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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Frequently asked questions from the previous class survey

- Does Spark try to satisfy wide dependencies first?
- In narrow & wide transformations does the data shuffling happen only when action is called on the transformation?
Topics covered in this lecture

- Alleviating inefficiencies with shuffles
- Spark Streaming
  - Architecture and Abstractions
  - Execution
  - Stateful and stateless transformations
  - Windowed operations
  - Performance considerations
  - Example

Two primary techniques to avoid performance problems associated with shuffles

- Shuffle Less
- Shuffle Better
Shuffle Less

- Preserve partitioning across narrow transformations to avoid reshuffling data
- Use the same partitioner on a sequence of wide transformations. This can be particularly useful:
  - To avoid shuffles during joins and ...
  - To reduce the number of shuffles required to compute a sequence of wide transformations

Shuffle Better

- Sometimes, computation cannot be completed without a shuffle
- However, not all wide transformations and not all shuffles are equally expensive or prone to failure
Shuffle Better

- By using wide transformations such as `reduceByKey` and `aggregateByKey` that can perform map-side reductions and that do not require loading all the records for one key into memory?
  - You can prevent memory errors on the executors and
  - Speed up wide transformations, particularly for aggregation operations

- Lastly, shuffling data in which records are distributed evenly throughout the keys, and which contain a high number of distinct keys?
  - Prevents out-of-memory errors on the executors and “straggler tasks”
Partitioners

- The partitioner defines **how records will be distributed** and thus which records will be completed by each task.

- Practically, a partitioner is actually an interface with two methods:
  - `numPartitions` that defines the number of partitions in the RDD after partitioning.
  - `getPartition` that defines a mapping from a key to the integer index of the partition where records with that key should be sent.

There are two implementations for the partitioner object provided by Spark:

- **HashPartitioner**
  - Determines the index of the child partition based on the hash value of the key.

- **RangePartitioner**
  - Assigns records whose keys are in the same range to a given partition.
  - Required for **sorting** since it ensures that by sorting records within a given partition, the entire RDD will be sorted.

- It is possible to define a custom partitioner.
Partitioners and transformations

- Unless a transformation is known to only change the value part of the key/value pair in Spark
  - The resulting RDD will not have a known partitioner
    - Even if the partitioning has not changed

Using narrow transformations that preserve partitioning

- Some narrow transformations, such as mapValues, preserve the partitioning of an RDD if it exists
- Common transformations like map and flatMap can change the key
  - So even if your function does not change the key, the resulting RDD will not have a known partitioner.
  - Instead, if you don’t want to modify the keys, call the mapValues function (defined only on pair RDDs)
    - It keeps the keys, and therefore the partitioner, exactly the same.
    - The mapPartitions function will also preserve the partition if the preservesPartitioning flag is set to true.
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, Scala, and 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)

Simple Streaming Example [1/2]

- 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”
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()`
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

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

Data from time 0 to 1

error lines from time 0 to 1

Data from time 1 to 2

error lines from time 1 to 2

Data from time 2 to 3

error lines from time 2 to 3

Data from time 3 to 4

error lines from time 3 to 4

DStreams support output operations, such as `print()`

- 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

![Diagram of Spark Streaming execution]

- Driver Program
- Streaming Context
  - Spark jobs to process received data
  - Spark Context

Worker Node
- Executor
  - Task
  - Receiver

Input Stream
- Data replicated to another node
- Output results in batches

Spark Streaming: Fault Tolerance

- 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

- 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 [1/6]

- **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.repartition(10)`
Examples of stateless transformations [5/6]

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

Examples of stateless transformations [6/6]

- `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)

Network Input
- Windowed Stream:
  - 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()**

### Network Input

<table>
<thead>
<tr>
<th>Time</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1</td>
<td>{1, 1}</td>
</tr>
<tr>
<td>t2</td>
<td>{4, 2}</td>
</tr>
<tr>
<td>t3</td>
<td>{9}</td>
</tr>
<tr>
<td>t4</td>
<td>{3}</td>
</tr>
<tr>
<td>t5</td>
<td>{3, 1}</td>
</tr>
<tr>
<td>t6</td>
<td>{1}</td>
</tr>
</tbody>
</table>

### Naïve reduce by Window

<table>
<thead>
<tr>
<th>Time</th>
<th>Value</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1</td>
<td>{1, 1}</td>
<td></td>
</tr>
<tr>
<td>t2</td>
<td>{4, 2}</td>
<td></td>
</tr>
<tr>
<td>t3</td>
<td>{9}</td>
<td></td>
</tr>
<tr>
<td>t4</td>
<td>{3}</td>
<td>20</td>
</tr>
<tr>
<td>t5</td>
<td>{3, 1}</td>
<td>22</td>
</tr>
<tr>
<td>t6</td>
<td>{1}</td>
<td>17</td>
</tr>
</tbody>
</table>

### Reduce by Window with + -

<table>
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<th>Time</th>
<th>Value</th>
<th>Result</th>
</tr>
</thead>
<tbody>
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<td>t1</td>
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<td>{3, 1}</td>
<td>22</td>
</tr>
<tr>
<td>t6</td>
<td>{1}</td>
<td>17</td>
</tr>
</tbody>
</table>

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

  [Chapter 10]

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

- **Processing Twitter Streams using Spark:**