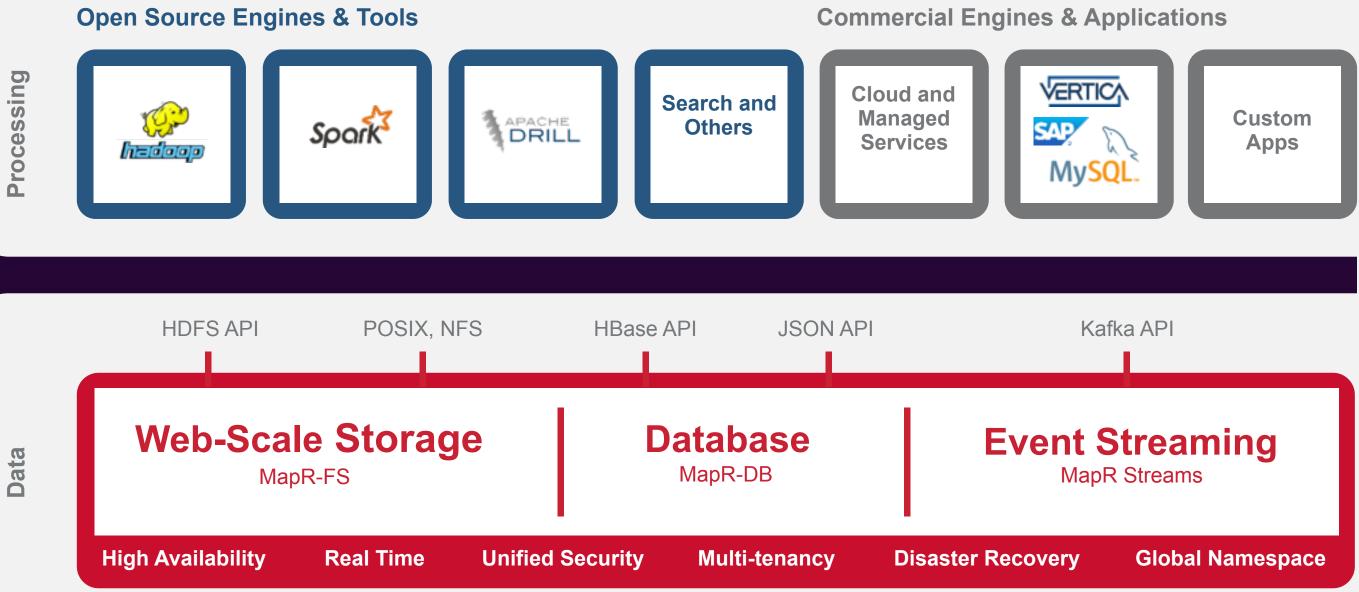
Build a Time Series Application with Spark and HBase

Tugdual Grall Technical Evangelist @tgrall tug@mapr.com MapR

MapR Converged Data Platform



Enterprise-Grade Platform Services

2

Unified Management and Monitoring



- Time Series
- Apache Spark & Spark Streaming
- Apache HBase
- Apache Kafka & MapR Streams
- Lab

About the Lab

- Use Spark & HBase in MapR Cluster
 - Option 1: Use a SandBox (Virtual Box VM located on USB Key)
 - Option 2: Use Cloud Instance (SSH/SCP only)

- Content: •
 - Option 1: spark-streaming-hbase-workshop.zip on USB •
 - Option 2: download zip from https://github.com/tgrall/mapr-streams-spark-hbase-workshop

Time Series

What is a Time Series?

- Stuff with timestamps
 - sensor measurements
 - system stats
 - log files

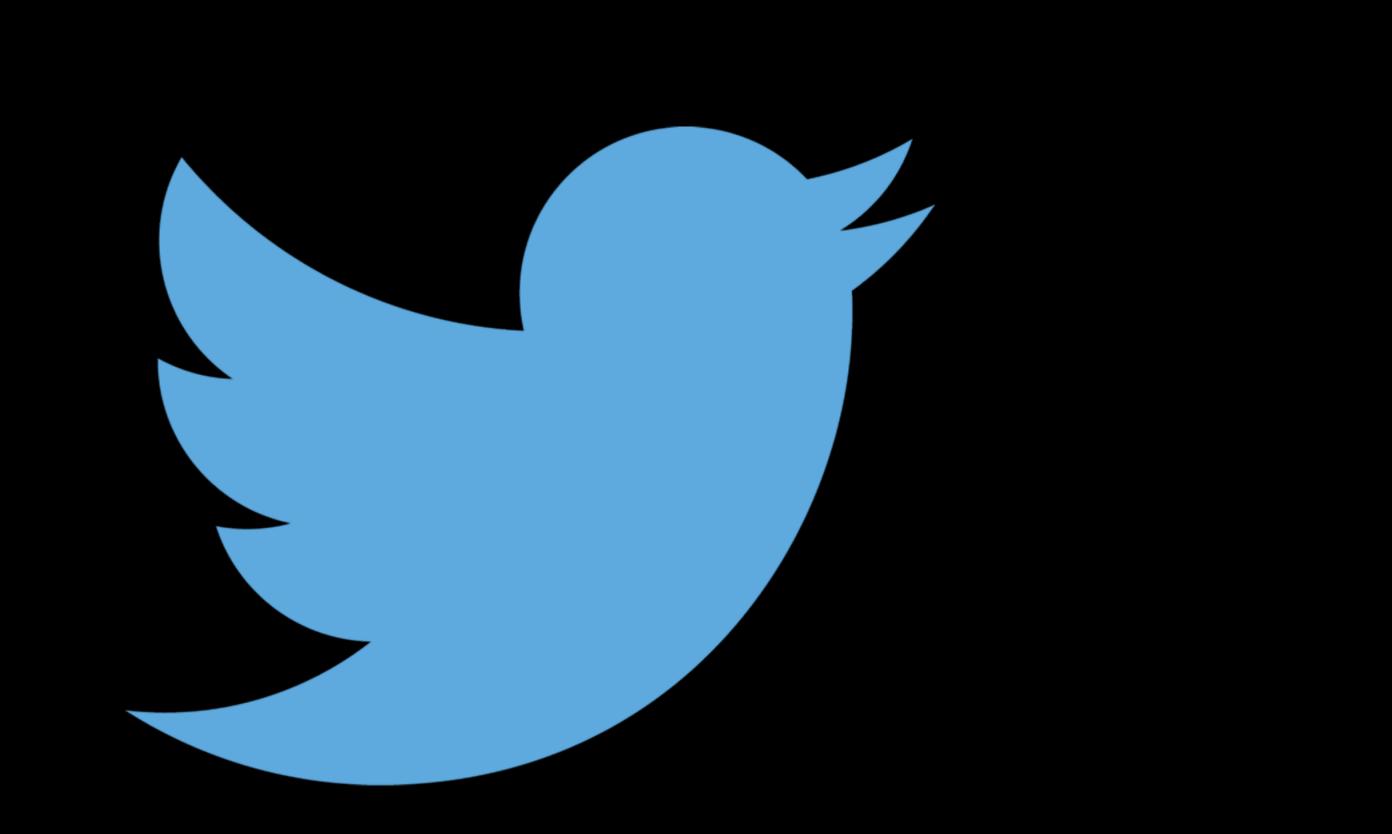
- - - -

Got Some Examples?

7

















45050 Brunder-High Bronet-Zuid







What do we need to do?

- Acquire
 - Measurement, transmission, reception
- Store
 - Individually, or grouped for some amount of time
- Retrieve ٠
 - Ad hoc, flexible, correlate and aggregate
- Analyze and visualize
 - We facilitate this via retrieval



Acquisition

Not usually our problem

- Sensors
- Data collection agents, raspberry pi •
- Transmission via LAN/Wan, Mobile Network, Satellites
- Receipt into system listening daemon or queue, or • depending on use case writing directly to the database



Storage Choice

- Flat files
 - Great for rapid ingest with massive data
 - Handles essentially any data type
 - Less good for data requiring frequent updates
 - Harder to find specific ranges
- Traditional RDBMS
 - Ingests up to ~10,000/ sec; prefers well structured (numerical) data; expensive
- NoSQL (such as MapR-DB or HBase)
 - Easily handle 10,000 rows / sec / node True linear scaling
 - Handles wide variety of data
 - Good for frequent updates
 - Easily scanned in a range

Specific Example

Consider oil drilling rigs

- When drilling wells, there are *lots* of moving parts
- Typically a drilling rig makes about **IOK samples**/s
- Temperatures, pressures, magnetics, machine vibration levels, salinity, voltage, currents, many others
- Typical project has 100 rigs



General Outline

10K samples / second / rig

x 100 rigs

- = IM samples / second
- But wait, there's more
 - Suppose you want to test your system
 - Perhaps with a year of data
 - And you want to load that data in << 1 year
- 100x real-time = 100M samples / second

Data Storage

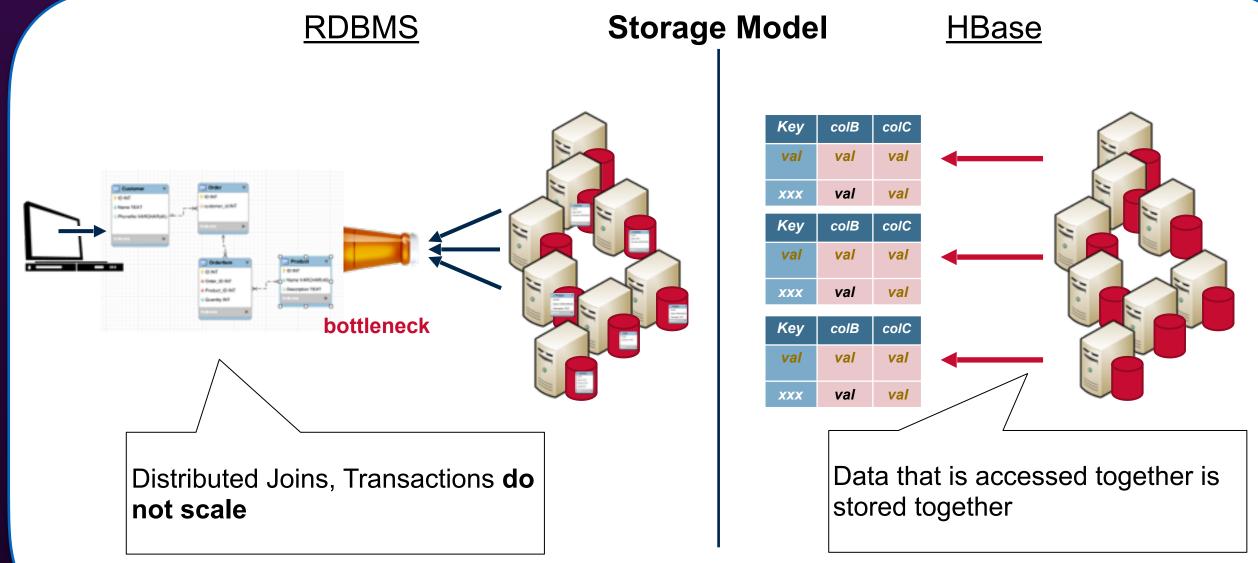
Кеу	13	43	73	103	
series-uid.time-window	4.5	5.2	6.1	4.9	

- Typical time window is one hour
- Column names are offsets in time window
- Find series-uid in separate table





Why do we need NoSQL / HBase? **Relational Model**



HBase is a ColumnFamily oriented Database

Customer id	Raw Data			Stats	
		CF_DATA	ł	C	CF_STA
RowKey	colA	colB	colC	colA	colB
series-abc.time-window	Val		val	val	
series-efg.time-window		val			val

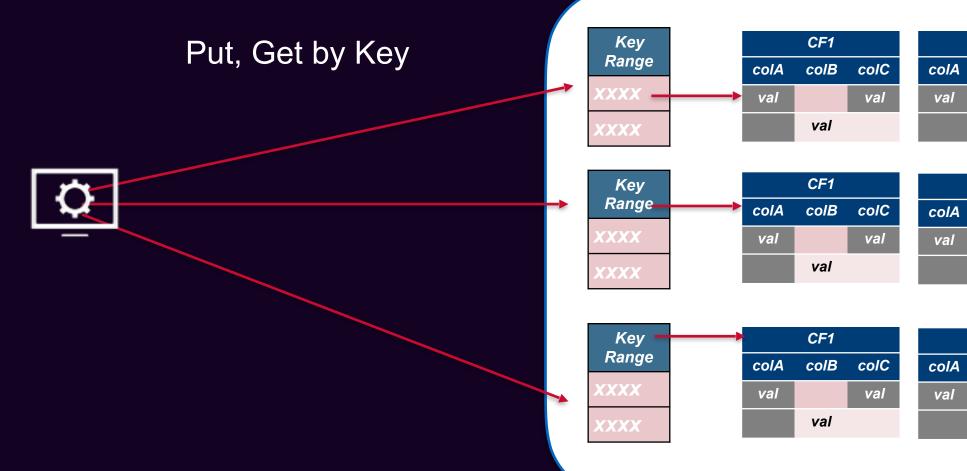
Data is accessed and stored together: •

- RowKey is the primary index •
- Column Families group similar data by row • key

S



HBase is a Distributed Database



Data is automatically distributed across the cluster

• Key range is used for horizontal partitioning



CF2 colA colB colC val χ_{C}^{\vee} val CF2 colA colB colC val $\chi_{\mathbb{C}}^{\times}$ val CF2 colB colC val val

Basic Table Operations

- Create Table, define Column Families before data is imported
 - but not the rows keys or number/names of columns
- · Low level API, technically more demanding
- Basic data access operations (CRUD):

put	Inserts data into rows (both create a
get	Accesses data from one row
scan	Accesses data from a range of rows
delete	Delete a row or a range of rows

fore data is imported nes of columns

and update)

S

or columns

Learn More

- Free Online Training: http://learn.mapr.com
 - DEV 320 Apache HBase Data Model and Architecture
 - DEV 325 Apache HBase Schema Design
 - DEV 330 Developing Apache HBase Applications: Basics
 - DEV 335 Developing Apache HBase Applications: Advanced



- Cluster Computing Platform
- Extends "MapReduce" with extensions
 - Streaming
 - Interactive Analytics
- Run in Memory





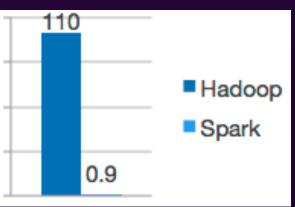
Fast

•

(s)	120
me	90
ng ti	60
unni	30
Ê	0

Logistic regression in Hadoop and Spark

100x faster than M/R





- Write programs quickly
- More Operators
- Interactive Shell
- Less Code

Ease of Development



- Scala
- Python
- Java
- SparkR

Multi Language Support



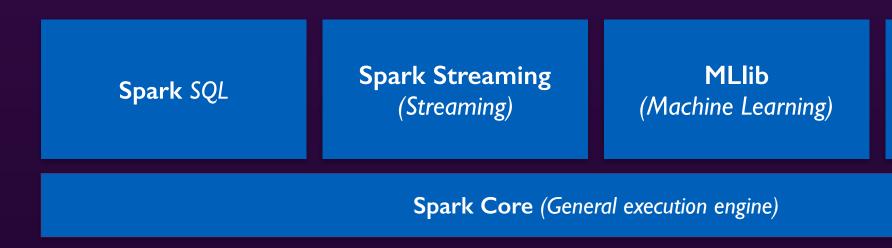
Deployment Flexibility

Deployment

 \bullet

- Local YARN \bullet •
 - Standalone Mesos
- Storage •
 - **S**3 • HDFS Cassandra •
 - MapR-FS •

Unified Platform



GraphX (Graph Computation)

Spark Components

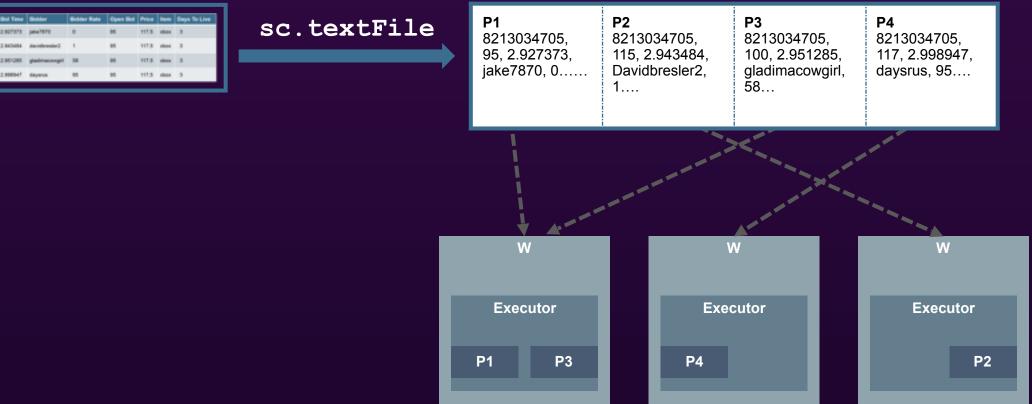


Worker			
Executor			
Task	Task		
•			



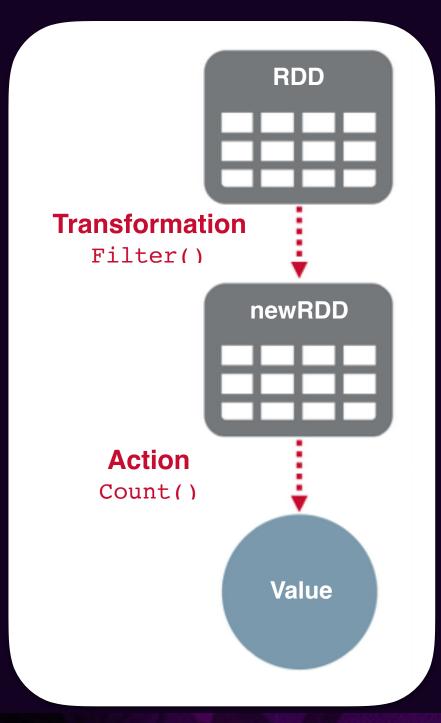
Spark Resilient Distributed Datasets

Sensor RDD



38

Spark Resilient Distributed Datasets



Spark Streaming





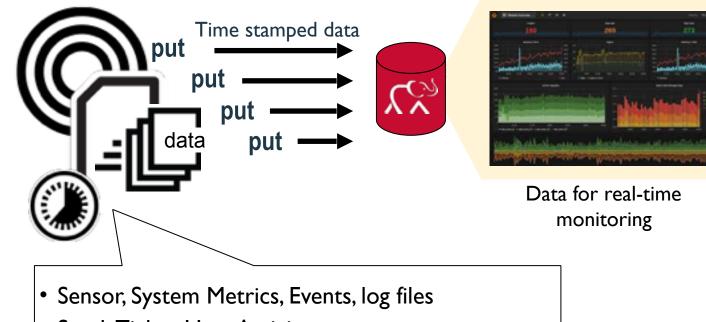
GraphX (Graph Computation)

What is Streaming?

- Data Stream:
 - Unbounded sequence of data arriving • continuously
- Stream processing:
 - Low latency processing, querying, and • analyzing of real time streaming data

Why Spark Streaming

- Many applications must process streaming data
- With the following Requirements:
 - Results in near-real-time
 - Handle large workloads
 - latencies of few seconds
- Use Cases
 - Website statistics, monitoring
 - IoT
 - Fraud detection
 - Social network trends
 - Advertising click monetization



- Stock Ticker, User Activity
- Hi Volume, Velocity

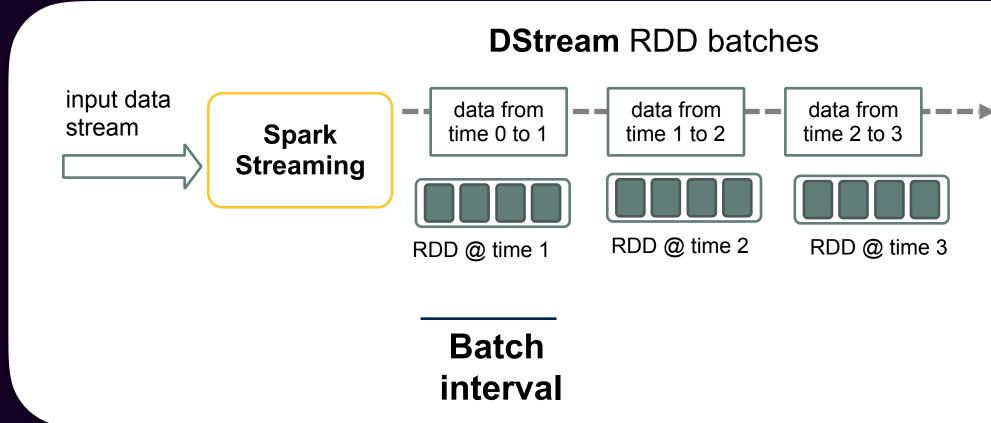
What is Spark Streaming?

- Enables scalable, high-throughput, fault-tolerant • stream processing of live data
- Extension of the core Spark •

Data Sources		Data Sinks
Kafka Flume HDFS/S3 Kinesis Twitter	Spark Streaming	HDFS Databases Dashboards

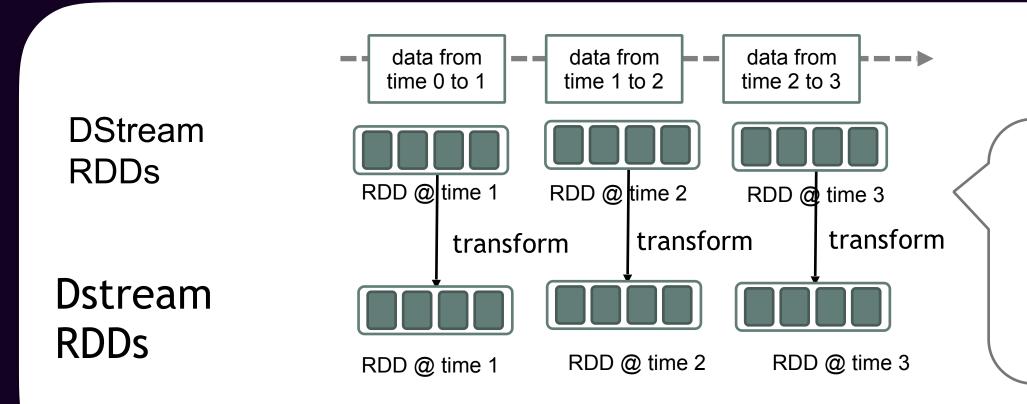
Spark Streaming Architecture

- Divide data stream into batches of X seconds •
 - Called DStream = sequence of RDDs \bullet



Process DStream

- Process using transformations
 - creates new RDDs

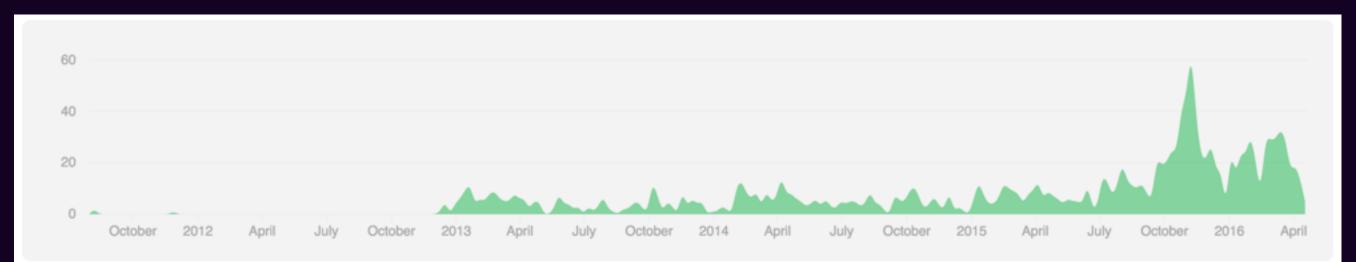


Transform map reduceByValue count



What is Kafka?

- http://kafka.apache.org/
- Created at LinkedIn, open sourced in 2011
- Implemented in Scala / Java
- Distributed messaging system built to scale



kafka

What for?



- Realtime Streaming
- Event Sourcing
- Logs •
- Change Data Capture •

Message Queue (!= ESB)

Key Concepts



- producers
- brokers (== node)

Feeds of messages are organised in **topics**

Processes that publish messages are called

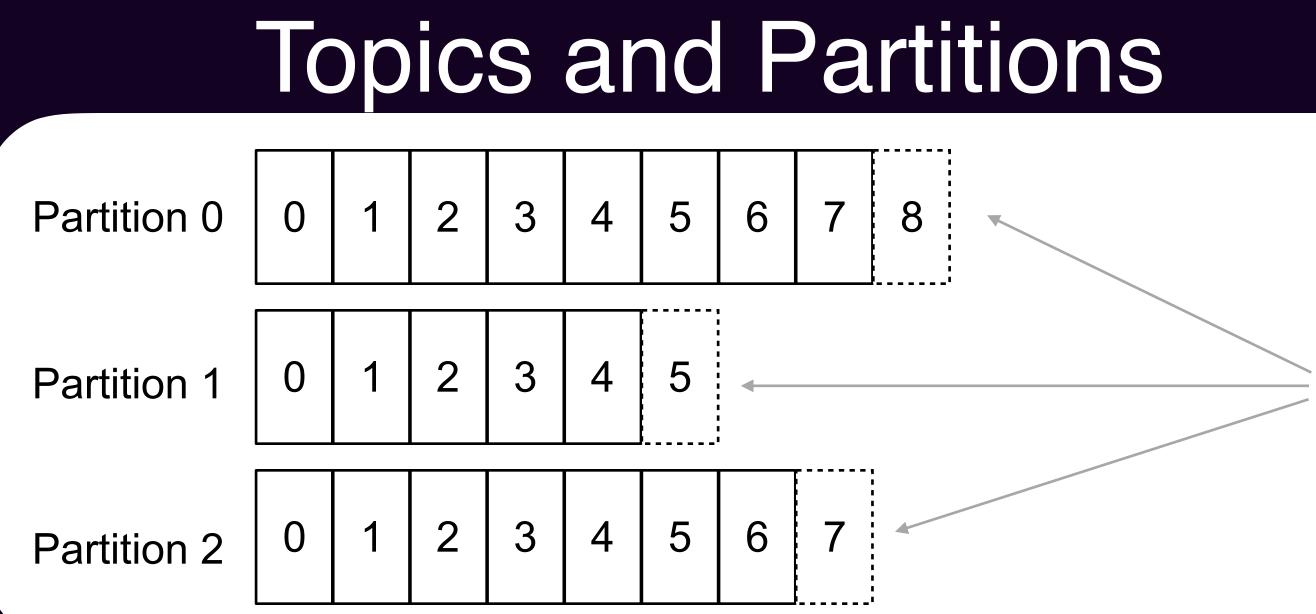
Processes that subscribed to topic and process messages are **consumers**

• A Kafka cluster is made of one or more

Key Features

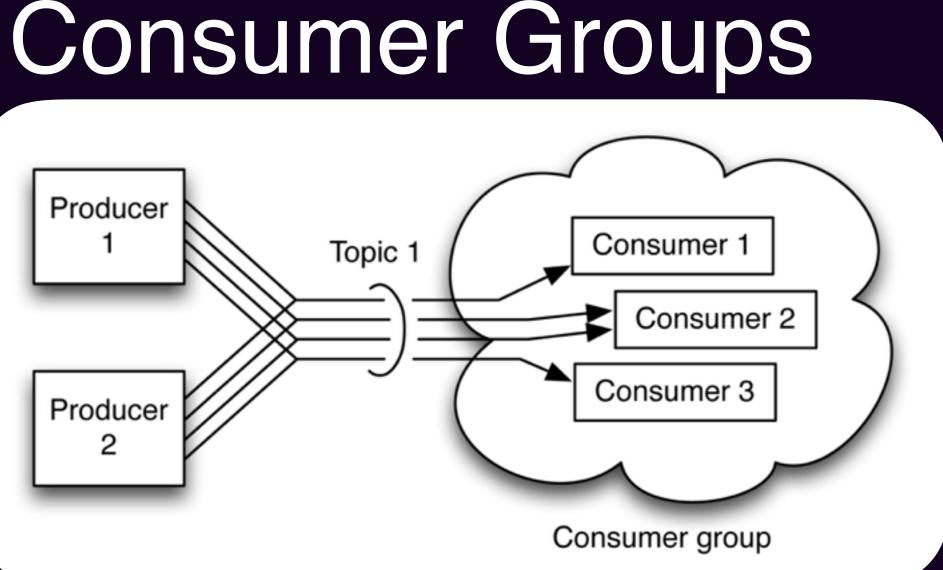


- Durable
- Scalable
 - Distributed
 - Stateless
- Fast
- At least once or at most once
 - You need to deal with it!



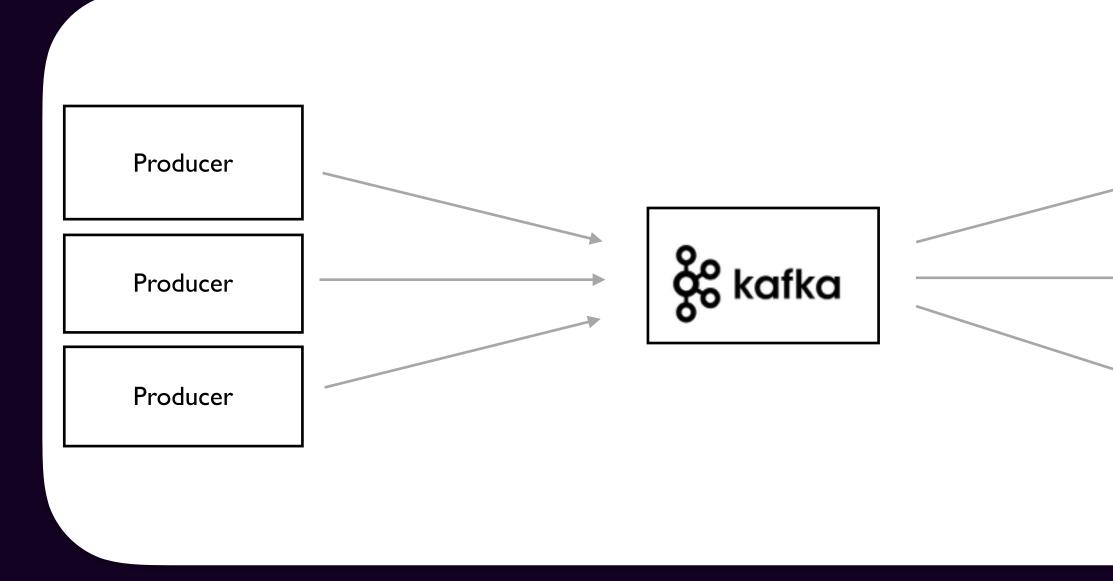
Split topics into partitions for scalability

Writes



- Single consumer abstraction for scalability
- Max 1 consumer per partition
- Any number of consumer groups

Big Picture

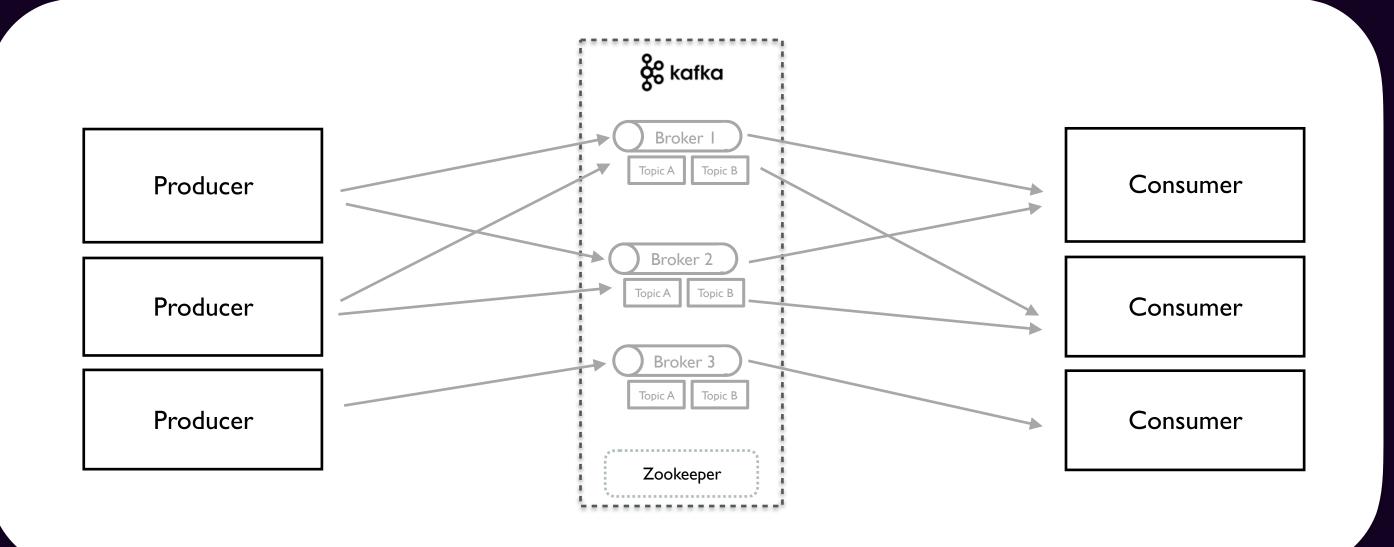


Consumer

Consumer

Consumer

More real life Kafka ...

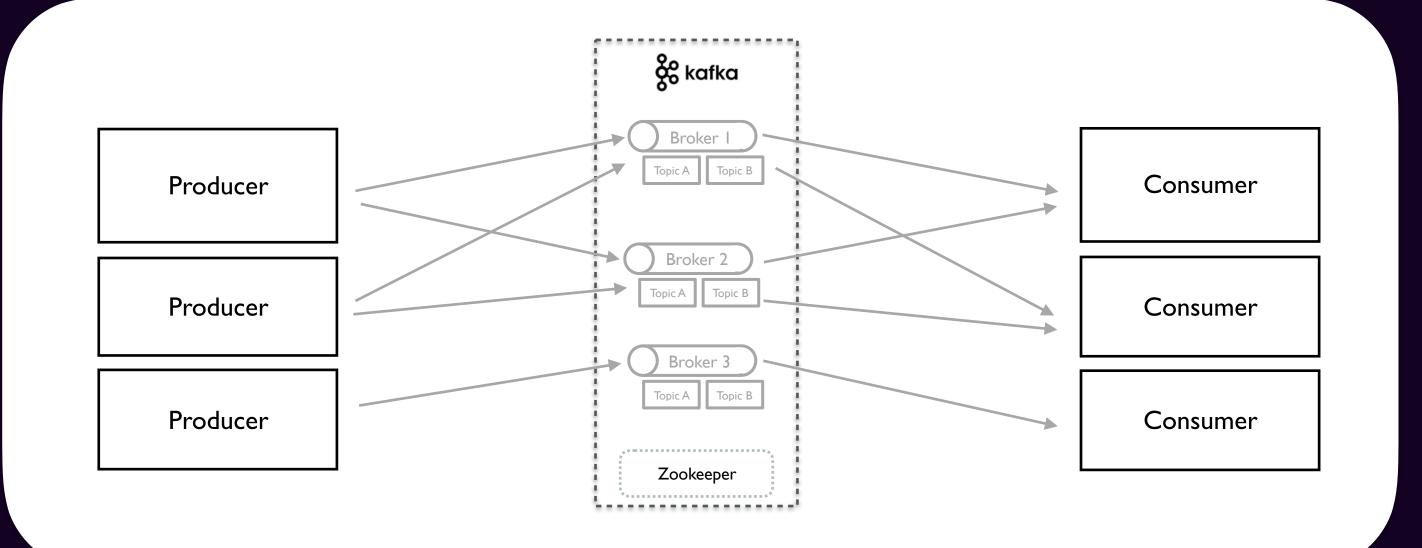




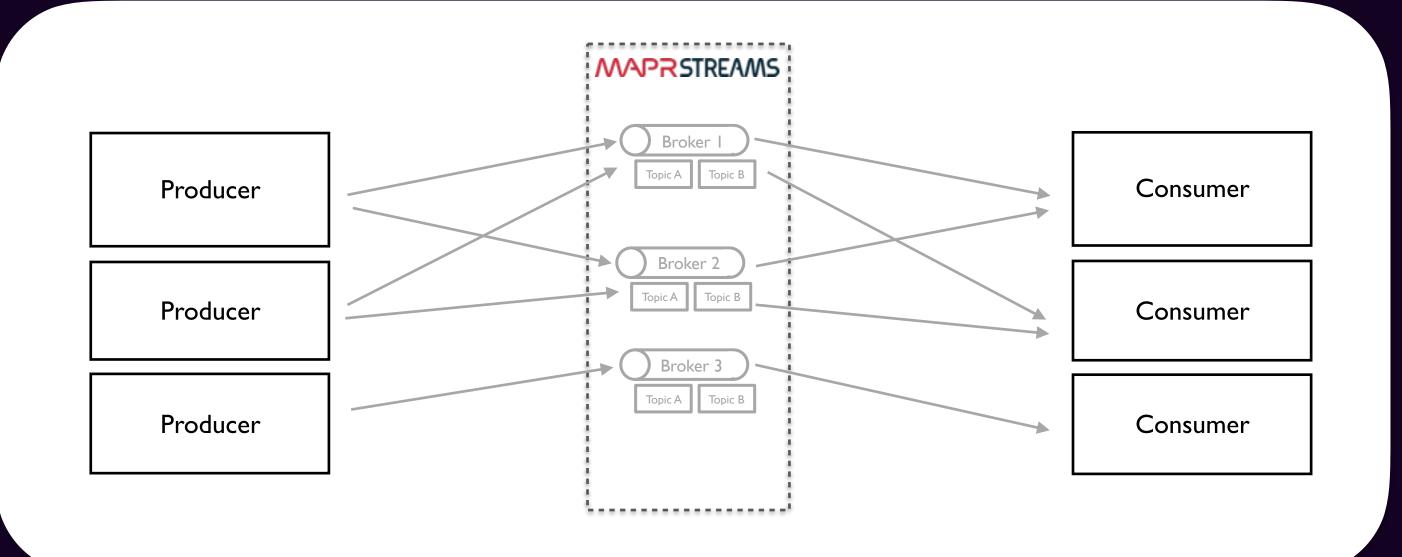
MapR Streams

- Distributed messaging system built to scale •
- Use Apache Kafka API 0.9.0
 - No code change
- Does not use the same "broker" architecture •
 - Log stored in MapR Storage (Scalable, Secured, Fast, Multi DC) •
 - No Zookeeper •

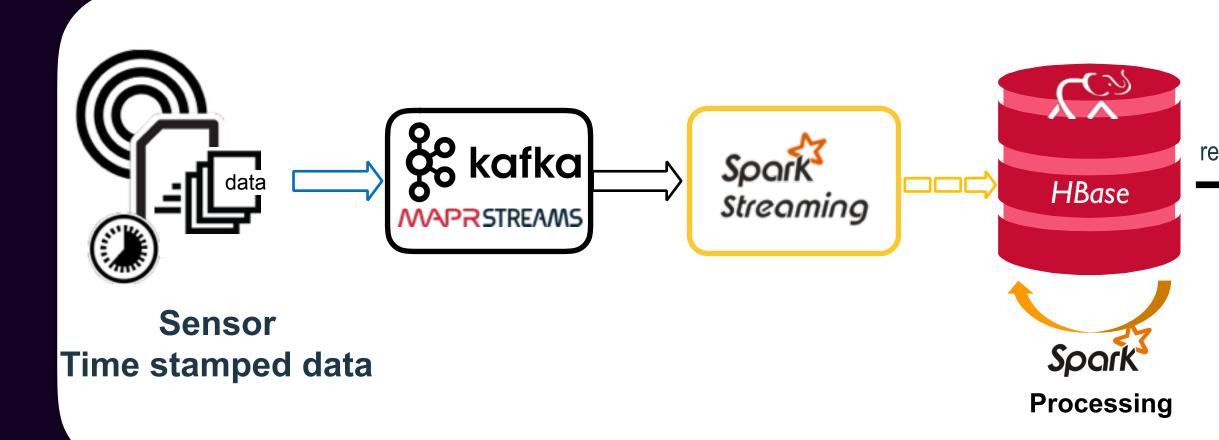
Kafka



MapR Streams



Time Series





Data for real-time monitoring

Lab "flow"

Convert Line of CSV data to Sensor Object

sensordata.csv COHUTTA, 3/10/14, 1:01, 10.27, 1.73, 881, 1.56, 85, 1.94 COHUTTA, 3/10/14, 1:02, 9.67, 1.731, 882, 0.52, 87, 1.79 COHUTTA, 3/10/14, 1:03, 10.47, 1.732, 882, 1.7, 92, 0.66 COHUTTA, 3/10/14, 1:05, 9.56, 1.734, 883, 1.35, 99, 0.68 COHUTTA, 3/10/14, 1:06, 9.74, 1.736, 884, 1.27, 92, 0.73 COHUTTA, 3/10/14, 1:08, 10.44, 1.737, 885, 1.34, 93, 1.54 COHUTTA, 3/10/14, 1:09, 9.83, 1.738, 885, 0.06, 76, 1.44 COHUTTA, 3/10/14, 1:11, 10.49, 1.739, 886, 1.51, 81, 1.83 COHUTTA, 3/10/14, 1:12, 9.79, 1.739, 886, 1.74, 82, 1.91 COHUTTA, 3/10/14, 1:13, 10.02, 1.739, 886, 1.24, 86, 1.79

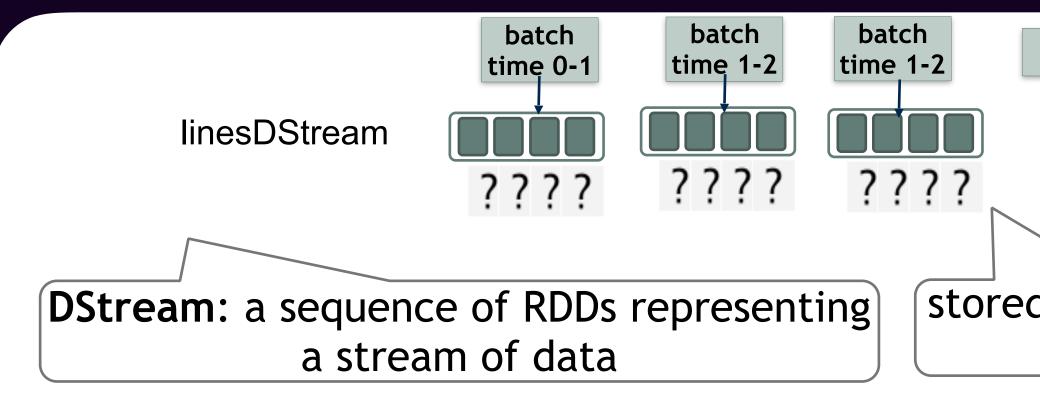
case class Sensor(resid: String, date: String, time: String, hz: Double, disp: Double, flo: Double, sedPPM: Double, psi: Double, chlPPM: Double)

```
def parseSensor(str: String): Sensor = {
val p = str.split(",")
Sensor (p(0), p(1), p(2), p(3).toDouble, p(4).toDouble, p(5).toDouble,
    p(6).toDouble, p(7).toDouble, p(8).toDouble)
```



Create a DStream

val ssc = new StreamingContext(sparkConf, Seconds(2)) val messages = KafkaUtils.createDirectStream[String, String]



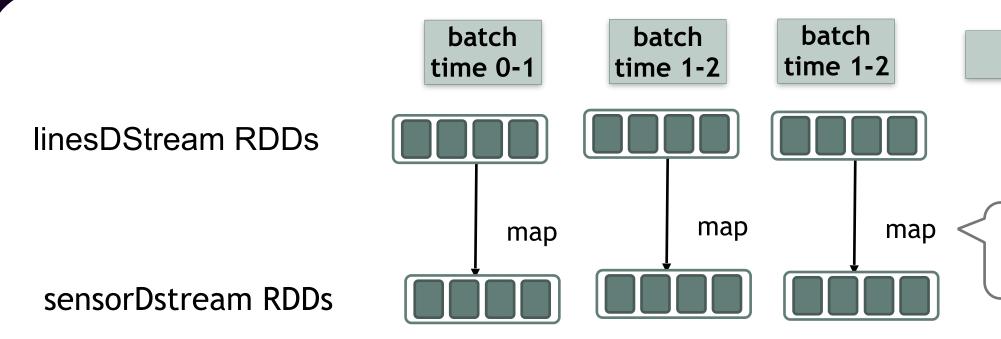
(ssc, kafkaParams, topicsSet)

stored in memory as an **RDD**

Process DStream

val messages = KafkaUtils.createDirectStream[String, String]

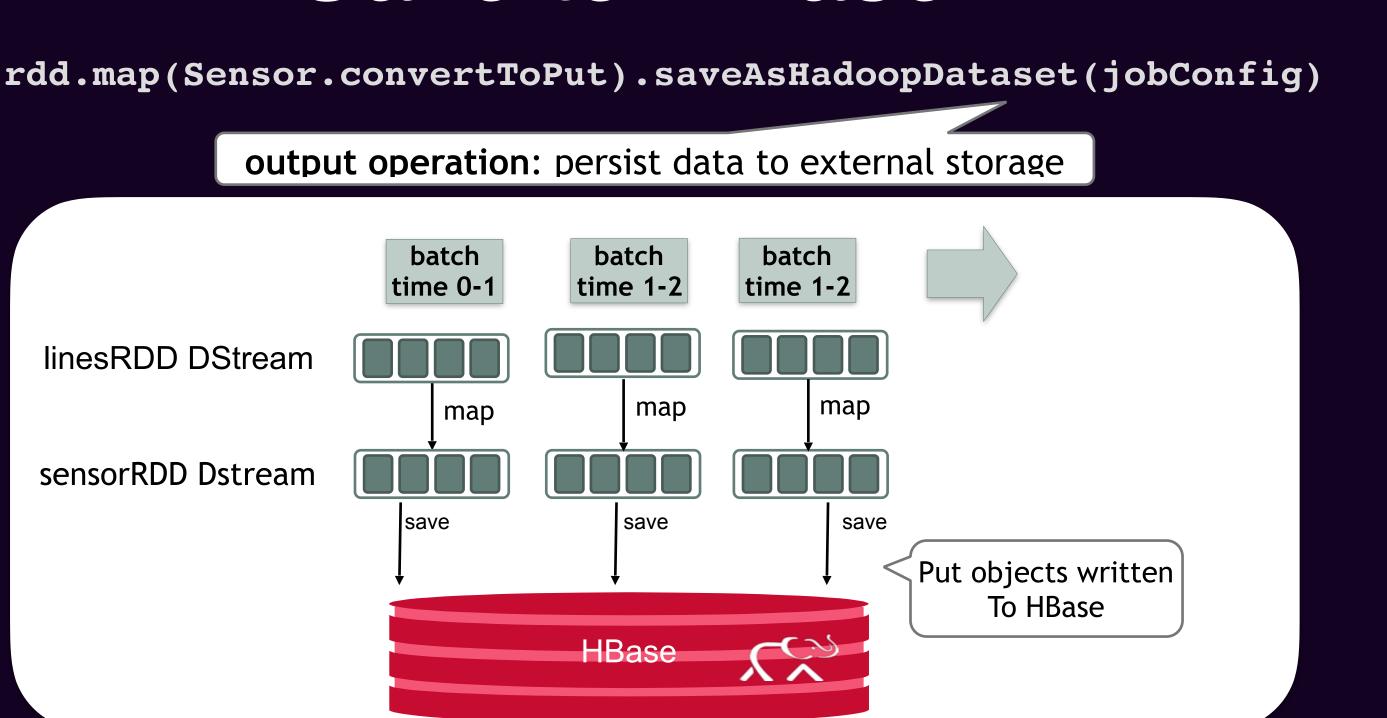
val sensorDStream = messages.map(_._2).map(Sensor.parseSensor)



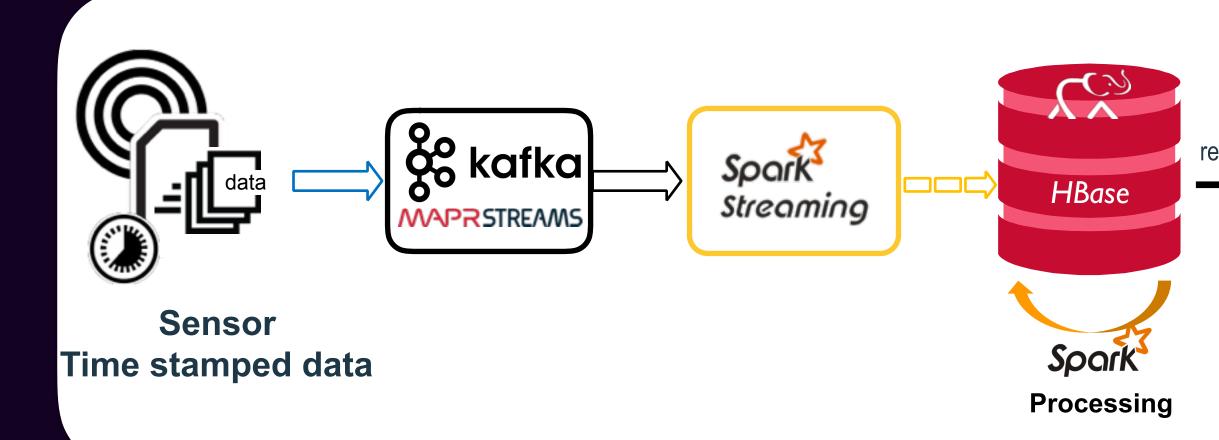
(ssc, kafkaParams, topicsSet)

new RDDs created for every batch

Save to HBase



Time Series





Data for real-time monitoring

Go!