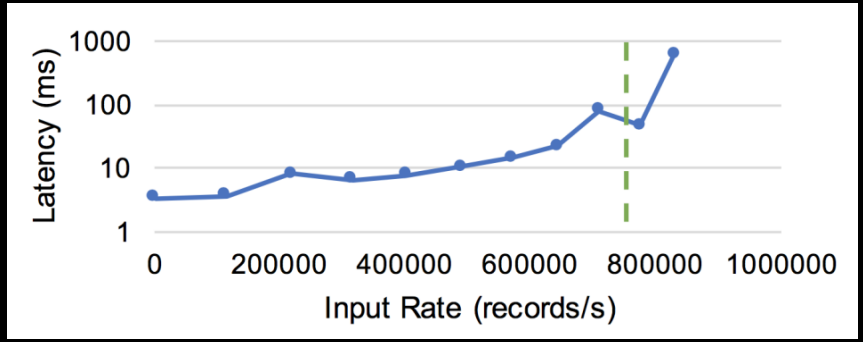
Continuous Processing Execution Mode

Micro-batch Processing (since 2.0 release)

- Lower end-to-end latencies of ~100ms
- Exactly-once fault-tolerance guarantees

Continuous Processing (since 2.3 release) [SPARK-20928]

- A new streaming execution mode (experimental)
- Low (~1 ms) end-to-end latency
- At-least-once guarantees



Continuous Processing

```
import org.apache.spark.sql.streaming.Trigger

spark
  .readStream
  .format("rate")
  .option("rowsPerSecond", "10")
  .option("")

spark
  .readStream
  .format("kafka")
  .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
  .option("subscribe", "topic1")
  .load()
  .selectExpr("CAST(key AS STRING)", "CAST(value AS STRING)")
  .writeStream
  .format("kafka")
  .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
  .option("topic", "topic1")
  .trigger(Trigger.Continuous("1 second"))
  .start()
```

The only change you need!

Continuous Processing

Continuous Processing

Supported Operations:

- Map-like Dataset operations
  - projections
  - selections
- All SQL functions
  - Except current_timestamp(), current_date() and aggregation functions

Supported Sources:

- Kafka source
- Rate source

Supported Sinks:

- Kafka sink
- Memory sink
- Console sink

This Talk

Continuous Processing

Streaming ML
+
Image Reader

PySpark Performance

Spark on Kubernetes

Databricks Delta

ML on Streaming

ML on Streaming

Model transformation/prediction on batch and streaming data with unified API.

After fitting a model or Pipeline, you can deploy it in a streaming job.

```
val streamOutput = transformer.transform(streamDF)
```

Demo

Notebook:

https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/1212468499849361/6491801434571 89/7151759854724023/latest.html

Image Support in Spark

Image Reader

Spark Image data source SPARK-21866 :

- Defined a standard API in Spark for reading images into DataFrames
- Deep learning frameworks can rely on this.

```
val df = ImageSchema.readImages("/data/images")
```

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PySpark

Introduced in Spark 0.7 (~2013); became first class citizen in the DataFrame API in Spark 1.3 (~2015)

Much slower than Scala/Java with user-defined functions (UDF), due to serialization & Python interpreter

Note: Most PyData tooling, e.g. Pandas, numpy, are written in C++

PySpark Performance

Fast data serialization and execution using vectorized formats [SPARK-22216] [SPARK-21187]

- Conversion from/to Pandas

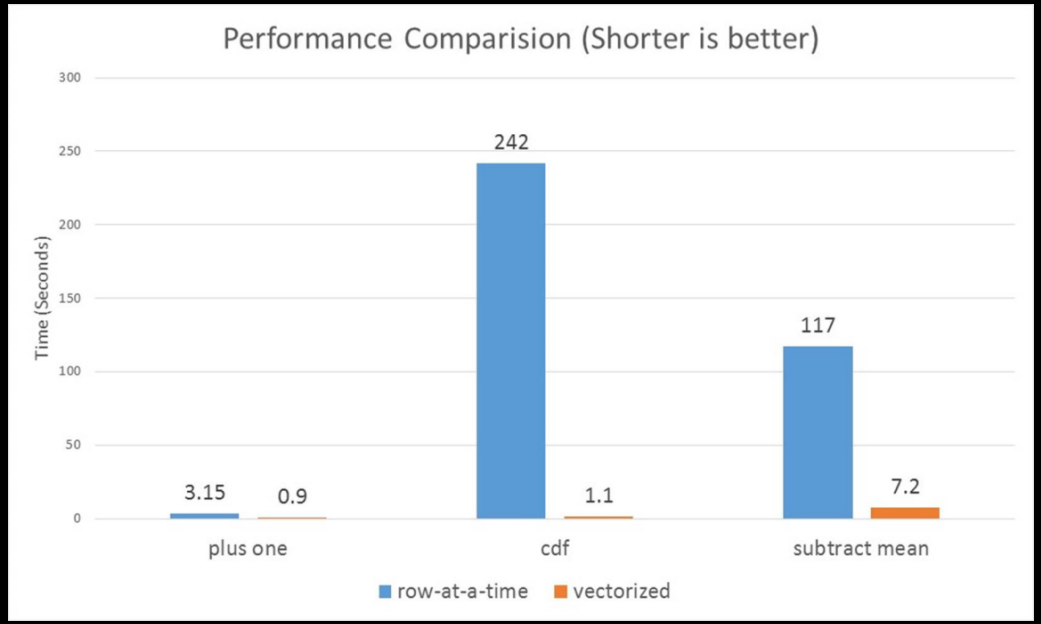
  df.*toPandas*()

  createDataFrame(pandas_df)

- Pandas/Vectorized UDFs: UDF using Pandas to process data
  - Scalar Pandas UDFs
  - Grouped Map Pandas UDFs

PySpark Performance

PySpark Performance



Blog "Introducing Vectorized UDFs for PySpark" http://dbricks.co/2rMwmW0

Pandas UDF

Scalar Pandas UDFs:

- Used with functions such as *select* and *withColumn*.
- The Python function should take *pandas.Series* as inputs and return a *pandas.Series* of the same length.

```
import pandas as pd
from pyspark.sql.functions import col, pandas_udf
from pyspark.sql.types import LongType

x = pd.Series([1, 2, 3])
# Create a Spark DataFrame, 'spark' is an existing SparkSession
df = spark.createDataFrame(pd.DataFrame(x, columns=["x"]))

# Declare the function and create the UDF
def multiply_func(a, b):
    return a * b
multiply = pandas_udf(multiply_func, returnType=LongType())

df.select(multiply(col("x"), col("x"))).show()
```

Pandas UDF

Grouped Map Pandas UDFs:

- **Split-apply-combine**
- A Python function that defines the computation for each group.
- The output schema

```
from pyspark.sql.functions import pandas_udf, PandasUDFType

df = spark.createDataFrame(
    [(1, 1.0), (1, 2.0), (2, 3.0), (2, 5.0), (2, 10.0)],
    ("id", "v"))

@pandas_udf("id long, v double", PandasUDFType.GROUPED_MAP)
def substract_mean(pdf):
    # pdf is a pandas.DataFrame
    v = pdf.v
    return pdf.assign(v=v - v.mean())

df.groupby("id").apply(substract_mean).show()
```

Demo

Notebook:

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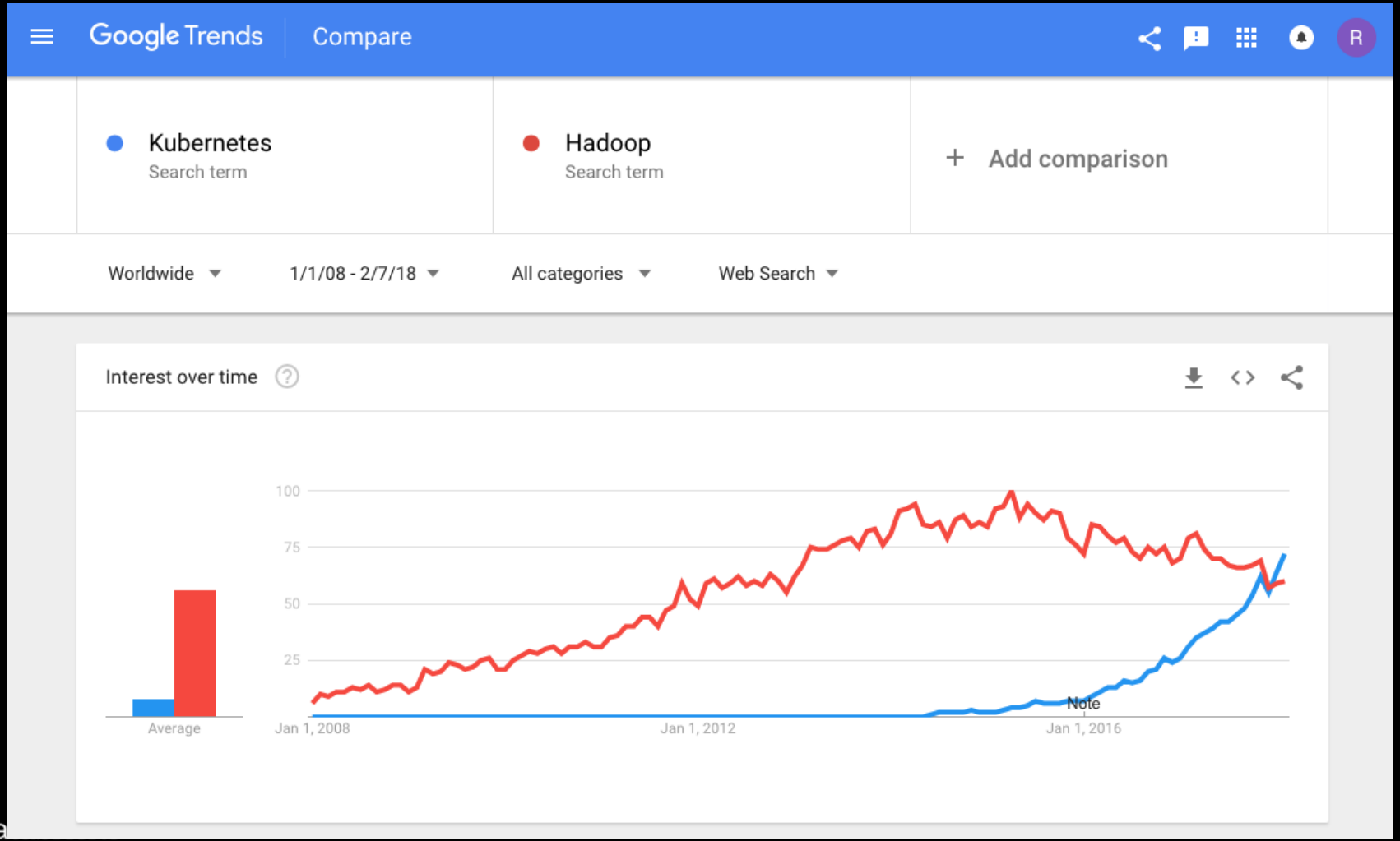
Google Trends
Compare
R
Kubernetes
Search term
Hadoop
Search term
+ Add comparison
Worldwide
1/1/08 - 2/7/18
All categories
Web Search
Interest over time
100
75
50
25
Average
Jan 1, 2008
Jan 1, 2012
Jan 1, 2016
Note

Native Spark App in K8S

- New Spark scheduler backend
- Driver runs in a Kubernetes pod created by the submission client and creates pods that run the executors in response to requests from the Spark scheduler. [K8S-34377] [SPARK-18278]
- Make direct use of Kubernetes clusters for multi-tenancy and sharing through Namespaces and Quotas, as well as administrative features such as Pluggable Authorization, and Logging.

Spark on Kubernetes

Supported:

- Supports Kubernetes 1.6 and up
- Supports cluster mode only
- Static resource allocation only
- Supports Java and Scala applications
- Can use container-local and remote dependencies that are downloadable

In roadmap (2.4):

- Client mode
- Dynamic resource allocation + external shuffle service
- Python and R support
- Submission client local dependencies + Resource staging server (RSS)
- Non-secured and Kerberized HDFS access (injection of Hadoop configuration)

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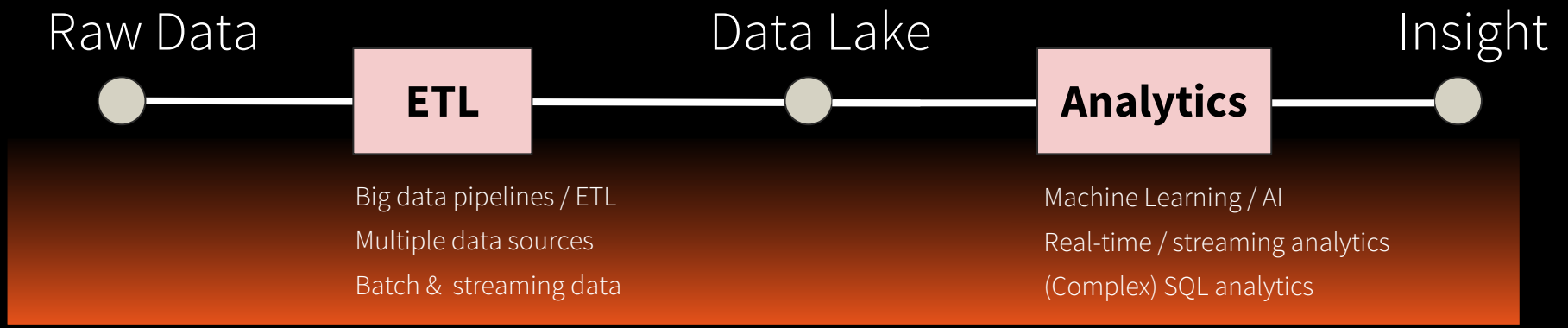
Databricks Delta

What is Databricks Delta?

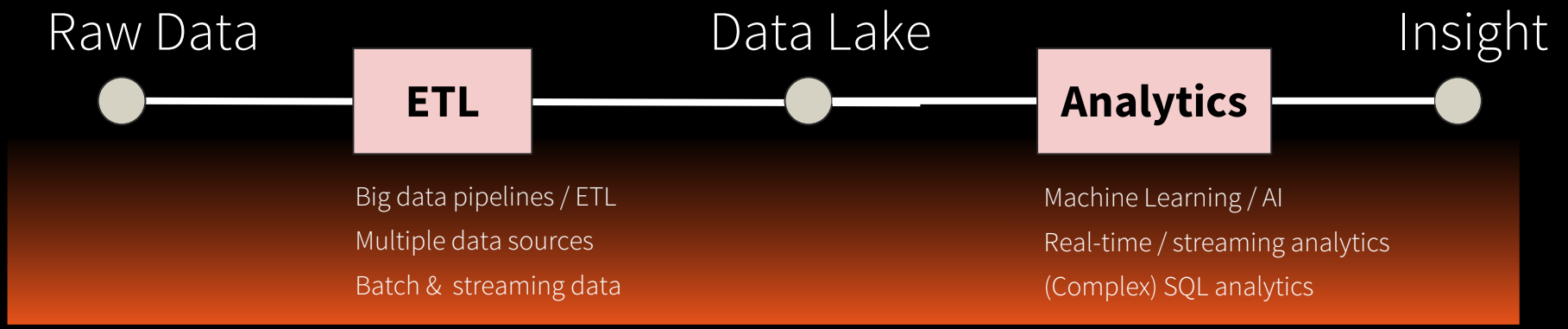
Delta is a data management capability that brings data reliability and performance optimizations to the cloud data lake.

Key Capabilities - Transactions & Indexing

Standard data pipelines with Spark



Yet challenges still remain



Reliability and Complexity

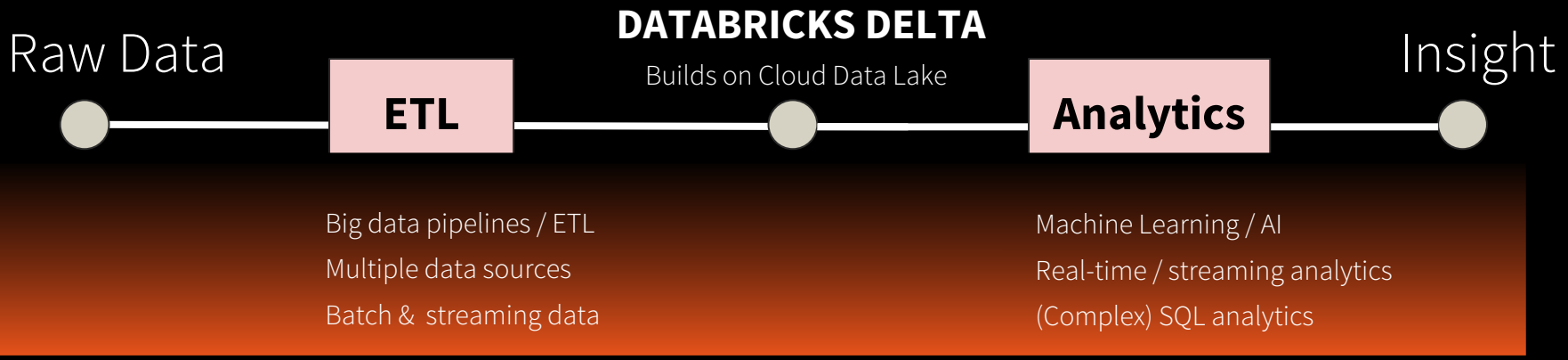
- Data corruption issues and broken pipelines
- Complex workarounds - tedious scheduling and multiple jobs/staging tables
- Many use cases require updates to existing data - not supported by Spark / Data lakes

Reliability & Performance Problems

- Performance degradation at scale for advanced analytics
- Stale and unreliable data slows analytic decisions

Streaming magnifies these challenges

Databricks Delta address these challenges



Reliability & Automation

Transactions guarantees eliminates complexity

Schema enforcement to ensure clean data

Upserts/Updates/Deletes to manage data changes

Seamlessly support streaming and batch

Performance & Reliability

Automatic indexing & caching

Fresh data for advanced analytics

Automated performance tuning

Databricks Delta Under the Hood

SCALE

- Use cloud object storage (e.g. AWS S3)
- Decouple compute & storage

RELIABILITY

- ACID compliant & data upserts
- Schema evolution

PERFORMANCE

- Intelligent partitioning & compaction
- Data skipping & indexing

LOW LATENCY

- Real-time streaming ingest
- Structured streaming

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Try these on Databricks Runtime 4.0 beta today!

Community edition:
https://community.cloud.databricks.com/

Thank you

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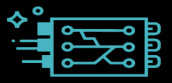
Various SQL Features

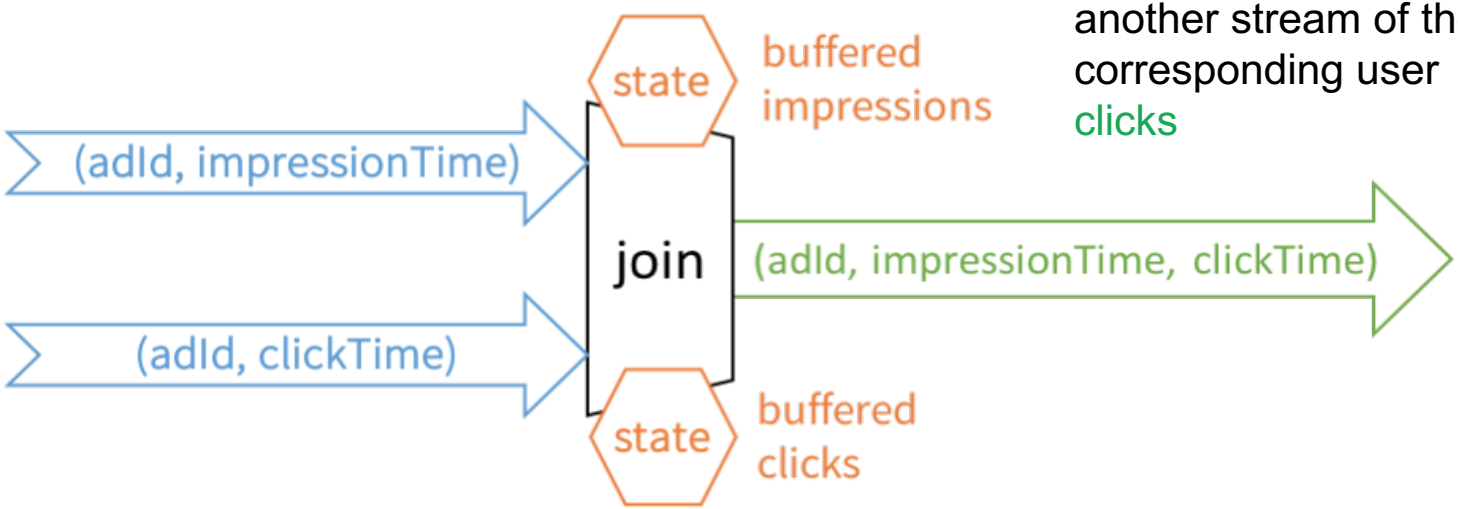
Stream-stream Joins



Stream-stream Join

Example: Ad Monetization

Join stream of ad impressions with another stream of their corresponding user clicks



Inner Join + Time constraints + Watermarks

Stream-stream Join

Time constraints

- Impressions can be 2 hours late
- Clicks can be 3 hours late
- A click can occur within 1 hour after the corresponding impression

```
val impressionsWithWatermark = impressions
      .withWatermark("impressionTime", "2 hours")

val clicksWithWatermark = clicks
      .withWatermark("clickTime", "3 hours")
```

Range Join

```
impressionsWithWatermark.join(
  clicksWithWatermark,
  expr("""
    clickAdId = impressionAdId AND
    clickTime >= impressionTime AND
    clickTime <= impressionTime + interval 1 hour
    """
  ))
```

Stream-stream Joins

Stream-stream Join

Inner	Supported, optionally specify watermark on both sides + time constraints for state cleanup
Left	Conditionally supported, must specify watermark on right + time constraints for correct results, optionally specify watermark on left for all state cleanup
Right	Conditionally supported, must specify watermark on left + time constraints for correct results, optionally specify watermark on right for all state cleanup
Full	Not supported.

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What's Wrong With V1?

- **Leak** upper level API in the data source (DataFrame/SQLContext)
- **Hard** to extend the Data Source API for more optimizations
- **Zero** transaction guarantee in the write APIs

Design Goals

- Java friendly (written in Java).
- No dependency on upper level APIs (DataFrame/RDD/…).
- Easy to extend, can add new optimizations while keeping backward compatibility.
- Can report physical information like size, partition, etc.
- Streaming source/sink support.
- A flexible and powerful, transactional write API.
- No change to end users.

Features in Spark 2.3

Data Source API V2

- Support both row-based scan and columnar scan.
- Column pruning and filter pushdown.
- Can report basic statistics and data partitioning.
- Transactional write API.
- Streaming source and sink support for both micro-batch and continuous mode.
- Spark 2.4 + : more enhancements

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UDF Enhancement

UDF Enhancements

- [SPARK-19285] Implement UDF0 (SQL UDF that has 0 arguments)
- [SPARK-22945] Add java UDF APIs in the functions object
- [SPARK-21499] Support creating SQL function for Spark UDAF(UserDefinedAggregateFunction)
- [SPARK-20586][SPARK-20416][SPARK-20668] Annotate UDF with Name, Nullability and Determinism

```
val foo = udf(() => Math.random()).asNondeterministic()
testData.select(foo())
```

Java UDF and UDAF

UDF
Enhancements

- Register Java UDF and UDAF as a SQL function and use them in PySpark.

```
# class MyDoubleAvg extends UserDefinedAggregateFunction
spark.udf.registerJavaUDAF("javaUDAF", "test.org.apache.spark.sql.MyDoubleAvg")
df = spark.createDataFrame([(1, "a"),(2, "b"), (3, "a")],["id", "name"])
df.registerTempTable("df")
spark.sql("SELECT name, javaUDAF(id) as avg from df group by name").collect()

# class JavaStringLength implements UDF1<String, Integer>
spark.udf.registerJavaFunction(
    "javaStringLength", "test.org.apache.spark.sql.JavaStringLength", "integer")
spark.sql("SELECT javaStringLength('test')").collect()
```

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Stable Codegen

- [SPARK-22510] [SPARK-22692] Stabilize the codegen framework to avoid hitting the 64KB JVM bytecode limit on the Java method and Java compiler constant pool limit.
- [SPARK-21871] Turn off whole-stage codegen when the bytecode of the generated Java function is larger than **spark.sql.codegen.hugeMethodLimit**. The limit of method bytecode for JIT optimization on HotSpot is 8K.

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Vectorized ORC Reader

- [SPARK-20682] Add new ORCFileFormat based on ORC 1.4.1. **spark.sql.orc.impl** = native (default) / hive (Hive 1.2.1)
- [SPARK-16060] Vectorized ORC reader **spark.sql.orc.enableVectorizedReader** = true (default) / false
- Enable filter pushdown for ORC files by default

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Performance

- [SPARK-21975] Histogram support in cost-based optimizer
- Enhancements in rule-based optimizer and planner
  [SPARK-22489] [SPARK-22916] [SPARK-22895] [SPARK-20758] [SPARK-22266] [SPARK-19122] [SPARK-22662] [SPARK-21652] (e.g., constant propagation)
- [SPARK-20331] Broaden support for Hive partition pruning predicate pushdown. (e.g. date = 20161011 or date = 20161014)
- [SPARK-20822] Vectorized reader for table cache

API

- Improved ANSI SQL compliance and Dataset/DataFrame APIs
- More built-in functions [SPARK-20746]
- Better Hive compatibility
  - [SPARK-20236] Support Dynamic Partition Overwrite
  - [SPARK-17729] Enable Creating Hive Bucketed Tables
  - [SPARK-4131] Support INSERT OVERWRITE DIRECTORY

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History Server Using K-V Store

Stateless and non-scalable History Server V1:

- Requires parsing the event logs (that means, so slow!)
- Requires storing app lists and UI in the memory (and then OOM!)

[SPARK-18085] **K-V store-based History Server V2:**

- Store app lists and UI in a persistent K-V store (LevelDB)
  - **spark.history.store.path** – once specified, LevelDB is being used; otherwise, in-memory KV-store (still stateless like V1)
  - V2 still can read the event log wrote by V1

Thank you