Challenges in Building Large-Scale Information Retrieval Systems

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Why Work on Retrieval Systems?

- Challenging blend of science and engineering
  - Many interesting, unsolved problems
  - Spans many areas of CS:
    - architecture, distributed systems, algorithms, compression, information retrieval, machine learning, UI, etc.
  - Scale far larger than most other systems

- Small teams can create systems used by hundreds of millions

Retrieval System Dimensions

- Must balance engineering tradeoffs between:
  - number of documents indexed
  - queries / sec
  - index freshness/update rate
  - query latency
  - information kept about each document
  - complexity/cost of scoring/retrieval algorithms
- Engineering difficulty roughly equal to the product of these parameters
- All of these affect overall performance, and performance per $

1999 vs. 2009

- # docs: ~70M to many billion
- queries processed/day:
- per doc info in index:
- update latency: months to minutes
- avg. query latency: <1s to <0.2s

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Google

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- More machines * faster machines: **~1000X**

Google

Constant Change

- Parameters change over time
  - often by many orders of magnitude
- Right design at X may be very wrong at 10X or 100X
  - ... design for ~10X growth, but plan to rewrite before ~100X
- Continuous evolution:
  - 7 significant revisions in last 10 years
  - often rolled out without users realizing we've made major changes

Rest of Talk

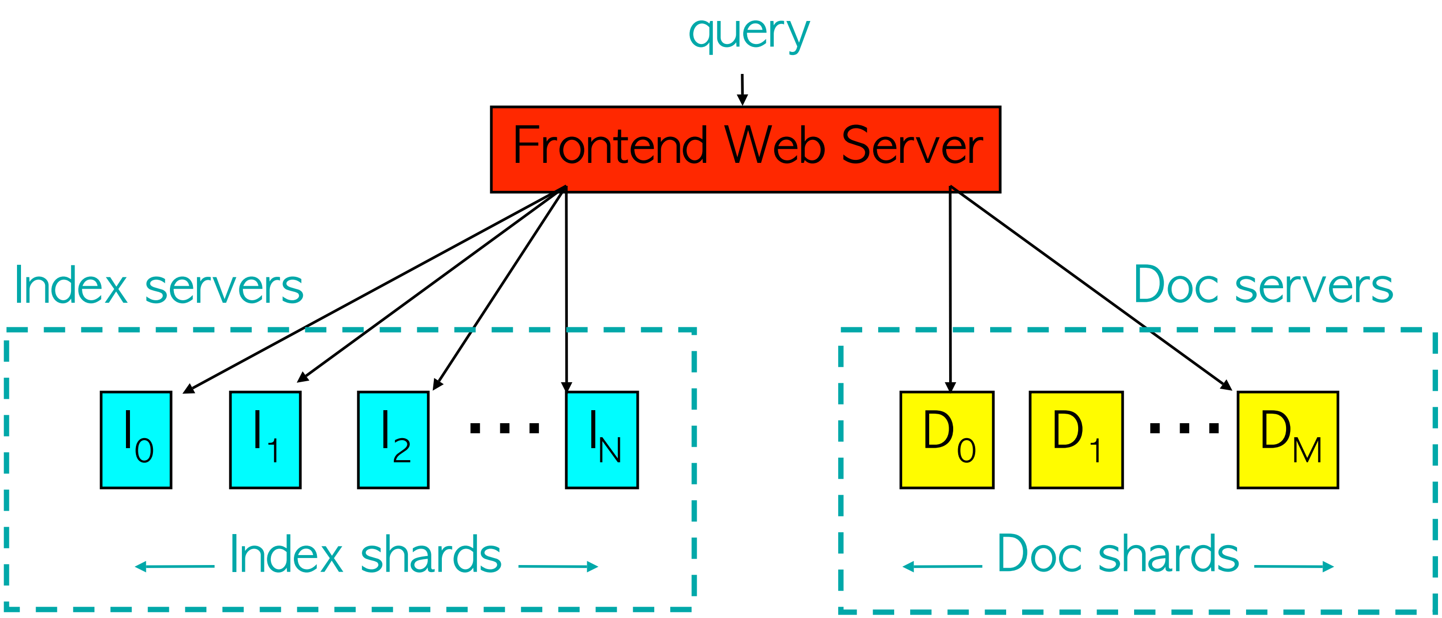
- Evolution of Google's search systems
  - several gens of crawling/indexing/serving systems
  - brief description of supporting infrastructure

  - Joint work with many, many people

- Interesting directions and challenges

"Google" Circa 1997 (google.stanford.edu)

Research Project, circa 1997



Google

Ways of Index Partitioning

- **By doc**: each shard has index for subset of docs
  - pro: each shard can process queries independently
  - pro: easy to keep additional per-doc information
  - pro: network traffic (requests/responses) small
  - con: query has to be processed by each shard
  - con: O(K*N) disk seeks for K word query on N shards

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  - con: query has to be processed by each shard
  - con: O(K*N) disk seeks for K word query on N shards
- **By word**: shard has subset of words for all docs
  - pro: K word query => handled by at most K shards
  - pro: O(K) disk seeks for K word query
  - con: much higher network bandwidth needed
    - data about each word for each matching doc must be collected in one place
  - con: harder to have per-doc information

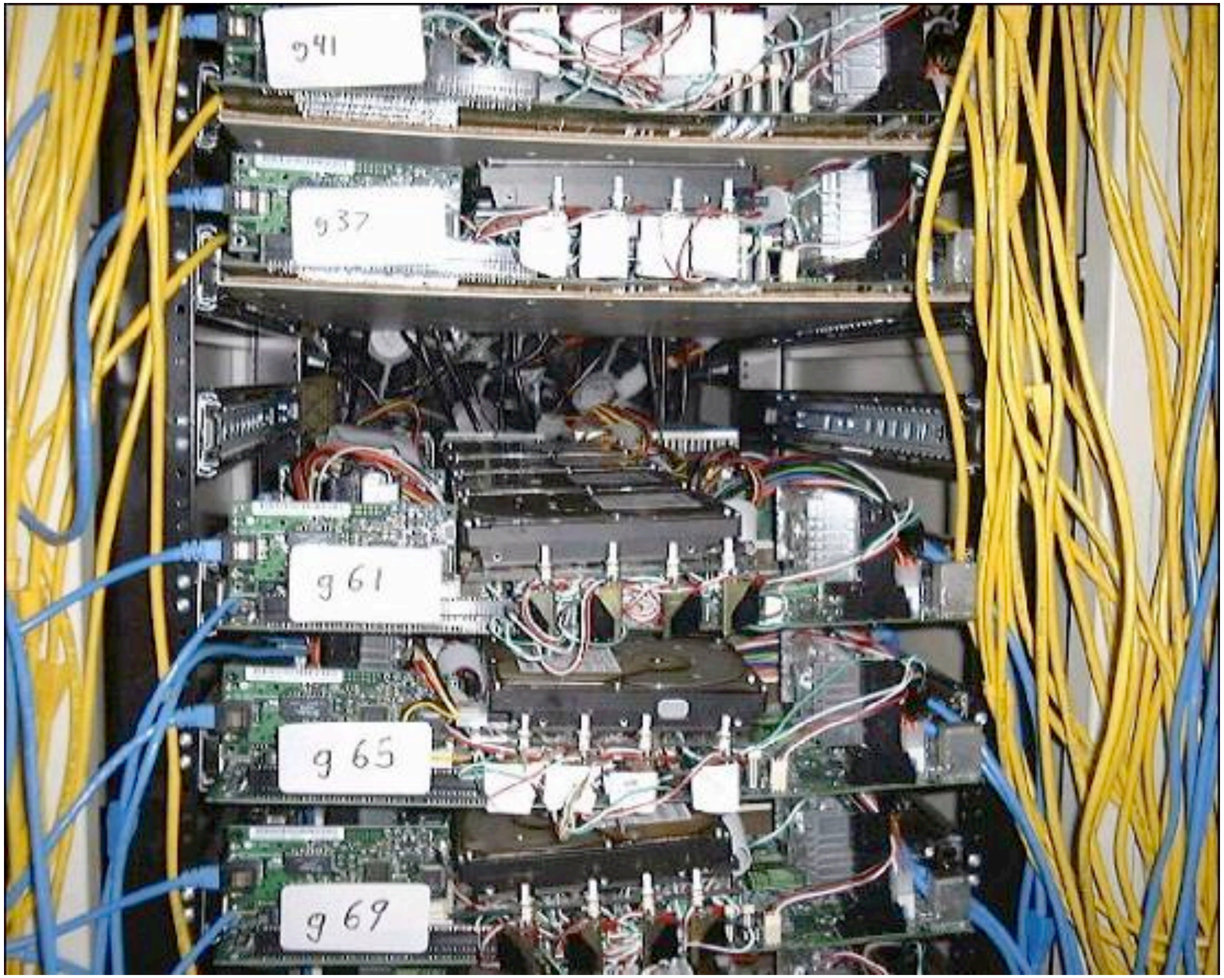
Ways of Index Partitioning

In our computing environment, by doc makes more sense

Basic Principles

- Documents assigned small integer ids (docids)
  - good if smaller for higher quality/more important docs
- Index Servers:
  - given (query) return sorted list of (score, docid, ...)
  - partitioned ("sharded") by docid
  - index shards are replicated for capacity
  - cost is O(# queries * # docs in index)
- Doc Servers
  - given (docid, query) generate (title, snippet)
  - map from docid to full text of docs on disk
  - also partitioned by docid
  - cost is O(# queries)

“Corkboards” (1999)



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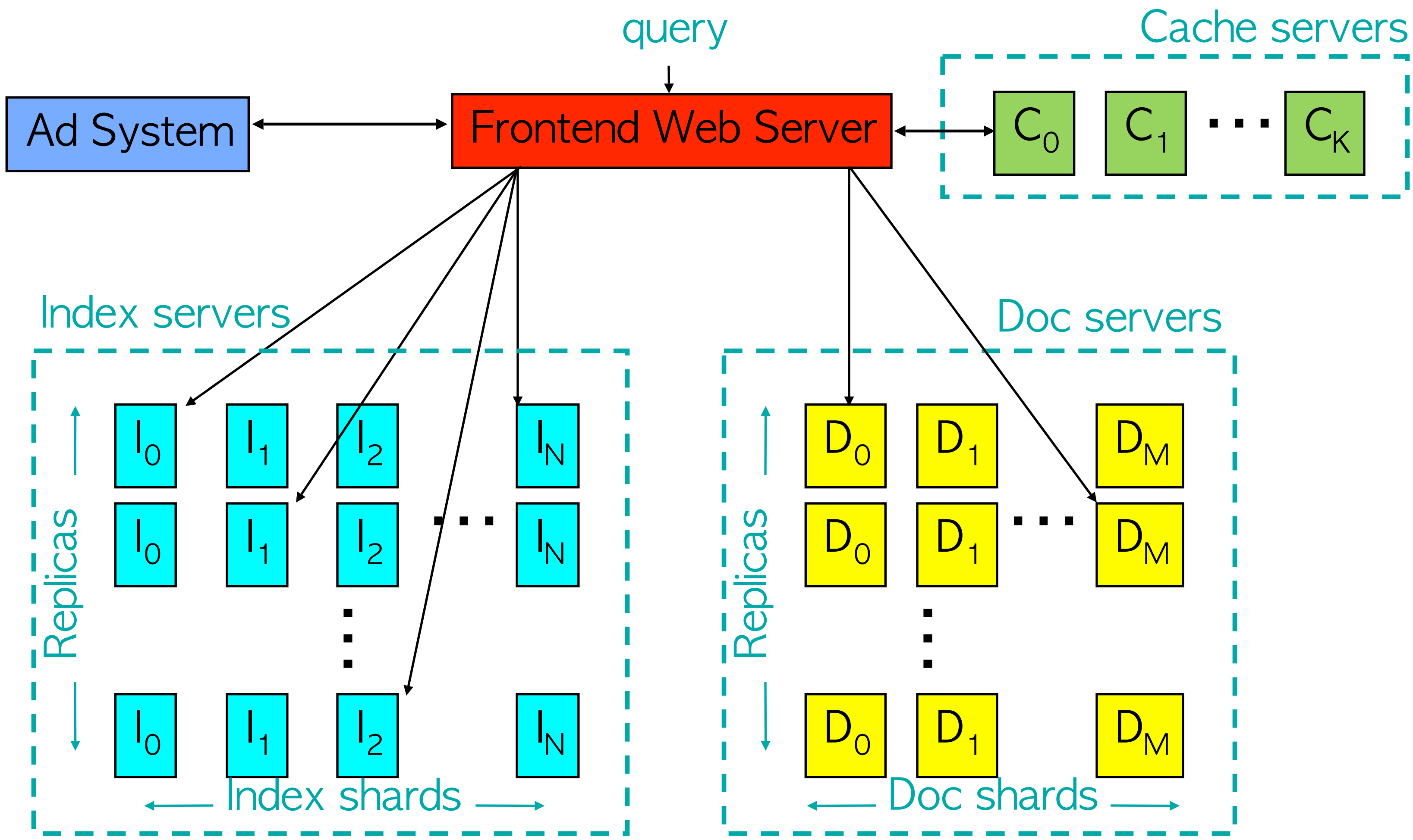
Serving System, circa 1999



Caching

- 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! 10s of machines do work of 100s or 1000s
  - reduce 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

Crawling (circa 1998-1999)

- Simple batch crawling system
  - start with a few URLs
  - crawl pages
  - extract links, add to queue
  - stop when you have enough pages
- Concerns:
  - don't hit any site too hard
  - prioritizing among uncrawled pages
    - one way: continuously compute PageRank on changing graph
  - maintaining uncrawled URL queue efficiently
    - one way: keep in a partitioned set of servers
  - dealing with machine failures

Indexing (circa 1998-1999)

- Simple batch indexing system
  - Based on simple unix tools
  - 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

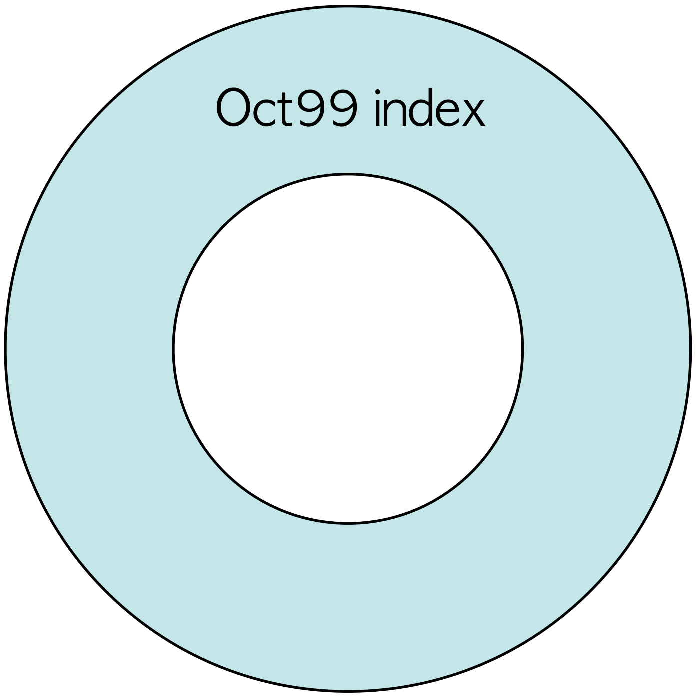
- “Programming with adversarial memory”
  - Led us to develop a file abstraction that stored checksums of small records and could skip and resynchronize after corrupted records

Index Updates (circa 1998-1999)

- 1998-1999: Index updates (~once per month):
  - Wait until traffic is low
  - Take some replicas offline
  - Copy new index to these replicas
  - Start new frontends pointing at updated index and serve some traffic from there

Index Updates (circa 1998-1999)

- Index server disk:
  - outer part of disk gives higher disk bandwidth



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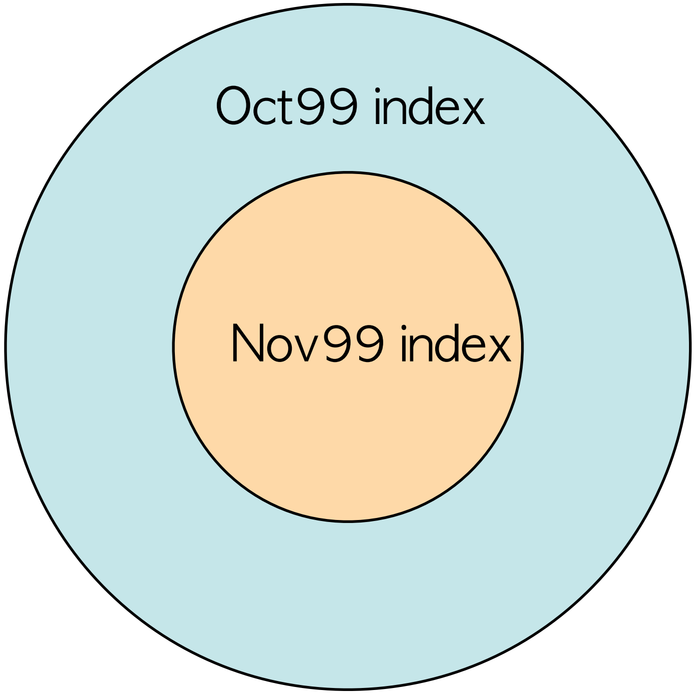
1. Copy new index to inner half of disk (while still serving old index)

2. Restart to use new index



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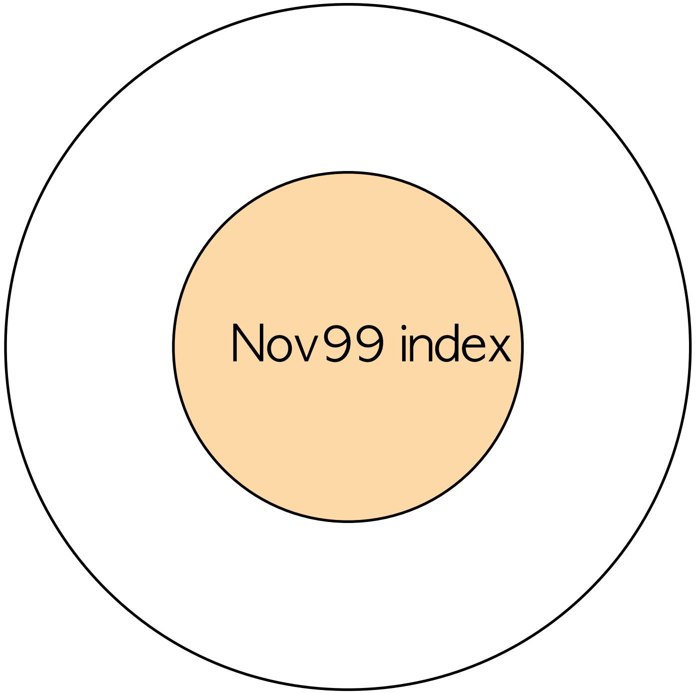

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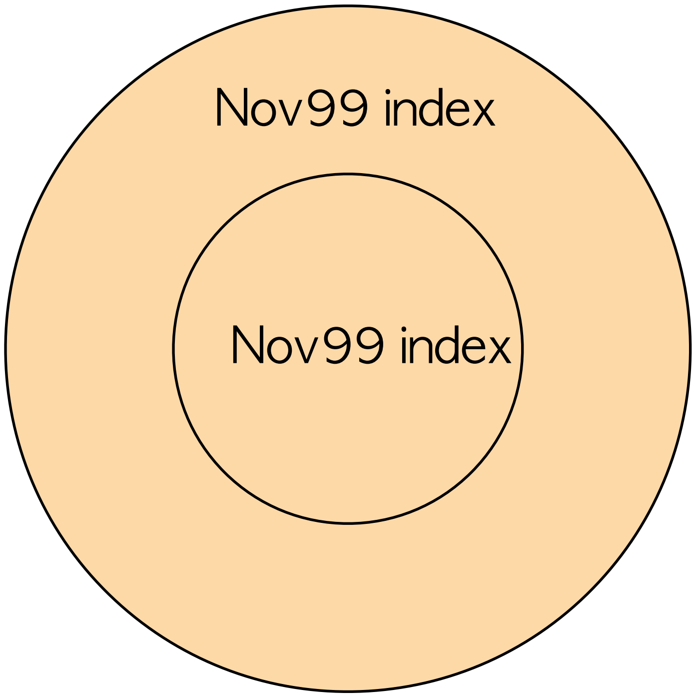

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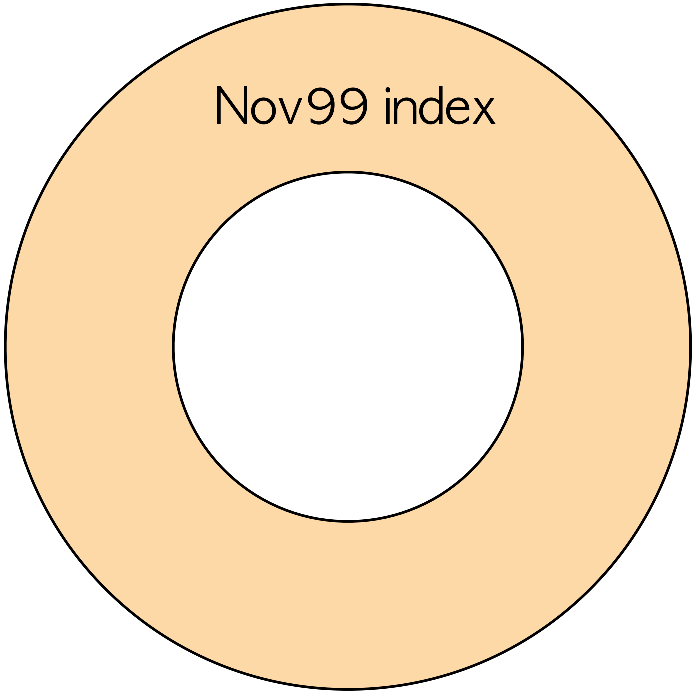

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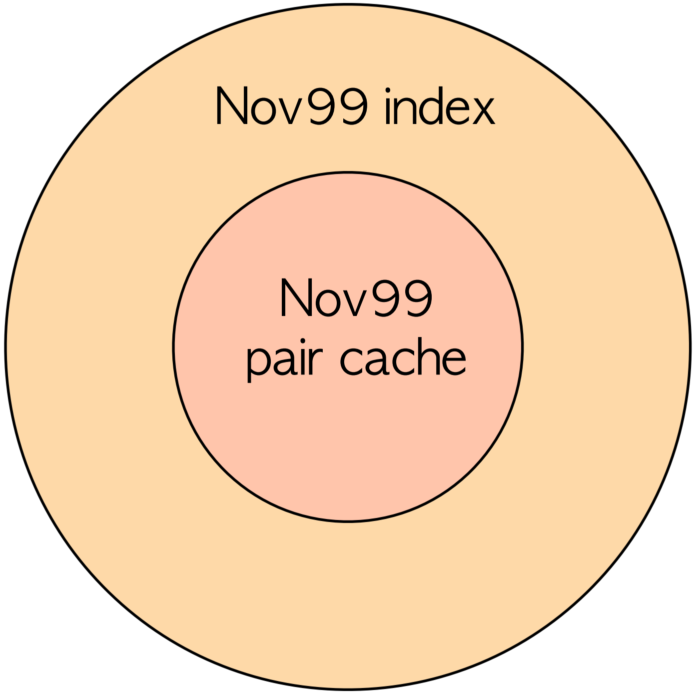
5. Wipe first copy of new index
6. Inner half now free for building various performance improving data structures



Pair cache: pre-intersected pairs of posting lists for commonly co-occurring query terms (e.g. “new” and “york”, or “barcelona” and “restaurants”)

Google Data Center (2000)

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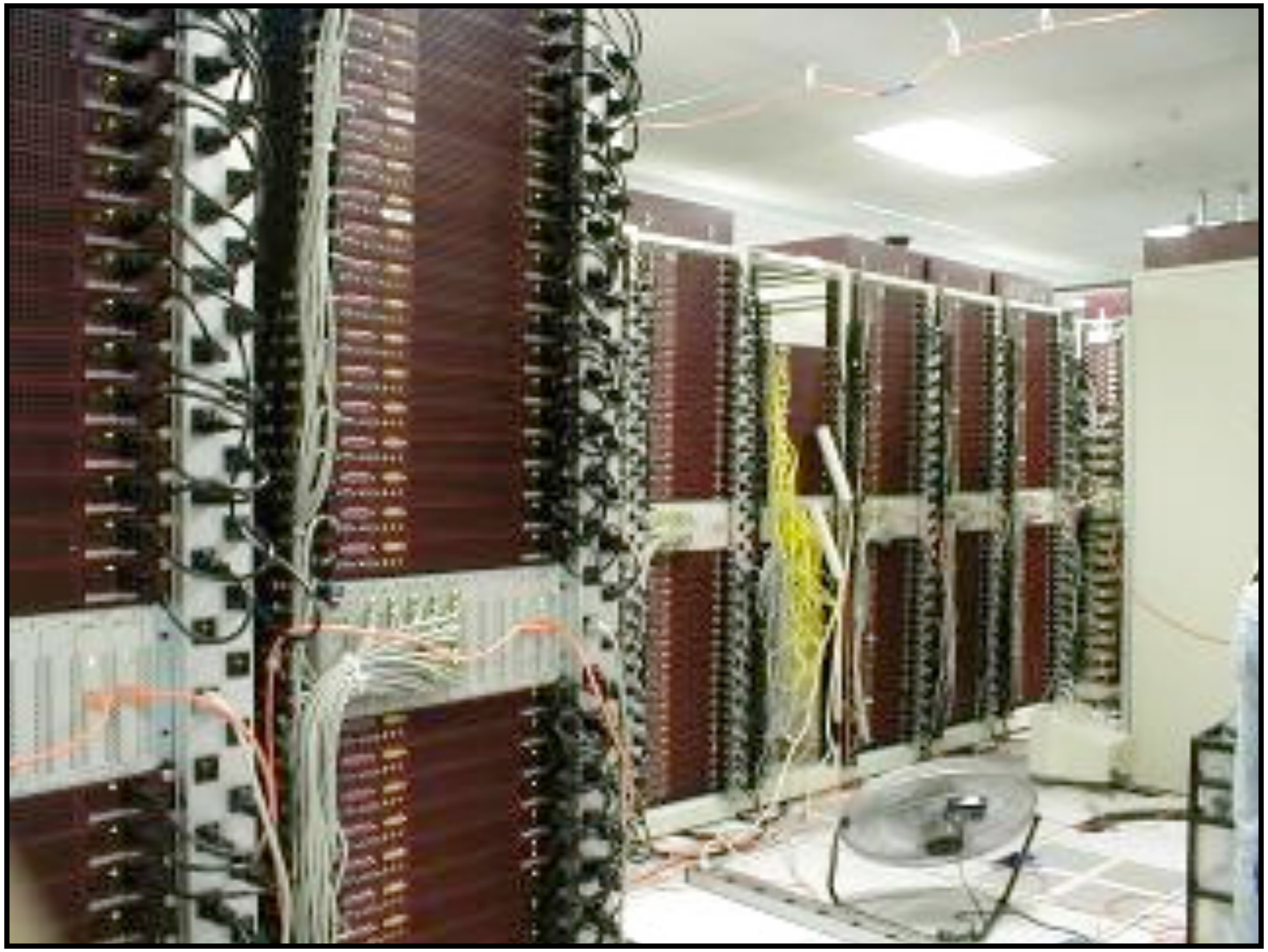

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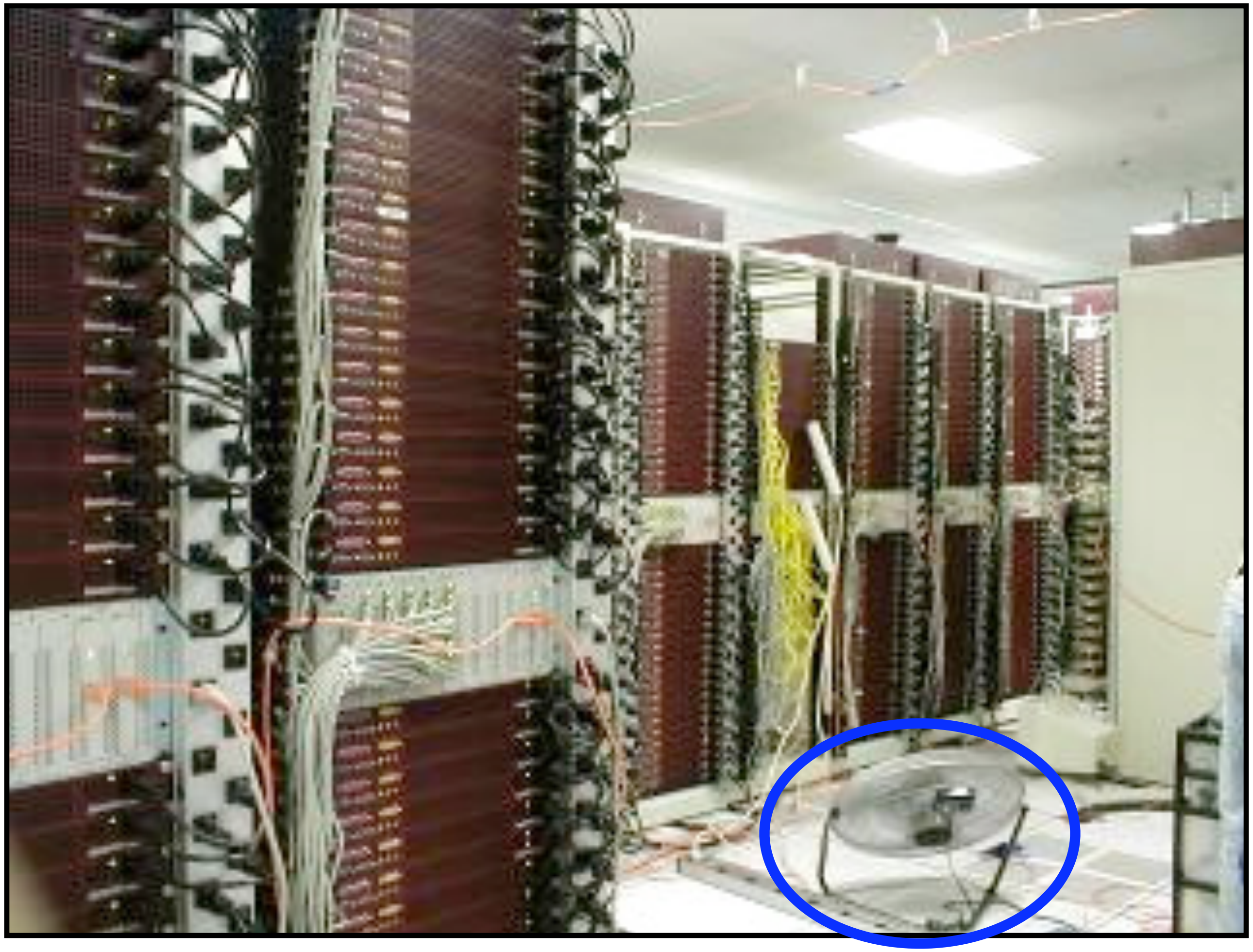
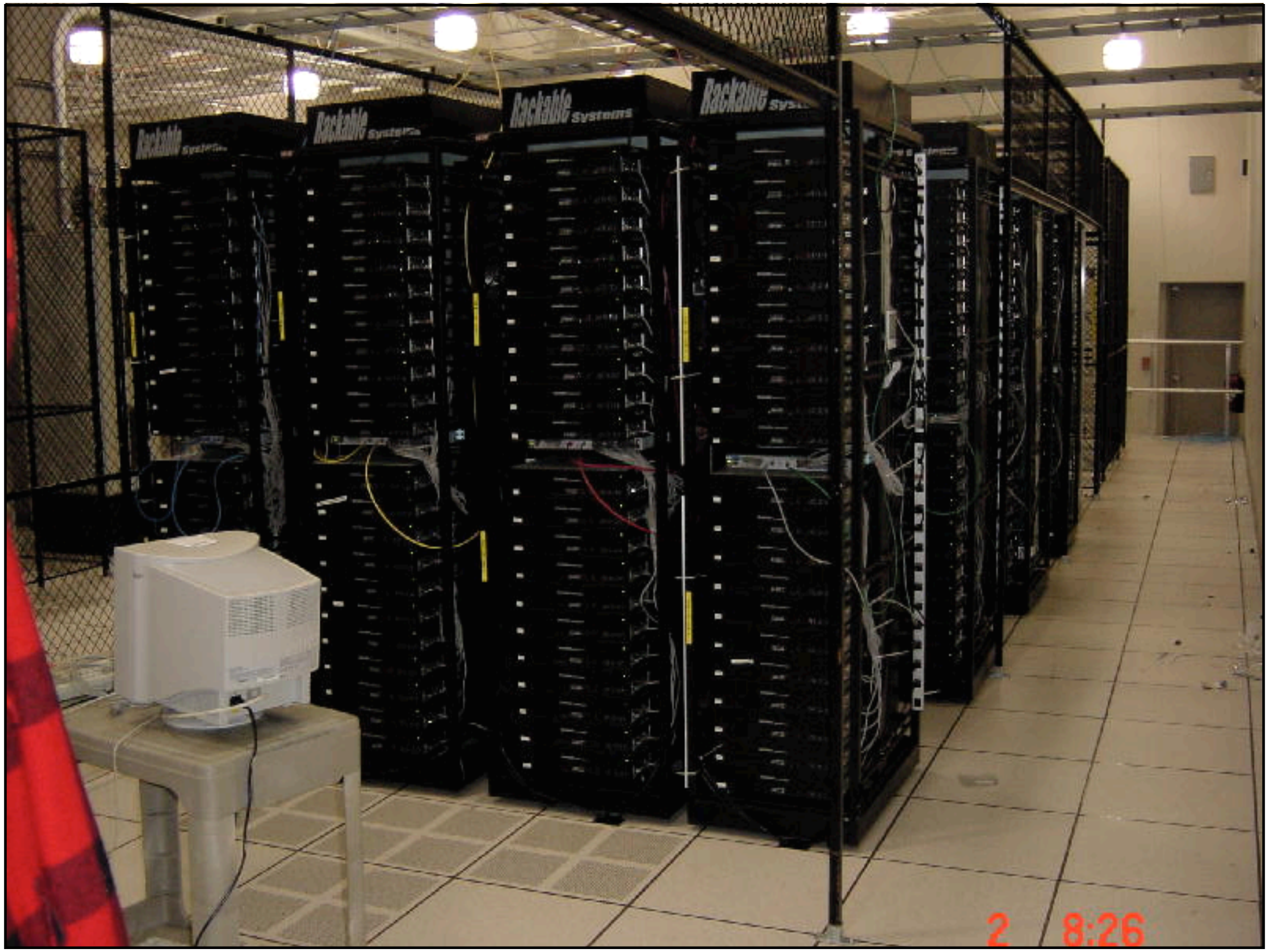


Google (new data center 2001)

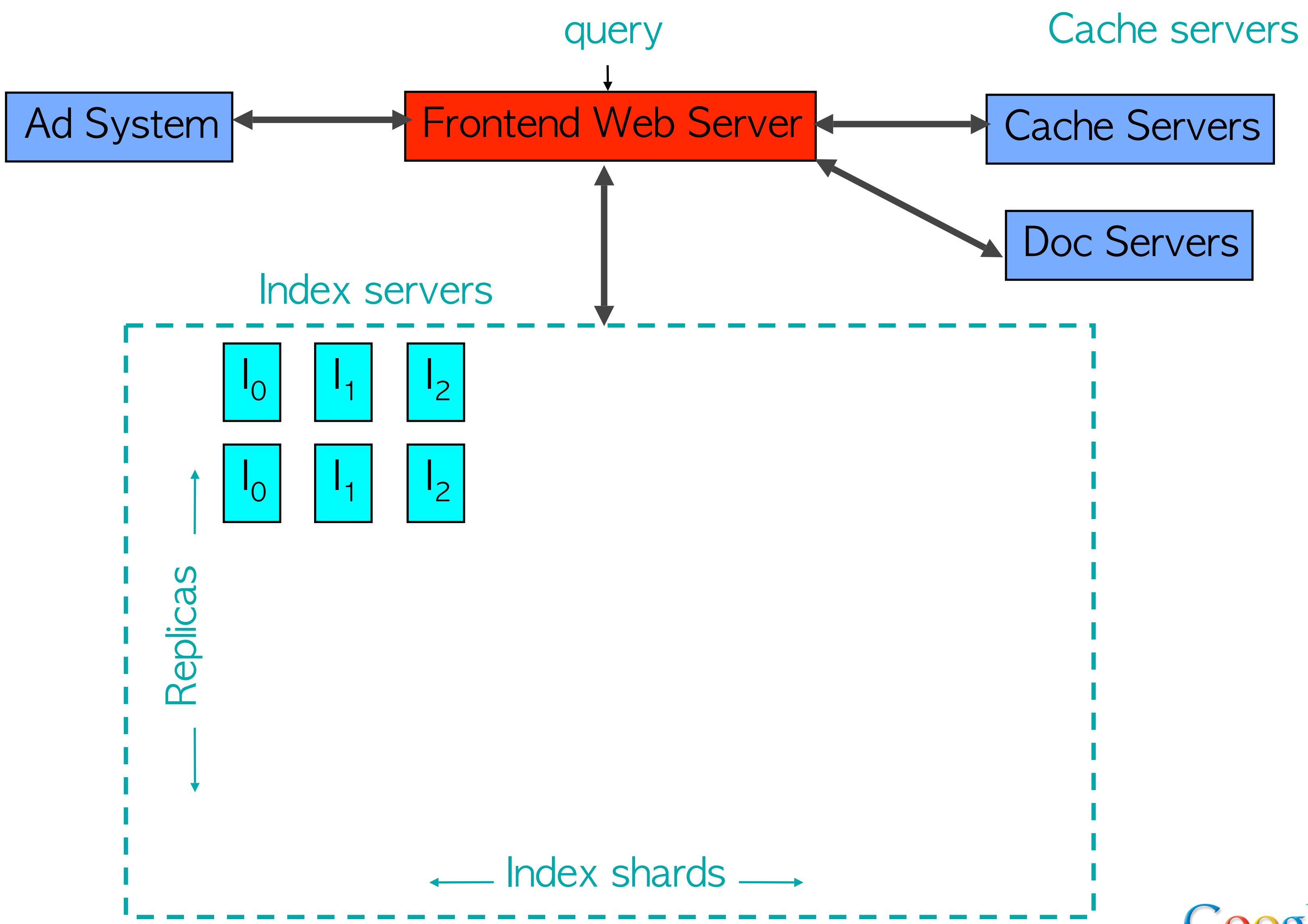
Google Data Center (3 days later)



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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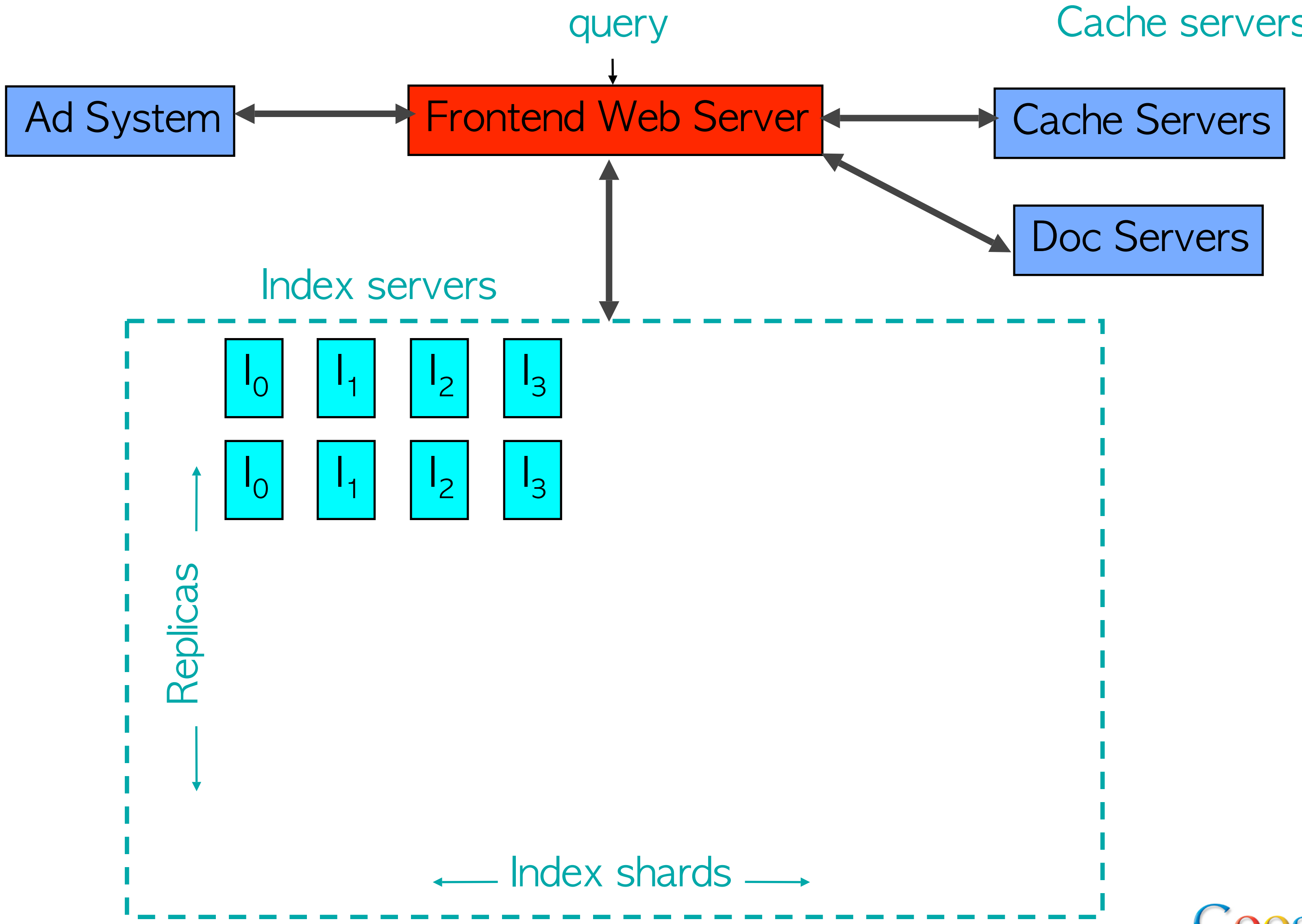

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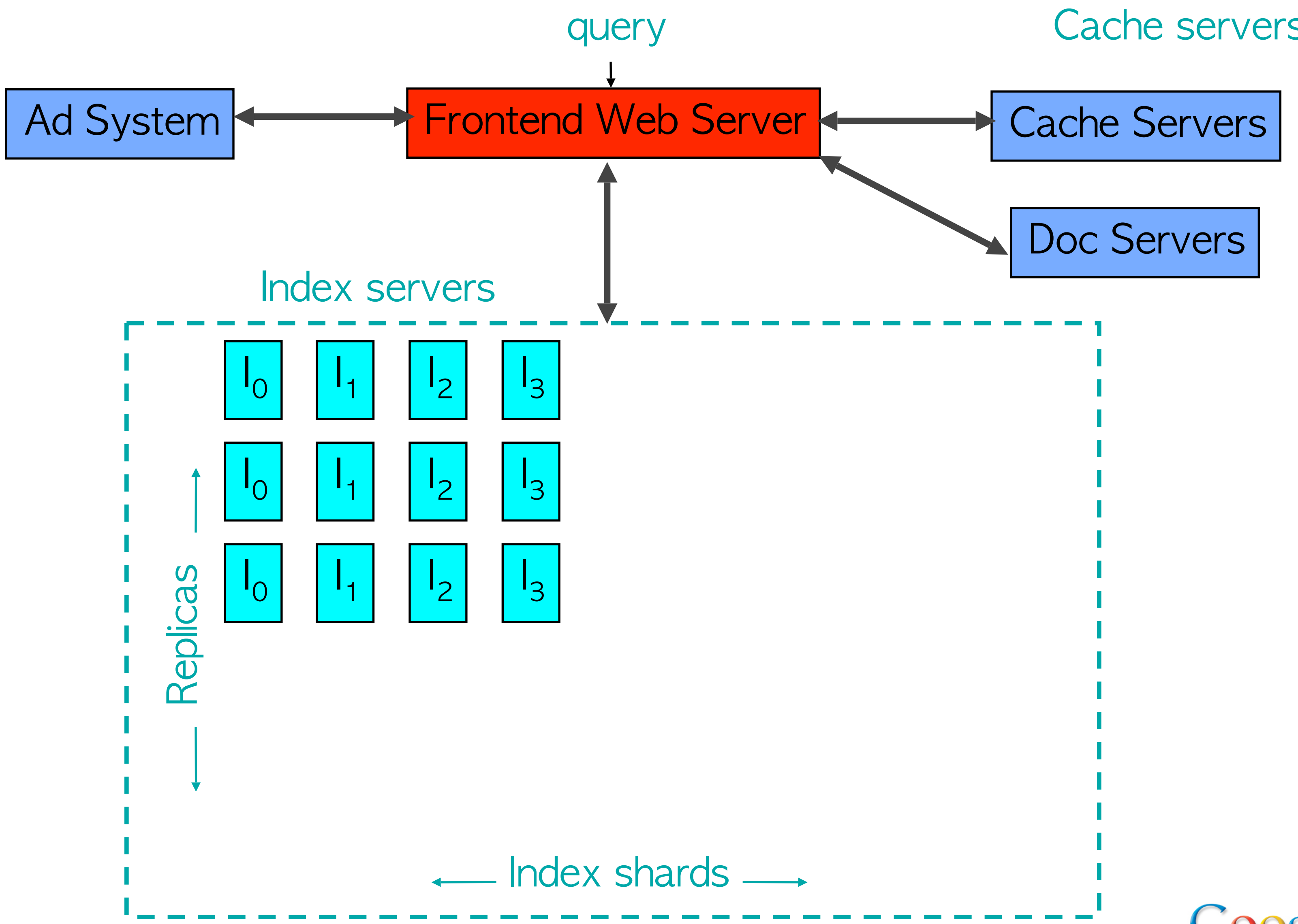

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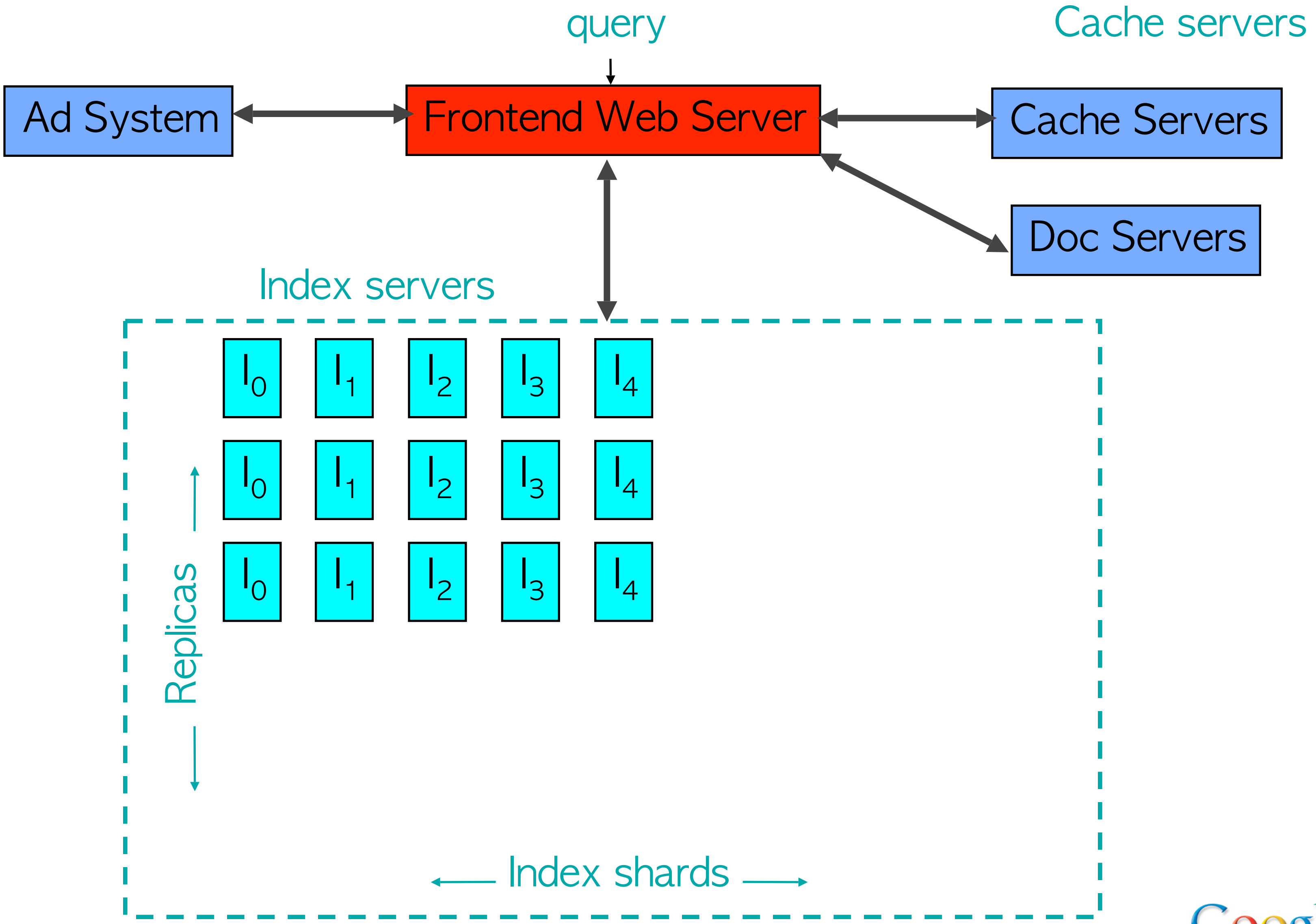

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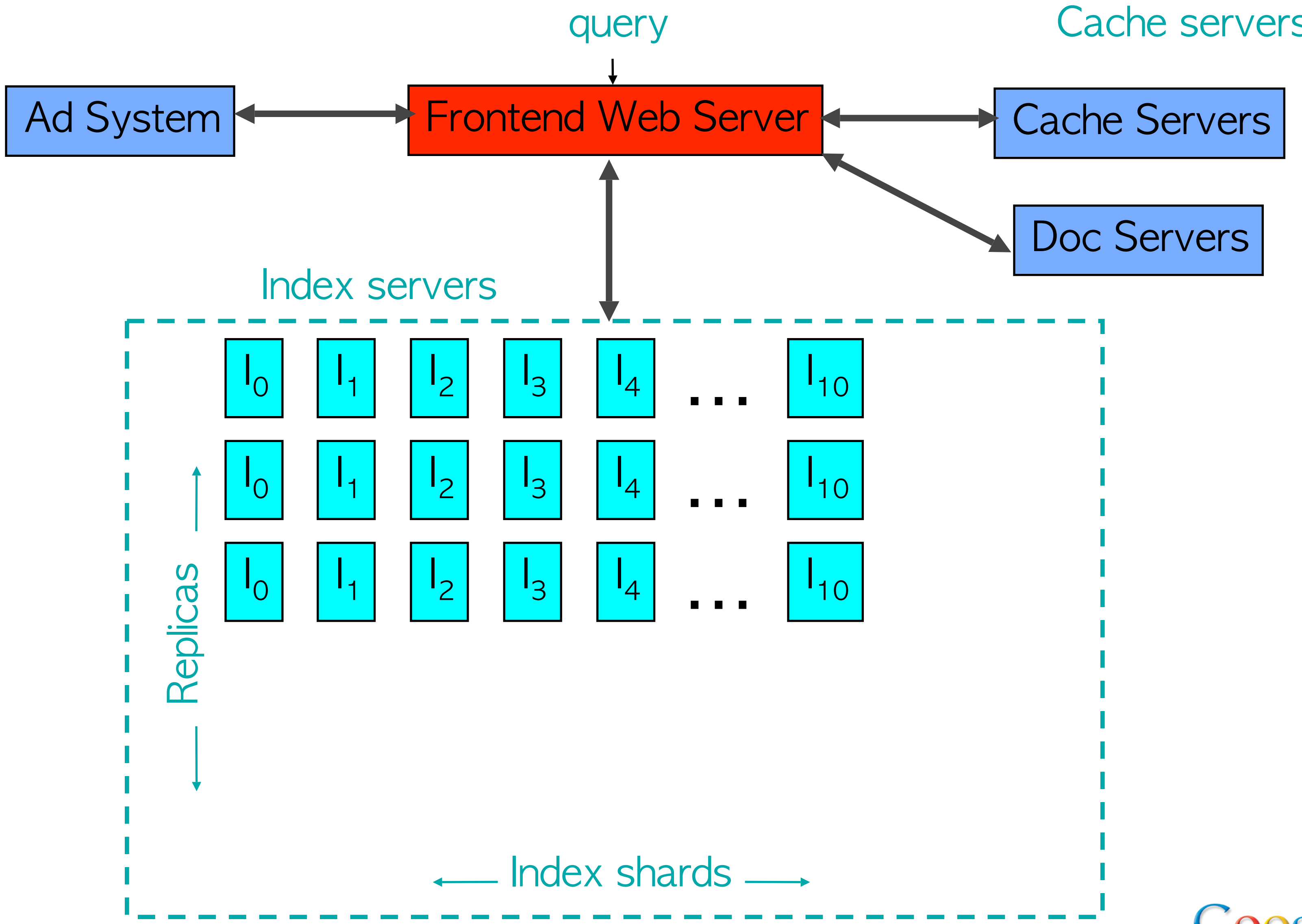

Google

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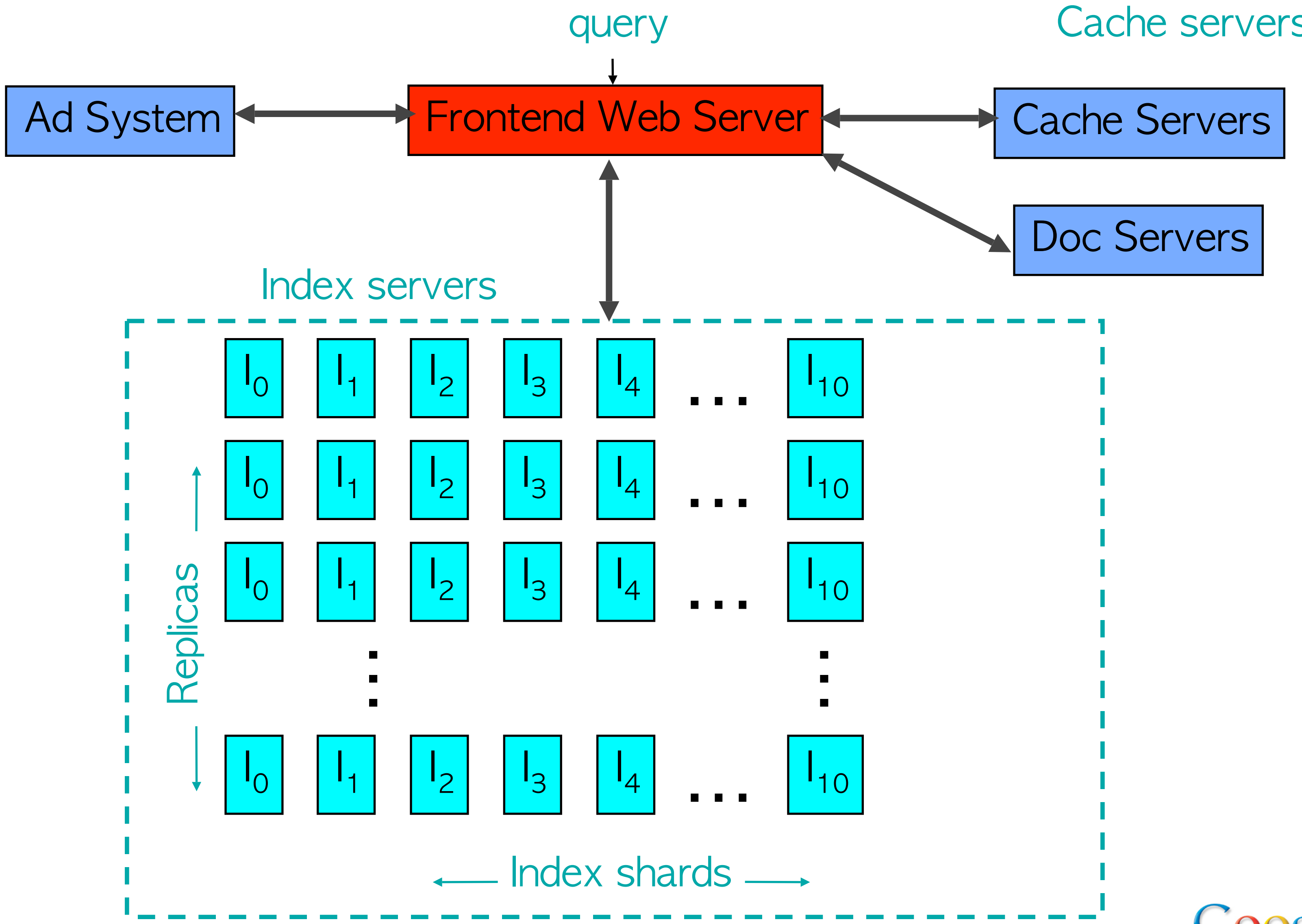

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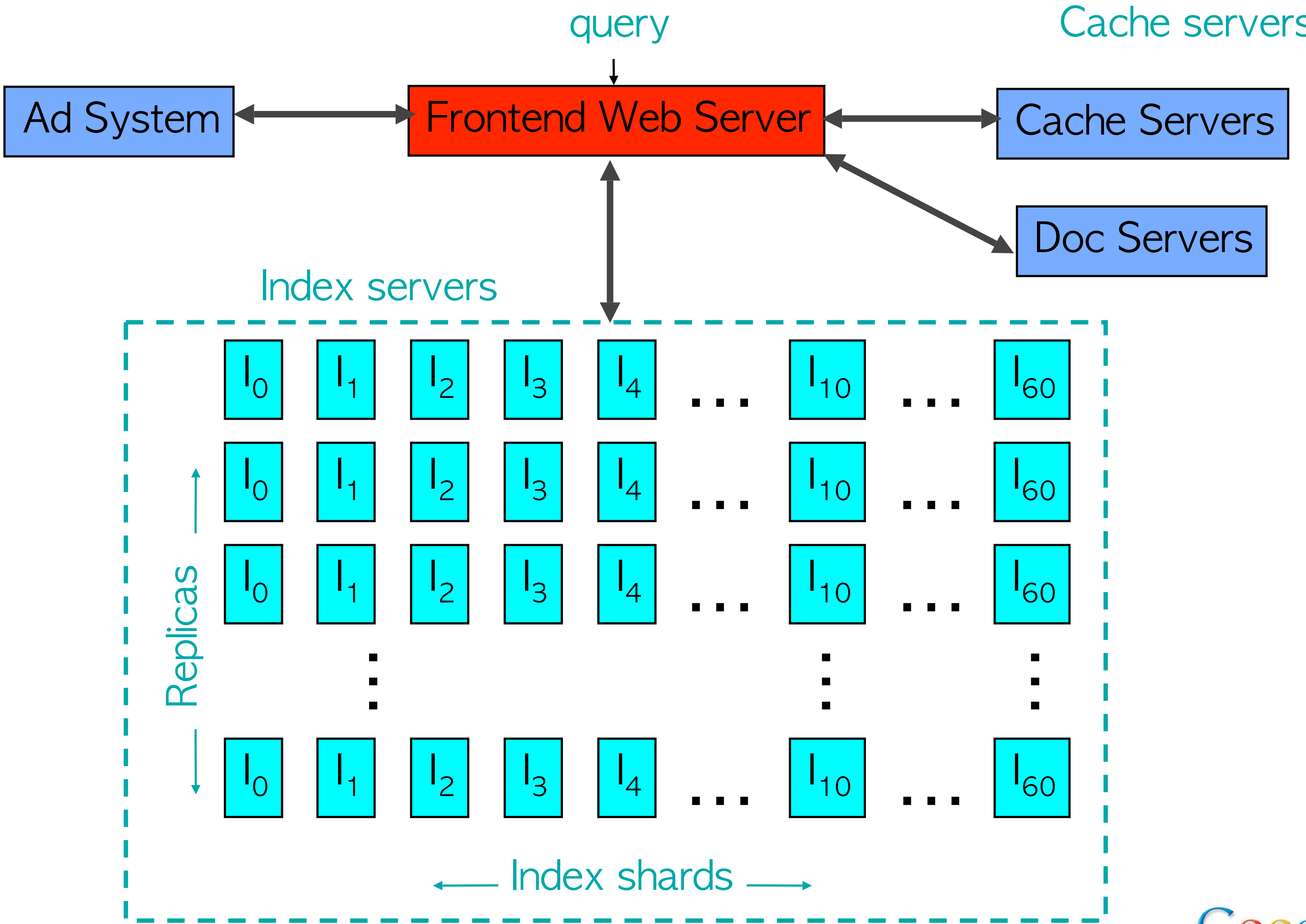


Implications

- Shard response time influenced by:
  - # of disk seeks that must be done
  - amount of data to be read from disk

- Big performance improvements possible with:
  - better disk scheduling
  - improved index encoding

Index Encoding circa 1997-1999

- Original encoding ('97) was very simple:

WORD →	docid+nhits:32b	hit: 16b	hit: 16b	...	docid+nhits:32b	hit: 16b

  - hit: position plus attributes (font size, title, etc.)
  - Eventually added skip tables for large posting lists

- Simple, byte aligned format
  - cheap to decode, but not very compact
  - ... required lots of disk bandwidth

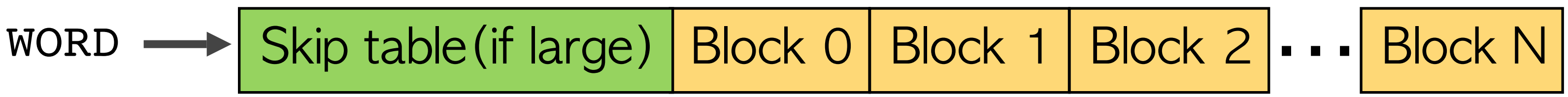
Encoding Techniques

- Bit-level encodings:
  - Unary: N '1's followed by a '0'
  - Gamma: $\log_2(N)$ in unary, then floor(log2(N)) bits
  - Rice_K: floor(N / 2^K) in unary, then N mod 2^K in K bits
    - special case of Golomb codes where base is power of 2
  - Huffman-Int: like Gamma, except $\log_2(N)$ is Huffman coded instead of encoded w/ Unary

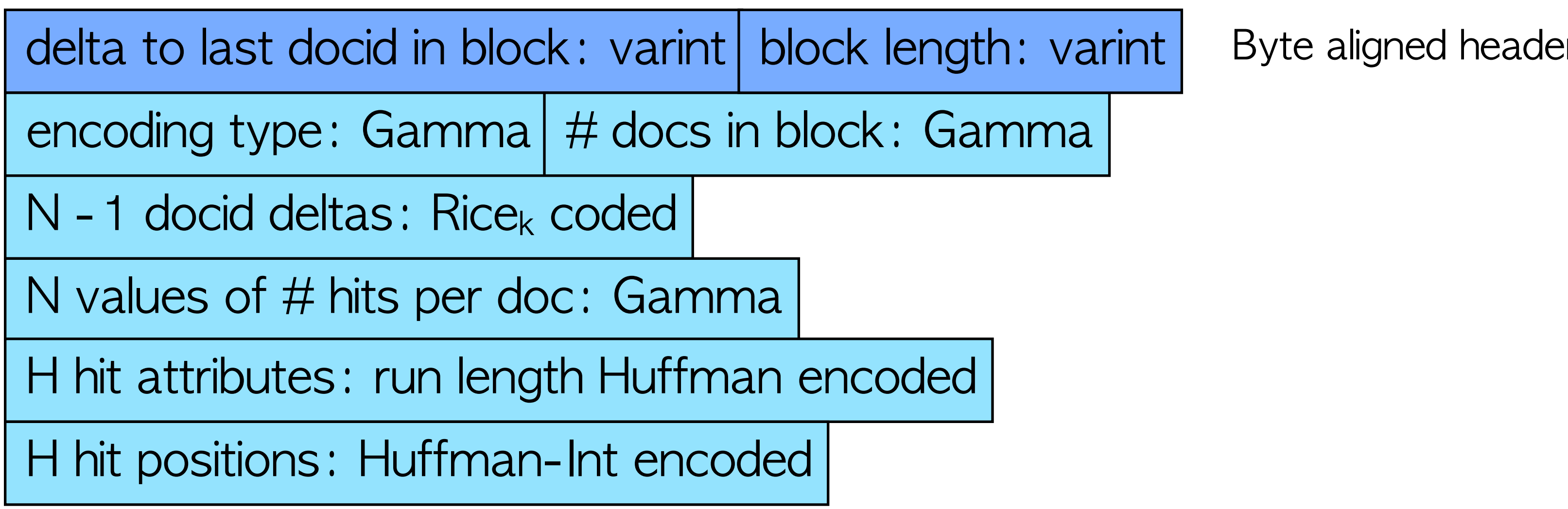
- Byte-aligned encodings:
  - varint: 7 bits per byte with a continuation bit
    - 0-127: 1 byte, 128-4095: 2 bytes, ...
  - ...

Block-Based Index Format

- Block-based, variable-len format reduced both space and CPU



Block format (with N documents and H hits):



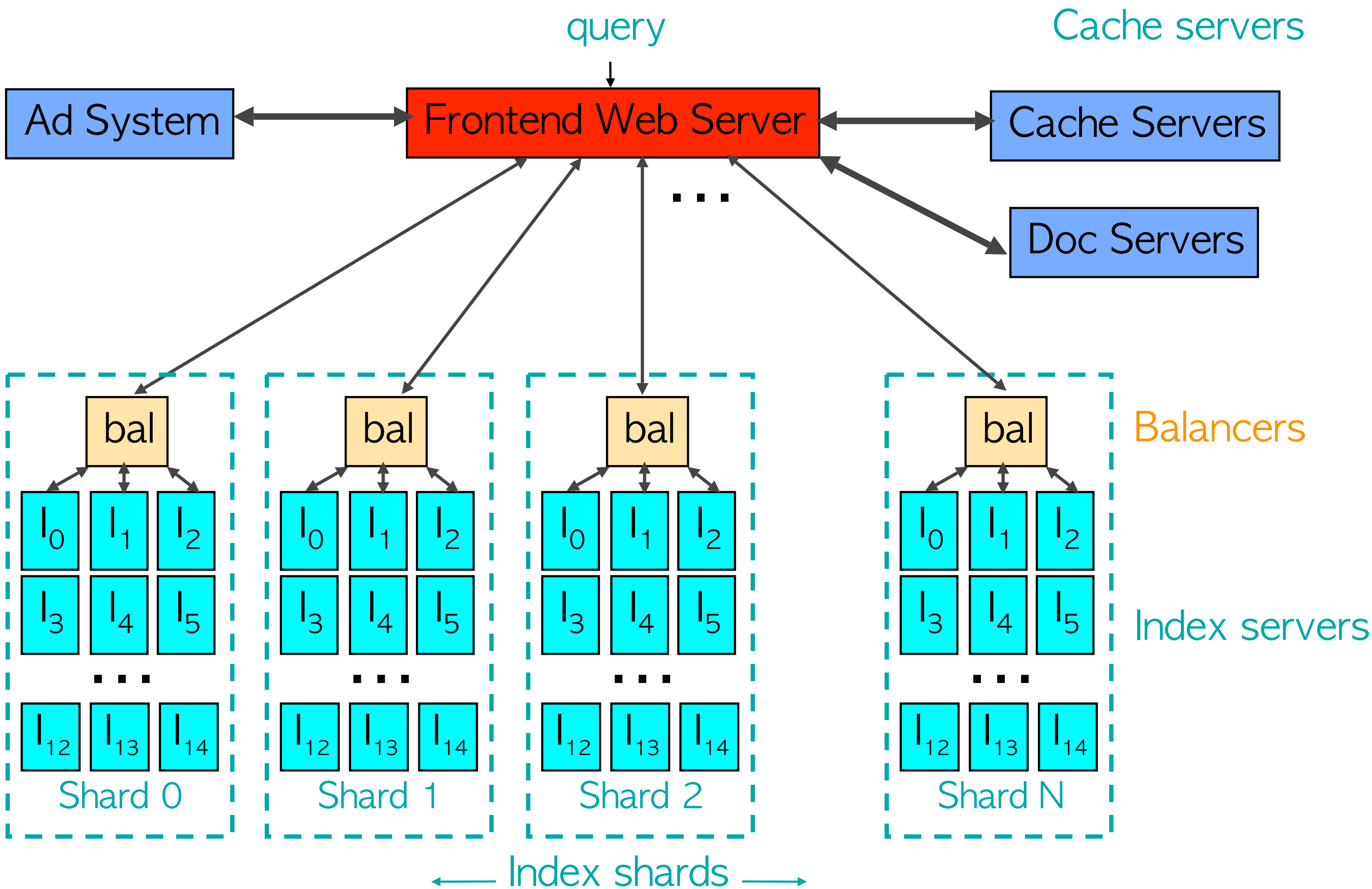
- Reduced index size by ~30%, plus much faster to decode

Implications of Ever-Wider Sharding

- Must add shards to keep response time low as index size increases
- ... but query cost increases with # of shards
  - typically >= 1 disk seek / shard / query term
  - even for very rare terms
- As # of replicas increases, total amount of memory available increases
  - Eventually, have enough memory to hold an **entire copy of the index in memory**
    - radically changes many design parameters

Google

Early 2001: In-Memory Index



In-Memory Indexing Systems

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

      `e.g. [ “circle of life” ]`

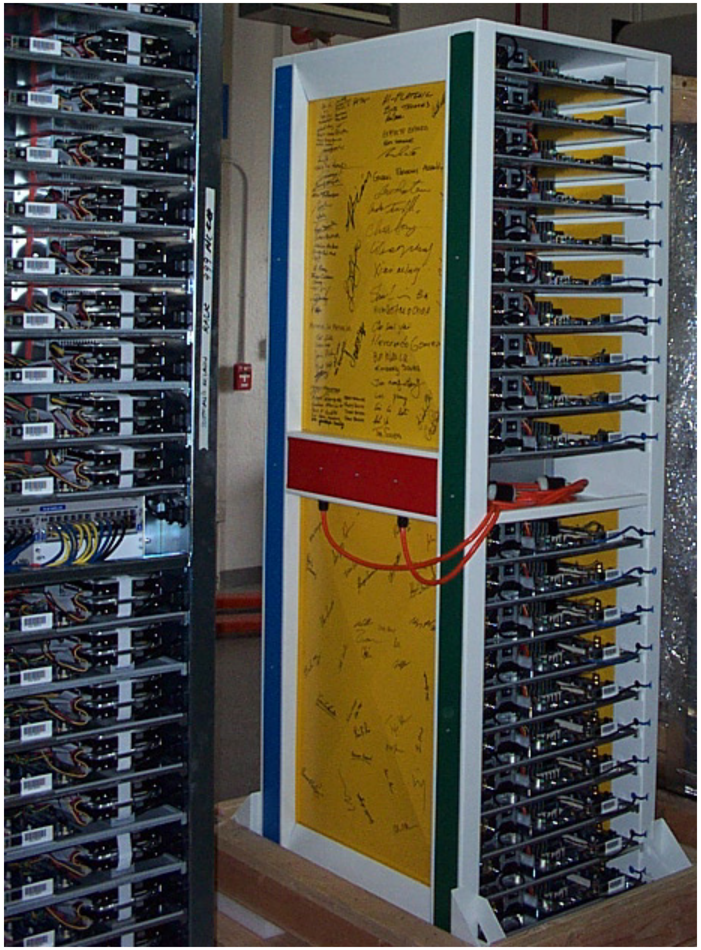
- Some issues:
  - Variance: touch 1000s of machines, not dozens
    - e.g. randomized cron jobs caused us trouble for a while
  - Availability: 1 or few replicas of each doc’s index data
    - Queries of death that kill all the backends at once: very bad
    - Availability of index data when machine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

Google

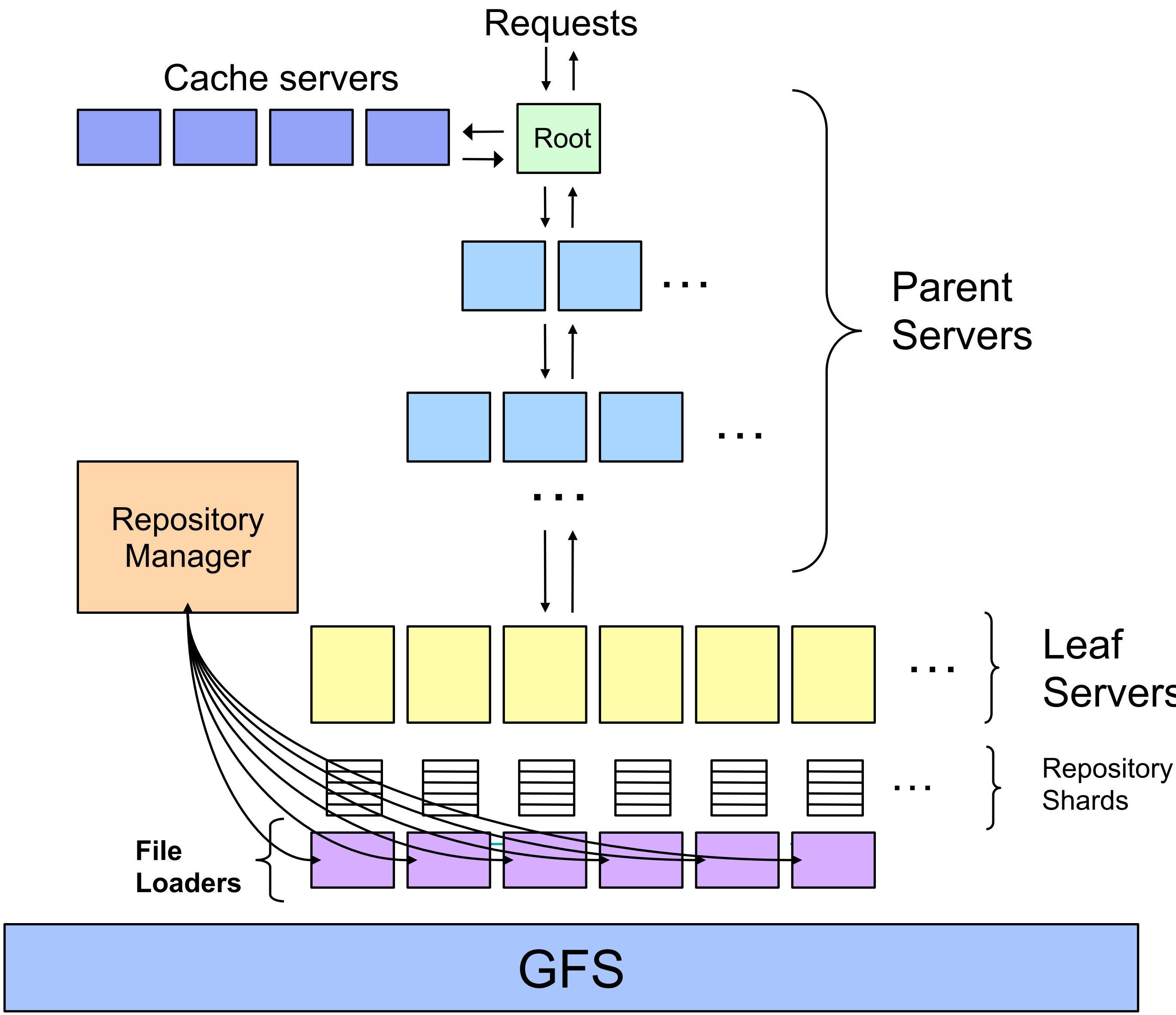
Larger-Scale Computing

Current Machines

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



Serving Design, 2004 edition

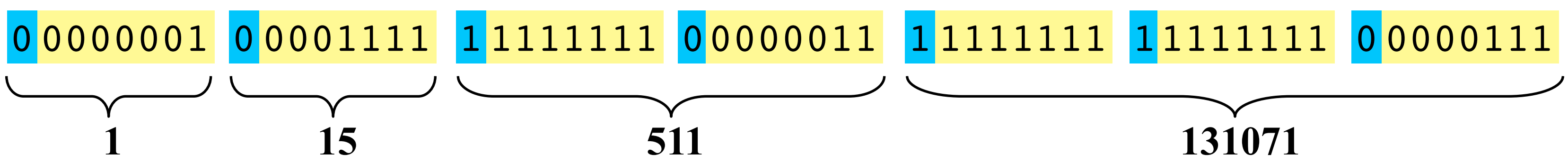


New Index Format

- Block index format 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



Little endian is used here (C/C++ on Intel CPUs). 511 = 0x01FF, but it will be actually saved as 0xFF01.

Byte-Aligned Variable-length Encodings

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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 as low 2 bits
  - Better: fewer branches, shifts, and masks
  - Con: Limited to 30-bit values, still some shifting to decode

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

weiw: should be "01 111111 00000111. This will give "00000111 111111" after dropping the 2 msbits and reversing the order of bytes. c.f., https://developers.google.com/protocol-buffers/docs/encoding

Group Varint Encoding

- Idea: encode groups of 4 values in 5-17 bytes
  - Pull out 4 2-bit binary lengths into single byte prefix

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`00000001` `00001111` `01111111` `00000011` `10111111` `11111111` `00000111`

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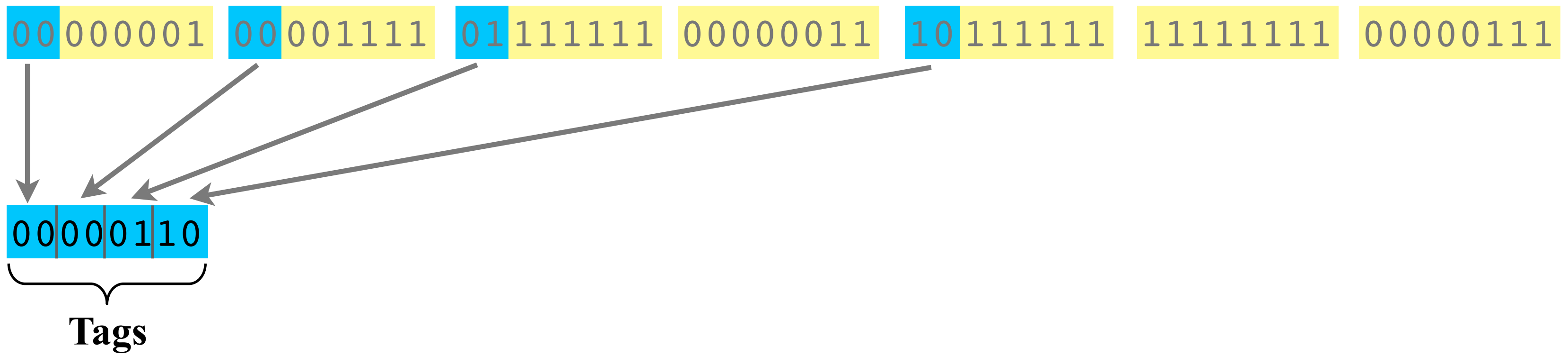

Google

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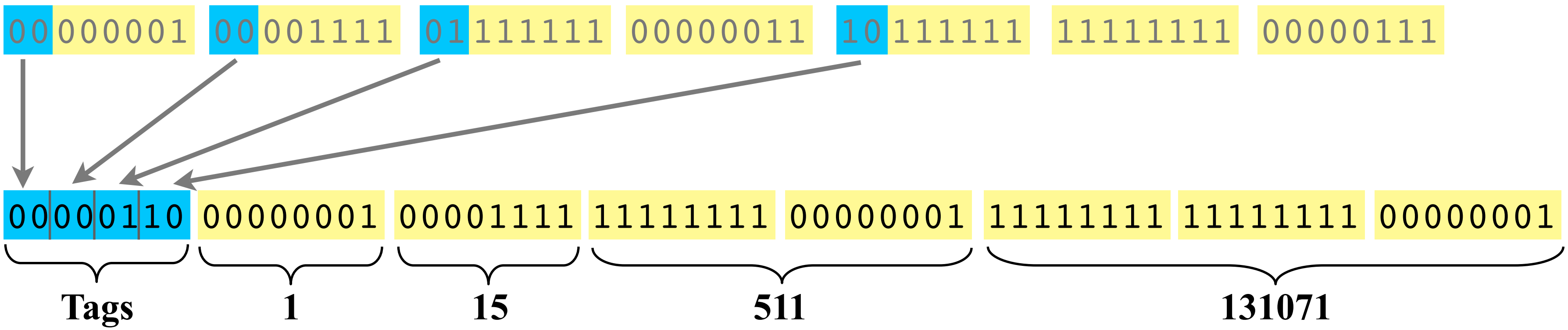

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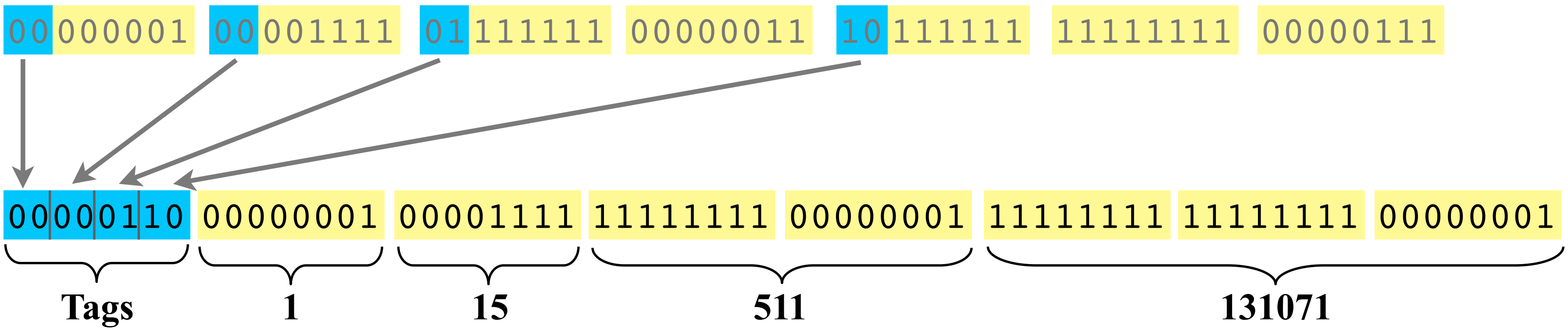

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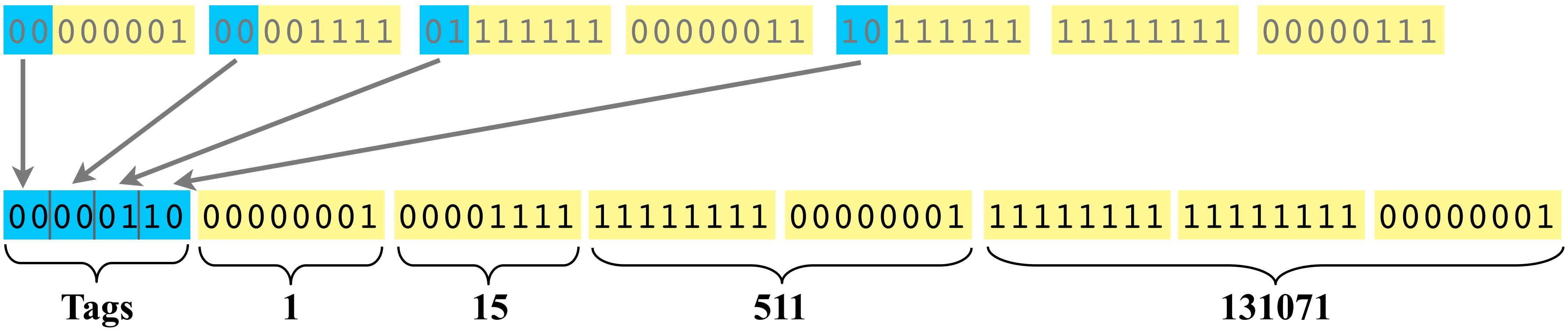

- Decode: Load prefix byte and use value to lookup in 256-entry table:

```
                    ...
00000110  →  Offsets: +1,+2,+3,+5; Masks: ff, ff, ffff, ffffff
                    ...
```

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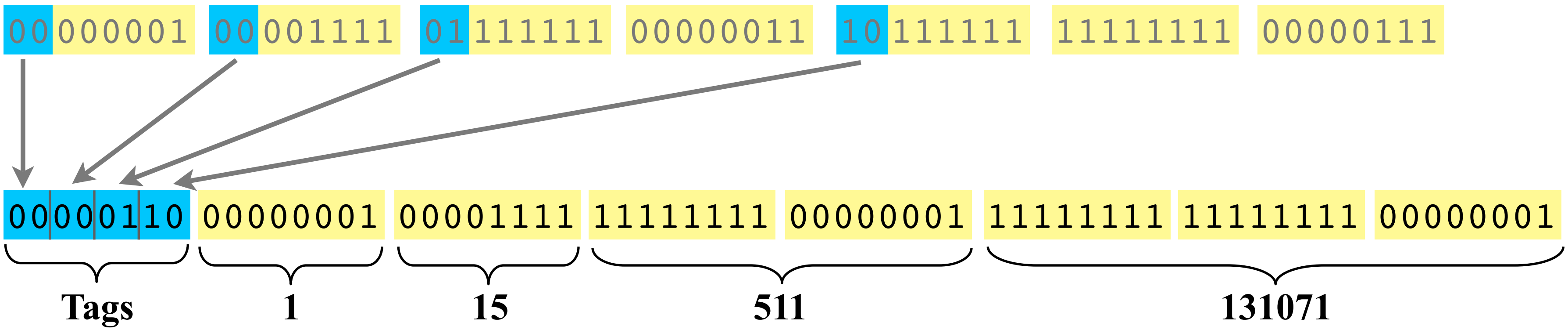

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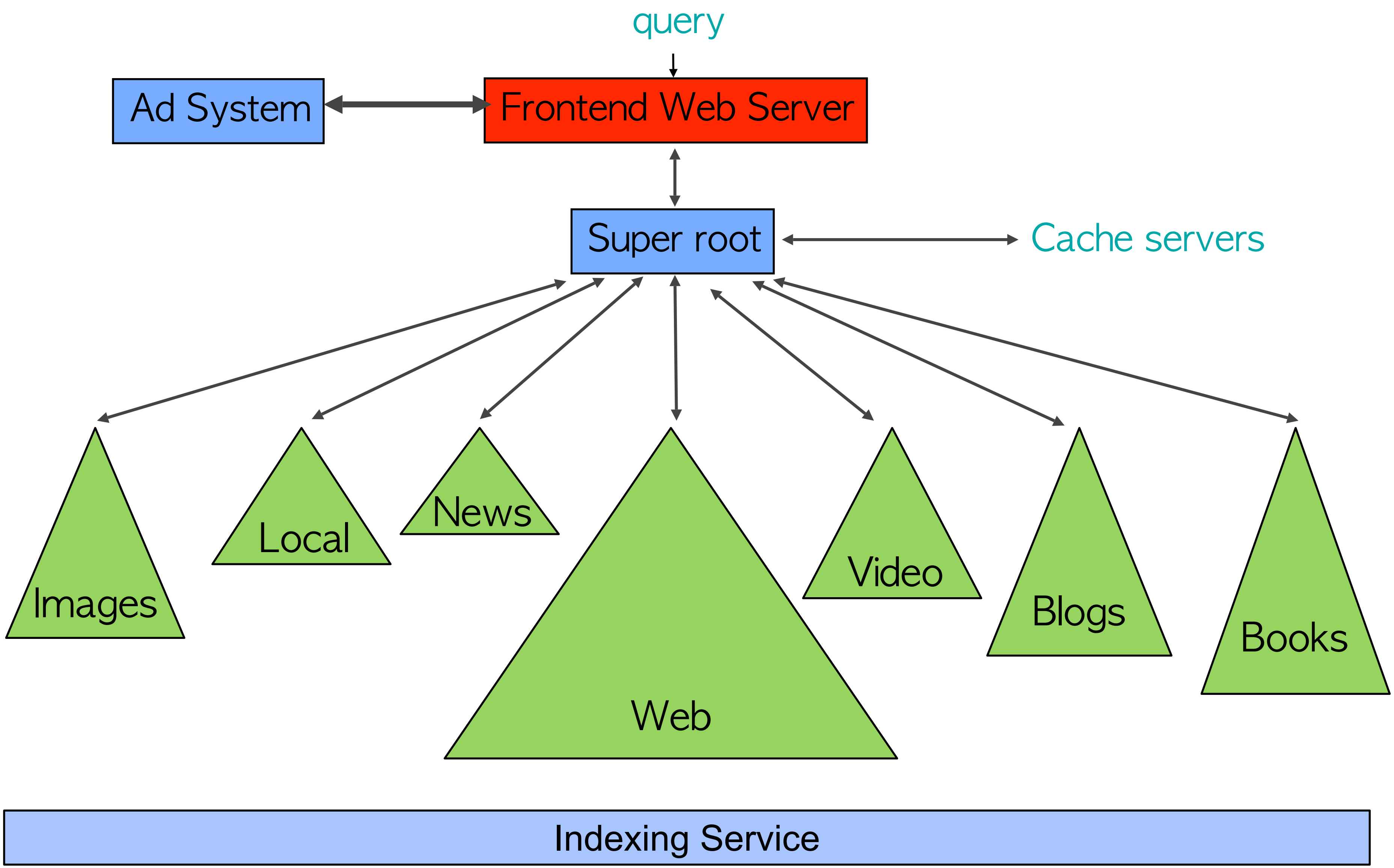
```
                   ...
00|00|01|10  →  Offsets: +1,+2,+3,+5; Masks: ff, ff, ffff, ffffff
                   ...
```

- 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



Index that? Just a minute!

- Low-latency crawling and indexing is tough
  - crawl heuristics: what pages should be crawled?
  - crawling system: need to crawl pages quickly
  - indexing system: depends on global data
    - PageRank, anchor text of pages that point to the page, etc.
    - must have online approximations for these global properties
  - serving system: must be prepared to accept updates while serving requests
    - very different data structures than batch update serving system

Flexibility & Experimentation in IR Systems

- Ease of experimentation hugely important
  - faster turnaround => more exps => more improvement
- Some experiments are easy
  - e.g. just weight existing data differently
- Others are more difficult to perform: need data not present in production index
  - Must be easy to generate and incorporate new data and use it in experiments

Infrastructure for Search Systems

- Several key pieces of infrastructure:
  - GFS: large-scale distributed file system
  - MapReduce: makes it easy to write/run large scale jobs
    - generate production index data more quickly
    - perform ad-hoc experiments more rapidly
    - ...
  - BigTable: semi-structured storage system
    - online, efficient access to per-document information at any time
    - multiple processes can update per-doc info asynchronously
    - critical for updating documents in minutes instead of hours

http://labs.google.com/papers/gfs.html

http://labs.google.com/papers/mapreduce.html

http://labs.google.com/papers/bigtable.html

Experimental Cycle, Part 1

- Start with new ranking idea

- Must be easy to run experiments, and to do so quickly:
  - Use tools like MapReduce, BigTable, to generate data...
  - Initially, run off-line experiment & examine effects
    - ...on human-rated query sets of various kinds
    - ...on random queries, to look at changes to existing ranking

  - Latency and throughput of this prototype don't matter

- ...iterate, based on results of experiments ...

Experimental Cycle, Part 2

- Once off-line experiments look promising, want to run live experiment
  - Experiment on tiny sliver of user traffic
  - Random sample, usually
    - but sometimes a sample of specific class of queries
      - e.g. English queries, or queries with place names, etc.

- For this, throughput not important, but latency matters
  - Experimental framework must operate at close to production latencies!

Experiment Looks Good: Now What?

- Launch!

- Performance tuning/reimplementation to make feasible at full load
  - e.g. precompute data rather than computing at runtime
  - e.g. approximate if "good enough" but much cheaper

- Rollout process important:
  - Continuously make quality vs. cost tradeoffs
  - Rapid rollouts at odds with low latency and site stability
    - Need good working relationships between search quality and groups chartered to make things fast and stable

Future Directions & Challenges

- A few closing thoughts on interesting directions...

Cross-Language Information Retrieval

- Translate all the world's documents to all the world's languages
  - increases index size substantially
  - computationally expensive
  - ... but huge benefits if done well

- Challenges:
  - continuously improving translation quality
  - large-scale systems work to deal with larger and more complex language models
    - to translate one sentence ⇒ ~1M lookups in multi-TB model

ACLs in Information Retrieval Systems

- Retrieval systems with mix of private, semi-private, widely shared and public documents
  - e.g. e-mail vs. shared doc among 10 people vs. messages in group with 100,000 members vs. public web pages
- Challenge: building retrieval systems that efficiently deal with ACLs that vary widely in size
  - best solution for doc shared with 10 people is different than for doc shared with the world
  - sharing patterns of a document might change over time

Automatic Construction of Efficient IR Systems

- Currently use several retrieval systems
  - e.g. one system for sub-second update latencies, one for very large # of documents but daily updates, ...
  - common interfaces, but very different implementations primarily for efficiency
  - works well, but lots of effort to build, maintain and extend different systems

- Challenge: can we have a single parameterizable system that automatically constructs efficient retrieval system based on these parameters?

Information Extraction from Semi-structured Data

- Data with clearly labelled semantic meaning is a tiny fraction of all the data in the world
- But there's lots semi-structured data
  - books & web pages with tables, data behind forms, ...

- Challenge: algorithms/techniques for improved extraction of structured information from unstructured/semi-structured sources
  - noisy data, but lots of redundancy
  - want to be able to correlate/combine/aggregate info from different sources

In Conclusion...

- Designing and building large-scale retrieval systems is a challenging, fun endeavor
  - new problems require continuous evolution
  - work benefits many users
  - new retrieval techniques often require new systems

- Thanks for your attention!

Thanks! Questions...?

- Further reading:

Ghemawat, Gobioff, & Leung. *Google File System*, SOSP 2003.

Barroso, Dean, & Hölzle. *Web Search for a Planet: The Google Cluster Architecture*, IEEE Micro, 2003.

Dean & Ghemawat. *MapReduce: Simplified Data Processing on Large Clusters*, OSDI 2004.

Chang, Dean, Ghemawat, Hsieh, Wallach, Burrows, Chandra, Fikes, & Gruber. *Bigtable: A Distributed Storage System for Structured Data*, OSDI 2006.

Brants, Popat, Xu, Och, & Dean. *Large Language Models in Machine Translation*, EMNLP 2007.

- These and many more available at:

  http://labs.google.com/papers.html

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