STORAGE: NoSQL DBMSs

Not only SQL

Introduction

What is NoSQL

Where does it come from, and why

Strengths of RDBMSs

ACID properties

- Provides guarantees in terms of consistency and concurrent accesses

Data integration and normalization of schemas

- Several application can share and reuse the same information

Standard model and query language

- The relational model and SQL are very well-known standards
- The same theoretical background is shared by the different implementations

Robustness

- Have been used for over 40 years

Weaknesses of RDBMS

Impedance mismatch

- Data are stored according to the relational model, but applications to modify them typically rely on the object-oriented model
- Many solutions, no standard
  - E.g.: Object Oriented DBMS (OODBMS), Object-Relational DBMS (ORDBMS), Object-Relational Mapping (ORM) frameworks

Painful scaling-out

- Not suited for a cluster architecture
- Distributing an RDBMS is neither easy nor cheap (e.g., Oracle RAC)

Consistency vs latency

- Consistency is a must – even at the expense of latency
- Today's applications require high reading/writing throughput with low latency

Schema rigidity

- Schema evolution is often expensive

What NoSQL means

The term has been first used in '98 by Carlo Strozzi

- It referred to an open-source RDBMS that used a query language different from SQL

In 2009 it was adopted by a meetup in San Francisco

- Goal: discuss open-source projects related to the newest databases from Google and Amazon
- Participants: Voldemort, Cassandra, Dynomite, HBase, Hypertable, CouchDB, MongoDB

Today, NoSQL indicates DBMSs adopting a different data model from the relational one

- NoSQL = Not Only SQL
- According to Strozzi himself, NoREL would have been a more proper noun

The first NoSQL systems

LiveJournal, 2003

- Goal: reduce the number of queries on a DB from a pool of web servers
- Solution: Memcached, designed to keep queries and results in RAM

Google, 2005

- Goal: handle Big Data (web indexing, Maps, Gmail, etc.)
- Solution: BigTable, designed for scalability and high performance on Petabytes of data

Amazon, 2007

- Goal: ensure availability and reliability of its e-commerce service 24/7
- Solution: DynamoDB, characterized by strong simplicity for data storage and manipulation

NoSQL common features

Not just rows and tables

- Several data model adopted to store and manipulate data

Freedom from joins

- Joins are either not supported or discouraged

Freedom from rigid schemas

- Data can be stored or queried without pre-defining a schema (*schemaless* or *soft-schema*)

Distributed, shared-nothing architecture

- Trivial scalability in a distributed environment with no performance decay
- Each workstation uses its own disks and RAM

SQL is dead, long live SQL!

- Some systems do adopt SQL (or a SQL-like language)

NoSQL in the Big Data world

NoSQL systems are mainly used for operational workloads (OLTP)

- Optimized for high read and write throughput on small amounts of data

Big Data technologies are mainly used for analytical workloads (OLAP)

- Optimized for high read throughput on large amounts of data

Can NoSQL systems be used for OLAP?

- Possibly, but through Big Data analytical tools (e.g., Spark)

Data models

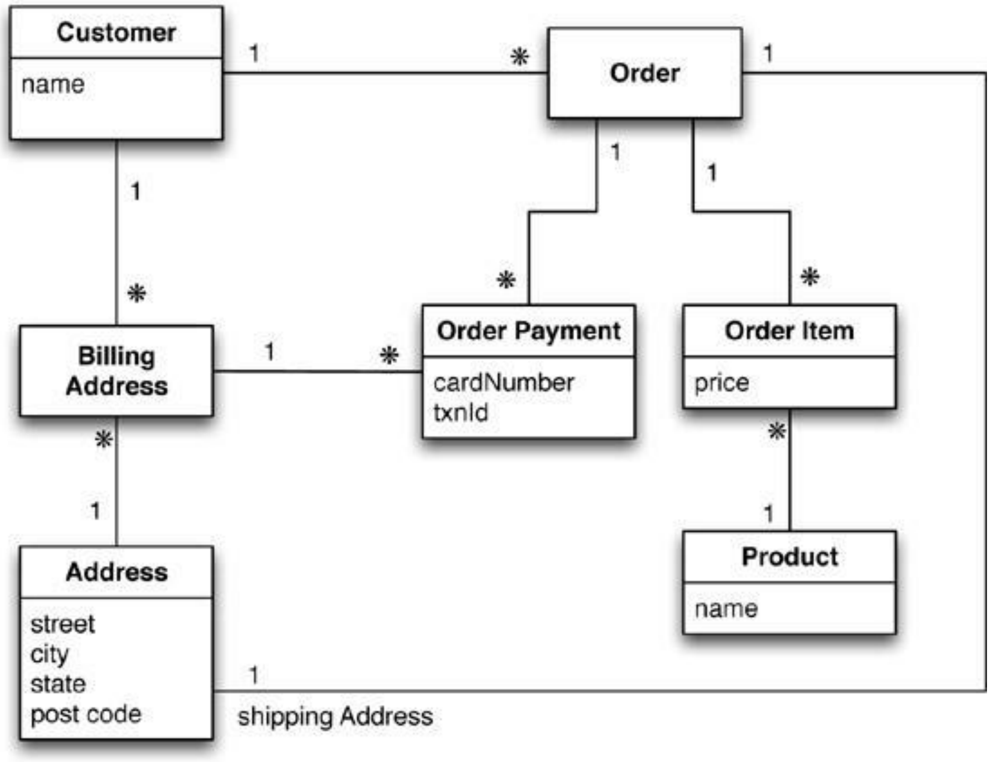
NoSQL: several data models

One of the key challenges is to understand which one fits best with the required application

Model	Description	Use cases
Key-value	Associates any kind of value to a string	Dictionary, lookup table, cache, file and images storage
Document	Stores hierarchical data in a tree-like structure	Documents, anything that fits into a hierarchical structure
Wide-column	Stores sparse matrixes where a cell is identified by the row and column keys	Crawling, high-variability systems, sparse matrixes
Graph	Stores vertices and arches	Social network queries, inference, pattern matching

Running example

Typical use case: customers, orders and products



Relational: data model

Based on tables and rows

Columns and their types are defined when a table is created.

Column names must be distinct.

Rows must contain data for each column.

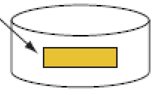
Individual cell values can be updated.

ID	ITEM_ID	PRICE	COLOR	SIZE
1	12744	14.99	green	large
2	56289	15.99	yellow	extra large
3	43589	13.99	blue	small
4	35734	24.45	red	medium

New rows are inserted at the end of a table.

insert

All data in a single row is grouped together on disk.



Columns may reference IDs of other tables.

Data modeling example: relational model

Customer	
Id	Name
1	Martin

Orders		
Id	CustomerId	ShippingAddressId
99	1	77

Product	
Id	Name
27	NoSQL Distilled

BillingAddress		
Id	CustomerId	AddressId
55	1	77

OrderItem			
Id	OrderId	ProductId	Price
100	99	27	32.45

Address	
Id	City
77	Chicago

OrderPayment				
Id	OrderId	CardNumber	BillingAddressId	txnId
33	99	1000-1000	55	abelif879rft

Graph: data model

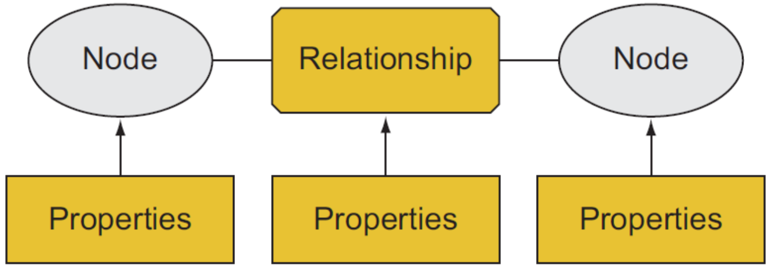
Each DB contains one or more graphs

Each graph contains vertices and arcs

- Vertices: usually represent real-world entities
  - E.g.: people, organizations, web pages, workstations, cells, books, etc.
- Arcs: represent directed relationships between the vertices
  - E.g.: friendship, work relationship, hyperlink, ethernet links, copyright, etc.
- Vertices and arcs are described by properties
- Arcs are stored as physical pointers

Most known specializations:

- Reticular data model
  - Parent-child or owner-member relationships
- Triplestore
  - Subject-predicate-object relationships (e.g., RDF)



Graph: querying

Graph databases usually model relationships-rich scenarios

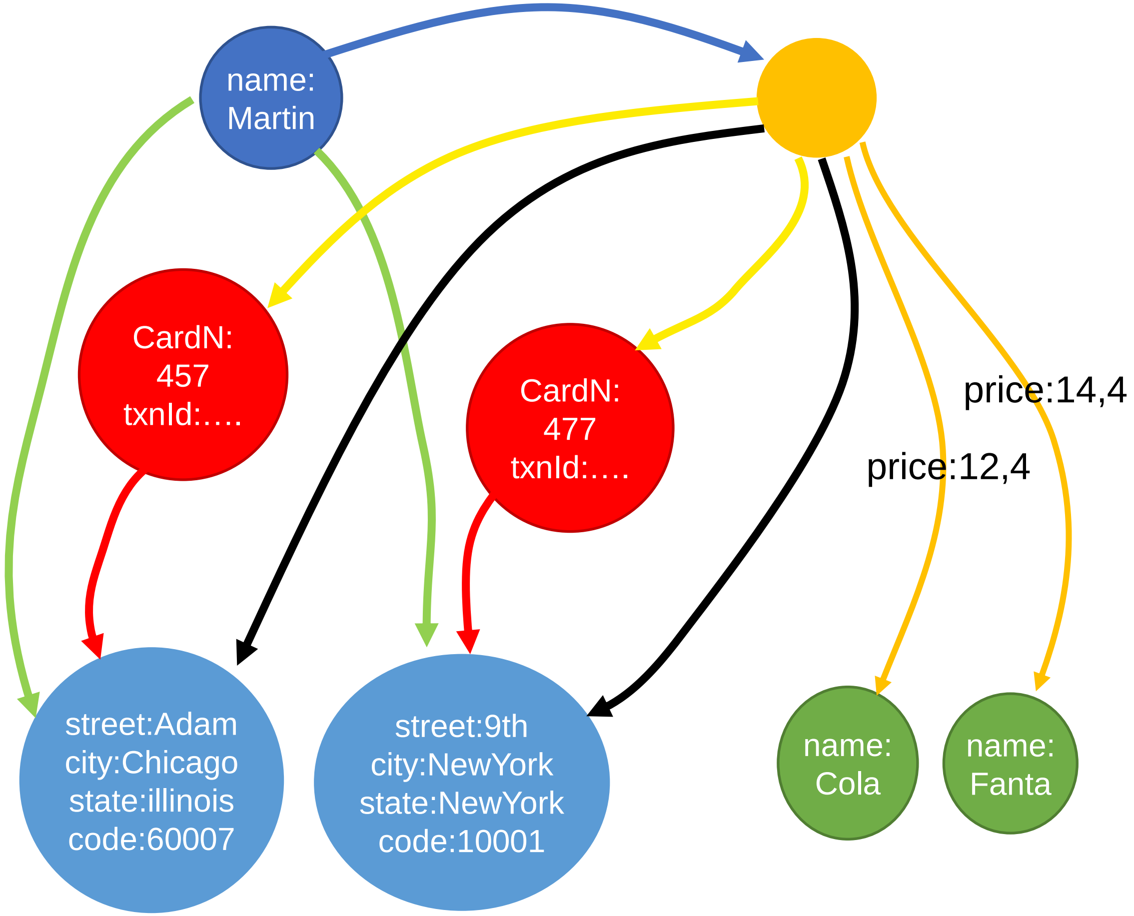
The query language simplifies the navigation of these relationships

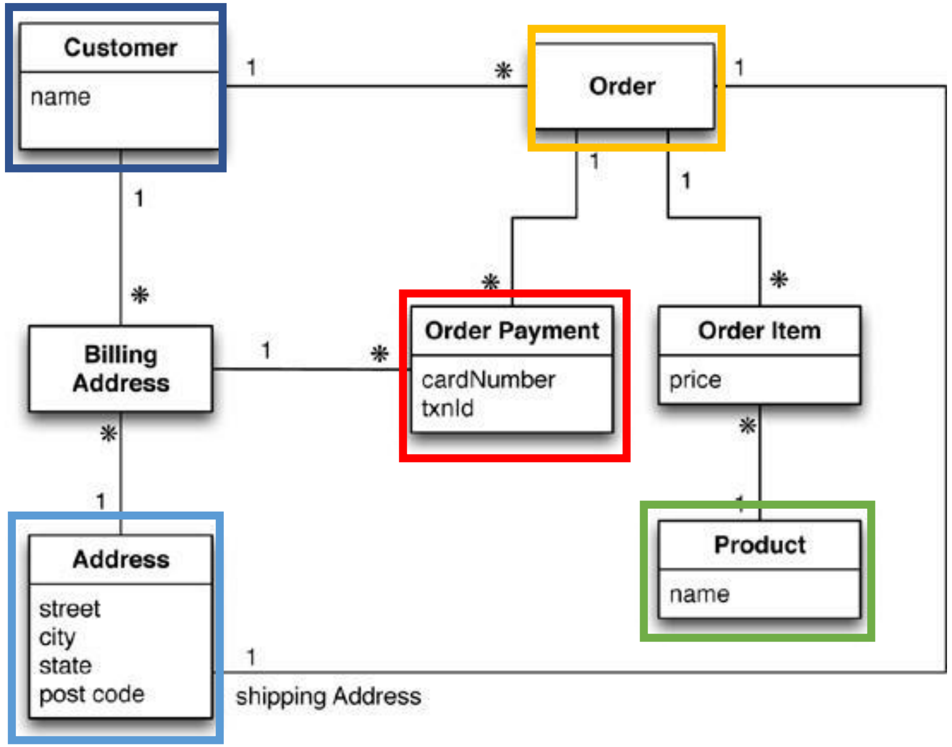
- Support for transactions
- Support for indexes, selections and projections
- **Query language based on detecting patterns**

Query	Pattern
Find friends of friends	(user)-[:KNOWS]-(friend)-[:KNOWS]-(foaf)
Find shortest path from A to B	shortestPath((userA)-[:KNOWS*..5]-(userB))
What has been bought by those who bought my same products?	(user)-[:PURCHASED]->(product)<-[:PURCHASED]-()-[:PURCHASED]->(otherProduct)

Data modeling example: graph model

IDs are implicitly handled; different edge colors imply different edge types





Graph vs Aggregate modeling

The graph data model is intrinsically different from the others

- Focused on the relationships rather than on the entities per-se
- **Limited scalability**: it is often impossible to shard a graph on several machines without "cutting" several arcs (i.e. having several cross-machine links)
  - Batch cross-machine queries: don’t follow relationships one by one, but "group them" to make less requests
  - Limit the depth of cross-machine node searches
- Data-driven modeling

Key-value, document and wide-column are called aggregate-oriented

- Aggregate = key-value pair, document, row (respectively)
- The aggregate is the atomic block (no guarantees for multi-aggregate operations)

Based on the concept of encapsulation

- Avoid joins as much as possible → achieve **high scalability**
  - Con: data denormalization → **potential inconsistencies in the data**
- Query-driven modeling

Document: data model

Each DB contains one or more collections (corresponding to tables)

Each collection contains a list of documents (usually JSON)

- Documents are hierarchically structured

Each document contains a set of fields

- The ID is mandatory

Each field corresponds to a key-value pair

- Key: unique string in the document
- Value: either simple (string, number, boolean) or complex (object, array, BLOB)
  - A complex field can contain other field

```
{
    "_id": 1234,
    "name": "Enrico",
    "address": {
        "city": "Cesena",
        "postalCode": 47522
    },
    "contacts": [ {
        "type": "office",
        "contact": "0547-338835"
    }, {
        "type": "skype",
        "contact": "egallinucci"
    } ]
}
```

Document: querying

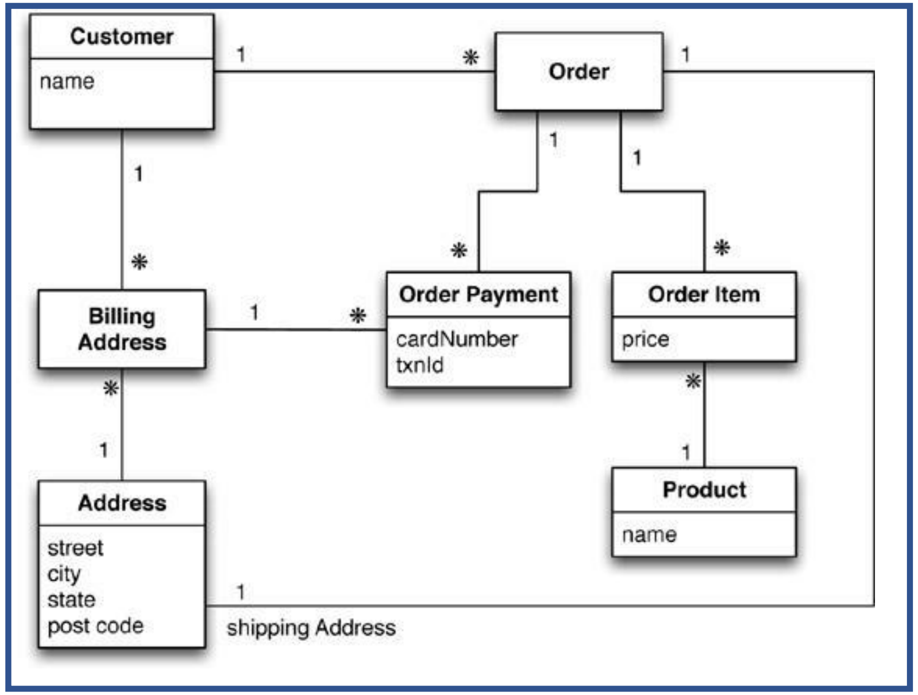
The query language is quite expressive

- Can create indexes on fields
- Can filter on the fields
- Can return more documents with one query
- Can select which fields to project
- Can update specific fields

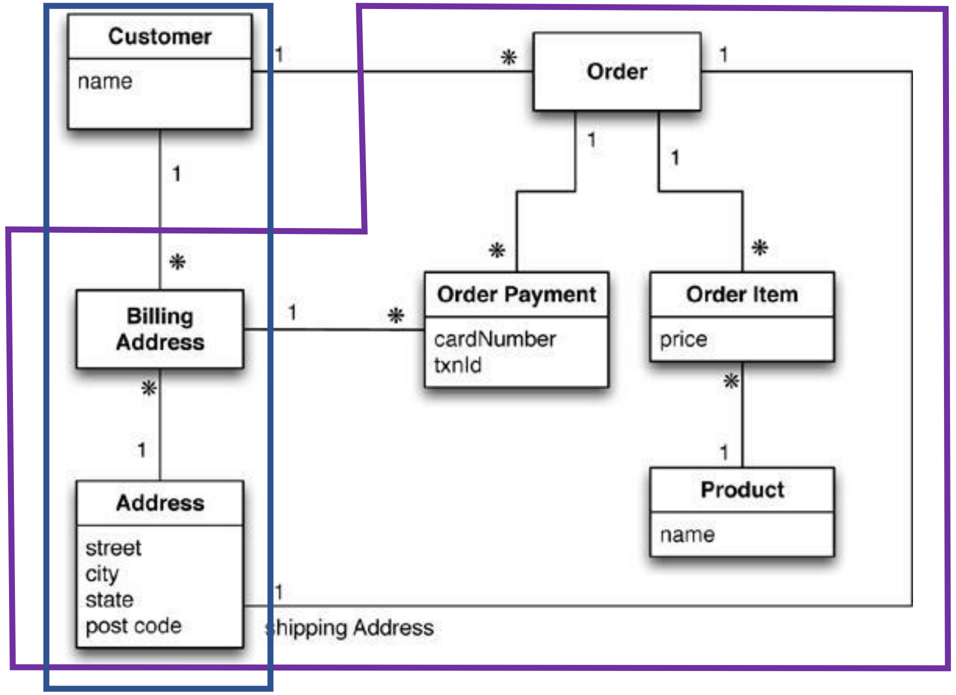
Different implementations, different functionalities

- Some enable (possibly materialized) views
- Some enable MapReduce queries
- Some provide connectors to Big Data tools (e.g., Spark, Hive)
- Some provide *full-text search* capabilities

Data modeling example: aggregate model (2)



Data modeling example: aggregate model (1)



Data modeling example: document model (1)

Customer collection

```
{
  "_id": 1,
  "name": "Martin",
  "adrs": [
    {"street":"Adam", "city":"Chicago", "state":"illinois", "code":60007},
    {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}
  ],
  "orders": [ {
    "orderpayments":[
      {"card":477, "billadrs": {"street":"Adam", "city":"Chicago", "state":"illinois", "code":60007}},
      {"card":457, "billadrs": {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}}
    ],
    "products":[
      {"id":1, "name":"Cola", "price":12.4},
      {"id":2, "name":"Fanta", "price":14.4}
    ],
    "shipAdrs": {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}
  }]
}
```

Product collection

```
{
  "_id":1,
  "name":"Cola",
  "price":12.4
},
{
  "_id":2,
  "name":"Fanta",
  "price":14.4
}
```

Data modeling example: document model (2)

```
{
  "_id": 1,
  "name": "Martin",
  "adrs": [
    {"street":"Adam", "city":"Chicago", "state":"illinois", "code":60007},
    {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}
  ]
}
```

Customer collection

```
{
  "_id":1,
  "name":"Cola",
  "price":12.4
},
{
  "_id":2,
  "name":"Fanta",
  "price":14.4
}
```

Product collection

```
{
  "_id": 1,
  "customer":1,
  "orderpayments":[
    {"card":477, "billadrs":{"street":"Adam", "city":"Chicago", "state":"illinois", "code":60007}},
    {"card":457, "billadrs":{"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}}
  ],
  "products": [
    {"id":1, "name":"Cola", "price":12.4},
    {"id":2, "name":"Fanta", "price":14.4}
  ],
  "shipAdrs": {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}
}
```

Order collection

Key-value: data model

Each DB contains one or more collections (corresponding to tables)

Each collection contains a list of key-value pairs

- Key: a unique string
  - E.g.: ids, hashes, paths, queries, REST calls
- Value: a BLOB (binary large object)
  - E.g.: text, documents, web pages, multimedia files

Looks like a simple dictionary

- The collection is indexed by key
- The value may contain several information
  - Definitions, synonyms and antonyms, images, etc.

Key	Value
image-12345.jpg	Binary image file
http://www.example.com/my-web-page.html	HTML of a web page
N:/folder/subfolder/myfile.pdf	PDF document
9e107d9d372bb6826bd81d3542a419d6	The quick brown fox jumps over the lazy dog
view-person?person-id=12345&format=xml	<Person><id>12345</id .</Person>
SELECT PERSON FROM PEOPLE WHERE PID="12345"	<Person><id>12345</id .</Person>

Key-value: querying

Three simple kinds of query:

- put($key as xs:string, $value as item())
  - Adds a key-value pair to the collection
  - If the key already exists, the value is replaced
- get($key as xs:string) as item()
  - Returns the value corresponding to the key (if it exists)
- delete($key as xs:string)
  - Deletes the key-value pair

Key	Value
user:1234:name	Enrico
user:1234:city	Cesena
post:9876:written-by	user:1234
post:9876:title	NoSQL Databases
comment:5050:reply-to	post:9876

The value is a *black box*: it cannot be queried!

- No "where" clauses
- No indexes on the values
- Schema information is often indicated in the key

Data modeling example: key-value model

Customer collection

key	value
cust-1:name	Martin
cust-1:adrs	[{"street":"Adam", "city":"Chicago", "state":"Illinois", "code":60007}, {"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}]

cust-1:ord-99	{
	"orderpayments": [
	{"card":477, "billadrs":
	{"street":"Adam", "city":"Chicago", "state":"illinois", "code":60007} },
	{"card":457, "billadrs":
	{"street":"9th", "city":"NewYork", "state":"NewYork", "code":10001}
	],
	"products": [
	{"id":1, "name":"Cola", "price":12.4},
	{"id":2, "name":"Fanta", "price":14.4}
	],
	"shipAdrs": {"street":"9th", "city":"NewYork", "state":"NewYork", code":10001}
	}

Product collection

key	value
p-1:name	Cola
p-2:name	Fanta

Wide column: data model

Each DB contains one or more column families (corresponding to tables)

Each column family contains a list of row in the form of a key-value pair

- Key: unique string in the column family
- Value: a set of columns

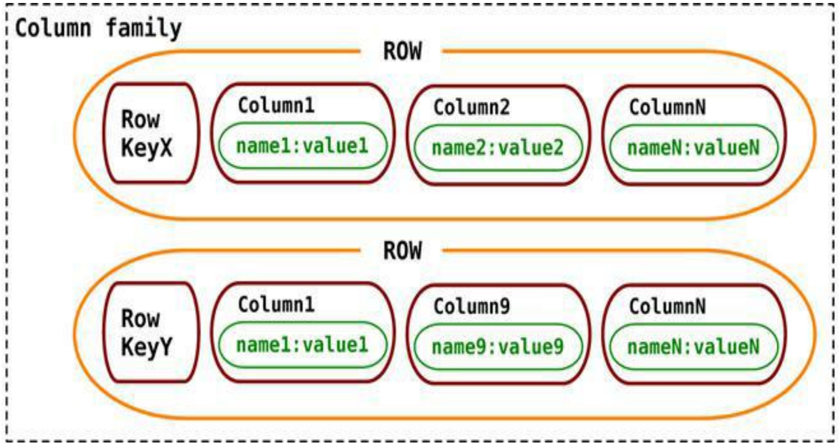
Each column is a key-value pair itself

- Key: unique string in the row
- Value: simple or complex (*supercolumn*)

Essentially a 2-dimensional key-value store

Rows specify only the columns
for which a value exists

- Particularly suited for sparse matrixes and many-to-many relationships



Wide column: querying

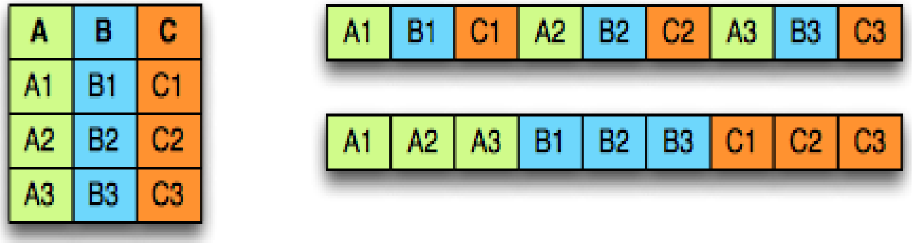
The query language expressiveness is in between key-value and document data models

- Column indexes are discouraged
- Can filter on column values (not always)
- Can return more rows with one query
- Can select which columns to project
- Can update specific columns (not always)

Given the similarity with the relational model, a SQL-like language is often used

Wide column: ≠ columnar

Do not mistake the wide column data model with the columnar storage used for OLAP applications



Row-oriented

Column-oriented

Row-oriented

- Pro: inserting a record is easy
- Con: several unnecessary data may be accessed when reading a record

Column-oriented

- Pro: only the required values are accessed
- Con: writing a record requires multiple accesses

Data modeling example: wide-column model

Ord	CustName	Pepsi	Cola	Fanta	…
1	Martin		12.4	14.4	
2	…	…			…

Order details column family

<table>
<tr><th>Ord</th><th>OrderPayments</th></tr>
<tr><td>1</td><td>
<table>
<tr><th>Card</th><th>Steet</th><th>City</th><th>State</th><th>Code</th></tr>
<tr><td>477</td><td>9th</td><td>NewYork</td><td>NewYork</td><td>10001</td></tr>
<tr><td>457</td><td>Adam</td><td>Chicago</td><td>Illinois</td><td>60007</td></tr>
</table>
</td></tr>
<tr><td>2</td><td>…</td></tr>
</table>

Order payments column family

Aggregate modeling strategy

The *aggregate* term comes from Domain-Driven Design

- An aggregate is a group of tightly coupled objects to be handled as a block
- Aggregates are the basic unit for data manipulation and consistency management

Advantages

- Can be distributed trivially
  - Data the should be used together (e.g., orders and details) are stored together
- Facilitate the developer's job
  - By surpassing the impedance mismatch problem

Disadvantages

- **No design strategy exists for aggregates**
  - It only depends on how they are meant to be used
- Can optimize only a limited set of queries
- Data denormalization → possible inconsistencies

RDBMSs are agnostic from this point of view

Sharding data

A look behind the curtain

Sharding data

One of the strengths of NoSQL systems is their scale-out capability

- *Aggregate data modeling*: well suited for being distributed within a cluster
- NoSQL systems can be used in a single server environment too
  - Graph databases do not scale as well as the others

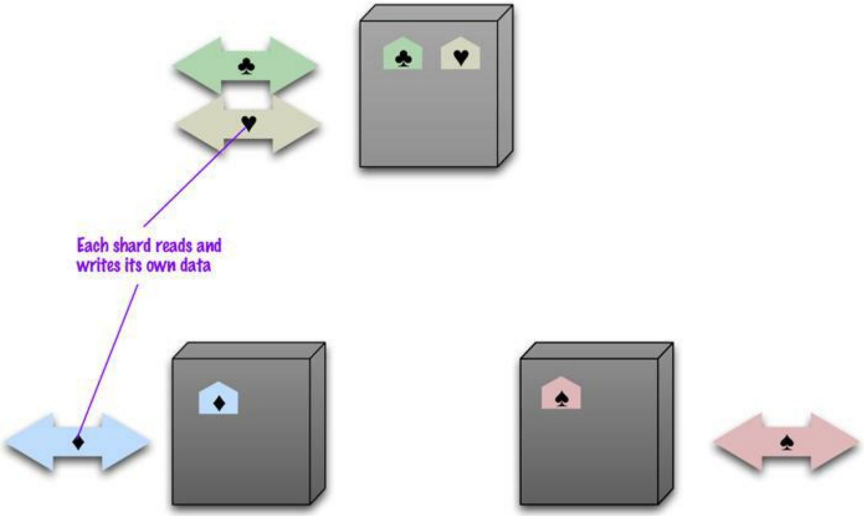
Two aspects must be considered when deploying on a cluster

- **Sharding**: distributing the data across different nodes
- **Replication**: creating copies of the data on several nodes

Sharding

Sharding: subdividing the data in *shards* that are stored in different machines

- Intrinsic in a distributed DB
- Improves the efficiency of the system
    - Read/write operations are distributed



A good *sharding strategy* is **fundamental** to optimize performances

- Usually based on one or more fields composing the sharding key

Sharding strategy

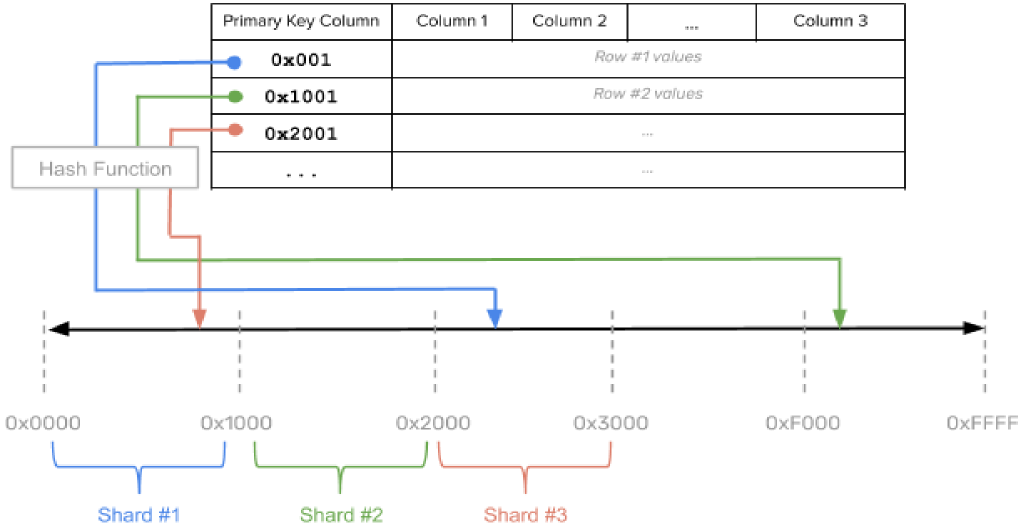
Thumbs-up rules for a sharding strategy:

1. Data-locality: stores the data close to those that need to access them
   - E.g., store orders of Italian customers in the European data center
2. Keep a balanced distribution
   - Each node should have the same percentage of data (more or less)
3. Keep together the data that must be accessed together
   - E.g., store each client’s orders in the same node

Sharding strategy

Hash strategy: a hash function is used to allocate data to partitions

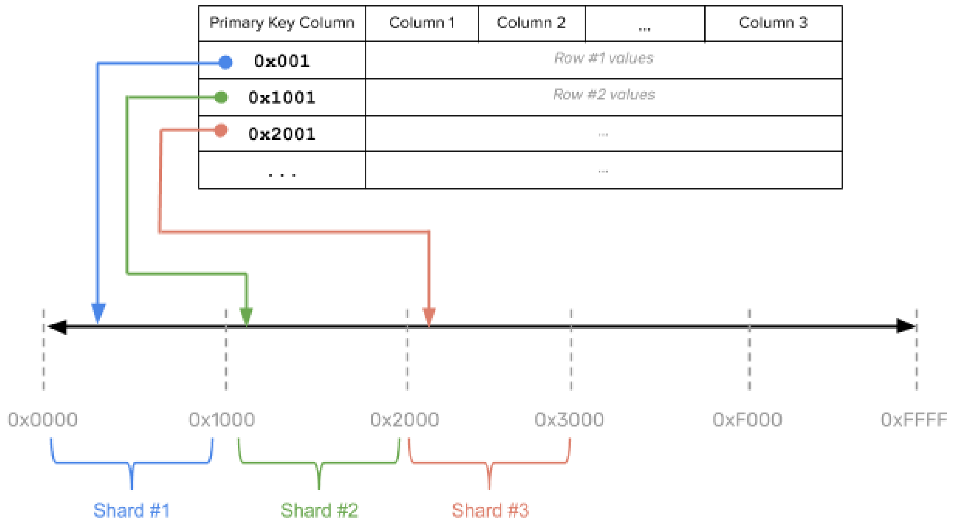
- Adopted by DynamoDB and Cassandra
- Pro: ensures even data distribution across nodes → massive scalability
- Pro: new nodes can be added without heavy data redistribution
- Con: range queries become inefficient



Sharding strategy

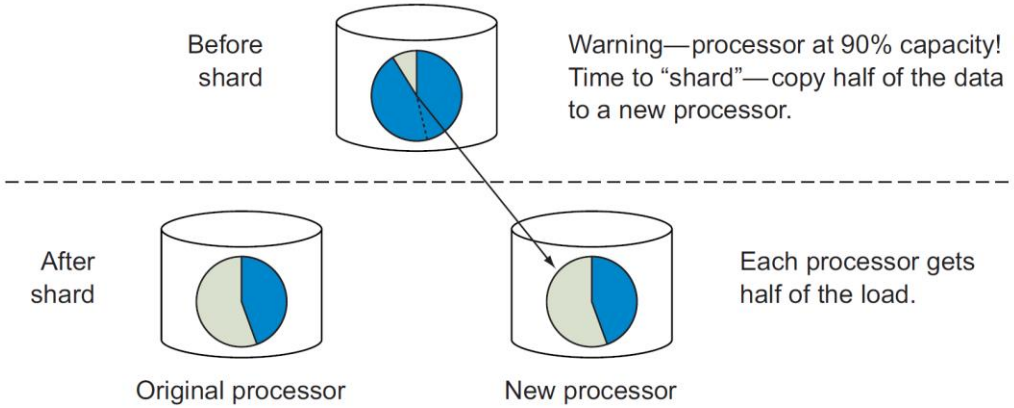
Range strategy: each partition contains a range of sorted data

- Adopted by HBase
- Pro: efficiently run range queries that work on the sharding key values
- Con: global ordering often generates hot spots → risk of bottlenecks
- Con: ranges are defined a priori and this can determine heavy data redistribution



Sharding strategy

Auto-sharding: the database distributes the data according to the workload



Beware: redefining (or choosing later) the sharding strategy can be quite expensive

Replication

Replication: the data is copied on several nodes

- Improves the robustness of the system
  - In case of node failure, replicas prevent data loss
- Improves the efficiency of the system
  - More users read the same data from different copies, in parallel
  - Higher chance of enforcing data-locality

How to distribute the replicas?

- Random (possibly *topology-aware*) distribution of each record
  - Similarly to HDFS blocks
- Replication of entire instances

Main issue: each update must be pushed to every replica

- Two techniques to handle updates: master-slave, peer to peer

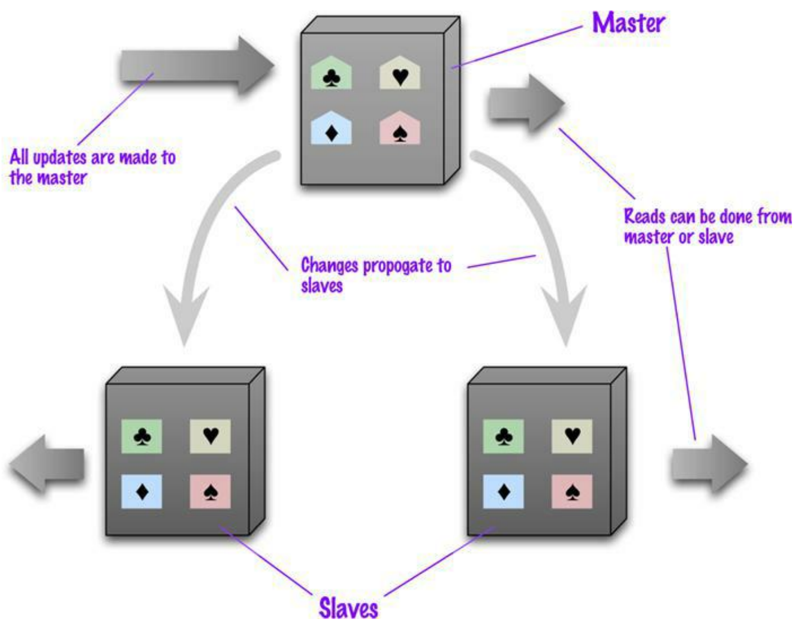
Master-Slave Replication

Master

- It's the manager of the data
- Handles each and every write operation
- Can be chosen or drawn

Slaves

- Enable read operations
- In sync with the master
- Can become master
  if the latter fails



Master-Slave Replication

Pros

- Easily handles many read requests
  - Slaves do not need the master to perform reads
- Useful when the workload mainly consists of reads
- Useful to avoid write conflicts

Cons

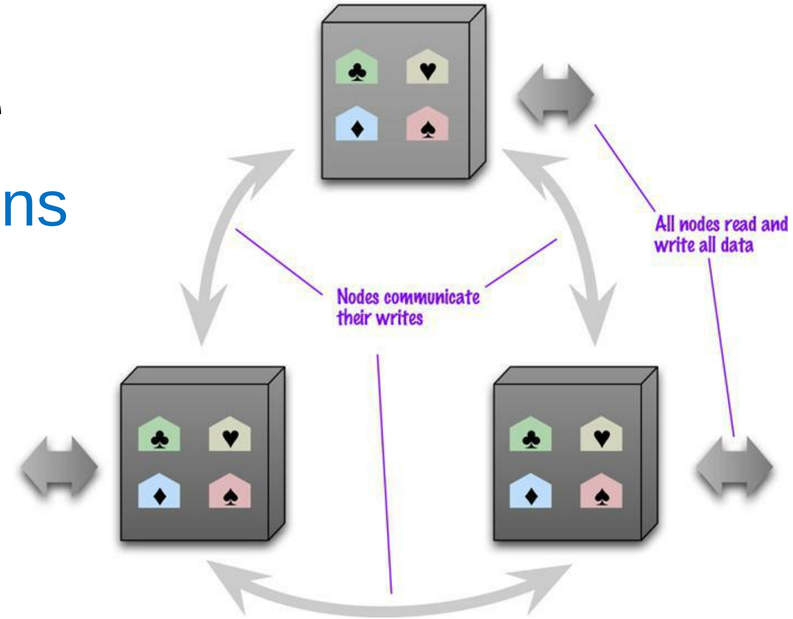
- The master is a bottleneck
  - **Only the master can handle writes**
  - In case of failure, a new master must be drawn
- Delay in write propagation can be a source of inconsistency
  - Two users may read different values at the same time
  - Read inconsistency can be problematic, but are relatively limited in time
- Not ideal when the workload mainly consists of writes

Peer-to-Peer Replication

Each node has the same importance

Each node can handle write operations

The loss of a node does not compromise reads nor writes



Peer-to-Peer Replication

Pro

- The failure of a node does not interrupt read nor write requests
- Write performances easily scale by adding new nodes

Cons

- Conflicts!
- Delay in write propagation can be a source of inconsistency
  - Same as with master-slave replication
- Two users may update the same value from different replicas
  - Write inconsistencies are way worse

Handling conflicts

Read conflicts

- Tolerate conflicts: the *inconsistency window* is usually limited
- *Read-your-writes*: read consistency is guaranteed for the data written by the same user
  - Applies only to reads that immediately follow a write operation
  - One way is to associate a user to a node (risk: unbalanced workloads)
  - Typically, versioning fields are used to ensure that the up-to-date version is read

Write conflicts (P2P model)

- Last write wins: in case of conflict, the latest update overrides the others
- Conflict prevention: enforce writes on the most recent version by verifying that the value hasn’t changed since the last read
- Conflict detection: preserve history, merge results, and let the user decide

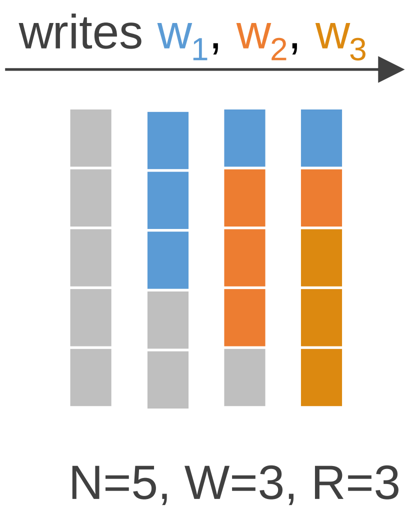
The quorum mechanism

The quorum mechanism ensures consistent IO under replication

- Based on contacting a majority of the nodes responsible for certain data
- The quorum is the minimum number of nodes that a distributed operation has to obtain in order to be allowed to perform an operation on a replicated data item

Each data item has N replicas

- Writing quorum: $W > N/2$
  - The write operation is allowed only if W replicas can be updated
  - Ensures that two write operations cannot occur concurrently
- Reading quorum: $R > N-W$
  - The read operation is allowed only if R replicas can be read
  - Ensures that (at least) one copy with the up-to-date value is read



Managing consistency

A look behind the curtain

RDBMS vs NoSQL: different philosophies

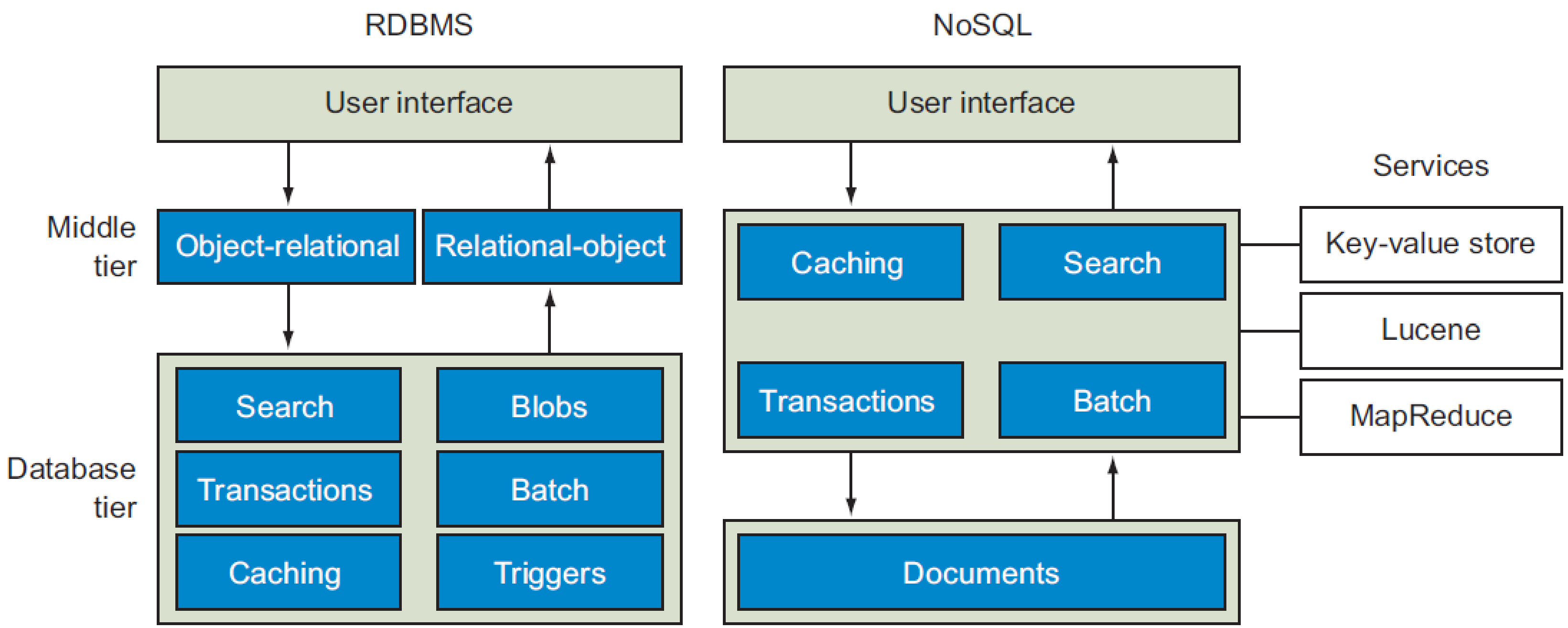
RDBMS come from decades of widespread usage

- Strong focus on data consistency
- Years of research activities to optimize performances
- Highly complex systems (triggers, caching, security, etc.)

NoSQL systems are designed to succeed where RDBMSs fail

- Strong focus on data sharding and high availability
- Quite simple systems (for now)
- Speed and manageability rather than consistency at all costs

RDBMS vs NoSQL: different philosophies



Consistency: an example

Consider 1000€ to be transferred from bank account A to B; the transfer is made by:

- Removing 1000€ from A
- Adding 1000€ to B

What should never happen

- The money is removed from A but not added to B
- The money is added twice to B
- A query on the database shows an intermediate state
  - E.g., A+B = 0€

RDBMS adopt transactions to avoid this kind of issue

Consistency in RDBMSs: ACID

Transactions guarantee four fundamental properties: ACID

Atomicity

- The transaction is indivisible: either it fully completes, or it fails
- It cannot be completed partially

Consistency

- The transaction leaves the DB in a consistent state
- Integrity constraints can never be violated

Isolation

- The transaction is independent from the others
- In case of concurrent transactions, the effect is the same of their sequential execution

Durability

- The DBMS protects the DB from failures

Consistency in RDBMSs: ACID

Implementation of ACID properties relies on locking mechanisms and logs

- Resources are locked, updates are logged
- In case of problems, rollback to the original state
- If no error occurs, unlock the resources

Consistency is guaranteed to the detriment of speed and availability

- User may have to wait
- Hard to replicate this mechanism in a distributed environment

But, sometimes, consistency is not that important

- E.g.: e-commerce application
- Shopping cart management requires speed and availability
- Order emission requires consistency

Consistency in NoSQL

Several attempts have been made to describe NoSQL properties with respect to ACID properties

- CAP theorem
- PACELC theorem
- BASE philosophy

They are not properties on which NoSQL systems rely

- Rather, they simply *try* to describe their behavior

Consistency in NoSQL: CAP

"Theorem": only two of the following three properties can be guaranteed

Consistency: the system is always consistent

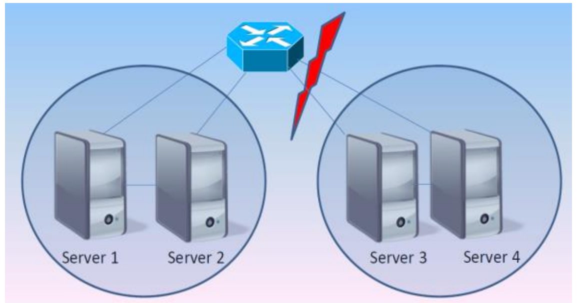
- Every node returns the same, most recent, successful write
- Every client has the same view of the data

Availability: the system is always available

- Every non-failing node returns a response for all read and write requests in a reasonable amount of time

Partition tolerance: the system continues to function and upholds its consistency guarantees in spite of network partitions

- In distributed systems, network partitioning is inevitably a possibility



Consistency in NoSQL: CAP

Three situations

- CA: the system cannot suffer from network partitioning (single server)
- AP: in case of partitioning, the system sacrifices consistency (overbooking)
- CP: in case of partitioning, the system sacrifices availability (bookings prevented)

Theorem interpretation is not trivial

- Asymmetric properties: consistency is sacrificed to favor speed at all times, not just when partitioning happens
- Different application requirements → different algorithms handle these properties more strictly/loosely

Consistency in NoSQL: relaxing CAP

Consider two users that want to book the same room when a network partition happens

CP: no one can book (A is sacrificed)

- Not the best solution

AP: both can book (C is sacrificed)

- Possible overbooking: writing conflict to handle

caP: only one can book

- The other will se the room available but cannot book it

This is admissible only in certain scenarios

- Finance? Blogs? E-commerce?

It’s important to understand:

- What is the tolerance to obsolete reads
- How large can the inconsistency window be

Consistency in NoSQL: PACELC

Evolution of the CAP theorem (less known, but more precise)

- if (**P**artition) then { **A**vaialbility or **C**onsistency? }
- **E**lse { **L**atency or **C**onsistency? }

Different behavior in case or in absence of partitioning

- PA: in case of partitioning, the system sacrifices consistency (overbooking)
- PC: in case of partitioning, the system sacrifices availability (bookings prevented)
- EL: otherwise, the system sacrifices consistency in favor of speed
- EC: otherwise, the system sacrifices speed in favor of consistency

Four situations:

- PA EL: system focused on speed and availability (main NoSQL philosophy)
- PA EC: consistency sacrificed only when partitioning happens
- PC EL: consistency enforced only when partitioning happens (e.g., Yahoo Sherpa)
- PC EC: system focused on consistency (RDBMS)

Consistency in NoSQL: BASE

The CAP theorem is often cited as a justification for the use of weaker consistency models, for example **BASE**

- *Basically Available Soft-state services with Eventual consistency*

Basic **A**vailability: the system should always be available

Soft-state: it is acceptable for the system to be temporarily inconsistent

Eventual consistency: eventually, the system becomes consistent

ACID

- Pessimistic approach (better safe than sorry)

BASE

- Optimistic approach (everything is going to be ok)
- Higher throughput is better than enforcing consistency

Consistency in NoSQL: summary

Source	Cause	Effect	Solution
Replication (MS and P2P)	Write propagation delay between replicas is slow	Read conflicts	- Tolerate - Read-your-writes - Quorum
Replication (P2P)	Two write operations can be issued on different replicas	Write conflicts	- Last write wins - Conflict prevention - Conflict detection - Quorum
Network partitioning	Inability to communicate with all replicas of a certain data	- Read conflicts - Possibly write conflicts	- Relax CAP - Prevent write conflicts - Handle read conflict as above
No ACID transactions	- An update over multiple records fails mid-query - Two updates over multiple records are interleaved	Unrecoverable inconsistency	- Each system provides its own mechanism to offer limited ACID-like transactions
Data de-normalization	The same data is repeated in different instances with different values	Inability to find the correct values	- Avoid denormalization if strong consistency is needed - Data cleaning before analysis

One size does not fit all

To each application its own data model

Key-Value: popular DBs

Redis (Data Structure server): http://redis.io/

- Supports complex fields (list, set, …) and operations on values (range, diff, …)

Memcached DB: http://memcached.org/

Riak: http://basho.com/riak/

Key-Value: when to use

Very simple use cases

- Independent data (no need to model relationships)
- The typical query is a simple lookup
- Need super-fast performance

Examples

- **Session information**
  - Each web session is identified by its own sessionId: All related data can be stored with a PUT request and returned with a GET request
- **User profiles, preferences**
  - Each user is uniquely identified (userId, username) and has her own preferences in terms of language, colors, timezone, products, etc. – data that fits well within an aggregate
- **Shopping cart, chat services**
  - Each e-commerce websites associates a shopping cart to a user; it can be stored as an aggregate identified by the user ID

Key-Value: real use cases

Crawling of web pages

- The URL is the key, the whole page content (HTML, CSS, JS, images, ..) is the value

Key	Value
http://www.example.com/index.html	<html>…
http://www.example.com/about.html	<html>…
http://www.example.com/products.html	<html>…
http://www.example.com/logo.png	Binary…

Twitter timeline

- The user ID is the key, the list of most recent tweets to be shown is the value

Amazon S3 (Simple Storage Service)

- A cloud-based file system service
- Useful for personal backups, file sharing, website or apps publication
- The more you store, the more you pay
  - Storage: approx. $0.03 per GB per month
  - Uploading files: approx. $0.005 per 1000 items
  - Downloading files: approx. $0.004 per 10,000 files* PLUS $0.09 per GB (first GB free)

Key-Value: when to avoid

Data with many relationships

- When relationships between data (in the same or in different collections) must be followed
- Some systems offer limited link-walking mechanisms

Multi-record operations

- Because operations (mostly) involve one record at a time

Querying the data

- If it is necessary to query the values, not just the key
- Few systems offer limited functionalities (e.g., Riak Search)

Document: popular DBs

MongoDB: http://www.mongodb.org

Couchbase: http://www.couchbase.com

CouchDB: http://couchdb.apache.org

Document: when to use

Higher expressiveness

- Store data according to a highly nested data model
- Need to formulate complex queries on many fields

Examples

- **Event logs**
  - Central repo to store event logs from many applications; shard on app name or event type
- **CMS, blogging platforms**
  - The absence of a predefined schema fits well within content management systems (CMS) or website management applications, to handle comments, registrations and user profiles
- **Web Analytics or Real-Time Analytics**
  - The ability to update only specific fields enables fast update of analytical metrics
  - Text indexing enables real-time sentiment analysis and social media monitoring
- **E-commerce applications**
  - Schema flexibility is often required to store products and orders, as well as to enable schema evolution without incurring into refactoring or migration costs

Document: real use cases

Adversting services

- MongoDB was born as a system for banner ads
  - 24/7 availability and high performance
  - Complex rules to find the right banner based on user’s interests
  - Handle several kinds of ads and show detailed analytics

Internet of Things

- Real-time management of sensor-based data
- Bosch uses MongoDB to capture data from cars (breaks, ABS, windscreen wiper, etc.) and aircrafts maintenance tools
  - Business rules are applied to warn the pilot when the breaking system pressure falls under a critical threshold, or the maintenance operator when the tool is used improperly
- Technogym uses MongoDB to capture data from gym equipment

Document: when to avoid

ACID transactions requirement

- If not for a few exceptions (e.g., RavenDB), document databases are not suited for cross-document atomicity

Queries on high-variety data

- If the aggregate structure continuously evolves, queries must be constantly updated (and normalization clashes with the concept of aggregate)

Wide column: popular DBs

Cassandra: http://cassandra.apache.org

HBase: https://hbase.apache.org

Google BigTable: https://cloud.google.com/bigtable

Wide column: when to use

Compromise between expressiveness and simplicity

- Limited (but some) requirements in terms of data model
- Limited (but some) requirements in terms of querying records

Examples

- **Event logs; CMS, blogging platforms**
  - Similarly to document databases, different applications may use different columns
- **Sparse matrixes**
  - While an RDBMS would store *null* values, a wide column stores only the columns for which a value is specified
- **GIS applications**
  - Pieces of a map (tiles) can be stored as couples of latitude and longitude

Wide column: real use cases

Google applications

- BigTable is the DB used by Google for most of its applications, including Search, Analytics, Maps and Gmail

User profiles and preferences

- Spotify uses Cassandra to store metadata about users, artists, songs, playlists, etc.

Manhattan

- After using Cassandra, Twitter ha developed its own proprietary NoSQL system to support most of its services

Wide column: when to avoid

Same as for document model

- ACID transactions requirement
- Queries on high-variety data

Need for full query expressiveness

- Joins are highly discouraged
- Limited support for filters and group bys

Graph: popular DBs

Neo4J: http://neo4j.com

TigerGraph: https://www.tigergraph.com/

Graph: when to use

Interlinked data

- Social networks are one of the most typical use case of graph databases (e.g., to store friendships or work relationships); every relationship-centric domain is a good one

Routing and location-based services

- Applications working on the TSP (Travelling Salesman Problem) problem
- Location-based application that, for instance, recommend the best restaurant nearby; in this case, relationships model the distance between node

Recommendation applications, fraud-detection

- Systems recommending «the products bought by your friends», or «the products bought by those who bought your same products»
- When relationships model behaviors, outlier detection may be useful to identify frauds

Graph: real use cases

Relationships analysis

- Finding common friends (e.g., friend-of-a-friend) in a social network
- Identifying clusters of phone calls that identify a criminal network
- Analyzing flows of money to identifying money recycling patterns or credit card theft
- Main users: law firms, police, intelligence agencies
  - https://neo4j.com/use-cases/fraud-detection/
- Useful for text analysis as well (Natural Language Processing)

Inference

- Creating rules that define new knowledge based on existing patterns (e.g., transitive relationships, trust mechanisms)

Graph: when to avoid

Data-intensive applications

- Traversing the graph is trivial, but analyzing the whole graph can be expensive
- There exist framework for distributed graph analysis (e.g., Apache Giraph), but they do not rely on a graph DB

Polyglot persistence

Polyglot persistence

Different databases are designed to solve different problems

Using a single DBMS to handle everything …

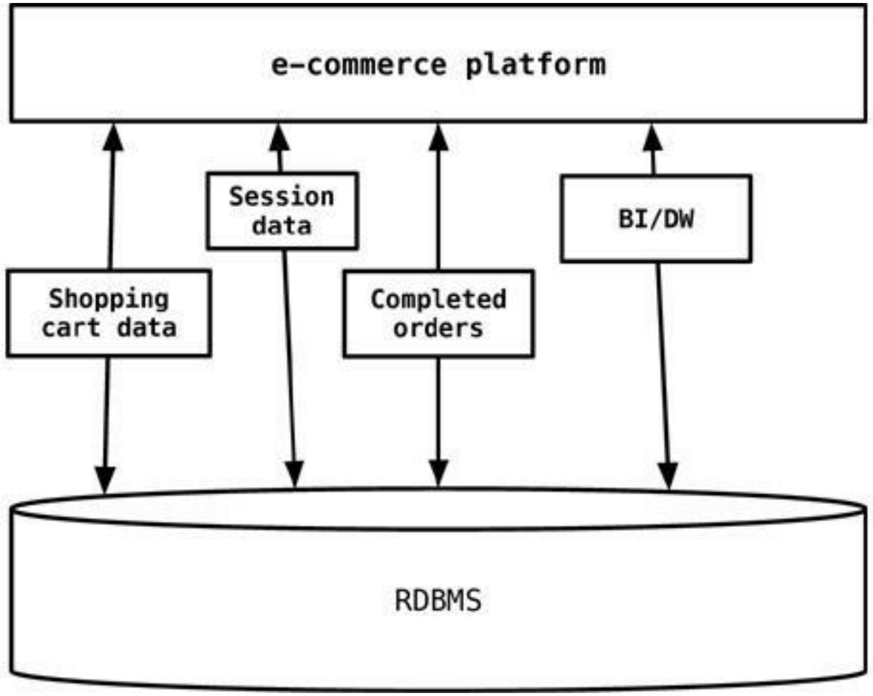
- Operational data
- Temporary session information
- Graph traversing
- OLAP analyses
- …

… usually lead to inefficient solutions

Each activity has its own requirements (availability, consistency, fault tolerance, etc.)

Traditional approach

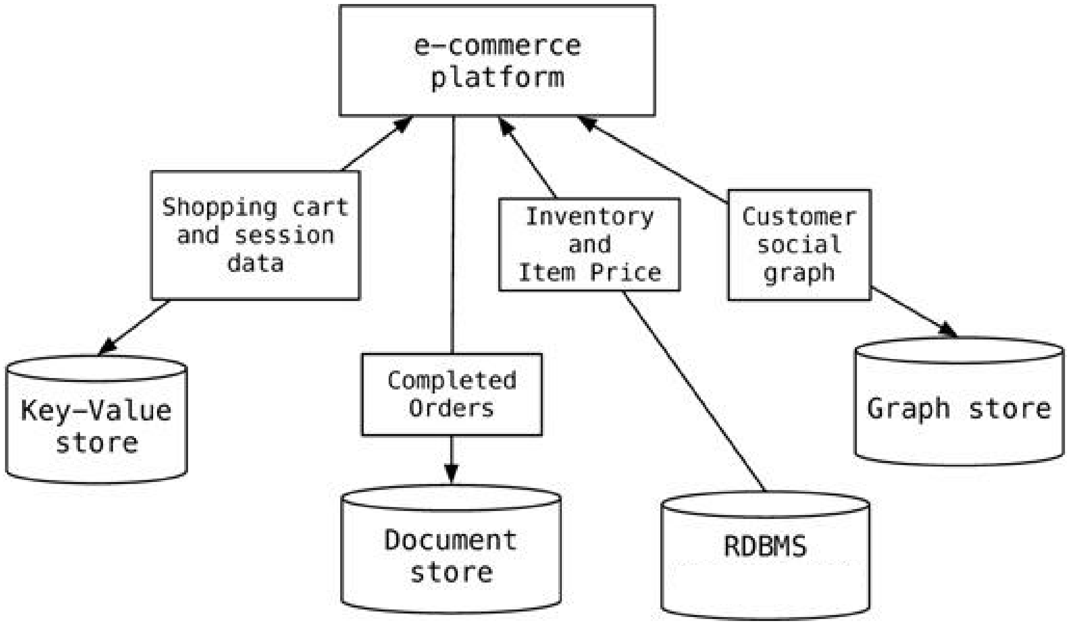
The *one-size-fits-all* solution



Polyglot data management

~~The *one-size-fits-all* solution~~

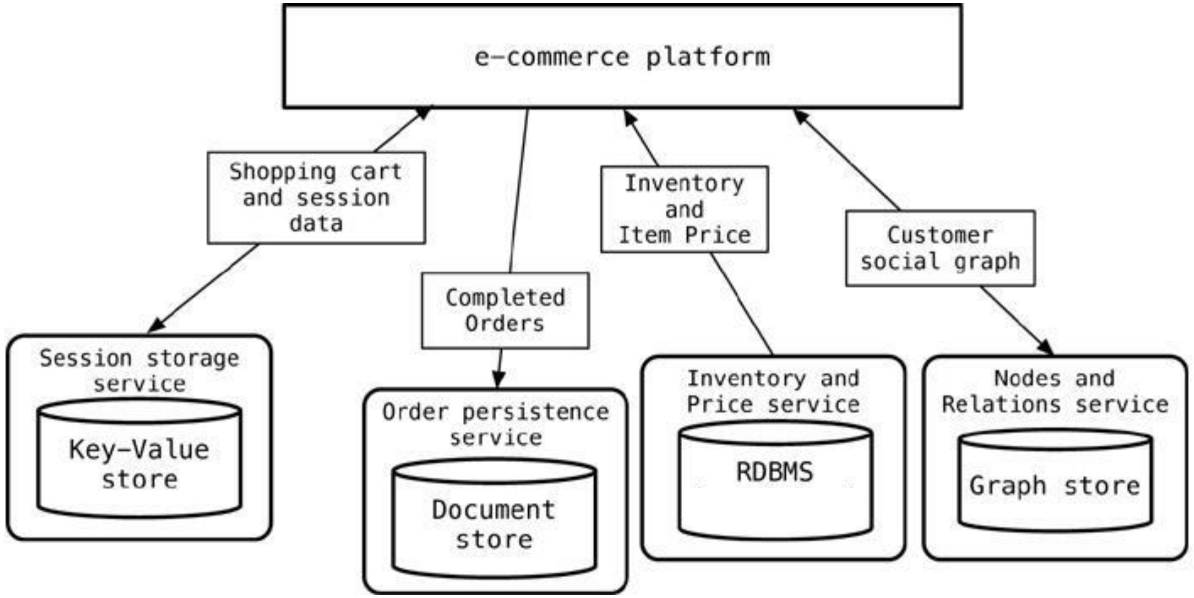
Replaced by the *polyglot* solution



Service-oriented polyglot data management

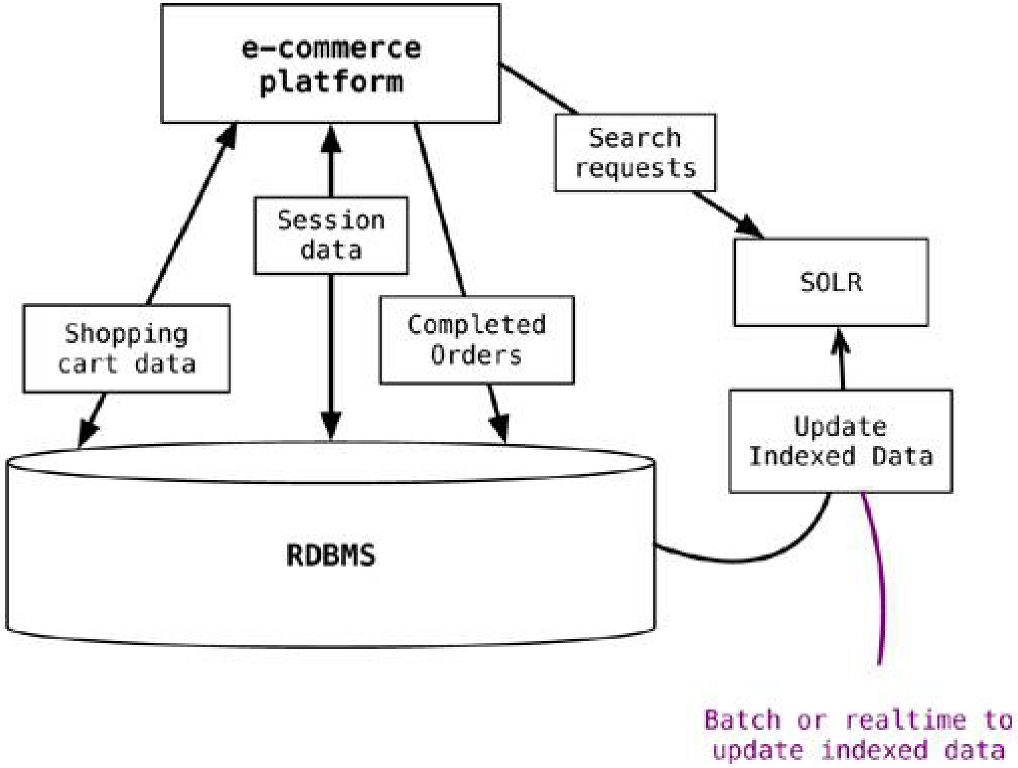
Each DB should be "embedded" within services, which offer API services to enable data access and manipulation

- Several NoSQL systems (e.g., Riak, Neo4J) already provide REST APIs



Supporting existing technologies

If the current solution cannot be changed, NoSQL systems can still support the existing ones



Beyond NoSQL

NewSQL systems

- Combine the benefits from both relational and NoSQL worlds
- Ensure scalability without compromising consistency, but by **compromising some availability**

Extended RDBMSs

- KV implementable as a table with two fields: a string key, and a blob value
- Cypher query language on top of a relational implementation of a graph
- Hstore data type in PostgreSQL for wide-column-like implementation
- **Scalabilty issue remains**

Multi-model NoSQL DBMSs

- ArangoDB, OrientDB
- **Support all NoSQL data models, but not the relational one**

Database-as-a-service

- All cloud providers offer storage services supporting all data models