TOR VERGATA
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Dipartimento di Ingegneria Civile e Ingegneria Informatica

NoSQL Data Stores

Corso di Sistemi e Architetture per Big Data
A.A. 2022/23
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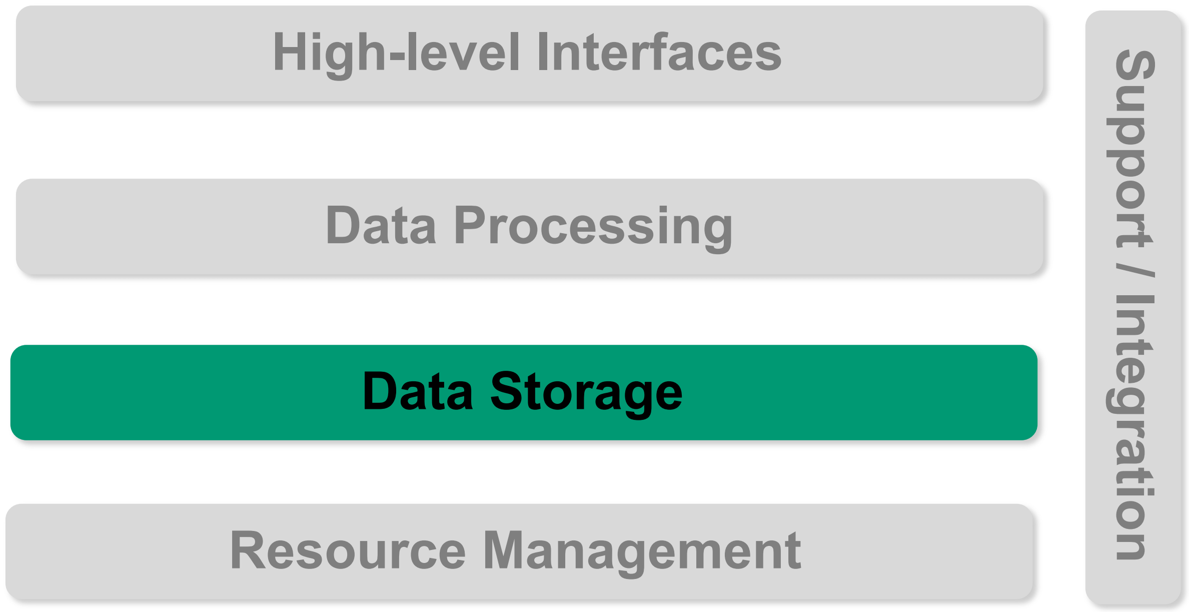
Laurea Magistrale in Ingegneria Informatica

The reference Big Data stack



Traditional RDBMSs

- Relational DBMSs (RDBMSs)
  – Traditional technology for storing structured data in web and business applications
- SQL is good
  – Rich language and toolset
  – Easy to use and integrate
  – Many vendors
- RDBMSs promise ACID guarantees

ACID properties

- **A**tomicity
  – All statements in a transaction are either executed or the whole transaction is aborted without affecting the database: "all or nothing" rule that is, transactions do not occur partially
- **C**onsistency
  – A database is in a consistent state before and after a transaction; it refers to the correctness of a database
- **I**solation
  – Transactions cannot see uncommitted changes in the database (i.e., the results of incomplete transactions are not visible to other transactions)
- **D**urability
  – Changes are written to disk (i.e., non-volatile memory) before a database commits a transaction so that committed data cannot be lost if a system failure occurs

RDBMS constraints

- Domain constraints
  - Restrict domain or set of possible values for each attribute
- Entity integrity constraints
  - No primary key value can be null
- Referential integrity constraints
  - To maintain consistency among tuples in two relations: every value of one attribute of a relation should exist as a value of another attribute in another relation
- Foreign key
  - To cross-reference between multiple relations: it is a key in a relation that matches the primary key of another relation

Pros and cons of RDBMS

Pros

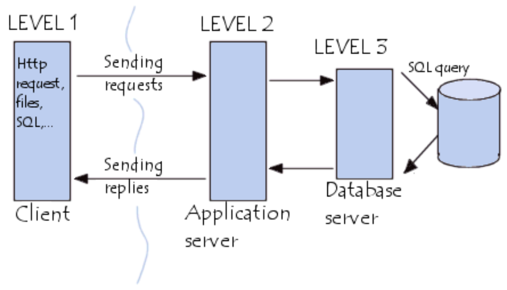
- Well-defined consistency model
- ACID guarantees
- Relational integrity maintained through entity and referential integrity constraints
- Well suited for OLTP apps
- Sound theoretical foundation
- Stable and standardized DBMSs available
- Well understood

Cons

- Performance as major constraint, scaling is difficult
- Limited support for complex data structures
- Complete knowledge of DB schema required to build new queries
- Commercial DBMSs are expensive
- Some DBMSs have field size limits
- Data integration from multiple RDBMSs can be cumbersome

RDBMS challenges

- Web apps cause spikes
  - Internet-scale data size
  - High read-write rates
  - Frequent schema changes



- Let's scale RDBMSs
  - But they were not designed to be distributed

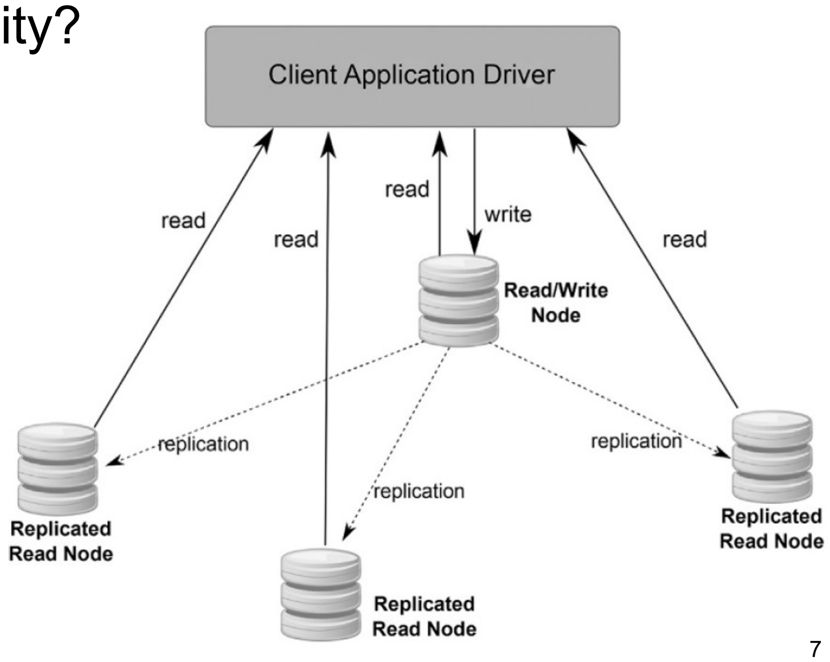
- How to scale RDBMSs?
  - Replication
  - Sharding

Replication

- Primary backup with master/worker architecture

✓ Replication improves read scalability

✗ Write scalability?



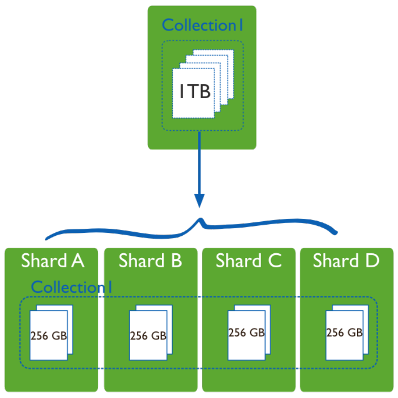
Sharding

- Horizontal partitioning of data across many separate servers

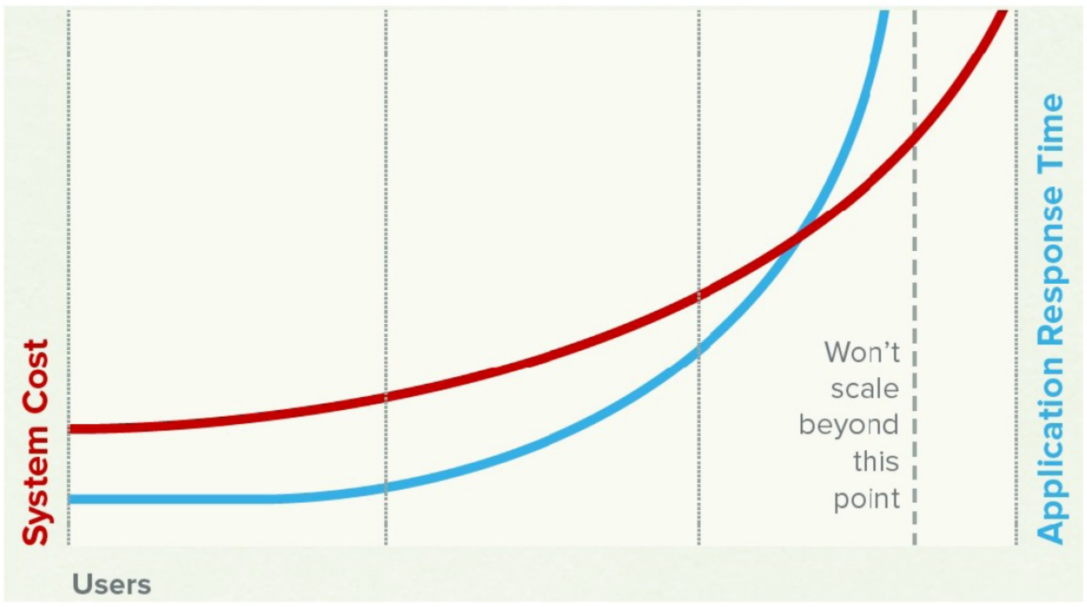
✓ Read and write operations scale

✗ Cannot execute transactions across shards (partitions)

- Consistent hashing can be use to determine *which* server any shard is assigned to
  - Hash both data and server using the same hash function in the same ID space



Scaling RDBMSs is expensive and inefficient



Source: Couchbase technical report

NoSQL data stores

DO YOU HAVE ANY EXPERTISE IN SQL?
NO
geek & poke
DOESN'T MATTER. WRITE: "EXPERT IN NO SQL"
Leverage the NoSQL boom

- NoSQL = **Not Only SQL**
  - SQL-style querying is not the crucial objective

NoSQL data stores: main features

- Support flexible schema
  - No requirement for fixed rows in a table schema
  - Well suited for agile development process
- Support horizontal scaling
  - Partitioning of data and processing over multiple nodes
- Provide high availability
  - By replicating data in multiple nodes, often geo-distributed
- Mainly utilize shared-nothing architecture
  - With exception of graph-based databases
- Avoid unneeded complexity
  - E.g., elimination of join operations
- Support weaker consistency models
  - **BASE** rather than ACID: compromising reliability for better performance

ACID vs BASE: ACID

- Two design philosophies at opposite ends of the consistency-availability spectrum
  - Keep in mind **CAP theorem**

*Pick two of **C**onsistency, **A**vailability and **P**artition tolerance*

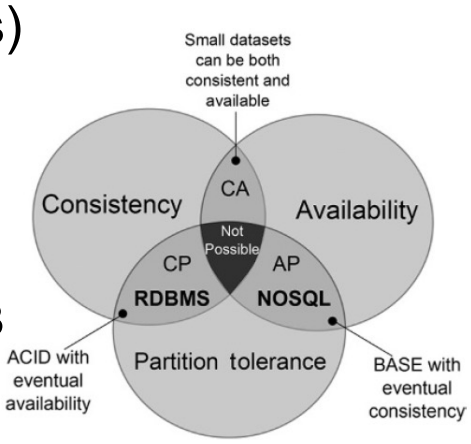
- ACID: traditional approach for RDBMSs
  - *Pessimistic* approach: prevents conflicts from occurring
    - Usually implemented with write locks managed by system
    - Leads to performance degradation and deadlocks (hard to prevent and debug)
  - Does not scale well when handling petabytes of data (remember of latency!)

ACID vs BASE: BASE

- **BASE**: **B**asically **A**vailable, **S**oft state, **E**ventual consistency
  - **B**asically **A**vailable: the system is available most of the time and there could exist a subsystem temporarily unavailable
  - **S**oft state: data is not durable that is, its persistence is in the hand of the user that must take care of refreshing it
  - **E**ventually consistent: the system eventually converges to a consistent state
- Optimistic approach
  - Lets conflicts occur, but detects them and takes action to sort them out: how?
    - *Conditional updates*: test the value just before updating
    - *Save both updates*: record that they are in conflict and then merge them

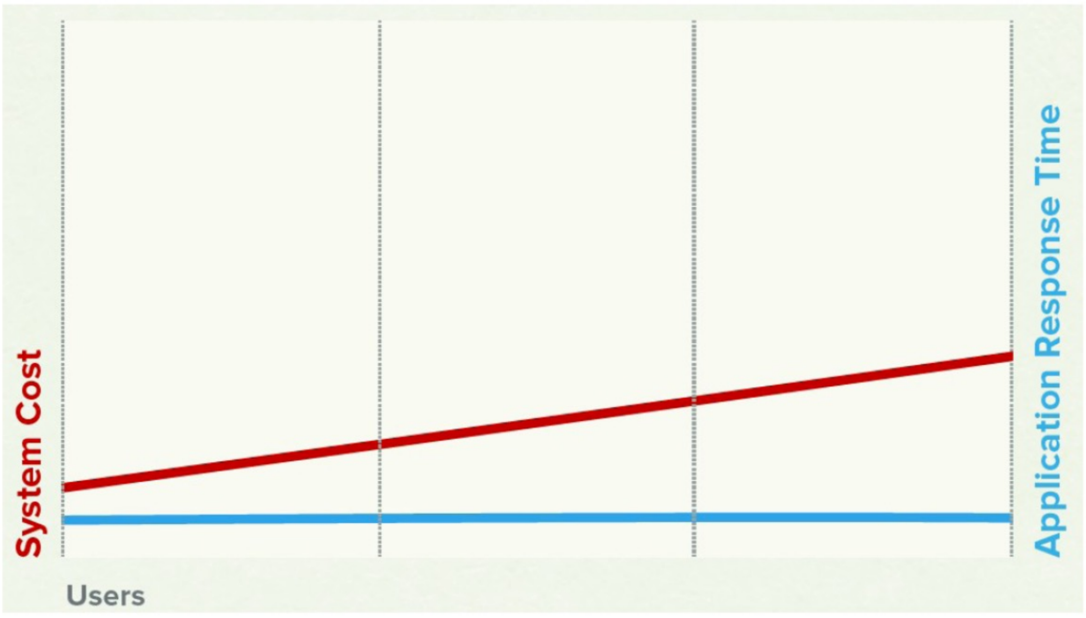
NoSQL and consistency

- Biggest change from RDBMS
  - RDBMS: strong consistency
  - Traditional RDBMS are CA systems (or CP systems, depending on configuration)
- Majority of NoSQL systems provide eventual consistency (i.e., AP systems)
- Some NoSQL systems provide strong consistency or *tunable* consistency
  - E.g., Cassandra and MongoDB



Small datasets can be both consistent and available
Consistency
CA
Availability
Not Possible
CP
AP
RDBMS
NOSQL
ACID with eventual availability
Partition tolerance
BASE with eventual consistency

NoSQL cost and performance



Source: Couchbase technical report

Pros and cons of NoSQL

Pros

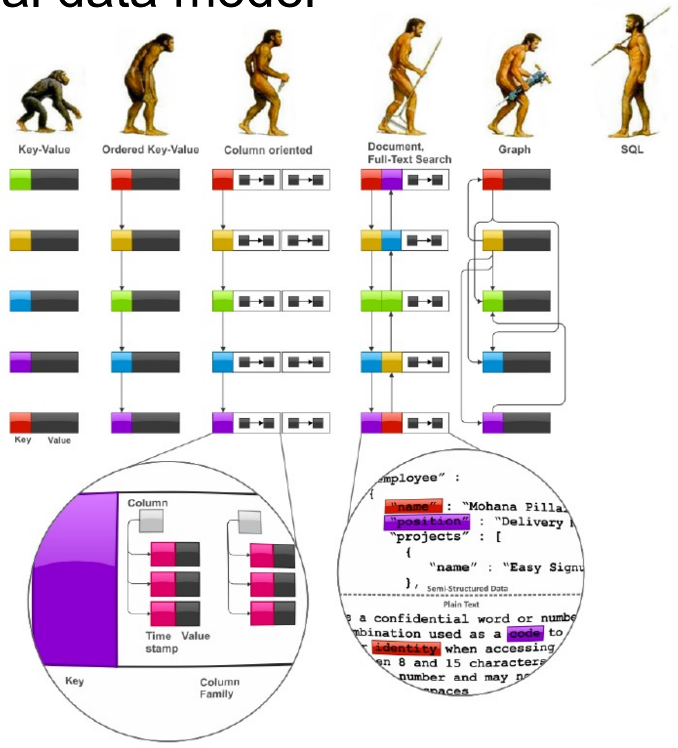
- Easy to scale-out
- Higher performance for massive data scale
- Allow data sharing across multiple servers
- HA and fault tolerance provided by data replication
- Most are either open-source or cheaper
- Support complex data structures and objects
- No fixed schema, support unstructured data
- Fast retrieval of data, suitable for real-time apps

Cons

- Many do not support ACID, less suitable for OLTP apps
- No common data storage model -> No well defined approach for DB design
- Lack of standardization (e.g., specific query languages)
- Less support for aggregation ops (e.g., sum, avg, count, group by)
- Many do not support join ops
- Lack of reference model can lead to solution lock-in

NoSQL data models

- A number of largely diverse data stores not based on relational data model



NoSQL data models

- *Data model*: set of constructs for representing information
  - Relational model: tables, columns and rows
- *Storage model*: how the data store management system stores and manipulates data internally
- A data model is usually independent of the storage model
- Data models for NoSQL systems:
  - Aggregate-oriented models: **key-value (KV)**, **document**, and **column-family**
  - **Graph-based** models

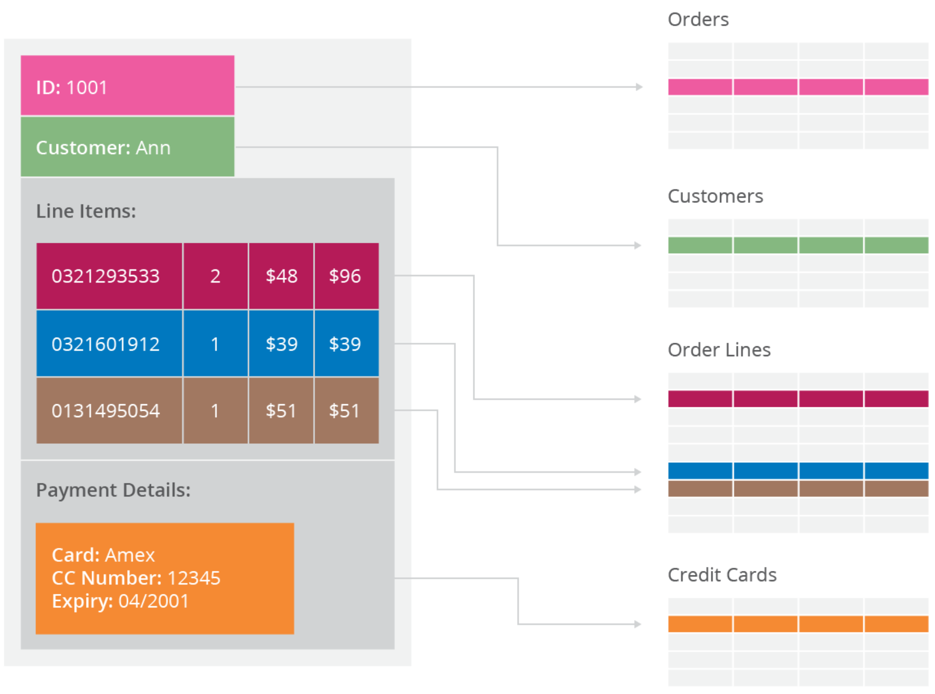
Aggregates

- Data as single unit with a complex structure
  - More structure than just a set of tuples
  - E.g., complex record with simple fields, arrays, records nested inside
- Aggregate pattern in Domain-Driven Design
  - Cluster of domain objects that we treat as a unit (e.g., order and its items, playlist and its songs)
  - Unit for data manipulation and consistency management
- Advantages of aggregates
  - Easier for application programmers to work with
  - Easier for data store systems to handle ops

See thght.works/1XqYKB0

Aggregates: example

- With NoSQL
- With RDBMS



Transactions?

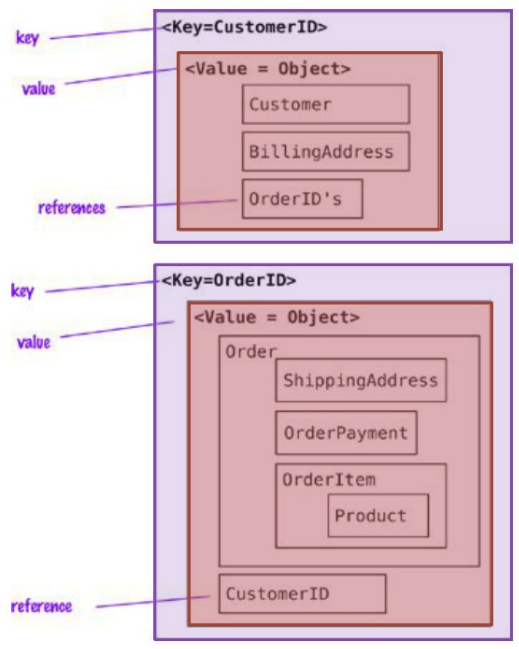
- Relational databases have ACID transactions
- Aggregate-oriented data stores
  - Support atomic transactions, but only *within* single aggregate
  - Most data stores don’t have ACID transactions that span multiple aggregates
    - In case of update over multiple aggregates: possible inconsistent reads

  ☞ Take it into account when deciding how to aggregate data
- Graph databases tend to support ACID transactions

Key-value (KV): data model

- Simple data model: data is represented as a schema-less collection of key-value pairs
  - Associative array (map or dictionary) as fundamental data model
- Strongly aggregate-oriented
  - Lots of aggregates
  - Each aggregate has a key
- Data model:
  - Set of <key, value> pairs
  - Value: aggregate instance
- Aggregate is opaque to data store
  - Just a big blob of mostly meaningless bits
- Access to aggregate: lookup based on its key
- Richer data models can be implemented on top

KV: data model example



KV: types of data stores

- Some data stores support key ordering
  - Data is stored sorted by key in a particular order (e.g., lexicographic) to handle keys more easily
- Some maintain data in RAM, while others employ HDDs, SSDs or even flash memory
- Some let developers implement user-defined functions (UDFs) to extend the data store processing capabilities
- Wide range of consistency models

KV: consistency

- Consistency ranges from weak (e.g., eventual) to strong (e.g., serializability)
  - Serializability: guarantee about transactions over multiple items
    - It guarantees that the execution of a set of transactions (with read and write operations) over multiple items is equivalent to some serial execution (total ordering) of the transactions
    - Gold standard in DB community: serializability is the traditional Isolation in ACID
  - Examples:
    - AP: Dynamo, Riak KV
    - CP: Redis, Berkeley DB

KV: query features

- Only query by the key!
  - There is a key and there is the rest of the data (the value)
- Basic ops: put(key,value), get(key), delete(key)
- Most KV data stores provide access operations on groups of related key-value pairs
- Cannot lookup for some attribute of the value
  - E.g., KV stores usually do not have a WHERE clause such as RDBMSs or if they do, it requires a slow scan of all values
- The key needs to be suitably chosen
  - E.g., session ID for storing session data
- What if we don't know the key?
  - Some KV system allows to search inside the value using a full-text search (e.g., using Apache Solr)

KV: suitable use cases

- Session info in web app
  - Each user session has a unique id: session id as key
  - Store session data using a single put, retrieve using get
- User profile and preferences
  - Almost every user has a unique user id, username, …, as well as preferences such as language, list of searched and recommended, …
  - Put preferences of a user into the value, so getting takes a single operation
- Shopping cart data
  - Put shopping information into the value, whose key is the user id
- Product recommendations

KV: products

- Amazon's Dynamo is the most notable example
  - Riak KV: open-source implementation
- Other KV data stores include:
  - Amazon DynamoDB: data model and name from Dynamo, but different implementation
  - Berkeley DB: open-source embedded library (not distributed!), key ordering (based on Btree+)
  - Oracle NoSQL Database
  - upscaledb
  - LevelDB: by Google, a KV storage library with key ordering
  - RocksDB: by Facebook, evolution of LevelDB
  - Memcached, Redis, Hazelcast: distributed in-memory KV data stores
  - Ehcache: Java-based cache
  - Aerospike: tunable consistency (AP or CP)

Document: data model

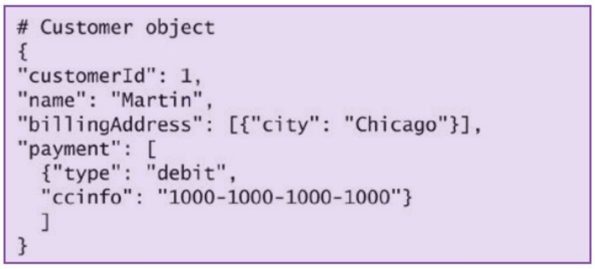
- Strongly aggregate-oriented
  - Lots of aggregates
  - Each aggregate has a key
- Document: collection of named fields and data
  - Encapsulates and encodes data in some standard formats or encodings: JSON, BSON, XML, YAML, …
- Similar to key-value store (unique key), but API or query/update language to query or update based on document's internal structure
  - Document content is no longer opaque
- Similar to column-family store, but values can have complex documents, instead of fixed format

Document: data model

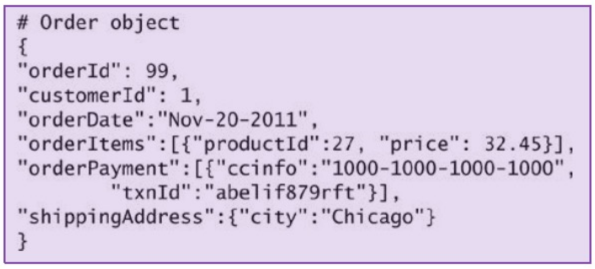
- Data model
  - A set of <key, document> pairs
  - Document: an aggregate instance
- Aggregate structure is visible
  - Limits on what we can place in it
- Access to aggregate
  - Queries based on the fields in the aggregate
- Flexible schema
  - Documents do not need to have same structure
  - Better flexibility: apps can store different data in documents as business requirements change
    - No need of schema migration efforts

Document: data model example

- JSON format



```
# Customer object
{
"customerId": 1,
"name": "Martin",
"billingAddress": [{"city": "Chicago"}],
"payment": [
  {"type": "debit",
  "ccinfo": "1000-1000-1000-1000"}
  ]
}
```



```
# Order object
{
"orderId": 99,
"customerId": 1,
"orderDate":"Nov-20-2011",
"orderItems":[{"productId":27, "price": 32.45}],
"orderPayment":[{"ccinfo":"1000-1000-1000-1000",
        "txnId":"abelif879rft"}],
"shippingAddress":{"city":"Chicago"}
}
```

Document: data store API

- Usual CRUD operations (not standardized)
  - Create (or insert)
  - Retrieve (or get, query, search, find)
    - Not only simple key-to-document lookup
    - Query language allows the user to retrieve documents based on the values of one or more fields
  - Update (or edit)
    - Not only the entire document but also individual fields of the document
  - Delete (or remove)
- Read and write operations over multiple fields in a single document are usually atomic
- Some document data stores support indexing to facilitate fast lookup of documents

KV vs. document data stores

- KV data store
  - A key plus a big blob of mostly meaningless bits
  - Can store whatever you like in the aggregate
  - Can only access an aggregate by lookup based on its key
- Document data store
  - A key plus a structured aggregate
  - More flexibility in accessing and updating data
    - Can query based on aggregate fields
    - Can retrieve/update part of the aggregate rather than the whole aggregate
  - Can create indexes based on aggregate content
    - In general, indexes speed up read accesses but slow down write accesses, thus should be designed carefully

KV vs. document data stores

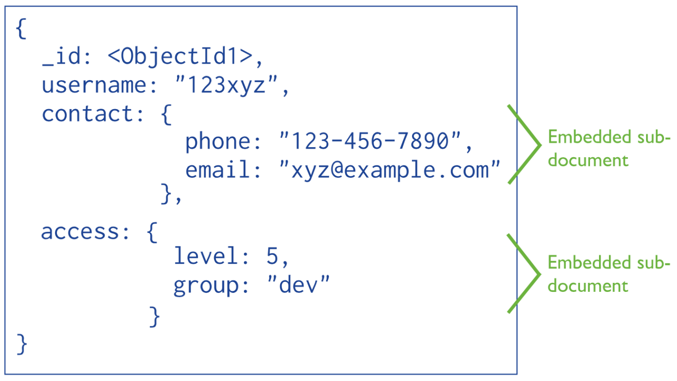
- The line between KV and document gets a bit blurry
  - People often use document store to do a simple KV style lookup
- Data stores classified as KV may allow you to structure data beyond just an opaque, e.g.,
  - Redis allows you to break down the aggregate into lists or sets
  - Riak KV allows you to put aggregates into buckets
  - Others support querying by search tools

Some data model design choices

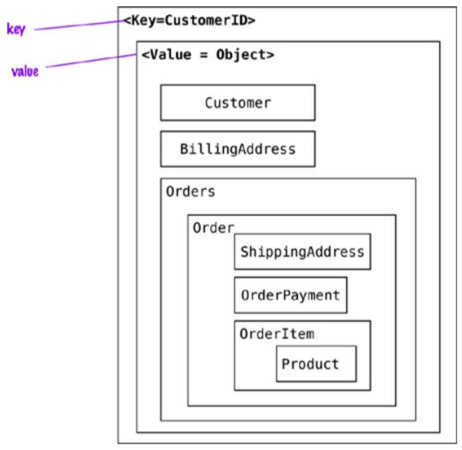
- Be careful: no universal rule
  - It depends on how your app tends to manipulate data!
- How to model 1:N relationship
  - Simple rule of thumb: how large is N?
    - One-to-few: embedding
    - One-to-many: referencing
    - One-to-squillions: parent-referencing
  - See some example www.mongodb.com/blog/post/6-rules-of-thumb-for-mongodb-schema-design-part-1

Some data model design choices

- Denormalization
  - Denormalized data models embed related data in a single document



```
{
  _id: <ObjectId1>,
  username: "123xyz",
  contact: {
              phone: "123-456-7890",
              email: "xyz@example.com"
            },
  access: {
             level: 5,
             group: "dev"
           }
}
```



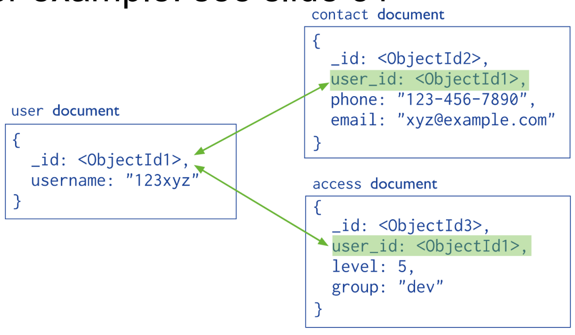
  - See docs.mongodb.com/manual/core/data-modeling-introduction

Some data model design choices

- Denormalization
  - Pros:
    - ✓ Store related pieces of information in same document: fewer queries and updates
    - ✓ Update data within same document in a single atomic write operation
  - Cons:
    - ✗ Document size limit (e.g., 16MB in MongoDB) docs.mongodb.com/manual/core/document
    - ✗ Cannot perform atomic update on multiple documents
    - ✗ Only makes sense when high read to write ratio

Some data model design choices

- Normalization
  - Normalized data models describe relationships using references between documents
    - Another example: see slide 31



```
{
  _id: <ObjectId1>,
  username: "123xyz"
}
```

```
{
  _id: <ObjectId2>,
  user_id: <ObjectId1>,
  phone: "123-456-7890",
  email: "xyz@example.com"
}
```

```
{
  _id: <ObjectId3>,
  user_id: <ObjectId1>,
  level: 5,
  group: "dev"
}
```

  - In general, use normalized data models
    - When embedding would result in duplication of data but would not provide sufficient read performance gains
    - To represent complex many-to-many relationships
    - To model large hierarchical datasets

Document: suitable use cases

- Good for storing and managing big data collections of semi-structured data with a varying number of fields
  - Textual documents, email messages, …
  - Conceptual documents like denormalized representations of DB entities (e.g., product, customer)
  - Sparse data in general, i.e., irregular (semi-structured) data that would require an extensive use of nulls in RDBMS
    - Nulls being placeholders for missing or nonexistent values
- Examples of use cases
  - Log data
  - Product data management (e.g., catalogue)
  - Content personalization
  - User comments (e.g., blog posts)

Document: when not to use

- Complex transactions spanning multiple documents
  - MongoDB 4.x supports distributed transactions but they incur greater performance cost over single-document writes
  - Consider embedding rather than referencing
- Queries against varying aggregate structure
  - Since data is saved as an aggregate, if aggregate structure constantly changes, the aggregate is saved at the lowest level of granularity. In this scenario, document data stores may not perform well

Document: products

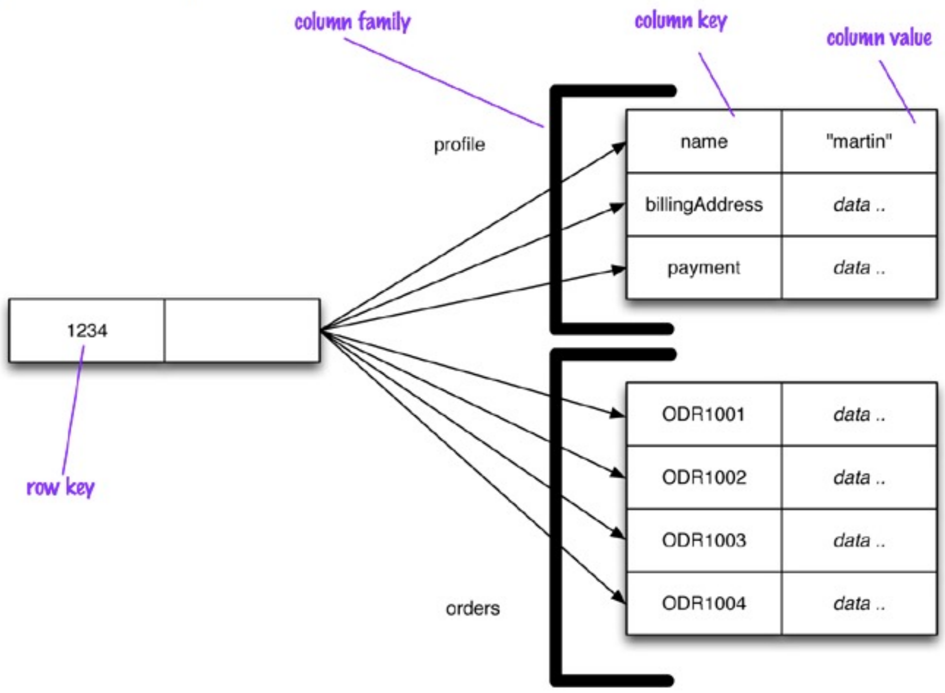
- MongoDB: the most popular
- Aerospike: both KV and document models
- ArangoDB
- Couchbase
- Apache CouchDB
- RavenDB: open source, student licence available
  - ACID, multi-master replication using Raft
- Cloud services
  - Amazon DocumentDB (with MongoDB compatibility)
  - Microsoft Azure CosmosDB
- Some of them (e.g., Aerospike, ArangoDB) are multi-model data stores

Column-family: data model

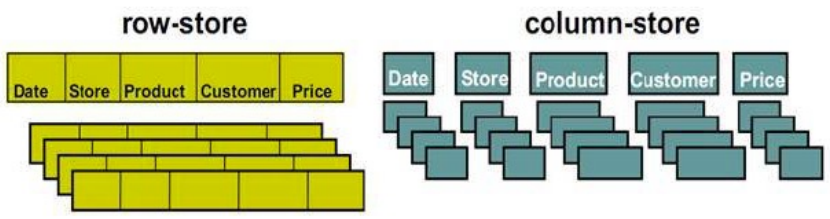
- Strongly aggregate-oriented
  - Lots of aggregates
  - Each aggregate has a key
- Data model: two-level map structure
  - A set of <row-key, aggregate> pairs
  - Each aggregate is a group of pairs <column-key, value>
  - Column: a set of data values of a particular type
- Similar to key-value store, but value can have multiple attributes (*columns*)
- Similar to document store because aggregate structure is visible
- Columns can be organized in families
  - Data usually accessed together

Column-family: data model example

- Representing customer information as column-family



Row-store vs. column-store organization



- Row-store systems: store and process data by rows
  - However, RDBMSs support indexes to improve performance of set-wide operations on whole tables
- Column-store systems: store and process data by columns
  - Can access data faster rather than scanning and discarding unwanted data in row, e.g., for aggregate queries (avg, max, …)
  - Examples: C-Store (pre-NoSQL), Vertica, MariaDB ColumnStore
  - Do not confuse them with column-family data stores

Column-family: features

- Column-family data stores: no column stores in the original sense of the term, because they have a two-level structure with column families
- Table's rows and columns can be split over multiple servers by means of sharding to achieve scalability
- In addition, column families are located on the same partition to facilitate query performance
- Column-family stores are suitable for read-mostly, read-intensive, large data repositories

Column-family: features

- Each column:
  - Has to be part of a single column family
  - Acts as unit for access
- Can get a particular column
  - See slide 43: `get('1234', 'name')`
- Can add any column to any row, and rows can have different columns
- Two ways to think about how data is structured:
  - Row-oriented
    - Each row is an aggregate (e.g., customer with id 1234)
    - Column families represent useful chunks of data within that aggregate (e.g., profile, order history)
  - Column-oriented
    - Each column family defines a record type (e.g., customer profiles)
    - A row is the join of records in all column families

Column-family: suitable use cases

- Queries that involve only a few columns
- Aggregation queries against vast amounts of data
  - E.g., average, maximum
- Apps with truly large volumes of data, such as PBs
- Apps that are geographically distributed over multiple data centers
  - See Cassandra geo-distribution

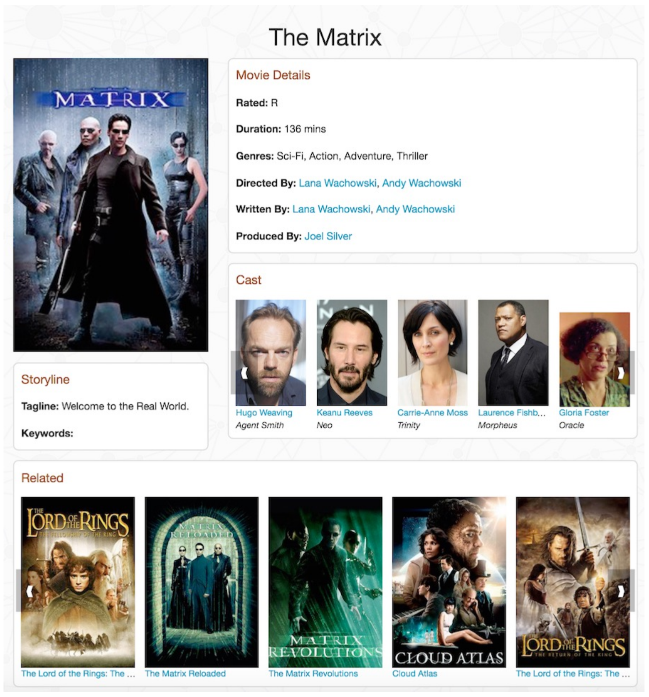
Column-family: products

- Google's Bigtable is the most notable, uses GFS for distributed data storage
- Apache HBase: open-source implementation of Bigtable on top of HDFS
  - Apache Phoenix: SQL query engine on top of HBase
- Other popular column-family data stores
  - Apache Accumulo: based on Bigtable design, uses HDFS to store data and Zookeeper for consensus
    - Different APIs and different nomenclature from HBase, but same in operational and architectural standpoint
    - Better security
  - Apache Cassandra
- Cloud services
  - Google Cloud Bigtable
  - HBase through Amazon EMR or Azure HDInsight

Graph: data model

- Uses graph structure with nodes, edges, and properties to represent stored data
  - Nodes are the entities
    - E.g., users, posts
  - Edges are the relationships between the entities
    - E.g., a user posts a comment
  - Edges can be directed or undirected
  - Nodes and edges also have a set of properties (attributes) consisting of key-value pairs
- Replaces relational tables with structured relational graphs of interconnected key-value pairs

Graph: data model example



The Matrix

Movie Details

Rated: R

Duration: 136 mins

Genres: Sci-Fi, Action, Adventure, Thriller

Directed By: Lana Wachowski, Andy Wachowski

Written By: Lana Wachowski, Andy Wachowski

Produced By: Joel Silver

Storyline

Tagline: Welcome to the Real World.

Keywords:

Cast

Hugo Weaving *Agent Smith*

Keanu Reeves *Neo*

Carrie-Anne Moss *Trinity*

Laurence Fishb... *Morpheus*

Gloria Foster *Oracle*

Related

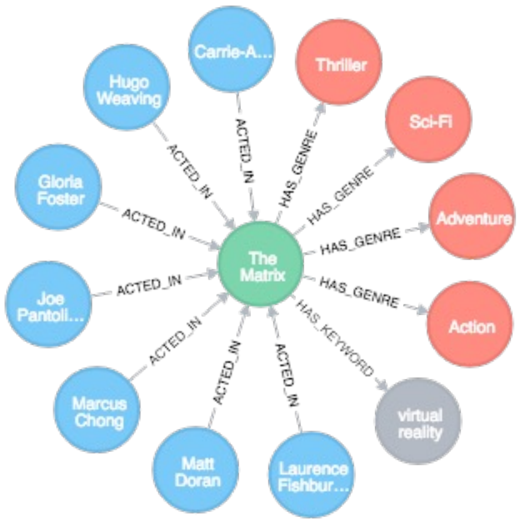
The Lord of the Rings: The ...

The Matrix Reloaded

The Matrix Revolutions

Cloud Atlas

The Lord of the Rings: The ...



github.com/neo4j-graph-examples/movies

Graph: data model

- Powerful data model
  - Differently from other types of NoSQL stores, it concerns itself with relationships
  - Focus on visual representation of information: more human-friendly than other NoSQL stores
  - Other types of NoSQL stores are poor for interconnected data
- Ad-hoc languages to query and manipulate data in graphs, e.g.,
  - Cypher: declarative language, see slides on Neo4j
  - Gremlin: functional, data-flow language

Graph databases: pros and cons

- Pros:
  - Explicit graph structure
  - Each node knows its adjacent nodes: as number of nodes increases, cost of local hop is the same
  - Can define indexes to make lookups more efficient
- Cons:
  - Sharding data by distributing it on multiple servers to achieve horizontal scalability
    - More difficult than for other types of NoSQL data stores
    - If graph data is stored on different servers, traversing multiple servers is not performance-efficient
  - Require a design effort with respect to SQL

Graph databases vs. aggregate-oriented stores

- Very different data models
- Aggregate-oriented data stores
  - Distributed on multiple servers, also geographically
  - Simple query languages
  - No ACID guarantees
- Graph databases
  - More likely to run on single server (but distributed architectures exist, e.g., OrientDB)
  - Graph-based query languages
  - ACID guarantees: transactions maintain consistency over multiple graph nodes and edges

Graph databases: suitable use cases

- Good for apps where you need to model entities and relationships between them, e.g.,
  - Social networking
  - Dependency analysis
  - Recommender systems
  - Fraud detection
  - Drug discovery
  - Network security
- Good for apps in which focus is on querying for relationships between entities and analyzing relationships
  - Computing relationships and querying related entities is simpler and faster than in RDBMS

Graph databases: products

- Neo4j
- InfiniteGraph: proprietary, distributed
- MemGraph: open source, in-memory
- NebulaGraph: open source, distributed
- OrientDB: open source, distributed, multi-model
- Apache Tinkerpop
  - Not properly a DB but rather a computing framework for graph databases (OLTP) and graph analytic systems (OLAP)
  - Gremlin as graph traversal language
- Cloud services:
  - Amazon Neptune
  - Azure Cosmos DB (multi-model)

Case studies

- Key-value data stores
  - Amazon's Dynamo (and Riak KV)
  - Redis
- Document-oriented data stores
  - MongoDB
- Column-family data stores
  - Google's Bigtable and Hbase
  - Cassandra
- Graph databases
  - Neo4j

In blue: Hands-on lessons

Case study: Amazon's Dynamo

- Highly available and scalable distributed key-value data store built for Amazon's platform
  - A very diverse set of Amazon applications with different storage requirements
  - Need for storage technologies that are always available on a commodity hardware infrastructure
    - E.g., shopping cart service: "Customers should be able to view and add items to their shopping cart even if disks are failing, network routes are flapping, or data centers are being destroyed by tornados"
  - Meet stringent Service Level Agreements (SLAs)
    - E.g., "service guaranteeing that it will provide a response within 300ms for 99.9% of its requests for a peak client load of 500 requests per second."

G. DeCandia et al., Dynamo: Amazon's highly available key-value store, *Proc. of ACM SOSP '07*

Dynamo: Features

- Simple key-value API
  - Simple operations to read (get) and write (put) objects uniquely identified by a key
  - Each operation involves only one object at time
- Focus on eventually consistent store
  - Sacrifice consistency for availability
  - BASE rather than ACID
- Efficient usage of resources
- Scale-out to manage increasing data or request rates
- Internal use
  - Security is not an issue since operation environment is assumed to be non-hostile

Dynamo: Design principles

- Sacrifice consistency for availability: AP system
- Use optimistic replication techniques
- Possible conflicting changes must be detected and resolved: *when* to resolve them and *who* resolves them?
  - *When*: execute conflict resolution *during reads* rather than writes, i.e., "always writeable" data store
  - *Who*: data store or application; if data store, use simple policy (e.g., "last write wins")
- Other key principles:
  - Incremental scalability
    - Scale-out with minimal impact on the system
  - Symmetry and decentralization
    - P2P techniques
  - Heterogeneity

Dynamo: API

- Each stored object has an associated key
- Simple API including `get` and `put` operations to read and write objects

  `get(key)`
    - Returns single object or list of objects with conflicting versions and context
    - Conflicts are handled on reads, never reject a write

  `put(key, context, object)`
    - Determines where the replicas of the object should be placed based on the associated key, and writes the replicas to disk
    - Context encodes system metadata, e.g., version number

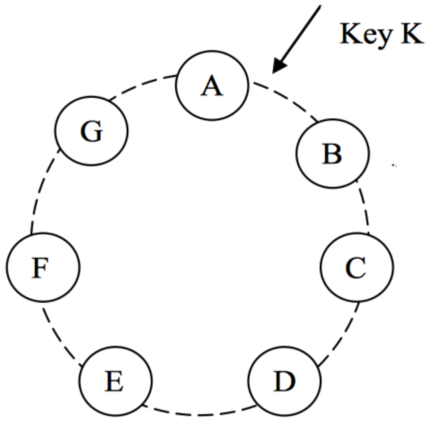
  – Both key and object treated as opaque array of bytes
  – Key: 128-bit MD5 hash applied to client supplied key

Dynamo: Used techniques

Problem	**Technique**	**Advantage**
Partitioning	Consistent hashing	Incremental scalability
High Availability for writes	Vector clocks with reconciliation during reads	Version size is decoupled from update rates
Handling temporary failures	Sloppy Quorum and hinted handoff	Provides high availability and durability guarantee when some of the replicas are not available
Recovering from permanent failures	Anti-entropy using Merkle trees	Synchronizes divergent replicas in the background
Membership and failure detection	Gossip-based membership protocol and failure detection	Preserves symmetry and avoids having a centralized registry for storing membership and node liveness information

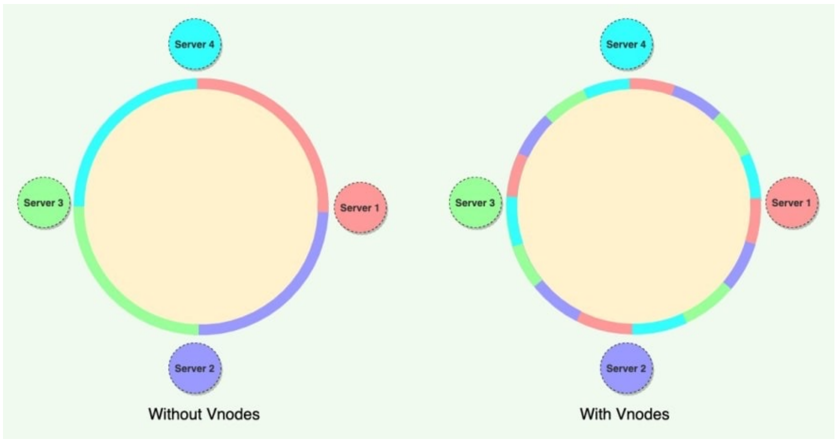
Dynamo: Data partitioning

- Consistent hashing: server nodes and data are both mapped on the same ring using MD5 hashing algorithm (similar to Chord)
  - MD5(key) -> node (position on ring)
  - Differently from Chord: zero-hop DHT, i.e., all nodes know about all nodes; complete routing table
  - The node handling the client request is known as *coordinator*



Dynamo: Data partitioning

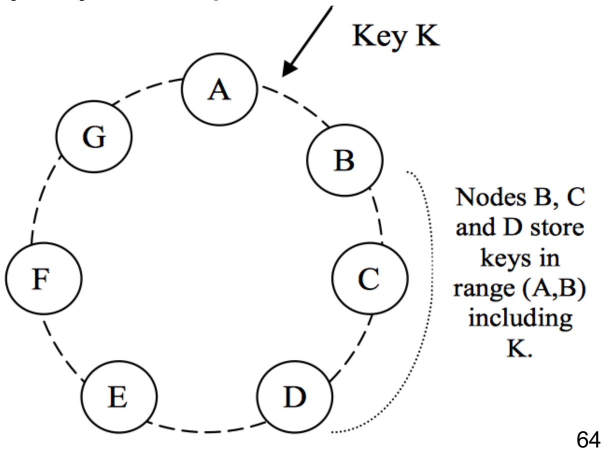
- To address load balance and heterogeneous servers, Dynamo introduces virtual nodes
  - Each physical node can be responsible for multiple virtual nodes
  - Powerful physical nodes can host more virtual nodes (# virtual nodes ∝ capacity)



Source: How to Use Consistent Hashing in a System Design Interview?

Dynamo: Replication

- Each object is replicated on *N* nodes
  - *N* is a configurable *replication factor*, set per application
  - The coordinator plus *N*-1 clockwise successor nodes
- *Preference list*: list of nodes that are responsible for storing a particular key
  - More than *N* nodes to account for node failures
  - See figure: object identified by key K is replicated on nodes B, C and D
    - Node D will store keys in ranges (A, B], (B, C], and (C, D]



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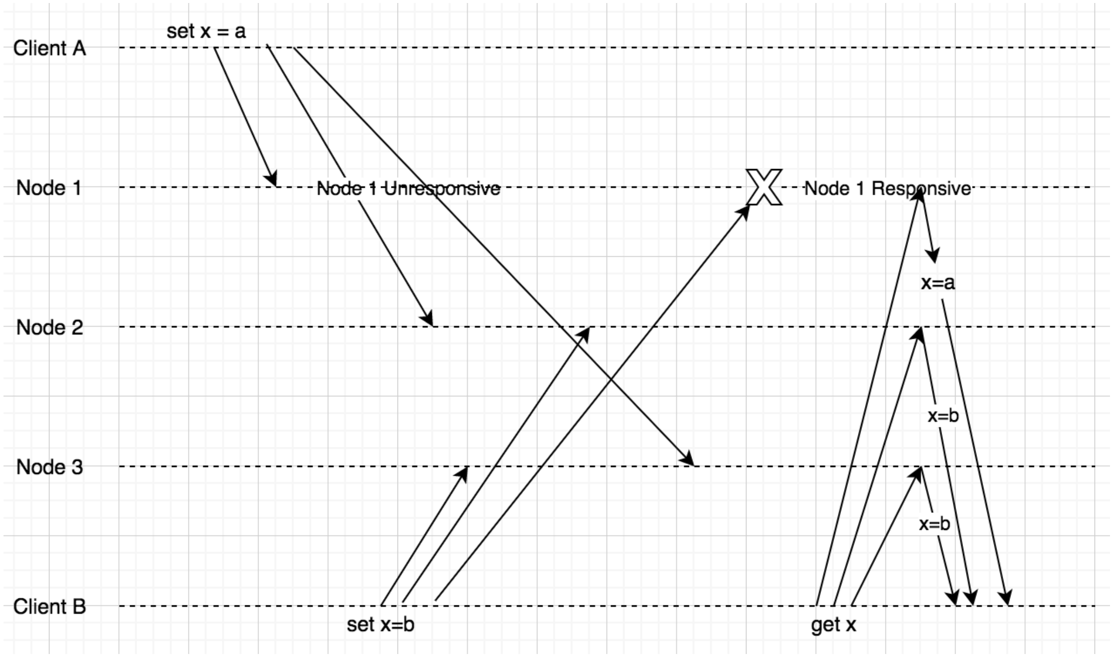
Dynamo: Data versioning

- `put()` may return to client before update has been applied to all replicas
- `get()` may return an object version that does not have the latest update
- Version branching can also happen due to node/network failures
- Problem: multiple conflicting versions of same object, that Dynamo needs to reconcile
- Solution: use vector clocks to capture causality among conflicting versions
  - If causality: older versions can be forgotten (last write wins)
  - If concurrent: conflict exists, requiring reconciliation

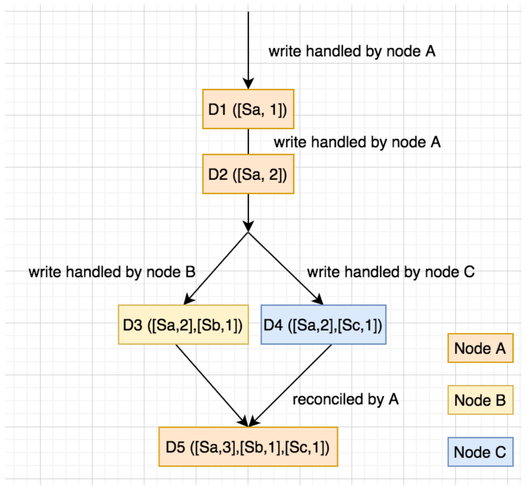
Dynamo: Data versioning

- Example: 2 conflicting versions of object x (x=a and x=b)



Dynamo: Data versioning

- Example: conflict resolution
  - A is the coordinator node for object x
  - Before 3rd write, A crashes and write is handled by B and C, but network partition between B and C occurs
  - When A resumes from crash, the two versions are reconciled



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Dynamo: put and get ops

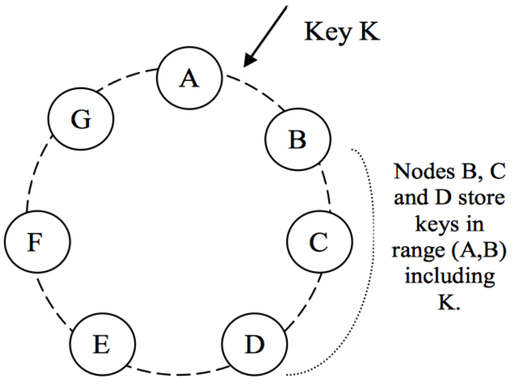
- *R* (*W*): minimum number of nodes that must participate in a successful read (write) op
- `put` op
  - The coordinator generates new vector clock and writes new version locally
  - Sends it to *N*-1 nodes
  - Waits for response from *W* nodes
- `get` op
  - The coordinator sends read requests to *N*-1 nodes
  - Waits for response from *R* nodes
  - If multiple conflicting versions, returns to client all versions that are causally unrelated (i.e., concurrent)
  - Conflicting versions are reconciled and winning version is written back

Dynamo: Sloppy quorum

- Setting $R + W > N$ yields a quorum-like protocol
  - `get` (or `put`) latency depends on the slowest replica
  - *R* and *W* are usually configured to be less than *N* to reduce latency
  - Typical configuration in Dynamo: $(N, R, W) = (3, 2, 2)$
    - To balance performance, durability, and availability
- *Sloppy* quorum
  - Due to network partitions, quorum might not exist
  - Sloppy quorum: create transient replicas (called *hinted* replicas)
    - *N* healthy nodes from the preference list (may not always be the first *N* nodes encountered while walking the ring)

Dynamo: Hinted handoff

- Hinted handoff for transient failures
- Consider *N* = 3; if A is temporarily down or unreachable, `put` will use D
- D knows that the replica belongs to A (since failure is transient)
- Later, D detects A is alive
  - Sends replica to A
  - Removes replica
- Again, "always writeable" principle



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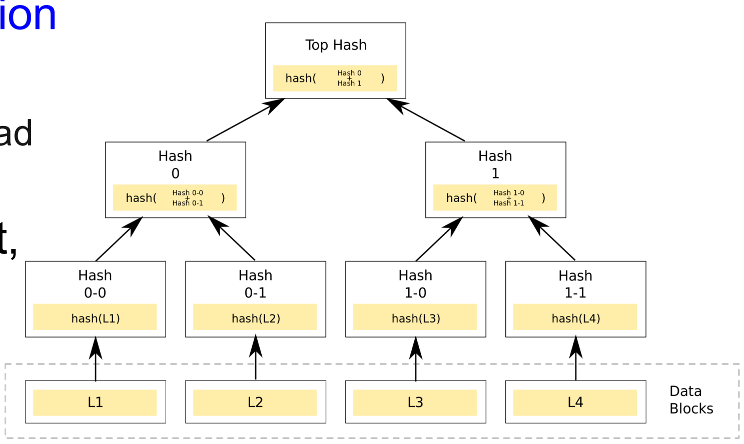
Dynamo: Membership management, failure detection and management

- Dynamo administrator explicitly adds and removes nodes
- Gossiping is used to propagate membership changes
  - Eventually consistent view
  - O(1) hop overlay
- Passive failure detection
  - Use pings only for detection from failed to alive
  - In the absence of client requests, node A doesn't need to know if node B is alive
- To recover after permanent failures or partitions and keep replicas synchronized, Dynamo uses an anti-entropy mechanism based on Merkle trees

Merkel tree

- Hash-based data structure that generalizes a hash list
- Tree structure in which every leaf node is a hash of a block of actual data and every non-leaf node is a hash of its child nodes
- Tree root summarizes all the data in one hash value
- Merkle trees are used in distributed systems for efficient data verification
  - Efficient because can transmit hashes instead of data blocks
- Used by Dynamo, Git, Cassandra, Bitcoin



Dynamo: Permanent failure management

- When a node fails and recovers, it needs to quickly determine whether it needs to resynchronize or not
  - Transferring entire (key, value) pairs for comparison is not viable
- Use Merkle trees to rapidly detect inconsistency and limit amount of transferred data
  - Nodes maintain Merkle tree of each key range
  - Exchange root of Merkle tree to check if the key ranges they store are updated
  - Tree branches can be checked without having to traverse the entire tree: a branch is traversed only when the hash values at the top of the branch differ
  - Amount of data transferred for synchronization is thus minimized

Riak KV

riakKV

- Distributed NoSQL key-value data store inspired by Dynamo
  - Open-source version docs.riak.com/riak/kv/latest
- Like Dynamo
  - Consistent hashing to partition and replicate data in a ring
  - Gossiping to propagate membership changes
  - Vector clocks to resolve conflicts
  - Nodes can be added and removed from Riak cluster as needed
  - Update conflicts can be solved in two ways:
    - Last write wins
    - Conflicting values are returned to client for resolution
- Search within aggregate by using Solr

Case study: Google's Bigtable

- Built on GFS, Chubby, SSTable
  - Data storage organized in tables, whose rows are distributed over GFS
- Available as Cloud service: Google Cloud Bigtable
- Underlies Google Cloud Datastore (NoSQL)
- Used by a number of Google apps, including:
  - Web indexing, MapReduce, Google Maps, Google Earth, YouTube and Gmail
- LevelDB is based on concepts from Bigtable, but not distributed
  - Stores entries lexicographically sorted by keys

Chang et al., Bigtable: A Distributed Storage System for Structured Data, *Proc. OSDI '06*

Bigtable: Motivation

- Lots of semi-structured data at Google
  - URLs, geographical locations, ...
- Big data
  - Billions of URLs, hundreds of millions of users, 100+TB of satellite image data, …

Bigtable: Main features

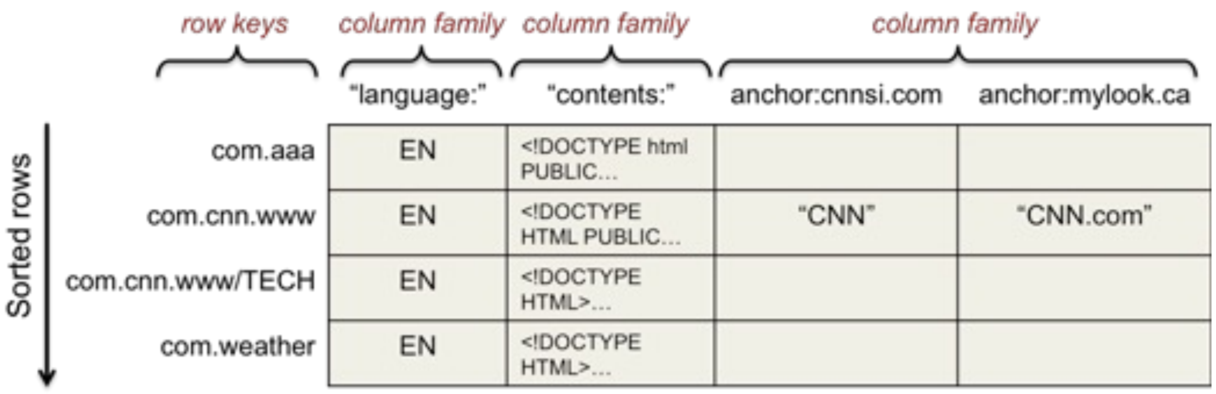
- Distributed storage structured as a large table
  - Distributed, multi-dimensional, sparse, sorted and time-based map
- Fault-tolerant
- Scalable and self-managing
- CP system: strong consistency and tolerance to network partition

Bigtable: Data model

- Table
  - Distributed, multi-dimensional, sparse, sorted and time-based **map**
  - Indexed by rows
- Rows
  - *Sorted* in lexicographical order by **row key**
  - Every read or write in a row is atomic: no concurrent ops on same row
- Columns
  - Basic unit of data access
  - *Sparse* table: different rows may have different columns
  - **Column family**: group of columns
    - Data within the column family are usually of same type
  - Column family allows for specific optimization for better access control, storage and data indexing
  - Column naming: *column-family:column*

Bigtable: Data model

- *Multi-dimensional*: rows, column families and columns provide a three-level naming hierarchy in identifying data



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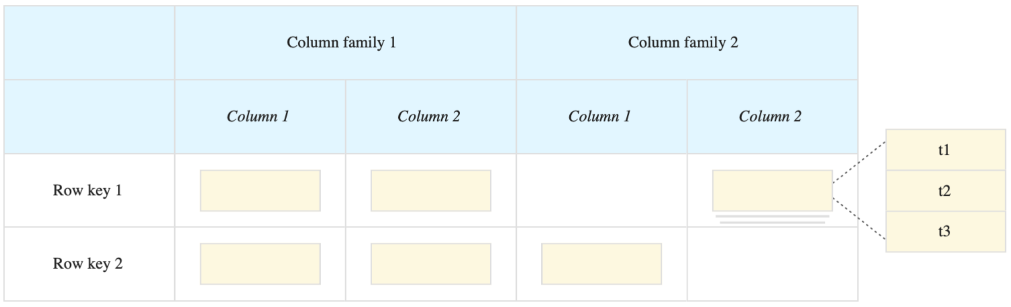
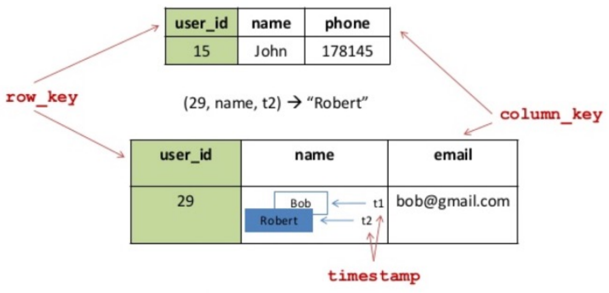
com.aaa	EN	<!DOCTYPE html PUBLIC…		
com.cnn.www	EN	<!DOCTYPE HTML PUBLIC…	"CNN"	"CNN.com"
com.cnn.www/TECH	EN	<!DOCTYPE HTML>…		
com.weather	EN	<!DOCTYPE HTML>…		

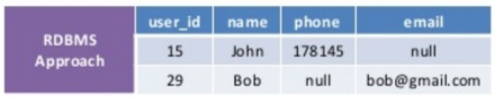
Bigtable: Data model

- *Time-based*
  – Multiple versions in each cell, each one having a timestamp



- Bigtable data model vs. relational data model

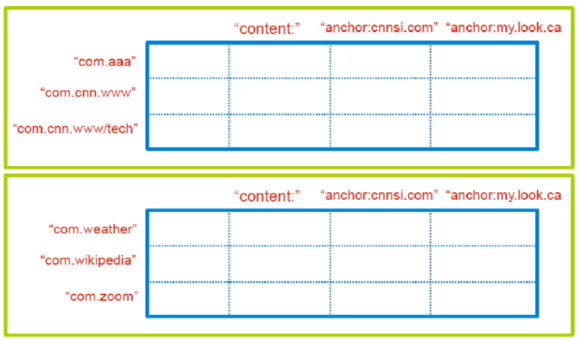




RDBMS Approach	user_id	name	phone	email
	15	John	178145	null
	29	Bob	null	bob@gmail.com

Bigtable: Tablet

- **Tablet**: group of consecutive rows of a table stored together
  - Basic unit for data storing and distribution
  - Table sorted by row keys: select row keys properly to improve data locality
- Each tablet is served by exactly one tablet server
- Auto-sharding: tablets split by Bigtable when they become too large

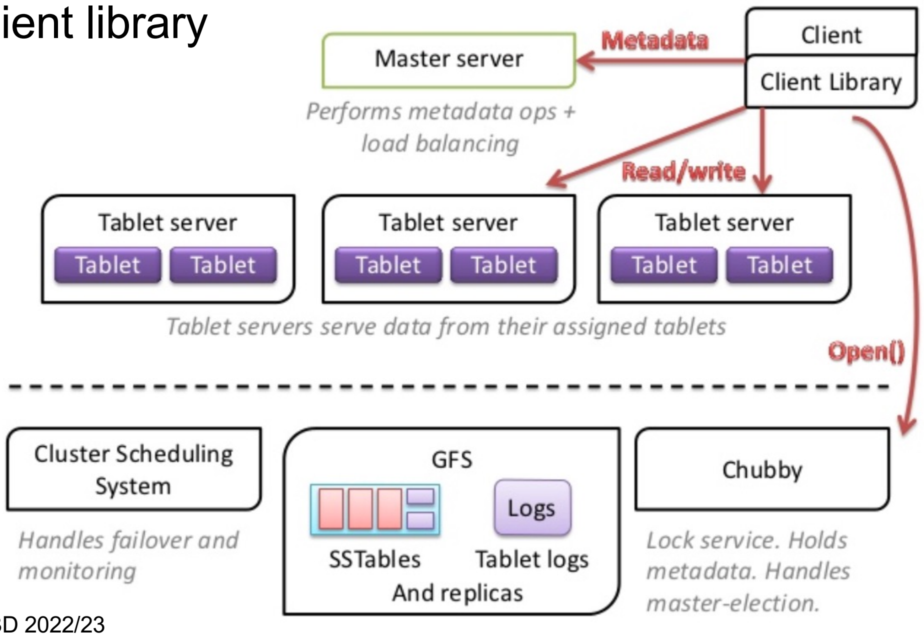


Bigtable: API

- Metadata ops
  - Create/delete tables and column families, change metadata
- Write ops: single-row, atomic
  - Write/delete cells in a row, delete all cells in a row
- Read ops: read arbitrary cells in a table
  - Each row read is atomic
  - One row, all or specific columns, certain timestamps, ...

Bigtable: Architecture

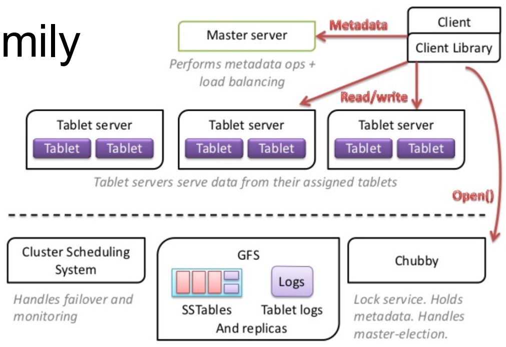
- Main components:
  - Master server
  - Tablet servers
  - Client library



Master server
Metadata
Client
Client Library
Performs metadata ops + load balancing
Read/write
Tablet server
Tablet
Tablet servers serve data from their assigned tablets
Open()
Cluster Scheduling System
Handles failover and monitoring
GFS
Logs
SSTables
Tablet logs
And replicas
Chubby
Lock service. Holds metadata. Handles master-election.

Bigtable: Master server

- Single master server
- Detects addition/deletion of tablet servers
- Assigns tablets to tablet servers
- Balances load among tablet servers
- Garbage collection of unneeded files in GFS
- Handles schema changes
  - e.g., table and column family creation



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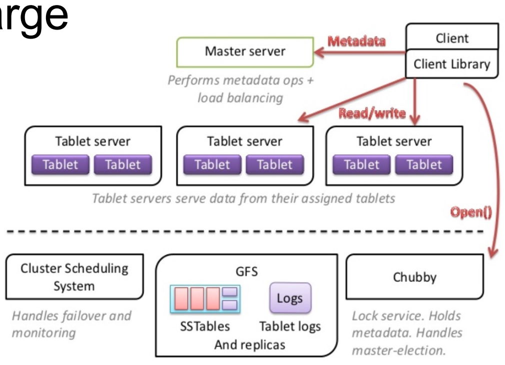
Bigtable: Tablet server

- Many tablet servers
- Can be added or removed dynamically
- Each tablet server:
  - Manages a set of tablets (typically 10-1000 tablets/server)
  - Handles read/write requests to tablets
  - Splits tablets when too large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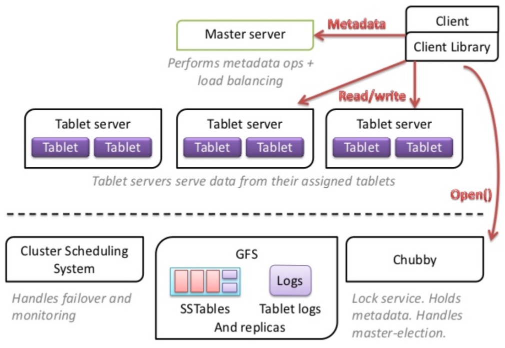
Bigtable: Client library

- Library that is linked into every client
- Client data does not go through master
  - Only metadata goes
  - Clients communicate directly with tablet servers for reads/writes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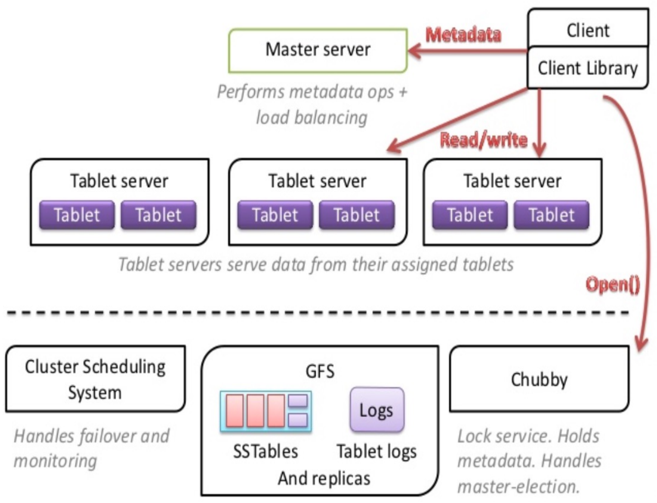
Bigtable: Building blocks

- External building blocks of Bigtable:
  - **Google File System** (GFS): data storage
  - **Chubby**: distributed lock service
  - **Cluster scheduler**: schedules jobs onto cluster servers



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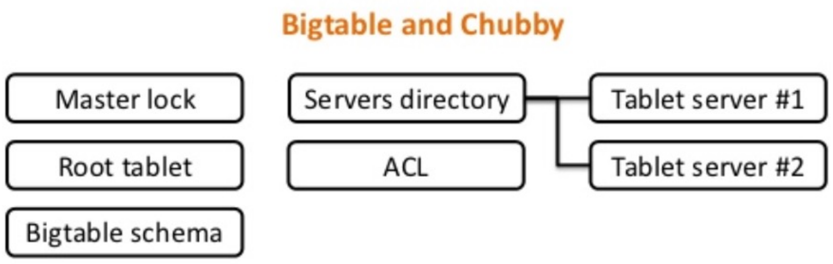
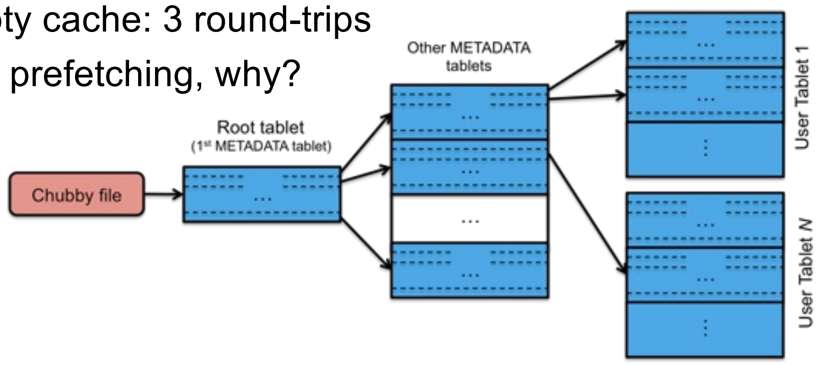
Bigtable: Chubby lock service

- Chubby: distributed and highly available lock service used in many Google's products
  - File system {directory/file} for locking
  - Paxos for consensus to keep replicas consistent
- Bigtable uses Chubby to:
  - Ensure there is only one active master (i.e., master lock)
  - Store bootstrap location of Bigtable data (i.e., root tablet)
  - Store Bigtable schema information
  - Discover tablet servers
  - Store access control lists (ACL)



Bigtable: Locating rows

- Three-level indexing hierarchy
- Chubby stores the location of root tablet
- Root tablet stores the location of all METADATA tablets in a special METADATA tablet
- Each METADATA tablet stores location of a set of user data tablets
- Client-side caching of tablet locations: efficiency!
  - Empty cache: 3 round-trips
  - Also prefetching, why?



Bigtable: Master startup

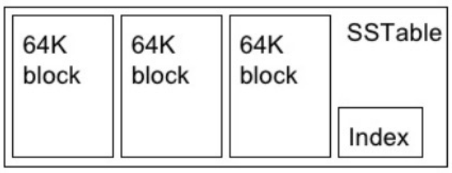
- At startup, master executes the following steps:
  - Grabs a unique master lock in Chubby (leader election)
  - Scans tablet servers directory in Chubby to find live servers
  - Communicates with live tablet servers to find which tablets are assigned to them
  - Scans METADATA tablets to learn the set of tablets that exist and determines the tablets not yet assigned to tablet servers

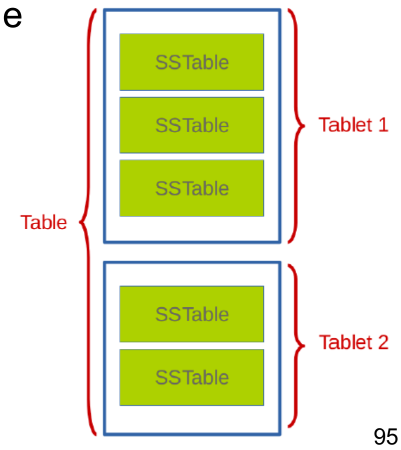
Bigtable: Tablet assignment

- Each tablet assigned to one tablet server at a time
- Master uses Chubby to keep tracks of live tablet serves and unassigned tablets
- When a tablet server starts, it creates and acquires an exclusive lock in Chubby
- Master detects the lock status of each tablet server by checking Chubby periodically
- Master is responsible for finding when tablet server is no longer serving its tablets and reassigning those tablets as soon as possible to other servers

Bigtable: SSTable

- Data is never stored in tablet servers; each server has pointers to a set of tablets that are stored on GFS
- Sorted Strings Table (**SSTable**): file format used to store Bigtable data durably
  - Persistent and immutable key-value map, sorted by keys
  - Stored as a series of 64KB blocks plus a block index
  - Block index is used to locate blocks
  - Index is loaded into memory when SSTable is opened
  - Each SSTable is stored in a GFS file





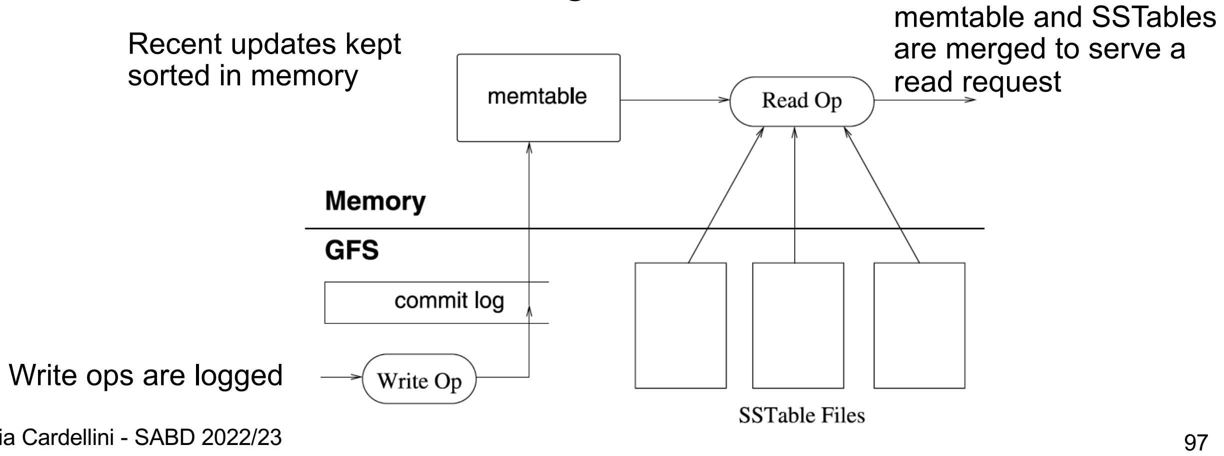
Bigtable: SSTable

- To speed-up reads, in-memory Bloom filter per SSTable to test if row data exists before accessing SSTables on disk

- Bloom filter: space and time-efficient probabilistic data structure used to know whether an element is present in a set
  - Probabilistic: the element either definitely is not in the set or may be in the set (i.e., false positives are possible but false negatives are not)

Bigtable: writing tablets and reading from tablets

- How to support fast writes with SSTables?
  - Write in memory!
- Updates committed to a separate commit log
- Recently committed writes are cached in memory in a memtable
- To serve reads, the tablet server merges SSTables and memtable into a single view


Recent updates kept sorted in memory
memtable
Read Op
memtable and SSTables are merged to serve a read request
Memory
GFS
commit log
Write ops are logged
Write Op
SSTable Files

Bigtable: Loading tablets

- To load a tablet, a tablet server:
  - Finds tablet location through its METADATA tablet
    - Metadata for a tablet contains list of SSTables
  - Read SSTables index blocks into memory
  - Read the commit log since the redo point and reconstructs the memtable

Bigtable: Consistency and availability

- Strong consistency: CP system
  - Only one tablet server is responsible for a given piece of data
  - Replication is handled by GFS
- Tradeoff with availability
  - If a tablet server fails, its portion of data is temporarily unavailable until a new tablet server is assigned

Comparing Dynamo and Bigtable

	Dynamo	Bigtable
Data model	Key-value	Column-family
API	Single value	Single value and range
Data partition	Random	Ordered
Optimized for	Writes	Reads
Consistency	Eventual	Atomic
Multiple versions	Version number	Timestamp
Replication	Quorum	GFS
Persistency	Local and replicated	Replicated and distributed file system
Architecture	Decentralized	Hierarchical (master/worker)

Cloud Bigtable

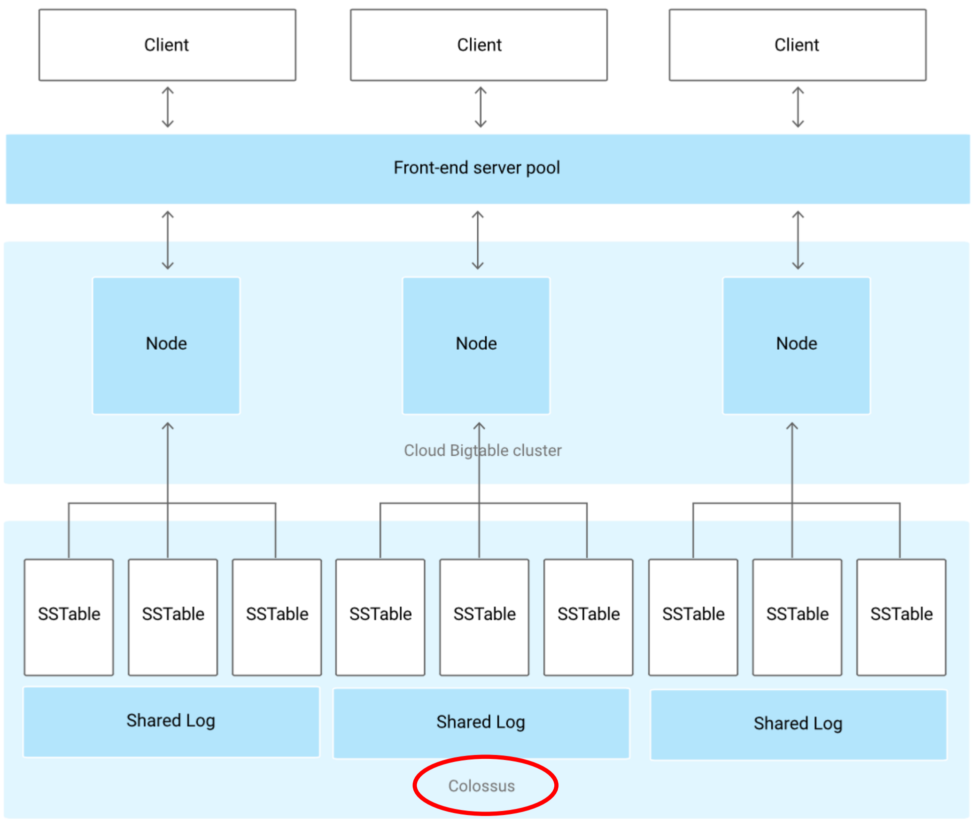
- Bigtable as Cloud service: same concepts!
- Sparsely populated table that can scale to billions of rows and thousands of columns
  - Table: sorted key-value map
  - Table composed of rows and columns
    - Each row describes a single entity
    - Each column contains individual values for each row
    - Each row/column intersection can contain multiple *cells* at different timestamps
    - Row indexed by a single row key
    - Columns that are related to one another are grouped together into a *column family*
      - Column identified by column family and column qualifier
  - Support of *multi-region* replication, but by default eventually consistent

Cloud Bigtable: use cases

- When to use
  - To store large amounts of single-keyed data with low latency for apps that need high throughput and scalability for non-structured key-value data
    - Single value no larger than 10 MB
    - At least 1 TB of data
  - Examples
    - Marketing data (e.g., purchase histories, customer preferences)
    - Financial data (e.g., transaction histories, stock prices)
    - IoT data (e.g., usage reports from energy meters and home appliances)
    - Time-series data (e.g., CPU and memory usage over time for multiple servers)

cloud.google.com/bigtable/docs/overview

Cloud Bigtable: architecture



Cloud Bigtable: usage

- Through command-line tools
  - Using cbt (native CLI in Go)
    cloud.google.com/bigtable/docs/cbt-overview
  - Using HBase shell
- Through Cloud Client Libraries for the Cloud Bigtable API

Cloud Bigtable: schema design example

- Dataset on Kaggle about New York City buses
  www.kaggle.com/stoney71/new-york-city-transport-statistics
- More than 300 bus routes and 5,800 vehicles following those routes
  - Timestamp, origin, destination, vehicle id, vehicle latitude and longitude, expected and scheduled arrival times
- Keep in mind
  - A table has only one index (row key), no secondary indexes
  - Rows are automatically sorted lexicographically by row key
  - Cloud Bigtable allows for queries using point lookups by row key or row-range scans
    - Try to avoid slow operations, i.e., multiple row lookups or full table scans
  - Keep all information for an entity in a single row

Cloud Bigtable: schema design example

- Queries about NYC buses
  - Get locations of a specific bus over an hour
  - Get locations of an entire bus line over an hour
  - Get locations of all buses in Manhattan in an hour
  - Get most recent locations of all buses in Manhattan in an hour
  - Get locations of an entire bus line over the month
  - Get locations of an entire bus line with a certain destination over an hour

Java code: codelabs.developers.google.com/codelabs/cloud-bigtable-intro-java

Cloud Bigtable: schema design example

- Row key design is crucial for Bigtable performance
- How to design the row key?
  - Consider how you will use the stored data
  - Keep row key reasonably short
  - Use human-readable values instead of hashing
  - Include multiple identifiers in row key

- Common mistake: make time the first value in row key
  - Can cause hotspots and result in poor performance: most queries would be managed by a single tablet server

Cloud Bigtable: schema design example

- How to design the row key for the NYC buses?

[Bus company/Bus line/Timestamp rounded down to the hour/Vehicle ID]

Row key	cf:VehicleLocation.Latitude	cf:VehicleLocation.Longitude	...
MTA/M86-SBS/1496275200000/NYCT_5824	40.781212 *@20:52:54.00*40.776163 *@20:43:19.00*40.778714 *@20:33:46.00*	-73.961942 *@20:52:54.00*-73.946949 *@20:43:19.00*-73.953731 *@20:33:46.00*	...
MTA/M86-SBS/1496275200000/NYCT_5840	40.780664 *@20:13:51.00*40.788416 *@20:03:40.00*	-73.958357 *@20:13:51.00* -73.976748 *@20:03:40.00*	...
MTA/M86-SBS/1496275200000/NYCT_5867	40.780281 *@20:51:45.00*40.779961 *@20:43:15.00*40.788416 *@20:33:44.00*	-73.946890 *@20:51:45.00*-73.959465 *@20:43:15.00*-73.976748 *@20:33:44.00*	...
...	...	...	...

Case study: Cassandra

cassandra

- Initially developed at Facebook
- A mixture of Amazon's Dynamo and Google's BigTable

amazon
Dynamo

P2P architecture (replication & partitioning), gossip-based discovery and error detection

Google
BigTable

Sparse column-oriented data model, storage architecture (SSTables, memtable, …)

facebook
Cassandra

- Some large production deployments:
  - Apple: over 75,000, over 10 PB of data
  - Netflix: 2,500 nodes, 420 TB, over 1 trillion requests per day

Cassandra: Features

- High availability and incremental scalability
- Robust support for systems spanning geo-distributed data centers
  - Asynchronous master-less replication allowing low latency operations
- Data model: structured key-value store where columns are added only to specified rows
  - Distributed multi-dimensional map indexed by row key
  - Different rows can have different number of columns and columns are grouped into column families
  - Emphasis on denormalization instead of normalization and joins
- Write-oriented system
  - On the contrary, Bigtable designed for intensive read workloads

Cassandra Query Language (CQL)

- SQL-like language http://cassandra.apache.org/doc/latest/cql/
- See music service example https://docs.datastax.com/en/cql-oss/3.1/cql/ddl/ddl_music_service_c.html

```
CREATE TABLE songs (
  id uuid PRIMARY KEY,
  title text,
  album text,
  artist text,
  data blob
 );
```

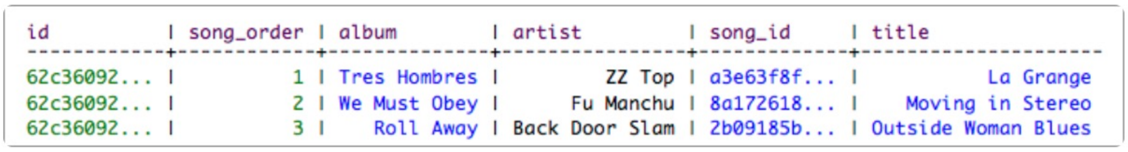
```
CREATE TABLE playlists (
  id uuid,
  song_order int,
  song_id uuid,
  title text,
  album text,
  artist text,
  PRIMARY KEY  (id, song_order ) );
```

```
INSERT INTO playlists (id, song_order, song_id, title, artist, album)
  VALUES (62c36092-82a1-3a00-93d1-46196ee77204, 4,
  7db1a490-5878-11e2-bcfd-0800200c9a66,
  'Ojo Rojo', 'Fu Manchu', 'No One Rides for Free');
```

Cassandra Query Language (CQL)

- Use SELECT to display table data

```
SELECT * FROM playlists;
```

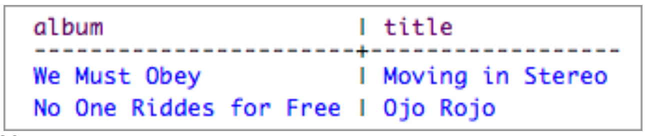


```
id           | song_order | album        | artist          | song_id     | title
-------------+------------+--------------+-----------------+-------------+--------------------
62c36092...  |          1 | Tres Hombres |          ZZ Top | a3e63f8f... |           La Grange
62c36092...  |          2 | We Must Obey |      Fu Manchu  | 8a172618... |     Moving in Stereo
62c36092...  |          3 |    Roll Away | Back Door Slam  | 2b09185b... | Outside Woman Blues
```

- To use artist as a filter, first create an index (because artist is not a partition key or clustering column) on artist and then query

```
CREATE INDEX ON playlists( artist );
```

```
SELECT album, title FROM playlists WHERE artist = 'Fu Manchu';
```



```
album                   | title
------------------------+------------------
We Must Obey            | Moving in Stereo
No One Riddes for Free  | Ojo Rojo
```

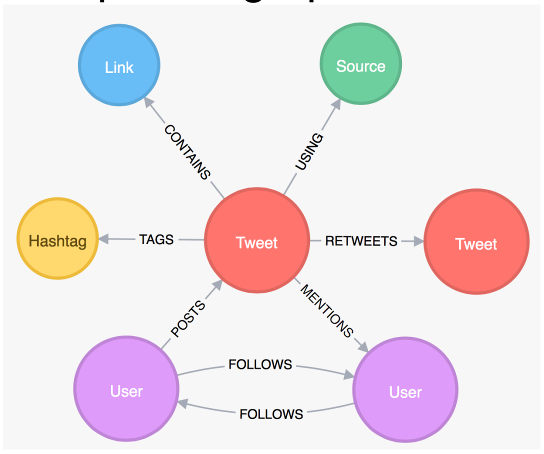
Cassandra: Consistency

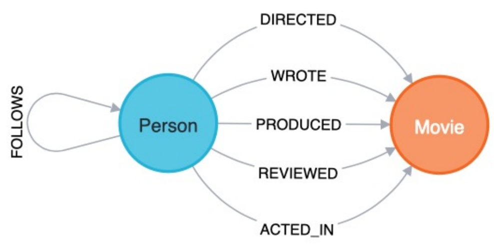
- Managed in decentralized fashion
  – No master node to coordinate reads and writes
- Based on quorum-based protocol
  – If R+W > N and W >= N/2 +1 you have strong consistency
  – Some available consistency levels http://bit.ly/2n26EdE
    - ONE: only a single replica must respond
    - QUORUM: a majority of the replicas must respond
    - ALL: all of the replicas must respond
    - LOCAL_QUORUM: a majority of the replicas in the local datacenter must respond
  – *Tunable* tradeoff between consistency and latency
- *Per-operation* tunable consistency (example in CQL)

```
SELECT points
  FROM fantasyfootball.playerpoints USING CONSISTENCY QUORUM
 WHERE playername = ‘Tom Brady’;
```

Case study: Neo4j

- Native graph database https://neo4j.com/
- Schema-less
- Supports ACID-compliant transactions
- Graph concepts
  - Nodes, relationships, labels, properties
- Examples of graph



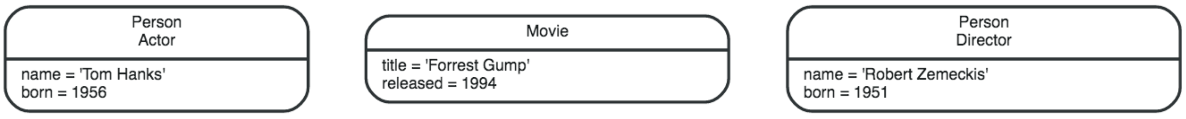


Neo4j: architecture

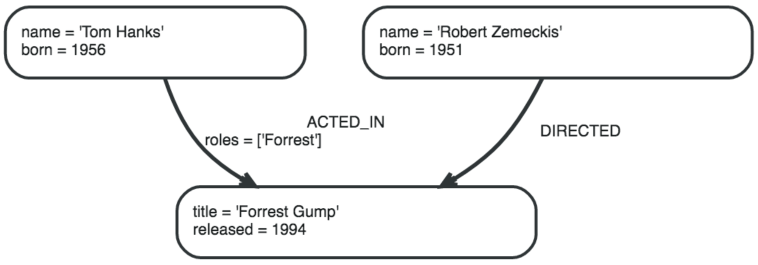
- Data replication managed via standard master-worker architecture
  - Single read/write master and multiple read-only workers
- Data sharding on multiple servers by means of server federation
- Improve data throughput via multi-level caching scheme
- However, community edition is only single-instance deployment

Neo4j: graphs

- Nodes can be tagged with labels
  - To shape the domain by grouping nodes into sets, so that all nodes with given label belongs to same set (e.g., Actor, Director)
- Properties are name-value pairs that are used to add qualities to nodes and relationships

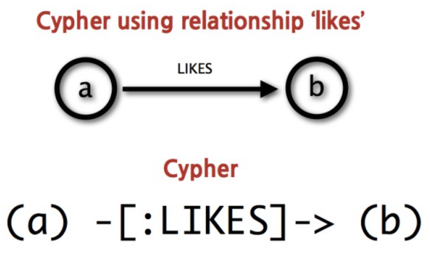


- Relationships provide directed, named, connections between two node entities



Neo4j: Cypher

- Cypher: declarative SQL-like query language
  - Designed to be human-readable
  - Nodes are between ( )
  - Edges are an arrow -> between two nodes



- Let's consider some queries related to movie database
  - See built-in example in Neo4j Desktop on movie database (169 nodes and 250 relationships)
  - Graph model on slide 114
- See neo4j.com/sandbox for more examples, including fraud detection and contact tracing

Cypher: create nodes and edges

- Create nodes with labels and properties

```
CREATE (TheMatrixReloaded:Movie {title:'The Matrix
Reloaded', released:2003, tagline:'Free your mind'})
CREATE (Keanu:Person {name:'Keanu Reeves', born:1964})
```

- Create edges with properties

```
CREATE (Keanu)-[:ACTED_IN {roles:['Neo']}]->
  (TheMatrixReloaded)
```

Cypher: search

- Use MATCH to search for a specified pattern (corresponds to SELECT in SQL)

- Find who directed Cloud Atlas movie

```
MATCH (m:Movie {title: 'Cloud Atlas'})<-[d:DIRECTED]-
(p:Person) return p.name
```

- Find all people who have co-acted with Tom Hanks in any movie

```
MATCH (tom:Person {name: "Tom Hanks"})-[:ACTED_IN]-
>(:Movie)<-[:ACTED_IN]-(p:Person) return p.name
```

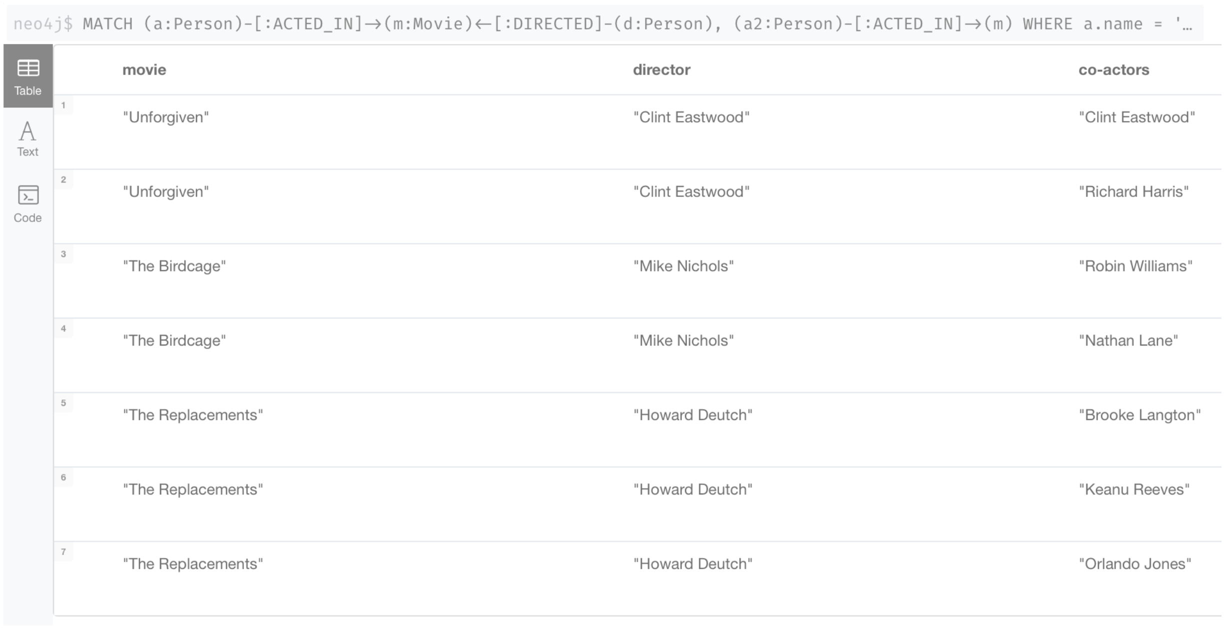
Cypher: search

- Retrieve all movies that Gene Hackman has acted it, along with the directors of the movies. In addition, retrieve the actors that acted in the same movies as Gene Hackman. Return the name of the movie, the name of the director, and the names of actors that worked with Gene Hackman

```
MATCH (a:Person)-[:ACTED_IN]->(m:Movie)<-
[:DIRECTED]-(d:Person), (a2:Person)-[:ACTED_IN]-
>(m) WHERE a.name = 'Gene Hackman' RETURN m.title
as movie, d.name AS director, a2.name AS `co-
actors`
```

  – Query result in tabular view on next slide

Cypher: search



```
neo4j$ MATCH (a:Person)-[:ACTED_IN]→(m:Movie)←[:DIRECTED]-(d:Person), (a2:Person)-[:ACTED_IN]→(m) WHERE a.name = '…
```

	movie	director	co-actors
1	"Unforgiven"	"Clint Eastwood"	"Clint Eastwood"
2	"Unforgiven"	"Clint Eastwood"	"Richard Harris"
3	"The Birdcage"	"Mike Nichols"	"Robin Williams"
4	"The Birdcage"	"Mike Nichols"	"Nathan Lane"
5	"The Replacements"	"Howard Deutch"	"Brooke Langton"
6	"The Replacements"	"Howard Deutch"	"Keanu Reeves"
7	"The Replacements"	"Howard Deutch"	"Orlando Jones"

Cypher: search for variable length paths

- Use MATCH to search for variable length paths
  - Nodes that are a variable number of `relationship->node` hops away can be found using

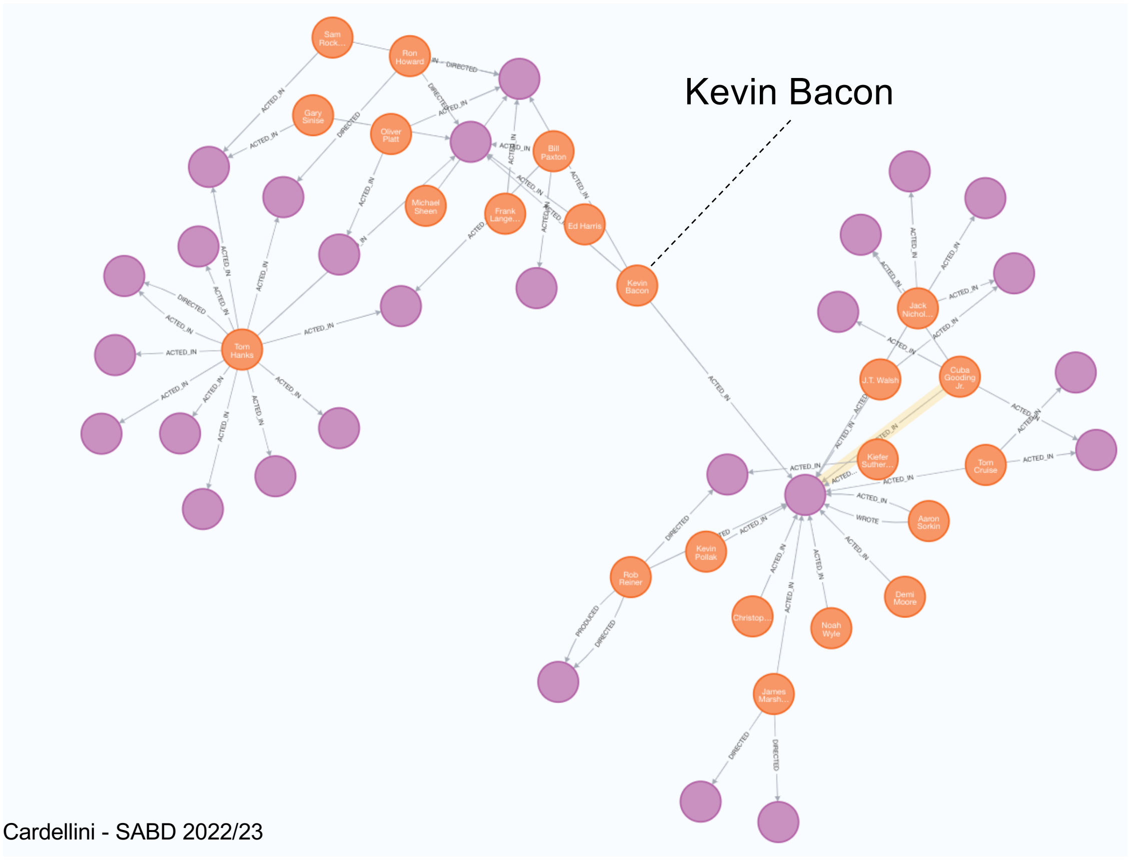
    `-[:TYPE*minHops..maxHops]->`

- Find movies and actors that are at most 3 hops away from Kevin Bacon

  ```
  MATCH (p:Person {name: 'Kevin Bacon'})-[*1..3]-
  (hollywood) return DISTINCT p, hollywood
  ```

  - `hollywood` refers to any node in the database (`Person` and `Movie` nodes)
  - We omit the arrow head because we don't care about the direction of the relationship
  - Query result as graph on next slide

Cypher: search for variable length paths



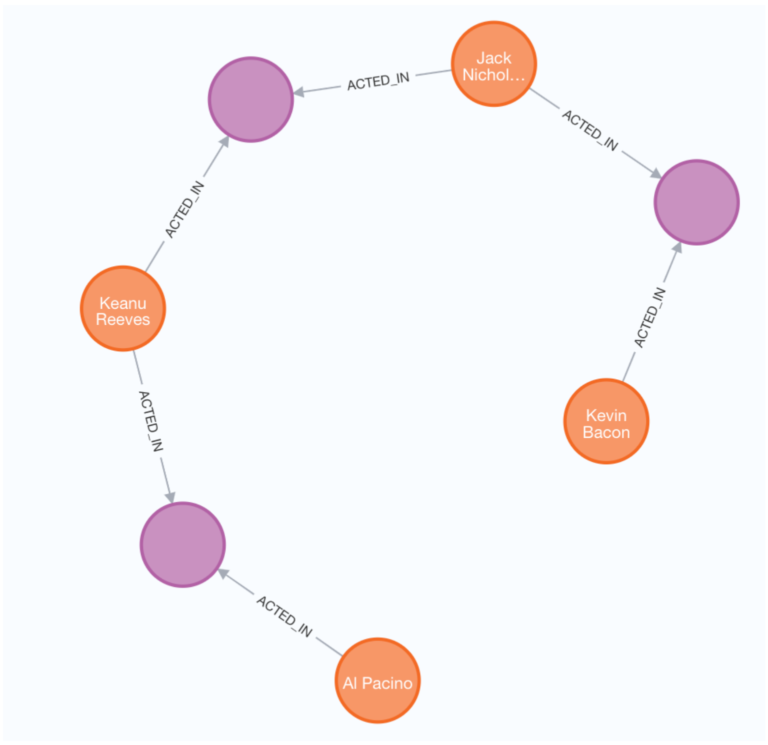
Cypher: search for shortest path

- Built-in support for shortest path queries
- Example: find shortest path between Kevin Bacon and Al Pacino

```
MATCH (KevinB:Person {name: 'Kevin Bacon'} ),
      (Al:Person {name: 'Al Pacino'}),
      p = shortestPath((KevinB)-[:ACTED_IN*]-(Al))
RETURN p
```

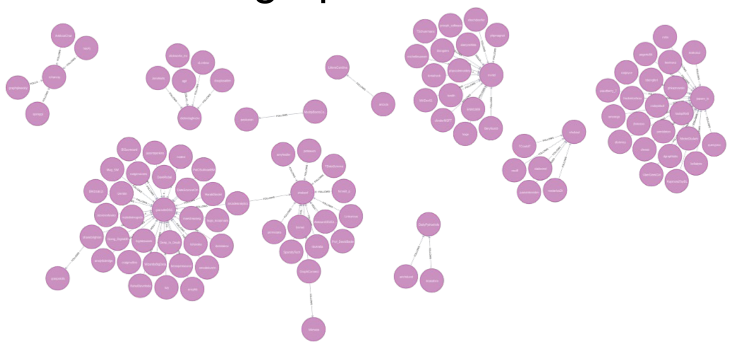
  – Query result as graph on next slide
  – `shortestPath` returns a single shortest path between two nodes
  – `allShortestPath` returns all the shortest paths between two nodes

Cypher: search for shortest path



Neo4j: graph algorithms

- Neo4j Graph Data Science (GDS) library contains many graph algorithms
- A portion of Twitter graph



- How to find influencers?
  - We can use centrality algorithms, for example degree centrality, betweenness centrality, and PageRank
- How to find communities?
  - We can use Louvain community detection algorithm

How to choose the right data store

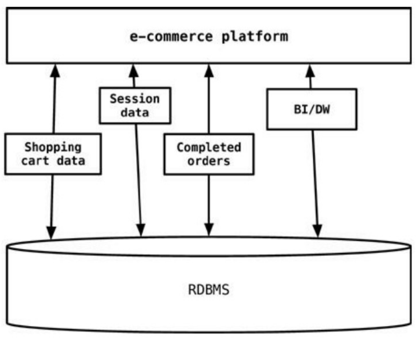
- Bad news: no one type that fits all
- Main factors to take into account
  - Data model, access pattern and data-related features
    - Access pattern: distribution of reads vs writes and random vs sequential access
    - Data-related features: volume, complexity, schema flexibility, durability
  - Query requirements
  - Non-functional properties
    - Performance, (auto-)scalability, consistency, partitioning, replication, load balancing, concurrency mechanisms, CAP tradeoffs, security, license model and cost, support

Performance comparison of NoSQL data stores

- Performance: important factor in choosing the right NoSQL data store solution
  - Throughput and latency as main metrics
- Bad news: many studies (both academic and industrial), no single “winner takes all” among NoSQL data stores
- Unsolved issue: no standard benchmark
  - Some studies use YCSB, others real datasets
  - Yahoo Cloud Serving Benchmark (YCSB): open-source workload generation tool github.com/brianfrankcooper/YCSB
- Be careful
  - Consider workload features: NoSQL data stores are mostly divided into read and write optimized
  - Parameters may be tuned for performance optimization
  - In some studies bias in data store setting (e.g., custom hardware, software setting)

Which data model/store to use?

- Different data models and data stores are designed to solve different problems
- Using a single data store engine for all of the requirements…
  - storing transactional data
  - caching session information
  - traversing graph of customers
  - performing OLAP operations



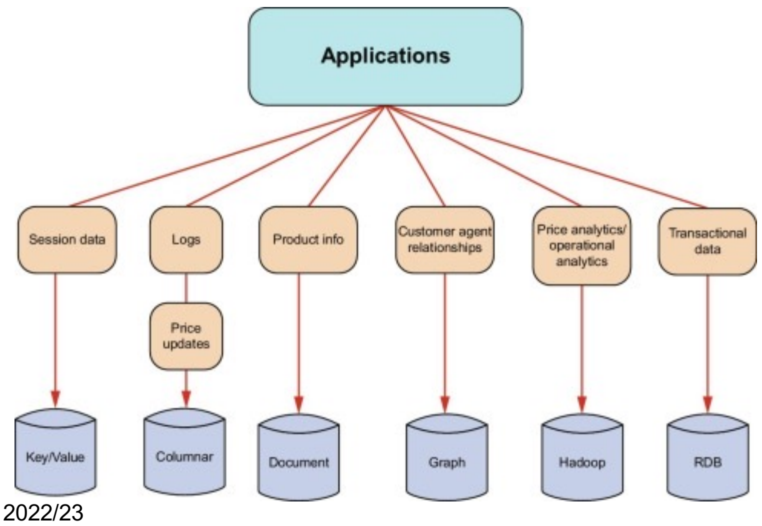
- … usually leads to non-performing solutions
- Also different needs for availability, consistency, etc.

Multi-model data management

- How to manage Variety of Big Data 3V model?
  1. **Polyglot persistence**
  2. **Multi-model databases**

Polyglot persistence

- Use multiple data storage technologies: polyglot persistence
  – Choose multiple data stores based upon the way data are used by apps or their components
  – Different kinds of data are best dealt with different data stores: pick the right tool for the right use case



Multi-model databases

- Second-generation of NoSQL products support multiple data models
- How?
  1. Tightly-integrated polystore: uses jointly multiple data storage technologies, chosen based upon the way data is being used by apps
  2. Single-store multi-model database: using one single, integrated backend

DBMS	Query language	Primary model	Secondary model	Storage strategy
ArangoDB	AQL	Document	Graph, KV	One engine
OrientDB	SQL-like	Graph	Document, KV	One engine
Redis	API	KV	Graph, Document	One engine
DynamoDB	API, PartiQL (SQL compatible)	Document, KV	Graph	Multiple engines
Cosmos DB	API, SQL	-	All	Multiple engines
Oracle 21c	SQL	Relational	All	Both

Multi-model databases

- With respect to polyglot persistence
  - ✓ Decrease in operational complexity and cost
  - ✓ No need to maintain data consistency across separate data stores
  - ✗ Performance not optimized for specific data model
  - ✗ Increased risk of vendor lock-in

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