APACHE:

BIG_DATA

NORTH_AMERICA

THE LINUX FOUNDATION

APACHE: BIG_DATA NORTH_AMERICA

MAY 16-18, 2017

MIAMI, FL

Starting with Apache Spark, Best Practices and Learning from the Field

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THE LINUX FOUNDATION

Disclaimer

Community Contributions

Agenda

Introduction to Apache Spark

Best Practices

Enterprise Solutions

Introduction to Apache Spark

What is Spark?

"Fast and expressive cluster computing system" –
Matei Zaharia, creator of Apache Spark

Design Goals

Distributed

Scalable

Resilient - Fault tolerant

Key Differentiators

In-memory processing

Friendly programming model

Rich expressive APIs

Why Spark?

Open Source Community

Over 1000 contributors

19,500+ commits

310+ Spark Packages

23,000+ questions on stackoverflow

user@spark.apache.org

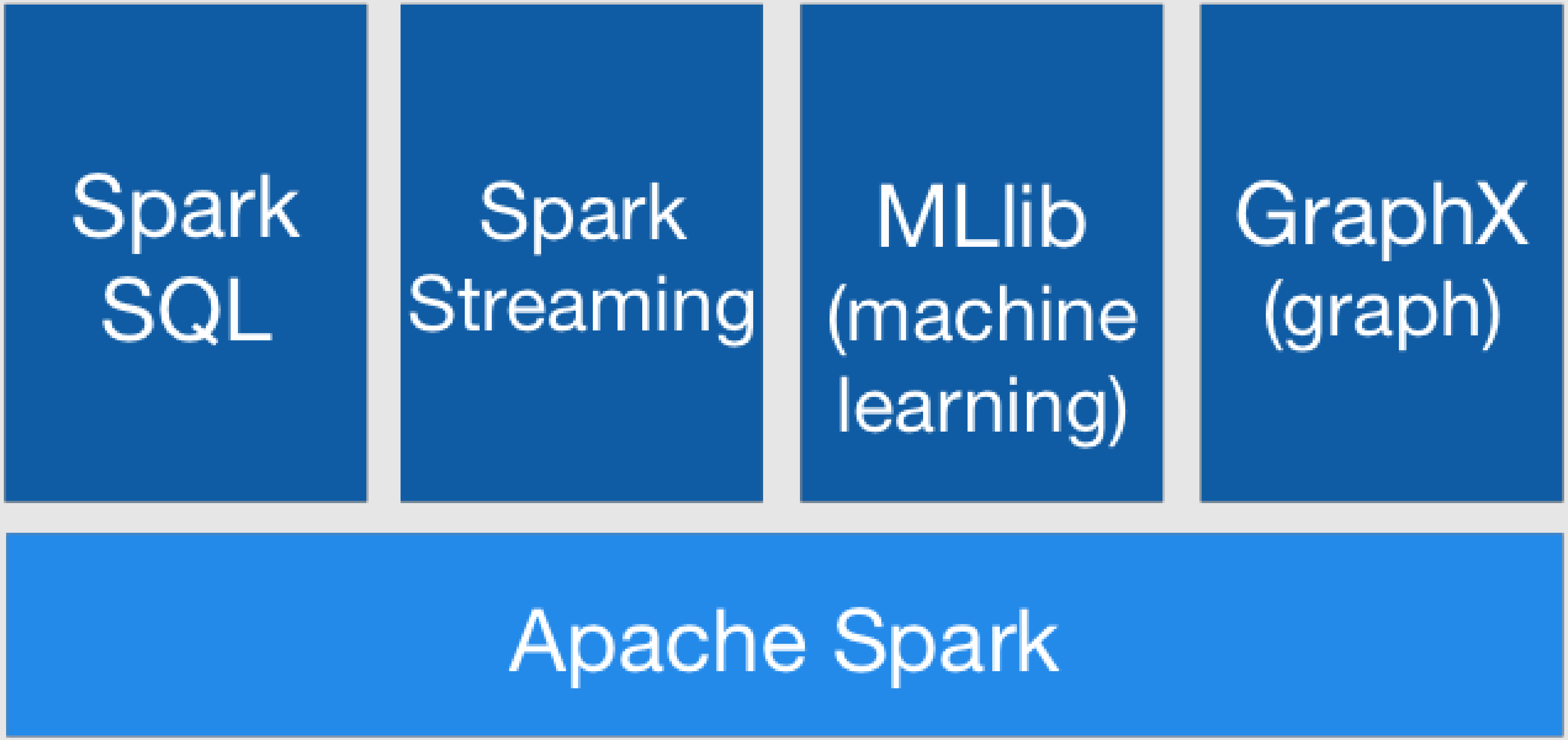
Why Spark?

Innovations

Catalyst, Tungsten

AMPLab becoming RISELab

- Drizzle – low latency execution, 3.5x lower than Spark Streaming
- Ernest – performance prediction, automatically choose the optimal resource config on the cloud


Spark SQL
Spark Streaming
MLlib (machine learning)
GraphX (graph)
Apache Spark

Spark Core

Foundation

Deployment

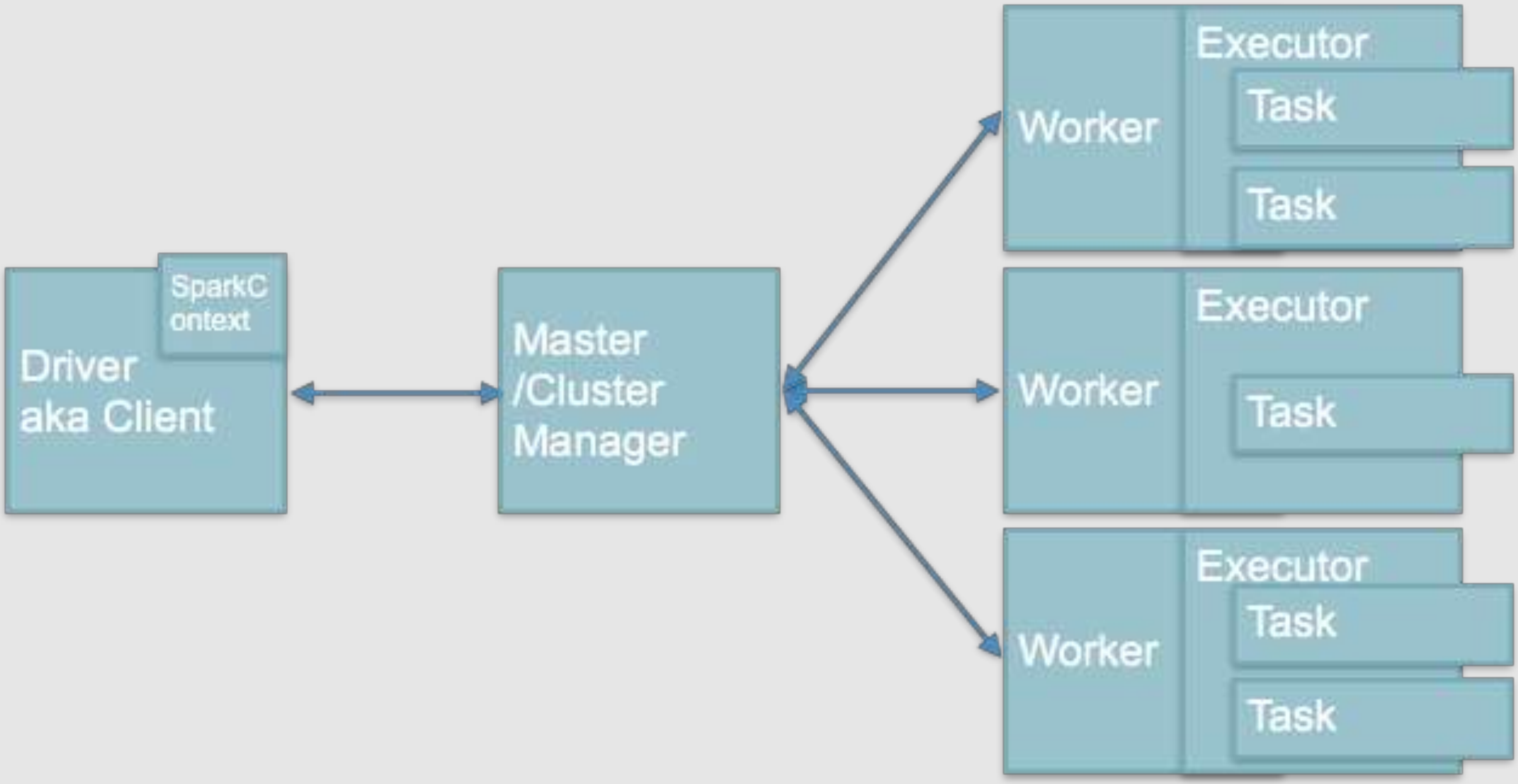
Scheduler

Resource Manager (aka Cluster Manager)

Executor

Diagnostics UI - Spark History Server, Spark UI

Architecture



Key Concepts

Parallelization, Partition

Transformation

Action

Shuffle

Parallelization

Doing multiple things at the same time

Partition

A unit of parallelization

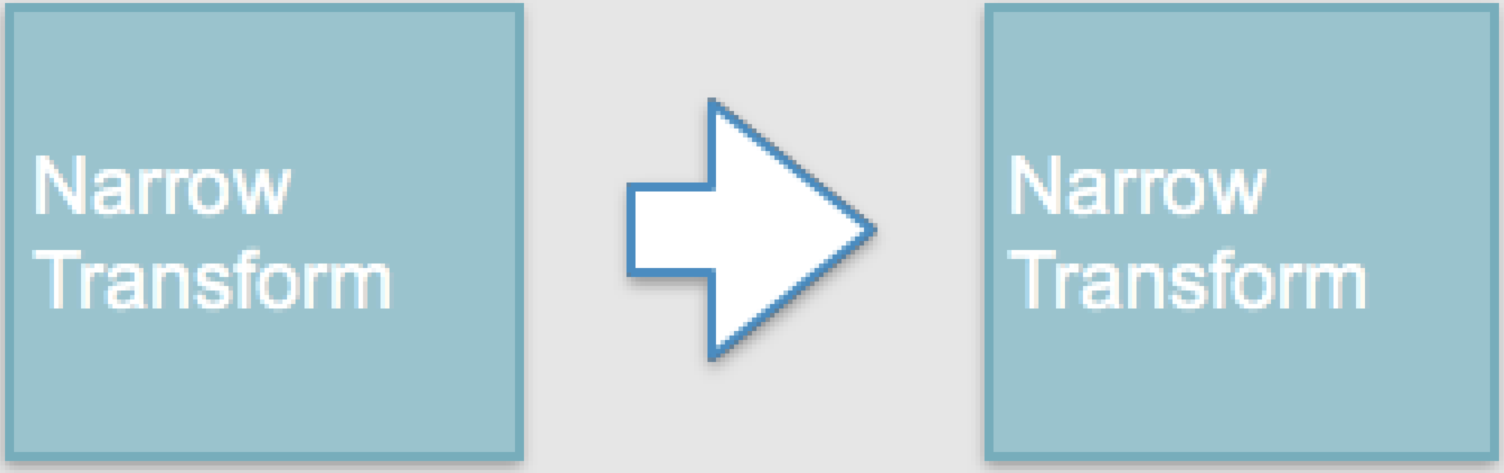
Transformation

Manipulating data - immutable

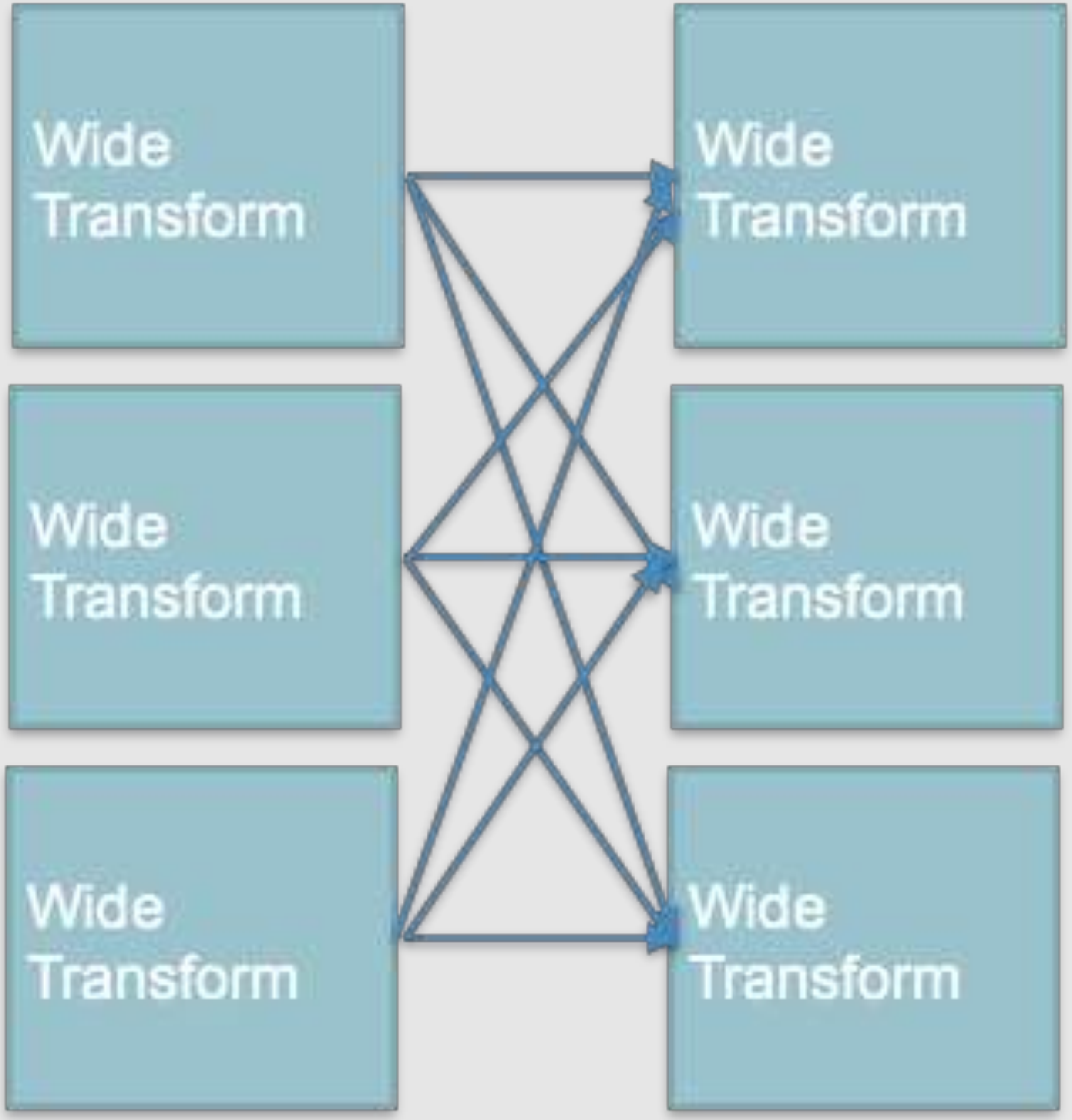
"Narrow"

"Wide"

Narrow Transformation



Wide Transformation



Why is shuffle costly?

Processing: sorting, serialize/deserialize, compression

Transfer: disk IO, network bandwidth/latency

Take up memory, or spill to disk for intermediate results ("shuffle file")

Action

Materialize results

Execute the chain of transformations that leads to output – *lazy evaluation*

count

collect -> take

write

SQL

DataFrame

Dataset

Data source

Execution engine - Catalyst

Key Concepts

Execution Plan

Predicate Pushdown

Dataset

Strong typing

Optimized execution

DataFrame

Table – Row and Column

Schema – name and data types

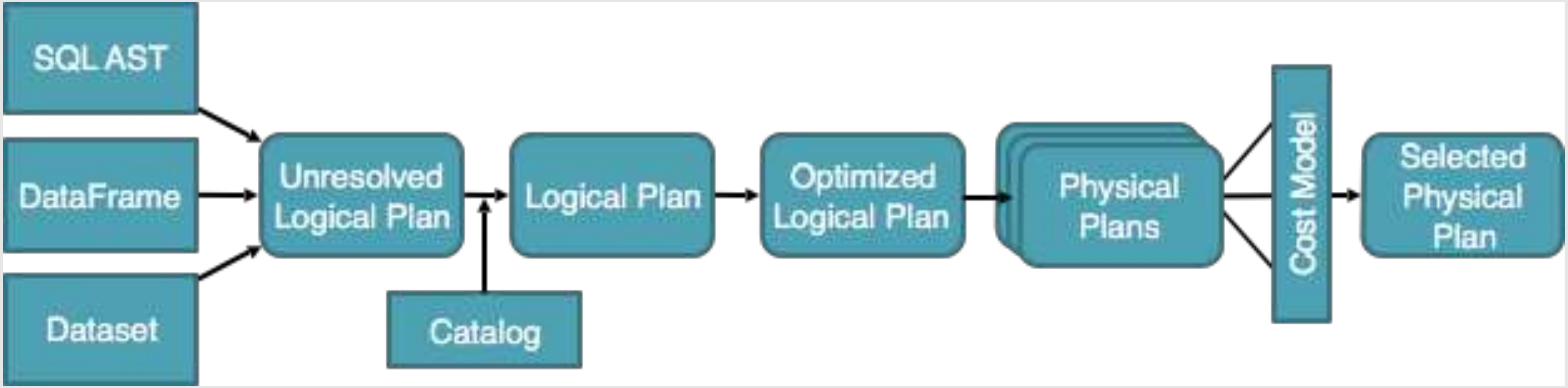
`Dataset[Row]`

Partition = set of Row's

Data Sources

"format" - Parquet, CSV, JSON, or Cassandra, HBase

Execution Plan



Predicate Pushdown

Ability to process expressions as early in the plan as possible

Predicate Pushdown Example

```
spark.read.jdbc(jdbcUrl, "food",
connectionProperties)

// with pushdown
spark.read.jdbc(jdbcUrl, "food",
connectionProperties).select("hotdog", "pizza",
"sushi")
```

Streaming

Discretized Streams (DStreams)

Receiver DStream

Direct DStream

Basic and Advanced Sources

Key Concepts

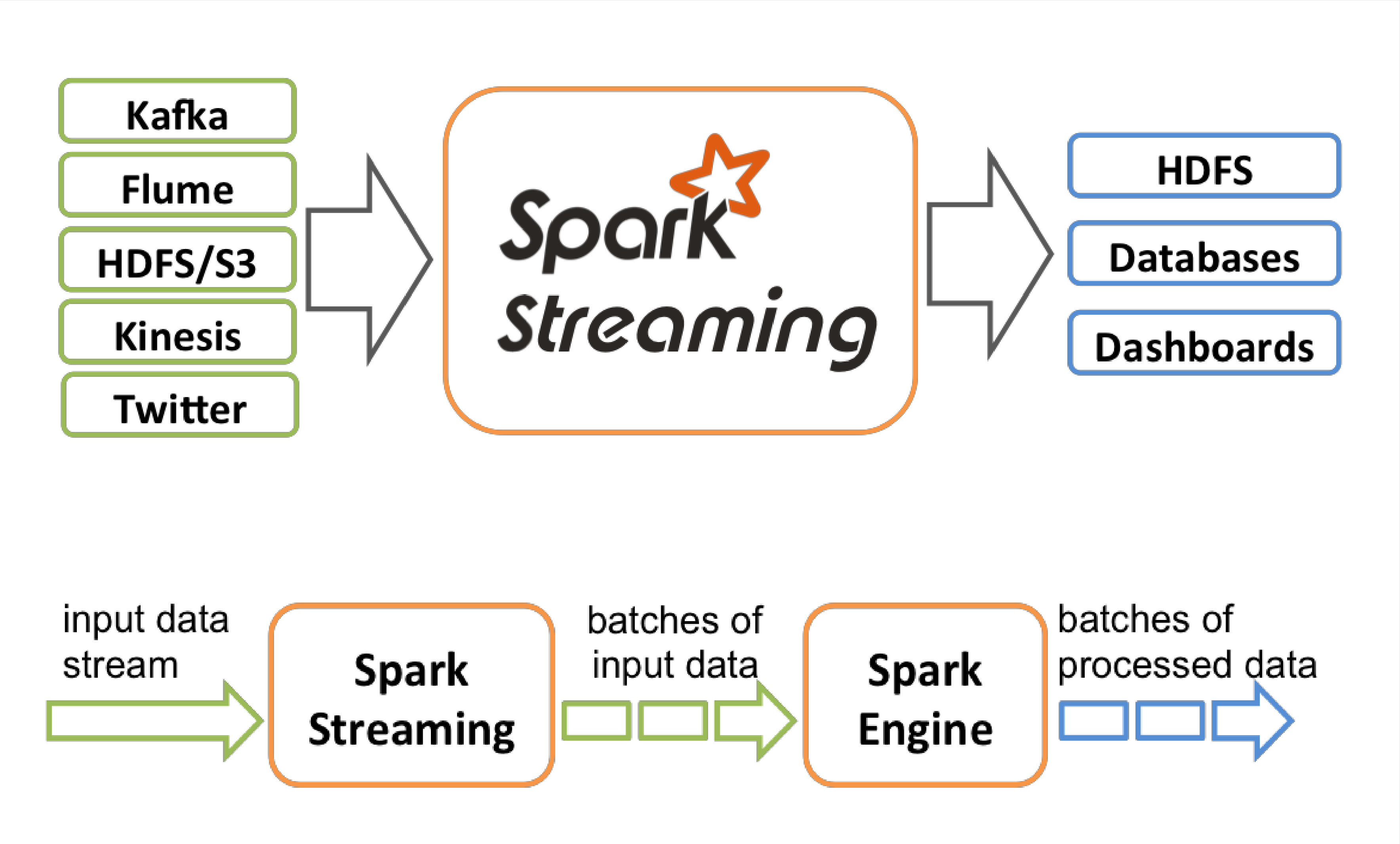
Source

Reliability

Receiver + Write Ahead Log (WAL)

Checkpointing

Streaming Source



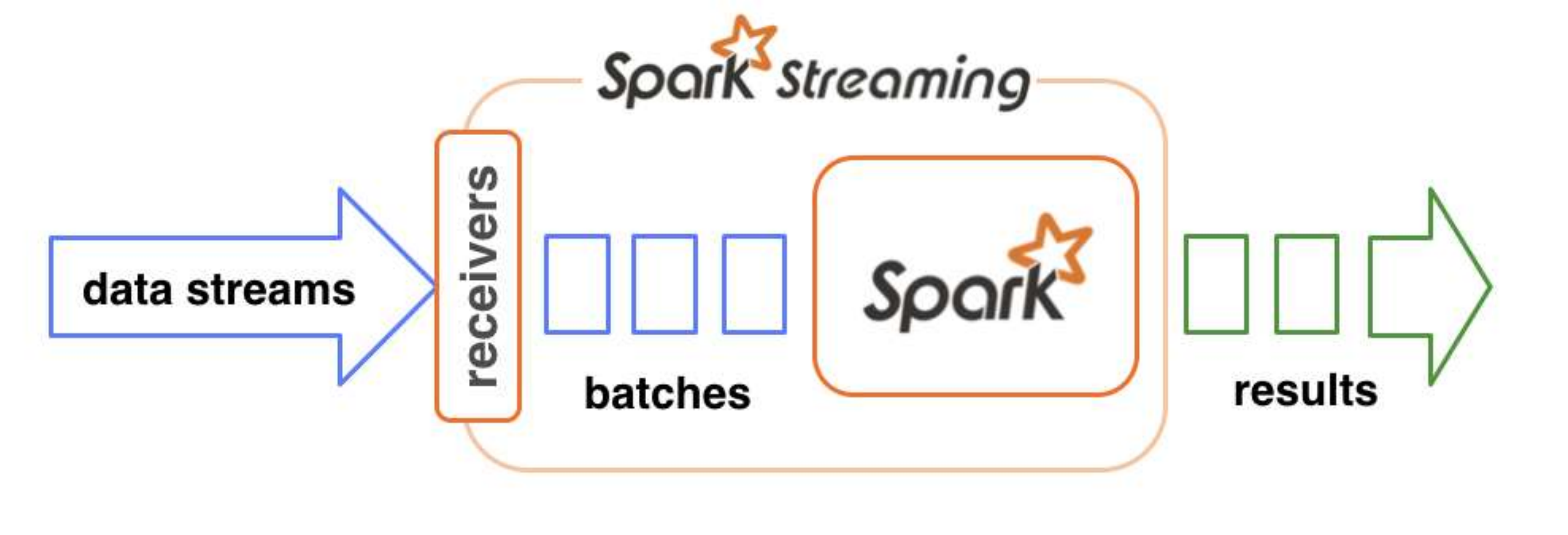
Batch

Micro-batch

batchInterval – how often when data is fetched

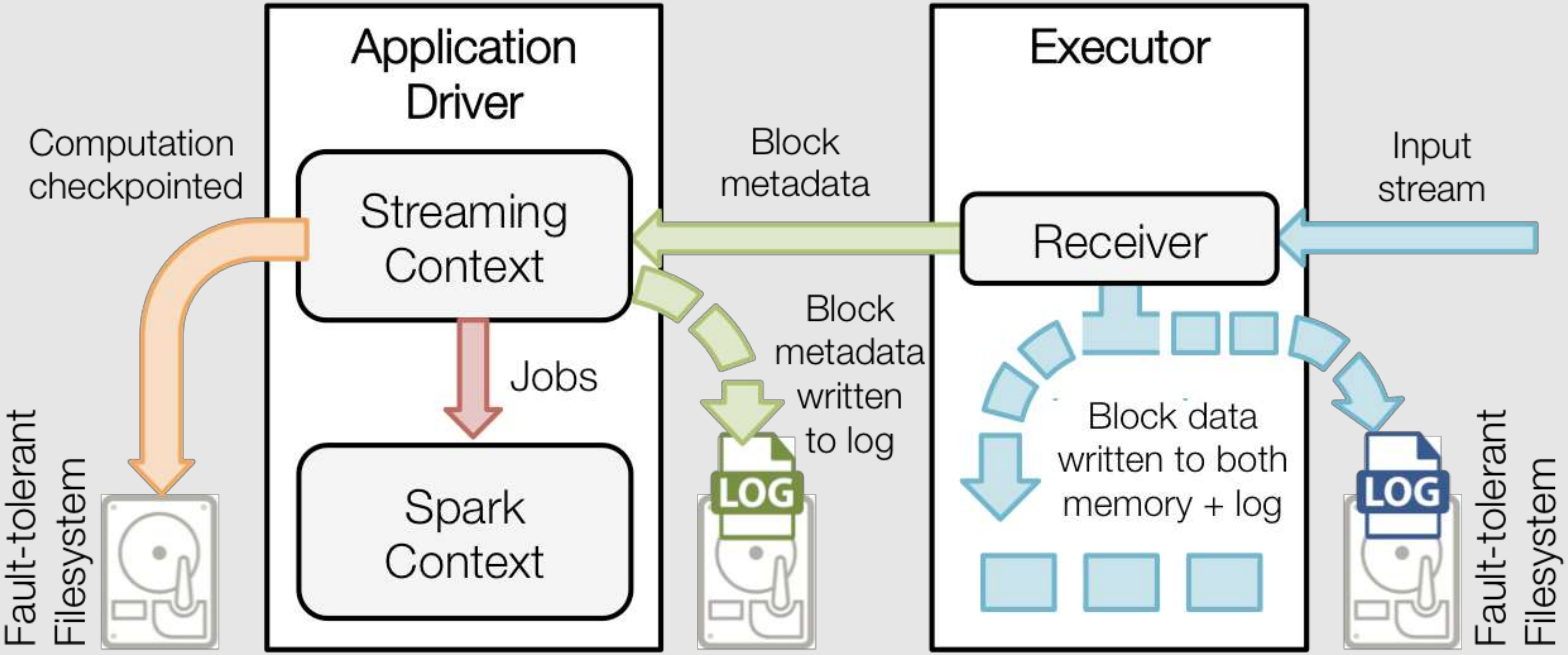
Receiver

Take data from source at batchInterval and get them into batch



Receiver WAL

WAL – Write Ahead Log



https://databricks.com/wp-content/uploads/2015/01/blog-ha-52.png

Direct DStream

Only for reliable messaging sources that supports read from position

Stronger fault-tolerance, exactly-once*

No receiver/WAL

– less resource, lower overhead

Checkpointing

Saving to reliable storage to recover from failure

1. Metadata checkpointing

`StreamingContext.checkpoint()`

2. Data checkpointing

`dstream.checkpoint()`

Machine Learning

ML Pipeline

Transformer

Estimator

Evaluator

MLlib ML Pipeline

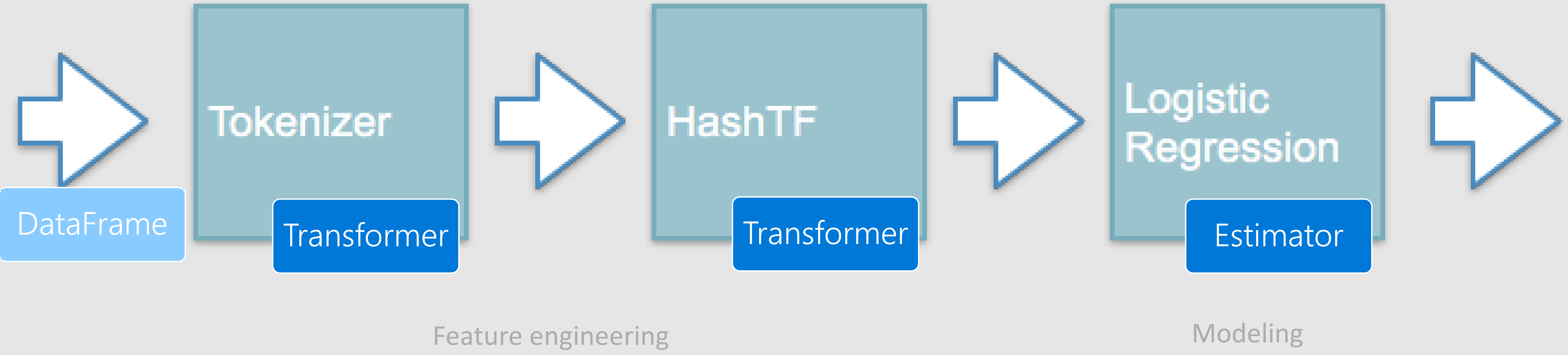
DataFrame-based

- leverage optimizations and support transformations

a sequence of algorithms

- `PipelineStages`

Pipeline Model



Transformers

Feature transformer

- take a DataFrame and its Column and append one or more new Column

Transformers

StopWordsRemover
Binarizer
SQLTransformer
VectorAssembler

Tokenizer
RegexTokenizer
NGram
HashingTF
OneHotEncoder

Estimators

An algorithm

DataFrame -> Model

A Model is a Transformer

LinearRegression

KMeans

Evaluator

Metric to measure Model performance on held-out test data

Evaluator

MulticlassClassificationEvaluator

BinaryClassificationEvaluator

RegressionEvaluator

MLWriter/MLReader

Pipeline persistence

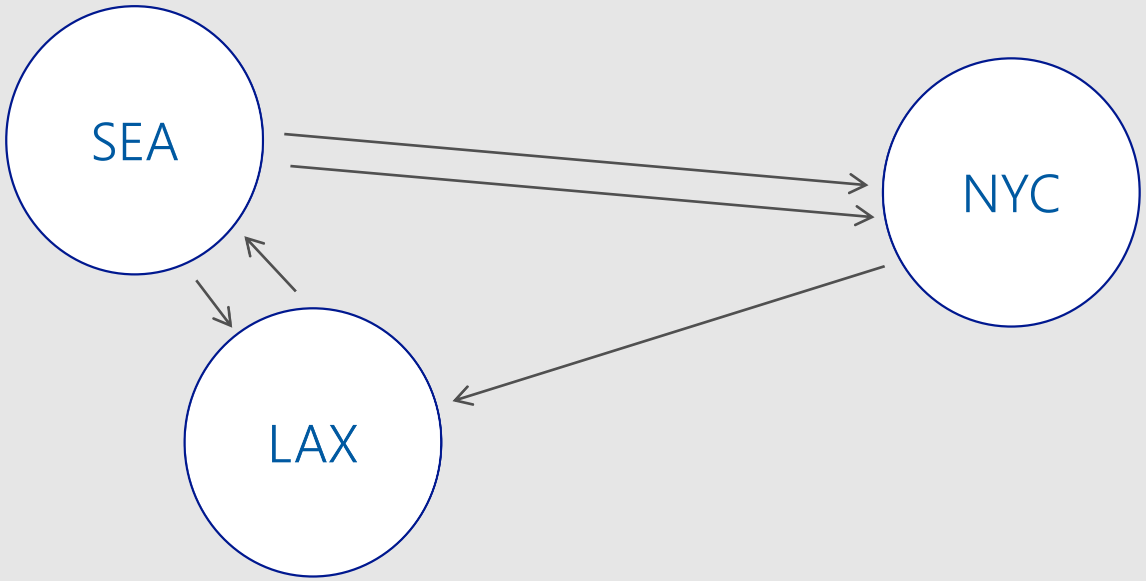
Include transformers, estimators, Params

Graph

Graph
Pregel
Graph Algorithms
Graph Queries

Property Graph

Directed multigraph with user properties on edges and vertices



Graph Algorithms

PageRank

ConnectedComponents

```
ranks =
tripGraph.pageRank(resetProbability=
0.15, maxIter=5)
```

GraphFrames

DataFrame-based

Simplify loading graph data, wrangling

Support Graph Queries

Graph Queries

Pattern matching

Mix pattern with SQL syntax

```
motifs = g.find("(a)-[e]->(b); (b)-
[e2]->(a); !(c)-[]->(a)").filter("a.id
= 'MIA'")
```

Structured Streaming

Structured Streaming Model

Source

Sink

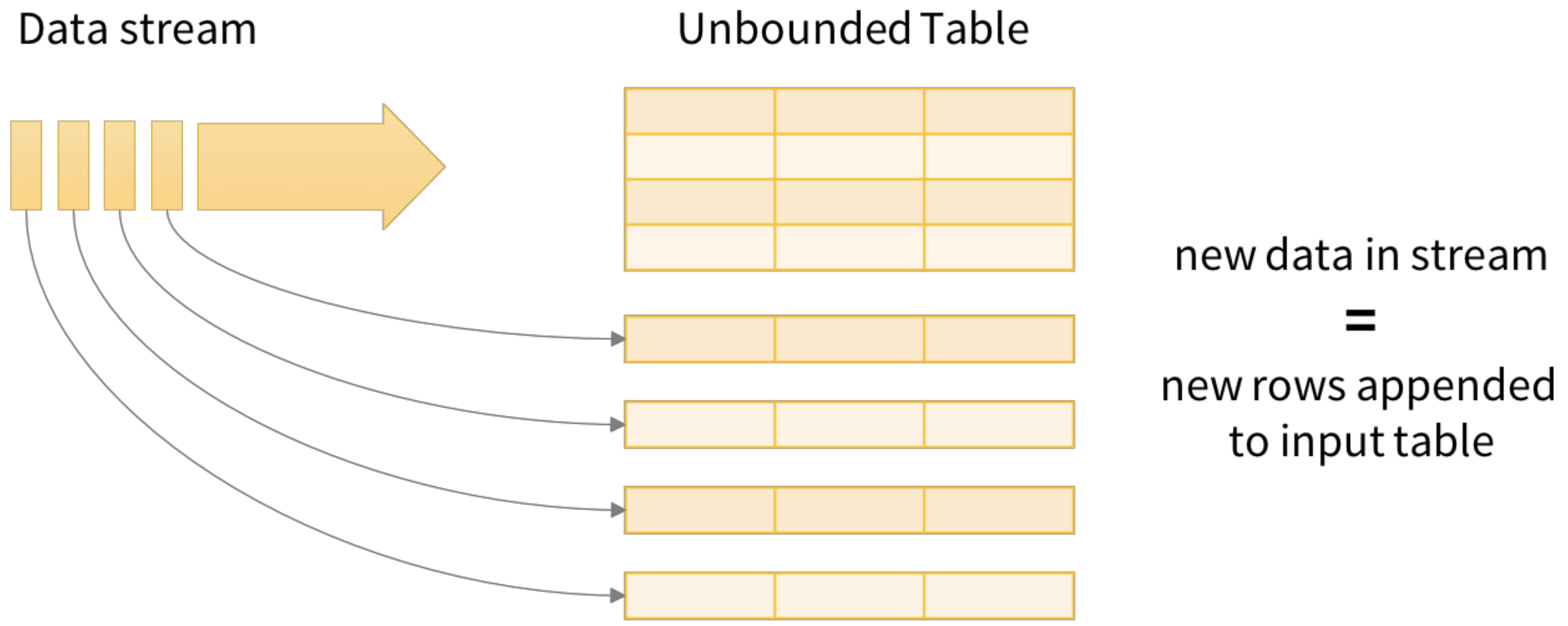
StreamingQuery

Continuous Application

Extending same DataFrame to include incremental execution of unbounded input

Reliability, correctness / exactly-once - checkpointing (2.1 JSON format)

Stream as Unbounded Input



Data stream as an unbounded Input Table

https://databricks.com/blog/2016/07/28/structured-streaming-in-apache-spark.html

Continuous Application

Watermark (2.1) - handling of late data

Streaming ETL, joining static data, partitioning, windowing

Sources

FileStreamSource

KafkaSource

MemoryStream (not for production)

TextSocketSource
MQTT

Sinks

FileStreamSink (new formats in 2.1)

ConsoleSink

ForeachSink (Scala only)

MemorySink – as Temp View

Read Static Data

```
staticDF = (
  spark
    .read
    .schema(jsonSchema)
    .json(inputPath)
)
```

Read *Streaming* Data

```
streamingDF = (
  spark
    .readStream
    .schema(jsonSchema)
    .option("maxFilesPerTrigger", 1)
    .json(inputPath)
)
# Take a list of files as a stream
```

Process Streaming Data

```
streamingCountsDF = (
  streamingDF
    .groupBy(
      streamingDF.word,
      window(
       streamingDF.time,
       "1 hour"))
    .count()
)
```

Write Streaming Data

```
query = (
  streamingCountsDF
    .writeStream
    .format("memory")
    .queryName("word_counts")
    .outputMode("complete")
    .start()
)
spark.sql("select count from word_counts order
by time")
```

Best Practices

Big Data

How much going in affects how much work it's going to take

Big Data

Size does matter!

CSV or JSON is "simple" but also tend to be big

JSON-> Parquet (compressed)
- 7x faster

Format also does matter

Recommended format - Parquet

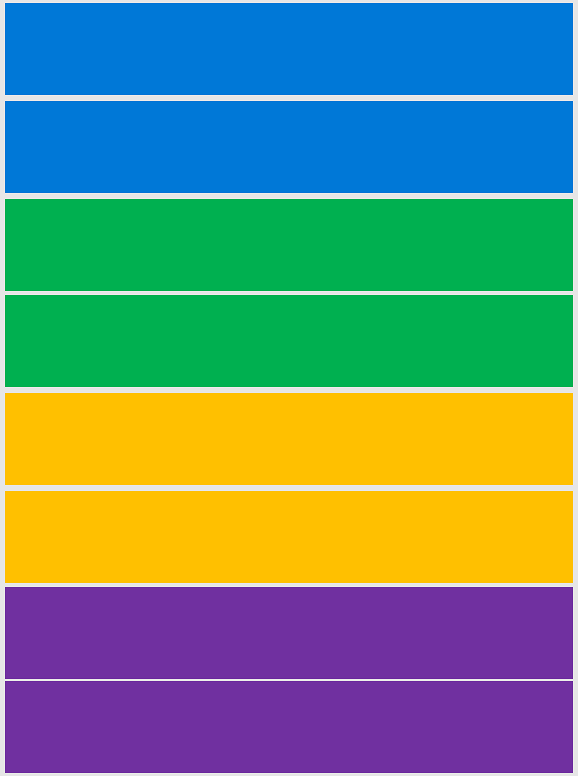
Default data source/format

- VectorizedReader
- Better dictionary decoding

Parquet Columnar Format

Column chunk co-located

Metadata and headers for skipping



Recommend Parquet

Smart format = less work

Benchmark Parquet -> ORC

- 3.7x to 6.3x slower

http://tech.marksblogg.com/billion-nyc-taxi-rides-spark-2-1-0-emr.html

Compression is a factor

gzip <100MB/s vs snappy 500MB/s

Tradeoffs: faster or smaller?

Spark 2.0+ defaults to snappy

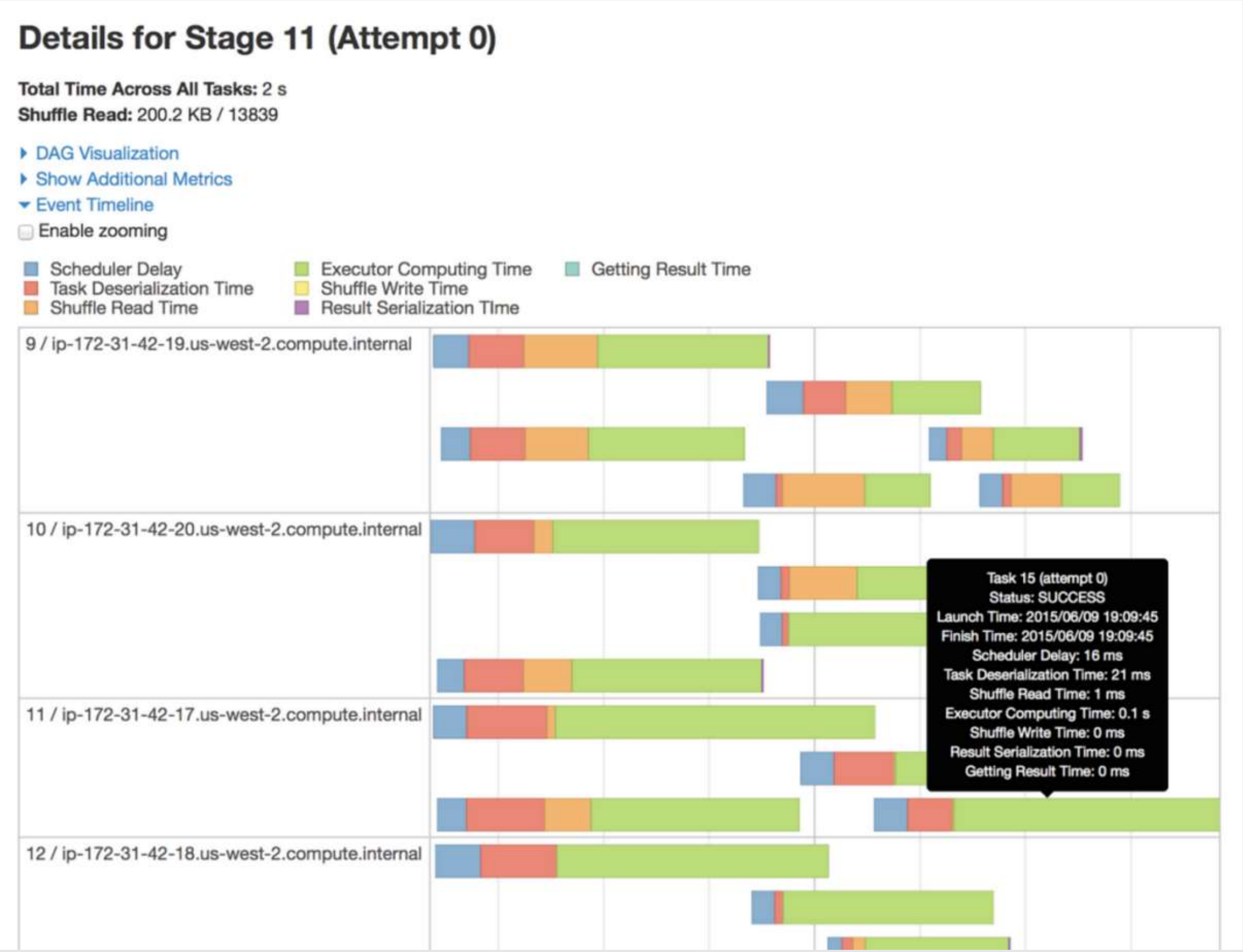
Sidenote: Table Partitioning

Storage data into groups of partitioning columns

Encoded path structure matches Hive

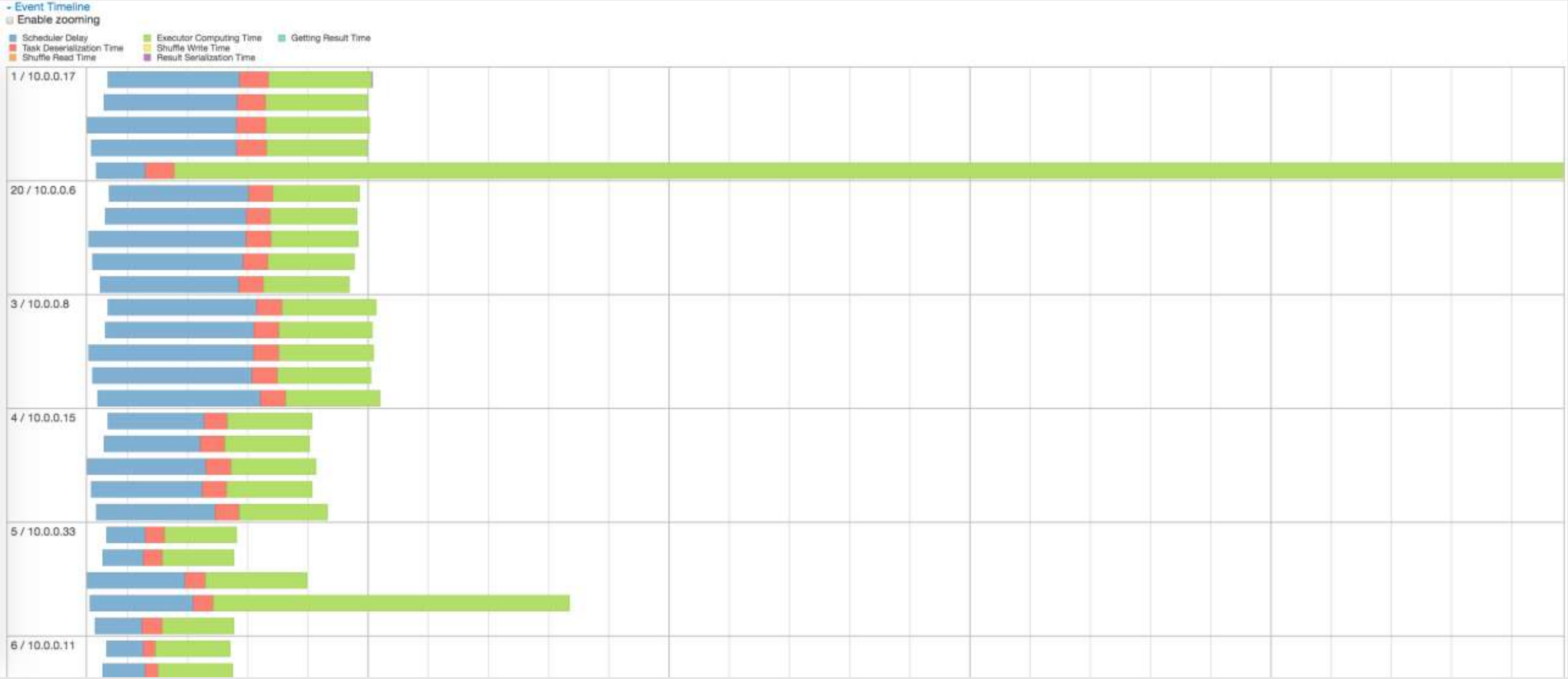
`table/event_date=2017-02-01`

Spark UI
Timeline view

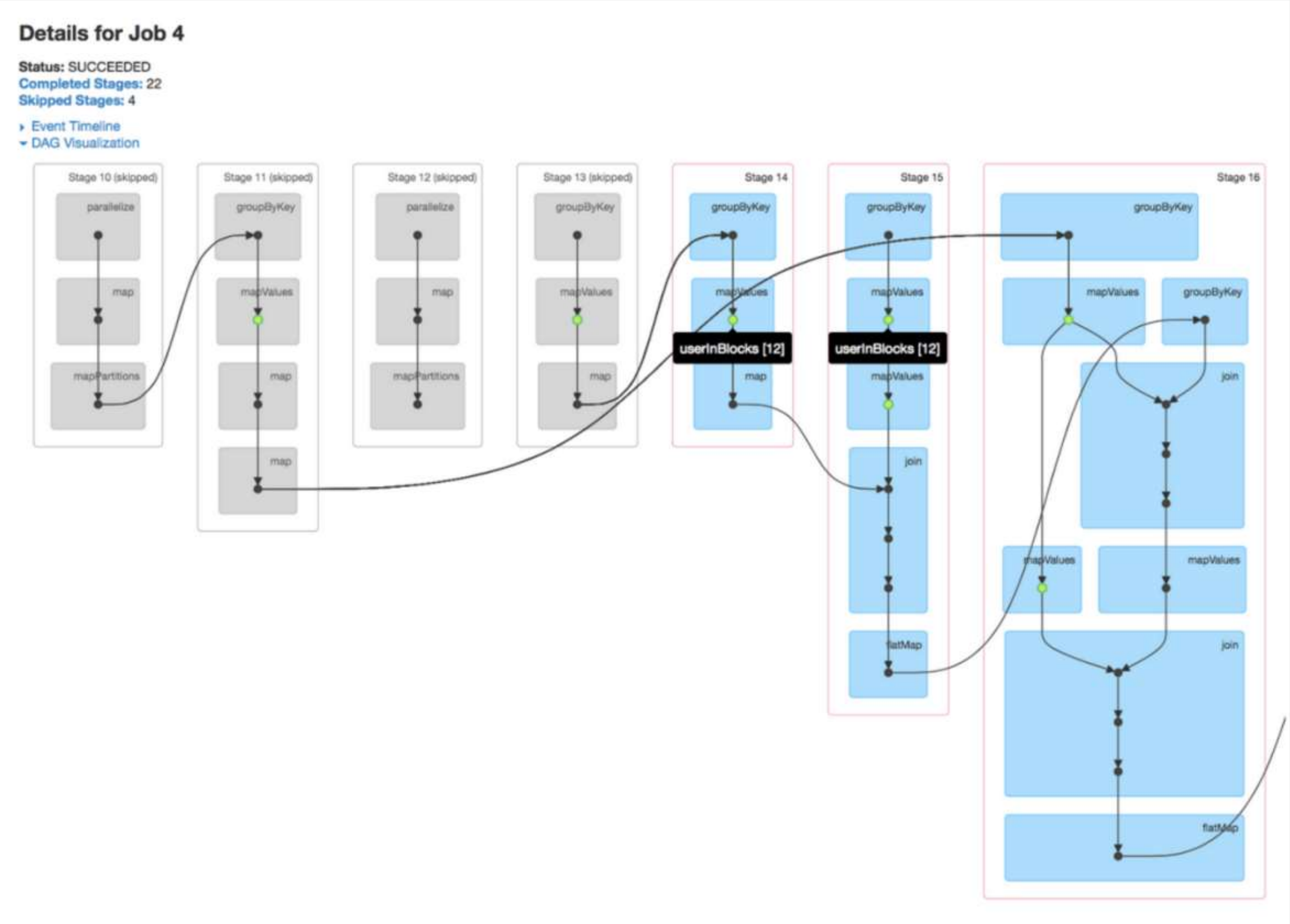


https://databricks.com/blog/2015/06/22/understanding-your-spark-application-through-visualization.html

Data Skew – uneven partitions



Spark UI DAG view



https://databricks.com/blog/2015/06/22/understanding-your-spark-application-through-visualization.html

Executor tab

Spark 2.0.0.2.5.2.1-1 | Jobs | Stages | Storage | Environment | Executors | SQL

Executors

Summary

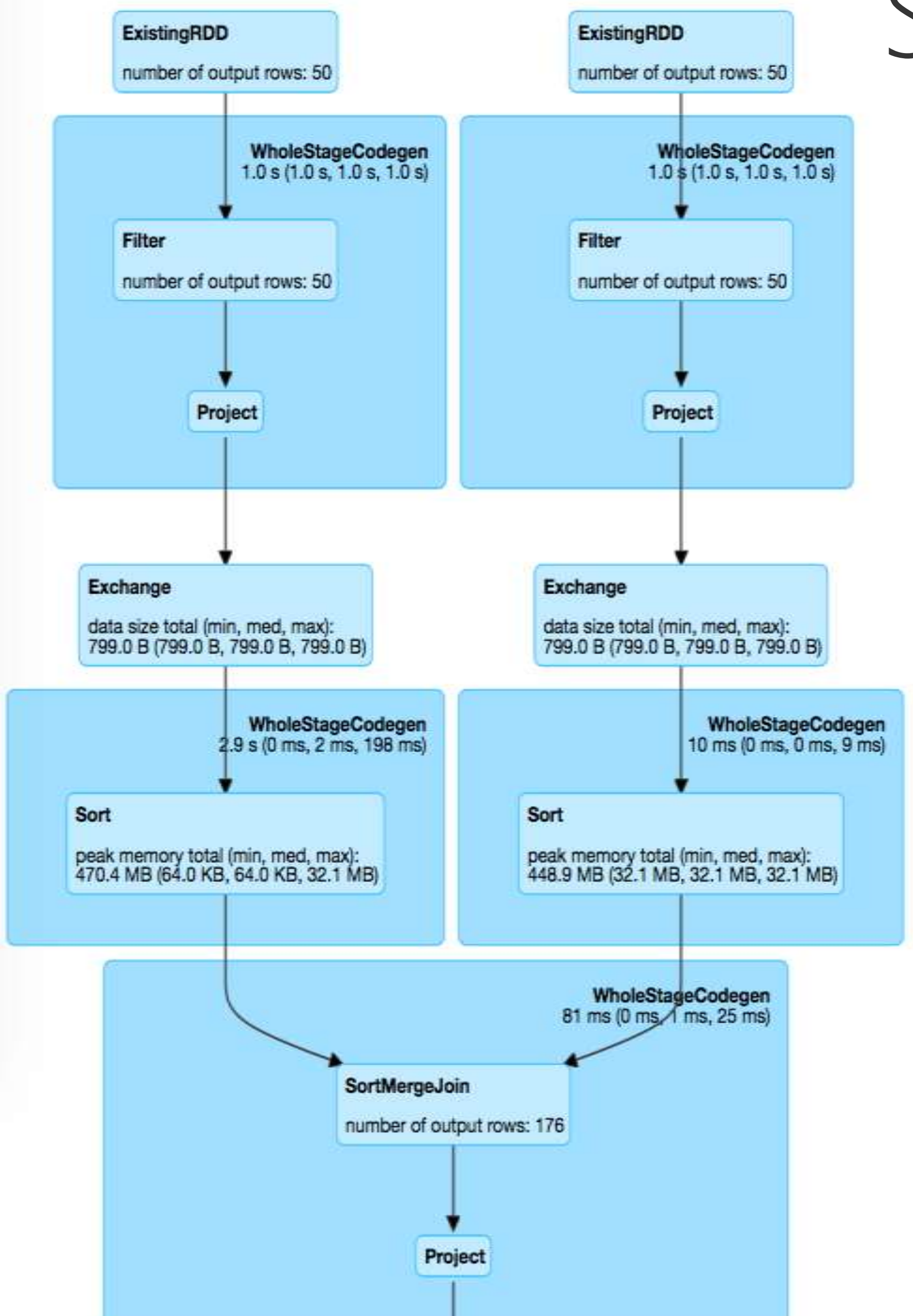
	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write
Active(21)	0	0.0 B / 892.3 GB	0.0 B	280	0	0	6529	6529	59.8 m (4.8 m)	308.2 MB	2.3 MB	2.5 MB
Dead(0)	0	0.0 B / 0.0 B	0.0 B	0	0	0	0	0	0 ms (0 ms)	0.0 B	0.0 B	0.0 B
Total(21)	0	0.0 B / 892.3 GB	0.0 B	280	0	0	6529	6529	59.8 m (4.8 m)	308.2 MB	2.3 MB	2.5 MB

Executors

Executor ID	Address	Status	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Logs
20	10.0.0.17:44627	Active	0	0.0 B / 42.5 GB	0.0 B	14	0	0	252	252	3.0 m (11.6 s)	14.4 MB	18.7 KB	134.6 KB	stdout stderr
19	10.0.0.27:34455	Active	0	0.0 B /	0.0 B	14	0	0	404	404	2.9 m	12.5	81.7	80.0	stdout

SQL tab

Succeeded Jobs: 3 4



▾ Details

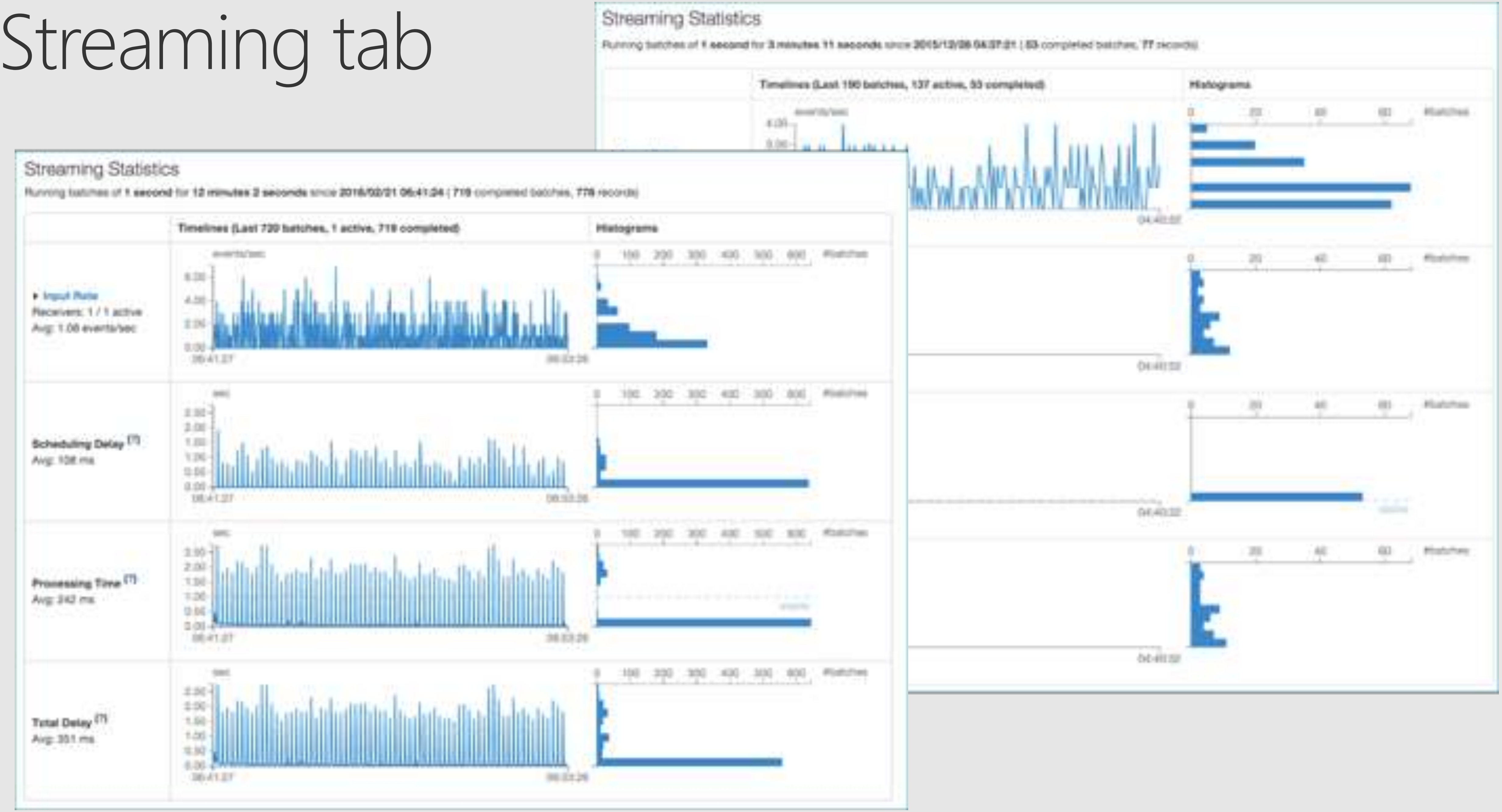
```
== Parsed Logical Plan ==
Aggregate [count(1) AS count#79L]
+- Sort [speed_y#49 ASC], true
   +- Join Inner, (speed_x#48 = speed_y#49)
      :- Project [speed#2 AS speed_x#48, dist#3]
      :  +- LogicalRDD [speed#2, dist#3]
      +- Project [speed#18 AS speed_y#49, dist#19]
         +- LogicalRDD [speed#18, dist#19]

== Analyzed Logical Plan ==
count: bigint
Aggregate [count(1) AS count#79L]
+- Sort [speed_y#49 ASC], true
   +- Join Inner, (speed_x#48 = speed_y#49)
      :- Project [speed#2 AS speed_x#48, dist#3]
      :  +- LogicalRDD [speed#2, dist#3]
      +- Project [speed#18 AS speed_y#49, dist#19]
         +- LogicalRDD [speed#18, dist#19]

== Optimized Logical Plan ==
Aggregate [count(1) AS count#79L]
+- Project
   +- Sort [speed_y#49 ASC], true
      +- Project [speed_y#49]
         +- Join Inner, (speed_x#48 = speed_y#49)
            :- Project [speed#2 AS speed_x#48]
            :  +- Filter isnotnull(speed#2)
            :     +- LogicalRDD [speed#2, dist#3]
            +- Project [speed#18 AS speed_y#49]
               +- Filter isnotnull(speed#18)
                  +- LogicalRDD [speed#18, dist#19]

== Physical Plan ==
*HashAggregate(keys=[], functions=[count(1)], output=[count#79L])
+- Exchange SinglePartition
   +- *HashAggregate(keys=[], functions=[partial_count(1)], output=[count#83L]
      +- *Project
         +- *Sort [speed_y#49 ASC], true, 0
```

Streaming tab



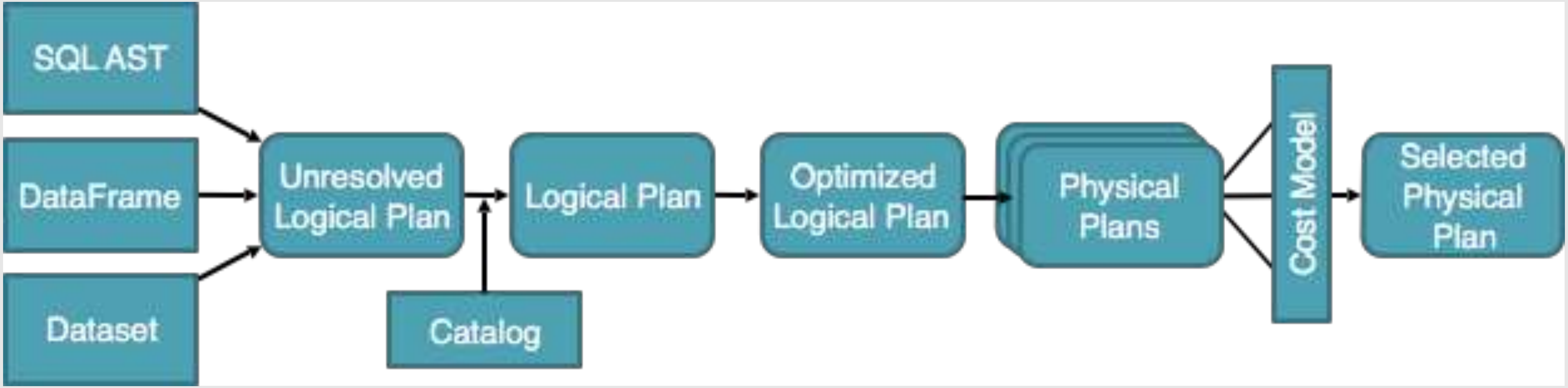
Understanding Queries

`explain()` is your friend

but it could be hard to understand at times

```
== Parsed Logical Plan ==
Aggregate [count(1) AS count#79L]
+- Sort [speed_y#49 ASC], true
   +- Join Inner, (speed_x#48 = speed_y#49)
      :- Project [speed#2 AS speed_x#48, dist#3]
      :  +- LogicalRDD [speed#2, dist#3]
      +- Project [speed#18 AS speed_y#49, dist#19]
         +- LogicalRDD [speed#18, dist#19]
```

Remember Execution Plan



```
== Physical Plan ==
*HashAggregate(keys=[], functions=[count(1)], output=[count#79L])
+- Exchange SinglePartition
   +- *HashAggregate(keys=[], functions=[partial_count(1)],
output=[count#83L])
      +- *Project
         +- *Sort [speed_y#49 ASC], true, 0
            +- Exchange rangepartitioning(speed_y#49 ASC, 200)
               +- *Project [speed_y#49]
                  +- *SortMergeJoin [speed_x#48], [speed_y#49], Inne
                     :- *Sort [speed_x#48 ASC], false, 0
                     :  +- Exchange hashpartitioning(speed_x#48, 200
                     :     +- *Project [speed#2 AS speed_x#48]
                     :        +- *Filter isnotnull(speed#2)
                     :           +- Scan ExistingRDD[speed#2,dist#3]
                     +- *Sort [speed_y#49 ASC], false, 0
                        +- Exchange hashpartitioning(speed_y#49, 200
```

UDF

Write you own custom transforms

But... Catalyst can't see through it (yet?!)

Always prefer to use builtin transforms as much as possible

UDF vs Builtin Example

Remember Predicate Pushdown?

```
val isSeattle = udf { (s: String) => s == "Seattle" }
cities.where(isSeattle('name))
*Filter UDF(name#2)
+- *FileScan parquet [id#128L,name#2] Batched: true, Format:
ParquetFormat, InputPaths: file:/Users/b/cities.parquet,
PartitionFilters: [], PushedFilters: [], ReadSchema:
struct<id:bigint,name:string>
```

UDF vs Builtin Example

Using Buildtin Expression

```
cities.where('name === "Seattle")
*Project [id#128L, name#2]
+- *Filter (isnotnull(name#2) && (name#2 = Seattle))
   +- *FileScan parquet [id#128L,name#2] Batched: true, Format:
ParquetFormat, InputPaths: file:/Users/b/cities.parquet,
PartitionFilters: [], PushedFilters: [IsNotNull(name),
EqualTo(name,Seattle)], ReadSchema:
struct<id:bigint,name:string>
```

UDF in Python

```
from pyspark.sql.types import IntegerType
sqlContext.udf.register("stringLengthInt", lambda x:
len(x), IntegerType())
sqlContext.sql("SELECT stringLengthInt('test')").take(1)
```

Avoid!

Why? Pickling, transfer, extra memory to run Python interpreter

- Hard to debug errors!

Going for Performance

Stored in compressed Parquet

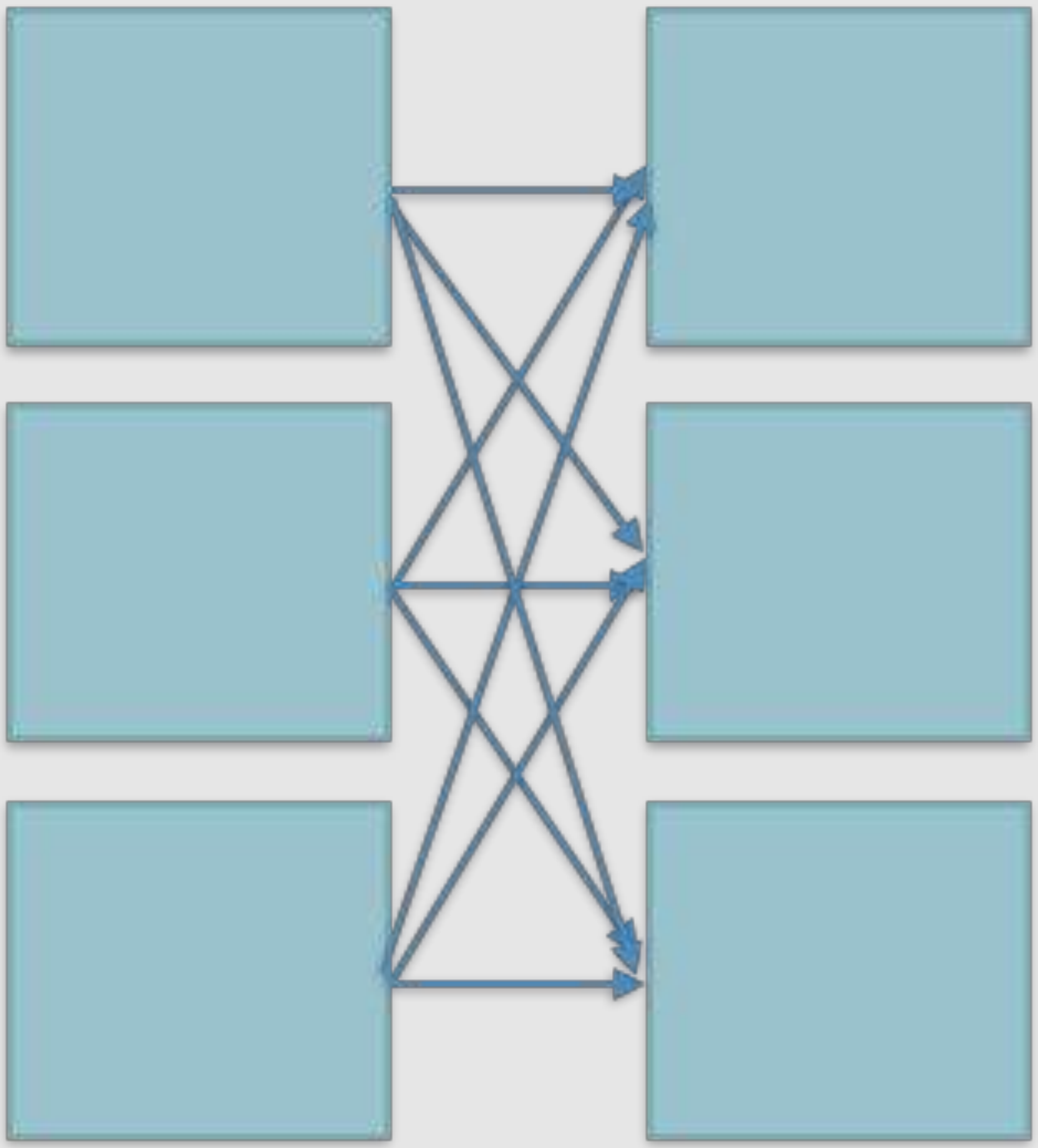
Partitioned table

Predicate Pushdown

Avoid UDF

Shuffling for Join

Can be very expensive



Optimizing for Join

Partition!

Narrow transform if left and right partitioned with same scheme

Optimizing for Join

Broadcast Join (aka Map-Side Join in Hadoop)

Smaller table against large table - avoid shuffling large table

Default 10MB auto broadcast

BroadcastHashJoin

```
left.join(right, Seq("id"), "leftanti").explain

== Physical Plan ==
*BroadcastHashJoin [id#50], [id#60], LeftAnti,
BuildRight
:- LocalTableScan [id#50, left#51]
+- BroadcastExchange
HashedRelationBroadcastMode(List(cast(input[0, int,
false] as bigint)))
   +- LocalTableScan [id#60]
```

Repartition

To `numPartitions` or by Columns

Increase parallelism – will shuffle

`coalesce()` – combine partitions in place

Cache

`cache()` or `persist()`

Flush least-recently-used (LRU)
- Make sure there is enough memory!

`MEMORY_AND_DISK` to avoid expensive recompute (but spill to disk is slow)

Streaming

Use Structured Streaming (2.1+)

If not…

If reliable messaging (Kafka) use Direct DStream

Metadata Checkpointing

Metadata - Config

Position from streaming source (aka offset)

- could get duplicates! (at-least-once)

Pending batches

Data Checkpointing

Persist stateful transformations

- data lost if not saved

Cut short execution that could grow *indefinitely*

Direct DStream

Checkpoint also store offset

Turn off auto commit

- do when in good state for exactly-once

Checkpointing

Stream/ML/Graph/SQL

- more efficient indefinite/iterative
- recovery

Generally *not* versioning-safe

Use *reliable* distributed *file system*

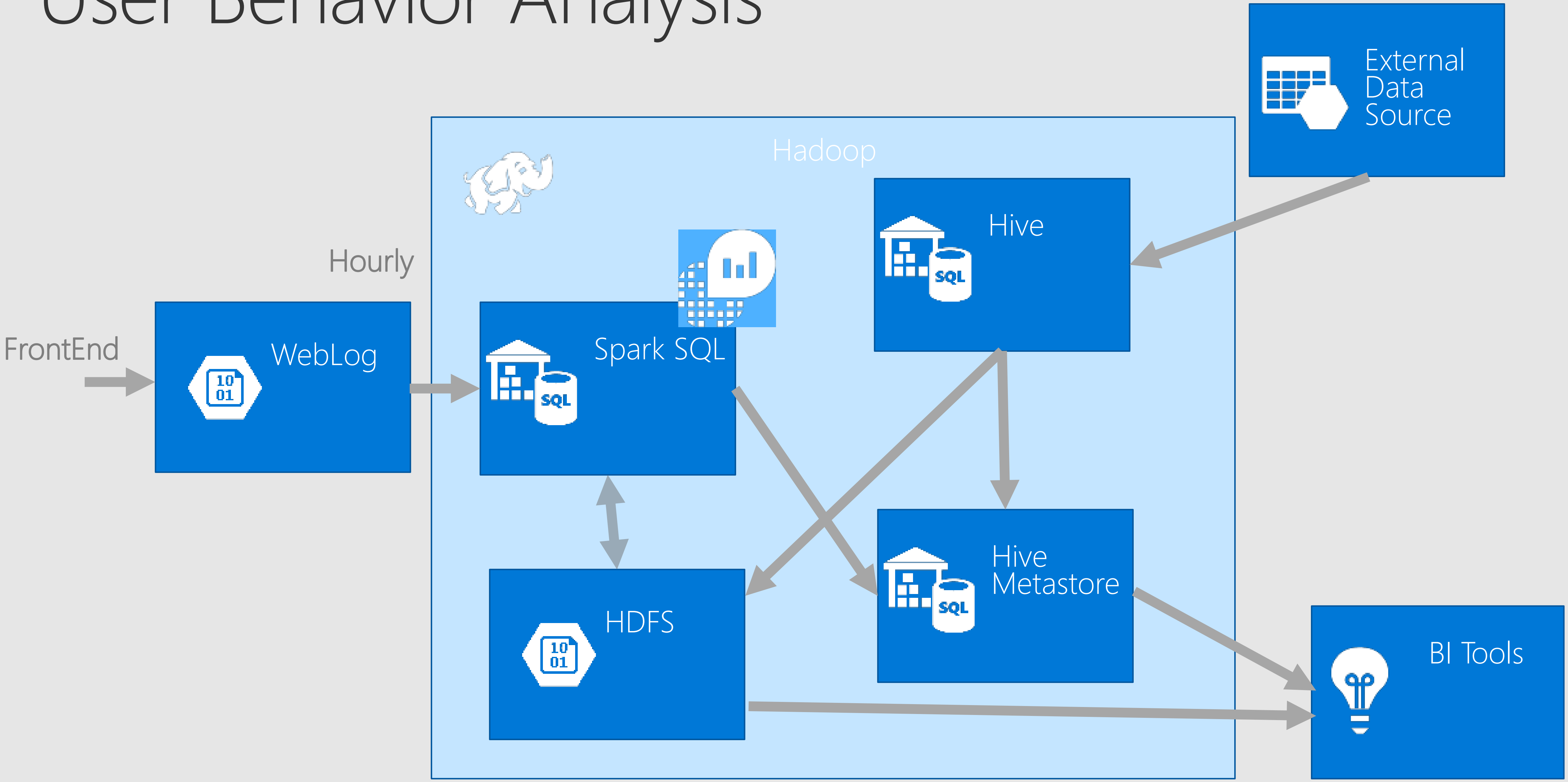
(caution on “object store”)

Building Solutions with Apache Spark

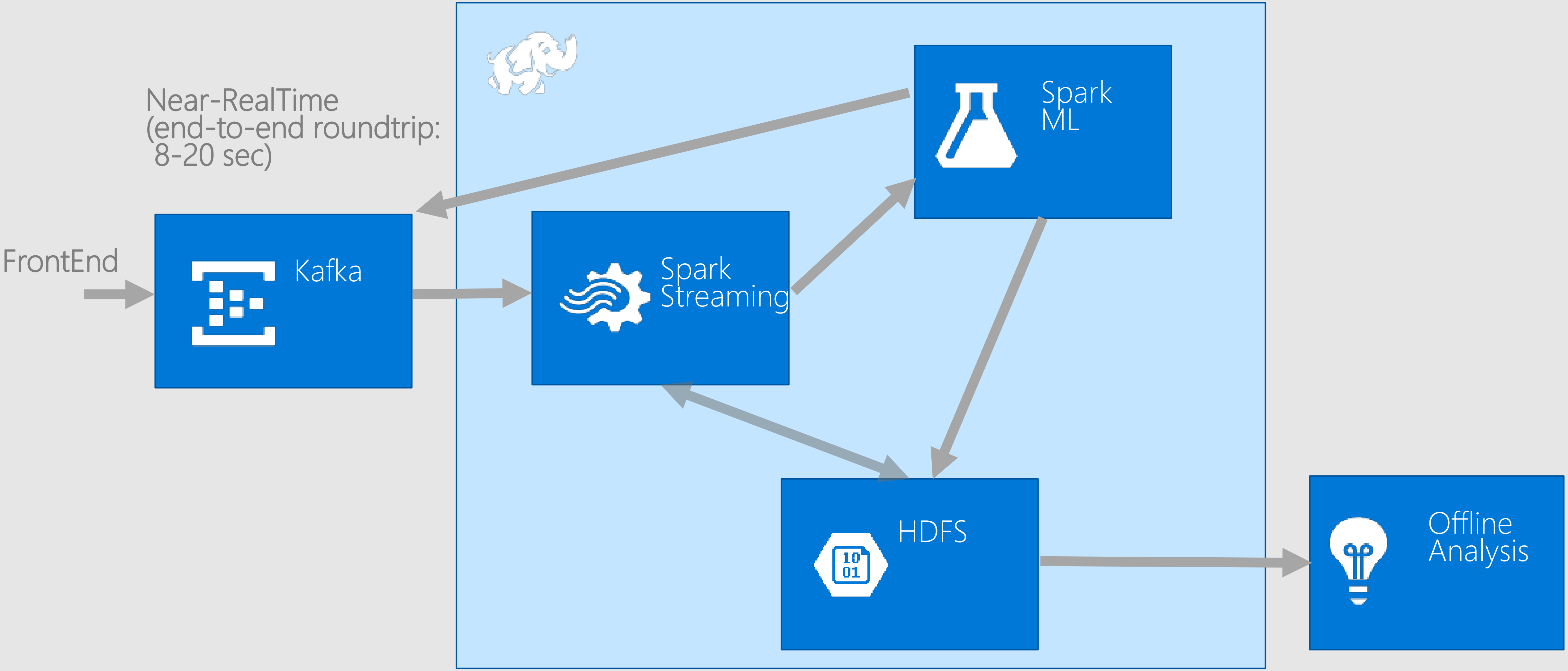
Building solutions with Apache Spark

1. ETL, statistical model –
   User behavior analysis
2. Streaming machine learning model –
   Natural Language Processing (NLP)
   and Topic Modeling

User Behavior Analysis



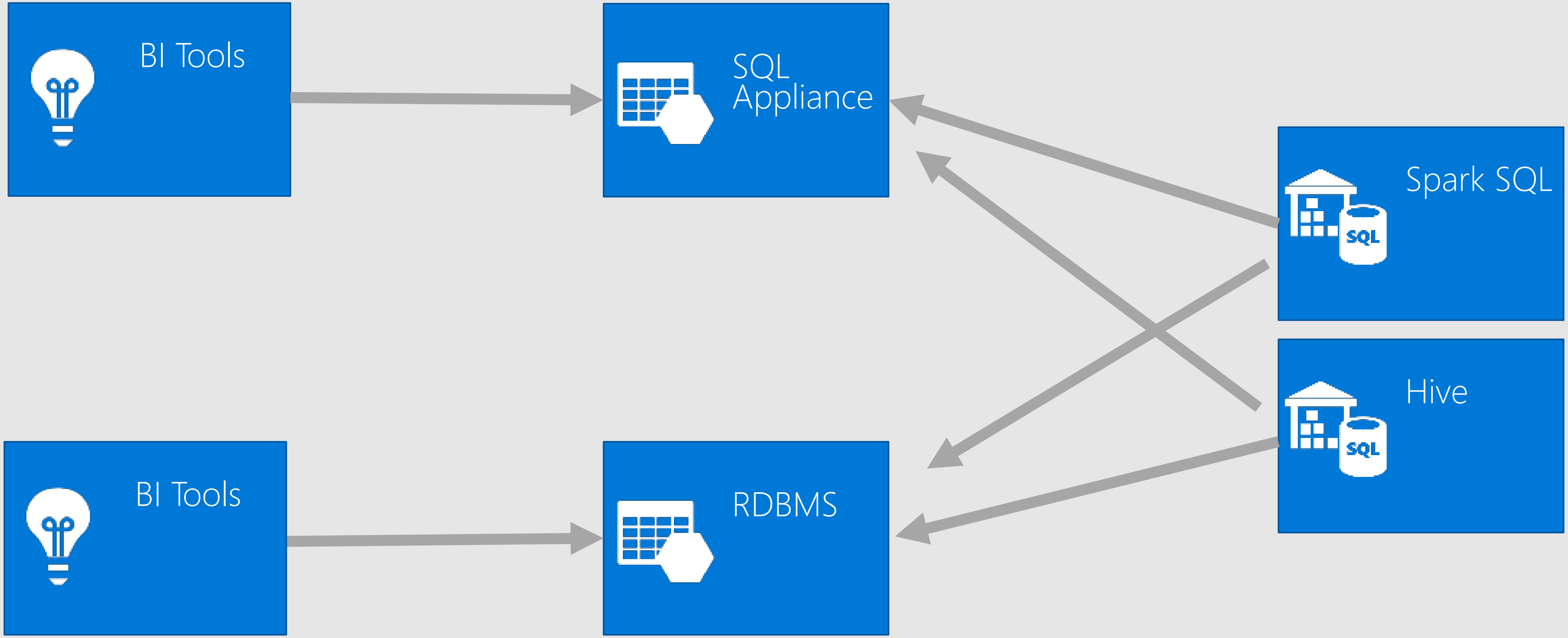
Streaming NLP and Topic Modeling



Enterprise solutions with Apache Spark
Consumer research group

- User Behavior
- Aggregated to Sales, Stores, Households
- Fast concurrent access

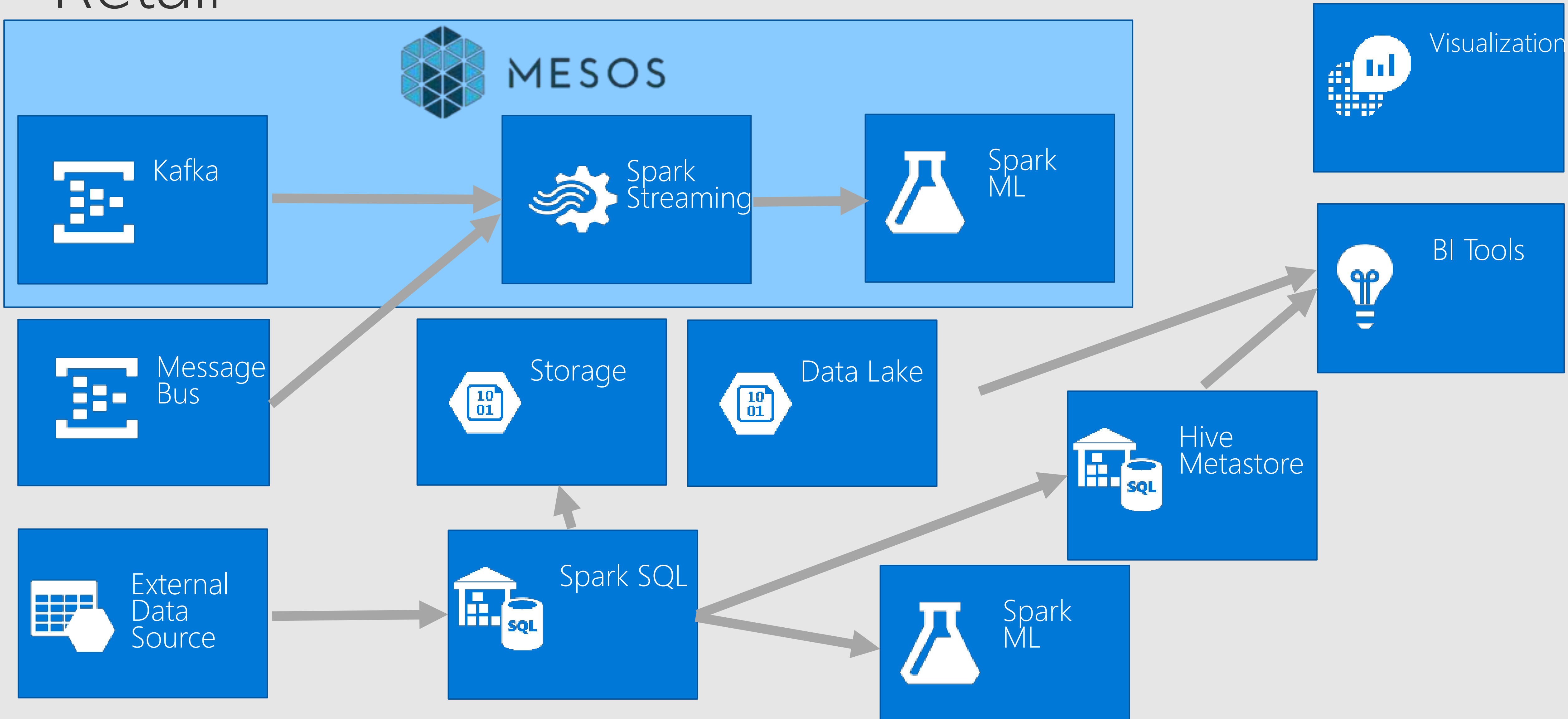
Enterprise solutions with Apache Spark
Consumer research group



Enterprise solutions with Apache Spark
Retail

- Lots of Machines
- Inventory
- IOT → Predictive Modeling
- Transactions

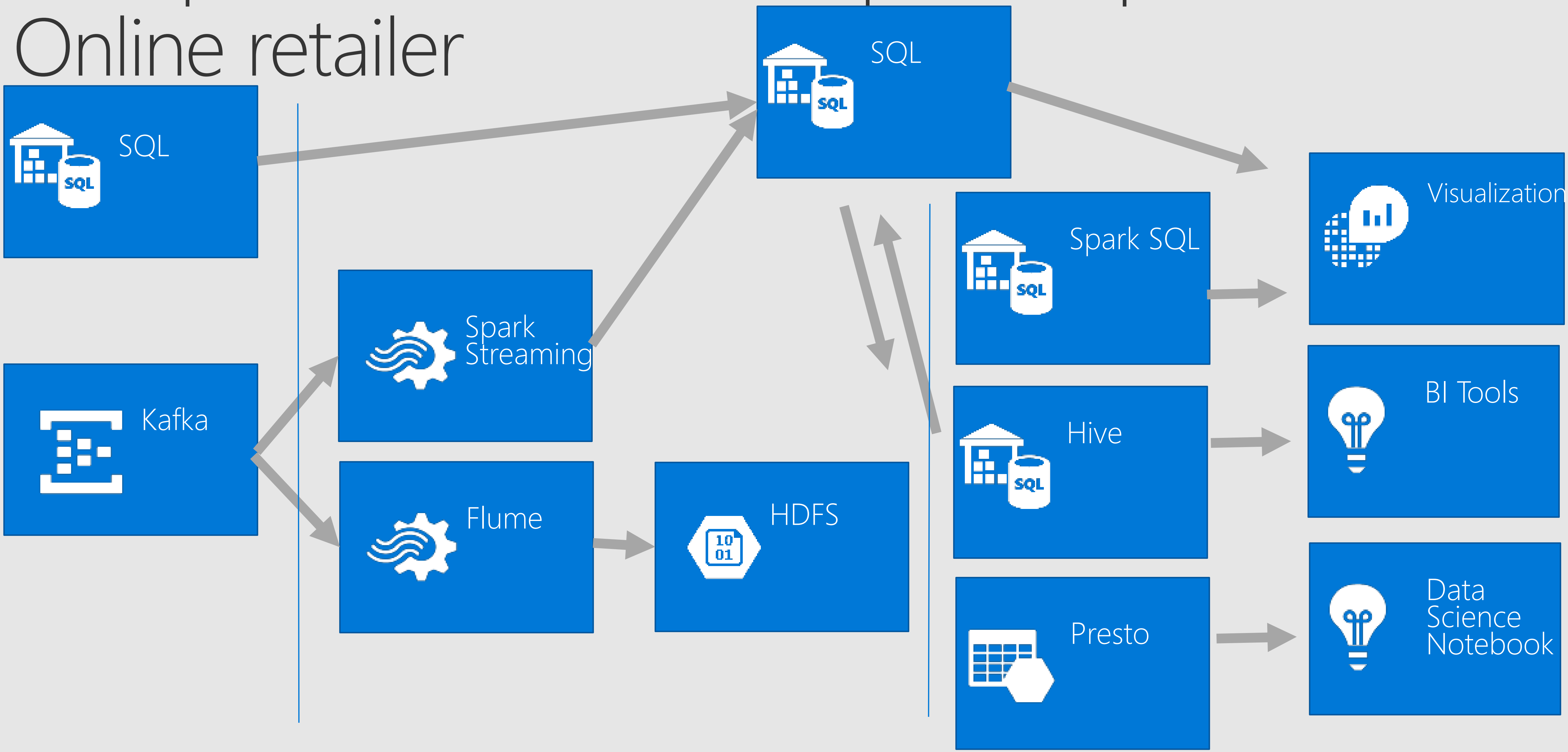
Enterprise solutions with Apache Spark
Retail



Enterprise solutions with Apache Spark
Online retailer

- Catalog
- Supply chain
- Accounting
- Pricing
- Search

Enterprise solutions with Apache Spark
Online retailer

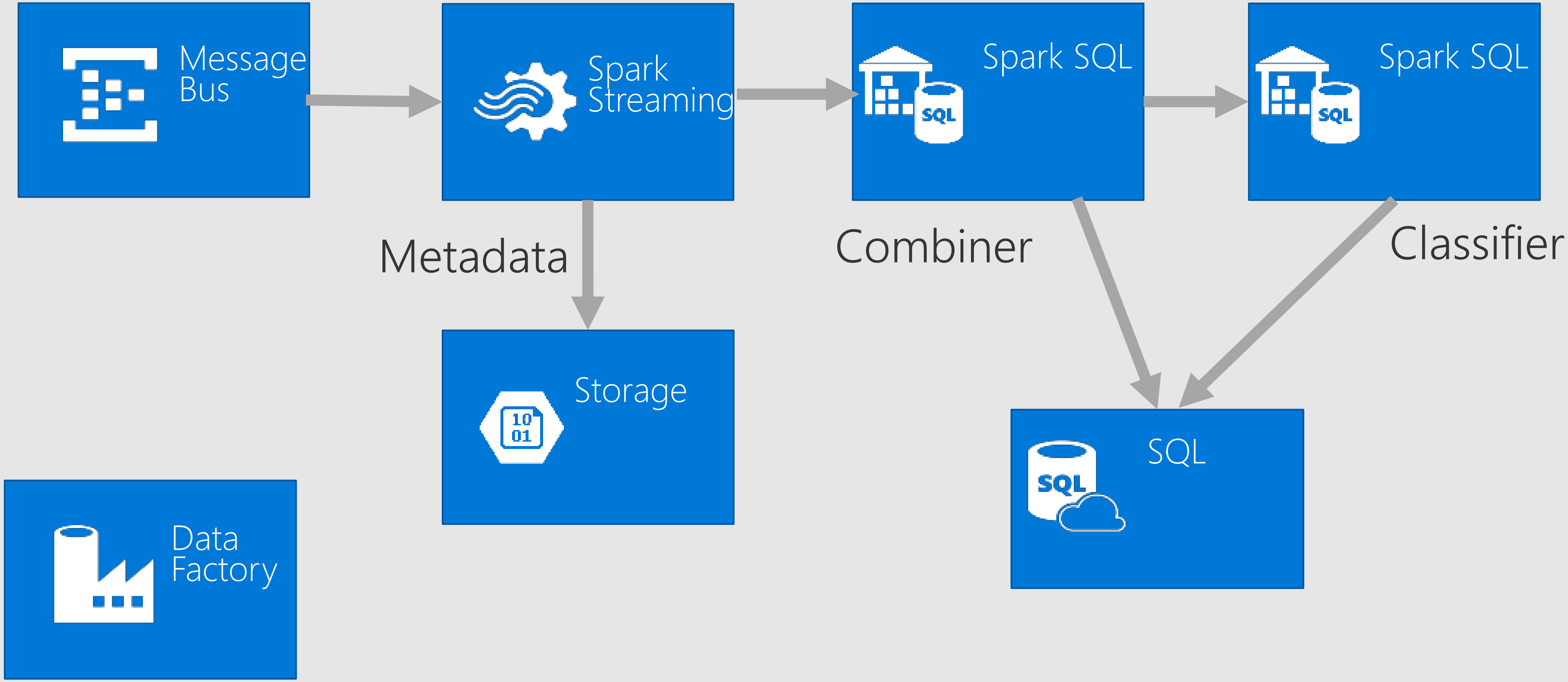


Enterprise solutions with Apache Spark
Finance

- Payments
- Subscriptions
- Transactions
- Auditing for mismatch, missing
- Monitoring metrics for latency, processing rate

Enterprise solutions with Apache Spark

Finance



Key Takeaways

Technology trend:
Moving to Streaming + Predictive

Key Takeaways

Why Streaming?

- Faster insight at scale
- Streaming ETL
- Triggers
- Latest data to static data
- Continuous learning

Question?

After session…

Contact me

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