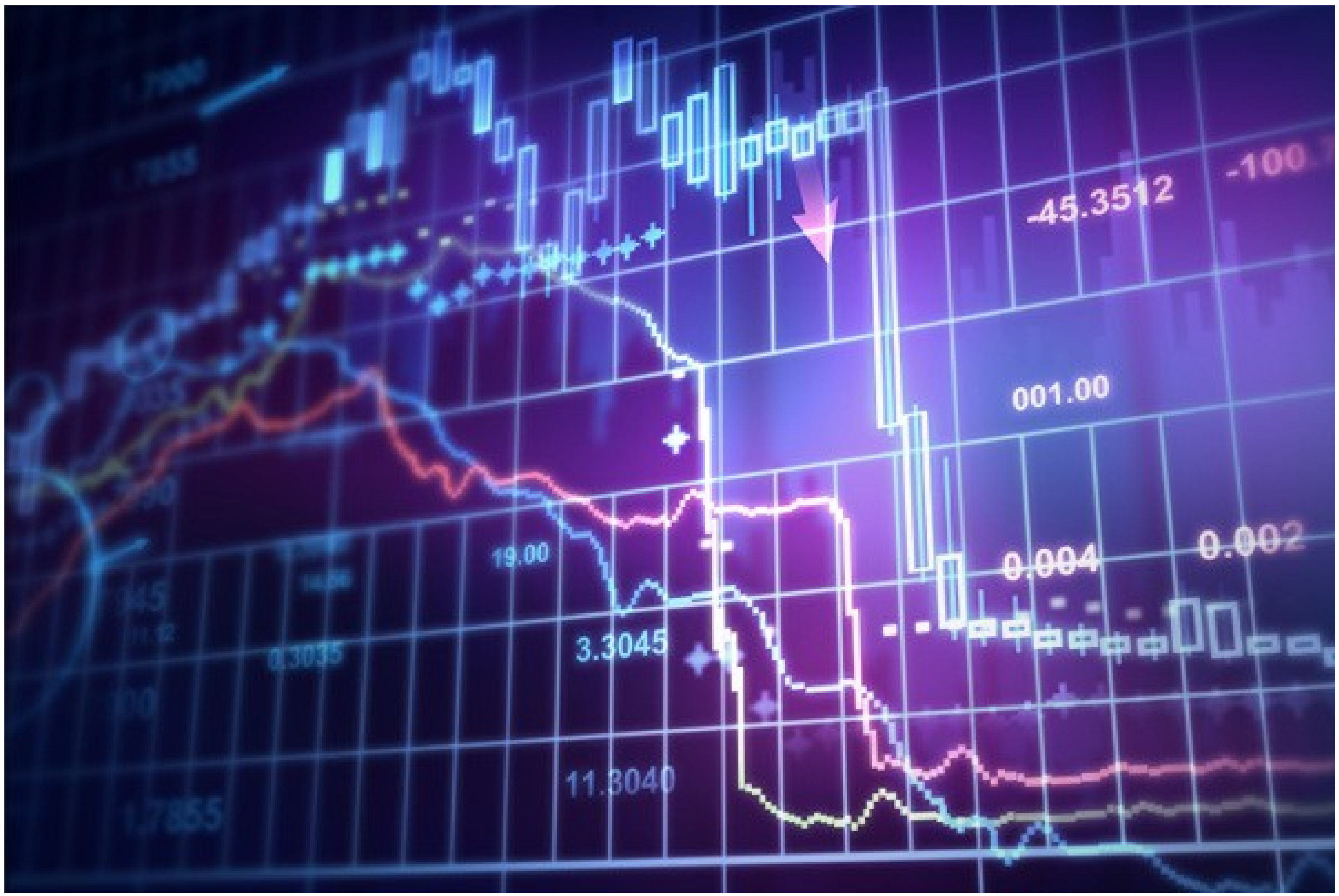
Time Series Databases and Streaming algorithms

Introduction and motivation for Time Series

Financial



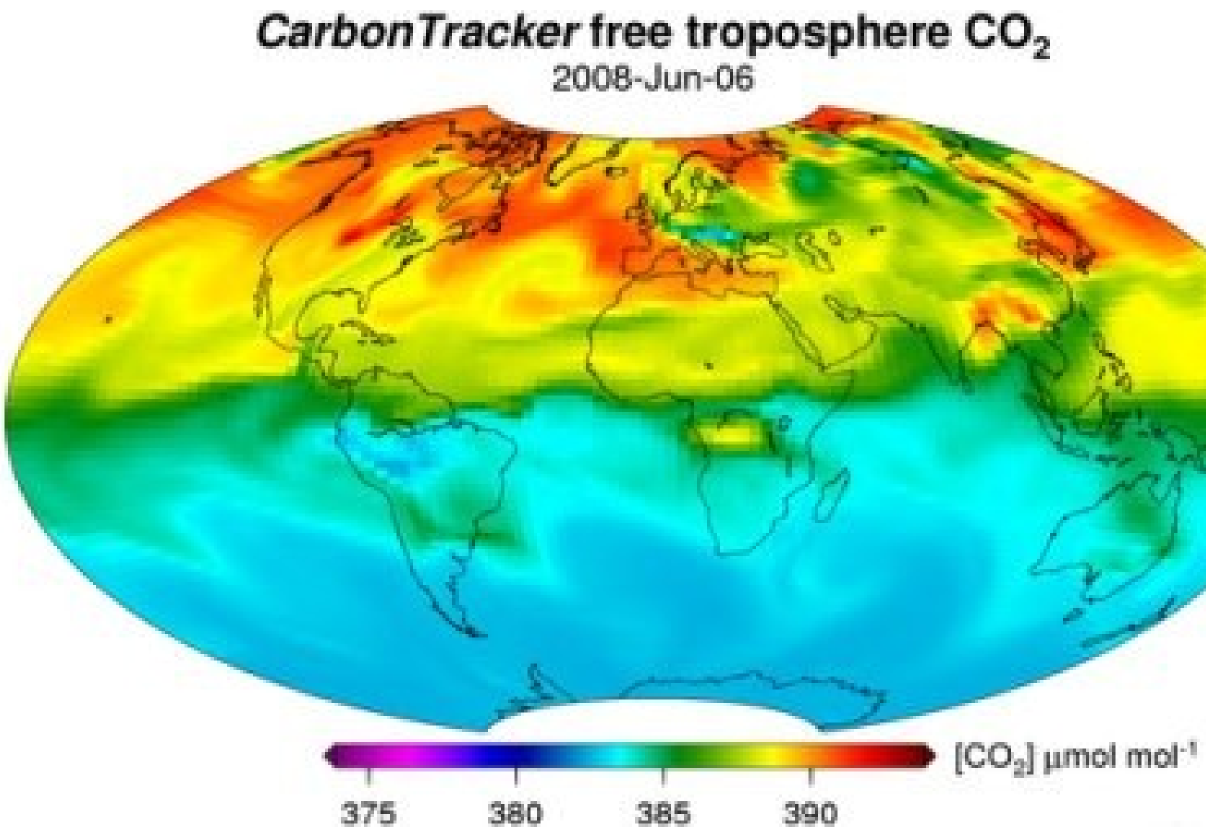
Internet of things

Domotics


Mi Plataforma
Preguntas y Respuestas
Reto
Causa
unicef
1,452
Entrada manual
enviar
Consumo
Periodo
Eficiencia

Predictive Maintenance

Environmental tracking



A time series is a sequence of data points, typically consisting of successive measurements made over a time interval.

Why Time Series Databases?

- High Volume of Data
- Large Quantities of Immutable Data
- Is Primarily Sorted Temporally
- Needs to Be Rolled Up To Gain Majority of Insights
- Needs to Be Normalized Across Multiple Time Zones

https://blog.tempoiq.com/blog/2013/01/25/characteristics-of-a-time-series-dataset-time-series-database-overview-part-2

Problems using Relational DBs

1. It's Difficult to Change the Sample Rate
2. It's Difficult To Use SQL Queries For Analysis
3. Time Zones Add Extra Complexity To Your Data Analysis

https://blog.tempoiq.com/blog/2013/04/22/optimizing-relational-databases-for-time-series-data-time-series-database-overview-part-3

Advantages of NoSQL

1. Greater simplicity in the DB engine
2. Ability to handle semi-structured and denormalized data
3. Potentially much higher scalability

Disadvantages of NoSQL

1. Higher complexity in the application
2. Loss of abstraction provided by the query optimizer

Basic Operations on Time Series Data

What do we need to do with TS

- Acquire
  - Measurement, trasnmission, reception
- Store
- Retrieve
- Analize and visualize

Rescaling

- Transform the range of variation to a given scale
- Useful for algorithms sensitive to the magnitude of the signal

Resampling

- Differences in sampling resolution
- Bring both series to the same sample frequency
- Requires a function for collapsing points together

Shifting

- Align series we know are misaligned
- Bad reference time, drifting clock, ...

Slicing

- Retrieve a time series based on a given time range

Dynamic Time Warping

- Used for measuring similarity between series that vary in time or speed
- Dynamic time warping is a sequence alignment technique used in speech recognition
- It is an algorithm that has $O(n^2)$ complexity

Subsequence Matching

- A sequence query is matched against a longer TS
- Also related with Chunking where we look for repeating patterns

Statistical measures

- Mean
- Median
- Standard Deviation
- Variance
- Quantiles

Statistical fitting

- Interpolation
- Linear models
- Non linear models

Data Storage for Time Series Data

Log Files

- Simplest solution
- Right solution when low number of time series or data fits in memory

```
1950    1  0.92000E+00
1950    2  0.40000E+00
1950    3 -0.36000E+00
1950    4  0.73000E+00
1950    5 -0.59000E+00
1950    6 -0.60000E-01
1950    7 -0.12600E+01
1950    8 -0.50000E-01
1950    9  0.25000E+00
1950   10  0.85000E+00
1950   11 -0.12600E+01
1950   12 -0.10200E+01
1951    1  0.80000E-01
1951    2  0.70000E+00
1951    3 -0.10200E+01
1951    4 -0.22000E+00
1951    5 -0.59000E+00
1951    6 -0.16400E+01
1951    7  0.13700E+01
1951    8 -0.22000E+00
1951    9 -0.13600E+01
1951   10  0.18700E+01
```

Advanced Log Files

- Same concept about storing TS in files
- Use a smart binary encoding format
- Allows less processing, aka no parsing
- Stores data more efficiently for scan readings

```
message AddressBook {
  required string owner;
  repeated string ownerPhoneNumbers;
  repeated group contacts {
    required string name;
    optional string phoneNumber;
  }
}
```

Advanced Log Files

- Lots of binary formats lately
  - Thrift
  - Avro
  - Parquet

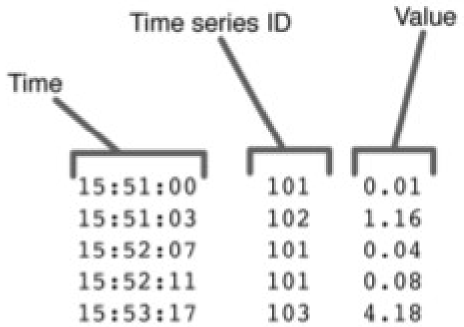
We created Parquet to make the advantages of compressed, efficient columnar data representation available to any project in the Hadoop ecosystem.

Relational Databases

- True and tested technology validated in multitude of scenarios
- Allows indexing out of the box
- Allows data replication and sharding (to some extent)

Relational Databases

- Use the Star Schema
- The fact table contains the measurements
- The dimension tables contains info about the series



Relational Databases

- The Star Schema can work reasonably to the hundreds of millions
- We can even implement the Star Schema in a NoSQL database
- When data grows this size several problems arise mostly related to the Star Schema itself.

Limitations of the Star Schema

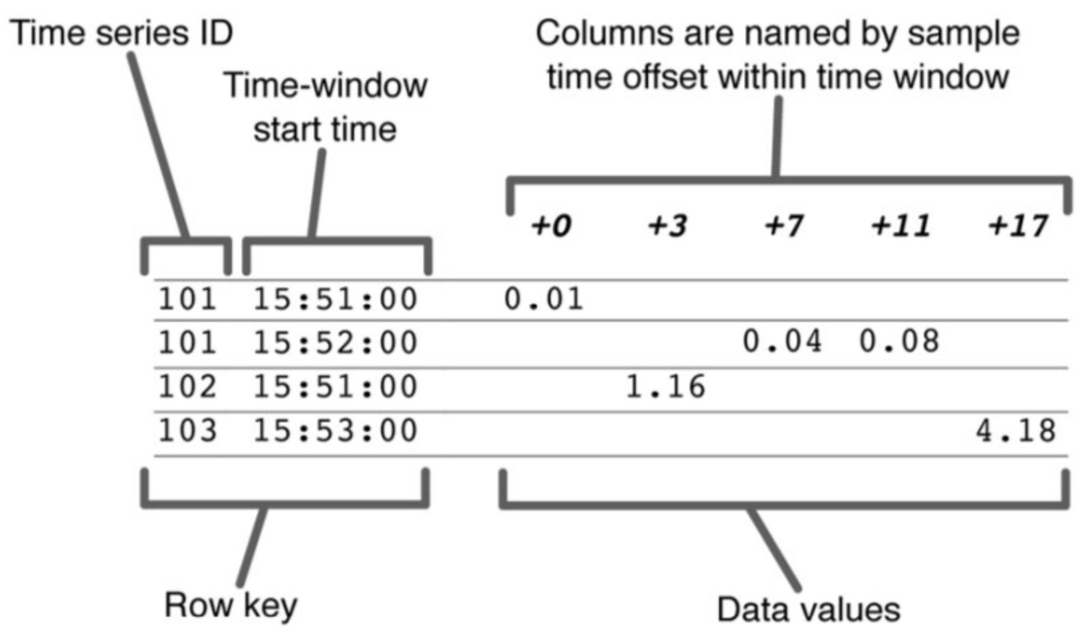
- It uses one row per measurement
- Limitants of retrieval speed:
  - number of rows scanned,
  - total number of values retrieved
  - total volume of data retrieved

NoSQL databases

- Most of TS DBs use a NoSQL engine
  - OpenTSB → Hbase
  - InfluxDB → BoltDB
  - Prometheus → LevelDB
  - Newts → Cassandra

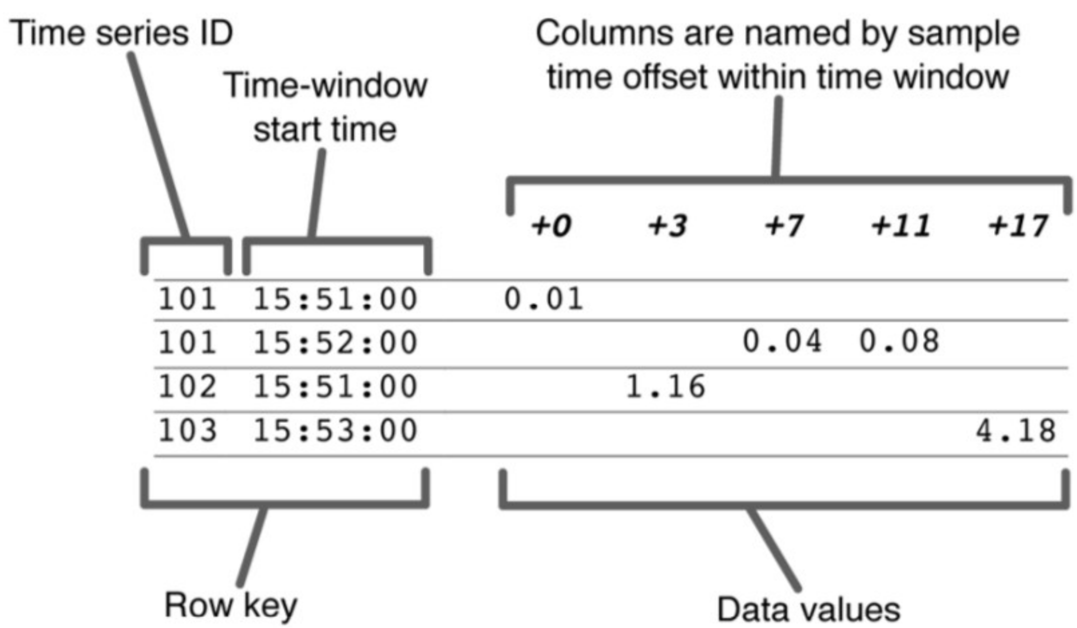
NoSQL databases

- Tall and narrow vs Short and wide table designs
- Short and wide denormalizes data
- Short and wide provides several advantages over the columnar data model



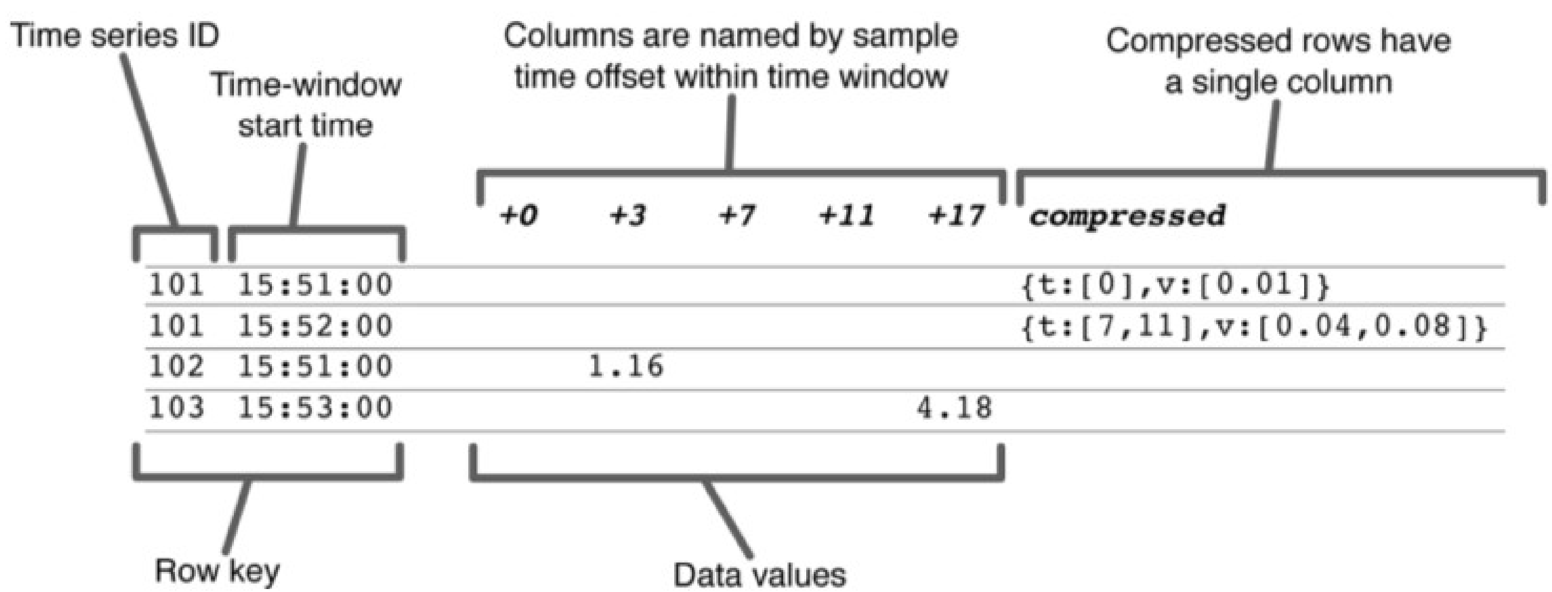
NoSQL databases

- Indexed by TS and timestamp the most common access pattern
- Retrieving data is an almost sequential reading from disk



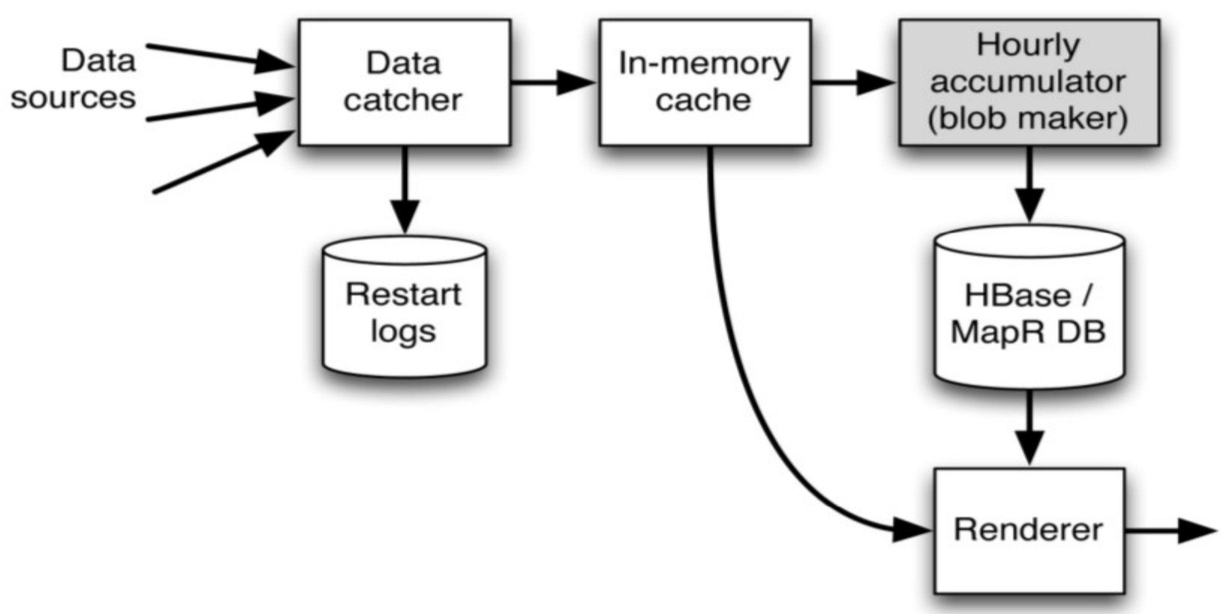
Improvements over the Wide Table Design

- Collapse all the data into a blob
- Compress the blob so less data has to be read
- Allow coexistence of wide table columns and the blob



Improvements over the Wide Table Design

- Avoid the reads in order to overcome insert bottlenecks
- Create a fallback system in order to prevent failures
- Allow access to the in-memory data



Why not with RDBMs?

- Why use a RDBMs when you're not using any of its strong points?
- Also some features, ie. transactions, get in your way for scaling

Time Series Databases

TempoIQ

OPENTSDB

Prometheus

InfluxDB

druid

InfluxDB

Features

- Written in Go
- Using BoltDB a its internal storage engine
- SQL-like language
- HTTP(S) API for querying data
- Stores metrics and event data
- Horizontally scalable

Key concepts

A **series** is a collection of data **points** along a **timeline** that share a common **key**, expressed as a **measurement** and **tag set** pairing, grouped under a **retention policy**

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Key concepts

- **Measurement**
  - It is the value being recorded
  - Can be shared amongst many series
  - All series under a given measurement have the same field keys and differ only in their tag set

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Key concepts

- **Tag**
  - It is a key-value pair.
  - A measurement could have several tags
  - Tags are indexed
  - Both the key and value are strings

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Key concepts

- **Point**
  - A point is a single collection of fields in a series.
  - It is uniquely identified by its series and timestamp

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Key concepts

- **Field**
  - A field is a key-value pair
  - It records an actual metric for a given point
  - They are not indexed
  - They are required at least 1 on each point

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Key concepts

- **Database**
  - similar in concept to RDBS groups series
- **Retention policy**
  - defines what to do with data that is older than the prescribed retention policy

https://influxdb.com/docs/v0.9/concepts/key_concepts.html

Logging points into InfluxDB

```
{
    "database": "mydb",
    "points": [
         {
            "measurement": "cpu_load",
            "tags": {
                "host": "server01",
                "core": "0"
            },
            "time": "2009-11-10T23:00:00Z",
            "fields": {
                "value": 0.45
            }
        },
        {
            "measurement": "cpu_load",
            "tags": {
                "host": "server01",
                "core": "1"
            },
            "time": "2009-11-10T23:00:00Z",
            "fields": {
                "value": 1.56
            }
        }
    ]
}
```

HTTP endpoint

/query GET
/write OPTIONS
/write POST
/ping GET
/ping HEAD
/data/process_continuous_queries POST

Query exploration

Queries like in RDBMs

```
SELECT * FROM cpu
WHERE cpu_1 = '1'
```

Querying by time

```
SELECT mean(value) FROM cpu
WHERE time > 12345678s
GROUP BY time(10m);
SELECT mean from "hour_summaries".cpu
WHERE time > now() - 7d
```

Dealing with Time

- Querying using time strings

```
SELECT value FROM response_times
WHERE time > '2013-08-12 23:32:01.232' and time < '2013-08-13';
```

- Relative time

```
SELECT value FROM response_times
WHERE time > now() - 1h limit 1000;
```

- Absolute time

```
SELECT value FROM response_times
WHERE time > now() - 1h limit 1000;
```

Dealing with missing values

- Use null, previous, none for missing values

```
SELECT COUNT(type) FROM events
WHERE time > now() - 3h
GROUP BY time(1h) fill(null)
```

```
SELECT COUNT(type) FROM events
WHERE time > now() - 3h
GROUP BY time(1h) fill(previous)
```

```
SELECT COUNT(type) FROM events
WHERE time > now() - 3h
GROUP BY time(1h) fill(none)
```

Write data

- Ingest data into InfluxDB using the HTTP API
- Create the Database

```
curl -G http://localhost:8086/query --data-urlencode "q=CREATE
DATABASE mydb
```

- Write data into the database

```
curl -i -XPOST 'http://localhost:8086/write?db=mydb' --data-binary
'cpu_load_short,host=server01,region=us-west value=0.64
1434055562000000000'
```

Hands on

- Import data from Standard&Poor
- Explore the performance of different encodings:
  - Several fields for a single point
  - Each column as a separate TS
- Create the following queries:
  - Select maximum opening price on a given period for each quote
  - Select the monthly average

Hands on (Advanced)

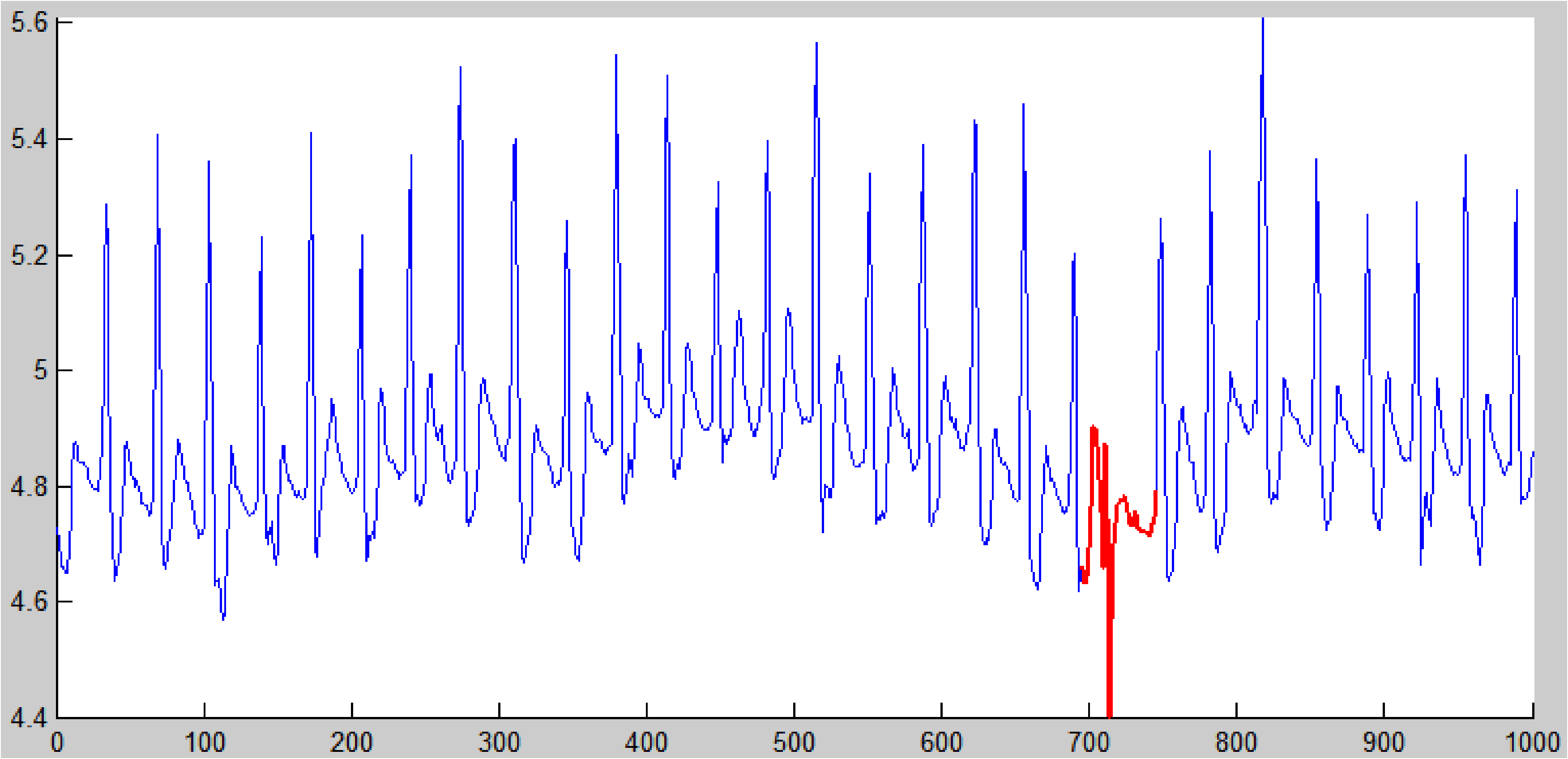
- Import extra dataset
- Compare loading and querying data between MySQL and InfluxDB

Streaming data

Algorithms for processing data streams in which the input is presented as a sequence of items and can be examined in only a few passes

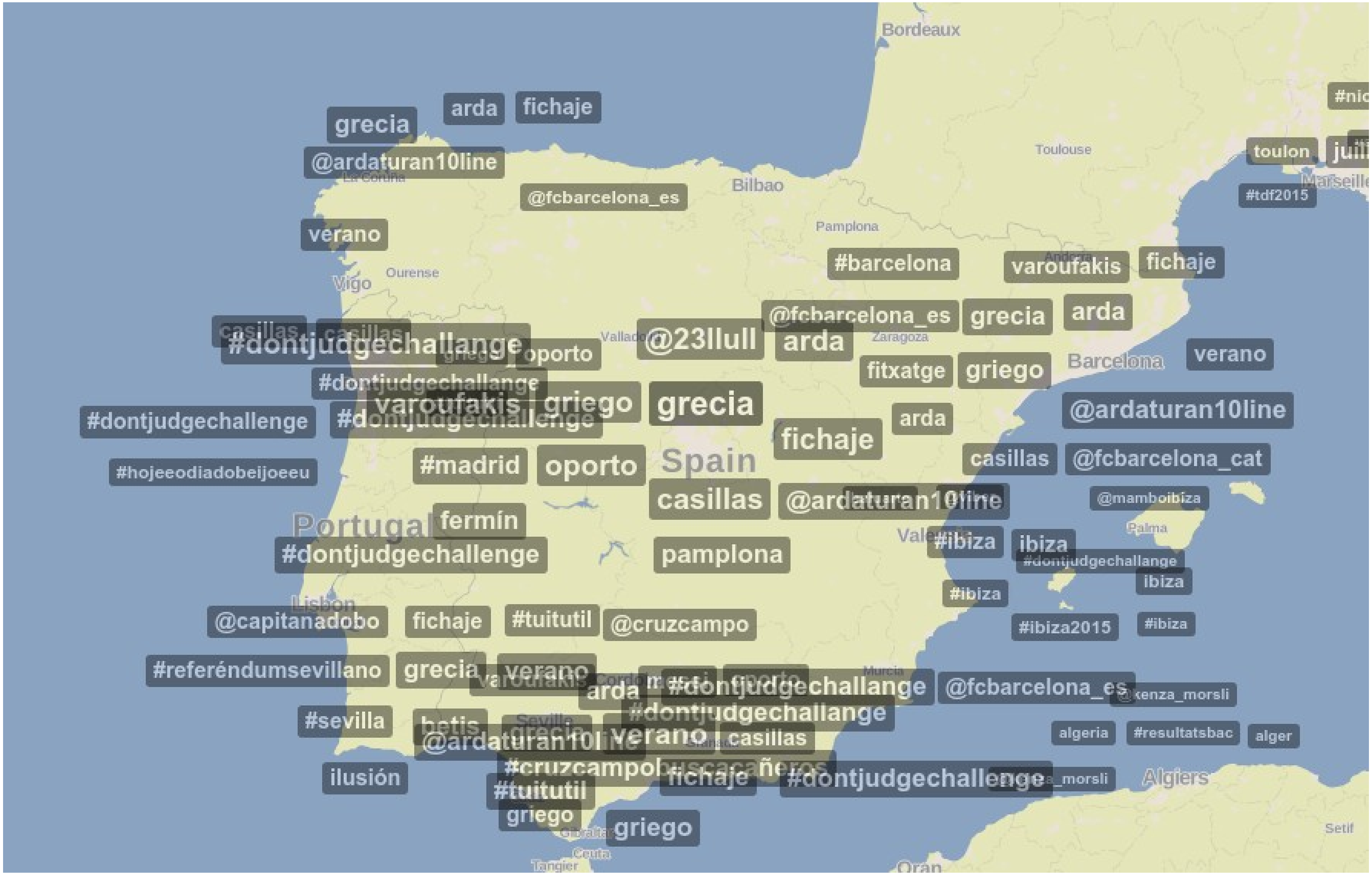
Examples

Examples: Anomaly Detection



Real Time Telemetry

Trends in Social Networks



Streaming algorithms

Characteristics of streaming algorithms

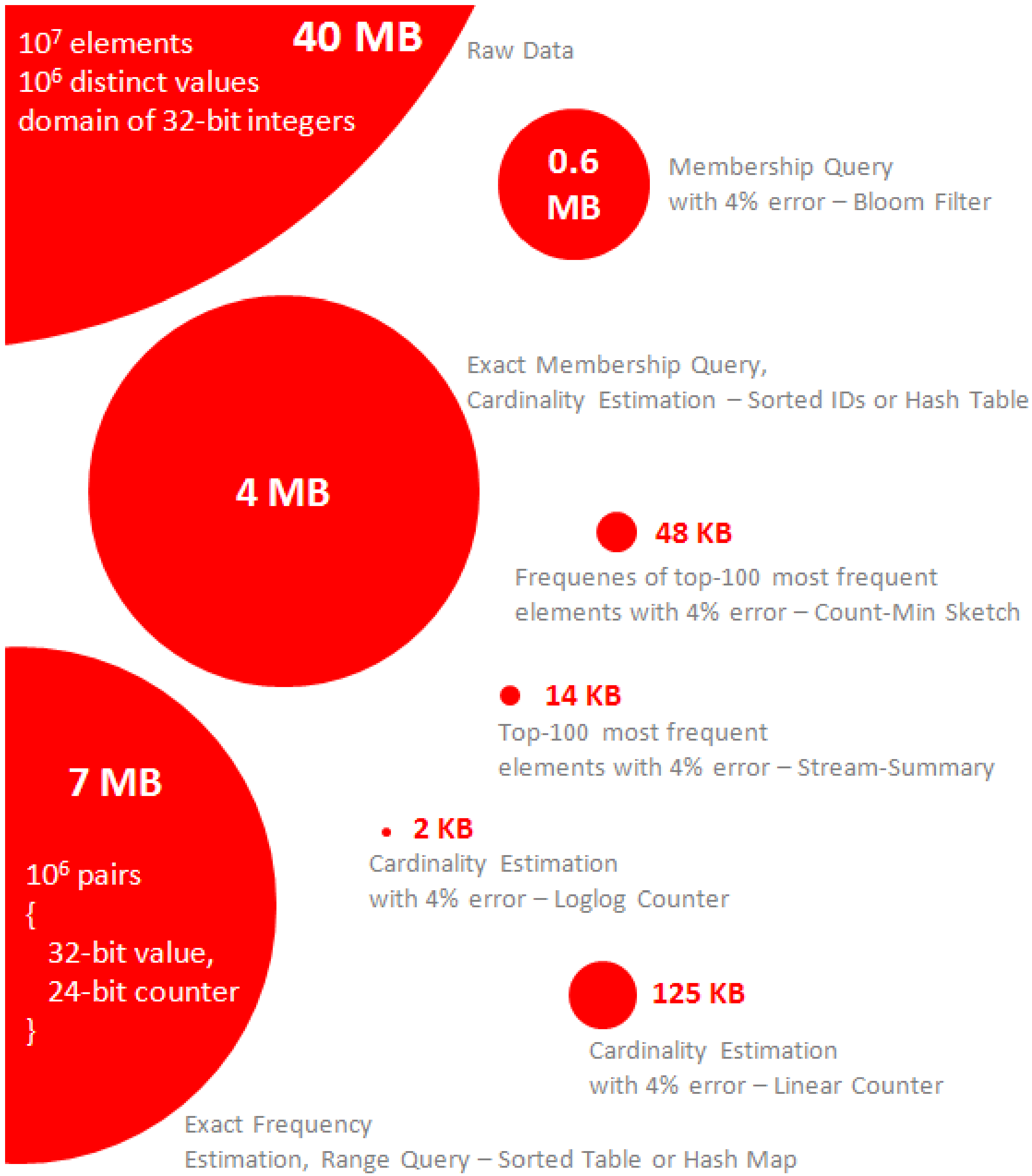
- Operates on a continuos stream of data
- Unknown or infinite size
- Only one pass, that allows following options:
  - Store it
  - Lose it
  - Store an approximation of it
- Limited processing time per item
- Limited total memory

These algorithms produce an approximate answer based on a summary or "sketch" of the data stream in memory

They have limited memory available to them (much less than the input size) and also limited processing time per item.

Questions to answer

- Frequency moments
- Counting distinct elements
- Heavy Hitters
- Anomaly detection / Membership query
- Online learning



https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/

Cardinality estimation
Linear Counting

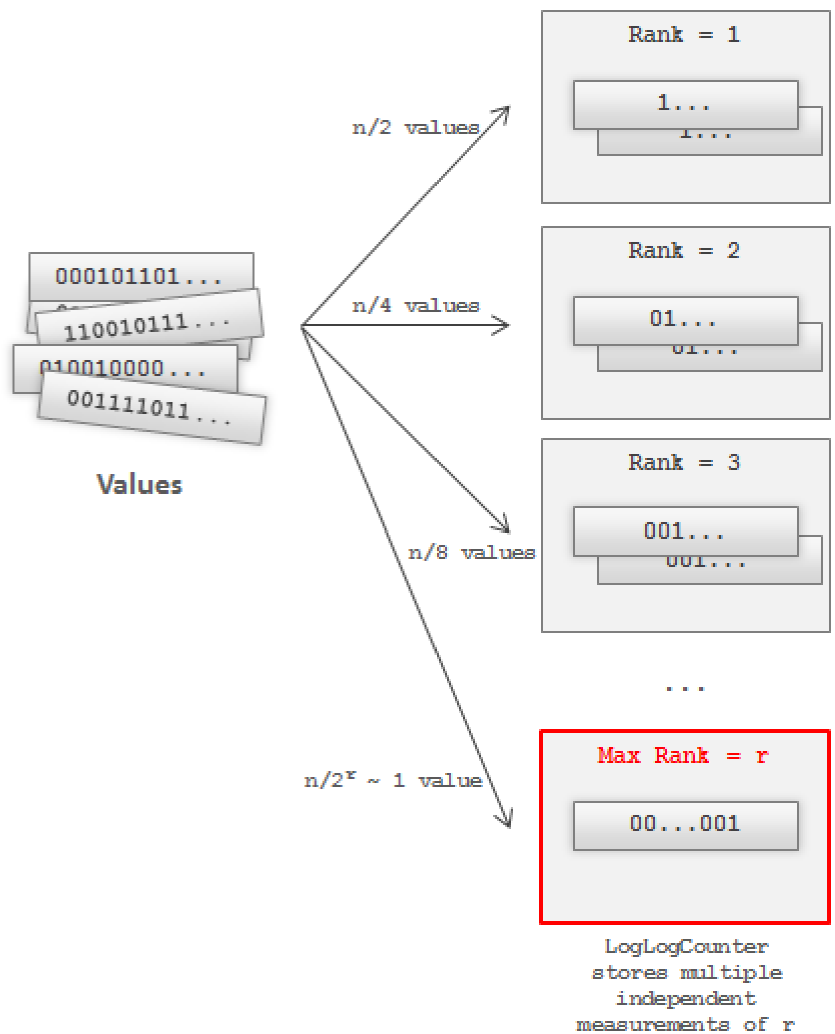
```
class LinearCounter {
    BitSet mask = new BitSet(m) // m is a design parameter

    void add(value) {
        int position = hash(value) // map the value to the range 0..m
        mask.set(position) // sets a bit in the mask to 1
    }
}
```

Load Factor is the ratio of distinct elements over the size m

Cardinality estimation Linear Counting

$$\hat{n} = -m \ln \frac{m-w}{m}$$	$\hat{n}$ - cardinality estimation w - mask weight (a number of 1's) m - mask size
$$bias(\frac{\hat{n}}{n}) = E(\frac{\hat{n}}{n}) - 1 = \frac{e^t - t - 1}{2n}$$	This equation expresses a bias of the estimation (the ratio between estimation and true cardinality) as a function of the load factor and expected cardinality (or upper bound). t - load factor, n/m E(.) - mathematical expectation n - maximum cardinality (or upper bound, or capacity)
$$m > \max(5, 1/(\varepsilon t)^2) \cdot (e^t - t - 1)$$	A practical formula that allow one to choose m by the standard error of the estimation. m - mask size ε - standard error of the estimation t - load factor, n/m

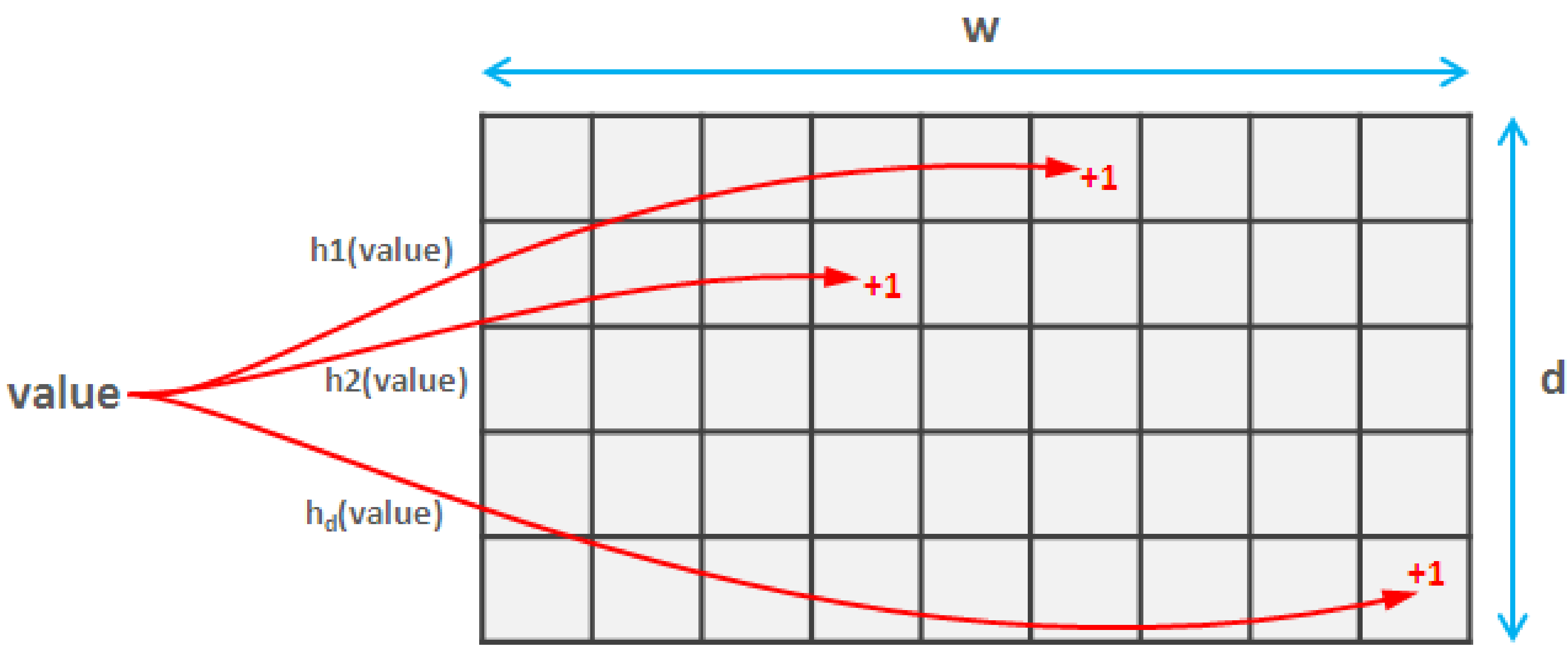
Cardinality estimation
Loglog Counting



Cardinality estimation
Loglog Counting

```
class LogLogCounter {
    int H            // H is a design parameter
    int m = 2^k           // k is a design parameter
    etype[] estimators = new etype[m] // etype is a design parameter

    void add(value) {
        hashedValue = hash(value)
        bucket = getBits(hashedValue, 0, k)
        estimators[bucket] = max(
            estimators[bucket],
            rank( getBits(hashedValue, k, H) )
        )
    }

    getBits(value, int start, int end)
    rank(value)
}
```

Frequency Estimation: Count-Min Sketch



Frequency Estimation: Count-Min Sketch

```
class CountMinSketch {
    long estimators[][] = new long[d][w]    // d and w are design parameters
    long a[] = new long[d]
    long b[] = new long[d]
    long p      // hashing parameter, a prime number. For example 2^31-1

    void initializeHashes() {
        for(i = 0; i < d; i++) {
            a[i] = random(p)    // random in range 1..p
            b[i] = random(p)
        }
    }

    void add(value) {
        for(i = 0; i < d; i++)
            estimators[i][ hash(value, i) ]++
    }

    long estimateFrequency(value) {
        long minimum = MAX_VALUE
        for(i = 0; i < d; i++)
            minimum = min(
                minimum,
                estimators[i][ hash(value, i) ]
            )
        return minimum
    }

    hash(value, i) {
        return ((a[i] * value + b[i]) mod p) mod w
    }
}
```

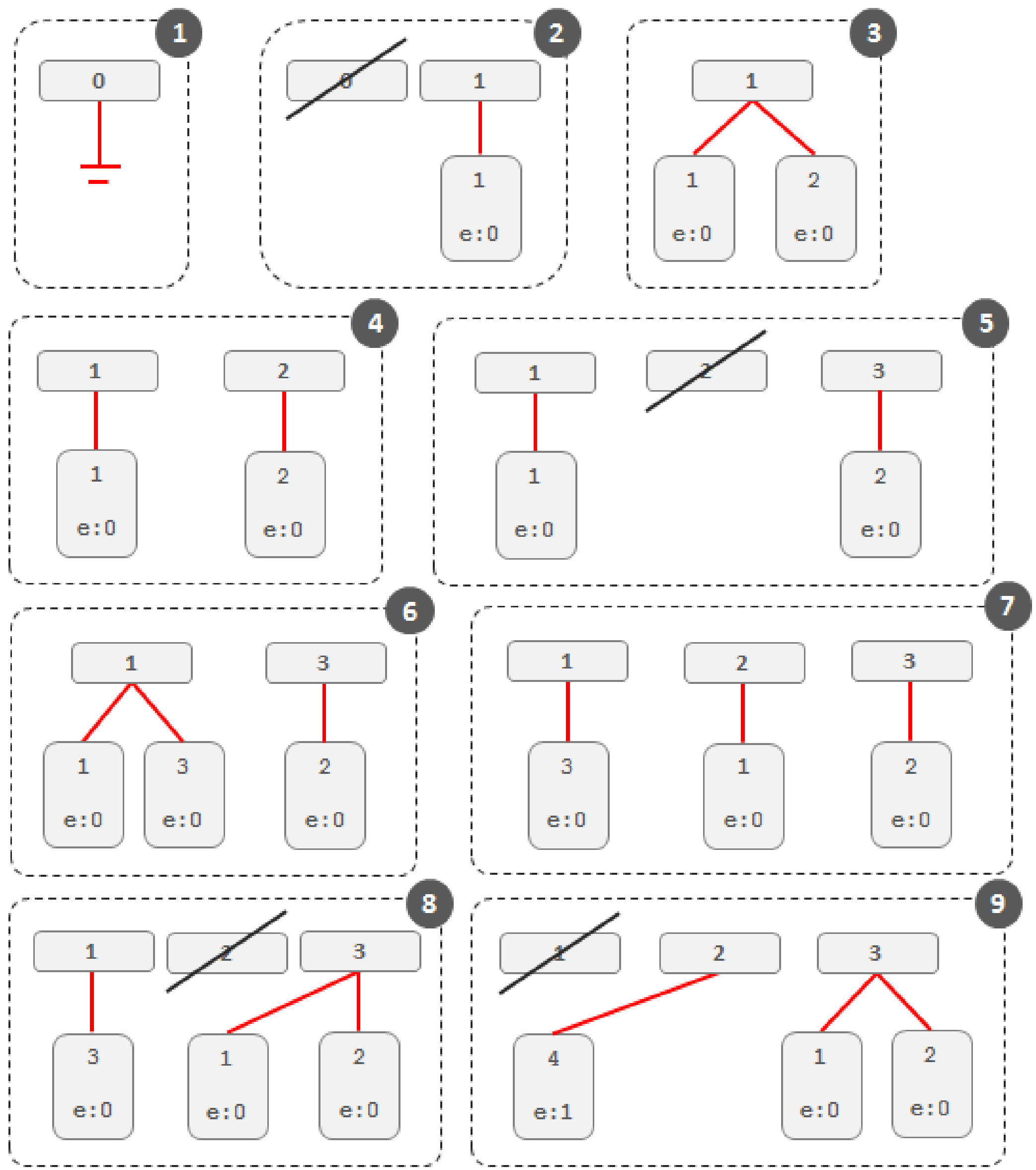
Frequency Estimation: Count-Mean-Min Sketch

```
class CountMeanMinSketch {
    // initialization and addition procedures as in CountMinSketch
    // n is total number of added elements

    long estimateFrequency(value) {
        long e[] = new long[d]
        for(i = 0; i < d; i++) {
            sketchCounter = estimators[i][ hash(value, i) ]
            noiseEstimation = (n - sketchCounter) / (w - 1)
            e[i] = sketchCounter - noiseEstimator
        }
        return median(e)
    }
}
```

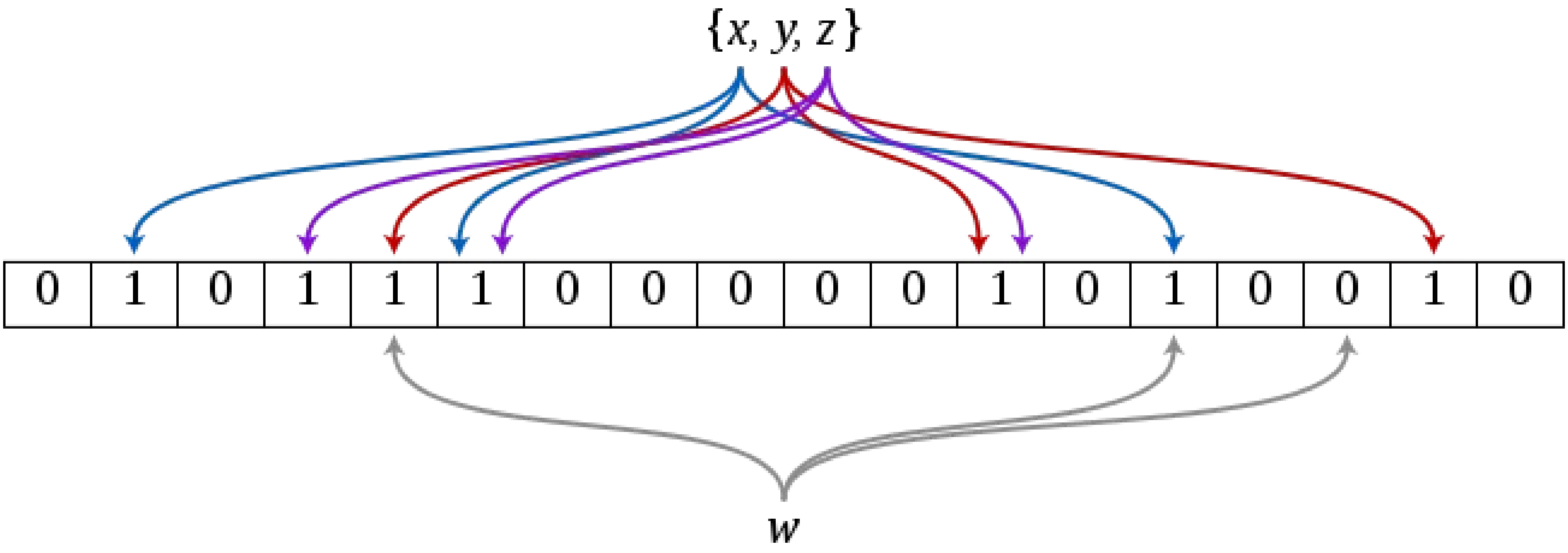
Heavy Hitters
Count-Min Sketch

```
class CountMeanMinSketch {
    // initialization and addition procedures as in CountMinSketch
    // n is total number of added elements

    long estimateFrequency(value) {
        long e[] = new long[d]
        for(i = 0; i < d; i++) {
            sketchCounter = estimators[i][ hash(value, i) ]
            noiseEstimation = (n - sketchCounter) / (w - 1)
            e[i] = sketchCounter - noiseEstimator
        }
        return median(e)
    }
}
```

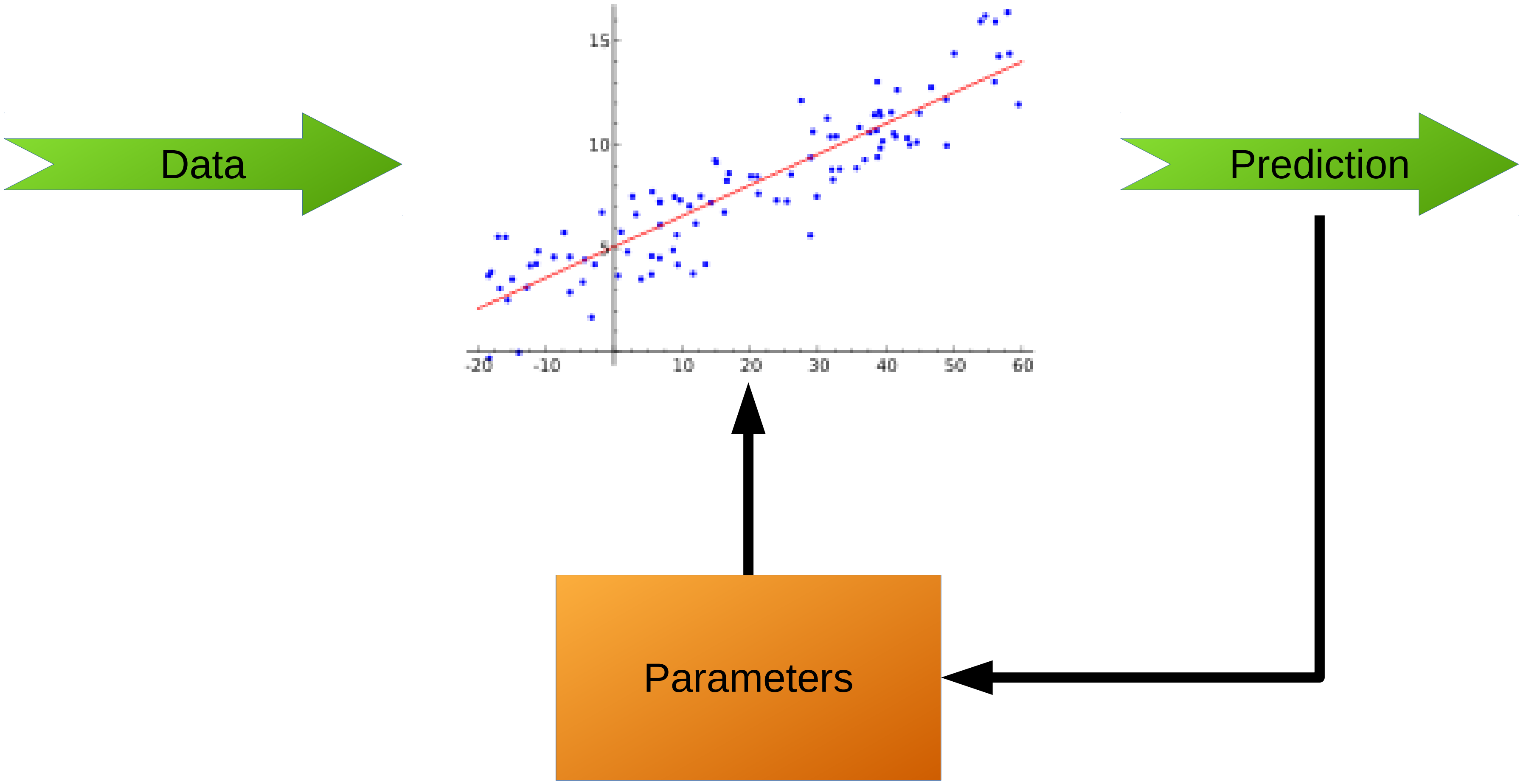
Heavy Hitters Stream-Summary



Membership Query
Bloom Filter



Online Learning



Feature Hashing

- John likes to watch movies.
- Mary likes movies too.
- John also likes football.

$$\begin{array}{c}
\begin{array}{ccccccccc} \text{John} & \text{likes} & \text{to} & \text{watch} & \text{movies} & \text{Mary} & \text{too} & \text{also} & \text{football} \end{array} \\
\begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}
\end{array}$$

Feature Hashing

```
function hashing_vectorizer(features : array of string, N : integer):
    x := new vector[N]
    for f in features:
        h := hash(f)
        x[h mod N] += 1
    return x
```

Can be extended to use signed hashing functions

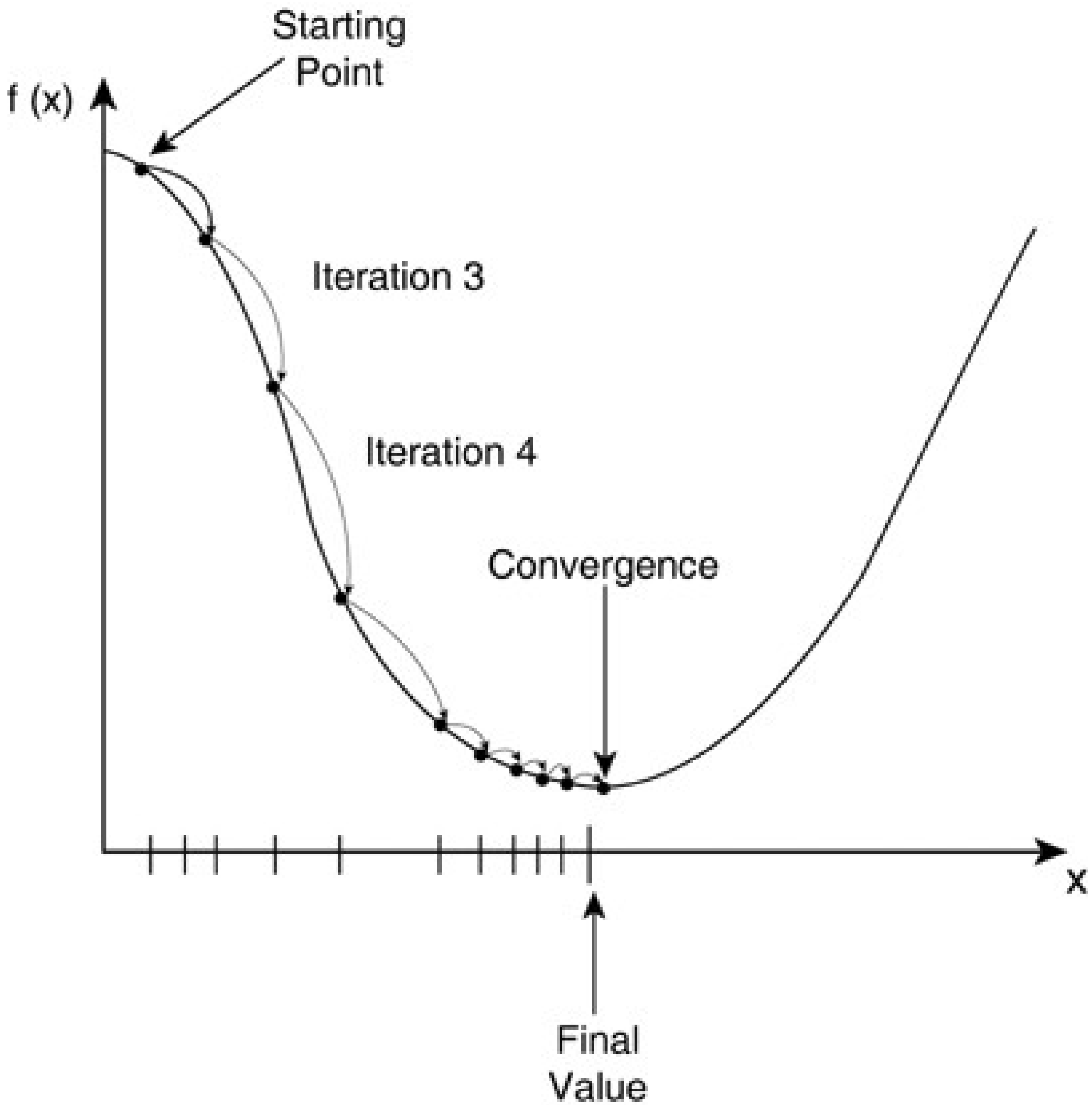
Pros:

- Extremely fast
- No memory footprint

Cons

- There is no way to reverse features

Stochastic Gradient Descents



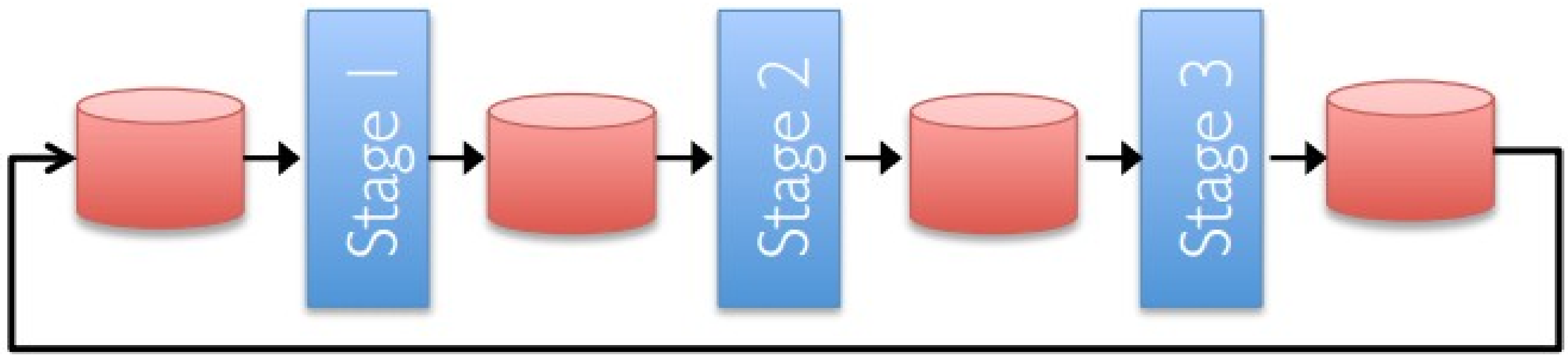
Apache Spark

Program Model + Storage System

Word Count

Raw Map Reduce Result

Problem with Iterative Algos



Disk I/O is very expensive

Oportunity for a new approach

- Keep data in memory
- Use a new distribution model

Spark

Lightning-Fast Cluster Computing

Spark Streaming

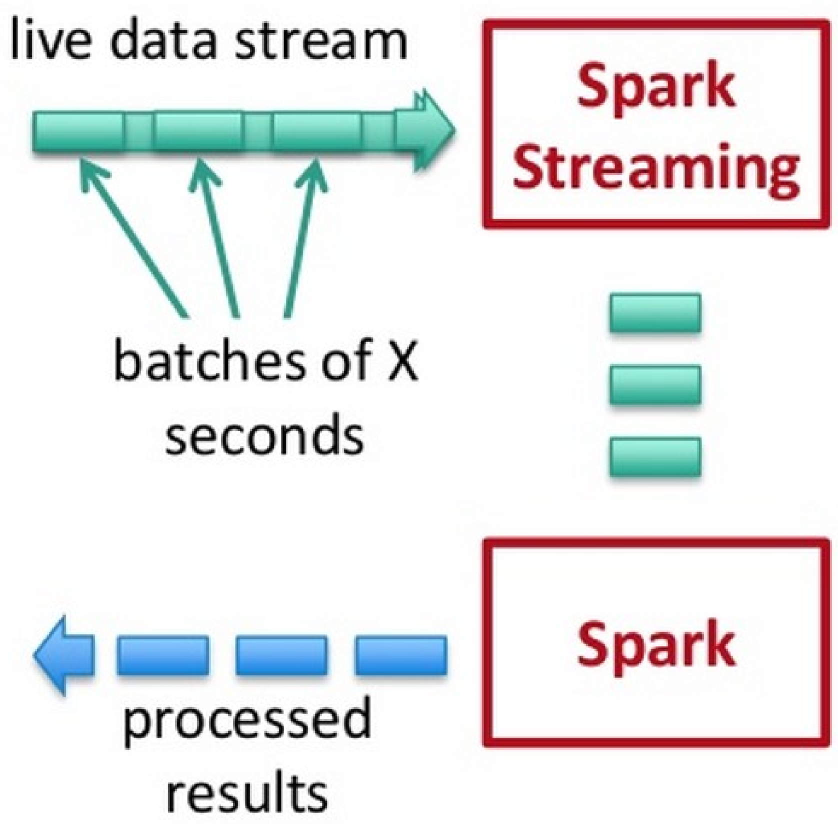
Resilient Distributed Dataset (RDDs)

- A distributed and immutable collection of objects
- Each RDD can be split into multiple partitions
- RDDs allow two types of operations:
- Transformations (lazy)
- Actions (non-lazy)

DStream

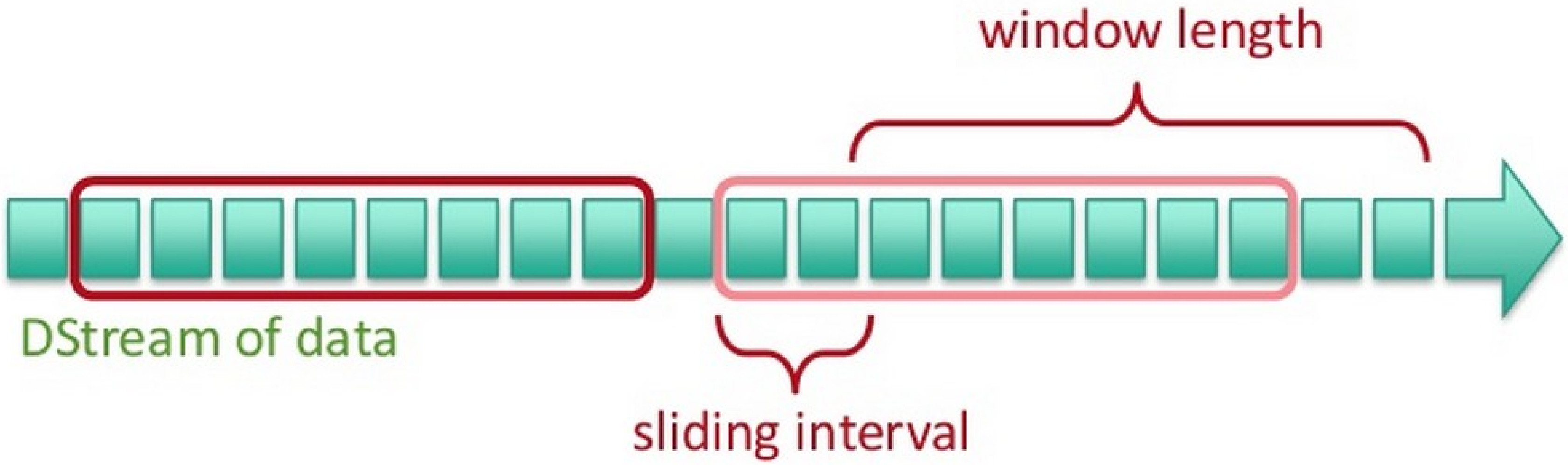
A sequence of RDDs representing a stream of data

DStreams

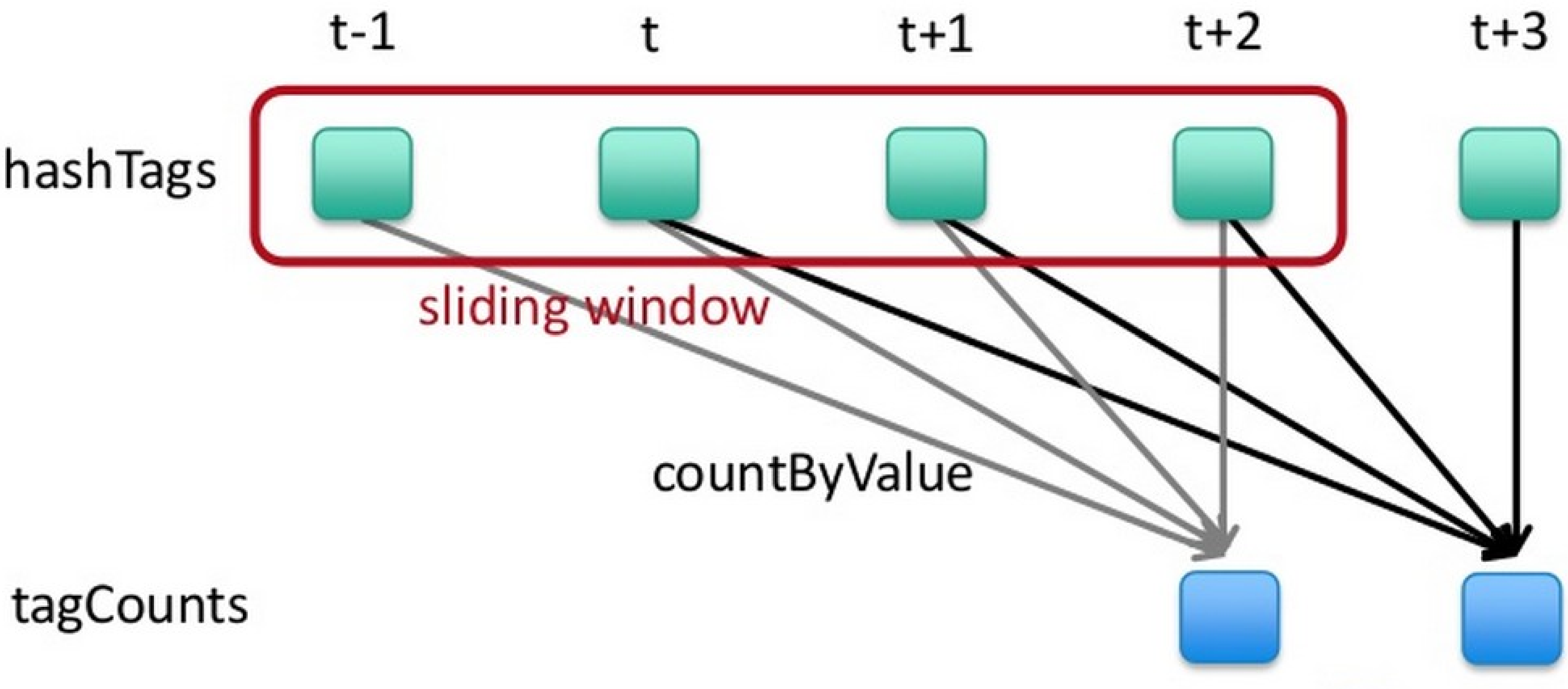


http://www.slideshare.net/spark-project/deep-divewithsparkstreaming-tathagatadassparkmeetup20130617

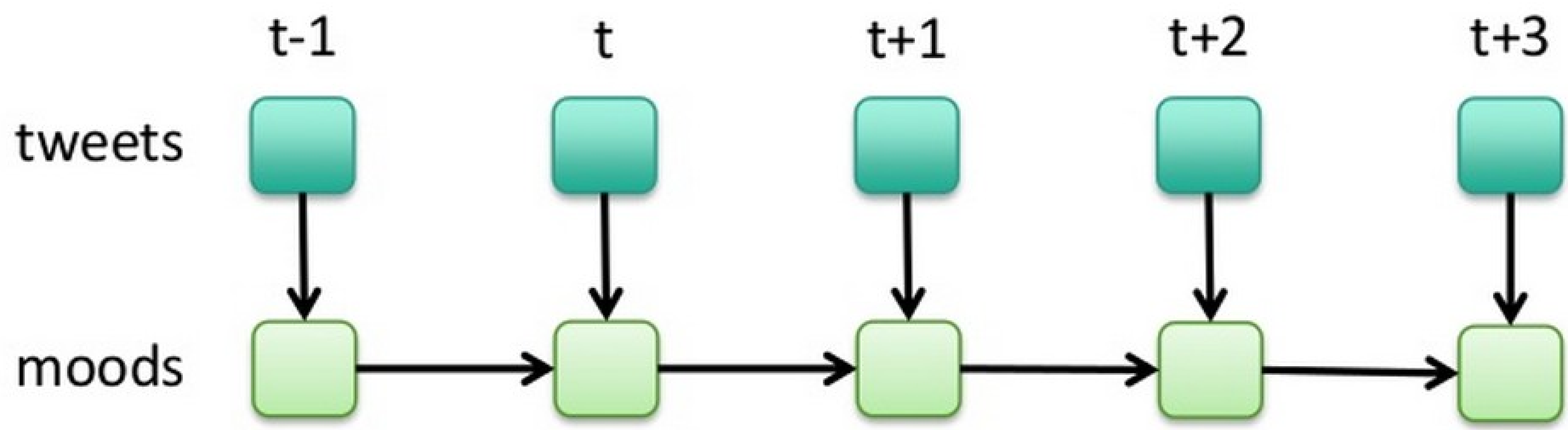
Windows



Windowing computations



Stateful computations



DStream API

http://spark.apache.org/docs/1.3.1/api/scala/index.html#org.apache.spark.streaming.dstream.DStream

Hands on Streaming

- Start the Spark server
- Create a Job
- Run netcat
- Send

Hands on Streaming (Advanced)

- Implement Count-Log on basic Spark

Setup environment

- Prerequisite:
  - Install latest version of Vagrant
    https://www.vagrantup.com/
  - Install latests version of Virtualbox
    https://www.virtualbox.org/
- Create the Virtual Machine:

```
vagrant init codezomb/trusty64-docker
vagrant up
```

http://blog.scottlowe.org/2015/02/10/using-docker-with-vagrant/

Setup environment

- Log in into the VM machine

```
vagrant ssh
```

- Install some Ubuntu packages

sudo apt-get update

```
sudo apt-get -y install docker
openjdk-7-jdk
```

- Pull docker images

```
docker pull tutum/influxdb
docker pull sequenceiq/spark:1.3.0
```

http://old.blog.phusion.nl/2013/11/08/docker-friendly-vagrant-boxes/

enerbyte
smart energy solutions

@tonicebrian, @Enerbyte

toni.cebrian@gmail.com

https://es.linkedin.com/in/tonicebrian

http://www.tonicebrian.com

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