GFS + MapReduce

CS 475, Fall 2019
Concurrent & Distributed Systems

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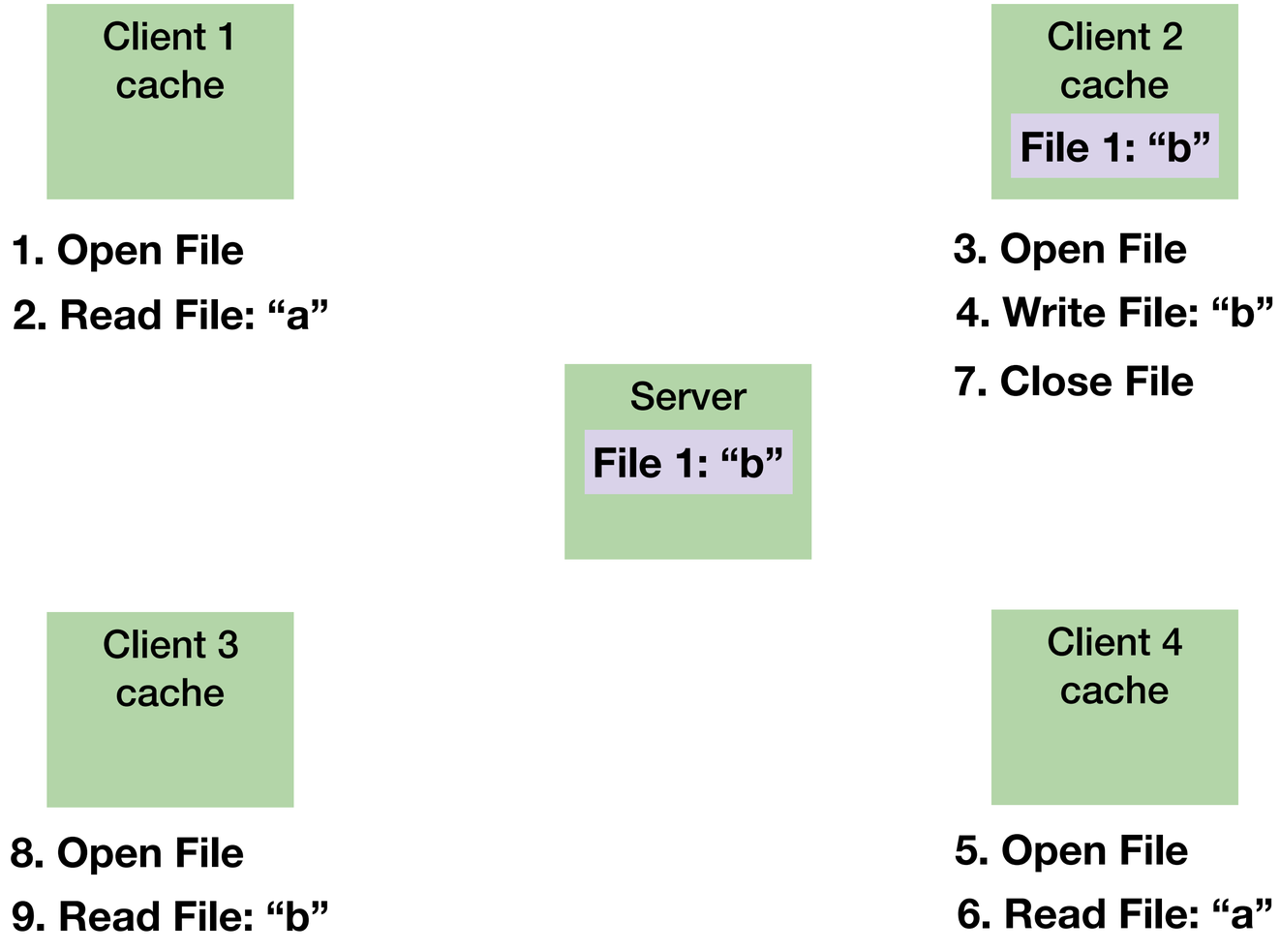
NFS Caching - Close-to-open



Note: in practice, client caches periodically check server to see if still valid

NFS Limitations

- Security: what if untrusted users can be root on client machines?
- Scalability: how many clients can share one server?
  - Writes always go through to server
  - Some writes are to “private,” unshared files that are deleted soon after creation
- Can you run NFS on a large, complex network?
  - Effects of latency? Packet loss? Bottlenecks?
- Important question: whose fault are these limitations? Are they intractable (because of the very problem we are trying to solve)? Or are we just not thinking hard enough?

Today

- Today:
  - Big data, big problems
- Additional readings for reference:
  - GFS, MapReduce papers, Podcast about Dropbox
- Project is out next week!
  - Fault-tolerant, sequentially consistent replicated key value store
  - Start thinking of groups (1 to **3** students per group)

More data, more problems

- I have a 1TB file
- I need to sort it
- …My computer can only read 60MB/sec
- …
- …
- …
- 1 day later, it's done

More data, more problems

- Think about scale:
  - Google indexes ~20 petabytes of web pages per **day** (as of 2008!)
  - Facebook has 2.5 petabytes of user data, increases by 15 terabytes/day (as of 2009!)

Distributing Computation

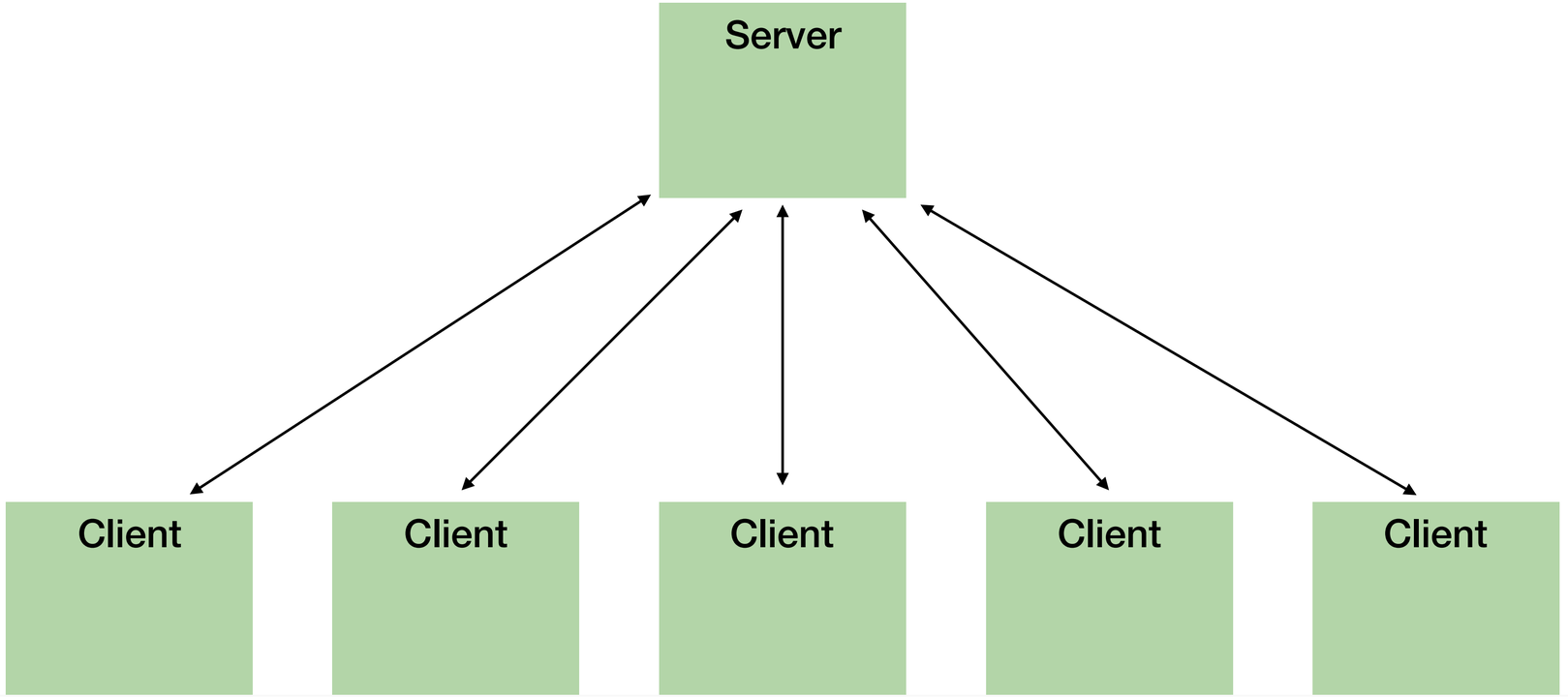
Distributing Computation

- Can't I just add 100 nodes and sort my file 100 times faster?
- Not so easy:
  - Sending data to/from nodes
  - Coordinating among nodes
  - Recovering when one node fails
  - Optimizing for locality
  - Debugging

Distributing Computation

- We begin to answer
  - 1. How do we store the data?
  - 2. How do we compute on this data?

NFS to the Rescue?



All files stored on the same server is bad because:
Fault tolerance (what if it crashes?)
Performance (what if we need to access 100's of GBs at a time?)
Scale (what if we need to store PBs of files?)
Plus, NFS' open-to-close caching can be weird

GFS (Google File System)

- Google apps observed to have specific R/W patterns (usually read recent data, lots of data, etc)
- Normal FS API (POSIX) is constraining (consider: NFS contains a ton of annoying glue to make it work with open/close/sync/seek etc)
- Hence, Google made their own FS

GFS

- Hundreds of thousands of regular servers
- Millions of regular disks
- Failures are normal
  - App bugs, OS bugs
  - Human Error
  - Disk failure, memory failure, network failure, etc
- Huge number of concurrent reads, writes

GFS Workload

- (Relatively) small total number of large files (>100MB) - millions
- Large, streaming reads (reading > 1MB at a time)
  - Throughput is more important than latency
- Large, sequential writes that always append to end of a file
  - Optimize for appends
- Multiple clients might append concurrently

GFS Design Goals

- Unified FS for all google platforms (e.g. gmail, youtube)
- Data + system availability
- Graceful + transparent failure handling
- Low synchronization overhead
- Exploit parallelism
- High throughput and low latency

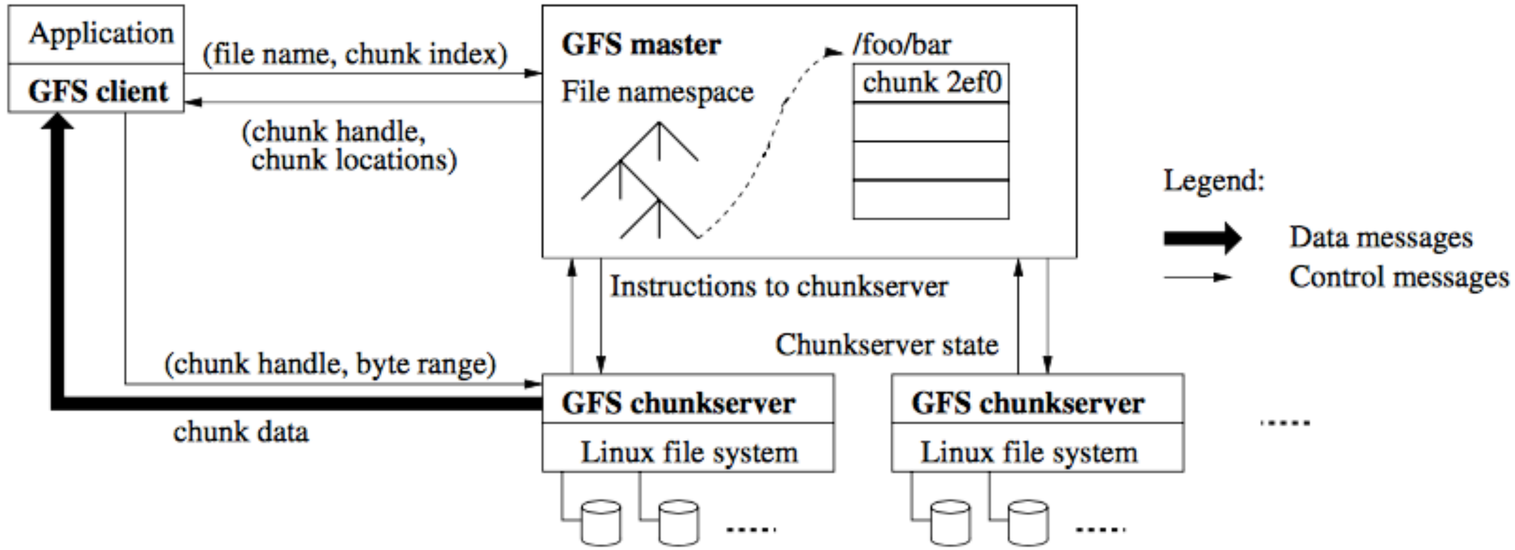
GFS Interface Design

- Non-standard API (e.g. not POSIX system calls)
- Normal filesystem hierarchy (directories, paths)
- Extra operations:
  - Snapshot (low cost file/directory tree copying)
  - Record append (append without locking)

GFS Architecture

- Servers:
  - Single master
  - Multiple backups (“chunk servers”)
- Base unit is a “Chunk”
  - Fixed-part of a file (typically 64MB)
  - Global ID: 64 bit unique ID, assigned by master upon creation
  - Read/write: specify chunk ID + byte range into file
  - Each chunk is replicated to at least 3 servers
  - Chunks are stored as plain files on chunk servers

GFS Architecture



GFS Architecture

- Single master server (can replicate to a backup too)
- Holds all metadata (in RAM!) - namespace, ACL, file-chunk mapping
  - In charge of migrating chunks, GC'ing chunks
- Data stored in 64MB chunks each with some ID
  - Compare to EXT-4's 4KB block
- Thousands of chunk servers
  - Chunks are replicated
  - Chunk servers don't cache anything in RAM, store chunks as regular files

GFS Architecture

GFS Metadata

- Master server is in charge of metadata
- File-chunk mapping
  - Stored on disk
- For each chunk:
  - Location of replicas holding the chunk
  - Identity of the master chunk server for this chunk
  - Stored ONLY in RAM - if crash, recover by asking all chunk servers

GFS Metadata Example

Chunk ID	Filename	Part of file	Master Chunk Server	Other Chunk Servers
1	/foo/bar	1 of 1	A, valid for 1 more minute	B, C
2	/another/file	1 of 2	B, valid for 1 more minute	A, C
3	/another/file	2 of 2	D, valid for 1 more minute	C, E

Note - can get very good parallelism by splitting chunks of the same file across different chunk servers

GFS Metadata

- File-chunk mapping stored on disk
- Chunk-chunk server mapping stored only in RAM: why?
  - If stored on disk, would need to update every time a chunk server comes/leaves, OR new chunk comes (remember: optimize for appends)
  - If stored on disk, would need to ensure that each update is flushed to disk to ensure consistency if master fails (and RAM is lost)
  - Hence: only store in RAM, recover from other chunk servers

GFS Client

- Makes metadata requests to master server
- Makes chunk requests to chunk servers
- Caches metadata
- Does not cache data (chunks)
  - Google's workload (streaming reads, appending writes) doesn't benefit from caching, so why bother with consistency nightmare

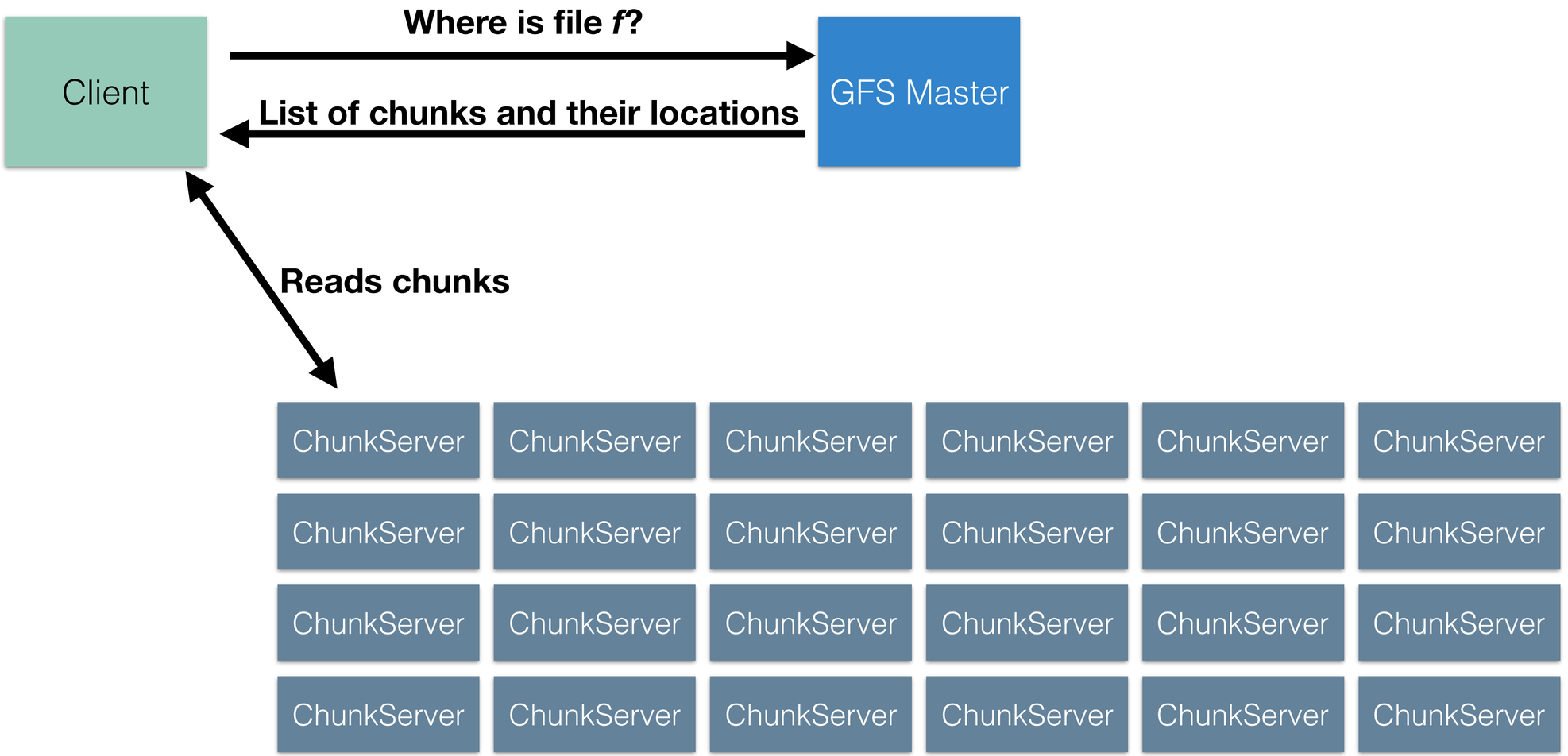
GFS Chunk Primaries

- There needs to be exactly one primary for each chunk
- GFS ensures this using *leases*
  - Master selects a chunk server and grants it a lease
  - The chunk server holds the lease for T seconds, and is primary
  - Chunk server can *refresh* lease endlessly
  - If chunk server fails to refresh it, falls out of being primary
- Like a lock, but needs to be renewed (like with a heart beat)

GFS Reads

- Client asks master for chunk ID, chunk version number, and location of replicas given a file name
- By default, GFS replicates each chunk to 3 servers
- Client sends read request to closest (in network topology) chunk server

GFS - Reads


Client
Where is file *f*?
GFS Master
List of chunks and their locations
Reads chunks
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
ChunkServer
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ChunkServer

GFS Writes

- Client asks master for replicas storing a chunk (one is arbitrarily declared primary)
- Client sends write request to all replicas
- Each replica acknowledges write to primary replica
- Primary coordinates commit between all of the replicas
- On success, primary replies to client

GFS Consistency

- Metadata changes are atomic. Occur only on a single machine, so no distributed issues.
- Changes to data are ordered as arbitrarily chosen by the primary chunk server for a chunk

Comparing GFS/NFS Issues

- Fault tolerance (what if it crashes?)
  - NFS: Crashing the server is bad
  - GFS: Crashing a chunk server is fine, crashing the primary is bad
- Performance (what if we need to access 100's of GBs at a time?)
  - NFS: Limited by single server's bandwidth
  - GFS: Limited only by number of chunk servers (can get good parallelism between 100 chunk servers each at 1GB/sec)
- Scale (what if we need to store PBs of files?)
  - NFS: Limited by storage of single server
  - GFS: Limited by amount of metadata that can be stored on single master
- Plus, NFS' open-to-close caching can be weird
  - GFS: No caching

GFS Summary

- Much more attractive than NFS for reading/writing large files
- Limitations:
  - Master is a huge bottleneck
  - Recovery of master is slow
- Lots of success at Google
- Performance isn't great for all apps (lots of small files?)
- Consistency needs to be managed by apps
- Replaced in 2010 by Google's Colossus system - eliminates master

Distributing Computation

- Lots of these challenges re-appear, regardless of our specific problem
  - How to split up the task
  - How to put the results back together
  - How to store the data (GFS)
- Enter, MapReduce

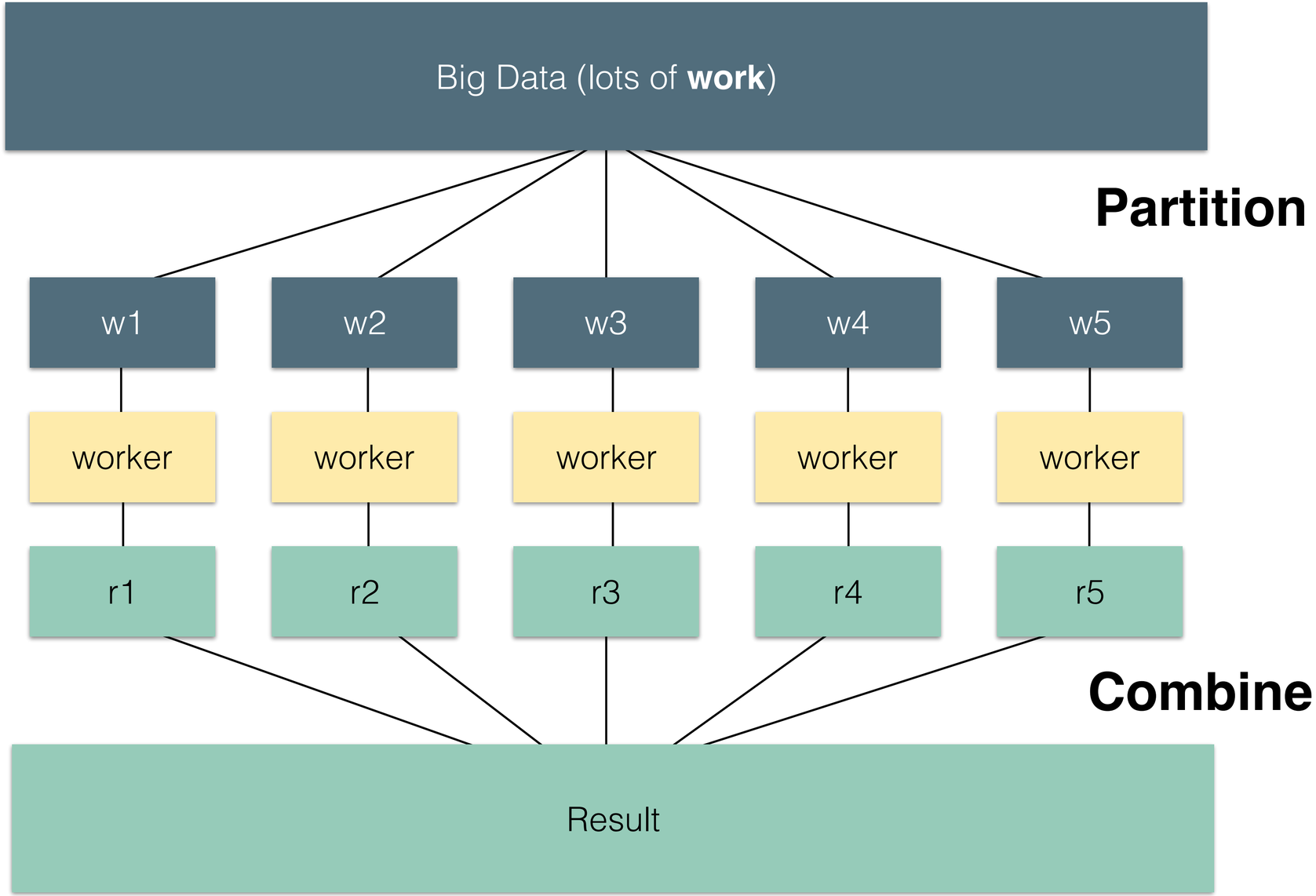
MapReduce

- A programming model for large-scale computations
  - Takes large inputs, produces output
  - No side-effects or persistent state other than that input and output
- Runtime library
  - Automatic parallelization
  - Load balancing
  - Locality optimization
  - Fault tolerance

MapReduce

- Partition data into splits (**map**)
- Aggregate, summarize, filter or transform that data (**reduce**)
- Programmer provides these two methods

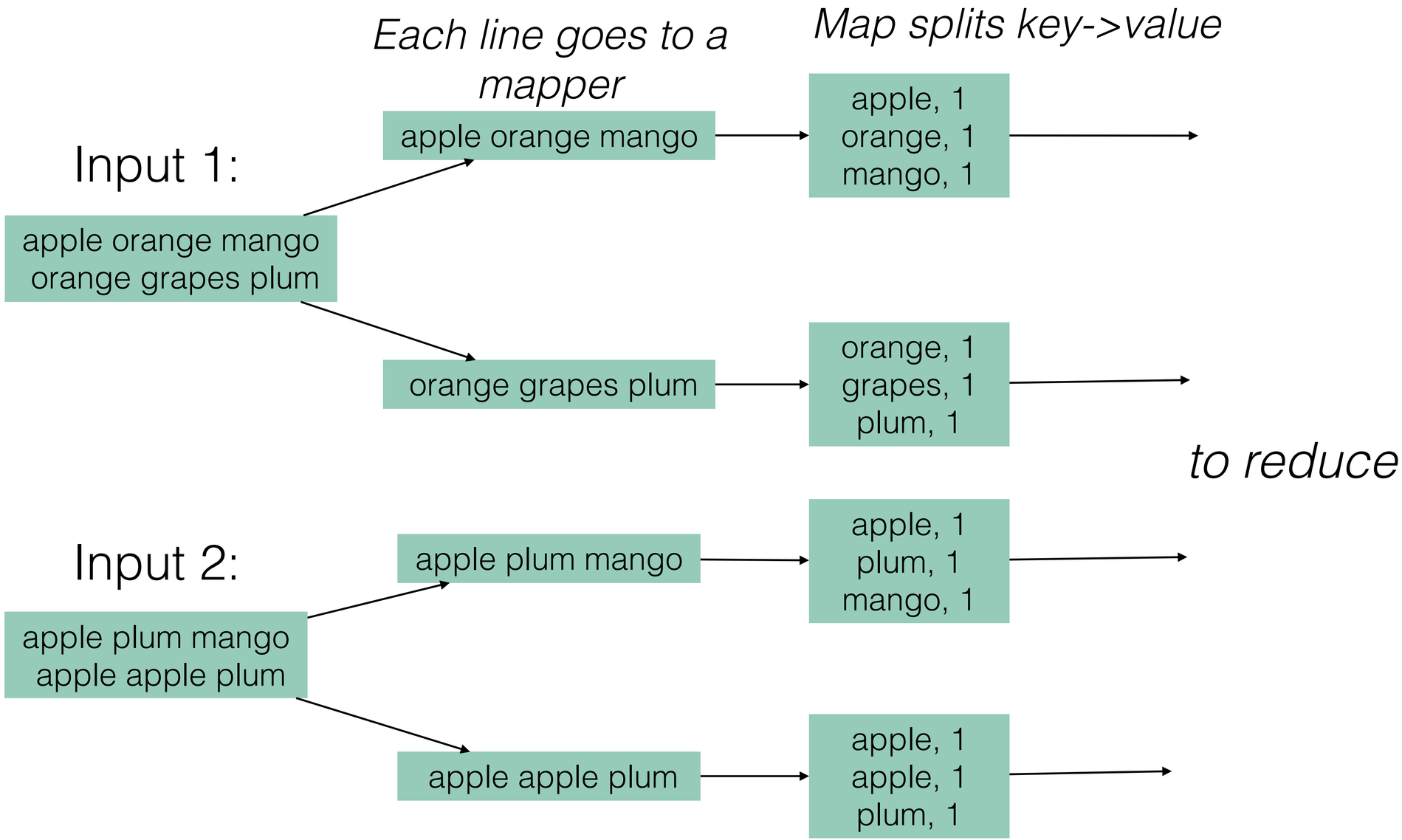
MapReduce: Divide & Conquer



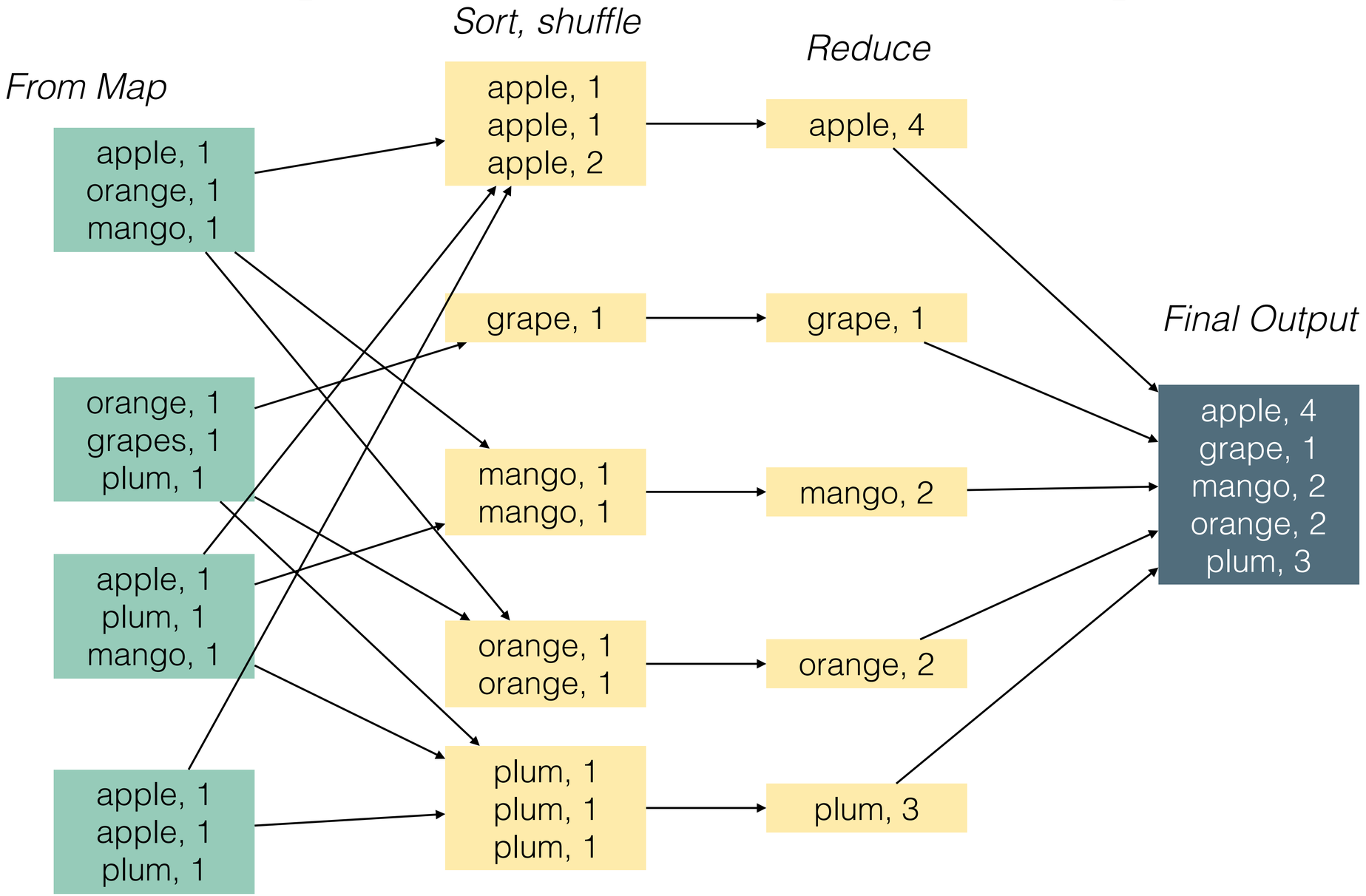
MapReduce: Example

- Calculate word frequencies in documents
- Input: files, one document per record
- **Map** parses documents into words
  - Key - Word
  - Value - Frequency of word
- **Reduce**: compute sum for each key

MapReduce: Example



MapReduce: Example

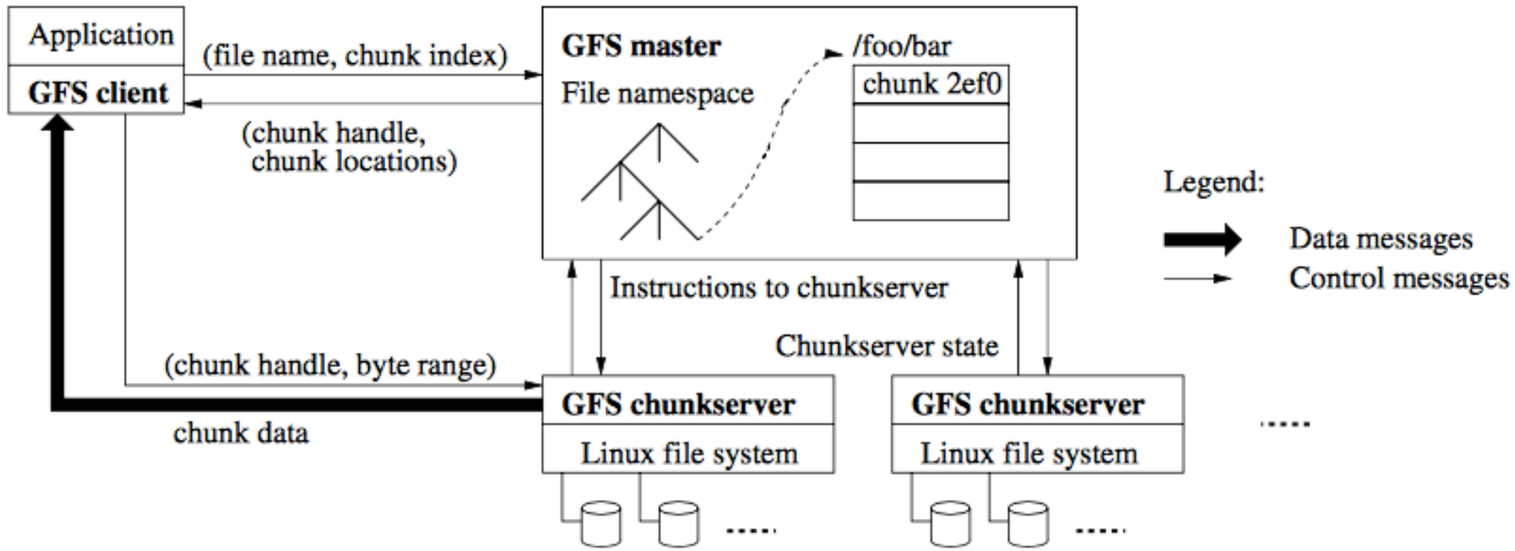


MapReduce Applications

- Distributed grep
- Distributed clustering
- Web link graph traversal
- Detecting duplicate web pages

MapReduce: Implementation

- Each worker node is **also** a GFS chunk server!



MapReduce: Scheduling

- One master, many workers
- Input data split into *M* map tasks (typically 64MB ea)
- *R* reduce tasks
- Tasks assigned to works dynamically; stateless and idempotent -> easy fault tolerance for workers
- Typical numbers:
  - 200,000 map tasks, 4,000 reduce tasks across 2,000 workers

MapReduce: Scheduling

- Master assigns map task to a free worker
  - Prefer "close-by" workers for each task (based on data locality)
  - Worker reads task input, produces intermediate output, stores locally (K/V pairs)
- Master assigns reduce task to a free worker
  - Reads intermediate K/V pairs from map workers
  - Reduce worker sorts and applies some *reduce* operation to get the output

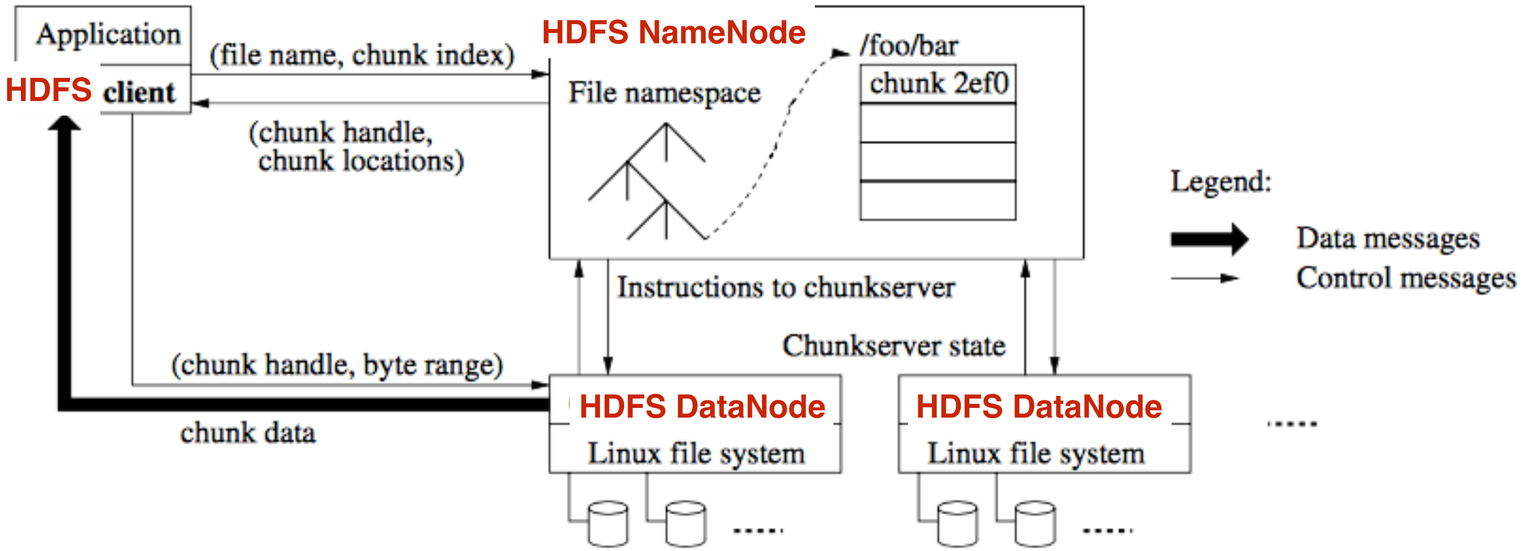
Fault tolerance via re-execution

- Ideally, fine granularity tasks (more tasks than machines)
- On worker-failure:
  - Re-execute completed and in-progress map tasks
  - Re-executes in-progress reduce tasks
  - Commit completion to master
- On master-failure:
  - Recover state (master checkpoints in a primary-backup mechanism)

MapReduce in Practice

- Originally presented by Google in 2003
- Widely used today (**Hadoop** is an open source implementation)
- Many systems designed to have easier programming models that compile into MapReduce code (Pig, Hive)

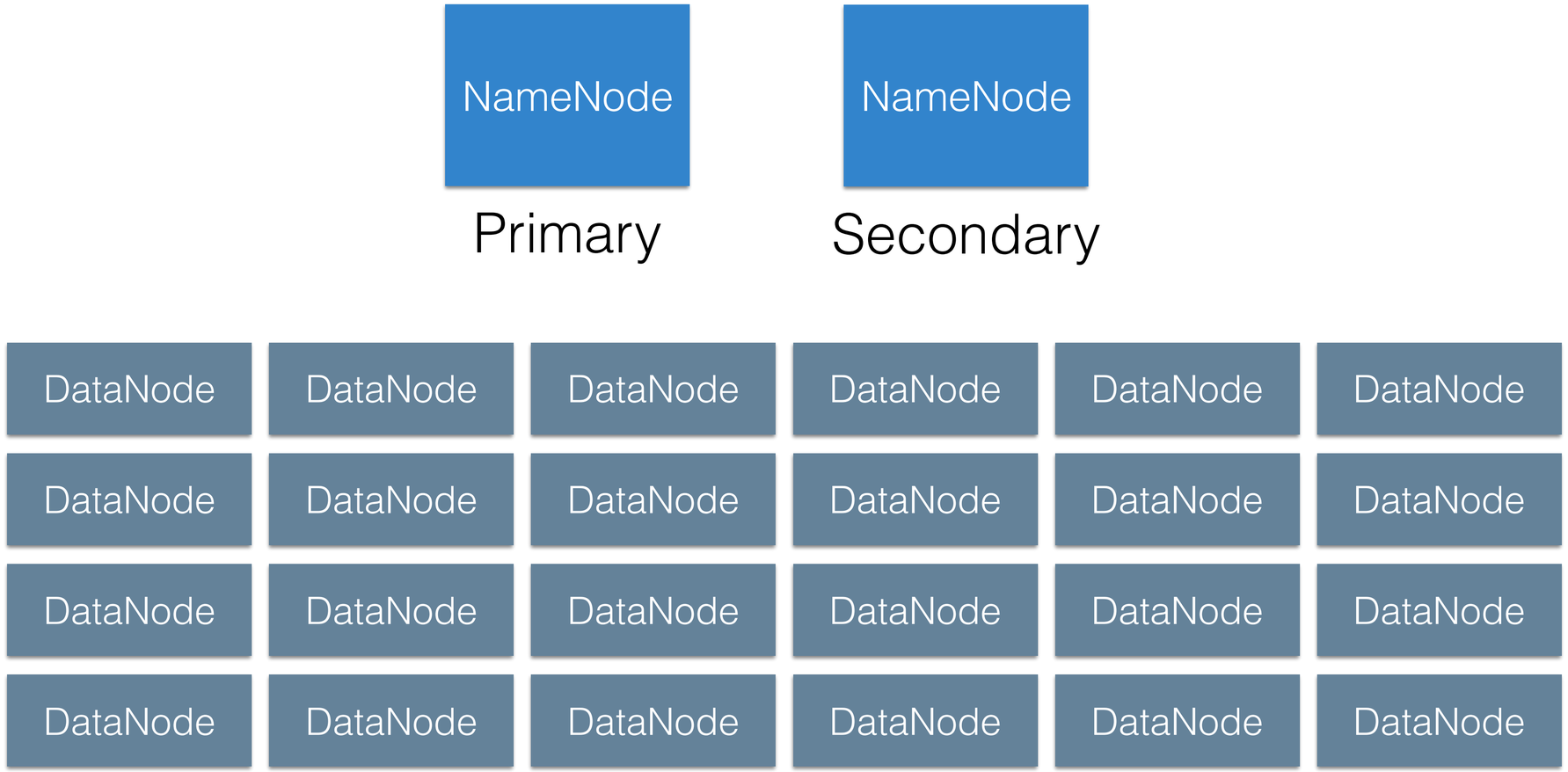
Hadoop: HDFS


Application
HDFS client
(file name, chunk index)
(chunk handle, chunk locations)
HDFS NameNode
File namespace
/foo/bar
chunk 2ef0
Instructions to chunkserver
Chunkserver state
(chunk handle, byte range)
chunk data
HDFS DataNode
Linux file system
HDFS DataNode
Linux file system
Legend:
Data messages
Control messages

HDFS (GFS Review)

- Files are split into blocks (128MB)
- Each block is replicated (default 3 block servers)
- If a host crashes, all blocks are re-replicated somewhere else
- If a host is added, blocks are rebalanced
- Can get awesome locality by pushing the map tasks to the nodes with the blocks (just like MapReduce)

Hadoop


NameNode
NameNode
Primary
Secondary
DataNode
DataNode
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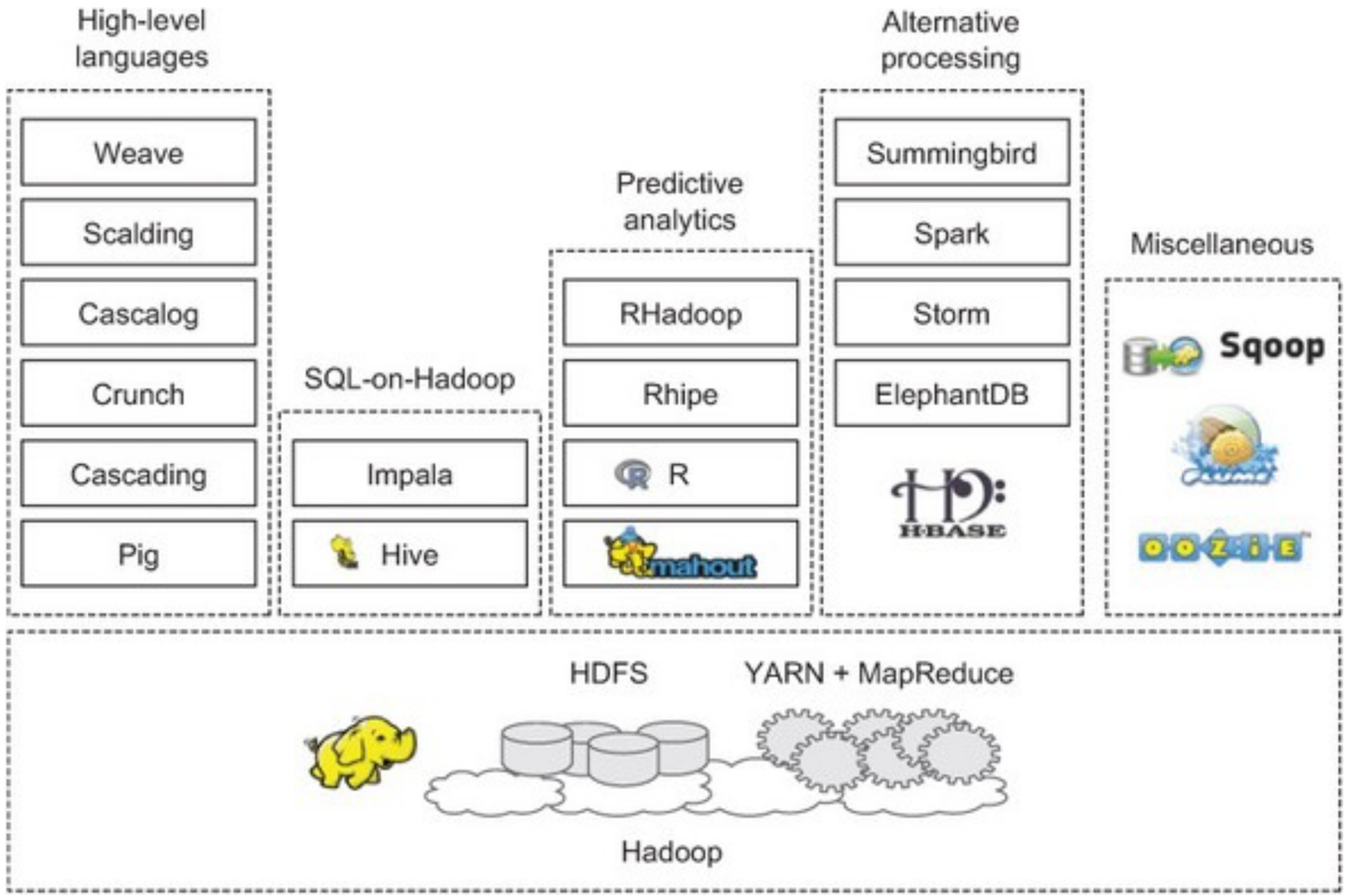
Hadoop Ecosystem



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