Structured Streaming Programming Guide

Overview

Structured Streaming is a scalable and fault-tolerant stream processing engine built on the Spark SQL engine. You can express your streaming computation the same way you would express a batch computation on static data. The Spark SQL engine will take care of running it incrementally and continuously and updating the final result as streaming data continues to arrive. You can use the Dataset/DataFrame API in Scala, Java, Python or R to express streaming aggregations, event-time windows, stream-to-batch joins, etc. The computation is executed on the same optimized Spark SQL engine. Finally, the system ensures end-to-end exactly-once fault-tolerance guarantees through checkpointing and Write-Ahead Logs. In short, *Structured Streaming provides fast, scalable, fault-tolerant, end-to-end exactly-once stream processing without the user having to reason about streaming.*

Internally, by default, Structured Streaming queries are processed using a *micro-batch processing* engine, which processes data streams as a series of small batch jobs thereby achieving end-to-end latencies as low as 100 milliseconds and exactly-once fault-tolerance guarantees. However, since Spark 2.3, we have introduced a new low-latency processing mode called **Continuous Processing**, which can achieve end-to-end latencies as low as 1 millisecond with at-least-once guarantees. Without changing the Dataset/DataFrame operations in your queries, you will be able to choose the mode based on your application requirements.

In this guide, we are going to walk you through the programming model and the APIs. We are going to explain the concepts mostly using the default micro-batch processing model, and then later discuss Continuous Processing model. First, let's start with a simple example of a Structured Streaming query - a streaming word count.

Quick Example

Let's say you want to maintain a running word count of text data received from a data server listening on a TCP socket. Let's see how you can express this using Structured Streaming. You can see the full code in Scala/Java/Python/R. And if you download Spark, you can directly run the example. In any case, let's walk through the example step-by-step and understand how it works. First, we have to import the necessary classes and create a local SparkSession, the starting point of all functionalities related to Spark.

Scala **Java** **Python** **R**

```scala
import org.apache.spark.sql.functions._
import org.apache.spark.sql.SparkSession

val spark = SparkSession
  .builder
  .appName("StructuredNetworkWordCount")
  .getOrCreate()

import spark.implicits._
```

Next, let’s create a streaming DataFrame that represents text data received from a server listening on localhost:9999, and transform the DataFrame to calculate word counts.

Scala Java Python R

```
// Create DataFrame representing the stream of input lines from connection to localhost:9999
val lines = spark.readStream
  .format("socket")
  .option("host", "localhost")
  .option("port", 9999)
  .load()

// Split the lines into words
val words = lines.as[String].flatMap(_.split(" "))

// Generate running word count
val wordCounts = words.groupBy("value").count()
```

This `lines` DataFrame represents an unbounded table containing the streaming text data. This table contains one column of strings named “value”, and each line in the streaming text data becomes a row in the table. Note, that this is not currently receiving any data as we are just setting up the transformation, and have not yet started it. Next, we have converted the DataFrame to a Dataset of String using `.as[String]`, so that we can apply the `flatMap` operation to split each line into multiple words. The resultant `words` Dataset contains all the words. Finally, we have defined the `wordCounts` DataFrame by grouping by the unique values in the Dataset and counting them. Note that this is a streaming DataFrame which represents the running word counts of the stream.

We have now set up the query on the streaming data. All that is left is to actually start receiving data and computing the counts. To do this, we set it up to print the complete set of counts (specified by `outputMode("complete")`) to the console every time they are updated. And then start the streaming computation using `start()`.

Scala Java Python R

```
// Start running the query that prints the running counts to the console
val query = wordCounts.writeStream
  .outputMode("complete")
  .format("console")
  .start()

query.awaitTermination()
```

After this code is executed, the streaming computation will have started in the background. The `query` object is a handle to that active streaming query, and we have decided to wait for the termination of the query using `awaitTermination()` to prevent the process from exiting while the query is active.

To actually execute this example code, you can either compile the code in your own Spark application, or simply run the example once you have downloaded Spark. We are showing the latter. You will first need to run Netcat (a small utility found in most Unix-like systems) as a data server by using

```
$ nc -lk 9999
```

Then, in a different terminal, you can start the example by using

Scala **Java** **Python** **R**

```
$ ./bin/run-example org.apache.spark.examples.sql.streaming.StructuredNetworkWord
Count localhost 9999
```

Then, any lines typed in the terminal running the netcat server will be counted and printed on screen every second. It will look something like the following.

```
# TERMINAL 1:
# Running Netcat

$ nc -lk 9999
apache spark
apache hadoop
```

Scala **Java** **Python** **R**

```
# TERMINAL 2: RUNNING StructuredNetworkWordCount

$ ./bin/run-example org.apache.spark.examples.sql.st
reaming.StructuredNetworkWordCount localhost 9999

-------------------------------------------
Batch: 0
-------------------------------------------
+------+-----+
| value|count|
+------+-----+
|apache|    1|
| spark|    1|
+------+-----+

-------------------------------------------
Batch: 1
-------------------------------------------
+------+-----+
| value|count|
+------+-----+
|apache|    2|
...
```

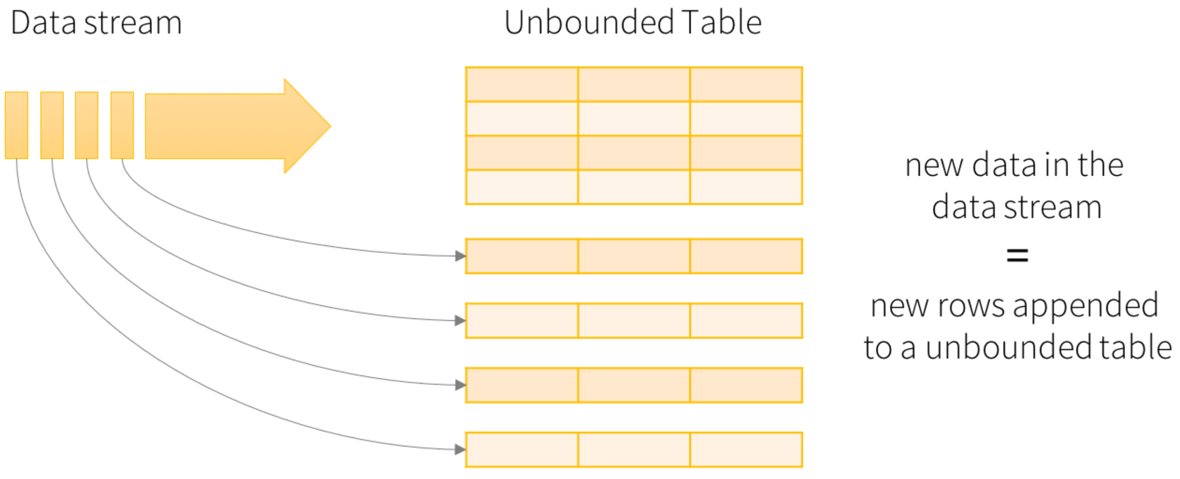
```
| spark|    1|
|hadoop|    1|
+------+-----+
...
```

Programming Model

The key idea in Structured Streaming is to treat a live data stream as a table that is being continuously appended. This leads to a new stream processing model that is very similar to a batch processing model. You will express your streaming computation as standard batch-like query as on a static table, and Spark runs it as an *incremental* query on the *unbounded* input table. Let’s understand this model in more detail.

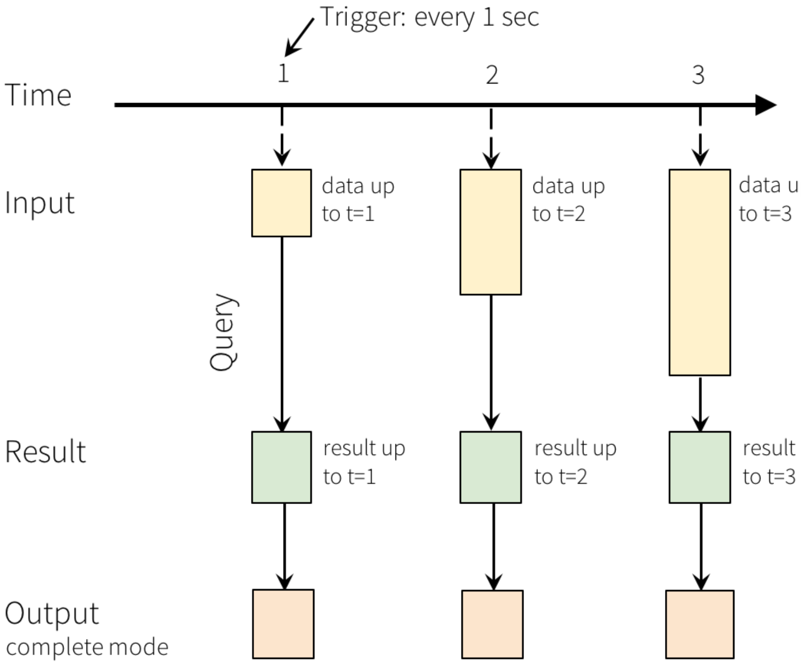
Basic Concepts

Consider the input data stream as the “Input Table”. Every data item that is arriving on the stream is like a new row being appended to the Input Table.


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

Data stream as an unbounded table

A query on the input will generate the “Result Table”. Every trigger interval (say, every 1 second), new rows get appended to the Input Table, which eventually updates the Result Table. Whenever the result table gets updated, we would want to write the changed result rows to an external sink.



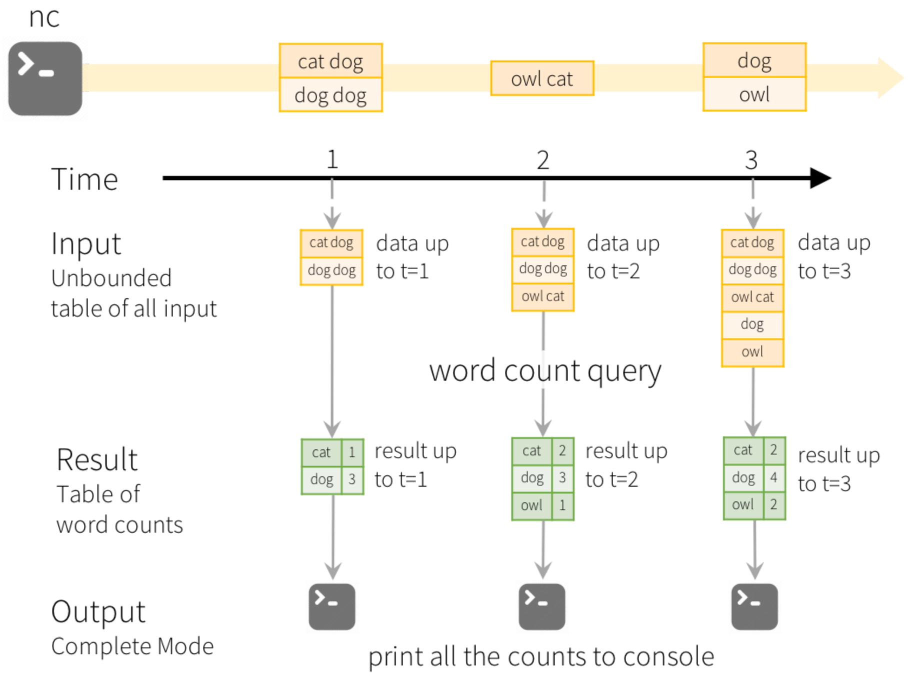
Programming Model for Structured Streaming

The “Output” is defined as what gets written out to the external storage. The output can be defined in a different mode:

- *Complete Mode* - The entire updated Result Table will be written to the external storage. It is up to the storage connector to decide how to handle writing of the entire table.
- *Append Mode* - Only the new rows appended in the Result Table since the last trigger will be written to the external storage. This is applicable only on the queries where existing rows in the Result Table are not expected to change.
- *Update Mode* - Only the rows that were updated in the Result Table since the last trigger will be written to the external storage (available since Spark 2.1.1). Note that this is different from the Complete Mode in that this mode only outputs the rows that have changed since the last trigger. If the query doesn't contain aggregations, it will be equivalent to Append mode.

Note that each mode is applicable on certain types of queries. This is discussed in detail later.

To illustrate the use of this model, let's understand the model in context of the Quick Example above. The first `lines` DataFrame is the input table, and the final `wordCounts` DataFrame is the result table. Note that the query on streaming `lines` DataFrame to generate `wordCounts` is *exactly the same* as it would be a static DataFrame. However, when this query is started, Spark will continuously check for new data from the socket connection. If there is new data, Spark will run an "incremental" query that combines the previous running counts with the new data to compute updated counts, as shown below.



Model of the Quick Example

Note that Structured Streaming does not materialize the entire table. It reads the latest available data from the streaming data source, processes it incrementally to update the result, and then discards the source data. It only keeps around the minimal intermediate *state* data as required to update the result (e.g. intermediate counts in the earlier example).

This model is significantly different from many other stream processing engines. Many streaming systems require the user to maintain running aggregations themselves, thus having to reason about fault-tolerance, and data consistency (at-least-once, or at-most-once, or exactly-once). In this model, Spark is responsible for updating the Result Table when there is new data, thus relieving the users from reasoning about it. As an example, let's see how this model handles event-time based processing and late arriving data.

Handling Event-time and Late Data

Event-time is the time embedded in the data itself. For many applications, you may want to operate on this event-time. For example, if you want to get the number of events generated by IoT devices every minute, then you probably want to use the time when the data was generated (that is, event-time in the data), rather than the time Spark receives them. This event-time is very naturally expressed in this model – each event from the devices is a row in the table, and event-time is a column value in the row. This allows window-based aggregations (e.g. number of events every minute) to be just a special type of grouping and aggregation on the event-time column – each time window is a group and each row can belong to multiple windows/groups. Therefore, such event-time-window-based aggregation queries can be defined consistently on both a static dataset (e.g. from collected device events logs) as well as on a data stream, making the life of the user much easier.

Furthermore, this model naturally handles data that has arrived later than expected based on its event-time. Since Spark is updating the Result Table, it has full control over updating old aggregates when there is late data, as well as cleaning up old aggregates to limit the size of intermediate state data. Since Spark 2.1, we have support for watermarking which allows the user to specify the threshold of late data, and allows the engine to accordingly clean up old state. These are explained later in more detail in the Window Operations section.

Fault Tolerance Semantics

Delivering end-to-end exactly-once semantics was one of key goals behind the design of Structured Streaming. To achieve that, we have designed the Structured Streaming sources, the sinks and the execution engine to reliably track the exact progress of the processing so that it can handle any kind of failure by restarting and/or reprocessing. Every streaming source is assumed to have offsets (similar to Kafka offsets, or Kinesis sequence numbers) to track the read position in the stream. The engine uses checkpointing and write-ahead logs to record the offset range of the data being processed in each trigger. The streaming sinks are designed to be idempotent for handling reprocessing. Together, using replayable sources and idempotent sinks, Structured Streaming can ensure **end-to-end exactly-once semantics** under any failure.

API using Datasets and DataFrames

Since Spark 2.0, DataFrames and Datasets can represent static, bounded data, as well as streaming, unbounded data. Similar to static Datasets/DataFrames, you can use the common entry point `SparkSession` (Scala/Java/Python/R docs) to create streaming DataFrames/Datasets from streaming sources, and apply the same operations on them as static DataFrames/Datasets. If you are not familiar with Datasets/DataFrames, you are strongly advised to familiarize yourself with them using the DataFrame/Dataset Programming Guide.

Creating streaming DataFrames and streaming Datasets

Streaming DataFrames can be created through the `DataStreamReader` interface (Scala/Java/Python docs) returned by `SparkSession.readStream()`. In R, with the `read.stream()` method. Similar to the read interface for creating static DataFrame, you can specify the details of the source – data format, schema, options, etc.

Input Sources

There are a few built-in sources.

- **File source** - Reads files written in a directory as a stream of data. Files will be processed in the order of file modification time. If `latestFirst` is set, order will be reversed. Supported file formats are text, CSV, JSON, ORC, Parquet. See the docs of the DataStreamReader interface for a more up-to-date list, and supported options for each file format. Note that the files must be atomically placed in the given directory, which in most file systems, can be achieved by file move operations.
- **Kafka source** - Reads data from Kafka. It's compatible with Kafka broker versions 0.10.0 or higher. See the Kafka Integration Guide for more details.
- **Socket source (for testing)** - Reads UTF8 text data from a socket connection. The listening server socket is at the driver. Note that this should be used only for testing as this does not provide end-to-end fault-tolerance guarantees.
- **Rate source (for testing)** - Generates data at the specified number of rows per second, each output row contains a `timestamp` and `value`. Where `timestamp` is a `Timestamp` type containing the time of message dispatch, and `value` is of `Long` type containing the message count, starting from 0 as the first row. This source is intended for testing and benchmarking.

Some sources are not fault-tolerant because they do not guarantee that data can be replayed using checkpointed offsets after a failure. See the earlier section on fault-tolerance semantics. Here are the details of all the sources in Spark.

Source	Options	Fault-tolerant	Notes
File source	`path`: path to the input directory, and common to all file formats. `maxFilesPerTrigger`: maximum number of new files to be considered in every trigger (default: no max) `latestFirst`: whether to process the latest new files first, useful when there is a large backlog of files (default: false) `fileNameOnly`: whether to check new files based on only the filename instead of on the full path (default: false). With this set to \`true\`, the following files would be considered as the same file, because their filenames, "dataset.txt", are the same: "file:///dataset.txt" "s3://a/dataset.txt" "s3n://a/b/dataset.txt" "s3a://a/b/c/dataset.txt" `maxFileAge`: Maximum age of a file that can be found in this directory, before it is ignored. For the first batch all files will be considered valid. If `latestFirst` is set to \`true\` and `maxFilesPerTrigger` is set, then this parameter will be ignored, because old files that are valid, and should be processed, may be ignored. The max age is specified with respect	Yes	Supports glob paths, but does not support multiple comma-separated paths/globs.

	to the timestamp of the latest file, and not the timestamp of the current system.(default: 1 week) `cleanSource`: option to clean up completed files after processing. Available options are "archive", "delete", "off". If the option is not provided, the default value is "off". When "archive" is provided, additional option `sourceArchiveDir` must be provided as well. The value of "sourceArchiveDir" must not match with source pattern in depth (the number of directories from the root directory), where the depth is minimum of depth on both paths. This will ensure archived files are never included as new source files. For example, suppose you provide '/hello?/spark/*' as source pattern, '/hello1/spark/archive/dir' cannot be used as the value of "sourceArchiveDir", as '/hello?/spark/*' and '/hello1/spark/archive' will be matched. '/hello1/spark' cannot be also used as the value of "sourceArchiveDir", as '/hello?/spark' and '/hello1/spark' will be matched. '/archived/here' would be OK as it doesn't match. Spark will move source files respecting their own path. For example, if the path of source file is `/a/b/dataset.txt` and the path of archive directory is `/archived/here`, file will be moved to `/archived/here/a/b/dataset.txt`. NOTE: Both archiving (via moving) or deleting completed files will introduce overhead (slow down, even if it's happening in separate thread) in each micro-batch, so you need to understand the cost for each operation in your file system before enabling this option. On the other hand, enabling this option will reduce the cost to list source files which can be an expensive operation. Number of threads used in completed file cleaner can be configured with`spark.sql.streaming.fileSource.cleaner.numThreads` (default: 1). NOTE 2: The source path should not be used from multiple sources or queries when enabling this option. Similarly, you must ensure the source path doesn't match to any files in output directory of file stream sink. NOTE 3: Both delete and move actions are best effort. Failing to delete or move files will not fail the streaming query. Spark may not clean up some source files in some circumstances - e.g. the application doesn't shut down gracefully, too many files are queued to clean up. For file-format-specific options, see the related methods in `DataStreamReader` (Scala/Java/Python/R). E.g. for "parquet" format options see `DataStreamReader.parquet()`. In addition, there are session configurations that affect certain file-formats. See the SQL Programming Guide for more details. E.g., for "parquet", see Parquet configuration section.		
Socket	`host`: host to connect to, must be specified	No	

Source	`port`: port to connect to, must be specified		
Rate Source	`rowsPerSecond` (e.g. 100, default: 1): How many rows should be generated per second. `rampUpTime` (e.g. 5s, default: 0s): How long to ramp up before the generating speed becomes `rowsPerSecond`. Using finer granularities than seconds will be truncated to integer seconds. `numPartitions` (e.g. 10, default: Spark's default parallelism): The partition number for the generated rows. The source will try its best to reach `rowsPerSecond`, but the query may be resource constrained, and `numPartitions` can be tweaked to help reach the desired speed.	Yes	
Kafka Source	See the Kafka Integration Guide.	Yes	

Here are some examples.

Scala **Java** **Python** **R**

```
val spark: SparkSession = ...

// Read text from socket
val socketDF = spark
  .readStream
  .format("socket")
  .option("host", "localhost")
  .option("port", 9999)
  .load()

socketDF.isStreaming    // Returns True for DataFrames that have streaming sources

socketDF.printSchema

// Read all the csv files written atomically in a directory
val userSchema = new StructType().add("name", "string").add("age", "integer")
val csvDF = spark
  .readStream
  .option("sep", ";")
  .schema(userSchema)      // Specify schema of the csv files
  .csv("/path/to/directory")    // Equivalent to format("csv").load("/path/to/dir
ectory")
```

These examples generate streaming DataFrames that are untyped, meaning that the schema of the DataFrame is not checked at compile time, only checked at runtime when the query is submitted. Some operations like `map`, `flatMap`, etc. need the type to be known at compile time. To do those, you can convert these untyped streaming DataFrames to typed streaming Datasets using the same methods as static DataFrame. See the SQL Programming Guide for more details. Additionally, more details on the supported streaming sources are discussed later in the document.

Schema inference and partition of streaming DataFrames/Datasets

By default, Structured Streaming from file based sources requires you to specify the schema, rather than rely on Spark to infer it automatically. This restriction ensures a consistent schema will be used for the streaming query, even in the case of failures. For ad-hoc use cases, you can reenable schema inference by setting `spark.sql.streaming.schemaInference` to `true`.

Partition discovery does occur when subdirectories that are named `/key=value/` are present and listing will automatically recurse into these directories. If these columns appear in the user-provided schema, they will be filled in by Spark based on the path of the file being read. The directories that make up the partitioning scheme must be present when the query starts and must remain static. For example, it is okay to add `/data/year=2016/` when `/data/year=2015/` was present, but it is invalid to change the partitioning column (i.e. by creating the directory `/data/date=2016-04-17/`).

Operations on streaming DataFrames/Datasets

You can apply all kinds of operations on streaming DataFrames/Datasets – ranging from untyped, SQL-like operations (e.g. `select`, `where`, `groupBy`), to typed RDD-like operations (e.g. `map`, `filter`, `flatMap`). See the SQL programming guide for more details. Let’s take a look at a few example operations that you can use.

Basic Operations - Selection, Projection, Aggregation

Most of the common operations on DataFrame/Dataset are supported for streaming. The few operations that are not supported are discussed later in this section.

Scala **Java** **Python** **R**

```
case class DeviceData(device: String, deviceType: String, signal: Double, time: D
ateTime)

val df: DataFrame = ... // streaming DataFrame with IOT device data with schema {
device: string, deviceType: string, signal: double, time: string }
val ds: Dataset[DeviceData] = df.as[DeviceData]    // streaming Dataset with IOT
```

```
 device data

// Select the devices which have signal more than 10
df.select("device").where("signal > 10")      // using untyped APIs
ds.filter(_.signal > 10).map(_.device)         // using typed APIs

// Running count of the number of updates for each device type
df.groupBy("deviceType").count()                          // using untyped API

// Running average signal for each device type
import org.apache.spark.sql.expressions.scalalang.typed
ds.groupByKey(_.deviceType).agg(typed.avg(_.signal))    // using typed API
```

You can also register a streaming DataFrame/Dataset as a temporary view and then apply SQL commands on it.

Scala Java Python R

```
df.createOrReplaceTempView("updates")
spark.sql("select count(*) from updates")  // returns another streaming DF
```

Note, you can identify whether a DataFrame/Dataset has streaming data or not by using `df.isStreaming`.

Scala Java Python R

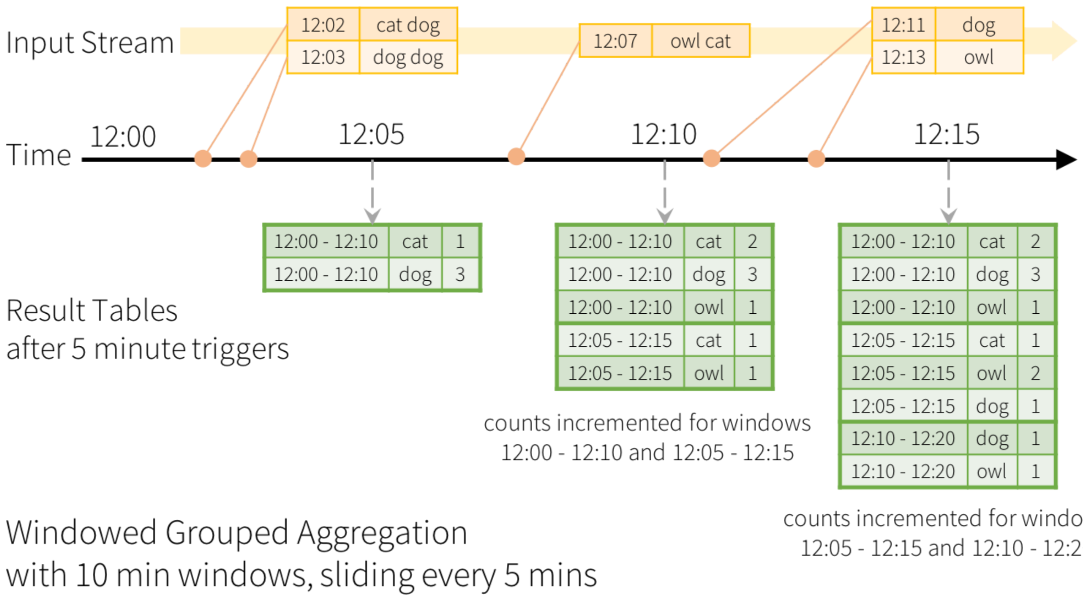
```
df.isStreaming
```

Window Operations on Event Time

Aggregations over a sliding event-time window are straightforward with Structured Streaming and are very similar to grouped aggregations. In a grouped aggregation, aggregate values (e.g. counts) are maintained for each unique value in the user-specified grouping column. In case of window-based aggregations, aggregate values are maintained for each window the event-time of a row falls into. Let's understand this with an illustration.

Imagine our quick example is modified and the stream now contains lines along with the time when the line was generated. Instead of running word counts, we want to count words within 10 minute windows, updating every 5 minutes. That is, word counts in words received between 10 minute windows 12:00 - 12:10, 12:05 - 12:15, 12:10 - 12:20, etc. Note that 12:00 - 12:10 means data that arrived after 12:00 but before 12:10. Now, consider a word that was received at 12:07. This word should increment the counts corresponding to two windows 12:00 - 12:10 and 12:05 - 12:15. So the counts will be indexed by both, the grouping key (i.e. the word) and the window (can be calculated from the event-time).

The result tables would look something like the following.


Input Stream
12:02
cat dog
12:03
dog dog
12:07
owl cat
12:11
dog
12:13
owl
Time
12:00
12:05
12:10
12:15
Result Tables
after 5 minute triggers
counts incremented for windows
12:00 - 12:10 and 12:05 - 12:15
counts incremented for windows
12:05 - 12:15 and 12:10 - 12:20
Windowed Grouped Aggregation
with 10 min windows, sliding every 5 mins

12:00 - 12:10	cat	1
12:00 - 12:10	dog	3

12:00 - 12:10	cat	2
12:00 - 12:10	dog	3
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	1

12:00 - 12:10	cat	2
12:00 - 12:10	dog	3
12:00 - 12:10	owl	1
12:05 - 12:15	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	1
12:10 - 12:20	dog	1
12:10 - 12:20	owl	1

Since this windowing is similar to grouping, in code, you can use `groupBy()` and `window()` operations to express windowed aggregations. You can see the full code for the below examples in Scala/Java/Python.

Scala **Java** **Python** **R**

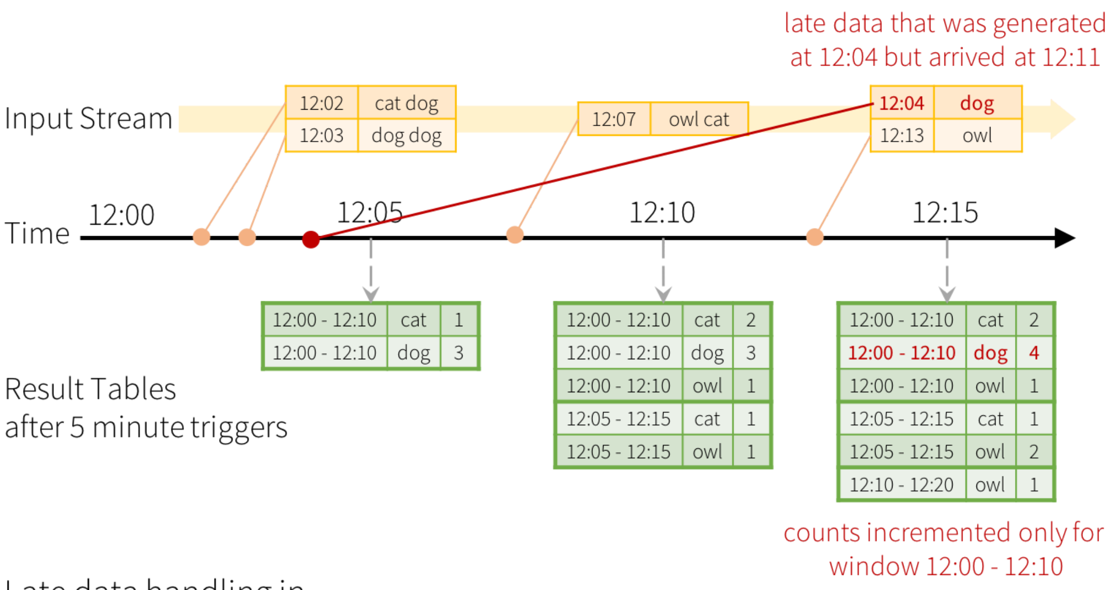
```
import spark.implicits._

val words = ... // streaming DataFrame of schema { timestamp: Timestamp, word: St
ring }

// Group the data by window and word and compute the count of each group
val windowedCounts = words.groupBy(
  window($"timestamp", "10 minutes", "5 minutes"),
  $"word"
).count()
```

Handling Late Data and Watermarking

Now consider what happens if one of the events arrives late to the application. For example, say, a word generated at 12:04 (i.e. event time) could be received by the application at 12:11. The application should use the time 12:04 instead of 12:11 to update the older counts for the window `12:00 - 12:10`. This occurs naturally in our window-based grouping – Structured Streaming can maintain the intermediate state for partial aggregates for a long period of time such that late data can update aggregates of old windows correctly, as illustrated below.



Late data handling in
Windowed Grouped Aggregation

However, to run this query for days, it’s 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, we have introduced **watermarking**, which lets the 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 until `(max event time seen by the engine - late threshold > T)`. In other words, late data within the threshold will be aggregated, but data later than the threshold will start getting dropped (see later in the section for the exact guarantees). Let’s understand this with an example. We can easily define watermarking on the previous example using `withWatermark()` as shown below.

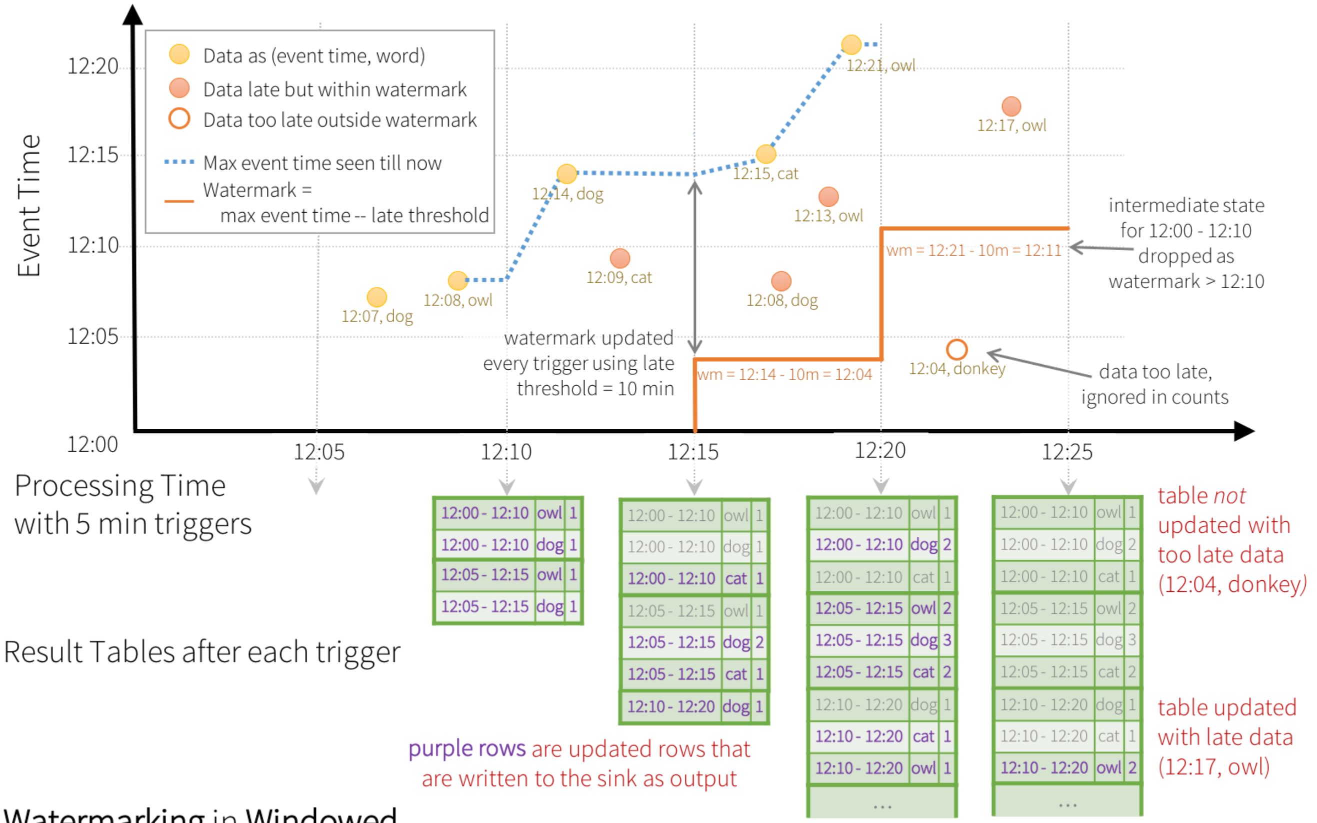
Scala **Java** **Python** **R**

```scala
import spark.implicits._

val words = ... // streaming DataFrame of schema { timestamp: Timestamp, word: String }

// Group the data by window and word and compute the count of each group
val windowedCounts = words
    .withWatermark("timestamp", "10 minutes")
    .groupBy(
        window($"timestamp", "10 minutes", "5 minutes"),
        $"word")
    .count()
```

In this example, we are defining the watermark of the query on the value of the column “timestamp”, and also defining “10 minutes” as the threshold of how late is the data allowed to be. If this query is run in Update output mode (discussed later in Output Modes section), the engine will keep updating counts of a window in the Result Table until the window is older than the watermark, which lags behind the current event time in column “timestamp” by 10 minutes. Here is an illustration.



12:00 - 12:10	owl	1
12:00 - 12:10	dog	1
12:05 - 12:15	owl	1
12:05 - 12:15	dog	1

12:00 - 12:10	owl	1
12:00 - 12:10	dog	1
12:00 - 12:10	cat	1
12:05 - 12:15	owl	1
12:05 - 12:15	dog	2
12:05 - 12:15	cat	1
12:10 - 12:20	dog	1

12:00 - 12:10	owl	1
12:00 - 12:10	dog	2
12:00 - 12:10	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	3
12:05 - 12:15	cat	2
12:10 - 12:20	dog	1
12:10 - 12:20	cat	1
12:10 - 12:20	owl	1
...		

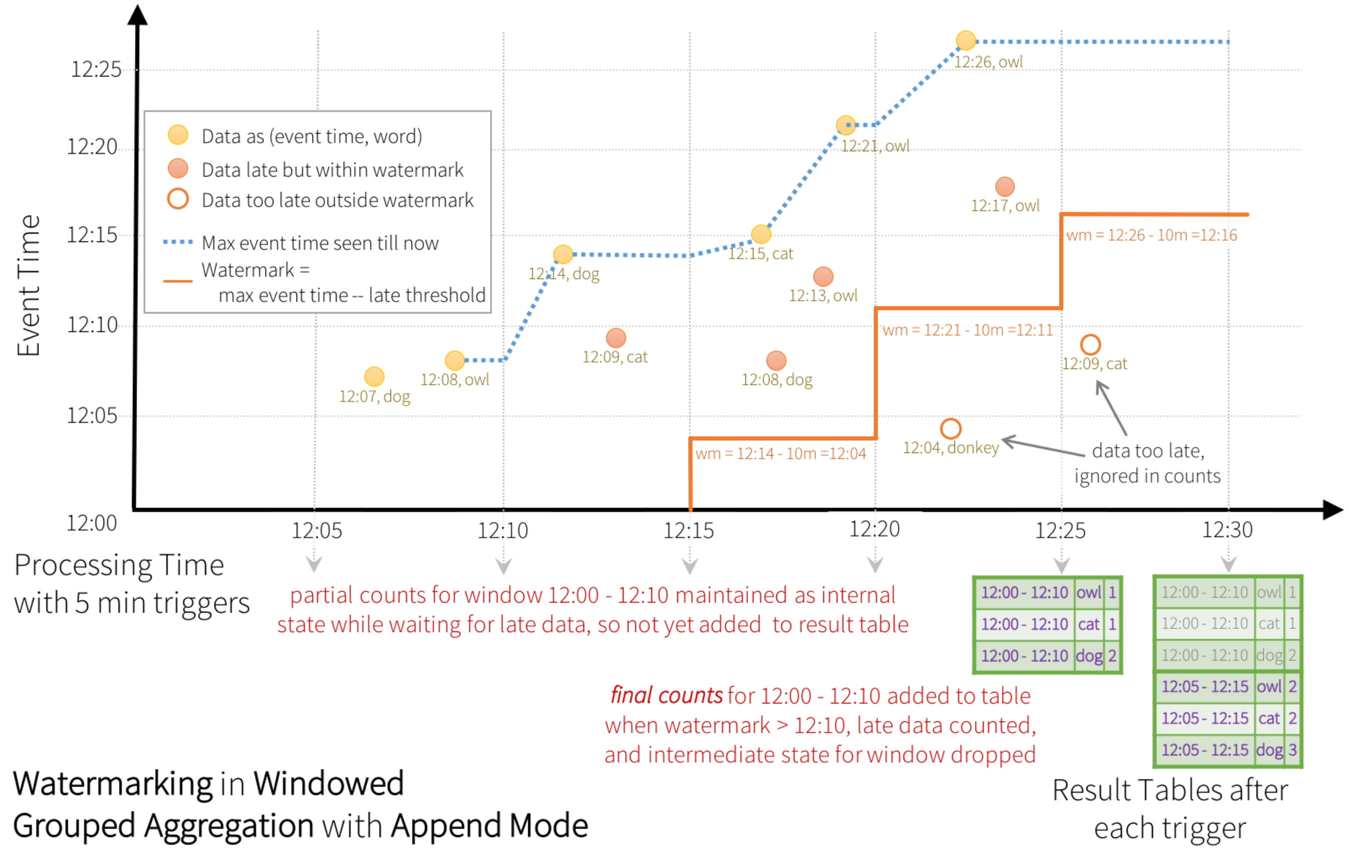
12:00 - 12:10	owl	1
12:00 - 12:10	dog	2
12:00 - 12:10	cat	1
12:05 - 12:15	owl	2
12:05 - 12:15	dog	3
12:05 - 12:15	cat	2
12:10 - 12:20	dog	1
12:10 - 12:20	cat	1
12:10 - 12:20	owl	2
...		

Watermarking in Windowed
Grouped Aggregation with Update Mode

As shown in the illustration, the maximum event time tracked by the engine is the *blue dashed line*, and the watermark set as `(max event time - '10 mins')` at the beginning of every trigger is the red line. For example, when the engine observes the data `(12:14, dog)`, it sets the watermark for the next trigger as `12:04`. This watermark lets the engine maintain intermediate state for additional 10 minutes to allow late data to be counted. For example, the data `(12:09, cat)` is out of order and late, and it falls in windows `12:00 - 12:10` and `12:05 - 12:15`. Since, it is still ahead of the watermark `12:04` in the trigger, the engine still maintains the intermediate counts as state and correctly updates the counts of the related windows. However, when the watermark is updated to `12:11`, the intermediate state for window `(12:00 - 12:10)` is cleared, and all subsequent data (e.g. `(12:04, donkey)`) is considered “too late” and therefore ignored. Note that after every trigger, the updated counts (i.e. purple rows) are written to sink as the trigger output, as dictated by the Update mode.

Some sinks (e.g. files) may not supported fine-grained updates that Update Mode requires. To work with them, we have also support Append Mode, where only the *final counts* are written to sink. This is illustrated below.

Note that using `withWatermark` on a non-streaming Dataset is no-op. As the watermark should not affect any batch query in any way, we will ignore it directly.


Event Time
12:25
12:20
12:15
12:10
12:05
12:00
Data as (event time, word)
Data late but within watermark
Data too late outside watermark
Max event time seen till now
Watermark =
max event time -- late threshold
12:07, dog
12:08, owl
12:14, dog
12:09, cat
12:15, cat
12:13, owl
12:08, dog
12:21, owl
12:04, donkey
12:26, owl
12:17, owl
12:09, cat
wm = 12:14 - 10m =12:04
wm = 12:21 - 10m =12:11
wm = 12:26 - 10m =12:16
data too late,
ignored in counts
12:05
12:10
12:15
12:20
12:25
12:30
Processing Time
with 5 min triggers
partial counts for window 12:00 - 12:10 maintained as internal
state while waiting for late data, so not yet added to result table
final counts for 12:00 - 12:10 added to table
when watermark > 12:10, late data counted,
and intermediate state for window dropped
Result Tables after
each trigger

12:00 - 12:10	owl	1
12:00 - 12:10	cat	1
12:00 - 12:10	dog	2

12:00 - 12:10	owl	1
12:00 - 12:10	cat	1
12:00 - 12:10	dog	2
12:05 - 12:15	owl	2
12:05 - 12:15	cat	2
12:05 - 12:15	dog	3

Watermarking in Windowed
Grouped Aggregation with Append Mode

Similar to the Update Mode earlier, the engine maintains intermediate counts for each window. However, the partial counts are not updated to the Result Table and not written to sink. The engine waits for “10 mins” for late date to be counted, then drops intermediate state of a window < watermark, and appends the final counts to the Result Table/sink. For example, the final counts of window `12:00 - 12:10` is appended to the Result Table only after the watermark is updated to `12:11`.

Conditions for watermarking to clean aggregation state

It is important to note that the following conditions must be satisfied for the watermarking to clean the state in aggregation queries *(as of Spark 2.1.1, subject to change in the future)*.

- **Output mode must be Append or Update.** Complete mode requires all aggregate data to be preserved, and hence cannot use watermarking to drop intermediate state. See the Output Modes section for detailed explanation of the semantics of each output mode.
- The aggregation must have either the event-time column, or a `window` on the event-time column.
- `withWatermark` must be called on the same column as the timestamp column used in the aggregate. For example, `df.withWatermark("time", "1 min").groupBy("time2").count()` is invalid in Append output mode, as watermark is defined on a different column from the aggregation column.
- `withWatermark` must be called before the aggregation for the watermark details to be used. For example, `df.groupBy("time").count().withWatermark("time", "1 min")` is invalid in Append output mode.

Semantic Guarantees of Aggregation with Watermarking

- A watermark delay (set with `withWatermark`) of “2 hours” guarantees that the engine will never drop any data that is less than 2 hours delayed. In other words, any data less than 2 hours behind (in terms of event-time) the latest data processed till then is guaranteed to be aggregated.
- However, the guarantee is strict only in one direction. Data delayed by more than 2 hours is not guaranteed to be dropped; it may or may not get aggregated. More delayed is the data, less likely is the engine going to process it.

Join Operations

Structured Streaming supports joining a streaming Dataset/DataFrame with a static Dataset/DataFrame as well as another streaming Dataset/DataFrame. The result of the streaming join is generated incrementally, similar to the results of streaming aggregations in the previous section. In this section we will explore what type of joins (i.e. inner, outer, etc.) are supported in the above cases. Note that in all the supported join types, the result of the join with a streaming Dataset/DataFrame will be the exactly the same as if it was with a static Dataset/DataFrame containing the same data in the stream.

Stream-static Joins

Since the introduction in Spark 2.0, Structured Streaming has supported joins (inner join and some type of outer joins) between a streaming and a static DataFrame/Dataset. Here is a simple example.

Scala **Java** **Python** **R**

```
val staticDf = spark.read. ...
val streamingDf = spark.readStream. ...

streamingDf.join(staticDf, "type")          // inner equi-join with a static DF
streamingDf.join(staticDf, "type", "right_join")  // right outer join with a static DF
```

Note that stream-static joins are not stateful, so no state management is necessary. However, a few types of stream-static outer joins are not yet supported. These are listed at the end of this Join section.

Stream-stream Joins

In Spark 2.3, we have added support for stream-stream joins, that is, you can join two streaming Datasets/DataFrames. The challenge of generating join results between two data streams is that, at any point of time, the view of the dataset is incomplete for both sides of the join making it much harder to find matches between inputs. Any row received from one input stream can match with any future, yet-to-be-received row from the other input stream. Hence, for both the input streams, we buffer past input as streaming state, so that we can match every future input with past input and accordingly generate joined results. Furthermore, similar to streaming aggregations, we automatically handle late, out-of-order data and can limit the state using watermarks. Let’s discuss the different types of supported stream-stream joins and how to use them.

Inner Joins with optional Watermarking

Inner joins on any kind of columns along with any kind of join conditions are supported. However, as the stream runs, the size of streaming state will keep growing indefinitely as *all* past input must be saved as any new input can match with any input from the past. To avoid unbounded state, you have to define additional join conditions such that indefinitely old inputs cannot match with future inputs and therefore can be cleared from the state. In other words, you will have to do the following additional steps in the join.

1. Define watermark delays on both inputs such that the engine knows how delayed the input can be (similar to streaming aggregations)
2. Define a constraint on event-time across the two inputs such that the engine can figure out when old rows of one input is not going to be required (i.e. will not satisfy the time constraint) for matches with the other input. This constraint can be defined in one of the two ways.
    1. Time range join conditions (e.g. `...JOIN ON leftTime BETWEEN rightTime AND rightTime + INTERVAL 1 HOUR`),
    2. Join on event-time windows (e.g. `...JOIN ON leftTimeWindow = rightTimeWindow`).

Let's understand this with an example.

Let's say we want to join a stream of advertisement impressions (when an ad was shown) with another stream of user clicks on advertisements to correlate when impressions led to monetizable clicks. To allow the state cleanup in this stream-stream join, you will have to specify the watermarking delays and the time constraints as follows.

1. Watermark delays: Say, the impressions and the corresponding clicks can be late/out-of-order in event-time by at most 2 and 3 hours, respectively.
2. Event-time range condition: Say, a click can occur within a time range of 0 seconds to 1 hour after the corresponding impression.

The code would look like this.

Scala **Java** **Python** **R**

```
import org.apache.spark.sql.functions.expr

val impressions = spark.readStream. ...
val clicks = spark.readStream. ...

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

Semantic Guarantees of Stream-stream Inner Joins with Watermarking

This is similar to the guarantees provided by watermarking on aggregations. A watermark delay of “2 hours” guarantees that the engine will never drop any data that is less than 2 hours delayed. But data delayed by more than 2 hours may or may not get processed.

Outer Joins with Watermarking

While the watermark + event-time constraints is optional for inner joins, for left and right outer joins they must be specified. This is because for generating the NULL results in outer join, the engine must know when an input row is not going to match with anything in future. Hence, the watermark + event-time constraints must be specified for generating correct results. Therefore, a query with outer-join will look quite like the ad-monetization example earlier, except that there will be an additional parameter specifying it to be an outer-join.

Scala Java Python R

```
impressionsWithWatermark.join(
  clicksWithWatermark,
  expr("""
    clickAdId = impressionAdId AND
    clickTime >= impressionTime AND
    clickTime <= impressionTime + interval 1 hour
    """),
  joinType = "leftOuter"      // can be "inner", "leftOuter", "rightOuter"
 )
```

Semantic Guarantees of Stream-stream Outer Joins with Watermarking

Outer joins have the same guarantees as inner joins regarding watermark delays and whether data will be dropped or not.

Caveats

There are a few important characteristics to note regarding how the outer results are generated.

- *The outer NULL results will be generated with a delay that depends on the specified watermark delay and the time range condition.* This is because the engine has to wait for that long to ensure there were no matches and there will be no more matches in future.
- In the current implementation in the micro-batch engine, watermarks are advanced at the end of a micro-batch, and the next micro-batch uses the updated watermark to clean up state and output outer results. Since we trigger a micro-batch only when there is new data to be processed, the generation of the outer

result may get delayed if there no new data being received in the stream. *In short, if any of the two input streams being joined does not receive data for a while, the outer (both cases, left or right) output may get delayed.*

Support matrix for joins in streaming queries

Left Input	**Right Input**	**Join Type**	
Static	Static	All types	Supported, since its not on streaming data even though it can be present in a streaming query
Stream	Static	Inner	Supported, not stateful
		Left Outer	Supported, not stateful
		Right Outer	Not supported
		Full Outer	Not supported
Static	Stream	Inner	Supported, not stateful
		Left Outer	Not supported
		Right Outer	Supported, not stateful
		Full Outer	Not supported
Stream	Stream	Inner	Supported, optionally specify watermark on both sides + time constraints for state cleanup
		Left Outer	Conditionally supported, must specify watermark on right + time constraints for correct results, optionally specify watermark on left for all state cleanup
		Right Outer	Conditionally supported, must specify watermark on left + time constraints for correct results, optionally specify watermark on right for all state cleanup
		Full Outer	Not supported

Additional details on supported joins:

- Joins can be cascaded, that is, you can do `df1.join(df2, ...).join(df3, ...).join(df4, ....)`.

- As of Spark 2.4, you can use joins only when the query is in Append output mode. Other output modes are not yet supported.
- As of Spark 2.4, you cannot use other non-map-like operations before joins. Here are a few examples of what cannot be used.
  - Cannot use streaming aggregations before joins.
  - Cannot use mapGroupsWithState and flatMapGroupsWithState in Update mode before joins.

Streaming Deduplication

You can deduplicate records in data streams using a unique identifier in the events. This is exactly same as deduplication on static using a unique identifier column. The query will store the necessary amount of data from previous records such that it can filter duplicate records. Similar to aggregations, you can use deduplication with or without watermarking.

- *With watermark* - If there is an upper bound on how late a duplicate record may arrive, then you can define a watermark on an event time column and deduplicate using both the guid and the event time columns. The query will use the watermark to remove old state data from past records that are not expected to get any duplicates any more. This bounds the amount of the state the query has to maintain.
- *Without watermark* - Since there are no bounds on when a duplicate record may arrive, the query stores the data from all the past records as state.

Scala **Java** **Python** **R**

```scala
val streamingDf = spark.readStream. ...  // columns: guid, eventTime, ...

// Without watermark using guid column
streamingDf.dropDuplicates("guid")

// With watermark using guid and eventTime columns
streamingDf
  .withWatermark("eventTime", "10 seconds")
  .dropDuplicates("guid", "eventTime")
```

Policy for handling multiple watermarks

A streaming query can have multiple input streams that are unioned or joined together. Each of the input streams can have a different threshold of late data that needs to be tolerated for stateful operations. You specify these thresholds using `withWatermarks("eventTime", delay)` on each of the input streams. For example, consider a query with stream-stream joins between `inputStream1` and `inputStream2`.

Scala

```
inputStream1.withWatermark("eventTime1", "1 hour")
  .join(
    inputStream2.withWatermark("eventTime2", "2 hours"),
    joinCondition)
```

While executing the query, Structured Streaming individually tracks the maximum event time seen in each input stream, calculates watermarks based on the corresponding delay, and chooses a single global watermark with them to be used for stateful operations. By default, the minimum is chosen as the global watermark because it ensures that no data is accidentally dropped as too late if one of the streams falls behind the others (for example, one of the streams stops receiving data due to upstream failures). In other words, the global watermark will safely move at the pace of the slowest stream and the query output will be delayed accordingly.

However, in some cases, you may want to get faster results even if it means dropping data from the slowest stream. Since Spark 2.4, you can set the multiple watermark policy to choose the maximum value as the global watermark by setting the SQL configuration `spark.sql.streaming.multipleWatermarkPolicy` to `max` (default is `min`). This lets the global watermark move at the pace of the fastest stream. However, as a side effect, data from the slower streams will be aggressively dropped. Hence, use this configuration judiciously.

Arbitrary Stateful Operations

Many usecases require more advanced stateful operations than aggregations. For example, in many usecases, you have to track sessions from data streams of events. For doing such sessionization, you will have to save arbitrary types of data as state, and perform arbitrary operations on the state using the data stream events in every trigger. Since Spark 2.2, this can be done using the operation `mapGroupsWithState` and the more powerful operation `flatMapGroupsWithState`. Both operations allow you to apply user-defined code on grouped Datasets to update user-defined state. For more concrete details, take a look at the API documentation (Scala/Java) and the examples (Scala/Java).

Though Spark cannot check and force it, the state function should be implemented with respect to the semantics of the output mode. For example, in Update mode Spark doesn't expect that the state function will emit rows which are older than current watermark plus allowed late record delay, whereas in Append mode the state function can emit these rows.

Unsupported Operations

There are a few DataFrame/Dataset operations that are not supported with streaming DataFrames/Datasets. Some of them are as follows.

- Multiple streaming aggregations (i.e. a chain of aggregations on a streaming DF) are not yet supported on streaming Datasets.
- Limit and take the first N rows are not supported on streaming Datasets.
- Distinct operations on streaming Datasets are not supported.
- Sorting operations are supported on streaming Datasets only after an aggregation and in Complete Output Mode.

- Few types of outer joins on streaming Datasets are not supported. See the support matrix in the Join Operations section for more details.

In addition, there are some Dataset methods that will not work on streaming Datasets. They are actions that will immediately run queries and return results, which does not make sense on a streaming Dataset. Rather, those functionalities can be done by explicitly starting a streaming query (see the next section regarding that).

- `count()` - Cannot return a single count from a streaming Dataset. Instead, use `ds.groupBy().count()` which returns a streaming Dataset containing a running count.
- `foreach()` - Instead use `ds.writeStream.foreach(...)` (see next section).
- `show()` - Instead use the console sink (see next section).

If you try any of these operations, you will see an `AnalysisException` like "operation XYZ is not supported with streaming DataFrames/Datasets". While some of them may be supported in future releases of Spark, there are others which are fundamentally hard to implement on streaming data efficiently. For example, sorting on the input stream is not supported, as it requires keeping track of all the data received in the stream. This is therefore fundamentally hard to execute efficiently.

Limitation of global watermark

In Append mode, if a stateful operation emits rows older than current watermark plus allowed late record delay, they will be "late rows" in downstream stateful operations (as Spark uses global watermark). Note that these rows may be discarded. This is a limitation of a global watermark, and it could potentially cause a correctness issue.

Spark will check the logical plan of query and log a warning when Spark detects such a pattern.

Any of the stateful operation(s) after any of below stateful operations can have this issue:

- streaming aggregation in Append mode
- stream-stream outer join
- `mapGroupsWithState` and `flatMapGroupsWithState` in Append mode (depending on the implementation of the state function)

As Spark cannot check the state function of `mapGroupsWithState`/`flatMapGroupsWithState`, Spark assumes that the state function emits late rows if the operator uses Append mode.

There's a known workaround: split your streaming query into multiple queries per stateful operator, and ensure end-to-end exactly once per query. Ensuring end-to-end exactly once for the last query is optional.

Starting Streaming Queries

Once you have defined the final result DataFrame/Dataset, all that is left is for you to start the streaming computation. To do that, you have to use the `DataStreamWriter` (Scala/Java/Python docs) returned through `Dataset.writeStream()`. You will have to specify one or more of the following in this interface.

- *Details of the output sink:* Data format, location, etc.
- *Output mode:* Specify what gets written to the output sink.
- *Query name:* Optionally, specify a unique name of the query for identification.

- *Trigger interval:* Optionally, specify the trigger interval. If it is not specified, the system will check for availability of new data as soon as the previous processing has been completed. If a trigger time is missed because the previous processing has not been completed, then the system will trigger processing immediately.
- *Checkpoint location:* For some output sinks where the end-to-end fault-tolerance can be guaranteed, specify the location where the system will write all the checkpoint information. This should be a directory in an HDFS-compatible fault-tolerant file system. The semantics of checkpointing is discussed in more detail in the next section.

Output Modes

There are a few types of output modes.

- **Append mode (default)** - This is the default mode, where only the new rows added to the Result Table since the last trigger will be outputted to the sink. This is supported for only those queries where rows added to the Result Table is never going to change. Hence, this mode guarantees that each row will be output only once (assuming fault-tolerant sink). For example, queries with only `select`, `where`, `map`, `flatMap`, `filter`, `join`, etc. will support Append mode.
- **Complete mode** - The whole Result Table will be outputted to the sink after every trigger. This is supported for aggregation queries.
- **Update mode** - (*Available since Spark 2.1.1*) Only the rows in the Result Table that were updated since the last trigger will be outputted to the sink. More information to be added in future releases.

Different types of streaming queries support different output modes. Here is the compatibility matrix.

Query Type		Supported Output Modes	Notes
Queries with aggregation	Aggregation on event-time with watermark	Append, Update, Complete	Append mode uses watermark to drop old aggregation state. But the output of a windowed aggregation is delayed the late threshold specified in `withWatermark()` as by the modes semantics, rows can be added to the Result Table only once after they are finalized (i.e. after watermark is crossed). See the Late Data section for more details. Update mode uses watermark to drop old aggregation state. Complete mode does not drop old aggregation state since by definition this mode preserves all data in the Result Table.
	Other aggregations	Complete, Update	Since no watermark is defined (only defined in other category), old aggregation state is not dropped.

			Append mode is not supported as aggregates can update thus violating the semantics of this mode.
Queries with `mapGroupsWithState`		Update	
Queries with `flatMapGroupsWithState`	Append operation mode	Append	Aggregations are allowed after `flatMapGroupsWithState`.
	Update operation mode	Update	Aggregations not allowed after `flatMapGroupsWithState`.
Queries with `joins`		Append	Update and Complete mode not supported yet. See the support matrix in the Join Operations section for more details on what types of joins are supported.
Other queries		Append, Update	Complete mode not supported as it is infeasible to keep all unaggregated data in the Result Table.

Output Sinks

There are a few types of built-in output sinks.

- **File sink** - Stores the output to a directory.

```
writeStream
    .format("parquet")        // can be "orc", "json", "csv", etc.
    .option("path", "path/to/destination/dir")
    .start()
```

- **Kafka sink** - Stores the output to one or more topics in Kafka.

```
writeStream
    .format("kafka")
    .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
    .option("topic", "updates")
    .start()
```

- **Foreach sink** - Runs arbitrary computation on the records in the output. See later in the section for more details.

```
writeStream
    .foreach(...)
    .start()
```

- **Console sink (for debugging)** - Prints the output to the console/stdout every time there is a trigger. Both, Append and Complete output modes, are supported. 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 every trigger.

```
writeStream
    .format("console")
    .start()
```

- **Memory sink (for debugging)** - The output is stored in memory as an in-memory table. Both, Append and Complete output modes, are supported. This should be used for debugging purposes on low data volumes as the entire output is collected and stored in the driver's memory. Hence, use it with caution.

```
writeStream
    .format("memory")
    .queryName("tableName")
    .start()
```

Some sinks are not fault-tolerant because they do not guarantee persistence of the output and are meant for debugging purposes only. See the earlier section on fault-tolerance semantics. Here are the details of all the sinks in Spark.

Sink	Supported Output Modes	Options	Fault-tolerant	Notes
File Sink	Append	`path`: path to the output directory, must be specified. For file-format-specific options, see the related methods in DataFrameWriter (Scala/Java/Python/R). E.g. for "parquet" format options see `DataFrameWriter.parquet()`	Yes (exactly-once)	Supports writes to partitioned tables. Partitioning by time may be useful.
Kafka Sink	Append, Update, Complete	See the Kafka Integration Guide	Yes (at-least-once)	More details in the Kafka Integration Guide
Foreach Sink	Append, Update, Complete	None	Yes (at-least-once)	More details in the next section
ForeachBatch Sink	Append, Update, Complete	None	Depends on the implementation	More details in the next section

Console Sink	Append, Update, Complete	`numRows`: Number of rows to print every trigger (default: 20) `truncate`: Whether to truncate the output if too long (default: true)	No	
Memory Sink	Append, Complete	None	No. But in Complete Mode, restarted query will recreate the full table.	Table name is the query name.

Note that you have to call `start()` to actually start the execution of the query. This returns a StreamingQuery object which is a handle to the continuously running execution. You can use this object to manage the query, which we will discuss in the next subsection. For now, let's understand all this with a few examples.

Scala **Java** **Python** **R**

```
// ========== DF with no aggregations ==========
val noAggDF = deviceDataDf.select("device").where("signal > 10")

// Print new data to console
noAggDF
  .writeStream
  .format("console")
  .start()

// Write new data to Parquet files
noAggDF
  .writeStream
  .format("parquet")
  .option("checkpointLocation", "path/to/checkpoint/dir")
  .option("path", "path/to/destination/dir")
  .start()

// ========== DF with aggregation ==========
val aggDF = df.groupBy("device").count()

// Print updated aggregations to console
aggDF
  .writeStream
  .outputMode("complete")
  .format("console")
  .start()
```

```
// Have all the aggregates in an in-memory table
aggDF
  .writeStream
  .queryName("aggregates")    // this query name will be the table name
  .outputMode("complete")
  .format("memory")
  .start()

spark.sql("select * from aggregates").show()   // interactively query in-memory t
able
```

Using Foreach and ForeachBatch

The `foreach` and `foreachBatch` operations allow you to apply arbitrary operations and writing logic on the output of a streaming query. They have slightly different use cases - while `foreach` allows custom write logic on every row, `foreachBatch` allows arbitrary operations and custom logic on the output of each micro-batch. Let's understand their usages in more detail.

ForeachBatch

`foreachBatch(...)` allows you to specify a function that is executed on the output data of every micro-batch of a streaming query. Since Spark 2.4, this is supported in Scala, Java and Python. It takes two parameters: a DataFrame or Dataset that has the output data of a micro-batch and the unique ID of the micro-batch.

Scala Java Python R

```
streamingDF.writeStream.foreachBatch { (batchDF: DataFrame, batchId: Long) =>
  // Transform and write batchDF
}.start()
```

With `foreachBatch`, you can do the following.

- **Reuse existing batch data sources** - For many storage systems, there may not be a streaming sink available yet, but there may already exist a data writer for batch queries. Using `foreachBatch`, you can use the batch data writers on the output of each micro-batch.
- **Write to multiple locations** - If you want to write the output of a streaming query to multiple locations, then you can simply write the output DataFrame/Dataset multiple times. However, each attempt to write can cause the output data to be recomputed (including possible re-reading of the input data). To avoid recomputations, you should cache the output DataFrame/Dataset, write it to multiple locations, and then uncache it. Here is an outline.

Scala

```
streamingDF.writeStream.foreachBatch { (batchDF: DataFrame, batchId: Long) =>
  batchDF.persist()
  batchDF.write.format(...).save(...)  // location 1
  batchDF.write.format(...).save(...)  // location 2
  batchDF.unpersist()
}
```

- **Apply additional DataFrame operations** - Many DataFrame and Dataset operations are not supported in streaming DataFrames because Spark does not support generating incremental plans in those cases. Using `foreachBatch`, you can apply some of these operations on each micro-batch output. However, you will have to reason about the end-to-end semantics of doing that operation yourself.

Note:

- By default, `foreachBatch` provides only at-least-once write guarantees. However, you can use the batchId provided to the function as way to deduplicate the output and get an exactly-once guarantee.
- `foreachBatch` does not work with the continuous processing mode as it fundamentally relies on the micro-batch execution of a streaming query. If you write data in the continuous mode, use `foreach` instead.

Foreach

If `foreachBatch` is not an option (for example, corresponding batch data writer does not exist, or continuous processing mode), then you can express your custom writer logic using `foreach`. Specifically, you can express the data writing logic by dividing it into three methods: `open`, `process`, and `close`. Since Spark 2.4, `foreach` is available in Scala, Java and Python.

Scala | **Java** | **Python** | **R**

In Scala, you have to extend the class `ForeachWriter` (docs).

```
streamingDatasetOfString.writeStream.foreach(
  new ForeachWriter[String] {

    def open(partitionId: Long, version: Long): Boolean = {
      // Open connection
    }

    def process(record: String): Unit = {
      // Write string to connection
    }

    def close(errorOrNull: Throwable): Unit = {
      // Close the connection
    }
  }
).start()
```

Execution semantics When the streaming query is started, Spark calls the function or the object’s methods in the following way:

- A single copy of this object is responsible for all the data generated by a single task in a query. In other words, one instance is responsible for processing one partition of the data generated in a distributed manner.
- This object must be serializable, because each task will get a fresh serialized-deserialized copy of the provided object. Hence, it is strongly recommended that any initialization for writing data (for example. opening a connection or starting a transaction) is done after the open() method has been called, which signifies that the task is ready to generate data.
- The lifecycle of the methods are as follows:
    - For each partition with partition_id:
        - For each batch/epoch of streaming data with epoch_id:
            - Method open(partitionId, epochId) is called.
            - If open(…) returns true, for each row in the partition and batch/epoch, method process(row) is called.
            - Method close(error) is called with error (if any) seen while processing rows.
- The close() method (if it exists) is called if an open() method exists and returns successfully (irrespective of the return value), except if the JVM or Python process crashes in the middle.
- **Note:** Spark does not guarantee same output for (partitionId, epochId), so deduplication cannot be achieved with (partitionId, epochId). e.g. source provides different number of partitions for some reasons, Spark optimization changes number of partitions, etc. See SPARK-28650 for more details. If you need deduplication on output, try out `foreachBatch` instead.

Triggers

The trigger settings of a streaming query define the timing of streaming data processing, whether the query is going to be executed as micro-batch query with a fixed batch interval or as a continuous processing query. Here are the different kinds of triggers that are supported.

Trigger Type	Description
unspecified (default)	If no trigger setting is explicitly specified, then by default, the query will be executed in micro-batch mode, where micro-batches will be generated as soon as the previous micro-batch has completed processing.
Fixed interval micro-batches	The query will be executed with micro-batches mode, where micro-batches will be kicked off at the user-specified intervals. • If the previous micro-batch completes within the interval, then the engine will wait until the interval is over before kicking off the next micro-batch. • 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 (i.e., it will not wait for the next interval boundary). • If no new data is available, then no micro-batch will be kicked off.
One-time micro-batch	The query will execute **only one** micro-batch to process all the available data and then stop on its own. This is useful in scenarios 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.
Continuous with fixed checkpoint interval *(experimental)*	The query will be executed in the new low-latency, continuous processing mode. Read more about this in the Continuous Processing section below.

Here are a few code examples.

Scala **Java** **Python** **R**

```
import org.apache.spark.sql.streaming.Trigger

// Default trigger (runs micro-batch as soon as it can)
df.writeStream
  .format("console")
  .start()

// ProcessingTime trigger with two-seconds micro-batch interval
df.writeStream
  .format("console")
  .trigger(Trigger.ProcessingTime("2 seconds"))
  .start()

// One-time trigger
df.writeStream
  .format("console")
  .trigger(Trigger.Once())
  .start()

// Continuous trigger with one-second checkpointing interval
df.writeStream
  .format("console")
  .trigger(Trigger.Continuous("1 second"))
  .start()
```

Managing Streaming Queries

The `StreamingQuery` object created when a query is started can be used to monitor and manage the query.

Scala **Java** **Python** **R**

```
val query = df.writeStream.format("console").start()   // get the query object

query.id          // get the unique identifier of the running query that persists across restarts from checkpoint data

query.runId       // get the unique id of this run of the query, which will be generated at every start/restart

query.name        // get the name of the auto-generated or user-specified name

query.explain()   // print detailed explanations of the query

query.stop()      // stop the query

query.awaitTermination()   // block until query is terminated, with stop() or with error

query.exception       // the exception if the query has been terminated with error

query.recentProgress  // an array of the most recent progress updates for this query

query.lastProgress    // the most recent progress update of this streaming query
```

You can start any number of queries in a single SparkSession. They will all be running concurrently sharing the cluster resources. You can use `sparkSession.streams()` to get the `StreamingQueryManager` (Scala/Java/Python docs) that can be used to manage the currently active queries.

Scala **Java** **Python** **R**

```
val spark: SparkSession = ...

spark.streams.active    // get the list of currently active streaming queries

spark.streams.get(id)   // get a query object by its unique id

spark.streams.awaitAnyTermination()   // block until any one of them terminates
```

Monitoring Streaming Queries

There are multiple ways to monitor active streaming queries. You can either push metrics to external systems using Spark's Dropwizard Metrics support, or access them programmatically.

Reading Metrics Interactively

You can directly get the current status and metrics of an active query using `streamingQuery.lastProgress()` and `streamingQuery.status()`. `lastProgress()` returns a `StreamingQueryProgress` object in Scala and Java and a dictionary with the same fields in Python. It has all the information about the progress made in the last trigger of the stream - what data was processed, what were the processing rates, latencies, etc. There is also `streamingQuery.recentProgress` which returns an array of last few progresses.

In addition, `streamingQuery.status()` returns a `StreamingQueryStatus` object in Scala and Java and a dictionary with the same fields in Python. It gives information about what the query is immediately doing - is a trigger active, is data being processed, etc.

Here are a few examples.

Scala Java Python R

```
val query: StreamingQuery = ...

println(query.lastProgress)

/* Will print something like the following.

{
  "id" : "ce011fdc-8762-4dcb-84eb-a77333e28109",
  "runId" : "88e2ff94-ede0-45a8-b687-6316fbef529a",
  "name" : "MyQuery",
  "timestamp" : "2016-12-14T18:45:24.873Z",
  "numInputRows" : 10,
  "inputRowsPerSecond" : 120.0,
  "processedRowsPerSecond" : 200.0,
  "durationMs" : {
    "triggerExecution" : 3,
    "getOffset" : 2
  },
  "eventTime" : {
    "watermark" : "2016-12-14T18:45:24.873Z"
  },
  "stateOperators" : [ ],
  "sources" : [ {
    "description" : "KafkaSource[Subscribe[topic-0]]",
    "startOffset" : {
      "topic-0" : {
        "2" : 0,
        "4" : 1,
        "1" : 1,
        "3" : 1,
        "0" : 1
      }
    },
    "endOffset" : {
      "topic-0" : {
        "2" : 0,
        "4" : 115,
        "1" : 134,
        "3" : 21,
        "0" : 534
      }
    },
    "numInputRows" : 10,
    "inputRowsPerSecond" : 120.0,
    "processedRowsPerSecond" : 200.0
  } ],
  "sink" : {
    "description" : "MemorySink"
  }
}
*/


println(query.status)

/*  Will print something like the following.
{
  "message" : "Waiting for data to arrive",
  "isDataAvailable" : false,
  "isTriggerActive" : false
}
*/
```

Reporting Metrics programmatically using Asynchronous APIs

You can also asynchronously monitor all queries associated with a `SparkSession` by attaching a `StreamingQueryListener` (Scala/Java docs). Once you attach your custom `StreamingQueryListener` object with `sparkSession.streams.attachListener()`, you will get callbacks when a query is started and stopped and when there is progress made in an active query. Here is an example,

Scala **Java** **Python** **R**

```
val spark: SparkSession = ...

spark.streams.addListener(new StreamingQueryListener() {
    override def onQueryStarted(queryStarted: QueryStartedEvent): Unit = {
        println("Query started: " + queryStarted.id)
    }
    override def onQueryTerminated(queryTerminated: QueryTerminatedEvent): Unit =
{
        println("Query terminated: " + queryTerminated.id)
    }
    override def onQueryProgress(queryProgress: QueryProgressEvent): Unit = {
        println("Query made progress: " + queryProgress.progress)
    }
})
```

Reporting Metrics using Dropwizard

Spark supports reporting metrics using the Dropwizard Library. To enable metrics of Structured Streaming queries to be reported as well, you have to explicitly enable the configuration `spark.sql.streaming.metricsEnabled` in the SparkSession.

Scala **Java** **Python** **R**

```
spark.conf.set("spark.sql.streaming.metricsEnabled", "true")
// or
spark.sql("SET spark.sql.streaming.metricsEnabled=true")
```

All queries started in the SparkSession after this configuration has been enabled will report metrics through Dropwizard to whatever sinks have been configured (e.g. Ganglia, Graphite, JMX, etc.).

Recovering from Failures with Checkpointing

In case of a failure or intentional shutdown, you can recover the previous progress and state of a previous query, and continue where it left off. This is done using checkpointing and write-ahead logs. You can configure a query with a checkpoint location, and the query will save all the progress information (i.e. range of offsets processed in each trigger) and the running aggregates (e.g. word counts in the quick example) to the checkpoint location. This checkpoint location has to be a path in an HDFS compatible file system, and can be set as an option in the DataStreamWriter when starting a query.

Scala **Java** **Python** **R**

```
aggDF
  .writeStream
  .outputMode("complete")
  .option("checkpointLocation", "path/to/HDFS/dir")
```

```
    .format("memory")
    .start()
```

Recovery Semantics after Changes in a Streaming Query

There are limitations on what changes in a streaming query are allowed between restarts from the same checkpoint location. Here are a few kinds of changes that are either not allowed, or the effect of the change is not well-defined. For all of them:

- The term *allowed* means you can do the specified change but whether the semantics of its effect is well-defined depends on the query and the change.
- The term *not allowed* means you should not do the specified change as the restarted query is likely to fail with unpredictable errors. `sdf` represents a streaming DataFrame/Dataset generated with sparkSession.readStream.

Types of changes

- *Changes in the number or type (i.e. different source) of input sources*: This is not allowed.
- *Changes in the parameters of input sources*: Whether this is allowed and whether the semantics of the change are well-defined depends on the source and the query. Here are a few examples.
    - Addition/deletion/modification of rate limits is allowed: `spark.readStream.format("kafka").option("subscribe", "topic")` to `spark.readStream.format("kafka").option("subscribe", "topic").option("maxOffsetsPerTrigger", ...)`
    - Changes to subscribed topics/files are generally not allowed as the results are unpredictable: `spark.readStream.format("kafka").option("subscribe", "topic")` to `spark.readStream.format("kafka").option("subscribe", "newTopic")`
- *Changes in the type of output sink*: Changes between a few specific combinations of sinks are allowed. This needs to be verified on a case-by-case basis. Here are a few examples.
    - File sink to Kafka sink is allowed. Kafka will see only the new data.
    - Kafka sink to file sink is not allowed.
    - Kafka sink changed to foreach, or vice versa is allowed.
- *Changes in the parameters of output sink*: Whether this is allowed and whether the semantics of the change are well-defined depends on the sink and the query. Here are a few examples.
    - Changes to output directory of a file sink are not allowed: `sdf.writeStream.format("parquet").option("path", "/somePath")` to `sdf.writeStream.format("parquet").option("path", "/anotherPath")`
    - Changes to output topic are allowed: `sdf.writeStream.format("kafka").option("topic", "someTopic")` to `sdf.writeStream.format("kafka").option("topic", "anotherTopic")`
    - Changes to the user-defined foreach sink (that is, the `ForeachWriter` code) are allowed, but the semantics of the change depends on the code.

- *Changes in projection / filter / map-like operations*: Some cases are allowed. For example:
  - Addition / deletion of filters is allowed: `sdf.selectExpr("a")` to `sdf.where(...).selectExpr("a").filter(...)`.
  - Changes in projections with same output schema are allowed: `sdf.selectExpr("stringColumn AS json").writeStream` to `sdf.selectExpr("anotherStringColumn AS json").writeStream`
  - Changes in projections with different output schema are conditionally allowed: `sdf.selectExpr("a").writeStream` to `sdf.selectExpr("b").writeStream` is allowed only if the output sink allows the schema change from `"a"` to `"b"`.
- *Changes in stateful operations*: Some operations in streaming queries need to maintain state data in order to continuously update the result. Structured Streaming automatically checkpoints the state data to fault-tolerant storage (for example, HDFS, AWS S3, Azure Blob storage) and restores it after restart. However, this assumes that the schema of the state data remains same across restarts. This means that *any changes (that is, additions, deletions, or schema modifications) to the stateful operations of a streaming query are not allowed between restarts*. Here is the list of stateful operations whose schema should not be changed between restarts in order to ensure state recovery:
  - *Streaming aggregation*: For example, `sdf.groupBy("a").agg(...)`. Any change in number or type of grouping keys or aggregates is not allowed.
  - *Streaming deduplication*: For example, `sdf.dropDuplicates("a")`. Any change in number or type of grouping keys or aggregates is not allowed.
  - *Stream-stream join*: For example, `sdf1.join(sdf2, ...)` (i.e. both inputs are generated with `sparkSession.readStream`). Changes in the schema or equi-joining columns are not allowed. Changes in join type (outer or inner) are not allowed. Other changes in the join condition are ill-defined.
  - *Arbitrary stateful operation*: For example, `sdf.groupByKey(...).mapGroupsWithState(...)` or `sdf.groupByKey(...).flatMapGroupsWithState(...)`. Any change to the schema of the user-defined state and the type of timeout is not allowed. Any change within the user-defined state-mapping function are allowed, but the semantic effect of the change depends on the user-defined logic. If you really want to support state schema changes, then you can explicitly encode/decode your complex state data structures into bytes using an encoding/decoding scheme that supports schema migration. For example, if you save your state as Avro-encoded bytes, then you are free to change the Avro-state-schema between query restarts as the binary state will always be restored successfully.

Continuous Processing

[Experimental]

Continuous processing is a new, experimental streaming execution mode introduced in Spark 2.3 that enables low (~1 ms) end-to-end latency with at-least-once fault-tolerance guarantees. Compare this with the default *micro-batch processing* engine which can achieve exactly-once guarantees but achieve latencies of ~100ms at best. For some types of queries (discussed below), you can choose which mode to execute them in without modifying the application logic (i.e. without changing the DataFrame/Dataset operations).

To run a supported query in continuous processing mode, all you need to do is specify a **continuous trigger** with the desired checkpoint interval as a parameter. For example,

Scala Java Python

```scala
import org.apache.spark.sql.streaming.Trigger

spark
  .readStream
  .format("kafka")
  .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
  .option("subscribe", "topic1")
  .load()
  .selectExpr("CAST(key AS STRING)", "CAST(value AS STRING)")
  .writeStream
  .format("kafka")
  .option("kafka.bootstrap.servers", "host1:port1,host2:port2")
  .option("topic", "topic1")
  .trigger(Trigger.Continuous("1 second"))  // only change in query
  .start()
```

A checkpoint interval of 1 second means that the continuous processing engine will record the progress of the query every second. The resulting checkpoints are in a format compatible with the micro-batch engine, hence any query can be restarted with any trigger. For example, a supported query started with the micro-batch mode can be restarted in continuous mode, and vice versa. Note that any time you switch to continuous mode, you will get at-least-once fault-tolerance guarantees.

Supported Queries

As of Spark 2.4, only the following type of queries are supported in the continuous processing mode.

- *Operations*: Only map-like Dataset/DataFrame operations are supported in continuous mode, that is, only projections (`select`, `map`, `flatMap`, `mapPartitions`, etc.) and selections (`where`, `filter`, etc.).
    - All SQL functions are supported except aggregation functions (since aggregations are not yet supported), `current_timestamp()` and `current_date()` (deterministic computations using time is challenging).
- *Sources*:
    - Kafka source: All options are supported.
    - Rate source: Good for testing. Only options that are supported in the continuous mode are `numPartitions` and `rowsPerSecond`.
- *Sinks*:
    - Kafka sink: All options are supported.
    - Memory sink: Good for debugging.
    - Console sink: Good for debugging. All options are supported. Note that the console will print every checkpoint interval that you have specified in the continuous trigger.

See Input Sources and Output Sinks sections for more details on them. While the console sink is good for testing, the end-to-end low-latency processing can be best observed with Kafka as the source and sink, as this allows the engine to process the data and make the results available in the output topic within milliseconds of the input data being available in the input topic.

Caveats

- Continuous processing engine launches multiple long-running tasks that continuously read data from sources, process it and continuously write to sinks. The number of tasks required by the query depends on how many partitions the query can read from the sources in parallel. Therefore, before starting a continuous processing query, you must ensure there are enough cores in the cluster to all the tasks in parallel. For example, if you are reading from a Kafka topic that has 10 partitions, then the cluster must have at least 10 cores for the query to make progress.
- Stopping a continuous processing stream may produce spurious task termination warnings. These can be safely ignored.
- There are currently no automatic retries of failed tasks. Any failure will lead to the query being stopped and it needs to be manually restarted from the checkpoint.

Additional Information

Notes

- Several configurations are not modifiable after the query has run. To change them, discard the checkpoint and start a new query. These configurations include:
    - `spark.sql.shuffle.partitions`
        - This is due to the physical partitioning of state: state is partitioned via applying hash function to key, hence the number of partitions for state should be unchanged.
        - If you want to run fewer tasks for stateful operations, `coalesce` would help with avoiding unnecessary repartitioning.
            - After `coalesce`, the number of (reduced) tasks will be kept unless another shuffle happens.
    - `spark.sql.streaming.stateStore.providerClass`: To read the previous state of the query properly, the class of state store provider should be unchanged.
    - `spark.sql.streaming.multipleWatermarkPolicy`: Modification of this would lead inconsistent watermark value when query contains multiple watermarks, hence the policy should be unchanged.

Further Reading

- See and run the Scala/Java/Python/R examples.
    - Instructions on how to run Spark examples
- Read about integrating with Kafka in the Structured Streaming Kafka Integration Guide
- Read more details about using DataFrames/Datasets in the Spark SQL Programming Guide
- Third-party Blog Posts
    - Real-time Streaming ETL with Structured Streaming in Apache Spark 2.1 (Databricks Blog)
    - Real-Time End-to-End Integration with Apache Kafka in Apache Spark's Structured Streaming (Databricks Blog)
    - Event-time Aggregation and Watermarking in Apache Spark's Structured Streaming (Databricks Blog)

Talks

- Spark Summit Europe 2017

  - Easy, Scalable, Fault-tolerant Stream Processing with Structured Streaming in Apache Spark - Part 1 slides/video, Part 2 slides/video
  - Deep Dive into Stateful Stream Processing in Structured Streaming - slides/video
- Spark Summit 2016
  - A Deep Dive into Structured Streaming - slides/video