HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Chapter 7

Stream processing

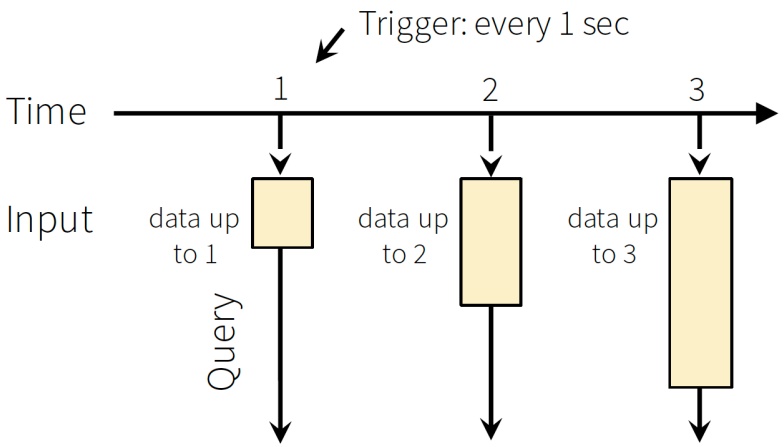
Structured streaming in Spark

Pain points with DStreams

- Processing with event-time, dealing with late data
  - DStream API exposes batch time, hard to incorporate event-time
- Interoperate streaming with batch AND interactive
  - RDD/DStream has similar API, but still requires translation
- Reasoning about end-to-end guarantees
  - Requires carefully constructing sinks that handle failures correctly
  - Data consistency in the storage while being updated

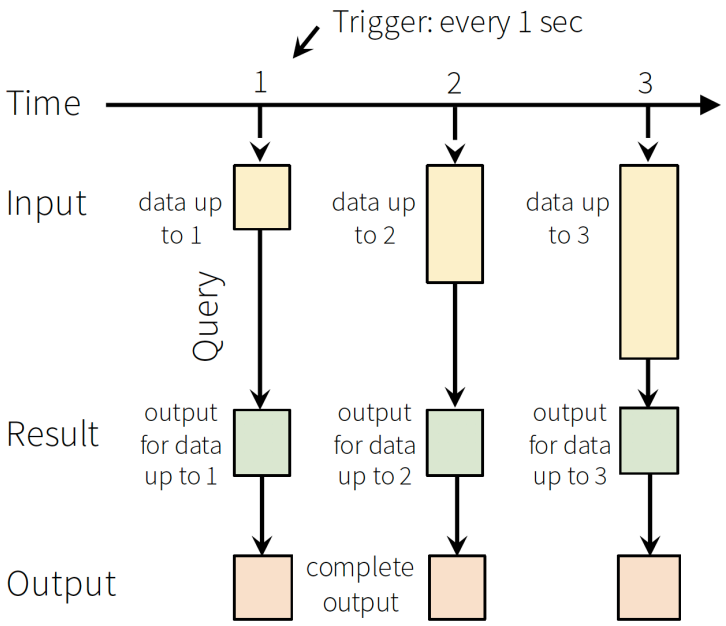
New model

- Input: data from source as an append-only table
- Trigger: how frequently to check input for new data
- Query: operations on input usual map/filter/reduce new window, session ops



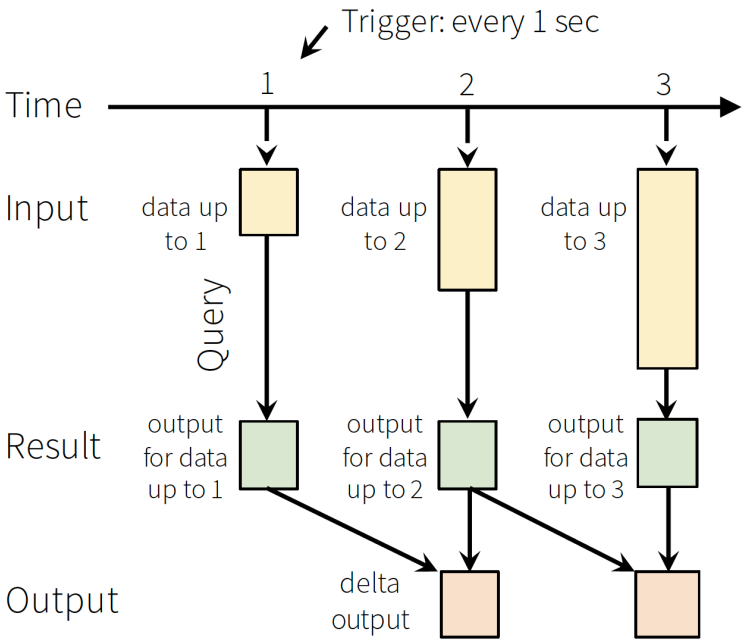
New model (2)

- Result: final operated table updated every trigger interval
- Output: what part of result to write to data sink after every trigger
- Complete output: Write full result table every time



New model (3)

- Delta output: Write only the rows that changed in result from previous batch
- Append output: Write only new rows
- *Not all output modes are feasible with all queries



Batch ETL with DataFrames

```
input = spark.read
        .format("json")
        .load("source-path")
result = input
        .select("device",
        "signal")
        .where("signal > 15")
result.write
        .format("parquet")
        .save("dest-path")
```

- Read from Json file
- Select some devices
- Write to parquet file

Streaming ETL with DataFrames

```
input = spark.read
        .format("json")
        .stream("source-path")
result = input
        .select("device", "signal")
        .where("signal > 15")
result.write
        .format("parquet")
        .startStream("dest-path")
```

- Read from Json file stream
  - Replace load() with stream()
- Select some devices
  - Code does not change
- Write to Parquet file stream
  - Replace save() with startStream()

Streaming ETL with DataFrames

```
input = spark.read
        .format("json")
        .stream("source-path")
result = input
        .select("device", "signal")
        .where("signal > 15")
result.write
        .format("parquet")
        .startStream("dest-path")
```

- read…stream() creates a streaming DataFrame, does not start any of the computation
- write…startStream() defines where & how to output the data and starts the processing

Streaming ETL with DataFrames

```
input = spark.read
        .format("json")
        .stream("source-path")
result = input
        .select("device", "signal")
        .where("signal > 15")
result.write
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```
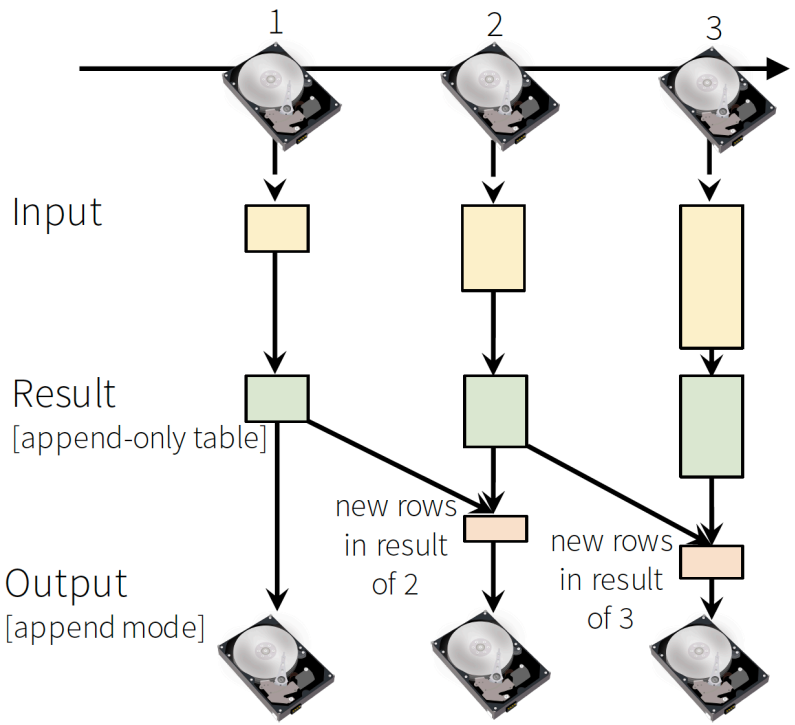



Continuous Aggregations

```
input.avg("signal")
```

- Continuously compute average signal across all devices

```
input.groupBy("device-type")
        .avg("signal")
```

- Continuously compute average signal of each type of device

Continuous Windowed Aggregations

```
input.groupBy(
        $"device-type",
        window($"event-
time-   col", "10 min"))
        .avg("signal")
```

- Continuously compute average signal of each type of device in last 10 minutes using event-time

- Simplifies event-time stream processing (not possible in DStreams) Works on both, streaming and batch jobs

Joining streams with static data

```
kafkaDataset = spark.read
        .kafka("iot-updates")
        .stream()

staticDataset = ctxt.read
        .jdbc("jdbc://", "iot-device-info")

joinedDataset =
        kafkaDataset.join(
        staticDataset,
"device-type")
```

- Join streaming data from Kafka with static data via JDBC to enrich the streaming data …
- … without having to think that you are joining streaming data

Output modes

Defines what is outputted every time there is a trigger
Different output modes make sense for different queries

- Append mode with non-aggregation queries

```
input.select("device", "signal")
        .write
        .outputMode("append")
        .format("parquet")
        .startStream("dest-path")
```

- Complete mode with aggregation queries

```
input.agg(count("*"))
        .write
        .outputMode("complete"
)
        .format("parquet")
        .startStream("dest-path")
```

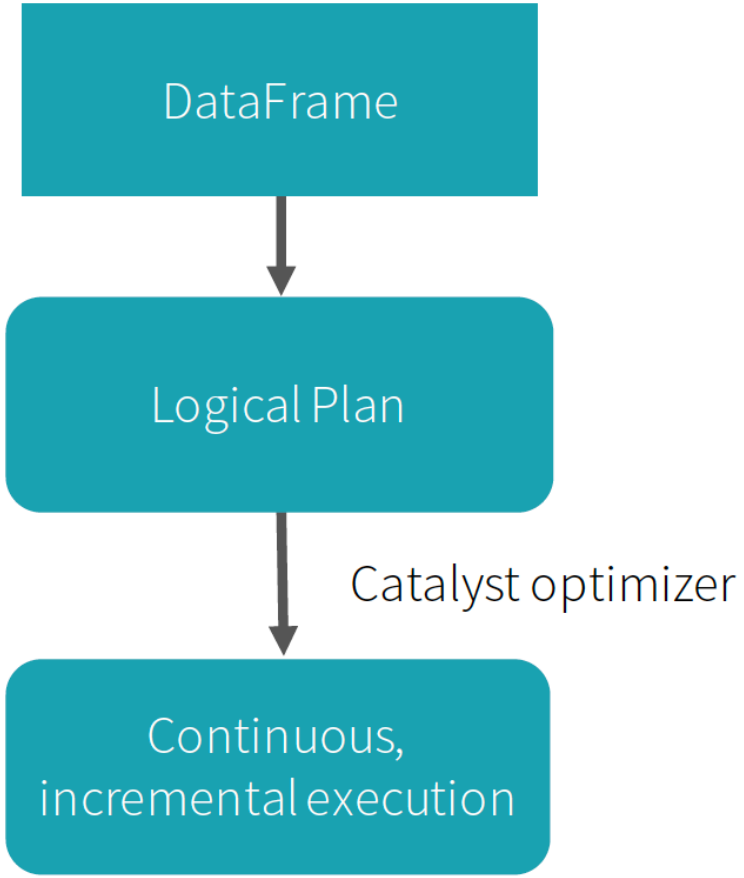
Query Management

```
query = result.write
        .format("parquet")
        .outputMode("append")
        .startStream("dest-path")

query.stop()
query.awaitTermination()
query.exception()

query.sourceStatuses()
query.sinkStatus()
```

- query: a handle to the running streaming computation for managing it
  - Stop it, wait for it to terminate
  - Get status
  - Get error, if terminated
- Multiple queries can be active at the same time
- Each query has unique name for keeping track

Query execution

- Logically
  - Dataset operations on table (i.e. as easy to understand as batch)
- Physically
  - Spark automatically runs the query in streaming fashion (i.e. incrementally and continuously)

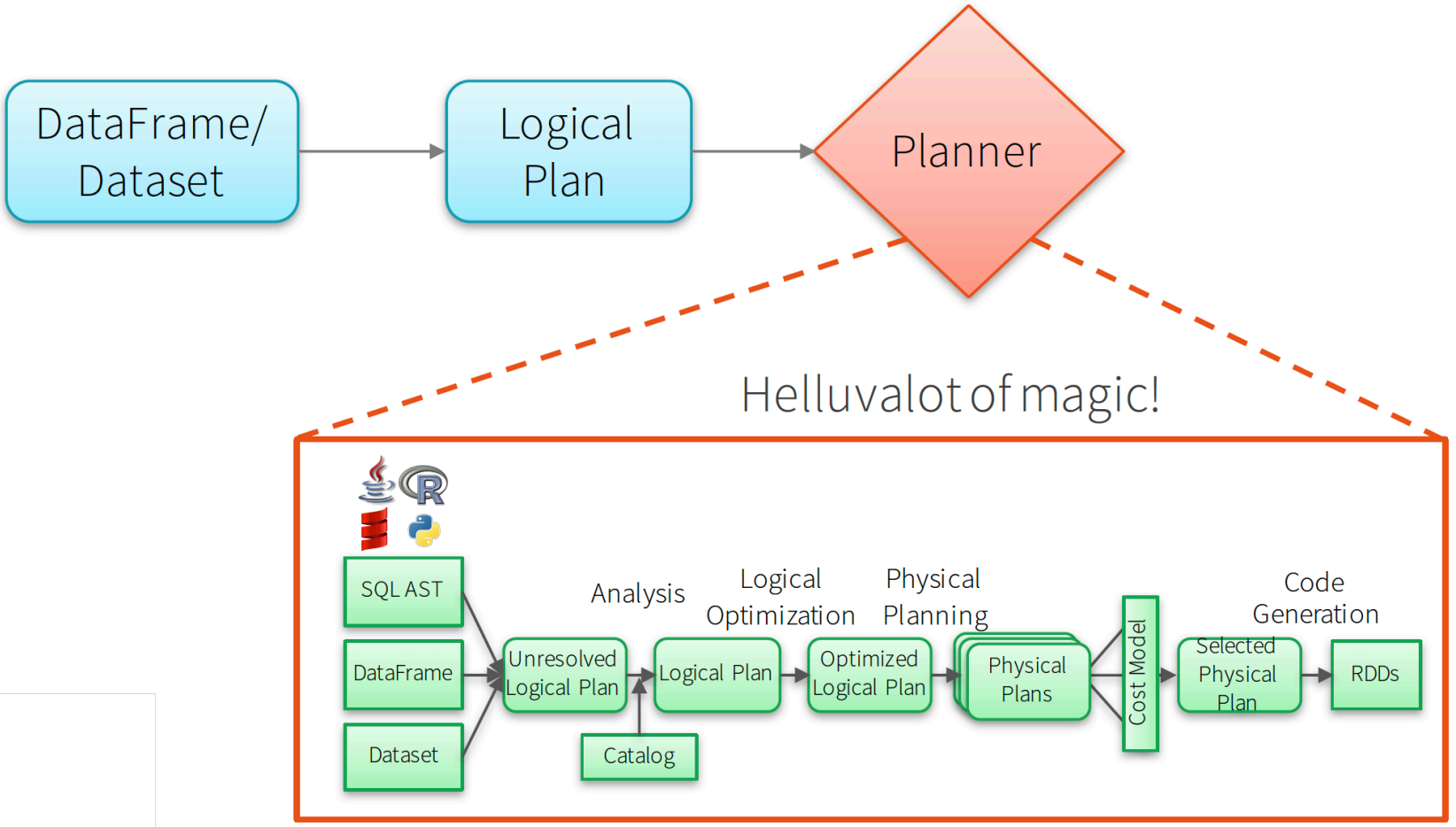


Structured Streaming

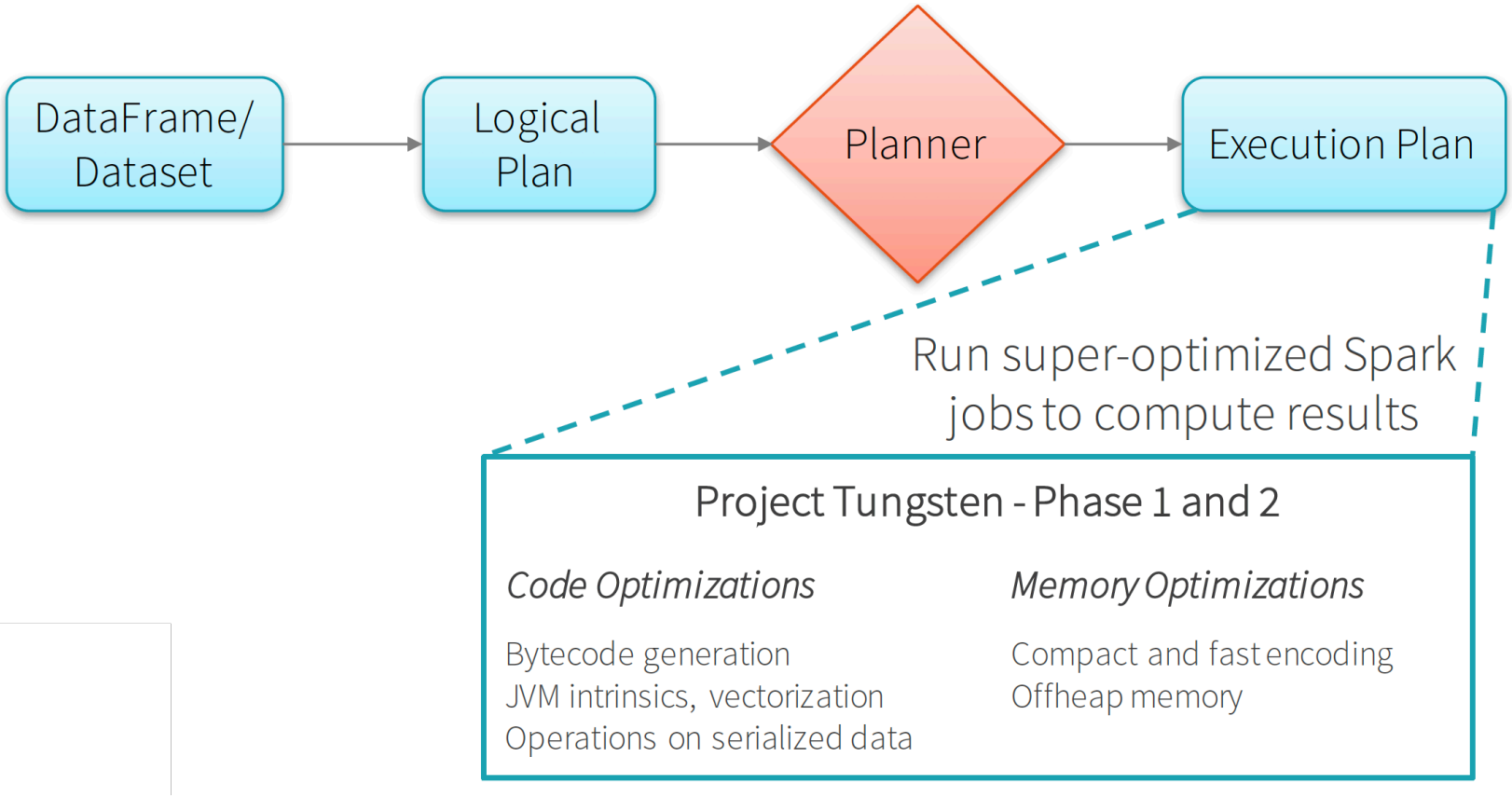
- High-level streaming API built on Datasets/DataFrames
  - Event time, windowing, sessions, sources & sinks
  - End-to-end exactly once semantics
- Unifies streaming, interactive and batch queries
  - Aggregate data in a stream, then serve using JDBC
  - Add, remove, change queries at runtime
  - Build and apply ML models

Internal execution

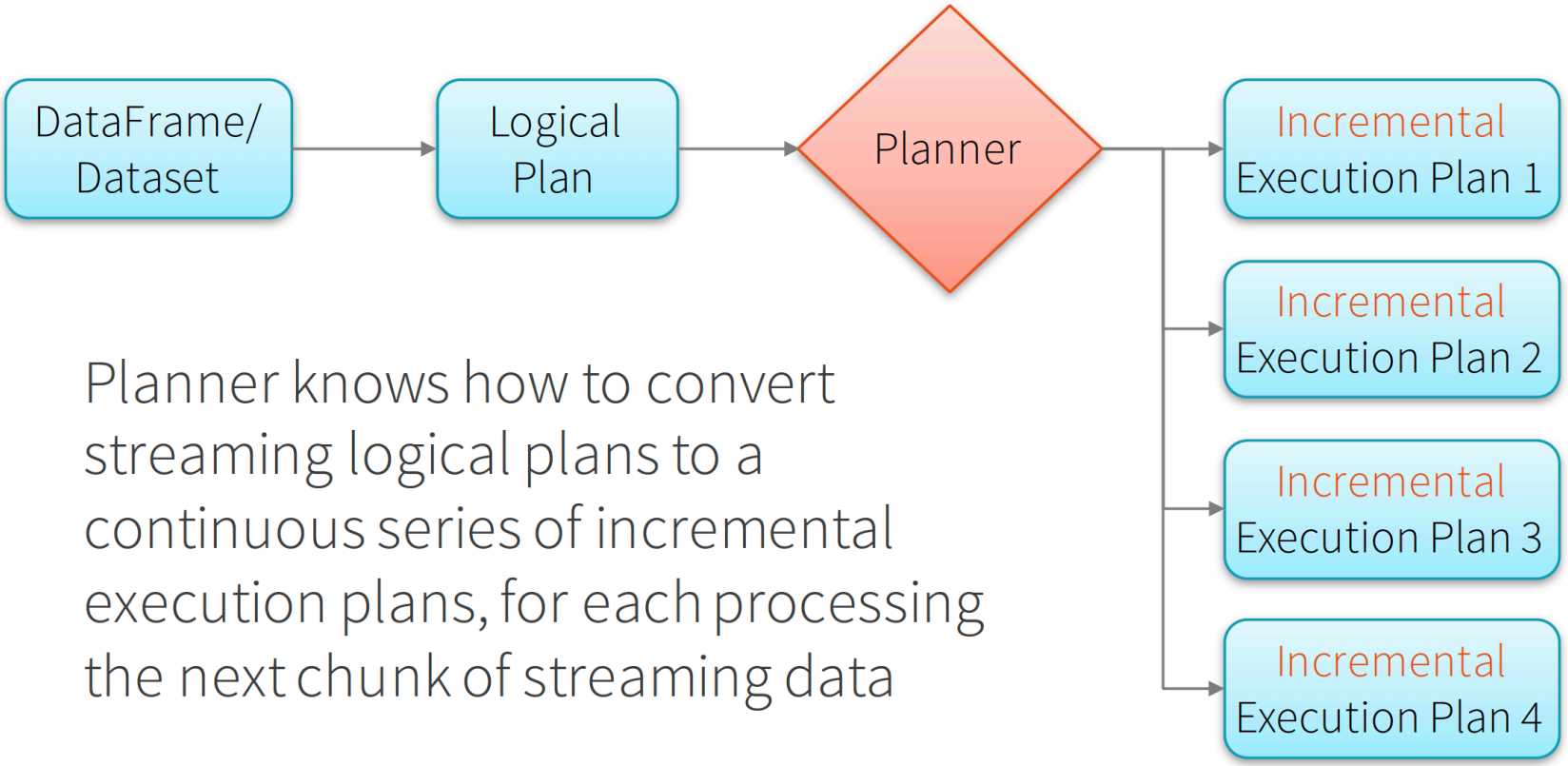
Batch Execution on Spark SQL



Batch Execution on Spark SQL

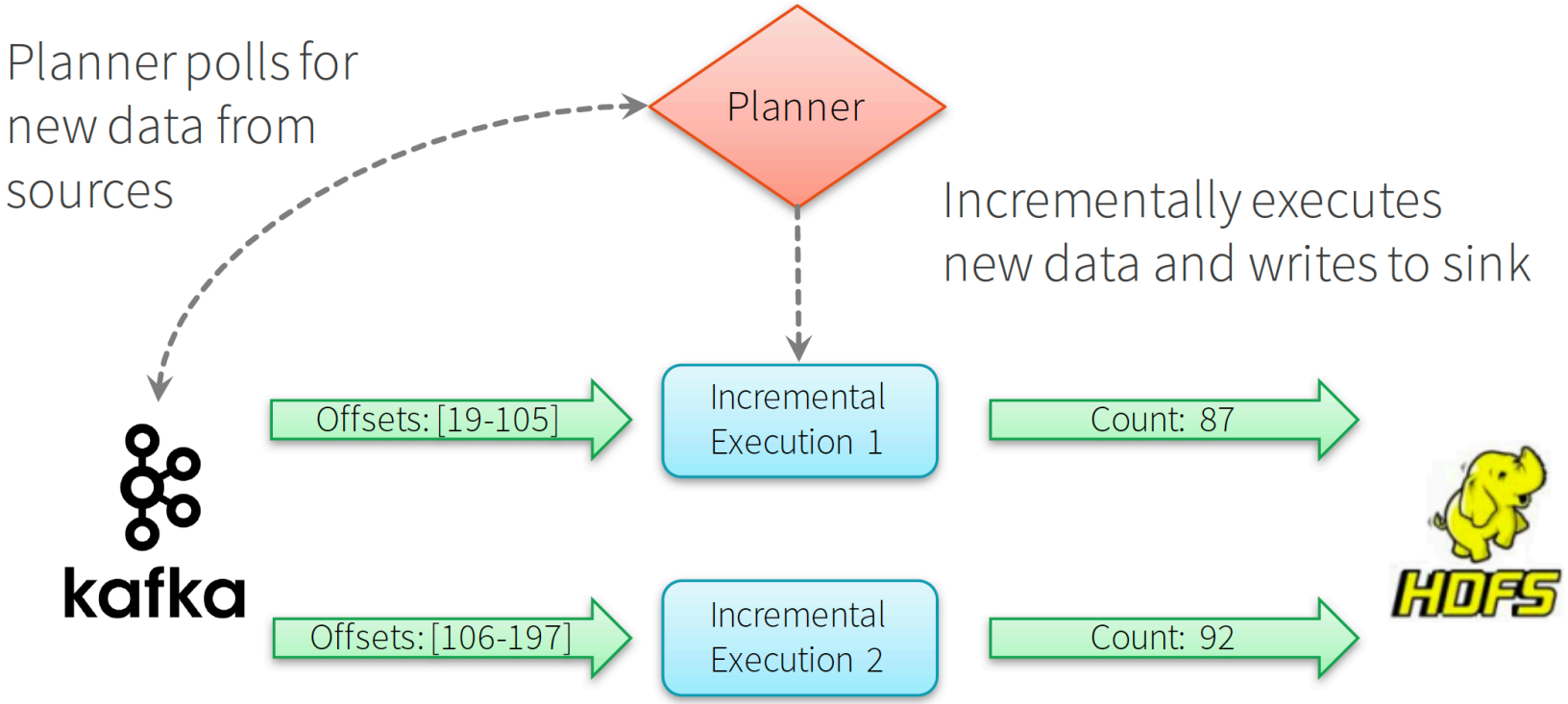


Continuous Incremental Execution



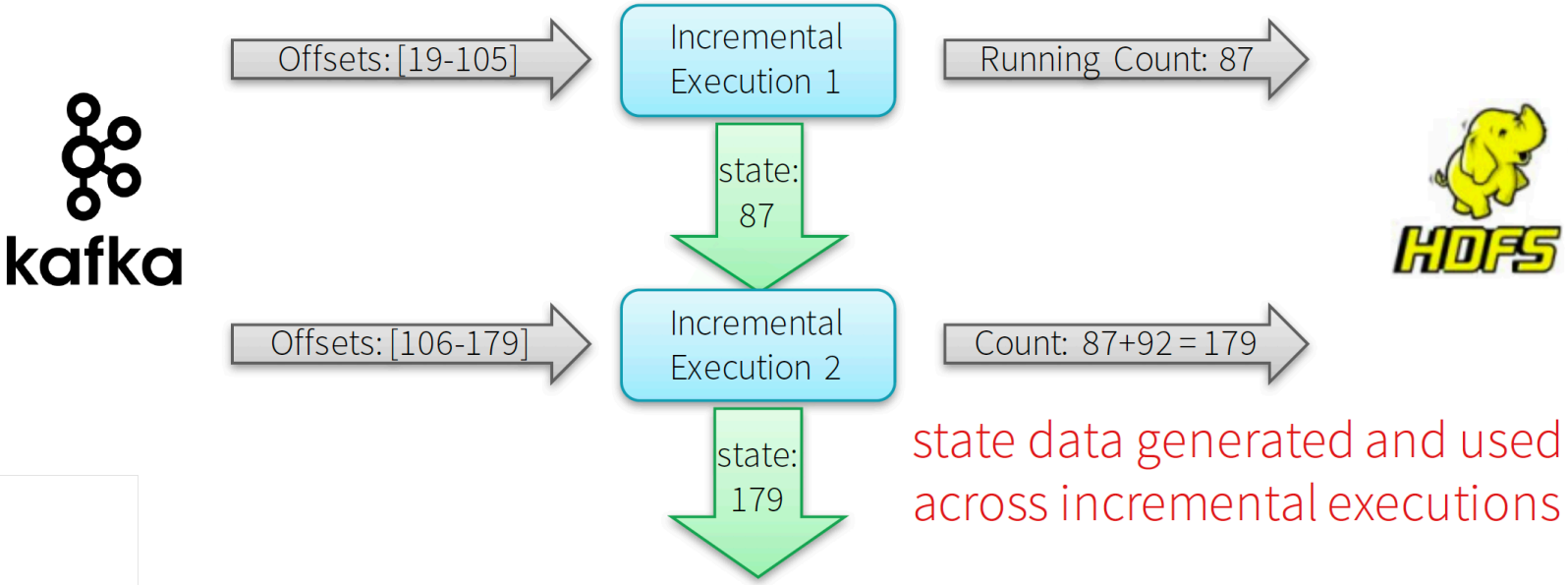
Planner knows how to convert streaming logical plans to a continuous series of incremental execution plans, for each processing the next chunk of streaming data

Continuous Incremental Execution



Continuous Aggregations

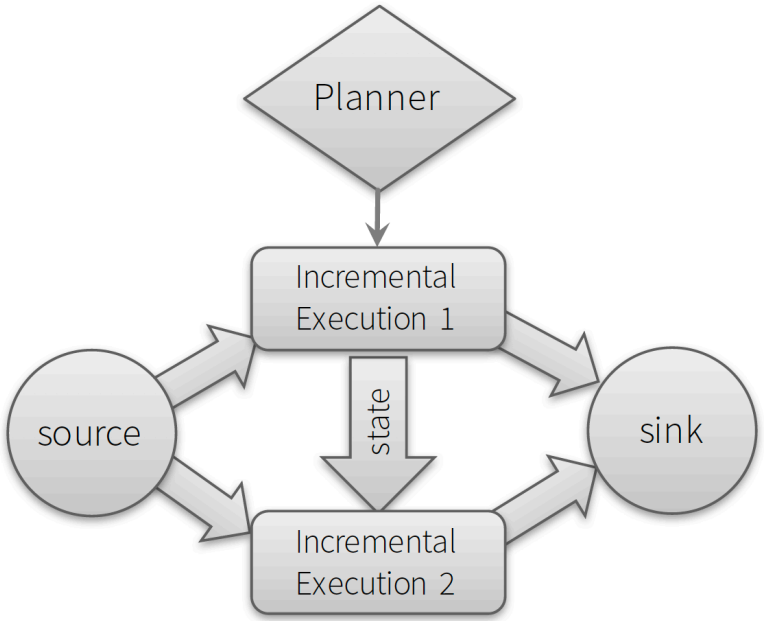
Maintain running aggregate as in-memory state backed by WAL in file system for fault-tolerance



state data generated and used across incremental executions

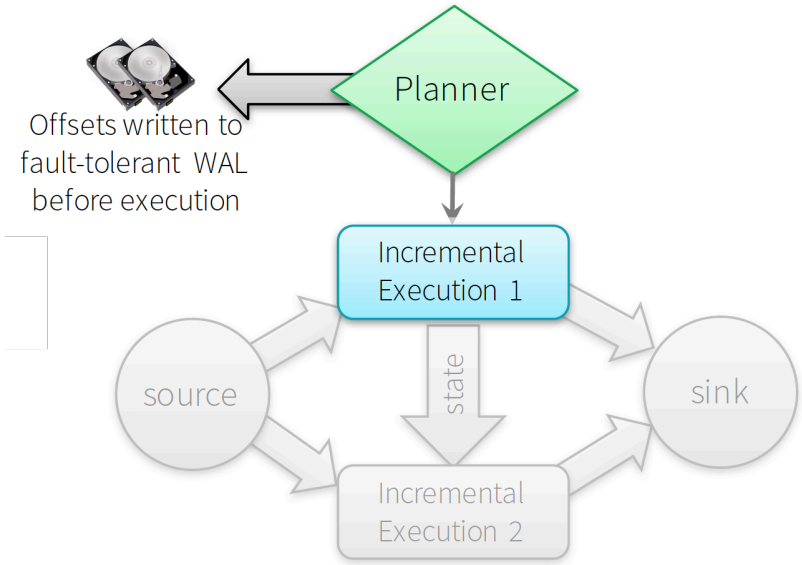
Fault-tolerance

- All data and metadata in the system needs to be recoverable / replayable



Fault-tolerant Planner

- Tracks offsets by writing the offset range of each execution to a write ahead log (WAL) in HDFS



Fault-tolerant Planner

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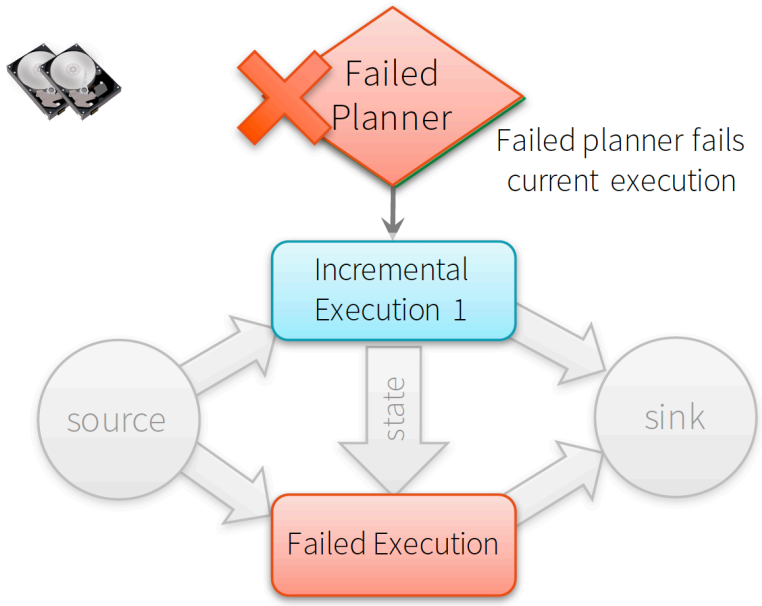
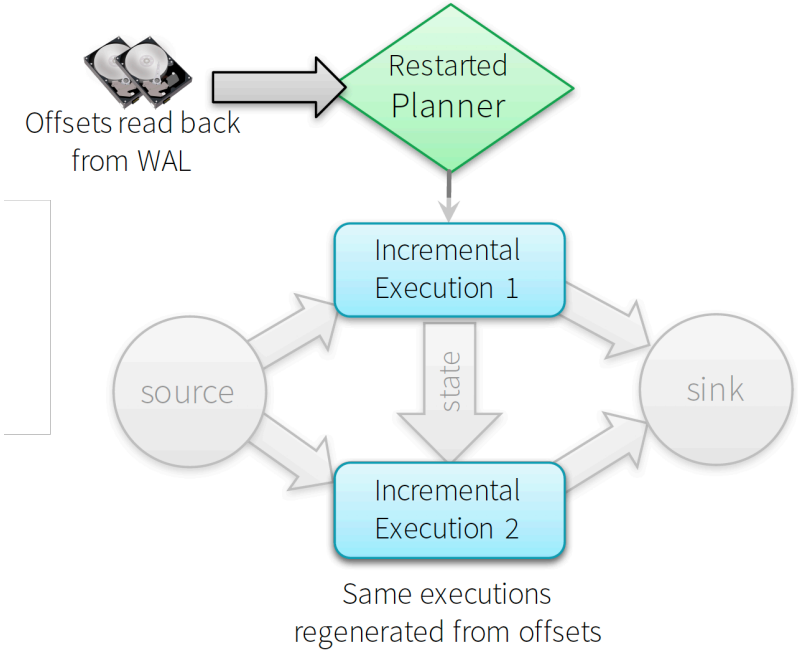


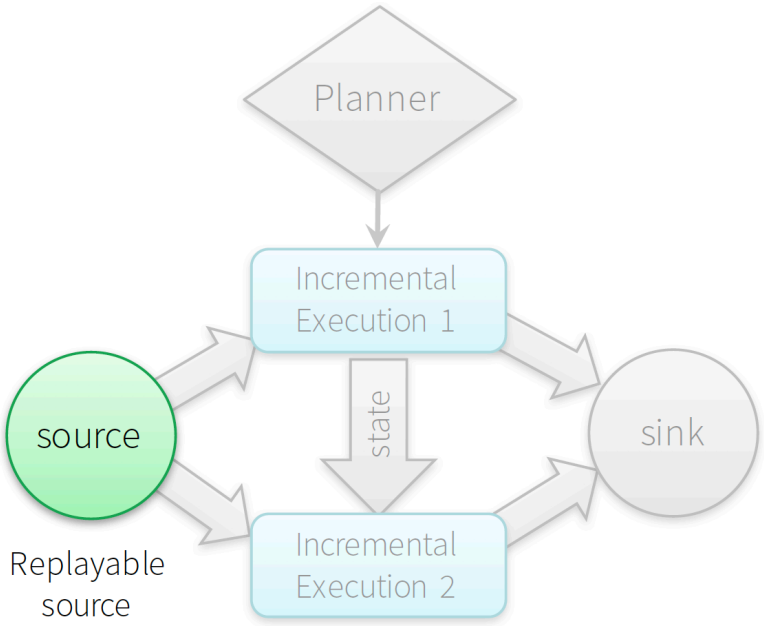
Fault-tolerant Planner

- Tracks offsets by writing the offset range of each execution to a write ahead log (WAL) in HDFS
- Reads log to recover from failures, and re-execute exact range of offsets



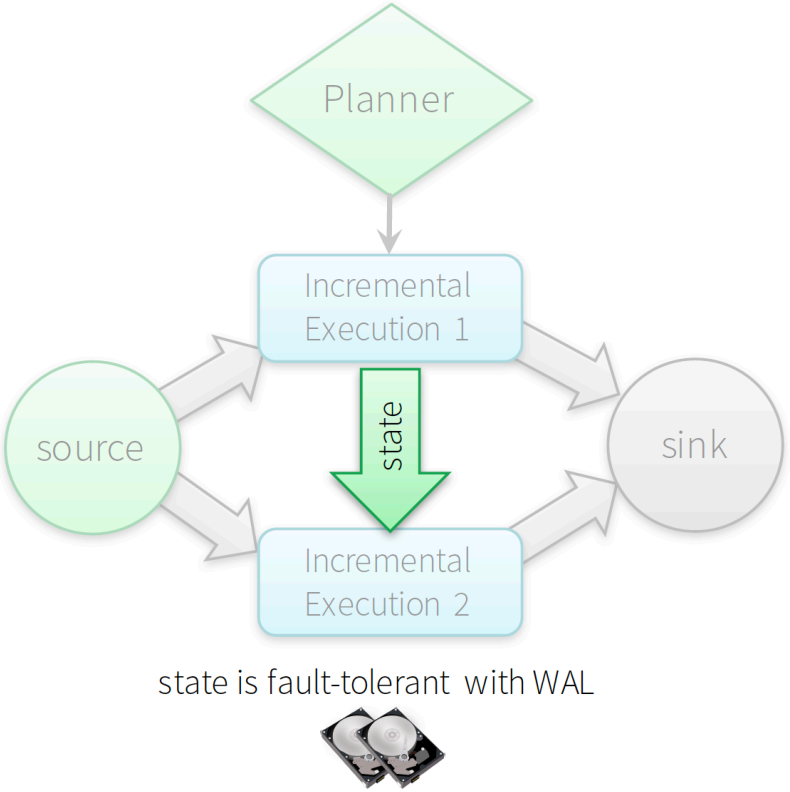
Fault-tolerant Sources

- Structured streaming sources are by design replayable (e.g. Kafka, Kinesis, files) and generate the exactly same data given offsets recovered by planner



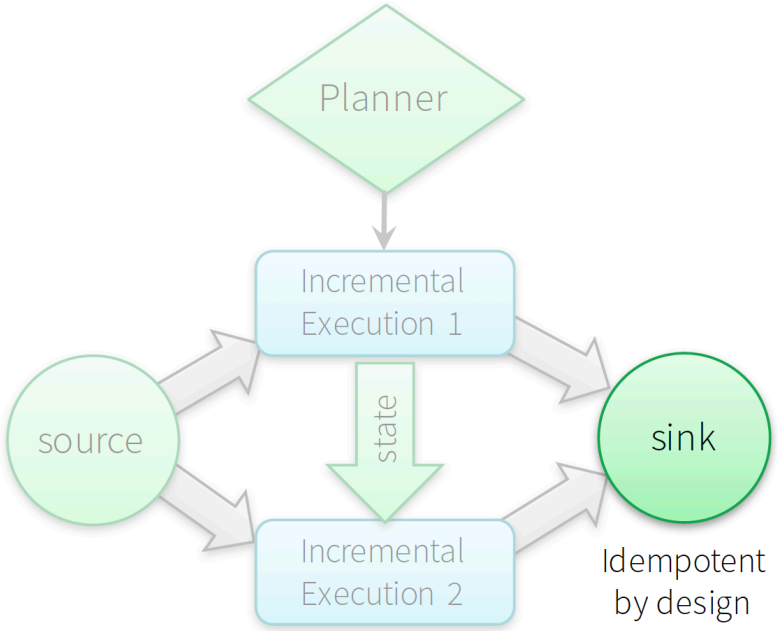
Fault-tolerant State

- Intermediate "state data" is a maintained in versioned, keyvalue maps in Spark workers, backed by HDFS
- Planner makes sure "correct version" of state used to reexecute after failure



Fault-tolerant Sink

- Sink are by design idempotent (deterministic), and handles re-executions to avoid double committing the output



Fault-tolerance

offset tracking in WAL

+

state management

+

fault-tolerant sources and sinks

=

end-to-end

exactly-once

guarantees

Structured streaming

Fast, fault-tolerant, exactly-once

stateful stream processing

without having to reason about streaming

Usecase

- https://mapr.com/blog/real-time-analysis-popular-uber-locations-spark-structured-streaming-machine-learning-kafka-and-mapr-db/

Usecase – Twitter sentiment analysis

Trending Topics can be used to create campaigns and attract larger audience.

Sentiment Analytics helps in crisis management, service adjusting and target marketing.

- Sentiment refers to the emotion behind a social media mention online.
- Sentiment Analysis is categorising the tweets related to particular topic and performing data mining using Sentiment Automation Analytics Tools.
- We will be performing Twitter Sentiment Analysis as our Use Case for Spark Streaming.

Figure: *Facebook And Twitter Trending Topics*

Problem statement

Problem Statement

To design a Twitter Sentiment Analysis System where we populate real time sentiments for crisis management, service adjusting and target marketing

Sentiment Analysis is used to:

- ❑ Predict the success of a movie
- ❑ Predict political campaign success
- ❑ Decide whether to invest in a certain company
- ❑ Targeted advertising
- ❑ Review products and services

Figure: *Twitter Sentiment Analysis For Nike*

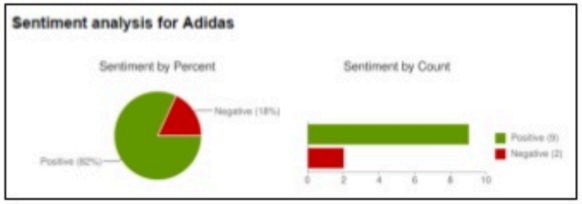


Figure: *Twitter Sentiment Analysis For Adidas*

Importing packages

```
//Import the necessary packages into the Spark Program
import org.apache.spark.streaming.{Seconds, StreamingContext}
import org.apache.spark.SparkContext._
import org.apache.spark.streaming.twitter._
import org.apache.spark.SparkConf
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark._
import org.apache.spark.rdd._
import org.apache.spark.rdd.RDD
import org.apache.spark.SparkContext._
import org.apache.spark.sql
import org.apache.spark.storage.StorageLevel
import scala.io.Source
import scala.collection.mutable.HashMap
import java.io.File
```

Twitter token authorization

```
object mapr {

 def main(args: Array[String]) {
 if (args.length < 4) {
 System.err.println("Usage: TwitterPopularTags <consumer key>
<consumer secret> " +
 "<access token> <access token secret> [<filters>]")
 System.exit(1)
 }

 StreamingExamples.setStreamingLogLevels()
 //Passing our Twitter keys and tokens as arguments for authorization
 val Array(consumerKey, consumerSecret, accessToken,
accessTokenSecret) = args.take(4)
 val filters = args.takeRight(args.length - 4)
```

Dstream transformation

```
// Set the system properties so that Twitter4j library used by twitter stream
// Use them to generate OAuth credentials
System.setProperty("twitter4j.oauth.consumerKey", consumerKey)
System.setProperty("twitter4j.oauth.consumerSecret", consumerSecret)
System.setProperty("twitter4j.oauth.accessToken", accessToken)
System.setProperty("twitter4j.oauth.accessTokenSecret",
accessTokenSecret)

val sparkConf = new
SparkConf().setAppName("Sentiments").setMaster("local[2]")
val ssc = new StreamingContext(sparkConf, Seconds(5))
val stream = TwitterUtils.createStream(ssc, None, filters)

//Input DStream transformation using flatMap
val tags = stream.flatMap { status =>
status.getHashtagEntities.map(_.getText)}
```

Generating tweet data

```
//RDD transformation using sortBy and then map function
tags.countByValue()
 .foreachRDD { rdd =>
 val now = org.joda.time.DateTime.now()
 rdd
 .sortBy(_._2)
 .map(x => (x, now))
 //Saving our output at ~/twitter/ directory
 .saveAsTextFile(s"~/twitter/$now")
 }

//DStream transformation using filter and map functions
val tweets = stream.filter {t =>
 val tags = t.getText.split("
").filter(_.startsWith("#")).map(_.toLowerCase)
 tags.exists { x => true }
}
```

Extracting sentiments

```
val data = tweets.map { status =>
val sentiment = SentimentAnalysisUtils.detectSentiment(status.getText)
val tagss = status.getHashtagEntities.map(_.getText.toLowerCase)
(status.getText, sentiment.toString, tagss.toString())
}

data.print()
//Saving our output at ~/ with filenames starting like twitterss
data.saveAsTextFiles("~/twitterss","20000")

ssc.start()
ssc.awaitTermination()
  }
}
```

Results

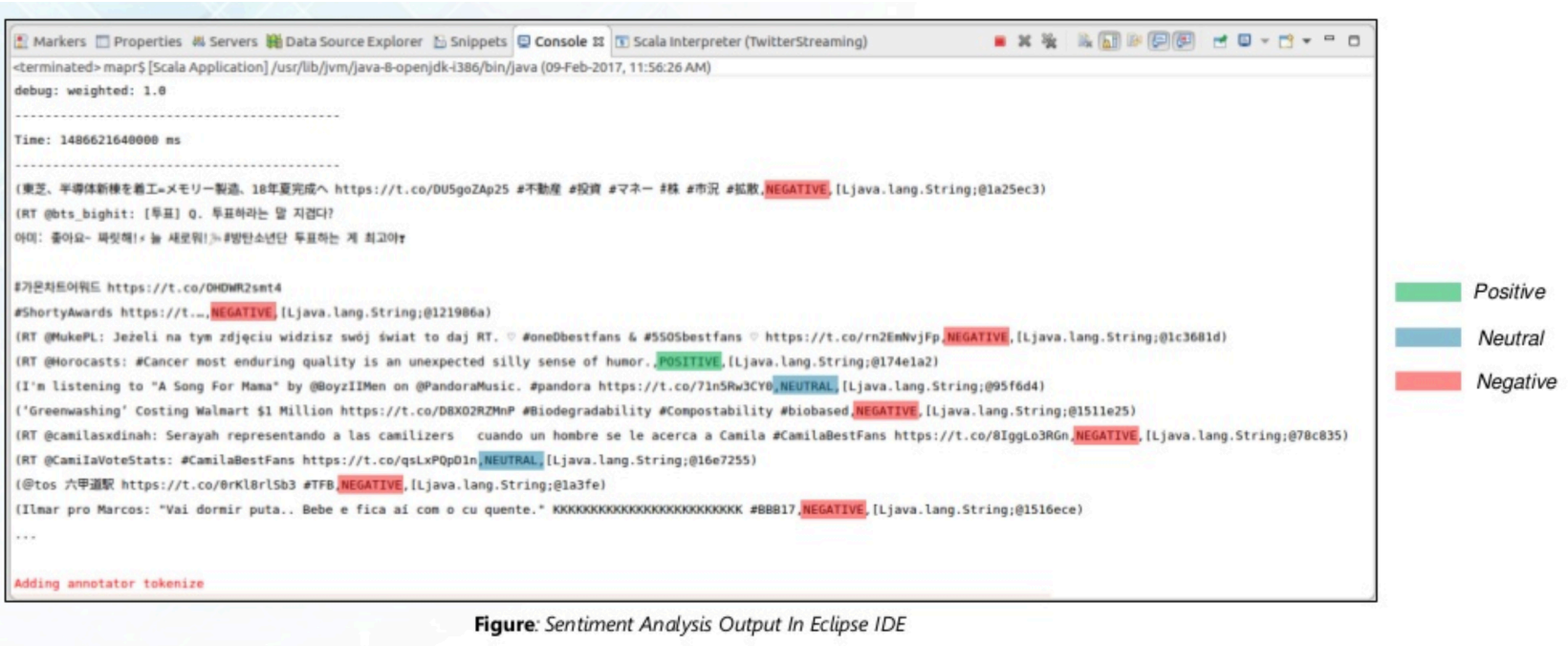


Figure: *Sentiment Analysis Output In Eclipse IDE*

Output directory

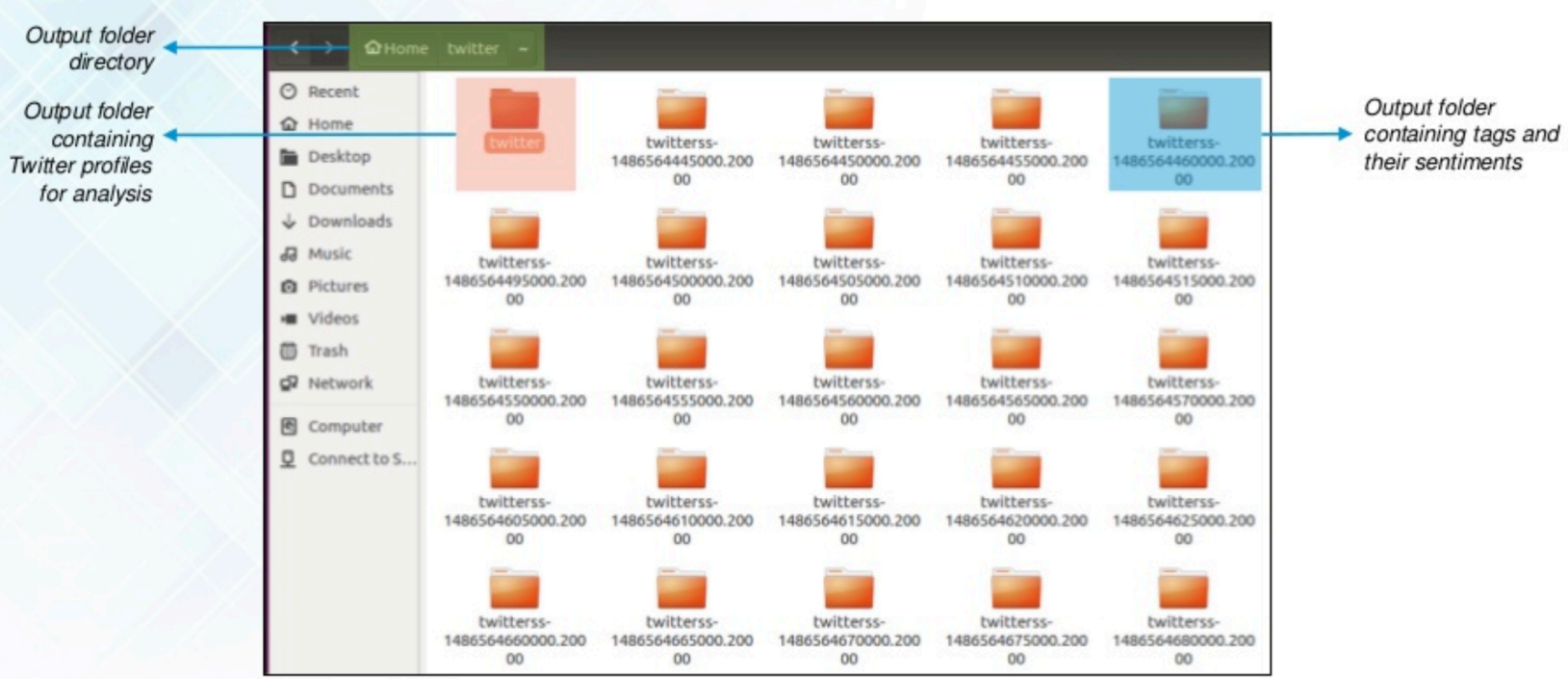


Figure: *Output folders inside our 'twitter' project folder*

Output usernames

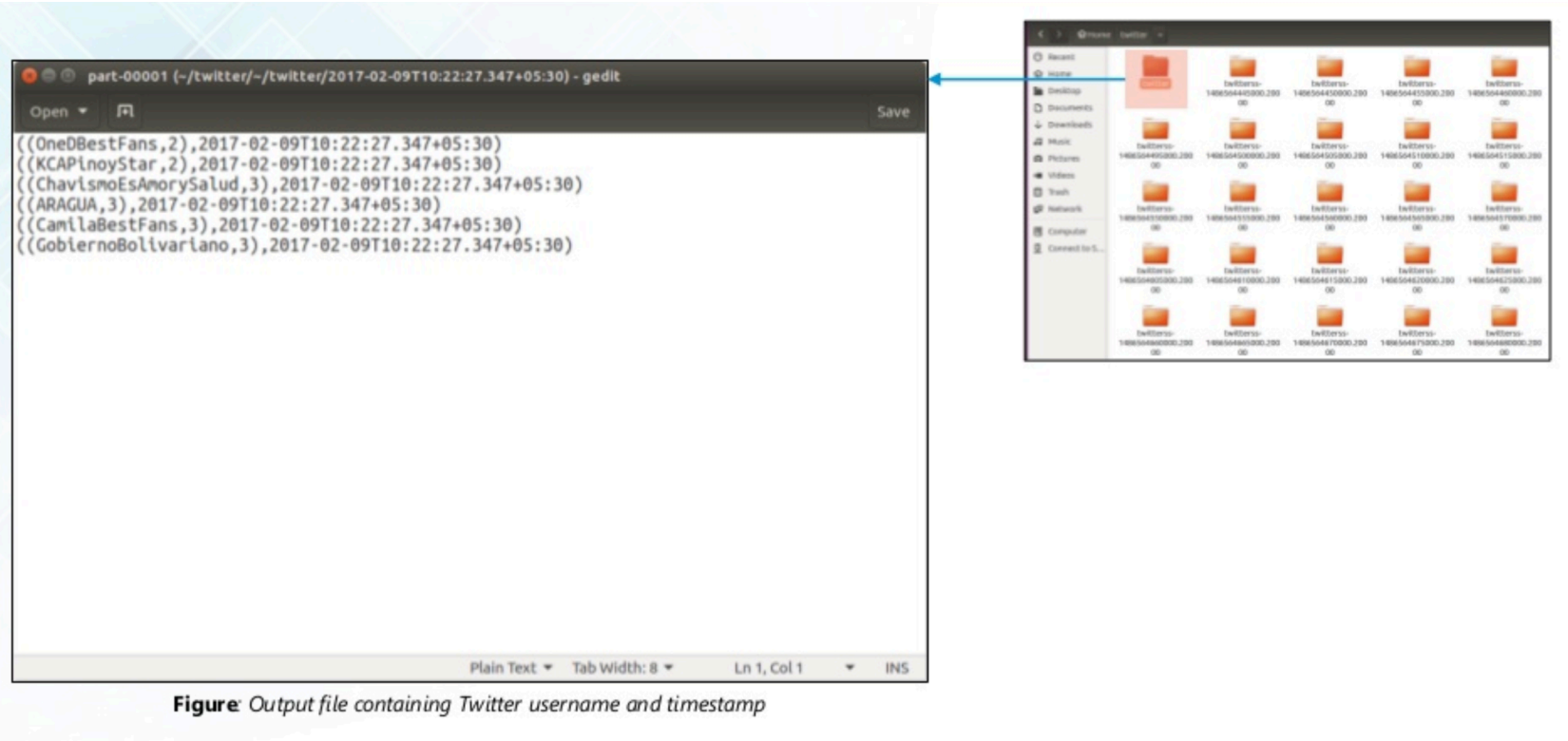


Figure: *Output file containing Twitter username and timestamp*

Output tweets and sentiments

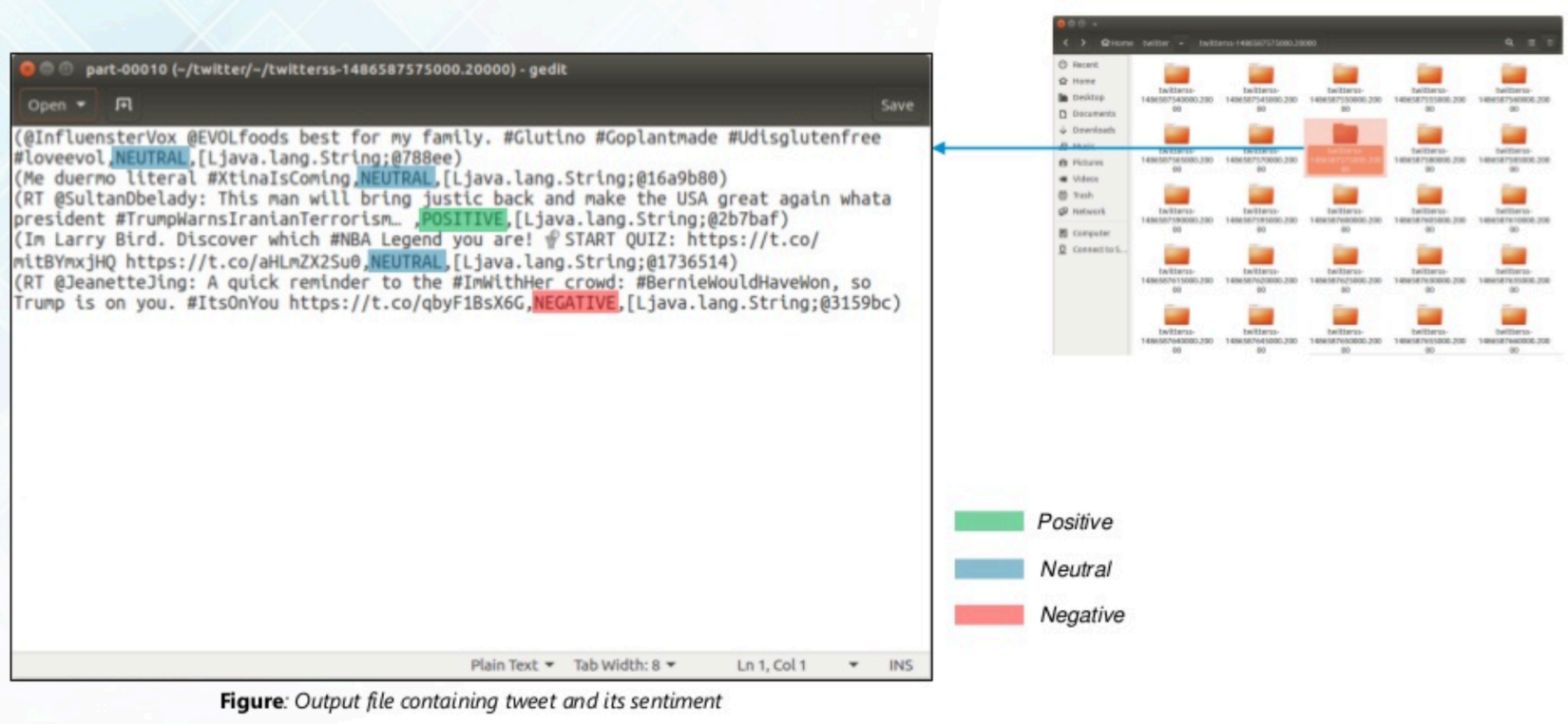


Figure: *Output file containing tweet and its sentiment*

Sentiments for Trump

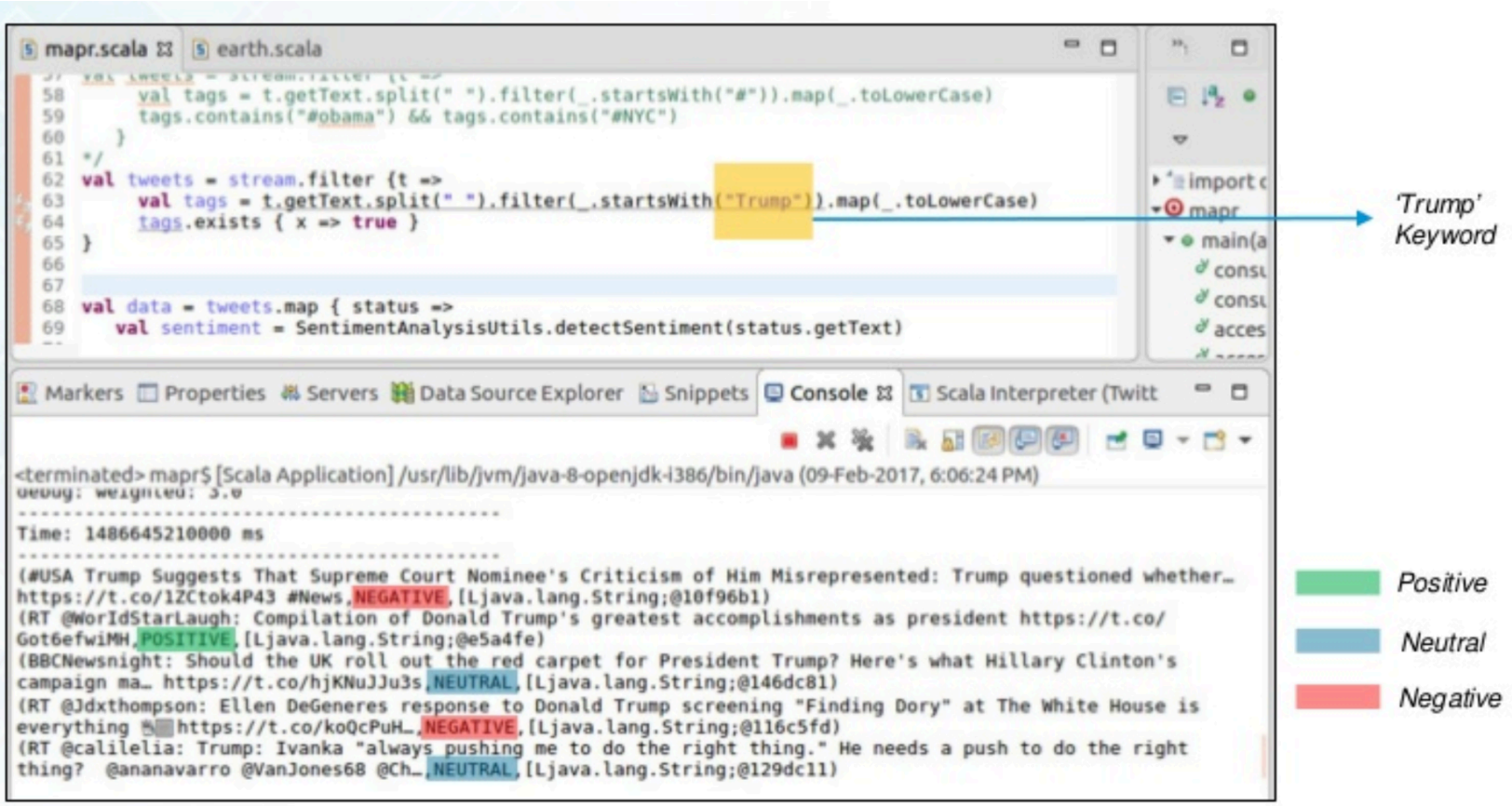


Figure: *Performing Sentiment Analysis on Tweets with 'Trump' Keyword*

Applying sentiment analysis

- As we have seen from our Sentiment Analysis demonstration, we can extract sentiments of particular topics just like we did for 'Trump'.
- Hence Sentiment Analytics can be used in crisis management, service adjusting and target marketing by companies around the world.

Companies using Spark Streaming for Sentiment Analysis have applied the same approach to achieve the following:

1. Enhancing the customer experience
2. Gaining competitive advantage
3. Gaining Business Intelligence
4. Revitalizing a losing brand

References

- Zaharia, Matei, et al. "Discretized streams: an efficient and fault-tolerant model for stream processing on large clusters." *Presented as part of the*. 2012.
- Armbrust, Michael, et al. "Structured streaming: A declarative API for real-time applications in apache spark." *Proceedings of the 2018 International Conference on Management of Data*. 2018.

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