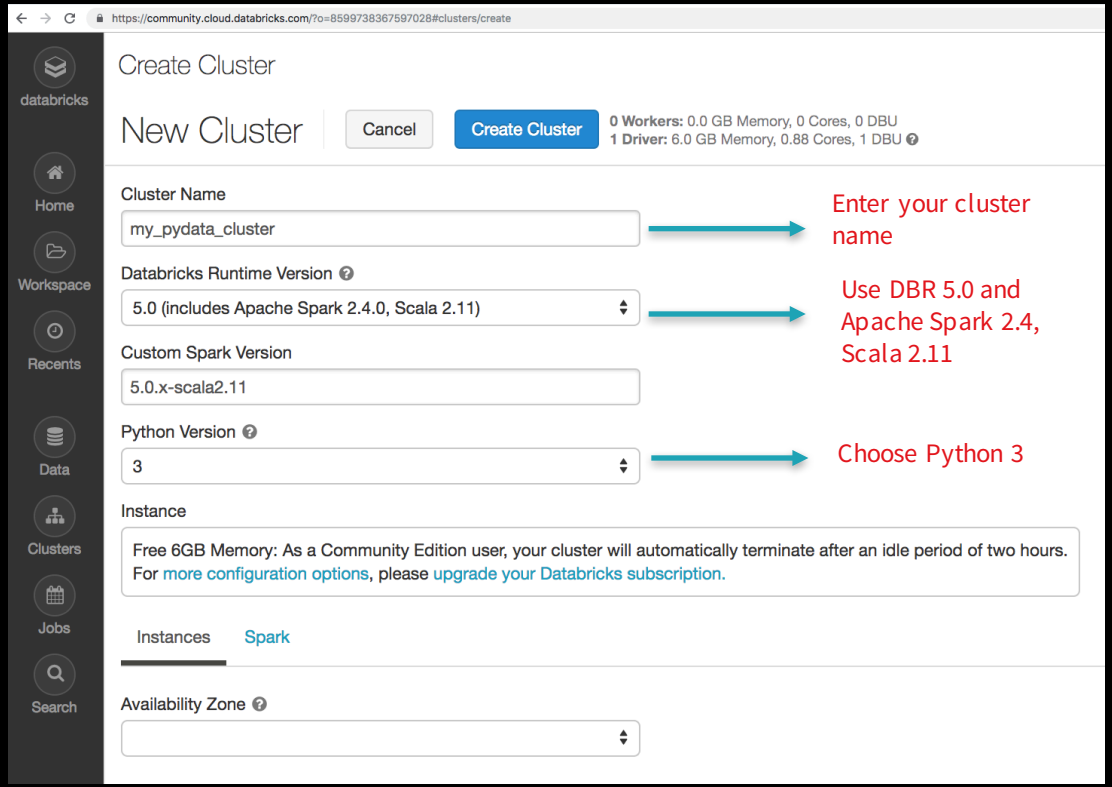
PyData https://dbricks.co/tutorial-pydata-miami



Writing Continuous Applications with Structured Streaming in PySpark

Jules S. Damji

PyData

PyData, Miami, FL Jan 11, 2019

databricks

I have used Apache Spark 2.x Before…

Apache Spark Community & Developer Advocate @ Databricks

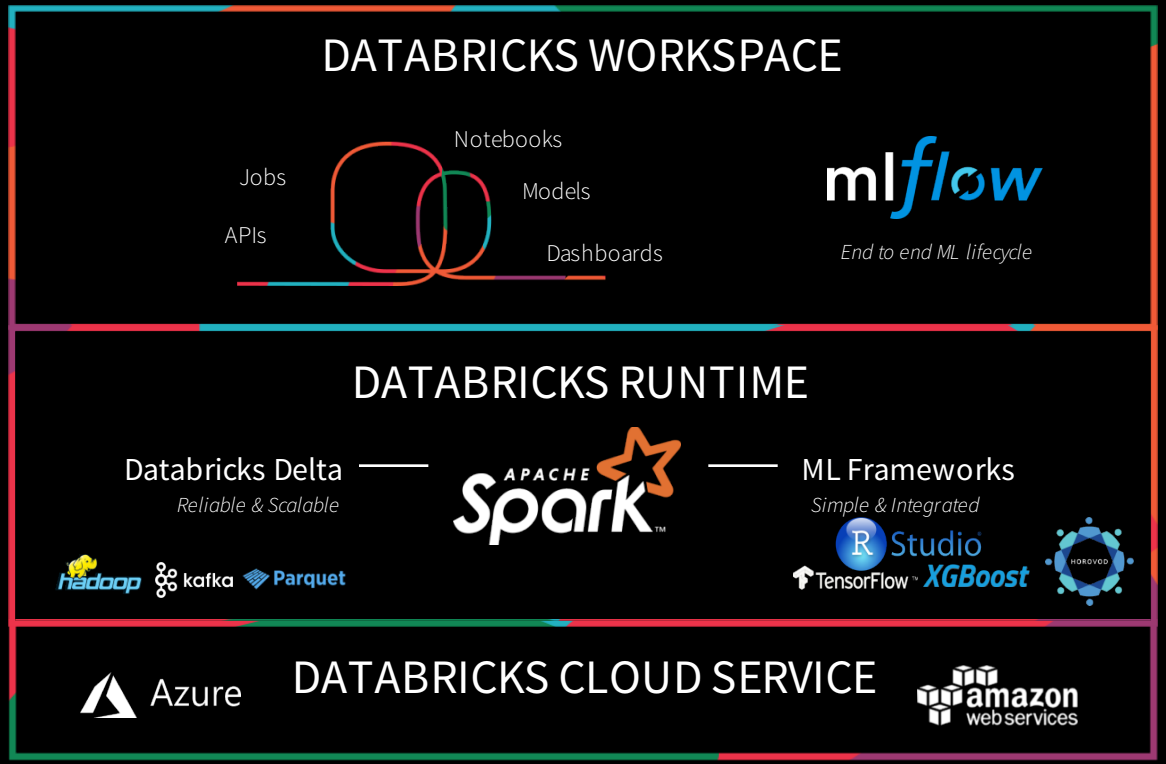
Developer Advocate @ Hortonworks

Software engineering @ Sun Microsystems, Netscape, @Home, VeriSign, Scalix, Centrify, LoudCloud/Opsware, ProQuest

Program Chair Spark + AI Summit

https://www.linkedin.com/in/dmatrix
@2twitme

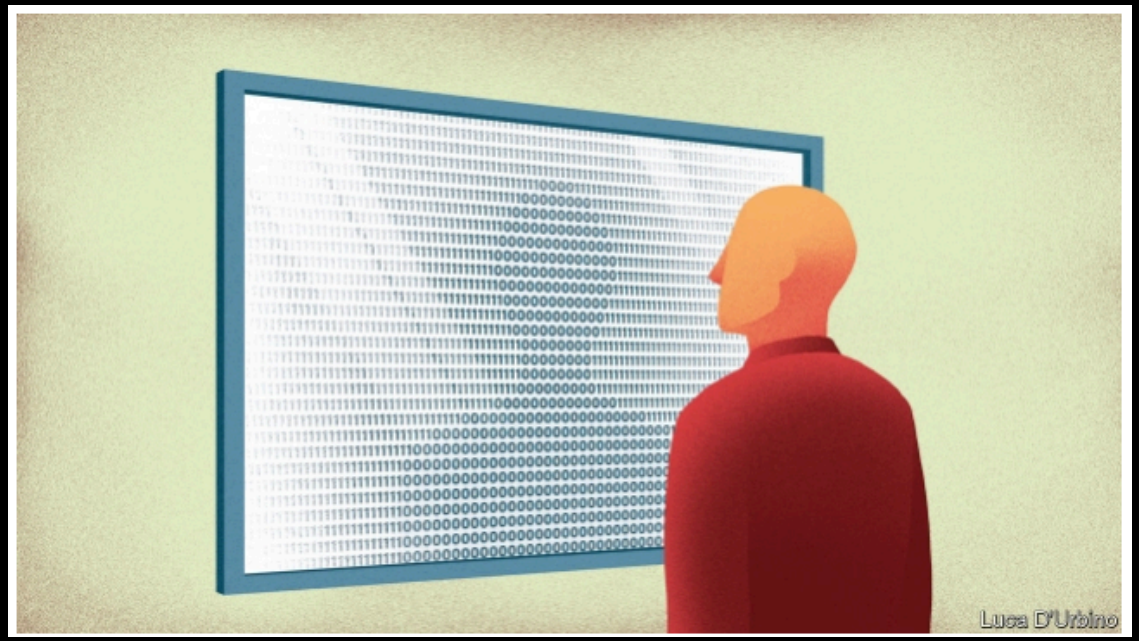
Databricks Unified Analytics Platform



Agenda for Today's Talk

- What and Why Apache Spark
- Why Streaming Applications are Difficult
- What's Structured Streaming
- Anatomy of a Continunous Application
- Tutorials & Demo
- Q & A

How to think about data in 2019 - 2020



“Data is the new oil"

What's Apache Spark & Why

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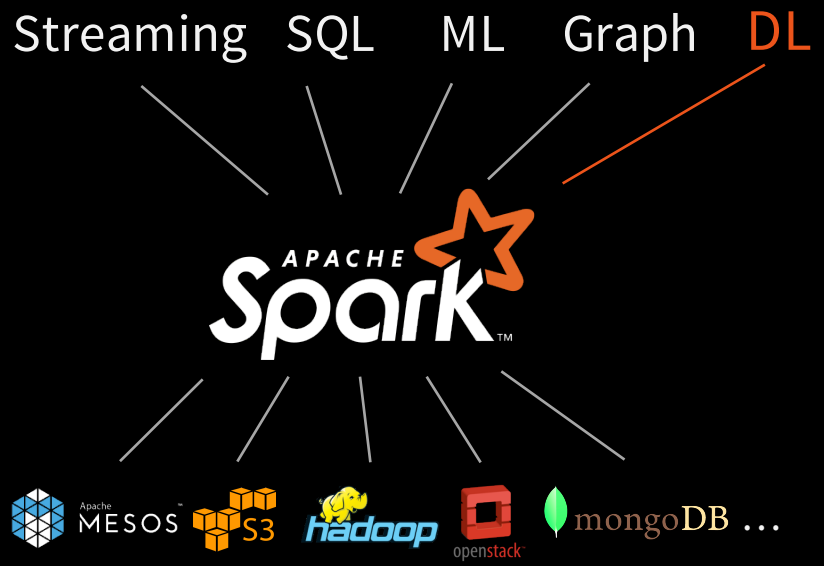
What is Apache Spark?

- General cluster computing engine that extends MapReduce
- Rich set of APIs and libraries
- Unified Engine
- Large community: 1000+ orgs, clusters up to 8000 nodes



Unique Thing about Spark

- Unification: same engine and same API for diverse use cases
  - Streaming, batch, or interactive
  - ETL, SQL, machine learning, or graph

Why Unification?

MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

Abstract

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a key/value pair to generate a set of intermediate key/value pairs, and a *reduce* function that merges all intermediate values associated with the same intermediate key. Many

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually large and the computations have to be distributed across hundreds or thousands of machines in order to finish in a reasonable amount of time. The issues of how to parallelize the computation, distribute the data, and handle failures conspire to obscure the original simple computation with large amounts of complex code to deal with

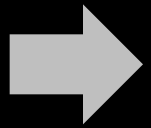
Why Unification?

- MapReduce: a general engine for batch processing

> We wrote the first version of the MapReduce library in February of 2003, and made significant enhancements to it in August of 2003, including the locality optimization, dynamic load balancing of task execution across worker machines, etc. Since that time, we have been pleasantly surprised at how broadly applicable the MapReduce library has been for the kinds of problems we work on. It has been used across a wide range of domains within Google, including:

Big Data Systems Yesterday

MapReduce



Pregel Giraph
Dremel Millwheel
Storm Impala
Drill S4 . . .

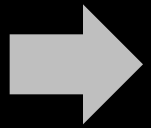
General batch processing

Specialized systems for new workloads

Hard to *combine* in pipelines

Big Data Systems Today

MapReduce



Pregel Giraph
Dremel Millwheel
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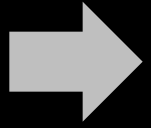
Drill S4 . . .



General batch processing

Specialized systems for new workloads

Unified engine

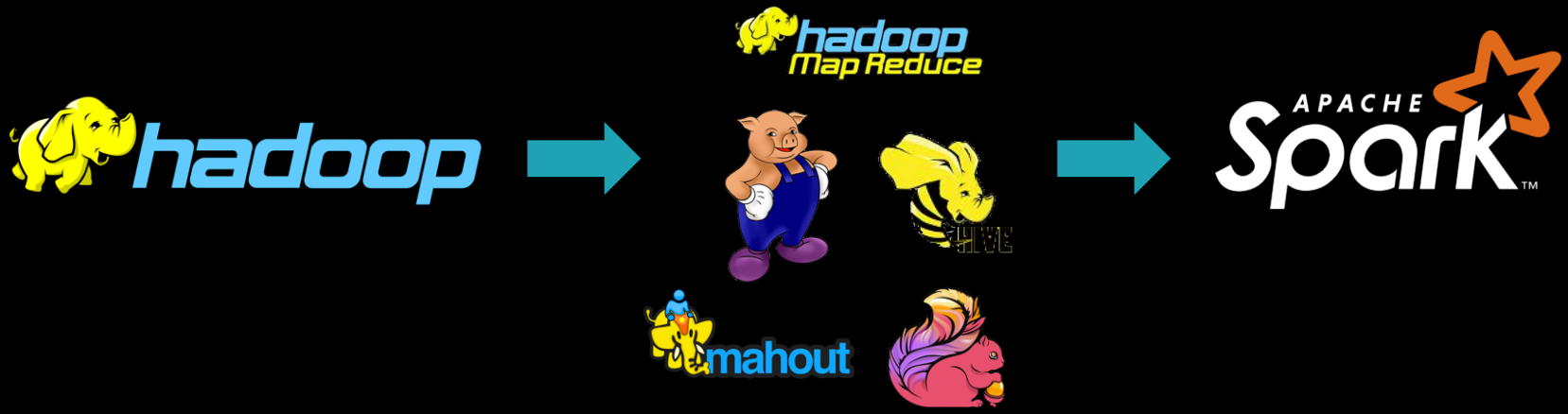
Benefits of Unification

1. Simpler to use and operate

2. Code reuse: e.g. only write monitoring, FT, etc once

3. New apps that span processing types: e.g. interactive queries on a stream, online machine learning

Faster, Easier to Use, Unified



First Distributed Processing Engine

Specialized Data Processing Engines

Unified Data Processing Engine

An Analogy

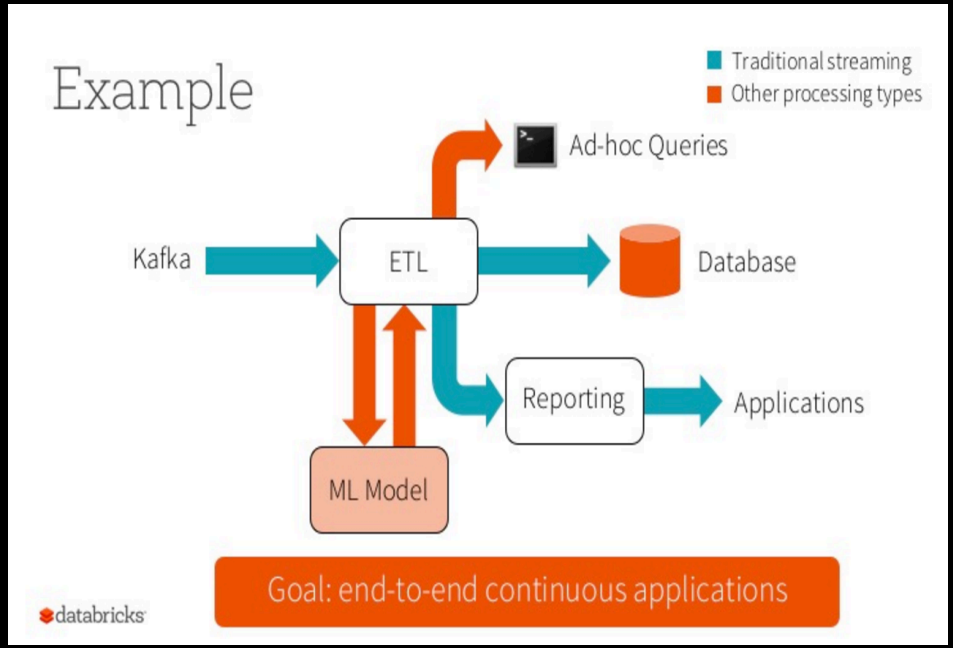
Specialized devices

New applications

Unified device

Why Streaming Applications are Inherently Difficult?

building robust stream processing apps is hard



Complexities in stream processing

COMPLEX DATA

Diverse data formats
(json, avro, txt, csv, binary, …)

Data can be dirty,
late, out-of-order

COMPLEX WORKLOADS

Combining streaming with
interactive queries

Machine learning

COMPLEX SYSTEMS

Diverse storage systems
(Kafka, S3, Kinesis, RDBMS, …)

System failures

Structured Streaming

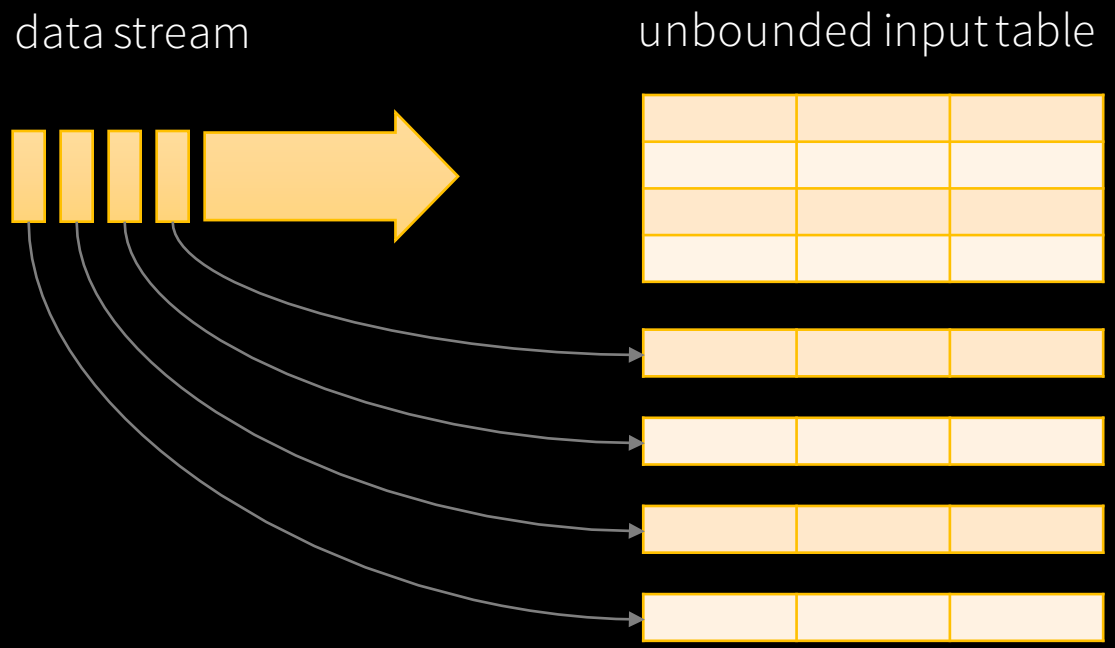
stream processing on Spark SQL engine
fast, scalable, fault-tolerant

rich, unified, high level APIs
deal with *complex data* and *complex workloads*

rich ecosystem of data sources
integrate with many *storage systems*

you
should not have to
reason about streaming

Treat Streams as Unbounded Tables



new data in the
data stream
=
new rows appended
to a unbounded table

you

should write queries

&

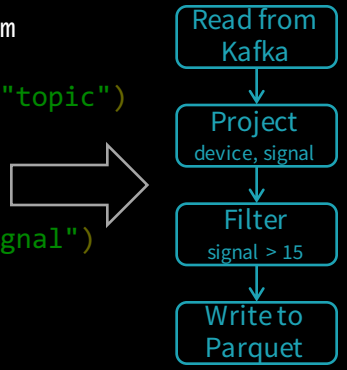
Apache Spark

should continuously update the answer

Apache Spark automatically *streamifies*!

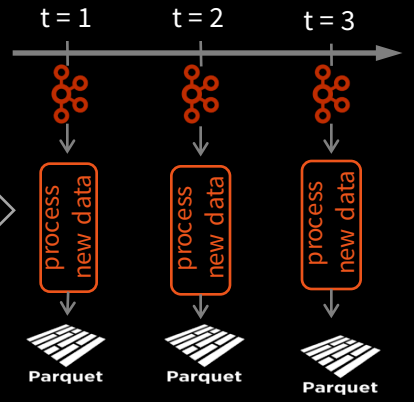
```
input = spark.readStream
  .format("kafka")
  .option("subscribe", "topic")
  .load()

result = input
  .select("device", "signal")
  .where("signal > 15")

result.writeStream
  .format("parquet")
  .start("dest-path")
```

DataFrames, Datasets, SQL



Logical Plan

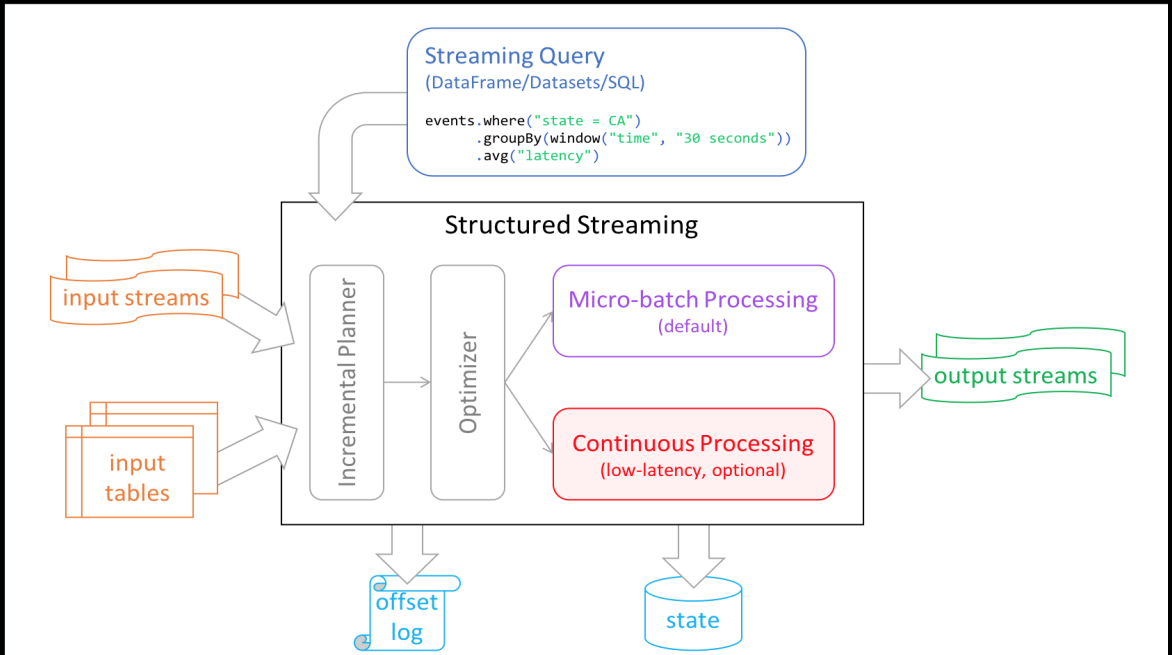
Optimized Physical Plan



Series of Incremental Execution Plans

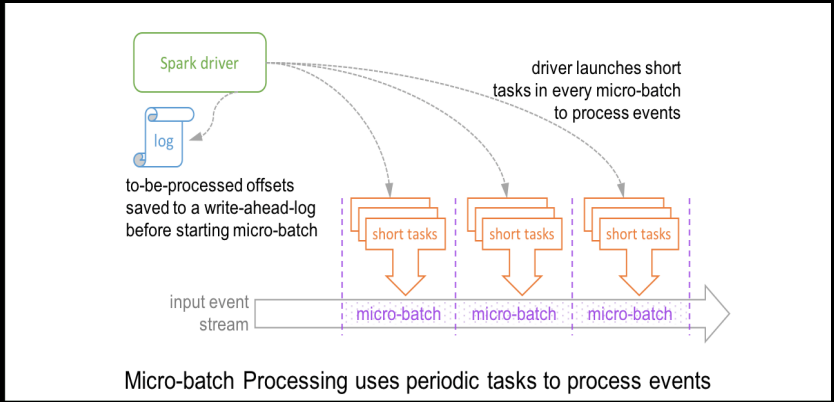
Spark SQL converts batch-like query to a series of incremental execution plans operating on new batches of data

Structured Streaming – Processing Modes

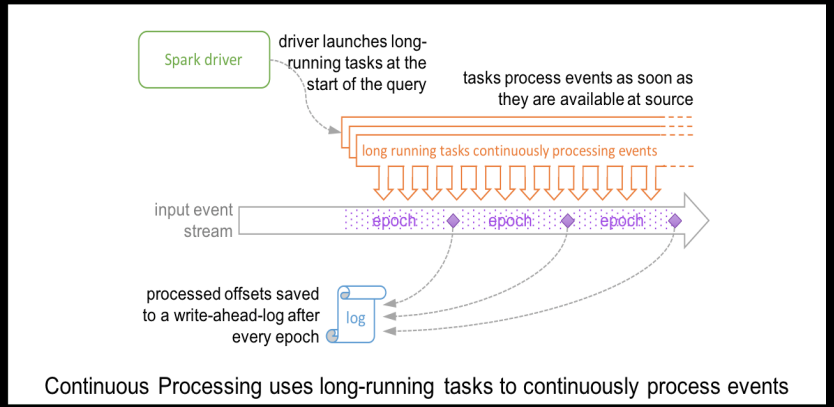


Structured Streaming processing modes: Micro-batch and Continuous Processing

Structured Streaming Processing Modes



Micro-batch Processing uses periodic tasks to process events



Continuous Processing uses long-running tasks to continuously process events

Simple Streaming ETL

Anatomy of a Streaming Query

Streaming word count

Anatomy of a Streaming Query: Step 1

```
spark.readStream
  .format("kafka")
  .option("subscribe", "input")
  .load()
```

Source

- Specify one or more locations to read data from
- Built in support for Files/Kafka/Socket, pluggable.

Anatomy of a Streaming Query: Step 2

```
from pyspark.sql import Trigger

spark.readStream
  .format("kafka")
  .option("subscribe", "input")
  .load()
  .groupBy(“value.cast("string") as key”)
  .agg(count("*") as “value”)
```

Transformation

- Using DataFrames, Datasets and/or SQL.
- Internal processing always exactly-once.

Anatomy of a Streaming Query: Step 3

```
from pyspark.sql import Trigger
spark.readStream
  .format("kafka")
  .option("subscribe", "input")
  .load()
  .groupBy(“value.cast("string") as key”)
  .agg(count("*") as “value”)
  .writeStream()
  .format("kafka")
  .option("topic", "output")

  .outputMode(OutputMode.Complete())
  .option("checkpointLocation", "…")
  .start()
```

Sink

- Accepts the output of each batch.
- When supported sinks are transactional and exactly once (Files).

Anatomy of a Streaming Query: Output Modes

```
from pyspark.sql import Trigger

spark.readStream
  .format("kafka")
  .option("subscribe", "input")
  .load()
  .groupBy(“value.cast("string") as key”)
  .agg(count("*") as 'value’)
  .writeStream()
  .format("kafka")
  .option("topic", "output")
  .trigger("1 minute")
  .outputMode("update")
        ("checkpointLocation", "…")
  .start()
```

Output mode – What's output

- Complete – Output the whole answer every time
- Update – Output changed rows
- Append – Output new rows only

Trigger – When to output

- Specified as a time, eventually supports data size
- No trigger means as fast as possible

Anatomy of a Streaming Query: Checkpoint

```
from pyspark.sql import Trigger

spark.readStream
  .format("kafka")
  .option("subscribe", "input")
  .load()
  .groupBy(“value.cast("string") as key”)
  .agg(count("*") as 'value)
  .writeStream()
  .format("kafka")
  .option("topic", "output")
  .trigger("1 minute")
  .outputMode("update")
  .option("checkpointLocation", "…")
  .withWatermark(“timestamp” “2 minutes”)
  .start()
```

Checkpoint & Watermark

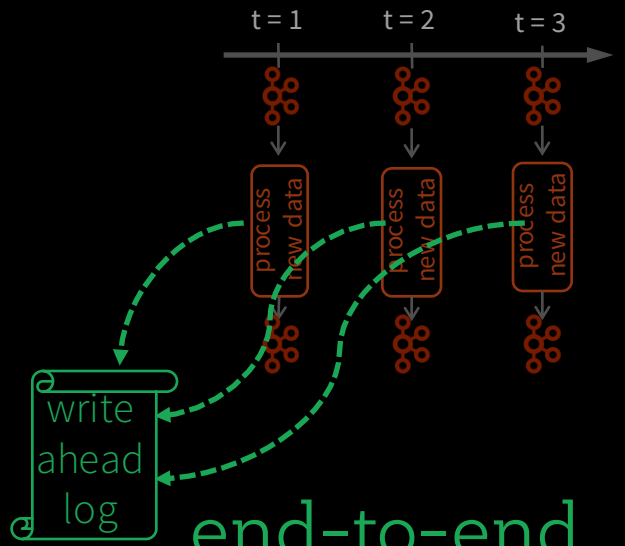
- Tracks the progress of a query in persistent storage
- Can be used to restart the query if there is a failure.
- *trigger(Trigger. Continunous(“ 1 second”))*

Set checkpoint location & watermark to drop very late events

Fault-tolerance with Checkpointing

Checkpointing – tracks progress (offsets) of consuming data from the source and intermediate state.

- Offsets and metadata saved as JSON
- Can resume after changing your streaming transformations



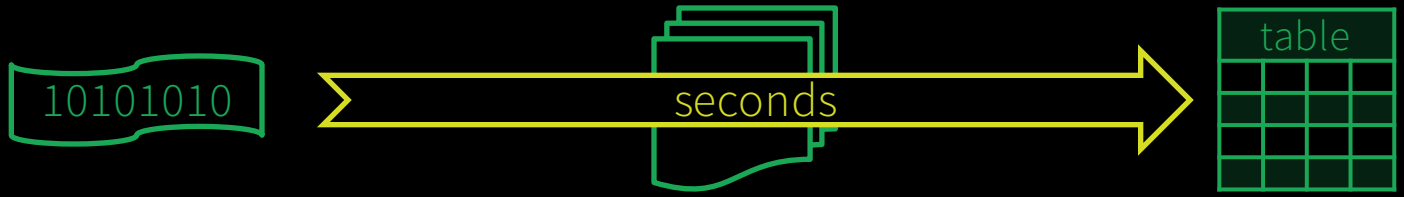
end-to-end exactly-once guarantees

Complex Streaming ETL

Traditional ETL

- Raw, dirty, un/semi-structured is data dumped as files
- Periodic jobs run every few hours to convert raw data to structured data ready for further analytics
- Hours of delay before taking decisions on latest data
- Problem: Unacceptable when time is of essence
  - [intrusion , anomaly or fraud detection, monitoring IoT devices, etc.]

Streaming ETL w/ Structured Streaming



Structured Streaming enables raw data to be available as structured data as soon as possible

Streaming ETL w/ Structured Streaming

Example

Json data being received in Kafka

Parse nested json and flatten it

Store in structured Parquet table

Get end-to-end failure guarantees

```
from pyspark.sql import Trigger

rawData = spark.readStream
  .format("kafka")
  .option("kafka.boostrap.servers",...)
  .option("subscribe", "topic")
  .load()

parsedData = rawData
  .selectExpr("cast (value as string) as json"))
  .select(from_json("json", schema).as("data"))
  .select("data.*") # do your ETL/Transformation

query = parsedData.writeStream
  .option("checkpointLocation", "/checkpoint")
  .partitionBy("date")
  .format("parquet")
  .trigger( Trigger. Continunous("5 second"))
  .start("/parquetTable")
```

Reading from Kafka

rawData dataframe has the following columns

```
raw_data_df = spark.readStream
  .format("kafka")
  .option("kafka.boostrap.servers",...)
  .option("subscribe", "topic")
  .load()
```

key	value	topic	partition	offset	timestamp
[binary]	*[binary]*	"topicA"	0	345	1486087873
[binary]	*[binary]*	"topicB"	3	2890	1486086721

Transforming Data

Cast binary *value* to string
Name it column *json*

```
parsedData = rawData
      .selectExpr("cast (value as string) as json")
      .select(from_json("json", schema).as("data"))
      .select("data.*")
```

Parse *json* string and expand into nested columns, name it *data*

Transforming Data

Cast binary *value* to string
Name it column *json*

```
parsedData = rawData
    .selectExpr("cast (value as string) as json")
    .select(from_json("json", schema).as("data"))
    .select("data.*")
```

Parse *json* string and expand into nested columns, name it data

Flatten the nested columns

powerful built-in Python APIs to perform complex data transformations

from_json, to_json, explode, ...
100s of functions

(see our blog post & tutorial)

Writing to Parquet

Save parsed data as Parquet table in the given path

Partition files by date so that future queries on time slices of data is fast

e.g. query on last 48 hours of data

```
query = parsedData.writeStream
      .option("checkpointLocation", ...)
      .partitionBy("date")
      .format("parquet")
      .start("/parquetTable") #pathname
```

Tutorials

PyData

databricks

Summary

- Apache Spark best suited for unified analytics & processing at scale
- Structured Streaming APIs Enables Continunous Applications
- Demonstrated Continunous Application

Resources

- Getting Started Guide with Apache Spark on Databricks
- docs.databricks.com
- Spark Programming Guide
- Structured Streaming Programming Guide
- Anthology of Technical Assets for Structured Streaming
- Databricks Engineering Blogs

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Thank You ☺

jules@databricks.com
@2twitme
https://www.linkedin.com/in/dmatrix/