Drinking from a fire hose
A packet in isolation seems fine
'Why then, do streams strain systems design?'
If processing lags the rate of arrival?
Impair, you will, your process’ survival

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Topics covered in this lecture
- Spark Streaming
  - Architecture and Abstractions
  - Execution
  - Stateful and stateless transformations
  - Windowed operations
  - Performance considerations
  - Example

Related Work


Spark Streaming
- Act on data as soon as it arrives:
  - Track statistics of page views in real time, detect anomalies, etc.
- Spark streaming:
  - Spark’s module for dealing with streaming data
  - Uses an API very similar to what we have seen with batch jobs (centered around RDDs)
- Available in Java and Scala
  - Recent support for Python
Spark Streaming: Core concepts

- Provides an abstraction called DStreams (discretized streams)
- A DStream is a sequence of data arriving over time
- Internally, a DStream is represented as a sequence of RDDs arriving at each time step

DStreams

- DStreams can be created from various input sources
  - Flume, Kafka, or HDFS
- Once built, DStreams offer two types of operations:
  - Transformations: Yields a new DStream
  - Output operations: Writes data to an external system
- Provides many of the same operations available on RDDs
  - PLUS new operations related to time (e.g., sliding windows)

Example

- Start by creating a StreamingContext
  - Main entry point for streaming functionality
  - Specify batch interval, specifying how often to process new data
- We will use socketTextStream() to create a DStream based on text data received over a port
- Transform DStream with filter to get lines that contain "error"

Example

```
JavaStreamingContext jssc = new JavaStreamingContext(conf, Durations.seconds(1));
JavaDStream<String> lines = jssc.socketTextStream("localhost", 7777);
JavaDStream<String> errorLines = lines.filter(new Function<String, Boolean>() {
  public Boolean call(String line) {
    return line.contains("error");
  }
});
```

Architecture & Abstraction
Spark Streaming Architecture

- Spark Streaming uses a micro-batch architecture
  - Streaming computation is treated as continuous series of batch computations on small batches of data
- Receives data from various input sources and groups into small batches
- New batches are created at regular intervals
  - At the start of each time interval, a new batch is created
  - Any data arriving in that interval is added to the batch
  - Size of batch is controlled by the batch interval

High-level architecture of Spark Streaming

DStream is a sequence of RDDs, where each RDD has one slice of data in stream

DStreams support output operations, such as the print() used in our example.

- Output operations are similar to RDD actions in that they write data to an external system
- But in Spark Streaming they run periodically on each time step, producing output in batches

DStreams and the transformations in our example

Spark Streaming: Execution

- For each input source, Spark Streaming launches receivers
  - Tasks running within the application’s executors that collect data from source and save as RDDs
  - Receives input data and replicates it (by default) to another executor for fault tolerance
  - Data is stored in memory of the executors in the same way that RDDs are cached
Spark Streaming: Execution

- StreamingContext in the driver program then periodically runs Spark jobs to:
  - Process this data and …
  - Combine it with RDDs from previous time steps

Spark Streaming: Fault Tolerance [1/2]

- Spark Streaming offers the same fault-tolerance properties for DStreams as Spark has for RDDs.
  - As long as a copy of the input data is still available, it can recompute any state derived from it using the lineage of the RDDs.
  - By rerunning the operations used to process it.

Spark Streaming: Fault Tolerance [2/2]

- By default, data is replicated across two nodes.
  - Can tolerate single worker failures.
  - Using lineage graphs to recompute any derived state is impractical.
  - Spark Streaming relies on checkpointing:
    - Saves state periodically.
    - Checkpoint every 5-10 batches of data.
    - When recovering, only go back to the last checkpoint.

Spark Streaming: Transformations

- Stateless transformations
  - Each batch does not depend on data of its previous batches.

- Stateful transformations
  - Use data or intermediate results from previous batches to compute results of the current batch.

Stateless Transformations
Stateless transformations

- Stateless transformations are simple RDD transformations being applied on every batch — that is, every RDD in a DStream.
- Many of the RDD transformations that we have looked at are also available on DStreams.

Examples of stateless transformations

- `map()`
  - Apply a function to each element in the DStream and return a DStream of the result
  - `ds.map(x => x + 1)`

- `flatMap()`
  - Apply a function to each element in the DStream and return a DStream of the contents of the iterators returned
  - `ds.flatMap(x => x.split(" "))`

- `filter()`
  - Return a DStream consisting of only elements that pass the condition passed to filter
  - `ds.filter(x => x != 1)`

- `repartition()`
  - Change the number of partitions of the DStream
    - Distributes the received batches across the specified number of machines in the cluster before processing
    - The physical manifestation of the DStream is different in this case
    - `ds.repartition(10)`

- `reduceByKey()`
  - Combine values with the same key in each batch
    - `ds.reduceByKey( (x, y) => x + y)`
Examples of stateless transformations

- `groupByKey()`
- Group values with the same key in each batch
- `ds.groupByKey()`

A note about stateless operations

- Although it may seem that they are being applied over the whole stream ...
  - Each DStream has multiple RDDs (batches)
  - Stateless transformation applies separately to each RDD
  - E.g. `reduceByKey()` will reduce data for each timestep, but not across timesteps

Stateful transformations

- Operations on DStreams that track data across time
  - Data from previous batches used to generate results for a new batch
- Two types of windowed operations
  - Act over sliding window of time periods
  - `updateStateByKey()` track state across events for each key

Stateful transformations and fault tolerance

- Requires checkpointing to be enabled in `StreamingContext` for fault tolerance
  - `ssc.checkpoint("hdfs://")`;

Windowed Transformations

- Compute results across a longer time period than the batch interval
- Two parameters: window and sliding durations
  - Both must be a multiple of the batch interval
  - Window duration controls how many previous batches of data are considered
    - `windowDuration/batchInterval`
    - If the batch interval is 10 seconds and the sliding window is 30 seconds ...
      - Last 3 batches
A windowed stream:
Window duration (3) & slide duration (2)

Network Input

Windowed Streams
Window 3, Slide 2

Every 2 time steps, we compute a result over the previous 3 time steps

Simplest window operation on a DStream

- `window()`
- Returns new DStream with data from the requested window
- Each RDD in the DStream resulting from `window()`, will contain data from multiple batches

Other operations on top of `window()`

- `reduceByWindow` and `reduceByKeyAndWindow`
- Includes a special form that allows reduction to be performed incrementally
  - Considering only the data coming into the window and the data that is going out
  - Special form requires an inverse of the reduce function
    - Such as `-` for `+`
    - More efficient for large windows if your function has an inverse

Difference between naïve and incremental `reduceByWindow()`

Maintaining state across batches

- `updateStateByKey()`
  - Provides access to a state variable for DStreams of key/value pairs
  - Given a DStream of (key, value) pairs
    - Construct a new DStream of (key, state) pairs by taking a function that specifies how to update the state for each key, given new events

**Performance Considerations in Spark Streaming**
Performance considerations

- **Batch size**
  - 500 milliseconds is considered a good minimum size
  - Start with a large batch size (~10 seconds) and work down to a smaller batch size
  - If processing times remain consistent, explore decreasing the batch size
  - If the processing times increase? You have reached the limit

- **Window size**
  - Has a great impact on performance
  - Consider increasing this for expensive operations

Garbage collections and memory usage

- **Cache RDDs in serialized form**
  - Using Kryo for serialization reduces this even more
  - Reduces space for in-memory representations

- **By default, Spark uses an in-memory cache**
  - Can also evict RDDs older than a certain time-period
  - spark.cleaner.ttl
  - This preemptive eviction of RDDs also reduces the garbage collection pressure

Levels of parallelism in data receiving

- Each input DStream creates a single receiver that receives a single stream of data
  - Receiving multiple data streams possible by creating multiple input DStreams
  - Each DStream must be configured to receive different partitions of the data stream from the source(s)

- For a Kafka DStream receiving data on two topics?
  - Split into two DStreams each receiving one topic
  - Two receivers would run and receive data in parallel

- **Another approach is to tune the receiver’s block interval**
  - Determined by spark.streaming.blockInterval
  - For most receivers, received data is coalesced into blocks of data before storing in memory
  - The number of blocks in each batch determines the number of tasks used to process the received data in a map-like transformation
  - Number of tasks per batch?
    - Batch interval/block interval

- **What if you did not want to receive data with multiple input streams?**
  - Explicitly repartition the input data stream
  - Repartitioning is done using the inputStream.repartition(<number of partitions>))
  - Distributes the received batches of data across the specified number of machines in the cluster before further processing
Data serialization

- Data received through receivers is stored with StorageLevel.MEMORY_AND_DISK_SER_2
- Data that does not fit in memory spills over to disk
- Input data and persisted RDDs generated by DStream transformations are automatically cleared
- If you are using a window operation of 10 minutes, then Spark Streaming will keep the last 10 minutes of data, and actively throw away older data
- Data can be retained for a longer duration by setting streamingContext.remember

Spark-streaming example

1. Create a JavaStreamingContext with Twitter authentication details:
2. Set SparkConf and Twitter credential setup:
3. Stream of hashtags from stream of tweets:
4. Step-by-step approach to finding the top 10 hashtags from a stream of tweets using counts (every second there is an output over data from the last 300 seconds):
   - Step 1: Create a SparkStream context and Twitter credential setup
   - Step 2: Map input DStream of Status to String
   - Step 3: Stream of hashtags from stream of tweets

Spark-streaming example

1. Step-by-step approach to finding the top 10 hashtags from a stream of tweets using counts (every second there is an output over data from the last 300 seconds):
   - Step 1: Create a SparkStream context and Twitter credential setup
   - Step 2: Map input DStream of Status to String
   - Step 3: Stream of hashtags from stream of tweets
Spark-streaming example [4/5]

- Step 4: Count the hashtag over 5 min window

```java
JavaPairDStream<String, Integer> hashtagtuples = hashTags.mapToPair(
    new PairFunction<String, String, Integer>() {
        public Tuple2<String, Integer> call(String input) {
            return new Tuple2<String, Integer>(input, 1);
        }
    });
```

- Aggregating over window of 5 min and slide of 1

```java
JavaPairDStream<String, Integer> counts = hashtagtuples.reduceByKeyAndWindow(
    new Function2<Integer, Integer, Integer>() {
        public Integer call(Integer int1, Integer int2) {
            return int1 + int2;
        }
    }, new Function2<Integer, Integer, Integer>() {
        public Integer call(Integer int1, Integer int2) {
            return int1 - int2;
        }
    }, new Duration(60 * 5 * 1000), new Duration(1 * 1000));
```

Spark-streaming example [5/5]

- Step 5: Find top 10 hashtags according to counts

```java
JavaPairDStream<Integer, String> swapCounts = counts.mapToPair(
    new PairFunction<Tuple2<String, Integer>, Integer, String>() {
        public Tuple2<Integer, String> call(Tuple2<String, Integer> input) {
            return input.swap();
        }
    });
```

```java
JavaPairDStream<Integer, String> sortedCount = swapCounts.transformToPair(
    new Function<JavaPairRDD<Integer, String>, JavaPairRDD<Integer, String>>() {
        public JavaPairRDD<Integer, String> call(JavaPairRDD<Integer, String> input) throws Exception {
            return input.sortByKey(false);
        }
    });
```

```java
sortedCount.foreach(
    new Function<JavaPairRDD<Integer, String>, Void>() {
        public Void call(JavaPairRDD<Integer, String> rdd) {
            String out = "Trending hashtags:
            for (Tuple2<Integer, String> t: rdd.take(10)) {
                out = out + t.toString() + 
            } System.out.println(out);
        }
    });
```

The contents of this slide-set are based on the following references: