CS 455: INTRODUCTION TO DISTRIBUTED SYSTEMS [SPARK STREAMING]

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Frequently asked questions from the previous class survey

- Can Spark repartition a wide transformation into a narrow transformation?
- Why have a temperature range till 130?
- How do you know how much data movement is too much?
- Reduce operation in Spark: how are values added up?
- Does it make sense to write your own partitioner?
- Are there Spark programs that will take a long time (months/years) to complete?

Topics covered in this lecture

- Spark Streaming
  - Architecture and Abstractions
  - Execution
  - Stateful and stateless transformations
  - Windowed operations
  - Performance considerations
  - Example

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");
          }
      };
```


Previous snippet only sets up the computation

- To start receiving the data?
  - Explicitly call `start()` on `StreamContext`
- SparkStreaming will start to schedule Spark jobs on the underlying SparkContext
  - Occurs in a **separate thread**
  - To keep application from terminating?
    - Also call `awaitTermination()`

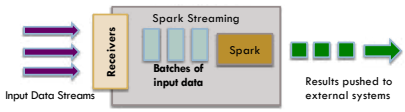
```
jssc.start();
jssc.awaitTermination()
```

ARCHITECTURE & ABSTRACTION

Spark Streaming Architecture

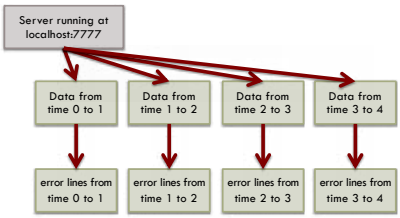
- Spark Streaming uses a **micro-batch** architecture
  - Streaming computation is treated as continuous series of batch computations on small **batches** of data
- Receives data from various input sources and groups into small batches
- New batches are **created at regular intervals**
  - At the start 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 and the transformations in our example



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**

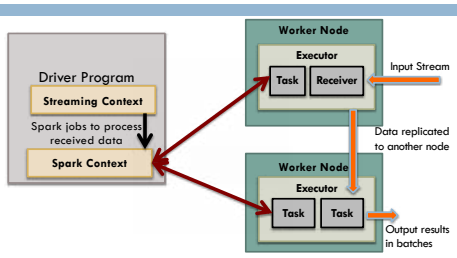
Spark Streaming: Execution

- 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: Execution



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? 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)`

Examples of stateless transformations

- `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(" ") )`

Examples of stateless transformations

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

Examples of stateless transformations

- `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)`

Examples of stateless transformations

- `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

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

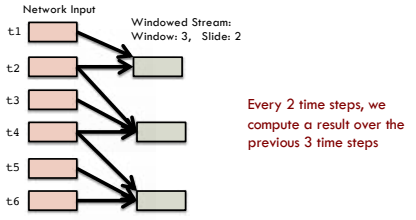
- Requires checkpointing to be enabled in `StreamingContext` for fault tolerance

```
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
  - `window Duration/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)



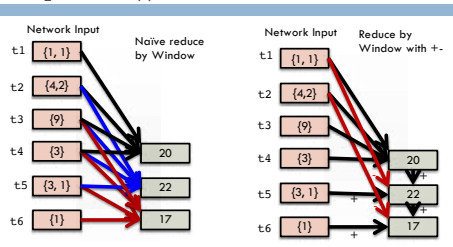
Simplest window operation on a DStream

- `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, event) 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 [1/4]

- 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

Levels of parallelism in data receiving [2/4]

- 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

Levels of parallelism in data receiving [3/4]

- Number of tasks per batch?
  - Batch interval/block interval
- Block interval of 200 ms will create 10 tasks per 2 second batches
- If the number of tasks is too low?
  - All available cores might not be available to use all the data
- To increase number of tasks for a given batch interval?
  - Reduce the block interval

Levels of parallelism in data receiving [4/4]

- 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 [1/2]

- 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 around the last 10 minutes of data, and actively throw away older data
  - Data can be retained for a longer duration by setting streamingContext.remember

Data serialization [2/2]

- RDDs generated by streaming computations may be persisted in memory
  - Persisted RDDs generated by streaming computations are persisted with StorageLevel.MEMORY_ONLY_SER
- If you are using batch intervals of a few seconds and no window operations?
  - You can try disabling serialization in persisted data
    - Reduce CPU overheads due to serialization, without excessive GC overheads.

Processing Twitter Streams using Spark

Spark-streaming example [1/5]

- 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

```
SparkConf sparkConf = new SparkConf().setAppName("Spark-
streaming-twitter-trends");

/*
Twitter authentication details … [Not included here]
*/
//JavaStreamigContext
JavaStreamingContext jssc =
      new JavaStreamingContext(sparkConf, new Duration(1000));

//Discretized stream of tweets
JavaDStream<Status> twitterStream = (JavaDStream<Status>)
TwitterUtils.createStream(jssc);
```


Spark-streaming example [2/5]

- Step-2: Map Input DStream of `Status` to `String`

```
//Discretized stream of Strings
JavaDStream<String> statuses = twitterStream.map(
    new Function<Status, String>() {
    public String call(Status status) {
        return status.getText();
    }
  }
);

statuses.print();

//trigger the execution of code
jssc.start();
jssc.awaitTermination();
```

Spark-streaming example [3/5]

- Step-3: Stream of hashtags from stream of tweets

```
//Tokenize words from status
JavaDStream<String> wordsFromStatuses = statuses.flatMap(
    new FlatMapFunction<String, String>() {
       public Iterable<String> call(String input) {
          return Arrays.asList(input.split(" "));
       }
    }
);

//Extract hashtags
JavaDStream<String> hashTags = wordsFromStatuses.filter(
    new Function<String, Boolean>() {
       public Boolean call(String word) {
          return word.startsWith("#");
       }
    }
);
```


Spark-streaming example [4/5]

- Step-4: Count the hashtag over 5 min window

```
//Mapping to tuple of (hashtag,1) in order to count
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 silde of 1s
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

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


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

- *Learning Spark: Lightning-Fast Big Data Analysis. 1st Edition. Holden Karau, Andy Konwinski, Patrick Wendell, and Matei Zaharia. O'Reilly. 2015. ISBN-13: 978-1449358624.* [Chapter 10]
- Spark Streaming Programming Guide: http://spark.apache.org/docs/latest/streaming-programming-guide.html#memory-tuning
- Processing Twitter Streams using Spark: https://databricks-training.s3.amazonaws.com/realtime-processing-with-spark-streaming.html