Building Software Systems at Google and Lessons Learned

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Plan for Today

- Evolution of various systems at Google
  - computing hardware
  - core search systems
  - infrastructure software

- Techniques for building large-scale systems
  - decomposition into services
  - design patterns for performance & reliability

  - Joint work with many, many people

Google Web Search: 1999 vs. 2010

- # docs: tens of millions to tens of billions
- queries processed/day:
- per doc info in index:
- update latency: months to tens of secs
- avg. query latency: <1s to <0.2s

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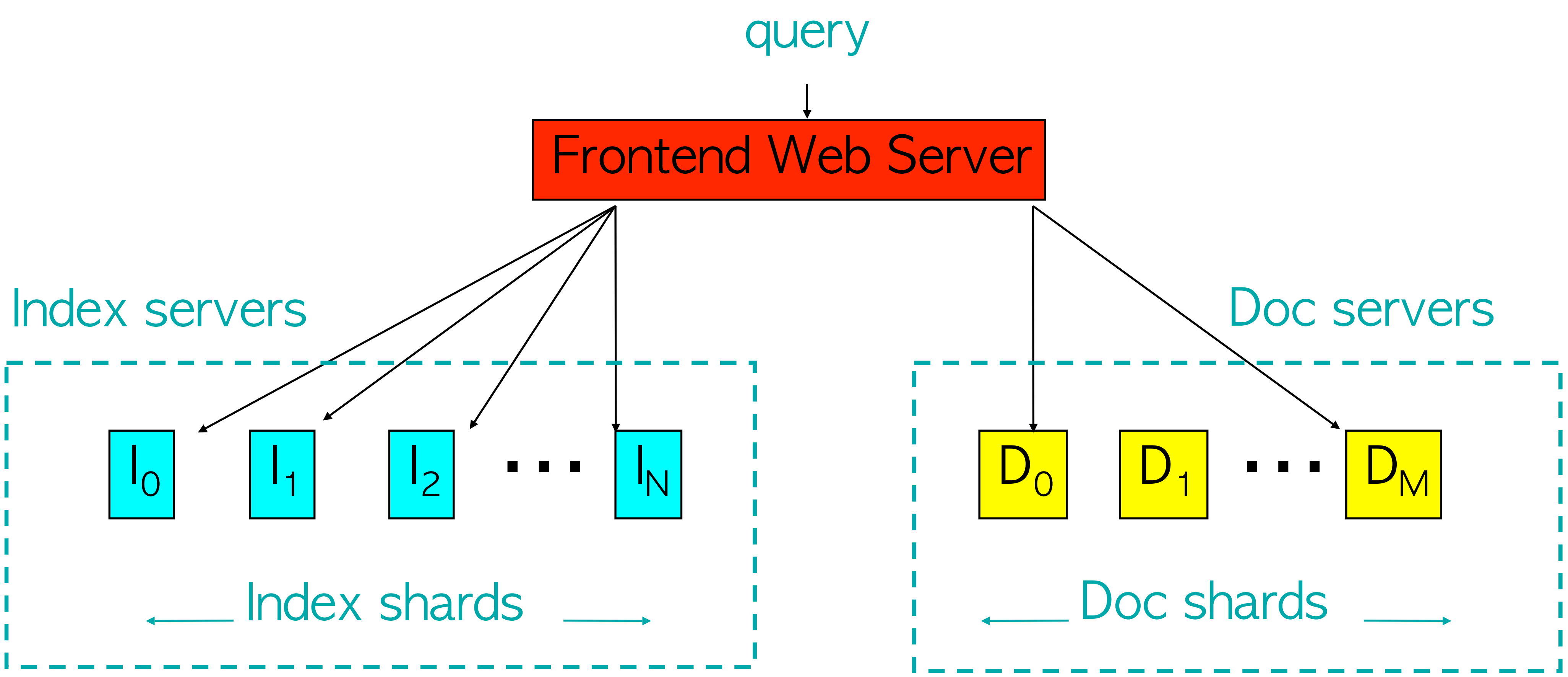
Continuous evolution:

– 7 significant revisions in last 11 years

– often rolled out without users realizing we've made major changes

“Google” Circa 1997 (google.stanford.edu)

Research Project, circa 1997



Basic Principles

- Index Servers:
  - given (query) return sorted list of <docid, score> pairs
  - partitioned (“sharded”) by docid
  - index shards are replicated for capacity
  - cost is O(# queries * # docs in index)

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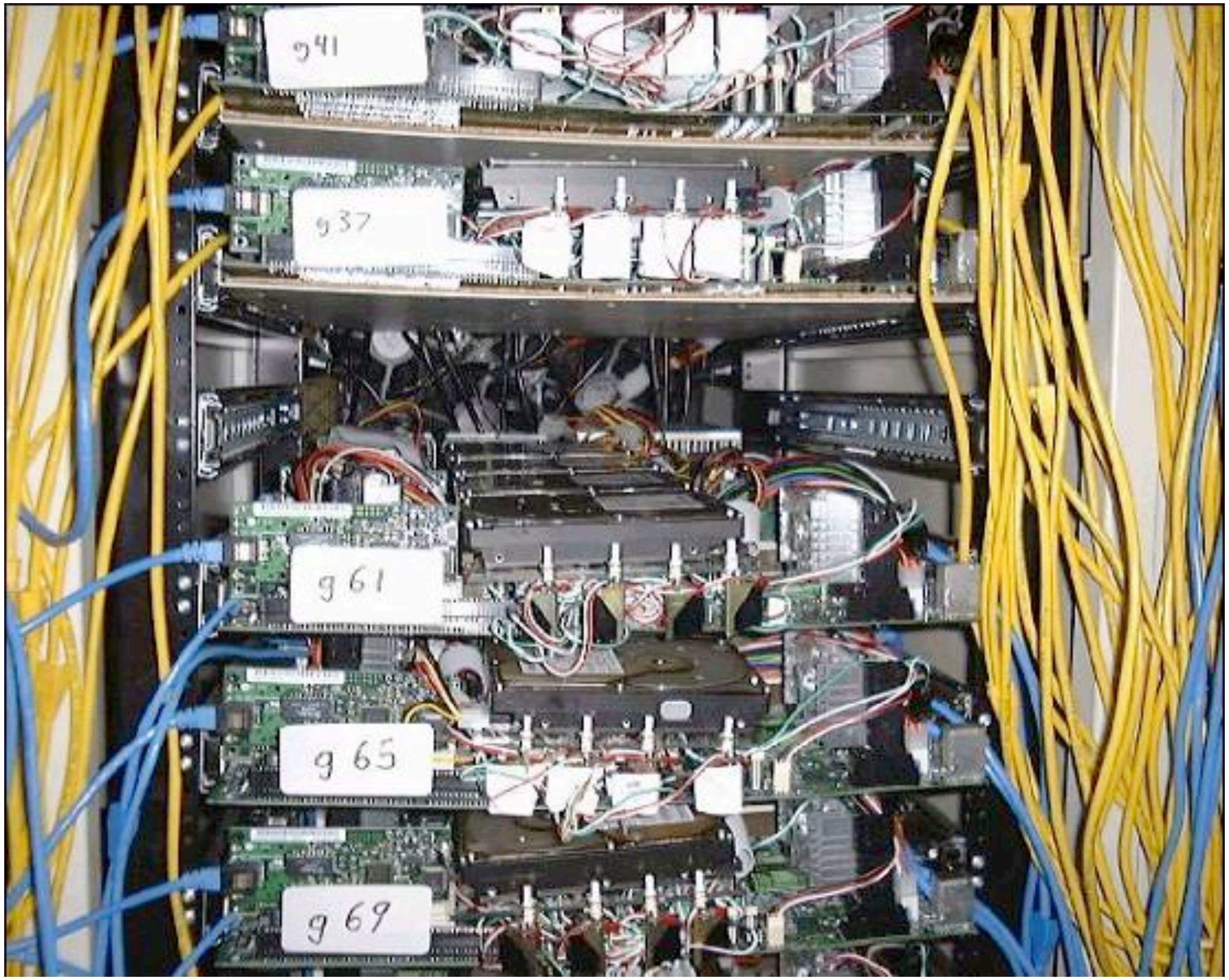
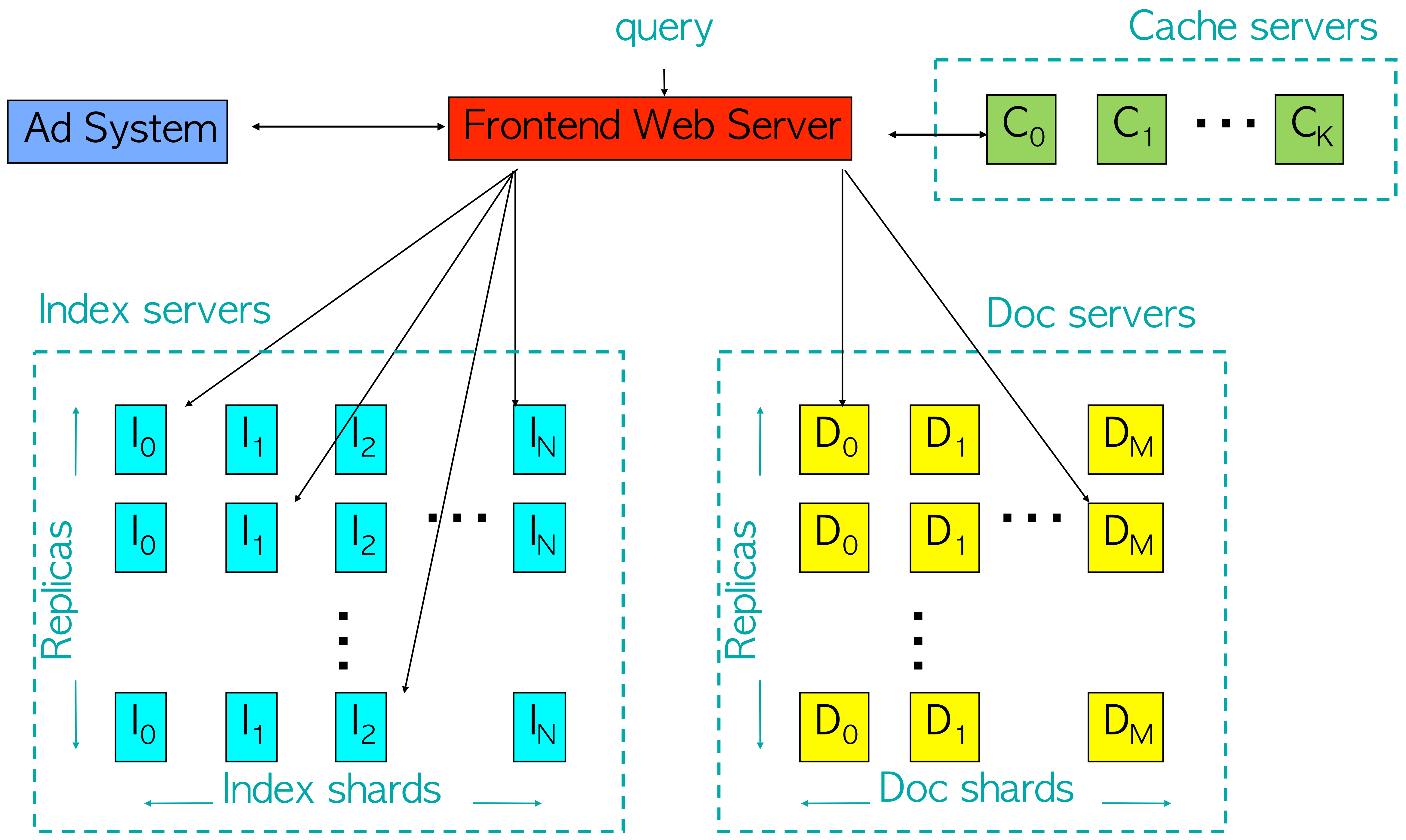
- Doc Servers
  - given (docid, query) generate (title, snippet)
    - snippet is query-dependent
  - map from docid to full text of docs (usually on disk)
  - also partitioned by docid
  - cost is O(# queries)

“Corkboards” (1999)



Serving System, circa 1999



Caching in Web Search Systems

- Cache servers:
  - cache both index results and doc snippets
  - hit rates typically 30-60%
    - depends on frequency of index updates, mix of query traffic, level of personalization, etc
- Main benefits:
  - performance! a few machines do work of 100s or 1000s
  - much lower query latency on hits
    - queries that hit in cache tend to be both popular and expensive (common words, lots of documents to score, etc.)
- Beware: big latency spike/capacity drop when index updated or cache flushed

Indexing (circa 1998-1999)

- Simple batch indexing system
  - No real checkpointing, so machine failures painful
  - No checksumming of raw data, so hardware bit errors caused problems
    - Exacerbated by early machines having no ECC, no parity
    - Sort 1 TB of data without parity: ends up "mostly sorted"
    - Sort it again: "mostly sorted" another way
- “Programming with adversarial memory”
  - Developed file abstraction that stores checksums of small records and can skip and resynchronize after corrupted records

Google Data Center (2000)

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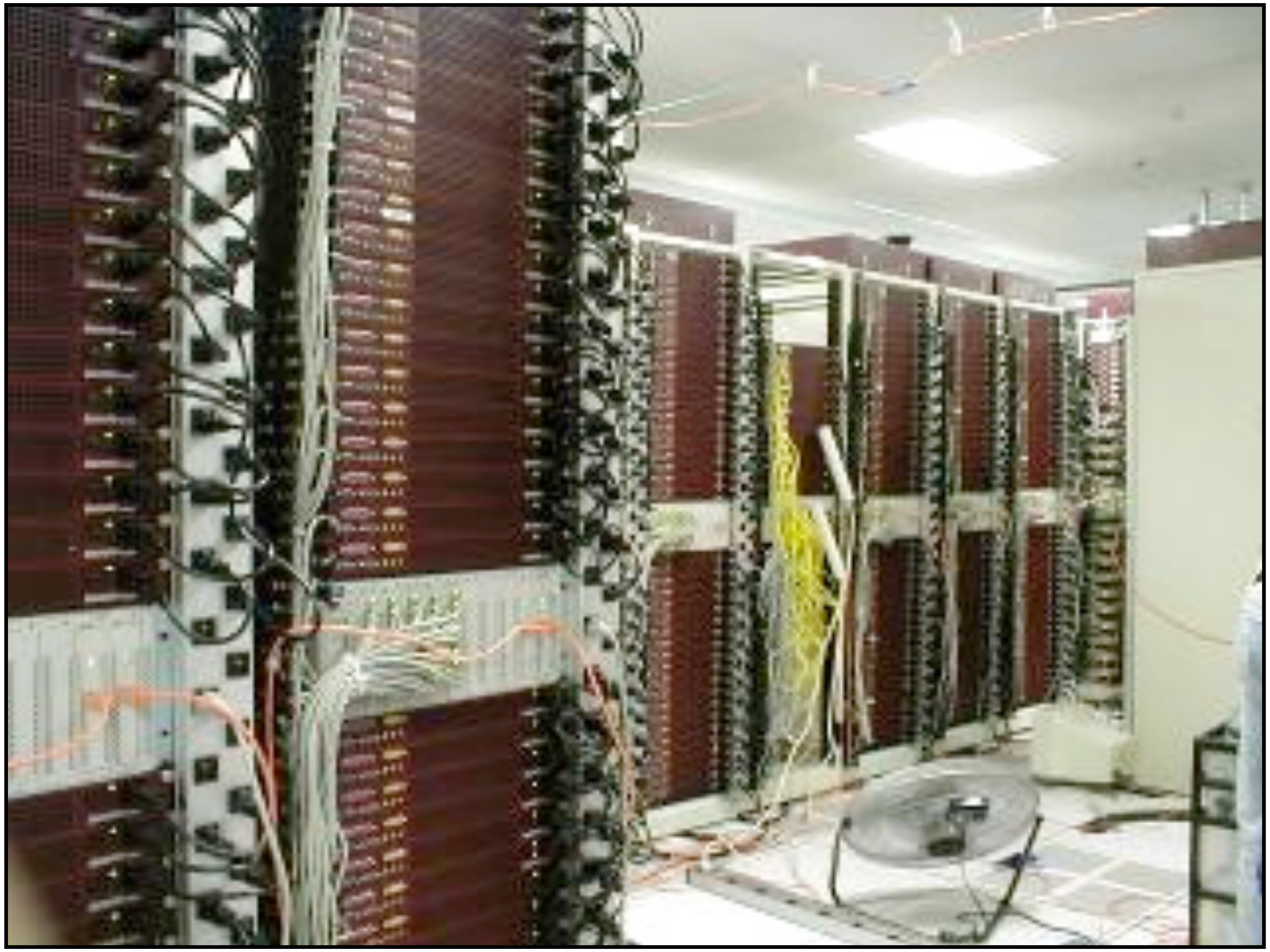

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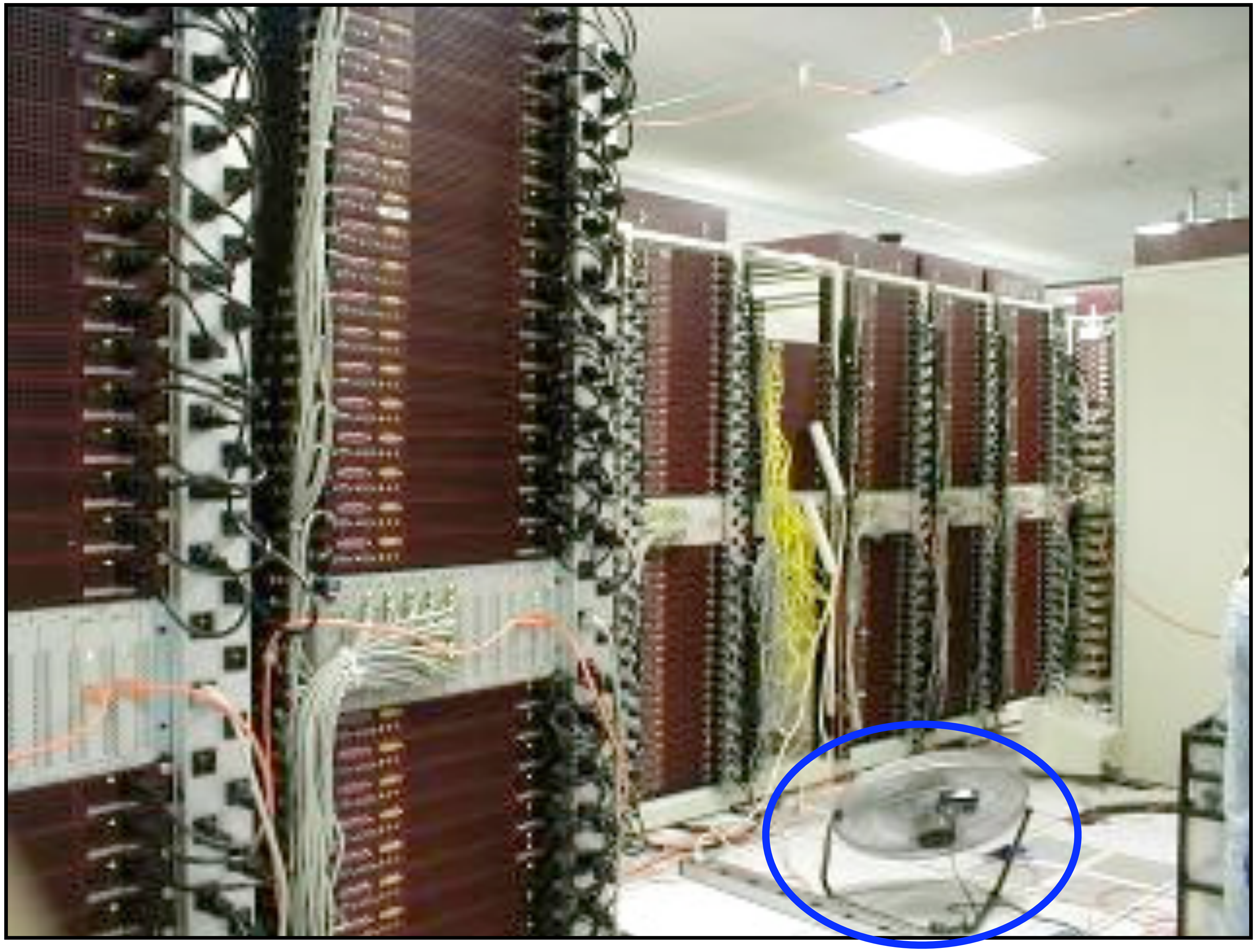
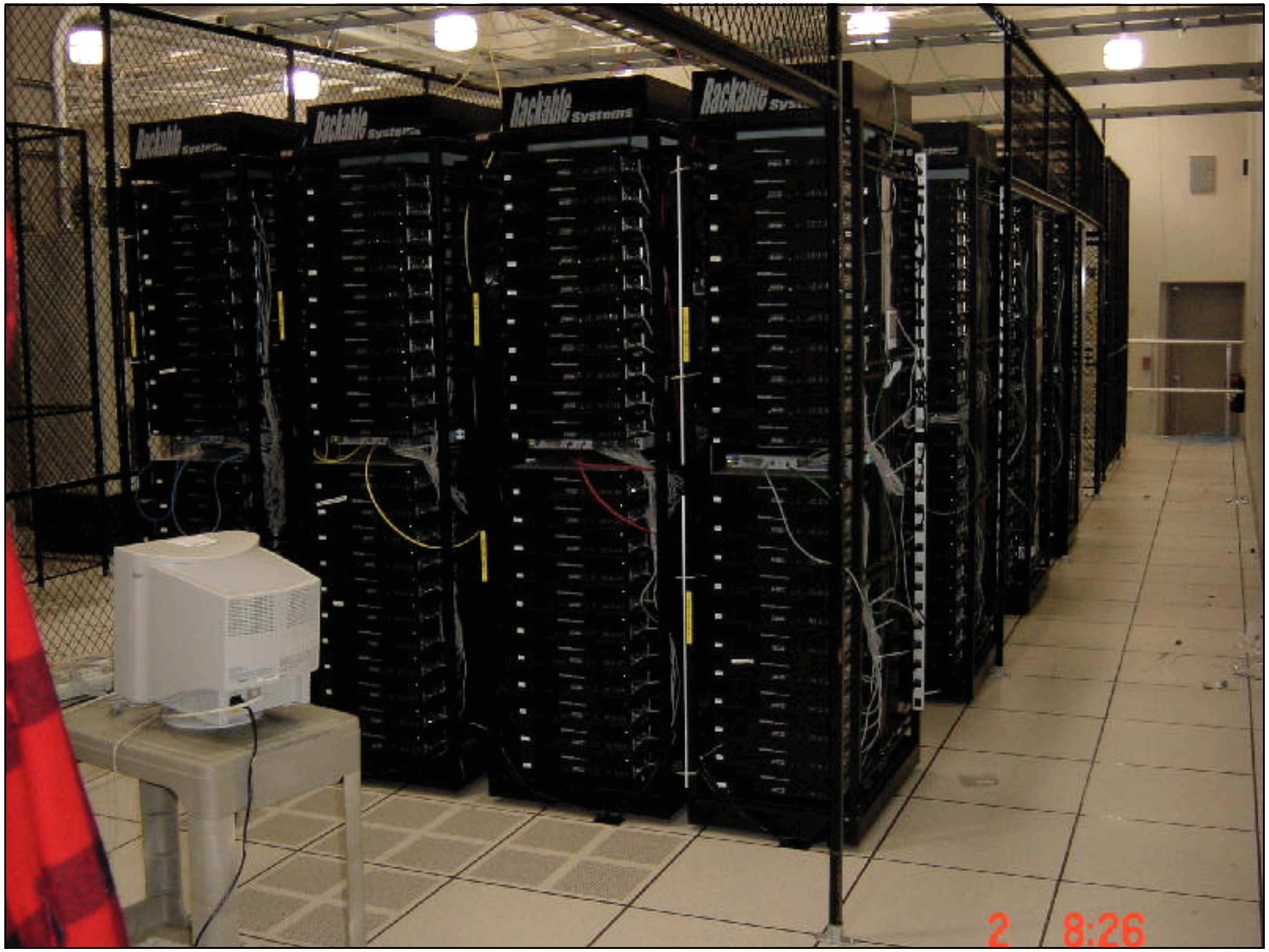


Google (new data center 2001)

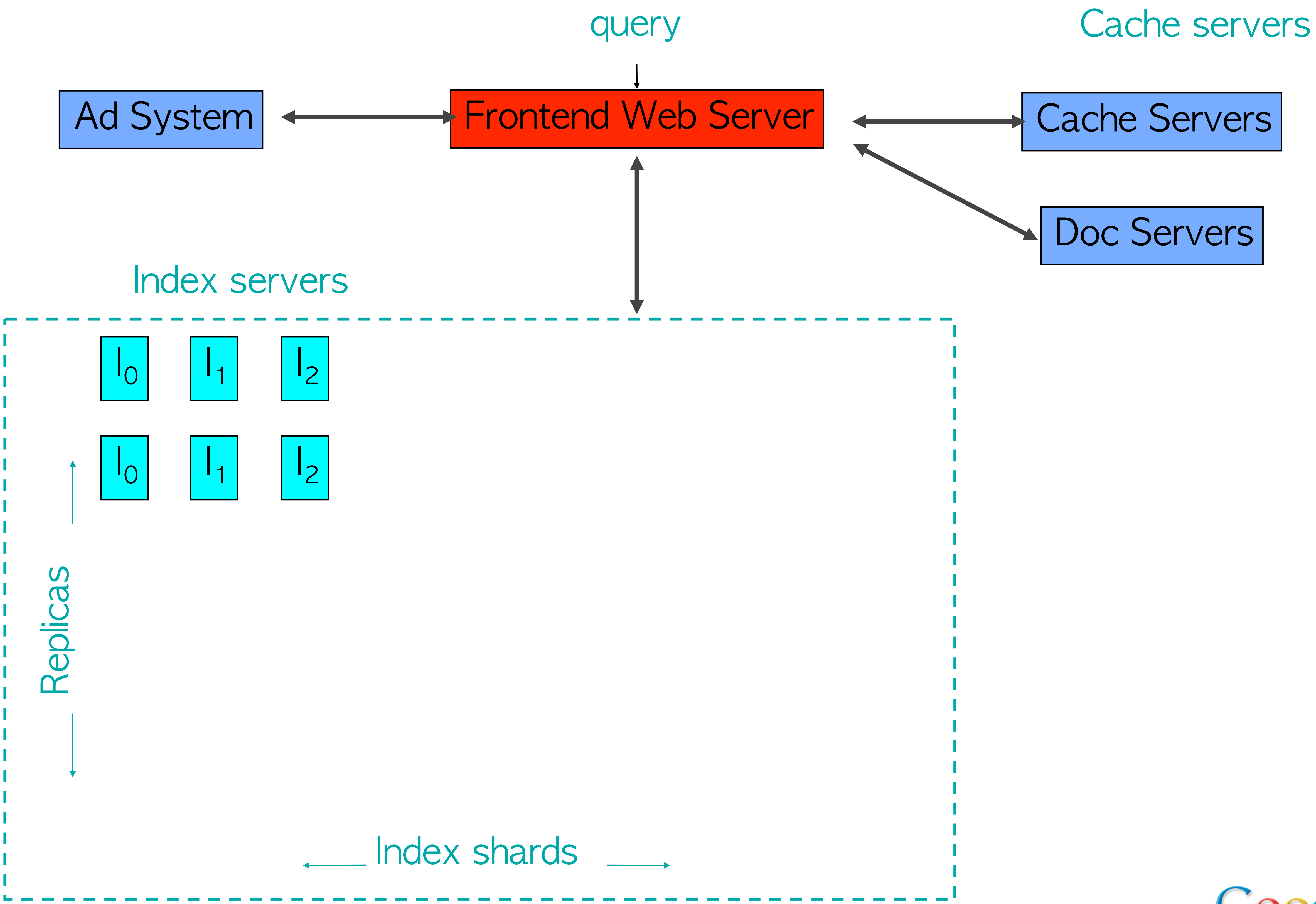
Google Data Center (3 days later)



Increasing Index Size and Query Capacity

- Huge increases in index size in ’99, ’00, ’01, ...
  - From ~50M pages to more than 1000M pages
- At same time as huge traffic increases
  - ~20% growth per month in 1999, 2000, ...
  - ... plus major new partners (e.g. Yahoo in July 2000 doubled traffic overnight)
- Performance of index servers was paramount
  - Deploying more machines continuously, but...
  - Needed ~10-30% software-based improvement every month

Dealing with Growth



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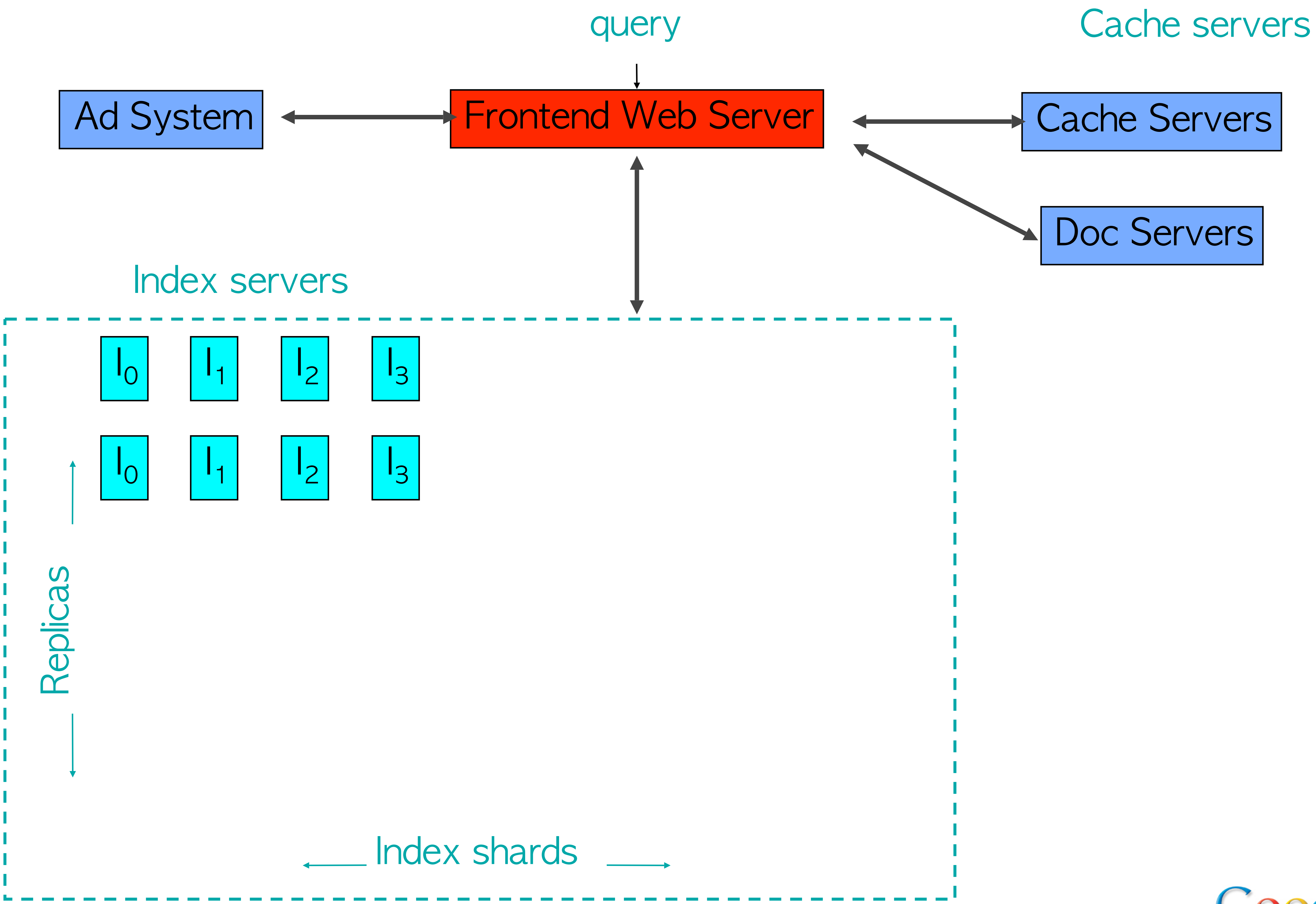

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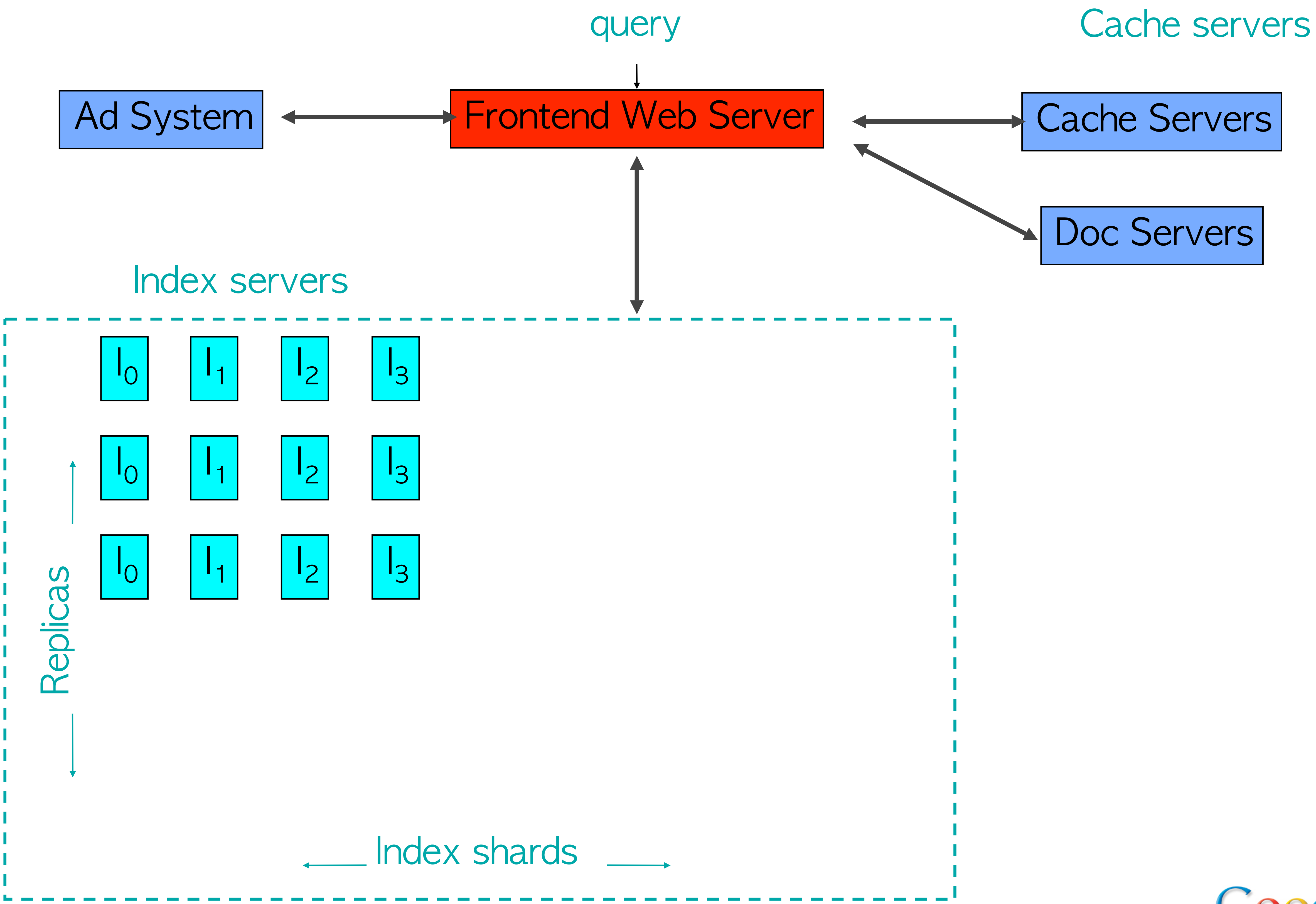

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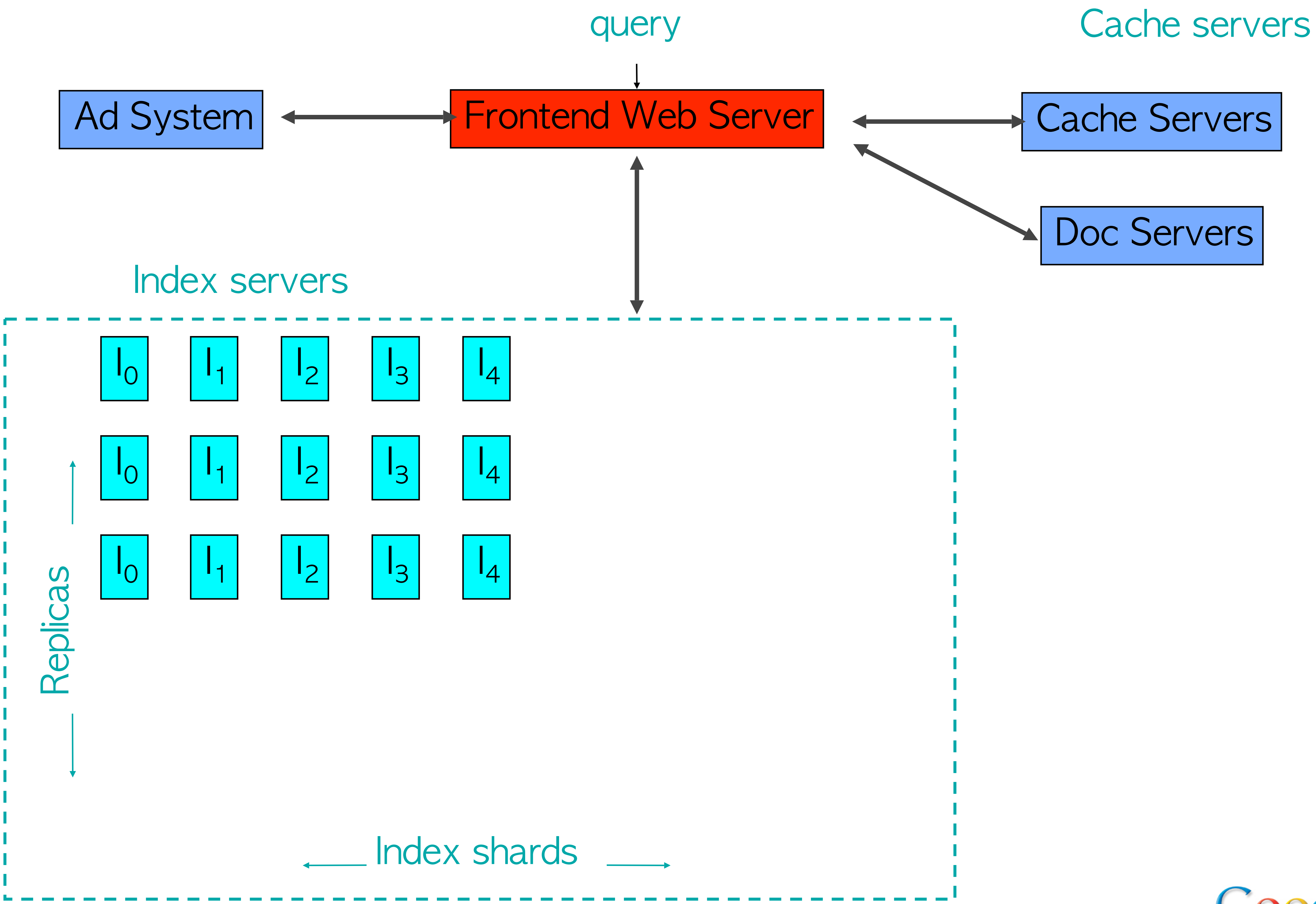

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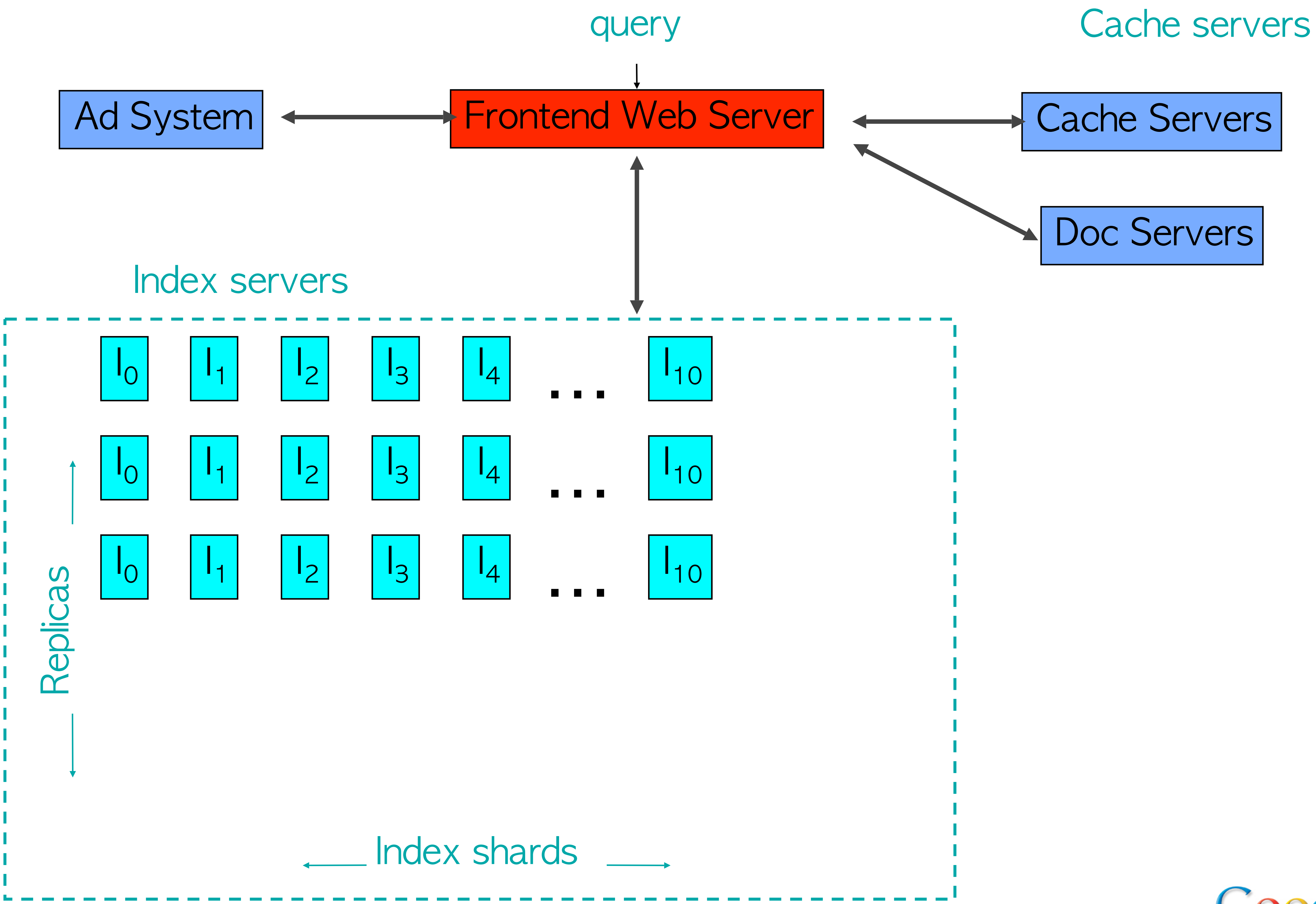
query
Cache servers
Ad System
Frontend Web Server
Cache Servers
Doc Servers
Index servers
I_0 I_1 I_2 I_3 I_4 … I_{10}
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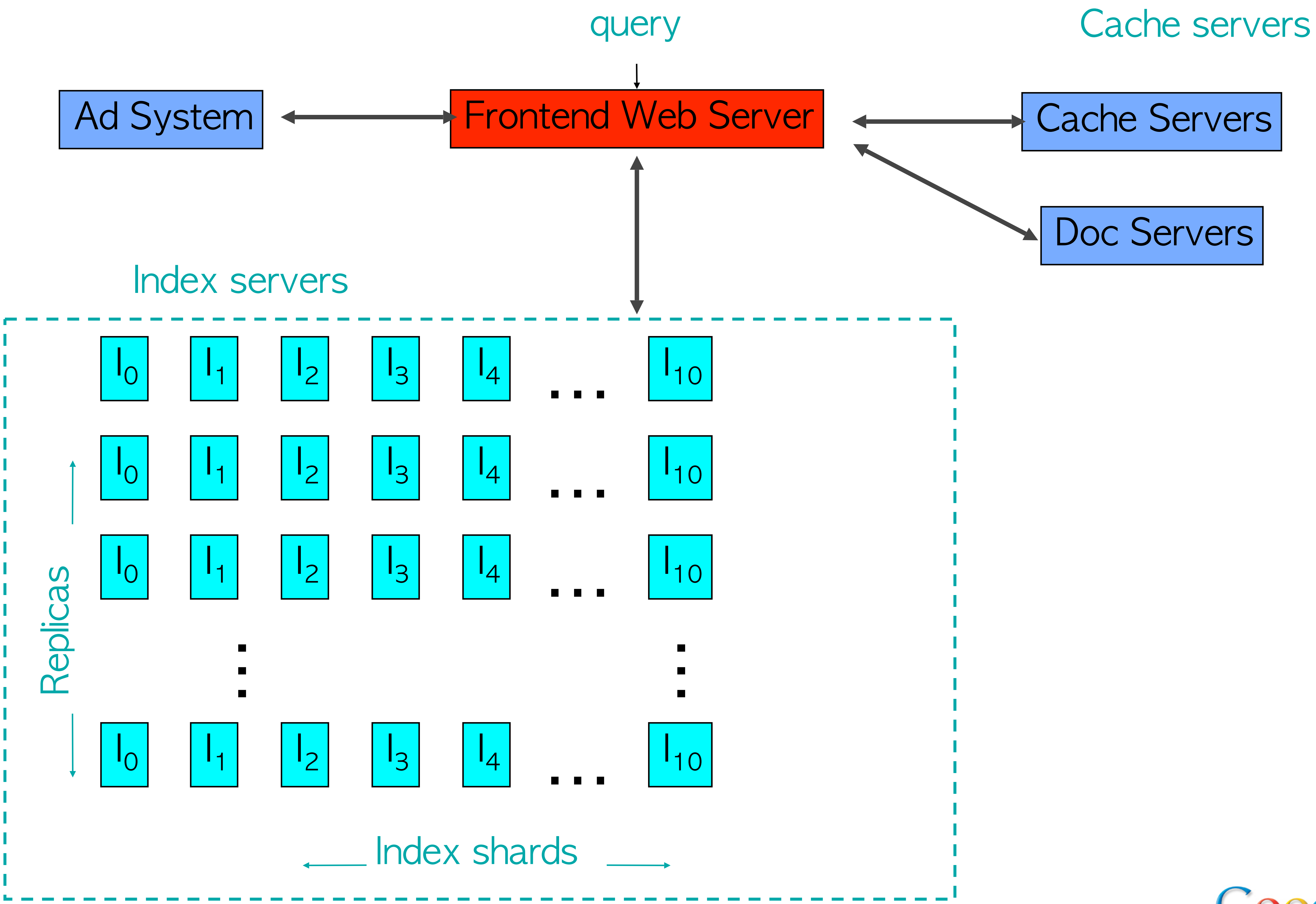
Replicas
Index shards

Dealing with Growth



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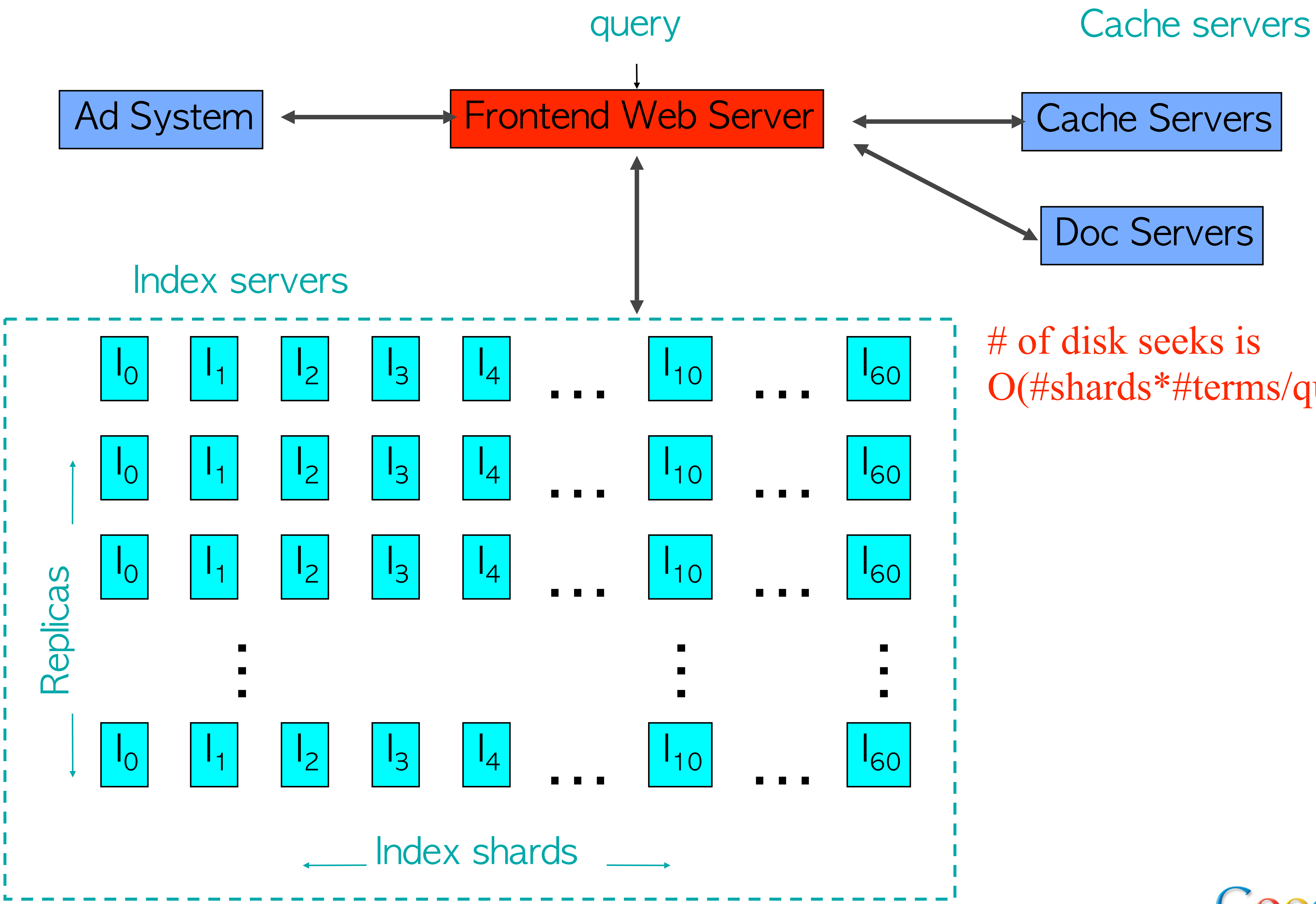
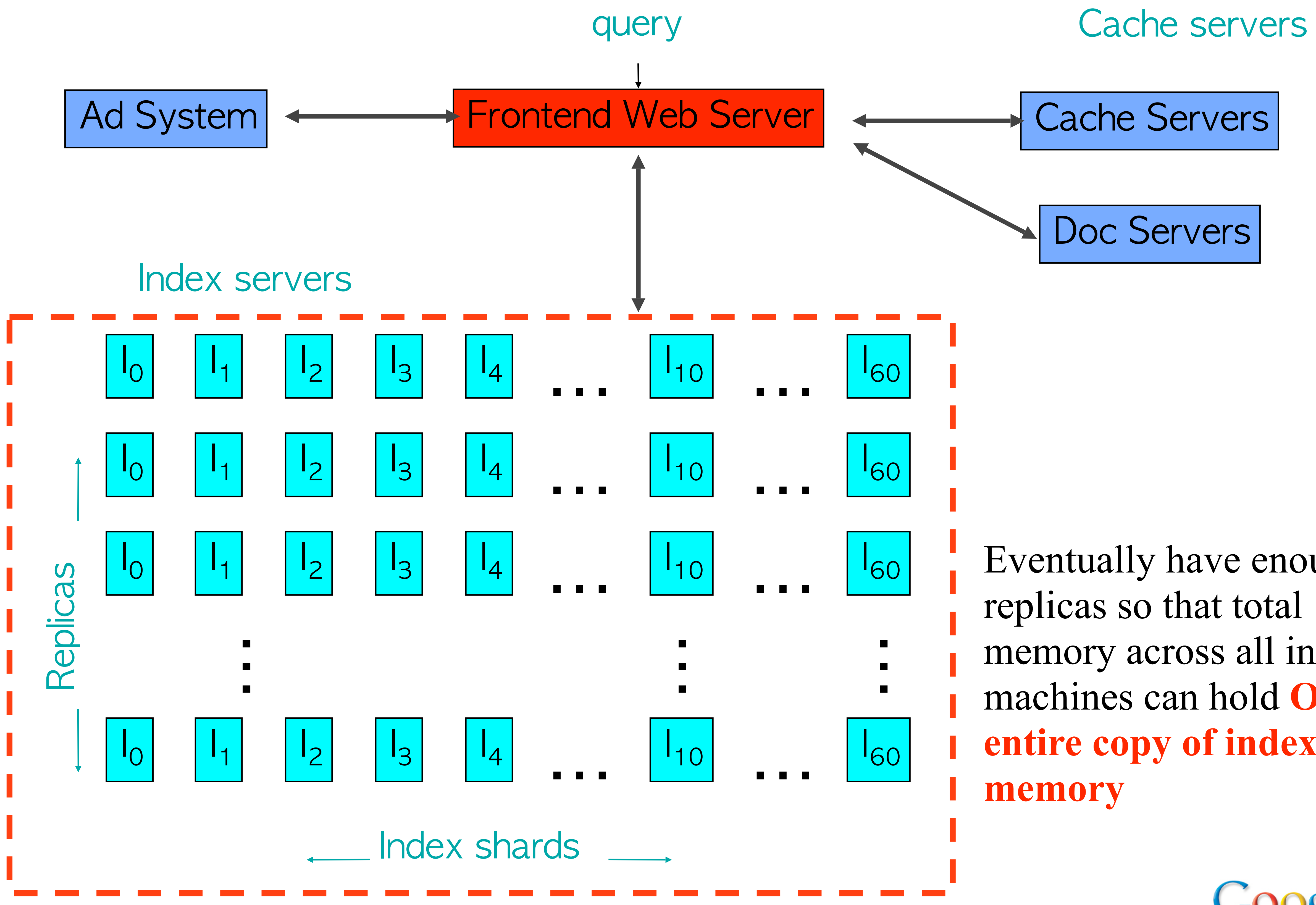


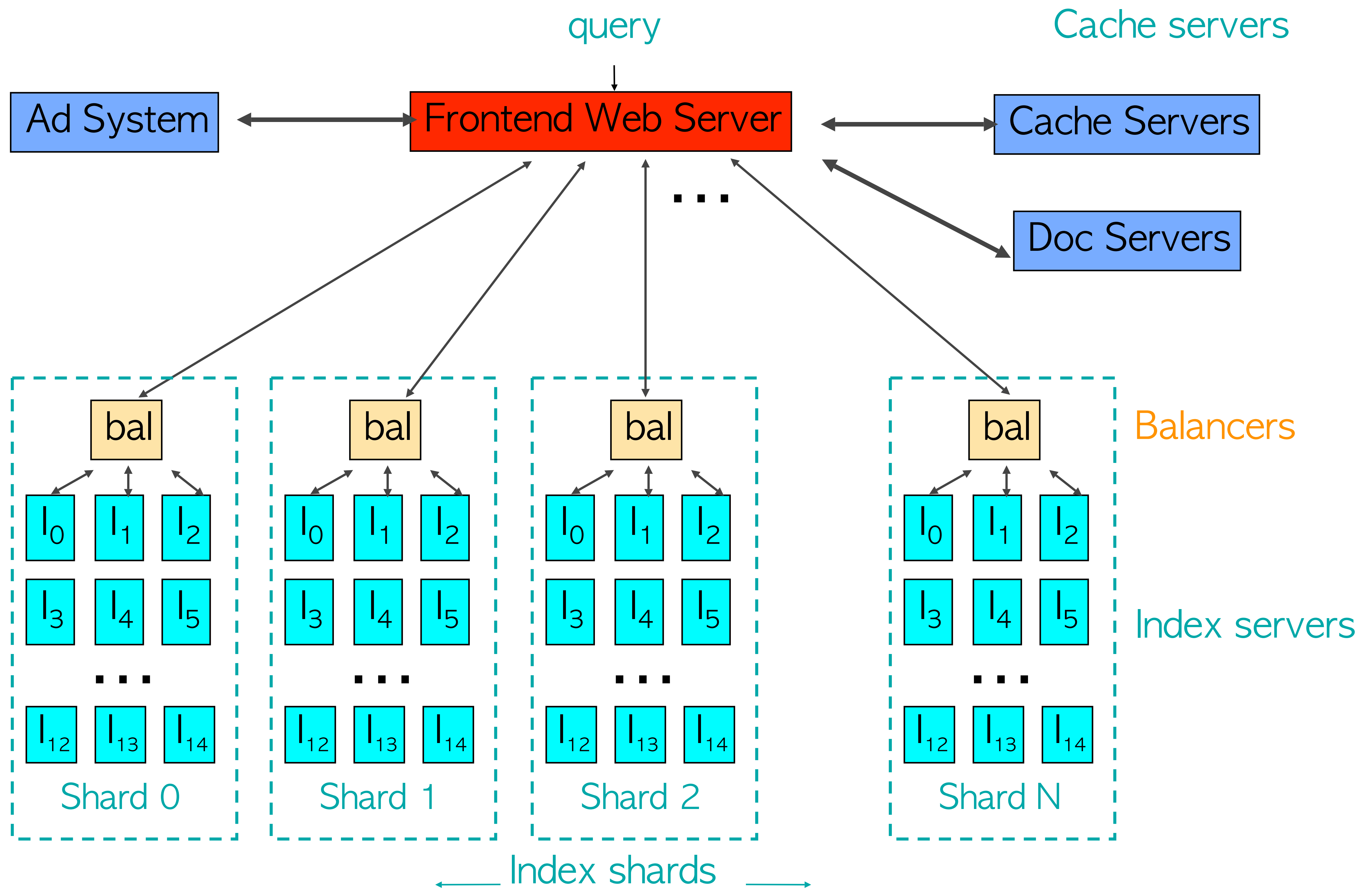
# of disk seeks is O(#shards*#terms/query)

Dealing with Growth



Eventually have enough replicas so that total memory across all index machines can hold **ONE entire copy of index in memory**

Early 2001: In-Memory Index



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In-Memory Indexing Systems

- Many positives:
  - big increase in throughput
  - big decrease in query latency
    - especially at the tail: expensive queries that previously needed GBs of disk I/O became much faster and cheaper

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e.g. [ “circle of life” ]
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- Some issues:
  - Variance: query touches 1000s of machines, not dozens
    - e.g. randomized cron jobs caused us trouble for a while
  - Availability: 1 or few replicas of each doc’s index data
    - Availability of index data when machine failed (esp for important docs): replicate important docs
    - Queries of death that kill all the backends at once: very bad

Canary Requests

- Problem: requests sometimes cause server process to crash
  - testing can help reduce probability, but can't eliminate

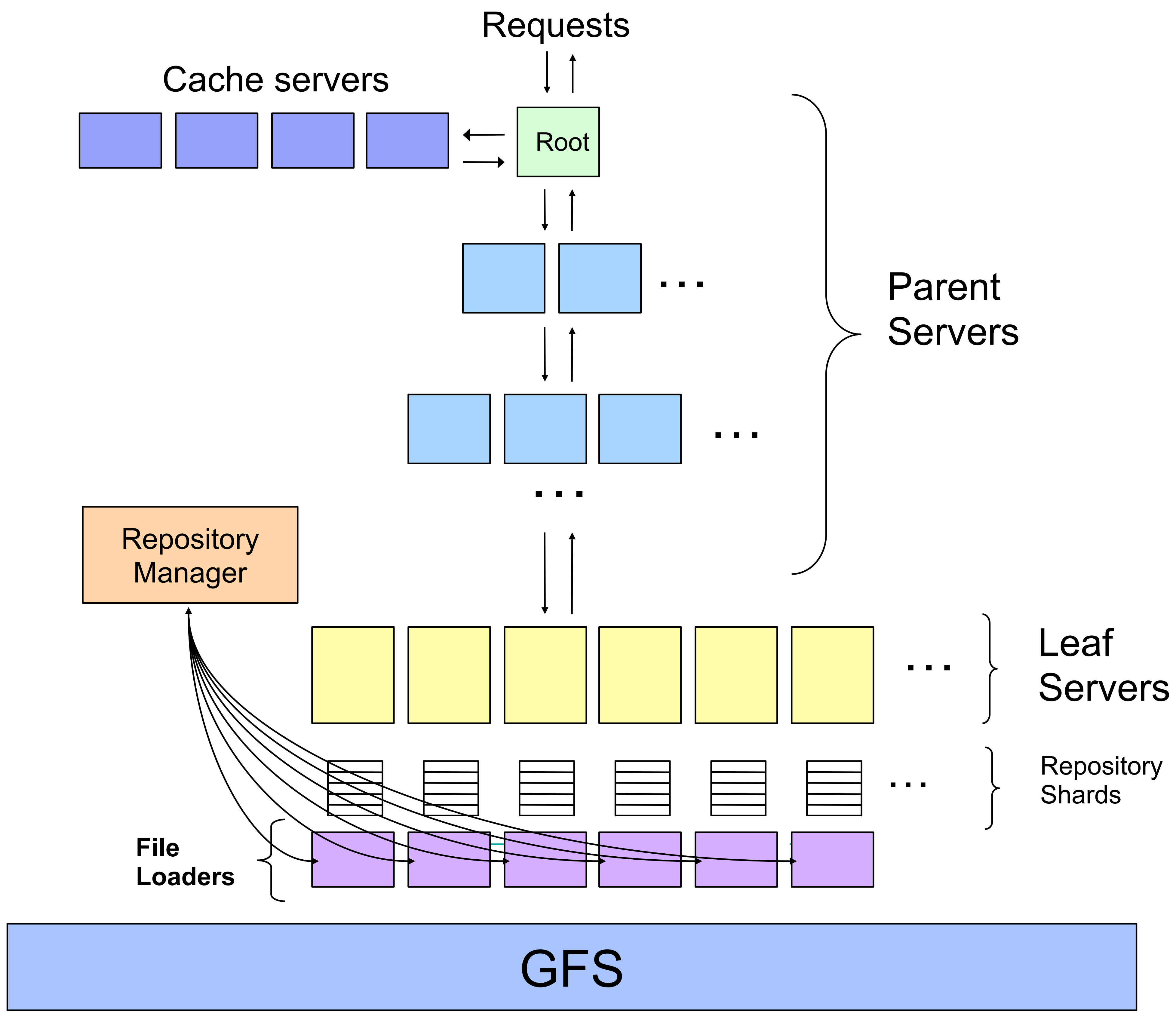
- If sending same or similar request to 1000s of machines:
  - they all might crash!
  - recovery time for 1000s of processes pretty slow

- Solution: send canary request first to one machine
  - if RPC finishes successfully, go ahead and send to all the rest
  - if RPC fails unexpectedly, try another machine

    (might have just been coincidence)
  - if fails *K* times, reject request

- Crash only a few servers, not 1000s

Query Serving System, 2004 edition



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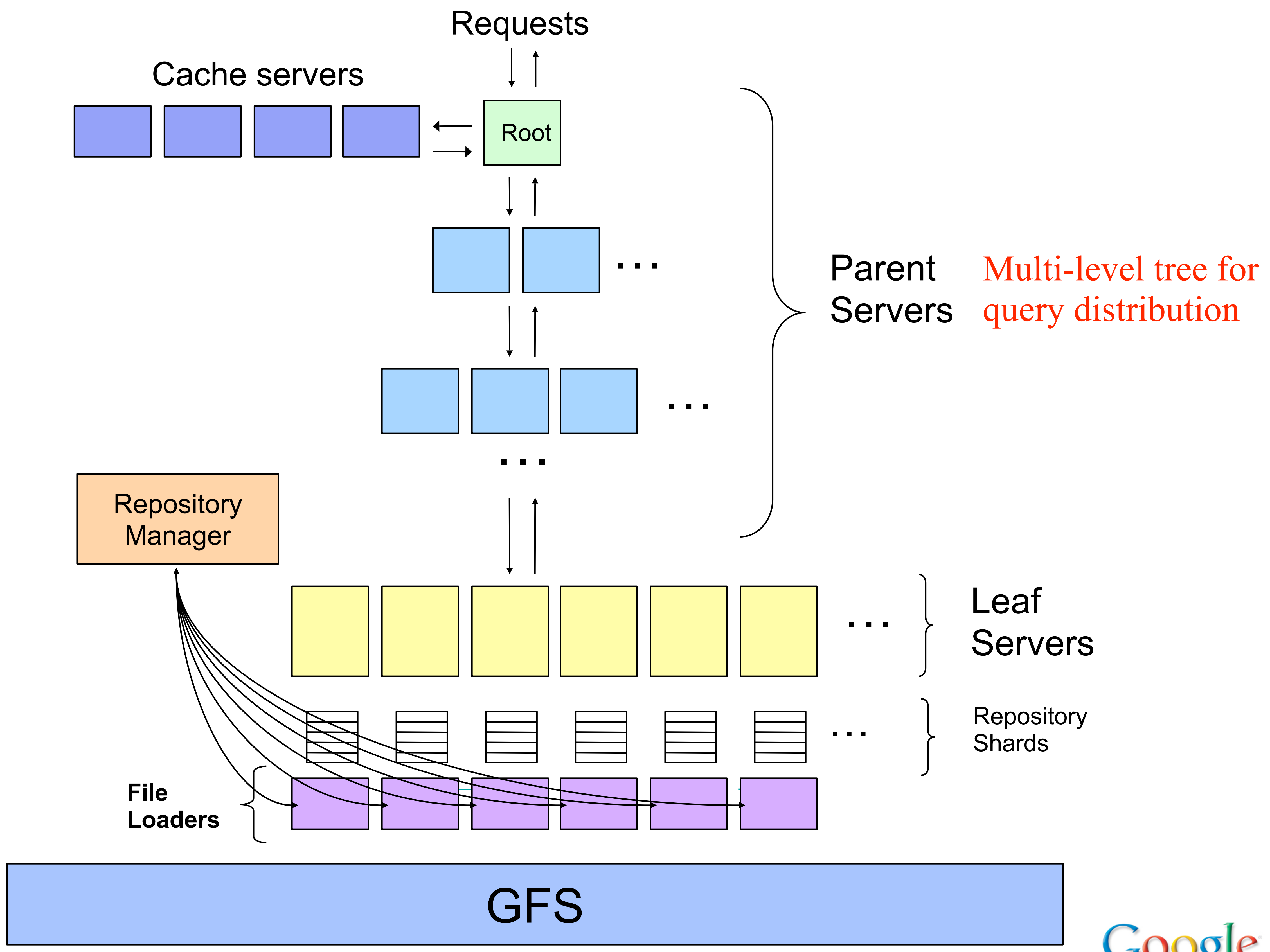

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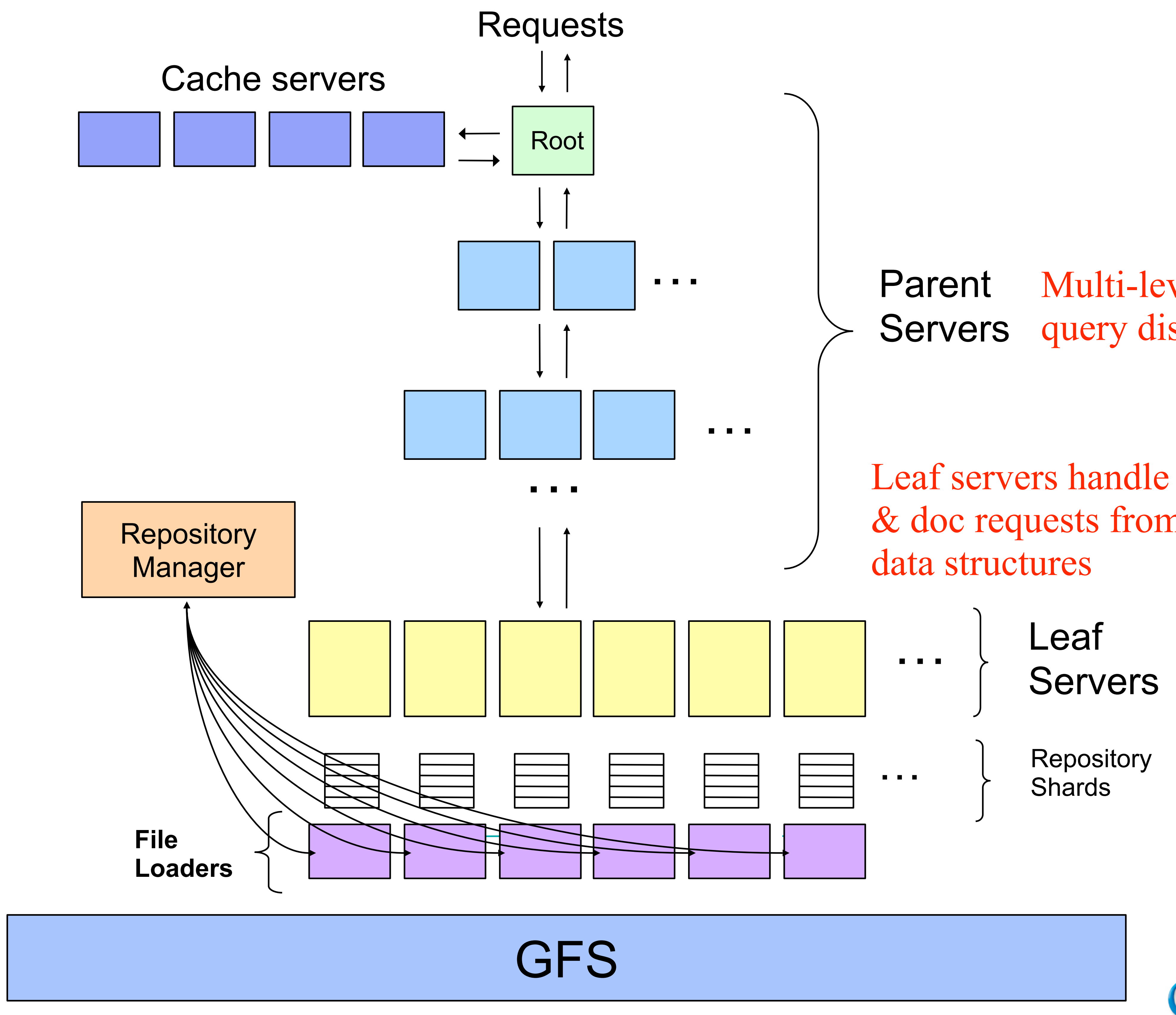

Multi-level tree for query distribution

Leaf servers handle both index & doc requests from in-memory data structures

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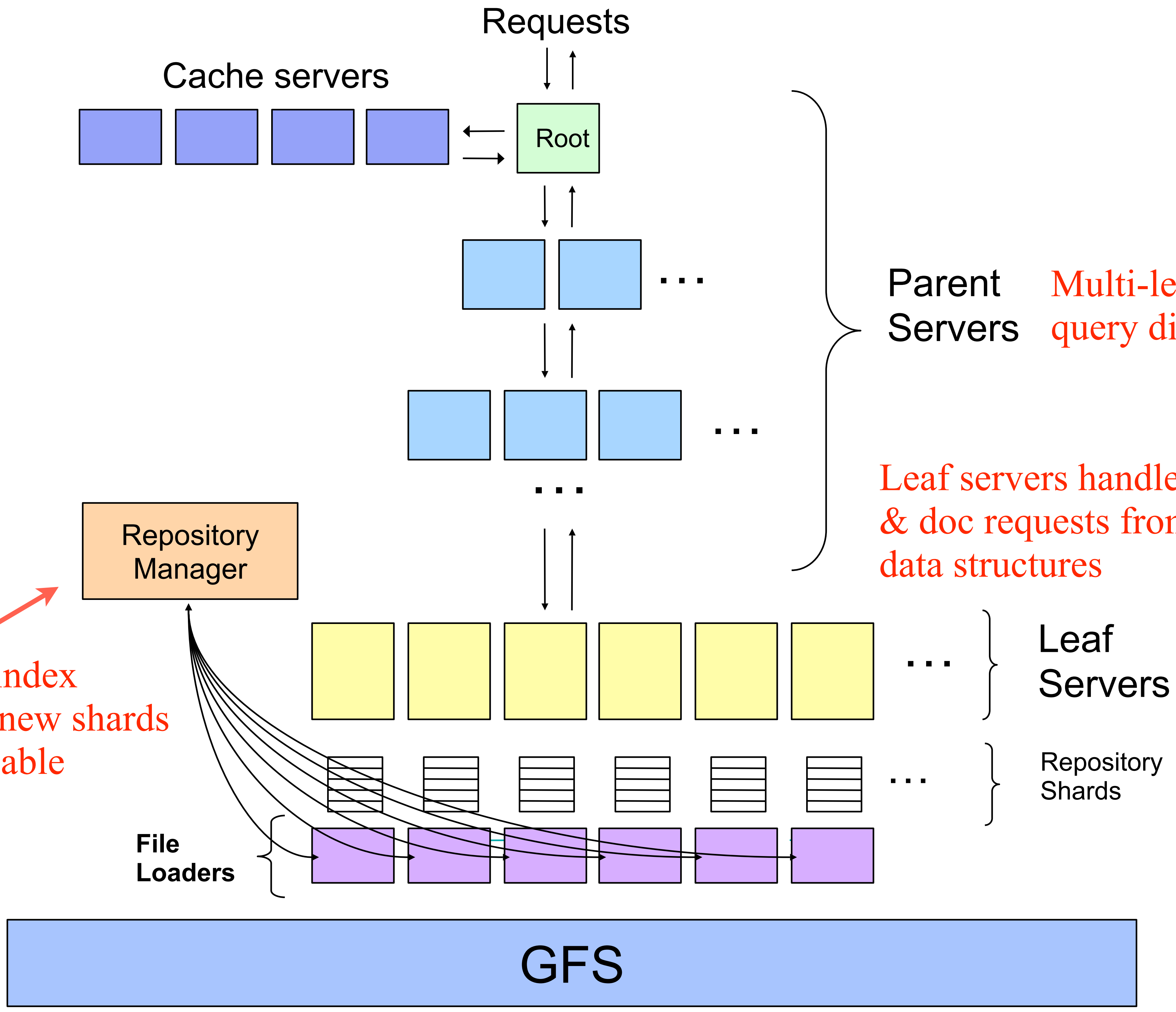


Multi-level tree for query distribution

Leaf servers handle both index & doc requests from in-memory data structures

Coordinates index switching as new shards become available

Features

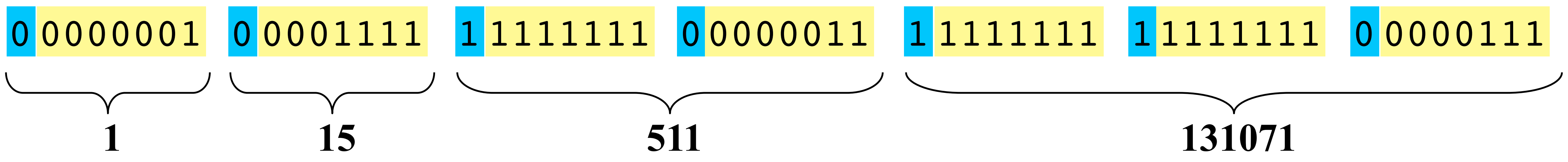
- Clean abstractions:
  - Repository
  - Document
  - Attachments
  - Scoring functions
- Easy experimentation
  - Attach new doc and index data without full reindexing
- Higher performance: designed from ground up to assume data is in memory

New Index Format

- Old disk and in-memory index used two-level scheme:
  - Each hit was encoded as (docid, word position in doc) pair
  - Docid deltas encoded with Rice encoding
  - Very good compression (originally designed for disk-based indices), but slow/CPU-intensive to decode
- New format: single flat position space
  - Data structures on side keep track of doc boundaries
  - Posting lists are just lists of delta-encoded positions
  - Need to be compact (can't afford 32 bit value per occurrence)
  - … but need to be very fast to decode

Byte-Aligned Variable-length Encodings

- Varint encoding:
  - 7 bits per byte with continuation bit
  - Con: Decoding requires lots of branches/shifts/masks



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$$\underbrace{0\,0000001}_{1}\quad\underbrace{0\,0001111}_{15}\quad\underbrace{1\,1111111\quad 0\,0000011}_{511}\quad\underbrace{1\,1111111\quad 1\,1111111\quad 0\,0000111}_{131071}$$

- Idea: Encode byte length using 2 bits
  - Better: fewer branches, shifts, and masks
  - Con: Limited to 30-bit values, still some shifting to decode

$$\underbrace{00\,000001}_{1}\quad\underbrace{00\,001111}_{15}\quad\underbrace{01\,111111\quad 00000011}_{511}\quad\underbrace{10\,111111\quad 11111111\quad 00000111}_{131071}$$

Group Varint Encoding

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```
00000001  00001111  01111111  00000111  10111111  11111111  00000111
```

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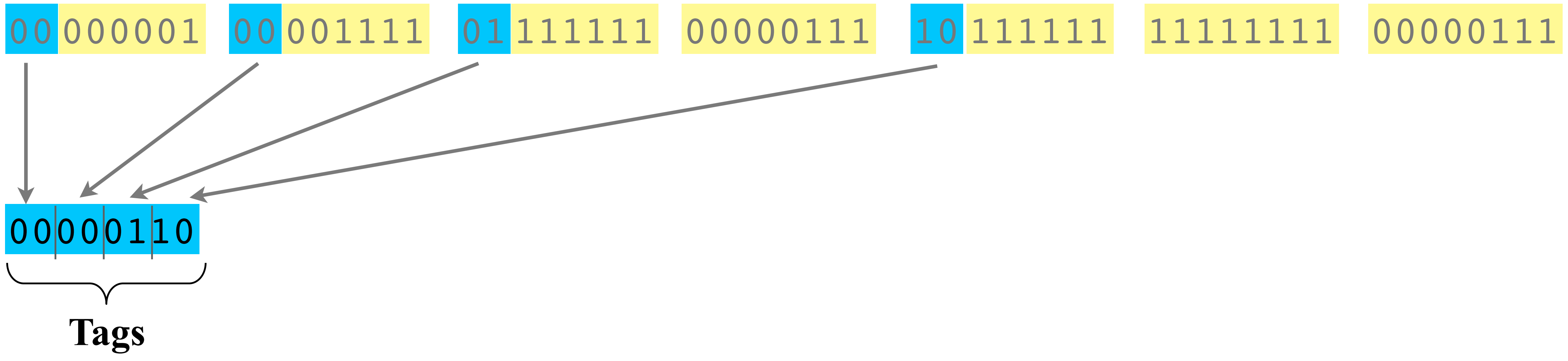

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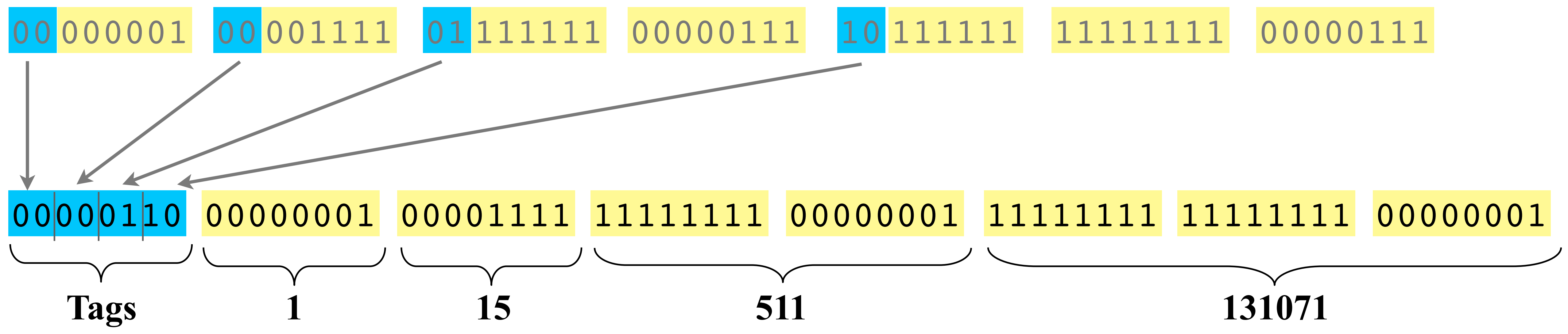

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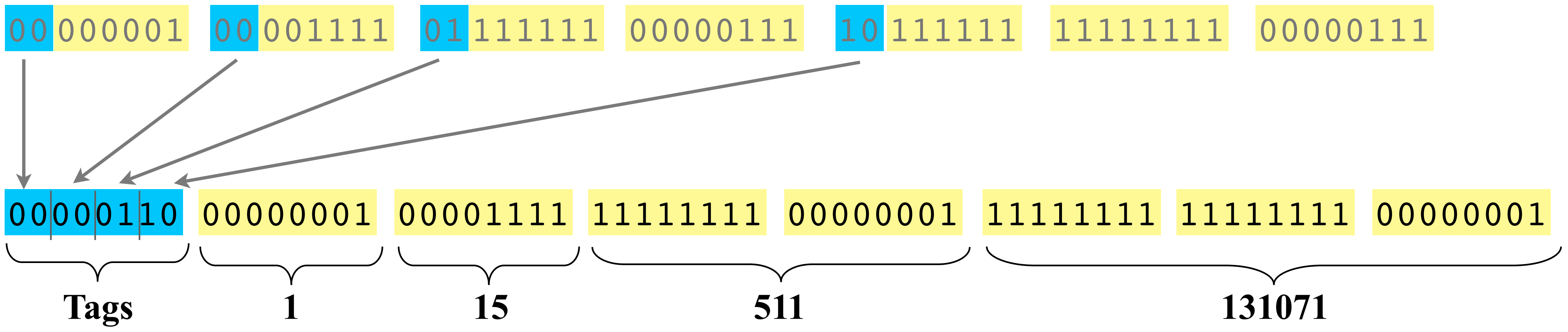

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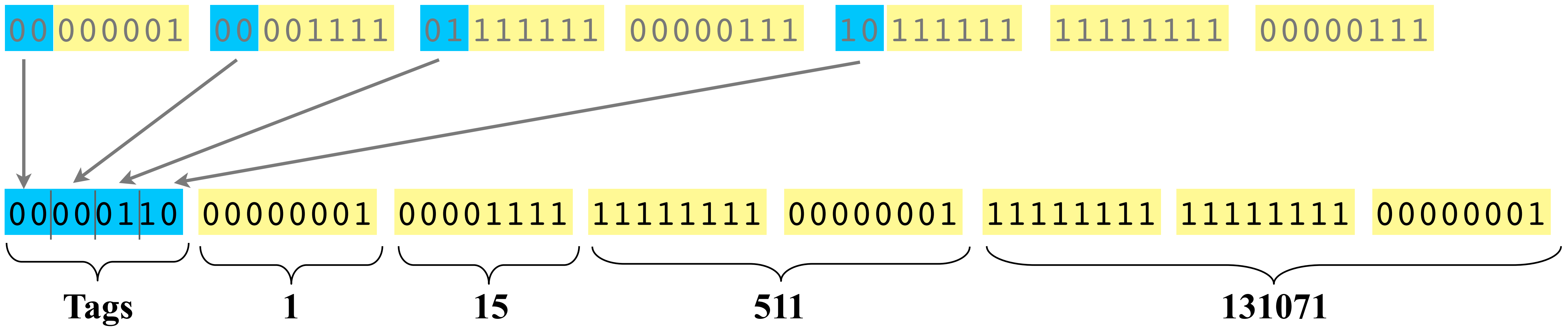

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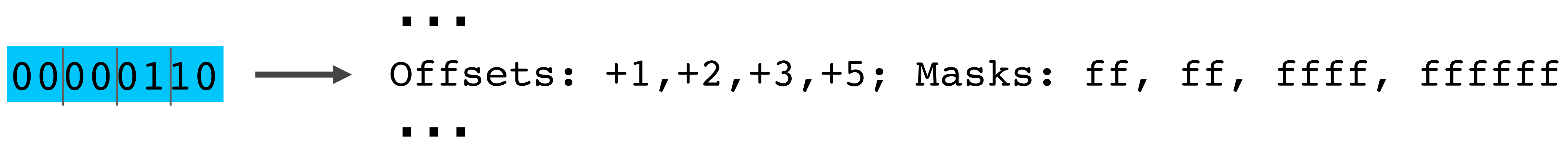

```
...
Offsets: +1,+2,+3,+5; Masks: ff, ff, ffff, ffffff
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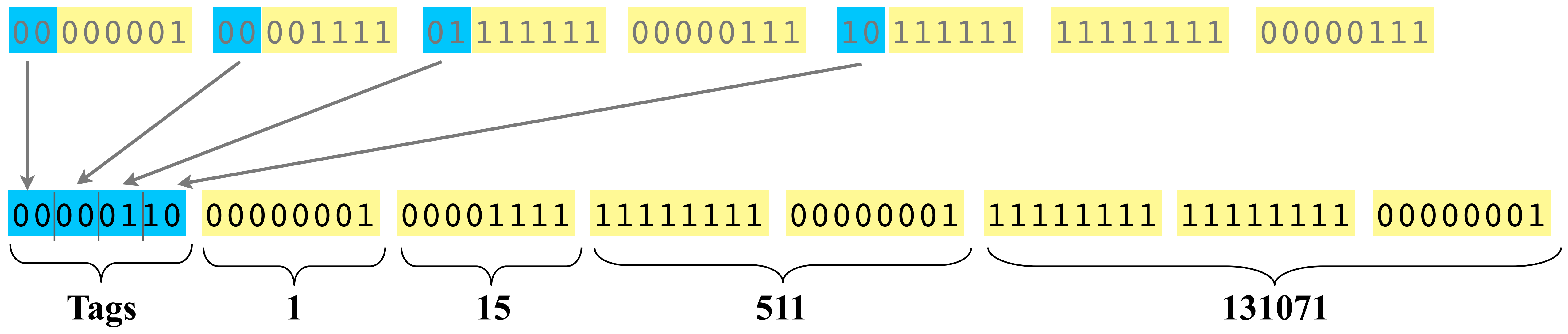

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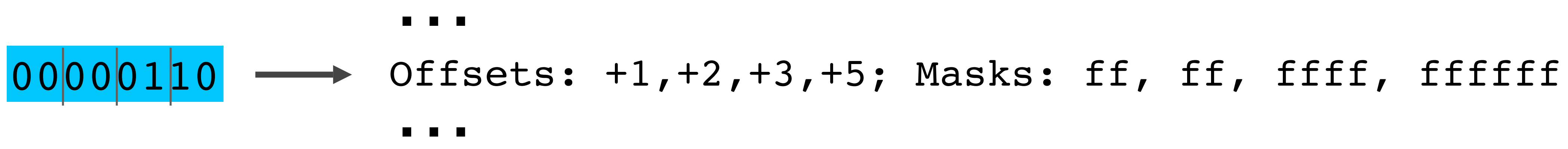

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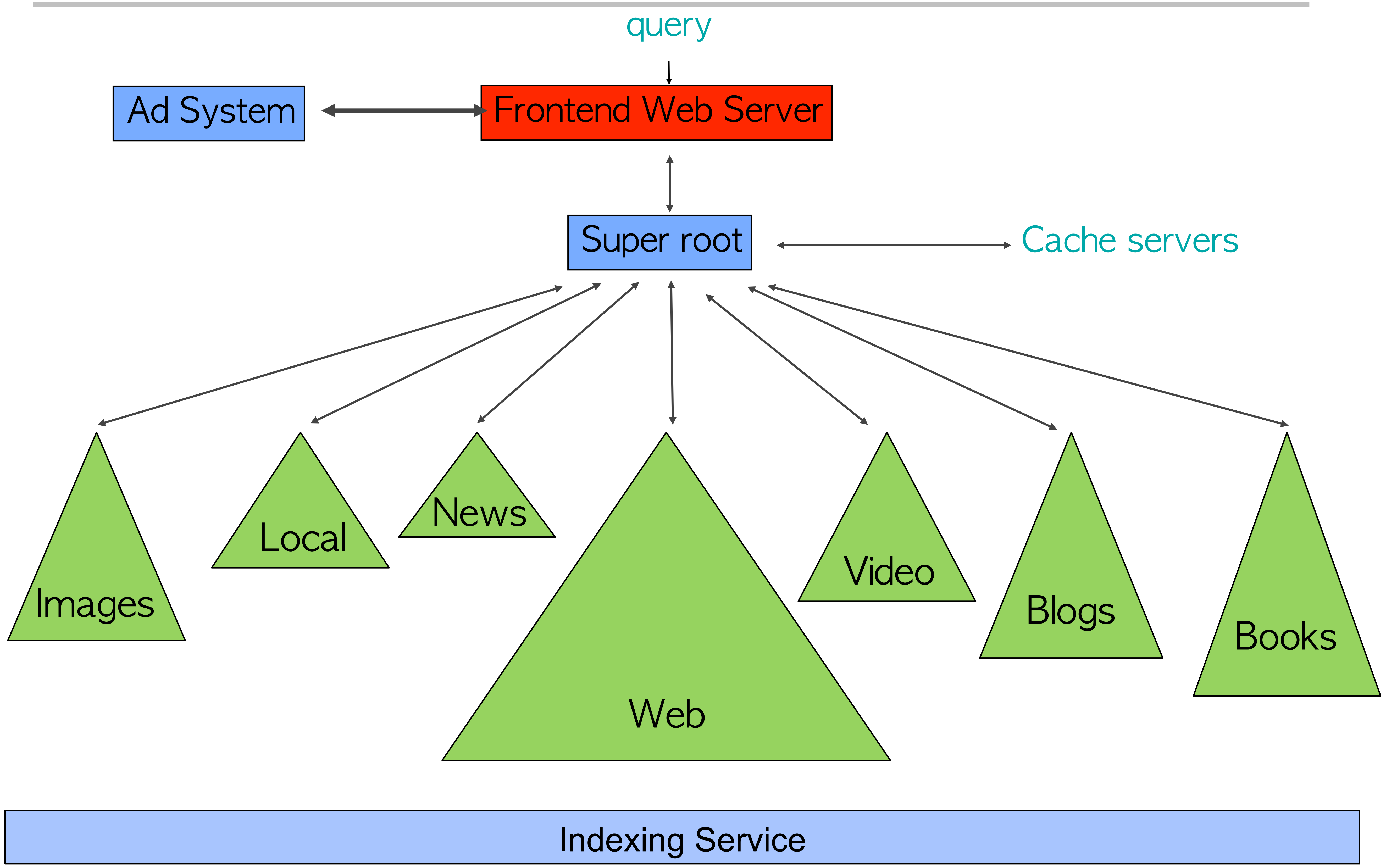
- Much faster than alternatives:
  - 7-bit-per-byte varint: decode ~180M numbers/second
  - 30-bit Varint w/ 2-bit length: decode ~240M numbers/second
  - Group varint: decode ~400M numbers/second

2007: Universal Search



Universal Search

- Search all corpora in parallel

- Performance: most of the corpora weren't designed to deal with high QPS level of web search

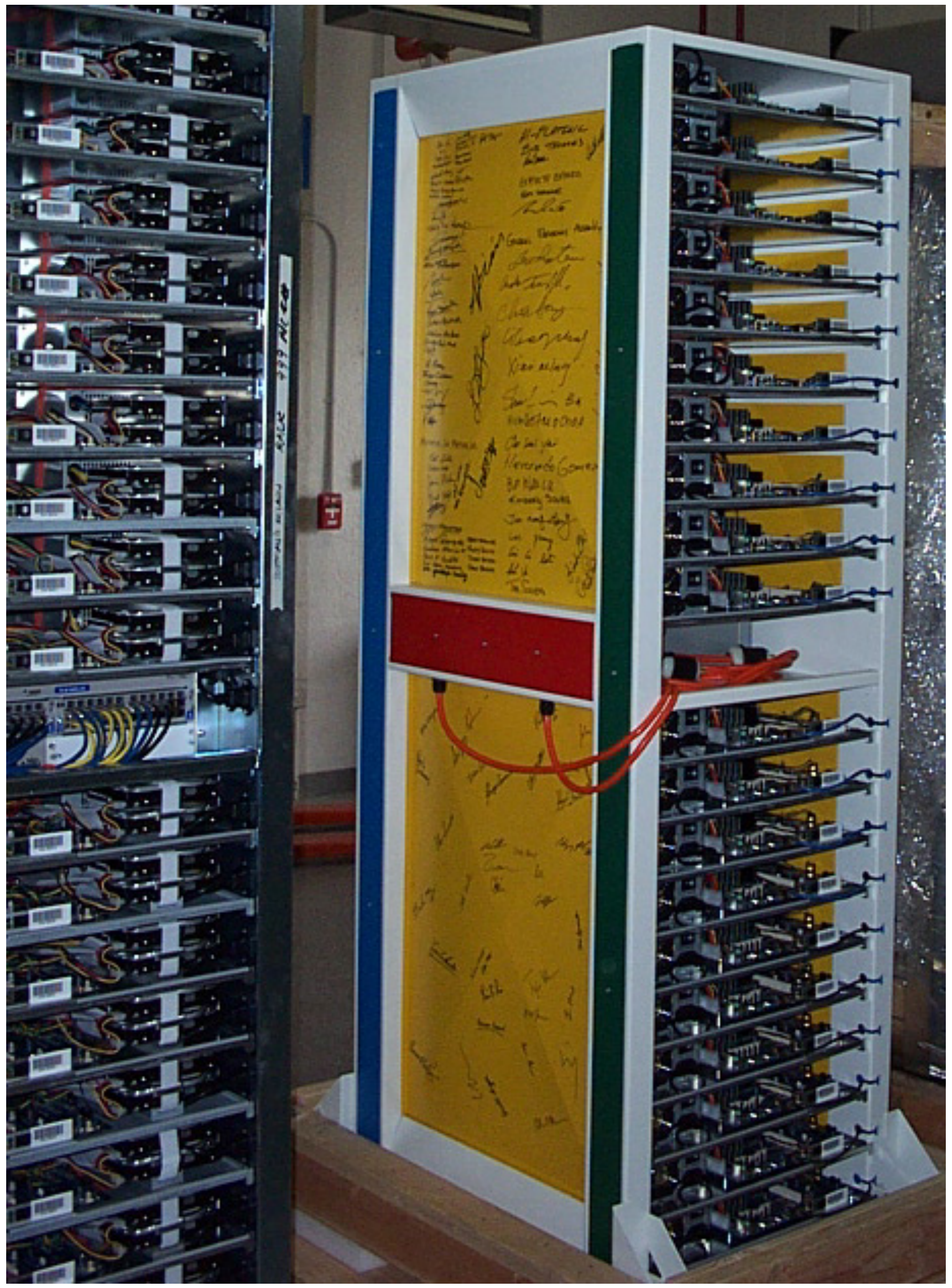
- Mixing: Which corpora are relevant to query?
  - changes over time

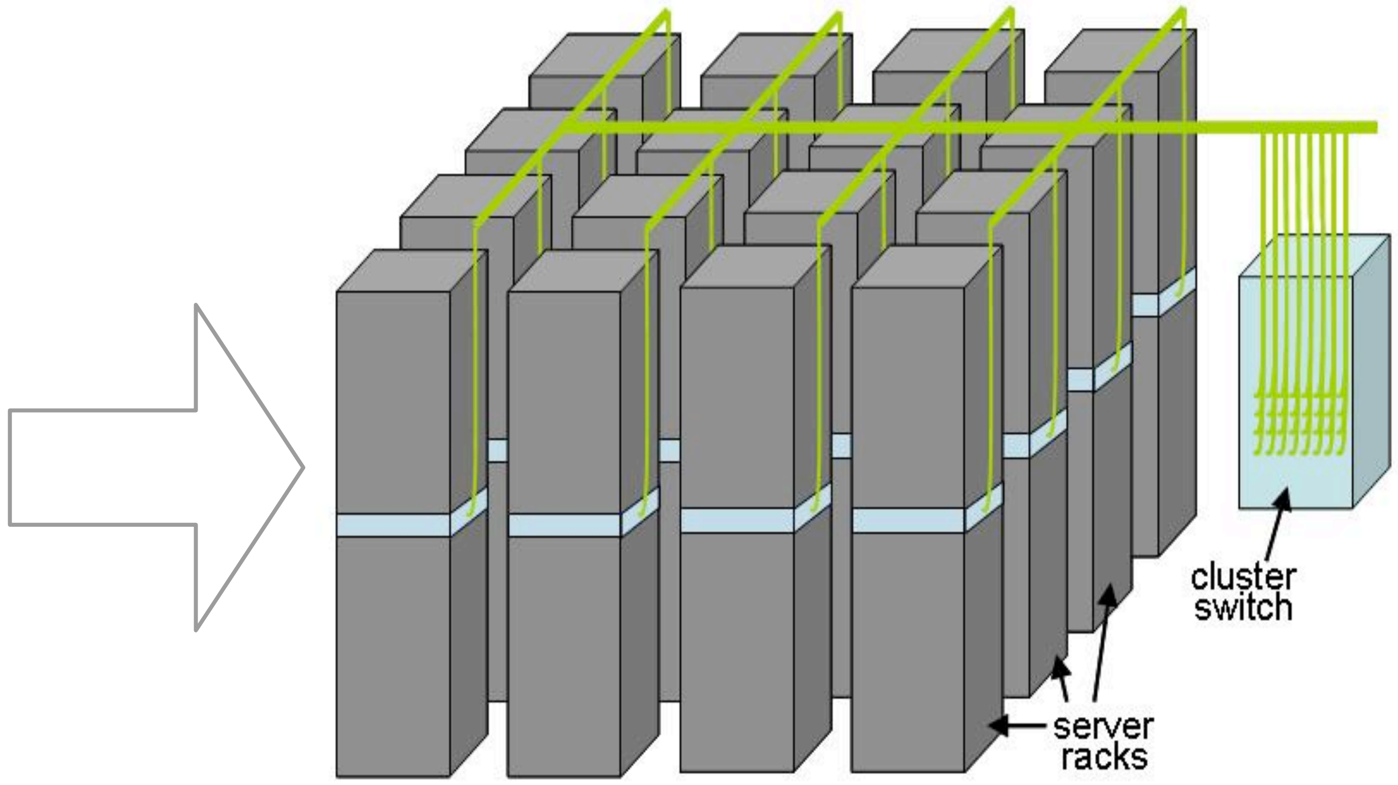
- UI: How to organize results from different corpora?
  - interleaved?
  - separate sections for different types of documents?

System Software Evolution

Machines + Racks

Clusters





- In-house rack design
- PC-class motherboards
- Low-end storage & networking hardware
- Linux
- + in-house software

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The Joys of Real Hardware

Typical first year for a new cluster:

~1 network rewiring (rolling ~5% of machines down over 2-day span)

~20 rack failures (40-80 machines instantly disappear, 1-6 hours to get back)

~5 racks go wonky (40-80 machines see 50% packetloss)

~8 network maintenances (4 might cause ~30-minute random connectivity losses)

~12 router reloads (takes out DNS and external vips for a couple minutes)

~3 router failures (have to immediately pull traffic for an hour)

~dozens of minor 30-second blips for dns

~1000 individual machine failures

~thousands of hard drive failures

slow disks, bad memory, misconfigured machines, flaky machines, etc.

Long distance links: wild dogs, sharks, dead horses, drunken hunters, etc.

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Reliability/availability must come from software!

Google

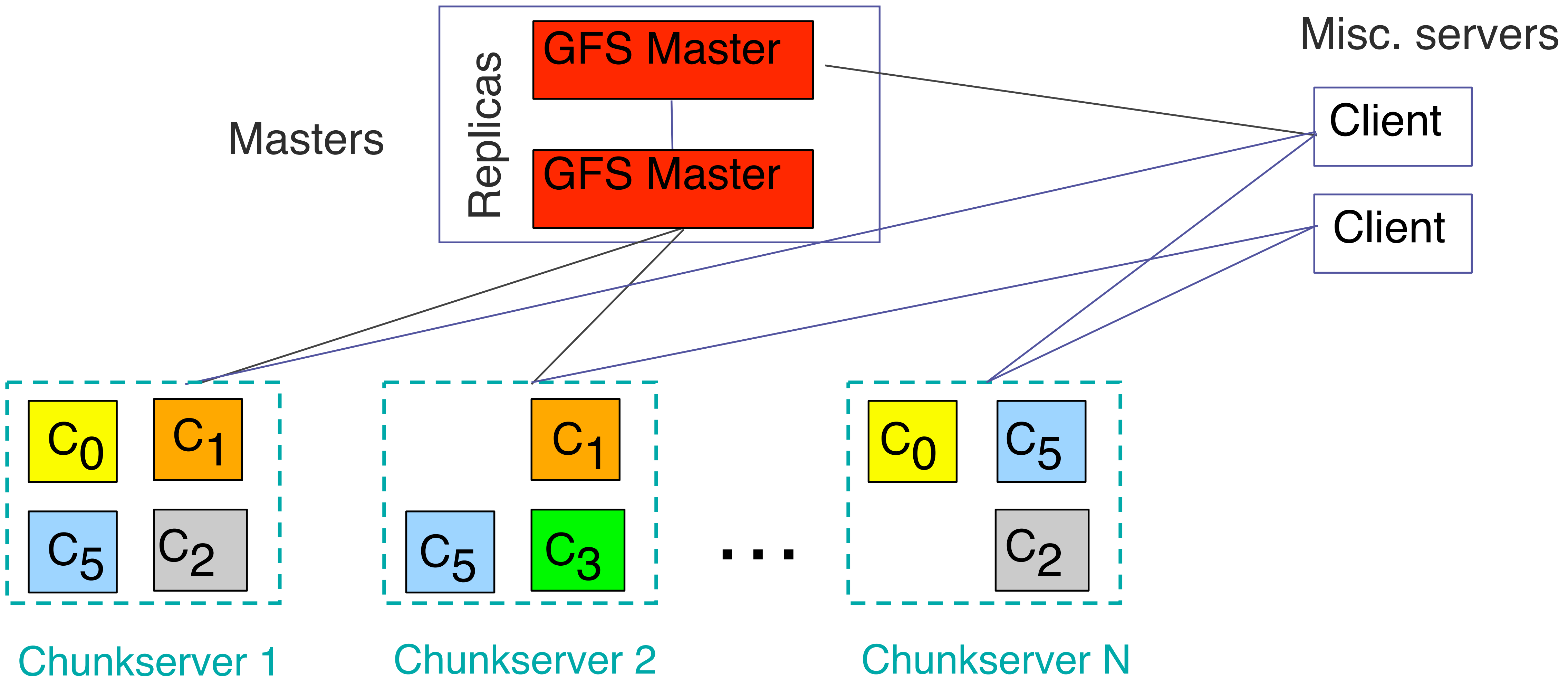
Low-Level Systems Software Desires

- If you have lots of machines, you want to:

- Store data persistently
  – w/ high availability
  – high read and write bandwidth

- Run large-scale computations reliably
  – without having to deal with machine failures

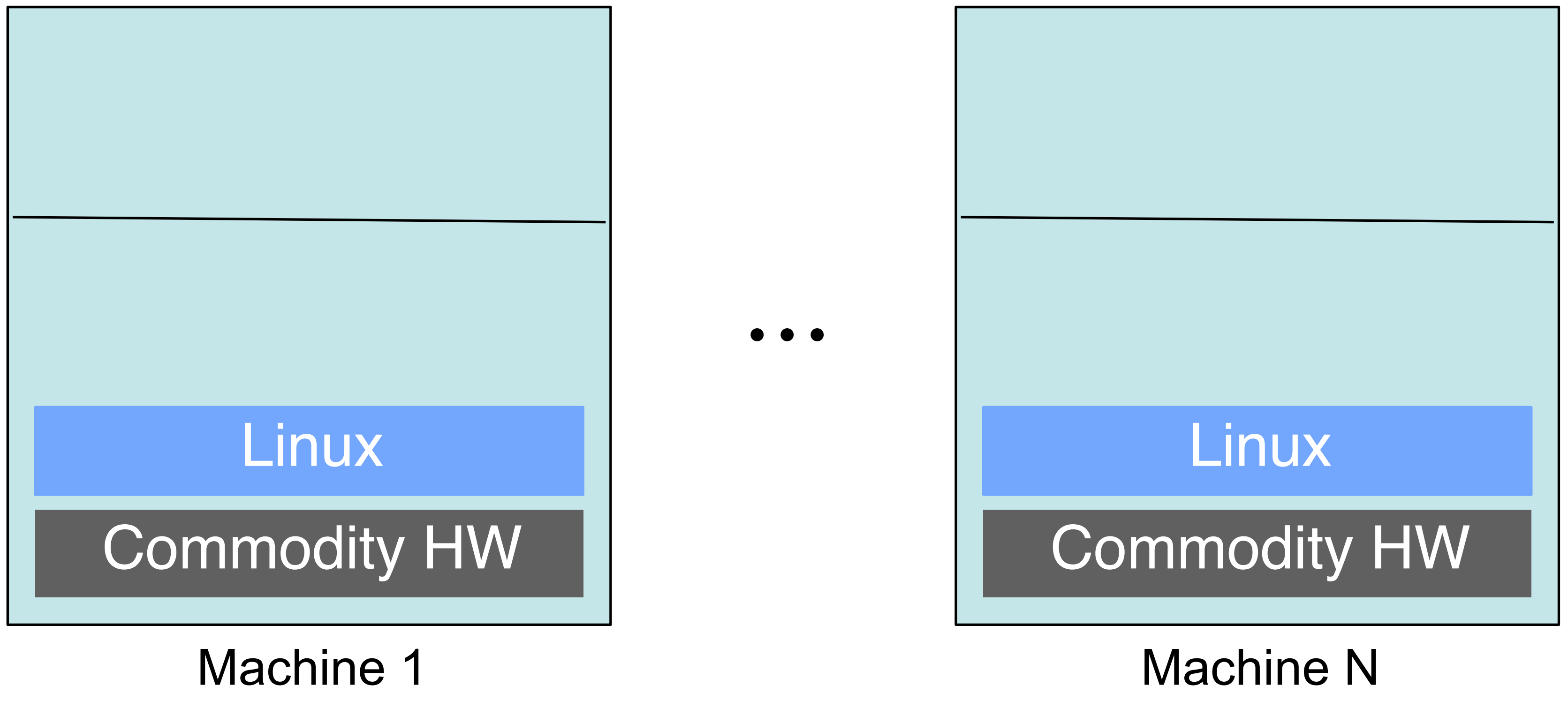
Google File System (GFS) Design



- Master manages metadata
- Data transfers are directly between clients/chunkservers
- Files broken into chunks (typically 64 MB)
- Chunks replicated across multiple machines (usually 3)

Google Cluster Software Environment

- Cluster is 5K-20K machines, typically one or handful of hw configurations
- File system (GFS or Colossus) + cluster scheduling system are core services
- Typically 100s to 1000s of active jobs (some w/1 task, some w/1000s)
    - mix of batch and low-latency, user-facing production jobs



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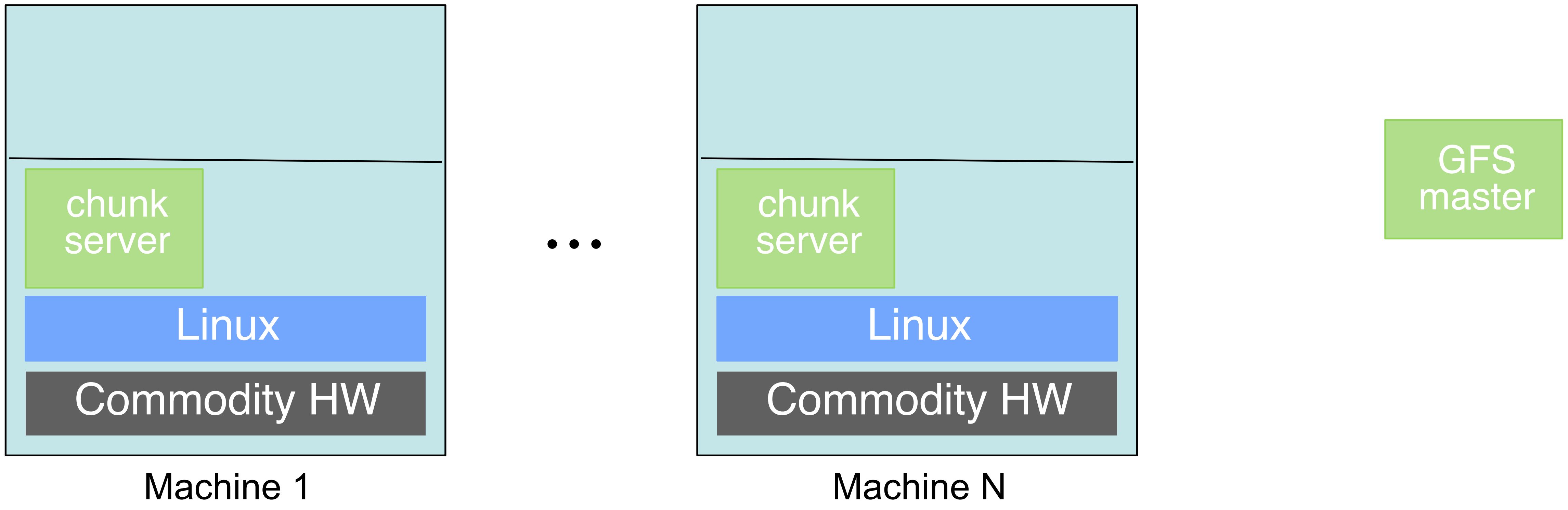

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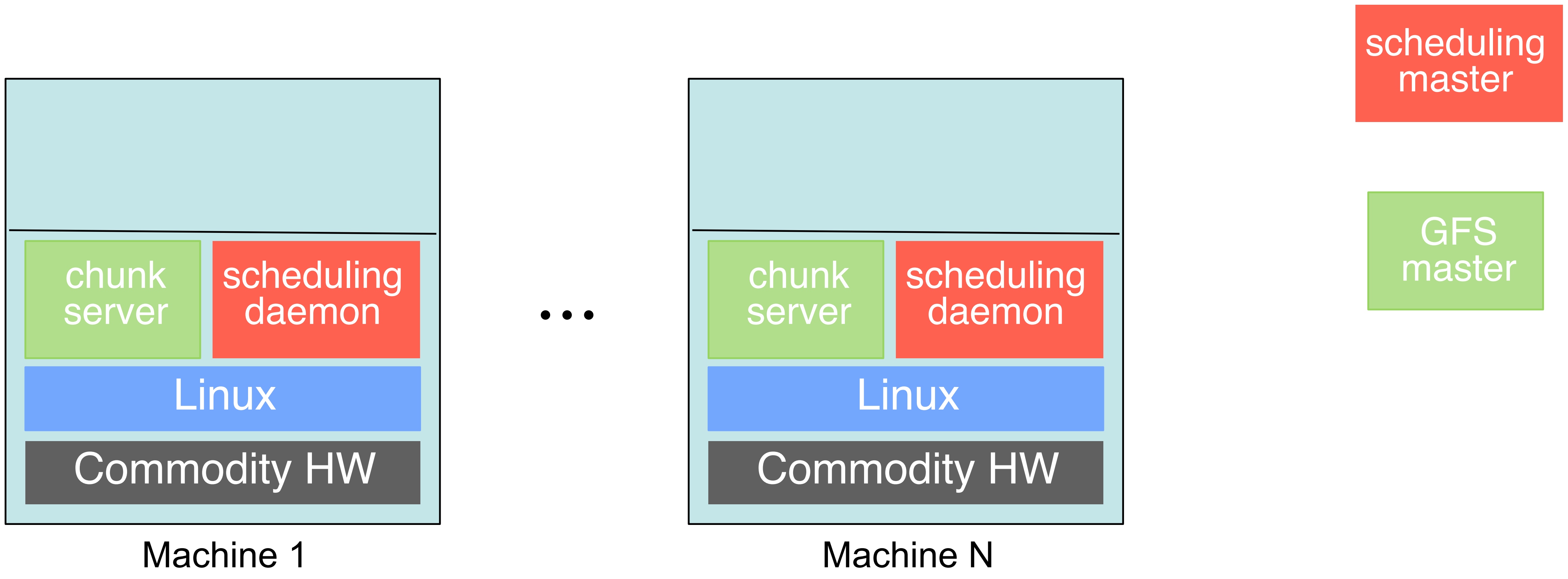

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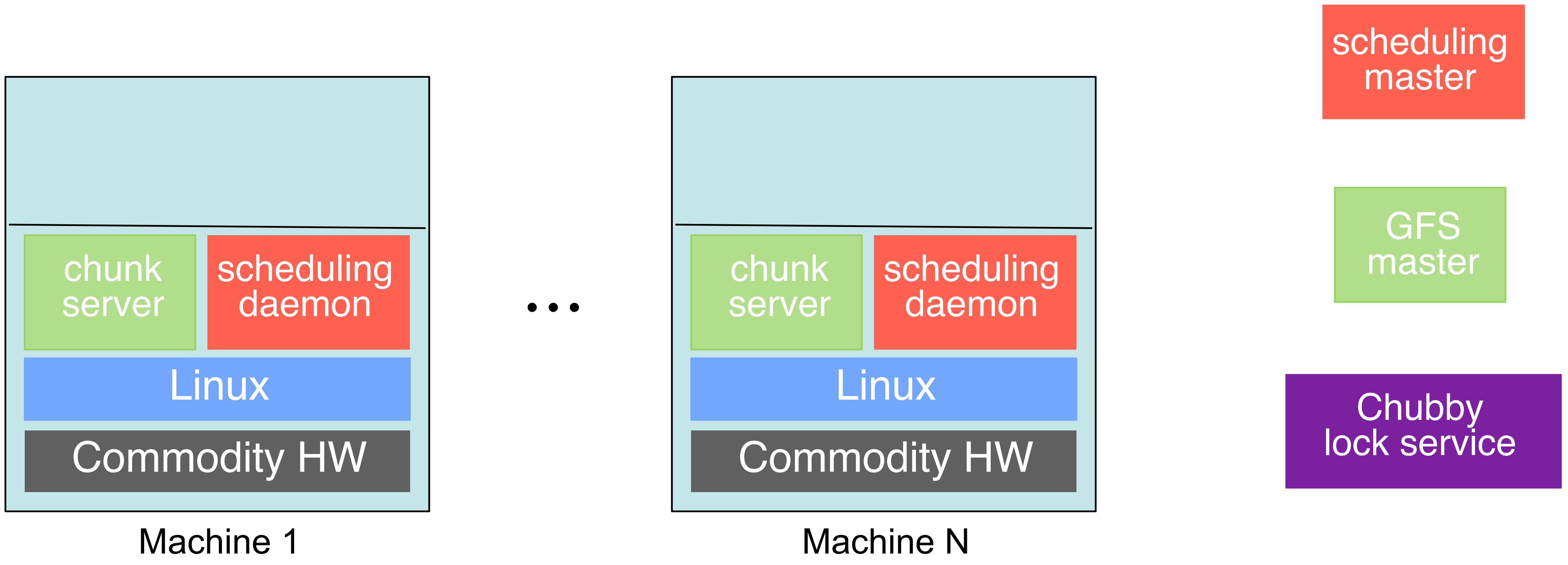

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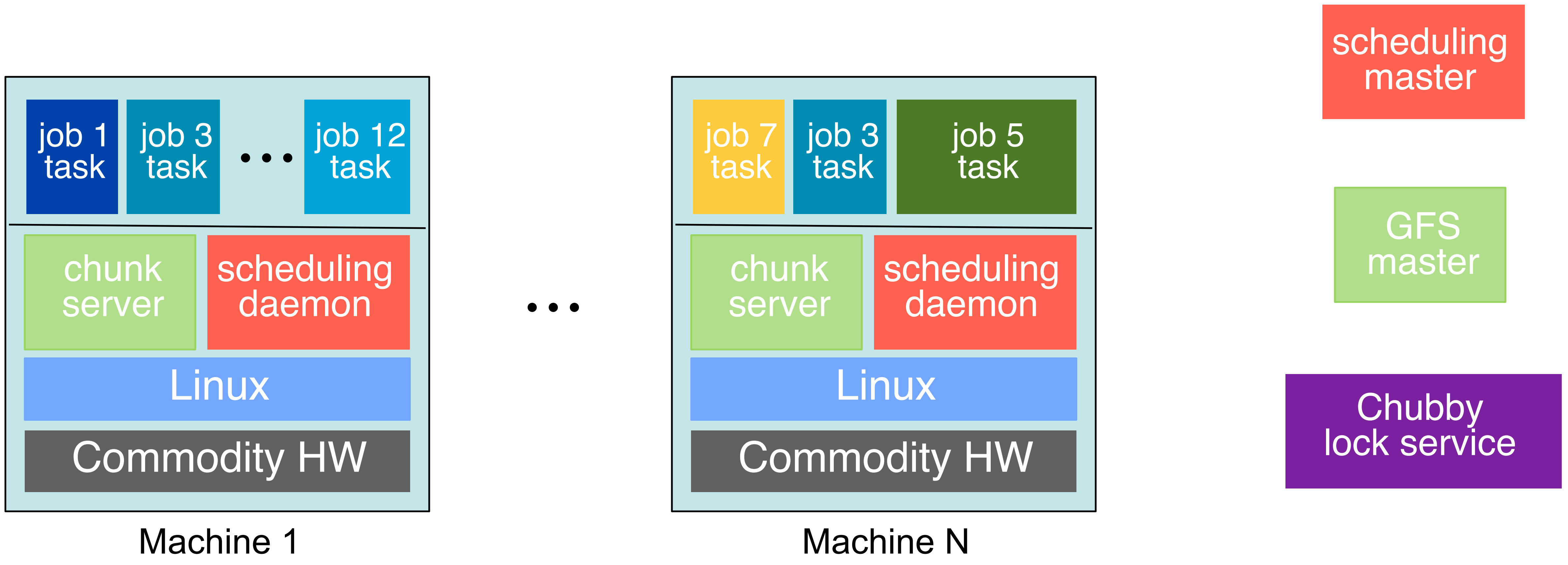
- Typically 100s to 1000s of active jobs (some w/1 task, some w/1000s)
    - mix of batch and low-latency, user-facing production jobs



Problem: lots of data

- Example: 20+ billion web pages x 20KB = 400+ terabytes

- One computer can read 50 MB/sec from disk
  - ~three months to read the web
- ~1,000 hard drives just to store the web

- Even more to *do* something with the data

Solution: spread work over many machines

- Good news: same problem with 1000 machines, < 3 hours

- Bad news: programming work
  - communication and coordination
  - recovering from machine failure
  - status reporting
  - debugging
  - optimization
  - locality

- Bad news II: repeat for every problem you want to solve

Google

MapReduce History

- 2003: Working on rewriting indexing system:
  - start with raw page contents on disk
  - many phases:
    - duplicate elimination, anchor text extraction, language identification, index shard generation, etc.
  - end with data structures for index and doc serving

- Each phase was hand written parallel computation:
  - hand parallelized
  - hand-written checkpointing code for fault-tolerance

MapReduce

- A simple programming model that applies to many large-scale computing problems
  - allowed us to express all phases of our indexing system
  - since used across broad range of computer science areas, plus other scientific fields
  - Hadoop open-source implementation seeing significant usage
- Hide messy details in MapReduce runtime library:
  - automatic parallelization
  - load balancing
  - network and disk transfer optimizations
  - handling of machine failures
  - robustness
  - **improvements to core library benefit all users of library!**

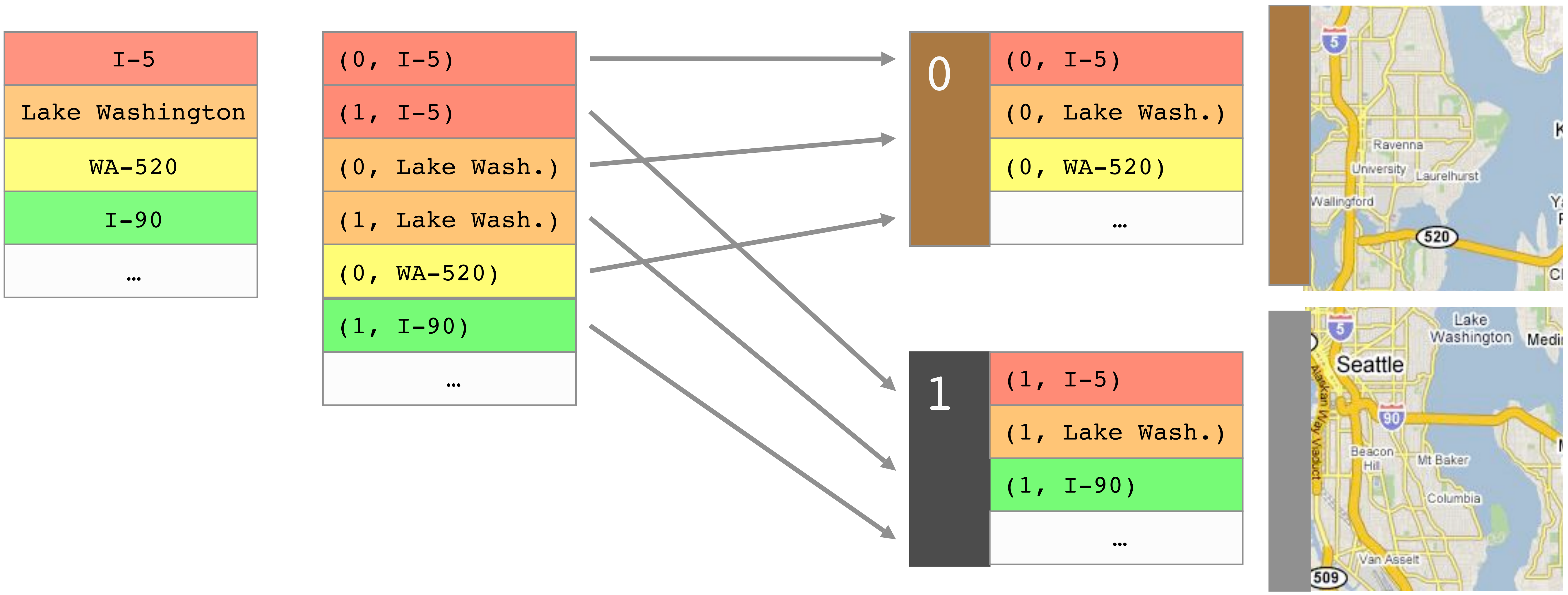
Typical problem solved by MapReduce

- Read a lot of data
- Map: extract something you care about from each record
- Shuffle and Sort
- Reduce: aggregate, summarize, filter, or transform
- Write the results

Outline stays the same,
User writes Map and Reduce functions to fit the problem

Example: Rendering Map Tiles

Input	Map	Shuffle	Reduce	Output
Geographic feature list	Emit feature to all overlapping latitude-longitude rectangles	Sort by key (key= Rect. Id)	Render tile using data for all enclosed features	Rendered tiles



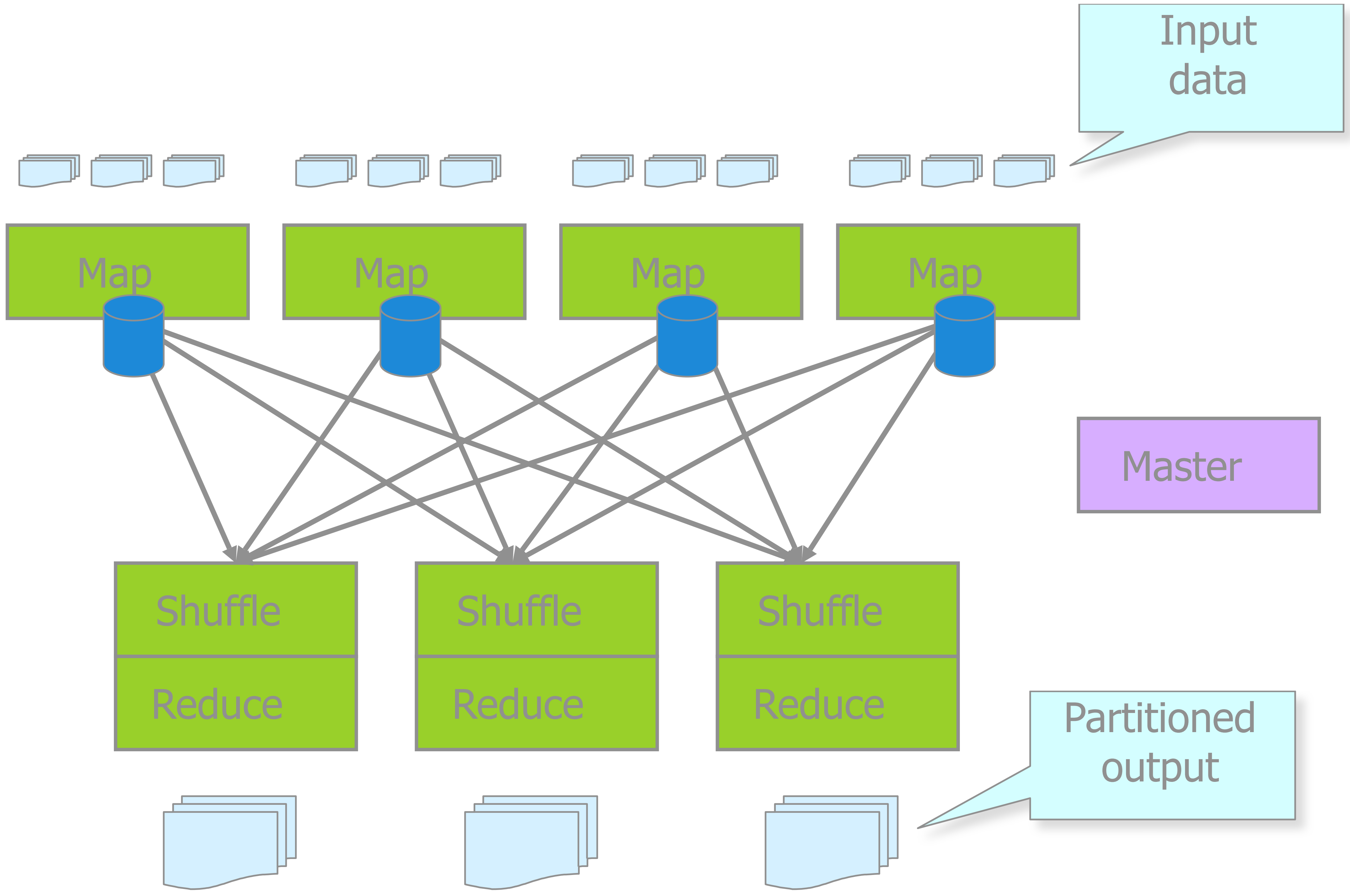
MapReduce: Scheduling

- **One master, many workers**
  - Input data split into *M* map tasks (typically 64 MB in size)
  - Reduce phase partitioned into *R* reduce tasks
  - Tasks are assigned to workers dynamically
  - Often: *M*=200,000; *R*=4,000; workers=2,000

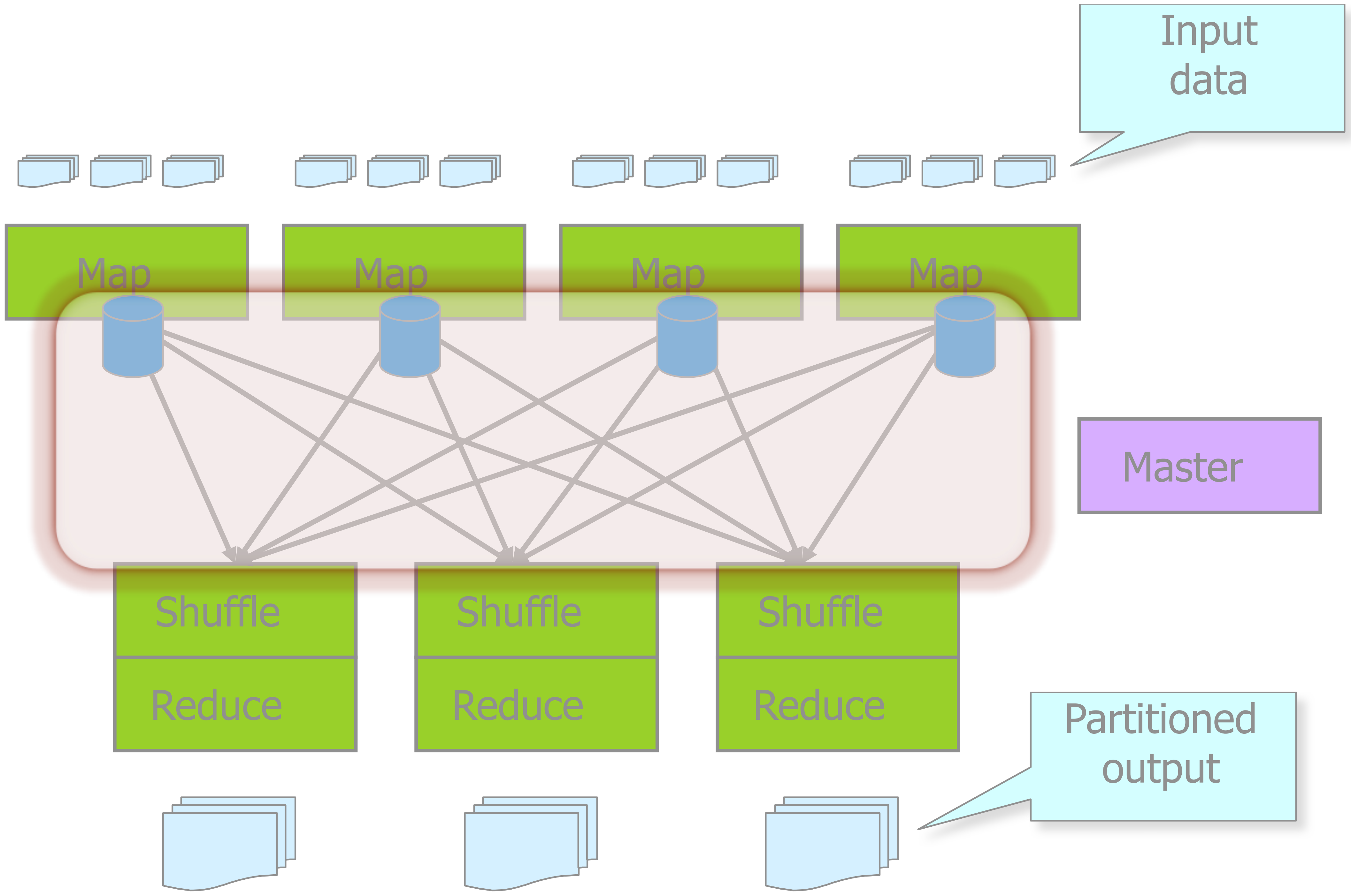
- **Master assigns each map task to a free worker**
  - Considers locality of data to worker when assigning task
  - Worker reads task input (often from local disk!)
  - Worker produces R **local files** containing intermediate k/v pairs

- **Master assigns each reduce task to a free worker**
  - Worker reads intermediate k/v pairs from map workers
  - Worker sorts & applies user's *Reduce* op to produce the output

Parallel MapReduce



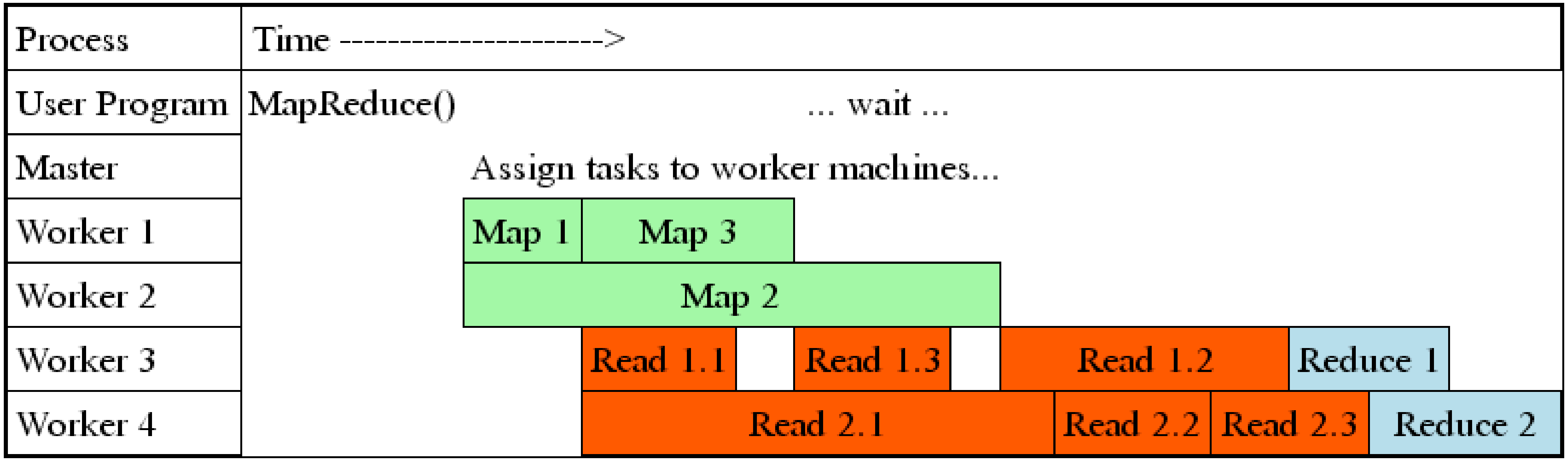
Parallel MapReduce



For large enough problems, it's more about disk and network performance than CPU & DRAM

Task Granularity and Pipelining

- Fine granularity tasks: many more map tasks than machines
  - Minimizes time for fault recovery
  - Can pipeline shuffling with map execution
  - Better dynamic load balancing



Fault tolerance: Handled via re-execution

On worker failure:

- Detect failure via periodic heartbeats
- Re-execute completed and in-progress map tasks
- Re-execute in progress reduce tasks
- Task completion committed through master

On master failure:

- State is checkpointed to GFS: new master recovers & continues

Very Robust: lost 1600 of 1800 machines once, but finished fine

Refinement: Backup Tasks

- Slow workers significantly lengthen completion time
  - Other jobs consuming resources on machine
  - Bad disks with soft errors transfer data very slowly
  - Weird things: processor caches disabled (!!)
- Solution: Near end of phase, spawn backup copies of tasks
  - Whichever one finishes first "wins"
- Effect: Dramatically shortens job completion time

Refinement: Locality Optimization

Master scheduling policy:

- Asks GFS for locations of replicas of input file blocks
- Map tasks typically split into 64MB (== GFS block size)
- Map tasks scheduled so GFS input block replica are on same machine or same rack

Effect: Thousands of machines read input at local disk speed

- Without this, rack switches limit read rate

MapReduce Usage Statistics Over Time

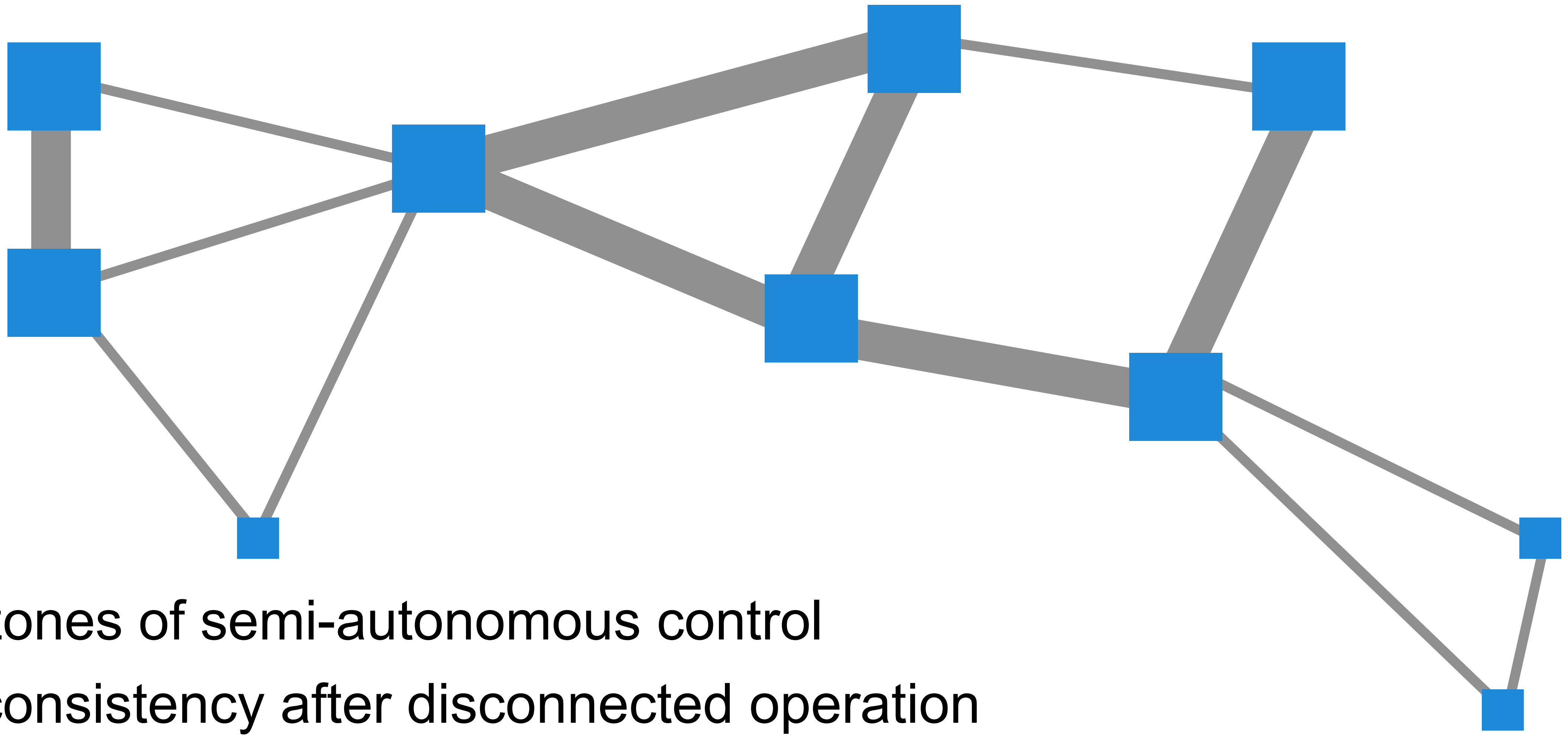
	Aug, ‘04	Mar, ‘06	Sep, '07	May, ’10
Number of jobs	29K	171K	2,217K	4,474K
Average completion time (secs)	634	874	395	748
Machine years used	217	2,002	11,081	39,121
Input data read (TB)	3,288	52,254	403,152	946,460
Intermediate data (TB)	758	6,743	34,774	132,960
Output data written (TB)	193	2,970	14,018	45,720
Average worker machines	157	268	394	368

Current Work: Spanner

- Storage & computation system that runs across many datacenters
  - single global namespace
    - names are independent of location(s) of data
    - fine-grained replication configurations
  - support mix of strong and weak consistency across datacenters
    - Strong consistency implemented with Paxos across tablet replicas
    - Full support for distributed transactions across directories/machines
  - much more automated operation
    - automatically changes replication based on constraints and usage patterns
    - automated allocation of resources across entire fleet of machines

Design Goals for Spanner

- Future scale: ~10^5 to 10^7 machines, ~10^{13} directories, ~10^{18} bytes of storage, spread at 100s to 1000s of locations around the world



  – zones of semi-autonomous control
  – consistency after disconnected operation
  – users specify high-level desires:
    "99%ile latency for accessing this data should be <50ms"
    "Store this data on at least 2 disks in EU, 2 in U.S. & 1 in Asia"

System Building Experiences and Patterns

- Experiences from building a variety of systems
  - A collection of patterns that have emerged
  - Not all encompassing, obviously, but good rules of thumb

Many Internal Services

- Break large complex systems down into many services!
- Simpler from a software engineering standpoint
  - few dependencies, clearly specified
  - easy to test and deploy new versions of individual services
  - ability to run lots of experiments
  - easy to reimplement service without affecting clients
- Development cycles largely decoupled
  - lots of benefits: small teams can work independently
  - easier to have many engineering offices around the world
- e.g. `google.com` search touches 200+ services
  - ads, web search, books, news, spelling correction, ...

Designing Efficient Systems

Given a basic problem definition, how do you choose "best" solution?

- Best might be simplest, highest performance, easiest to extend, etc.

Important skill: ability to estimate performance of a system design

– without actually having to build it!

Numbers Everyone Should Know

L1 cache reference	0.5 ns
Branch mispredict	5 ns
L2 cache reference	7 ns
Mutex lock/unlock	25 ns
Main memory reference	100 ns
Compress 1K w/cheap compression algorithm	3,000 ns
Send 2K bytes over 1 Gbps network	20,000 ns
Read 1 MB sequentially from memory	250,000 ns
Round trip within same datacenter	500,000 ns
Disk seek	10,000,000 ns
Read 1 MB sequentially from disk	20,000,000 ns
Send packet CA->Netherlands->CA	150,000,000 ns

Back of the Envelope Calculations

How long to generate image results page (30 thumbnails)?

Design 1: Read serially, thumbnail 256K images on the fly

```
30 seeks * 10 ms/seek + 30 * 256K / 30 MB/s = 560 ms
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(Ignores variance, so really more like 30-60 ms, probably)

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Lots of variations:

- caching (single images? whole sets of thumbnails?)
- pre-computing thumbnails
- …

Back of the envelope helps identify most promising…

Know Your Basic Building Blocks

Core language libraries, basic data structures, protocol buffers, GFS, BigTable, indexing systems, MapReduce, …

Not just their interfaces, but understand their implementations (at least at a high level)

If you don’t know what’s going on, you can’t do decent back-of-the-envelope calculations!

Designing & Building Infrastructure

Identify common problems, and build software systems to address them in a general way

- Important to not try to be all things to all people
  - Clients might be demanding 8 different things
  - Doing 6 of them is easy
  - …handling 7 of them requires real thought
  - …dealing with all 8 usually results in a worse system
    - more complex, compromises other clients in trying to satisfy everyone

Designing & Building Infrastructure (cont)

Don't build infrastructure just for its own sake:

- Identify common needs and address them
- Don't imagine unlikely potential needs that aren't really there

Best approach: use your own infrastructure (especially at first!)

- (much more rapid feedback about what works, what doesn't)

Design for Growth

Try to anticipate how requirements will evolve

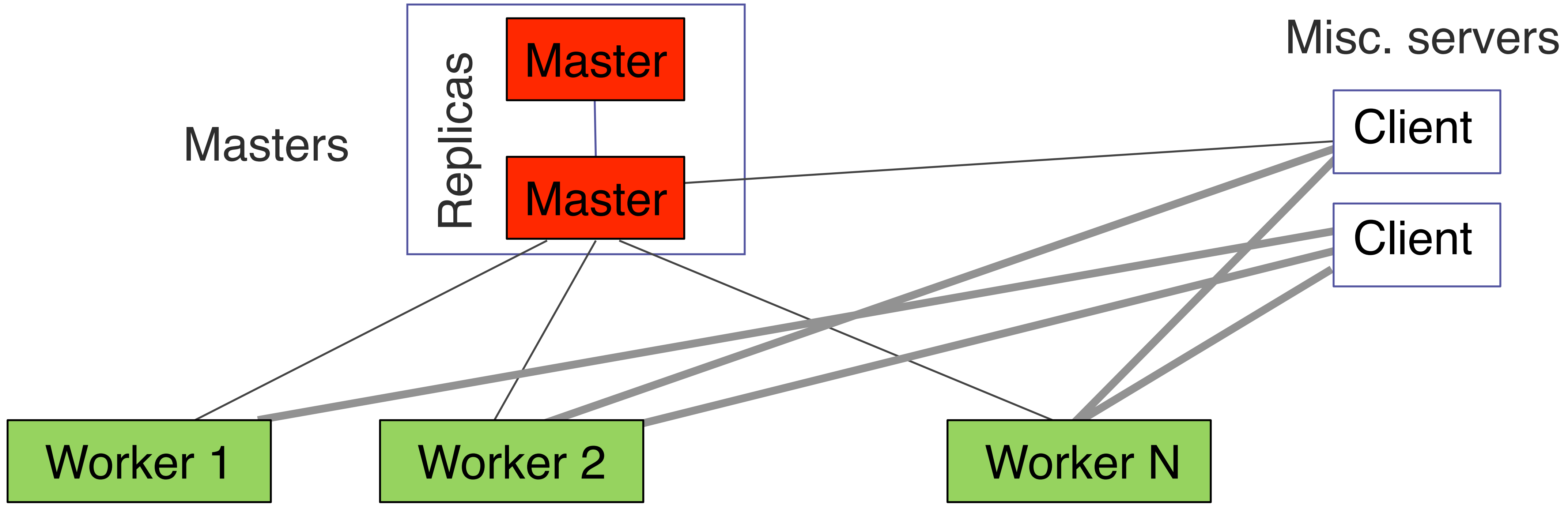
- keep likely features in mind as you design base system

Don’t design to scale infinitely:

- ~5X - 50X growth good to consider
- >100X probably requires rethink and rewrite

Pattern: Single Master, 1000s of Workers

- Master orchestrates global operation of system
  - load balancing, assignment of work, reassignment when machines fail, etc.
  - ... but client interaction with master is fairly minimal



- Examples:
  - GFS, BigTable, MapReduce, file transfer service, cluster scheduling system, ...

Pattern: Single Master, 1000s of Workers (cont)

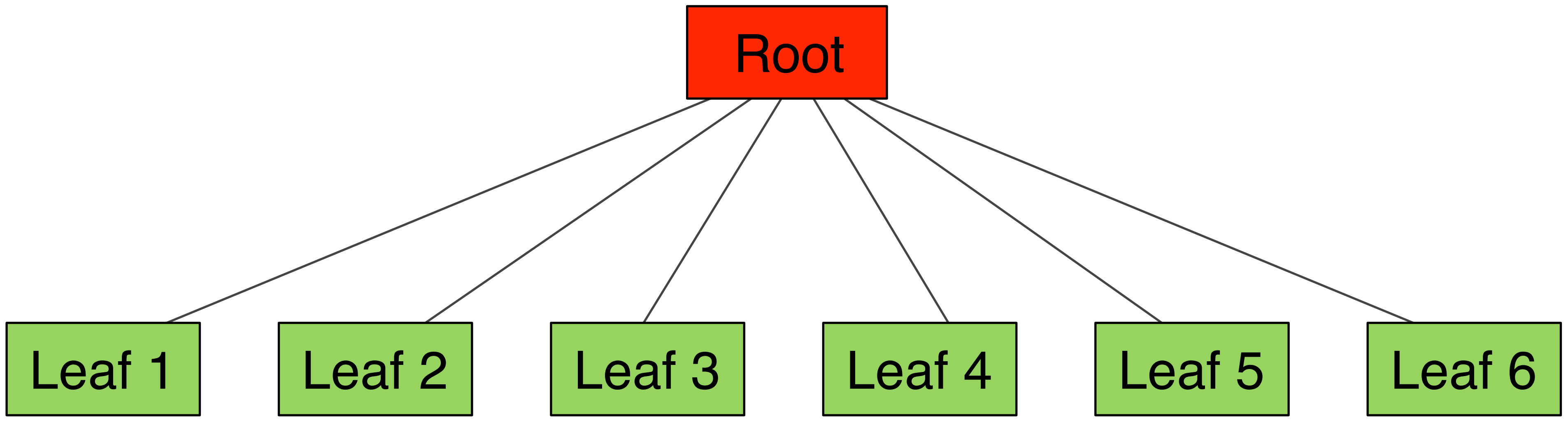
- Often: hot standby of master waiting to take over
- Always: bulk of data transfer directly between clients and workers

- Pro:
  - simpler to reason about state of system with centralized master

- Caveats:
  - careful design required to keep master out of common case ops
  - scales to 1000s of workers, but not 100,000s of workers

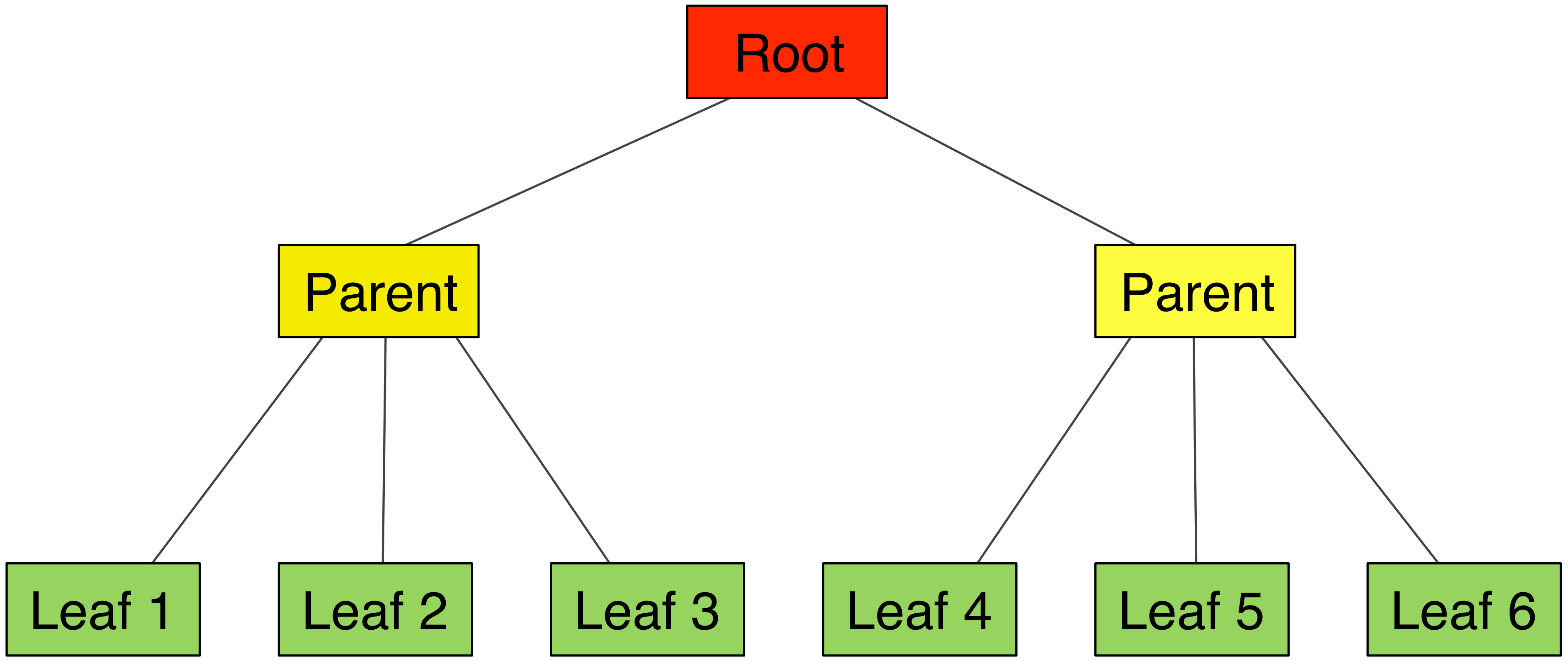
Pattern: Tree Distribution of Requests

- Problem: Single machine sending 1000s of RPCs overloads NIC on machine when handling replies
  - wide fan in causes TCP drops/retransmits, significant latency
  - CPU becomes bottleneck on single machine



Pattern: Tree Distribution of Requests

- Solution: Use tree distribution of requests/responses
  - fan in at root is smaller
  - cost of processing leaf responses spread across many parents
- Most effective when parent processing can trim/combine leaf data
  - can also co-locate parents on same rack as leaves



Pattern: Backup Requests to Minimize Latency

- Problem: variance high when requests go to 1000s of machines
  - last few machines to respond stretch out latency tail substantially

- Often, multiple replicas can handle same kind of request
- When few tasks remaining, send backup requests to other replicas
- Whichever duplicate request finishes first wins
  - useful when variance is unrelated to specifics of request
  - increases overall load by a tiny percentage
  - decreases latency tail significantly

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- Examples:

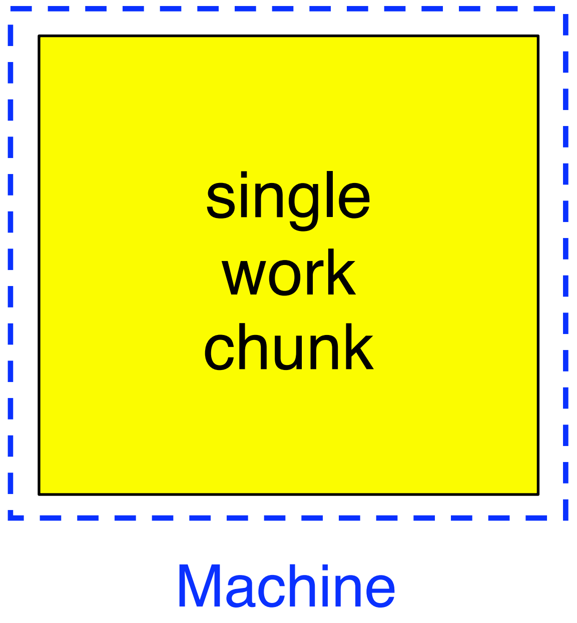
– MapReduce backup tasks (granularity: many seconds)

– various query serving systems (granularity: milliseconds)

Pattern: Multiple Smaller Units per Machine

- Problems:
  - want to minimize recovery time when machine crashes
  - want to do fine-grained load balancing

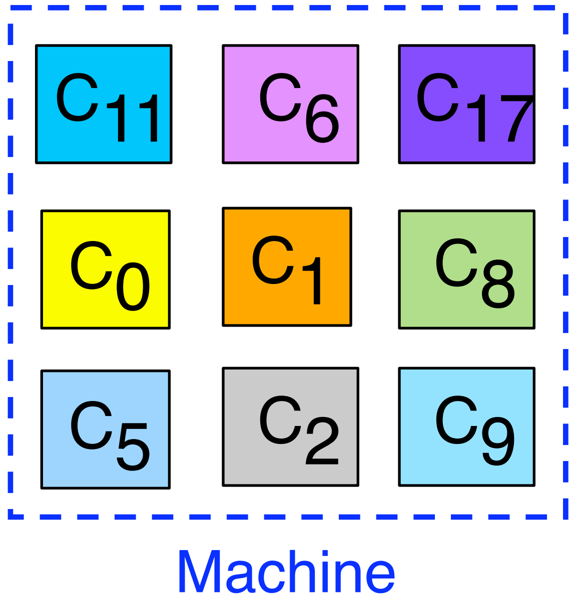
- Having each machine manage 1 unit of work is inflexible
  - slow recovery: new replica must recover data that is O(machine state) in size
  - load balancing much harder



Pattern: Multiple Smaller Units per Machine

- Have each machine manage many smaller units of work/data
  - typical: ~10-100 units/machine
  - allows fine grained load balancing (shed or add one unit)
  - fast recovery from failure (N machines each pick up 1 unit)

- Examples:
  - map and reduce tasks, GFS chunks, Bigtable tablets, query serving system index shards



Pattern: Elastic Systems

- Problem: Planning for exact peak load is hard
  - overcapacity: wasted resources
  - undercapacity: meltdown

- Design system to adapt:
  - automatically shrink capacity during idle period
  - automatically grow capacity as load grows

- Make system resilient to overload:
  - do something reasonable even up to 2X planned capacity
    - e.g. shrink size of index searched, back off to less CPU intensive algorithms, drop spelling correction tips, etc.
  - more aggressive load balancing when imbalance more severe

Pattern: Combine Multiple Implementations

- Example: Google web search system wants all of these:
  - freshness (update documents in ~1 second)
  - massive capacity (10000s of requests per second)
  - high quality retrieval (lots of information about each document)
  - massive size (billions of documents)

- Very difficult to accomplish in single implementation

- Partition problem into several subproblems with different engineering tradeoffs. E.g.
  - realtime system: few docs, ok to pay lots of $$$/doc
  - base system: high # of docs, optimized for low $/doc
  - realtime+base: high # of docs, fresh, low $/doc

Final Thoughts

Today: exciting collection of trends:

- large-scale datacenters +
- increasing scale and diversity of available data sets +
- proliferation of more powerful client devices

Many interesting opportunities:

- planetary scale distributed systems
- development of new CPU and data intensive services
- new tools and techniques for constructing such systems

- Fun and interesting times are ahead of us!

Thanks! Questions...?

Further reading:

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These and many more available at: http://labs.google.com/papers.html