CSEP 544: Lecture 10

Column-Oriented Databases and NoSQL

Announcement

Take home final: 3/15-16

- Online Webquiz
  - Need your UW NET ID, check that it works!
  - I will also email the final in pdf form (e.g. to print)
- Opens Friday night, closes Sunday night
- No time limits:
  - Work, save, take a break, return later…
- No need to run code
- Questions?
  - Email me and cc Priya
- Watch your email
  - E.g. corrections
- No discussion of the final with colleagues
- When you are done:
  - Submit and receive confirmation code!

Today's Agenda

- Column-oriented databases
- No-SQL
- Evaluation forms

Column-Oriented Databases

Brief discussion of the paper:
The Design and Implementation of Modern Column-Oriented Database Systems

Column-Oriented Databases

- Main idea:
  - Physical storage: complete vertical partition; each column stored separately: R.A, R.B, R.A
  - Logical schema: remains the same R(A,B,C)

- Main advantage:
  - Improved transfer rate: disk to memory, memory to CPU, better cache locality
  - Other advantages (next)

Key Architectural Trends (Sec.1)

- Virtual IDs
- Block-oriented and vertical processing
- Late materialization
- Column-specific compression

Key Architectural Trends (Sec.1)

- Virtual IDs
  - Offsets (arrays) instead of keys
- Block-oriented and vertical processing
  - Iterator model: one tuple→one block of tuples
- Late materialization
  - Postpone tuple reconstruction in query plan
- Column-specific compression
  - Much better than row-compression (why?)

Discussion

- What are “covering indexes” (pp. 204)
  And what is their connection to column-oriented databases?

- What is the main takeaway from Fig. 1.2?

Discussion

- What are “covering indexes” (pp. 204) And what is their connection to column-oriented databases?
  - A set of indexes that can completely answer the query; one index ≈ one column
- What is the main takeaway from Fig. 1.2?
  - Column-oriented databases don’t work! Unless you really optimize them well

Compression (Sec. 4)

- What is the advantage of compression in databases?

- Discuss main column-at-a-time compression techniques

Compression (Sec. 4)

- What is the advantage of compression in databases?

- Discuss main column-at-a-time compression techniques
  - Row-length encoding: F,F,F,F,M,M→4F,2M
  - Bit-vector (see also bit-map indexes)
  - Dictionary. More generally: Ziv-Lempel

Late Materialization (Sec. 4)

- What is it?

- Discuss $\Pi_C(\sigma_{A='a' \wedge B='b'}(R(A,B,C,D,\ldots))$

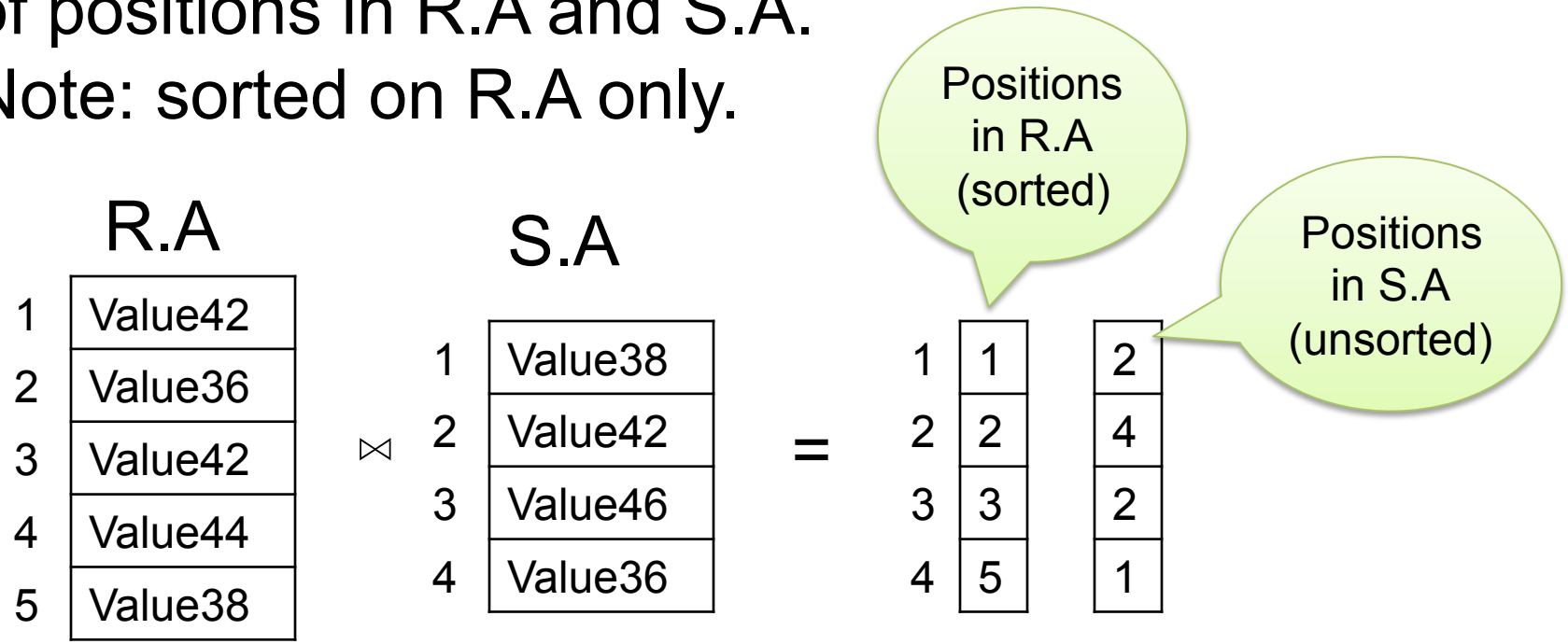
Late Materialization (Sec. 4)

- What is it?
  - The result is an array of positions

- Discuss $\Pi_C(\sigma_{A='a' \wedge B='b'}(R(A,B,C,D,\ldots))$
  - Retrieve positions in column A: 2, 4, 5, 9, 25…
  - Retrieve positions in column B: 3, 4, 7, 9,12,..
  - Intersect: 4, 9, …
  - Lookup values in column C: C[4], C[9], …

Joins (Sec. 4)

The result of a join R.A ⋈ S.A is an array of positions in R.A and S.A.
Note: sorted on R.A only.

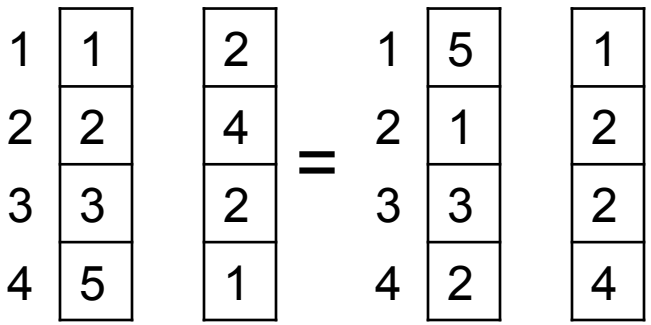


Jive-Join (Sec. 4)

Problem: accessing the values in the second table has poor memory locality

Solution: re-sort by the second coljun, fetch, sort back

E.g. $\Pi_{S.C}(R(A,\ldots) \bowtie S(B,C,\ldots))$



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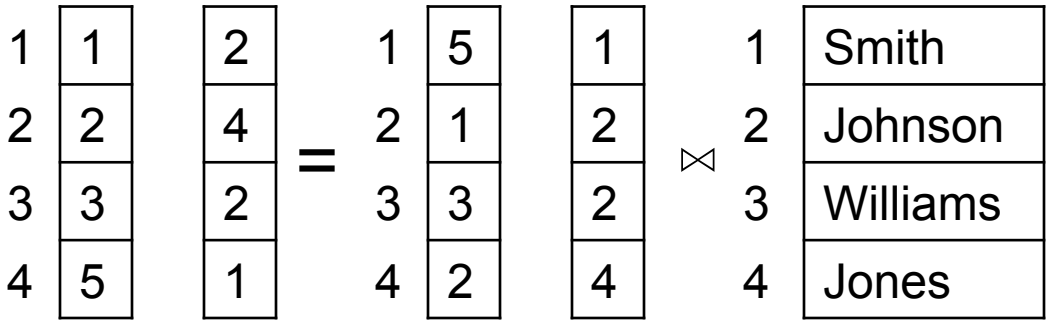

Sort on positions in S.B

Lookup S.C (this is a merge-join; why?)

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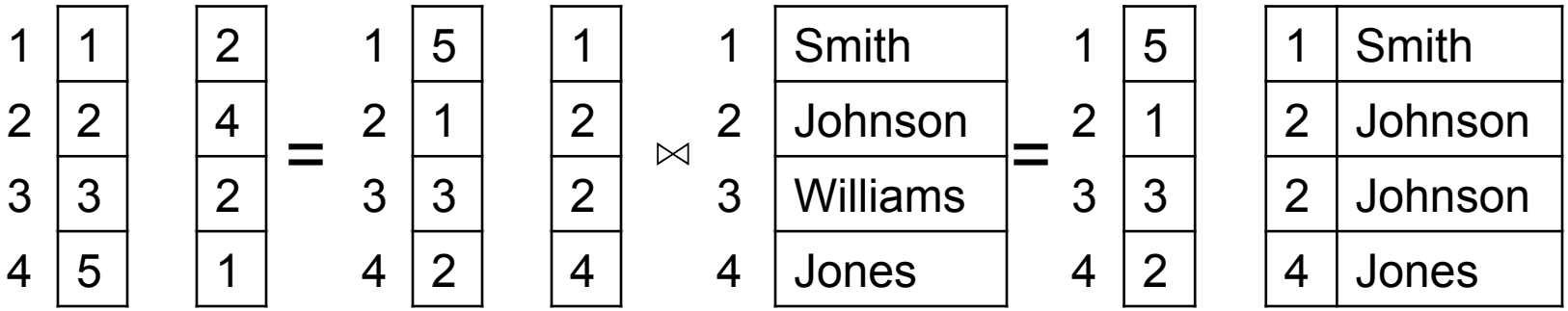

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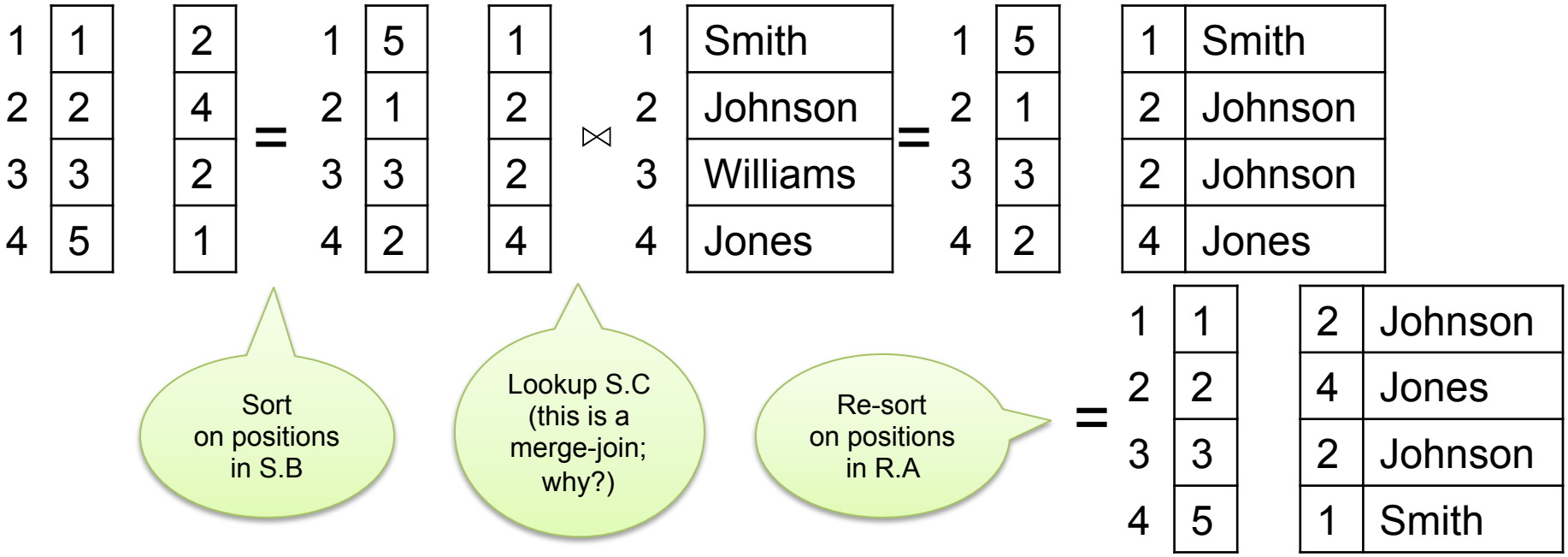


NoSQL Databases

Based on paper by Cattell, in SIGMOD Record 2010

NoSLQ: Overview

- Main objective: implement distributed state
  - Different objects stored on different servers
  - Same object replicated on different servers
- Main idea: give up some of the ACID constraints to improve performance
- Simple interface:
  - Write (=Put): needs to write all replicas
  - Read (=Get): may get only one
- Eventual consistency ← Strong consistency

Cattell, SIGMOD Record 2010

NoSQL

"Not Only SQL" or "Not Relational".
Six key features:

1. Scale horizontally "simple operations"
2. Replicate/distribute data over many servers
3. Simple call level interface (contrast w/ SQL)
4. Weaker concurrency model than ACID
5. Efficient use of distributed indexes and RAM
6. Flexible schema

Outline of this Lecture

- Main techniques and concepts:
  - Distributed storage using DHTs
  - Consistency: 2PC, vector clocks
  - The CAP theorem
- Overview of No-SQL systems (Cattell)
- Short case studies:
  - Dynamo, Cassandra, PNUTS
- Critique (c.f. Stonebraker)

Main Techniques and Concepts

Main Techniques, Concepts

- Distributed Hash Tables
- Consistency: 2PC, Vector Clocks
- The CAP theorem

A Note

- These techniques belong to a course on distributed systems, and not databases

- We will mention them because they are very relevant to NoSQL, but this is not an exhaustive treatment

Distributed Hash Table

Implements a distributed storage

- Each key-value pair (k,v) is stored at some server h(k)
- API: write(k,v); read(k)

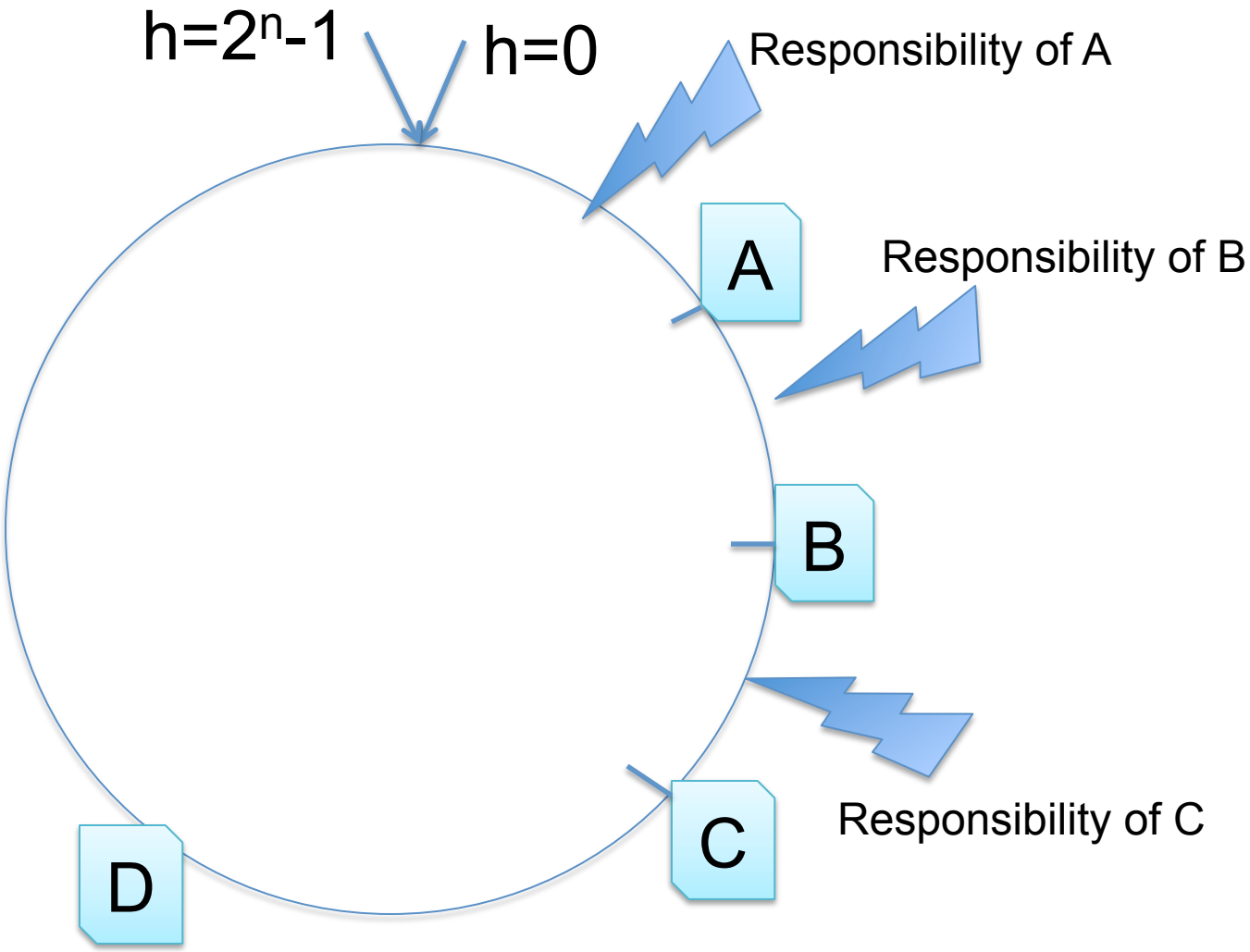
Use standard hash function: service key k by server h(k)

- Problem 1: a client knows only one server, does't know how to access h(k)

- Problem 2. if new server joins, then N → N+1, and the entire hash table needs to be reorganized

- Problem 3: we want replication, i.e. store the object at more than one server

Distributed Hash Table



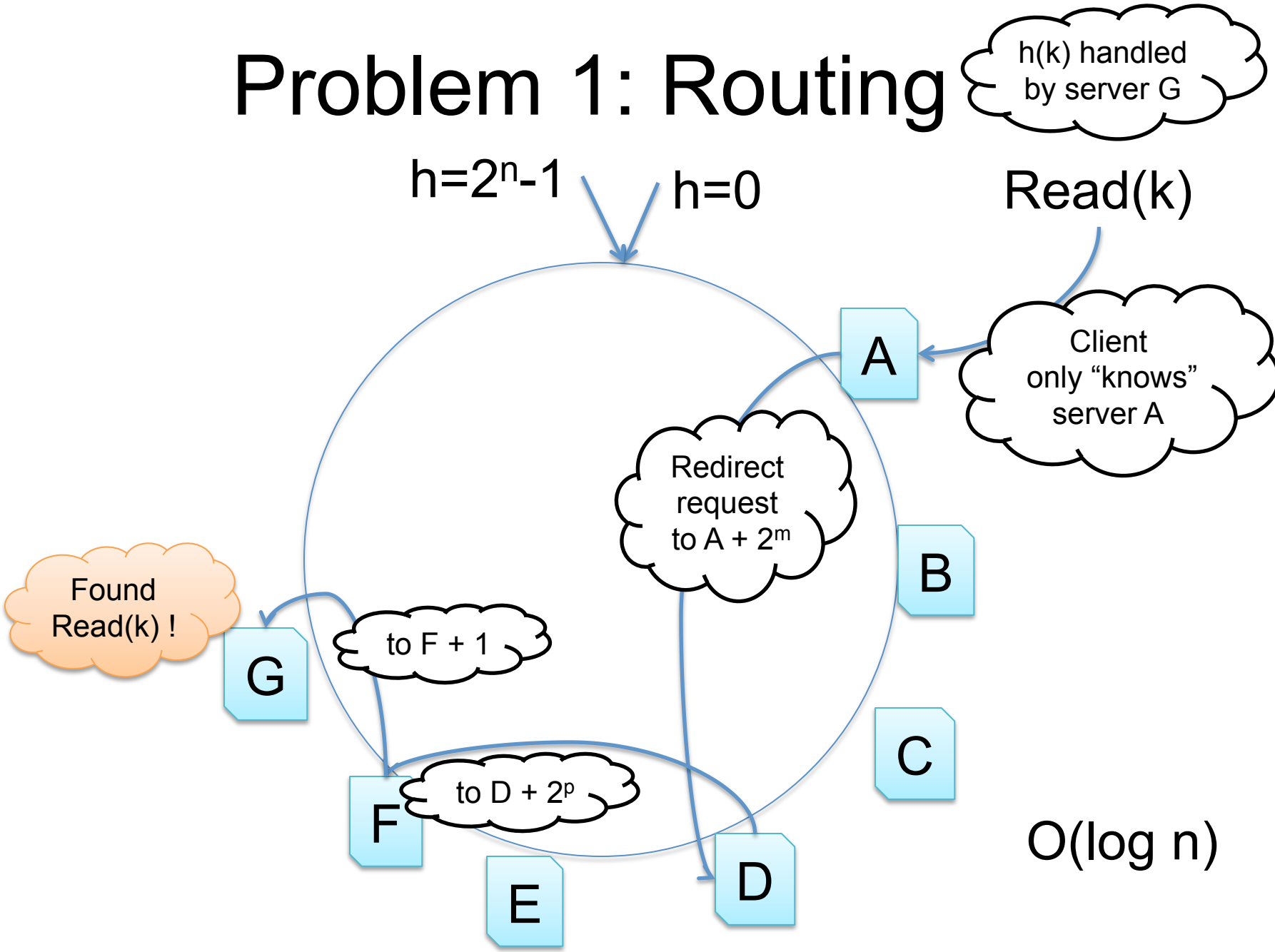
Problem 1: Routing

A client doesn't know server h(k), but some other server

- Naive routing algorithm:
  - Each node knows its neighbors
  - Send message to nearest neighbor
  - Hop-by-hop from there
  - Obviously this is O(n), So no good

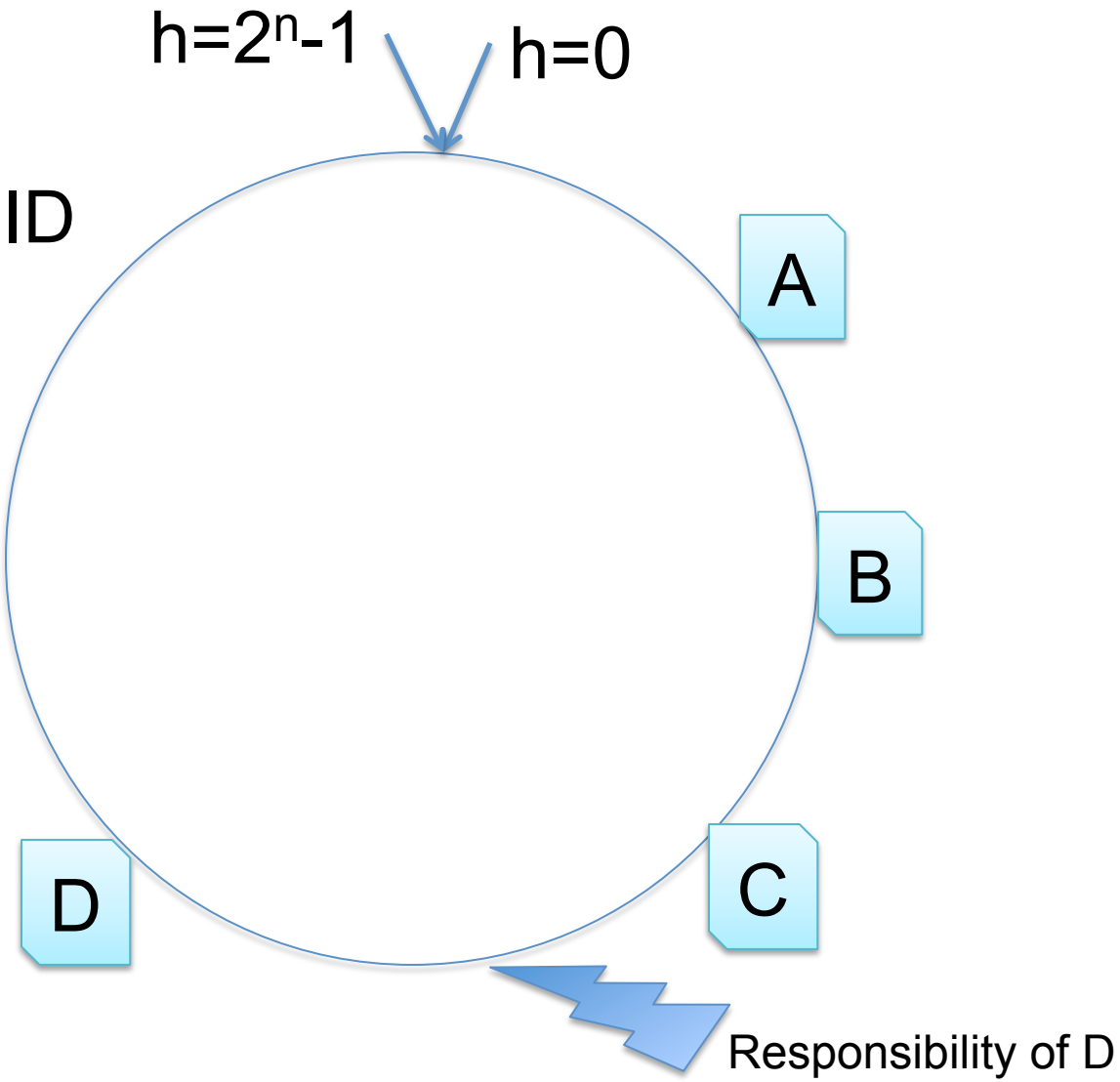
- Better algorithm: "finger table"
  - Memorize locations of other nodes in the ring
  - a, a + 2, a + 4, a + 8, a + 16, ... a + 2^n – 1
  - Send message to closest node to destination
  - Hop-by-hop again: this is log(n)

Problem 1: Routing



Problem 2: Joining

When X joins:
select random ID



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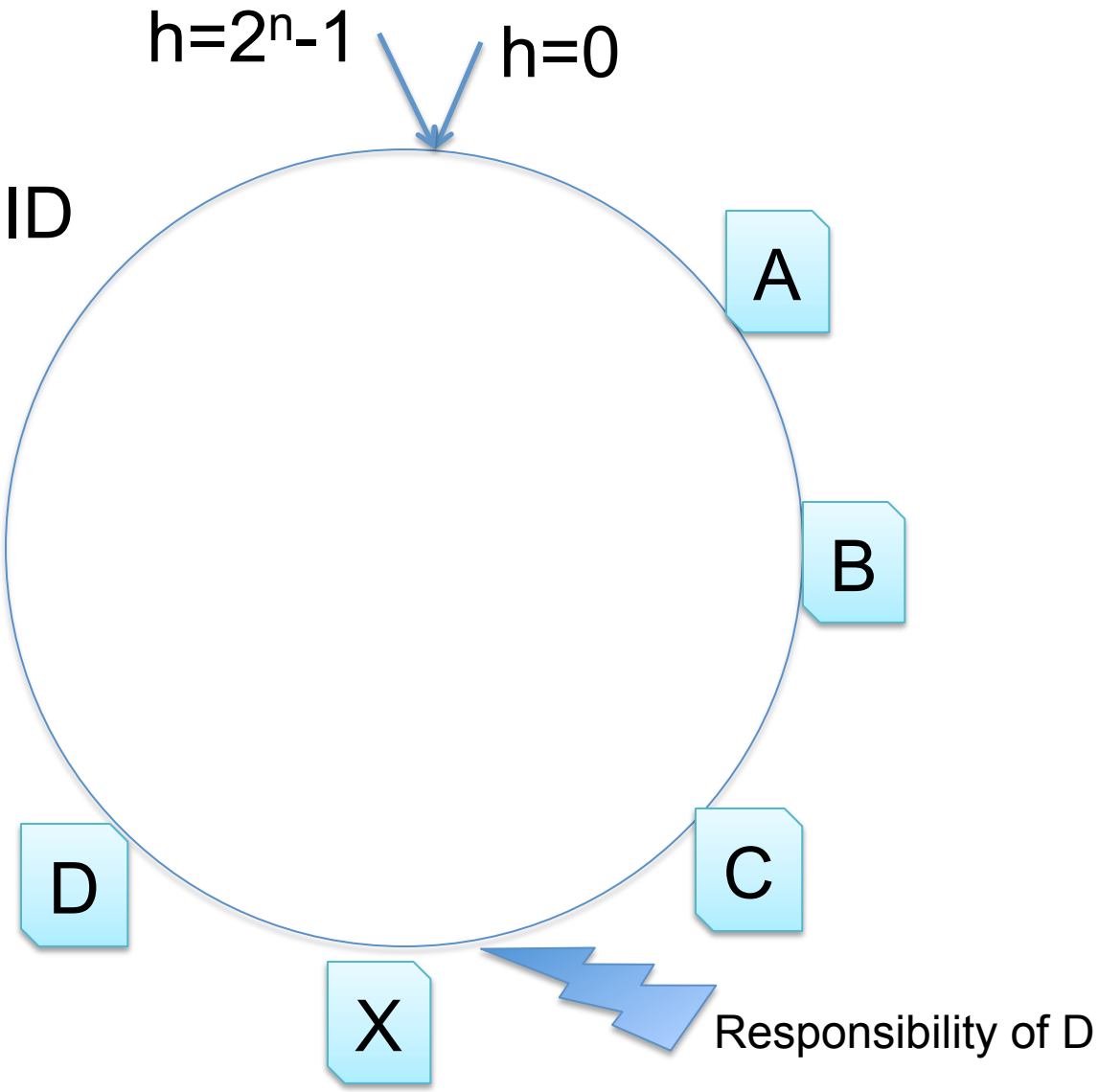
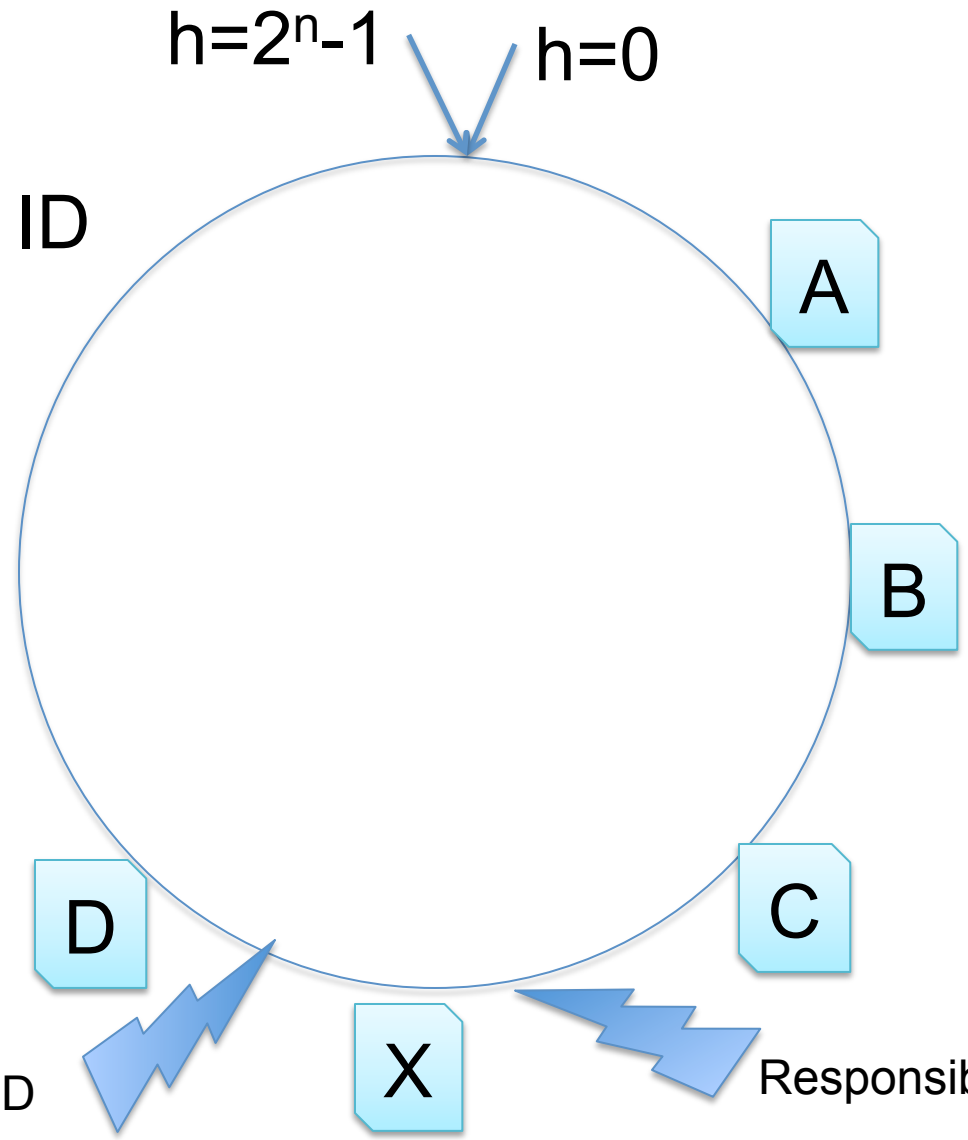


Problem 2: Joining

When X joins:
select random ID

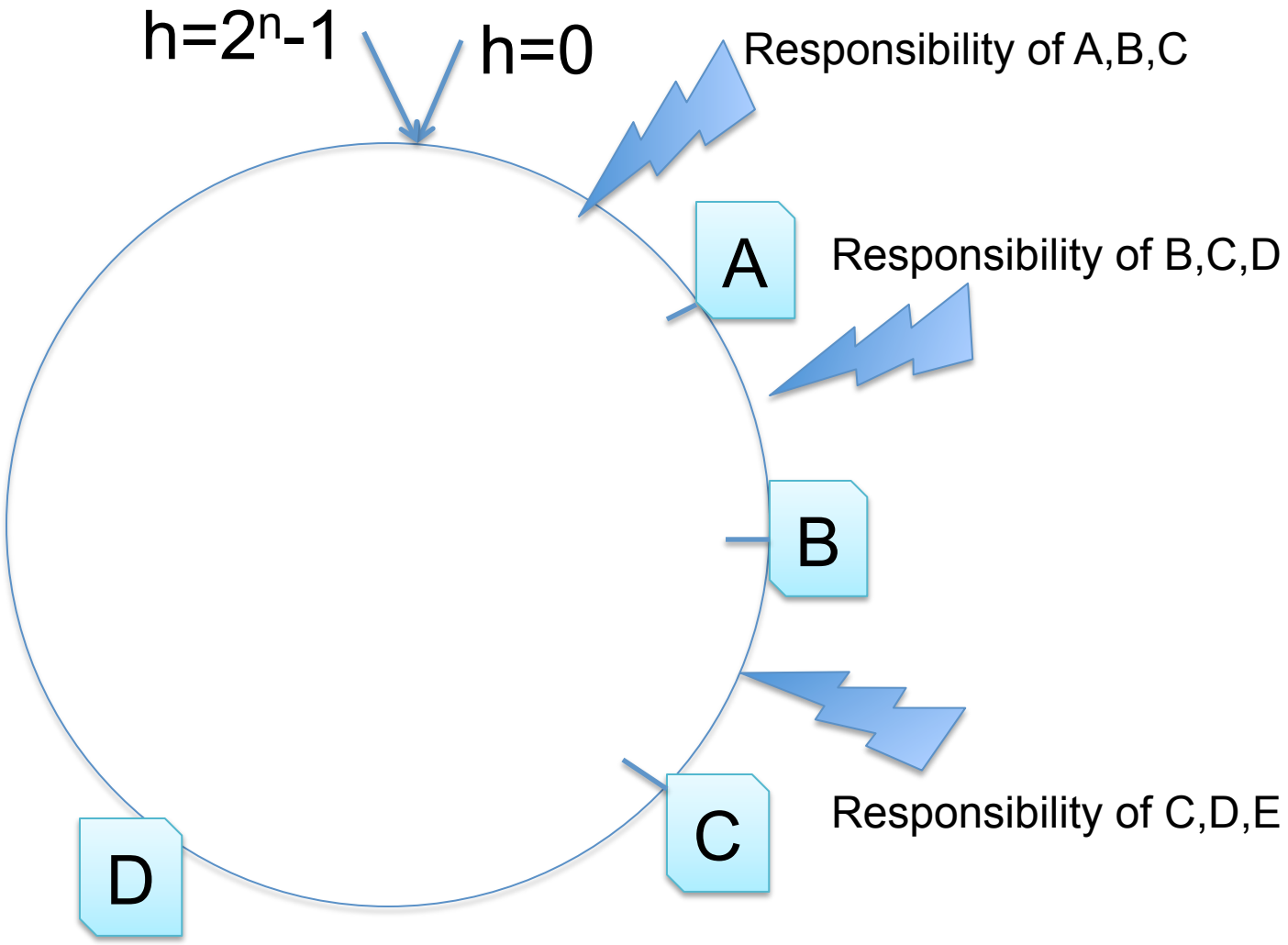
Redistribute
the load at D



Problem 3: Replication

- Need to have some degree of replication to cope with node failure
- Let N=degree of replication
- Assign key k to h(k), h(k)+1, …, h(k)+N-1

Problem 3: Replication



Consistency

- ACID
  - Two phase commit
  - Paxos (will not discuss)
- Eventual consistency
  - Vector clocks

Two Phase Commit

- Multiple servers run parts of the same transaction
- They all must commit, or none should commit
- Two-phase commit is a complicated protocol that ensures that
- 2PC can also be used for WRITE with replication: commit the write at all replicas before declaring success

Two Phase Commit

Assumptions:

- Each site logs actions at that site, but there is no global log
- There is a special site, called the *coordinator*, which plays a special role
- 2PC involves sending certain messages: as each message is sent, it is logged at the sending site, to aid in case of recovery

Two Phase Commit

Book, Sec. 21.13.1

1. Coordinator sends *prepare* message

2. Subordinates receive *prepare* statement; force-write **<prepare>** log entry; answers *yes* or *no*

3. If coordinator receives only *yes*, force write **<commit>**, sends *commit* messages;
   If at least one *no*, or timeout, force write **<abort>**, sends *abort* messages

4. If subordinate receives *abort*, force-write **<abort>**, sends *ack* message and aborts; if receives *commit*, force-write **<commit>**, sends *ack*, commits.

5. When coordinator receives all *ack*, writes **<end log>**

Two Phase Commit

- ACID properties, but expensive
- Relies on central coordinator: both performance bottleneck, and single-point-of-failure
- Solution: Paxos = distributed protocol
  - Complex: will not discuss at all

Vector Clocks

- An extension of Multiversion Concurrency Control (MVCC) to multiple servers

- Standard MVCC:
  each data item X has a timestamp t:
  X_4, X_9, X_{10}, X_{14}, …, X_t

- Vector Clocks:
  X has set of [server, timestamp] pairs
  X([s1,t1], [s2,t2],…)

Dynamo:2007

Vector Clocks

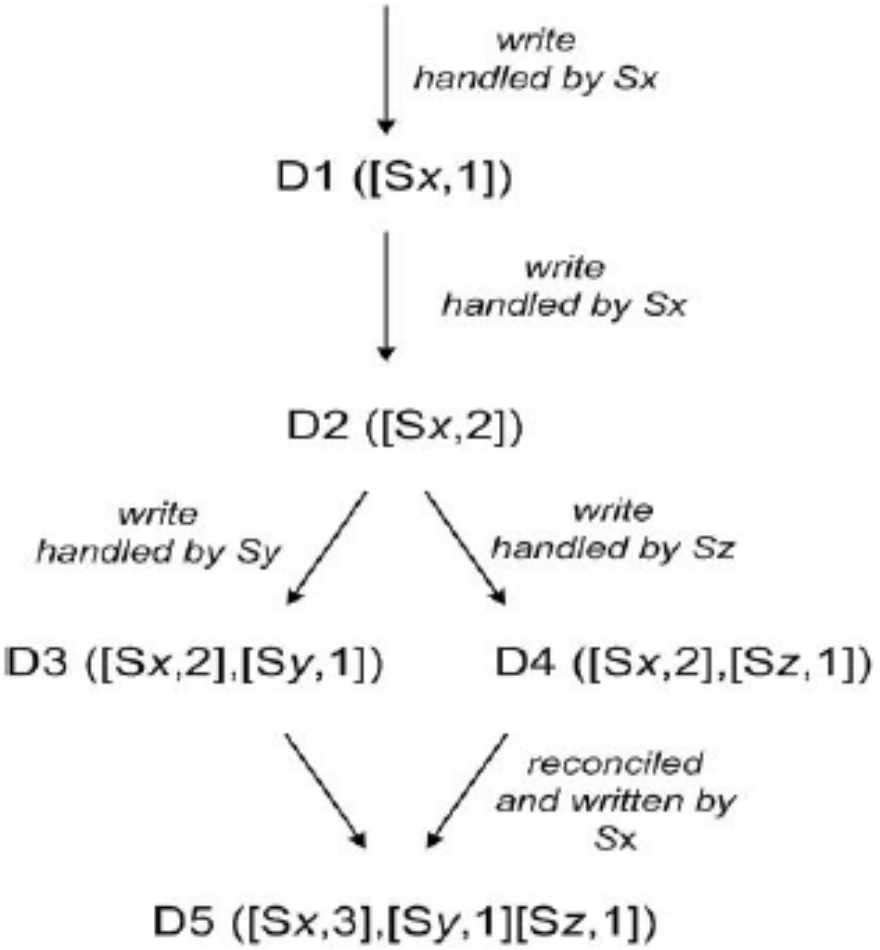


Figure 3: Version evolution of an object over time.

Vector Clocks: Example

- A client writes D1 at server SX:
  D1 ([SX,1])
- Another client reads D1, writes back D2; also handled by server SX:
  D2 ([SX,2]) (D1 garbage collected)
-
-
-

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- Another client reads D2, writes back D3; handled by server SY:
  D3 ([SX,2], [SY,1])
-
-

Vector Clocks: Example

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- Another client reads D2, writes back D3; handled by server SY:
  D3 ([SX,2], [SY,1])
- Another client reads D2, writes back D4; handled by server SZ:
  D4 ([SX,2], [SZ,1])
-

Vector Clocks: Example

- A client writes D1 at server SX:
  D1 ([SX,1])
- Another client reads D1, writes back D2; also handled by server SX:
  D2 ([SX,2]) (D1 garbage collected)
- Another client reads D2, writes back D3; handled by server SY:
  D3 ([SX,2], [SY,1])
- Another client reads D2, writes back D4; handled by server SZ:
  D4 ([SX,2], [SZ,1])
- Another client reads D3, D4: CONFLICT !

Vector Clocks: Meaning

- A data item D[(S1,v1),(S2,v2),…] means a value that represents version v1 for S1, version v2 for S2, etc.
- If server Si updates D, then:
  - It must increment vi, if (Si, vi) exists
  - Otherwise, it must create a new entry (Si,1)

Vector Clocks: Conflicts

- A data item D *is an ancestor* of D' if for all (S,v)∈D there exists (S,v')∈D' s.t. v ≤ v'

- Otherwise, D and D' are on parallel branches, and it means that they have a conflict that needs to be reconciled semantically

Vector Clocks: Conflict or not?

Data 1	Data 2	Conflict ?
([SX,3],[SY,6])	([SX,3],[SZ,2])	

Vector Clocks: Conflict or not?

Data 1	Data 2	Conflict ?
([SX,3],[SY,6])	([SX,3],[SZ,2])	Yes

Vector Clocks: Conflict or not?

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([SX,3])	([SX,5])	

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([SX,3],[SY,10])	([SX,3],[SY,6],[SZ,2])	

Vector Clocks: Conflict or not?

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([SX,3])	([SX,5])	No
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Vector Clocks: Conflict or not?

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([SX,3])	([SX,5])	No
([SX,3],[SY,6])	([SX,3],[SY,6],[SZ,2])	No
([SX,3],[SY,10])	([SX,3],[SY,6],[SZ,2])	Yes
([SX,3],[SY,10])	([SX,3],[SY,20],[SZ,2])	

Vector Clocks: Conflict or not?

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([SX,3],[SY,10])	([SX,3],[SY,6],[SZ,2])	Yes
([SX,3],[SY,10])	([SX,3],[SY,20],[SZ,2])	No

CAP Theorem

Brewer 2000:

You can only have two of the following three:

- Consistency
- Availability
- Tolerance to Partitions

CAP Theorem: No Partitions

- CA = Consistency + Availability

- Single site database
- Cluster database

- Need 2 phase commit
- Need cache validation protocol

Brewer 2000

CAP Theorem: No Availability

- CP = Consistency + tolerance to Partitions

- Distributed databases
- Majority protocols

- Make minority partitions unavailable

Brewer 2000

CAP Theorem: No Consistency

- AP = Availability + tolerance to Partitions

- DNS
- Web caching

Brewer 2000

CAP Theorem: Criticism

- Not really a “theorem”, since definitions are imprecise: a real theorem was proven a few years later, but under more limiting assumptions
- Many tradeoffs possible
- D.Abadi: “CP makes no sense” because it suggest *never* available. A, C asymmetric!
  - No “C” = *all the time*
  - No “A” = *only when the network is partitioned*

Cattell, SIGMOD Record 2010

Overview of No-SQL systems

Cattell, SIGMOD Record 2010

Early "Proof of Concepts"

- Memcached: demonstrated that in-memory indexes (DHT) can be highly scalable
- Dynamo: pioneered *eventual consistency* for higher availability and scalability
- BigTable: demonstrated that persistent record storage can be scaled to thousands of nodes

Cattell, SIGMOD Record 2010

ACID v.s. BASE

- ACID = Atomicity, Consistency, Isolation, and Durability

- BASE = Basically Available, Soft state, Eventually consistent

Cattell, SIGMOD Record 2010

Terminology

- Simple operations = key lookups, read/writes of one record, or a small number of records
- Sharding = horizontal partitioning by some key, and storing records on different servers in order to improve performance.
- Horizontal scalability = distribute both data *and* load over many servers
- Vertical scaling = when a dbms uses multiple cores and/or CPUs

Not exactly same as horizontal partitioning

Definitely different from vertical partitioning

Cattell, SIGMOD Record 2010

Data Model

- Tuple = row in a relational db
- Document = nested values, extensible records (think XML or JSON)
- Extensible record = families of attributes have a schema, but new attributes may be added
- Object = like in a programming language, but without methods

Cattell, SIGMOD Record 2010

1. Key-value Stores

Think “file system” more than “database”

- Persistence,
- Replication
- Versioning,
- Locking
- Transactions
- Sorting

Cattell, SIGMOD Record 2010

1. Key-value Stores

- Voldemort, Riak, Redis, Scalaris, Tokyo Cabinet, Memcached/Membrain/Membase

- Consistent hashing (DHT)
- Only primary index: lookup by key
- No secondary indexes
- Transactions: single- or multi-update TXNs
  - locks, or MVCC

Cattell, SIGMOD Record 2010

2. Document Stores

- A "document" = a pointerless object = e.g. JSON = nested or not = schema-less

- In addition to KV stores, may have secondary indexes

Cattell, SIGMOD Record 2010

2. Document Stores

- SimpleDB, CouchDB, MongoDB, Terrastore

- Scalability:
  - Replication (e.g. SimpleDB, CounchDB – means entire db is replicated),
  - Sharding (MongoDB);
  - Both

Cattell, SIGMOD Record 2010

3. Extensible Record Stores

- Typical Access: Row ID, Column ID, Timestamp

- Rows: sharding by primary key
  - BigTable: split table into *tablets* = units of distribution
- Columns: "column groups" = indication for which columns to be stored together (e.g. customer name/address group, financial info group, login info group)

- HBase, HyperTable, Cassandra, PNUT, BigTable

Cattell, SIGMOD Record 2010

4. Scalable Relational Systems

- Means RDBS that are offering sharding
- Key difference: NoSQL make it difficult or impossible to perform large-scope operations and transactions (to ensure performance), while scalable RDBMS do not *preclude* these operations, but users pay a price only when they need them.
- MySQL Cluster, VoltDB, Clusterix, ScaleDB, Megastore (the new BigTable)

Cattell, SIGMOD Record 2010

Application 1

- Web application that needs to display lots of customer information; the users data is rarely updated, and when it is, you know when it changes because updates go through the same interface. Store this information persistently using a KV store.

Key-value store

Cattell, SIGMOD Record 2010

Application 2

- Department of Motor Vehicle: lookup objects by multiple fields (driver's name, license number, birth date, etc); "eventual consistency" is ok, since updates are usually performed at a single location.

Document Store

Cattell, SIGMOD Record 2010

Application 3

- eBay stile application. Cluster customers by country; separate the rarely changed "core" customer information (address, email) from frequently-updated info (current bids).

Extensible Record Store

Cattell, SIGMOD Record 2010

Application 4

- Everything else (e.g. a serious DMV application)

Scalable RDBMS

Short Case Studies

Case Study 1: Dynamo

- Developed at Amazon, published 2007
- It is probably in SimpleDB today, I couldn't confirm
- Was the first to demonstrate that eventual consistency can work

Case Study 1: Dynamo

Key features:

- Service Level Agreement (SLN): at the 99th percentile, and not on mean/median/variance (otherwise, one penalizes the heavy users)
  - "Respond within 300ms for 99.9% of its requests"

Case Study 1: Dynamo

Key features:

- DHT with replication:
  - Store value at k, k+1, …, k+N-1
- Eventual consistency through vector clocks
- Reconciliation at read time:
  - Writes never fail (“poor customer experience”)
  - Conflict resolution: “last write wins” or application specific

Aboulnaga'2011

Case Study 2: Cassandra

- Cassandra stores semi-structured rows that belong to column families
  - Rows are accessed by a ***key***
  - Rows are replicated and distributed by hashing keys
- Multi-master replication for each row
  - Enables Cassandra to run in multiple data centers
  - Also gives us partition tolerance

Aboulnaga'2011

Case Study 2: Cassandra

- Client controls the consistency vs. latency trade-off for each read and write operation
  - write(1)/read(1) – fast but not necessarily consistent
  - write(ALL)/read(ALL) – consistent but may be slow
- Client decides the serialization order of updates
- Scalable, elastic, highly available
  - Like many other cloud storage systems!

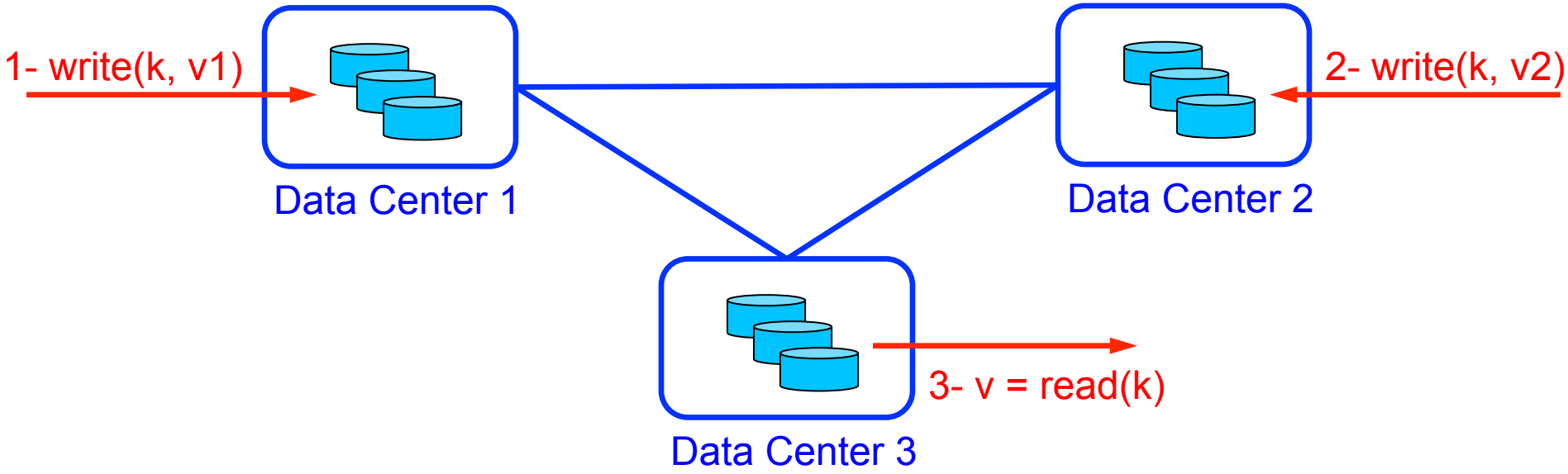
Aboulnaga'2011

Consistency vs. Latency

- value = read(1, key, column)
  - Send read request to all replicas of the row (based on key)
  - Return first response received to client
  - Returns quickly but may return stale data
- value = read(ALL, key, column)
  - Send read request to all replicas of the row (based on key)
  - Wait until all replicas respond and return ***latest version*** to client
  - Consistent but as slow as the slowest replica
- write(1) vs. write(ALL)
  - Send write request to all replicas
  - ***Client provides a timestamp for each write***
- Other consistency levels are supported

Aboulnaga'2011

Consistency vs. Latency



- Which *v* is returned to the read()?
  - write(1)/read(1): possibly *v1*, and ***eventually*** *v2*
  - write(ALL)/read(1): guaranteed to return *v2* if successful
  - write(1)/read(ALL): guaranteed to return *v2* if successful

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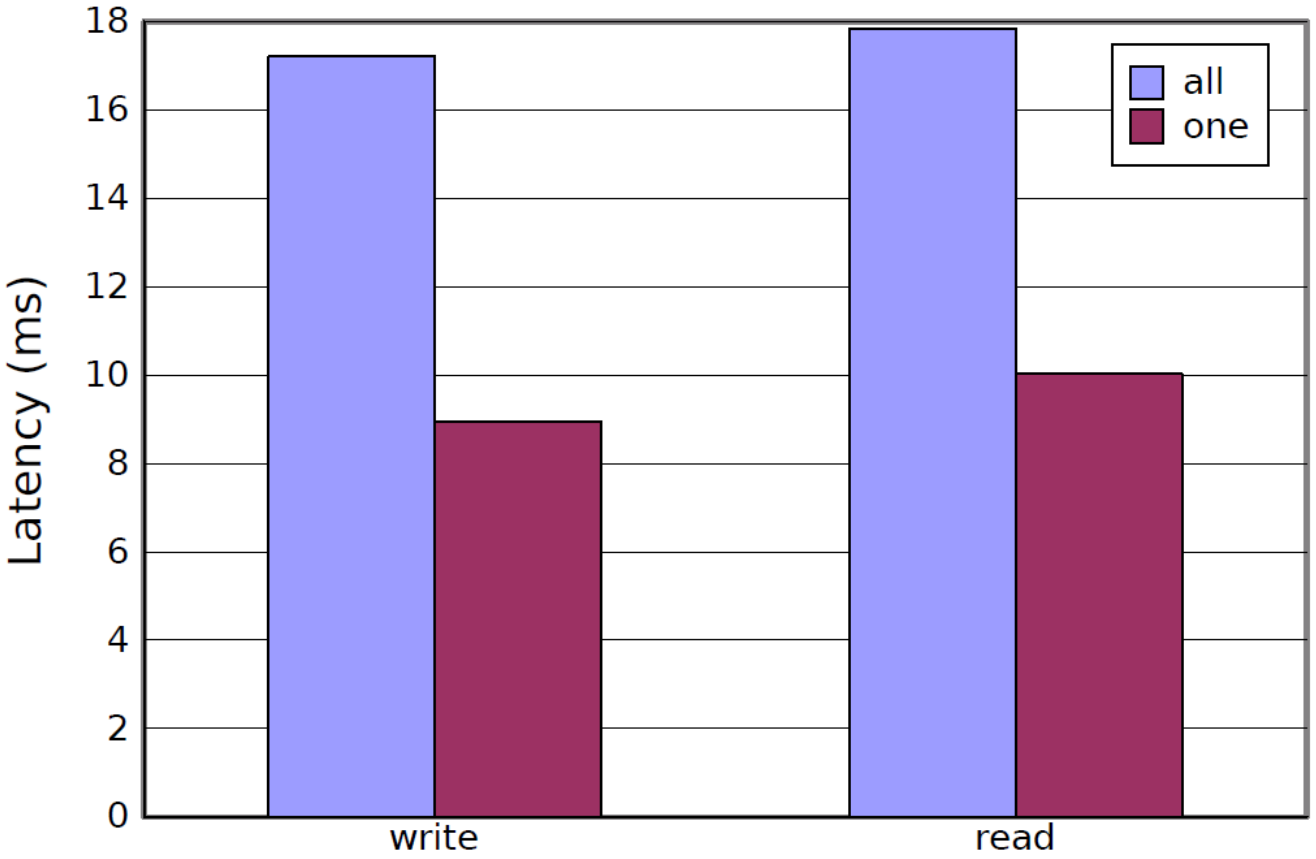
Consistency vs. Latency



Experiment on Amazon EC2 – Yahoo! Cloud Serving Benchmark (YCSB) – 4 Cassandra Nodes Same EC2 Availability Zone

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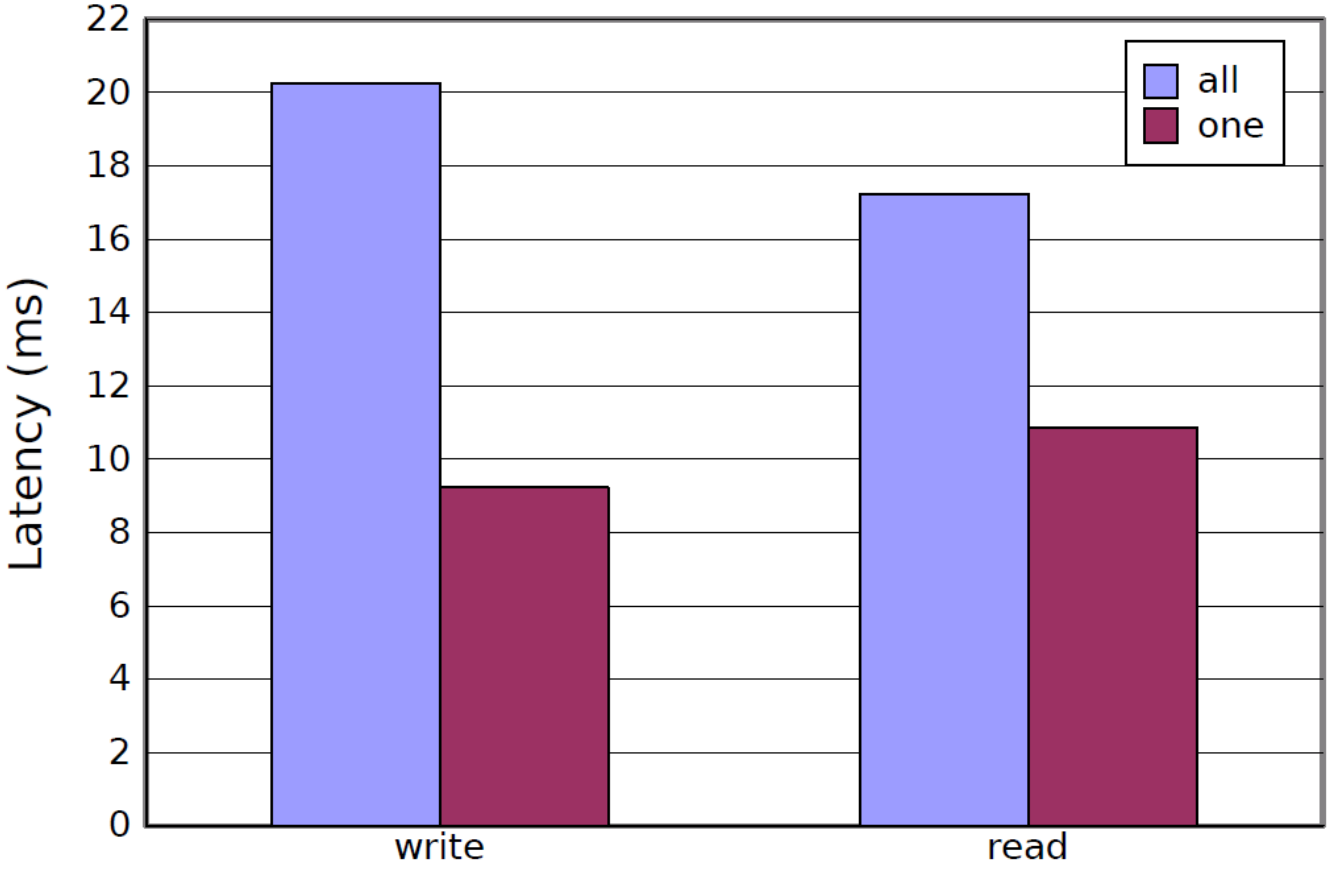
Consistency vs. Latency



Two EC2 Availability Zones
Same EC2 Geographic Region

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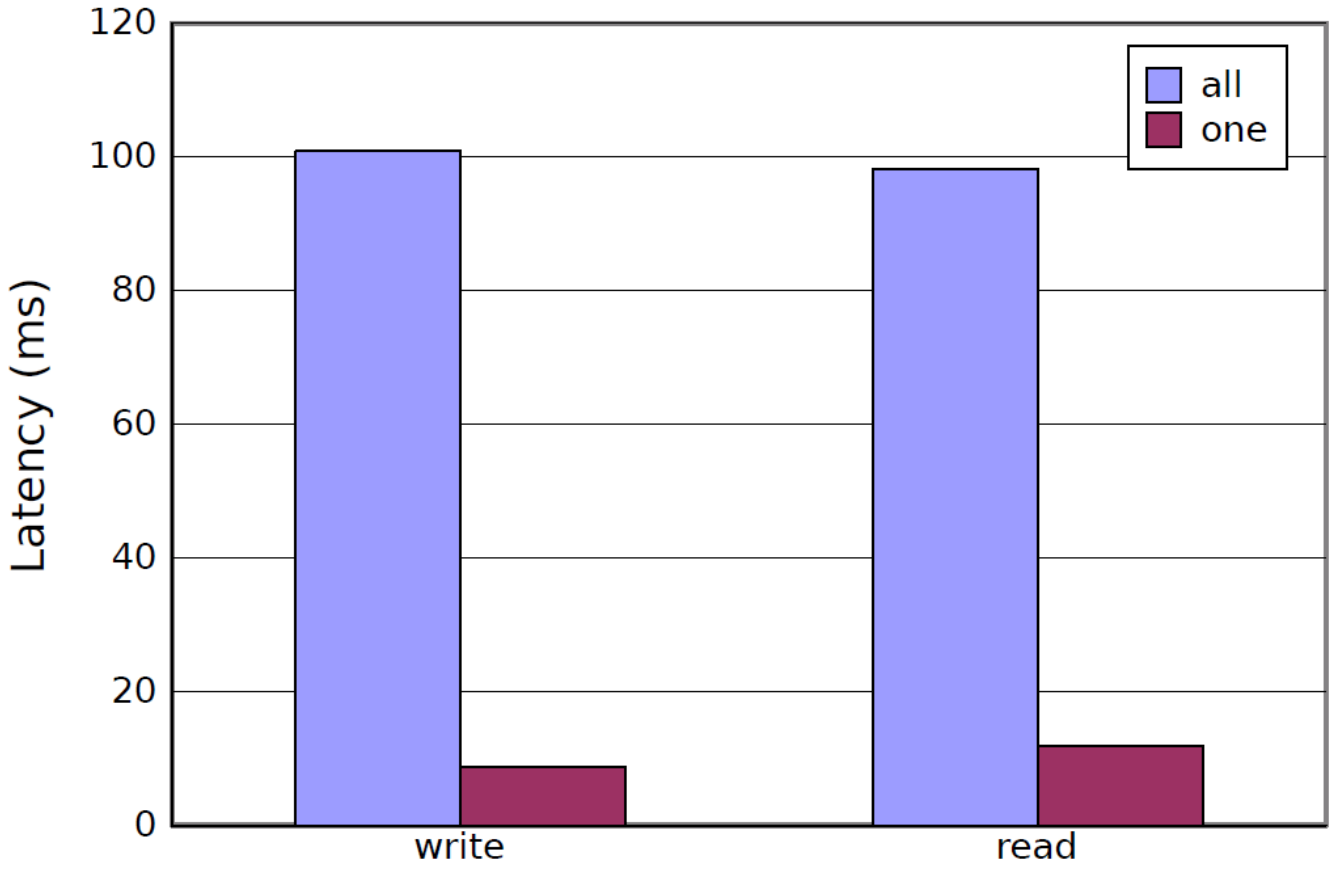
Consistency vs. Latency

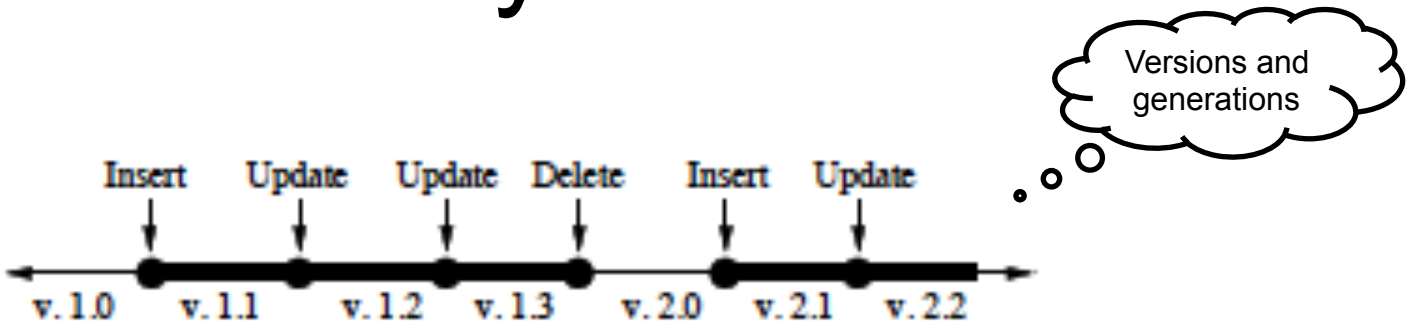


Two EC2 Regions
(US East and US West)

Case Study 3: PNUTS

- Yahoo; the only system that has a benchmark, and thorough experimental evaluation

Case Study 3: PNUTS



- Read-any = returns any stable version
- Read-critical(required_version) = reads a version that is strictly newer
- Read-latest = reads absolute latest
- Test-and-set-write(required_version) = writes only if current version is the required one

Criticism

Stonebraker, CACM'2010 (blog 1)

Criticism

- Two ways to improve OLTP performance:
  - Sharding over shared-nothing
  - Improve per-server OLTP performance
- Recent RDBMs do provide sharding: Greenplum, Aster Data, Vertica, ParAccel
- Hence, the discussion is about single-node performance

Criticism (cont'd)

- Single-node performance:
- Major performance bottleneck: communication with DBMS using ODBC or JDBC
  - Solution: stored procedures, OR embedded databases
- Server-side performance (next slide)

Criticism (cont'd)

Server-side performance: abut 25% each

- Logging
  - Everything written twice; log must be forced
- Locking
  - Needed for ACID semantics
- Latching
  - This is when the DBMS itself is multithreaded; e.g. latch for the lock table
- Buffer management

Criticism (cont'd)

Main take-away:

- NoSQL databases give up 1, or 2, or 3 of those features
- Thus, performance improvement can only be modest
- Need to give up all 4 features for significantly higher performance
- On the downside, NoSQL give up ACID

Criticism (cont'd)

Who are the customers of NoSQL?

- Lots of startups
- Very few enterprises. Why? most applications are traditional OLTP on structured data; a few other applications around the "edges", but considered less important

Stonebraker, CACM'2011 (blog 2)

Criticism (cont'd)

- No ACID Equals No Interest
  - Screwing up mission-critical data is no-no-no
- Low-level Query Language is Death
  - Remember CODASYL?
- NoSQL means NoStandards
  - One (typical) large enterprise has 10,000 databases. These need accepted standards