LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

FAKULTÄT FÜR MATHEMATIK, INFORMATIK UND STATISTIK
INSTITUT FÜR INFORMATIK

LEHRSTUHL FÜR DATENBANKSYSTEME
UND DATA MINING

Lecture Notes to

Big Data Management and Analytics

Winter Term 2017/2018

Stream Processing

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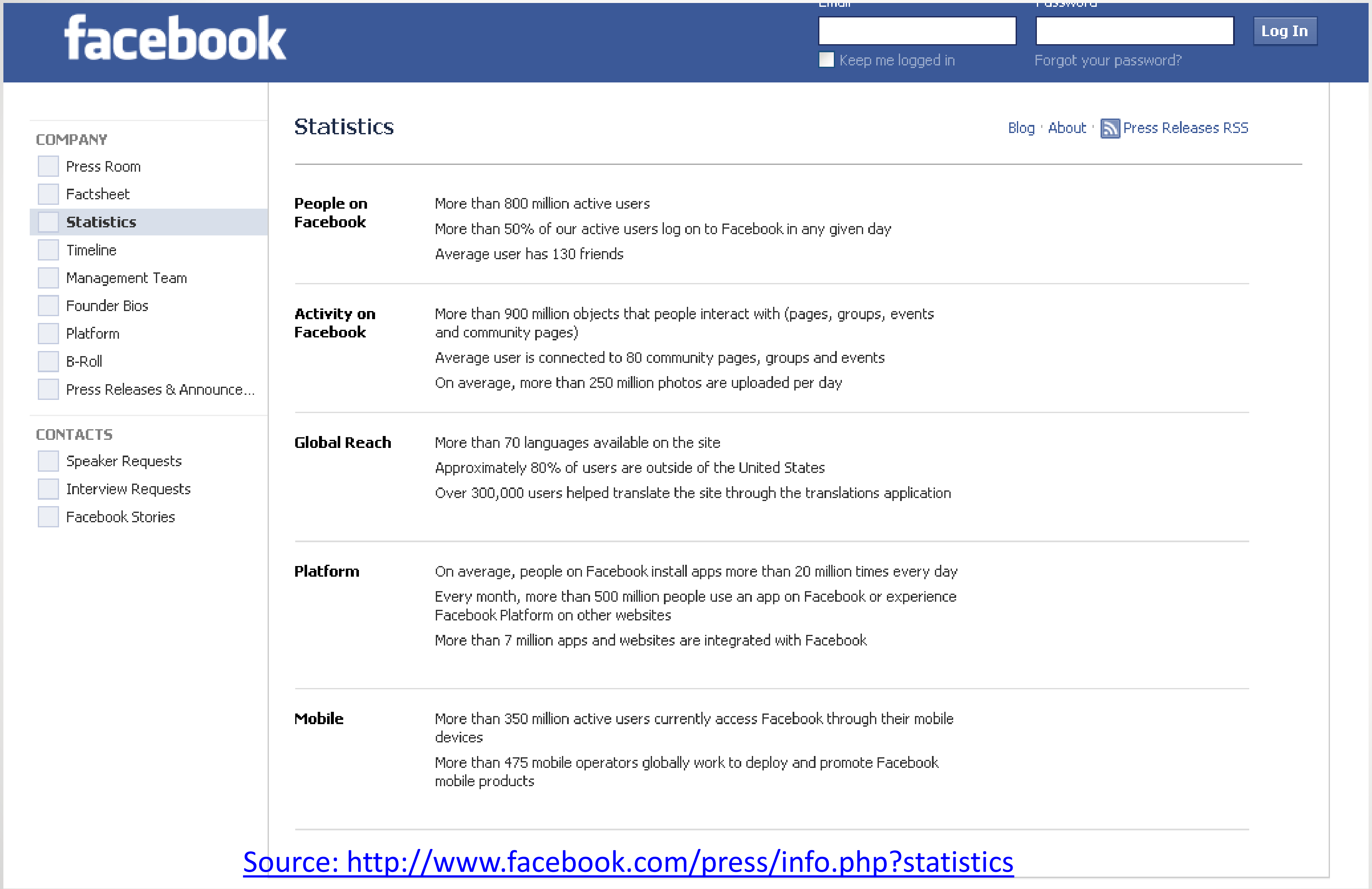
DBS

Example application: Facebook



Statistics

People on Facebook

More than 800 million active users

More than 50% of our active users log on to Facebook in any given day

Average user has 130 friends

Activity on Facebook

More than 900 million objects that people interact with (pages, groups, events and community pages)

Average user is connected to 80 community pages, groups and events

On average, more than 250 million photos are uploaded per day

Global Reach

More than 70 languages available on the site

Approximately 80% of users are outside of the United States

Over 300,000 users helped translate the site through the translations application

Platform

On average, people on Facebook install apps more than 20 million times every day

Every month, more than 500 million people use an app on Facebook or experience Facebook Platform on other websites

More than 7 million apps and websites are integrated with Facebook

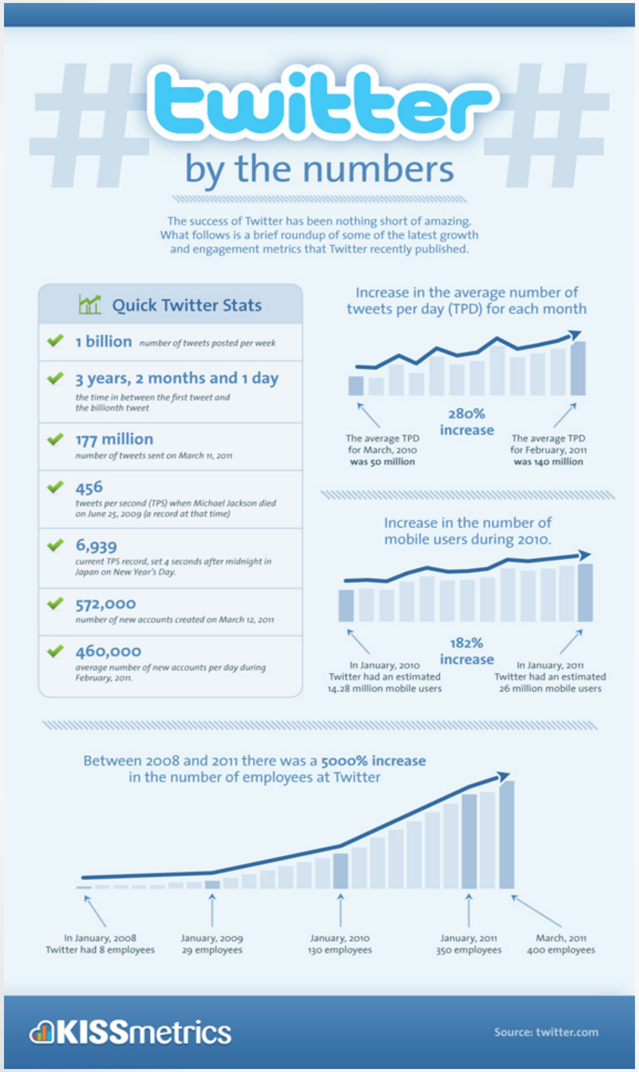
Mobile

More than 350 million active users currently access Facebook through their mobile devices

More than 475 mobile operators globally work to deploy and promote Facebook mobile products

Source: http://www.facebook.com/press/info.php?statistics

Example application: Twitter



twitter by the numbers

The success of Twitter has been nothing short of amazing. What follows is a brief roundup of some of the latest growth and engagement metrics that Twitter recently published.

Quick Twitter Stats

- ✓ **1 billion** *number of tweets posted per week*
- ✓ **3 years, 2 months and 1 day** *the time in between the first tweet and the billionth tweet*
- ✓ **177 million** *number of tweets sent on March 11, 2011*
- ✓ **456** *tweets per second (TPS) when Michael Jackson died on June 25, 2009 (a record at that time)*
- ✓ **6,939** *current TPS record, set 4 seconds after midnight in Japan on New Year's Day.*
- ✓ **572,000** *number of new accounts created on March 12, 2011*
- ✓ **460,000** *average number of new accounts per day during February, 2011.*

Increase in the average number of tweets per day (TPD) for each month

The average TPD for March, 2010 **was 50 million**

280% increase

The average TPD for February, 2011 **was 140 million**

Increase in the number of mobile users during 2010.

In January, 2010 Twitter had an estimated 14.28 million mobile users

182% increase

In January, 2011 Twitter had an estimated 26 million mobile users

Between 2008 and 2011 there was a **5000% increase** in the number of employees at Twitter

In January, 2008 Twitter had 8 employees

January, 2009 29 employees

January, 2010 130 employees

January, 2011 350 employees

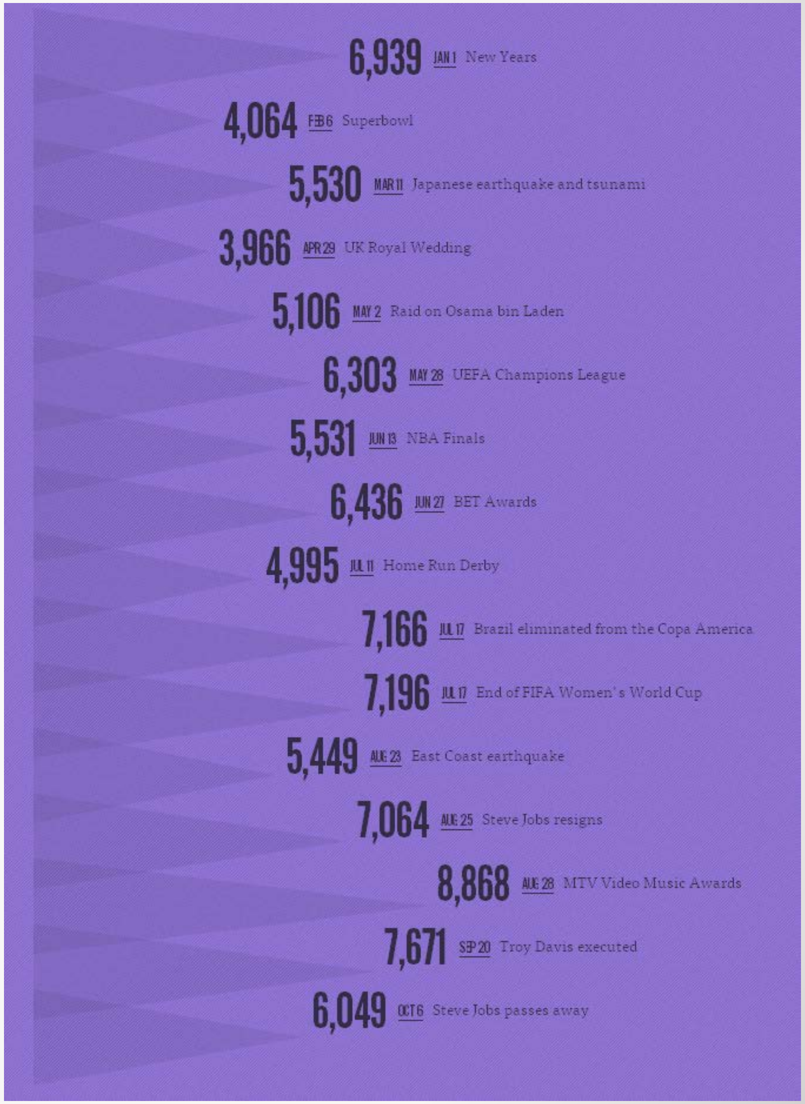
March, 2011 400 employees

KISSmetrics

Source: twitter.com

[Source: http://blog.kissmetrics.com/twitter-statistics/](http://blog.kissmetrics.com/twitter-statistics/)

Tweets per second



6,939	JAN 1	New Years
4,064	FEB 6	Superbowl
5,530	MAR 11	Japanese earthquake and tsunami
3,966	APR 29	UK Royal Wedding
5,106	MAY 2	Raid on Osama bin Laden
6,303	MAY 28	UEFA Champions League
5,531	JUN 13	NBA Finals
6,436	JUN 27	BET Awards
4,995	JUL 11	Home Run Derby
7,166	JUL 17	Brazil eliminated from the Copa America
7,196	JUL 17	End of FIFA Women's World Cup
5,449	AUG 23	East Coast earthquake
7,064	AUG 25	Steve Jobs resigns
8,868	AUG 28	MTV Video Music Awards
7,671	SEP 20	Troy Davis executed
6,049	OCT 6	Steve Jobs passes away

Example application: CERN

- Experiments at CERN are generating an entire petabyte (1PB=10^6 GB) of data every second as particles fired around the Large Hadron Collider (LHC) at velocities approaching the speed of light are smashed together
- "We don't store all the data as that would be impractical. Instead, from the collisions we run, we only keep the few pieces that are of interest, the rare events that occur, which our filters spot and send on over the network," he said.
- This still means CERN is storing 25PB of data every year – the same as 1,000 years' worth of DVD quality video – which can then be analyzed and interrogated by scientists looking for clues to the structure and make-up of the universe.

Source: http://public.web.cern.ch/public/en/LHC/Computing-en.html
Source: http://www.v3.co.uk/v3-uk/news/2081263/cern-experiments-generating-petabyte

Stream Processing

Outline

- 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

Stream Processing

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
  → Data objects cannot be stored

- Single scan

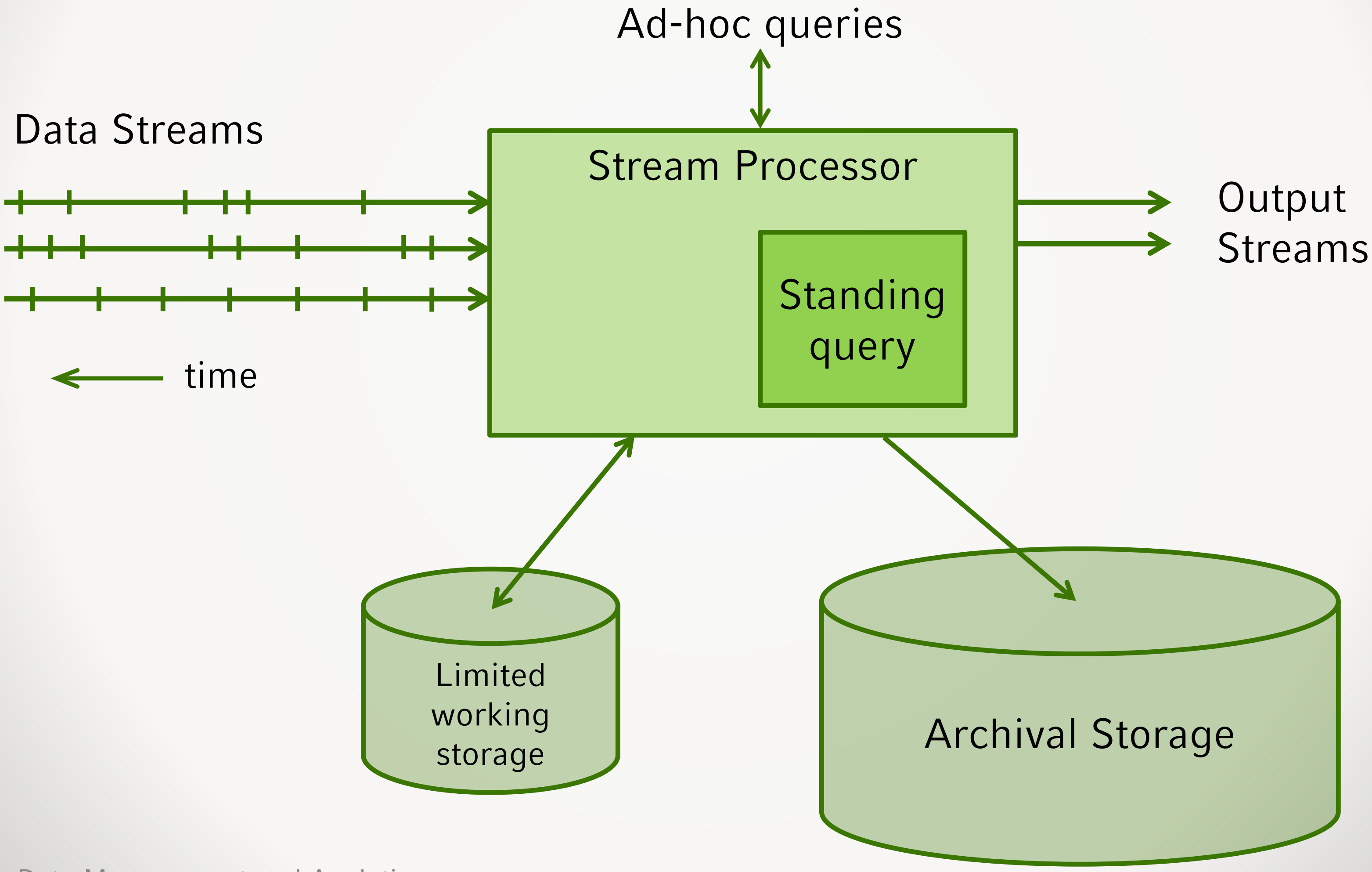
Stream Processing

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

Stream Processing

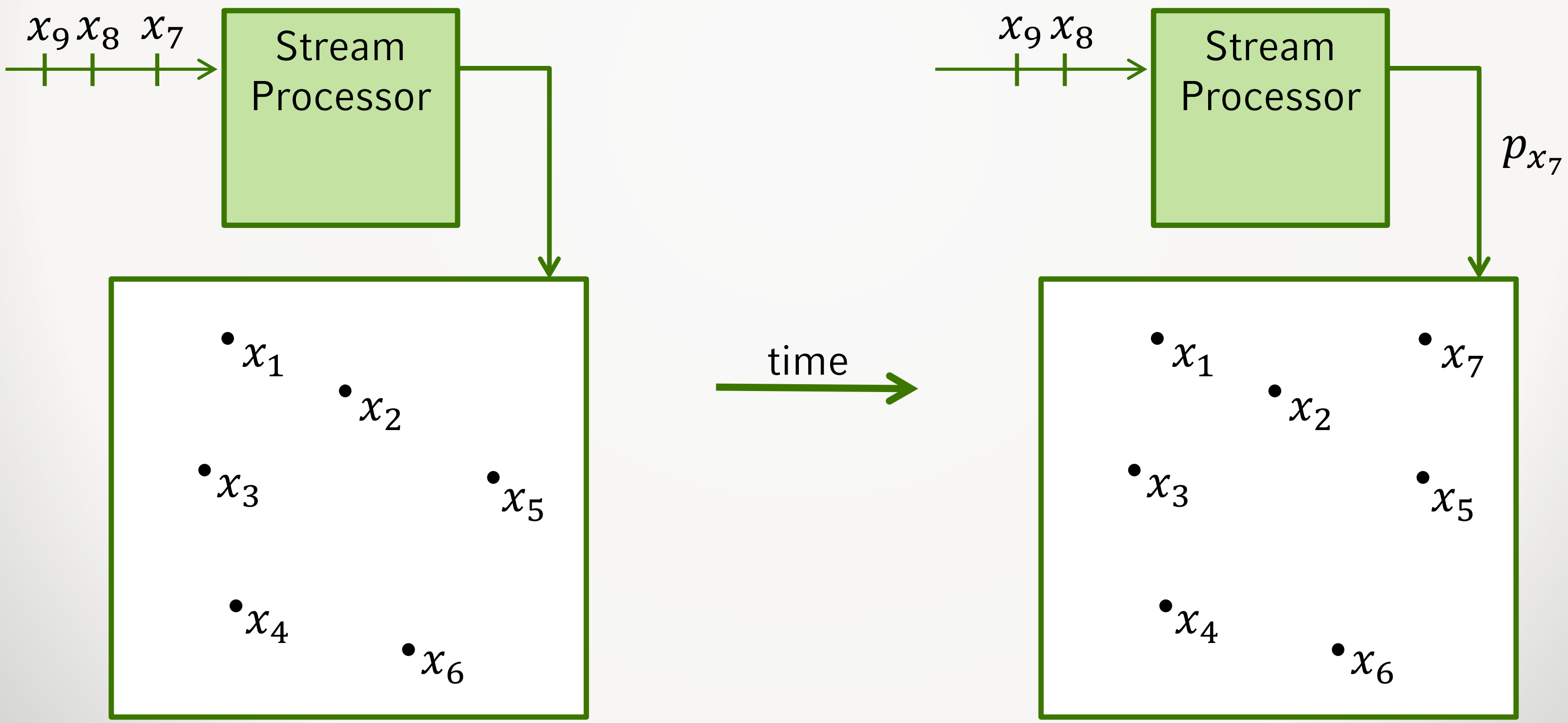
Data Stream Management System



Stream Processing

Data Stream Models – Insert-Only Model

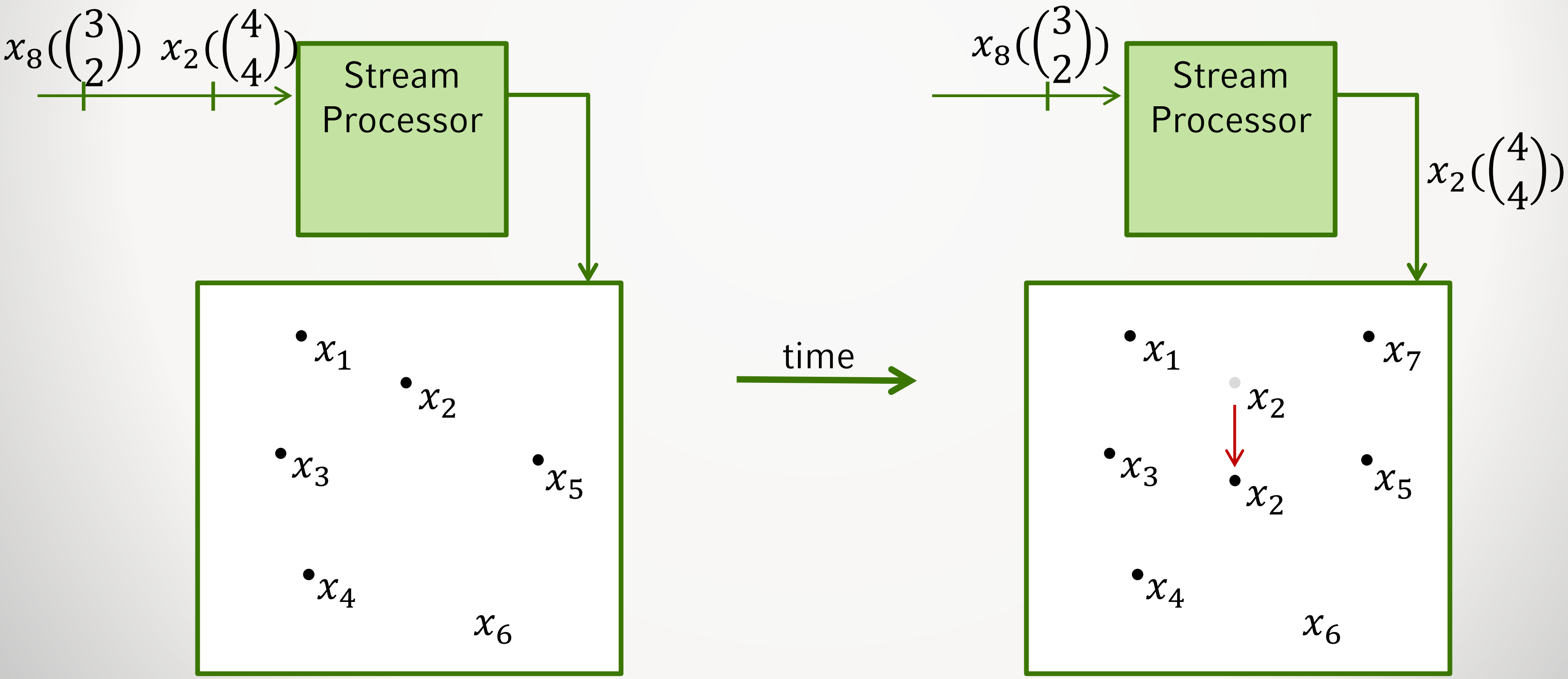
- Once an element x_i is seen, it cannot be changed



Stream Processing

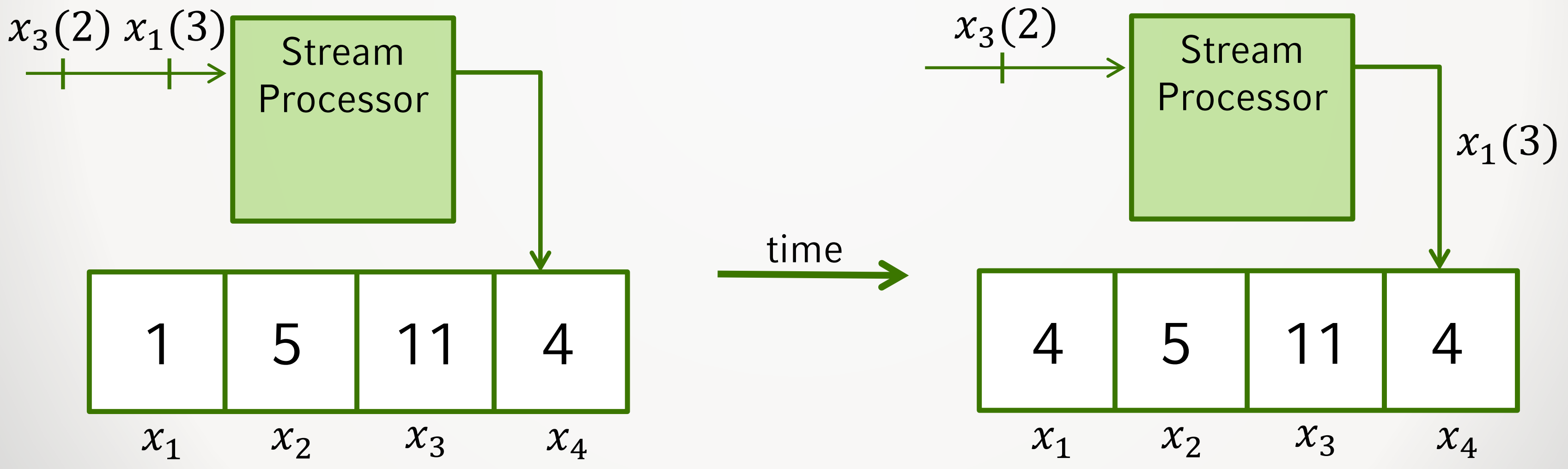
Data Stream Models – Insert-Delete Model

- 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



x_1	x_2	x_3	x_4
1	5	11	4

x_1	x_2	x_3	x_4
4	5	11	4

Stream Processing

Streaming Methods

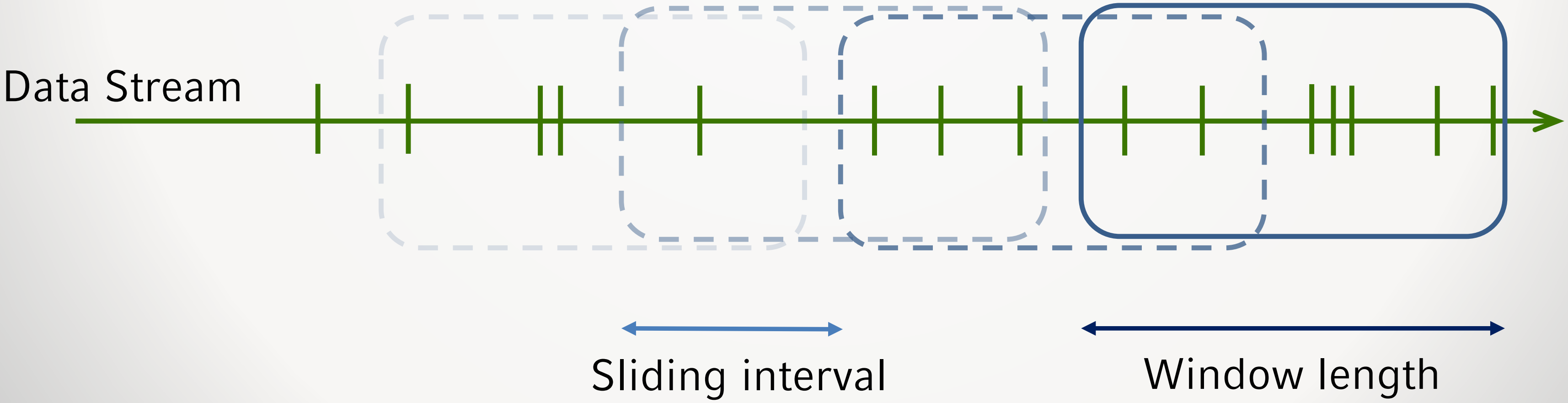
- Huge amount of data vs. limited resources in space → impractical to store all data
- Solutions:
  - Storing summaries of previously seen data
  - „Forgetting“ stale data
- But: Trade-off between storage space and the ability to provide precise query answers

Stream Processing

Streaming Methods – Sliding Windows

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

- Timestamp-based:

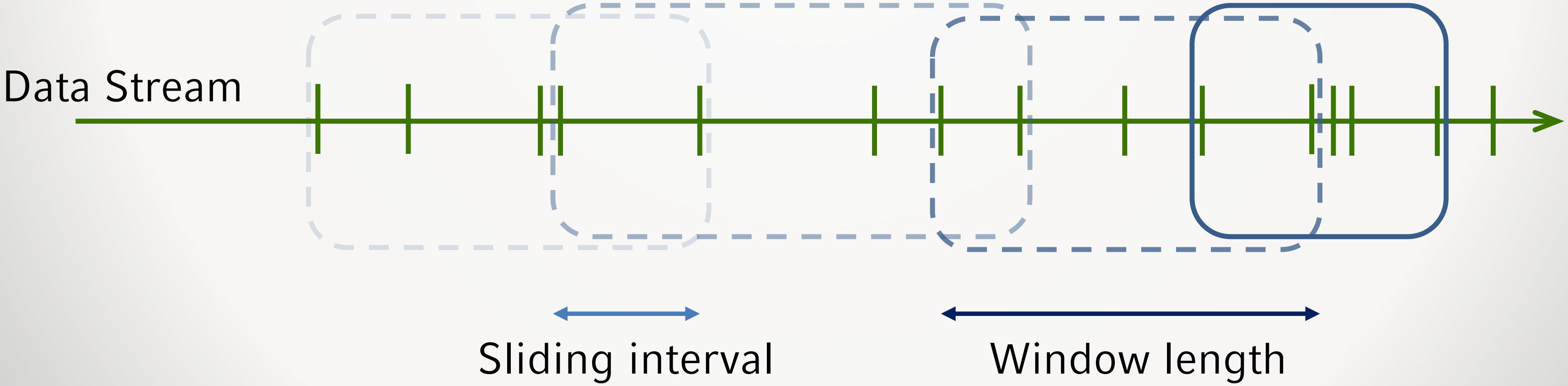


Stream Processing

Streaming Methods – Sliding Windows

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

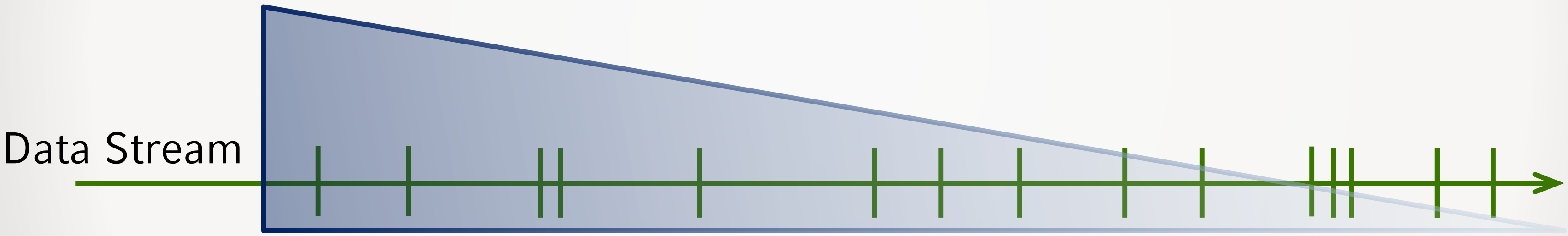
- Sequence-based:



Stream Processing

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 epoch, resp. after a certain amount of occurring 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
  → 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 $\mathrm{M} \leq k$ 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

Stream Processing

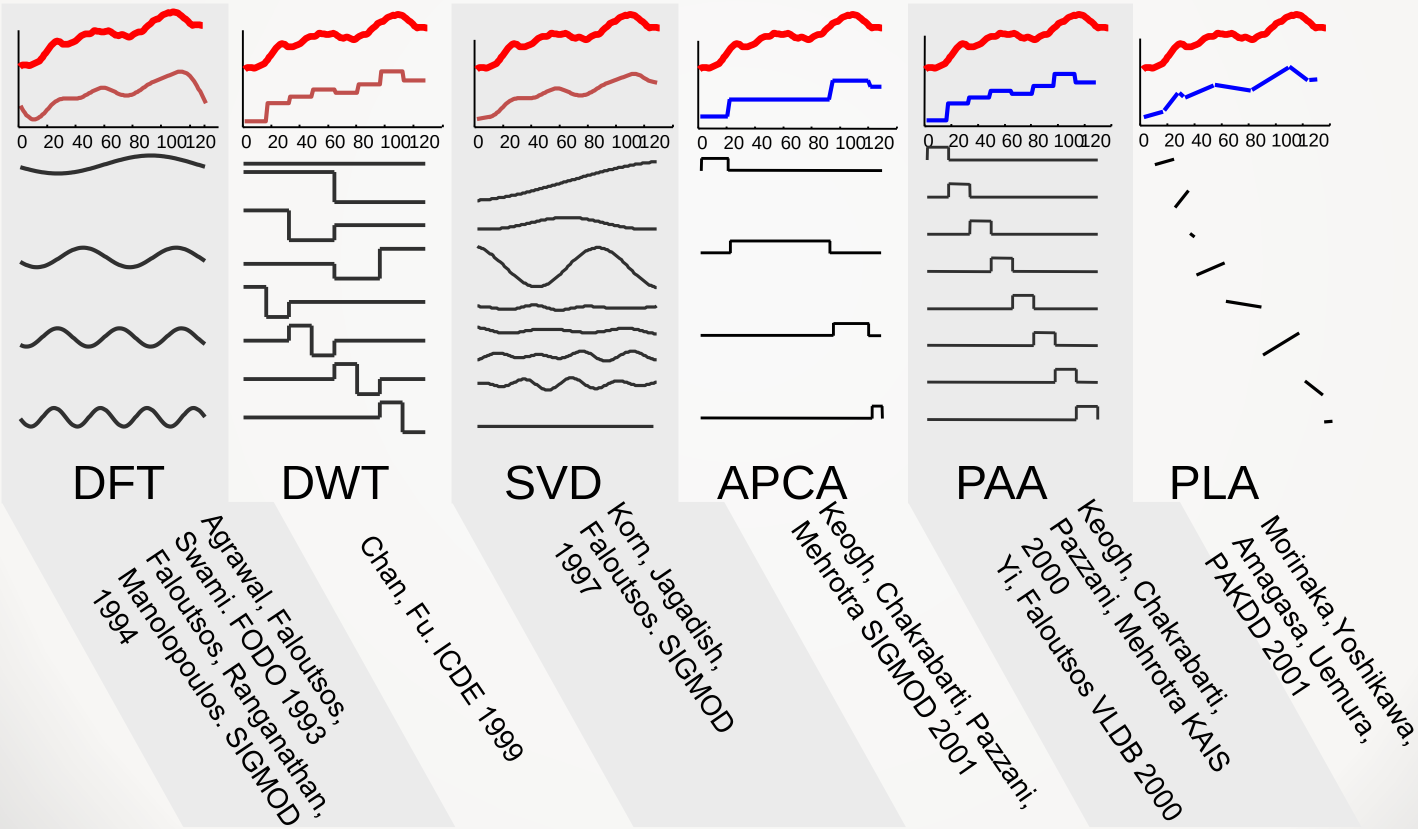
Streaming Methods – Data Synopsis & Histograms

- Summaries of data objects often 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:

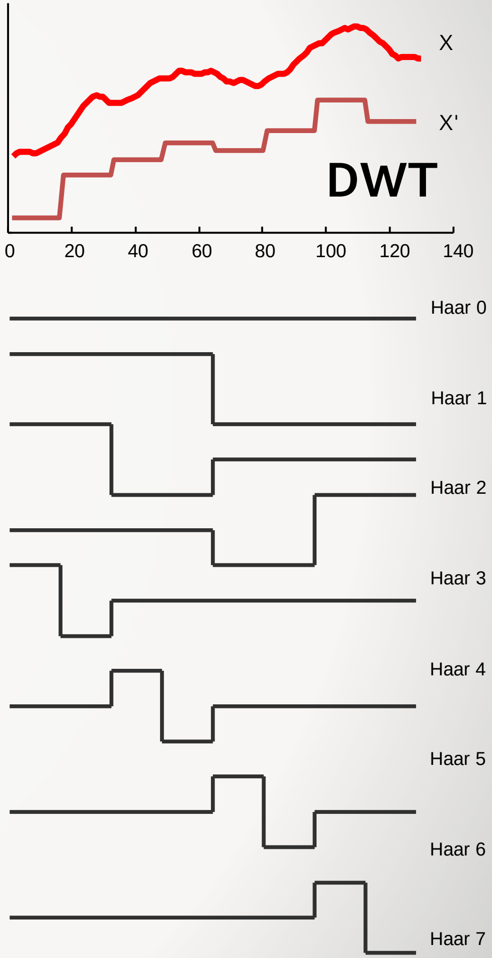


Stream Processing

Discrete Wavelet Transformation (DWT)

Idea:

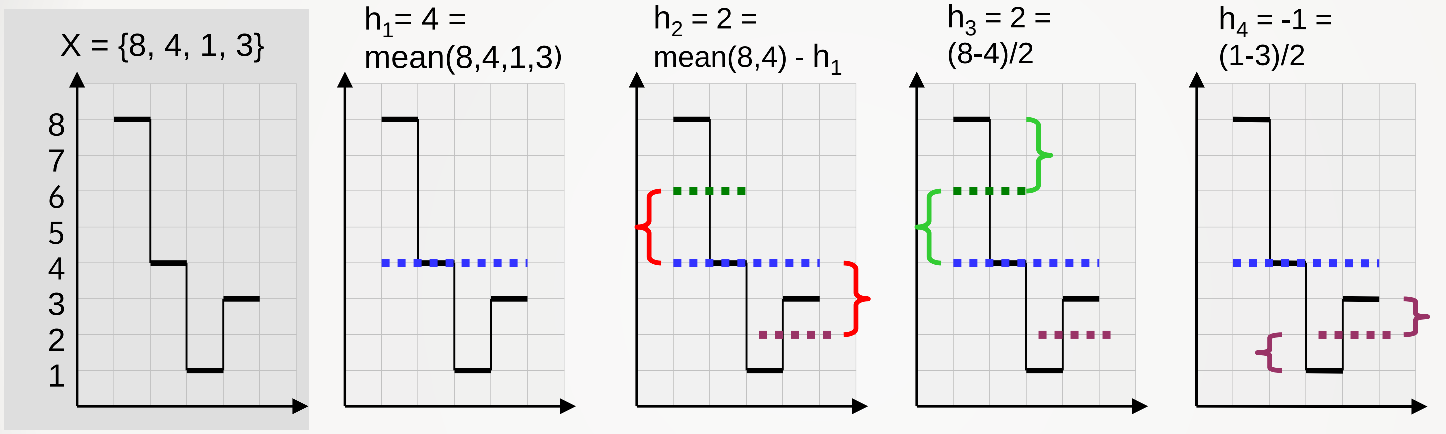
- Sequence represented as linear combination of basic wavelet functions
- Wavelet transformation decomposes a signal into several groups of coefficients at different scales
- Small coefficients can be eliminated
  → Small errors when reconstructing the signal
  →Take only the first function coefficients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



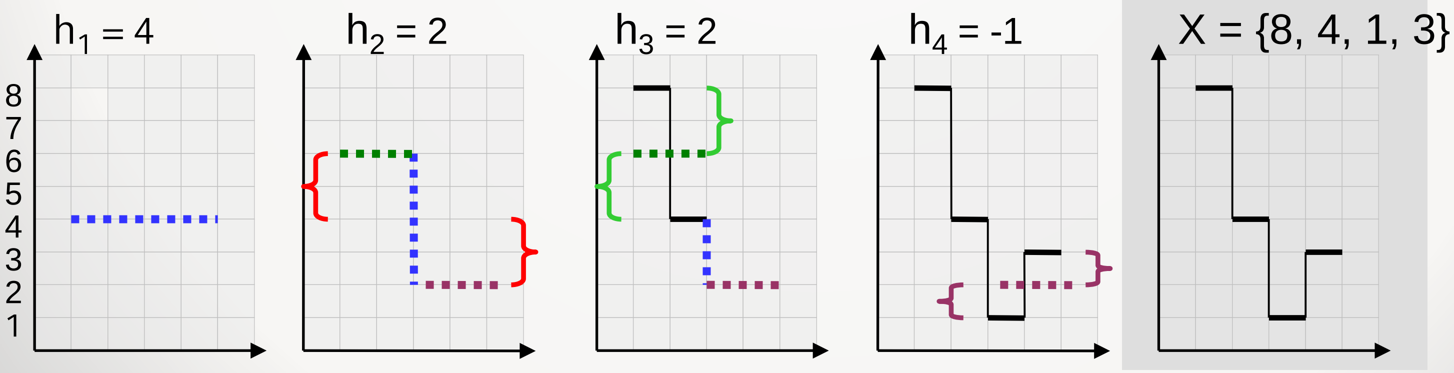
Stream Processing

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:



Stream Processing

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:

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

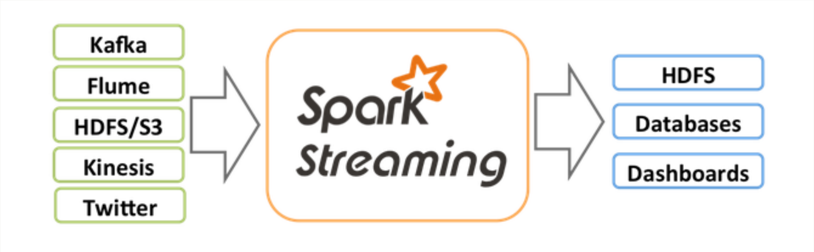
$s_3 = 4.375,\ d_3 = \{1.625\}$

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

Stream Processing

Spark Streaming

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

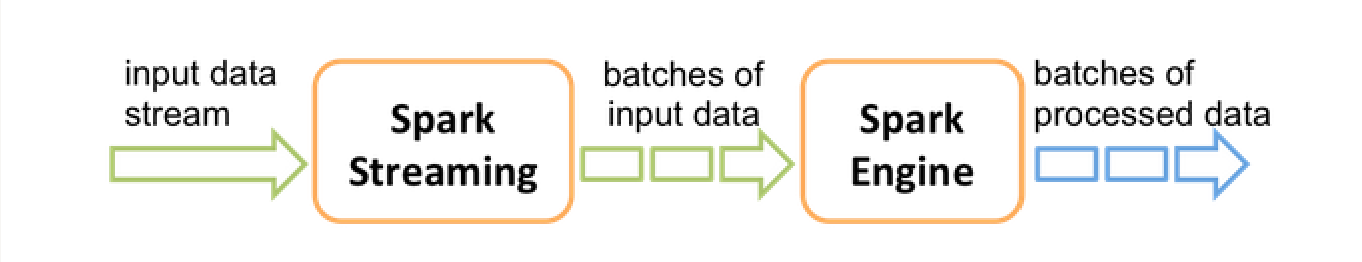


- Stream processing might be combined with other Spark libraries (e.g. Spark MIlib)

Stream Processing

Spark Streaming

- Spark's Streaming Workflow:

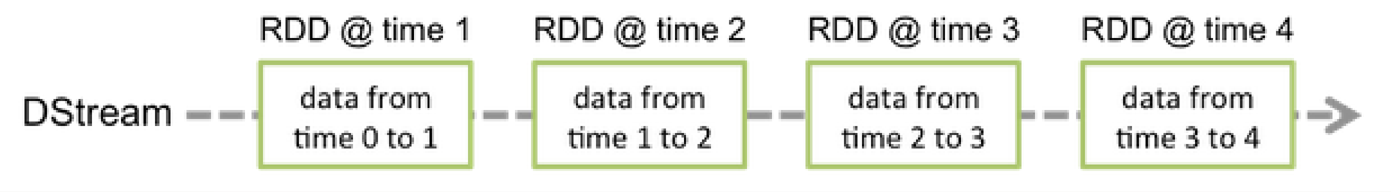


- Streaming engine receives data from input streams
- Data stream is divided into several microbatches, i.e. sequences of RDDs
- Microbatches are processed by Spark engine
- The result is a data stream of batches of processed data

Stream Processing

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
```

Stream Processing

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()`

Stream Processing

Spark Streaming

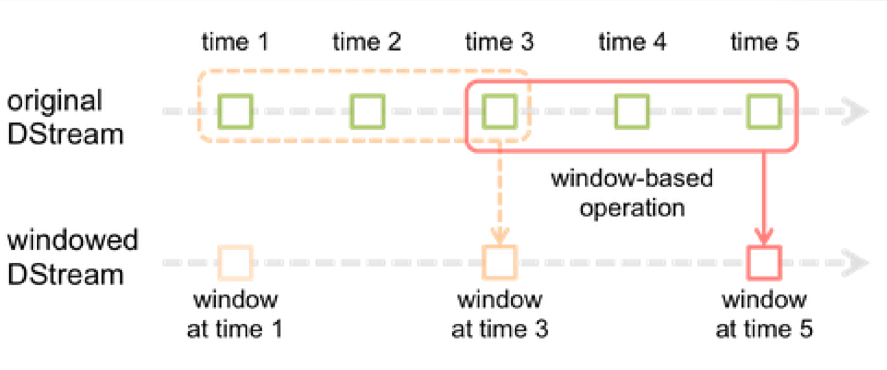
```
#Create a local StreamingContext with two working threads and batch
#interval of 1 sec
sc = SparkContext(“local[2]“,“NetworkWordCount“)
ssc = StreamingContext(sc, 1)

#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()
```

Stream Processing

Spark Streaming

- Support of window operations

- Two basic parameters:
  - windowLength
  - slideInterval



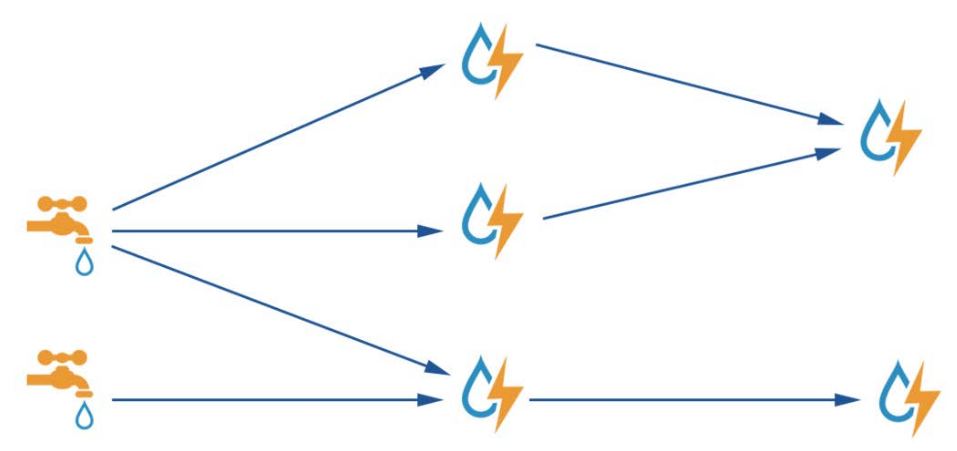
- Support of many transformations for windowed DStreams

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

Stream Processing

Apache Storm

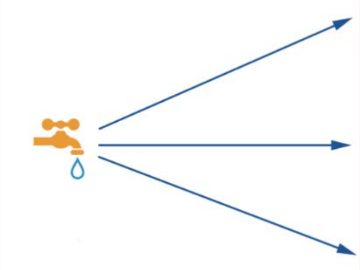
- Alternative to Spark Streaming
- Support of Real-time Processing
- Three abstractions:
  - Spouts
  - Bolts
  - Topologies



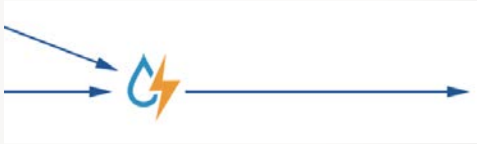
Stream Processing

Apache Storm

APACHE STORM™ Distributed • Resilient • Real-time



- 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)

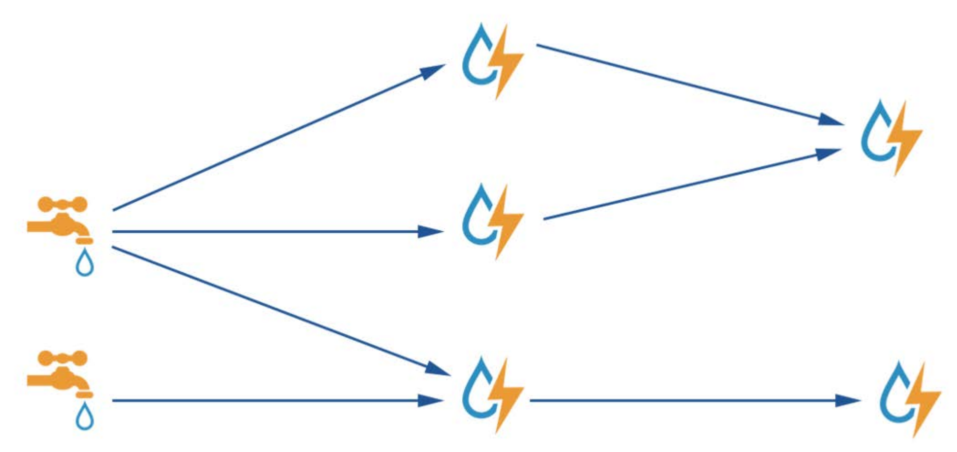


- Bolts:
  - Processes any number of input streams
  - Produces any number of output streams
  - Holds most of the logic of the computations (functions, filters,…)

Stream Processing

Apache Storm

- 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



Stream Processing

Apache Storm

- 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 integer, float, short, Boolean, string 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

Stream Processing

Apache Storm

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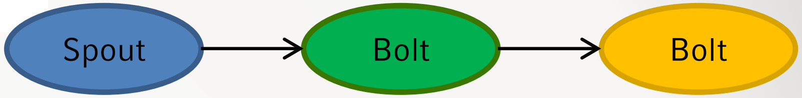


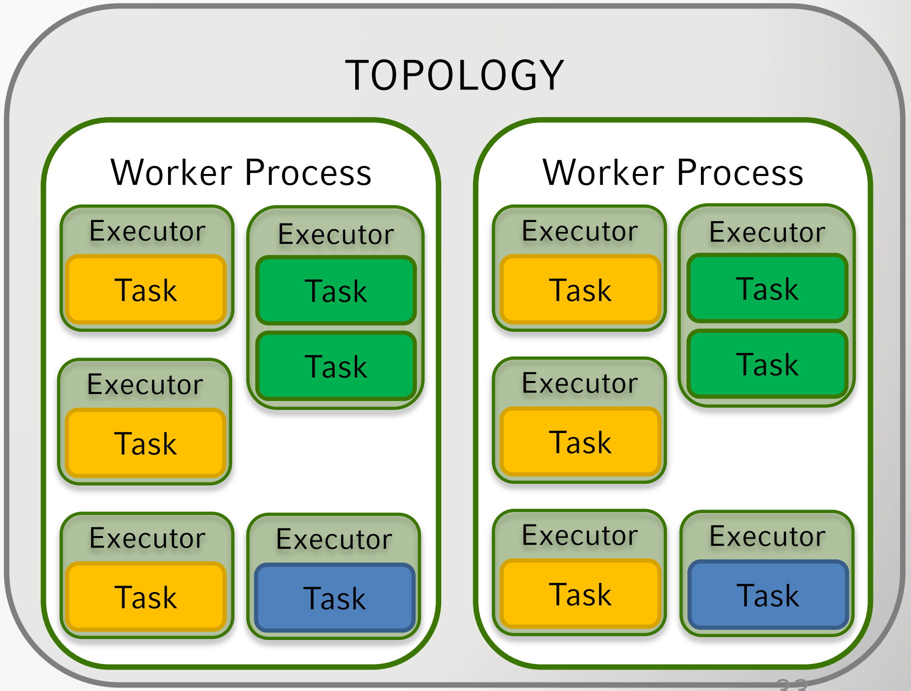
```
Config conf = new Config();
conf.setNumWorkers(2); // use two worker processes

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()
    );
```



Stream Processing

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