Search Engine Architecture

2. Big Data Storage

Noted slides adapted from Lin et al.'s Big Data Infrastructure, UMD Spring 2015 with cosmetic changes.

Source: Wikipedia (Clouds) via Big Data Infrastructure 2015

Computing in the Cloud

- Before clouds…
  - Grids
  - Connection machine
  - Vector supercomputers
  - …
- Cloud computing means many different things:
  - Big data
  - Rebranding of web 2.0
  - Utility computing
  - Everything as a service

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

What is Cloud Computing?

- Cloud computing means computing resources available “on demand”
  - Resources can include storage, compute cycles, or software built on top (e.g. database as a service)
  - On demand means fast setup/teardown, pay-as-you-go
- For big data, clouds are attractive for several reasons
  - Access to large infrastructure that is hard to operate
  - Bursty workloads benefiting from pay-as-you-go
  - Recent years have seen major growth of cloud computing in most software domains

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Everything as a Service

- Utility computing = Infrastructure as a Service (IaaS)
  - Why buy machines when you can rent cycles?
  - Examples: Amazon's EC2, Rackspace
- Platform as a Service (PaaS)
  - Give me nice API and take care of the maintenance, upgrades, …
  - Example: Google App Engine, Amazon RDS
- Software as a Service (SaaS)
  - Just run it for me!
  - Example: Gmail, Salesforce

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Benefits for Users

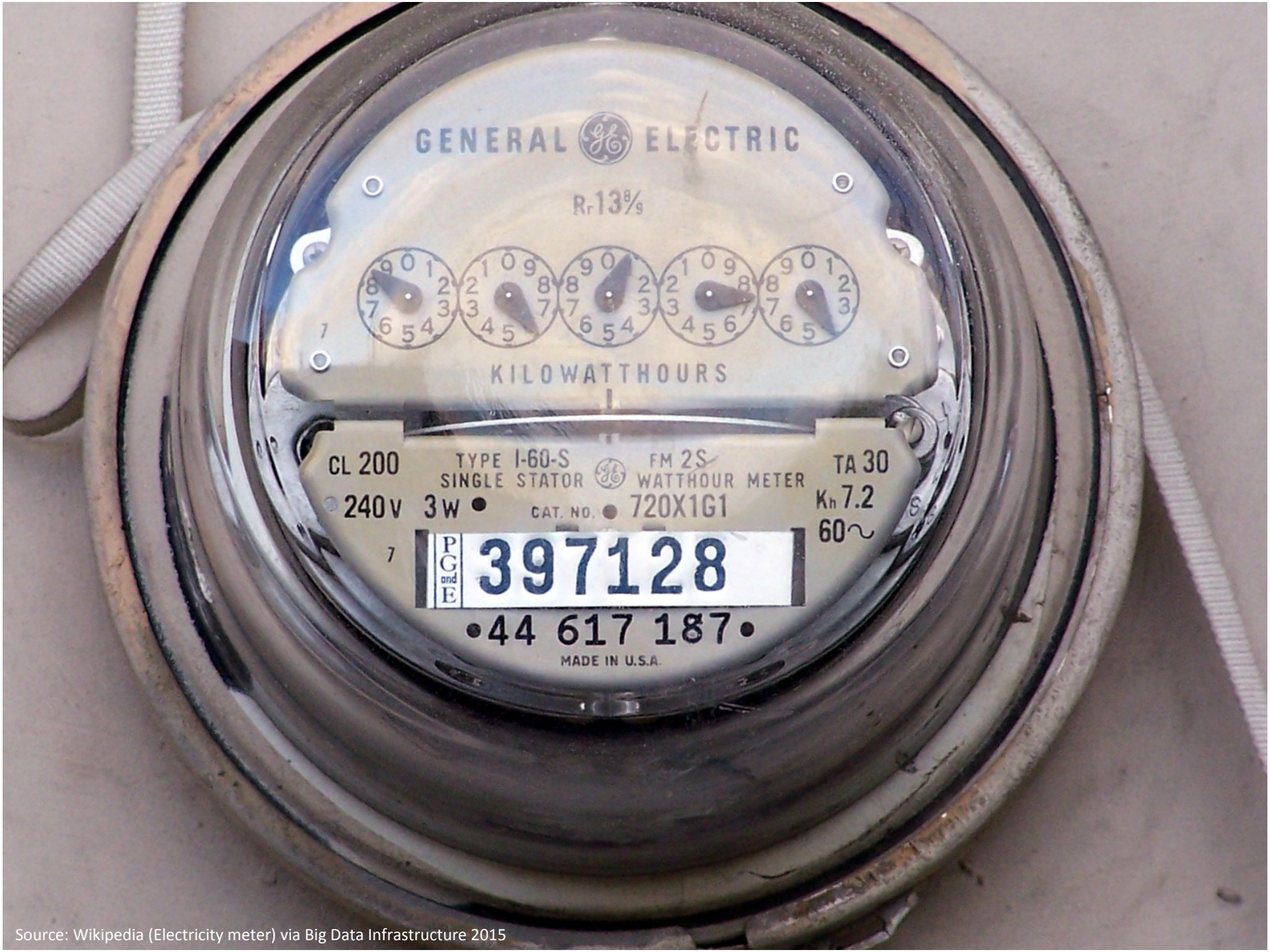
- Fast deployment
  - Cloud services can start in minutes, without long setup
- Outsourced management
  - Provider handles administration, reliability, security
- Lower costs
  - Benefit from economies of scale of provider
  - Only pay for resources while in use
- Elasticity
  - Easy to acquire lots of infrastructure for a short period

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Benefits for Providers

- Economies of scale
  - Share expertise and resources across many customers
  - Lower costs per user due to scale
- Fast deployment
  - Compared to traditional software sales cycles, new features reach users directly
- Optimization across users

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.



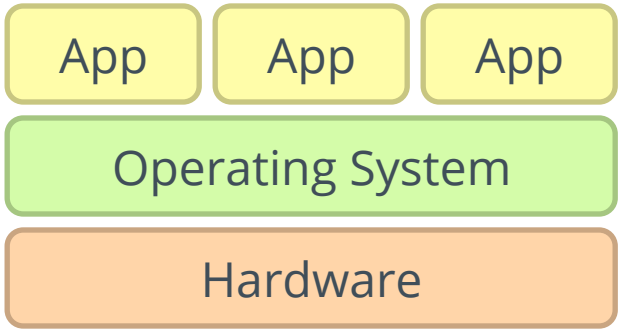
Source: Wikipedia (Electricity meter) via Big Data Infrastructure 2015

Utility Computing

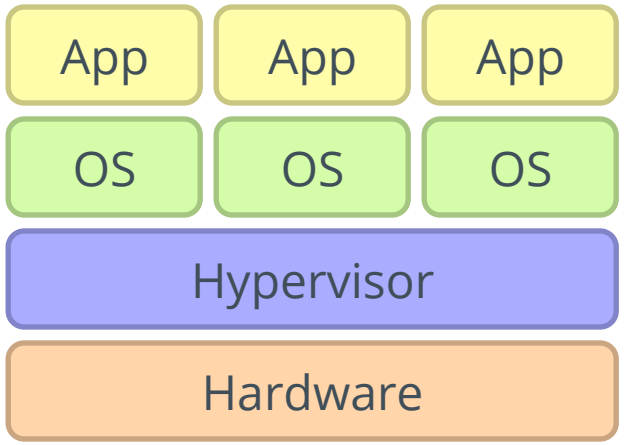
- What?
  - Computing resources as a metered service (“pay as you go”)
  - Ability to dynamically provision virtual machines
- Why?
  - Cost: capital vs. operating expenses
  - Scalability: “infinite” capacity
  - Elasticity: scale up or down on demand
- Does it make sense?
  - Benefits to cloud users
  - Business case for cloud providers

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Virtualization



Traditional Stack



Virtualized Stack

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Who cares?

- Ready-made big data problems
  - Social media, user-generated content = big data
  - Examples: Facebook friend suggestions, Google ad placement
  - Business intelligence: gather everything in a data warehouse and run analytics to generate insight
- Utility computing provides:
  - Ability to provision clusters on-demand in the cloud
  - Lower barrier to entry for tackling big data problems
  - Commoditization and democratization of big data capabilities

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Source: Google via Big Data Infrastructure 2015

The Fundamental Problem

- We want to keep track of *mutable* state in a *scalable* manner
- Assumptions:
  - State organized in terms of many “records”
  - State unlikely to fit on single machine, must be distributed

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Three Core Ideas

- Partitioning (sharding)
  - For scalability
  - For latency
- Replication
  - For robustness (availability)
  - For throughput
- Caching
  - For latency

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Lots of problems…

- How do we keep replicas in sync?
- How do we synchronize transactions across multiple partitions?
- What happens to the cache when the underlying data changes?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

What do RDBMSes provide?

- Relational model with schemas
- Powerful, flexible query language
- Transactional semantics: ACID
- Rich ecosystem, lots of tool support

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

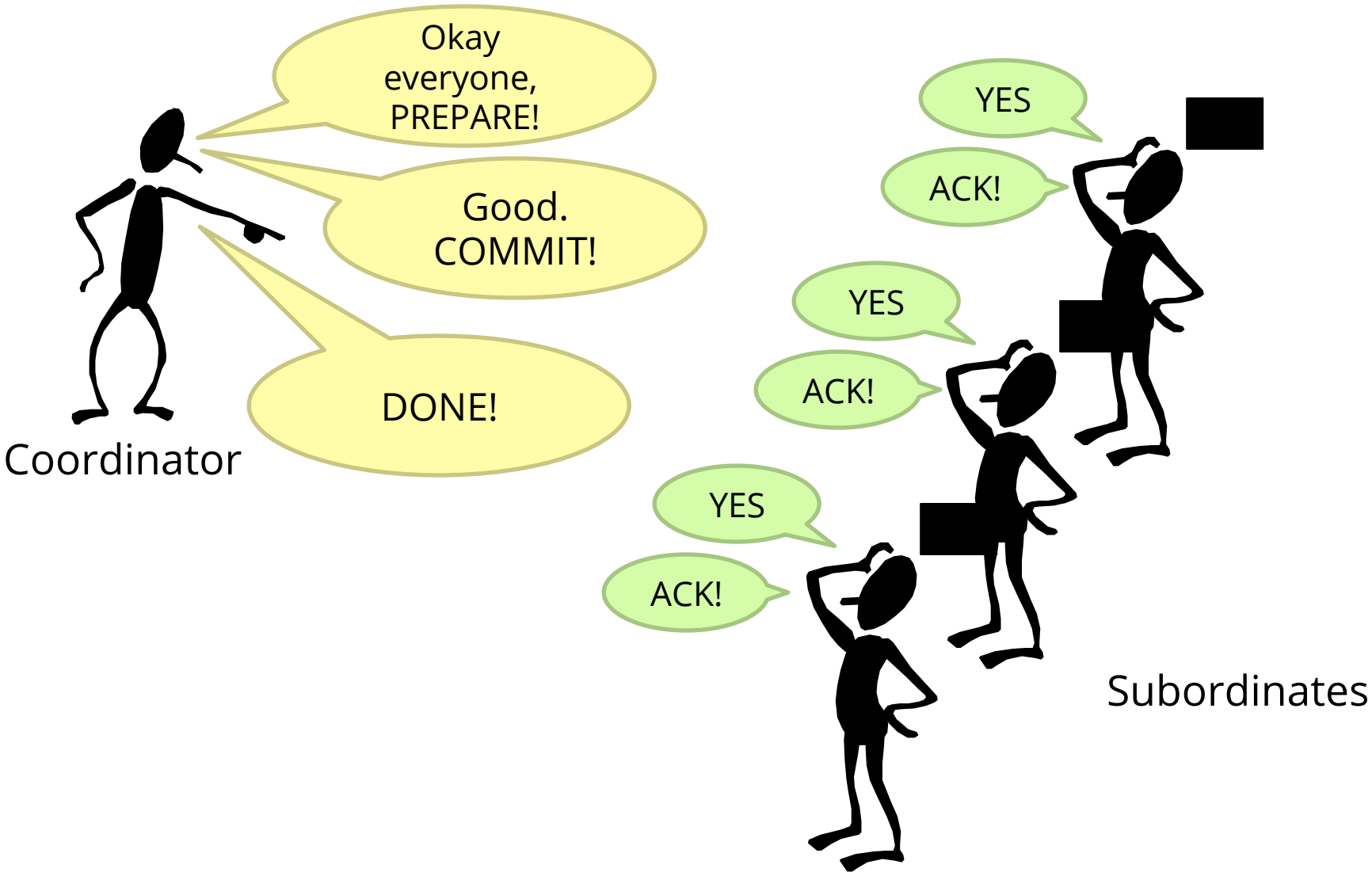
How do RDBMSes do it?

- Transactions on a single machine: (relatively) easy!
- Partition tables to keep transactions on a single machine
  - Example: partition by user
- What about transactions that require multiple machines?
  - Example: transactions involving multiple users

Solution: Two-Phase Commit

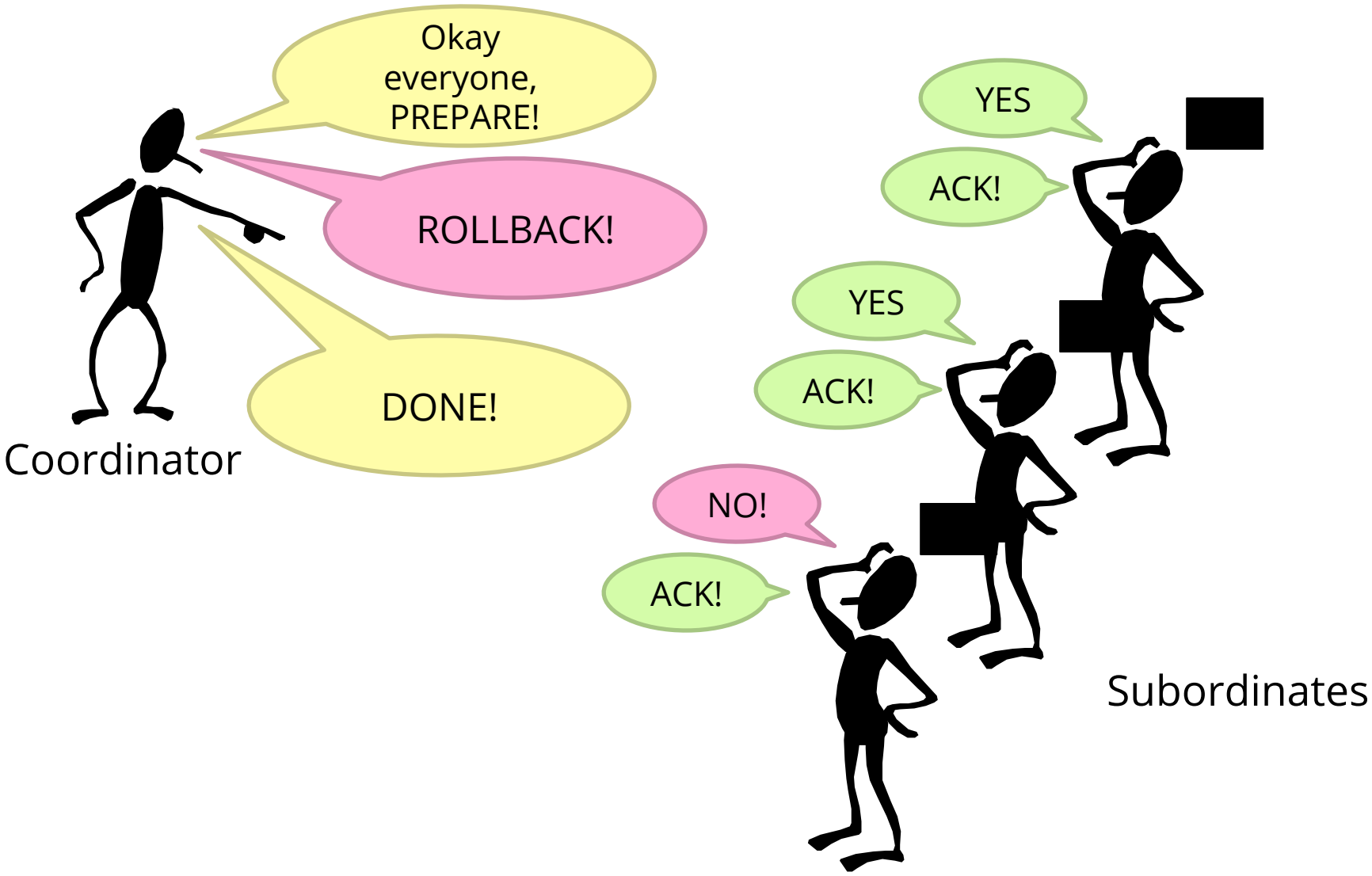
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

2PC: Sketch



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

2PC: Sketch



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

2PC: Assumptions and Limitations

- Assumptions:
  - Persistent storage and write-ahead log at every node
  - WAL is never permanently lost
- Limitations:
  - It's blocking and slow
  - What if the coordinator dies?

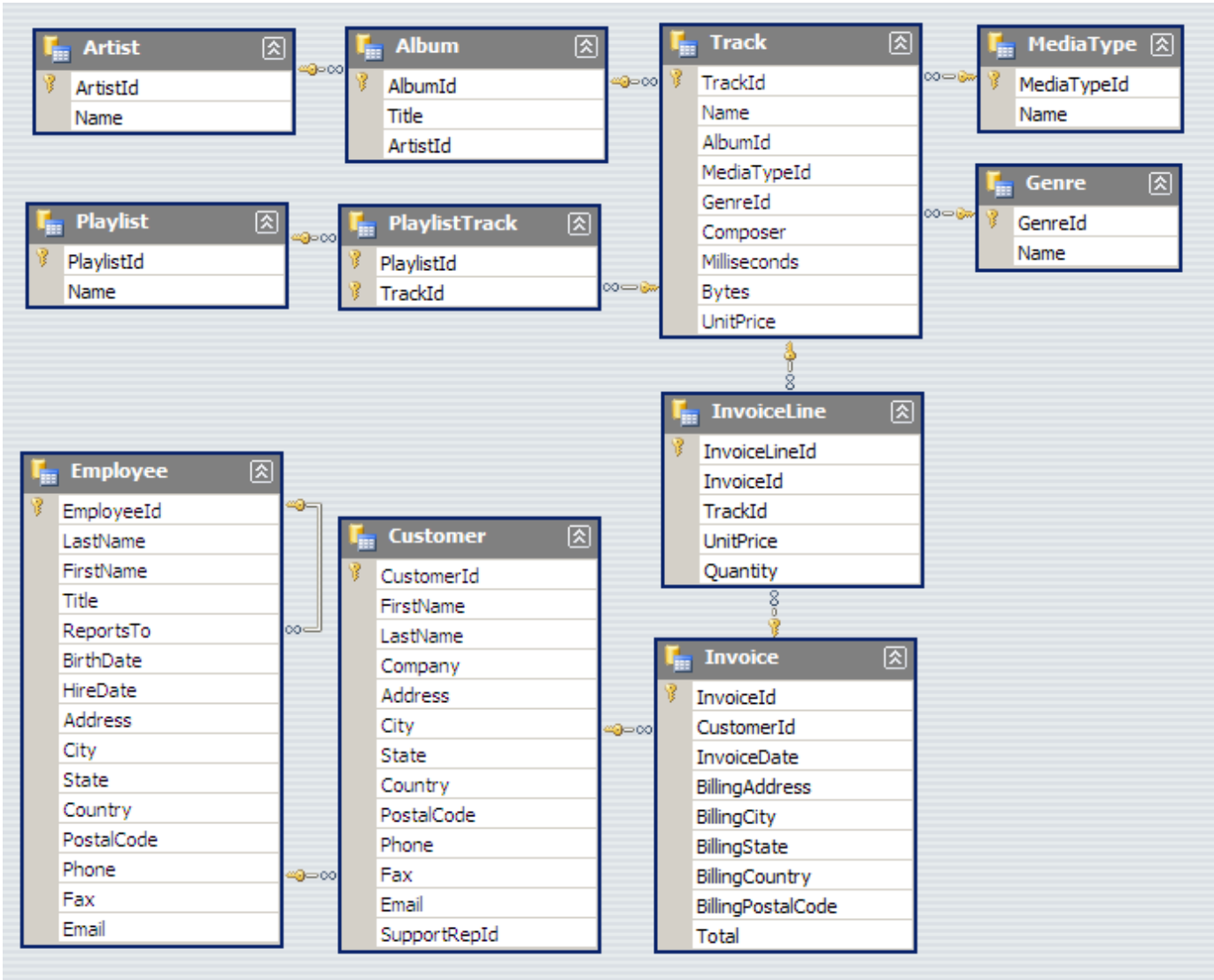
Solution: Paxos!
(details beyond scope of this course)

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

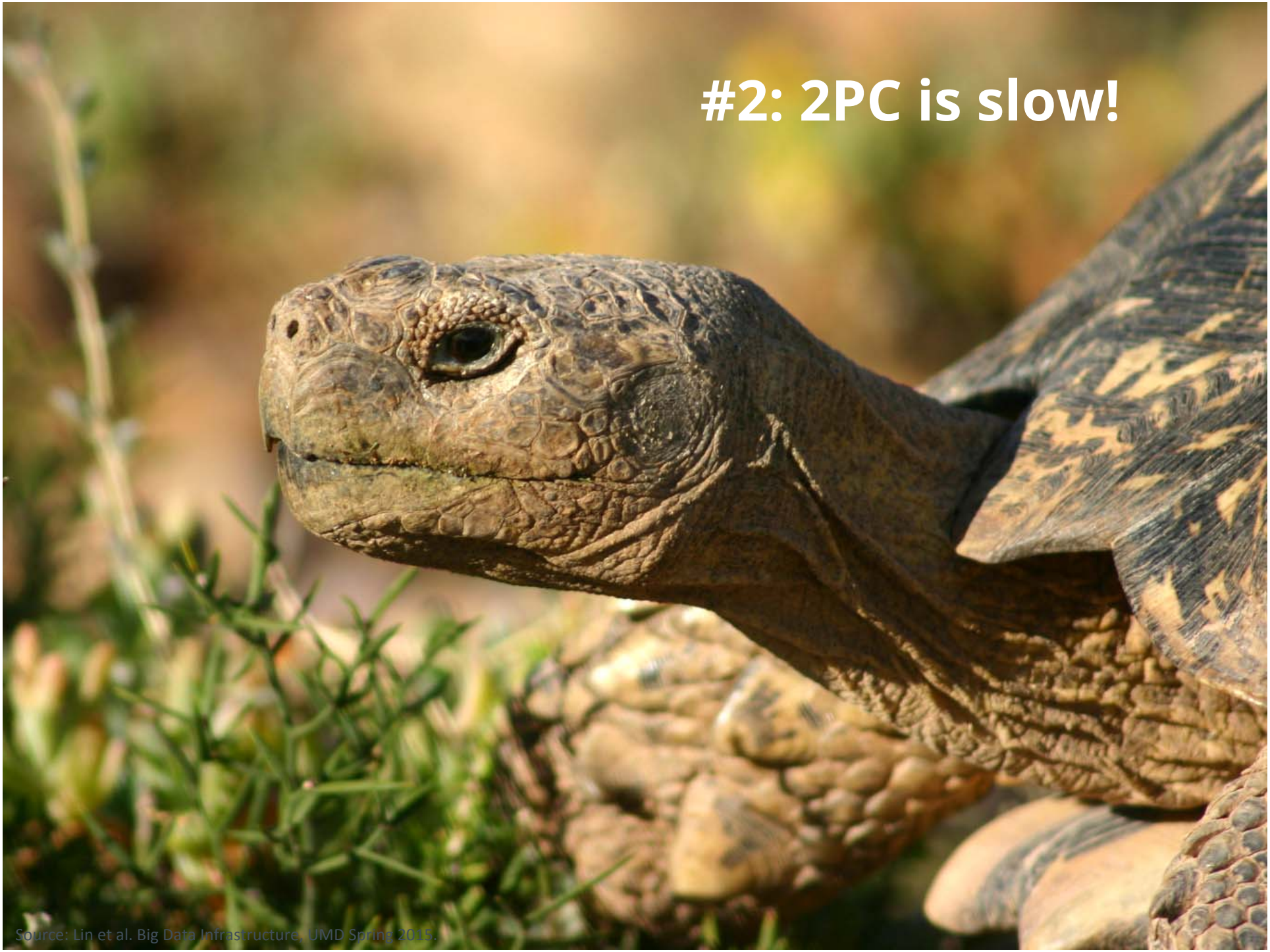
RDBMSes: Pain Points

Source: www.flickr.com/photos/spencerdahl/6075142688/ via Big Data Infrastructure 2015

#1: Must design up front, painful to evolve



Source: Lin et al. Data-Intensive Computing with MapReduce, UMD Spring 2013.



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

#3: Cost!

Source: www.flickr.com/photos/gnusinn/3080378658/

What do RDBMSes provide?

- Relational model with schemas
- Powerful, flexible query language
- Transactional semantics: ACID
- Rich ecosystem, lots of tool support

What if we want *a la carte*?

Source: www.flickr.com/photos/vidiot/18556565/

Features *a la carte*?

- What if I'm willing to give up consistency for scalability?
- What if I'm willing to give up the relational model for something more flexible?
- What if I just want a cheaper solution?

Enter… NoSQL!

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

NoSQL (Not only SQL)

- Horizontally scale “simple operations”
- Replicate/distribute data over many servers
- Simple call interface
- Weaker concurrency model than ACID
- Efficient use of distributed indexes and RAM
- Flexible schemas

Source: Cattell (2010). Scalable SQL and NoSQL Data Stores. *SIGMOD Record*.

(Major) Types of NoSQL databases

- Key-value stores
- Column-oriented databases
- Document stores
- Graph databases

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Key-Value Stores

Source: Wikipedia (Keychain)

Key-Value Stores: Data Model

- Stores associations between keys and values
- Keys are usually primitives
  - For example, ints, strings, raw bytes, etc.
- Values can be primitive or complex: usually opaque to store
  - Primitives: ints, strings, etc.
  - Complex: JSON, HTML fragments, etc.

Key-Value Stores: Operations

- Very simple API:
  - Get – fetch value associated with key
  - Put – set value associated with key
- Optional operations:
  - Multi-get
  - Multi-put
  - Range queries
- Consistency model:
  - Atomic puts (usually)
  - Cross-key operations: who knows?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Key-Value Stores: Implementation

- Non-persistent:
  - Just a big in-memory hash table
- Persistent
  - Wrapper around a traditional RDBMS

What if data doesn't fit on a single machine?

Simple Solution: Partition!

- Partition the key space across multiple machines
  - Let's say, hash partitioning
  - For *n* machines, store key *k* at machine *h(k)* mod *n*
- Okay… But:
  1. How do we know which physical machine to contact?
  2. How do we add a new machine to the cluster?
  3. What happens if a machine fails?

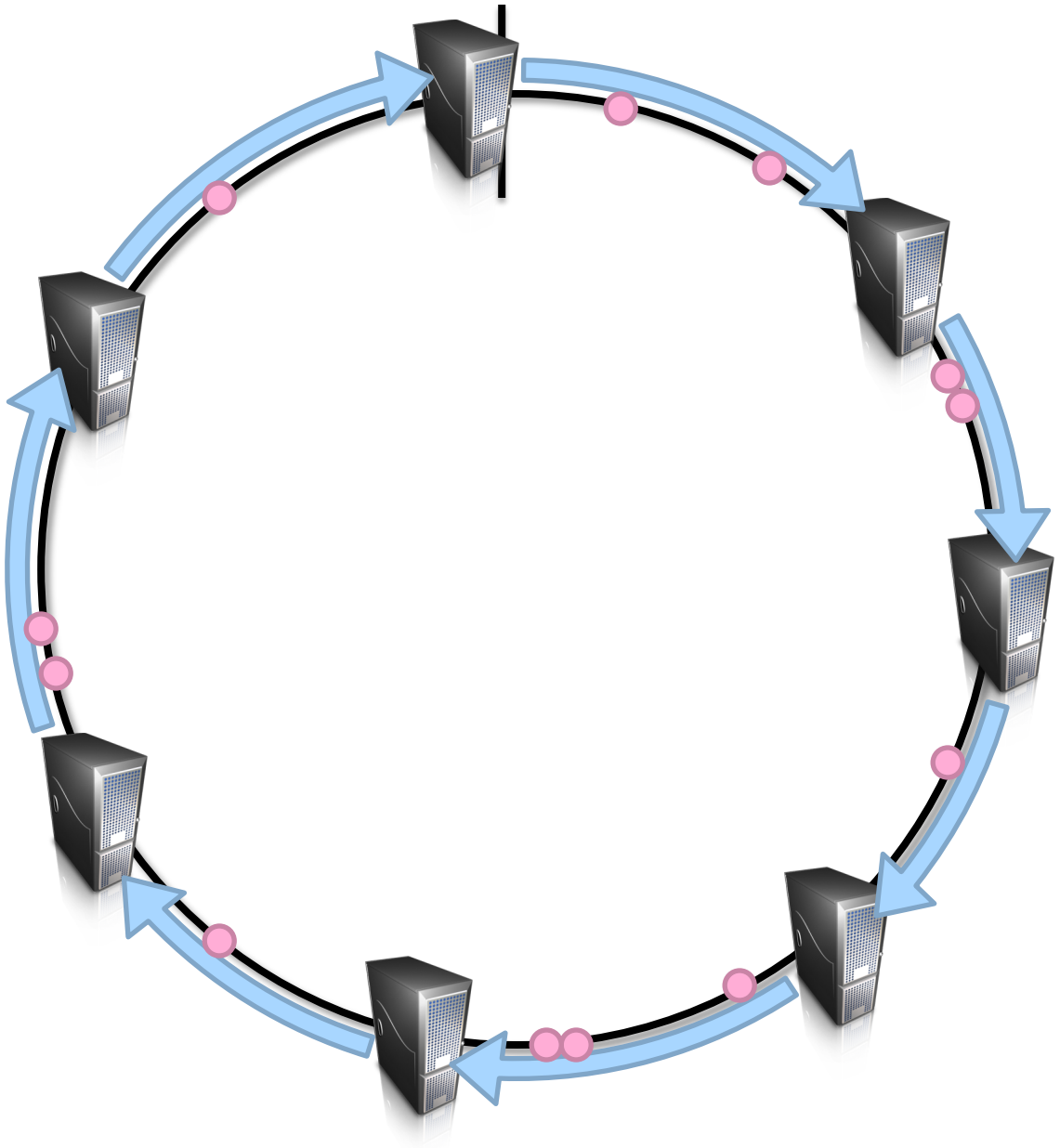
See the problems here?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Clever Solution

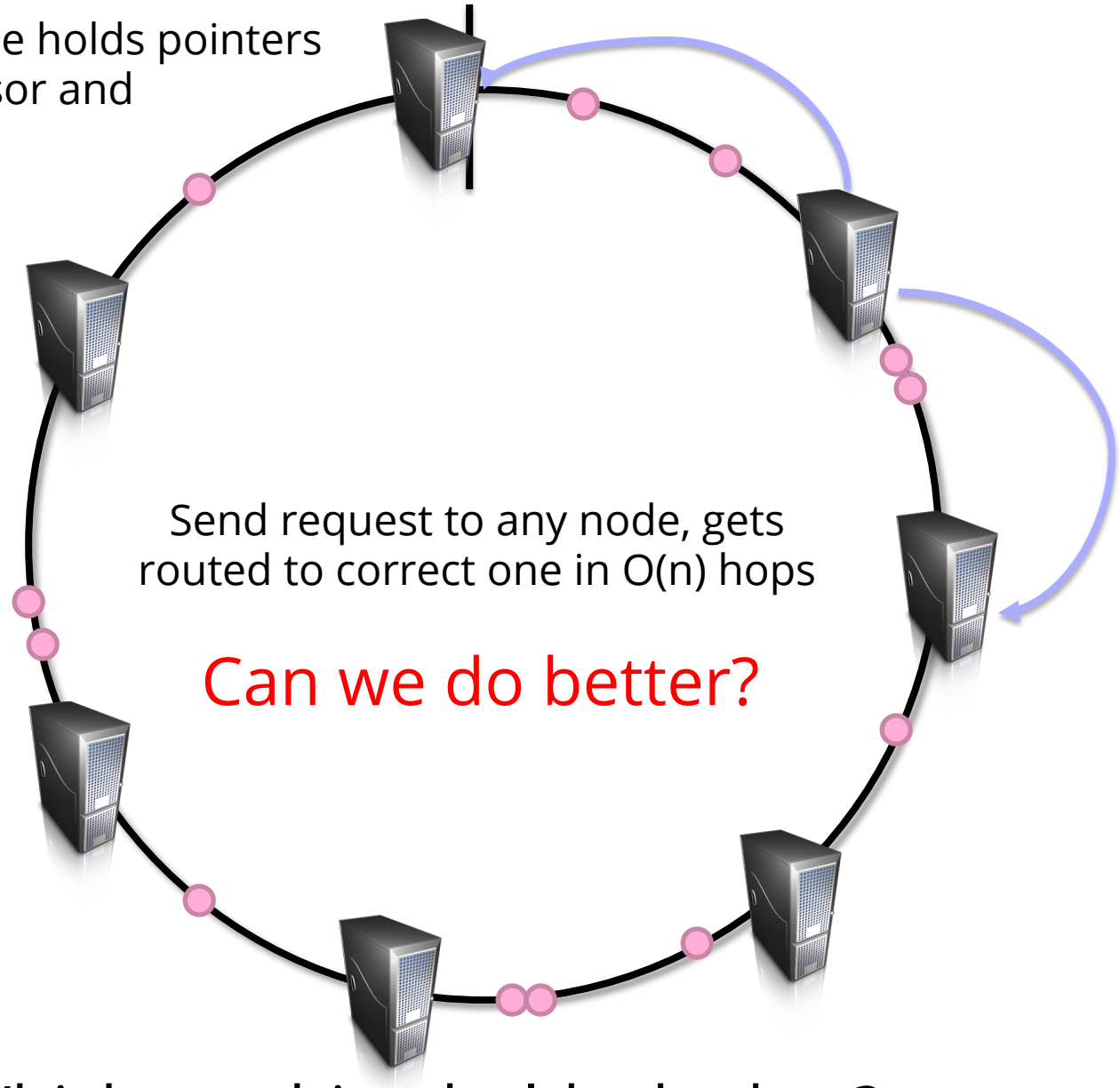
- Hash the keys
- Hash the machines also!

Distributed hash tables!



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Each machine holds pointers to predecessor and successor

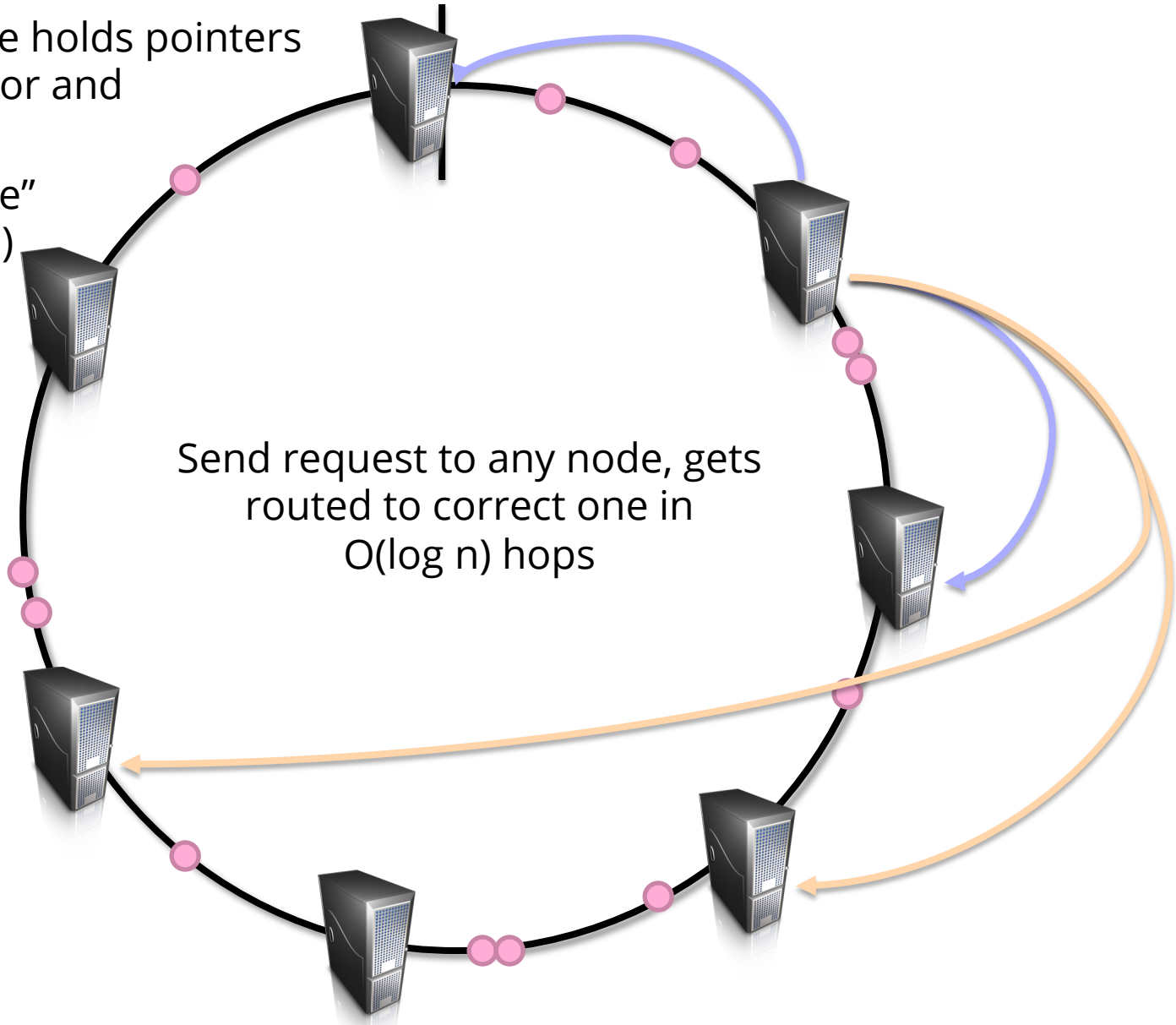


Routing: Which machine holds the key?

Source: Lin et al. Data-Intensive Computing with MapReduce, UMD Spring 2013.

Each machine holds pointers to predecessor and successor

+ “finger table” (+2, +4, +8, …)



Routing: Which machine holds the key?

Simpler Solution

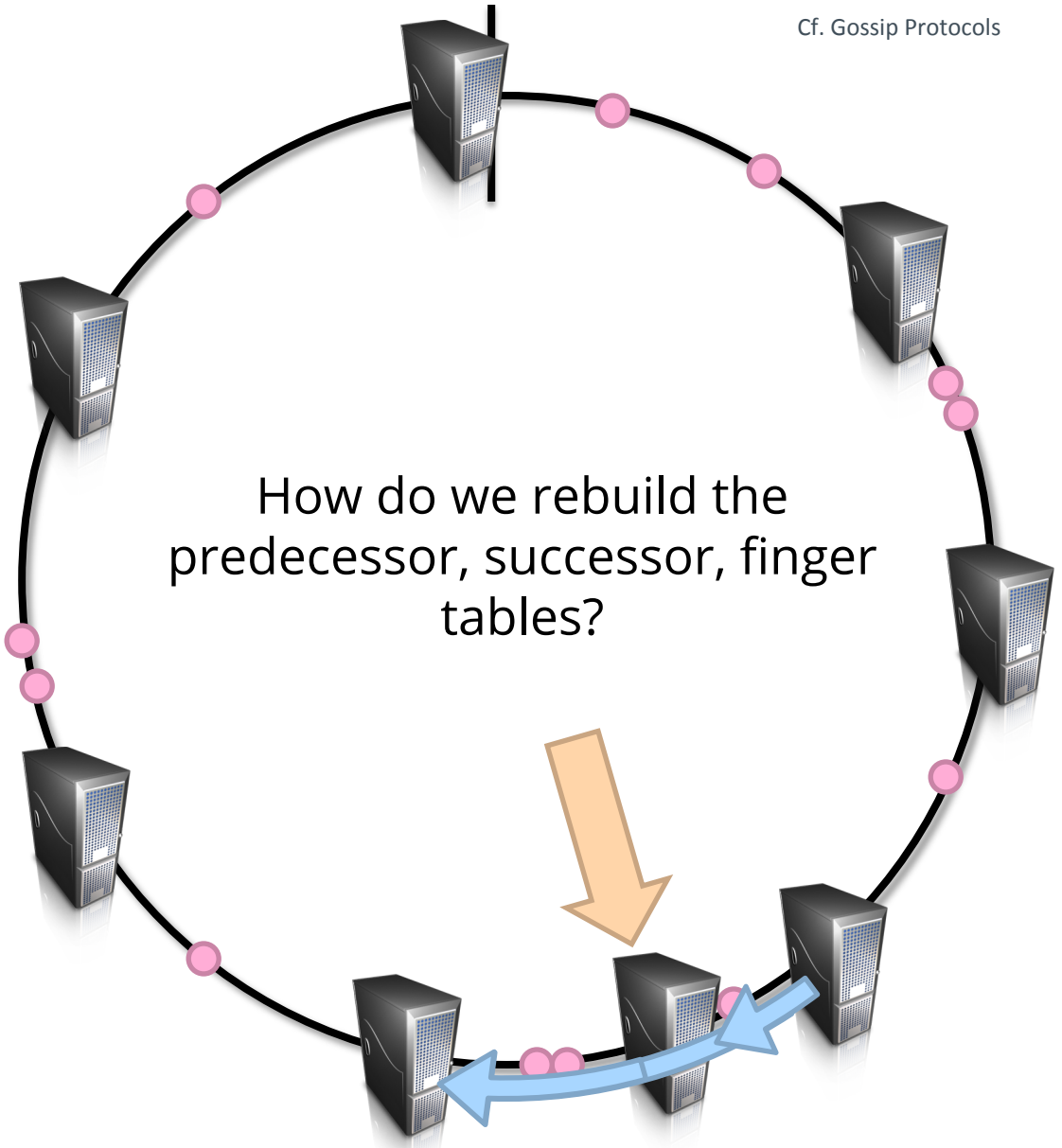
Service Registry

Routing: Which machine holds the key?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Stoica et al. (2001). Chord: A Scalable Peer-to-peer Lookup Service for Internet Applications. *SIGCOMM.*

Cf. Gossip Protocols



New machine joins: What happens?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Another Refinement: Virtual Nodes

- Don’t directly hash servers
- Create a large number of virtual nodes, map to physical servers
  - Better load redistribution in event of machine failure
  - When new server joins, evenly shed load from other servers

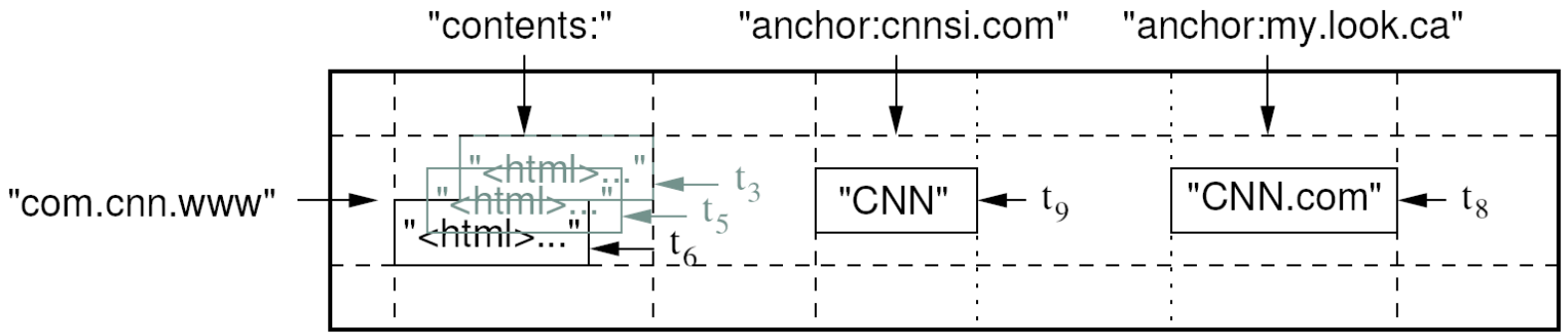
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Bigtable

Source: Wikipedia (Table)

Data Model

- A table in Bigtable is a sparse, distributed, persistent multidimensional sorted map
- Map indexed by a row key, column key, and a timestamp
  - (row:string, column:string, time:int64) → uninterpreted byte array
- Supports lookups, inserts, deletes
  - Single row transactions only



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Rows and Columns

- Rows maintained in sorted lexicographic order
  - Applications can exploit this property for efficient row scans
  - Row ranges dynamically partitioned into tablets
- Columns grouped into column families
  - Column key = *family:qualifier*
  - Column families provide locality hints
  - Unbounded number of columns
  - Column entries are sparse for each row

At the end of the day, it's all key-value pairs!

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

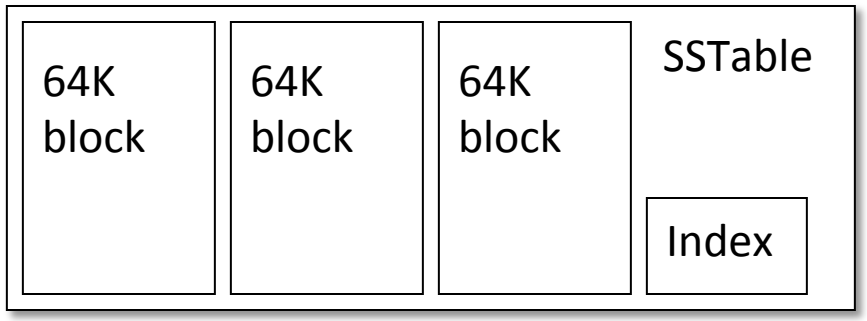
Bigtable Building Blocks

- GFS
- Chubby
- SSTable

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

SSTable

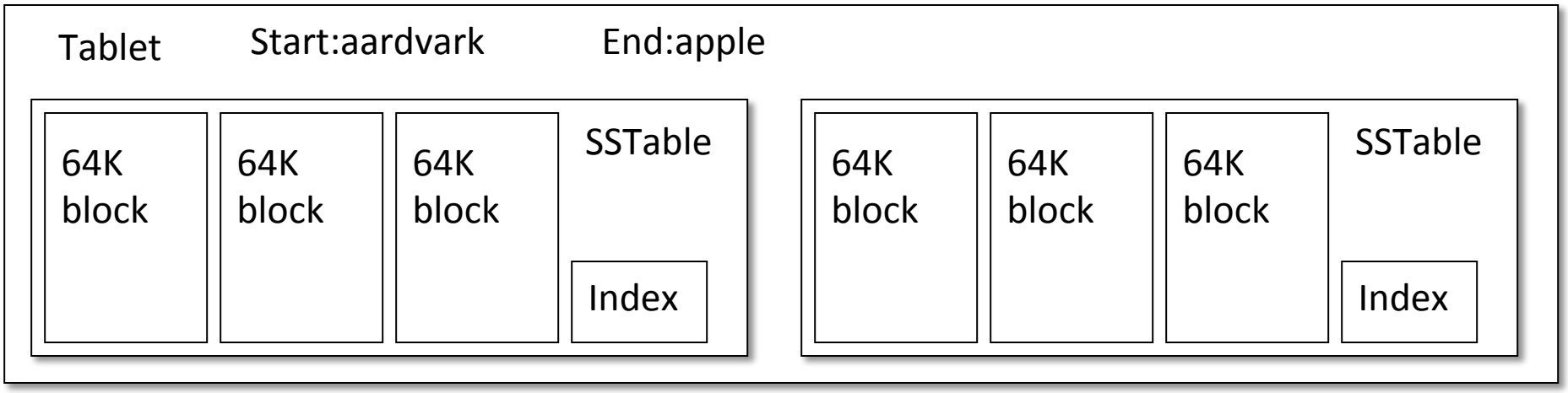
- "Sorted String Table" – a variant of log-structured merge trees
- *Persistent, ordered immutable* map from keys to values
  - Stored in GFS
- Sequence of blocks on disk plus an index for block lookup
  - Can be completely mapped into memory
- Supported operations:
  - Look up value associated with key
  - Iterate key/value pairs within a key range



Source: Graphic from slides by Erik Paulson via Big Data Infrastructure 2015

Tablet

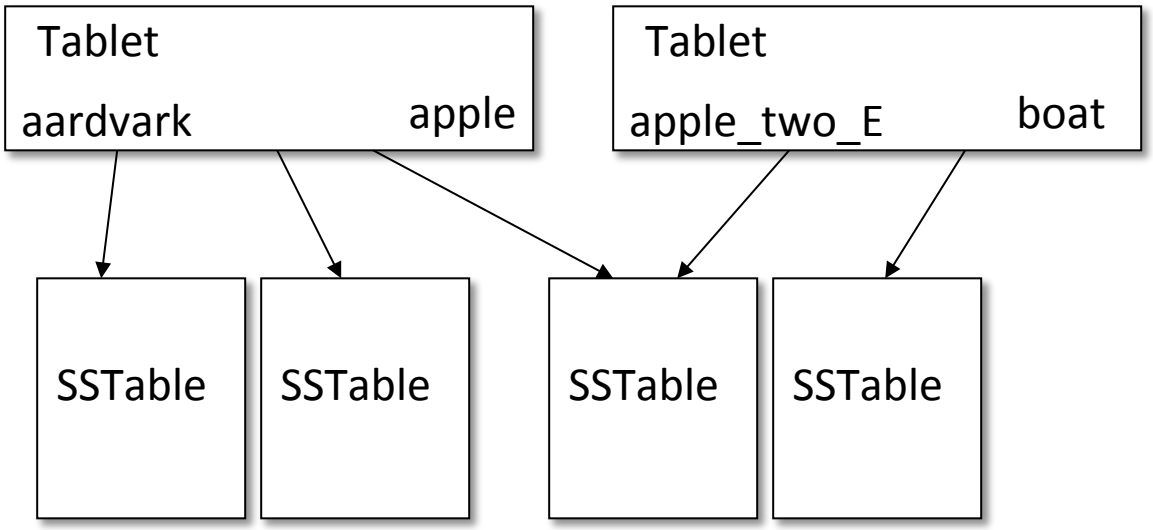
- Dynamically partitioned range of rows
- Built from multiple SSTables



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Table

- Multiple tablets make up the table
- SSTables can be shared



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Architecture

- Client library
- Single master server
- Tablet servers

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Bigtable Master

- Assigns tablets to tablet servers
- Detects addition and expiration of tablet servers
- Balances tablet server load
- Handles garbage collection
- Handles schema changes

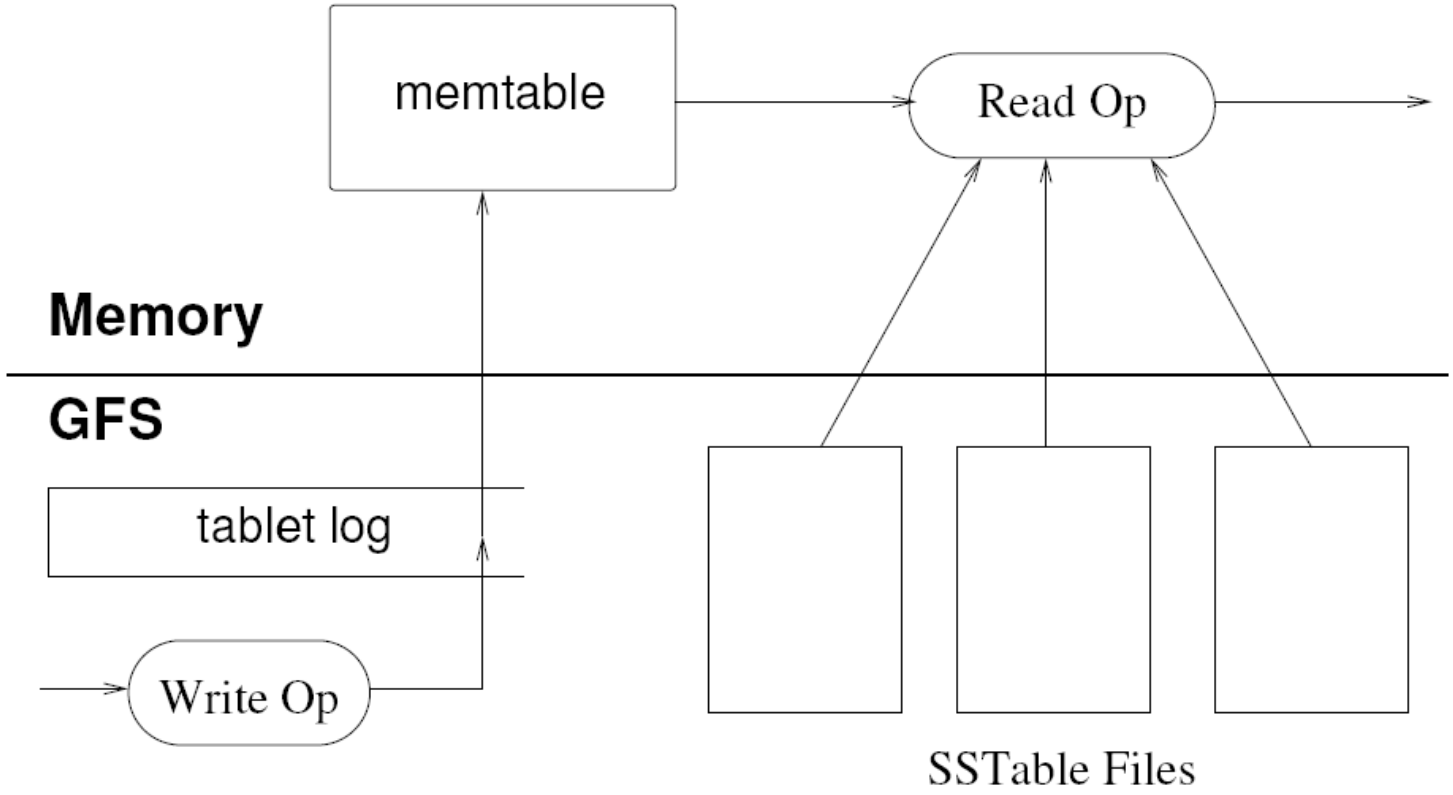
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Bigtable Tablet Servers

- Each tablet server manages a set of tablets
  - Typically between ten to a thousand tablets
  - Each 100-200 MB by default
- Handles read and write requests to the tablets
- Splits tablets that have grown too large

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Tablet Serving



Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Compactions

- Minor compaction
  - Converts the memtable into an SSTable
  - Reduces memory usage and log traffic on restart
- Merging compaction
  - Reads the contents of a few SSTables and the memtable, and writes out a new SSTable
  - Reduces number of SSTables
- Major compaction
  - Merging compaction that results in only one SSTable
  - No deletion records, only live data
- Key point: sequential writes only
  - What about SSDs? Is this point obsolete?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Bigtable Applications

- Data source and data sink for MapReduce
- Google's web crawl
- Google Earth
- Google Analytics

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Challenges

- Keep it simple!
- Keep it flexible!
- Push functionality onto application

… and it's still hard to get right!
Example: splitting and compaction storms

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Back to consistency…

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Consistency Scenarios

- People you don't want seeing your pictures:
  - Alice removes Mom from list of people who can view photos
  - Alice posts embarrassing pictures from Spring Break
  - Can Mom see Alice's photo?
- Why am I still getting messages?
  - Bob unsubscribes from mailing list
  - Message sent to mailing list right after
  - Does Bob receive the message?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Three Core Ideas

- Partitioning (sharding)
  - For scalability
  - For latency
- Replication
  - For robustness (availability)
  - For throughput
- Caching
  - For latency

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

CAP "Theorem" (Brewer, 2000)

Consistency

Availability

Partition tolerance

... pick two

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

CAP Tradeoffs

- CA = consistency + availability
  - E.g., parallel databases that use 2PC
- AP = availability + tolerance to partitions
  - E.g., DNS, web caching

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Is this helpful?

- CAP not really even a “theorem” because vague definitions
  - More precise formulation came a few years later

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Abadi Says…

- CP makes no sense!
- CAP says, in the presence of P, choose A or C
  - But you'd want to make this tradeoff even when there is no P
- Fundamental tradeoff is between consistency and latency
  - Not available = (very) long latency

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Move over, CAP

- PACELC (“pass-elk”)
- PAC
  - If there’s a partition, do we choose A or C?
- ELC
  - Else, do we choose latency or consistency?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Replication possibilities

- Update sent to all replicas at the same time
  - To guarantee consistency you need something like Paxos
- Update sent to a master
  - Replication is synchronous
  - Replication is asynchronous
  - Combination of both
- Update sent to an arbitrary replica

All these possibilities involve tradeoffs!
"eventual consistency"

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

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Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

“Units of Consistency”

- Single record:
  - Relatively straightforward
  - Complex application logic to handle multi-record transactions
- Arbitrary transactions:
  - Requires 2PC/Paxos
- Middle ground: entity groups
  - Groups of entities that share affinity
  - Co-locate entity groups
  - Provide transaction support within entity groups
  - Example: user + user’s photos + user’s posts etc.

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

More “Units of Consistency”

- CRDTs – “Conflict-free Replicated Data Type”
  - E.g. sets, counters
- Vector clocks
  - First read old record and vector clock value
  - Then send this vector clock with new, updated value
  - Push conflict-resolution back to the application
- Tunable availability vs. consistency
  - All, One, Quorum
  - $R + W \geq N$

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Three Core Ideas

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  - For scalability
  - For latency
- Replication
  - For robustness (availability)
  - For throughput
- Caching
  - For latency

This is really hard!

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Three Core Ideas

- Partitioning (sharding)
  - For scalability
  - For latency
- Replication
  - For robustness (availability)
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- Caching
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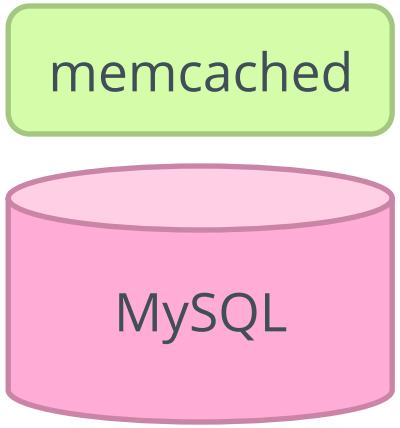
Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Facebook Architecture



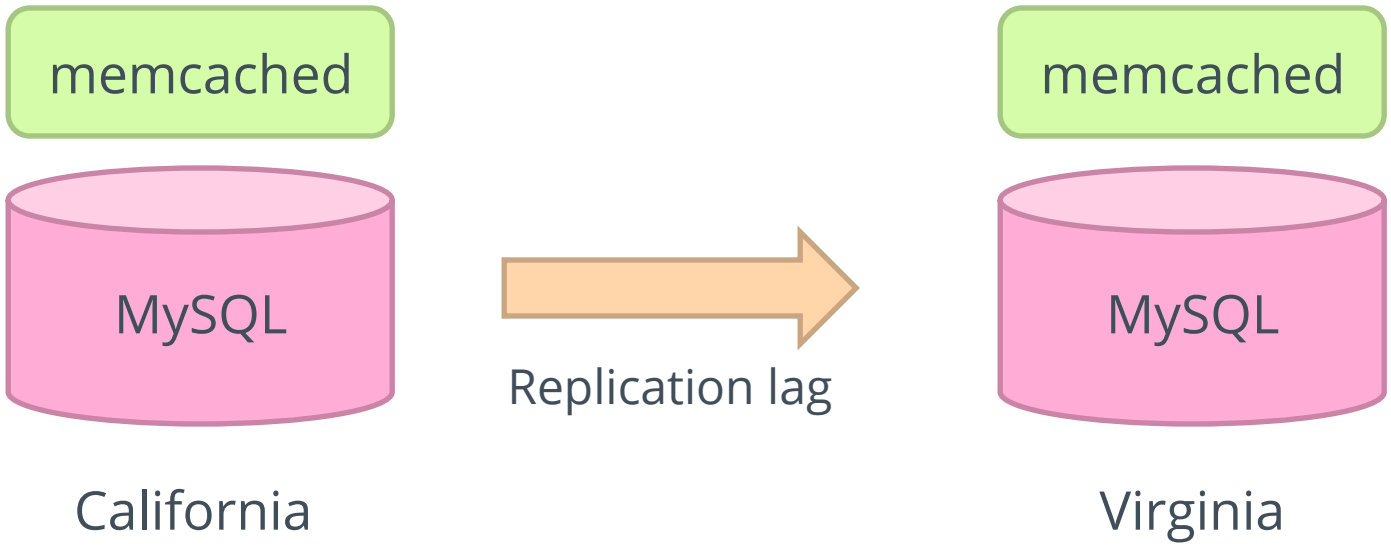
Read path:
Look in memcached
Look in MySQL
Populate in memcached

Write path:
Write in MySQL
Remove in memcached

Subsequent read:
Look in MySQL ✔
Populate in memcached

Source: www.facebook.com/note.php?note_id=23844338919 via Big Data Infrastructure 2015

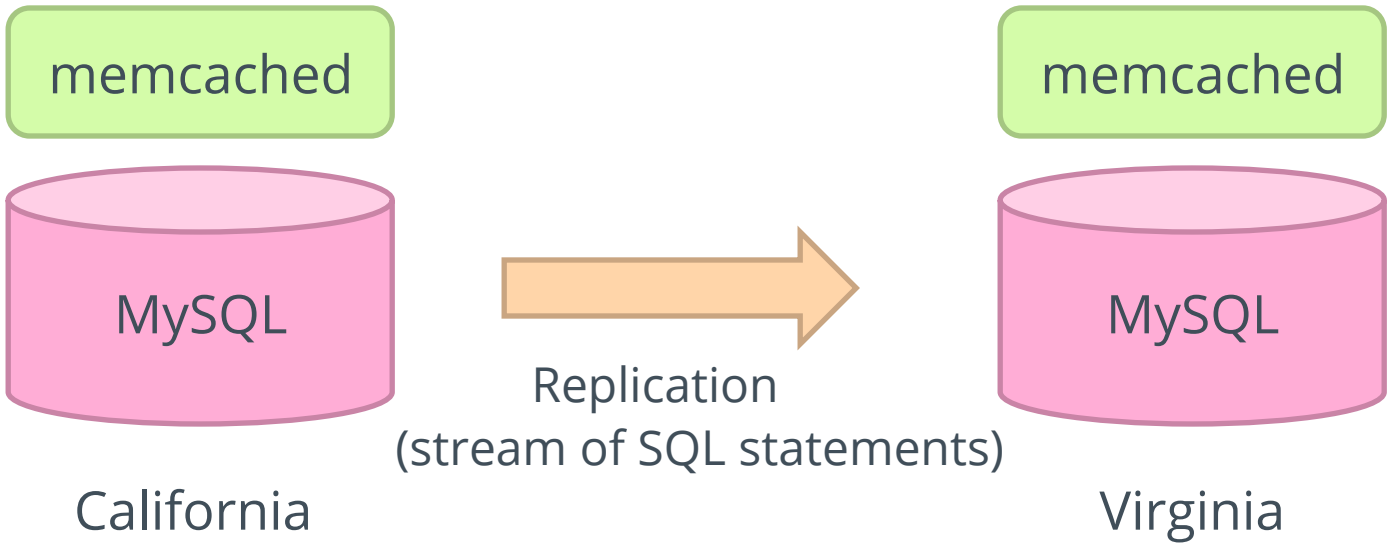
Facebook Architecture: Multi-DC



1. User updates first name from “Jason” to “Monkey”.
2. Write “Monkey” in master DB in CA, delete memcached entry in CA and VA.
3. Someone goes to profile in Virginia, read VA slave DB, get “Jason”.
4. Update VA memcache with first name as “Jason”.
5. Replication catches up. “Jason” stuck in memcached until another write!

Source: www.facebook.com/note.php?note_id=23844338919 via Big Data Infrastructure 2015

Facebook Architecture



Solution: Piggyback on replication stream, tweak SQL

```
REPLACE INTO profile (`first_name`) VALUES ('Monkey’)
WHERE `user_id`='jsobel' MEMCACHE_DIRTY 'jsobel:first_name'
```

Source: www.facebook.com/note.php?note_id=23844338919 via Big Data Infrastructure 2015

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  - For latency
- Replication
  - For robustness (availability)
  - For throughput
- Caching
  - For latency

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Google's Spanner

- Features:
  - Full ACID translations across multiple datacenters, across continents!
  - External consistency: wrt globally-consistent timestamps!
- How?
  - TrueTime: globally synchronized API using GPSes and atomic clocks exposes uncertainty
  - Use 2PC but use Paxos to replicate state
- Tradeoffs?

Source: Lin et al. Big Data Infrastructure, UMD Spring 2015.

Applications

- Cassandra
  - DHT, column families, LSM trees
- Riak
  - DHT, key-value, LSM trees
- LevelDB
  - Embeddable, key-value, LSM trees
- RocksDB
  - Embeddable, key-value, LSM trees
- Elasticsearch
  - Consistent hashing, inverted index, LSM trees
- Redis
  - Consistent hashing, key-value, AOF + snapshots