



NoSQL

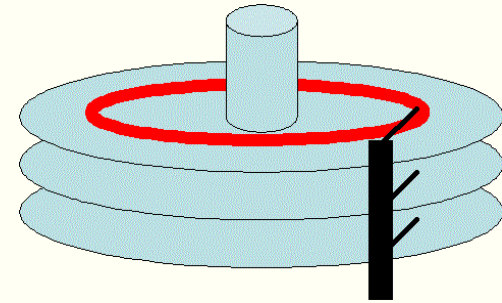
Column Store, Document DB



Row Store and Column Store

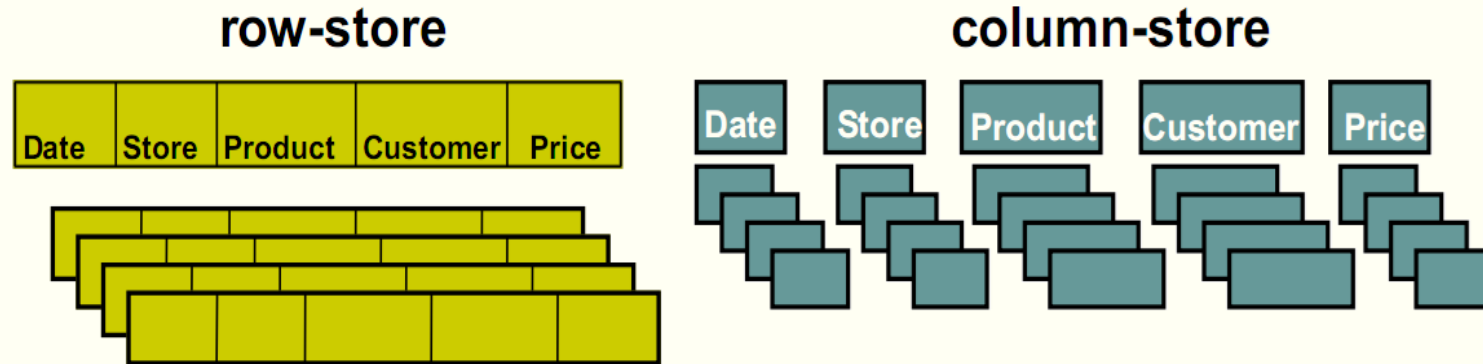
- Most of the queries does not process all the attributes of a particular relation.

- For example the query
 - ✓ Select c.name and c.address
 - ✓ From CUSTOMER as c
 - ✓ Where c.region=Pullman;



- Only process three attributes of the relation CUSTOMER. But the customer relation can have more than three attributes.
- more I/O efficient for read-only queries as they read, only those attributes which are accessed by a query.

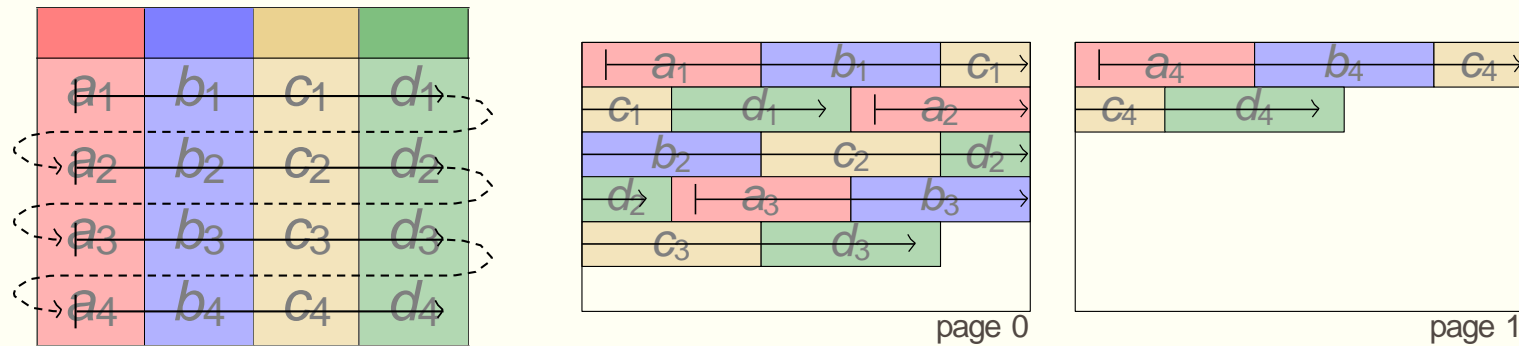
Row Store and Column Store



- In row store data are stored in the disk tuple by tuple.
- Where in column store data are stored in the disk column by **column**

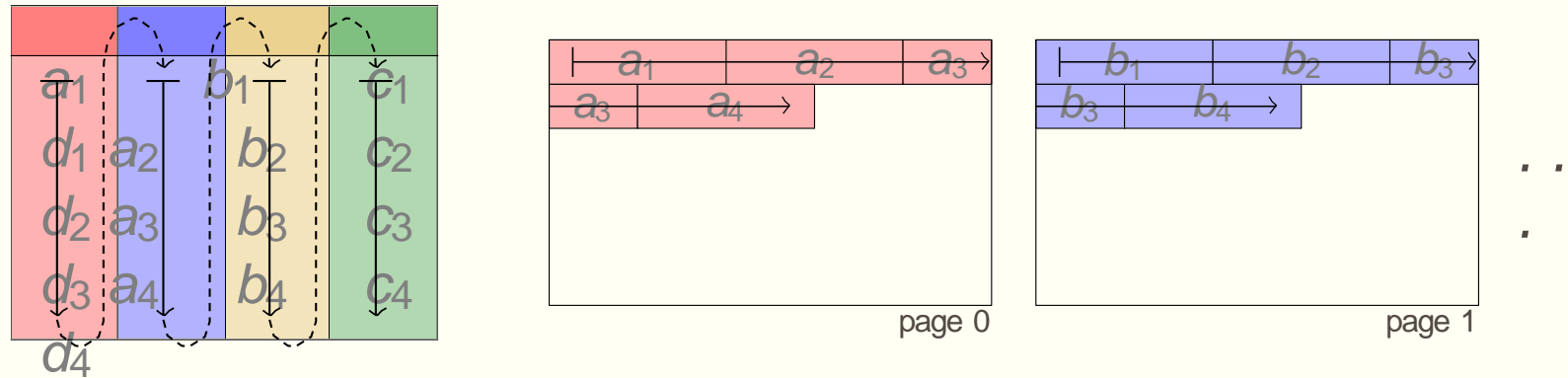
Row Stores

- In a row-store, a.k.a. row-wise storage or n-ary storage model, NSM: all rows of a table are stored sequentially on a database page.



Column-stores

- a.k.a. column-wise storage or decomposition storage model, DSM:



The Effect on Query Processing

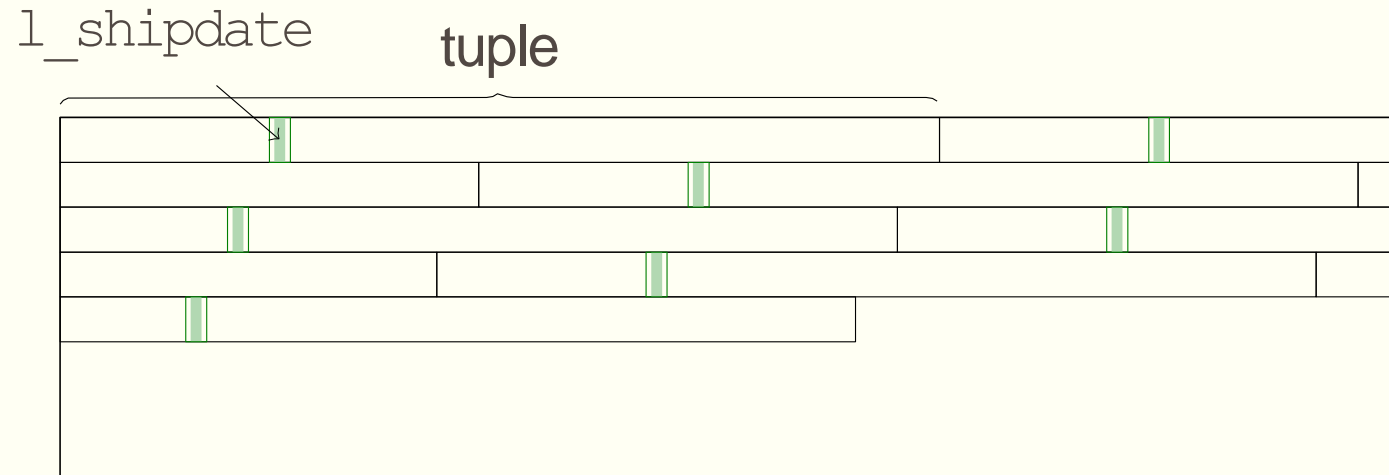
Consider, e.g., a selection query:

```
SELECT COUNT(*)  
FROM lineitem  
WHERE l_shipdate = "2017-10-19"
```

This query typically involves a full table scan.

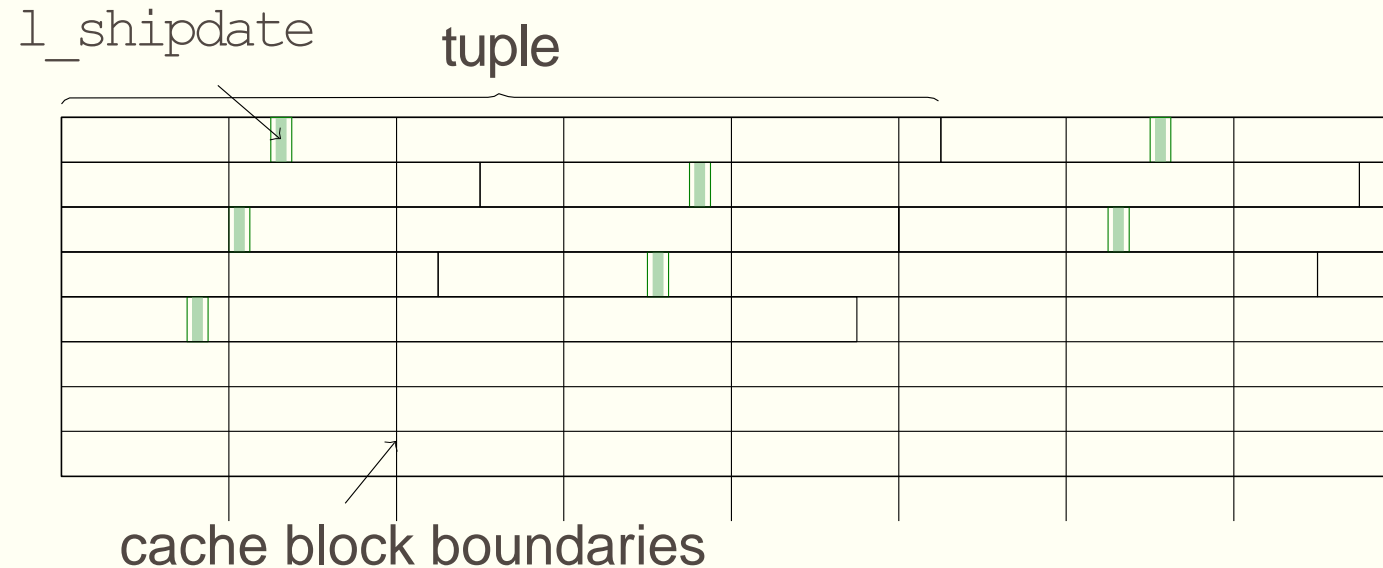
A Full Table Scan in a Row Store

- In a row-store, all rows of a table are stored sequentially on a database page.



A full table scan in a row-store

- In a row-store, all rows of a table are stored sequentially on a database page.

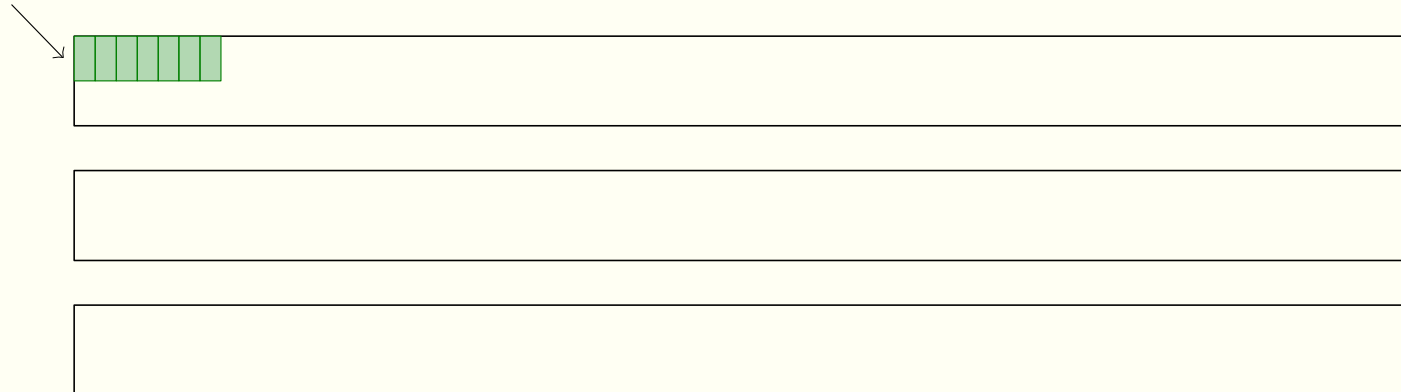


With every access to a `l_shipdate` field, load a large amount of irrelevant information into the cache.

A “Full Table Scan” on a Column Store

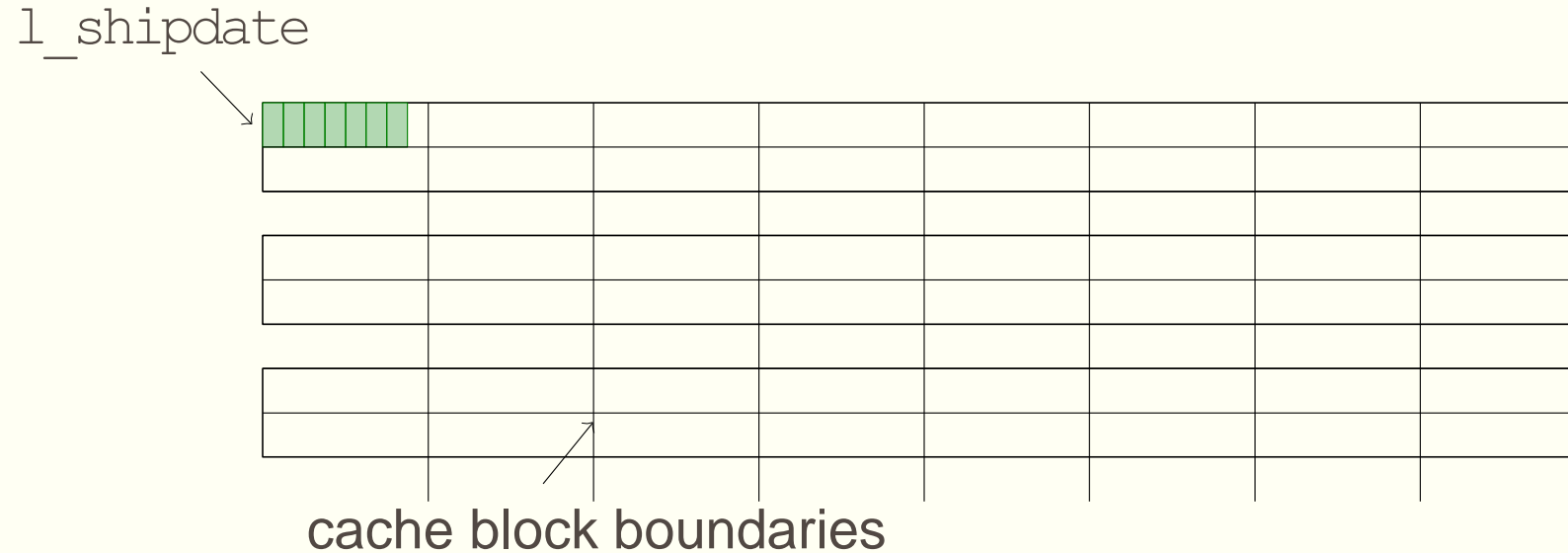
- In a column-store, all values of one column are stored sequentially on a database page.

l_shipdate



A “Full Table Scan” on a Column Store

- In a column-store, all values of one column are stored sequentially on a database page.



All data loaded into caches by a “`l_shipdate` scan” is now actually **relevant** for the query.

Column-store Advantages

- Less data has to be fetched from memory.
- Amortize cost for fetch over more tuples.
 - The same arguments hold also for in-memory based systems (we will see soon).
 - Additional benefit: Data compression might work better.

Why Column Store

- Can be significantly faster than row stores for some applications
 - Fetch only required columns for a query
 - Better cache effects
 - Better compression (similar attribute values within a column)
- But can be slower for other applications
 - OLTP with many row inserts, ..
- Long war between the column store and row store camps :-)

Row Store and Column Store

Row Store	Column Store
(+) Easy to add/modify a record	(+) Only need to read in relevant data
(-) Might read in unnecessary data	(-) Tuple writes require multiple accesses

Column stores are suitable for **read-mostly, read-intensive, large data repositories**

Column Stores - Data Model

- Standard relational logical data model
 - EMP(name, age, salary, dept)
 - DEPT(dname, floor)
- Table – collection of projections
- Projection – set of columns
- Horizontally partitioned into segments with segment identifier

EMP1

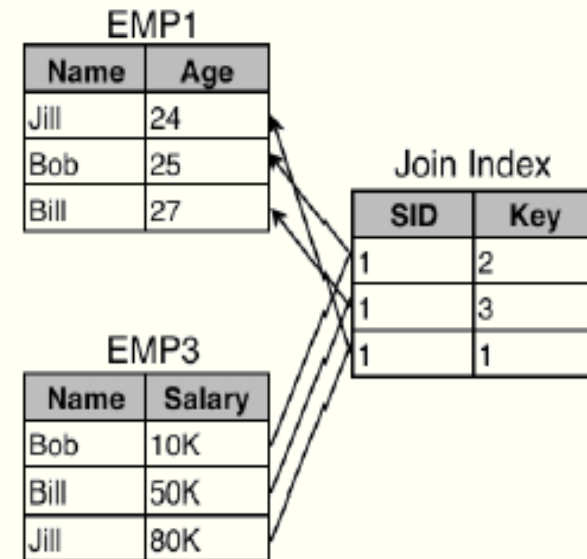
Name	Age
Jill	24
Bob	25
Bill	27

EMP3

Name	Salary
Bob	10K
Bill	50K
Jill	80K

Column Stores - Data Model

- To answer queries, projections are joined using Storage keys and join indexes
- Storage Keys:
 - Within a segment, every data value of every column is associated with a unique Skey
 - Values from different columns with matching Skey belong to the same logical row



Query Execution - Operators

- **Select:** Same as relational algebra, but produces a bit string
- **Project:** Same as relational algebra
- **Join:** Joins projections according to predicates
- **Aggregation:** SQL like aggregates
- **Sort:** Sort all columns of a projection
- **Decompress:** Converts compressed column to uncompressed representation
- **Mask**(Bitstring B, Projection Cs) => emit only those values whose corresponding bits are 1
- **Concat:** Combines one or more projections sorted in the same order into a single projection
- **Permute:** Permutes a projection according to the ordering defined by a join index
- **Bitstring operators:** Band – Bitwise AND, Bor – Bitwise OR, Bnot – complement

Row Store Vs Column Store

- One can obtain the performance benefits of a column-store using a row-store by making some changes to the physical structure of the row store.
 - Vertically partitioning
 - Using index-only plans
 - Using materialized views

Vertical Partitioning

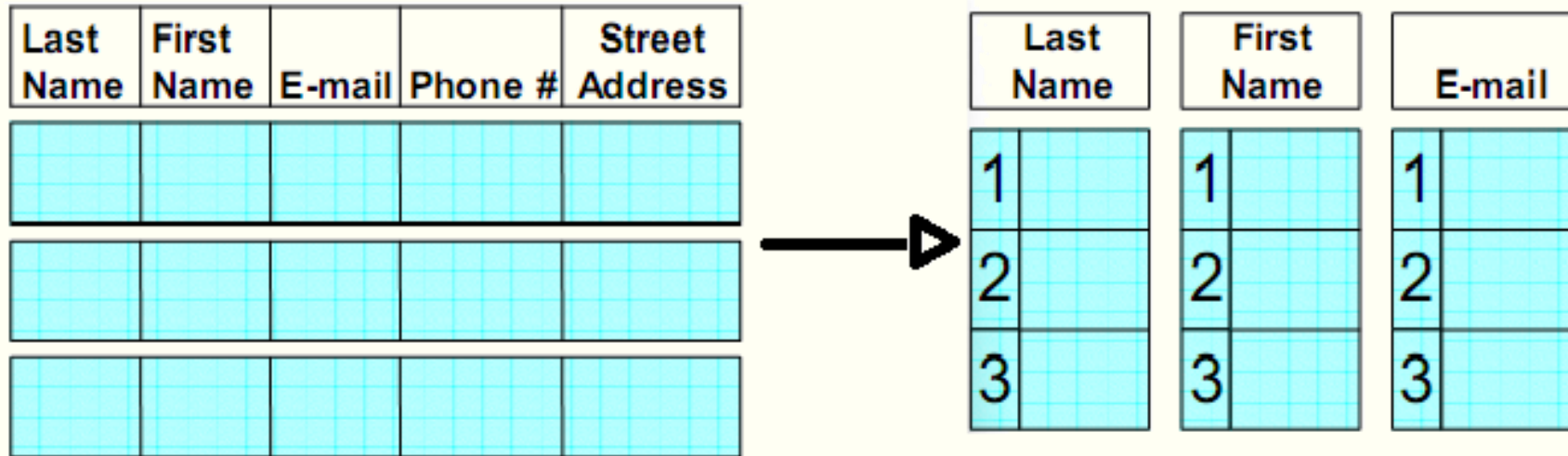
- Process:

- Full Vertical partitioning of each relation
 - Each column = 1 Physical table
 - by adding integer position column to every table
- Join on Position for multi column fetch

- Problems:

- “Position” - Space and disk bandwidth
- Header for every tuple – further space wastage
 - e.g. 24 byte overhead in PostgreSQL

Vertical Partitioning: Example



Vertical Partitioning

Index-only plans

- **Process:**

- Add B+Tree index for every Table.column
- Plans never access the actual tuples on disk
- Headers are not stored, so per tuple overhead is less

- **Problem:**

- Separate indices may require full index scan, which is slower
- Eg:

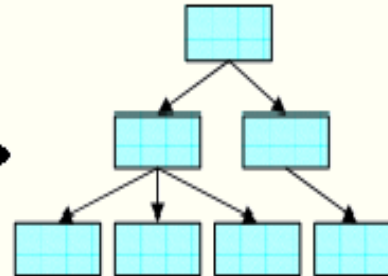
```
SELECT AVG(salary)
FROM emp
WHERE age > 40
```
- Composite index with (age, salary) key helps.

Index-Only Plans

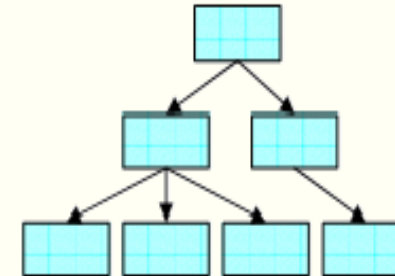
Last Name	First Name	E-mail	Phone #	Street Address



Last Name Index



First Name Index



Index Every Column

Materialized Views

- **Process:**

- Create 'optimal' set of MVs for given query workload
- Objective:
 - Provide just the required data
 - Avoid overheads
 - Performs better

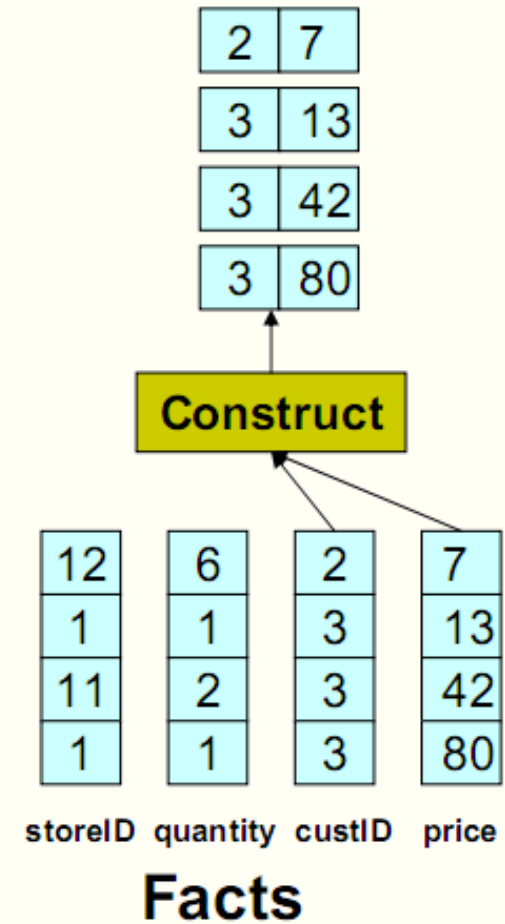
- Expected to perform better than other two approach

- **Problems:**

- Practical only in limited situation
- Require knowledge of query workloads in advance

Materialized Views: Example

- Select F.custID
from Facts as F
where F.price>20

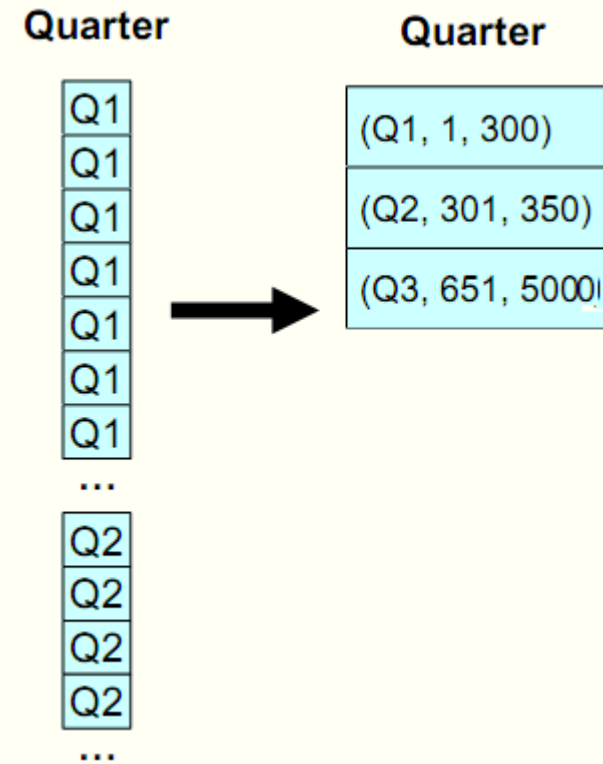


Optimizing Column oriented Execution

- Different optimization for column-oriented database
 - Compression
 - Late Materialization
 - Block Iteration

Compression

- column can be super-compressible
- E.g. Run length encoding



Compression

- Low information entropy (high data value locality) leads to High compression ratio
- Advantage
 - Disk Space is saved
 - Less I/O
 - CPU cost decrease if we can perform operation without decompressing
- Light weight compression schemes do better

Late Materialization

- Most query results entity-at-a-time not column-at-a-time
- Idea: Delay Tuple Construction
- Might avoid constructing it altogether
- Intermediate position lists might need to be constructed
 - `SELECT R.a FROM R WHERE R.c = 5 AND R.b = 10`
 - Output of each predicate is a bit string
 - Perform Bitwise AND
 - Use final position list to extract R.a

Block Iteration

- Operators operate on blocks of tuples at once
- Iterate over blocks rather than tuples
- If column is fixed width, it can be operated as an array
- Minimizes per-tuple overhead
- Exploits potential for parallelism
- Can be applied even in Row stores – IBM DB2 implements it


Document DB

- Documents are the main concept.
- A Document-oriented database stores and retrieves documents (XML, JSON, BSON and so on).
- Documents are:
 - Self-describing
 - Hierarchical tree data structures (maps, collection and scalar values)

What is a Document DB?

- Document databases store documents in the value part of the key-value store

```
{  
  name: "sue",  
  age: 26,  
  status: "A",  
  groups: [ "news", "sports" ]  
}
```



← field: value
← field: value
← field: value
← field: value

- Documents may have different attributes
- Different from relational databases where columns stores the same type of values or null

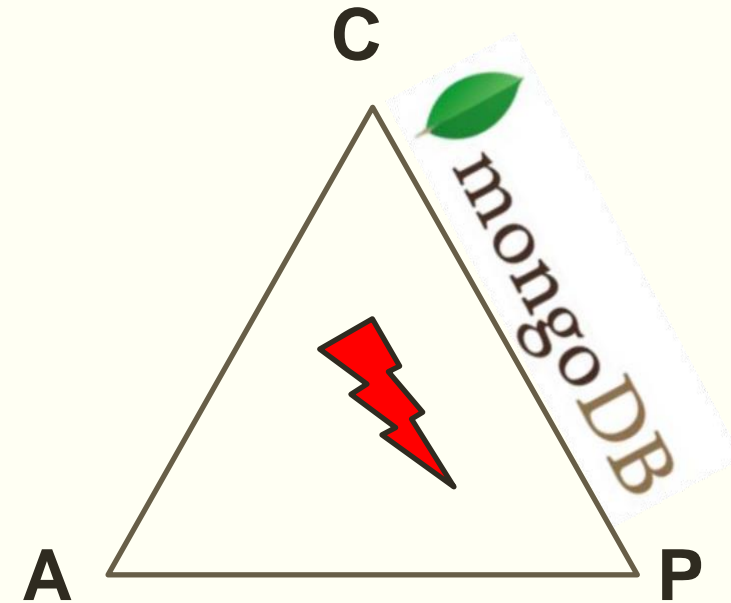
MongoDB

- MongoDB Features
 - Document-Oriented storage
 - Index Support
 - Replication & Availability
 - Auto-Sharding
 - Ad-hoc Querying
 - Fast In-Place Updates
 - Map/Reduce functionality

MongoDB: CAP approach

▪ Focus on Consistency and Partition tolerance

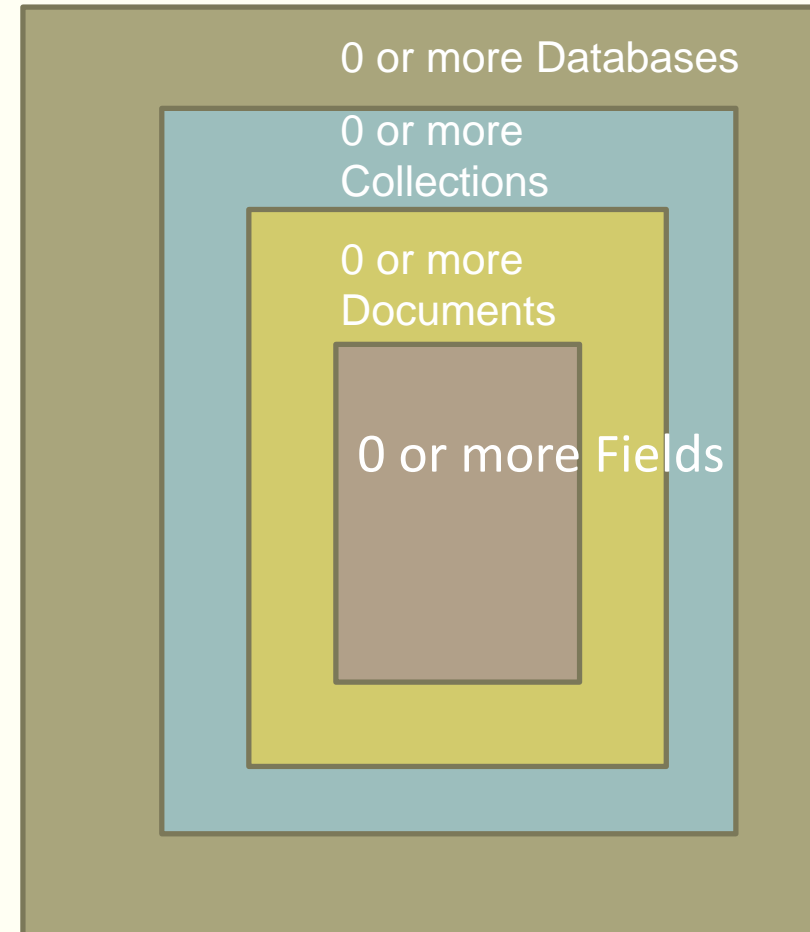
- **Consistency**
 - all replicas contain the same version of the data
- **Availability**
 - system remains operational on failing nodes
- **Partition tolerance**
 - multiple entry points
 - system remains operational on system split



CAP Theorem:
satisfying all three at the same time is
impossible

MongoDB: Hierarchical Objects

- A MongoDB instance may have zero or more **databases**.
- A **database** may have zero or more **collections**.
- A **collection** may have zero or more **documents**.
- A **document** may have one or more **fields**.
- MongoDB **Indexes** function much like their RDBMS counterparts.

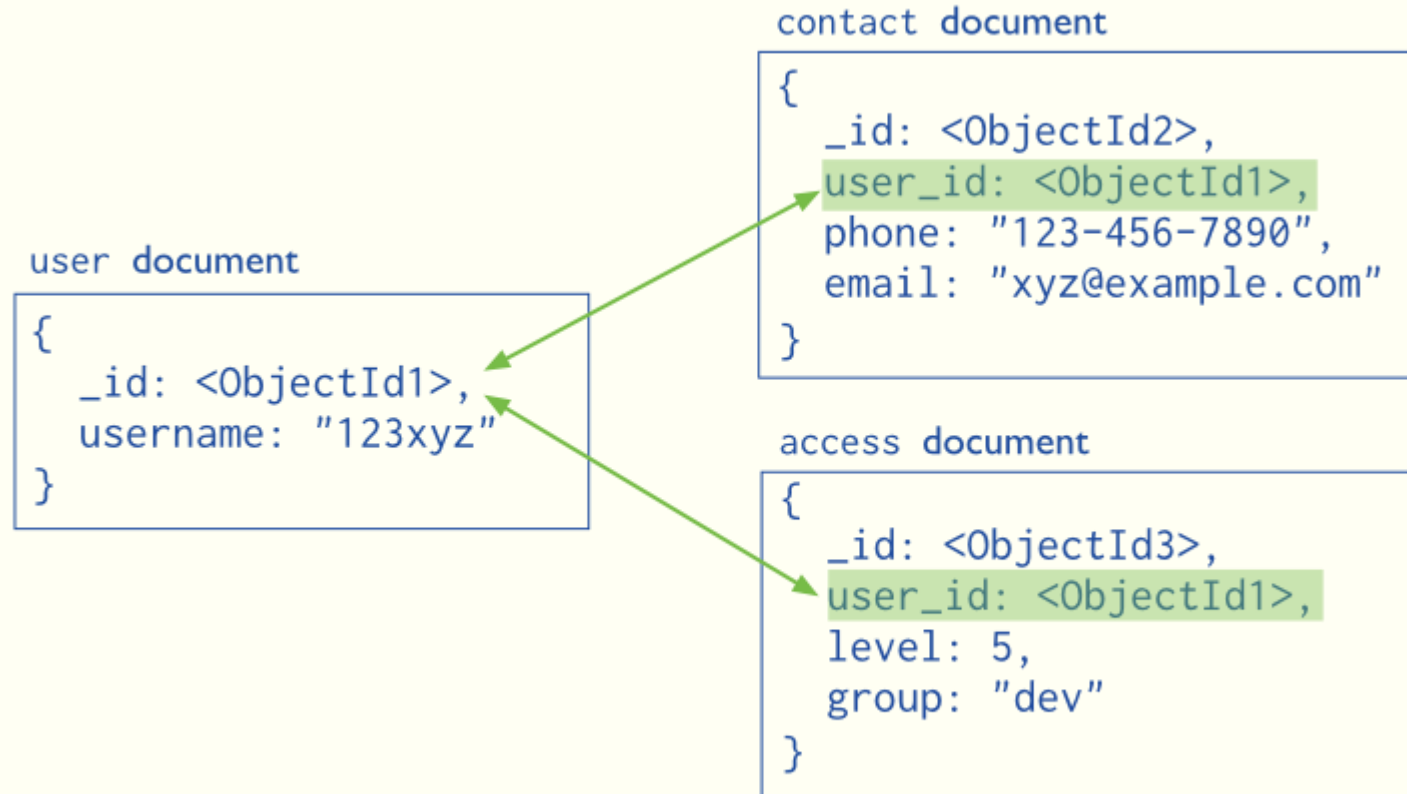


The _id Field

- By default, each document contains an _id field. This field has a number of special characteristics:
 - Value serves as primary key for collection.
 - Value is unique, immutable, and may be any non-array type.
 - Default data type is ObjectId, which is “small, likely unique, fast to generate, and ordered.”

```
{ "_id" : "37010",  
  "city" : "ADAMS",  
  "pop" : 2660,  
  "state" : "TN", }
```

Documents: Structure References



Documents: Structure Embedded

```
{  
  _id: <ObjectId>,  
  username: "123xyz",  
  contact: {  
    phone: "123-456-7890",  
    email: "xyz@example.com"  
  },  
  access: {  
    level: 5,  
    group: "dev"  
  }  
}
```



Embedded sub-document



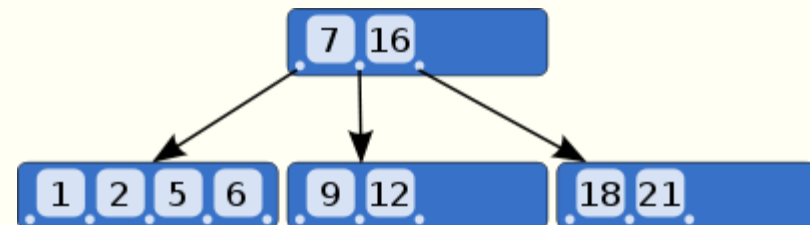
Embedded sub-document

RDB Concepts to Document DB

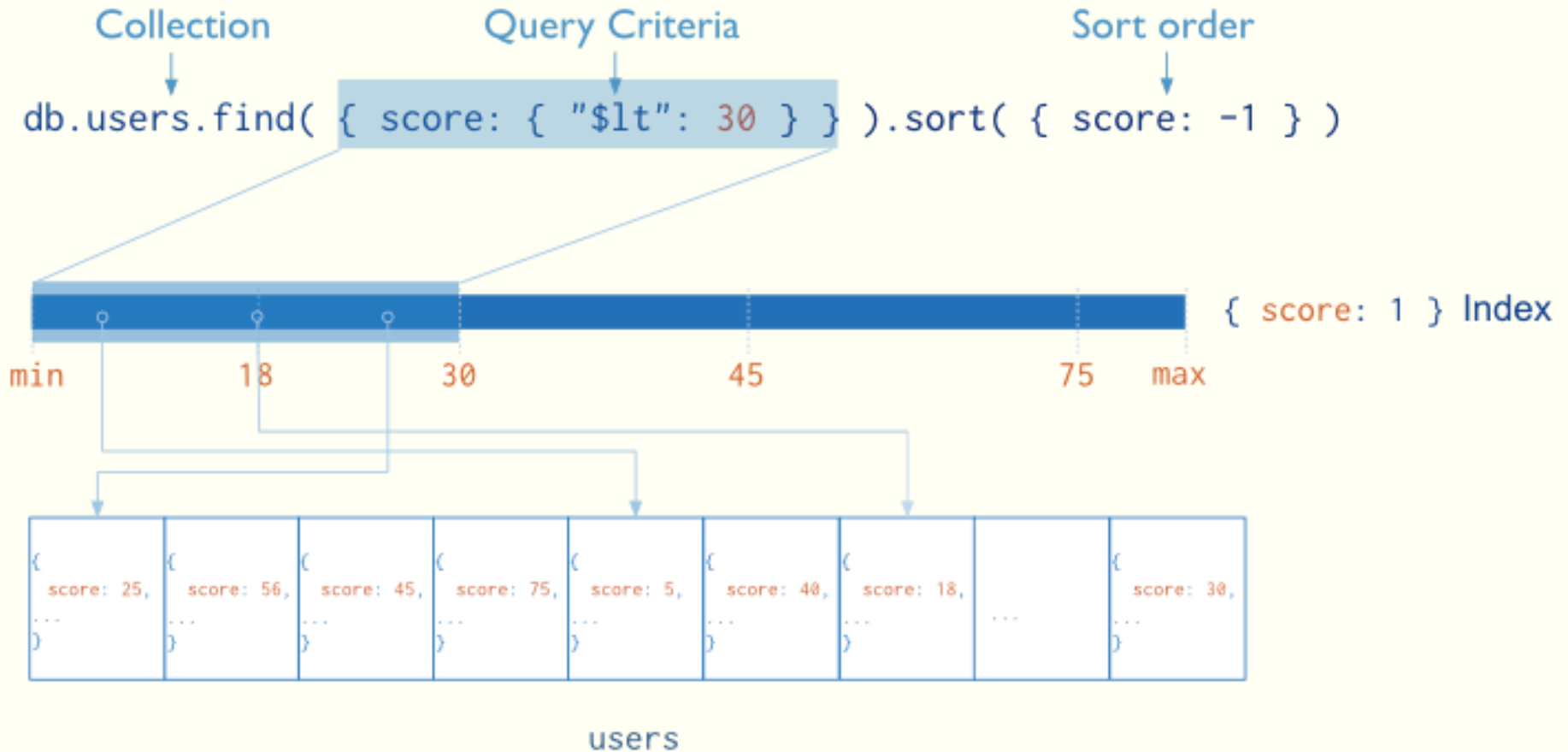
RDBMS		MongoDB
Database	➡	Database
Table, View	➡	Collection
Row	➡	Document (BSON)
Column	➡	Field
Index	➡	Index
Join	➡	Embedded Document
Foreign Key	➡	Reference
Partition	➡	Shard

Documents: Indexing

- Indexes allows efficient queries on MongoDB.
- They are used to limit the number of documents to inspect (Otherwise, scan every document in a collection)
- By default MongoDB create indexes only on the `_id` field
- Indexes are created using B-tree and stores data of fields ordered by values.
- In addition, returns sorted results by using the index.



Documents: Indexing



CRUD

■ Create

- `db.collection.insert(<document>)`
- `db.collection.save(<document>)`
- `db.collection.update(<query>, <update>, { upsert: true })`

■ Read

- `db.collection.find(<query>, <projection>)`
- `db.collection.findOne(<query>, <projection>)`

■ Update

- `db.collection.update(<query>, <update>, <options>)`

■ Delete

- `db.collection.remove(<query>, <justOne>)`

CRUD Example

```
> db.user.insert({  
  first: "John",  
  last : "Doe",  
  age: 39  
})
```

```
> db.user.find ()  
{  
  "_id" : ObjectId("51..."),  
  "first" : "John",  
  "last" : "Doe",  
  "age" : 39  
}
```

```
> db.user.update(  
  {"_id" :  
  ObjectId("51...")},  
  { $set: {  
    age: 40,  
    salary: 7000}  
  }  
)
```

```
> db.user.remove({  
  "first": /^J/  
})
```

Query Interface

```
db.users.find(  
  { age: { $gt: 18 } },  
  { name: 1, address: 1 }  
) .limit(5)
```

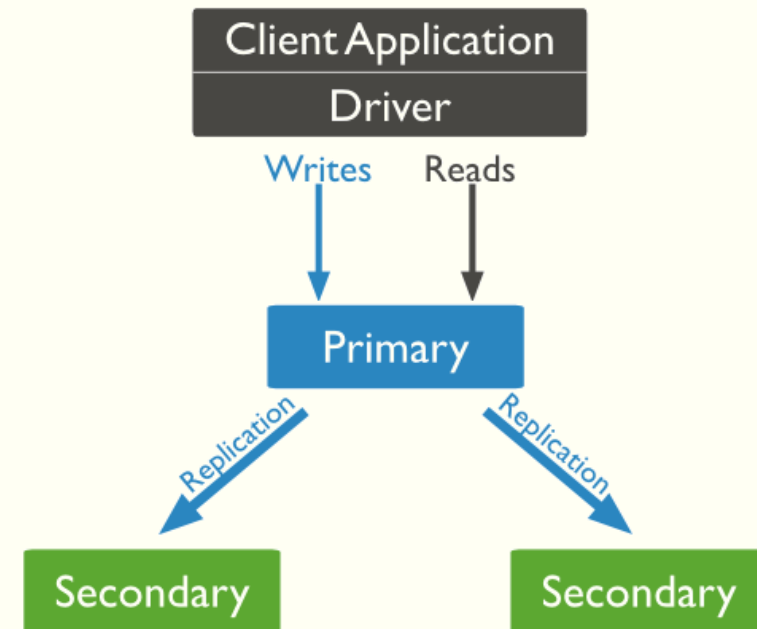
← collection
← query criteria
← projection
← cursor modifier

```
SELECT _id, name, address  
FROM   users  
WHERE  age > 18  
LIMIT 5
```

← projection
← table
← select criteria
← cursor modifier

Replication of Data

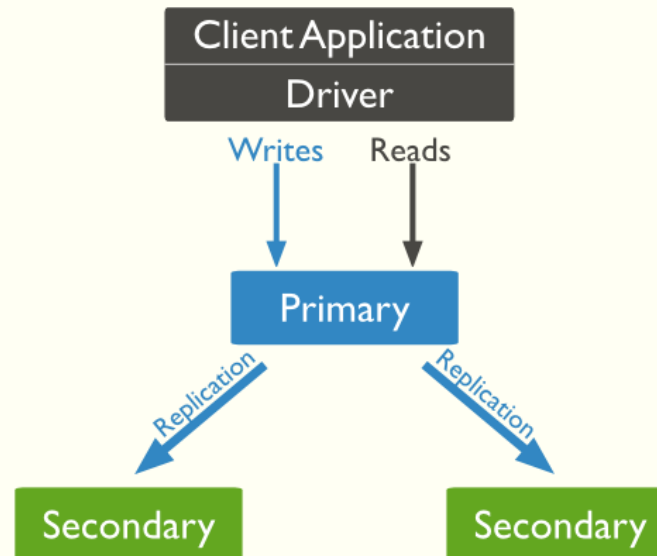
- Ensures redundancy, backup, and automatic failover
 - Recovery manager in the RDMS
- Replication through groups of servers known as replica sets
 - **Primary set** – set of servers that client tasks direct updates to
 - **Secondary set** – set of servers used for duplication of data
 - If the primary set fails the secondary sets 'vote' to elect the new primary set



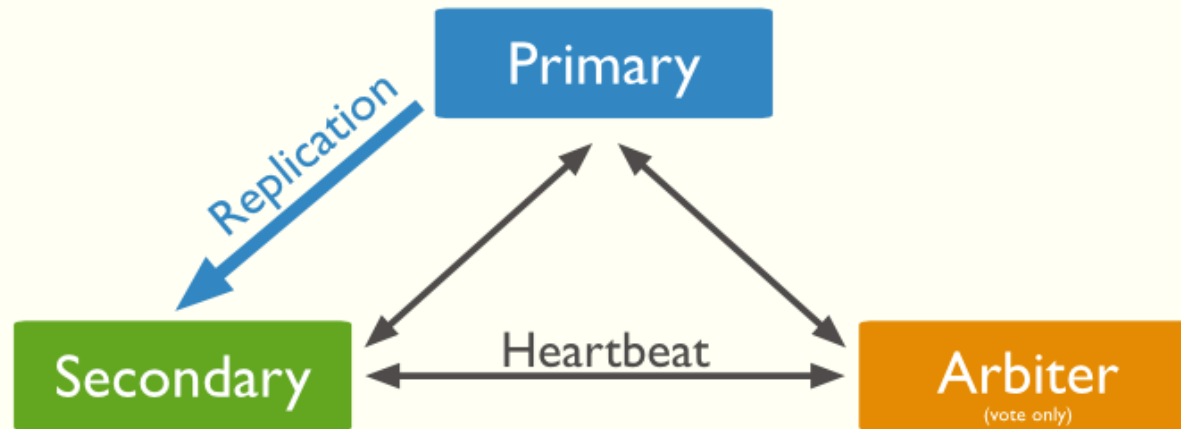
Scaling: Heavy Reads

- Scaling is achieved by adding more read slaves
- All the reads can be directed to the slaves.
- When a node is added it will sync with the other nodes -- no need to stop the cluster.

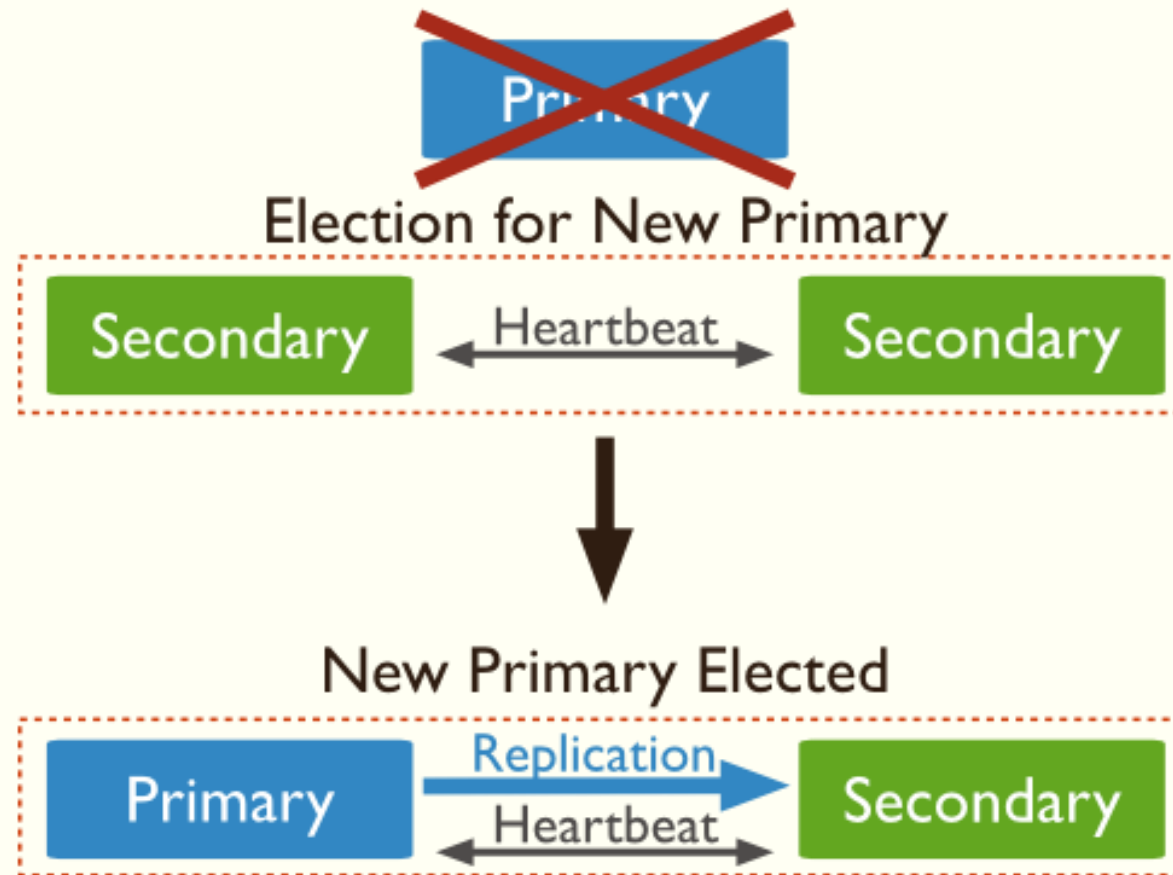
```
rs.add("mongo_address:27017")
```



Data Replication

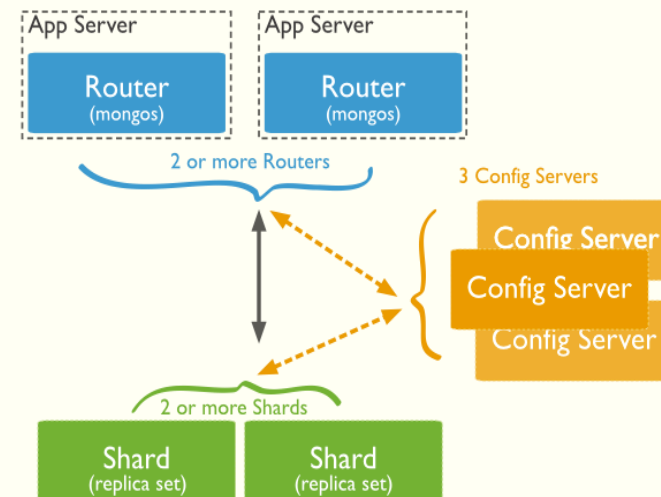
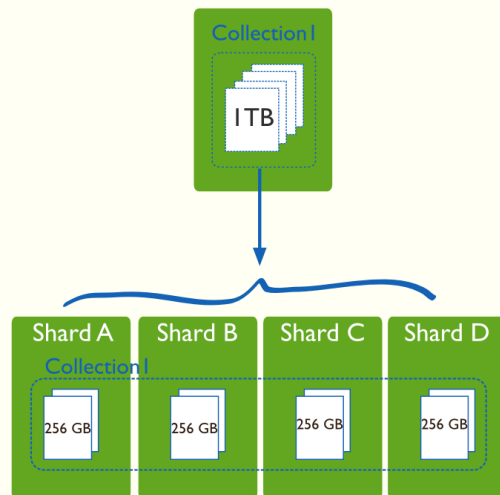


Automatic Failover



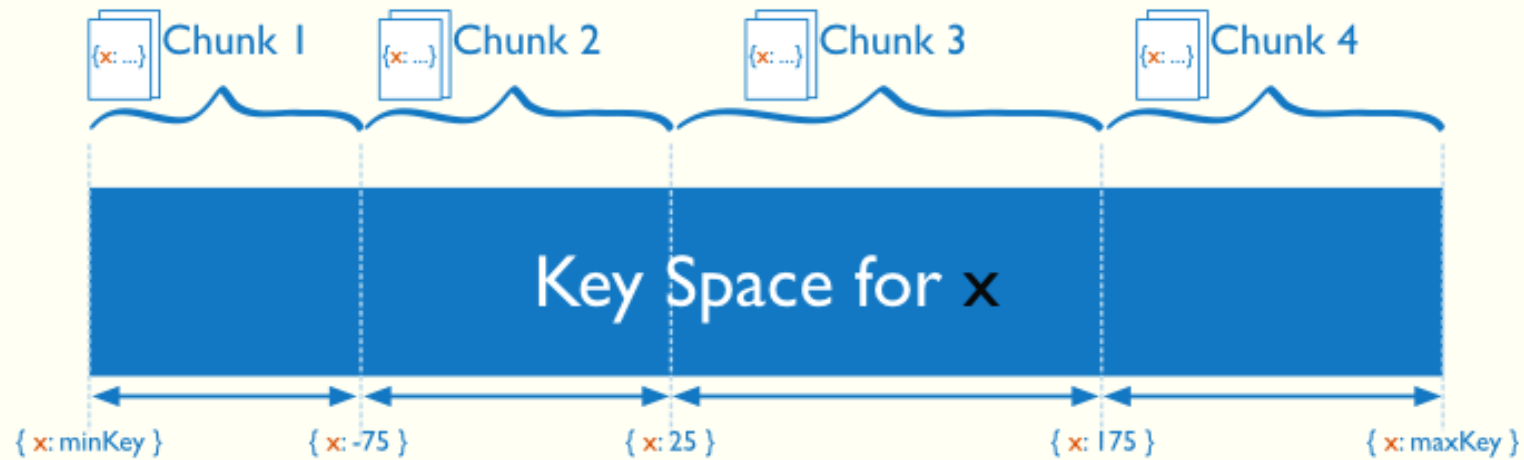
Sharding in MongoDB

- **Sharding**, or horizontal scaling divides the data set and distributes the data over multiple servers.
- Each shard is an independent database, and collectively, the shards make up a single logical database.
- Query Routers: interface to client and direct queries
- Config Server: store cluster's metadata.



Range Based Sharding

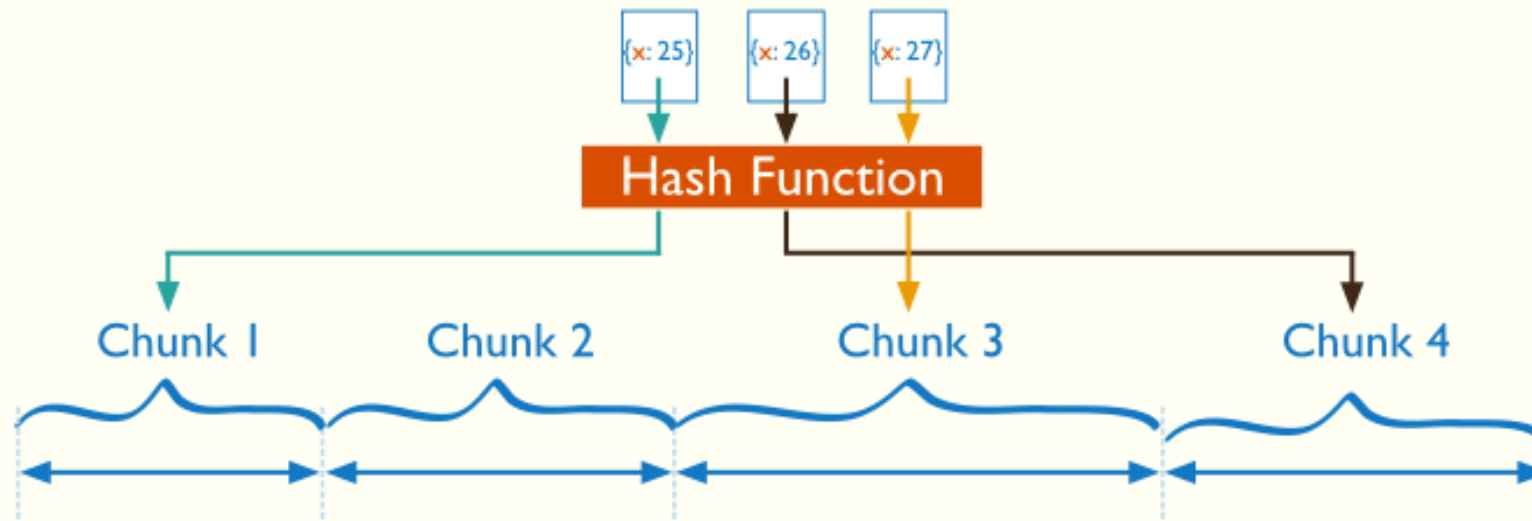
- divides the data set into ranges determined by the shard key values to provide range based partitioning.



- supports more efficient range queries
- However, result in an uneven distribution of data.

Hash Based Sharding

- computes a hash of a field's value, and then uses these hashes to create chunks



- More likely to ensure even distribution of data at the expense of efficient range queries.

Document Store: Advantages

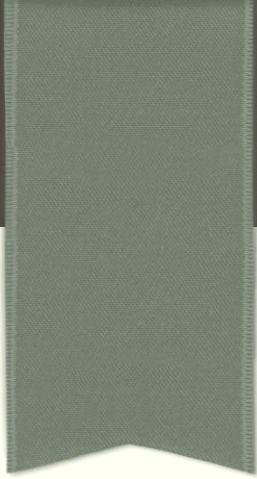
- Documents are independent units
- Application logic is easier to write. (JSON).
- Schema Free:
 - Unstructured data can be stored easily, since a document contains whatever keys and values the application logic requires.
 - In addition, costly migrations are avoided since the database does not need to know its information schema in advance.

Suitable Use Cases

- **Event Logging:** where we need to store different types of event (order_processed, customer_logged).
- **Content Management System:** the schema-free approach is well suited
- **Web analytics or Real-Time Analytics:** useful to update counters, page views and metrics in general.

When Not to Use

- **Complex Transactions:**
 - atomic cross-document operations
- **Queries against Varying Aggregate Structure:**
 - i.e., when the structure of the aggregates vary because of continuous data evolutions



Graph Database

Motivations

- The necessity to represent, store and manipulate complex data make RDBMS somewhat obsolete
- Problem 1: Violations of the 1NF
 - Multi-valued attributes
 - Complex attributes
- Problem 2 : Accommodate Changes
 - acquiring data from autonomous dynamic sources or Web
 - RDBMS require schema renormalization
- Problem 3: Unified representation for:
 - Data
 - Knowledge (Schemas are a subset of this)
 - Queries [results + def]
 - Models (Concepts)

Existing Approaches

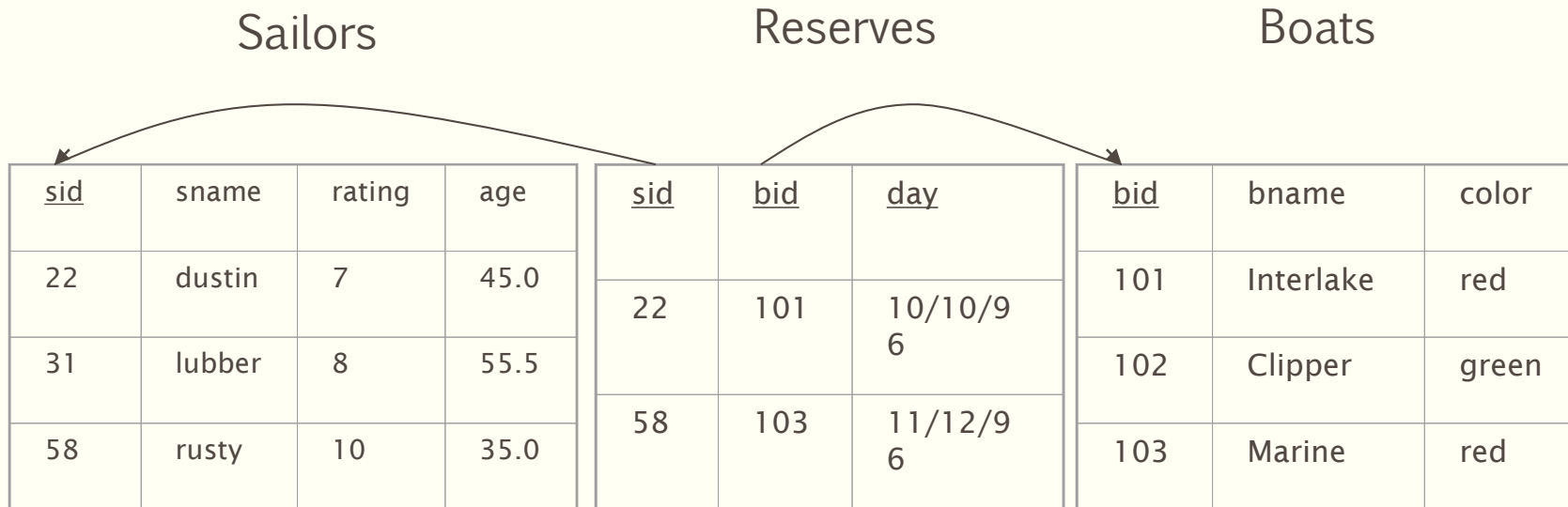
- RDBMS
 - Need schema renormalization
- Approaches that try to fix the above-mentioned problems:
 - OO Databases [P1], [P2] - graphs [but procedural]
 - XML Databases [P1] (somewhat [P3]) – trees
 - OORDBMS [P1] – graphs with foreign keys
 - RDF triple stores [P1, P2], somewhat [P3]
- Others
 - Datalog – more efficient fragment of Prolog
 - Network Models - graphs
 - Hierarchical Models – trees

What is a Graph Database?

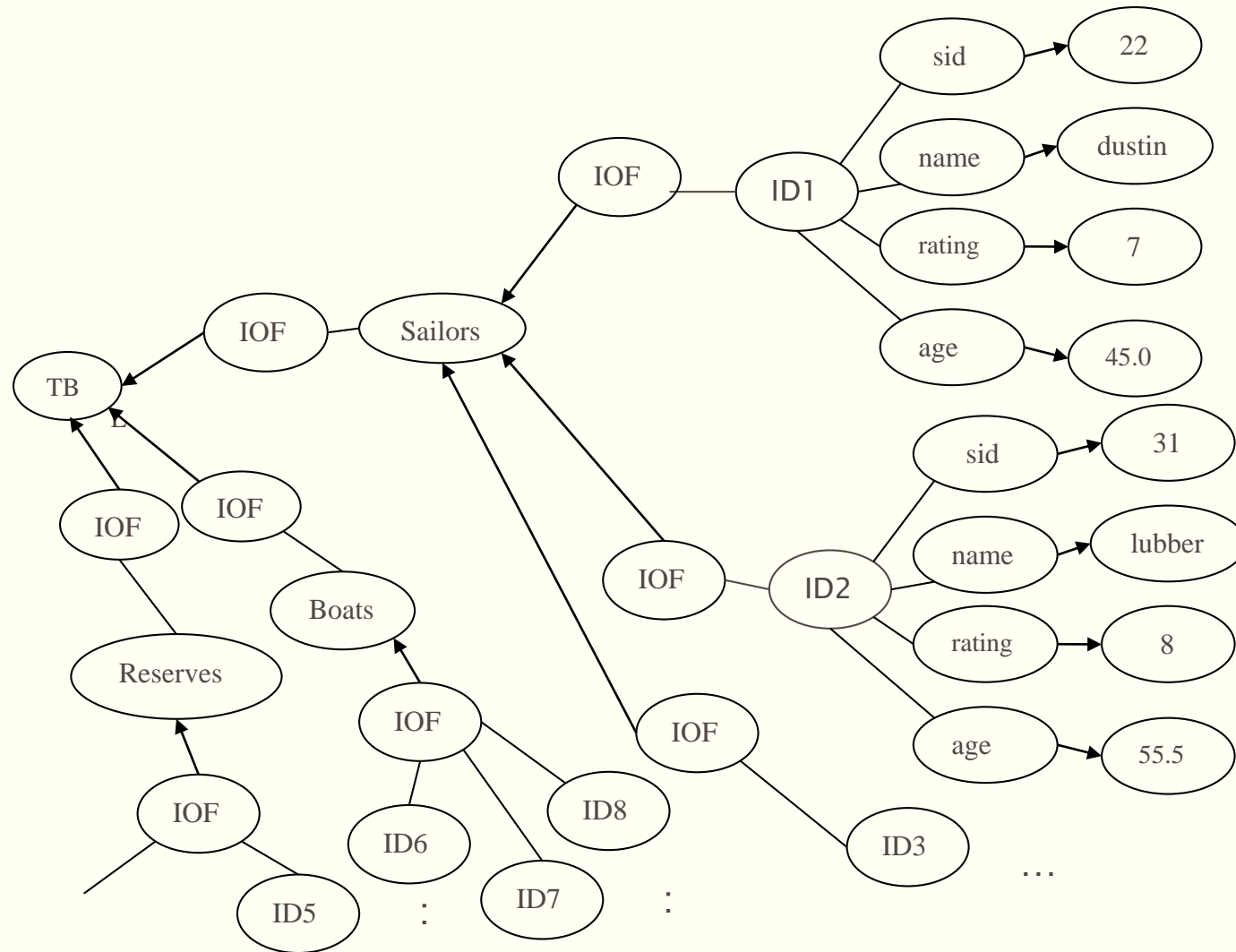
- A database with an explicit graph structure: Each node knows its adjacent nodes
- As the number of nodes increases, the cost of a local step (or hop) remains the same; Plus an Index for lookups
- Express Queries as Traversals. Fast deep traversal instead of slow SQL queries that span many table joins.
- Very natural to express graph related problem with traversals (recommendation engine, find shortest path etc..)
- Seamless integration with various existing programming languages.
 - Two design principle: Declarativity & Change
- Distinguish between “Database for graph as object”!

Database Representation

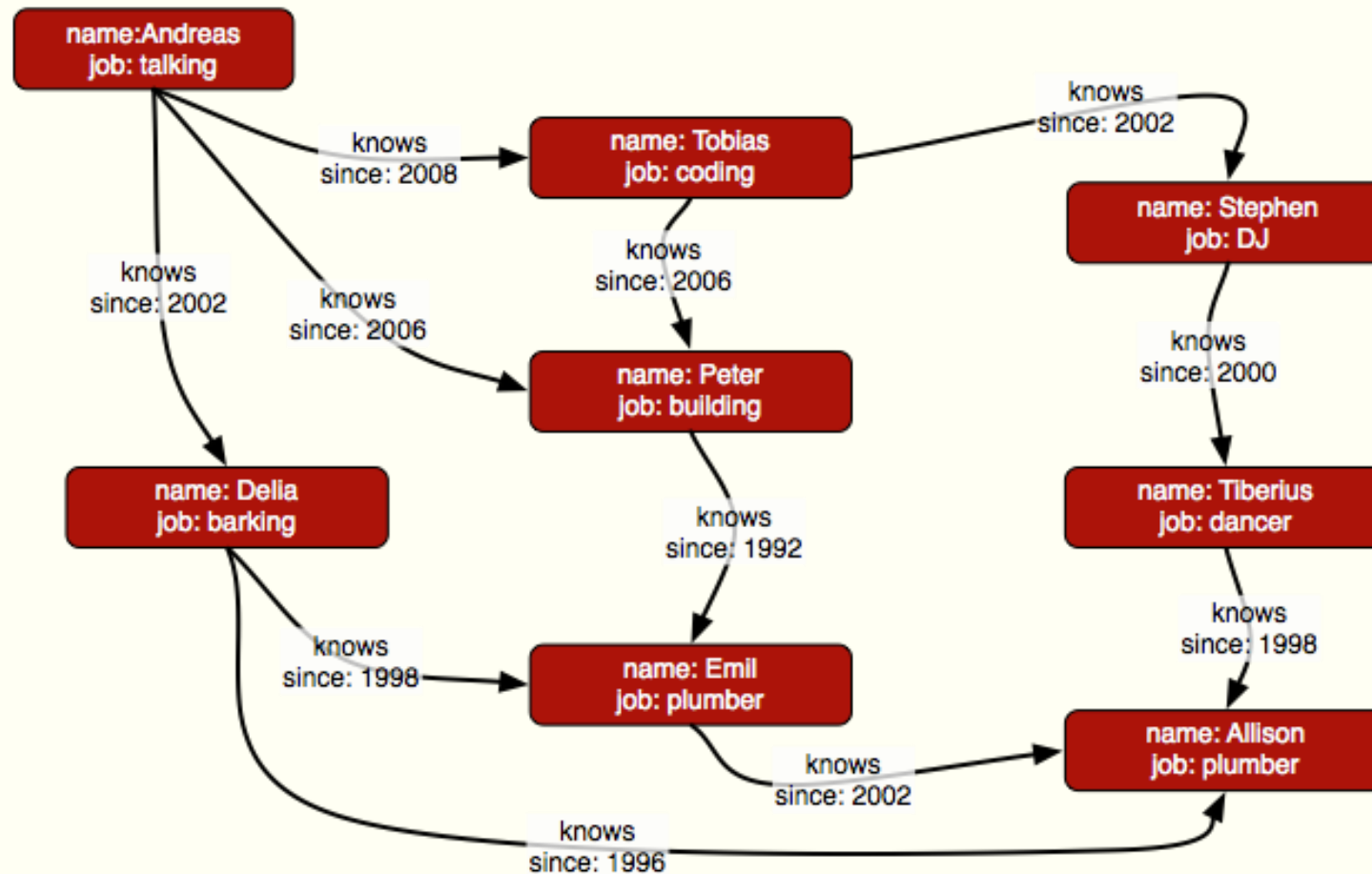
- Sailors(sid:integer, sname:char(10), rating: integer, age:real)
- Boats(bid:integer, bname:char(10), color:char(10))
- Reserve(sid:integer, bid:integer, day:date)



Graph Representation

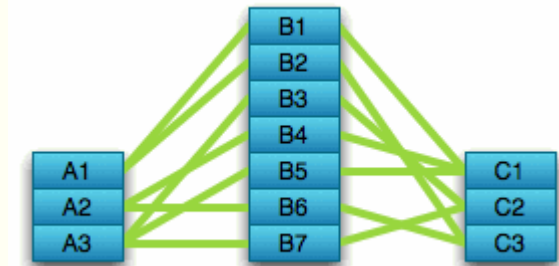


Property Graph

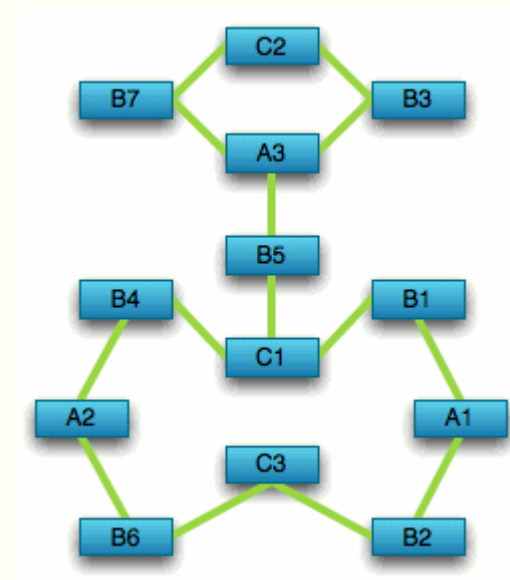


Compared to Relational Databases

Optimized for aggregation



Optimized for connections

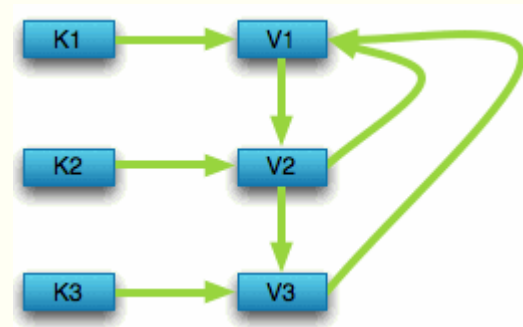


Compared to Key-Value Store

Optimized for
simple look-ups



Optimized for
traversing connected data



Social Network “path exists” Performance

- Experiment:
 - ~1k persons
 - Average 50 friends per person
 - `pathExists(a,b)` limited to depth 4

	# persons	query time
Relational database	1000	2000ms
Neo4j	1000	2ms
Neo4j	1000000	2ms

Neo4j?

- A Graph Database + Lucene Index
- Property Graph
- Full ACID (atomicity, consistency, isolation, durability) (?)
- High Availability (with Enterprise Edition)
- 32 Billion Nodes, 32 Billion Relationships, 64 Billion Properties
- Embedded Server
- REST API

Good For

- Highly connected data (social networks)
- Recommendations (e-commerce)
- Path Finding (how do I know you?)
- A* (Least Cost path)
- Data First Schema (bottom-up, but you still need to design)

Summary

- SQL Databases
 - Predefined Schema
 - Standard definition and interface language
 - Tight consistency (ACID)
 - Well defined semantics
- NoSQL Database
 - No predefined Schema
 - Per-product definition and interface language
 - Getting an answer quickly is more important than getting a correct answer (BASE)

Summary: noSQL Common Advantages

- Cheap, easy to implement (open source)
- Data are replicated to multiple nodes (therefore identical and fault-tolerant) and can be partitioned
 - Down nodes easily replaced
 - No single point of failure
- Easy to distribute
- Don't require a schema
- Can scale up and down
- Relax the data consistency requirement (CAP)

Summary: What are we giving up?

- joins
- group by
- order by
- ACID transactions (none are strict ACID!)
- SQL as a sometimes frustrating but still powerful query language
- easy integration with other applications that support SQL