# 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

- Can you edit the schema that Spark infers?
  - Yes: schema hints to override, also transforms/type-casting
- Df1→Df2→Df3: Transformations on Df2 only apply to Df2, and do not cascade down to Df1?

# Topics covered in this lecture

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

# Spark Streaming

# 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.

# 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()`

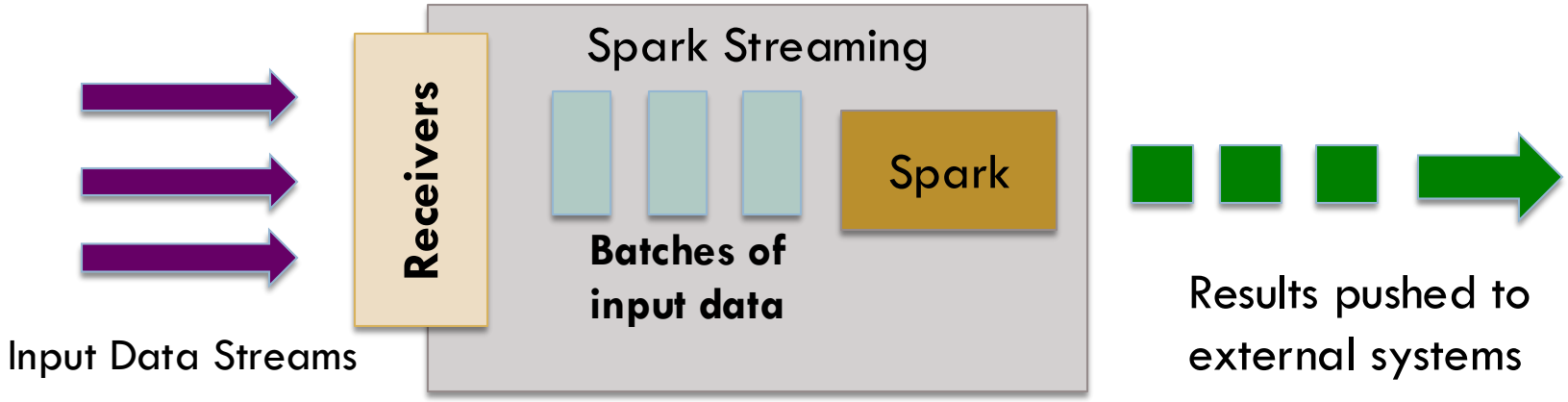
```
jssc.start();
jssc.awaitTermination()
```

# Architecture & Abstractions

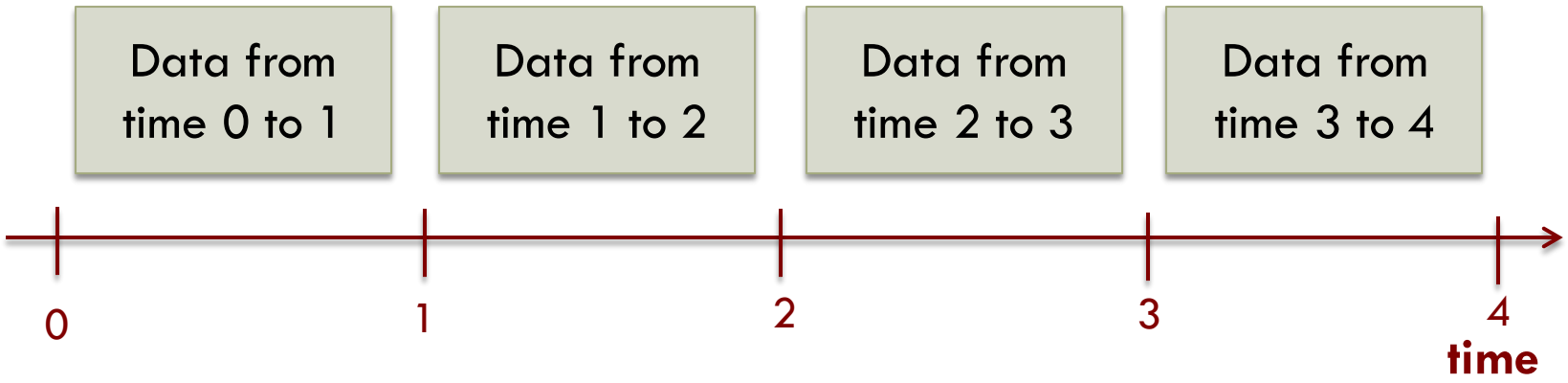
# Spark Streaming Architecture

- 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*

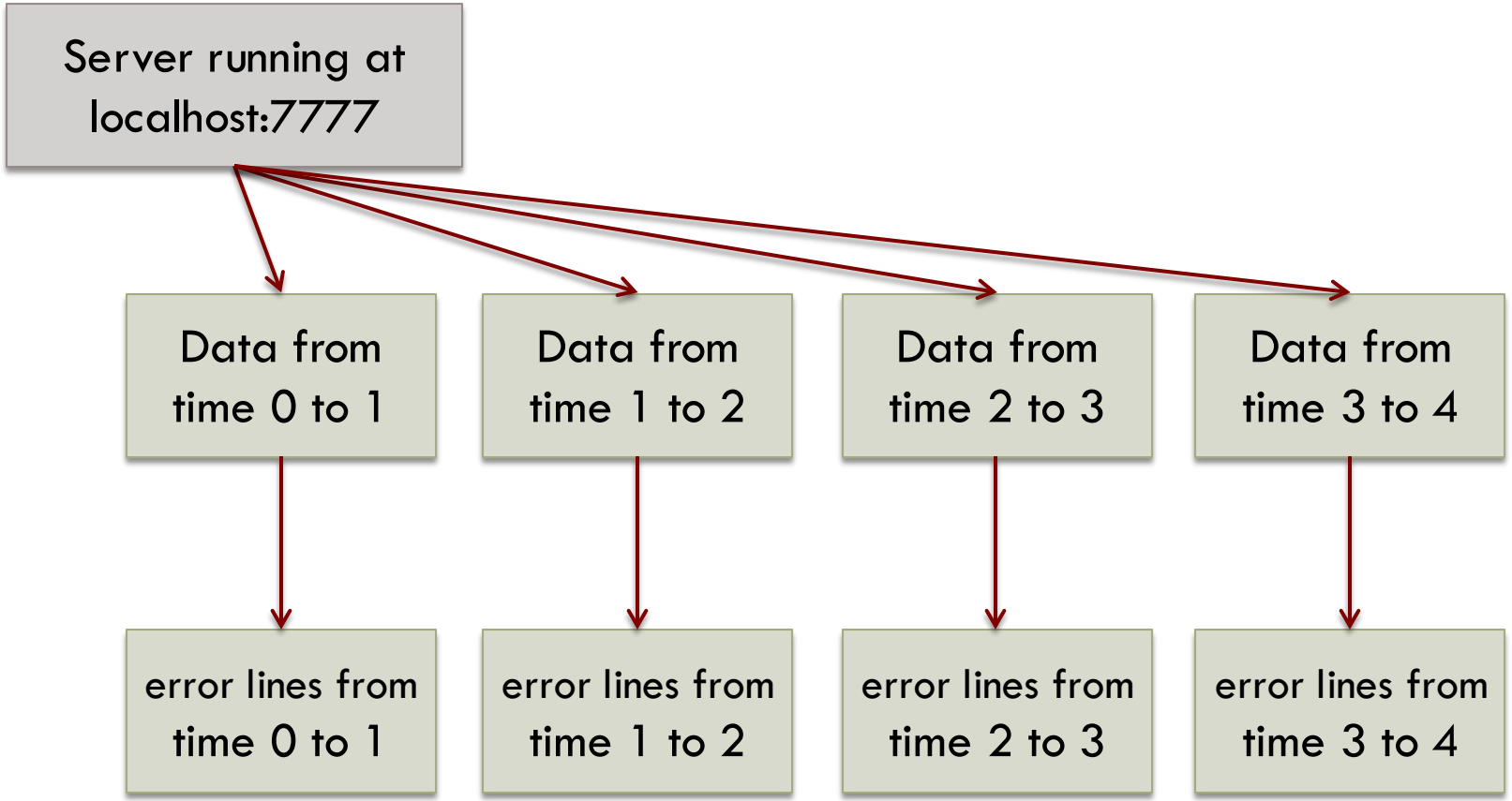
# High-level architecture of Spark Streaming



# 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 `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**

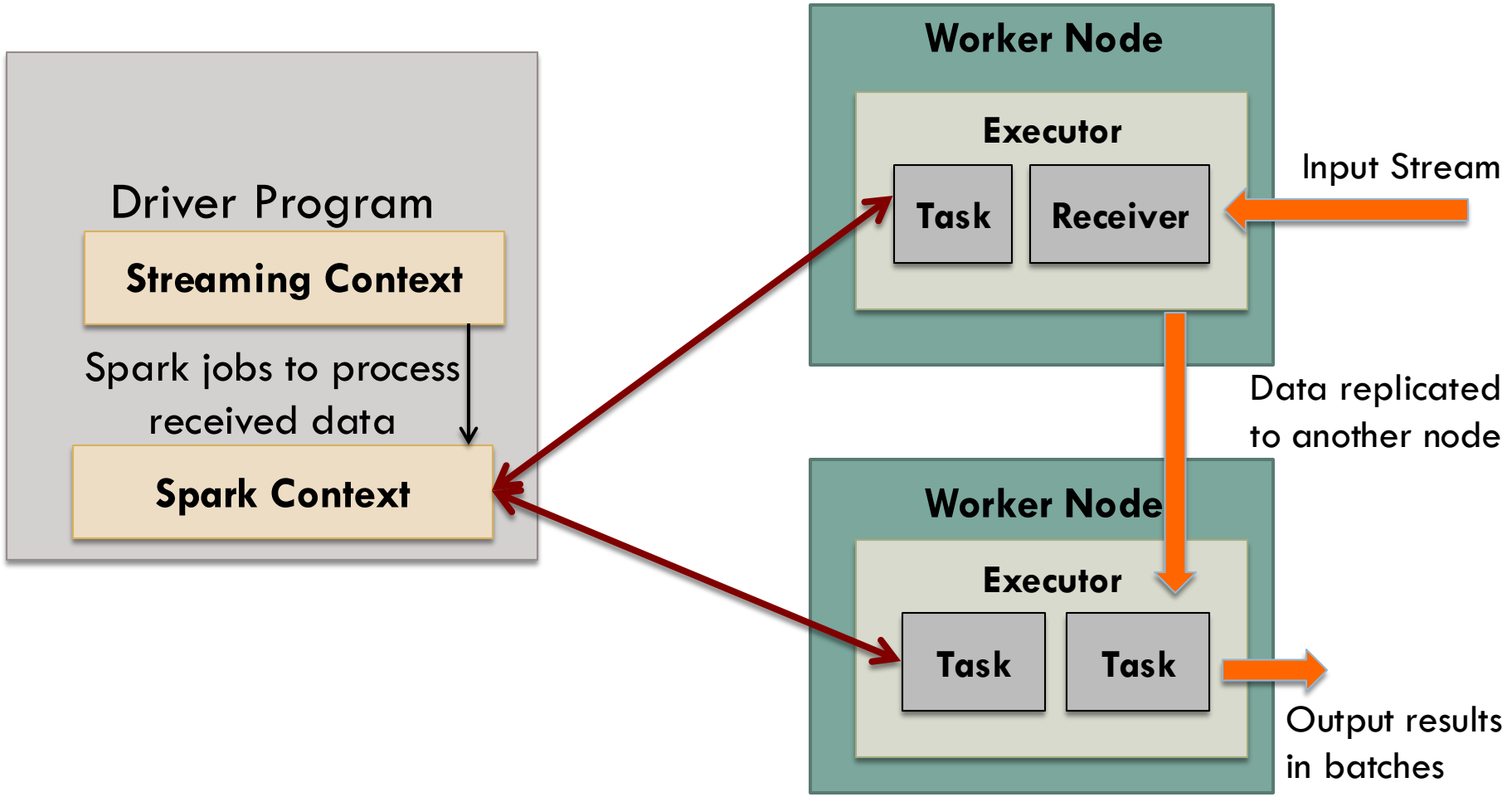
# For each input source, Spark Streaming launches **receivers**

- 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 Summary



# 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

No, Time, thou shalt not boast that I do change:
Thy pyramids built up with newer might
To me are nothing novel, nothing strange;
They are but dressings of a former sight.
Our dates are brief, and therefore we admire

*Sonnet 123: No, Time, thou shalt not boast that I do change*
William Shakespeare; Year 1609

# 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

# 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

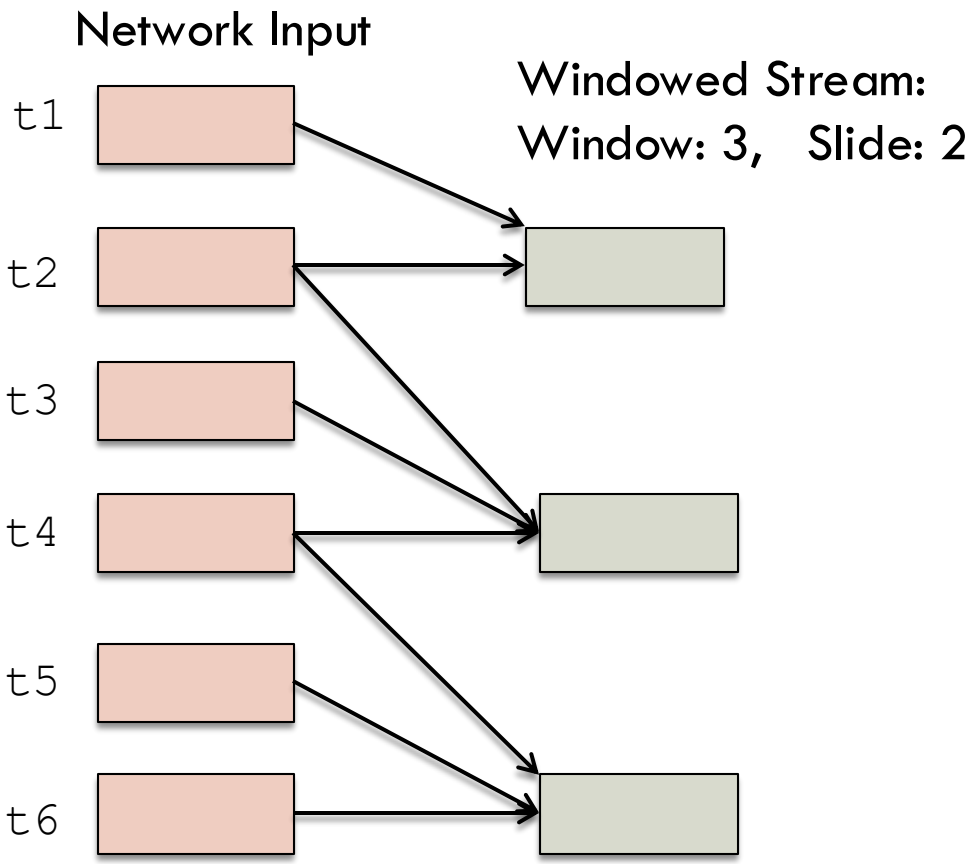
- Requires checkpointing to be enabled in `StreamingContext` for fault tolerance

```
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)




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

# Simplest window operation on a DStream

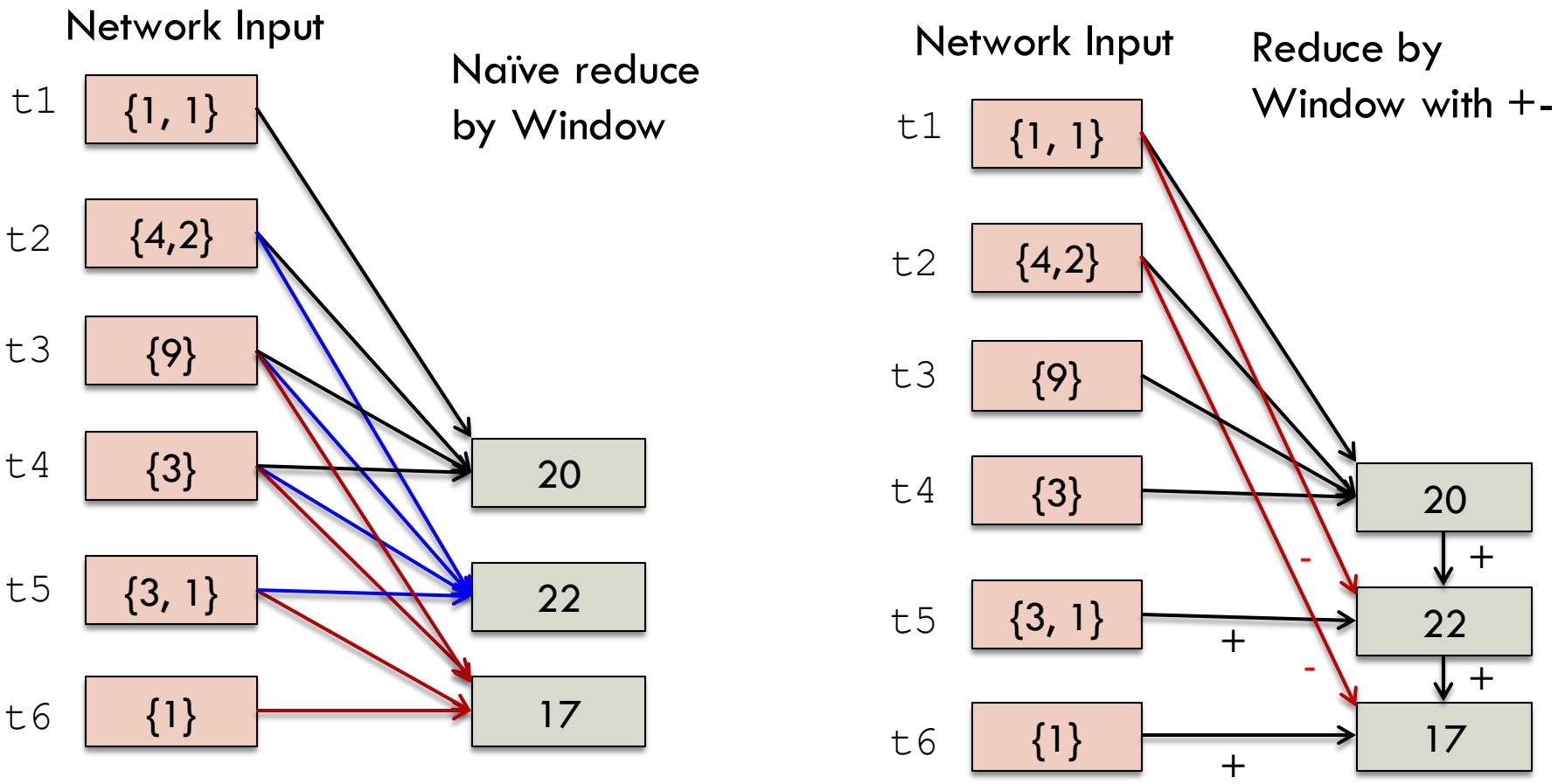
- `window()`
- Returns new DStream with data from the requested window
- Each RDD in the DStream resulting from `window()`, will contain data from multiple batches

# Other operations on top of `window()`

- `reduceByWindow` **and** `reduceByKeyAndWindow`

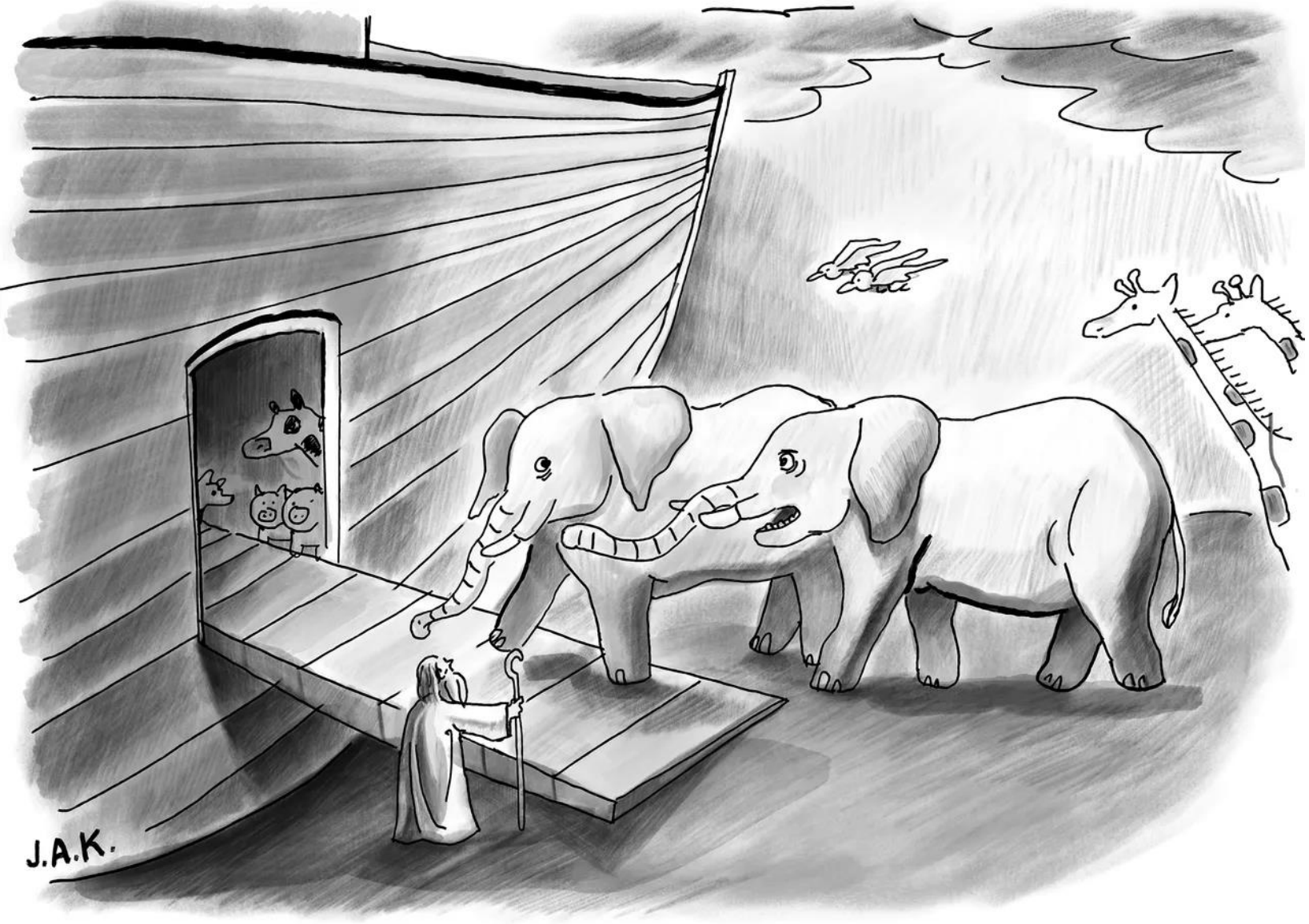
- Includes a special form that allows reduction to be performed **incrementally**
  - Considering only the data coming into the window and the data that is going out
  - Special form requires an **inverse** of the reduce function
    - Such as – for +
  - More efficient for large windows if your function 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: WHAT TO WATCH FOR

*"You insist we're 'just friends,' but then you invite me to stuff like this."*

Jason Adam Katzenstein.
October 7, 2025. *New Yorker*.

# 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 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.

# 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