Distributed systems

Lecture 15: Replication, quorums, consistency, CAP, and Amazon/Google case studies

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(With thanks to Dr Robert N. M. Watson and Dr Steven Hand)

Last time

- General issue of **consensus**:
  - How to get processes to agree on something
  - FLP says "impossible" in **asynchronous networks** with at least 1 (more) failure … but in practice we're OK!
  - General idea useful for **leadership elections**, **distributed mutual exclusion**: relies on being able to detect failures
- **Distributed transactions**:
  - Need to commit a set of "sub-transactions" across multiple servers – want **all-or-nothing semantics**
  - Use **atomic commit** protocol like 2PC
- **Replication**:
  - **Performance**, **load-balancing**, and **fault tolerance**
  - Introduction to **consistency**

From last lecture…

Replication and consistency

- More challenging if clients can perform updates
- For example, imagine **x** has value **3** (in all replicas)
  - **C1** requests **write(x, 5)** from **S4**
  - **C2** requests **read(x)** from **S3**
  - What should occur?
- With **strong consistency**, the distributed system behaves as if there is **no replication present**:
  - i.e. in above, **C2** should get the value **5**
  - requires coordination between all servers
- With **weak consistency**, **C2** may get 3 or 5 (or …?)
  - Less satisfactory, but much easier to implement
  - Recall **close-to-open consistency** in NFS

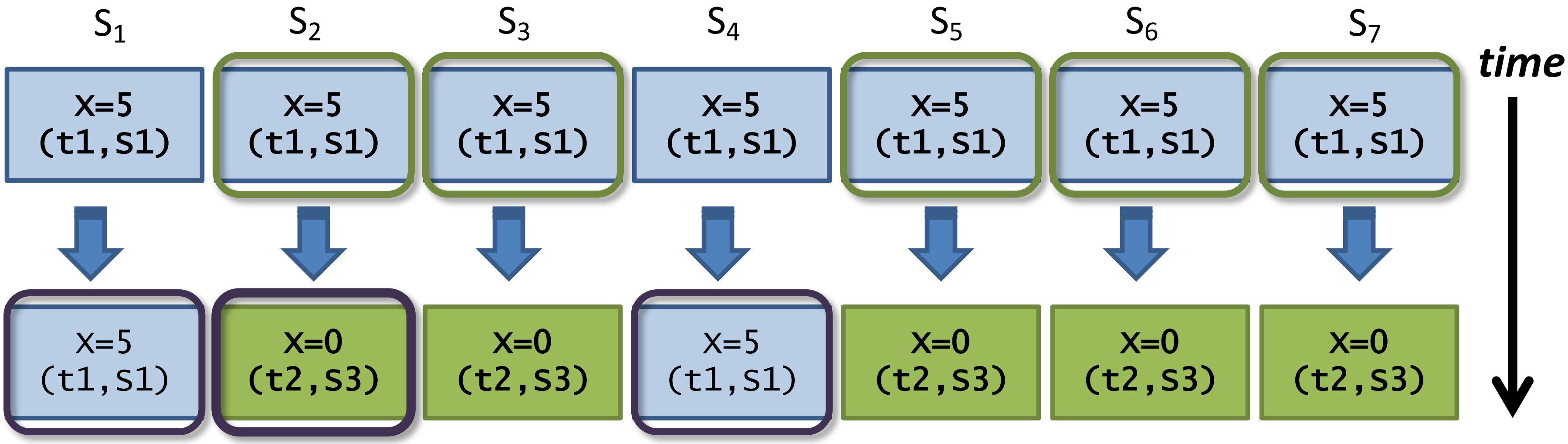
Achieving strong consistency

- Goal: impose **total order** on updates to some state **x**
  - Ensure update propagated to replicas **before** later reads
- Simple **lock-step** solution for replicated object:
  1. When $\mathbf{S_i}$ receives update for **x**, locks **x** at all other replicas
  2. Make change to **x** on $\mathbf{S_i}$
  3. Propagate $\mathbf{S_i}$'s change to **x** to all other replicas
  4. Other servers send ACK to $\mathbf{S_i}$
  5. After ACKs received, instruct replicas to unlock **x**
  6. Once $\mathbf{C_j}$ has ACK for its write to $\mathbf{S_i}$, any $\mathbf{C_k}$ will see update
- Need to handle failure (of replica, of network)
  - Add step to tentatively apply update, and only actually apply ("commit") update if all replicas agree
- We've reinvented distributed transactions & 2PC!

Quorum systems

- Transactional consistency works, but:
  - High overhead, and
  - Poor availability during update (worse if crash!)
- An alternative is a **quorum system**:
  - Imagine there are **N** replicas, a **write quorum Q_w**, and a **read quorum Q_r**
  - Constraint on writes: $Q_w > N/2$
  - Constraint on reads: $(Q_w + Q_r) > N$
- To perform a write, must update Q_w replicas
  - Ensures a majority of replicas have new value
- To perform a read, must read Q_r replicas
  - Ensures that we read *at least one* updated value

Example



- Seven replicas (N=7), $\mathbf{Q_w} = 5$, $\mathbf{Q_r} = 3$
- All objects have associated version **(T, S)**
  - **T** is logical timestamp, initialized to zero
  - **S** is a server ID (used to break ties)
- Any write will update at least $\mathbf{Q_w}$ replicas
- Performing a read is easy:
  - Choose replicas to read from until get $\mathbf{Q_r}$ responses
  - Correct value is the one with highest version

Quorum systems: writes

- Performing a write is trickier:
  - Must ensure get entire quorum, or cannot update
  - Hence need a commit protocol (as before)
- In fact, transactional consistency is a quorum protocol with $\mathbf{Q_w = N}$ and $\mathbf{Q_r = 1}$!
  - But when $\mathbf{Q_w < N}$, additional complexity since must bring replicas up-to-date before updating
- Quorum systems are good when expect failures
  - Additional work on update, additional work on reads…
  - … but increased **availability** during failure
- How might client-server traffic scale with $\mathbf{Q_w/Q_r}$?

Weak consistency

- Maintaining strong consistency has costs:
  - Need to coordinate updates to all (or $\mathbf{Q_w}$) replicas
  - Slow… and will block other accesses for the duration
- **Weak consistency** systems provides fewer guarantees:
  - E.g. $\mathbf{C_1}$ updates (replica of) object **Y** at $\mathbf{S_3}$
  - $\mathbf{S_3}$ lazily propagates changes to other replicas
- We can do this by reducing quorum parameters
  - $\mathbf{Q_r}$: Clients can potentially read **stale** value from other $\mathbf{S_x}$
  - $\mathbf{Q_w}$: Writes may **conflict**: >1 **Y** values w/same timestamp
- Considerably more **efficient** and more **available**:
  - Less waiting for replicas on read and write…
  - … hence is also more available (i.e. fault tolerant)
- But it can be harder to reason about possible outcomes

FIFO consistency

- As with group communication primitives, various ordering guarantees possible
- **FIFO consistency**: all updates originating at $\mathbf{S_i}$ (on behalf of a client) occur in the same order at all replicas
  - As with FIFO multicast, can buffer for as long as we like!
  - But says nothing about how $\mathbf{S_i}$'s updates are interleaved with $\mathbf{S_j}$'s at another replica (may put $\mathbf{S_j}$ first, or $\mathbf{S_i}$, or mix)
- Still useful in some circumstances
  - E.g. single user accessing different replicas at disjoint times
  - I.e., client will see its writes **serialized**
  - Essentially primary replication with primary = last accessed
- E.g., sufficient for multiple mail clients interacting with the same mailbox independently (phone, tablet)

Eventual consistency

- FIFO consistency doesn't provide very nice semantics:
  - E.g. $\mathbf{C_1}$ writes $\mathbf{V_1}$ of file **f** to $\mathbf{S_1}$
  - Later $\mathbf{C_1}$ reads **f** from $\mathbf{S_2}$, and writes $\mathbf{V_2}$
  - Much later, $\mathbf{C_1}$ reads **f** from $\mathbf{S_3}$ and gets $\mathbf{V_1}$ – changes lost!
- What happened?
  - $\mathbf{V_1}$ arrived at $\mathbf{S_3}$ after $\mathbf{V_2}$, thus overwrote it (stoooopid $\mathbf{S_3}$)
- A desirable property in weakly consistent systems is that they **converge to a more correct state**
  - I.e. in the absence of further updates, every replica will eventually end up with the same latest version
- This is called **eventual consistency**

Implementing eventual consistency

- Servers $\mathbf{S_i}$ keep a **version vector** $\mathbf{V_i(O)}$ for each object **O**
  - For each update of **O** on $\mathbf{S_i}$, increment $\mathbf{V_i(O)[i]}$
  - (essentially a **vector clock** as a per-object version number)
- Servers synchronize pair-wise from time to time
  - For each object **O**, compare $\mathbf{V_i(O)}$ to $\mathbf{V_j(O)}$
  - If $\mathbf{V_i(O)} < \mathbf{V_j(O)}$, $\mathbf{S_i}$ gets an up-to-date copy from $\mathbf{S_j}$
  - If $\mathbf{V_j(O)} < \mathbf{V_i(O)}$, $\mathbf{S_j}$ gets an up-to-date copy from $\mathbf{S_i}$
- But if $\mathbf{V_i(O)} \sim \mathbf{V_j(O)}$ we have a **write conflict**:
  - Concurrent updates have occurred at 2 or more servers
  - Must apply some kind of reconciliation method
  - (similar to revision control systems, and equally painful)
- Coda filesystem (next lecture) uses this approach

Amazon's Dynamo [2007]

- Storage service used within Amazon's web services
- Designed to prioritize availability above consistency:
  - SLA to give bounded response time 99.99% of the time
  - If customer wants to add something to shopping basket and there's a failure… still want addition to 'work'
  - Even if get (temporarily) inconsistent view… fix later!
- Built around notion of a so-called **sloppy quorum**:
  - Have **N**, $\mathbf{Q_w}$, $\mathbf{Q_r}$ as we saw earlier… but don't actually require that $\mathbf{Q_w > N/2}$, or that $\mathbf{(Q_w + Q_r) > N}$
  - Instead make tunable: **lower Q values = higher availability**; and higher read (or write) throughput
  - Also let system continue during failure

– Application must handle (reconcile?) inconsistency

Session guarantees

- Eventual consistency seems great, but how can you program to it?
  - Need to know **something** about guarantees to the client
- These are called **session guarantees**:
  - Not system wide, just for one (identified) client
  - Client must be a more active participant
  - E.g. client maintains version vectors of objects it reads/writes
- Example: **Read Your Writes (RYW)**:
  - If $\mathbf{C_i}$ writes a new value to **x**, a later read of **x** should see the update … even if $\mathbf{C_i}$ is now reading from another replica
  - Need $\mathbf{C_i}$ to remember highest ID of any update it made
  - Only read from a server if it has seen that update
- E.g., Webmail: Exchange stale message read/delete flags between sessions for greater scalability

Session guarantees + availability

- There are many variations on session guarantees
  - All deal with allowable state on replica given history of accesses by a specific client
- Session guarantees are weaker than strong consistency, but stronger than ‘pure’ weak consistency:
  - But this means that they **sacrifice availability**
  - I.e. choosing not to allow a read or write if it would break a session guarantee means not allowing that operation!
  - ‘Pure’ weak consistency would allow the operation
- Can we get the best of both worlds?

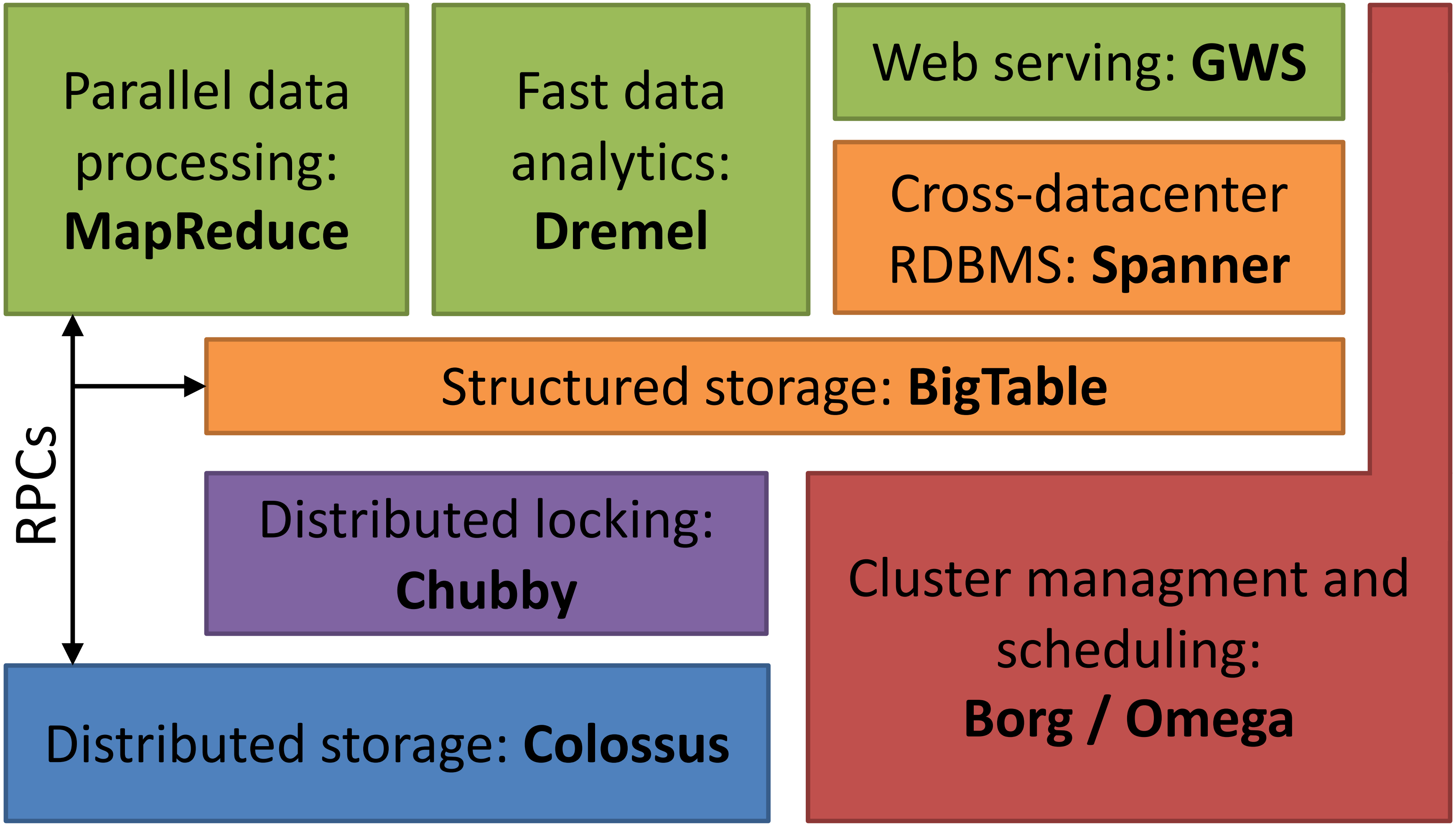
Consistency, Availability & Partitions (CAP)

- Short answer: No ;-)
- The **CAP Theorem** (Brewer 2000, Gilbert & Lynch 2002) says you can only guarantee two of:
  - **Consistent data, Availability, Partition-tolerance**
- … in a single system.
- In local-area systems, can sometimes drop partition-tolerance by using redundant networks
- In the wide-area, this is not an option:
  - **Must choose between consistency & availability**
  - Most Internet-scale systems ditch consistency
- **NB**: this doesn't mean things are always inconsistent, just that they're not **guaranteed** to be consistent

A Google datacentre

- **MapReduce**
  - Scalable distributed computation model
- **BigTable**
  - Distributed storage with weak consistency
- **Spanner**
  - Distributed storage with strong consistency
- Many spiffy distributed systems at Google
  - E.g., **Dapper**: trace RPCs and distributed events

Google: architecture overview



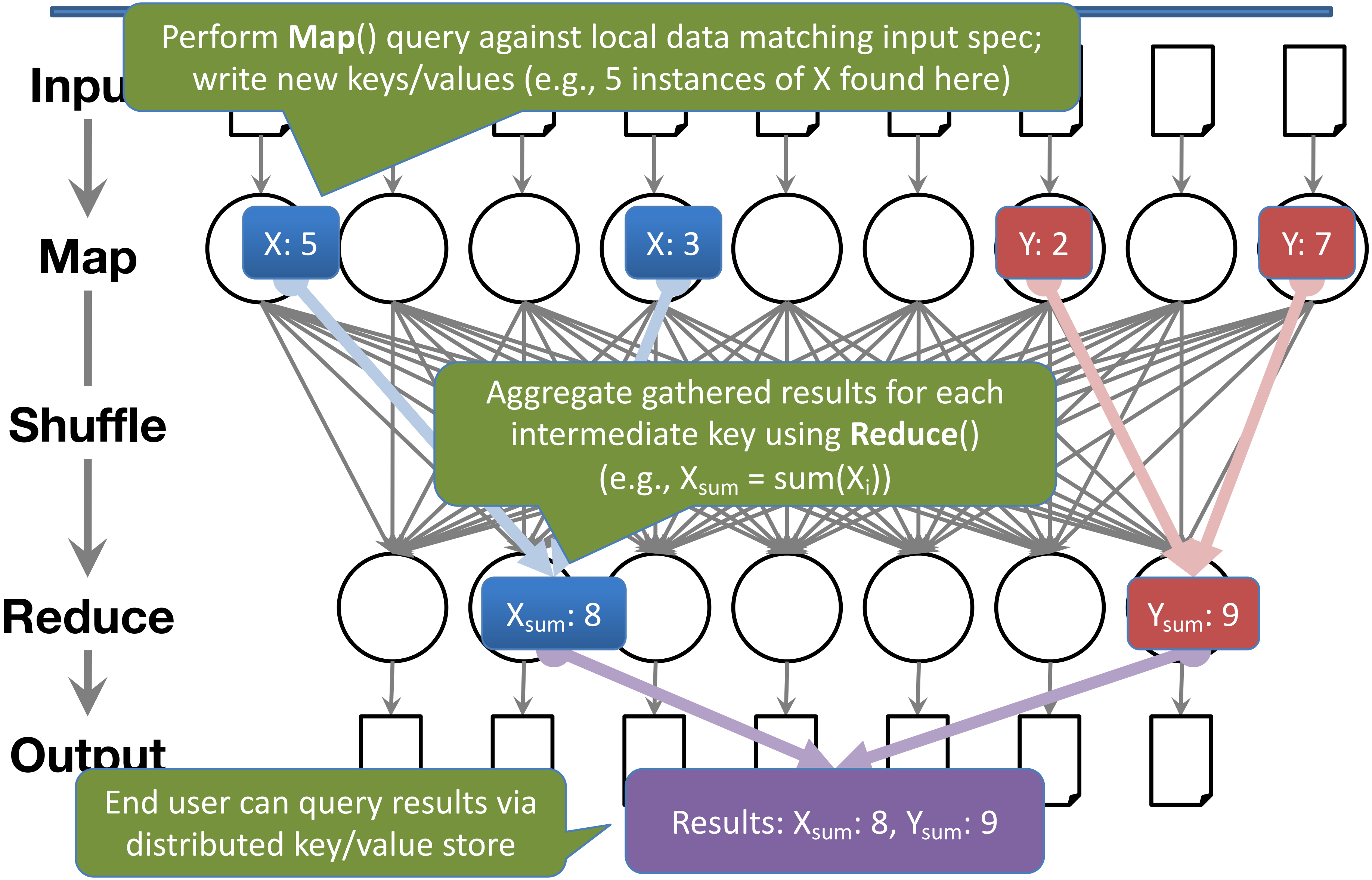
Google's MapReduce [2004]

- **Specialized** programming framework for scale
  - Run a program on 100s to 10,000s machines
- Framework takes care of:
  - Parallelization, distribution, load-balancing, scaling up (or down) & fault-tolerance
  - **Locality**: compute close to (distributed) data
- Programmer implements two methods
  - **map**(**key**, **value**) → list of <**key'**, **value'**> pairs
  - **reduce**(**key'**, **value'**) → **result**
  - Inspired by functional programming
  - Reduce data movement by computing close to data source

– E.g., for every word, count documents using word(s):

  - Extract words from local documents in **map**() phase
  - Aggregate and generate sums in **reduce**() phase

MapReduce: for each key, sum values



MapReduce example programs

- **Sorting** data is trivial (map, reduce both identity function)
  - Works since the shuffle step essentially sorts data
- **Distributed grep** (search for words)
  - **map**: emit a line if it matches a given pattern
  - **reduce**: just copy the intermediate data to the output
- **Count URL access frequency**
  - **map**: process logs of web page access; output <URL, *n*>
  - **reduce**: add all values for the same URL
- **Reverse web-link graph**
  - **map**: output <target, source> for each link to *target in a page*
  - **reduce**: concatenate the list of all source URLs associated with a target. Output <target, list(source)>

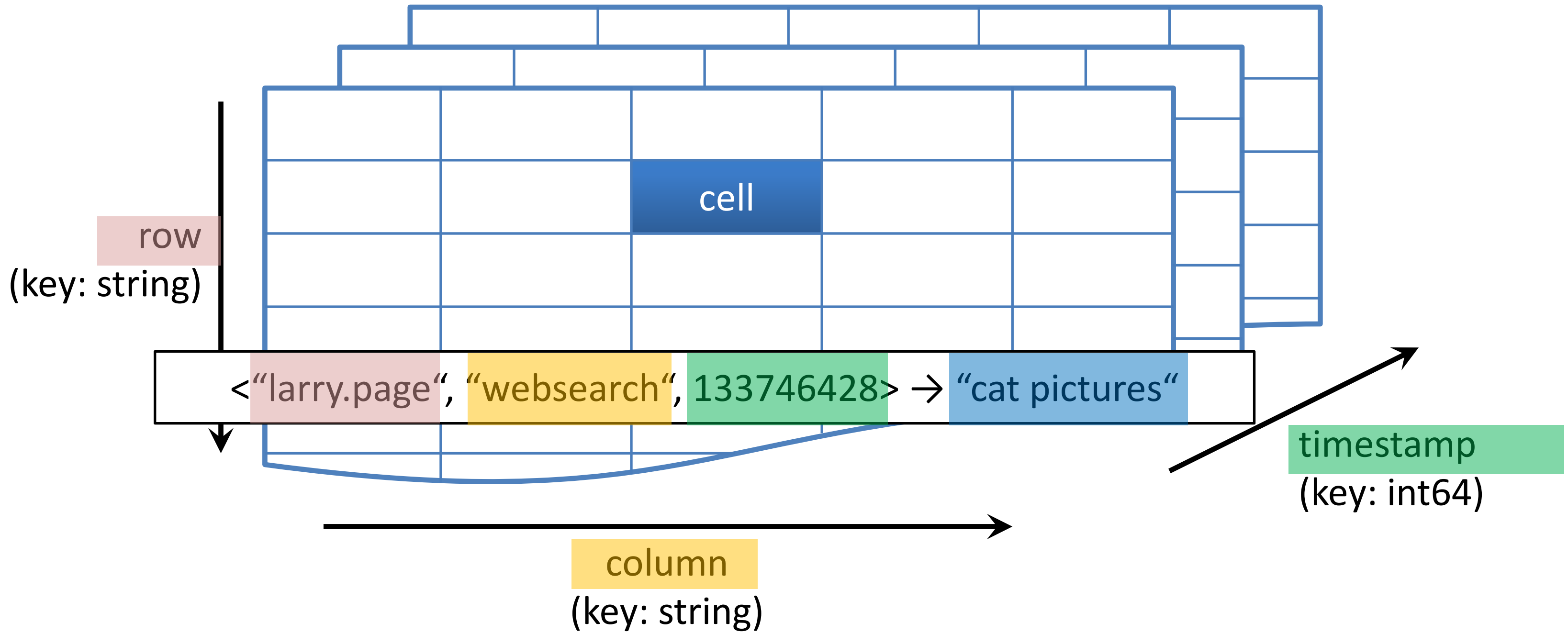
MapReduce: pros and cons

- **Extremely simple**, and:
  - Can **auto-parallelize** (since operations on every element in input are independent)
  - Can **auto-distribute** (since rely on underlying Colossus/BigTable distributed storage)
  - Gets **fault-tolerance** (since tasks are idempotent, i.e. can just re-execute if a machine crashes)
- Doesn't really use **any** of the sophisticated algorithms we've seen (except storage replication)

– Limited to batch jobs and computations that are expressible as a **map**() followed by a **reduce**()

Google’s BigTable [2006]

- “Three-dimensional” structured key-value store:
  - *<row key, column key, timestamp> → value*



- Effectively a distributed, sorted, sparse map
  - Versioned web contents by URL, user activity history, web logs, …

Google's BigTable [2006]

- Distributed **tablets** (~1 GB max) hold subsets of **map**
  - Adjacent rows have user-specifiable locality
  - E.g., store pages for a particular website in the same tablet
- On top of **Colossus**, which handles replication and fault tolerance: *only one (active) server per tablet!*
- Reads & writes within a row are **transactional**
  - Independently of the number of columns touched
  - **But:** no cross-row transactions possible
- META0 tablet is "root" for name resolution
  - Filesystem meta stored in BigTable itself
- Use **Chubby** to elect master (META0 tablet server), and to maintain list of tablet servers & schemas
  - 5-way replicated **Paxos consensus** on data in **Chubby**

Google's Spanner [2012]

- **BigTable** insufficient for some consistency needs
- Often have transactions across >1 datacenters
  - May buy app on Play Store while travelling in the U.S.
  - Hit U.S. server, but customer billing data is in U.K.
- **Spanner** offers **transactional consistency**: full RDBMS power, ACID properties, at global scale!
- Wide-area consistency is hard
  - Due to long delays and clock skew
- Secret sauce: **hardware-assisted clock sync**
  - Using GPS and atomic clocks in datacenters
  - Use global timestamps and **Paxos** to reach consensus
  - Still have a period of uncertainty for write TX: **wait it out**!

Comparison

	Dynamo	BigTable	Spanner
Consistency	eventual	weak(ish)	strong
Availability	high throughput, low latency		low throughput, high latency
Expressivity	simple key-value	row transactions	full transactions

Summary + next time

- Strong, weak, and eventual consistency
- Quorum replication
- Session guarantees
- CAP theorem
- Amazon/Google case studies

- Distributed-system security
  – Access control, capabilities, RBAC, single-system sign on
- Distributed storage system case studies
  – NASD, AFS3, and Coda