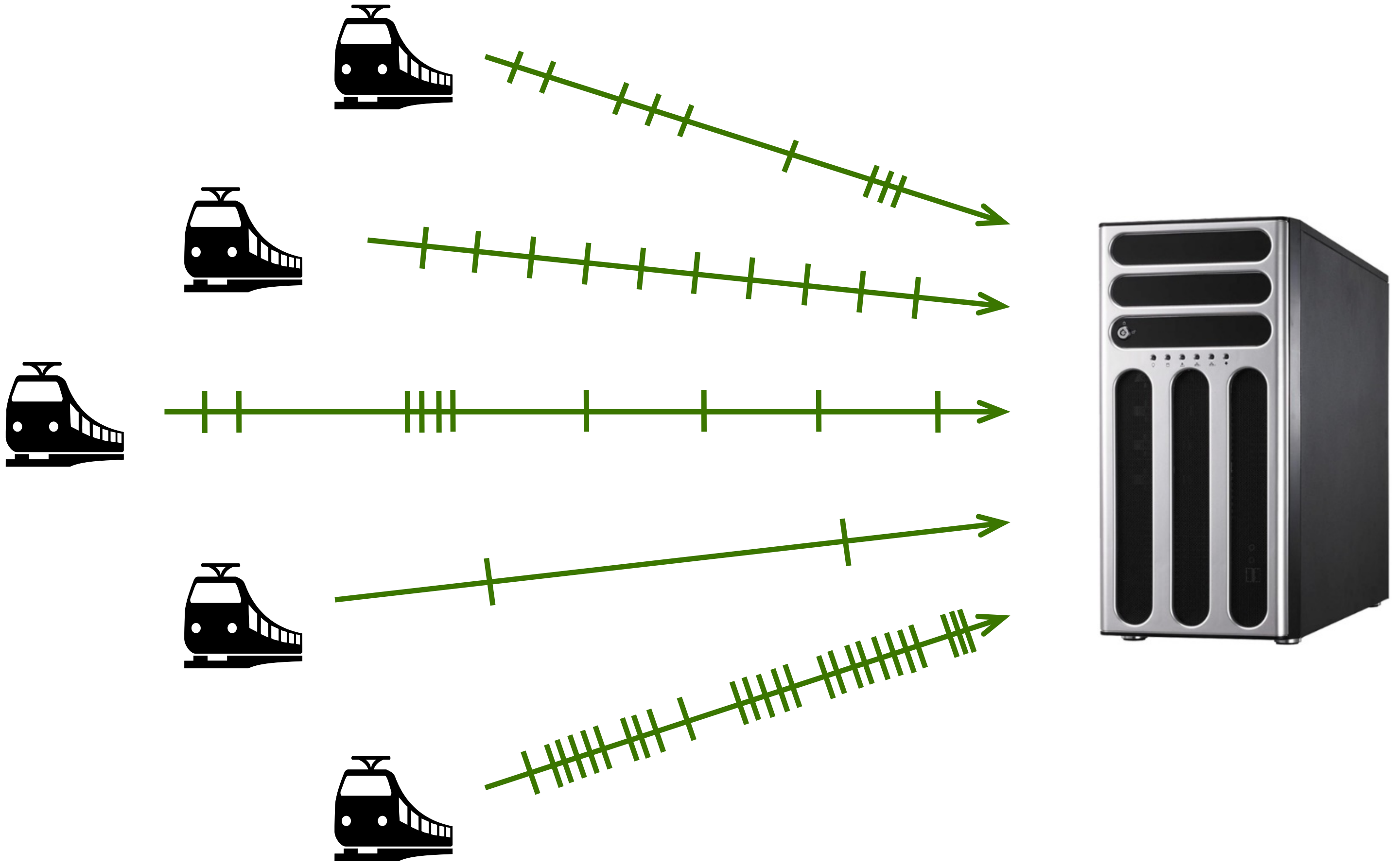
Chapter 5:

Stream Processing

Today‘s Lesson

- Data Streams & Data Stream Management System
- Data Stream Models
  - Insert-Only
  - Insert-Delete
  - Additive
- Streaming Methods
  - Sliding Windows & Ageing
  - Data Synopsis
- Stream Processing – Concepts & Tools
  - Micro-Batching with Apache Spark Streaming
  - Real-time Stream Processing with Apache Storm

Data Streams



Data Streams

- Definition:
  A data stream can be seen as a continuous and potentially infinite stochastic process in which events occur independently from another

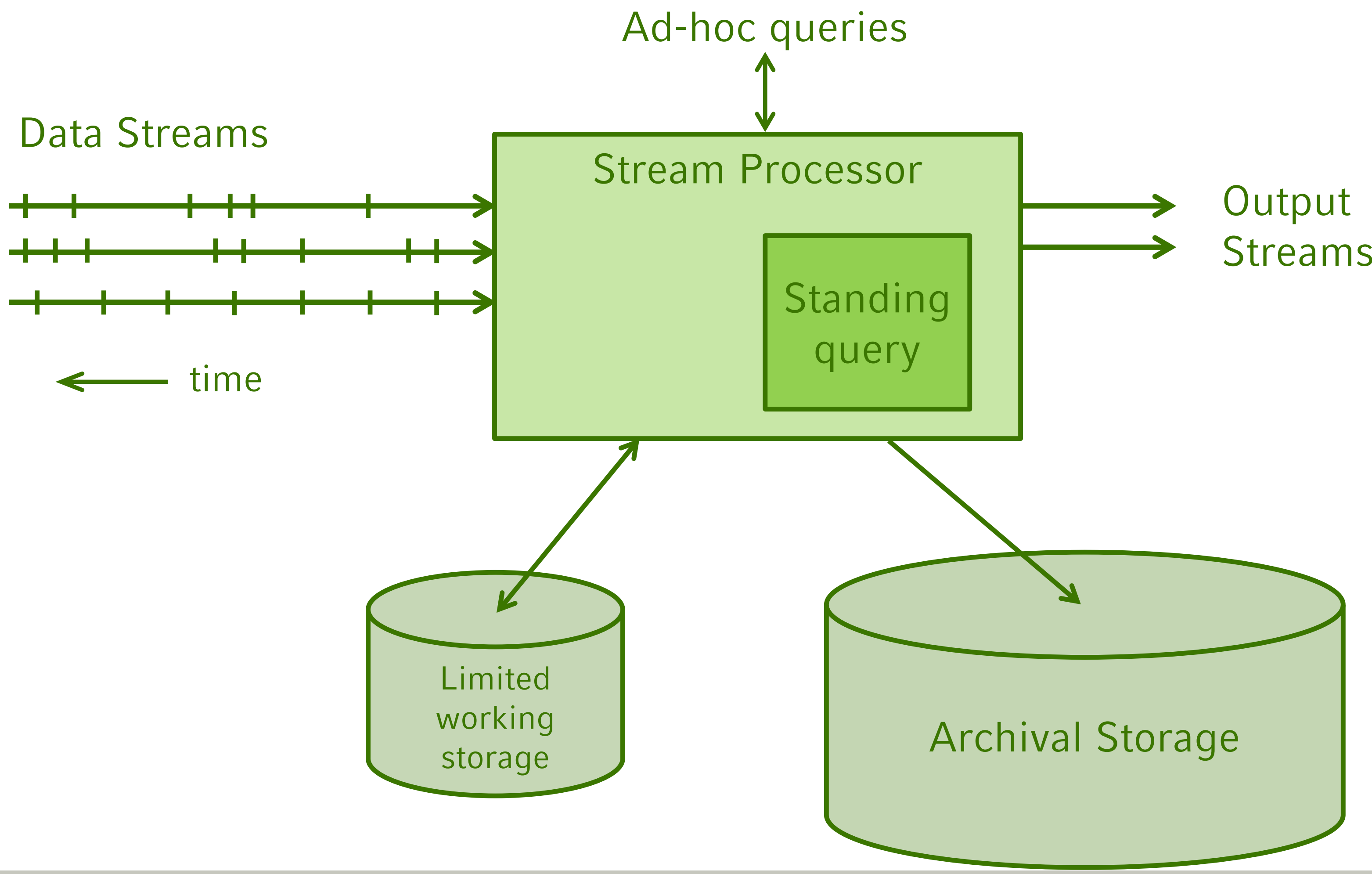
- Huge amount of data
  $\rightarrow$ Data objects cannot be stored

- Single scan

Data Streams – Key Characteristics

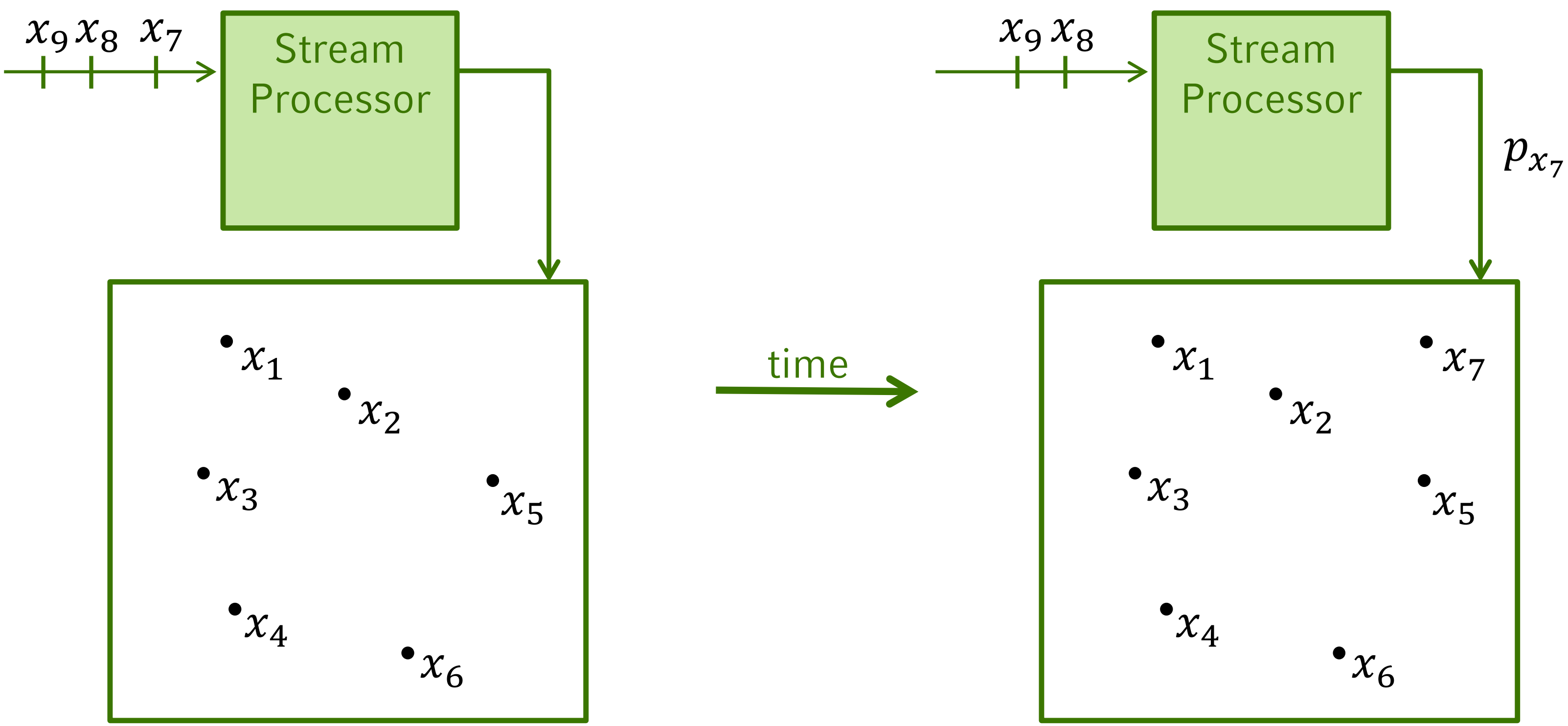
- The data elements in the stream arrive on-line
- The system has no control over the order in which data elements arrive (either within a data stream or across multiple data streams)
- Data streams are potentially unbound in size
- Once an element has been processed it is discarded or archived

Data Stream Management System



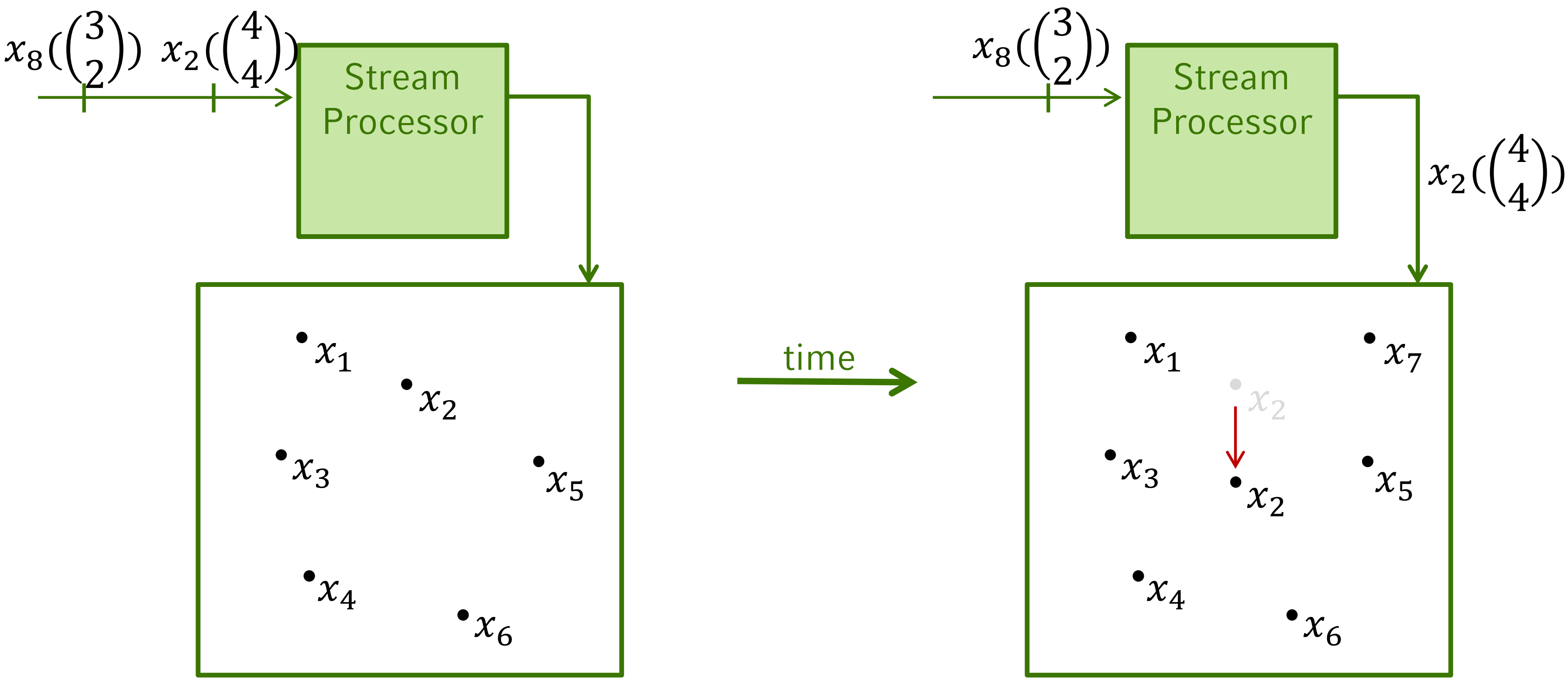
Data Stream Models – Insert-Only Model

- Once an element x_i is seen, it cannot be changed



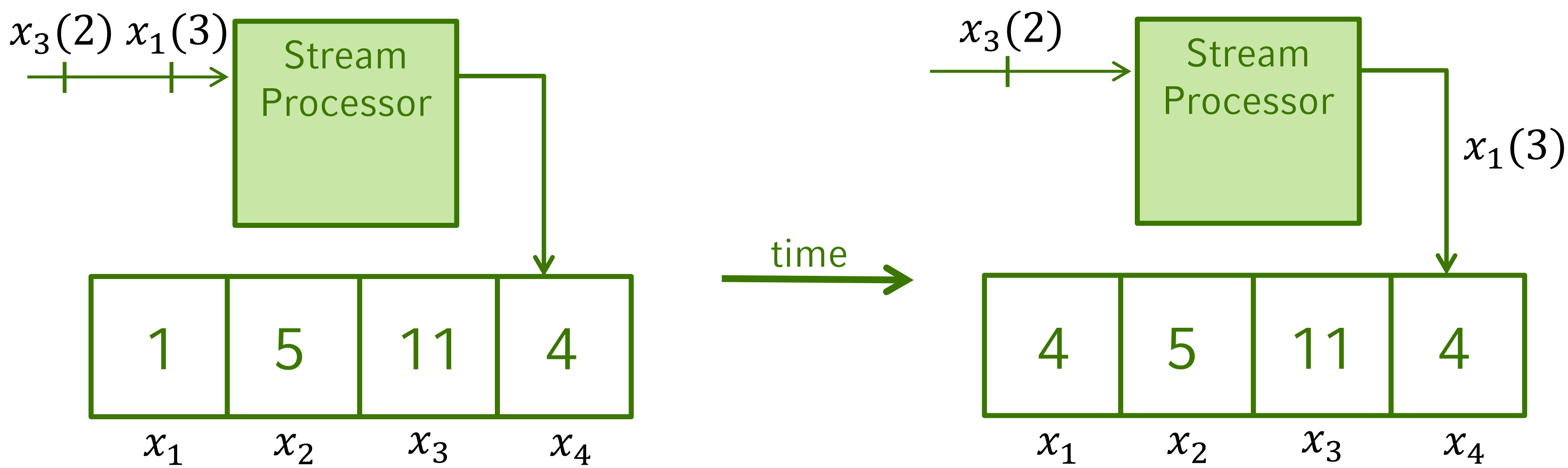
Data Stream Models – Insert-Delete Model

- Elements x_i can be deleted or updated



Data Stream Models – Additive Model

- Each element x_i is an increment to the previous version of the given data object



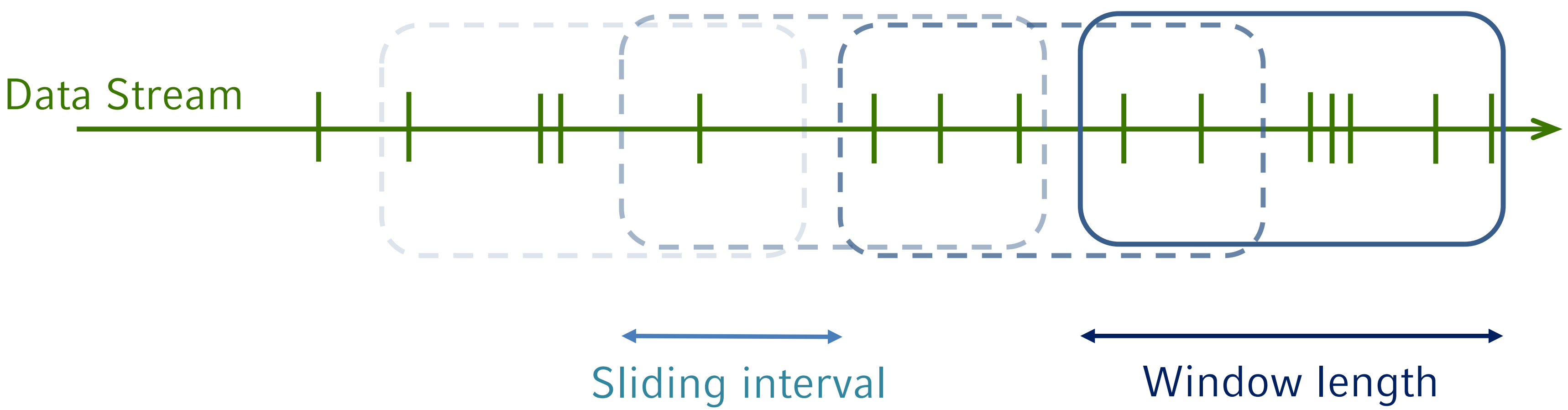
Streaming Methods

- Huge amount of data vs. limited resources in space → impractical to store all data
- Solutions:
  - Storing summaries of previously seen data
  - „Forgetting“ stale data
- But: Trade-off between storage space and the ability to provide precise query answers

Streaming Methods – Sliding Windows

- Idea: Keep most recent stream elements in main memory and discard older ones

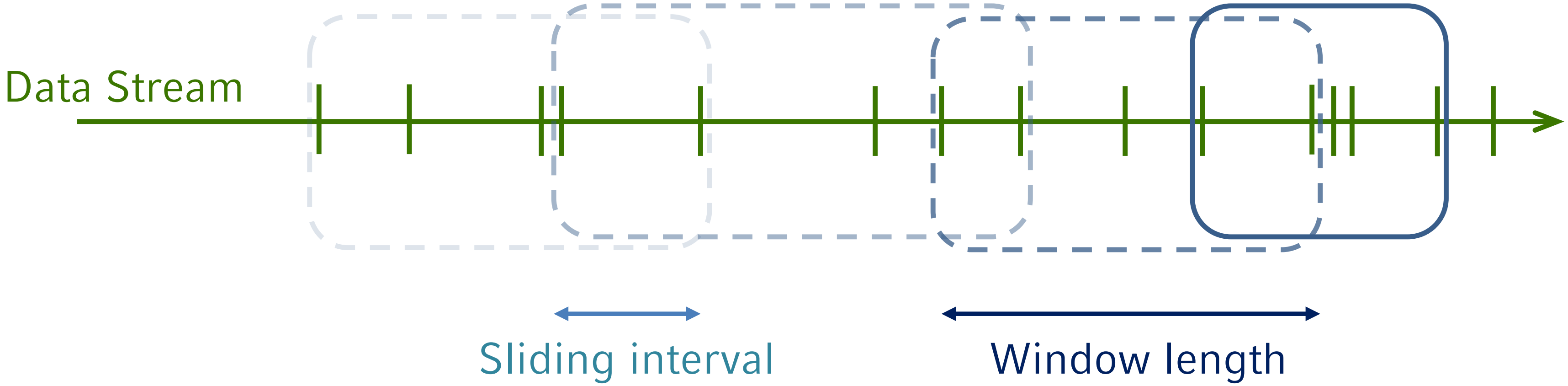
- Timestamp-based:



Streaming Methods – Sliding Windows

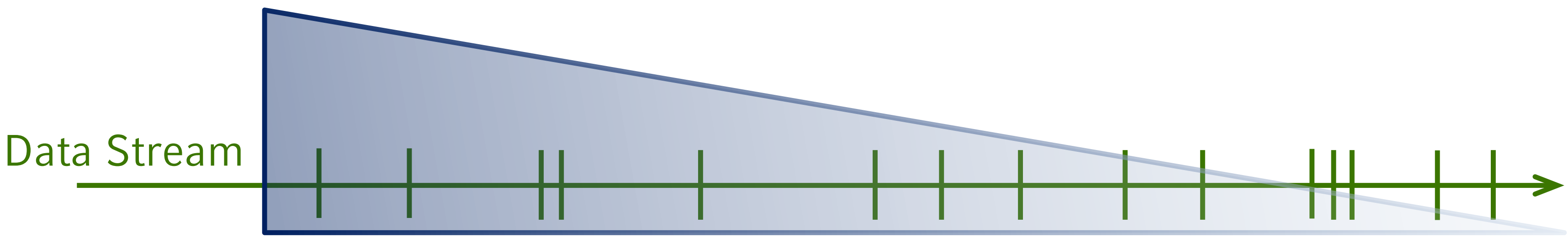
- Idea: Keep most recent stream elements in main memory and discard older ones

- Sequence-based:



Streaming Methods – Ageing

- Idea: Keep only the summary in main memory and discard objects as soon as they are processed



- Multiply the summary with a decay factor after each time epoche, resp. after a certain amount of occuring elements

Streaming Methods

- High velocity of incoming data vs. limited resources in time → impossible to process all data
- Solutions:
  - Data reduction
  - Data approximation
- But: Trade-off between processing speed and the ability to provide precise query answers

Streaming Methods – Sampling

- Select a subset of the data
  $\rightarrow$ Reduce the amount of data to process
- Difficulty: Obtaining a *representative* sample
- Simplest form: *random sampling*
  - Reservoir Sampling
  - Min-Wise Sampling

Reservoir Sampling Algorithm
input: Stream S, Size of reservoir k
begin
  Insert first k objects into reservoir;
  foreach $v \in S$ **do**
    Let i be the position of v;
    M := random integer in range $1..i$;
    if $M \leq k$ **then**
      Insert v into reservoir;
      Delete an instance from the reservoir at random;

- Load Shedding: Discard some fractions of data if the arrival rate of the stream might overload the system

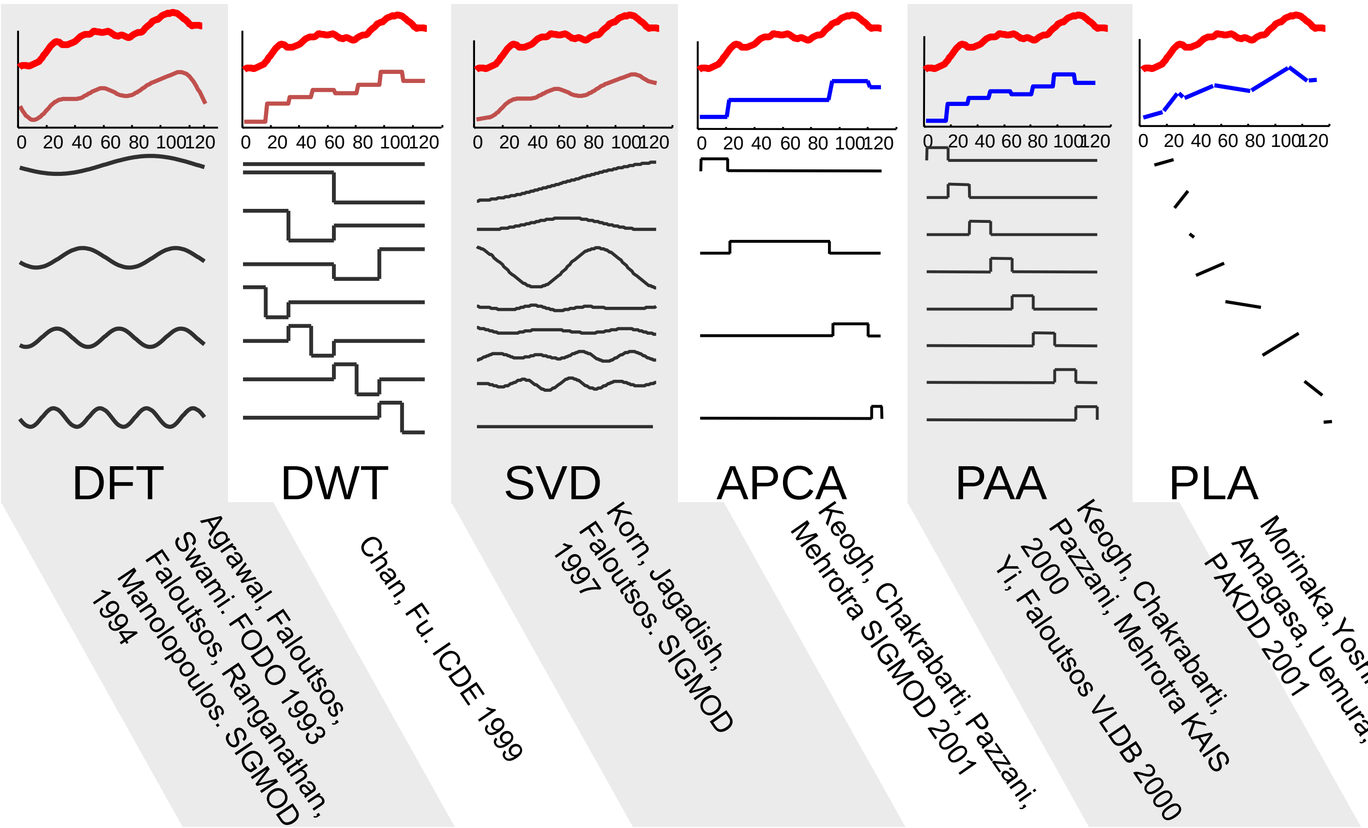
Streaming Methods – Data Synopsis & Histograms

- Summaries of data objects oftenly used to reduce the amount of data
  - e.g. Microclusters that describe groups of similar objects

- Histograms are used to approximate the frequency distribution of element values
  - Commonly used for query optimizers (e.g. range queries)

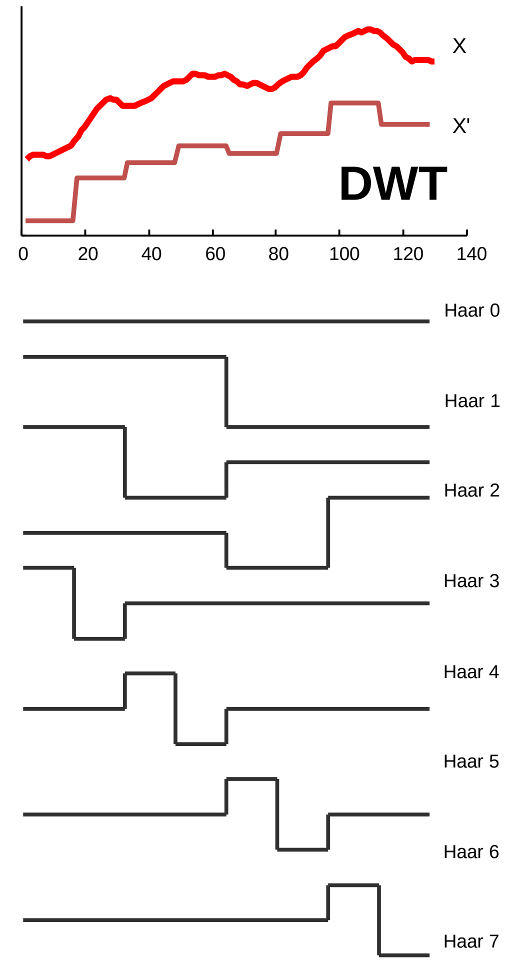
Stream Processing

- Overview of techniques to build a summary (reduced representation) of a sequence of numeric attributes:



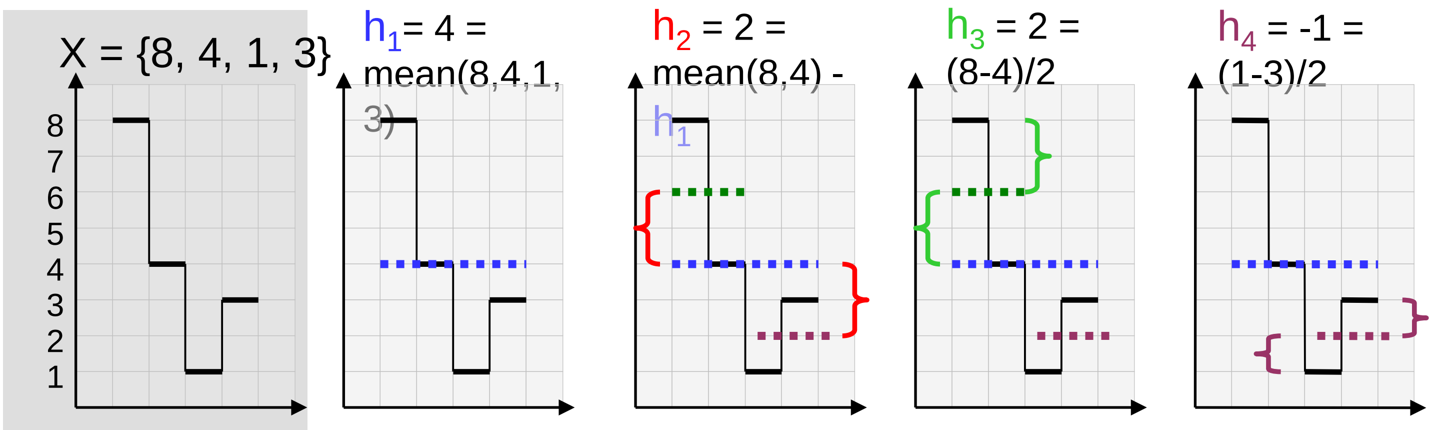
Diskrete Wavelet Transformation (DWT)

- Idea:
  - Sequence represented as linear combination of basic wavelet functions
  - Wavelet transformation decomposes a signal into several groups of coefficients at different scales
  - Small coefficients can be eliminated
    → Small errors when reconstructing the signal
    →Take only the first function coefficents
  - Often: Haar-wavelets used (easy to implement)

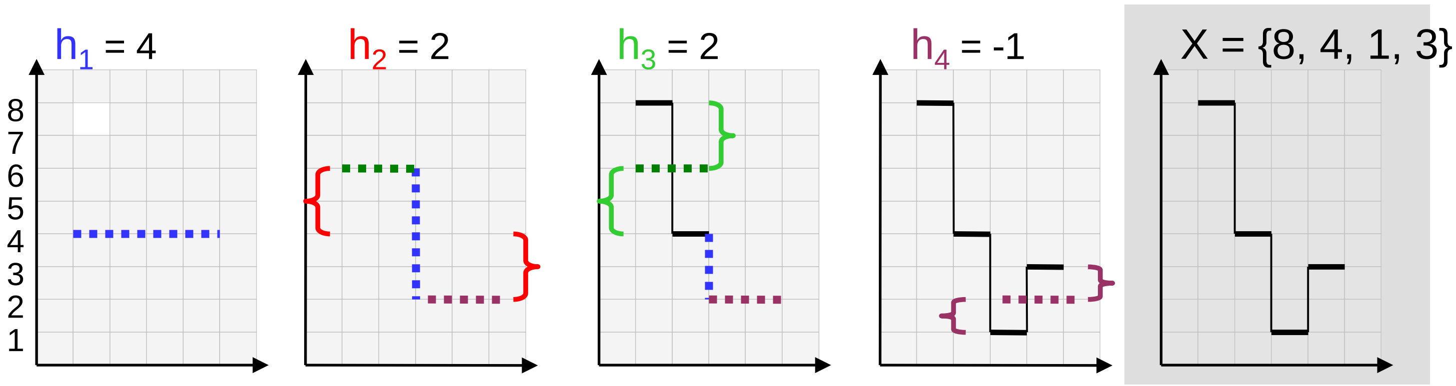


Example:

Step-wise transformation of sequence(stream) X=<8,4,1,3> into Haar-wavelet representation H=[4,2,2,-1]



(Lossless) Reconstruction of original sequence (stream) from Haar-wavelet representation:



Haar Wavelet Transformation

Input sequence:

$$S = (2, 5, 8, 9, 7, 4, -1, 1)$$

Haar Wavelet Transform Algorithm
input: Sequence $S = (x_0, x_1, \dots, x_{2n}, x_{2n+1})$ of even length
output: Sequence of wavelet coefficients
begin
Transform S into a sequence of two-component-vectors $((s_0, d_0), \dots, (s_n, d_n))$ where $\begin{pmatrix} s_i \\ d_i \end{pmatrix} = \frac{1}{2} \cdot \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \cdot \begin{pmatrix} x_i \\ x_{i+1} \end{pmatrix}$;
Separate the sequences s and d;
Recursively transform sequence s;

Step 1:

$s_1 = (2+5, 8+9, 7+4, -1+1)/2$, $d_1 = (2-5, 8-9, 7-4, -1-1)/2$

$s_1 = (3.5, 8.5, 5.5, 0)$, $d_1 = \{-1.5, -0.5, 1.5, -1\}$

Step 2:

$s_2 = (3.5+8.5, 5.5+0)/2$, $d_2 = (3.5-8.5, 5.5-0)/2$

$s_2 = (6, 2.75)$, $d_2 = \{-2.5, 2.75\}$

Step 3:

$s_3 = (6+2.75)/2$, $d_3 = (6-2.75)/2$

$s_3 = 4.375$, $d_3 = \{1.625\}$

$\rightarrow$ Wavelet coefficients $\{4.375, 1.625, -2.5, 2.75, -1.5, -0.5, 1.5, -1\}$

Spark Streaming

- Spark's Streaming Framework build on top of Spark's Core API
- Data ingestion from several different data sources

- Stream processing might be combined with other Spark libraries (e.g. Spark MIlib)

Spark Streaming

Spark Streaming

- Spark's Streaming Workflow:

- Streaming engine receives data from input streams
- Data stream is divided into several microbatches, i.e. sequences of RDDs
- Microbatches are processed by Spark engine
- The result is a data stream of batches of processed data

Spark Streaming

- DStreams (Discretized Streams) as basic abstraction

- Any operation applied on a DStream translates to operations on the underlying RDDs (computed by Spark Engine)
- StreamingContext objects as starting points

```
sc = SparkContext(master, appName)
ssc = StreamingContext(sc, 1) #params: SparkContext, time interval
```

Spark Streaming

General schedule for a Spark Streaming application:

1. Define the StreamingContext `ssc`
2. Define the input sources by creating input DStreams
3. Define the streaming computations by applying transformations and output operations to Dstreams
4. Start receiving data and processing it using `ssc.start()`
5. Wait for the processing to be stopped (manually or due to any error) using `ssc.awaitTermination()`
6. The processing can be manually stopped using `ssc.stop()`

Spark Streaming

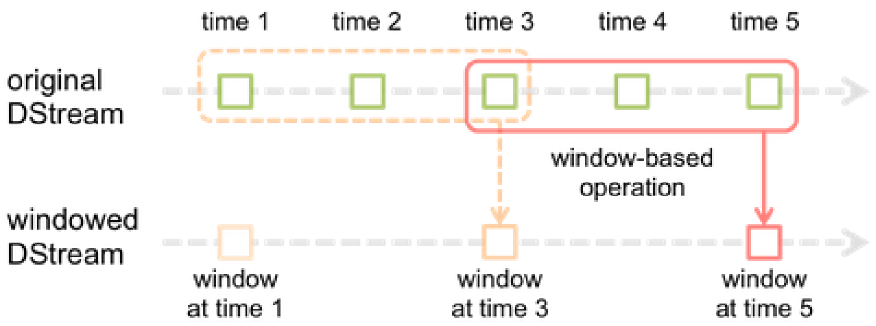
Spark Streaming

```
#Create a local StreamingContext with two working threads and batch
#interval of 1 sec
sc = SparkContext("local[2]","NetworkWordCount")
ssc = StreamingContext(sc, 1)

#Create a DStream that will connect to localhost:9999
lines = ssc.socketTextStream("localhost", 9999)
#Split each line into words
words = lines.flatMap(lambda line: line.split(" "))
#Count each word in each batch
pairs = words.map(lambda word: (word,1))
wordCounts = pairs.reduceByKey(lambda x, y: x + y)
#Print the first ten elements of each RDD of this DStream to the console
wordCounts.pprint()

#Start the computation and wait for it to terminate
ssc.start()
ssc.awaitTermination()
```

Spark Streaming

Spark Streaming

- Support of window operations
- Two basic parameters:
  - windowLength
  - slideInterval



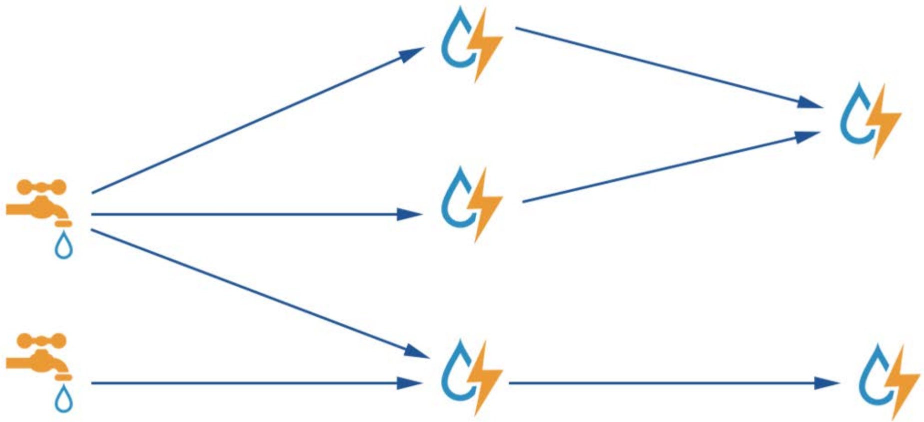
- Support of many transformations for windowed DStreams

```
#Reduce last 30 sec of data, every 10 sec
winWordCounts = pairs
          .reduceByKeyAndWindow(lambda x,y: x+y, 30, 10)
```

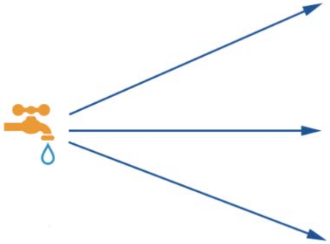
Apache Storm

APACHE STORM™ Distributed • Resilient • Real-time

- Alternative to Spark Streaming
- Support of Real-time Processing
- Three abstractions:
  - Spouts
  - Bolts
  - Topologies



Apache Storm



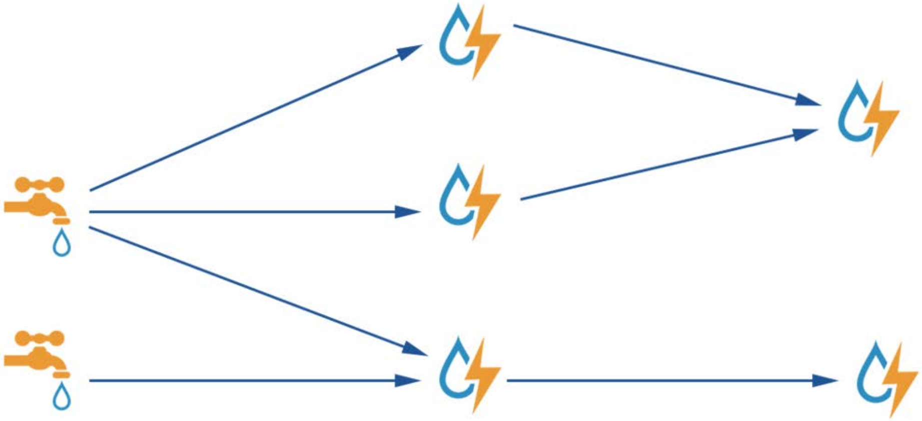
- Spouts:
  - Source of streams
  - Typically reads from queuing brokers (e.g. Kafka, RabbitMQ)
  - Can also generate its own data or read from external sources (e.g. Twitter)

- Bolts:
  - Processes any number of input streams
  - Produces any number of output streams
  - Holds most of the logic of the computations (functions, filters,…)

Apache Storm

APACHE STORM™ Distributed • Resilient • Real-time

- Topologies:
  - Network of spouts and bolts
  - Each edge represents a bolt subscribing to the output stream of some other spout or bolt
  - A topology is an arbitrarily complex multi-stage stream computation

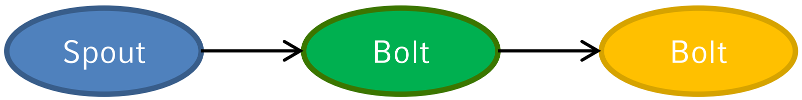


Apache Storm

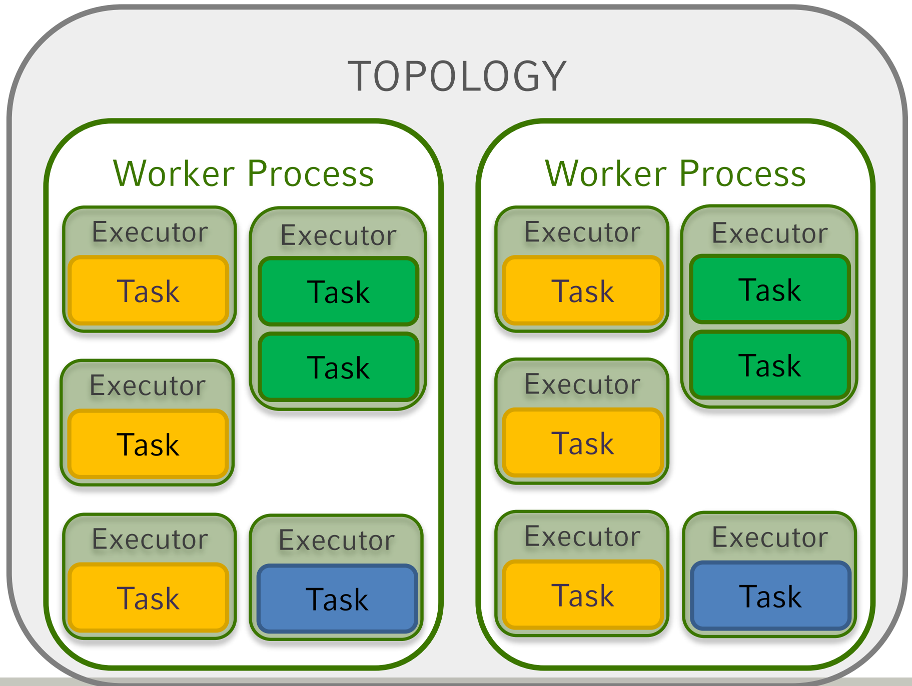
APACHE STORM™
Distributed • Resilient • Real-time

- Streams:
  - Core abstraction in Storm
  - A stream is an unbounded sequence of tuples that is processed and created in parallel in a distributed fashion
  - Tuples can contain standard types like integers, floats, shorts, booleans, strings and so on
  - Custom types can be used if a own serializer is defined
  - A stream grouping defines how that stream should be partitioned among the bolt's tasks

Apache Storm




```
Config conf = new Config();
conf.setNumWorkers(2); // use two worker processes

topologyBuilder.setSpout("blue-spout", new BlueSpout(), 2); // set parallelism hint to 2

topologyBuilder.setBolt("green-bolt", new GreenBolt(), 2)
               .setNumTasks(4)
               .shuffleGrouping("blue-spout");
// 4 Tasks spread across 2 Executors and the
// tuples shall be randomly distributed across
// the bolt‘s tasks, each bolt shall get an
// equal number of tuples

topologyBuilder.setBolt("yellow-bolt",
                         new YellowBolt(), 6)
               .shuffleGrouping("green-bolt");

StormSubmitter.submitTopology(
        "mytopology",
        conf,
        topologyBuilder.createTopology()
    );
```



Further Reading

- Joao Gama: *Knowledge Discovery from Data Streams* (http://www.liaad.up.pt/area/jgama/DataStreamsCRC.pdf)
- Jure Leskovec, Anand Rajaraman, Jeff Ullman: *Mining of Massive Datasets*
- Holden Karau, Andy Konwinski, Patrick Wendell, Matei Zaharia: *Learning Spark - Lightning-Fast Big Data Analysis*
- http://spark.apache.org/docs/latest/streaming-programming-guide.html
- http://storm.apache.org/documentation/Concepts.html