CS 455: INTRODUCTION TO DISTRIBUTED SYSTEMS

[SPARK STREAMING]

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?
‘Imperil, you will, your process’ survival

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Related Work


Topics covered in this lecture

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

```java
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()`

```java
jssc.start();
jssc.awaitTermination();
```
Spark Streaming Architecture

- Spark Streaming uses a **micro-batch** architecture
  - Streaming computation is treated as a **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

- Input Data Streams
- **Receivers**
- **Spark Streaming**
- **Batches of input data**
- **Spark**
- Results pushed to external systems
DStream is a sequence of RDDs, where each RDD has one slice of data in stream

DStreams and the transformations in our example

Server running at localhost:7777
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

Diagram:
- Driver Program
- Streaming Context
- Spark jobs to process received data
- Spark Context
- Worker Node
- Executor
- Task
- Receiver
- Task
- Data replicated to another node
- Output results in batches
- Input Stream
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 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 [2/6]

- `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 [3/6]

- `filter()`
- Return a DStream consisting of only elements that pass the condition passed to `filter`
- `ds.filter(x => x != 1)`
Examples of stateless transformations  [4/6]

- 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
    - \( ds\text{.repartition}(10) \)

Examples of stateless transformations  [5/6]

- reduceByKey()
  - Combine values with the same key in each batch
    - \( ds\text{.reduceByKey}( (x, y) \rightarrow x + y ) \)
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
  
  ```java
  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)

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

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Difference between naïve and incremental reduceByWindow()

<table>
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<th>Network Input</th>
<th>Naïve reduce by Window</th>
<th>Network Input</th>
<th>Reduce by Window with +–</th>
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</tr>
</tbody>
</table>

\[
\begin{align*}
\text{Naïve reduce by Window:} & \quad 20 + 22 + 17 = 59 \\
\text{Reduce by Window with +–:} & \quad 20 + 22 + 17 = 69
\end{align*}
\]
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

- **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

- 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

- 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

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Data serialization

- 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

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

/*
Twitter authentication details ... [Not included here]
*/
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**

```java
// 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**

```java
// 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

Step-4: Count the hashtag over 5 min window

```java
// 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 slide 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

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(); } });
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 = "Trending 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


- **Spark Streaming Programming Guide:**
  http://spark.apache.org/docs/latest/streaming-programming-guide.html#memory-tuning

- **Processing Twitter Streams using Spark:**