Large-Scale Data Management and Distributed Systems

V. NoSQL Databases

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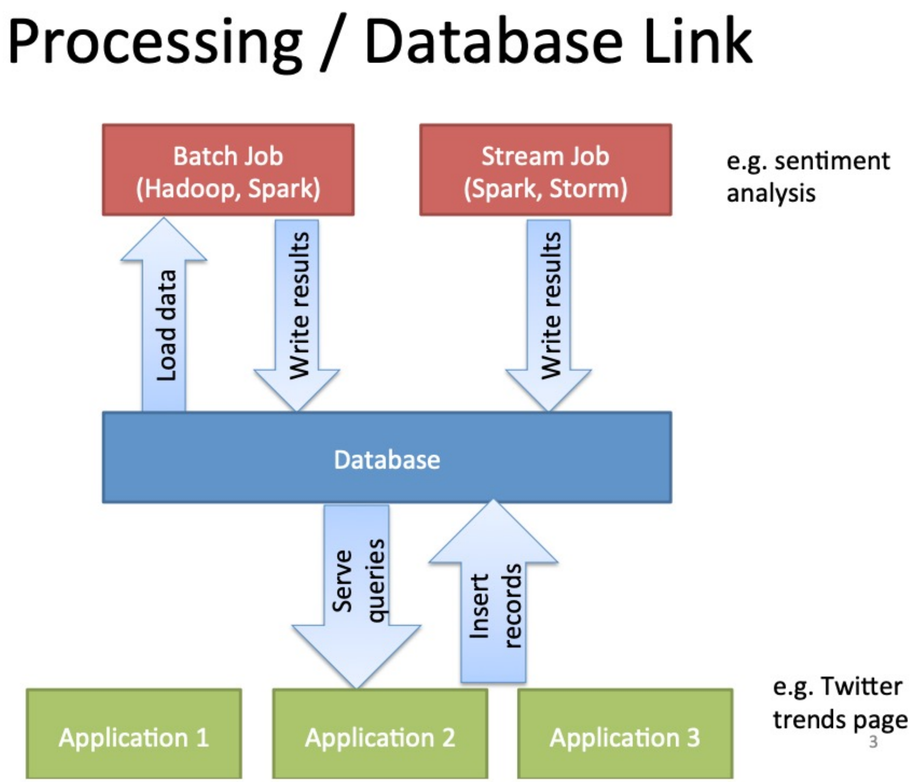
References

- Lecture notes of V.Leroy
- Lecture notes of F.Zanon Boito
- Lecture notes of FT.Ropars
- *Designing Data-Intensive Applications* by Martin Kleppmann
  - Chapter 2 and 7

In this lecture

- Motivations for NoSQL databases
- ACID properties and CAP Theorem
- A landscape of NoSQL databases

Data is Central !



Data Depends on the App !

Stock management

Health insurance management

Health records management

Payroll

Shopping

Tweet news

TikTok "news"...

...

Design questions

- **Structure** ? – schema ?
- **Access** ? – whole/part ?
- **Queries** ? – simple, complex ?
- **Volume** ? – centralized/distributed ?
- **Evolution** ? – add attributes ?
- **Guarantees** ? – types ?

Common Patterns of Data Accesses

Large-scale data processing

- Batch processing: Hadoop, Spark, etc.
- Perform some computation/transformation over a full dataset
- Process all data

Selective query

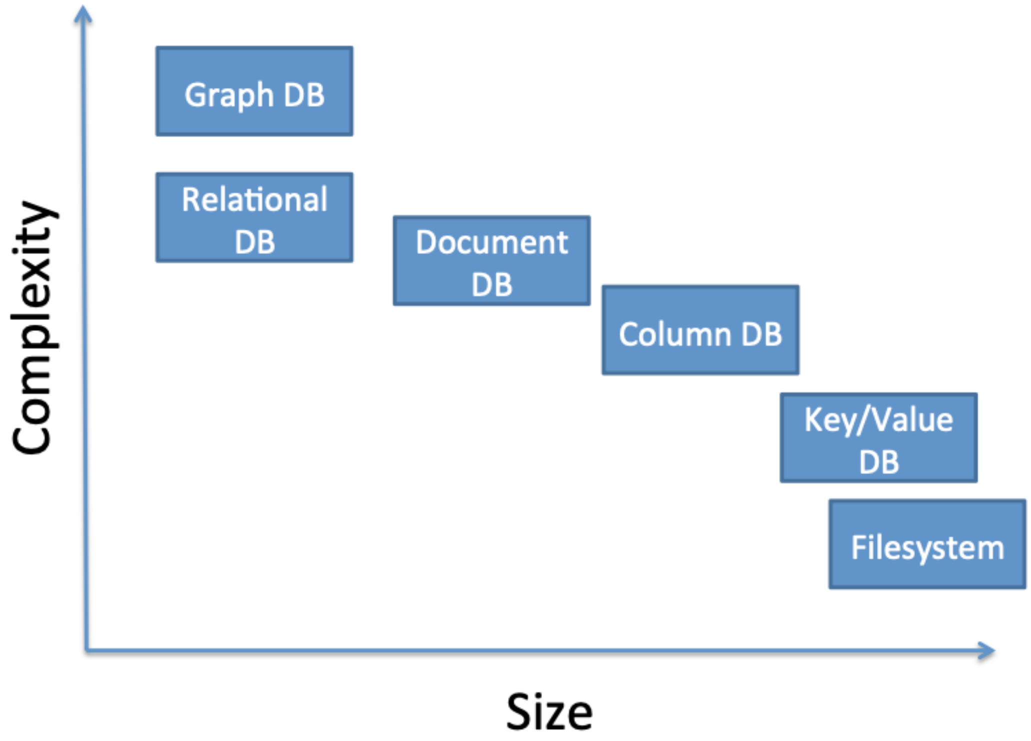
- Access a specific part of the dataset
- Manipulate only data needed (1 record among millions)
- Main purpose of a database system

Types of Databases

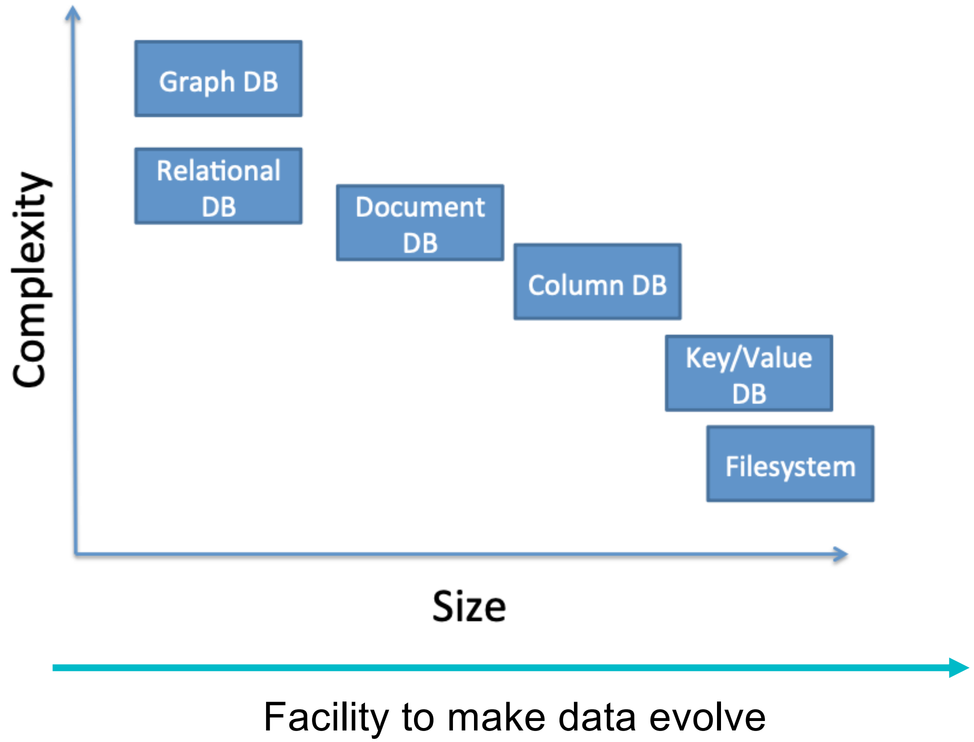
So far we used HDFS

- A file system can be seen as a very basic database
  - Directories / files to organize data
  - Very simple queries (file system path)
  - Very good scalability, fault tolerance …
- Other end of the spectrum: relational databases
  - SQL query language, very expressive
  - Limited scalability
  - Very complex data evolutivity

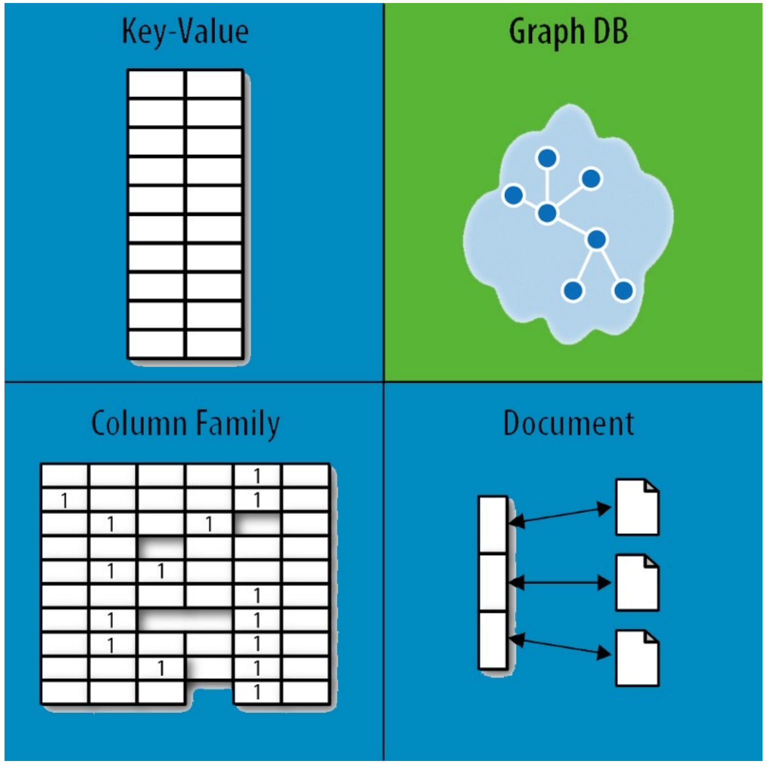
Size / Complexity

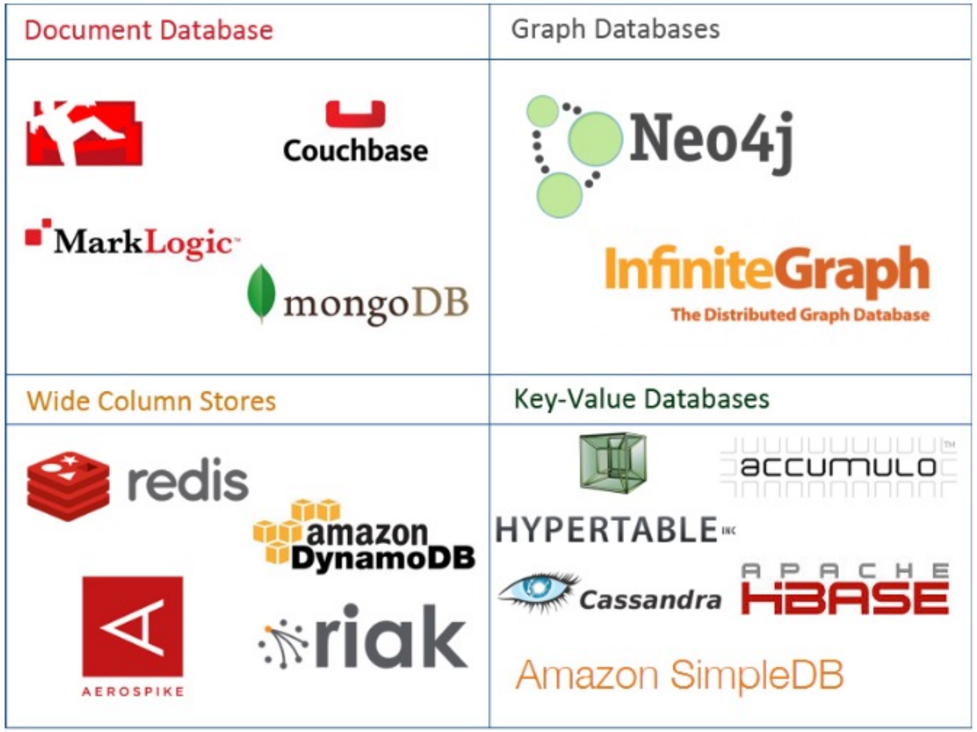


Size / Complexity / Facility to Change Data



The NoSQL Jungle





Relational Databases: SQL

- Born in the 70's – Still heavily used
- Data is organized into relations (in SQL: tables)
- Each relation is an unordered collection of tuples (rows)

Students

ID#	Name	Phone	DOB
500	Matt	555-4141	06/03/70
501	Jenny	867-5309	3/15/81
502	Sean	876-9123	10/31/82

ID#	ClassID	Sem
500	1001	Fall02
501	1002	Fall02
501	1002	Spr03
502	1003	S203

Takes_Course

ClassID	Title	ClassNum
1001	Intro to Informatics	I101
1002	Data Mining	I400
1003	Internet and Society	I400

Courses

SQL: Structured Query Language

- Separate the data from the code
  - High-level language
  - Space for optimization strategies
- Powerful query language
  - Clean semantics
  - Operations on sets
- Support for transactions

Motivations for Alternative Models

Limitations of Relational Databases

- Performance and scalability
  - Difficult to partition the data (in general run on a single server)
  - Need to scale up to improve performance
- Lack of flexibility
  - Will to easily change the schema
  - Need to express different relations
  - Not all data are well structured
- Few open source solutions
- Mismatch between the relational model and object-oriented programming model

Illustration of the Object-Relational Mismatch

Figure by M. Kleppmann

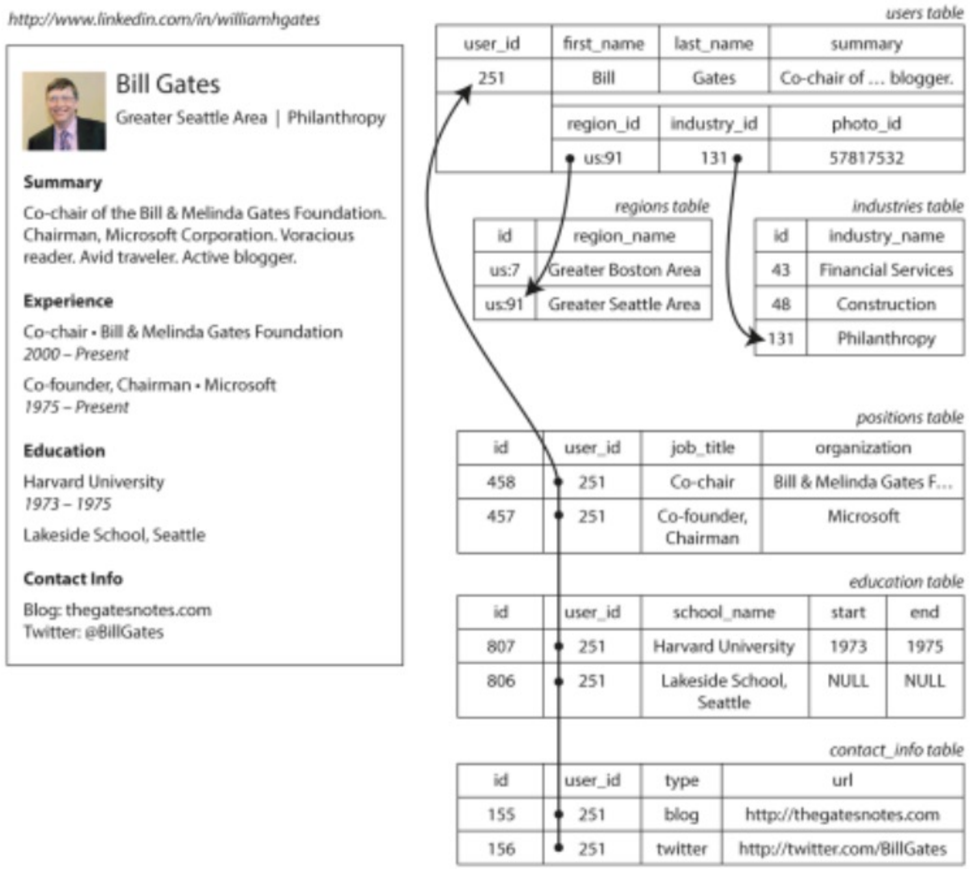


Figure: A CV in a relation database

Illustration of the Object-Relational Mismatch

Figure by M. Kleppmann


```
{
  "user_id":251,
  "first_name": "Bill",
  "last_name": "Gates",
  "summary": "Co—chair of the Bill & Melinda Gates; Active blogger.",
  "region_id": "us:91",
  "industry_id": 131,
  "photo_url": "/p/7/000/253/05b/308dd6e.jpg",
  "positions": [
    {"job_title": "Co—chair", "organization": "Bill & Melinda Gates
          Foundation"},
    {"job_title": "Co—founder, Chairman", "organization": "Microsoft"}
  ],
  "education": [
    {"school_name": "Harvard University", "start": 1973, "end": 1975},
    {"school_name": "Lakeside School, Seattle", "start": null, "end": null}
  ],
  "contact_info": {
    "blog": "http://thegatesnotes.com",
    "twitter": "http://twitter.com/BillGates"
  }
}
```


Figure: A CV in a JSON document

NoSQL

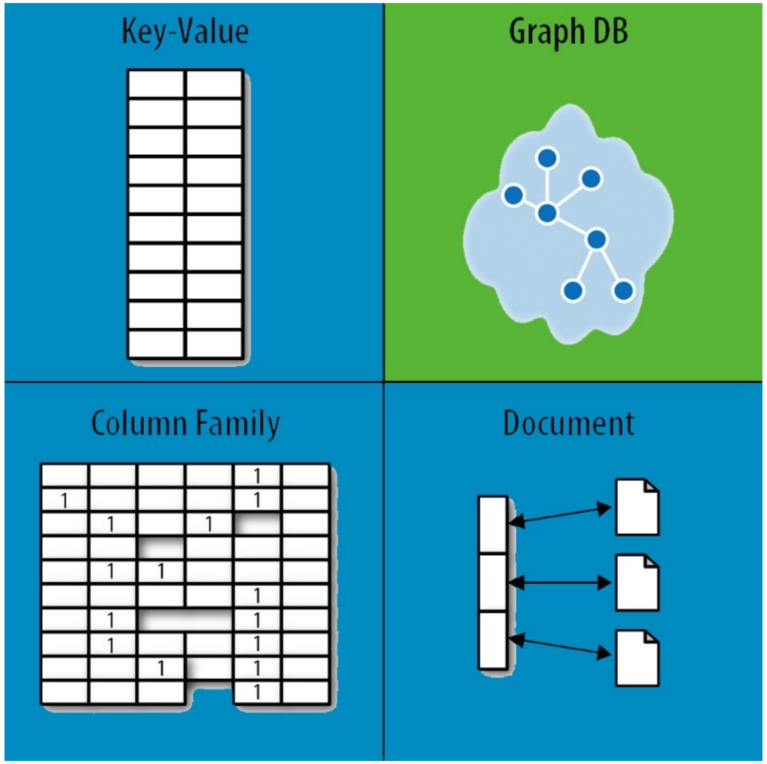
What is NoSQL?

- A hashtag
  - NoSQL approaches were existing before the name became famous •
- No SQL
- New SQL
- Not only SQL
  - Relational databases will continue to exist alongside non-relational datastores

A variety of NoSQL solutions

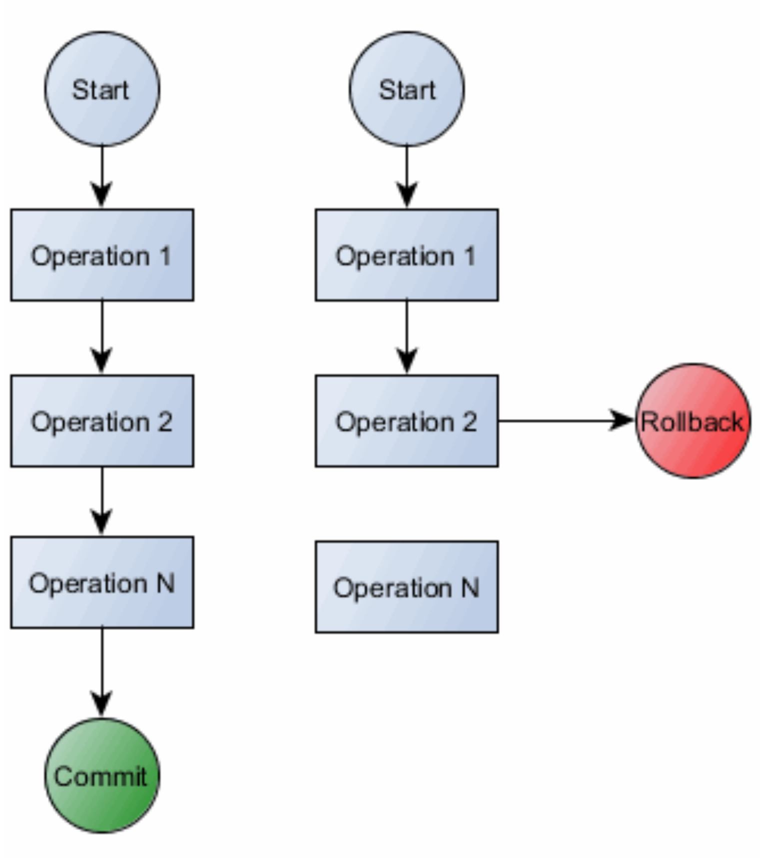
Difference with relational databases

- Properties = guarantees
- Data models = data structure
- Underlying architecture = implementation and performance

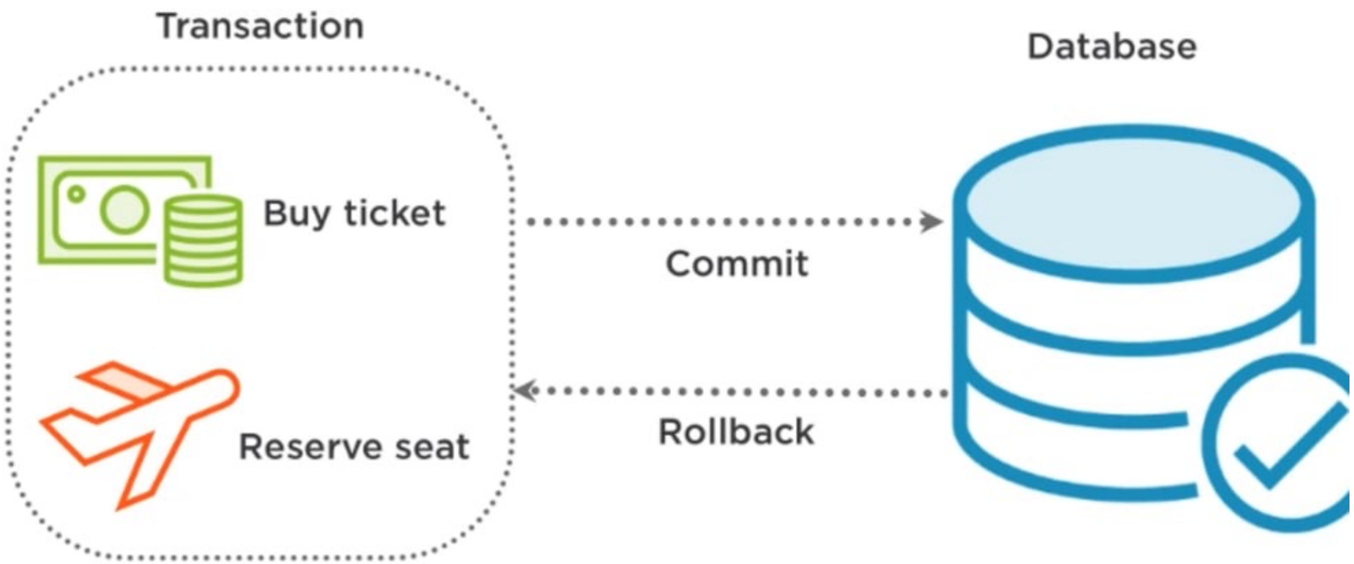


On Guarantees : Transactions

- The concept of transaction
  - Groups several read and write operations into a logical unit
  - A group of reads and writes are executed as one operation:
    - The entire transaction succeeds (commit)
    - or the entire transaction fails (abort, rollback)
- If a transaction fails,
  the application can safely retry



Example of Transaction

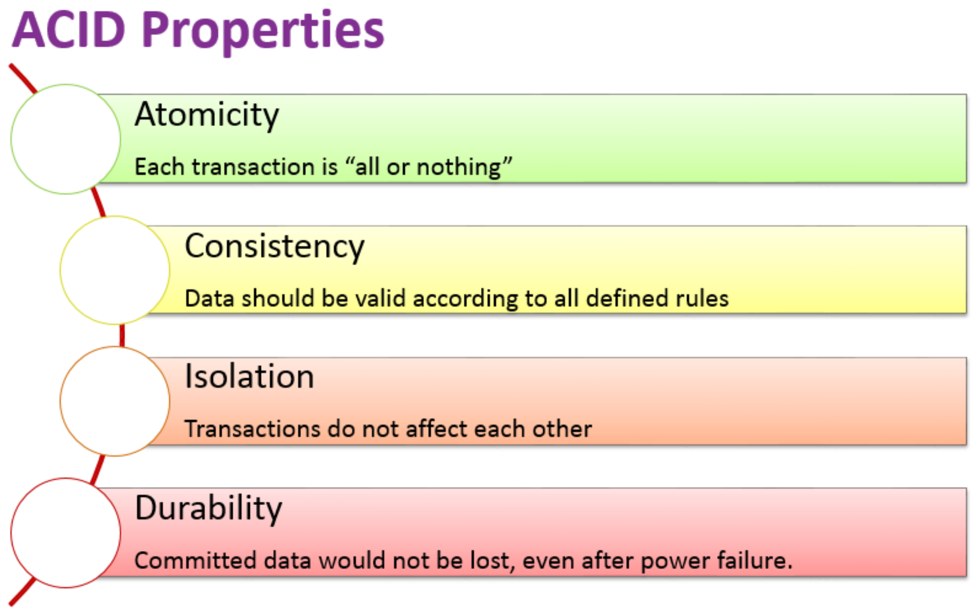


Why Transactions ?

- Crashes may occur at any time
  - On the database side
  - On the application side
  - The network might not be reliable
- Several clients may write to the database at the same time

ACID Properties

- Having such properties make the life of developers easy, but:
  - ACID properties are not the same in all databases
  - It is not even the same in all SQL databases
- NoSQL solutions tend to provide weaker safety guarantees
  - To have better performance, scalability, etc.



Atomicity

Description

- A transactions succeeds completely or fails completely
  - If a single operation in a transaction fails, the whole transaction should fail
  - If a transaction fails, the database is left unchanged
- It should be able to deal with any faults in the middle of a transaction
- If a transaction fails, a client can safely retry

In the NoSQL context:

- Atomicity is still ensured

Consistency

Description

- Ensures that the transaction brings the database from a valid state to another valid state
  - All university staff is paid at the end of month
- It is a property of the **application**, not of the database

In the NoSQL context:

- Consistency is (often) not discussed

Durability

Description

- Ensures that once a transaction has committed successfully, data will not be lost
  - Even if a server crashes (flush to a storage device, replication)

In the NoSQL context:

- Durability is also ensured

Isolation

Description

- Concurrently executed transactions are isolated from each other
  - We need to deal with concurrent transactions that access the same data
- Serializability
  - High level of isolation where each transaction executes as if it was the only transaction applied on the database
    - As if the transactions are applied serially, one after the other
  - Many SQL solutions provide a lower level of isolation

In the NoSQL context:

- Let us have a look at the **CAP** theorem

The CAP Theorem (E. Brewer, 2000)

3 properties of databases

Consistency

- What guarantees do we have on the value returned by a read operation?
  - It strongly relates to Isolation in ACID (and not to consistency)

Availability

- The system should always accept updates

Partition tolerance

- The system should be able to deal with a partitioning of the network

The CAP Theorem States

It is impossible to have a system that provides Consistency, Availability, and Partition tolerance at the same time.

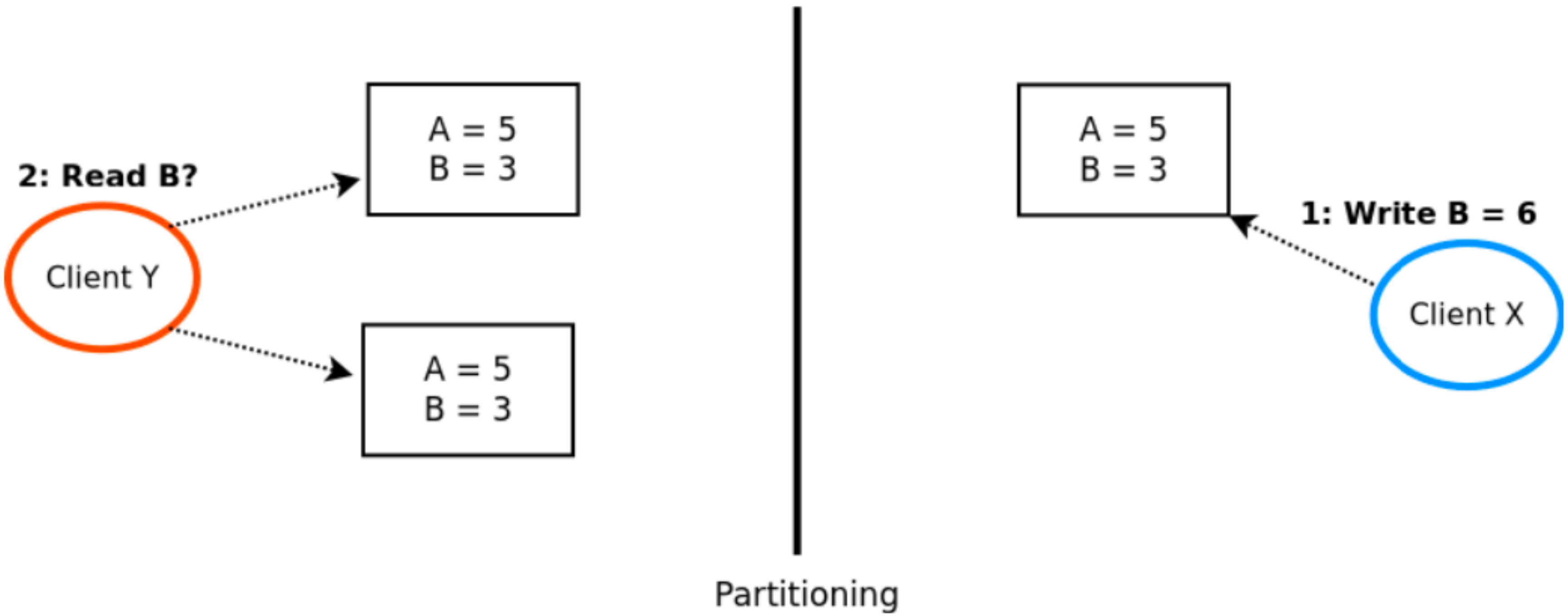
Partitionning (failures) are inevitable in a large scale distributed setting => need to **choose between availability and consistency**

In the CAP theorem:

- Consistency is meant as linearizability (the strongest consistency guarantee)
- Availability is meant as total availability

In practice, different trade-offs can be provided

The Intuition Behind CAP



The impact of CAP on ACID for NoSQL

The main consequence

- No NoSQL database with strong Isolation

The othe ACID properties ?

- Atomicity
  - Each side should ensure atomicity
- Durability
  - Should never be compromised

Key-Value Store

- Data are stored as key-value pairs
  - The value can be a data structure (eg, a list)
- In general, only support single-object transactions
  - In this case, key-value pairs
- Examples:
  - Redis
  - Voldemort
- Use case:
  - Scalable cache for data
  - Note that some solutions ensure durability by writing data to disk

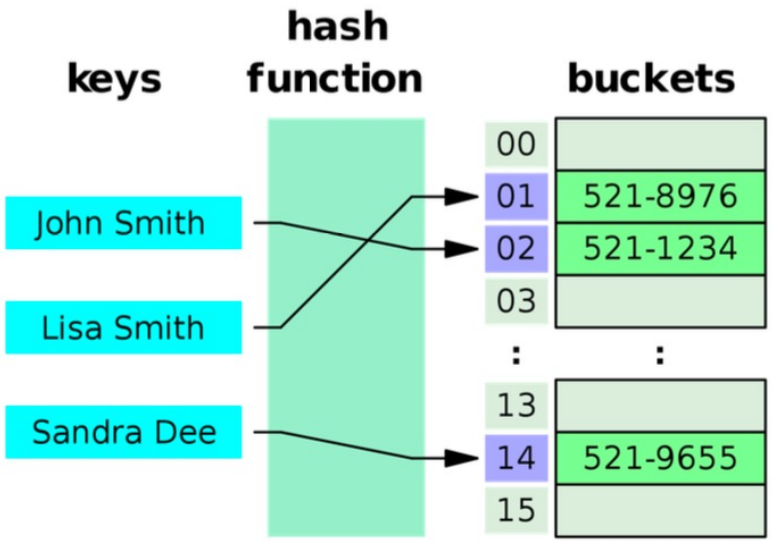
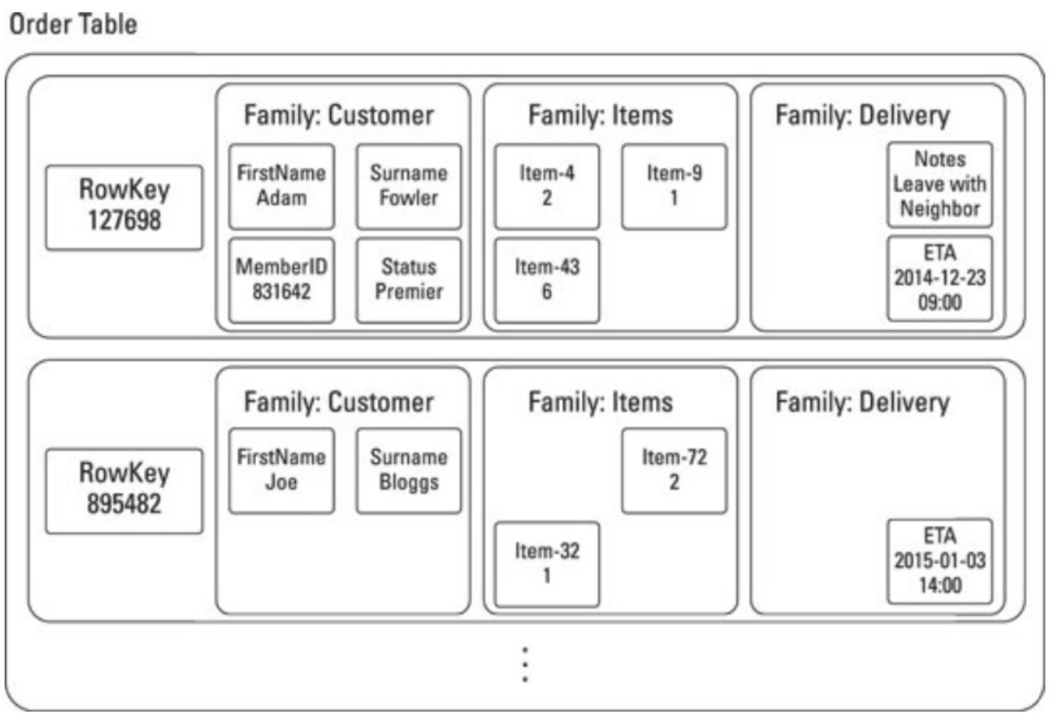


Image by J. Stolfi

Column Family Stores

- Data are organized in rows and columns (Tabular data store)
  - The data are arranged based on the rows
  - Column families are defined by users to improve performance
  - Group related columns together
- Only support single-object transactions
  - In this case, a row
- Examples:
  - BigTable/HBase
  - Cassandra
- Use case:
  - Data with some structure with the goal of achieving scalability and high throughput
  - Provide more complex lookup operations than KV stores

Column Family Stores



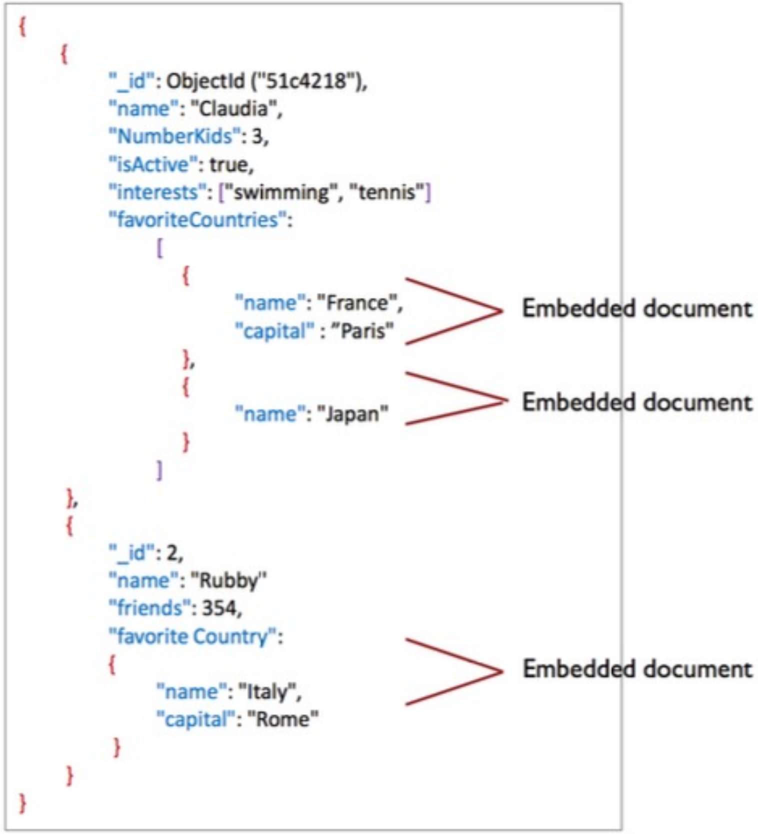
Note that not a row does not need to have an entry for all columns

Document Databases

- Data are organized in Key-Document pairs
  - A document is a nested structure with embedded metadata
  - No definition of a global schema
  - Popular formats: XML, JSON
- Only support single-object transactions
  - In this case, a document or a field inside a document
- Examples:
  - MongoDB
  - CouchDB
- Use case:
  - An alternative to relational databases for structured data
  - Offer a richer set of operations compared to KV stores:
    - Update, Find, etc.

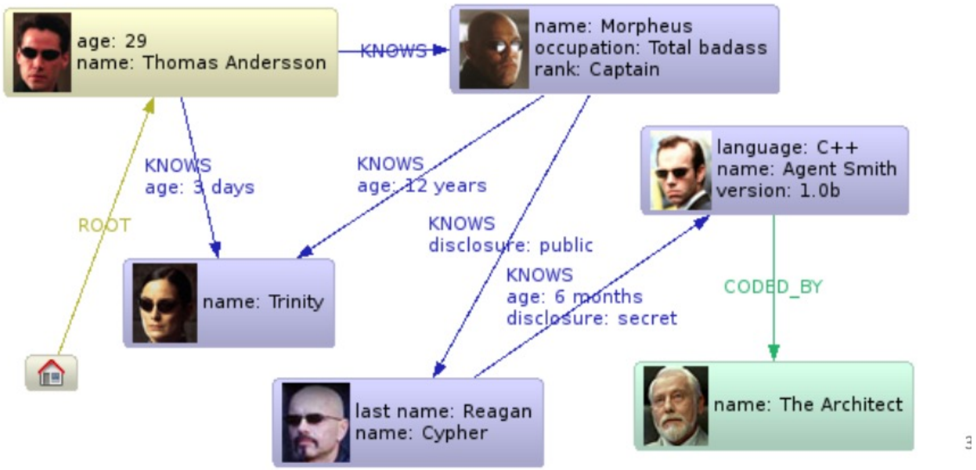
Document Databases

A document can have one or more documents inside.



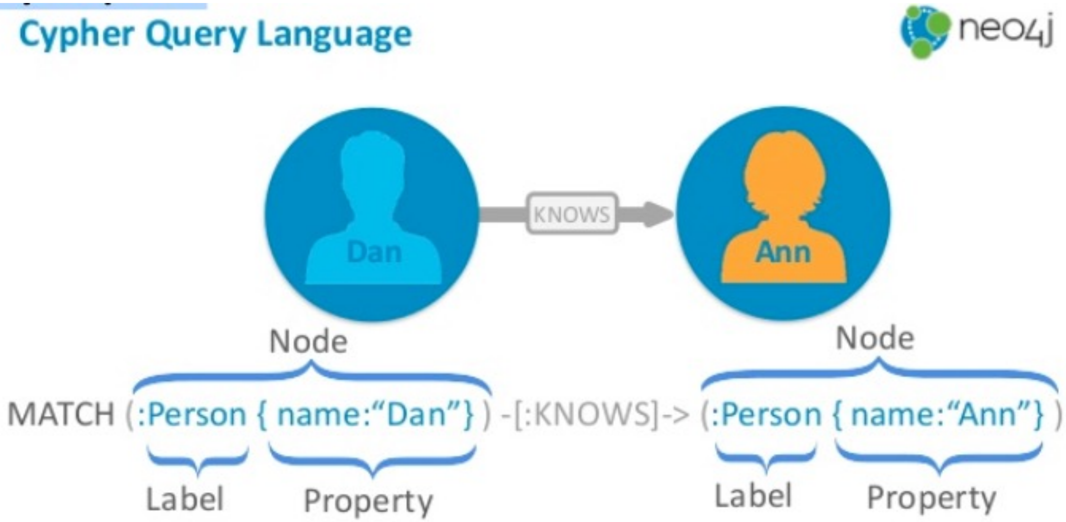
Graph Databases

- Represent data as graphs
  - Nodes / relationships with properties as K/V pairs



Graph DB : Neo4j

- Rich data format
  - Query language as paSern matching
  - Limited scalability : replicacation to scale reads, writes need to be done to every replica



Relationships in Data

- Many-to-one
  - Example: Many people went to the same university
- One-to-Many: An item may have several entries of the same kind
  - Example: One person may have had several positions during her career
  - Document DB allow storing such information easily and allow simple read operations
- Many-to-Many
  - Example: Several persons may have worked in the same company.
  - Graph DB

Many-to-One

Relational vs Document DB

Relational databases use a foreign key

- Consistency and low memory footprint (normalization)
- Easy updates and support for joins
- Difficult to scale

Document databases duplicate data

- Efficient read operations
- Easy to scale
- Higher memory footprint and updates are more difficult (risk of consistency issues)
  - Transactions on multiple objects could be very useful in this case
- Join operations have to be implement by the application

Google BigTable

- Column family data store
- Data storage system used by many Google services: Youtube,Google maps, Gmail, etc.
  - Paper published by Google in 2006 (F. Chang et al)
- Now available as a service on Google Cloud
- Many ideas reused in other NoSQL databases

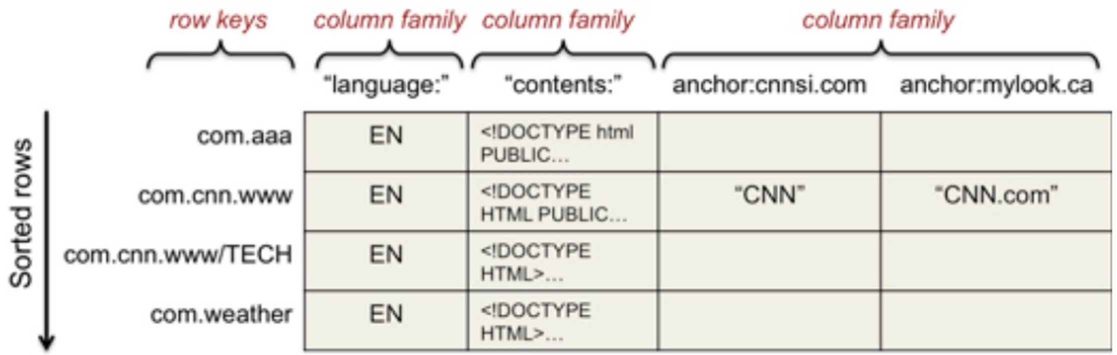
Motivations

- A system that can stores very large amount of data
  - TB or PB of data
  - A very large number of entries
  - Small entries (each entry is an array of bytes)
- A simple data model
  - Key-value pairs (A key identifies a row)
  - Multi-dimensional data
  - Sparse data
  - Data are associated with timestamps
- Works at very large scale
  - Thousands of machines
  - Millions of users

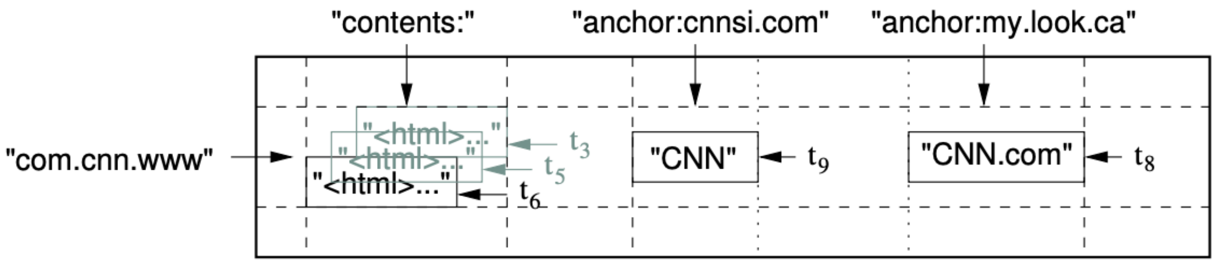
About the Data Model

- Rows are identified by keys (arbitrary strings)
  - Modifications on one row are atomic
  - Rows are maintained in lexicographic order
- Columns are grouped in columns families
  - Columns can be sparse
  - Clients can ask to retrieve a column family for one row
- Each cell can contain multiple versions indexed by a timestamp
  - Assigned by BigTable or by the client
  - Most recent versions are accessed first
  - GC politics: Keep last n versions or Keep all new-enough versions

About the Data Model



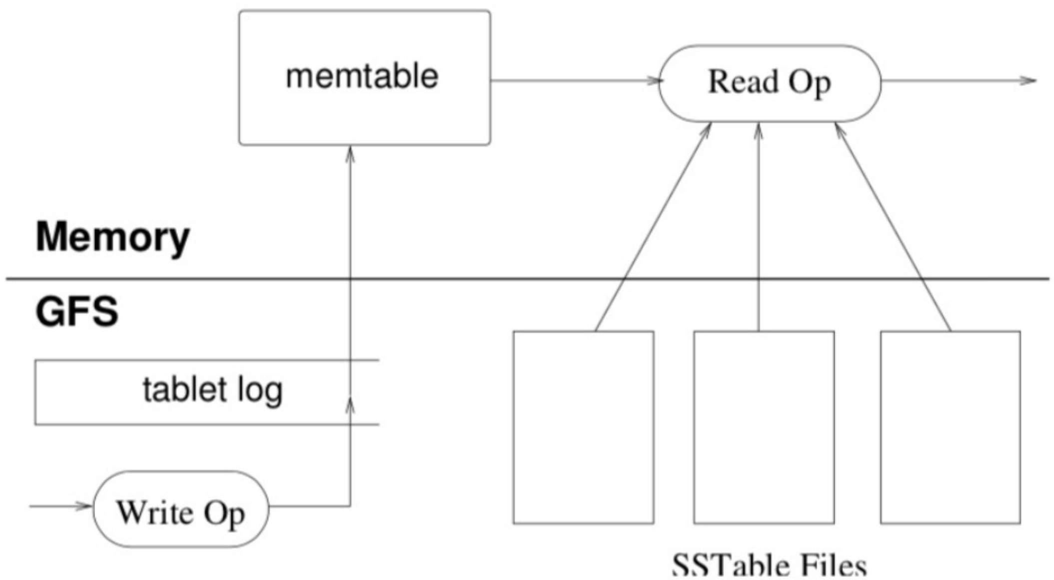
	"language:"	"contents:"	anchor:cnnsi.com	anchor:mylook.ca
com.aaa	EN	<!DOCTYPE html PUBLIC…		
com.cnn.www	EN	<!DOCTYPE HTML PUBLIC…	"CNN"	"CNN.com"
com.cnn.www/TECH	EN	<!DOCTYPE HTML>…		
com.weather	EN	<!DOCTYPE HTML>…		



Building Blocks of BigTable

- A master
  - Assign tablets to severs
  - With the help of a locking service
- Tablet servers
  - Store the tables (divided in tablets)
  - Process client requests
- Tablets
  - Stored as SSTables (Sorted string tables)
  - Stored in the Google File System for durability

Implementation of Tablets



Write Operation

- Data stored in memory (Memtable)
  - Any update is written to a commit log on GFS for durability
  - The log is shared between all hosted tablets
- Periodic writes to disk
  - When the Memtable becomes too big:
    - Copied as a new SSTable to GFS
    - Multiple SSTables are created if locality groups are defined (based on column families)
    - Reduces the memory footprint and reduces the amount of work to do during recovery
    - SSTables are immutable (no problem of concurrency control)

Read Operation

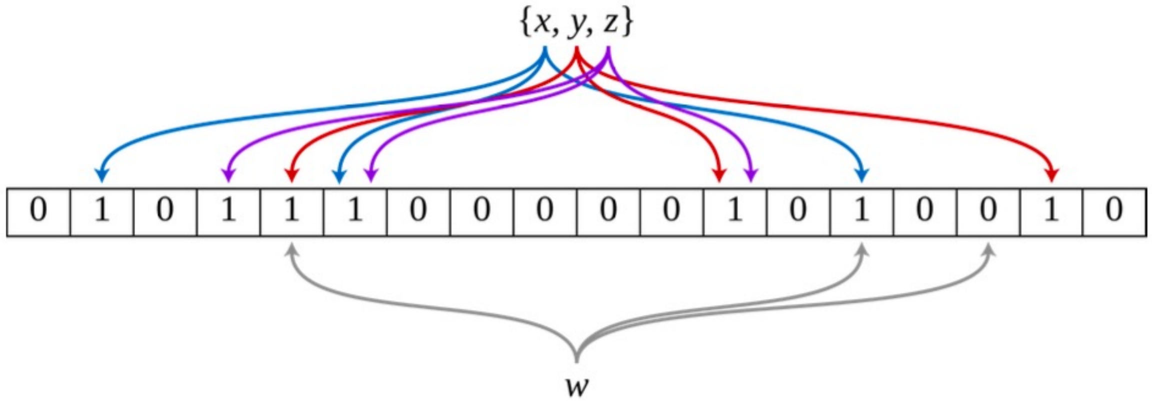
- The state of the tablet = the Memtable + all SSTables
  - A merged view needs to be created
  - The Memtable and the SSTables may contain delete operations
- Locality groups help improving the performance of read operations
- Major compaction
  - When the number of SSTables becomes too big, merge them into a single SSTable
  - Allow reclaiming resources for deleted data
  - Improve the performance of read operations

Bloom Filters and Reads

- During a read operation, potentially several SSTables need to be read
- How to avoid reading all SSTables when not needed?
  - Use of Bloom filters (1970 !)
  - Data structure that allows us to know if a SStable contains an entry for a given key-column pair
- Bloom filter
  - Implements a membership function (is X in the set?)
  - If the bloom filter answers no: it is guaranteed that X is not present
  - If the bloom filter answers yes: the element is in the set with a high probability
  - Good trade-off between accuracy and memory footprint

About bloom filters

- A vector of n bits and k hash functions
- On insert:
  - Compute the k hash values
  - Set the corresponding bits to 1 in the vector
- On lookup:
  - Compute the k hash values
  - Test whether all bits are set to 1

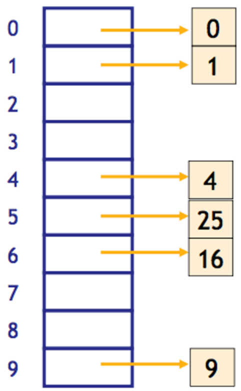


Apache Cassandra

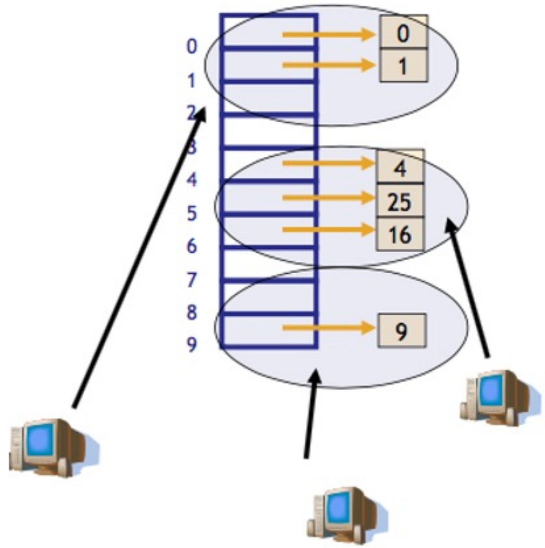
- Column family data store
- Paper published by Facebook in 2010 (A. Lakshman and P. Malik)
  - Used for implementing search functionalities
  - Released as open source
- Build on top of several ideas introduced by BigTable
  - Warning: Many changes in the design have been made since the first version of Cassandra

Partionning in Cassandra

Ideas from DHT = Distributed Hash Tables

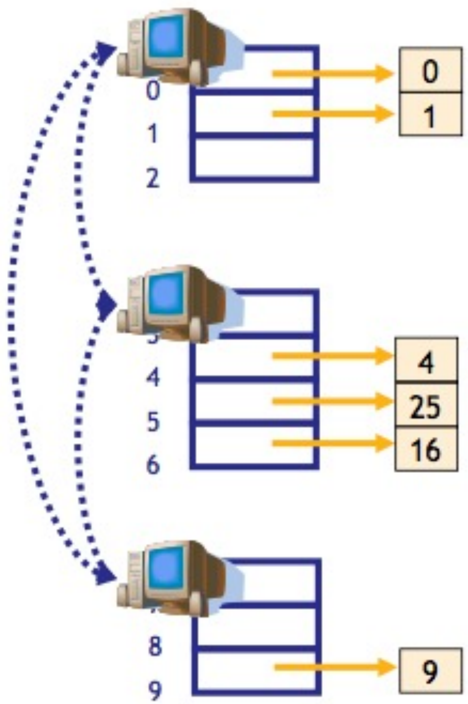


- Hash function: hash(x) = x mod 10
- Insert numbers 0, 1, 4, 9, 16, and 25
- Easy to find if a given key is present in the table



DHT: Principle

- In a DHT, each node is responsible for one or more hash buckets
  - As nodes join and leave, the responsibilities change
- Nodes communicate among themselves to find the responsible node
  - Scalable communications make DHTs efficient
- DHTs support all the normal hash table operations



Lectures of **Prof. Jussi Kangasharju,**
http://www.cs.helsinki.fi/u/jakangas/

Partionning in Cassandra

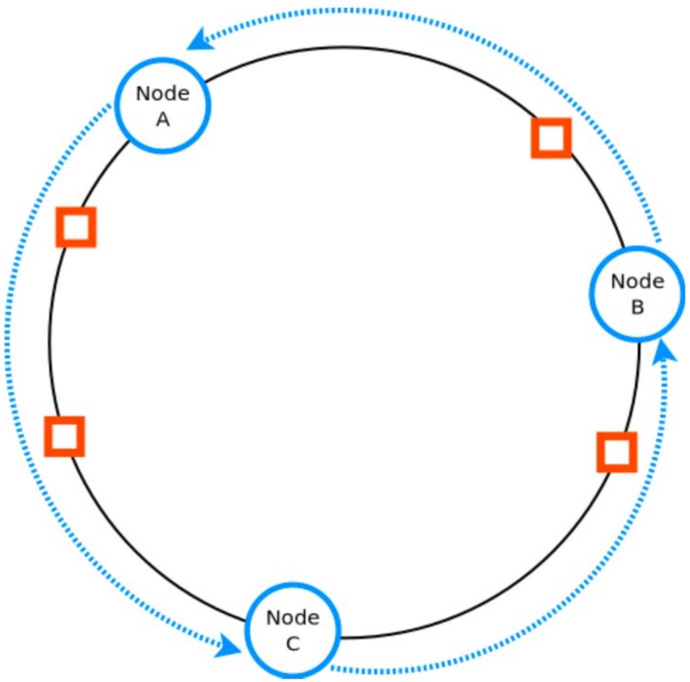
Partitioning based on a hashed name space

- Data items are identified by keys
- Data are assigned to nodes based on a hash of the key
- Tries to avoid hot spots

Namespace represented as a ring

- Allows increasing incrementally the size of the system
- Each node is assigned a random identifier
  - Defines the position of a node in the ring
- The nodes is responsible for all the keys in the range between its identifier and the one of the previous node.

Partionning in Cassandra



Limits : High risk of imbalance

- Some nodes may store more keys than others
- Nodes are not necessarily well distributed on the ring, especially true with a low number of nodes

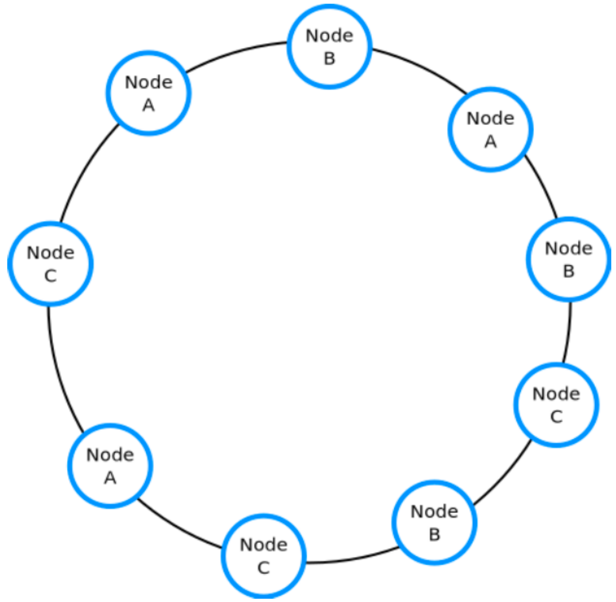
Issues when nodes join or leave the system

- When a node joins, it gets part of the load of its successor
- When a node leaves, all the corresponding keys are assigned to the successor

Partitioning and Virtual Nodes

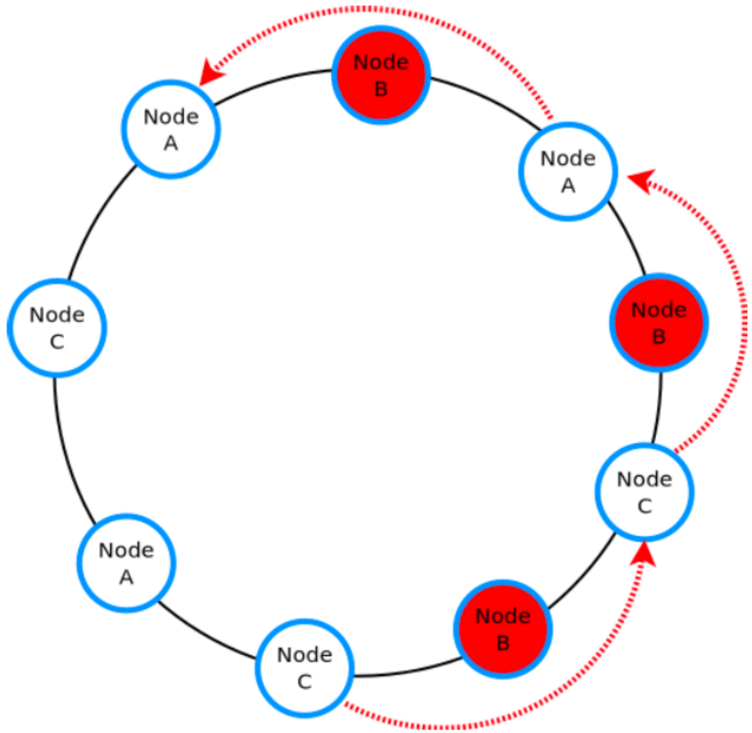
Concept of virtual nodes

Assign multiple random positions to each node



The key space is better distributed between the nodes

Partitioning and virtual nodes



If a node crashes, the load is redistributed between multiple nodes

Partitioning and Replication

Items are replicated for fault tolerance.

- Simple strategy
  - Place replicas on the next R nodes in the ring
- Topology-aware placement
  - Iterate through the nodes clockwise until finding a node meeting the required condition
  - For example a node in a different rack

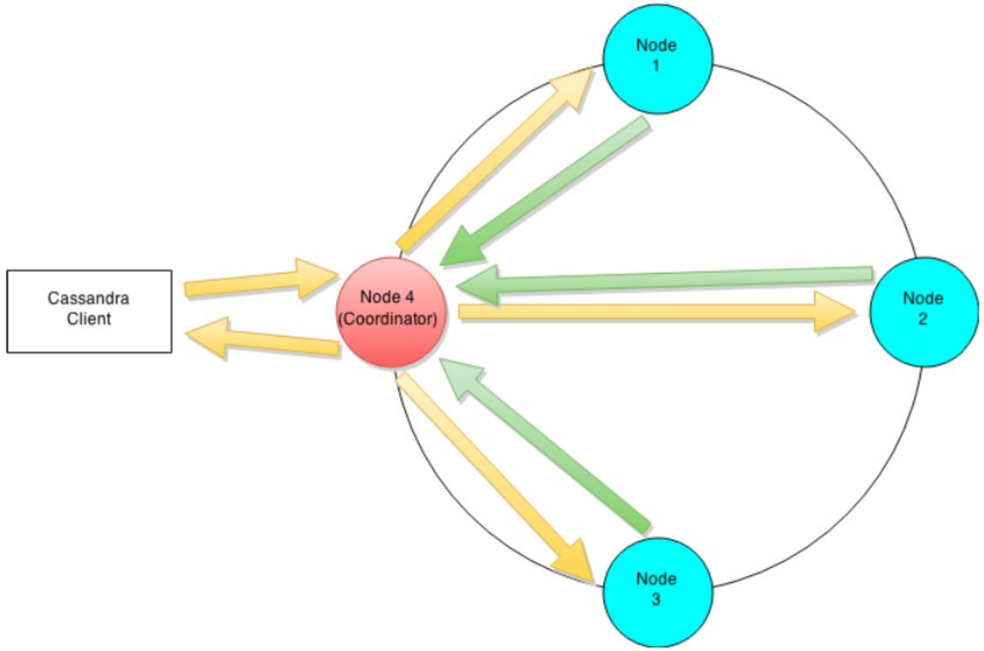
Replication in Cassandra

Replication is based on **quorums**

- A read/write request might be sent to a subset of the replicas
  - To tolerate f faults, it has to be sent to f + 1 replicas
- Consistency
  - The user can choose the level of consistency
  - Trade-off between consistency and performance (and availability)
- Eventual consistency
  - If an item is modified, readers will eventually see the new value

A Read/Write request

Figure from `https://dzone.com/articles/introduction-apache-cassandras`



- A client can contact any node in the system
- The coordinator contacts all replicas
- The coordinator waits for a specified number of responses before sending an answer to the client

Consistency Levels

ONE (default level)

- The coordinator waits for one ack on write before answering the client
- The coordinator waits for one answer on read before answering the client
- Lowest level of consistency
  - Reads might return stale values
  - We will still read the most recent values in most cases

QUORUM

- The coordinator waits for a majority of acks on write before answering the client
- The coordinator waits for a majority of answers on read before answering the client
- High level of consistency
  - At least one replica will return the most recent value

References

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