Spark Structured Streaming

What is Spark Structured Streaming?

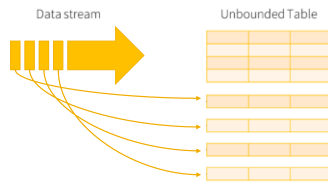
- Structured Streaming is a scalable and fault-tolerant stream processing engine that is built on the Spark SQL engine
- Input data are represented by means of (streaming) DataFrames
- Structured Streaming uses the existing Spark SQL APIs to query data streams
  - The same methods we used for analyzing "static" DataFrames
- A set of specific methods that are used to define
  - Input and output streams
  - Windows

Input data model

- Each input data stream is modeled as a table that is being continuously appended
  - Every time new data arrive they are appended at the end of the table
  - i.e., each data stream is considered an unbounded input table

Input data model

- New input data in the stream = new rows appended to an unbounded table



Data stream as an unbounded table

Queries

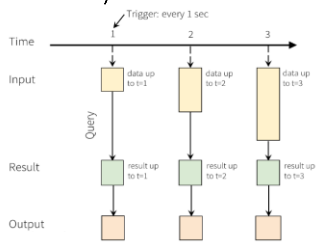
- The expressed queries are incremental queries that are run incrementally on the unbounded input tables
  - The arrive of new data triggers the execution of the incremental queries
  - The result of a query at a specific timestamp is the one obtained by running the query on all the data arrived until that timestamp
    - i.e., "stateful queries" are executed
  - Aggregation queries combine new data with the previous results to optimize the computation of the new results

Queries

- The queries can be executed
  - As micro-batch queries with a fixed batch interval
    - Standard behavior
    - Exactly-once fault-tolerance guarantees
  - As continuous queries
    - Experimental
    - At-least-once fault-tolerance guarantees

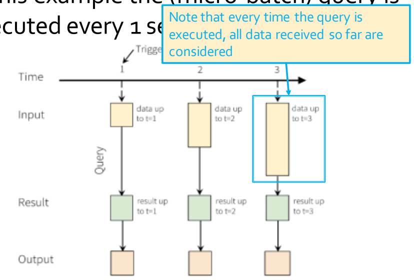
Queries

- In this example the (micro-batch) query is executed every 1 second



Queries

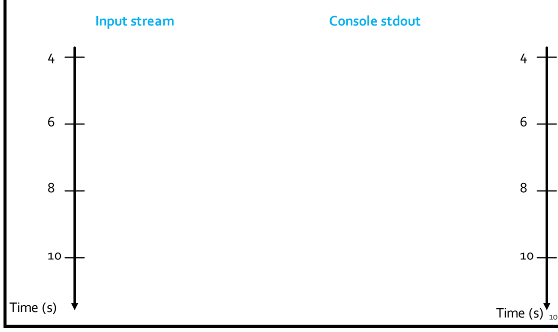
- In this example the (micro-batch) query is executed every 1 second



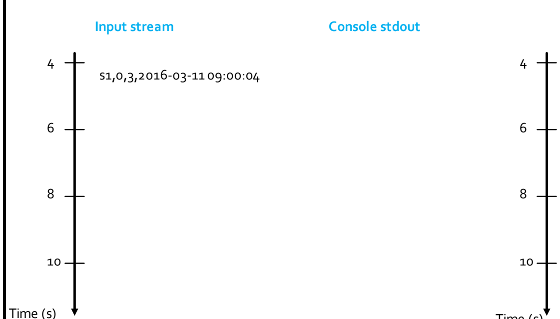
Example

- Input
  - A stream of records retrieved from localhost:9999
  - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
  - Each input reading has the format
    - stationId,# free slots,#used slots,timestamp
- For each stationId, print on the standard output the total number of received input reading with a number of free slots equal to 0
  - Print the requested information when new data are received by using the micro-batch processing mode
  - Suppose the batch-duration is set to 2 seconds

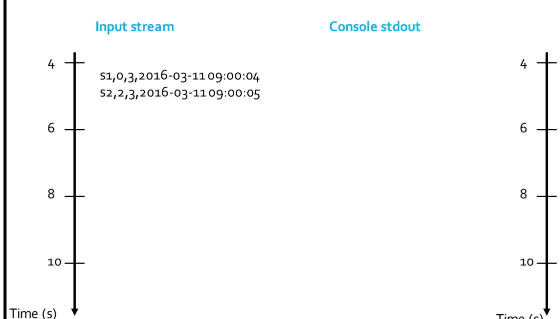
Example



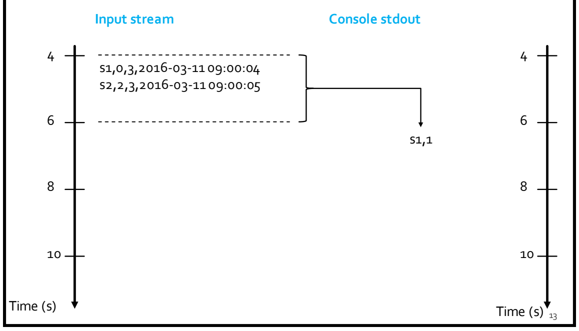
Example



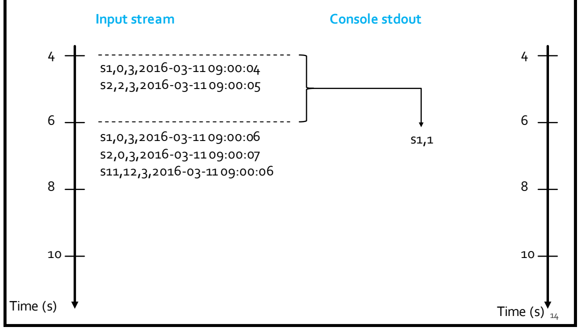
Example



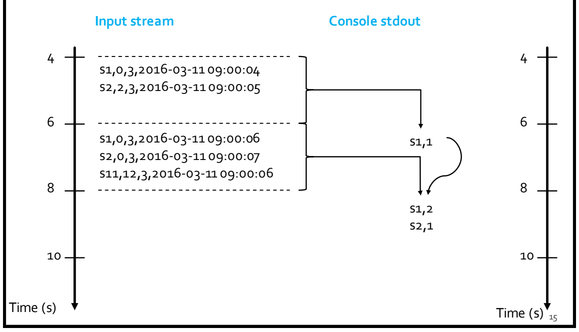
Example



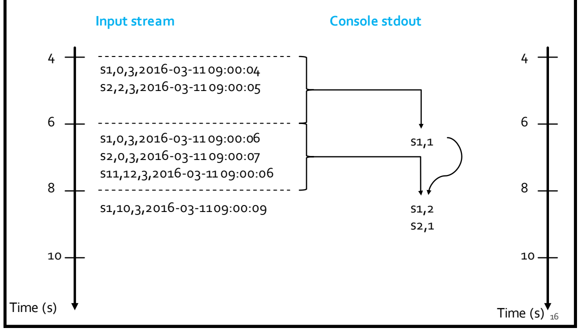
Example



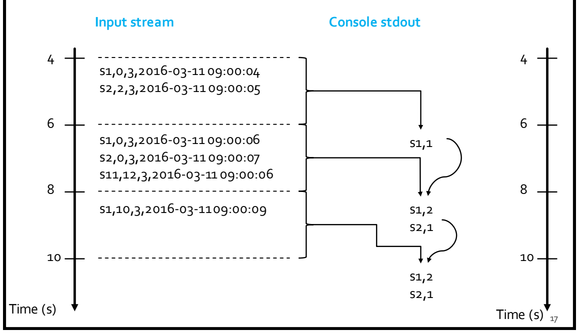
Example



Example



Example



Key concepts

- Input sources
- Transformations
- Outputs
  - External destinations/sinks
  - Output Modes
- Query run/execution
- Triggers

Input sources

- File source
  - Reads files written in a directory as a stream of data
  - Each line of the input file is an input record
  - Supported file formats are text, csv, json, orc, parquet, ..
- Kafka source
  - Reads data from Kafka
  - Each Kafka message is one input record

Input sources

- Socket source (for debugging purposes)
  - Reads UTF8 text data from a socket connection
  - This type of source **does not provide end-to-end fault-tolerance guarantees**
- Rate source (for debugging purposes)
  - Generates data at the specified number of rows per second
  - Each generated row contains a timestamp and value of type long

Input sources

- The **readStream** property of the SparkSession class is used to create DataStreamReaders
- The methods **format()** and **option()** of the DataStreamReader class are used to specify the input streams
  - Type, location, …
- The method **load()** of the DataStreamReader class is used to return DataFrames associated with the input data streams

Input sources

- In this example the (streaming) DataFrame recordsDF is created and associated with the input stream of type socket
  - Address: localhost
  - Input port: 9999

```
recordsDF = spark.readStream \
.format("socket") \
.option("host", "localhost") \
.option("port", 9999) \
.load()
```


Transformations

- Transformations are the same of DataFrames
- However, there are **restrictions on** some types of queries/**transformations that cannot be executed incrementally**

Transformations

- **Unsupported** operations
  - Multiple streaming aggregations (i.e. a chain of aggregations on a streaming DataFrame)
  - Limit and take first N rows
  - Distinct operations
  - Sorting operations are supported on streaming DataFrames only after an aggregation and in complete output mode
  - Few types of outer joins on streaming DataFrames are not supported

Outputs

- Sinks
  - They are instances of the class DataStreamWriter and are used to specify the external destinations and store the results in the external destinations
- File sink
  - Stores the output to a directory
  - Supported file formats are text, csv, json, orc, parquet, ..
- Kafka sink
  - Stores the output to one or more topics in Kafka
- Foreach sink
  - Runs arbitrary computation on the output records

25

Outputs

- Console sink (for debugging purposes)
  - Prints the computed output to the console every time a new batch of records has been analyzed
  - This should be used for debugging purposes on low data volumes as the entire output is collected and stored in the driver's memory after each computation
- Memory sink (for debugging purposes)
  - The output is stored in memory as an in-memory table
  - This should be used for debugging purposes on low data volumes as the entire output is collected and stored in the driver's memory

26

Output modes

- We must define how we want Spark to write output data in the external destinations
- Supported output modes:
  - Append
  - Complete
  - Update
- The supported output mode depend on the query type

27

Output modes

- Append mode
  - Default mode
  - Only the new rows added to the computed result since the last trigger (computation) will be outputted
  - This mode is supported for only those queries where rows added to the result is never going to change
    - This mode guarantees that each row will be output only once
  - Queries with only select, filter, map, flatMap, filter, join, etc. support append mode

28

Output modes

- Complete mode
  - The whole computed result will be outputted to the sink after every trigger (computation)
  - This mode is supported for aggregation queries

29

Output modes

- Update mode
  - Only the rows in the computed result that were updated since the last trigger (computation) will be outputted
- The complete list of supported output modes for each query type is available at
  - https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html#output-modes

30

Outputs

- The **writeStream** property of the SparkSession class is used to create DataStreamWriters
- The methods **outputMode()**, **format()** and **option()** of the DataStreamWriter class are used to specify the output destination
  - Data format, location, output mode, etc.

31

Outputs

- In this example
  - The DataStreamWriter streamWriterRes is created and associated with the console
  - The output mode is set to append

```
streamWriterRes = stationIdTimestampDF \
.writeStream \
.outputMode("append") \
.format("console")
```

32

Query run/execution

- To start executing the defined queries/structured streaming applications you must explicitly invoke the **start()** action on the defined sinks (DataStreamWriter objects associated with the external destinations in which the results will be stored)
- You can start several queries in the same application
- Structured streaming queries run forever
  - You must explicitly stop/kill them otherwise they will run forever

33

Triggers

- For each Spark structured streaming query we can specify when new input data must be processed
- And whether the query is going to be executed
  - as a micro-batch query with a fixed batch interval
  - or as a continuous processing query (experimental)
- The trigger type for each query is specified by means of the **trigger()** method of the DataStreamWriter class

34

Trigger Types

- No trigger type is explicitly specified
  - Default trigger setting
  - The query will be executed in **micro-batch mode**
  - Each micro-batch is generated and processed as soon as the previous micro-batch has been processed

35

Trigger Types

- Fixed interval micro-batches
  - The query will be executed in **micro-batch mode**
  - Micro-batches will be processed at the user-specified intervals
    - The parameter processingTime of the trigger method() is used to specify the micro-batch size
    - If the previous micro-batch completes within its interval, then the engine will wait until the interval is over before processing the next micro-batch

36

Trigger Types

- If the previous micro-batch takes longer than the interval to complete (i.e. if an interval boundary is missed), then the next micro-batch will start as soon as the previous one completes

Trigger Types

- One-time micro-batch
  - The query will be executed in **micro-batch mode**
  - But the query will be **executed only one time** on one single micro-batch containing all the available data of the input stream
    - After the single execution the query stops on its own

Trigger Types

- This trigger type is useful when you want to periodically spin up a cluster, process everything that is available since the last period, and then shutdown the cluster
  - In some case, this may lead to significant cost savings

Trigger Types

- Continuous with fixed checkpoint interval (**experimental**)
  - The query will be executed in the new low-latency, **continuous processing mode**
  - **At-least-once** fault-tolerance guarantees

Sparks Structured Streaming: Example 1

- Problem specification
  - Input
    - A stream of records retrieved from localhost:9999
    - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
    - Each input reading has the format
      - stationId,# free slots,#used slots,timestamp
  - Output
    - For each input reading with a number of free slots equal to 0 print on the standard output the value of stationId and timestamp
    - Use the standard micro-batch processing mode

Sparks Structured Streaming: Example 1

```
from pyspark.sql.types import *
from pyspark.sql.functions import split

# Create a "receiver" DataFrame that will connect to localhost:9999
recordsDF = spark.readStream\
.format("socket") \
.option("host", "localhost") \
.option("port", 9999) \
.load()
```

Sparks Structured Streaming: Example 1

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
# New columns:
# - stationId
# - freeslots
# - usedslots
# - timestamp

readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```

43

Sparks Structured Streaming: Example 1

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
```

withColumn () is used to add new columns.
It is a standard DataFrame method.

withColumn () returns a DataFrame with the same columns of the input DataFrame and the new defined column

```
readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```

44

Sparks Structured Streaming: Example 1

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
```

For each new column you must specify:
- Name
- The SQL function that is used to define its value in each record

The cast() method is used to specify the data type of each defined column.

```
readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```

45

Sparks Structured Streaming: Example 1

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Select stationid and timestamp
# Use the standard select transformation
stationIdTimestampDF = fullReadingsDF.select("stationId", "timestamp")
```

46

Sparks Structured Streaming: Example 1

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Select stationid and timestamp
# Use the standard select transformation
stationIdTimestampDF = fullReadingsDF.select("stationId", "timestamp")
```

Standard DataFrame transformations

47

Sparks Structured Streaming: Example 1

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Select stationid and timestamp
# Use the standard select transformation
stationIdTimestampDF = fullReadingsDF.select("stationId", "timestamp")

# The result of the structured streaming query will be stored/printed on
# the console "sink".
# append output mode
queryFilterStreamWriter = stationIdTimestampDF \
.writeStream \
.outputMode("append") \
.format("console")
```

48

Sparks Structured Streaming: Example 1

```
# Start the execution of the query (it will be executed until it is explicitly stopped)
queryFilter = queryFilterStreamWriter.start()
```


Sparks Structured Streaming: Example 2

- Problem specification
  - Input
    - A stream of records retrieved from localhost:9999
    - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
    - Each input reading has the format
      - stationId,# free slots,#used slots,timestamp
  - Output
    - For each stationId, print on the standard output the total number of received input reading with a number of free slots equal to 0
    - Print the requested information when new data are received by using the standard micro-batch processing mode

Sparks Structured Streaming: Example 2

```
from pyspark.sql.types import *
from pyspark.sql.functions import split

# Create a "receiver" DataFrame that will connect to localhost:9999
recordsDF = spark.readStream\
.format("socket") \
.option("host", "localhost") \
.option("port", 9999) \
.load()
```


Sparks Structured Streaming: Example 2

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
# New columns:
# - stationId
# - freeslots
# - usedslots
# - timestamp

readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```


Sparks Structured Streaming: Example 2

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")
```


Sparks Structured Streaming: Example 2

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for each stationId
# The standard groupBy method is used
countsDF = fullReadingsDF\
.groupBy("stationId")\
.agg({"*":"count"})
```

Sparks Structured Streaming: Example 2

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for each stationId
# The standard groupBy method is used
countsDF = fullReadingsDF\
.groupBy("stationId")\
.agg({"*":"count"})
```

Standard DataFrame transformations

55

Sparks Structured Streaming: Example 2

```
# The result of the structured streaming query will be stored/printed on
# the console "sink"
# complete output mode
# (append mode cannot be used for aggregation queries)
queryCountStreamWriter = countsDF \
.writeStream \
.outputMode("complete") \
.format("console")

# Start the execution of the query (it will be executed until it is explicitly stopped)
queryCount = queryCountStreamWriter.start()
```

56

Event Time and Window Operations

57

Event Time and Window Operations

- Input streaming records are usually characterized by a time information
  - It is the **time when the data was generated**
  - It is usually called **event-time**
- For many applications, you want to operate by taking into consideration the event-time and windows containing data associated with the same event-time range

58

Event Time and Window Operations

- For example
  - Compute the number of events generated by each monitored IoT device every minute based on the event-time
    - For each window associated with one distinct minute consider only the data with an event-time inside that minute/window and compute the number of events for each IoT device
    - One computation for each minute/window
  - You want to use the time when the data was generated (i.e., the event-time) rather than the time Spark receives them

59

Event Time and Window Operations

- Spark allows defining **windows based on** the **time-event** input column
- And then apply aggregation functions over each window

60

Event Time and Window Operations

- For each structured streaming query on which you want to apply a window computation you must
  - Specify the name of the time-event column in the input (streaming) DataFrame
  - The characteristics of the (sliding) windows
    - windowDuration
    - slideDuration
      - Do not set it if you want non-overlapped windows, i.e., if you want to a slideDuration equal to windowDuration
- You can set different window characteristics for each query of your application

Event Time and Window Operations

- The **window(timeColumn, windowDuration, slideDuration=None)** function is used inside the standard **groupBy()** one to specify the characteristics of the windows
- Windows can be used only with queries that are applying aggregation functions

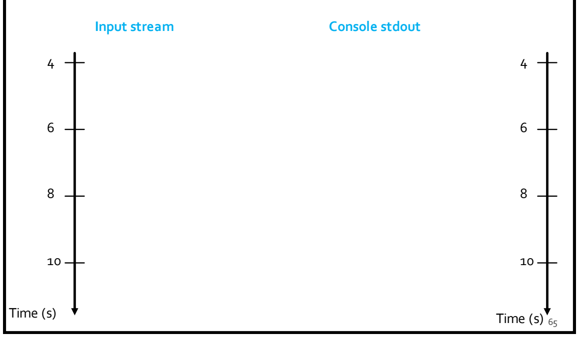
Event Time and Window Operations: Example 3

- Problem specification
  - Input
    - A stream of records retrieved from localhost:9999
    - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
    - Each input reading has the format
      - stationId,# free slots,#used slots,timestamp
    - **timestamp** is the **event-time column**

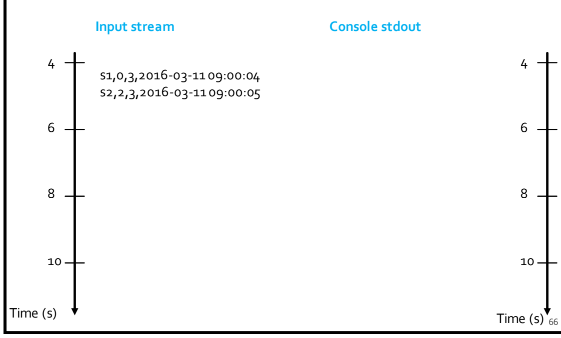
Event Time and Window Operations: Example 3

- Output
  - For each stationId, print on the standard output the total number of received input reading with a number of free slots equal to 0 in each window
  - The query is executed for each window
  - Set windowDuration to 2 seconds and no slideDuration
    - i.e., non-overlapped windows

Event Time and Window Operations: Example 3



Event Time and Window Operations: Example 3



Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1

8

10

Time (s)

Time (s)

67

Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1

The returned result has a column called window.
It contains the time slot associated with the window
[from timestamp, to timestamp)

8

10

Time (s)

Time (s)

68

Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

s1,0,3,2016-03-11 09:00:06
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8

10

Time (s)

Time (s)

69

Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

s1,0,3,2016-03-11 09:00:06
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8

[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s2,1

10

Time (s)

Time (s)

70

Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

s1,0,3,2016-03-11 09:00:06
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8

s1,10,3,2016-03-11 09:00:09

10

Time (s)

Time (s)

71

Event Time and Window Operations: Example 3

Input stream

Console stdout

4

s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6

s1,0,3,2016-03-11 09:00:06
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8

s1,10,3,2016-03-11 09:00:09

10

[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s2,1

Time (s)

Time (s)

72

Event Time and Window Operations: Example 3

```
from pyspark.sql.types import *
from pyspark.sql.functions import split
from pyspark.sql.functions import window

# Create a "receiver" DataFrame that will connect to localhost:9999
recordsDF = spark.readStream\
.format("socket") \
.option("host", "localhost") \
.option("port", 9999) \
.load()
```

73

Event Time and Window Operations: Example 3

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
# New columns:
# - stationId
# - freeslots
# - usedslots
# - timestamp

readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```

74

Event Time and Window Operations: Example 3

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")
```

75

Event Time and Window Operations: Example 3

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for each stationId in each window.
# windowDuration = 2 seconds
# no overlapping windows
countsDF = fullReadingsDF\
.groupBy(window(fullReadingsDF.timestamp, "2 seconds"), "stationId")\
.agg({"*":"count"})\
.sort("window")
```

76

Event Time and Window Operations: Example 3

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for each stationId in each window.
# windowDuration = 2 seconds
# no overlapping windows
countsDF = fullReadingsDF\
.groupBy(window(fullReadingsDF.timestamp, "2 seconds"), "stationId")\
.agg({"*":"count"})\
.sort("window")
```

Specify window characteristics

77

Event Time and Window Operations: Example 3

```
# The result of the structured streaming query will be stored/printed on
# the console "sink"
# complete output mode
# (append mode cannot be used for aggregation queries)
queryCountWindowStreamWriter = countsDF \
.writeStream \
.outputMode("complete") \
.format("console")\
.option("truncate", "false")

# Start the execution of the query (it will be executed until it is explicitly stopped)
queryCountWindow = queryCountWindowStreamWriter.start()
```

78

Late data

- Sparks handles data that have arrived later than expected based on its event-time
  - They are called late data
- Spark has full control over updating old aggregates when there are late data
  - Every time new data are processed the result is computed by combining old aggregate values and the new data by considering the event-time column instead of the time Spark receives the data

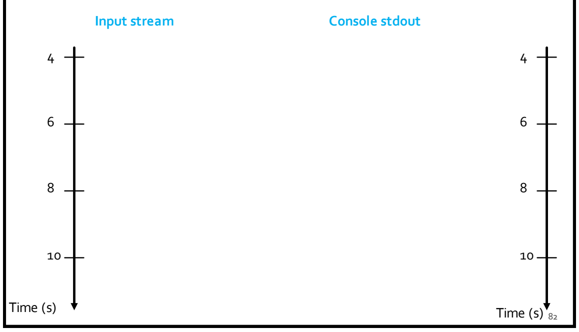
Late data: Running example

- Problem specification
  - Input
    - A stream of records retrieved from localhost:9999
    - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
    - Each input reading has the format
      - stationId,# free slots,#used slots,timestamp
    - timestamp is the event-time column

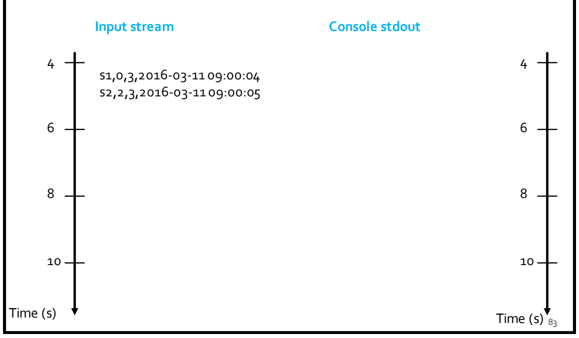
Late data: Running example

- Output
  - For each stationId, print on the standard output the total number of received input reading with a number of free slots equal to 0 in each window
  - The query is executed for each window
  - Set windowDuration to 2 seconds and no slideDuration
    - i.e., non-overlapped windows

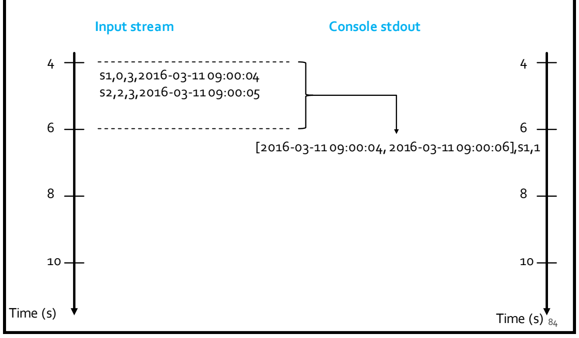
Late data: Running example



Late data: Running example



Late data: Running example



Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8

10

Time (s) | Time (s)

85

Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8
[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s2,1

10

Time (s) | Time (s)

86

Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8
s1,0,3,2016-03-11 09:00:06
s1,10,3,2016-03-11 09:00:09

10

Time (s) | Time (s)

87

Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8
s1,0,3,2016-03-11 09:00:06
s1,10,3,2016-03-11 09:00:09

Late data that was generated at 2016-03-11 09:00:06 but arrived at 2016-03-11 09:00:08

10

Time (s) | Time (s)

88

Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:00:07
s11,12,3,2016-03-11 09:00:06

8
s1,0,3,2016-03-11 09:00:06
s1,10,3,2016-03-11 09:00:09

10
[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s2,1

Time (s) | Time (s)

89

Late data: Running example

Input stream | Console stdout

4
s1,0,3,2016-03-11 09:00:04
s2,2,3,2016-03-11 09:00:05

6
s2,0,3,2016-03-11 09:0
s11,12,3,2016-03-11 09

The result consider also late data and assign them to the right window by considering the event-time information

8
s1,0,3,2016-03-11 09:00:06
s1,10,3,2016-03-11 09:00:09

10
[2016-03-11 09:00:04, 2016-03-11 09:00:06],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s1,1
[2016-03-11 09:00:06, 2016-03-11 09:00:08],s2,1

Time (s) | Time (s)

90

Late data: Running example

- The code is the same of "Event Time and Window Operations: Example 3"
- Late data are automatically handled by Spark

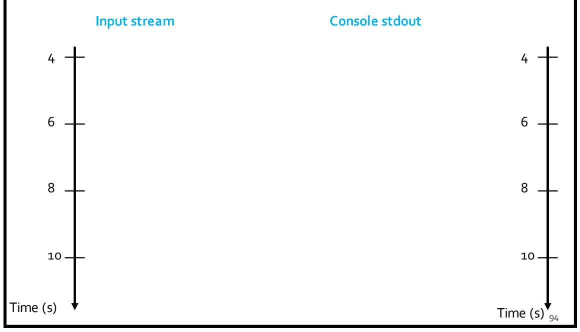
Event Time and Window Operations: Example 4

- Problem specification
  - Input
    - A stream of records retrieved from localhost:9999
    - Each input record is a reading about the status of a station of a bike sharing system in a specific timestamp
    - Each input reading has the format
      - stationId,# free slots,#used slots,timestamp
    - **timestamp** is the **event-time column**

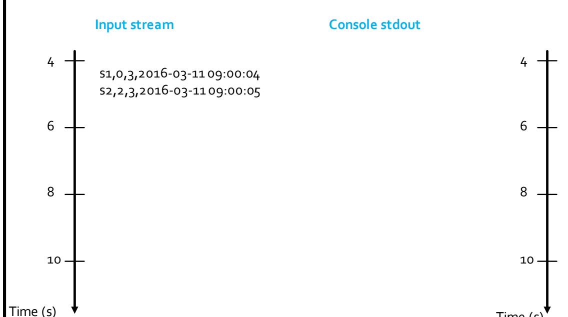
Event Time and Window Operations: Example 4

- Output
  - For each window, print on the standard output the total number of received input reading with a number of free slots equal to 0
  - The query is executed for each window
  - Set windowDuration to 2 seconds and no slideDuration
    - i.e., non-overlapped windows

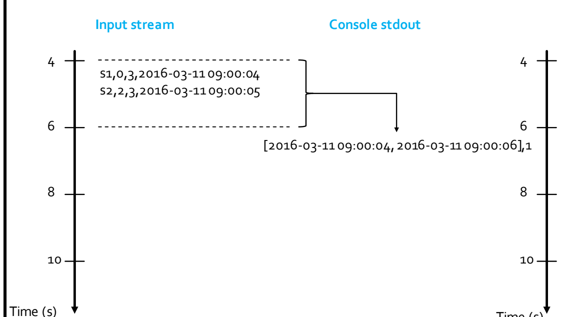
Event Time and Window Operations: Example 4



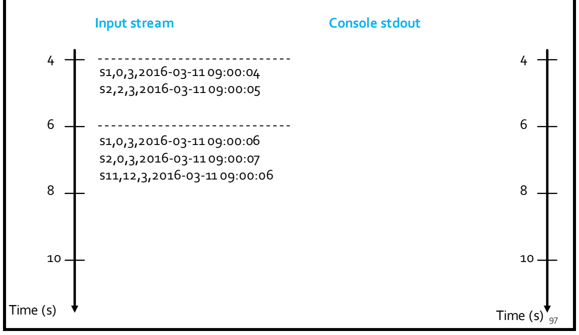
Event Time and Window Operations: Example 4



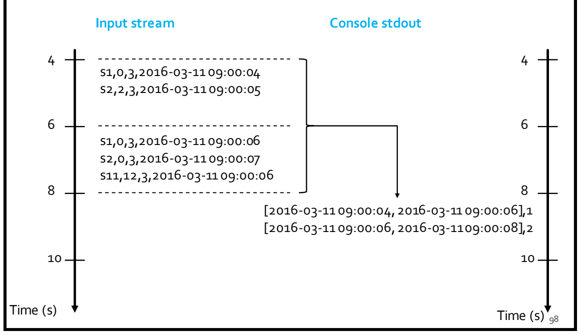
Event Time and Window Operations: Example 4



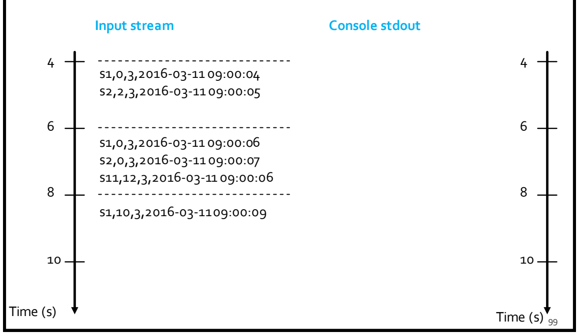
Event Time and Window Operations: Example 4



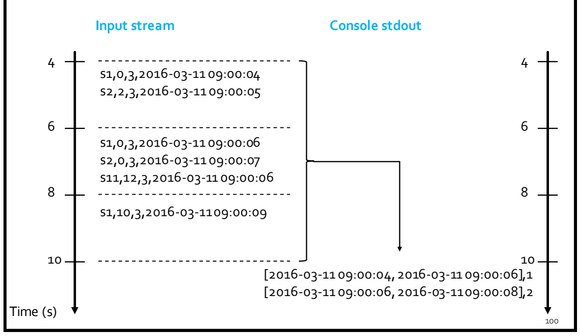
Event Time and Window Operations: Example 4



Event Time and Window Operations: Example 4



Event Time and Window Operations: Example 4



Event Time and Window Operations: Example 4

```
from pyspark.sql.types import *
from pyspark.sql.functions import split
from pyspark.sql.functions import window

# Create a "receiver" DataFrame that will connect to localhost:9999
recordsDF = spark.readStream\
.format("socket") \
.option("host", "localhost") \
.option("port", 9999) \
.load()
```


Event Time and Window Operations: Example 4

```
# The input records are characterized by one single column called value
# of type string
# Example of an input record: s1,0,3,2016-03-11 09:00:04
# Define four more columns by splitting the input column value
# New columns:
# - stationId
# - freeslots
# - usedslots
# - timestamp

readingsDF = recordsDF\
.withColumn("stationId", split(recordsDF.value, ',')[0].cast("string"))\
.withColumn("freeslots", split(recordsDF.value, ',')[1].cast("integer"))\
.withColumn("usedslots", split(recordsDF.value, ',')[2].cast("integer"))\
.withColumn("timestamp", split(recordsDF.value, ',')[3].cast("timestamp"))
```

Event Time and Window Operations: Example 4

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")
```


Event Time and Window Operations: Example 4

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for in each window.
# windowDuration = 2 seconds
# no overlapping windows
countsDF = fullReadingsDF\
.groupBy(window(fullReadingsDF.timestamp, "2 seconds"))\
.agg({"*":"count"})\
.sort("window")
```


Event Time and Window Operations: Example 4

```
# Filter data
# Use the standard filter transformation
fullReadingsDF = readingsDF.filter("freeslots=0")

# Count the number of readings with a number of free slots equal to 0
# for in each window.
# windowDuration = 2 seconds
# no overlapping windows
countsDF = fullReadingsDF\
.groupBy(window(fullReadingsDF.timestamp, "2 seconds"))\
.agg({"*":"count"})\
.sort("window")
```

We define one group for each window

Event Time and Window Operations: Example 4

```
# The result of the structured streaming query will be stored/printed on
# the console "sink"
# complete output mode
# (append mode cannot be used for aggregation queries)
queryCountWindowStreamWriter = countsDF \
.writeStream \
.outputMode("complete") \
.format("console")\
.option("truncate", "false")

# Start the execution of the query (it will be executed until it is explicitly stopped)
queryCountWindow = queryCountWindowStreamWriter.start()
```


Watermarking

Watermarking

- Watermarking is a feature of Spark that allows the user to specify the threshold of late data, and allows the engine to accordingly clean up old state
- Results related to old event-times are not needed in many real streaming applications
  - They can be dropped to improve the efficiency of the application
  - Keeping the state of old results is resource expensive
- Every time new data are processed only recent records are considered

Watermarking

- Specifically, to run windowed queries for days, it is necessary for the system to bound the amount of intermediate in-memory state it accumulates
  - This means the system needs to know when an old aggregate can be dropped from the in-memory state because the application is not going to receive late data for that aggregate any more
- To enable this, in Spark 2.1, watermarking has been introduced

Watermarking

- Watermarking lets the Spark Structured Streaming engine automatically track the current event time in the data and attempt to clean up old state accordingly
- You can define the watermark of a query by specifying the event time column and the threshold on how late the data is expected to be in terms of event time
  - For a specific window ending at time T, the engine will maintain state and allow late data to update the state/the result until

    max event time seen by the engine < T + late threshold
  - In other words, late data within the threshold will be aggregated, but data later than T+threshold will be dropped

Join Operations

Join Operations

- Spark Structured Streaming manages also join operations
  - Between two streaming DataFrames
  - Between a streaming DataFrame and a static DataFrame
- The result of the streaming join is generated incrementally

Join Operations

- Join between two streaming DataFrames
- For both input streams, past input streaming data must be buffered/recorded in order to be able to match every future input record with past input data and accordingly generate joined results
- Too many resources are needed for storing all the input data
- Hence, **old data must be discarded**
  - You must **define watermark thresholds on both input streams** such that the engine knows how delayed the input can be and drop old data

Join Operations

- The methods **join()** and **withWatermark()** are used to join streaming DataFrames
- The join method is similar to the one available for static DataFrame

Join Operations: Example

```
from pyspark.sql.functions import expr
impressions = spark.readStream. ...
clicks = spark.readStream. ...

# Apply watermarks on event-time columns
impressionsWithWatermark = impressions.withWatermark("impressionTime", "2
    hours")

clicksWithWatermark = clicks.withWatermark("clickTime", "3 hours")

# Join with event-time constraints
impressionsWithWatermark.join(
 clicksWithWatermark,
 expr("""
  clickAdId = impressionAdId AND clickTime >= impressionTime AND
  clickTime <= impressionTime + interval 1 hour
  """) )
```

115