Module 11

Spark SQL and Spark Streaming

Thanachart Numnonda, Executive Director, IMC Institute

Mr.Aekanun Thongtae, Big Data Consultant, IMC Institute

Thanisa Numnonda, Faculty of Information Technology,

King Mongkut’s Institute of Technology Ladkrabang

Spark SQL

Introduction to SparkSQL

- Spark SQL is a Spark module for structured data processing

- Spark SQL supports the execution of SQL queries written using either a basic SQL syntax or HiveQL
  - Catalyst optimizer: built inside Spark SQL:
    - Built-in mechanism to fetch data from some external data sources. For example, JSON, JDBC, Parquet, MySQL, Hive, PostgreSQL, HDFS, S3, and so on
    - Designed to optimize all phases of query execution: analysis, logical optimization, physical planning, and code generation to compile parts of queries to Java bytecode.

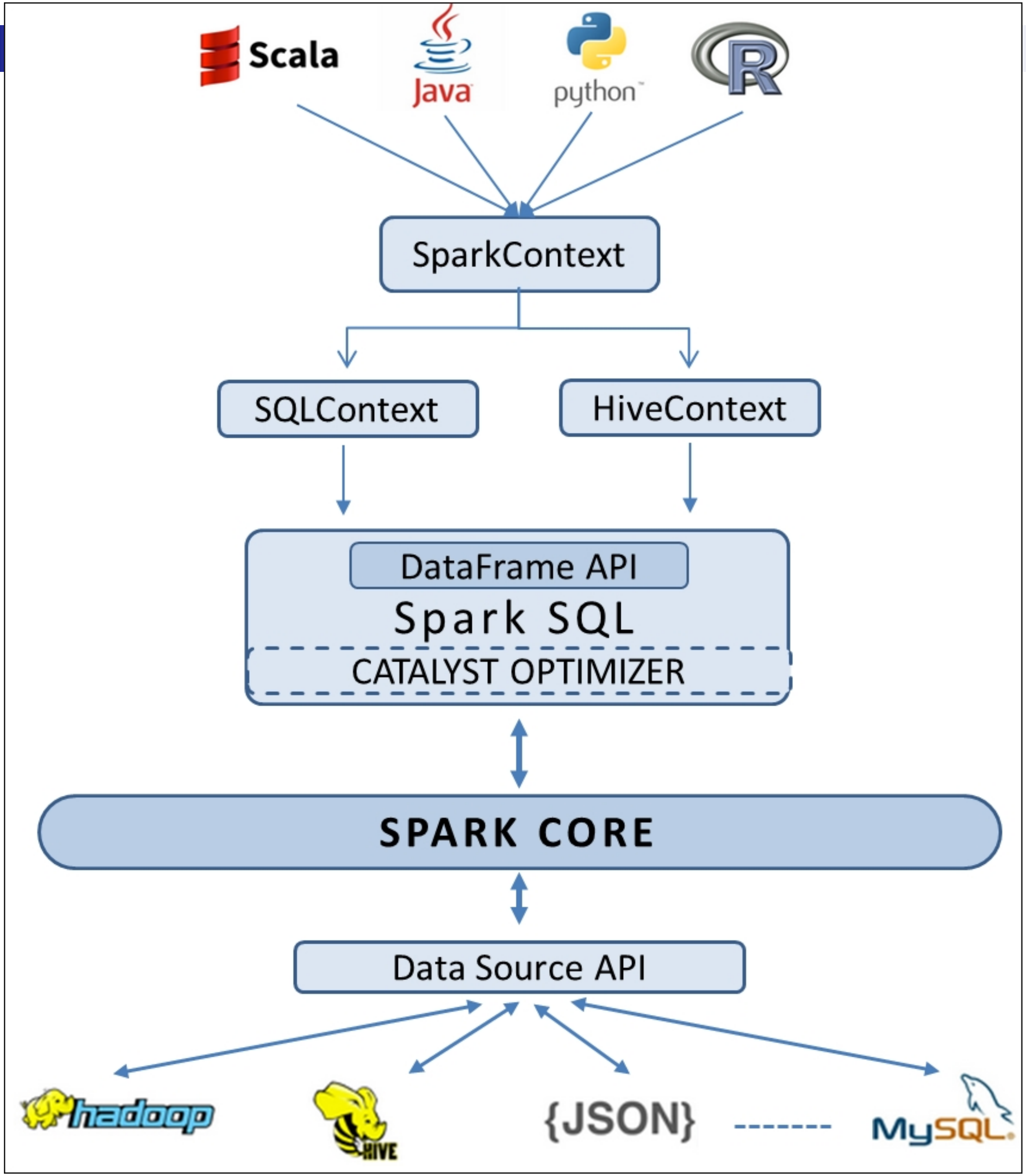
- Three ways to <u>interact with Spark SQL</u>: SQL, DataFrame API and Dataset API.

DataFrame

- DataFrame is an immutable distributed collection of data. Unlike an RDD, data is organized into named columns, like a table in a relational database.

- DataFrame API was built as one more level of abstraction on top of Spark SQL.
- Allow you use a two-dimensional data structure that usually has labelled rows and columns is called a DataFrame (R, Python-Pandas)

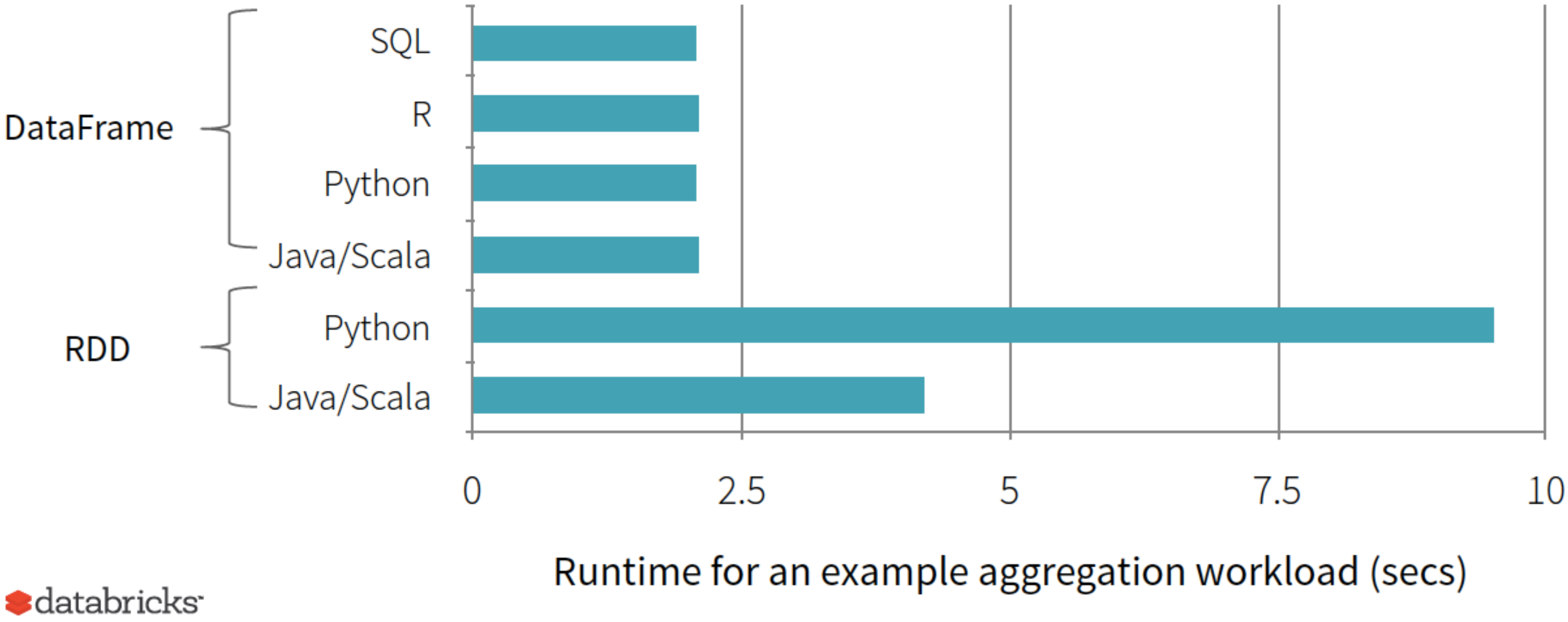
- The DataFrame API builds on the Spark SQL query optimizer to automatically execute code efficiently on a cluster of machines.


Scala
Java
python
R
SparkContext
SQLContext
HiveContext
DataFrame API
Spark SQL
CATALYST OPTIMIZER
SPARK CORE
Data Source API
hadoop
HIVE
{JSON}
MySQL

RDDs vs. DataFrames: Similarities

- Both are fault-tolerant, partitioned data abstractions in Spark
- Both can handle disparate data sources
- Both are lazily evaluated (execution happens when an output operation is performed on them), thereby having the ability to take the most optimized execution plan
- Both APIs are available in all four languages: Scala, Python, Java, and R

Benefit of Logical Plan: Performance Parity Across Languages



Source: Jump start into Apache Spark and Databricks

RDDs vs. DataFrames: Differences

- DataFrames are a higher-level abstraction than RDDs.

- The definition of RDD implies defining a Directed Acyclic Graph (DAG) whereas defining a DataFrame leads to the creation of an Abstract Syntax Tree (AST). An AST will be utilized and optimized by the Spark SQL catalyst engine.

- RDD is a general data structure abstraction whereas a DataFrame is a specialized data structure to deal with two-dimensional, table-like data.

When to use RDDs?

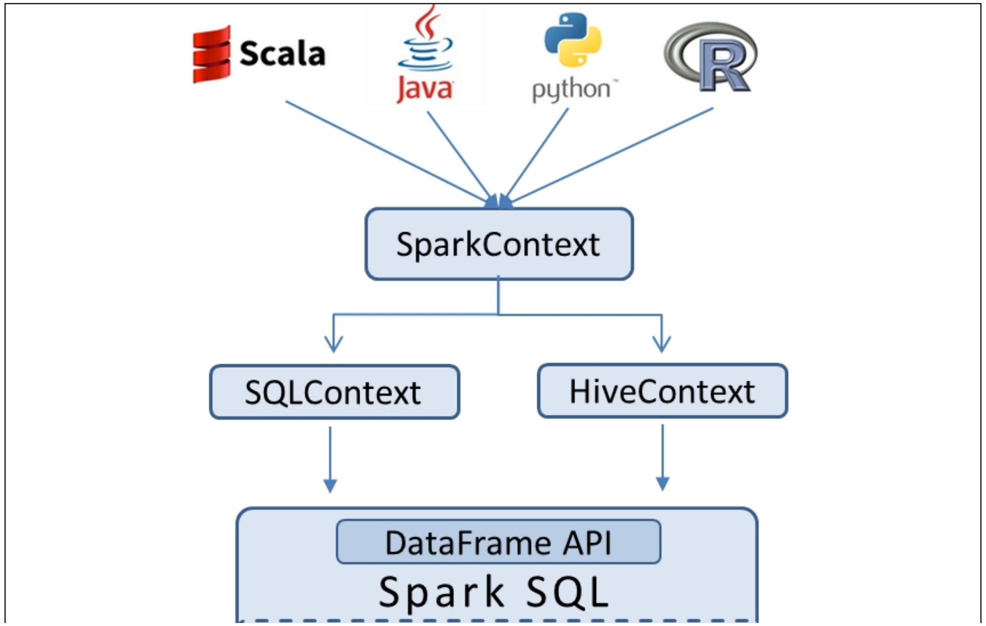
- Low-level transformation and actions and control on your dataset;
- Data is unstructured, such as media streams or streams of text;
- Manipulate your data with functional programming constructs than domain specific expressions;
- Don’t care about imposing a schema, such as columnar format, while processing or accessing data attributes by name or column; and
- Forgo some optimization and performance benefits available with DataFrames and Datasets for structured and semi-structured data.

Get Access to the SparkSQL

- Use DataFrame API to entry point:
  - SQLContext or
  - HiveContext

- SQLContext: RDDs, JSON, JDBC

- HiveContext: Hive Tables



Creating DataFrames: RDDs

Python:

```
   //Create a list of colours
>>> colors = ['white','green','yellow','red','brown','pink']
//Distribute a local collection to form an RDD
//Apply map function on that RDD to get another RDD containing colour, length tuples
>>> color_df = sc.parallelize(colors)
        .map(lambda x:(x,len(x))).toDF(["color","length"])

>>> color_df
DataFrame[color: string, length: bigint]

>>> color_df.dtypes        //Note the implicit type inference
[('color', 'string'), ('length', 'bigint')]

>>> color_df.show()  //Final output as expected. Order need not be the same as shown
+------+------+
| color|length|
+------+------+
| white|     5|
| green|     5|
|yellow|     6|
|   red|     3|
| brown|     5|
|  pink|     4|
+------+------+
```

Creating DataFrames: JSON

Python:

```
//Pass the source json data file path
>>> df = sqlContext.read.json("./authors.json")
>>> df.show() //json parsed; Column names and data    types inferred implicitly
+----------+---------+
|first_name|last_name|
+----------+---------+
|      Mark|    Twain|
|   Charles|  Dickens|
|    Thomas|    Hardy|
+----------+---------+
```

HDFS (Hadoop Ecosystem)

Creating DataFrames: JDBC

Python:

```
//Launch shell with driver-class-path as a command line argument
pyspark --driver-class-path /usr/share/   java/mysql-connector-java.jar
   //Pass the connection parameters
>>> peopleDF = sqlContext.read.format('jdbc').options(
                        url = 'jdbc:mysql://localhost',
                        dbtable = 'test.people',
                        user = 'root',
                        password = 'mysql').load()
   //Retrieve table data as a DataFrame
>>> peopleDF.show()
+----------+---------+------+----------+----------+---------+
|first_name|last_name|gender|       dob|occupation|person_id|
+----------+---------+------+----------+----------+---------+
|    Thomas|    Hardy|     M|1840-06-02|    Writer|      101|
|     Emily|   Bronte|     F|1818-07-30|    Writer|      102|
| Charlotte|   Bronte|     F|1816-04-21|    Writer|      103|
|   Charles|  Dickens|     M|1812-02-07|    Writer|      104|
+----------+---------+------+----------+----------+---------+
```

SparkSQL can leverage the Hive metastore

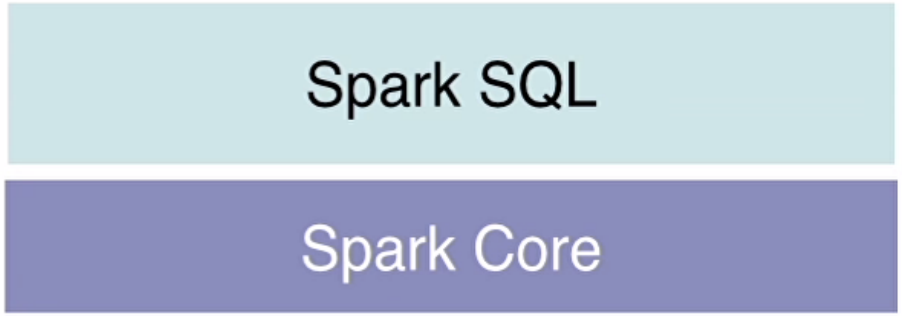
- Hive Metastore can also be leveraged by a wide array of applications
  - Spark
  - Hive
  - Impala
- Available from HiveContext

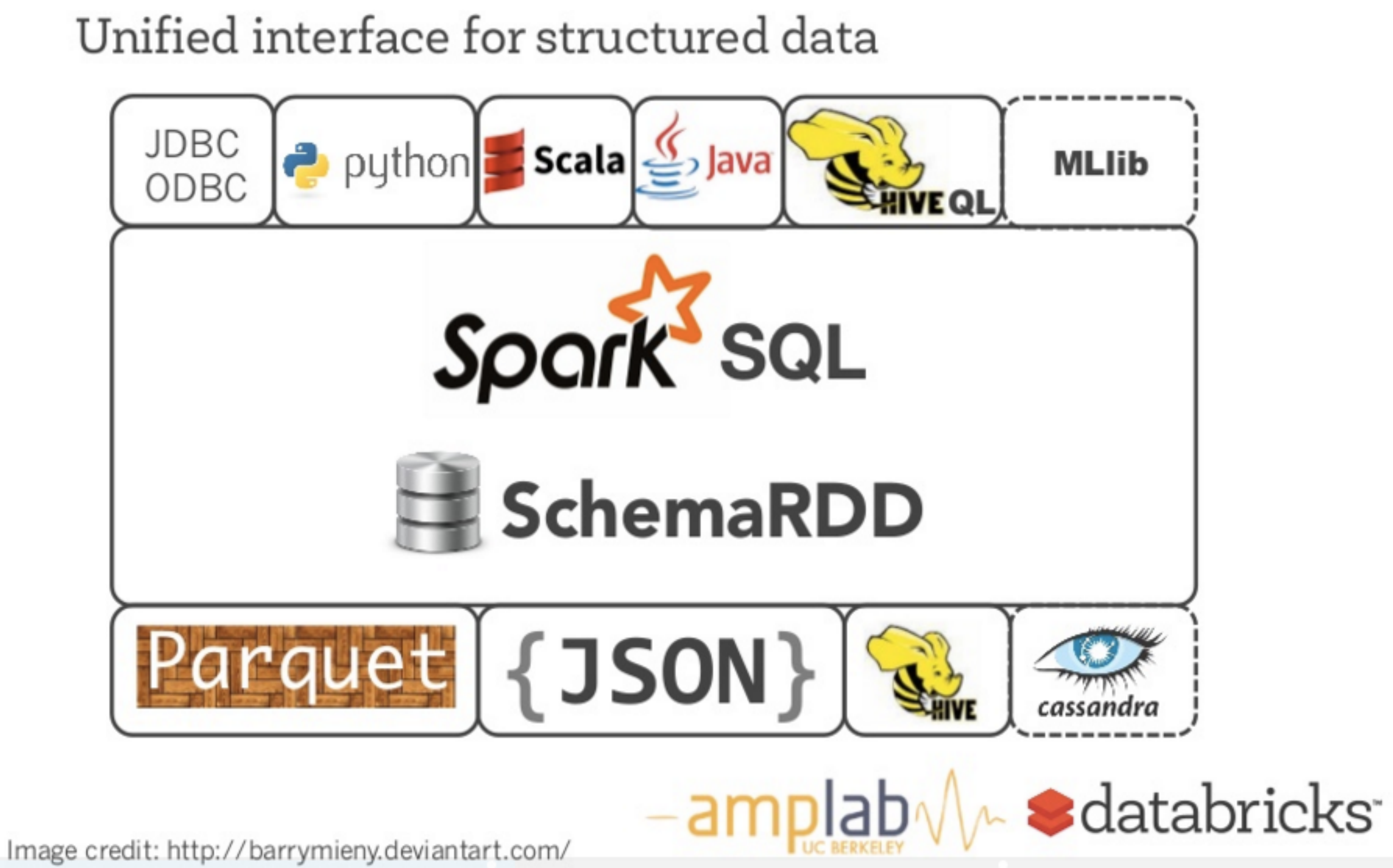
SparkSQL: HiveContext

```
context = ps.HiveContext(sc)

# query with SQL
results = context.sql(
  "SELECT * FROM people”)

# apply Python transformation
names = results.map(lambda p: p.name)
```




Unified interface for structured data
JDBC
ODBC
python
Scala
Java
HIVE QL
MLlib
Spark SQL
SchemaRDD
Parquet
{JSON}
HIVE
cassandra
amplab
UC BERKELEY
databricks
Image credit: http://barrymieny.deviantart.com/

Hands-on: Spark SQL

DataFrames Operations (LAB 1)

DataFrames Operations

Create a local collection of colors first

```
>>> colors = ['white','green','yellow','red','brown','pink']
```

Distribute the local collection to form an RDD
Apply map function on that RDD to get another RDD containing colour, length tuples and convert that RDD to a DataFrame

```
>>> color_df = sc.parallelize(colors)
        .map(lambda x:(x,len(x))).toDF(['color','length'])
```

Check the object type

```
>>> color_df
```

DataFrames Operations

Check the schema.

```
>>> color_df.dtypes
```

Check row count

```
>>> color_df.count()
```

Look at the table contents. You can limit displayed rows by passing parameter to show .

```
>>> color_df.show(2)
```

DataFrames Operations

List out column names.

```
>>> color_df.columns
```

Drop a column. The source DataFrame color_df remains the same.
Spark returns a new DataFrame which is being passed to show.

```
>>> color_df.drop('length').show()
```

Convert to JSON format.

```
>>> color_df.toJSON().first()
```

DataFrames Operations

Filter operation is similar to WHERE clause in SQL.
You specify conditions to select only desired columns and rows.
Output of filter operation is another DataFrame object that is usually passed on to some more operations.
The following example selects the colors having a length of four or five only and label the column as "mid_length" filter.

```
>>> color_df.filter(color_df.length.between(4,5))
      .select(color_df.color.alias("mid_length")).show()
```

DataFrames Operations

This example uses multiple

```
>>> color_df.filter(color_df.length > 4) .filter(color_df[0]!="white").show()
```

Sort the data on one or more columns sort.
A simple single column sorting in default (ascending) order.

```
>>> color_df.drop('length').show()
```

DataFrames Operations

First filter colors of length more than 4 and then sort on multiple columns.
The Filtered rows are sorted first on the column length in default ascending order.
Rows with same length are sorted

```
>>> color_df.filter(color_df['length']>=4).sort("length",
'color',ascending=False).show()
```

DataFrames Operations

You can use orderBy instead, which

```
>>> color_df.orderBy('length','color').take(4)
```

Alternative syntax, for single or multiple columns.

```
>>> color_df.sort(color_df.length.desc(),   color_df.color.asc()).show()
```

DataFrames Operations

GroupBy

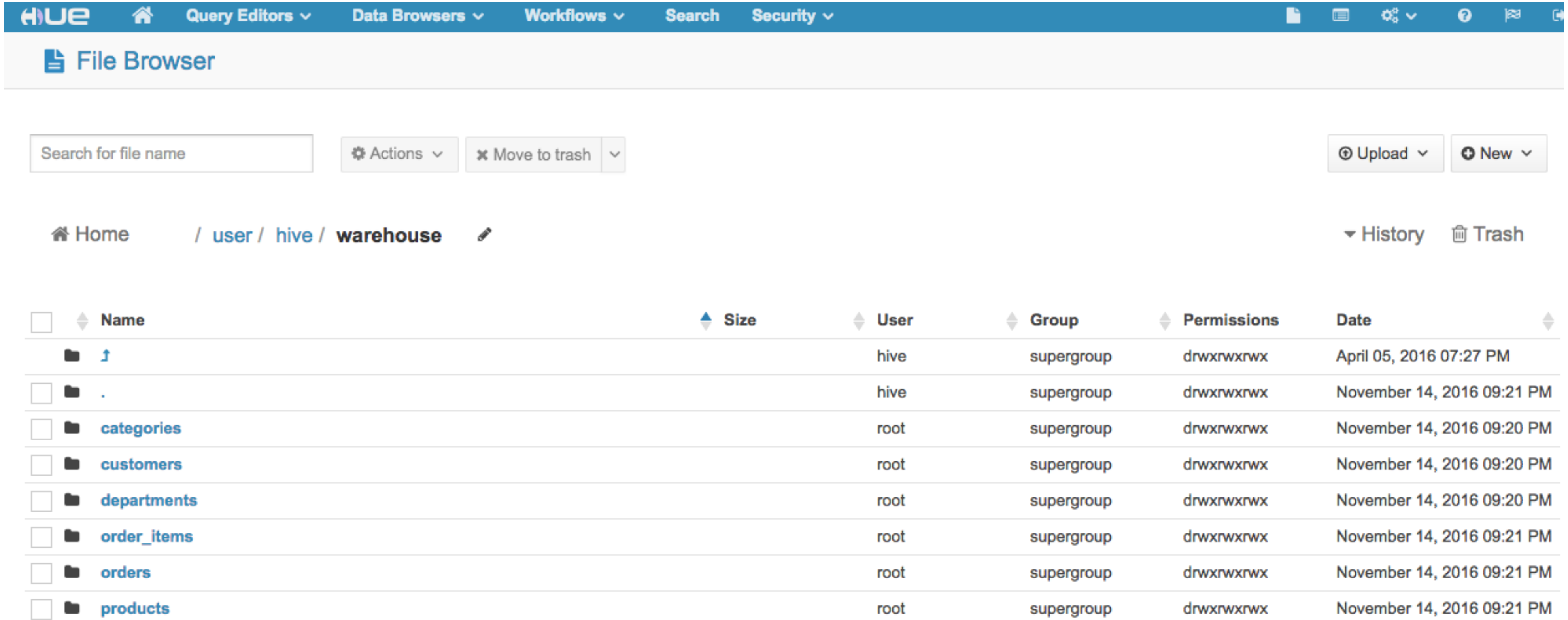
```
>>> color_df.groupBy('length').count().show()
```

Adapted from Srinivas Duvvuri and Bikramaditya Singhal,"Spark for Data Science," Packt Publishing, 2016

Create DataFrames from Hive Tables (LAB 2)

Importing all tables to Hive with Compression

```
$sqoop import  --connect
"jdbc:mysql://quickstart.cloudera:3306/retail_db"  --username
root --password cloudera --table orders --hive-import --hive-
overwrite  --create-hive-table -m 1
```



Link Hive Metastore with Spark-Shell

Copy the configuration file

```
$cp  /usr/lib/hive/conf/hive-site.xml   /usr/lib/spark/conf/
```

Running Spark

```
$pyspark
```

Exercise : HiveContext

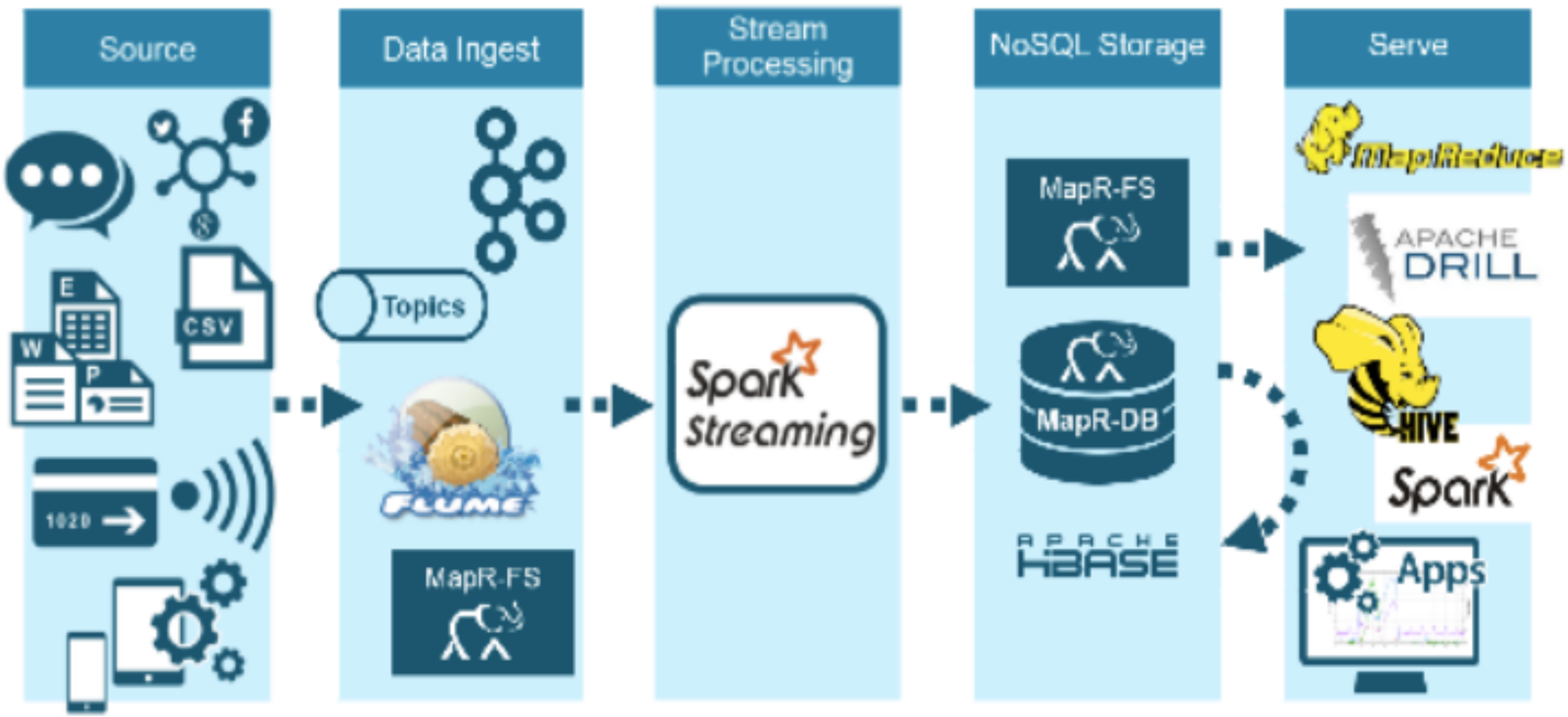
```
>>> sqlContext = HiveContext(sc)
>>> result = sqlContext.sql("SELECT * FROM orders")
>>> result.show()
```

order_id	order_date	order_customer_id	order_status
1	2013-07-25 00:00:...	11599	CLOSED
2	2013-07-25 00:00:...	256	PENDING_PAYMENT
3	2013-07-25 00:00:...	12111	COMPLETE
4	2013-07-25 00:00:...	8827	CLOSED
5	2013-07-25 00:00:...	11318	COMPLETE
6	2013-07-25 00:00:...	7130	COMPLETE
7	2013-07-25 00:00:...	4530	COMPLETE
8	2013-07-25 00:00:...	2911	PROCESSING
9	2013-07-25 00:00:...	5657	PENDING_PAYMENT
10	2013-07-25 00:00:...	5648	PENDING_PAYMENT
11	2013-07-25 00:00:...	918	PAYMENT_REVIEW
12	2013-07-25 00:00:...	1837	CLOSED
13	2013-07-25 00:00:...	9149	PENDING_PAYMENT
14	2013-07-25 00:00:...	9842	PROCESSING
15	2013-07-25 00:00:...	2568	COMPLETE
16	2013-07-25 00:00:...	7276	PENDING_PAYMENT
17	2013-07-25 00:00:...	2667	COMPLETE
18	2013-07-25 00:00:...	1205	CLOSED
19	2013-07-25 00:00:...	9488	PENDING_PAYMENT
20	2013-07-25 00:00:...	9198	PROCESSING

only showing top 20 rows

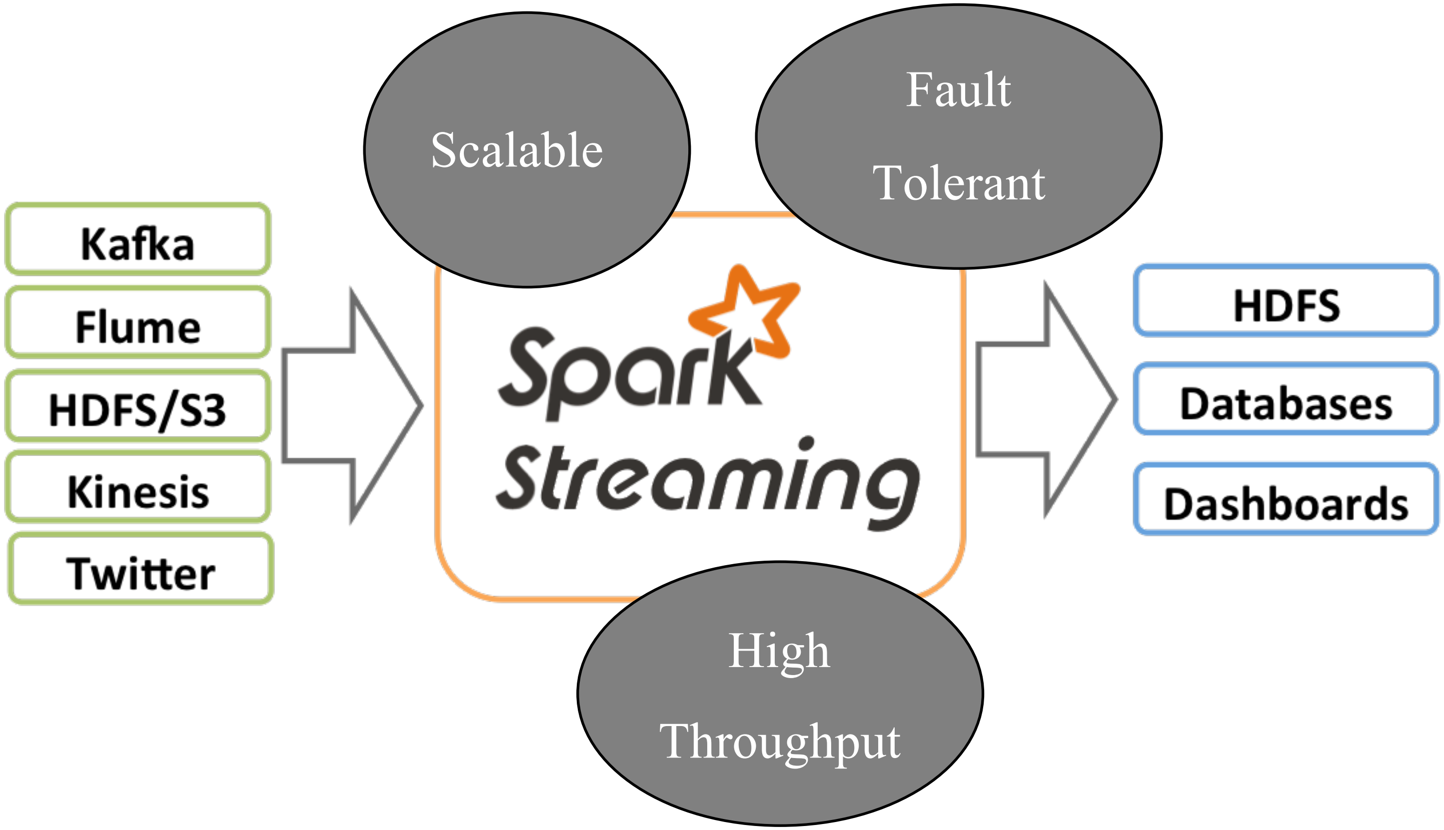
Spark Streaming

Stream Process Architecture



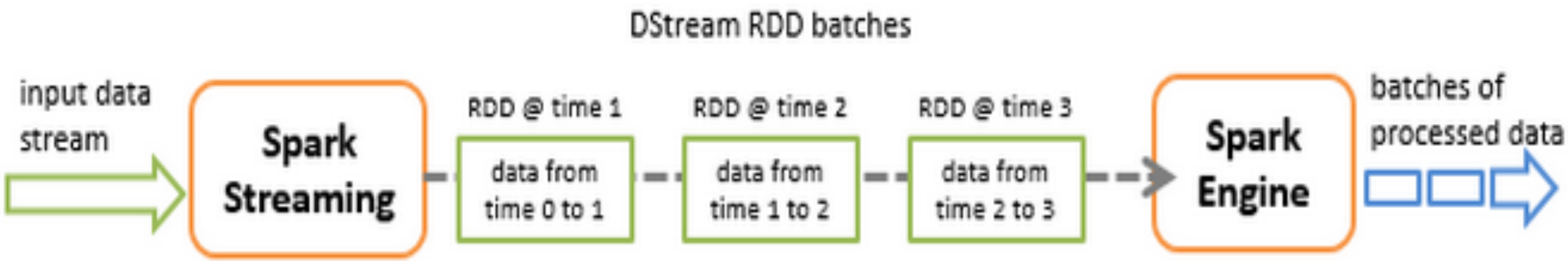
Source: MapR Academy

Overview: Various ingestion & Great features



Source: spark.apache.org

Overview: DStreams



- DStreams can be created either from (1) input data streams or by (2) applying high-level operations on other DStreams.
- DStream is represented as a sequence of RDDs.

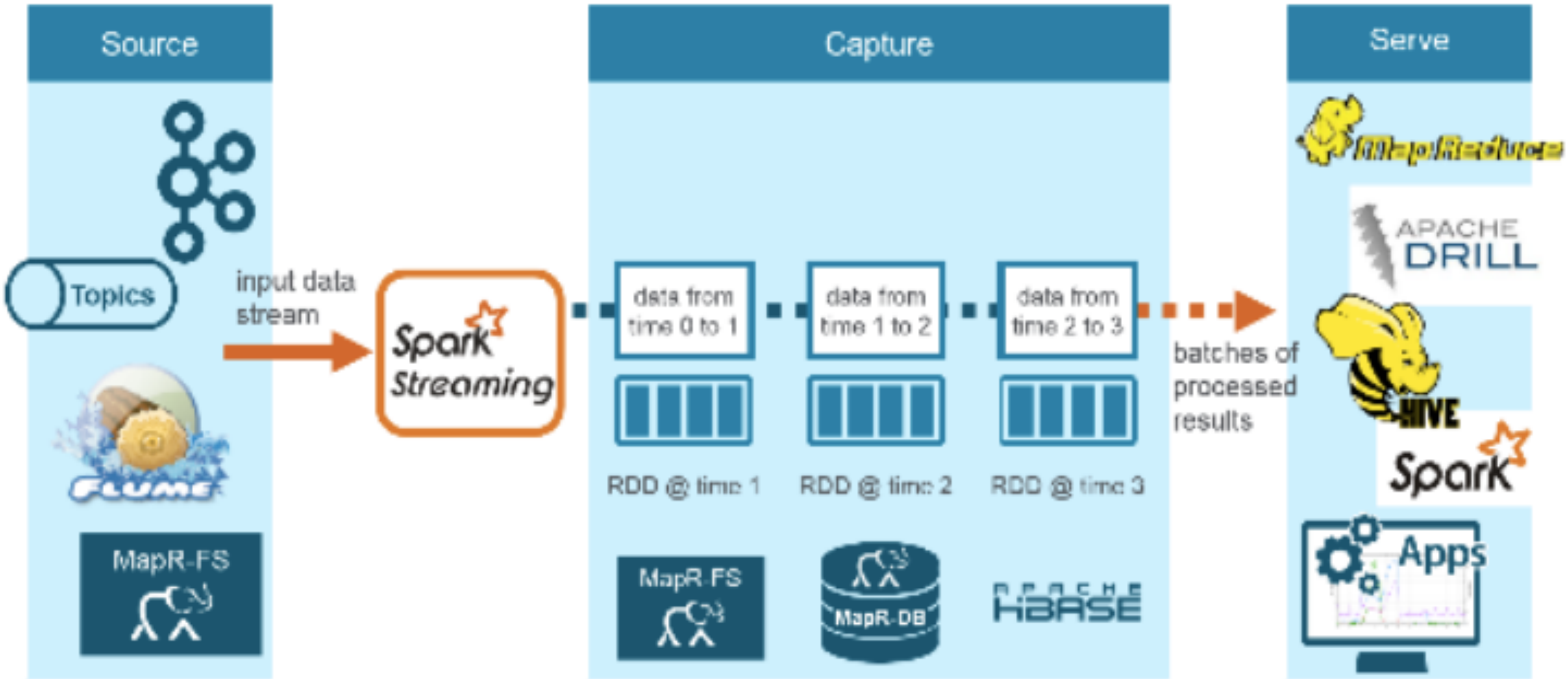
Source: spark.apache.org

Overview: Micro-batches

"Spark Streaming receives live input data streams and <u>divides the data into batches</u>, which are then processed by the <u>Spark engine</u> to generate the final stream of results in batches."

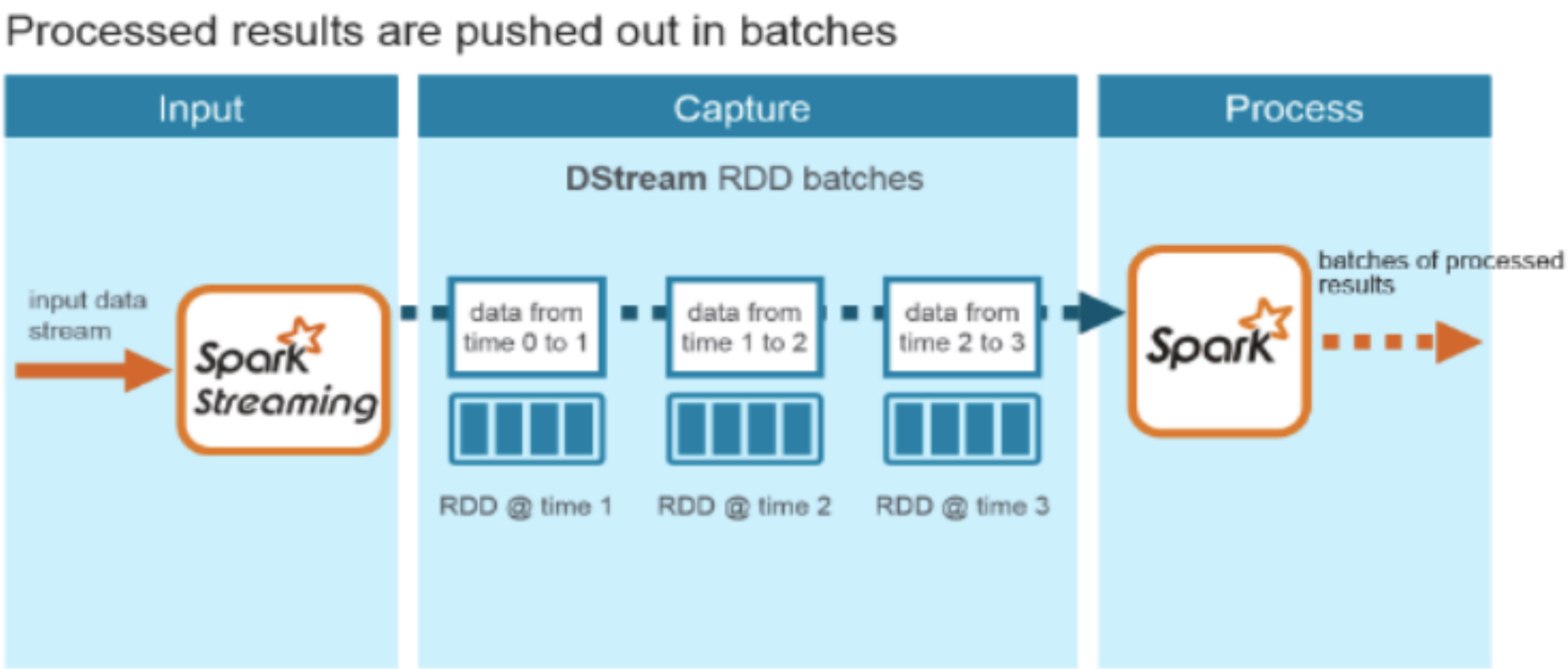
Source: spark.apache.org

Spark Streaming Architecture



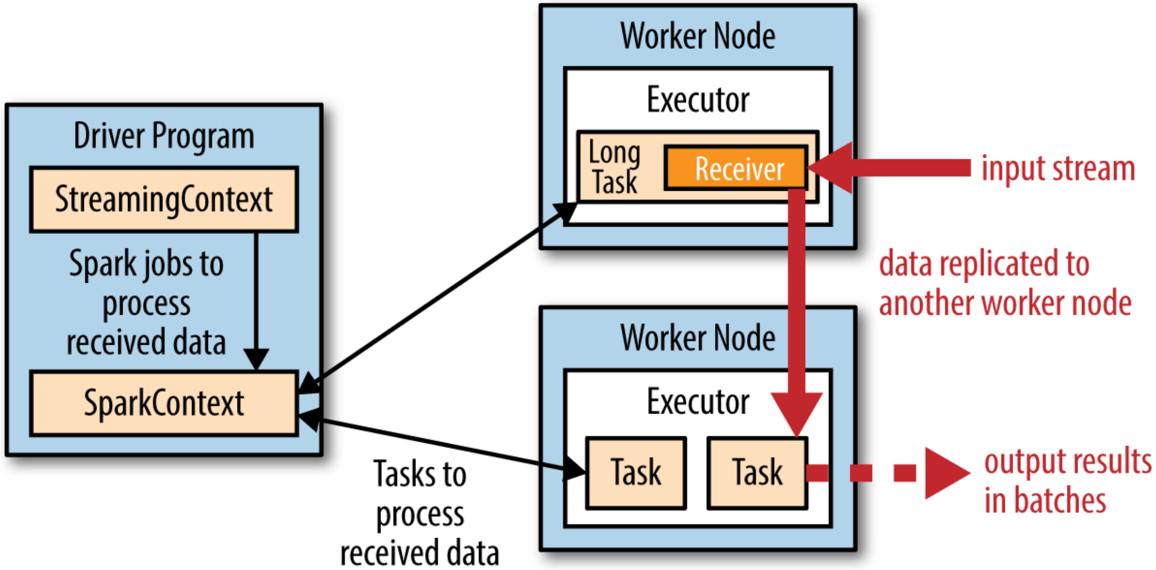
Source: MapR Academy

Processing Spark DStreams



Source: MapR Academy

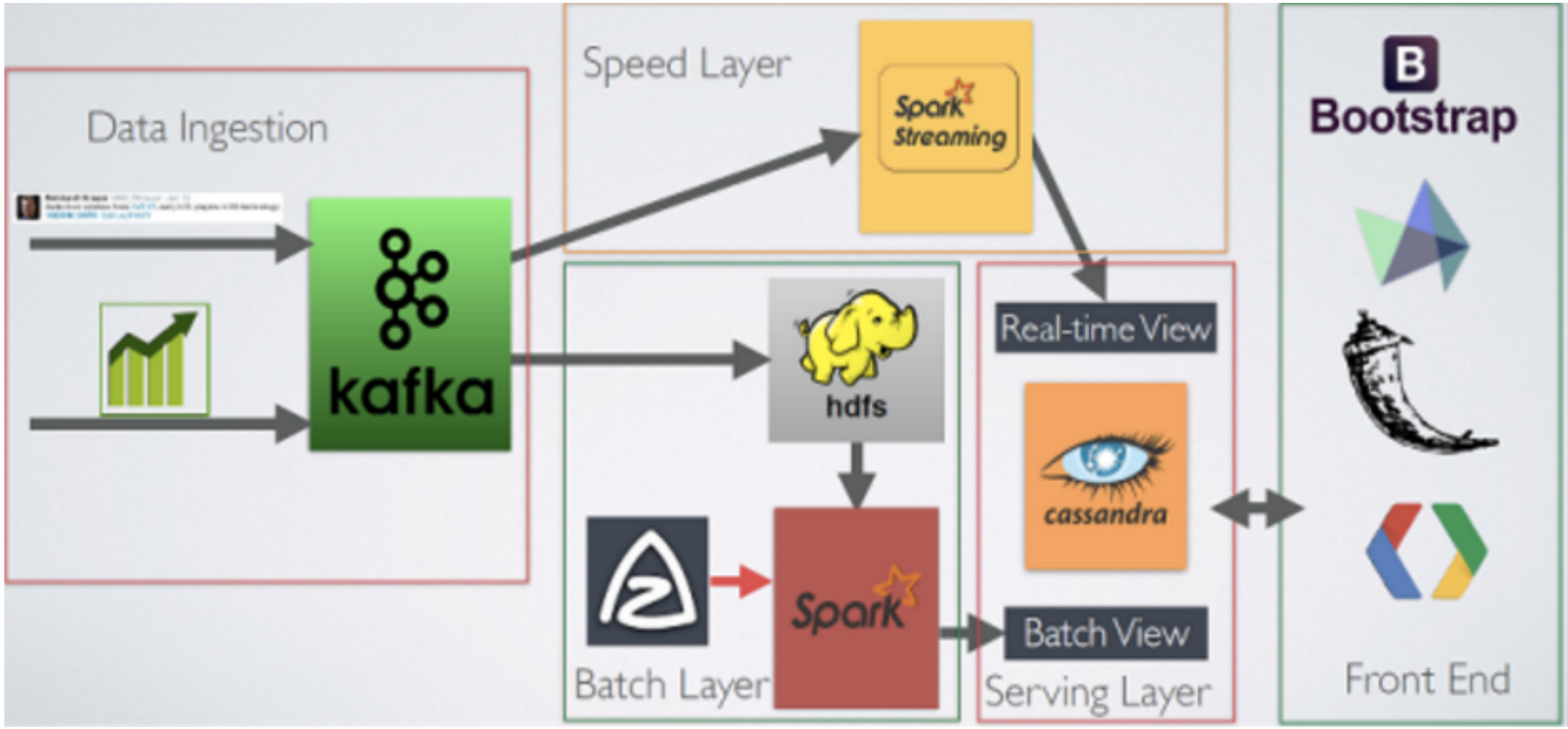
Initializing StreamingContext



After a context is defined, you have to do the following.

1. Define the input sources by creating input DStreams.
2. Define the streaming computations by applying transformation and output operations to DStreams.
3. Start receiving data and processing it using streamingContext.start().
4. The processing can be manually stopped using streamingContext.stop().

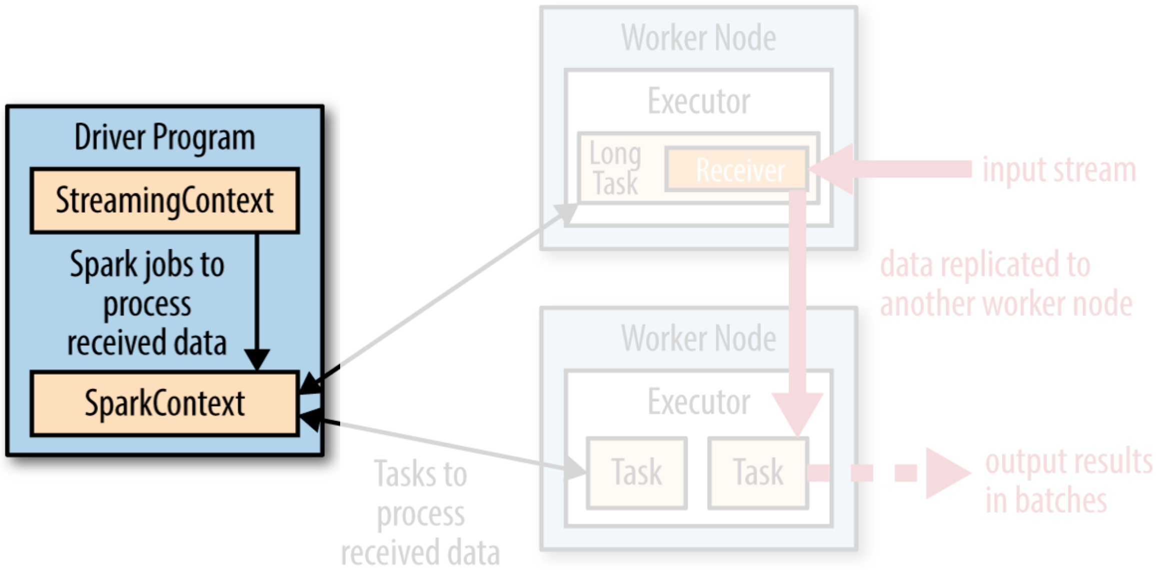
Use Case: Lambda Architecture



Source: http://www.insightdataengineering.com/

Hands-on: Spark Streaming

Initializing StreamingContext



 # Create a local StreamingContext and batch interval of 1 second

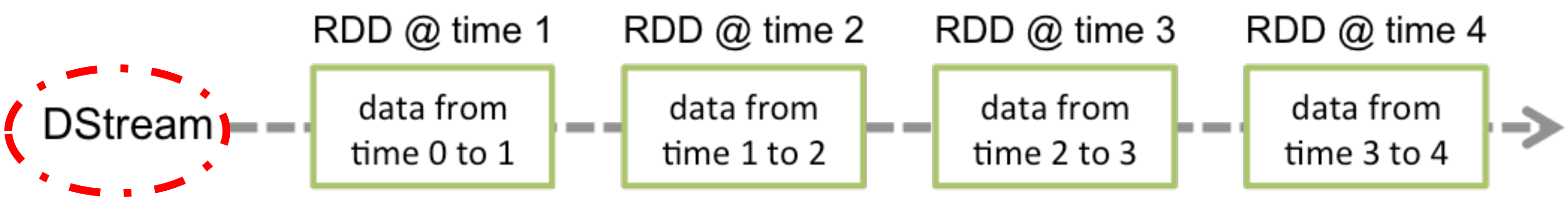
```
>>> from pyspark.streaming import StreamingContext

>>> ssc = StreamingContext(sc, 1)
```

Create a DStream & Define a source

 # Create a DStream that will connect to hostname:port, like localhost:9999

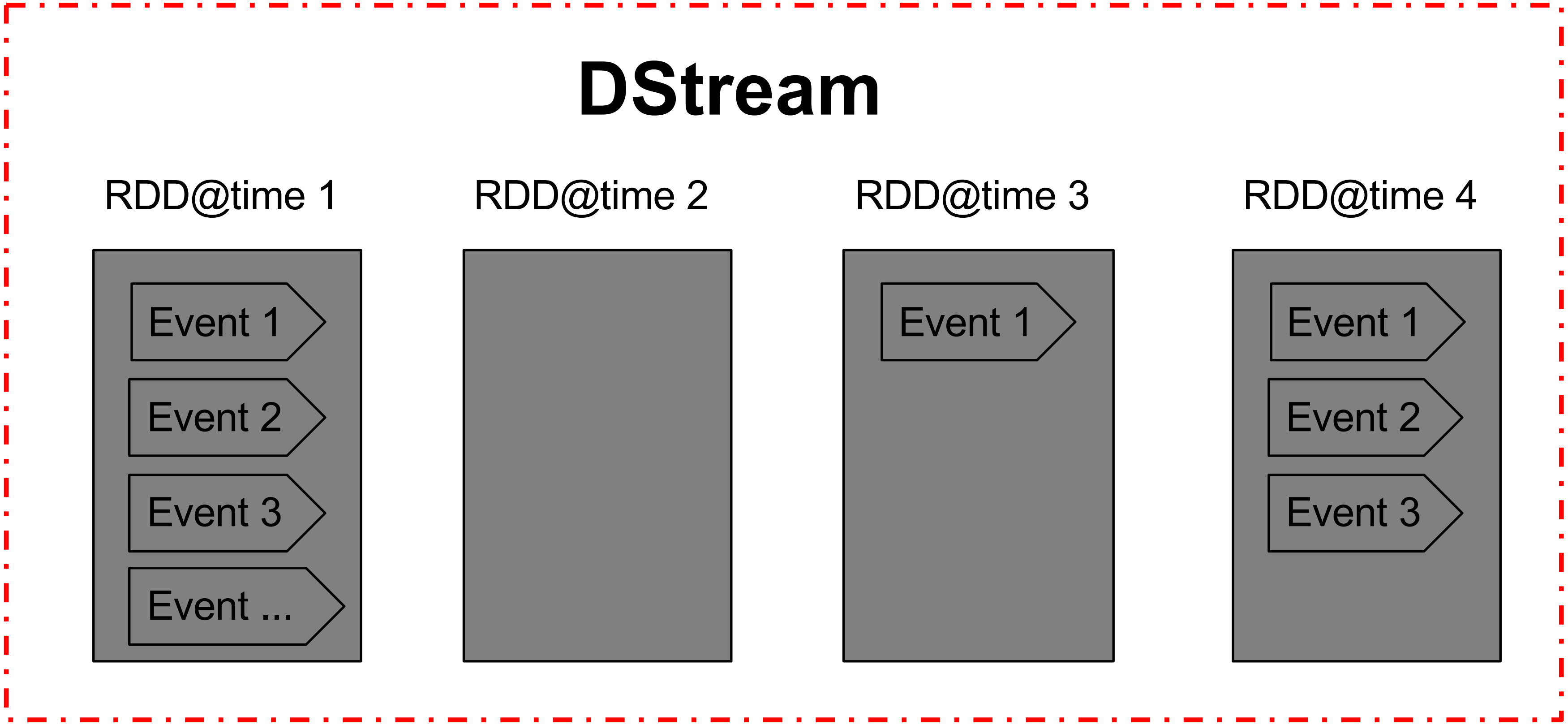
```
>>> lines = ssc.socketTextStream("localhost", 9999)
```

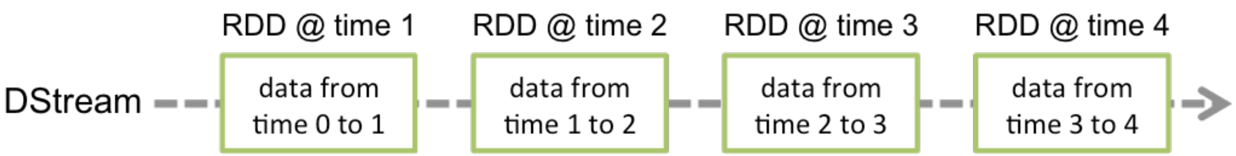


Source: spark.apache.org

Inside DStream

Each record (event) in this DStream is a line of text !



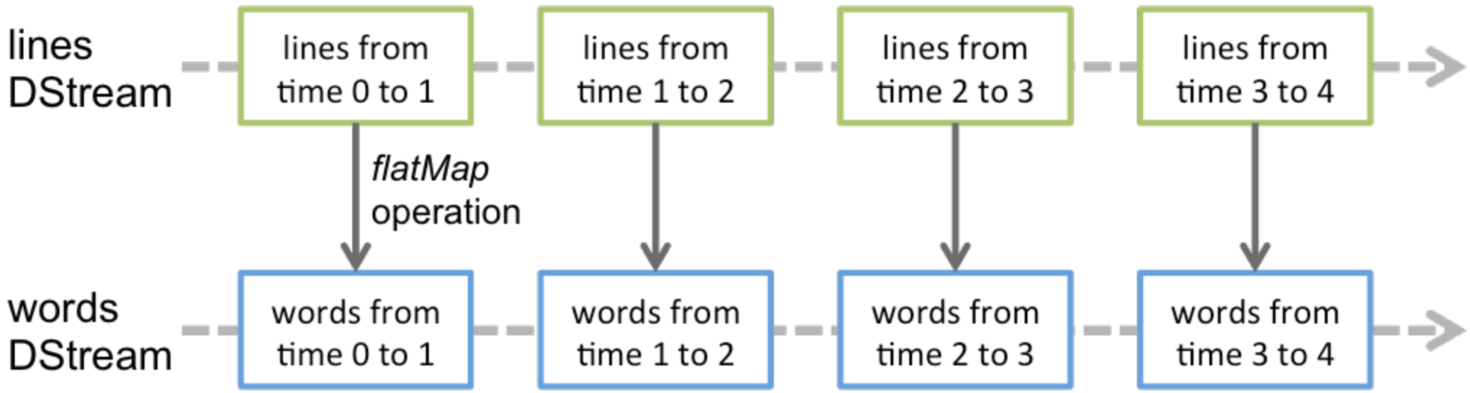


Get words from lines

 # Split each line into words

```
>>> words = lines.flatMap(lambda line: line.split(" "))
```

New DStream.



Source: spark.apache.org

Count and Print

```
# Count each word in each batch

>>> pairs = words.map(lambda word: (word, 1))

>>> wordCounts = pairs.reduceByKey(lambda x, y: x + y)


# Print the first ten elements of each RDD generated in this
DStream to the console

>>> wordCounts.pprint()
```

Source: spark.apache.org

Let's Start !

 # Start the computation

```
>>> ssc.start()
```

 # if you want to stop the computation, launch a following.

```
>>> ssc.stop()
```

Source: spark.apache.org

Netcat

 # Open new terminal (SSH) to connect same instance, and run a following ***<u>on the Cloudera</u>****.*

nc -lk 9999

```
# TERMINAL 1:
# Running Netc
at

$ nc -lk 9999

hello world



...
```

TERMINAL 2: Run PySpark-NetworkWordCount

```
-------------------------------------------
Time: 2014-10-14 15:25:21
-------------------------------------------
(hello,1)
(world,1)
...
```

Source: spark.apache.org