Big Data: motivation and overview

Current Trends in Artificial Intelligence

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(Short) Formal definition of machine learning

Learning requires (more) data!

More data? Big Data!

Application

(Short) Formal definition of machine learning

$$f(\mathbb{X}, \vec{\omega}) = \vec{y} \tag{1}$$

- f Model
- $\mathbb{X}$ Matrix of the features (input data)
- $\vec{y}$ Output vector
  - $\vec{y}$ is continuous = regression
  - $\vec{y}$ is discrete = classification (supervised) or clustering (unsupervised)
  - $\vec{y}$ is symbolic = decision problem
- $\vec{\omega}$ Weights of the model f
  - Determining $\vec{\omega}$ = train the model, learn

Learning requires (more) data!

Learning Determining the weights of the model using a training dataset.

Training dataset Set of features (and output values) representative of the problem, as **big** as possible.

Points	**Attributes**		
0	$x_1[0]$	$x_2[0]$	$x_3[0]$
1	$x_1[1]$	$x_2[1]$	$x_3[1]$
2	$x_1[2]$	$x_2[2]$	$x_3[2]$
$\vdots$	$\vdots$	$\vdots$	$\vdots$

- **Problem** How to store this data?

Spreadsheet storage

	A	B	C	D	E	F
1	week	day	time	value		
2	7	6	0.03999999910593	272		
3	7	6	0.090000003576279	260		
4	7	6	0.140000000596046	259		
5	7	6	0.189999997615814	261		
6	7	6	0.239999994635582	270		
7	7	6	0.28999999165535	270		
8	7	6	0.340000003576279	270		
9	7	6	0.389999985694885	260		
10	7	6	0.439999997615814	261		
11	7	6	0.490000009536743	266		
12	7	6	0.540000021457672	510		
13	7	6	0.589999973773956	259		
14	7	6	1.03999996185303	257		
15	7	6	1.0900000333786	265		
16	7	6	1.13999998569489	255		
17	7	6	1.19000005722046	268		
18	7	6	1.24000000953674	266		
19	7	6	1.28999996185303	258		
20	7	6	1.3400000333786	270		
21	7	6	1.38999998569489	261		
22	7	6	1.44000005722046	255		
23	7	6	1.49000000953674	270		
24	7	6	1.53999996185303	265		
25	7	6	1.5900000333786	263		
26	7	6	2.03999996185303	266		

Figure: Time series in a spreadsheet

- Limited to 1 million rows per file
- Cheesy
- Limited access to 1 user at a time, poor availability
- Sequential reading

$\Rightarrow$ Not suitable!

Relational database management system

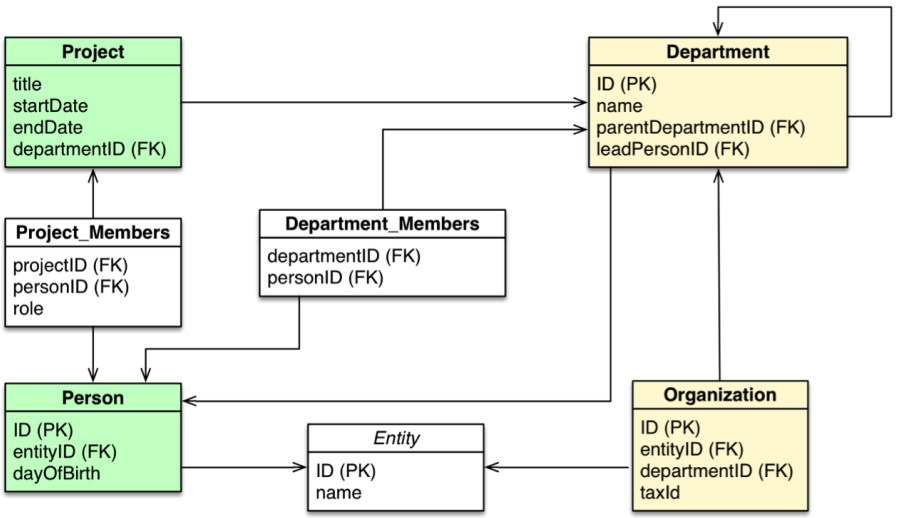

Figure: Relational model (`neo4j.com`)

- Greater capacity ($> 1\,\mathrm{M}$ rows)
- Guaranteed consistency through ACID properties (atomicity, consistency, isolation, durability)
- Relations ("shortcuts") between tables
- Structured query language (SQL) to retrieve data
- Better availability through serving systems (MySQL, SQLServer, PostgreSQL)

Relational database management system

- RDBMS limitations:
  - Fixed data schema: defined *a priori*, no missing data allowed
  - Server bound
- Problems:
  - What if there is missing data?
  - What if the data varies in size, format, structure? How to combine heterogeneous data sources?
  - What if the workload become too heavy for the server (too many requests for the CPU, to much data for the HDD)?

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    - Create separated tables and try to link them.
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    - KIWI (kill it whit iron) = hardware upgrade.

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    - **Use flexible schema.**
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    - Create separated tables and try to link them.
    - **Use flexible schema.**
  - What if the workload become too heavy for the server (too many requests for the CPU, to much data for the HDD)?
    - KIWI (kill it whit iron) = hardware upgrade.
    - **Distribute the load on multiple machines.**

More data? Big Data!

Remember, back in 2006...

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- More data, more variety, more requests.
- Google develops Bigtable, which later inspired

More data? Big Data!

The 3 Vs of Big Data:

- **Variety** Data of many different types are to be stored...
- **Velocity** it's coming fast...
- **Volume** and there is a **lot** of it!

Scalability

Ability to adapt when the order of magnitude changes.

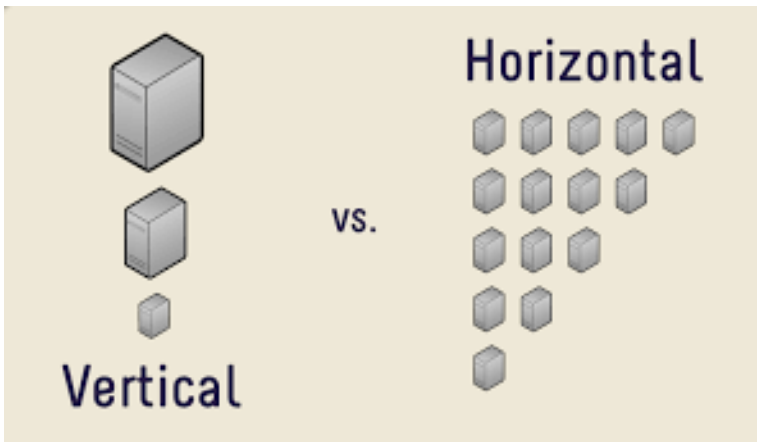


Figure: Vertical and horizontal scalability (`premaseem.files.wordpress.com`).

Consistency: from ACID to BASE

- Problem ACID does not support partitioning across multiple nodes.
- BASE: basically available, soft state, eventually consistent

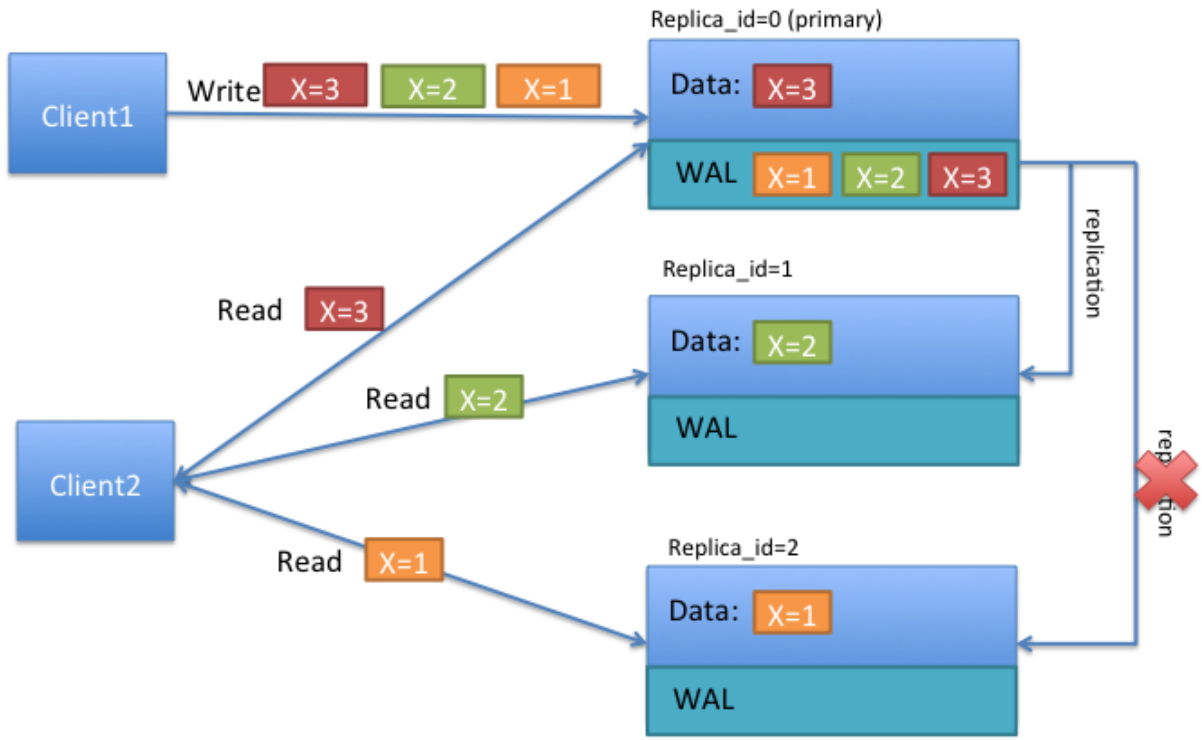


Figure: Consistency issue for distributed database systems (`hbase.apache.org`).

CAP theorem

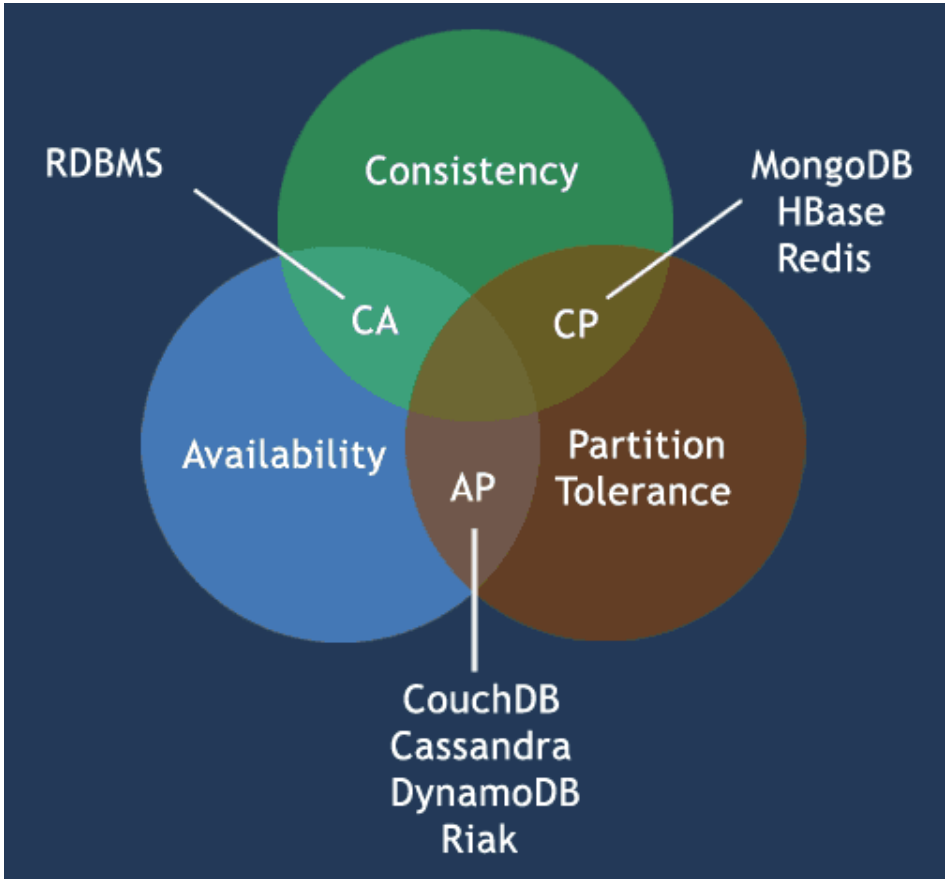


Figure: The CAP theorem: any database system has to drop either the consistency, the availability or the partition tolerance (`w3resource.com`).

NoSQL technologies

- NoSQL = not only SQL, NewSQL = distributed relational database
- Shared-nothing (distributed) architecture ⇒ CP, AP
- Supported operations: CRUD (create, read, update, delete) and scan.
- Classification:

key-value	unique ID	value	

columnar		Family 0		Family 1
	unique ID	column 0	column 1	column 2

document	unique ID	{attr0: value0, attr1: value1}	
graph	unique ID	arcs	vertices
search engines	inverted ID	plain text or document	

NoSQL technologies

More than 200 different systems!

Figure: Logos of some NoSQL database systems.

Hadoop

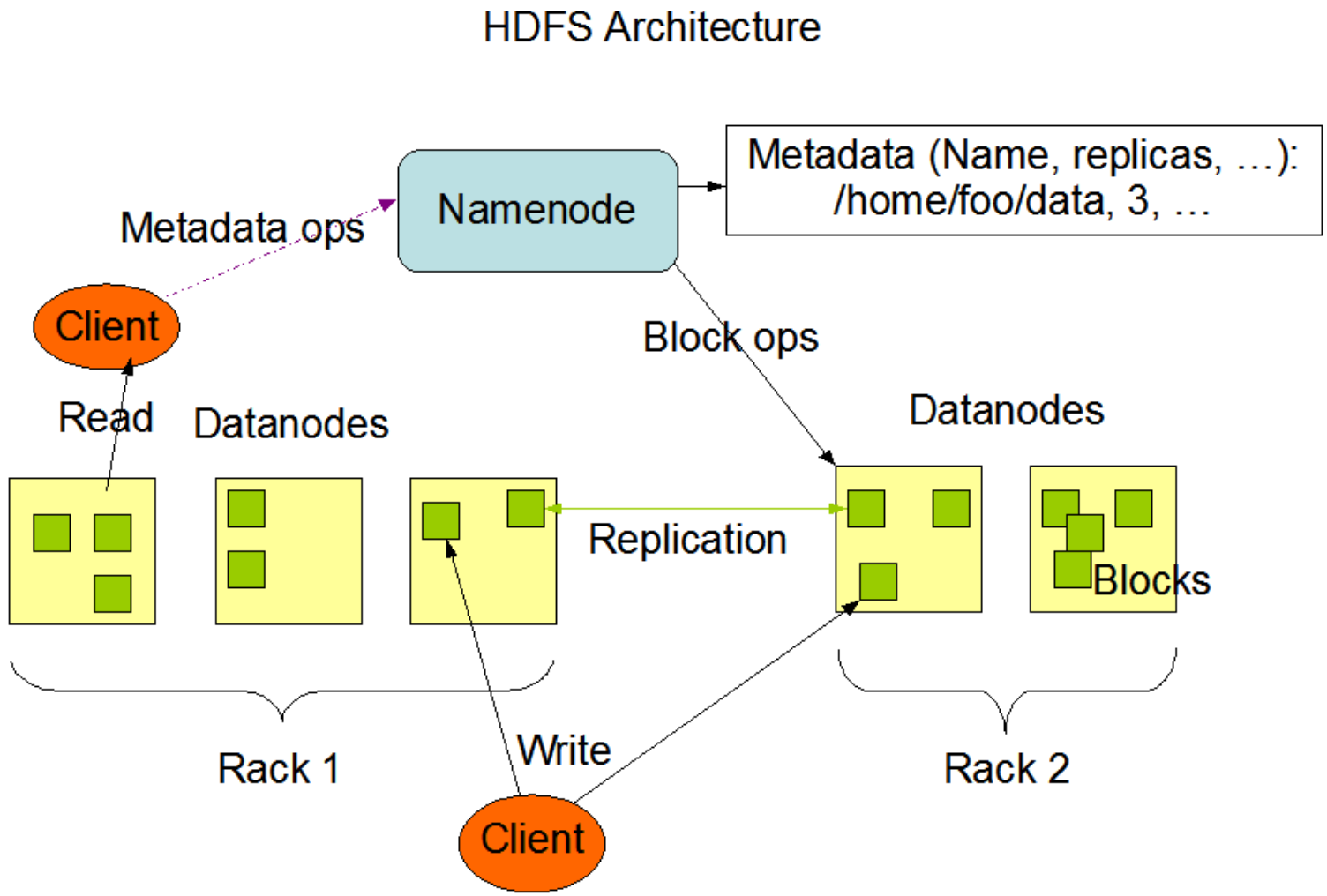


Figure: Architecture of the Hadoop distributed file system, the *Namenode* acts as master of the infrastructure (`hadoop.apache.org`).

On top of Hadoop: HBase

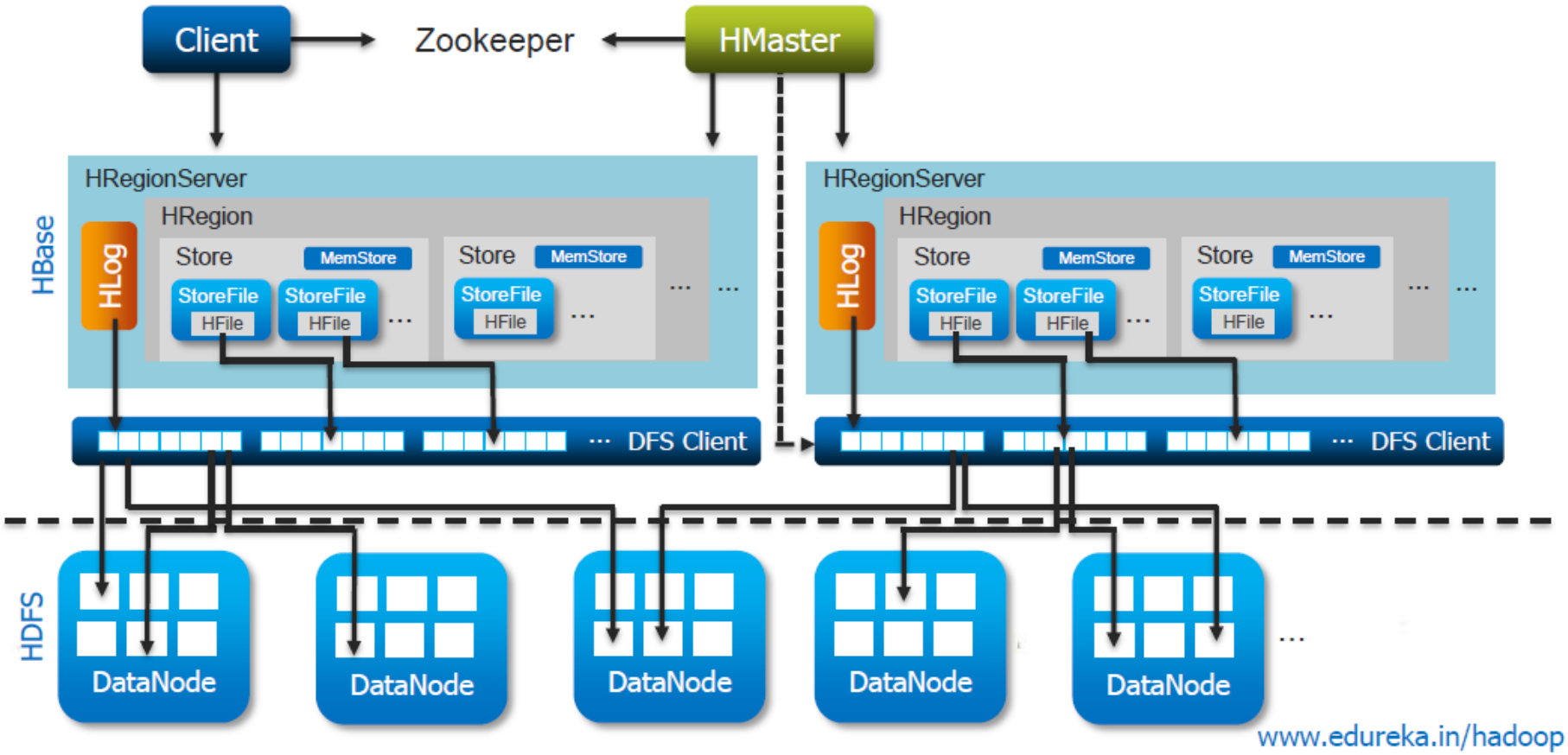


Figure: HBase architecture (`eureka.co`).

Cassandra

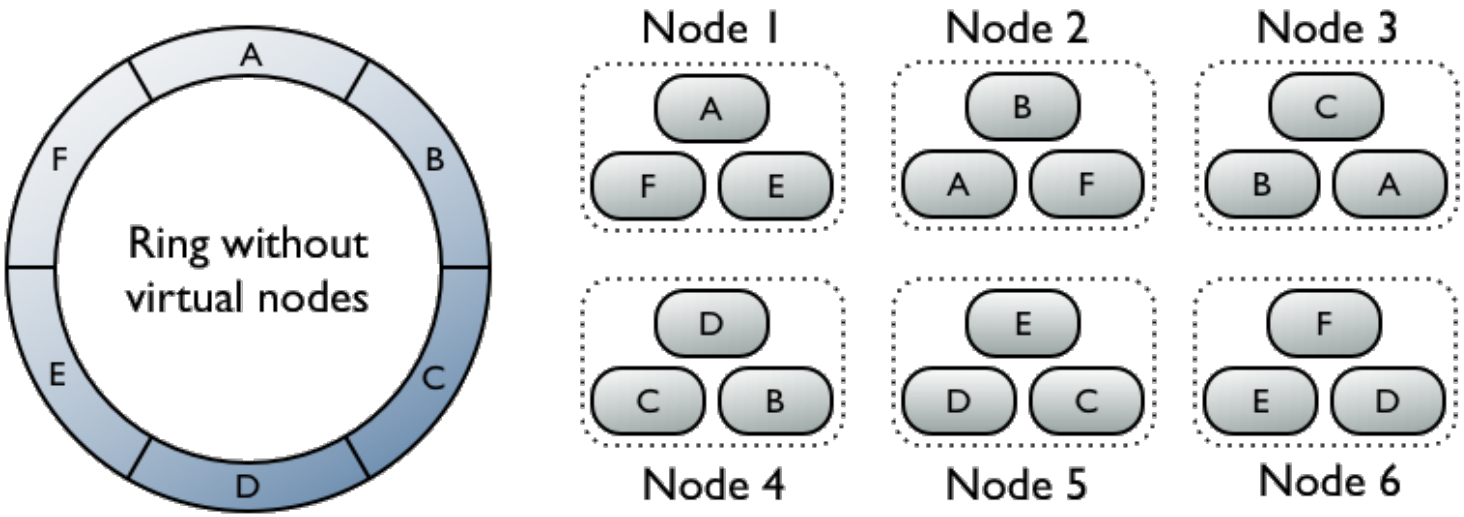


Figure: Cassandra's ring strategy for splitting (`docs.datastax.com`).

Cassandra

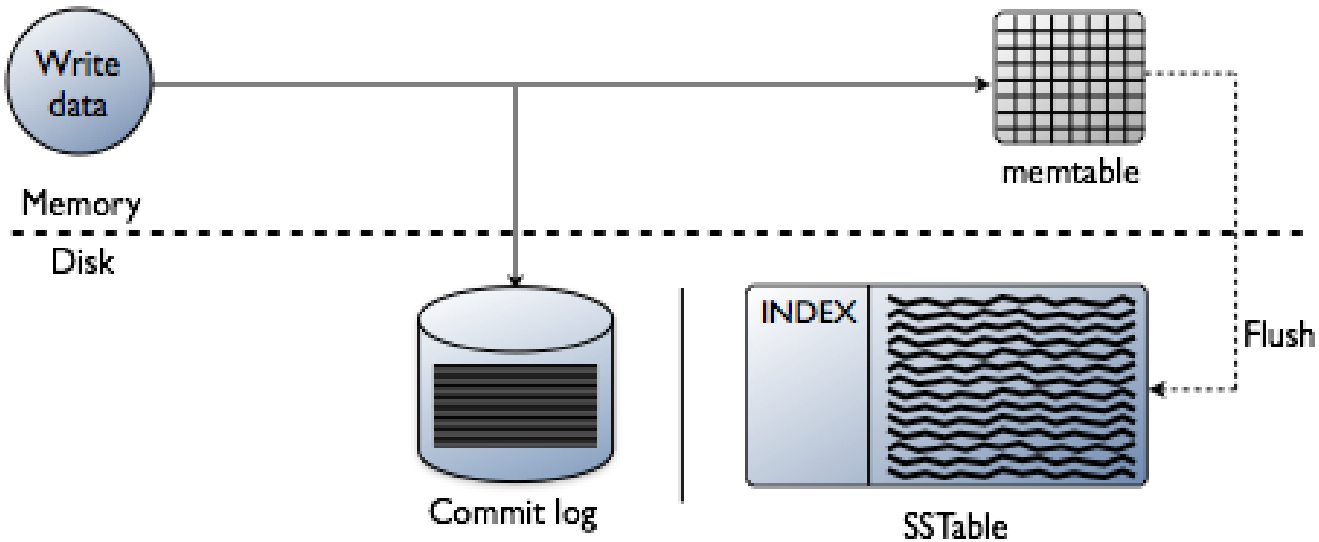


Figure: Cassandra's writing process (`docs.datastax.com`).

- No master: nodes use gossiping to exchange metadata about the current state
- Compaction: too many *SSTables* $\Rightarrow$ merge in one bigger *SSTable*.

Cassandra

```
Connected to IRIDIA at node001:9042.
[cqlsh 5.0.1 | Cassandra 3.11.2 | CQL spec 3.4.4 | Native protocol v4]
Use HELP for help.
cassandra@cqlsh> USE test;
cassandra@cqlsh:test> SELECT * FROM temp WHERE year=2018 AND week=8 AND day>3 ALLOW FILTERING;

 id                    | year | week | day | time | value
-----------------------+------+------+-----+------+-------
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.04 | 21.78
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.09 | 21.86
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.14 | 21.92
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.19 | 21.94
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.24 | 21.93
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.29 | 21.88
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.34 |  21.8
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.39 | 21.72
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.44 | 21.66
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.49 | 21.61
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.54 | 21.61
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 0.59 |  21.6
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.04 | 21.62
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.09 | 21.71
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.14 | 21.84
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.19 | 21.98
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.24 | 22.09
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.29 | 22.12
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.34 | 22.06
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.39 | 21.95
 B827EBA6DBA1::bedroom | 2018 |    8 |   4 | 1.44 | 21.82
```

Figure: Result of a SELECT query in CQL.

Elasticsearch

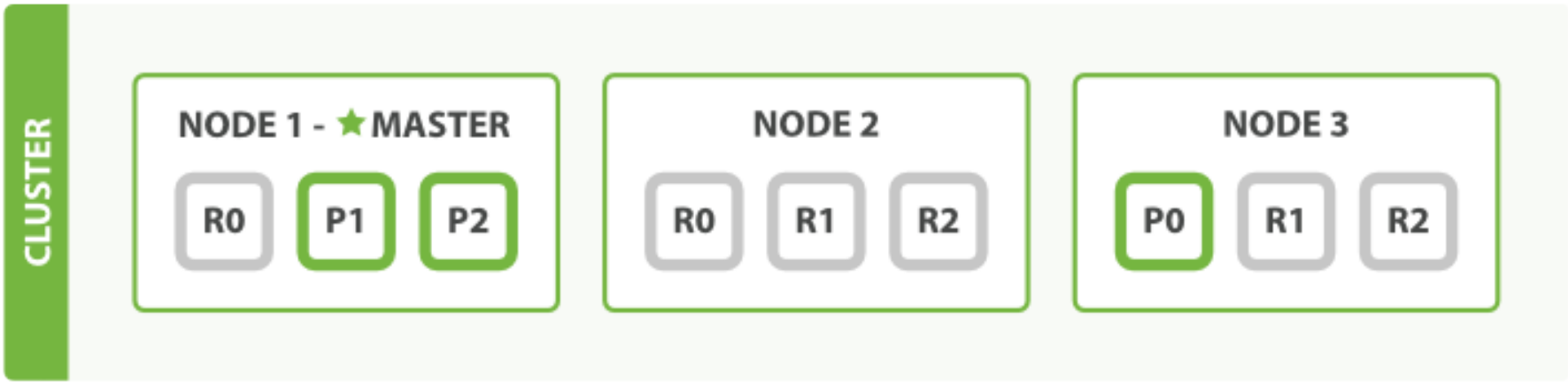


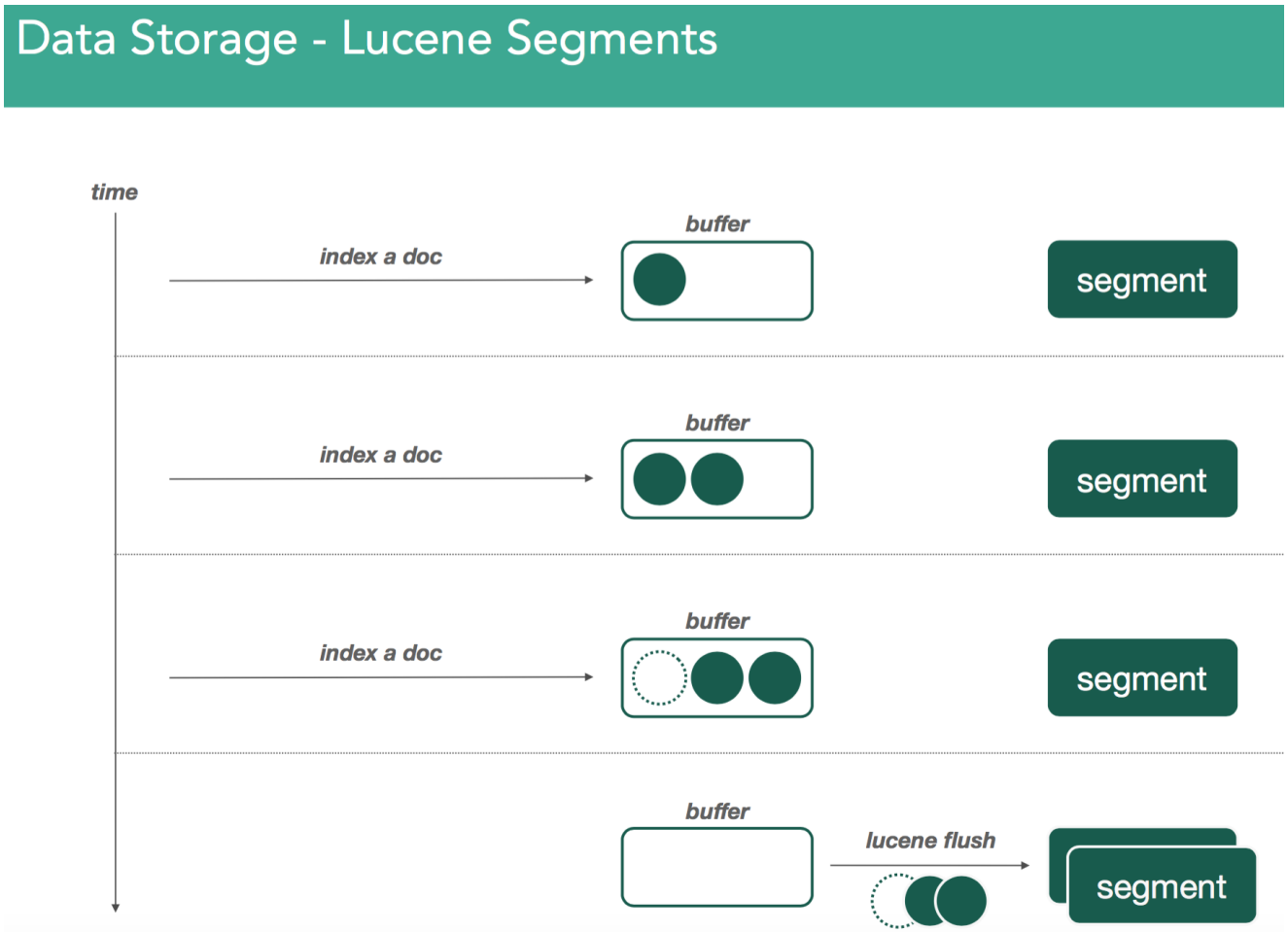
Figure: Sharding and replication with elasticsearch (`elastic.co`).

2 types of nodes:

Master Allocates the shards and the replicas to the other nodes.

Datanode Indexes, stores and reads the documents.

Elasticsearch



elastic.co

Elasticsearch - Lucene backend

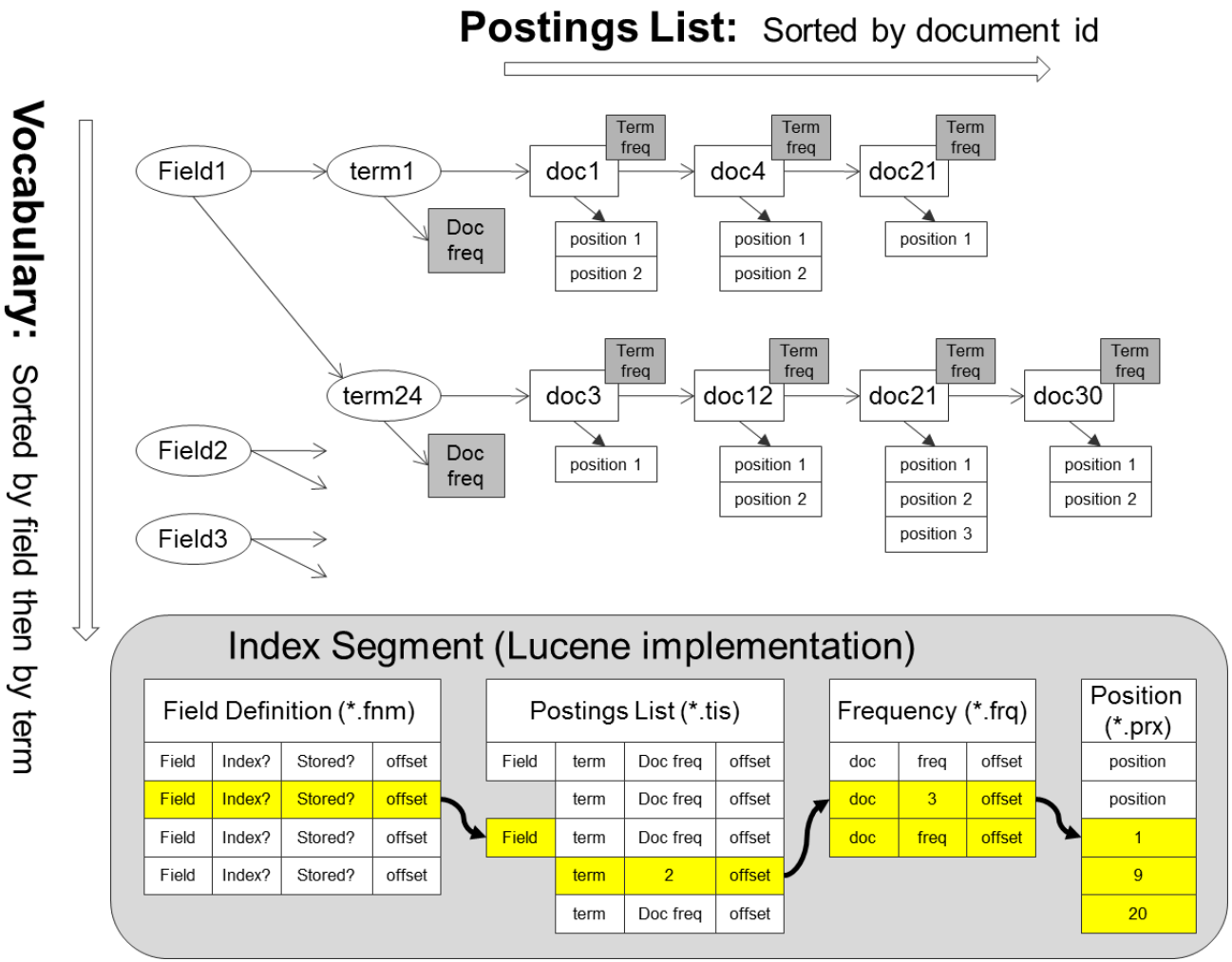


Figure: Lucene indexing process (`4.bp.blogspot.com`).

Distributed data processing

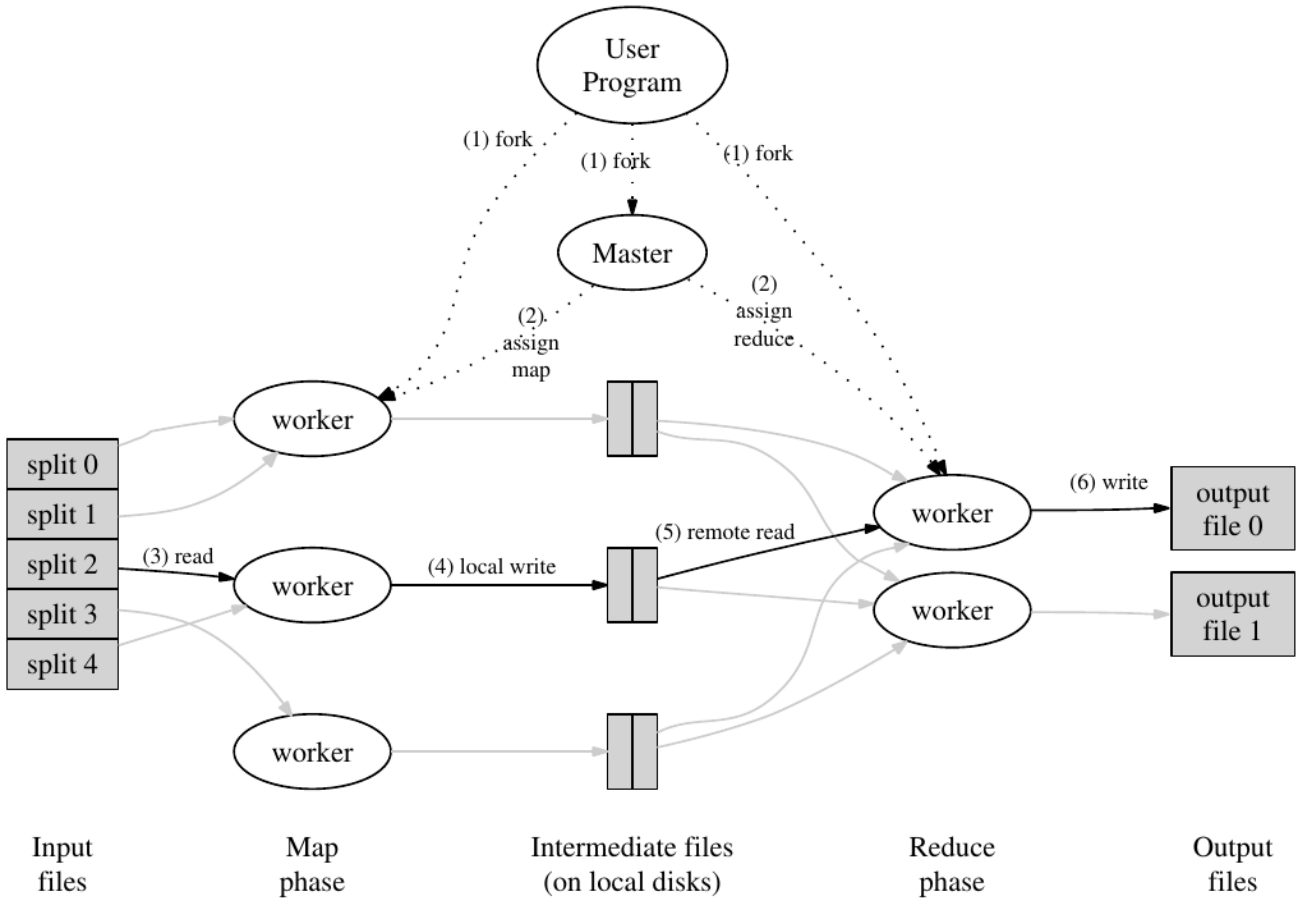


Figure: MapReduce: Distributed processing method for cluster computing (Dean *et al.*, 2004).

Batch processing

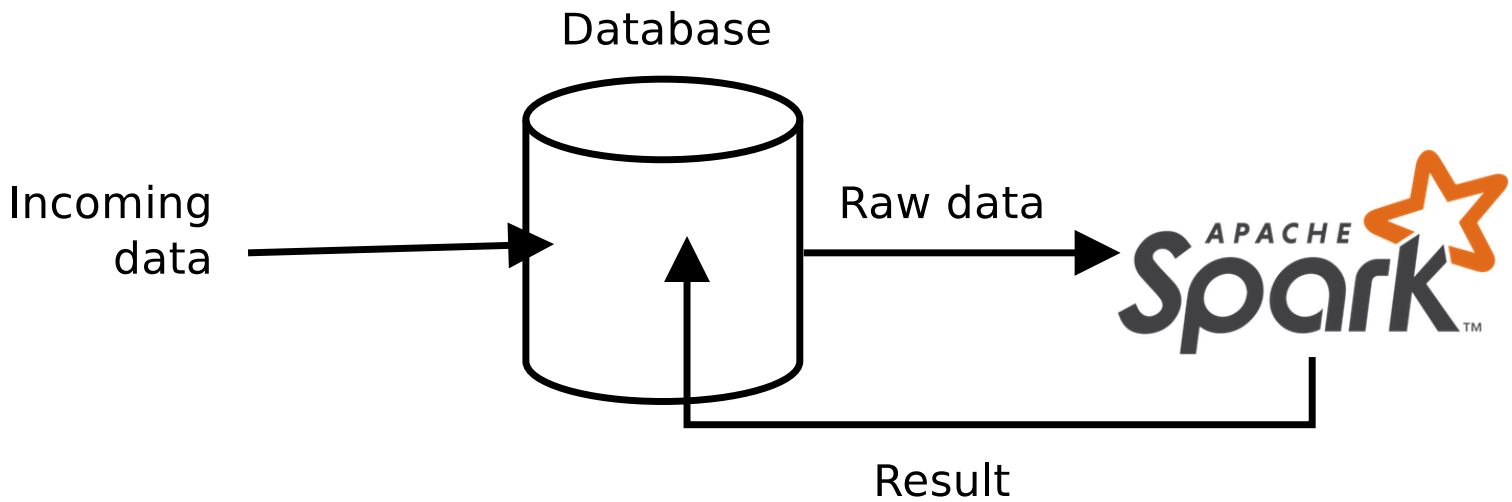


Figure: Distributed batch processing, *e.g.* with Apache Spark.

Streaming analytics

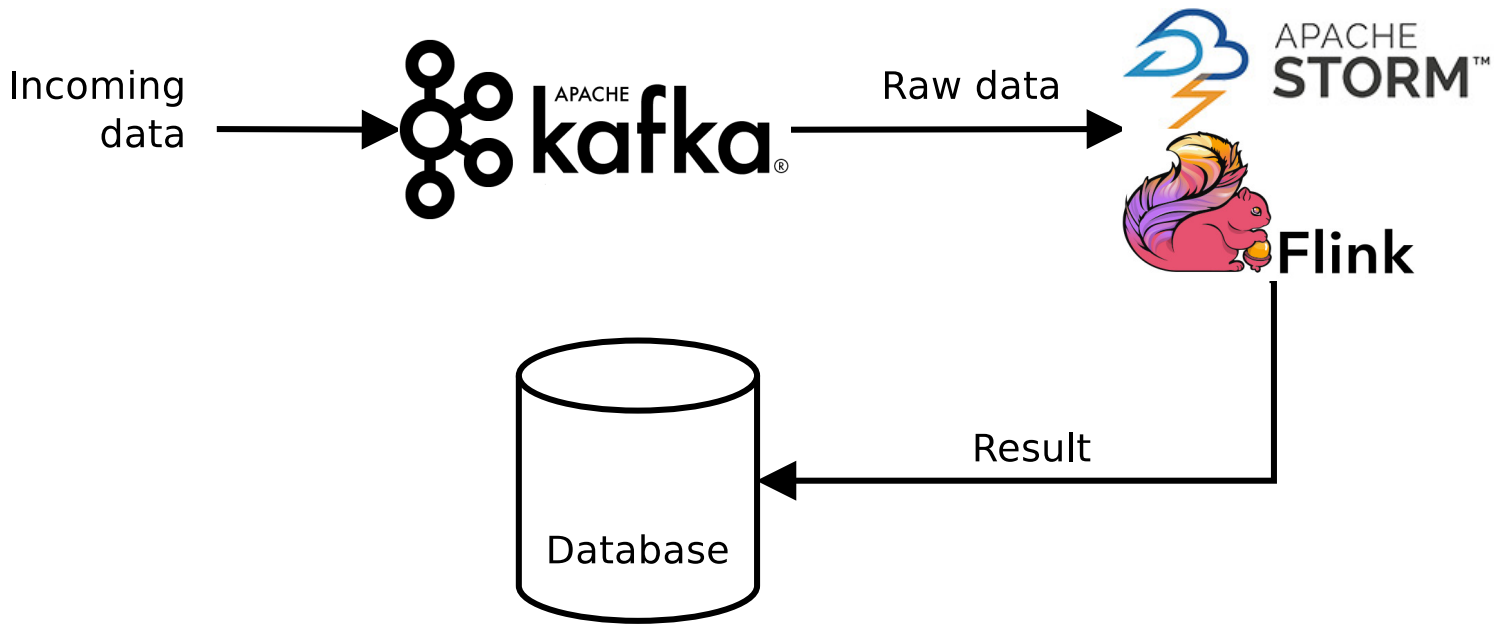


Figure: Distributed streaming analytics using *e.g.* Apache Storm or Flink.

Benchmarking with YCSB

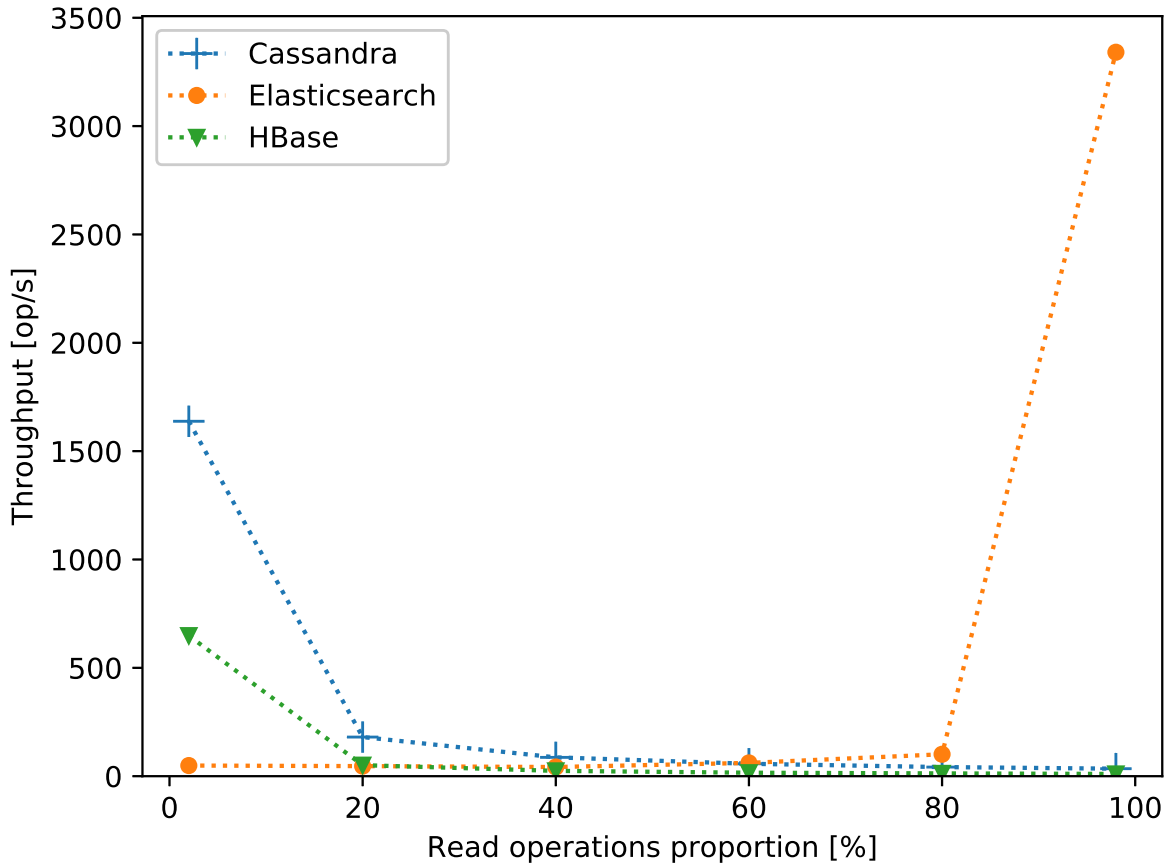
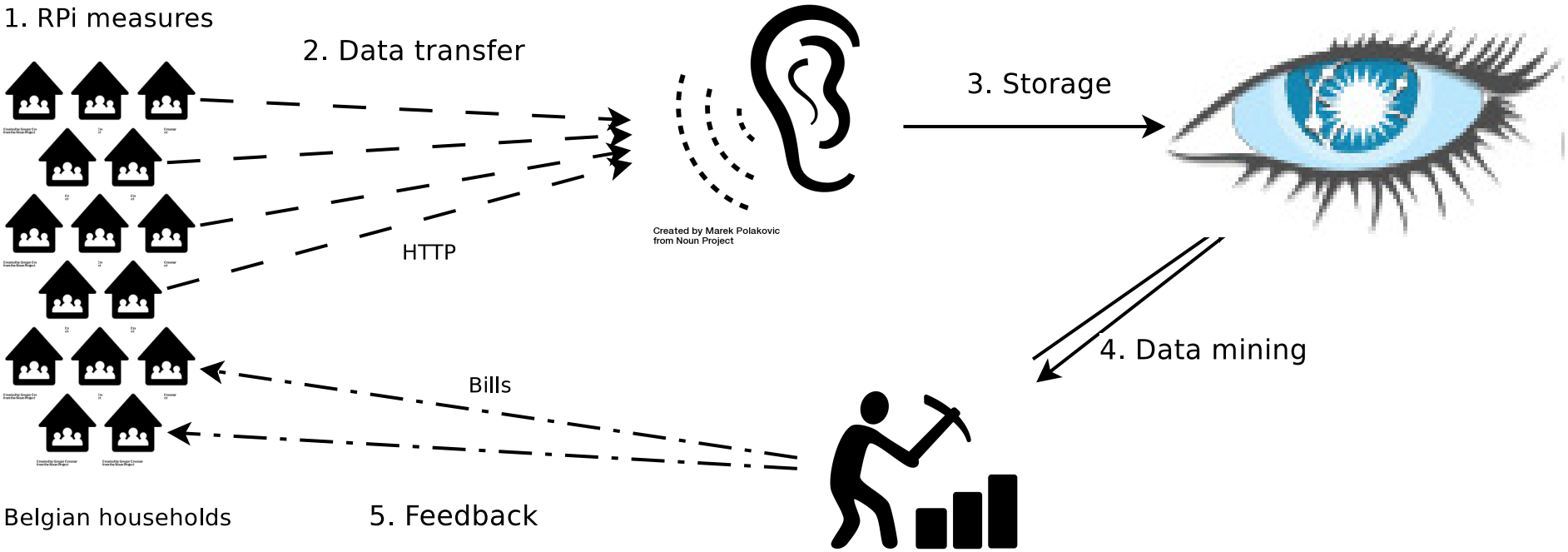


Figure: Throughput for 48 YCSB clients against a 11-nodes cluster for a varying read operations proportion with 1 M rows of 32×8 B.

Application



"Household" by Gregor Cresnar/thenounproject.com/CC BY 3.0
"Listen" by Marek Polakovic/thenounproject.com/CC BY 3.0

Figure: Dataflow for IoT application in household energy monitoring.

Application

Figure: Prototypes of home sensors.

Application

Wikimedia Foundation:
`https://grafana.wikimedia.org/`

References

[1][2][3]


Alejandro Corbellini et al. “Persisting big-data: The NoSQL landscape”. In: *Information Systems* 63 (2017), pp. 1–23.


Jeffrey Dean and Sanjay Ghemawat. “MapReduce: Simplified Data Processing on Large Clusters”. In: *OSDI 04*. 2004.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