noSQL Databases

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  - noSQL vs RDBMS
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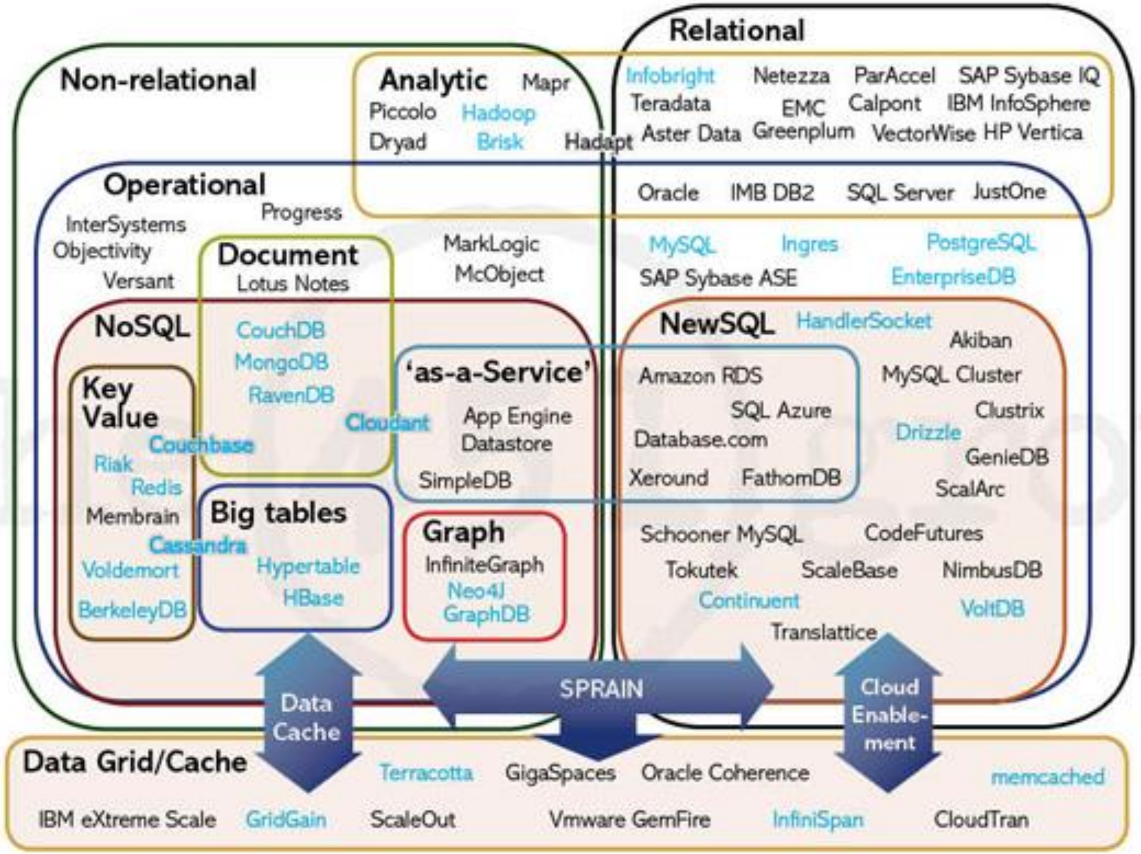
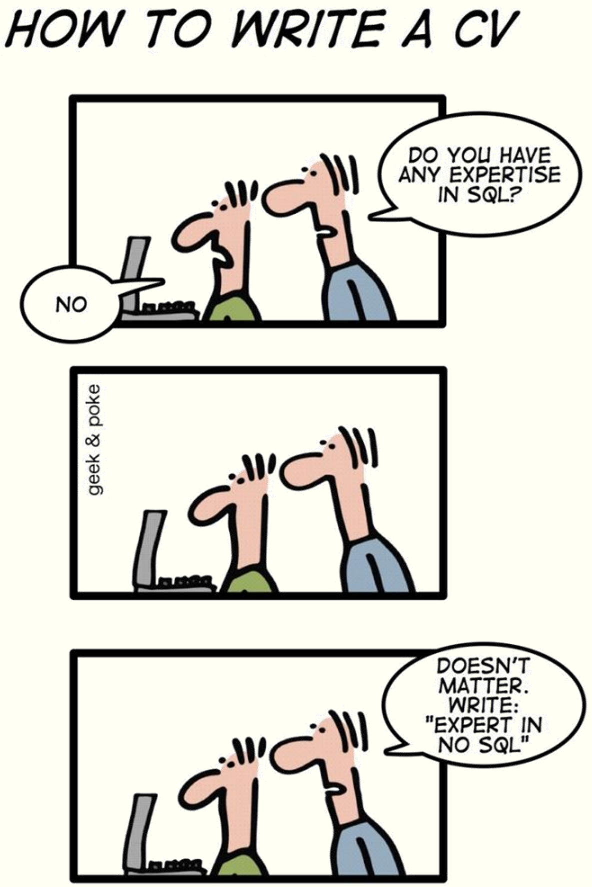
- Graph databases


Non-relational
Analytic
Mapr
Piccolo
Hadoop
Dryad
Brisk
Hadapt
Relational
Infobright
Netezza
ParAccel
SAP Sybase IQ
Teradata
EMC
Calpont
IBM InfoSphere
Aster Data
Greenplum
VectorWise
HP Vertica
Oracle
IMB DB2
SQL Server
JustOne
Operational
Progress
InterSystems
Objectivity
Versant
Document
Lotus Notes
MarkLogic
McObject
MySQL
Ingres
PostgreSQL
SAP Sybase ASE
EnterpriseDB
NoSQL
CouchDB
MongoDB
RavenDB
Key Value
Couchbase
Riak
Redis
Membrain
Cassandra
Voldemort
BerkeleyDB
Cloudant
'as-a-Service'
App Engine Datastore
SimpleDB
NewSQL
HandlerSocket
Akiban
Amazon RDS
SQL Azure
Database.com
Xeround
FathomDB
MySQL Cluster
Clustrix
Drizzle
GenieDB
ScalArc
Big tables
Hypertable
HBase
Graph
InfiniteGraph
Neo4J
GraphDB
Schooner MySQL
CodeFutures
Tokutek
ScaleBase
NimbusDB
Continuent
VoltDB
Translattice
Data Cache
SPRAIN
Cloud Enable-ment
Data Grid/Cache
Terracotta
GigaSpaces
Oracle Coherence
memcached
IBM eXtreme Scale
GridGain
ScaleOut
Vmware GemFire
InfiniSpan
CloudTran

noSQL: Concept

- NoSQL is a non-relational database management system, different from traditional RDBMS
- Carlo Strozzi used the term NoSQL in 1998 to name his lightweight, open-source relational database that did not expose the standard SQL interface
- In 2009, Eric Evans reused the term to refer databases which are non-relational, distributed, and does not conform to ACID
- The NoSQL term should be used as in the Not-Only-SQL and not as No to SQL or Never SQL



Leverage the NoSQL boom

Motives Behind NoSQL

- Big data.
- Scalability.
- Data format.
- Manageability.

Scalability

- Scale up, Vertical scalability.
  - Increasing server capacity.
  - Adding more CPU, RAM.
  - Managing is hard.
  - Possible down times
- Scale out, Horizontal scalability.
  - Adding servers to existing system with little effort, aka Elastically scalable.
  - Shared nothing.
  - Use of commodity/cheap hardware.
  - Heterogeneous systems.
  - Controlled Concurrency (avoid locks).
  - Service Oriented Architecture.
    - Decentralized to reduce bottlenecks.
    - Avoid Single point of failures.
  - Asynchrony.

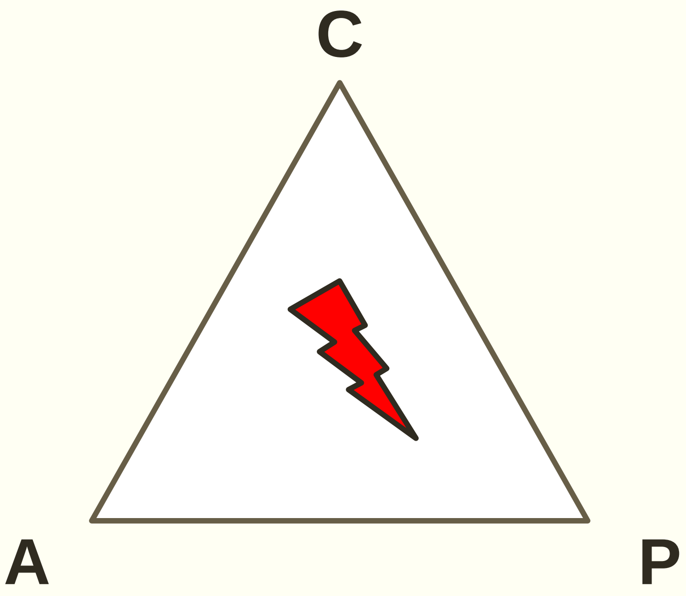
CAP Theorem

- Also known as Brewer's Theorem by Prof. Eric Brewer, published in 2000 at UC Berkeley.
- http://www.cs.berkeley.edu/~brewer/cs262b-2004/PODC-keynote.pdf

Eric Brewer 2001

CAP Theory

- **C**onsistency
  - All replicas contain the same version of data
  - Client always has the same view of the data (no matter what node)
- **A**vailability
  - System remains operational on failing nodes
  - All clients can always read and write
- **P**artition tolerance
  - multiple entry points
  - System remains operational on system split (communication malfunction)
  - System works well across physical network partitions



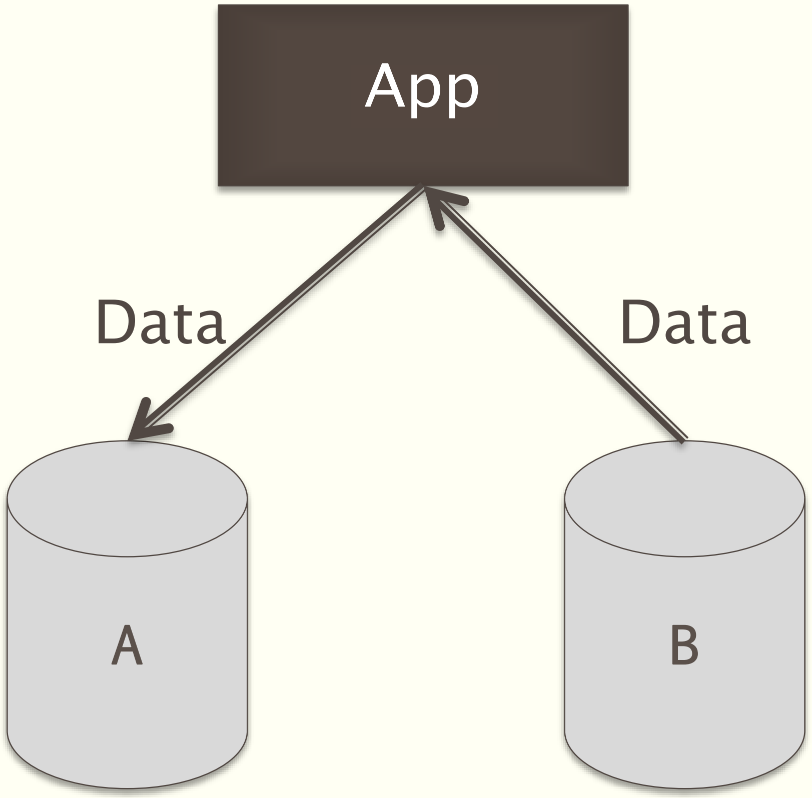
CAP Theorem: satisfying all three at the same time is impossible

CAP Theorem

"Of three properties of a shared data system: data consistency, system availability and tolerance to network partitions, only two can be achieved **at any given moment**."
Proven by Nancy Lynch et al. MIT labs.

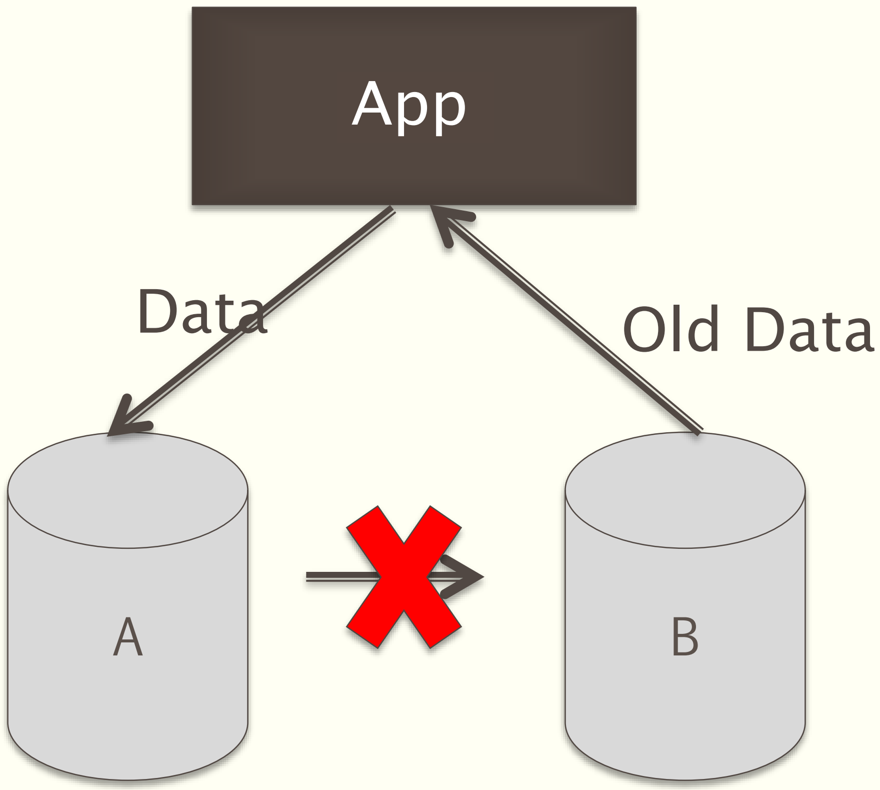
- What the CAP theorem really says:
  - If you cannot limit the number of faults and requests can be directed to any server and you insist on serving every request you receive then you cannot possibly be consistent
- How it is interpreted:
  - You must always give something up: consistency, availability or tolerance to failure and reconfiguration

Proof: A Trivial Two-node System



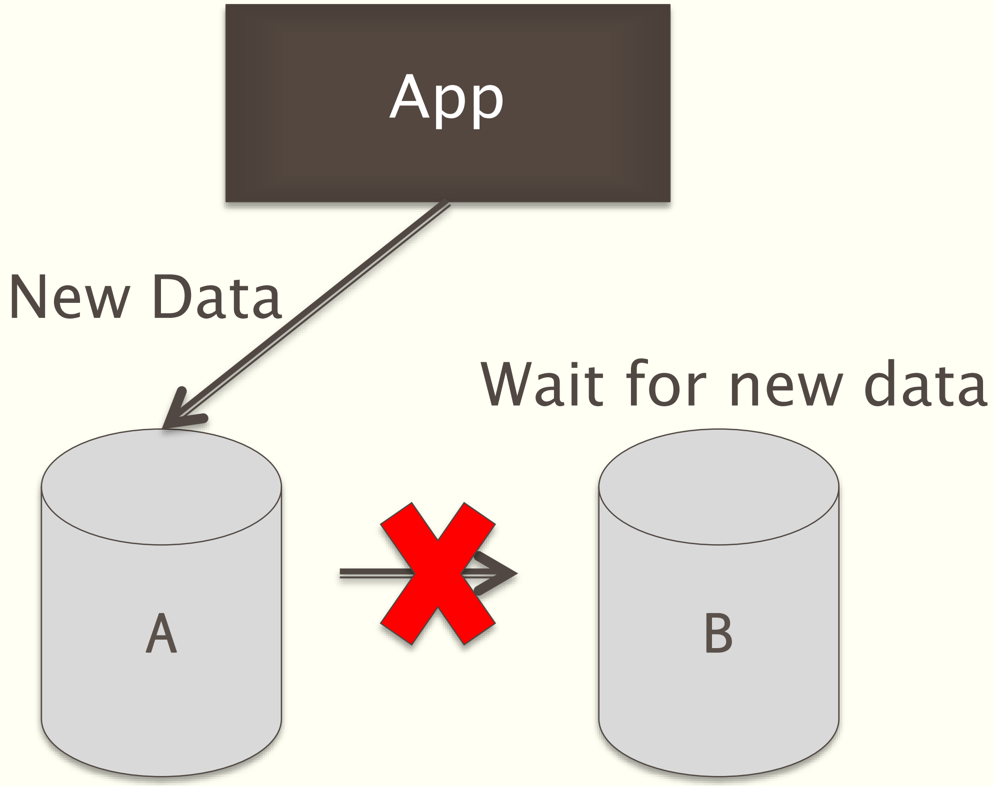
A Simple Proof

Available and partitioned
Not consistent, we get back old data.



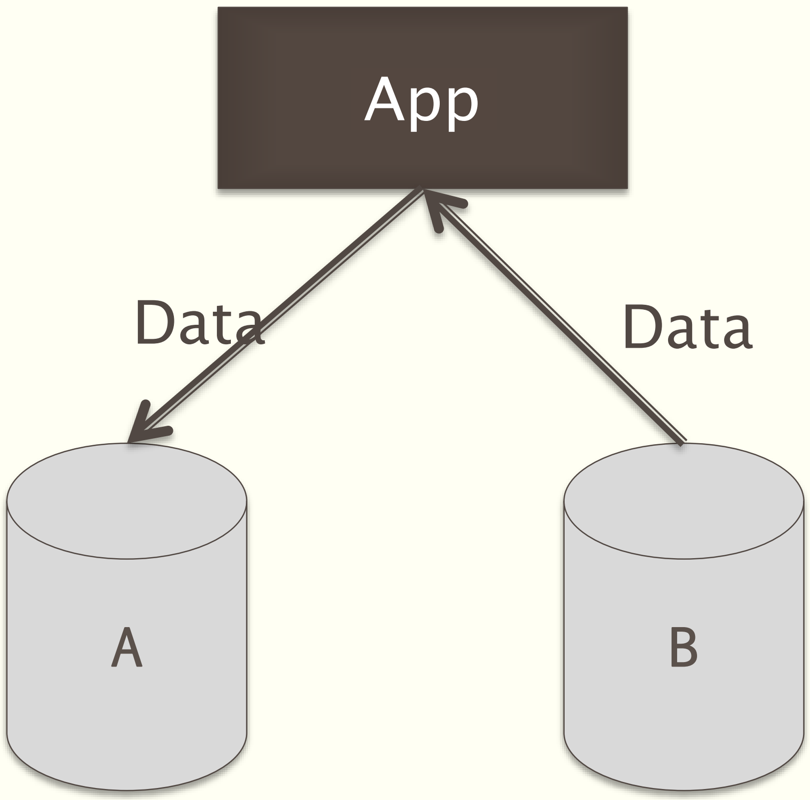
A Simple Proof

Consistent and partitioned
Not available, waiting…

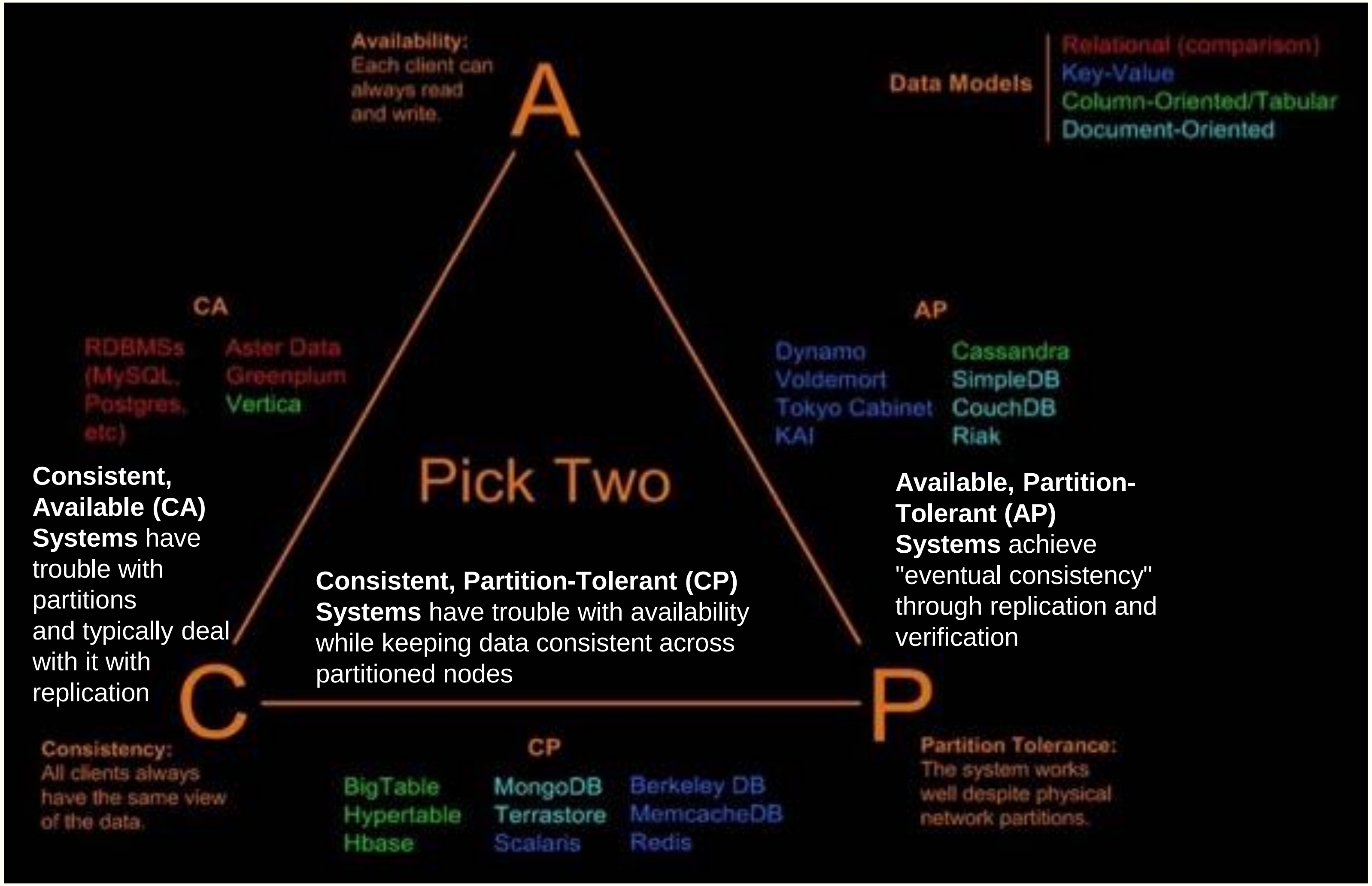


A Simple Proof

Consistent and Available
No partition.



Visual Guide to NoSQL Systems



Consistent, Available (CA) Systems have trouble with partitions and typically deal with it with replication

Consistent, Partition-Tolerant (CP) Systems have trouble with availability while keeping data consistent across partitioned nodes

Available, Partition-Tolerant (AP) Systems achieve "eventual consistency" through replication and verification

http://blog.nahurst.com/visual-guide-to-nosql-systems

Consistency: ACID vs BASE

ACID

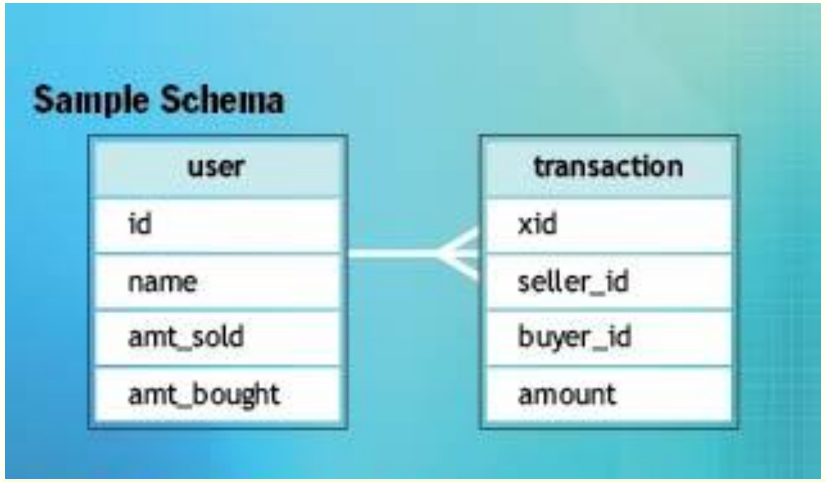
- Databases require 4 properties:
  - Atomicity: When an update happens, it is "all or nothing"
  - Consistency: The state of various tables much be consistent (relations, constraints) at all times.
  - Isolation: Concurrent execution of transactions produces the same result as if they occurred sequentially.
  - Durability: Once committed, the results of a transaction persist against various problems like power failure etc.
- These properties ensure that data is protected even with complex updates and system failures.
- Any data store can achieve Atomicity, Isolation and Durability but do you always need consistency? No.
- By giving up ACID properties, one can achieve higher performance and scalability.

BASE

- Acronym contrived to be the opposite of ACID
  - **B**asically **A**vailable,
  - **S**oft state,
  - **E**ventually Consistent
- Characteristics
  - Weak consistency – stale data OK
  - Availability first
  - Best effort
  - Approximate answers OK
  - Simpler and faster

A Toy Example

Pritchett, D.:
BASE: An Acid Alternative
(queue.acm.org/detail.cfm?id=1394128)




```
Begin transaction
  Insert into transaction(id, seller_id, buyer_id, amount);
  Queue message "update user("seller", seller_id, amount)";
  Queue message "update user("buyer", buyer_id, amount)";
End transaction
For each message in queue
  Begin transaction
    Dequeue message
    If message.balance == "seller"
      Update user set amt_sold=amt_sold + message.amount
              where id=message.id;
    Else
      Update user set amt_bought=amt_bought + message.amount
              where id=message.id;
    End if
  End transaction
End for
```

RDB ACID to NoSQL BASE

Pritchett, D.: BASE: An Acid Alternative (queue.acm.org/detail.cfm?id=1394128)

Atomicity

Consistency

Isolation

Durability

Basically

Available

Soft-state

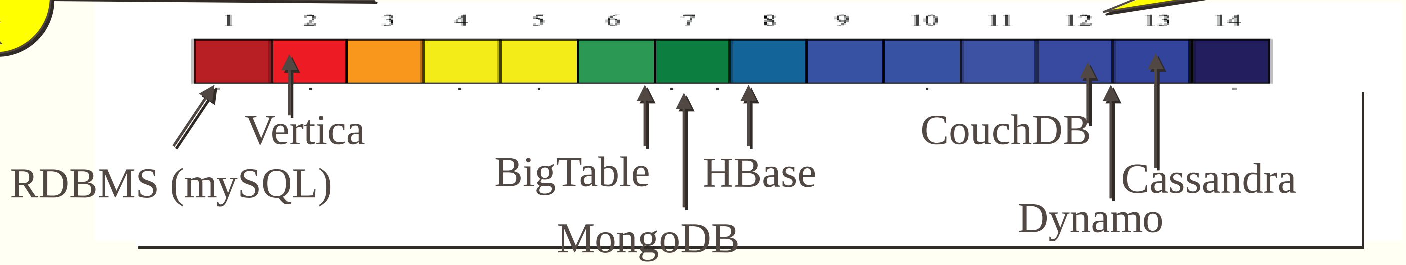
(State of system may change over time)

Eventually consistent

(Asynchronous propagation)

Data constraints
Smaller,
Schema-driven,
Normalized,
Relational,
Pre-social network

Unstructured data
Big data
Non-relational,
Schema-less,
Distributed,
open-linked data



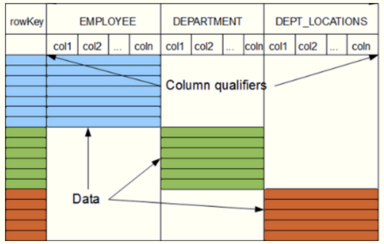
A Clash of cultures

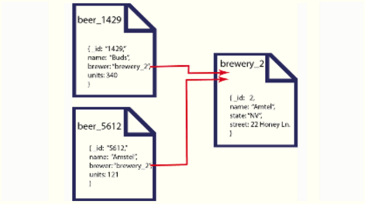
- ACID:
  - Strong consistency.
  - Less availability.
  - Pessimistic concurrency.
  - Complex.
- BASE:
  - Availability is the most important thing. Willing to sacrifice for this (CAP).
  - Weaker consistency (Eventual).
  - Best effort.
  - Optimistic.
  - Simple and fast.

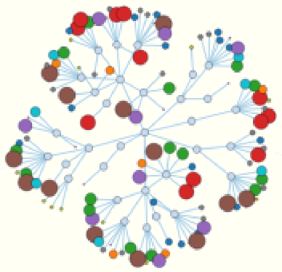
noSQL Data Models

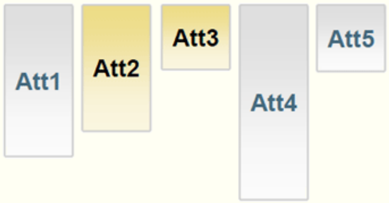
- Key/Value Pairs
- Row/tabular
- Columns
- Documents
- Graphs
- and correspondingly...

key	value
firstName	Bugs
lastName	Bunny
location	Earth







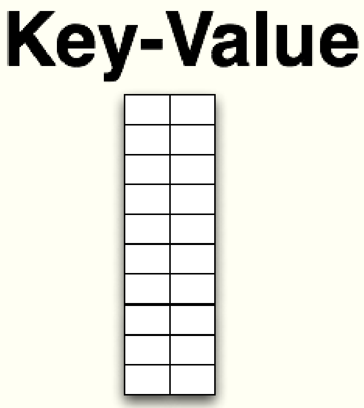


Categories of NoSQL storages

- Key-Value
  - memcached
  - Redis
  - Dynamo
- Tabular
  - BigTable, HBase
- Column Family
  - Cassandra
- Document-oriented
  - MongoDB
- Graph (beyond noSQL)
  - Neo4j
  - TITAN

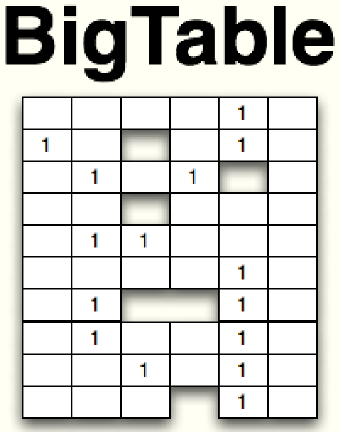
Key-Value Stores

- "Dynamo: Amazon's Highly Available Key-Value Store" (2007)
- Data model:
  - Global key-value mapping
  - Highly fault tolerant (typically)
- Examples:
  - Riak, Redis, Voldemort



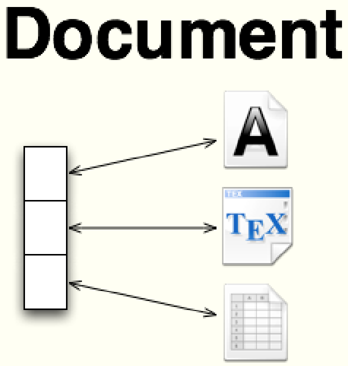
Column Family (BigTable)

- Google's "Bigtable: A Distributed Storage System for Structured Data" (2006)
- Data model:
  - A big table, with column families
  - Map-reduce for querying/processing
- Examples:
  - HBase, HyperTable, Cassandra



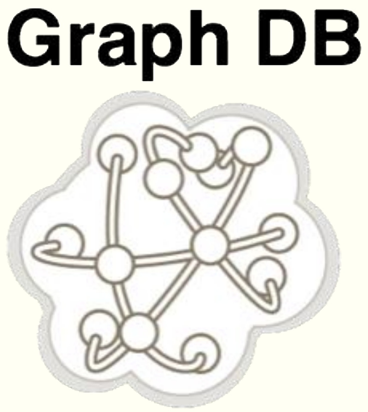
Document Databases

- Data model
  - Collections of documents
  - A document is a key-value collection
  - Index-centric, lots of map-reduce
- Examples
  - CouchDB, MongoDB

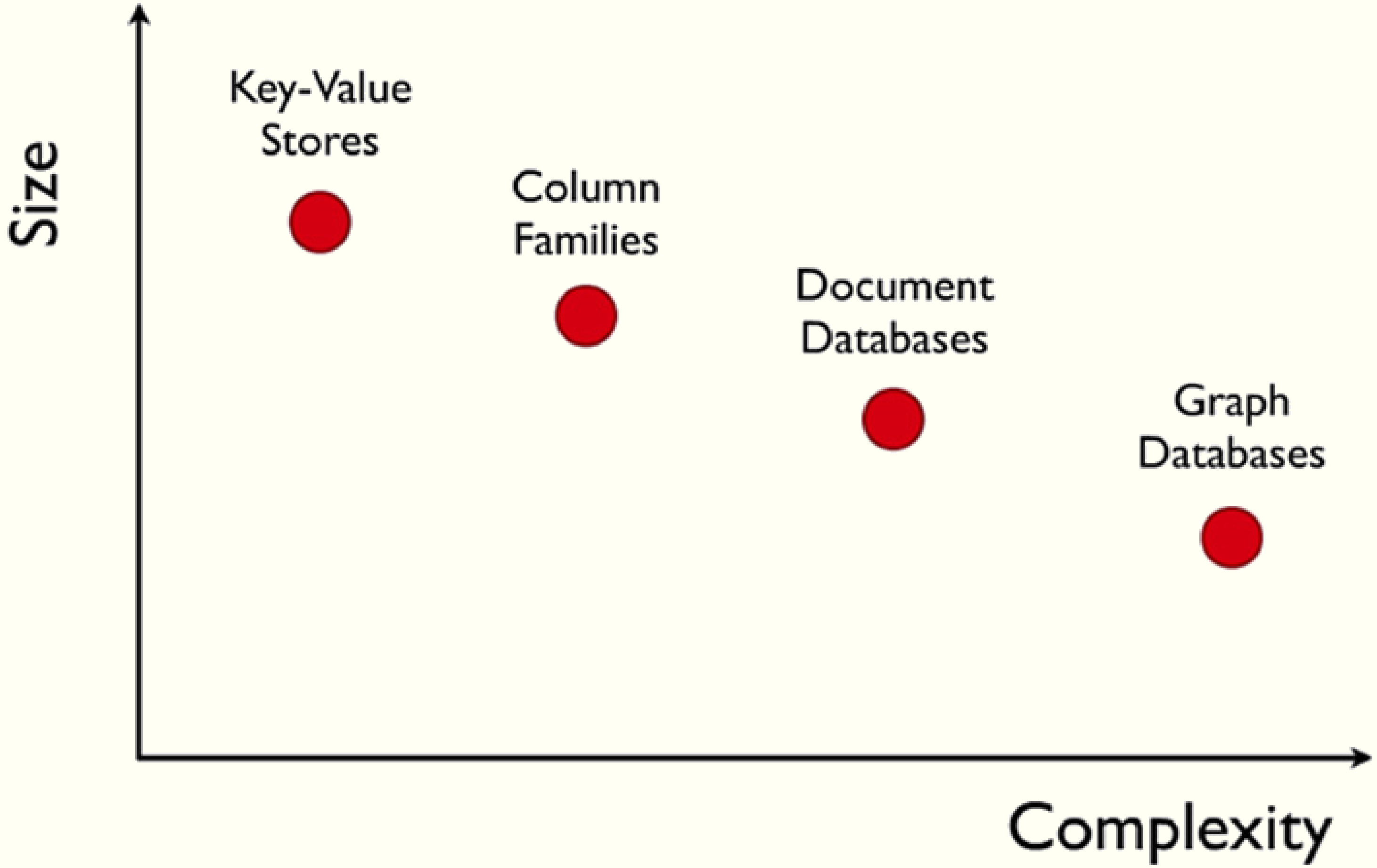


Graph Databases

- Data model:
  - Nodes with properties
  - Named relationships with properties
  - Hypergraph, sometimes
- Examples:
  - Neo4j, Sones GraphDB, OrientDB, InfiniteGraph, AllegroGraph



Complexity



Key-Value Stores
Column Families
Document Databases
Graph Databases
Size
Complexity

Key Value Stores and Relational Table

- KV-stores seem very simple. They can be viewed as two-column (key, value) tables with a single key column.
- But they can be used to implement more complicated relational tables:

State	ID	Population	Area	Senator_1
Alabama	1	4,822,023	52,419	Sessions
Alaska	2	731,449	663,267	Begich
Arizona	3	6,553,255	113,998	Boozman
Arkansas	4	2,949,131	53,178	Flake
California	5	38,041,430	163,695	Boxer
Colorado	6	5,187,582	104,094	Bennet
…	…			

Index

KV-stores and Relational Tables

- The KV-version of the previous table includes one table indexed by the actual key, and others by an ID.

State	ID
Alabama	1
Alaska	2
Arizona	3
Arkansas	4
California	5
Colorado	6
…	…

ID	Population
1	4,822,023
2	731,449
3	6,553,255
4	2,949,131
5	38,041,430
6	5,187,582
…	…

ID	Area
1	52,419
2	663,267
3	113,998
4	53,178
5	163,695
6	104,094
…	…

ID	Senator_1
1	Sessions
2	Begich
3	Boozman
4	Flake
5	Boxer
6	Bennet
…	…

KV-stores and Relational Tables

- We can add indices with new KV-tables:
- Thus KV-tables are used for column-based storage, as opposed to row-based storage typical in older DBMS.

State	ID
Alabama	1
Alaska	2
Arizona	3
Arkansas	4
California	5
Colorado	6
…	…

Index

ID	Population
1	4,822,023
2	731,449
3	6,553,255
4	2,949,131
5	38,041,430
6	5,187,582
…	…

Senator_1	ID
Sessions	1
Begich	2
Boozman	3
Flake	4
Boxer	5
Bennet	6
…	…

Index_2

OR: the value field can contain complex data

Key-Values: Examples

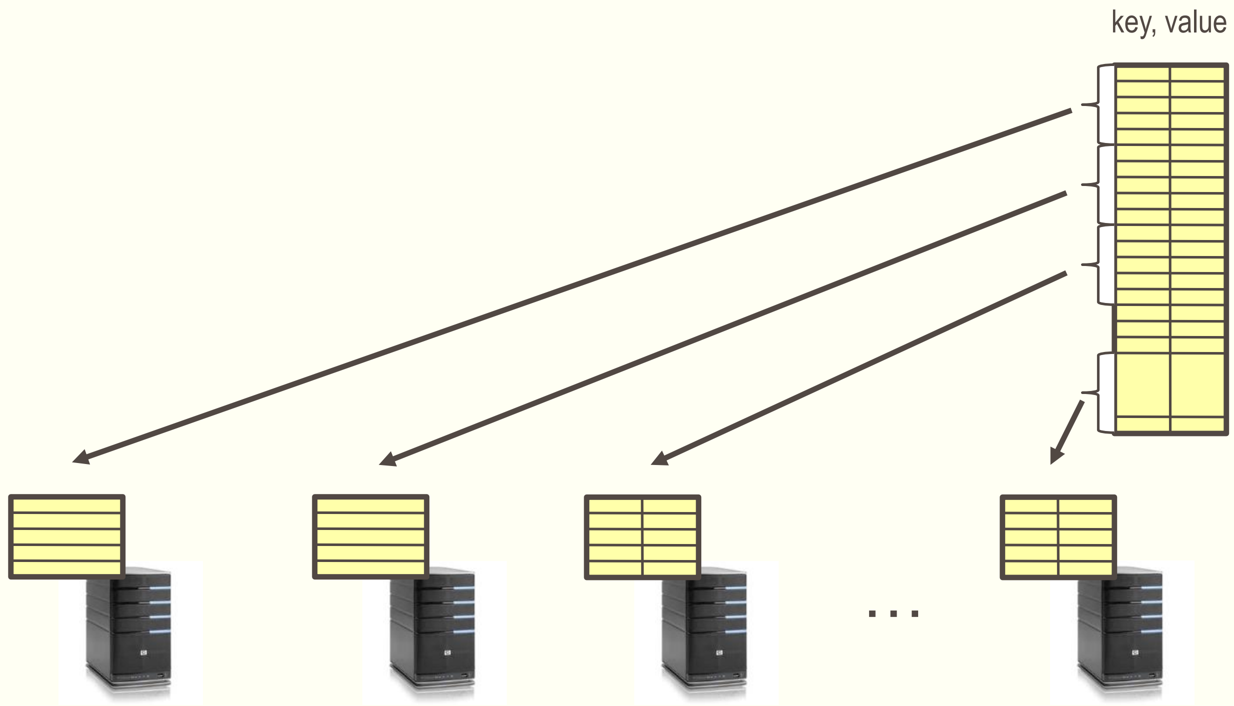
- Amazon:
  - Key: customerID
  - Value: customer profile (e.g., buying history, credit card, ..)
- Facebook, Twitter:
  - Key: UserID
  - Value: user profile (e.g., posting history, photos, friends, …)
- iCloud/iTunes:
  - Key: Movie/song name
  - Value: Movie, Song
- Distributed file systems
  - Key: Block ID
  - Value: Block

System Examples

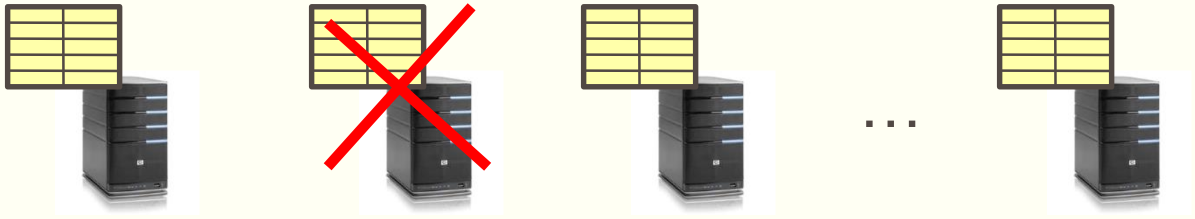
- **Google File System, Hadoop Dist. File Systems (HDFS)**
- **Amazon**
    - Dynamo: internal key value store used to power Amazon.com (shopping cart)
    - Simple Storage System (S3)
- **BigTable/HBase/Hypertable:** distributed, scalable data storage
- **Cassandra**: “distributed data management system” (Facebook)
- **Memcached:** in-memory key-value store for small chunks of arbitrary data (strings, objects)
- **eDonkey/eMule:** peer-to-peer sharing system

Key-Value Store

- Also called a Distributed Hash Table (DHT)
- Main idea: partition set of key-values across many machines



Challenges



- **Fault Tolerance:** handle machine failures without losing data and without degradation in performance
- **Scalability:**
  - Need to scale to thousands of machines
  - Need to allow easy addition of new machines
- **Consistency:** maintain data consistency in face of node failures and message losses
- **Heterogeneity** (if deployed as peer-to-peer systems):
  - Latency: 1ms to 1000ms
  - Bandwidth: 32Kb/s to several GB/s

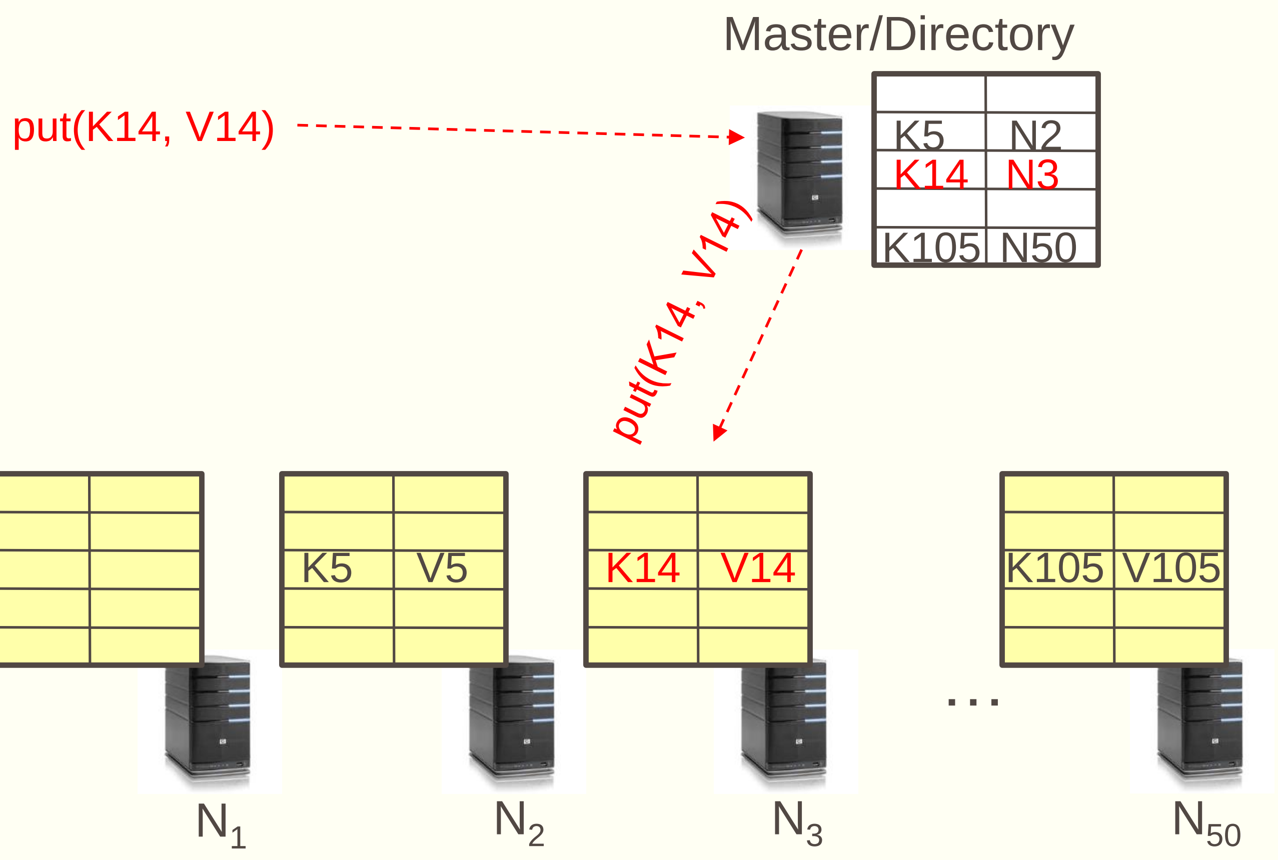
Key Operators

- put(key, value): where do you store a new (key, value) tuple?
- get(key): where is the value associated with a given “key” stored?

- And, do the above while providing
  - Fault Tolerance
  - Scalability
  - Consistency

Directory-Based Architecture

- Have a node maintain the mapping between **keys** and the **machines (nodes)** that store the **values** associated with the **keys**



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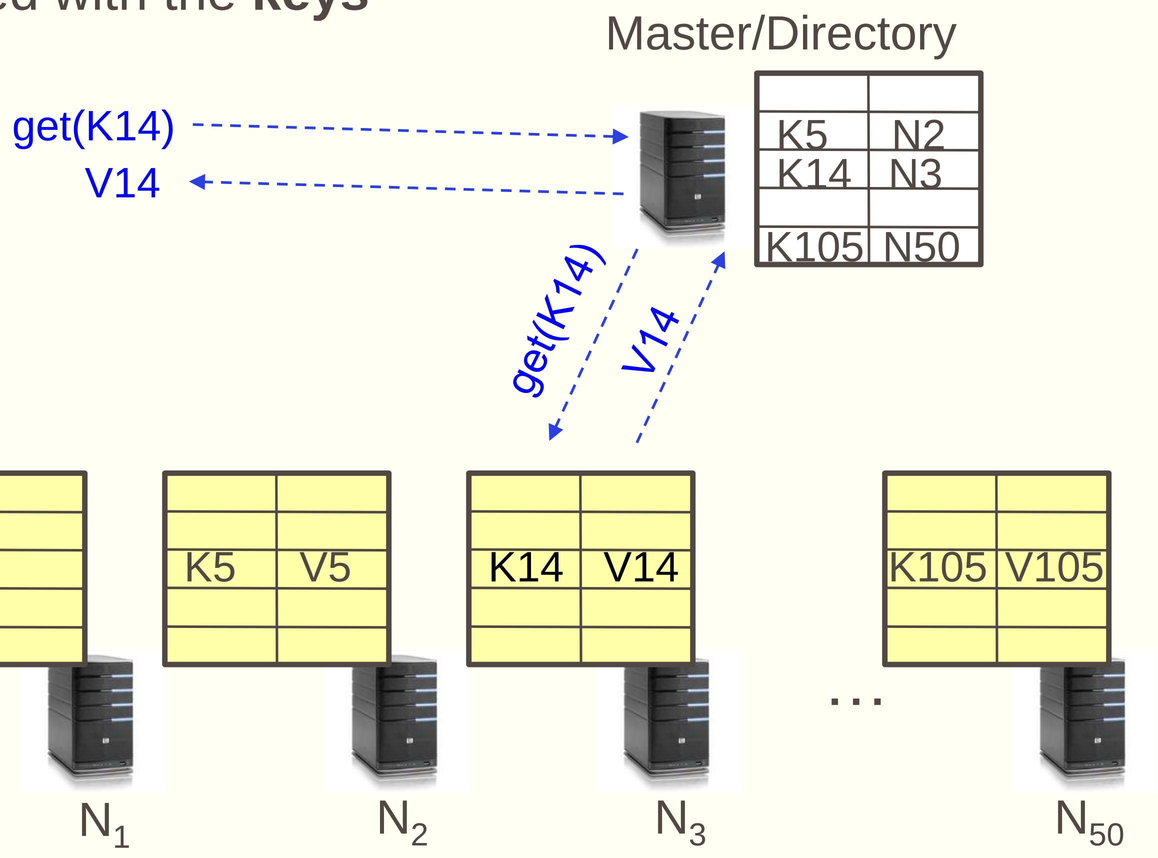
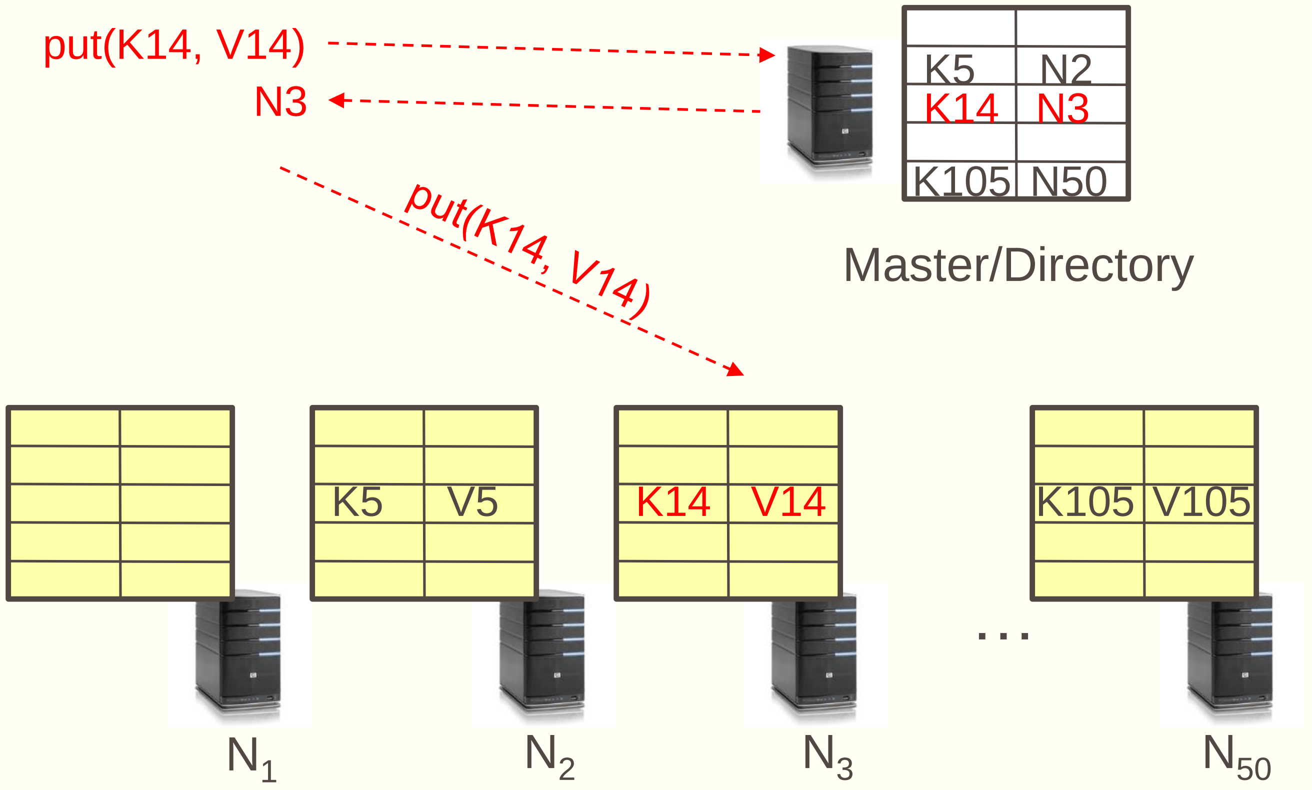


Having the master relay the requests ： recursive query

Directory-Based Architecture

- Another method: **iterative query** (this slide)
  - Return node to requester and let requester contact node



Directory-Based Architecture

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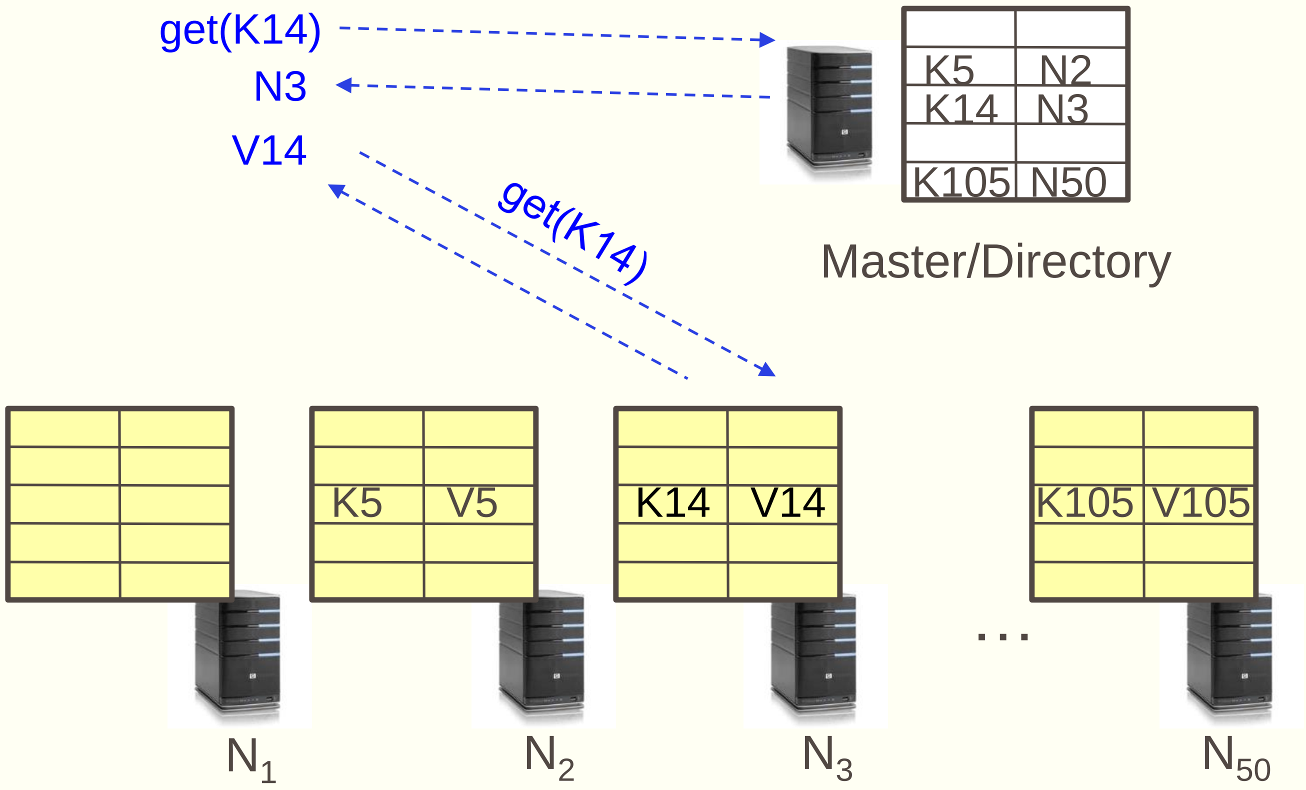
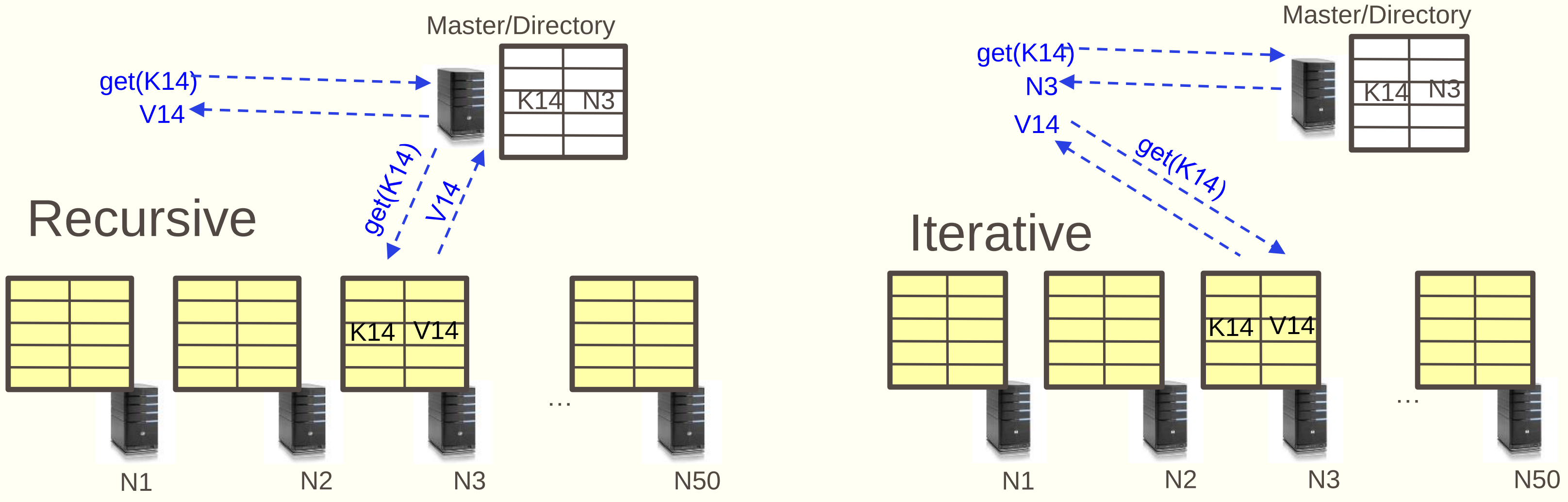


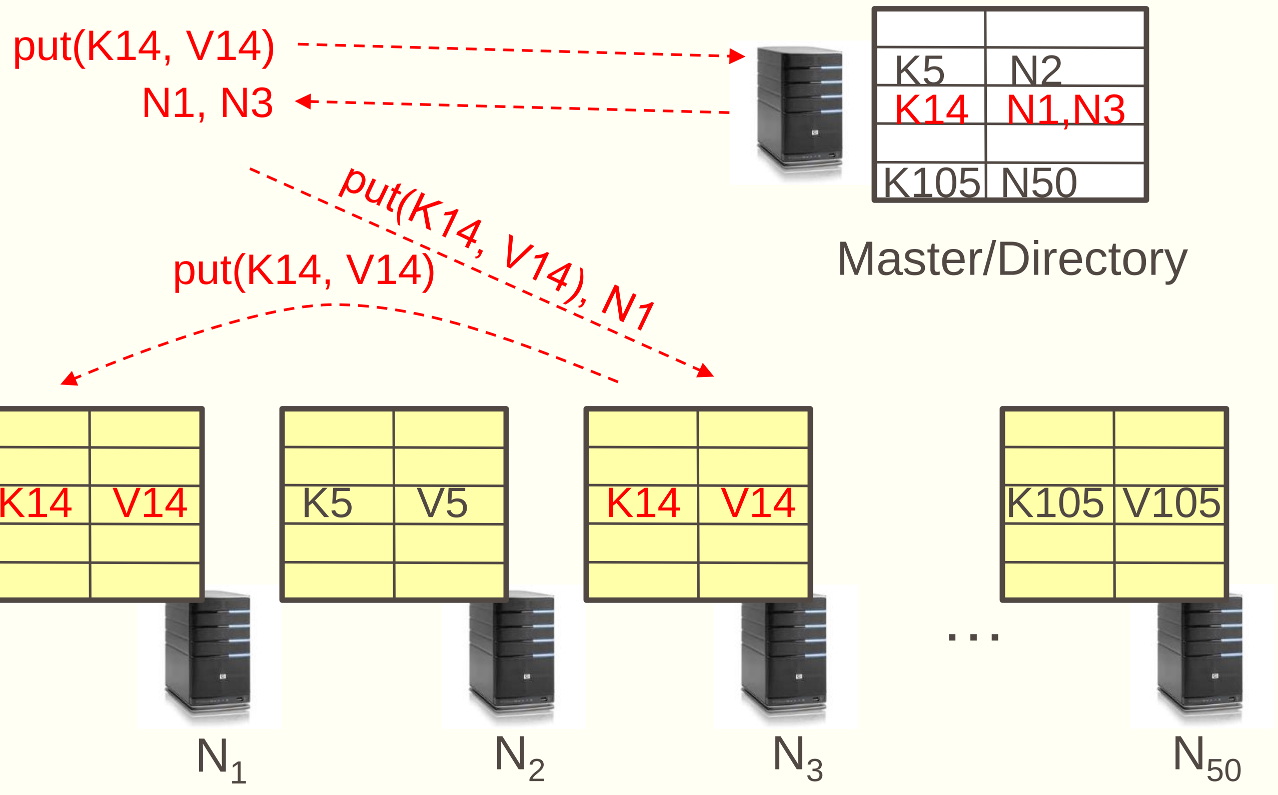
Recursive Vs. Iterative Query



- Recursive Query:
  - Advantages:
    - Faster (latency), as typically master/directory closer to nodes
    - Easier to maintain consistency, as master/directory can serialize puts()/gets()
  - Disadvantages: scalability bottleneck, as all "Values" go through master/directory
- Iterative Query
  - Advantages: more scalable
  - Disadvantages: slower (latency), harder to enforce data consistency

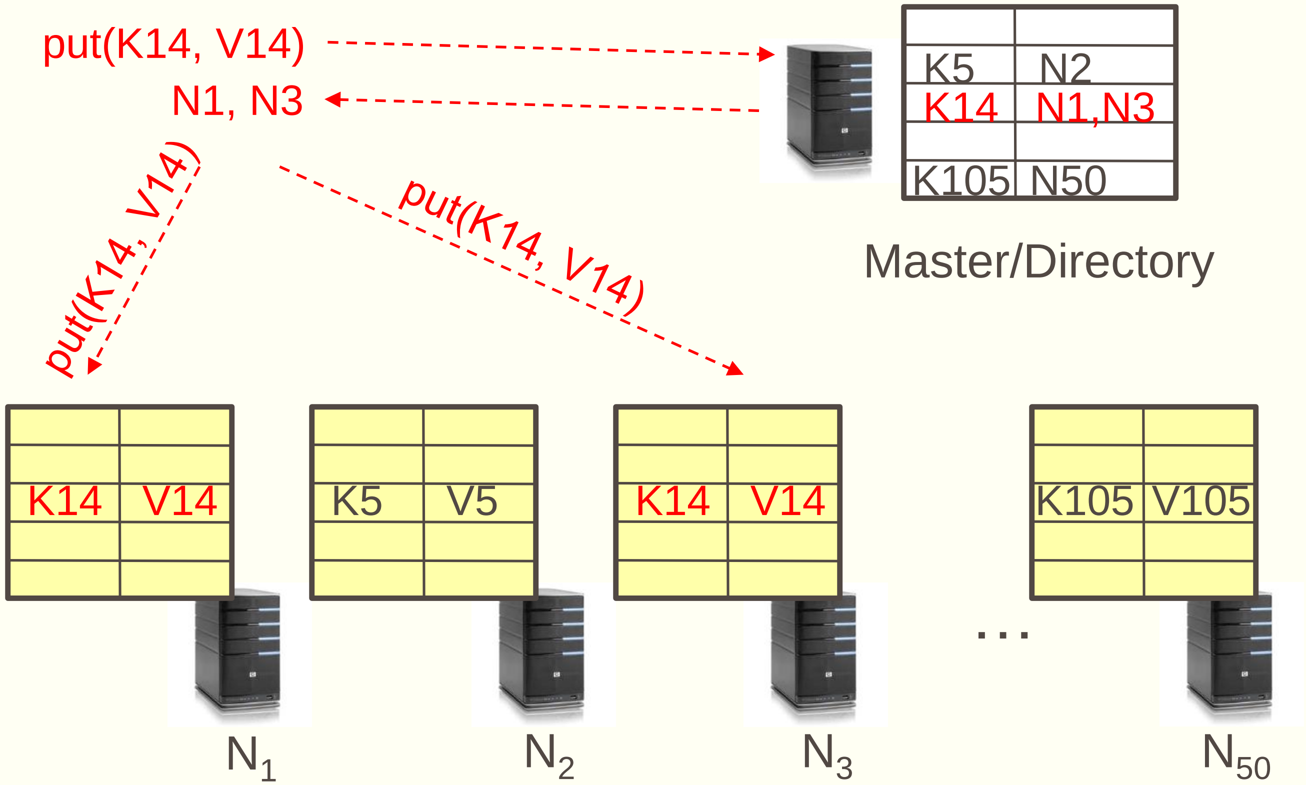
Fault Tolerance

- Replicate value on several nodes
- Usually, place replicas on different racks in a datacenter to guard against rack failures



Fault Tolerance

- Again, we can have
  - **Recursive** replication (previous slide)
  - **Iterative** replication (this slide)

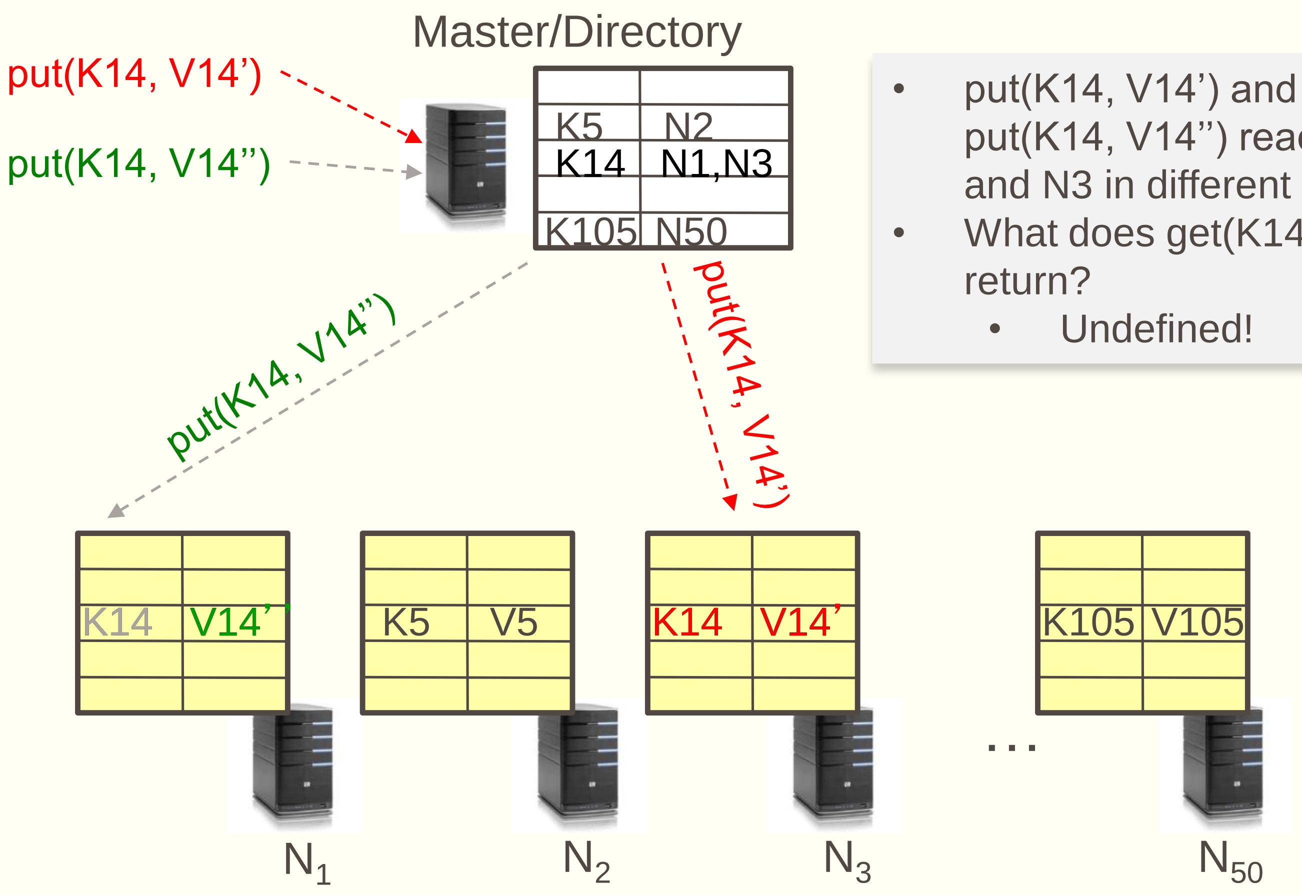


Consistency

- How close does a distributed system emulate a single machine in terms of read and write semantics?
- **Q:** Assume **put(K14, V14')** and **put(K14, V14'')** are concurrent, what value ends up being stored?
- **Q:** Assume a client calls **put(K14, V14)** and then **get(K14)**, what is the result returned by **get()**?
- Above semantics, not trivial to achieve in distributed systems

Concurrent Writes (Updates)

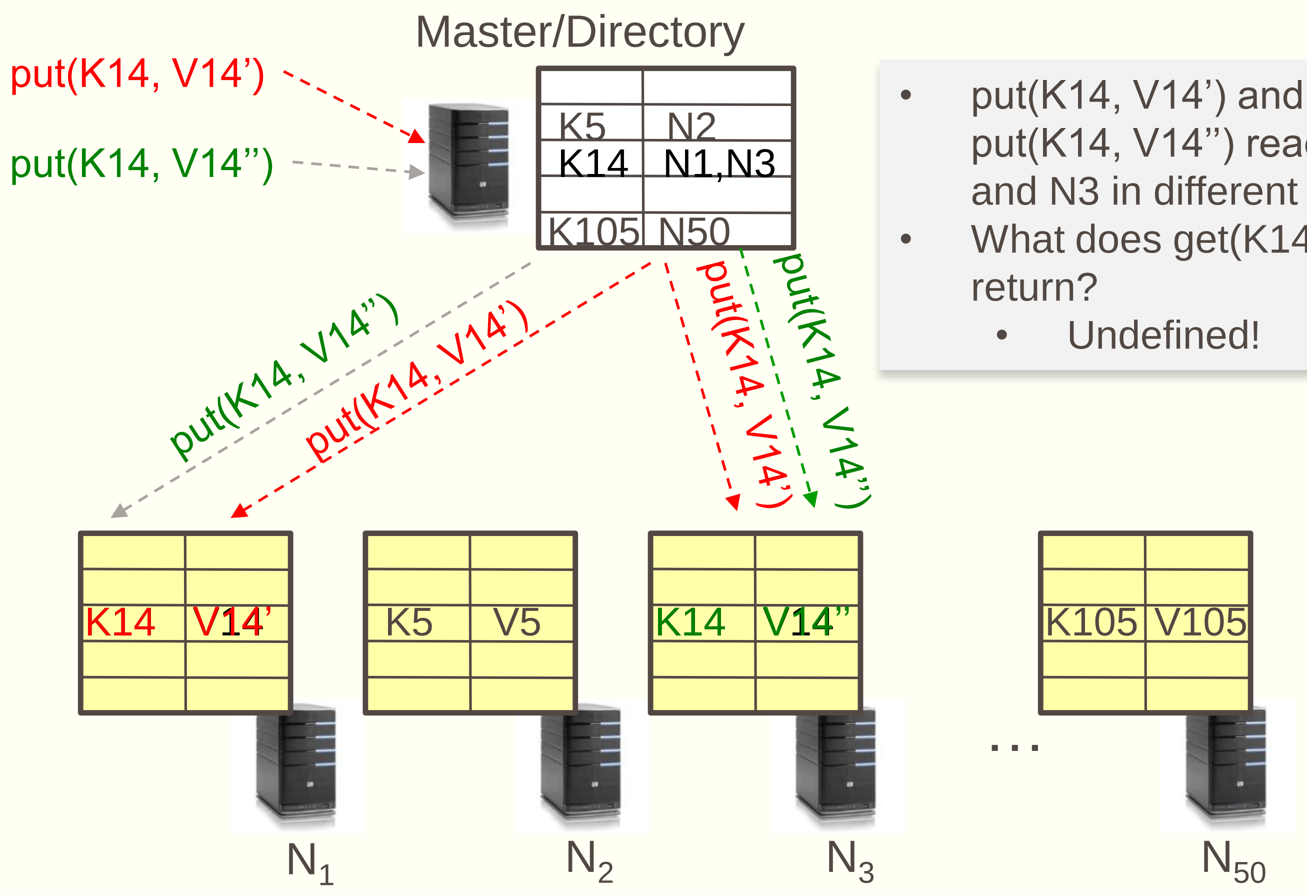
- If concurrent updates (i.e., puts to same key) may need to make sure that updates happen in the same order



- put(K14, V14') and put(K14, V14'') reach N1 and N3 in different order
- What does get(K14) return?
  - Undefined!

Concurrent Writes (Updates)

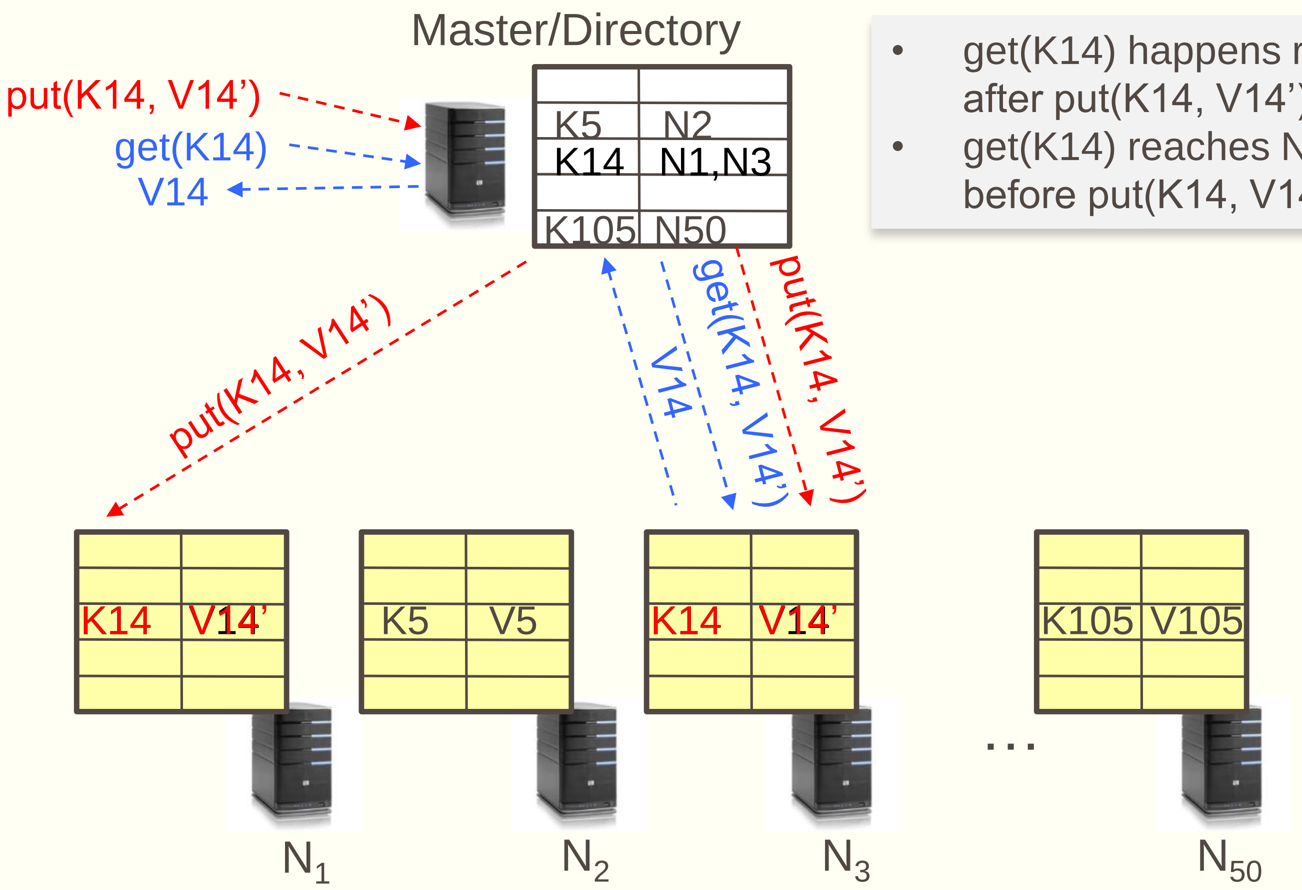
- If concurrent updates (i.e., puts to same key) may need to make sure that updates happen in the same order



- put(K14, V14') and put(K14, V14'') reach N1 and N3 in different order
- What does get(K14) return?
  - Undefined!

Read after Write

- Read not guaranteed to return value of latest write
  - Can happen if Master processes requests in different threads



- get(K14) happens right after put(K14, V14')
- get(K14) reaches N3 before put(K14, V14')!

Quorum Consensus

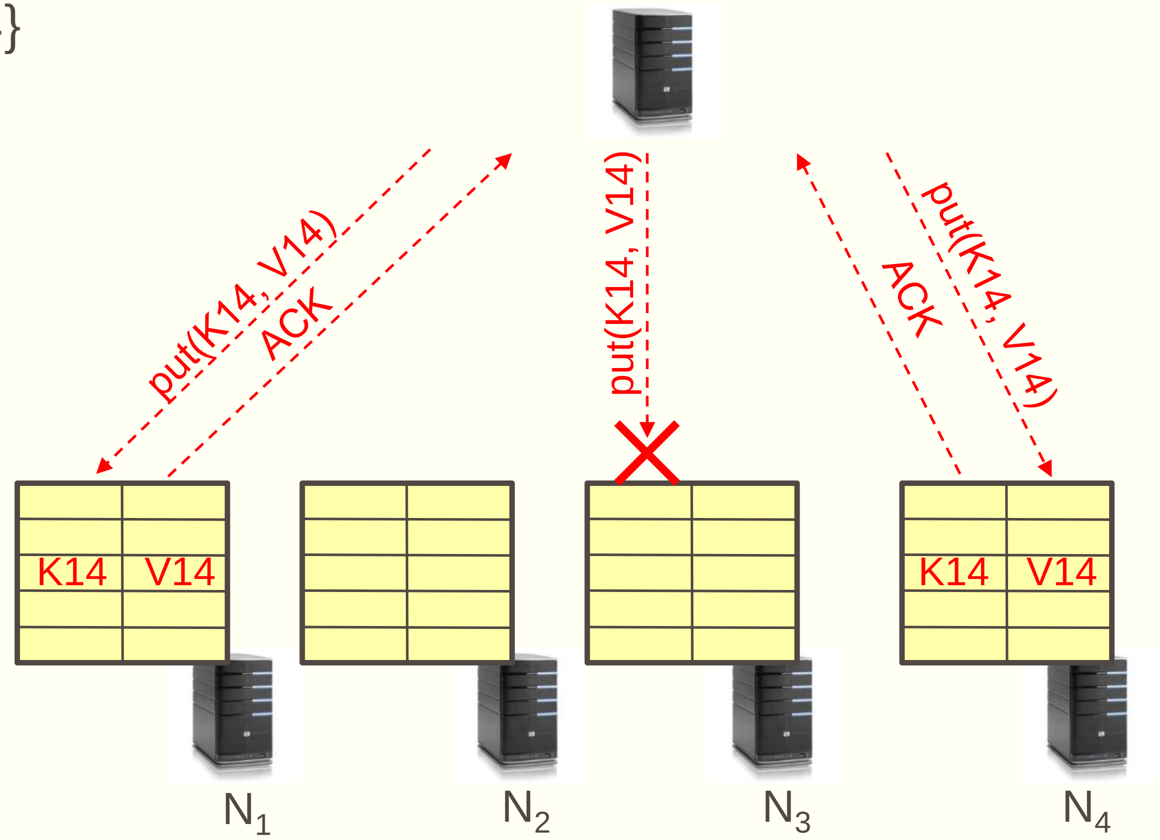
- Improve **put()** and **get()** operation performance

- Define a replica set of size N
- **put()** waits for acks from at least W replicas
- **get()** waits for responses from at least R replicas
- $W+R > N$

- Why does it work?
  - There is at least one node that contains the update

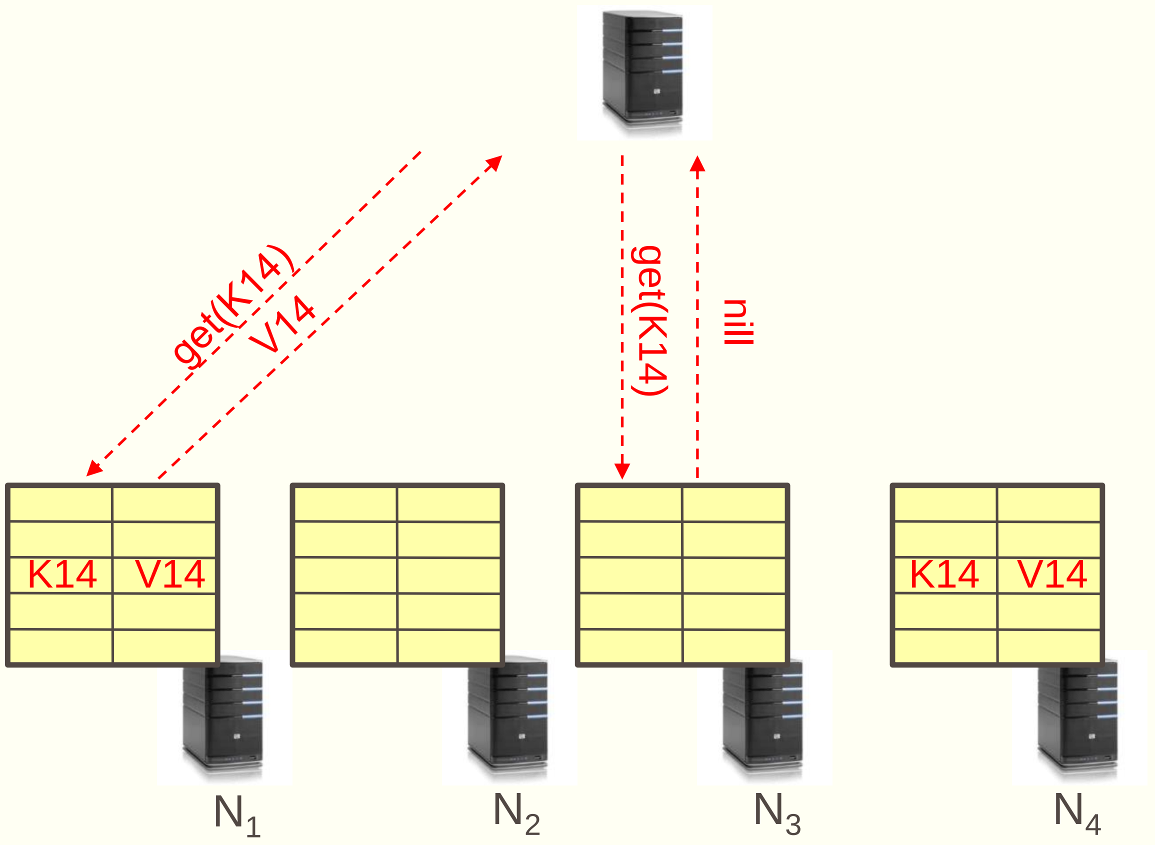
Quorum Consensus Example

- N=3, W=2, R=2
- Replica set for K14: {N1, N3, N4}
- Assume put() on N3 fails



Quorum Consensus Example

- Now, issuing get() to any two nodes out of three will return the answer



Scalability

- Storage: use more nodes
- Request Throughput:
  - Can serve requests from all nodes on which a value is stored in parallel
  - Large “values” can be broken into blocks (HDFS files are broken up this way)
  - Master can replicate a popular value on more nodes
- Master/directory scalability:
  - Replicate it
  - Partition it, so different keys are served by different masters/directories

Scalability: Load Balancing

- Directory keeps track of the storage availability at each node
  - Preferentially insert new values on nodes with more storage available
- What happens when a new node is added?
  - Move values from the heavy loaded nodes to the new node
- What happens when a node fails?
  - Need to replicate values from failed node to other nodes

Replication Challenges

- Need to make sure that a value is replicated correctly

- How do you know a value has been replicated on every node?
  - Wait for acknowledgements from every node

- What happens if a node fails during replication?
  - Pick another node and try again

- What happens if a node is slow?
  - Slow down the entire put()? Pick another node

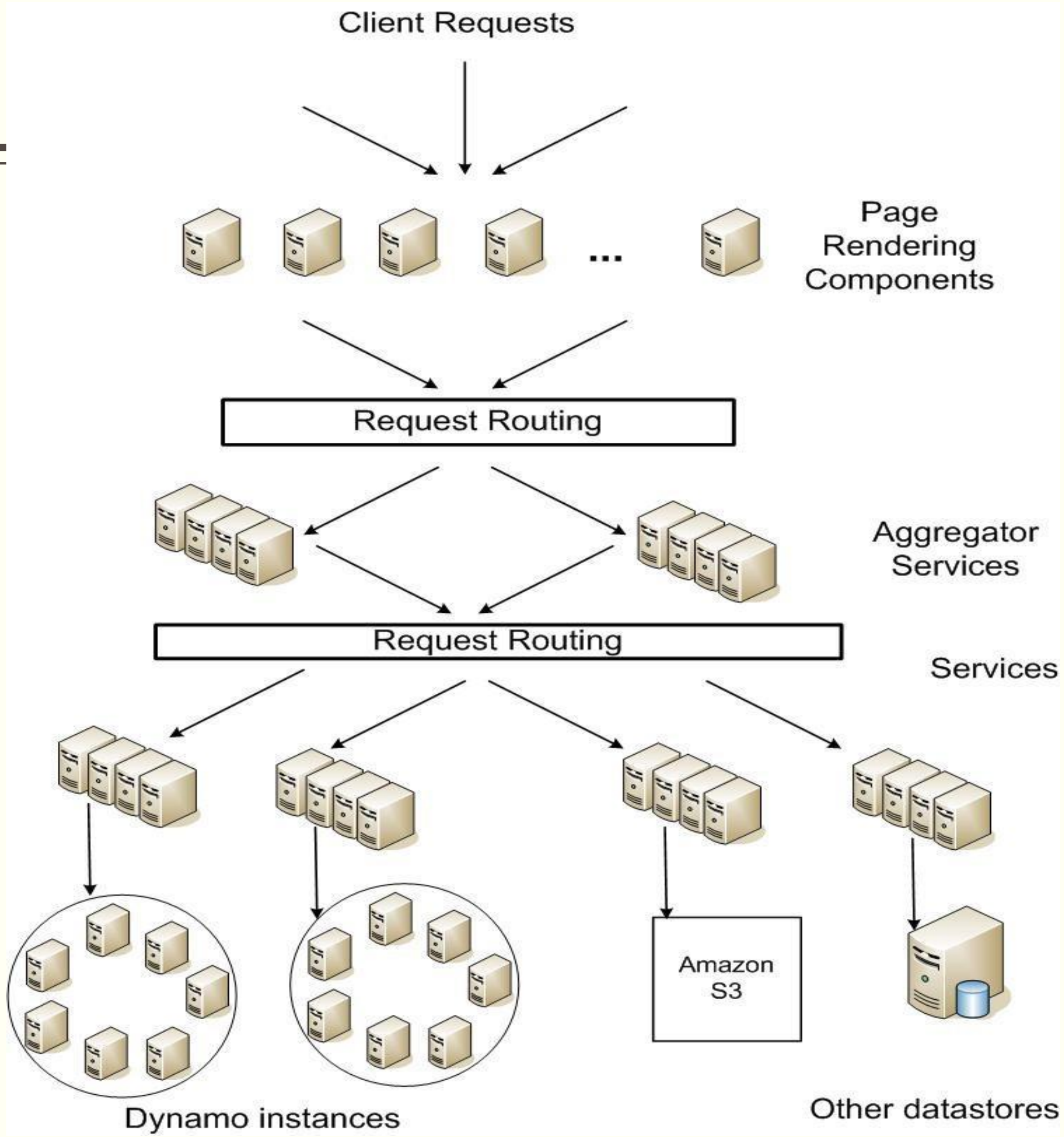
- In general, with multiple replicas
  - Slow puts and fast gets

Summary: Key-Value Store

- Very large-scale storage systems
- Two operations
  - put(key, value)
  - value = get(key)
- Challenges
  - Fault Tolerance → replication
  - Scalability → serve get()'s in parallel; replicate/cache hot tuples
  - Consistency → quorum consensus to improve put/get performance
- System case study: Dynamo

Amazon Platform Architecture

- simple read and write operations to a data item that is uniquely identified by a key.
- Most of Amazon's services can work with this simple query model and do not need any relational schema.
- targeted applications - store objects that are relatively small (usually less than 1 MB)
- Dynamo targets applications that operate with weaker consistency (the "C" in ACID) if this results in high availability.

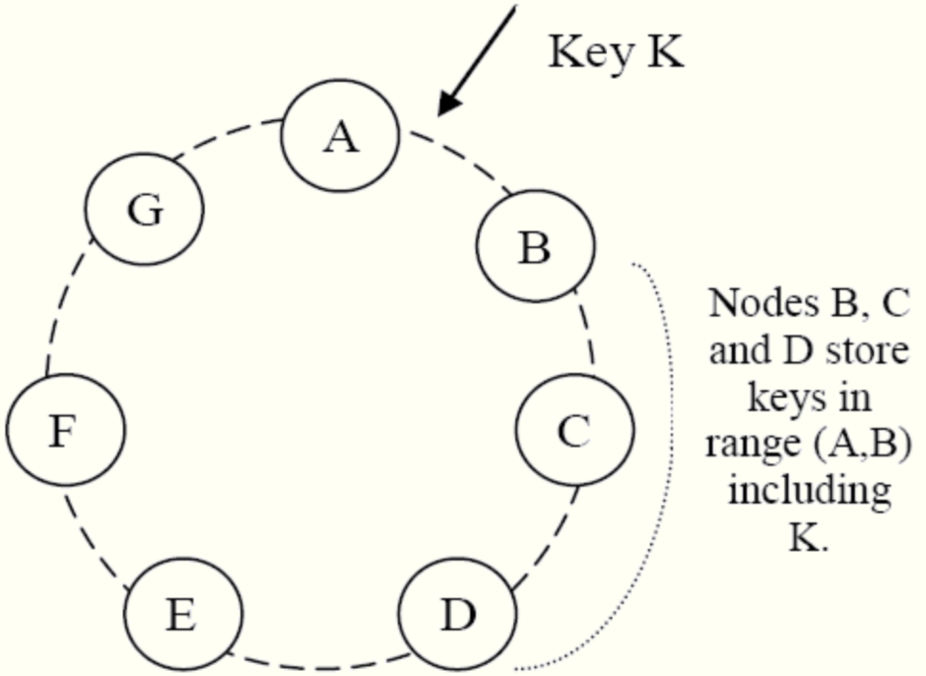


System Architecture

- Partitioning
- High Availability for writes
- Handling temporary failures
- Recovering from permanent failures
- Membership and failure detection

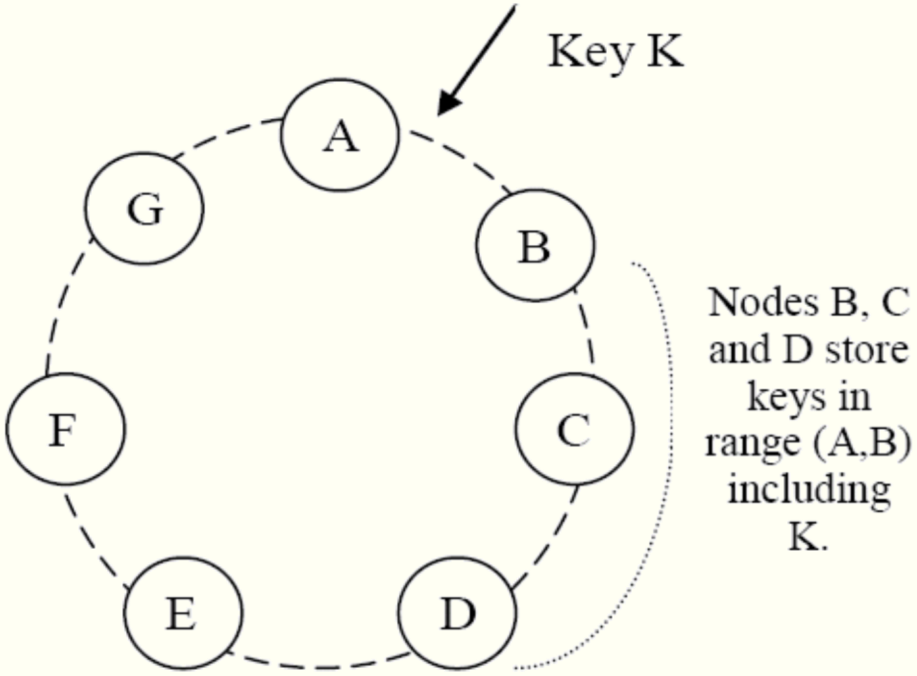
Partition Algorithm

- *Consistent hashing*: the output range of a hash function is treated as a fixed circular space or "ring".
- *"Virtual Nodes":* Each node can be responsible for more than one virtual node.



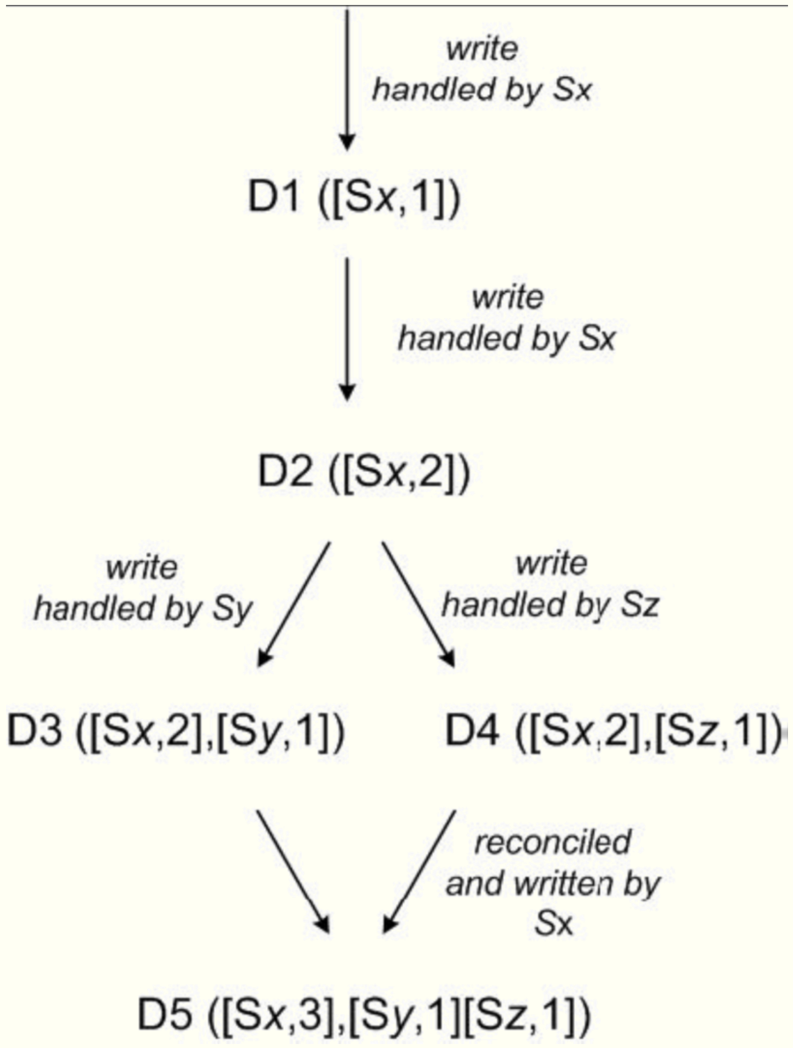
Replication

- Each data item is replicated at N hosts.
- “preference list”: The list of nodes that is responsible for storing a particular key.



Vector Clock

- A vector clock is a list of (node, counter) pairs.
- Every version of every object is associated with one vector clock.
- *If the counters on the first object's clock are less-than-or-equal to all of the nodes in the second clock, then the first is an ancestor of the second and can be forgotten.*



Summary of Techniques Used in Dynamo and Their Advantages

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.