Spark Streaming Understanding

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Spark Streaming is the previous generation of Spark's streaming engine. There are no longer updates to Spark Streaming and it's a legacy project. There is a newer and easier to use streaming engine in Spark called Structured Streaming. You should use Spark Structured Streaming for your streaming applications and pipelines. See Structured Streaming Programming Guide.

Overview

Spark Streaming is an extension of the core Spark API that enables scalable, high-throughput, fault-tolerant stream processing of live data streams. Data can be ingested from many sources like Kafka, Kinesis, or TCP sockets, and can be processed using complex algorithms expressed with high-level functions like `map`, `reduce`, `join` and `window`. Finally, processed data can be pushed out to filesystems, databases, and live dashboards. In fact, you can apply Spark's machine learning and graph processing algorithms on data streams.

Internally, it works as follows. Spark Streaming receives live input data streams and divides the data into batches, which are then processed by the Spark engine to generate the final stream of results in batches.

Spark Streaming provides a high-level abstraction called *discretized stream* or *DStream*, which represents a continuous stream of data. DStreams can be created either from input data streams from sources such as Kafka, and Kinesis, or by applying high-level operations on other DStreams. Internally, a DStream is represented as a sequence of RDDs.

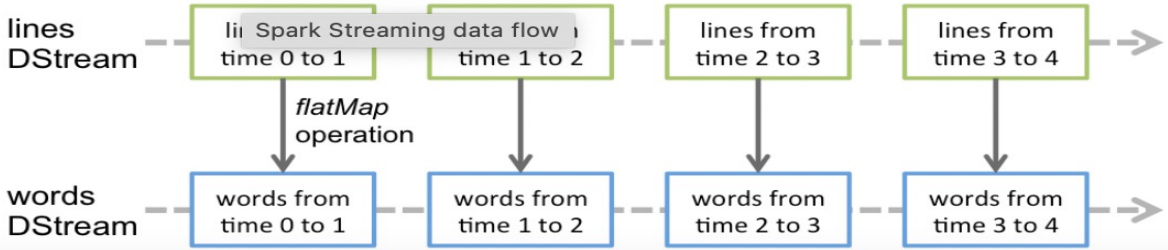
This guide shows you how to start writing Spark Streaming programs with DStreams. You can write Spark Streaming programs in Scala, Java or Python (introduced in Spark 1.2), all of which are presented in this guide. You will find tabs throughout this guide that let you choose between code snippets of different languages.

Note: There are a few APIs that are either different or not available in Python. Throughout this guide, you will find the tag **Python API** highlighting these differences.

Discretized Streams (DStreams)

Discretized Stream or **DStream** is the basic abstraction provided by Spark Streaming. It represents a continuous stream of data, either the input data stream received from source, or the processed data stream generated by transforming the input stream. Internally, a DStream is represented by a continuous series of RDDs, which is Spark's abstraction of an immutable, distributed dataset (see Spark Programming Guide for more details). Each RDD in a DStream contains data from a certain interval, as shown in the following figure.

Any operation applied on a DStream translates to operations on the underlying RDDs. For example, in the earlier example of converting a stream of lines to words, the `flatMap` operation is applied on each RDD in the `lines` DStream to generate the RDDs of the `words` DStream. This is shown in the following figure.



Transformations on DStreams

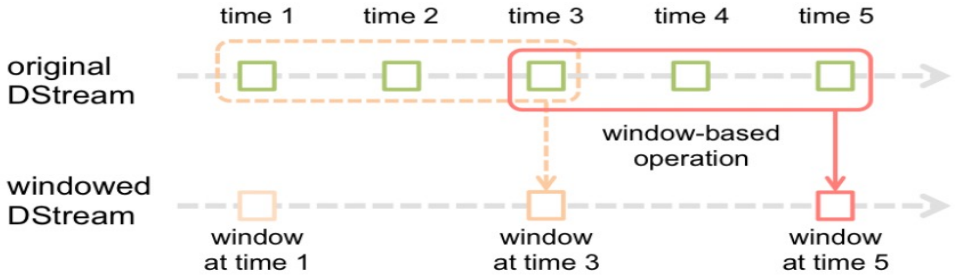
Similar to that of RDDs, transformations allow the data from the input DStream to be modified. DStreams support many of the transformations available on normal Spark RDD's. Some of the common ones are as follows.

Transformation	Meaning
map(*func*)	Return a new DStream by passing each element of the source DStream through a function *func*.
flatMap(*func*)	Similar to map, but each input item can be mapped to 0 or more output items.
filter(*func*)	Return a new DStream by selecting only the records of the source DStream on which *func* returns true.
repartition(*numPartitions*)	Changes the level of parallelism in this DStream by creating more or fewer partitions.
union(*otherStream*)	Return a new DStream that contains the union of the elements in the source DStream and *otherDStream*.
count()	Return a new DStream of single-element RDDs by counting the number of elements in each RDD of the source DStream.
reduce(*func*)	Return a new DStream of single-element RDDs by aggregating the elements in each RDD of the source DStream using a function *func* (which takes two arguments and returns one). The function should be associative and commutative so that it can be computed in parallel.

countByValue()	When called on a DStream of elements of type K, return a new DStream of (K, Long) pairs where the value of each key is its frequency in each RDD of the source DStream.
reduceByKey(*func*, [*numTasks*])	When called on a DStream of (K, V) pairs, return a new DStream of (K, V) pairs where the values for each key are aggregated using the given reduce function. **Note:** By default, this uses Spark's default number of parallel tasks (2 for local mode, and in cluster mode the number is determined by the config property `spark.default.parallelism`) to do the grouping. You can pass an optional `numTasks` argument to set a different number of tasks.
join(*otherStream*, [*numTasks*])	When called on two DStreams of (K, V) and (K, W) pairs, return a new DStream of (K, (V, W)) pairs with all pairs of elements for each key.
cogroup(*otherStream*, [*numTasks*])	When called on a DStream of (K, V) and (K, W) pairs, return a new DStream of (K, Seq[V], Seq[W]) tuples.
transform(*func*)	Return a new DStream by applying a RDD-to-RDD function to every RDD of the source DStream. This can be used to do arbitrary RDD operations on the DStream.
updateStateByKey(*func*)	Return a new "state" DStream where the state for each key is updated by applying the given function on the previous state of the key and the new values for the key. This can be used to maintain arbitrary state data for each key.

Window Operations

Spark Streaming also provides *windowed computations*, which allow you to apply transformations over a sliding window of data. The following figure illustrates this sliding window.



As shown in the figure, every time the window *slides* over a source DStream, the source RDDs that fall within the window are combined and operated upon to produce the RDDs of the windowed DStream. In this specific case, the operation is applied over the last 3 time units of data, and slides by 2 time units. This shows that any window operation needs to specify two parameters.

- *window length* - The duration of the window (3 in the figure).
- *sliding interval* - The interval at which the window operation is performed (2 in the figure).

These two parameters must be multiples of the batch interval of the source DStream (1 in the figure).

Let's illustrate the window operations with an example. Say, you want to extend the earlier example by generating word counts over the last 30 seconds of data, every 10 seconds. To do this, we have to apply the `reduceByKey` operation on the `pairs` DStream of `(word, 1)` pairs over the last 30 seconds of data. This is done using the operation `reduceByKeyAndWindow`.

Transformation	Meaning
window(*windowLength*, *slideInterval*)	Return a new DStream which is computed based on windowed batches of the source DStream.
countByWindow(*windowLength*, *slideInterval*)	Return a sliding window count of elements in the stream.
reduceByWindow(*func*, *windowLength*, *slideInterval*)	Return a new single-element stream, created by aggregating elements in the stream over a sliding interval using *func*. The function should be associative and commutative so that it can be computed correctly in parallel.
reduceByKeyAndWindow(*func*, *windowLength*, *slideInterval*, [*numTasks*])	When called on a DStream of (K, V) pairs, returns a new DStream of (K, V) pairs where the values for each key are aggregated using the given reduce function *func* over batches in a sliding window. **Note:** By default, this uses Spark's default number of parallel tasks (2 for local mode, and in cluster mode the number is determined by the config property `spark.default.parallelism`) to do the grouping. You can pass an optional `numTasks` argument to set a different number of tasks.
reduceByKeyAndWindow(*func*, *invFunc*, *windowLength*, *slideInterval*, [*numTasks*])	A more efficient version of the above `reduceByKeyAndWindow()` where the reduce value of each window is calculated incrementally using the reduce values of the previous window. This is done by reducing the new data that enters the sliding window, and "inverse reducing" the old data that leaves the window. An example would be that of "adding" and "subtracting" counts of keys as the window slides. However, it is applicable only to "invertible reduce functions", that is, those reduce functions which have a corresponding "inverse reduce" function (taken as parameter *invFunc*). Like in

Output Operations on DStreams

Output operations allow DStream's data to be pushed out to external systems like a database or a file systems. Since the output operations actually allow the transformed data to be consumed by external systems, they trigger the actual execution of all the DStream transformations (similar to actions for RDDs). Currently, the following output operations are defined:

Output Operation	Meaning
print()	Prints the first ten elements of every batch of data in a DStream on the driver node running the streaming application. This is useful for development and debugging. Python API This is called **pprint()** in the Python API.
saveAsTextFiles(*prefix*, [*suffix*])	Save this DStream's contents as text files. The file name at each batch interval is generated based on *prefix* and *suffix*: *"prefix-TIME_IN_MS[.suffix]"*.
saveAsObjectFiles(*prefix*, [*suffix*])	Save this DStream's contents as `SequenceFiles` of serialized Java objects. The file name at each batch interval is generated based on *prefix* and *suffix*: *"prefix-TIME_IN_MS[.suffix]"*. Python API This is not available in the Python API.
saveAsHadoopFiles(*prefix*, [*suffix*])	Save this DStream's contents as Hadoop files. The file name at each batch interval is generated based on *prefix* and *suffix*: *"prefix-TIME_IN_MS[.suffix]"*. Python API This is not available in the Python API.
foreachRDD(*func*)	The most generic output operator that applies a function, *func*, to each RDD generated from the stream. This function should push the data in each RDD to an external system, such as saving the RDD to files, or writing it over the network to a database. Note that the function *func* is executed in the driver process running the streaming application, and will usually have

Benefits

- Load balancing
- Extended analytics
- Interoperable with other API's[MLIB,SQL etc.,]
- Fast failure recovery
- Performance

Assignment

Spark Streaming

vs

Spark Structured Streaming

Q&A ?