INGI2145: CLOUD COMPUTING (Fall 2015)

Cloud Basics & Storage

1 October 2015

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Announcements

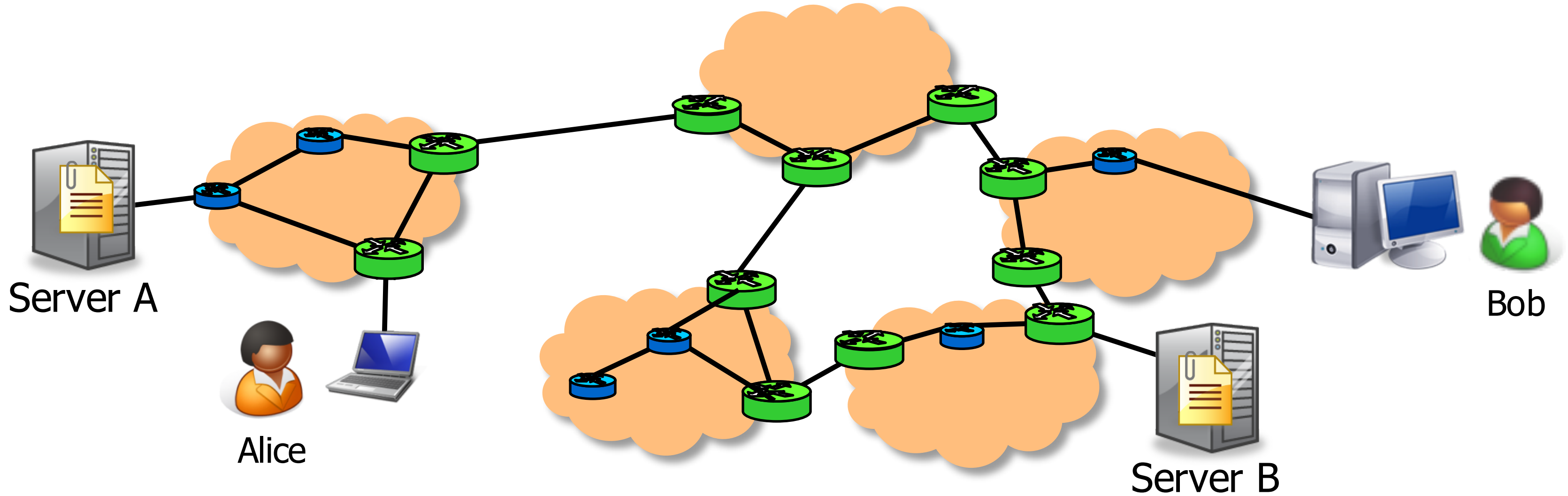
- First homework assignment will be announced next week
  - You will need to be setup with AWS
  - Next week's lab (9 Oct) will cover important background for this assignment
- Tomorrow's lab session is about Amazon Storage Services
  - Bring your own laptop
  - Lab will be in BARB 91

Plan for today

- Distributed programming and its challenges
  - Faults, failures, and what we can do about them
  - Network partitions, CAP theorem, relaxed consistency
- Cloud basics
  - Anatomy of Cloud applications
  - Scaling: stateless, caching, and sharding
- Cloud storage
  - Overview
  - KVS and current systems
- Amazon Dynamo

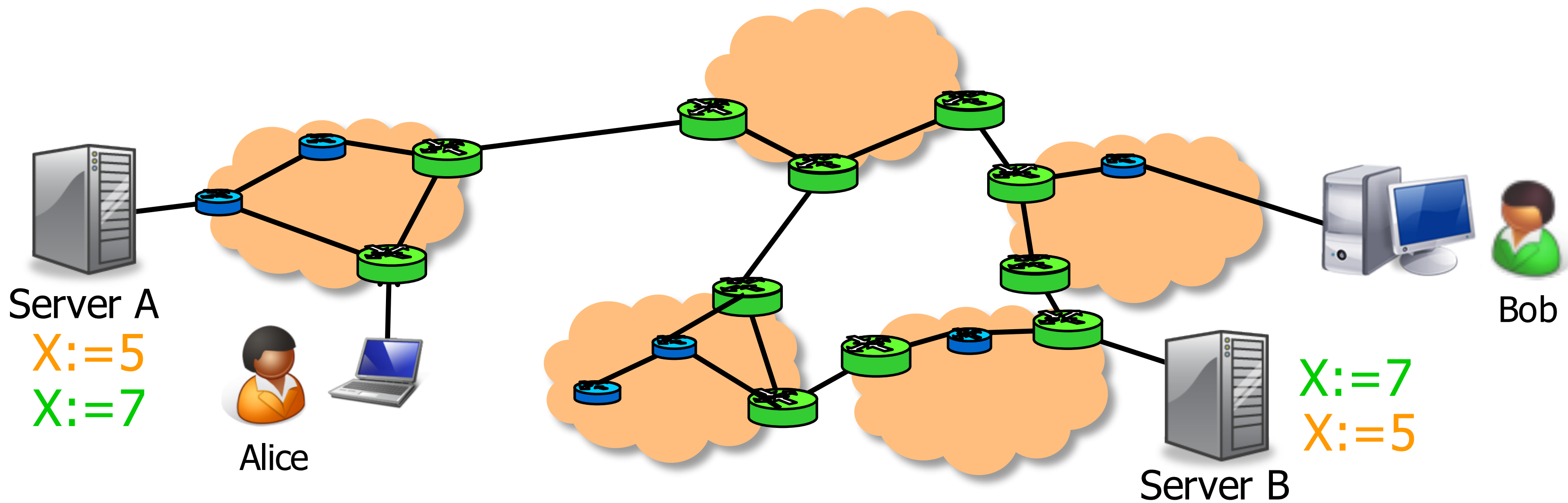
NEXT

Masking faults with replication



- Alice can store her data on both servers
- Bob can get the data from either server
  - A single crash fault on a server does not lead to a failure
  - Availability is maintained
  - What about other types of faults, or multiple faults?

Problem: Maintaining consistency



- What if multiple clients are accessing the same set of replicas?
  - Requests may be ordered differently by different replicas
  - Result: Inconsistency! (remember race conditions?)
  - For what types of requests can this happen?
  - What do we need to do to maintain consistency?

Types of consistency

- Strong consistency
  - After an update completes, any subsequent access will return the updated value
- Weak consistency
  - Updated value not guaranteed to be returned immediately, only after some conditions are met (inconsistency window)
- Eventual consistency
  - A specific type of weak consistency
  - If no new updates are made to the object, eventually all accesses will return the last updated value

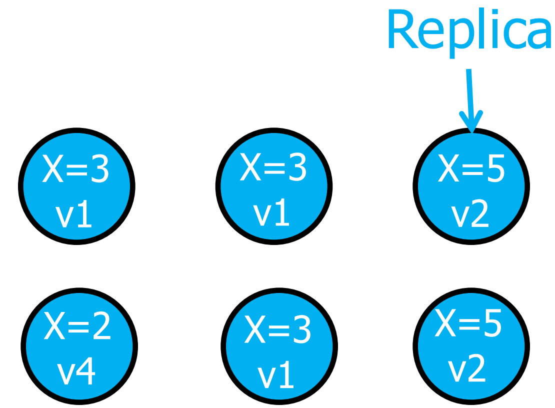
Eventual consistency variations

- Causal consistency
  - If client A has communicated to client B that it has updated a data item, a subsequent access by B will return the updated value, and a write is guaranteed to supersede the earlier write. Client C that has no causal relationship to client A is subject to the normal eventual consistency rules
- Read-your-writes consistency
  - Client A, after it has updated a data item, always accesses the updated value and will never see an older value
- Session consistency
  - Like previous case but in the context of a session, for as long as the sessions remains alive

Eventual consistency variations

- Monotonic read consistency
  - If client A has has seen a particular value for the object, any subsequent accesses will never return any previous values
- Monotonic write consistency
  - In this case the system guarantees to serialize the writes by the same process
  - Systems that do not guarantee this level of consistency are notoriously hard to program
- Few consistency properties can be combined
  - monotonic reads + read-your-writes most desirable for eventual consistency. Why?

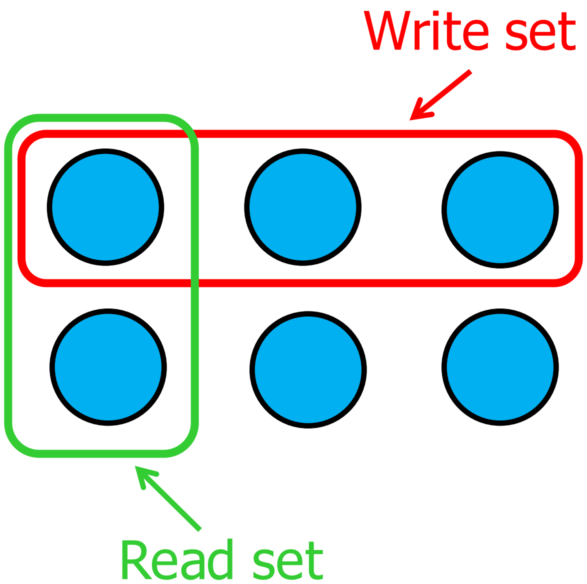
Example: Storage system



- Scenario: Replicated storage
  - We have N nodes that can store data
  - Data contains a monotonically increasing timestamp
- To write a value:
  - Pick W replicas and write the value to each, using a fresh timestamp (say, the current wallclock time)
- To read a value:
  - Pick R replicas and read the value from each
  - Return the value with the highest timestamp
  - If any replicas had a lower timestamp, send them the newer value

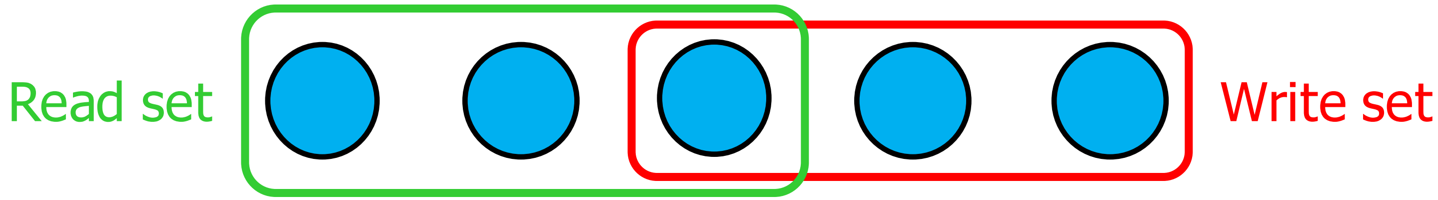
How to set N, R, and W

- For strong consistency?
  - What happens otherwise?
  - Will the data ever become consistent again?
- To avoid conflicting writes?
- To make reads fast? Writes?
- To minimize the risk of data loss?
- Let's do some examples!
  - N=2, W=2, R=1
  - N=2, W=1, R=1



Strong consistency: Quorum principle

- Majority quorum
  - Always write to and read from a majority of nodes
    - At least one node knows the most recent value
  - Pro: tolerate up to $\lceil N/2 \rceil - 1$ crashes
  - Con: have to read/write $\lfloor N/2 \rfloor + 1$ values

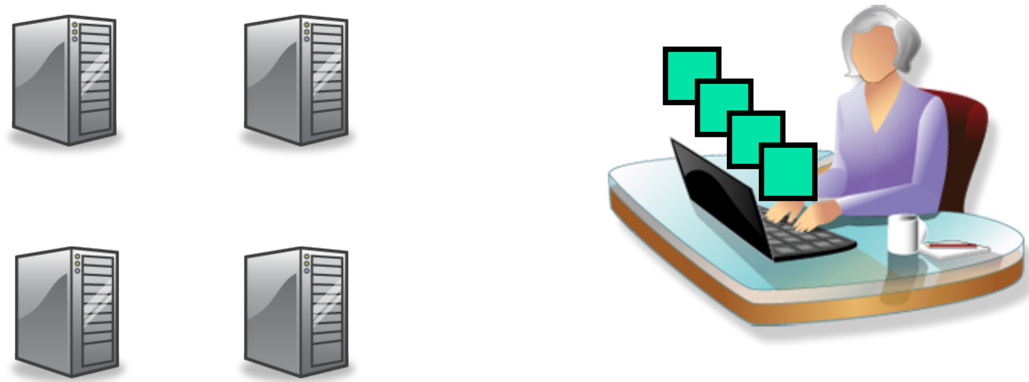


- Read/write quorums
  - Read R nodes, write W nodes, s.t. $R + W > N$
  - Pro: adjust performance of reads/writes
  - Con: availability can suffer

Consensus

- Replicas need to agree on a single order in which to execute client requests
  - How can we do this?
  - Does the specific order matter?
- Problem: What if some replicas are faulty?
  - Crash fault: Replica does not respond; no progress (bad)
  - Byzantine fault: Replica might tell lies, corrupt order (worse)
- Solution: Consensus protocol
  - Paxos (for crash faults), PBFT (for Byzantine faults)
  - Works as long as no more than a certain fraction of the replicas are faulty (PBFT: one third)

How do consensus protocols work?



- Idea: Correct replicas 'outvote' faulty ones
  - Clients send requests to each of the replicas
  - Replicas coordinate and each return a result
  - Client chooses one of the results, e.g., the one that is returned by the largest number of replicas
  - If a small fraction of the replicas returns the wrong result, or no result at all, they are 'outvoted' by the other replicas

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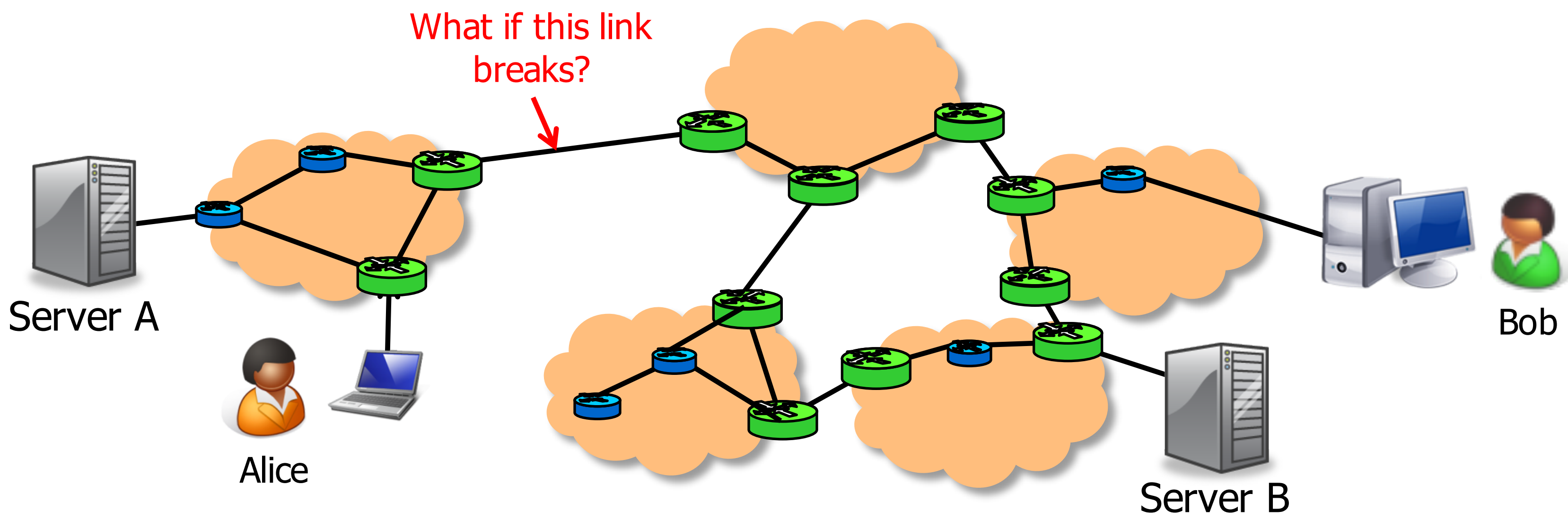
Network partitions



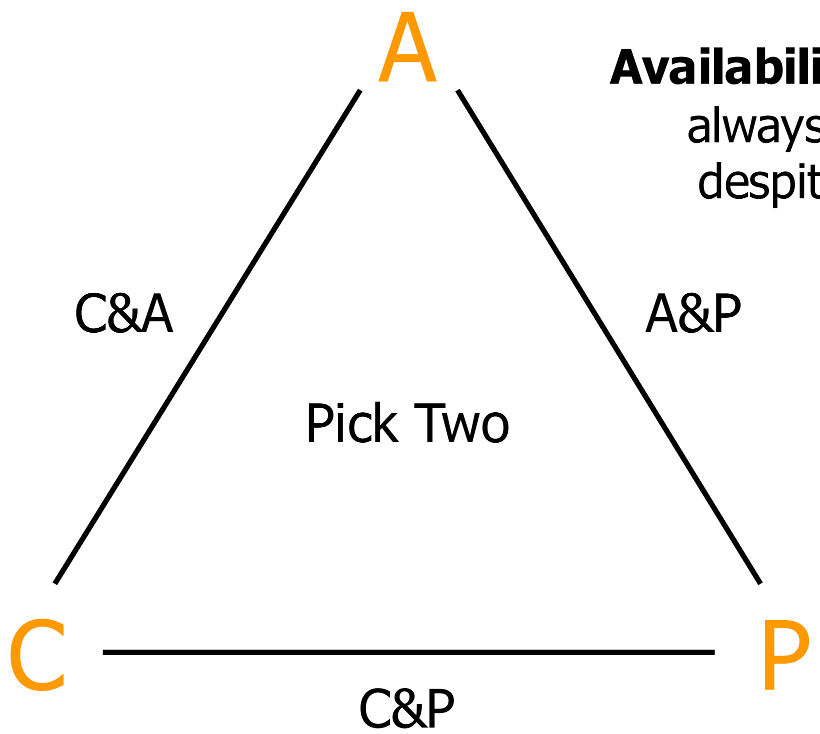
- Network can partition
  - Hardware fault, router misconfigured, undersea cable cut, ...
  - Result: Gobal connectivity is lost
  - What does this mean for the properties of our system?

The CAP theorem

- What we want from a web system:
  - Consistency: All clients single up-to-data copy of the data, even in the presence of concurrent updates
  - Availability: Every request (including updates) received by a non-failing node in the system must result in a response, even when faults occur
  - Partition-tolerance: Consistency and availability hold even when the network partitions

- Can we get all three?
  - CAP theorem: We can get <u>at most two</u> out of the three
    - Which ones should we choose for a given system?
  - Conjecture by Brewer; proven by Gilbert and Lynch

Visual CAP



Availability: Each client can always read and write despite node failures

Consistency: All clients always have the same view of the data at the same time

Partition-tolerance: The system continues to operate despite arbitrary message loss

Common CAP choices

- Example #1: Consistency & Partition tolerance
  - Many replicas + consensus protocol
  - Do not accept new write requests during partitions
  - Certain functions may become unavailable

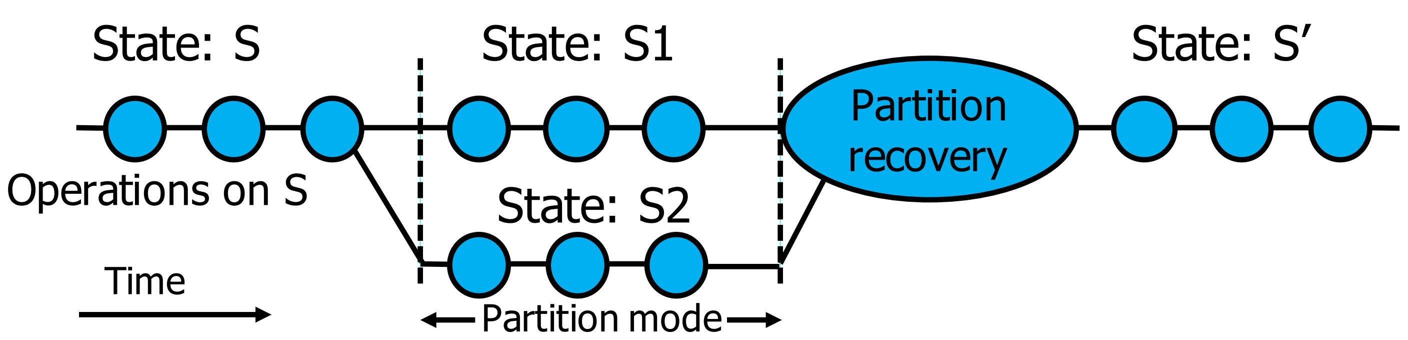
- Example #2: Availability & Partition tolerance
  - Many replicas + relaxed consistency
  - Continue accepting write requests
  - Clients may see inconsistent state during partitions

“2 of 3” view is misleading

- Meaning of C&A over P is unclear
  - If a partition occurs, the choice must be reverted to C or A
  - No reason to forfeit C or A when system is not partitioned
- Choice of C and A can occur many times within the same system at fine granularity
- Three properties are more of a continuous
  - Availability is 0 to 100
  - Many levels of consistency
  - Disagreement within the system whether a partition exists
- The modern CAP goal should be to maximize application-specific combinations of C and A

Dealing with partitions

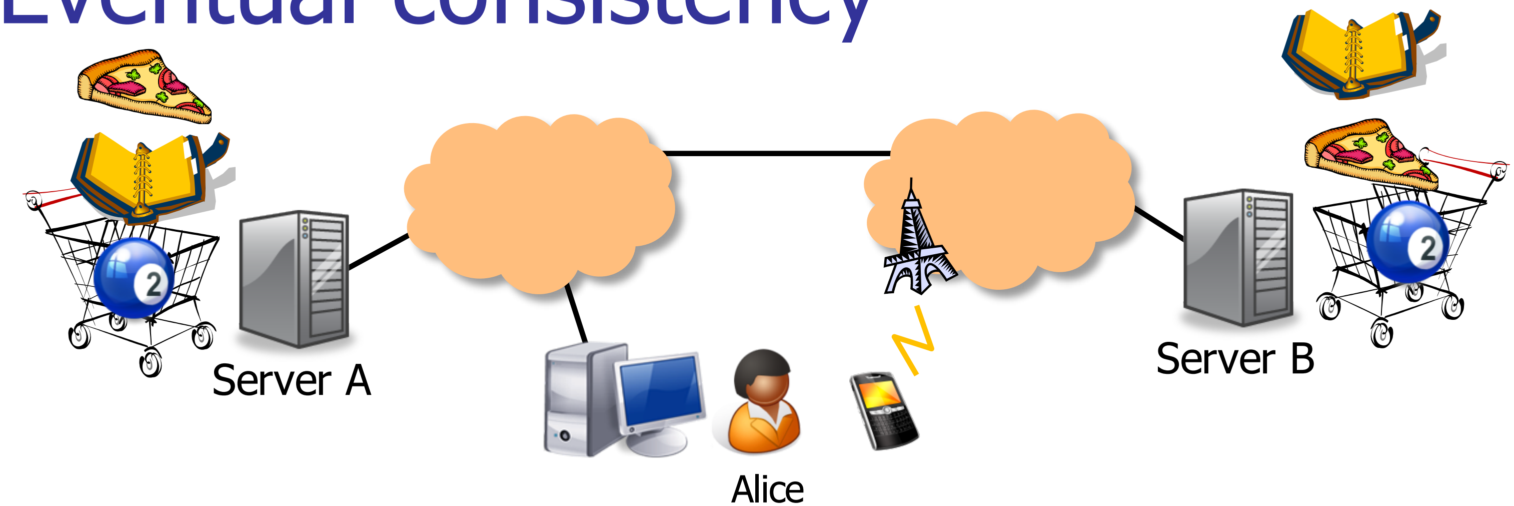
- Detect partition
- Enter an explicit partition mode that can limit some operations
- Initiate partition recovery when communication is restored
  - Restore consistency and compensate for mistakes made while the system was partitioned



Which operations should proceed?

- Depends primarily on the invariants that the system intends to maintain
- If an operation is allowed and turns out to violate an invariant, the system must restore the invariant during recovery
  - Example: 2 objects are added with the same (unique) key; to restore, we check for duplicate keys and merge objects
- If invariant cannot be violated, system must prohibit or modify the operation (e.g. record the intent and execute it after)
  - Example: delay charging the credit card; user does not see system is not available

Eventual consistency



- Idea: Optimistically allow updates
  - Don't coordinate with ALL replicas before returning response
  - But ensure that updates reach all replicas eventually
    - What do we do if conflicting updates were made to different replicas?
  - Good: Decouples replicas. Better performance, availability under partitions
  - (Potentially) bad: Clients can see inconsistent state

Partition recovery

- State on both sides must become consistent
- Compensation for mistakes during partition
- Start from state at the time of the partition and roll forward both sets of operations in some way, maintaining consistency
- The system must also merge conflicts
  - constraint certain operations during partition mode so that conflicts can always be merged automatically
  - detect conflicts and report them to a human
  - use commutative operations as a general framework for automatic state convergence
    - commutative replicated data types (CRDTs)

Compensate for mistakes

- Tracking and limitation of partition-mode operations ensures the knowledge of which invariants could have been violated
  - trivial ways such as “last writer wins”, smarter approaches that merge operations, and human escalation
- For externalized mistakes typically requires some history about externalized outputs
- System could execute orders twice
  - If the system can distinguish two intentional orders from two duplicate orders, it can cancel one of the duplicates
  - If externalized, send an e-mail explaining the order was accidentally executed twice but that the mistake has been fixed and to attach a coupon for a discount

Relaxed consistency: ACID vs. BASE

- Classical database systems: ACID semantics
  - Atomicity
  - Consistency
  - Isolation
  - Durability

- Modern Internet systems: BASE semantics
  - Basically Available
  - Soft-state
  - Eventually consistent

Recap: Consistency and partitions

- Use replication to mask limited # of faults
  - Can achieve strong consistency by having replicas agree on a common request ordering
  - Even non-crash faults can be handled, as long as there are not too many of them (typical limit: 1/3)

- Partition tolerance, availability, consistency?
  - Can't have all three (CAP theorem)
  - Typically trade-off between C and A
  - If service works with weaker consistency guarantees, such as eventual consistency, can get a compromise (BASE)

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Recap: Cloud benefits

- Elastic, just-in-time infrastructure
- More efficient resource utilization
- Pay for what you use
- Potential to reduce processing time
  - Parallelization
- Leverage multiple data centers
  - High availability, lower response times

- How do applications exploit these benefits?

Today's Cloud applications

- Web applications
  - Client/server paradigm
  - Request/response messaging pattern
  - Interactive communication
- Processing pipelines
  - Examples: Indexing, data mining, image processing, video transcoding, document processing
- Batch processing systems
  - Example: report generation, fraud detection, analytics, backups, automated testing

Many styles of system

- Near the edge of the application focus is on vast numbers of clients and rapid response
- Inside we find data-intensive services that operate in a pipelined manner, asynchronously
- Deep inside the application we see a world of virtual computer clusters that are scheduled to share resources and on which applications like MapReduce (Hadoop) are very popular

Example: Obama for America AWS

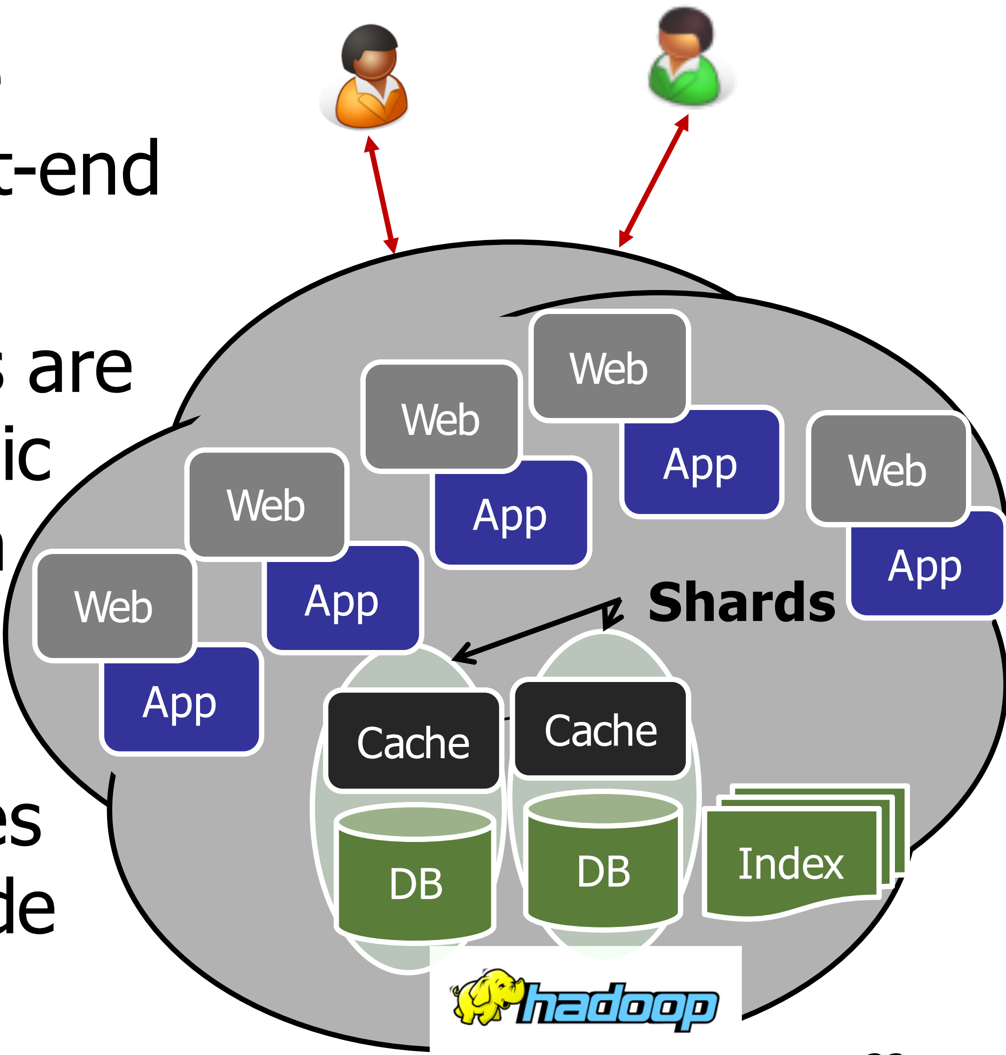
http://awsofa.info/

How are Cloud apps structured?

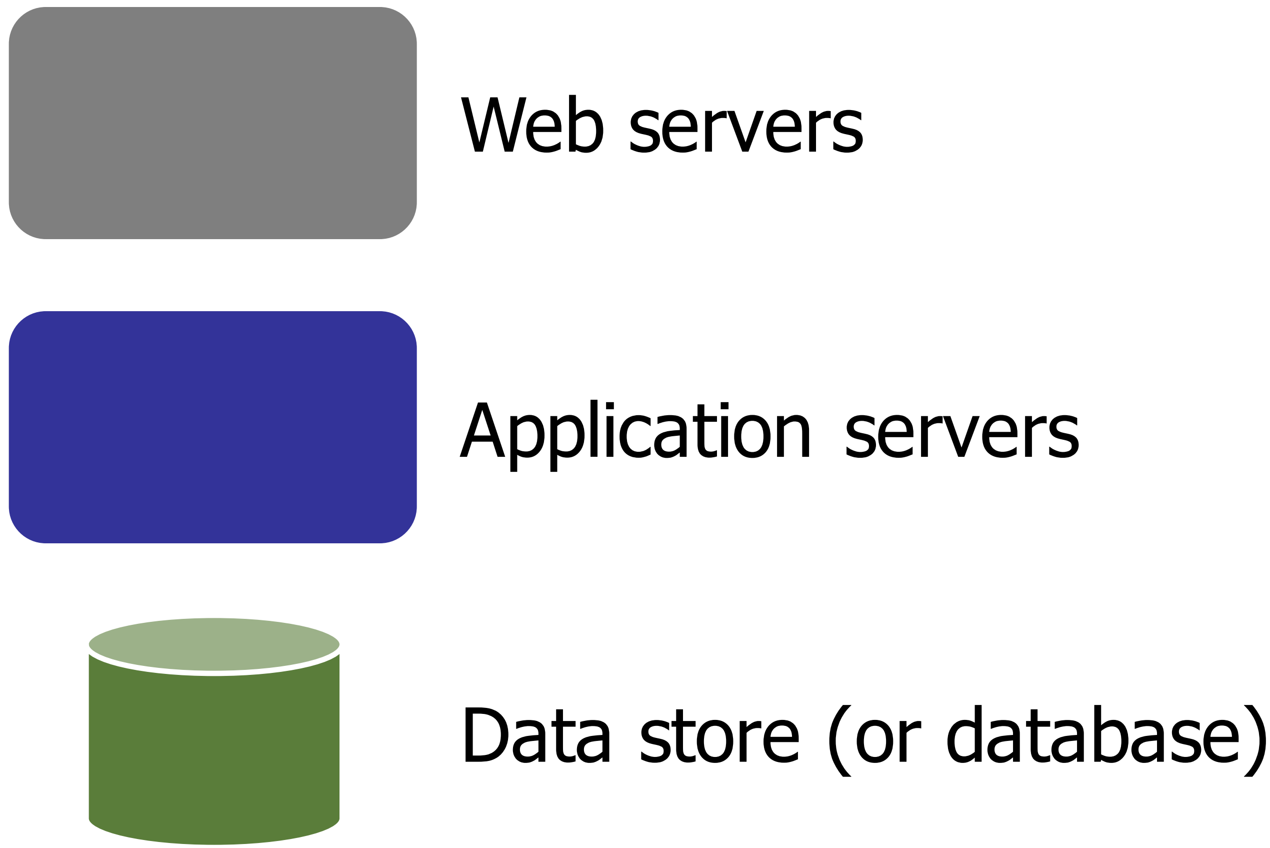
- Clients talk to application using Web browsers or the Web services standards
  - But this only gets us to the outer "skin" of the data center, not the interior
  - Consider Amazon: it can host entire company web sites (like Netflix.com), data (S3), servers (EC2), databases (RDS) and even virtual desktops!

Big picture overview

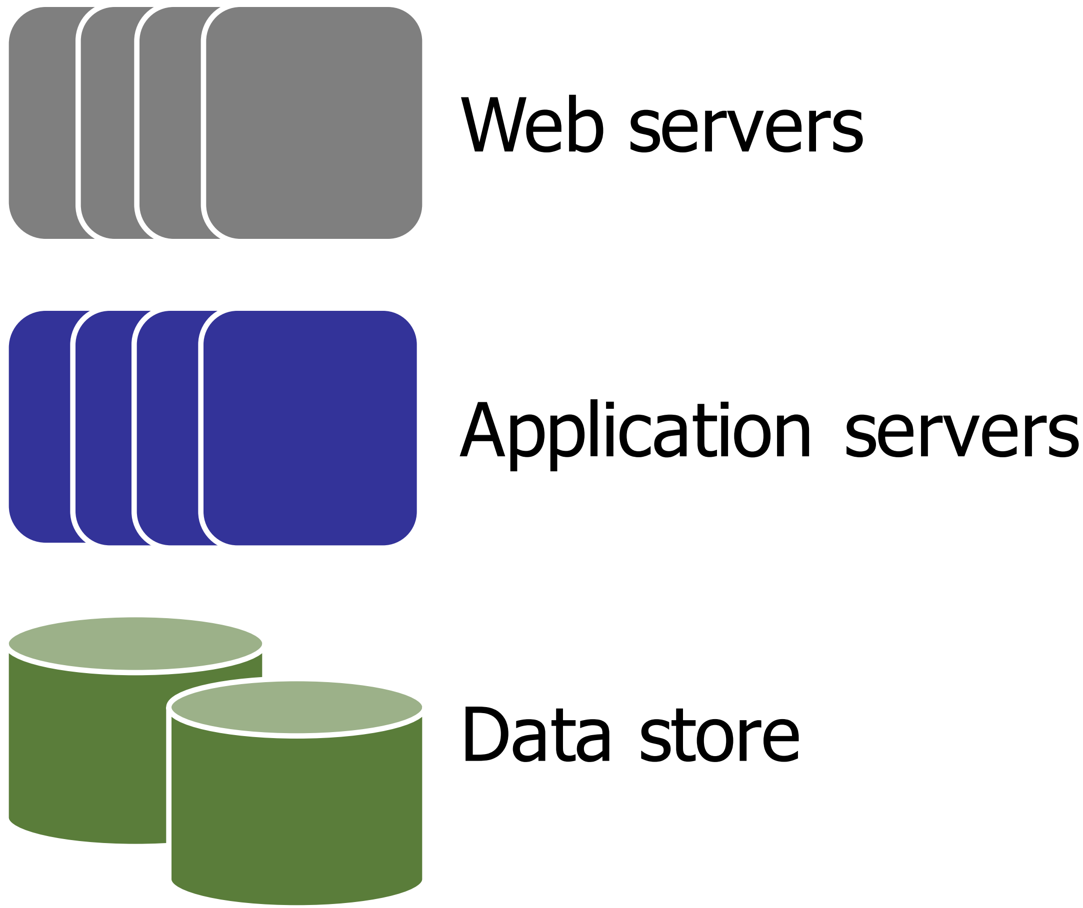
- Client requests are handled in by front-end Web servers
- Application servers are invoked for dynamic content generation and run app logic
  - PHP, Java, Python, …
- Back-end databases manage and provide access to data



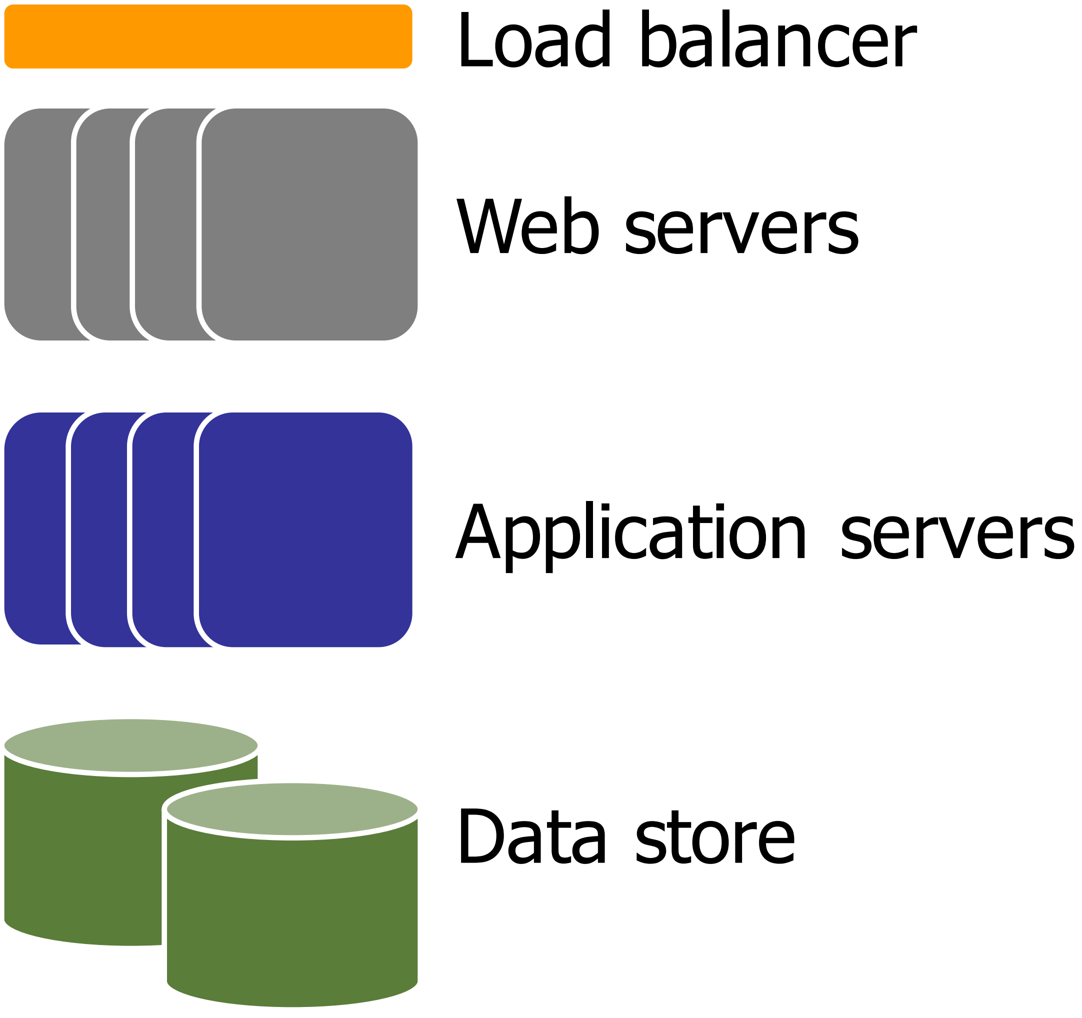
Applications with multiple tiers



Redundancy at each tier



Load balancer



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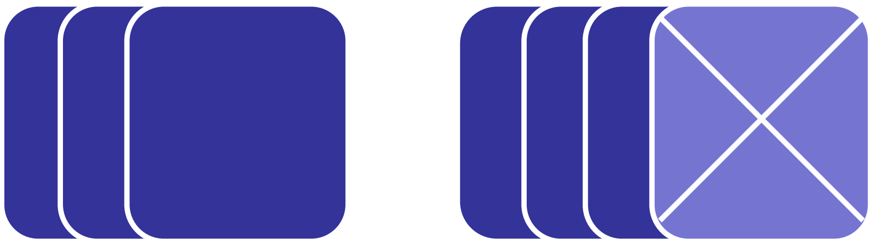
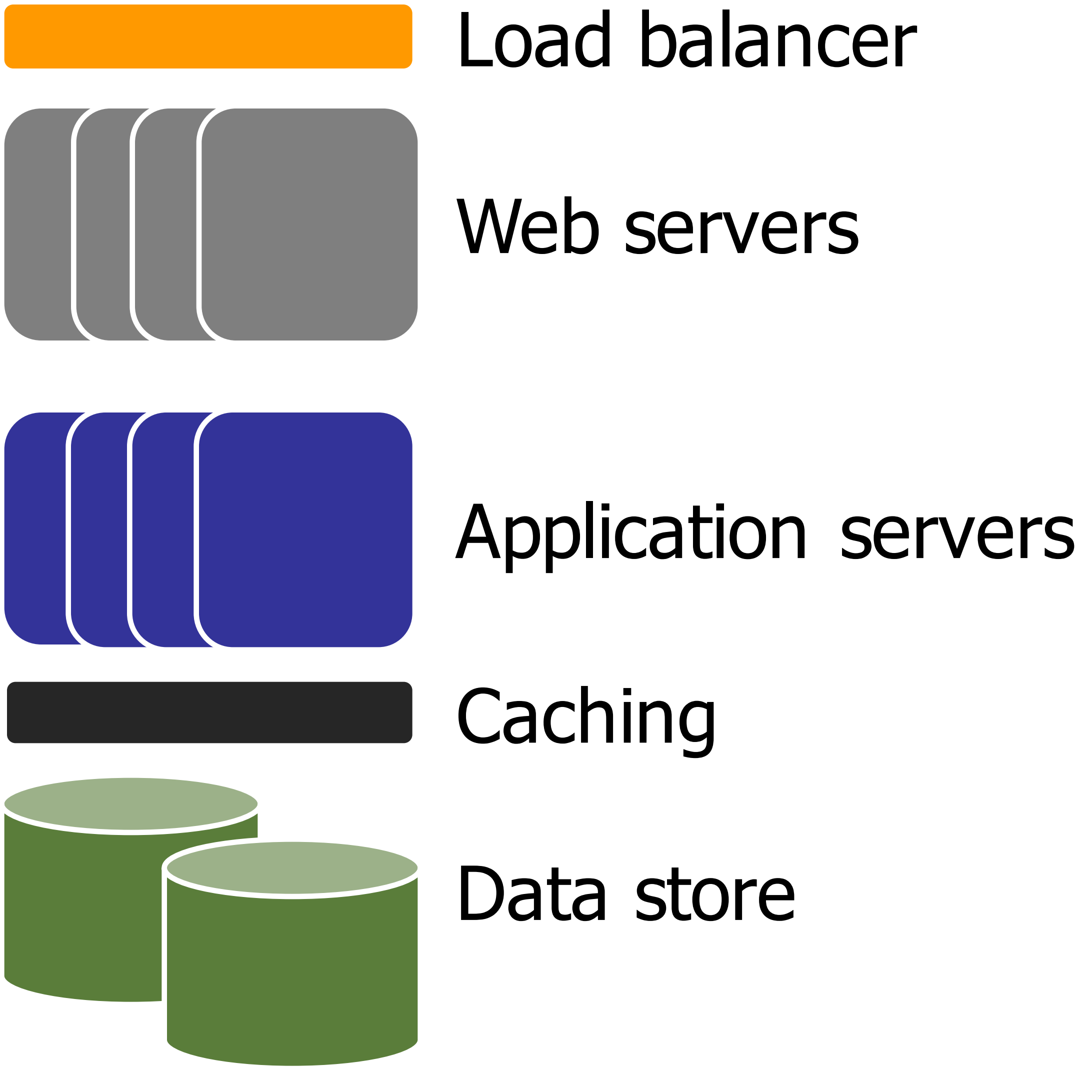
Stateless servers are easiest to scale

- Views a client request as an independent transaction and responds to it
- Advantages:
  - Simpler and easier to scale: does not maintain state
  - More robust: tolerating instance failures does not require overheads restoring state



Stateless servers

Caching

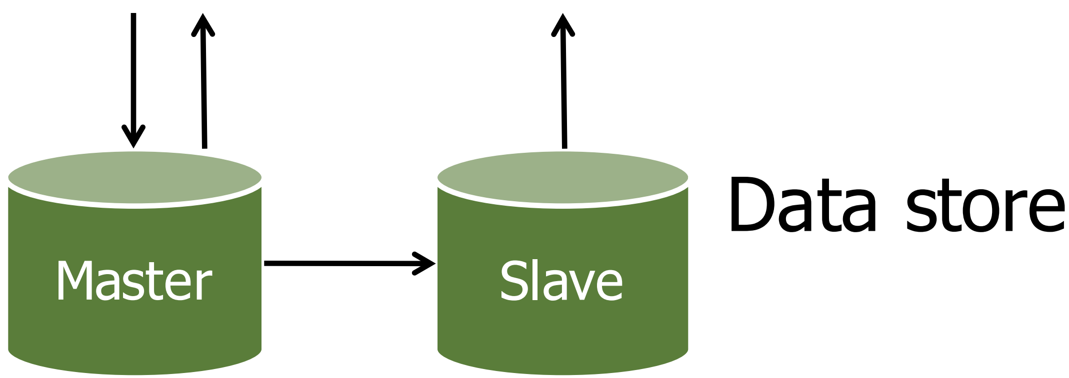

Load balancer
Web servers
Application servers
Caching
Data store

Caching

- Caching is central to responsiveness
  - Basic idea is to always used cached data if at all possible, so the inner services (data stores) are shielded from “online” load
  - Caching is only temporary storage, hence it is stateless
  - We can add multiple cache serves to spread loads
- Must think hard about patterns of data access
  - Some data needs to be heavily replicated to offer very fast access on vast numbers of nodes
  - In principle the level of replication should match level of load and the degree to which the data is needed

Stateful servers require attention

- Scaling a relational database is challenging
- Traditional approach is replication
  - Data is written to a master server and then replicated to one or more slave servers (synchronously or asynchronously)
  - Read operations can be handled by the slaves
  - All writes happen on the master



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  - All writes happen on the master
- Cons:
  - Master becomes the write bottleneck
  - Master is a single point of failure
  - As load increases, cost of replication increases
  - Slaves may fall behind and serve stale data

Sharding

- Data partitioning strategy
- Basic idea: split data between multiple machines and have a way to make sure you always access data from the right place
  - Typically define a sharding key and create a shard mapping (e.g., consistent hashing: shard_idx = hash(key) mod N)
  - Other partitioning schemes exist: e.g., allocate whole tables on the same machine

Benefits of sharding

- Increased read and write throughput
- High availability
- Possibility of doing more work in parallel within the application server

- Challenge: picking a good partitioning scheme
  - Otherwise risk of having hotspots in the system due to load imbalance

Sharding used in many ways

- Sharding is not only for partitioning data within a database
- Applies essentially to every application tier
  - Notion of sharding is cross-cutting

- Example: partition data across caching servers
- Two popular in-memory caching systems:
  - memcached: distributed object caching system
  - redis: distributed data structure server (also works as store)

And it isn’t just about updates

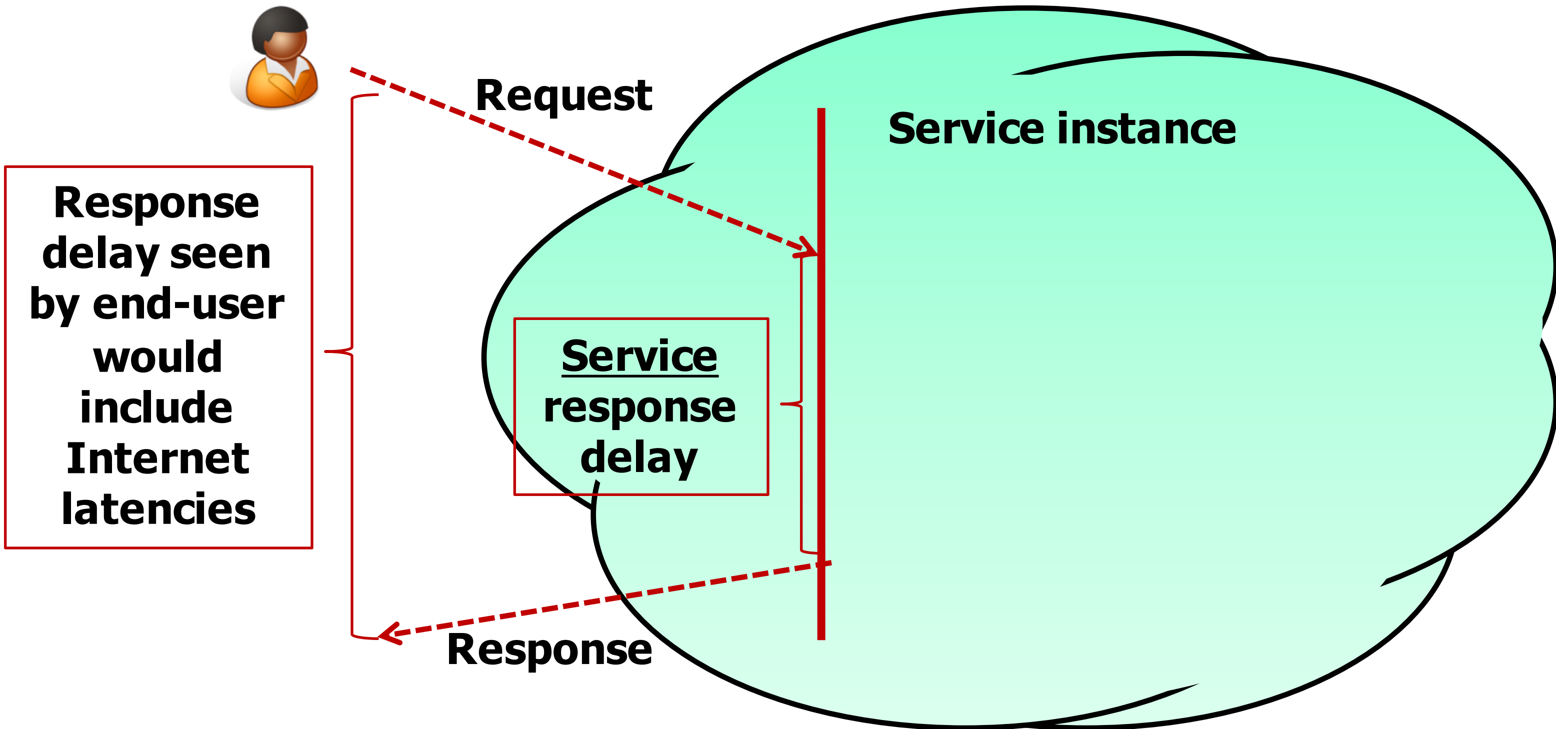
- Should also be thinking about patterns that arise when doing reads (“queries”)
  - Some can just be performed by a single representative of a service
  - But others might need the parallelism of having several (or even a huge number) of machines do parts of the work concurrently
- The term sharding is used for data, but here we might talk about “parallel computation on a shard”

First-tier parallelism

- Parallelism is vital for fast interactive services
- Key question:
  - Request has reached some service instance X
  - Will it be faster…
    - … For X to just compute the response
    - … Or for X to subdivide the work by asking subservices to do parts of the job?
- Glimpse of an answer
  - When you make a search on Bing, the query is processed in parallel by even 1000s of servers that run in real-time on your request!
- Parallel actions must focus on the critical path

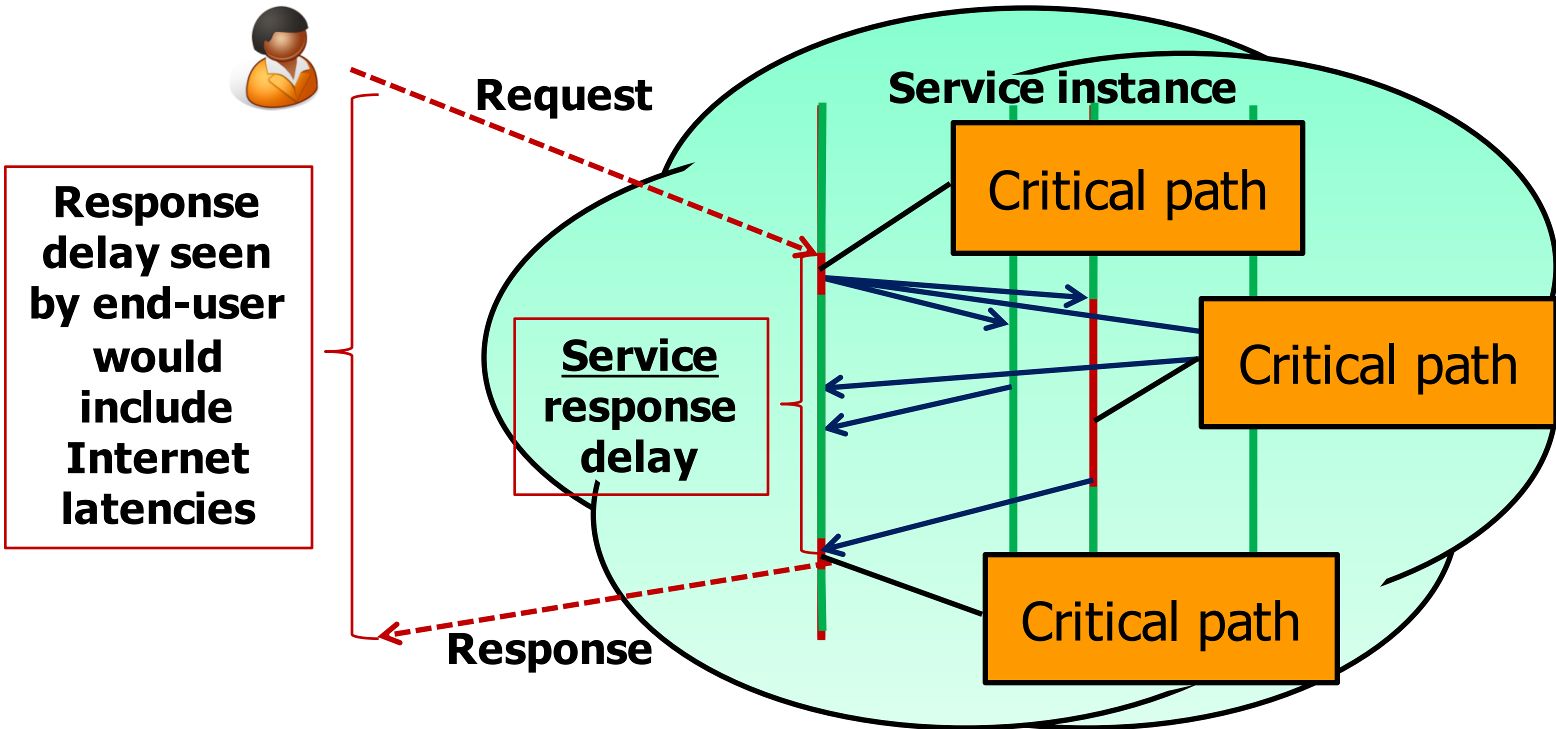
What does "critical path" mean?

- Focus on delay until a client receives a reply
- Critical path are actions that contribute to this delay

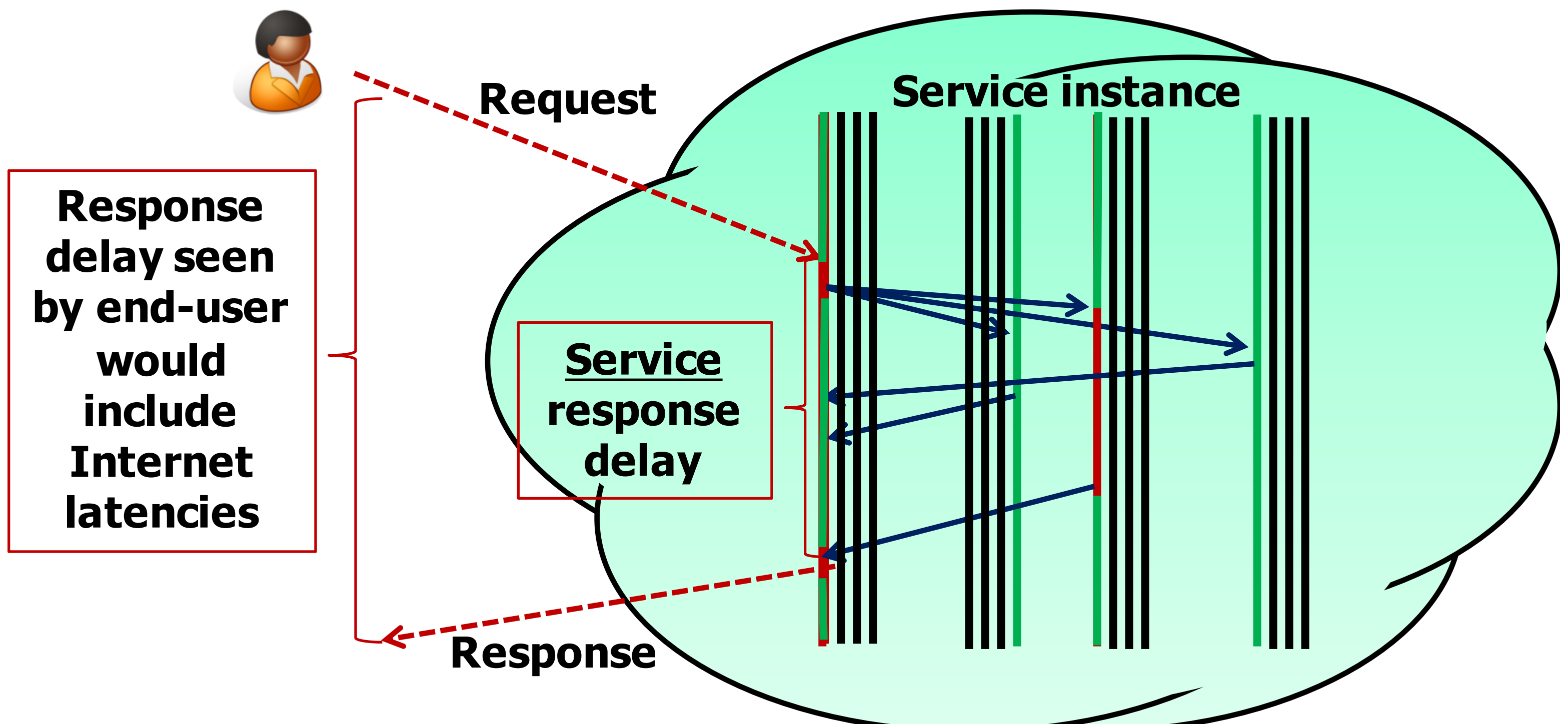


Parallel speedup

- In this example of a parallel read-only request, the critical path centers on the middle "subservice"



With replicas we just load balance



What if a request triggers updates?

- If updates are done “asynchronously” we might not experience much delay on the critical path
  - Cloud systems often work this way
  - Avoids waiting for slow services to process the updates but may force the tier-one service to “guess” the outcome
  - For example, store in the master database and replicate to the slave in the background
- Many cloud systems use these sorts of “tricks” to speed up response time

What if we send updates without waiting?

- Several issues now arise
  - Are all the replicas applying updates in the same order?
    - Might not matter unless the same data item is being changed
    - But then clearly we do need some “agreement” on order
  - What if the leader replies to the end user but then crashes and it turns out that the updates were lost in the network?
    - Data center networks can be surprisingly lossy at times
    - Also, bursts of updates can queue up
- Such issues result in *inconsistency*

Is inconsistency a bad thing?

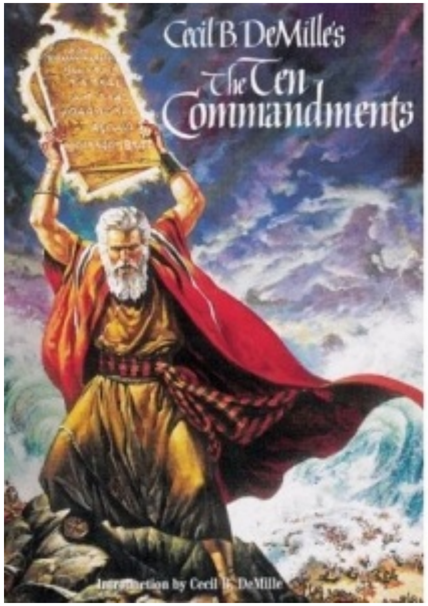
- How much consistency is really needed in the first tier of the cloud?
  - Think about YouTube videos. Would consistency be an issue here?
  - What about the Amazon "number of units available" counters. Will people notice if those are a bit off?
- Puzzle: can you come up with a general policy for knowing how much consistency a given thing needs?

eBay's Five Commandments

- As described by Randy Shoup at LADIS 2008

Thou shalt…

1. **Partition Everything**
2. **Use Asynchrony Everywhere**
3. **Automate Everything**
4. **Remember: Everything Fails**
5. **Embrace Inconsistency**



Recap

- Cloud applications are multi-tiered systems
- Caching can enable significant speedups for read-heavy workloads
- Sharding provides opportunities for parallelization and improve read/write throughputs
- Asynchronous operations decouple systems and enable quicker responses at the expense strong consistency

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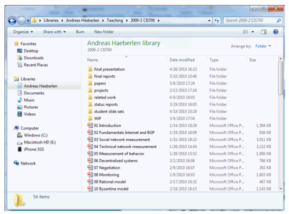
Complex service, simple storage



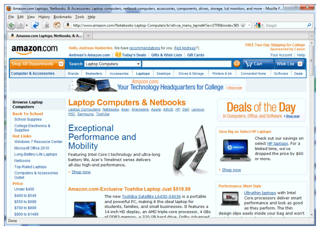
Variable-size files
- read, write, append
- move, rename
- lock, unlock
- ...

Operating system

Fixed-size blocks
- read
- write

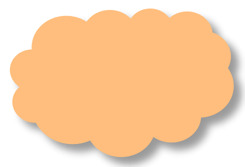
- PC users see a rich, powerful interface
  - Hierarchical namespace (directories); can move, rename, append to, truncate, (de)compress, view, delete files, ...
- But the actual storage device is very simple
  - HDD only knows how to read and write fixed-size data blocks
- Translation done by the operating system

Analogy to cloud storage



Shopping carts
Friend lists
User accounts
Profiles
...

Web service



Key/value store
- read, write
- delete

- Many cloud services have a similar structure
  - Users see a rich interface (shopping carts, product categories, searchable index, recommendations, ...)
- But the actual storage service is very simple
  - Read/write 'blocks', similar to a giant hard disk
- Translation done by the web service

What's Wrong with Relational DBs?

- Most applications interact through a database
- Recall RDBMS:
  - Manage data access, enforce data integrity, control concurrency, support recovery after a failure
- Many applications push traditional RDBMS solutions to the limit by demanding:
  - High scalability
  - Very large amounts of data
  - Minimal latency
  - High availability
- Solution is far from ideal

Ideal data stores on the Cloud

- Many situations need hosting of large data sets
  - Examples: Amazon catalog, eBay listings, Facebook pages, …
- Ideal: Abstraction of a 'big disk in the clouds', which would have:
  - Perfect durability – nothing would ever disappear in a crash
  - 100% availability – we could always get to the service
  - Zero latency from anywhere on earth – no delays!
  - Minimal bandwidth utilization – we only send across the network what we absolutely need
  - Isolation under concurrent updates – make sure data stays consistent

The inconveniences of the real world

- Why isn't this feasible?

- The "cloud" exists over a physical network
  - Communication takes time, esp. across the globe
  - Bandwidth is limited, both on the backbone and endpoint
- The "cloud" has imperfect hardware
  - Hard disks crash
  - Servers crash
  - Software has bugs

- Can you map these to the previous desiderata?

Finding the right tradeoff

- In practice, we can't have everything
  - ... but most applications don't really need 'everything'!
- Some observations:
  1. Read-only (or read-mostly) data is easiest to support
     - Replicate it everywhere! No concurrency issues!
     - But only some kinds of data fit this pattern – examples?
  2. Granularity matters: "Few large-object" tasks generally tolerate longer latencies than "many small-object" tasks
     - Fewer requests, often more processing at the client
     - But it's much more expensive to replicate or to update!
  3. Maybe it makes sense to develop separate solutions for large read-mostly objects vs. small read-write objects!
     - Different requirements → different technical solutions

Many situations need hosting of large data sets

Examples: Amazon catalog, eBay listings, Facebook pages, …

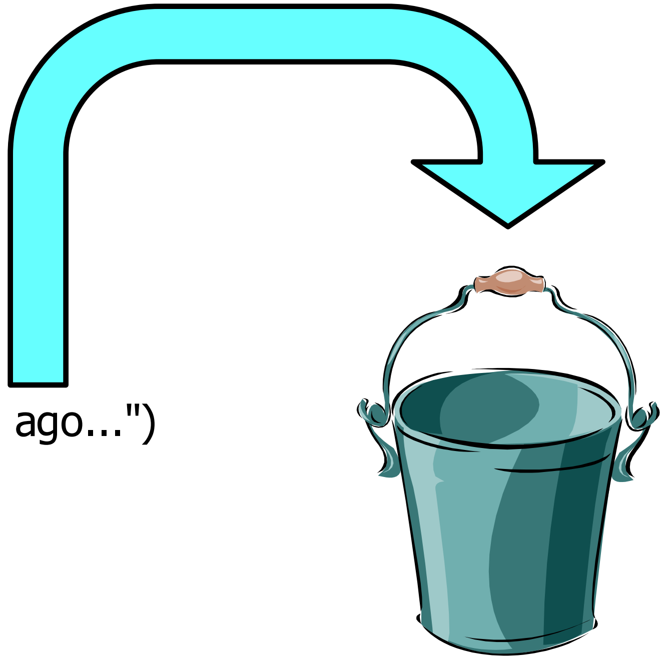
- General trend:

From performance at any cost to …
reliability at the lowest possible cost

Plan for today

- Distributed programming and its challenges
  - Faults, failures, and what we can do about them
  - Network partitions, CAP theorem, relaxed consistency
- Cloud basics
  - Anatomy of Cloud applications
  - Scaling: stateless, caching, and sharding
- Cloud storage
  - Overview
  - KVS and current systems NEXT
- Amazon Dynamo

Key-value stores



Keys Values

(bob, bschmitt@foo.com)

(gettysburg, "Four score and seven years ago...")

(29ck2dxa1, 0128ckso1$9#*!!8349e)

(windows, )

- The key-value store (KVS) is a simple abstraction for managing persistent state
  - Data is organized as (key,value) pairs
  - Only three basic operations:
    - PUT(key, value)
    - GET(key) → value
    - Delete(key)

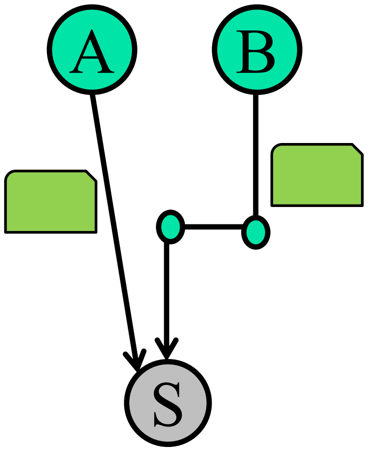
Examples of KVS

- Where have you seen this concept before?

- Conventional examples outside the cloud:
  - In-memory associative arrays and hash tables – limited to a single application, only persistent until program ends
  - On-disk indices (like BerkeleyDB)
  - "Inverted indices" behind search engines
  - Database management systems – multiple KVSs++
  - Distributed hashtables
    - Decentralized distributed systems inspired by P2P (see LSINF2345)
    - Examples: Chord/Pastry

Supporting an Internet service with a KVS

- We'll do this through a central server, e.g., a Web or application server



- Two main issues:
  1. There may be multiple concurrent requests from different clients
     - These might be GETs, PUTs, DELETEs, etc.
  2. These requests may come from different parts of the network, with message propagation delays
     - It takes a while for a request to make it to the server!
     - We'll have to handle requests in the order received (why?)

Managing concurrency in a KVS

- What happens if we do multiple GET operations in parallel?
  - ... over different keys?
  - ... over the same key?
- What if we do multiple PUT operations in parallel? or a GET and a PUT?
- What is the unit of protection (concurrency control) that is necessary here?

Concurrency control

- Most systems use locks on individual items
  - Each requestor asks for the lock
  - A lock manager processes these requests (typically in FIFO order) as follows:
    - Lock manager grants the lock to a requestor
    - Requestor makes modifications
    - Then releases the lock when it's done

Limitations of per-key concurrency control

- Suppose I want to transfer credits from my WoW account to my friend's?
  - … while someone else is doing a GET on my (and her) credit amounts to see if they want to trade?

- This is where one needs a database management system (DBMS) or transaction processing manager (app server)
  - Allows for "locking" at a higher level, across keys and possibly even systems (see LINGI2172 for more details)
- Could you implement higher-level locks within the KVS? If so, how?

No longer one-size-fits-all solution

Specialized data stores

- Example: Amazon's solutions

- Dynamo [SOSP'07]
  - Many services only store and retrieve data by primary key
    - Examples: user preferences, shopping cart, best seller lists
  - Don't require querying and management RDBMS functionality
- Simple Storage Service (S3)
  - Need to store large objects that change infrequently
    - Examples: virtual machines, pictures

Specialized data stores

- Example: Google's solutions

- The Google File System [SOSP'03]
  - Distributed file system for large data-intensive applications
  - No POSIX API; focus on multi-GB files divided in fixed-size chunks (64 MB); mostly mutated by appending new data
  - Single master node maintains all file metadata
- Bigtable [OSDI'06]
  - Distributed storage system for structured data
  - Data model is a sparse multi-dimensional sorted map indexed by row and column keys and a timestamp
  - Each value in the map is opaque to the storage system

Specialized data stores

- Example: Facebook's solutions
- Cassandra [Ladis'09]
  - A distributed storage system for large sets of structured data
  - Optimized for very high write throughput; no master nodes
- Haystack [OSDI'10]
  - Object store system optimized for photos
  - In 2010, over 260 billion images; 20 PB of data; 60 TB/week
  - Data written once, read often, never modified, rarely deleted
- TAO [ATC'13]
  - A read-optimized graph data store to serve the social graph
  - Sustains 1 billion reads/s on a changing data set of many PBs
  - Explicitly favors availability over consistency

Specialized data stores

- Example: LinkedIn’s solutions

- Kafka [NetDB’11]
  - A high-throughput distributed messaging system
  - Pub/sub architecture designed for aggregating log data
  - Messages are persisted on disk for durability and replicated for fault tolerance; guarantees at-least-once delivery
- Voldemort
  - A distributed key-value store supporting only get/put/delete
  - Inspired by Amazon’s Dynamo: tunable consistency, highly available

Plan for today

- Distributed programming and its challenges ✓
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- Amazon Dynamo ← NEXT

Amazon Web Services (AWS)

- [Vogels09] At the foundation of Amazon's cloud computing are infrastructure services such as
  - Amazon's S3 (Simple Storage Service), SimpleDB, and EC2 (Elastic Compute Cloud)
  - These provide the resources for constructing Internet-scale computing platforms and a great variety of applications.
- The requirements placed on these infrastructure services are very strict; need to
  - Score high in security, scalability, availability, performance, and cost-effectiveness, and
  - Serve millions of customers worldwide, continuously.

AWS

- Observation
  - Vogels does not emphasize consistency
  - AWS is in AP, sacrificing consistency
- AWS follows BASE philosophy
- BASE (vs ACID)
  - Basically Available
  - Soft state
  - Eventually consistent

Why Amazon favors availability over consistency?

"even the slightest outage has significant financial consequences and impacts customer trust"

- Surely, consistency violations may as well have financial consequences and impact customer trust
  - But not in (a majority of) Amazon's services
  - NB: Billing is a separate story

Amazon Dynamo

- Not exactly part of the AWS offering
  - however, Dynamo and similar Amazon technologies **are** used to power parts of AWS (e.g., S3)
- Dynamo powers internal Amazon services
- Hundreds of them!
  - Shopping cart, Customer session management, Product catalog, Recommendations, Order fullfillment, Bestseller lists, Sales rank, Fraud detection, etc.
- So what is Amazon Dynamo?
  - A highly available key-value storage system
  - Favors high availability over consistency under failures

Key-value store

- put(key, object)
- get(key)
  - We talk also about *writes/reads (the same here as put/get)*
- In Dynamo case, the put API is put(key, context, object)
  - where context holds some critical metadata (will discuss this in more details)
- Amazon services (see previous slide)
  - Predominantly do not need transactional capabilities of RDBMs
  - Only need primary-key access to data!
- Dynamo: stores relatively small objects (typically <1MB)

Amazon Dynamo: Features

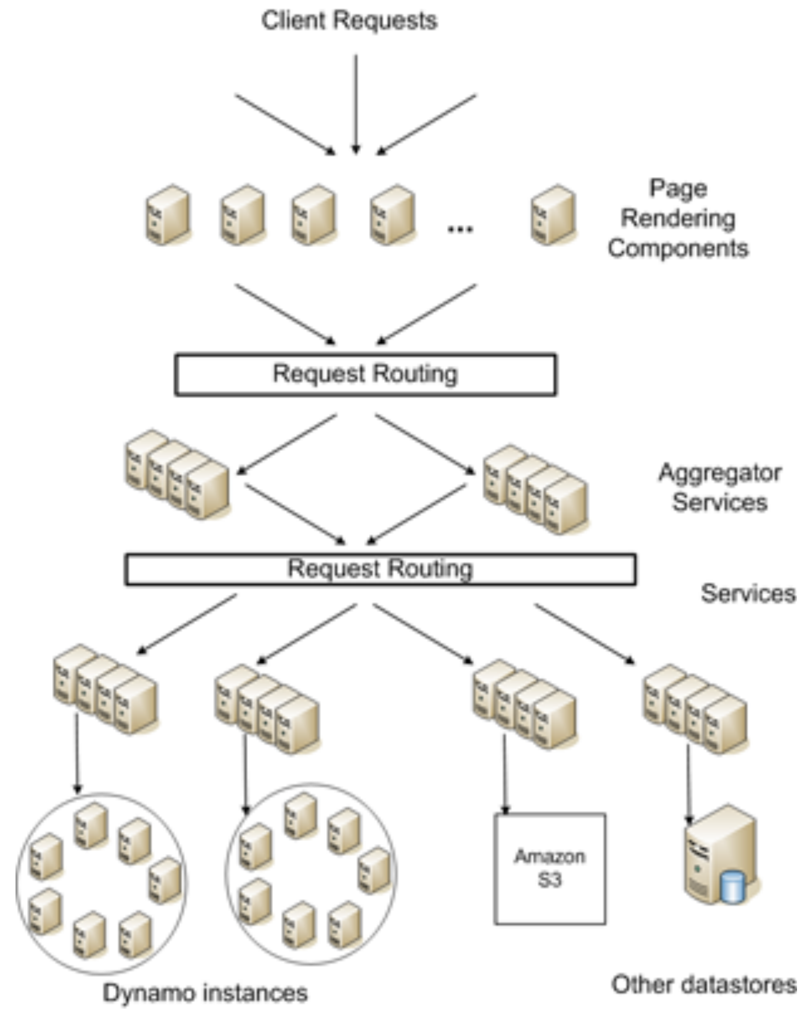
- High performance (low latency)
- Highly scalable (hundreds of server nodes)
- "Always-on" available (especially for writes)
- Partition/Fault-tolerant
- Eventually consistent
- Dynamo uses several techniques to achieve these features
  - Which also comprise a nice subset of a general distributed system toolbox

Amazon Dynamo: Key Techniques

- Consistent hashing [Karger97]
  - For data partitioning, replication and load balancing
- Sloppy Quorums
  - Boosts availability in presence of failures
  - might result in inconsistent versions of keys (data)
- Vector clocks [Fidge88/Mantern88]
  - For tracking causal dependencies among different versions of the same key (data)
- Gossip-based group membership protocol
  - For maintaining information about alive nodes
- Anti-entropy protocol using hash/Merkle trees
  - Background synchronization of divergent replicas

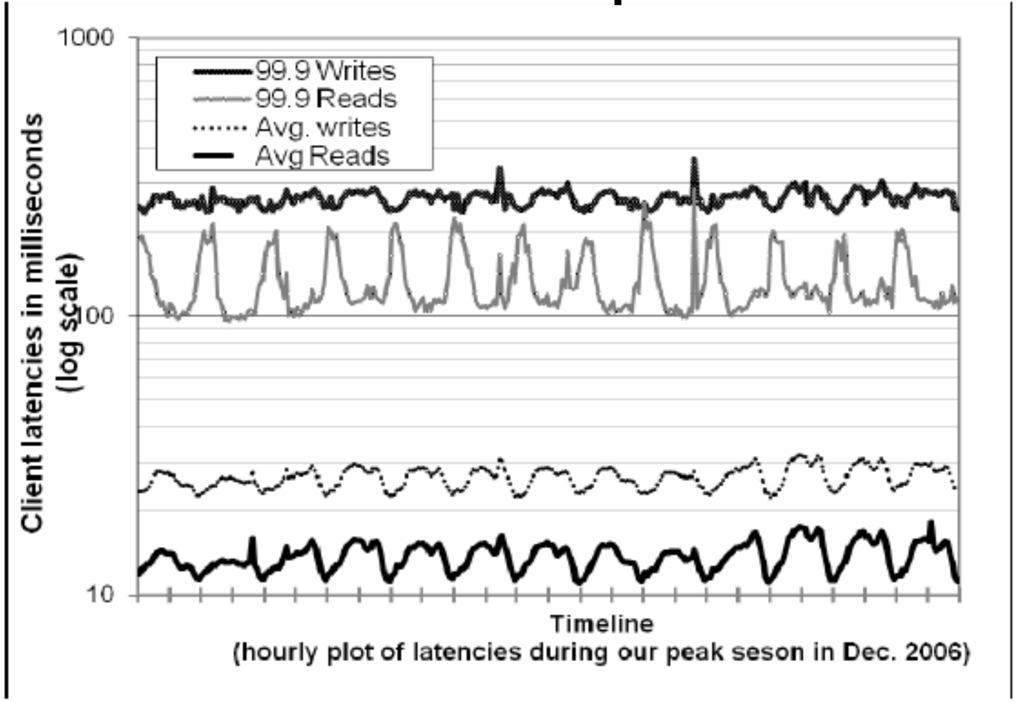
Amazon SOA platform

- **Runs on commodity hardware**
  - This is low-end server class rather than low-end PC
- **Stringent latency requirements**
  - Measured at 99.9%
    - Part of SLAs
- **Every service runs its own Dynamo instance**
  - Only internal services use Dynamo
  - No Byzantine nodes



SLAs and three nines

- Sample SLA
  - A service XYZ guarantees to provide a response within 300 ms for 99.9% of requests for a peak load of 500 req/s
- Amazon focuses on 99.9 percentile



Dynamo design decisions

- "always-writable" data store
  - Think shopping cart: must be able to add/remove items
- If unable to replicate the changes?
  - Replication is needed for fault/disaster tolerance
  - Allow creations multiple versions of data (vector clocks)
  - Reconcile and resolve conflicts during reads
- How/who should reconcile
  - Application: depending on e.g., business logic
    - Complicates programmer's life, flexible
  - Dynamo: deterministically, e.g., "last-write" wins
    - Simpler, less flexible, might loose some value wrt. Business logic

Dynamo architecture

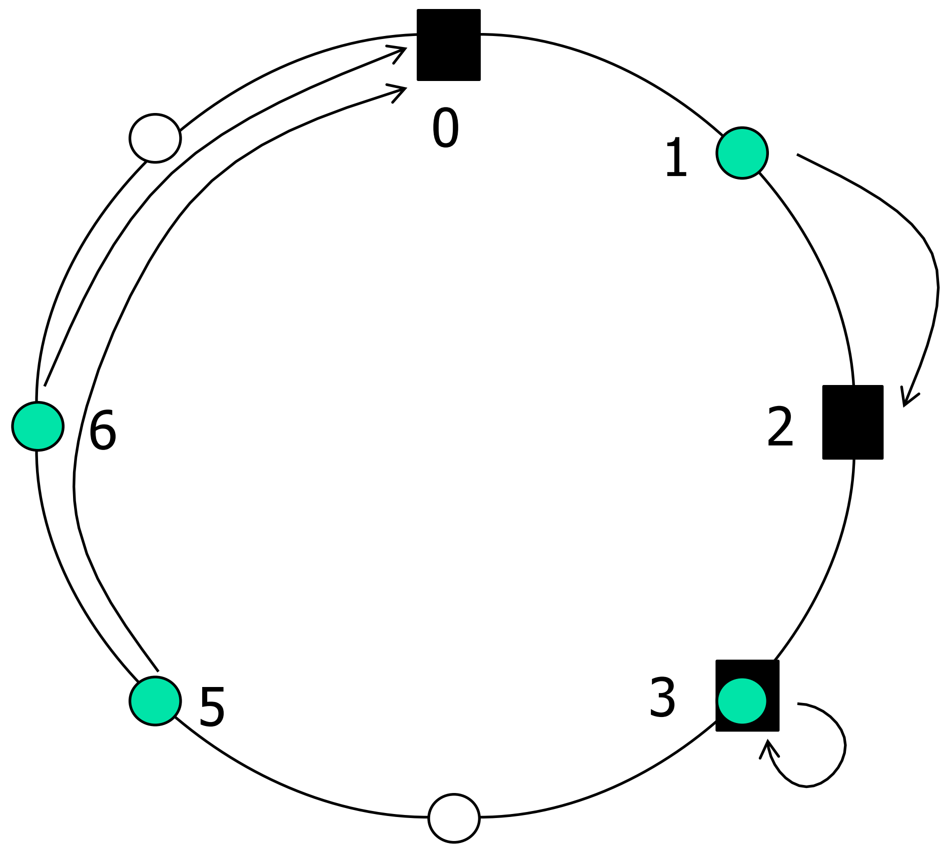
- Scalable and robust components for
  - Load balancing, membership/fault detection, failure recovery, replica synchronization, overload handling, state transfer, concurrency, job scheduling, request marshalling, request routing, system monitoring and alarming, configuration management
- We focus on techniques for
  - Partitioning, replication, versioning, membership, failure-handling, scaling

Partitioning using consistent hashing

- Dynamo dynamically partitions a set of *keys* over a set of storage *nodes*
  - Used also in many DHTs (e.g., Chord)
- Hashes of *keys* give key m-bit *identifiers*
  - (MD5, can use SHA-1, …)
- Consistent hashing
  - Identifiers are ordered in an identifier circle
- Partitioning
  - A key is assigned to the closest **successor node** id
  - i.e., key k is assigned to the first node with id $\geq k$
    - or if such a node does not exist to the node with smallest id (circle)

Consistent hashing: Example

- m=3: 3-bit namespace
- 3 nodes (0,2,3)
- 4 keys (1,3,5,6)
- Node 0 stores keys 5,6
- Node 2 stores key 1
- Node 3 stores key 3



Consistent hashing

- Designed to let nodes enter and leave the network with minimal disruption
  - Key to incremental scalability

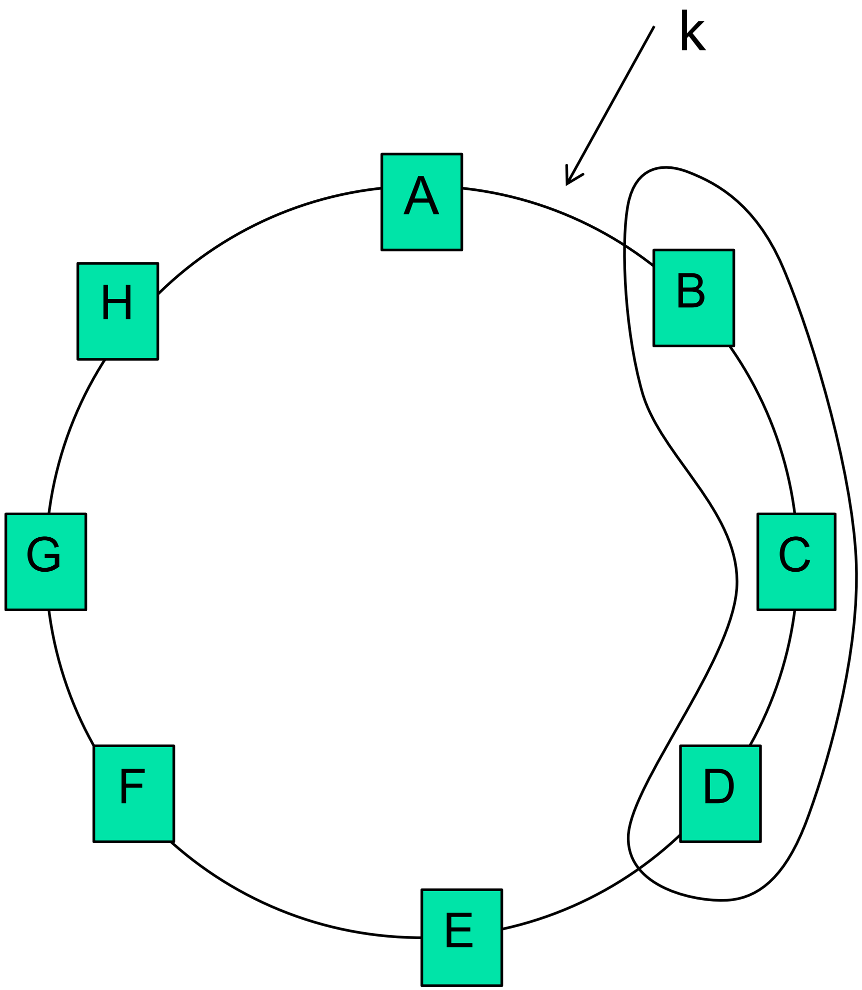
- Maintainance
  - When node *n* joins
    - certain keys previously assigned to *n*'s successor now become assigned to *n*.
  - When node *n* leaves
    - all of *n*'s assigned keys are reassigned to *n*'s successor.

Consistent hashing: Properties

- Assume N nodes and K keys. Then (with high probability) [Karger97]
  - Each node is responsible for at most $(1+\varepsilon)K/N$ keys
  - When $N+1^{st}$ node joins/leaves, $O(K/N)$ keys change hands (optimal)
- $\varepsilon=O(\log N)$
  - Can have $\varepsilon \to 0$ with "virtual" nodes
- "Virtual" nodes
  - Each physical node mapped multiple times to the circle
    - **Load balancing!**
  - Dynamo employs virtual nodes — also in order to leverage heterogeneity among physical nodes

Replication

- **To achieve high availability and durability**
  - Each data item (key) replicated at N nodes
  - N is configurable per Dynamo instance
- **Assume N=3**
  - For key k, B is the 1st successor node (coordinator)
  - B replicates k to N-1 further successor nodes (C and D)
- **B, C and D**
  - are ***preference list*** for k
- **Virtual nodes**
  - Same physical nodes skipped in a preference list



Data versioning

- Replication performed after a response is sent to a client
  - This is called *asynchronous replication*
  - May result in inconsistencies under partitions
    - Read does not return the last value. **Eventual consistency!**
- But operations should not be lost
  - "add to cart" should not be rejected but also not forgotten
  - If "add to cart" is performed when latest version is not available it is performed on an older version
  - We may have different versions of a key/value pair

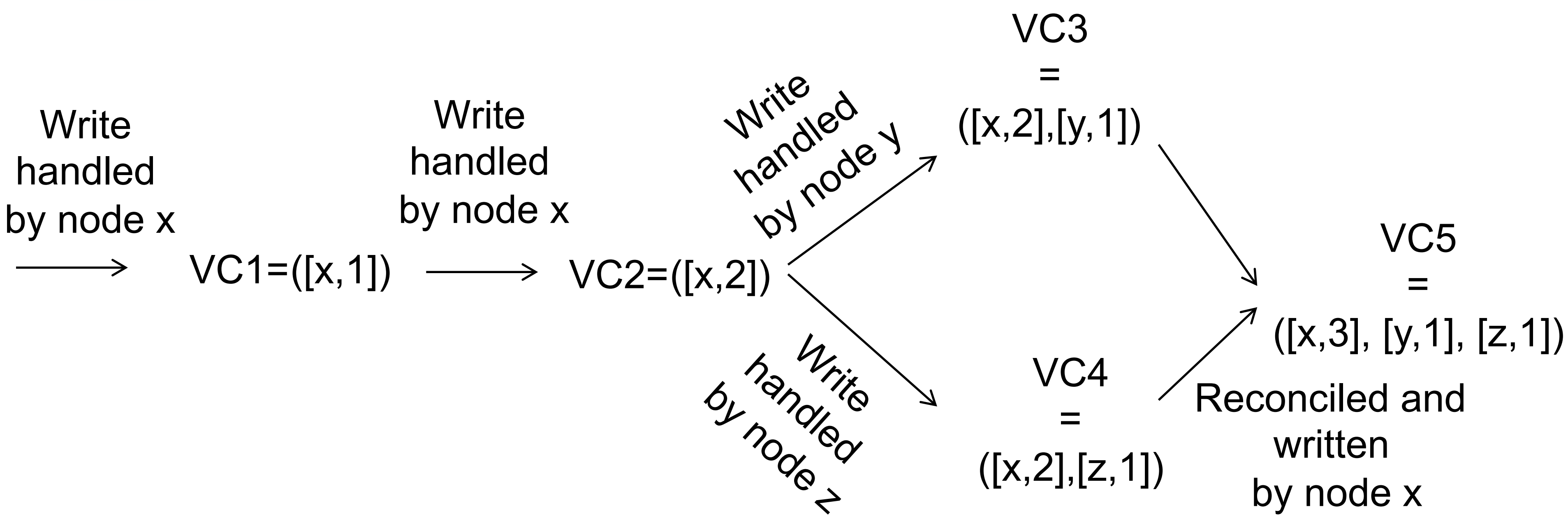
Data versioning

- Once a partition heals versions are merged
  - The goal is not to lose any "add to cart"
- Most of the time there will be no partitions and the system will be consistent
  - New versions subsume all previous ones
- It is vital to understand that the application must know that different versions might exist
  - This is the Achilles' heel of eventual consistency (more difficult to reason about, program with)
- Key data versioning technique: Vector clocks
  - Capture causality between different versions of an object

Vector clocks in Dynamo

- Each write to a key k is associated with a vector clock VC(k)
- VC(k) is an array (map) of integers
  - In theory: one entry VC(k)[i] for each node i
- When node i handles a write of key k it increments VC(k)[i]
  - VCs are included in the context of the put call
- In practice:
  - VC(k) will not have many entries (only nodes from the preference list should normally have entries), and
  - Dynamo truncates entries if more than a threshold (say 10)

Vector clocks in Dynamo



NB: one VC per key

Number of different versions (#DV)

- These are the evidence of consistency violations (#DV>1)
- 24h experiment on the shopping cart
  - #DV=1: 99.94% of requests (all but 1 in cca 1700 req)
  - #DV=2: 0.00057% of requests
  - #DV=3: 0.00047% of requests
  - …
- Attributed to busy robots (automated client programs)
  - Rarely visible to humans

Handling puts and gets (failure-free case)

- Any Dynamo storage node can receive get/put request for any key. This node is selected by
  - Generic load balancer
  - By a client library that immediately goes to coordinator nodes in a preference list
- If the request comes from the load balancer
  - Any node can coordinate a read request
  - For a write request, the node routes the request a node in the key's preference list
- Each node has routing info to all other nodes
  - 0-hop DHT
  - ***Not the most scalable, but latency is critical***

Handling puts and gets

- Extended preference list
  - N nodes from preference list + some additional nodes (following the circle) to account for failures
- Failure-free case
  - Nodes from preference list are involved in get/put
- Failures
  - First N alive nodes from extended preference list are involved

Dynamo's quorums

- Two configurable parameters
  - R number of nodes that need to participate in a get
  - W number of nodes that need to participate in a write
  - R + W > N (a quorum system)
- **Handling put** (by coordinator) // rough sketch

  Generate new VC, Write new version locally

  Send value, VC to N selected nodes from preference list

  Wait for W-1
- **Handling get** (by coordinator) // rough sketch

  Send READ to N selected nodes from preference list

  Wait for R

  Select highest versions per VC, return all such versions (causally unrelated)

  Reconcile/merge different versions

  Writeback reconciled version

Of choices of R, W

- R, W smaller than N
  - To decrease latency
  - Slowest replica dictates the latency

- W=1
  - Always-available for writes
  - Yields R=N (reads pay the penalty)

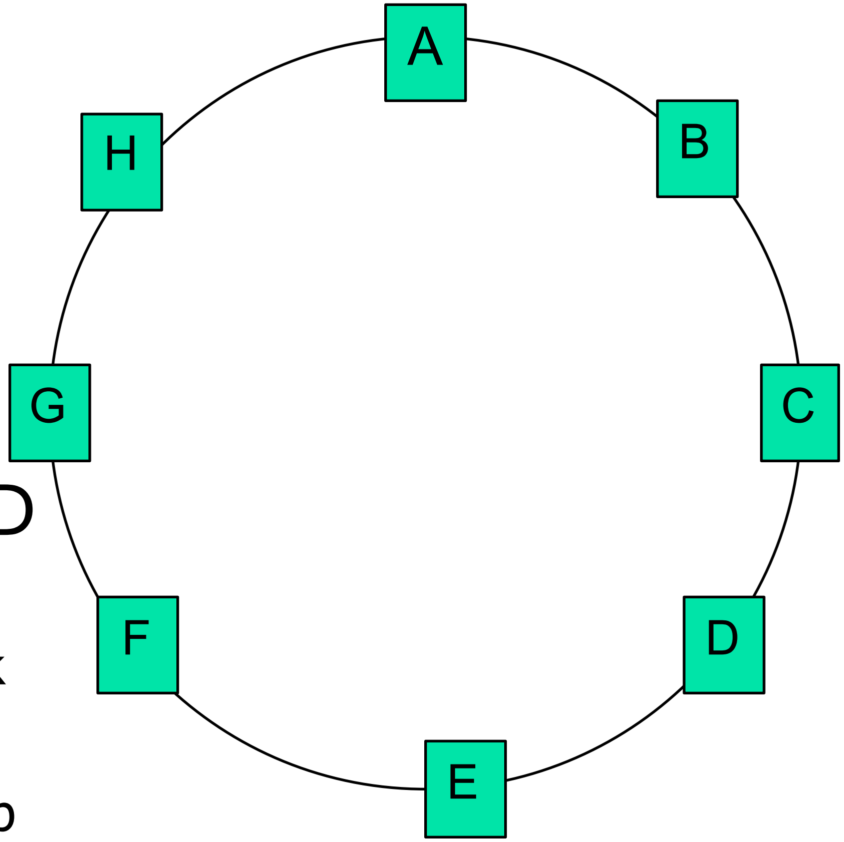
- Most often in Dynamo (W,R,N)=(2,2,3)

Handling failures

- N selected nodes are the first N healthy nodes
  - Might change from request to request
  - Hence these quorums are "Sloppy" quorums
- "Sloppy" vs. strict quorums
  - "sloppy" allow availability under a much wider range of partitions (failures) but sacrifice consistency
- Also, important to handle failures of an entire data center
  - Power outages, cooling failures, network failures, disasters
  - Preference list accounts for this (nodes spread across data centers)

Handling temporary failures: hinted handoff

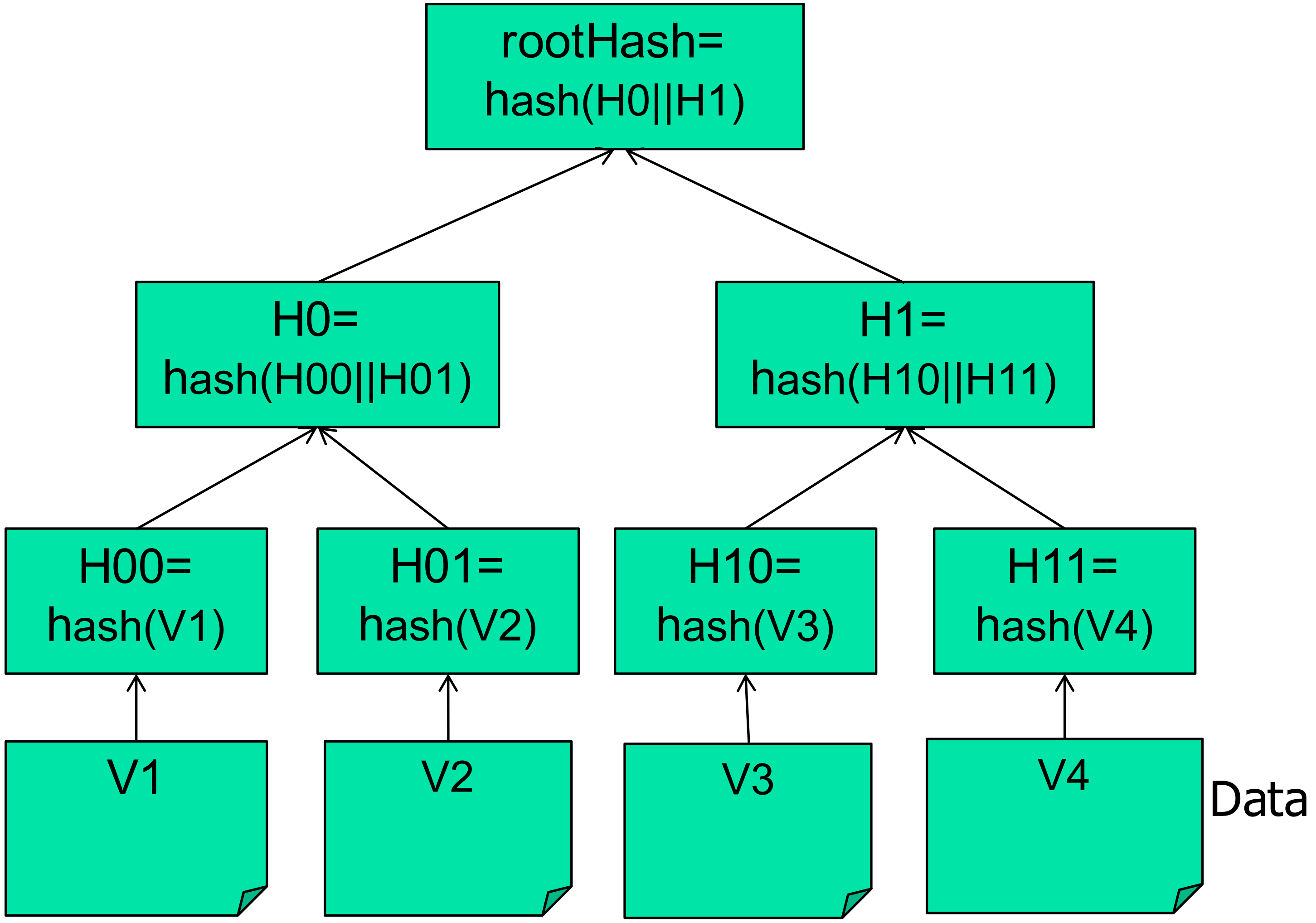
- If a replica in the preference list is down then another replica is created on a new node
- Assume again N=3
- A replica A is down
- Coordinator will involve D
  - With a hint that this D substitutes A until A comes back again
  - When D gets info A is back up it hands back the data to A



Anti-entropy synchronization using hash/Merkle trees

- Each Dynamo node keeps a Merkle tree for each of its key ranges
  - Remember, one key range per virtual node
- Compares the root of the tree with replicas
  - If equal, all keys in a range are equal (replicas in sync)
  - If not equal
    - Traverse the branches of the tree to pinpoint the children that differ
    - The process continues to all leaves
    - Synchronize on those keys that differ

Merkle trees



Membership

- Node outages temporary
  - Not considered as permanent leaves
- Dynamo relies on administrator explicitly declaring joins/leaves on any Dynamo node
  - This triggers membership changes (with the aid of seeds)
- Membership info are also eventually consistent — propagated by background gossip protocol
  - Node contacts a random node every 1s
  - 2 nodes reconcile the membership info
  - This gossip used also for exchanging partitioning/placement metadata

Failure detection

- Unreliable failure detection (FD)
  - Used, e.g., to refresh the healthy node info in the extended preference list
- With steady load node A will find out if node B is unavailable
  - E.g., if B does not respond to A's messages
  - But this is clearly unreliable, B might be partitioned not faulty
  - Then, A periodically checks on B to see if B recovers
- In the absence of traffic A might not find out B is unavailable
  - But this info anyway does not matter w/o traffic
  - Dynamo has in-band FD, rather than a dedicated component

Dynamo: Summary

- An eventually consistent highly available key value store
  - AP in the CAP space
- Focuses on low latency, SLAs
  - Very low latency writes, reconciliation in reads
- Key techniques used in many other distributed systems
  - Consistent hashing, (sloppy) quorum-based replication, vector clocks, gossip-based membership, Merkle-tree based synchronization

Stay tuned

Next time you will learn about:

A programming model for the Cloud