Map Reduce & GFS

CS 475, Spring 2018
Concurrent & Distributed Systems

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Review CAP Theorem

- Pick two of three:
  - Consistency: All nodes see the same data at the same time (strong consistency)
  - Availability: Individual node failures do not prevent survivors from continuing to operate
  - Partition tolerance: The system continues to operate despite message loss (from network and/or node failure)
- **You can not have all three, ever***
  - If you relax your consistency guarantee, you might be able to guarantee THAT…

Review: CAP Theorem

- C+A: Provide strong consistency and availability, assuming there are no network partitions
- C+P: Provide strong consistency in the presence of network partitions; minority partition is unavailable
- A+P: Provide availability even in presence of partitions; no strong consistency guarantee

Relaxing Consistency

- We can relax two design principles:
  - How stale reads can be
  - The ordering of writes across the replicas

Eventual Consistency

- Allow stale reads, but ensure that reads will **eventually** reflect the previously written values
  - Eventually: milliseconds, seconds, minutes, hours, years…
- Writes are NOT ordered as executed
  - Allows for conflicts. Consider: Dropbox
- Git is eventually consistent

Announcements

- HW4 Due Friday
- Project is out!!!
  - http://www.jonbell.net/gmu-cs-475-spring-2018/final-project/
  - (Hey, it could be worse)
- Today:
  - Big data problems
- Additional readings:
  - GFS, MapReduce papers

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?s

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: CFS contains a ton of annoying glue to make it work)
- 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

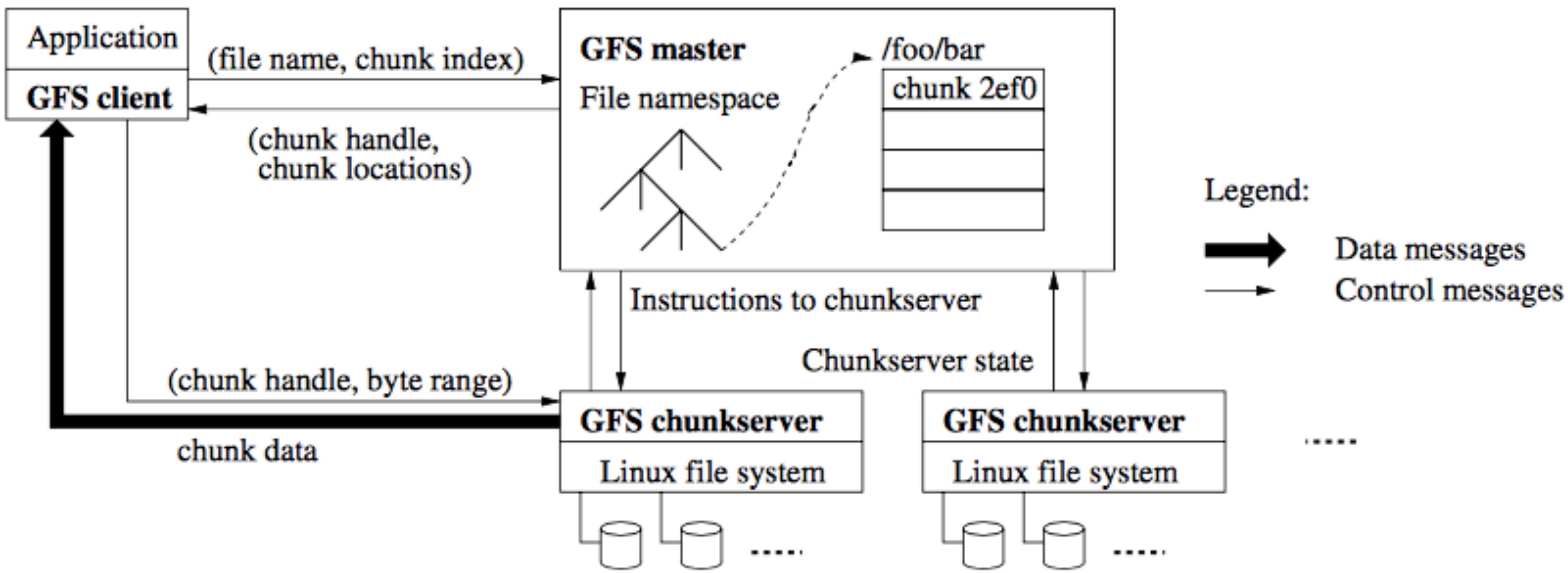
GFS Workload

- (Relatively) small total number of large files (>100MB) - millions
- Large, streaming reads (reading > 1MB at a time)
- Large, sequential writes that always append to end of a file
- 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 Architecture



GFS Architecture

- Single master server (RSM replication to backups)
  - 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 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 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 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 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 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

GFS Summary

- Limitations:
  - Master is a huge bottleneck
  - Recovery of master is slow
- Lots of success at Google
- Performance isn't great for all apps
- 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

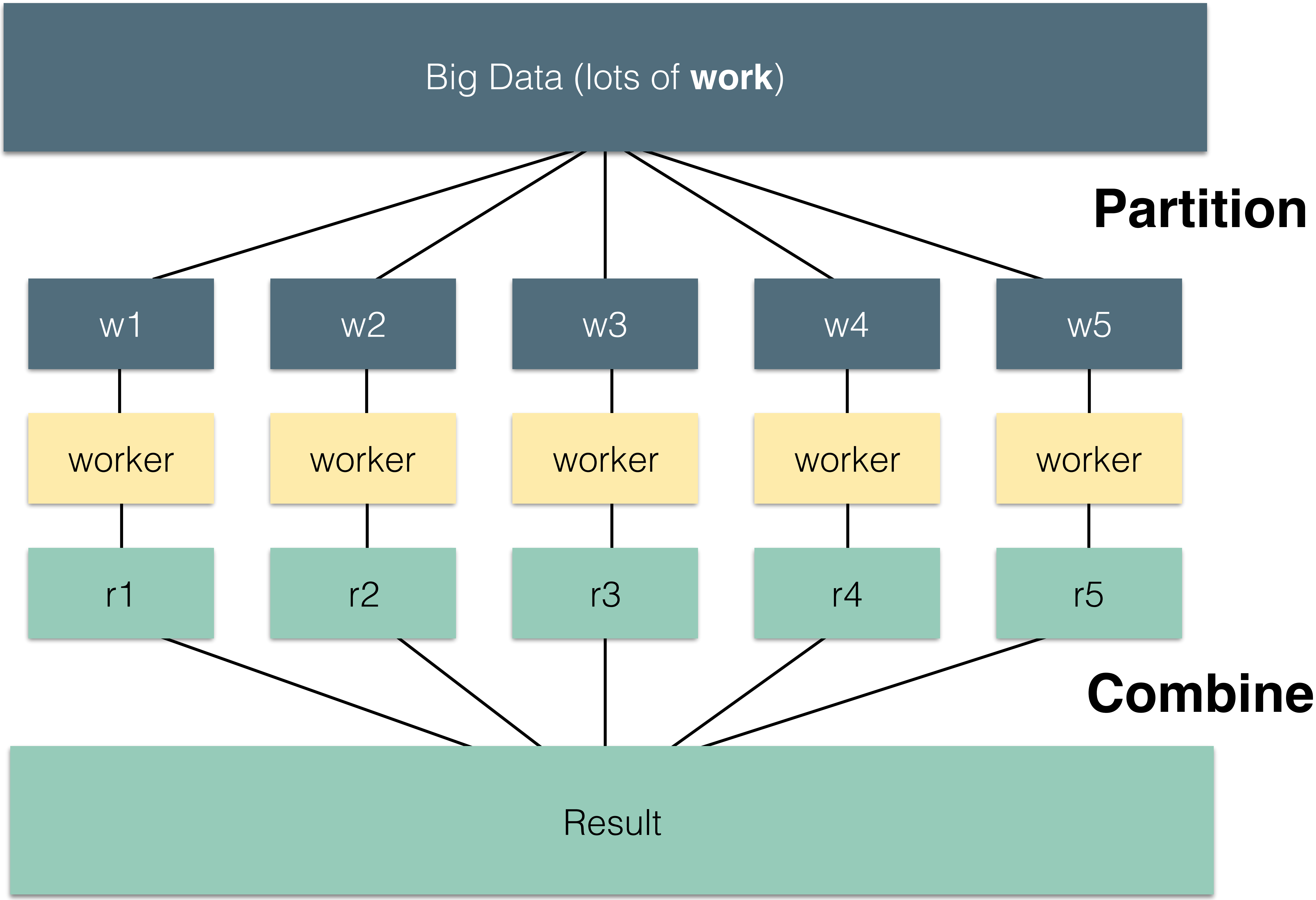
MapReduce

- 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

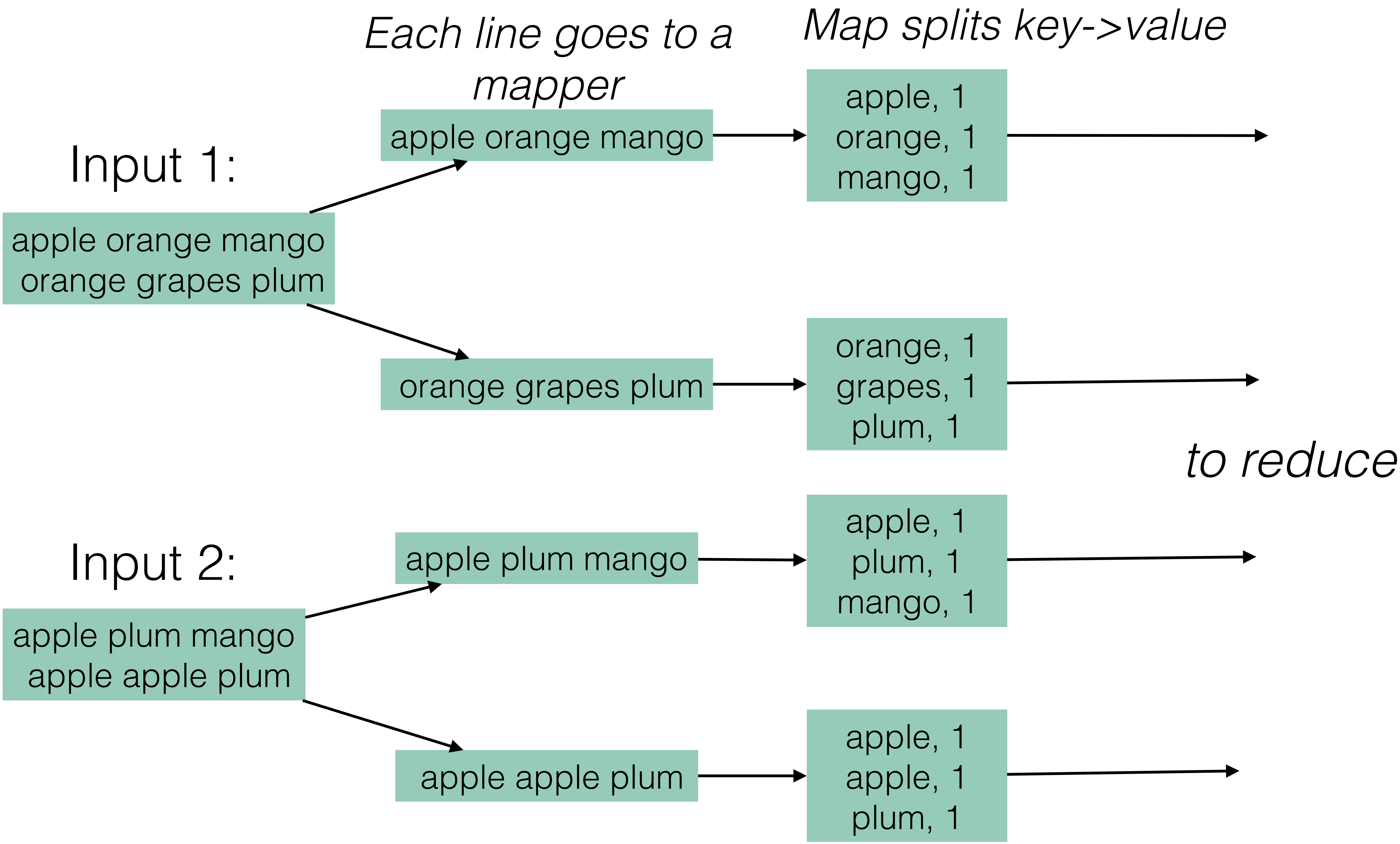
MapReduce: Divide & Conquer



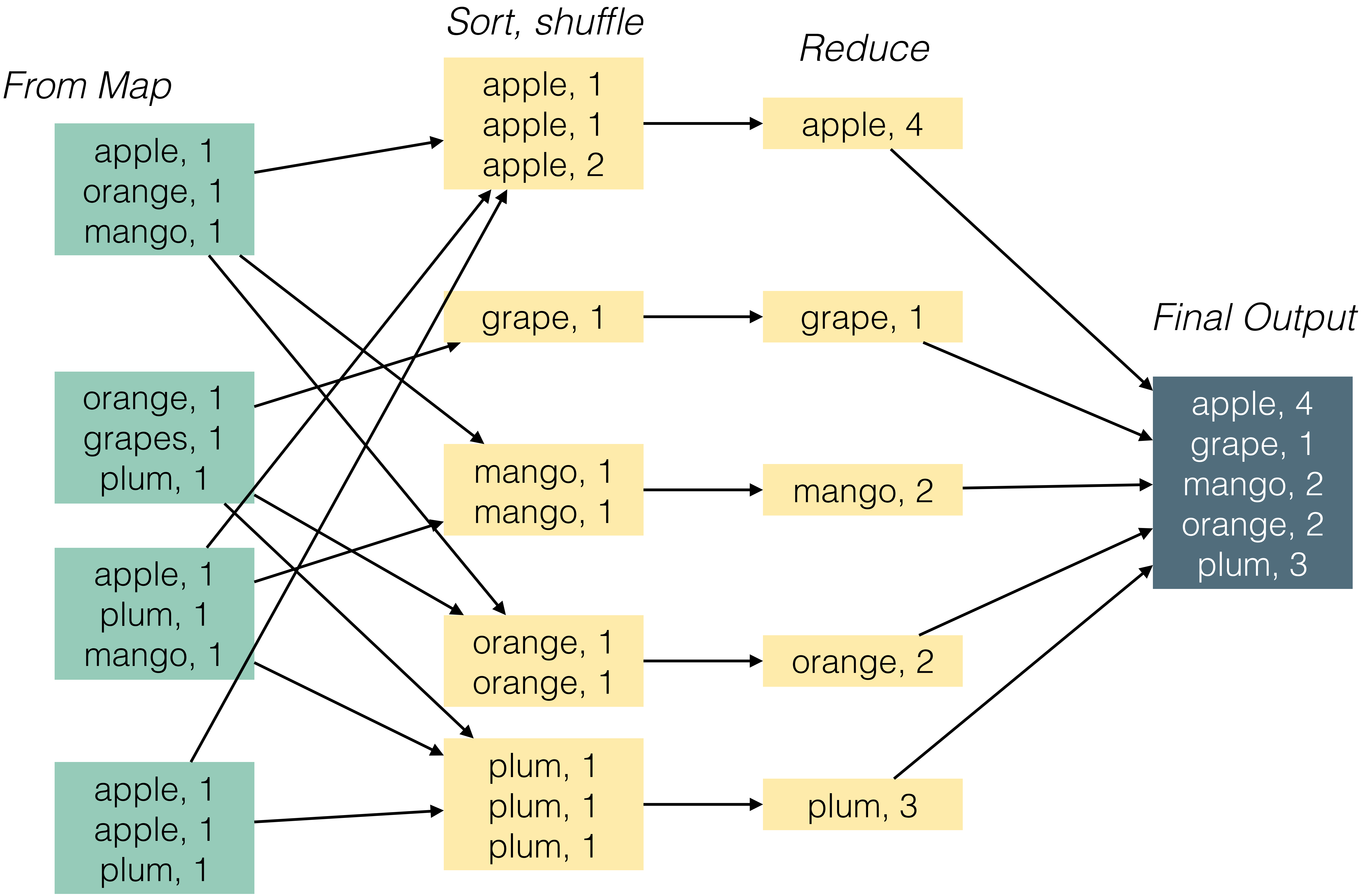
MapReduce: Example

- 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

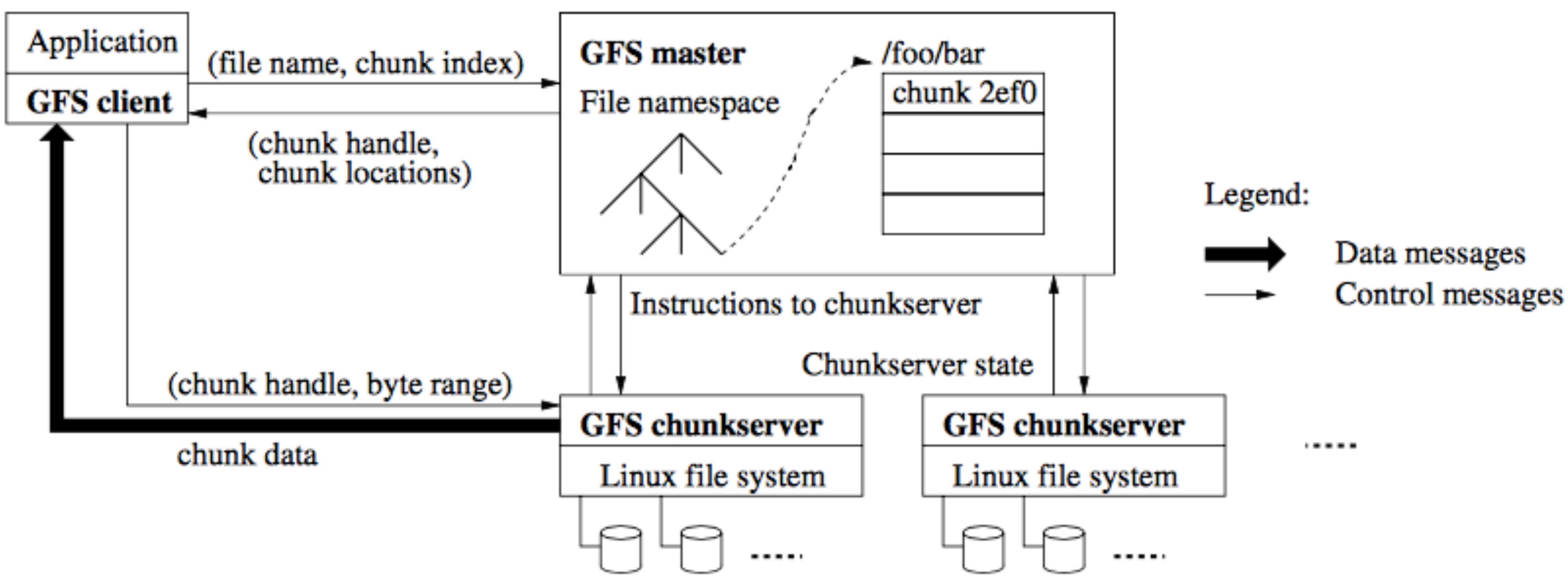


MapReduce Applications

- 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

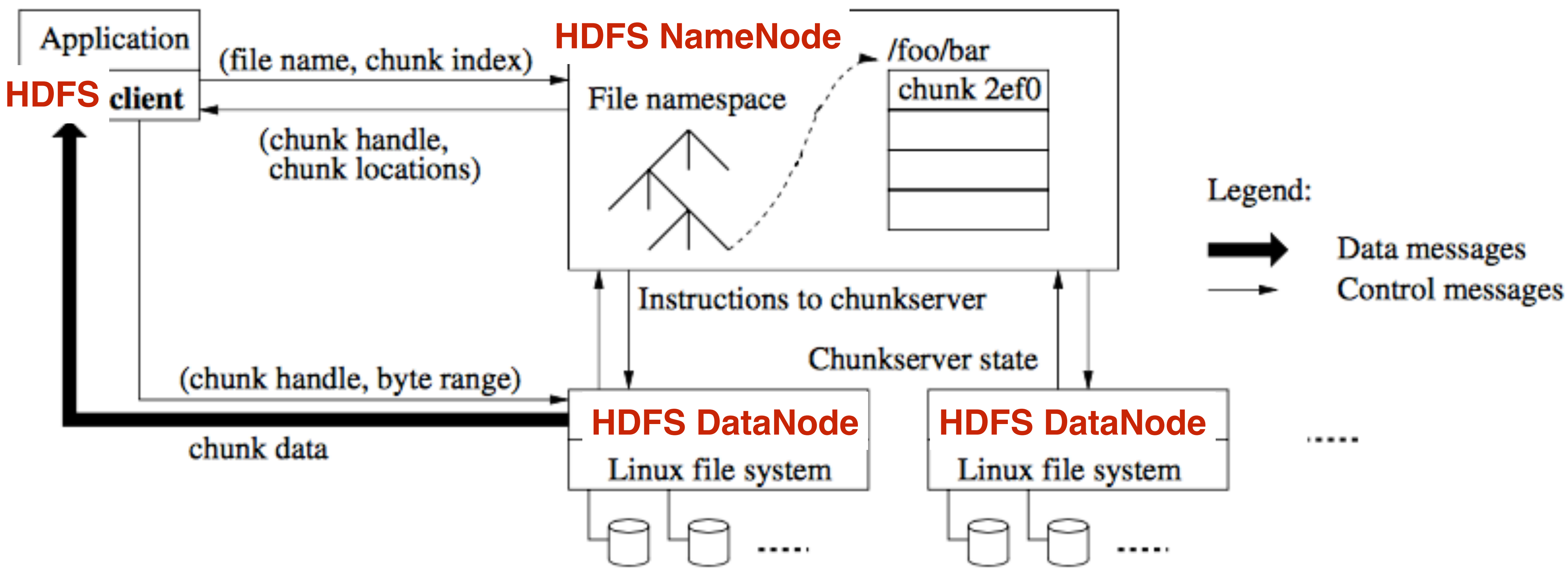
Fault tolerance via re-execution

- 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
Legend:
Data messages
Control messages
Instructions to chunkserver
Chunkserver state
(chunk handle, byte range)
chunk data
HDFS DataNode
Linux file system
HDFS DataNode
Linux file system

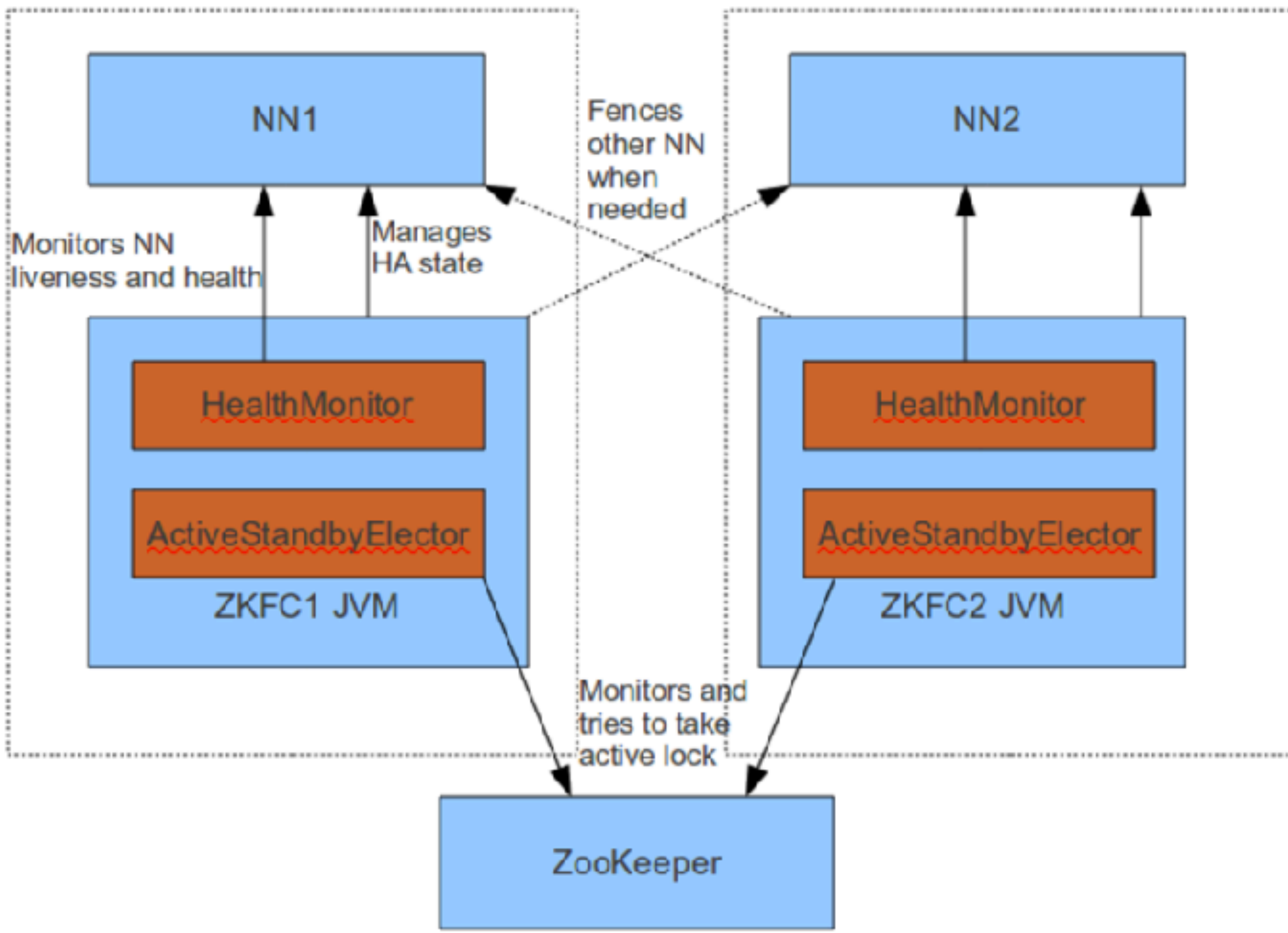
HDFS (GFS Review)

- 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 + ZooKeeper

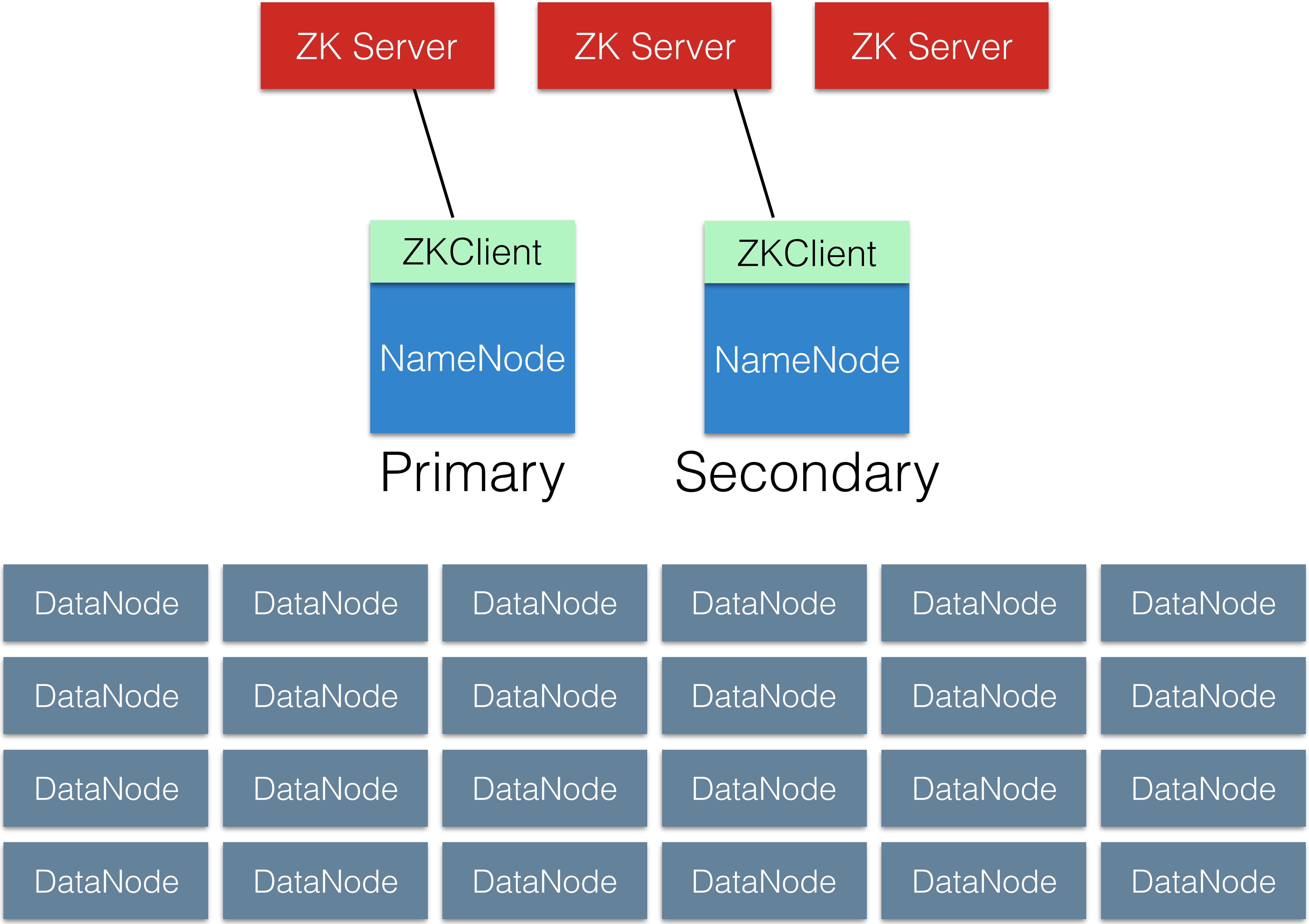
- Hadoop uses ZooKeeper for automatic failover for HDFS
- Run a ZooKeeper client on each NameNode (master)
- Primary NameNode and standbys all maintain session in ZK, primary holds an ephemeral lock
- If primary doesn't maintain contact it session expires, triggering a failure (handled by the client)

Hadoop + ZooKeeper

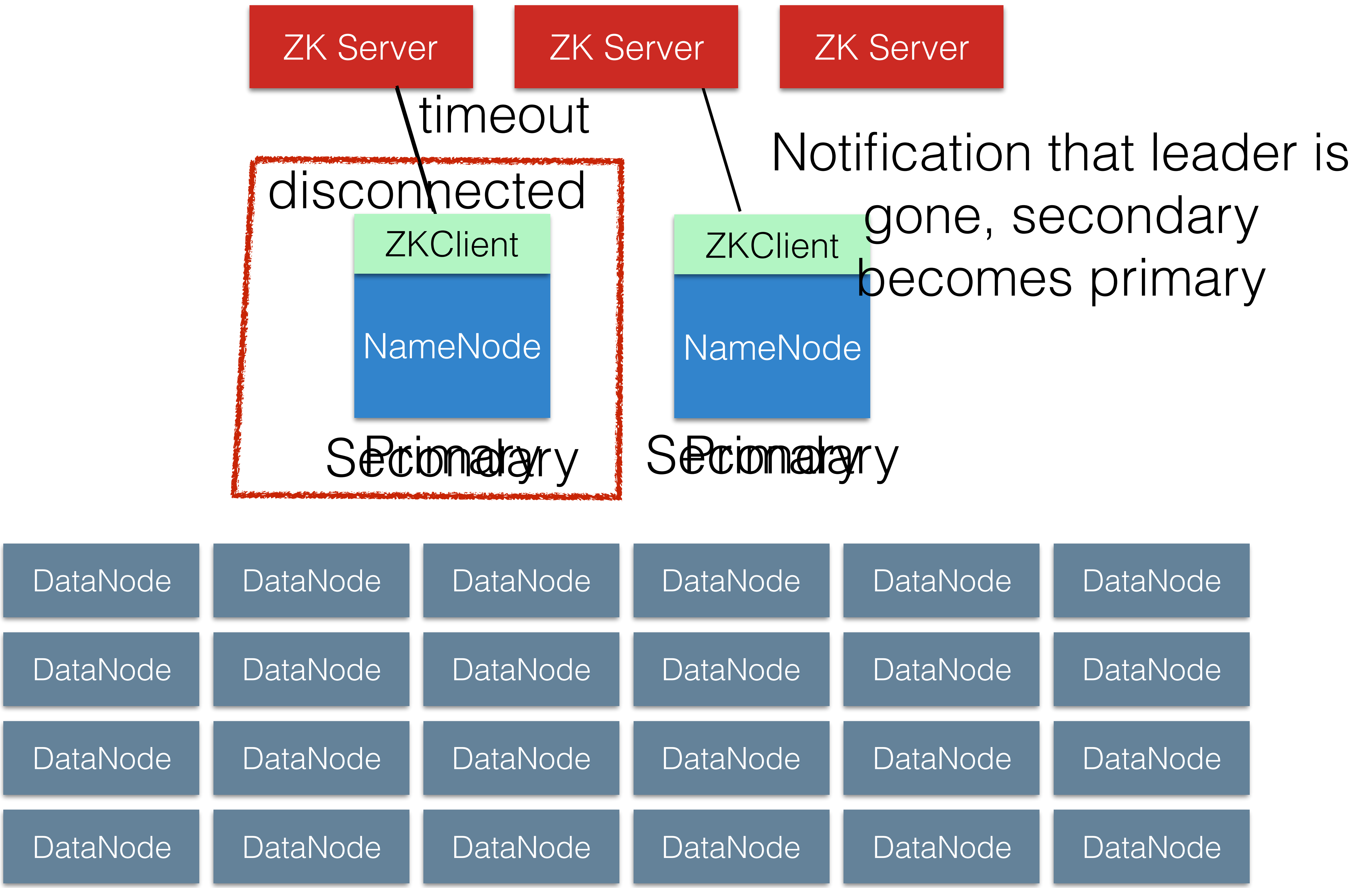


https://issues.apache.org/jira/secure/attachment/12519914/zkfc-design.pdf

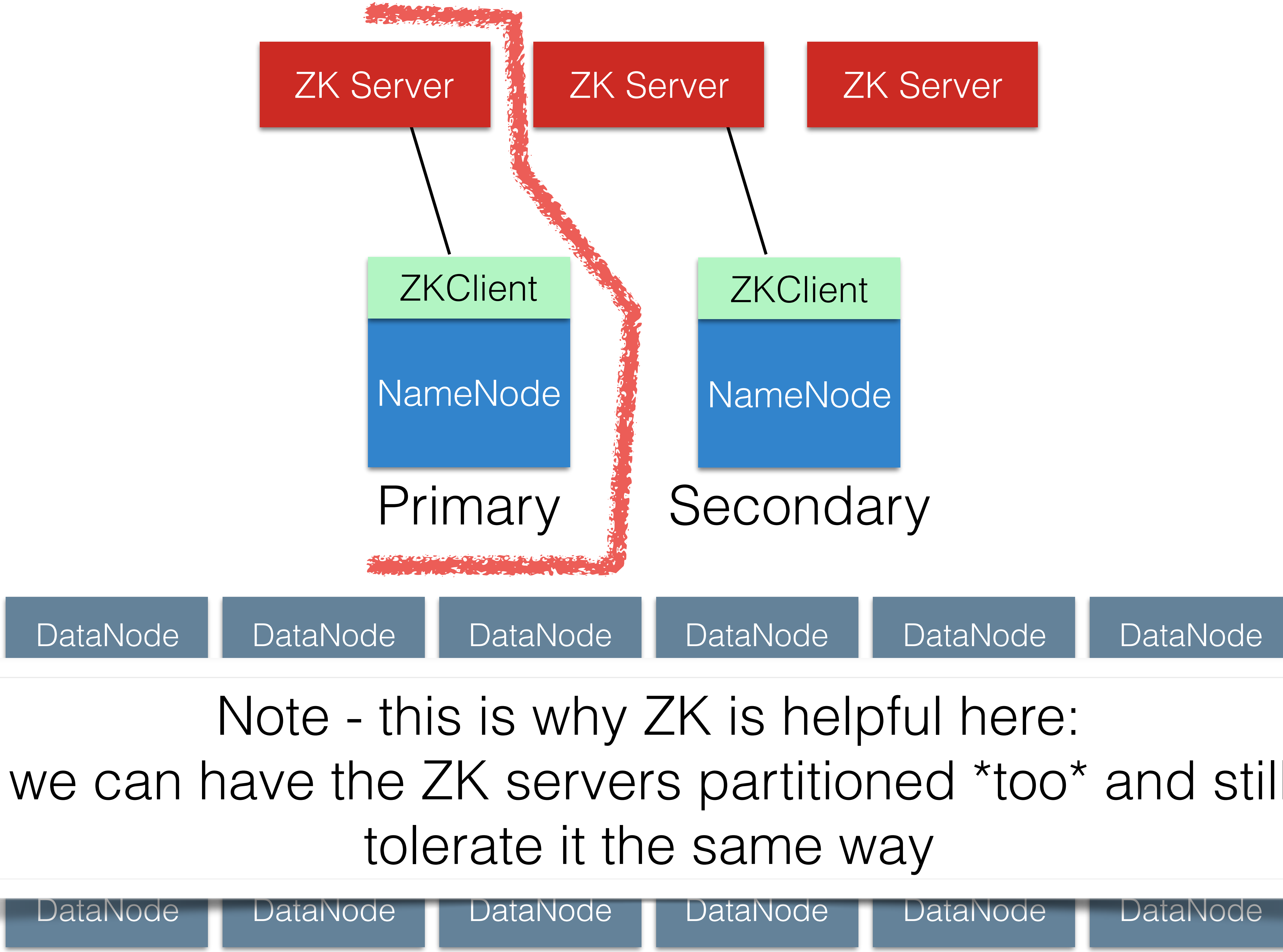
Hadoop + ZooKeeper



Hadoop + ZooKeeper



Hadoop + ZooKeeper



Note - this is why ZK is helpful here:
we can have the ZK servers partitioned *too* and still tolerate it the same way

Hadoop + ZooKeeper

- Why run ZK client in a different process?
- Why run ZK client on the same machine?
- Can this config still lead to unavailability?
- Can this config lead to inconsistency?

Hadoop Ecosystem