# CS x55: 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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## 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?

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## 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 [1/2]

- 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 [2/2]

- By using wide transformations such as `reduceByKey` and `aggregateByKey` that can preform 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"



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# PARTITIONERS



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## 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

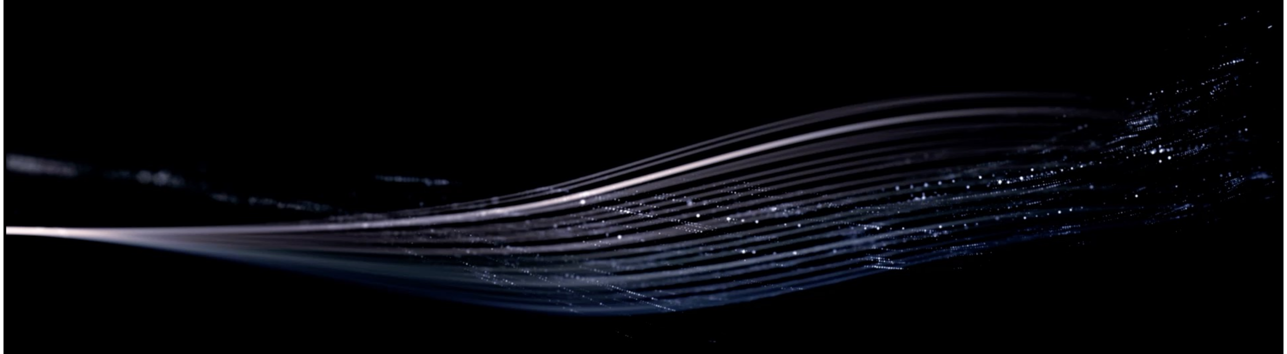
## Partitioners and transformations

- 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.



## SPARK STREAMING

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## Related Work

Thilina Buddhika*, Sangmi Lee Pallickara, and Shrideep Pallickara. Pebbles: Leveraging Sketches for Processing Voluminous, High Velocity Data Streams. IEEE Transactions on Parallel and Distributed Systems. Vol 32 (8) pp 2005 - 2020. 2021.

Thilina Buddhika*, Ryan Stern*, Kira Lindburg*, Kathleen Ericson*, and Shrideep Pallickara. Online Scheduling and Interference Alleviation for Low-latency, High-throughput Processing of Data Streams. IEEE Transactions on Parallel and Distributed Systems. Vol. 28(12) pp 3553-3569. 2017.

Thilina Buddhika* and Shrideep Pallickara. Neptune: Real Time Stream Processing for Internet of Things and Sensing Environments. Proceedings of the 30th IEEE International Parallel & Distributed Processing Symposium. pp 1143-1152. Chicago, USA. 2016.



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## 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"

## Simple Streaming Example [2/2]

```
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

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## 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*

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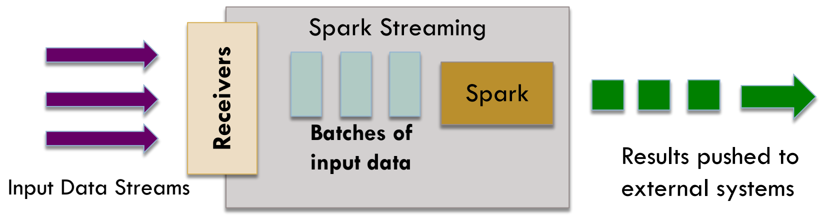
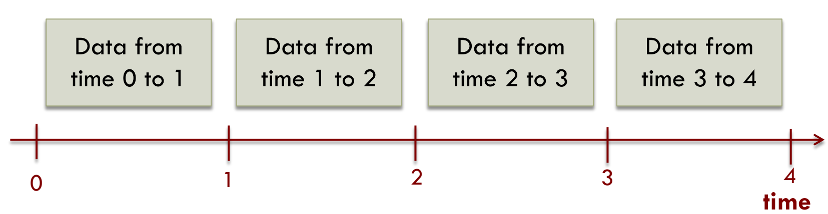
## High-level architecture of Spark Streaming

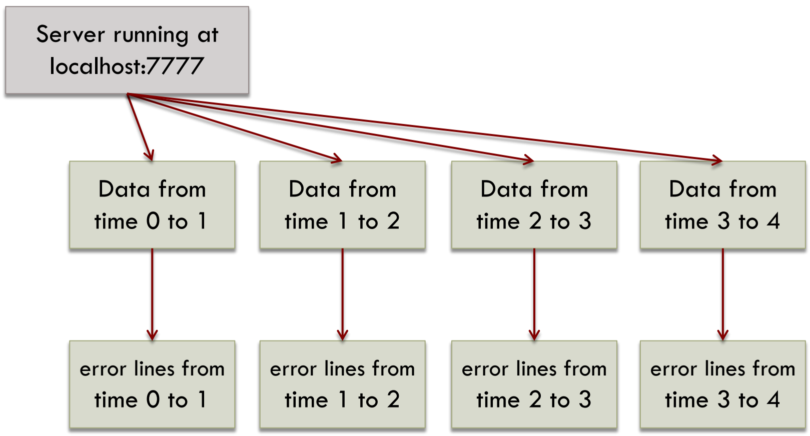





## DStream is a sequence of RDDs, where each RDD has one slice of data in stream



## DStreams and the transformations in our example






## DStreams support output operations, such as `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

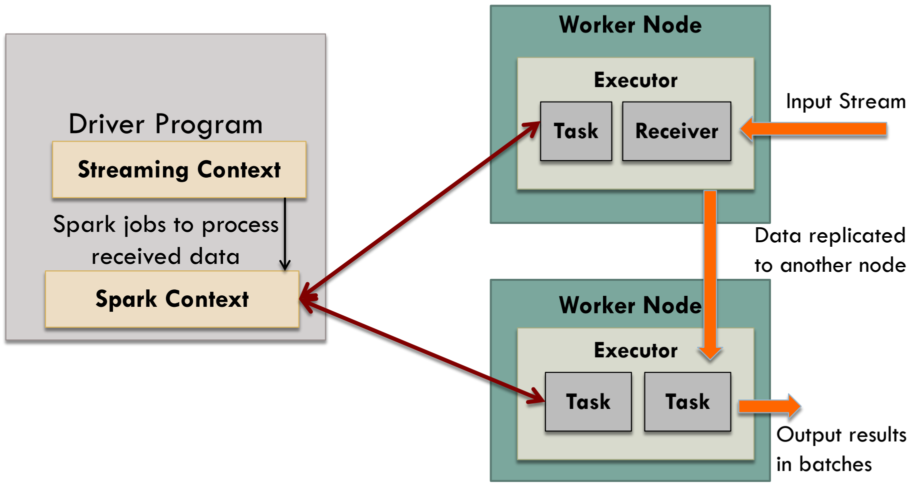
- For each input source, Spark Streaming launches receivers
  - Tasks running within the application's executors that collect data from source and save as RDDs
  - Receives input data and replicates it (by default) to another executor for fault tolerance
  - Data is **stored in memory of the executors**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



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## 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



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## 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 [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

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## STATEFUL TRANSFORMATIONS

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## 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

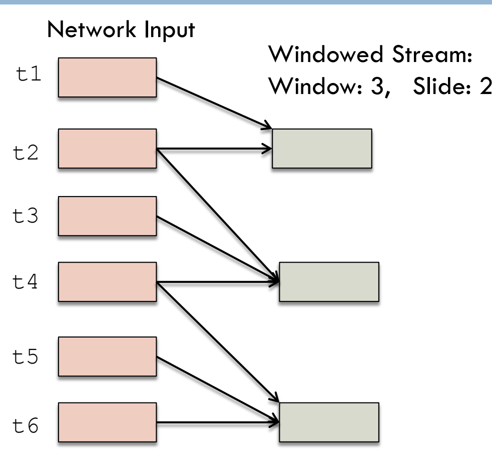
```
ssc.checkpoint("hdfs:// …");
```

## 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)




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

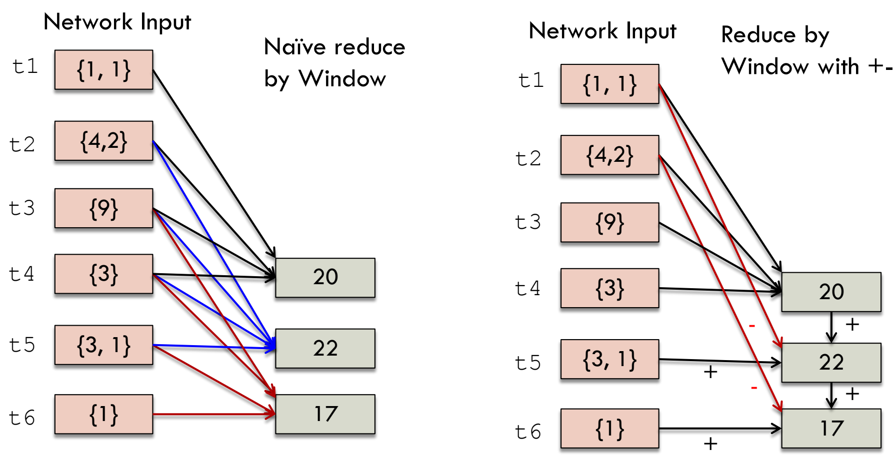




## Other operations on top of `window()`

- `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

## 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