Hadoop Distributed File System

Requirements/Features

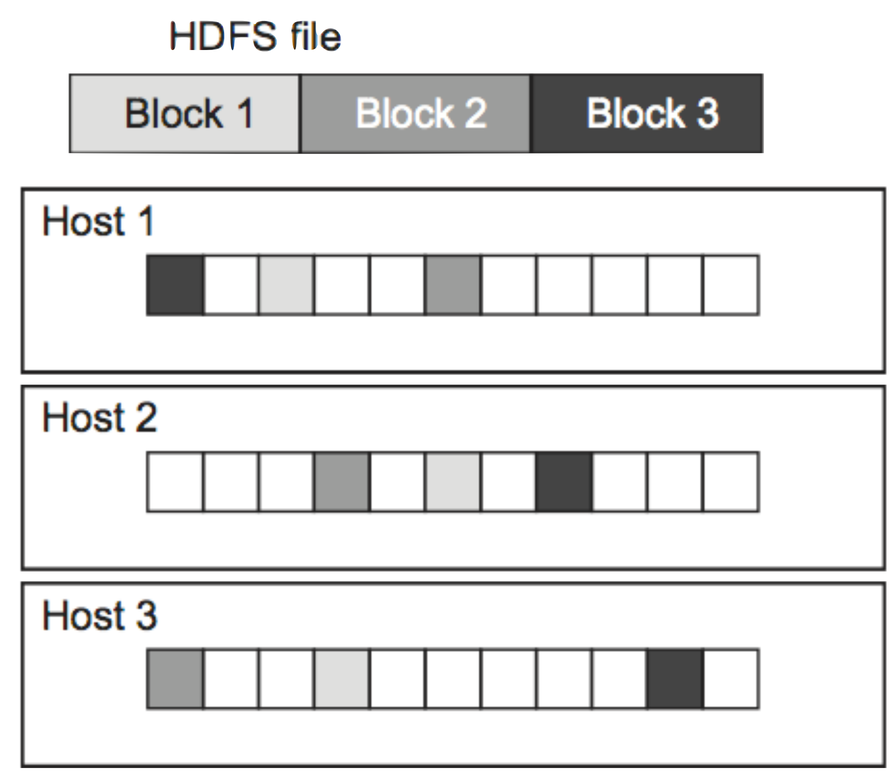
- Highly fault-tolerant
  - Failure is the norm rather than exception
- High throughput
  - May consist of thousands of server machines, each storing part of the file system's data
- Suitable for applications with large data sets
  - Time to read the whole file is more important than the reading the first record
  - Not fit for
    - Low latency data access
    - Lost of small files
    - Multiple writers, arbitrary file modifications
- Streaming access to file system data
- Can be built out of commodity hardware

Organization

- Files are divided into **chunks** (or **blocks**)
  - typically 64/128 megabytes in size
- Blocks are **replicated** at **different** compute nodes (usually 3+)
- Nodes holding copies of one block are located on **different racks**
- **Block size** and the **degree of replication** can be decided by the **user**
- A special file (the **master node**) stores, for each file, the positions of its blocks
- The master node is itself **replicated**
- A **directory** (or **tree**) for the file system knows where to find the master node
- The directory itself can be **replicated**
- All participants using the DFS know where the directory copies are

Blocks

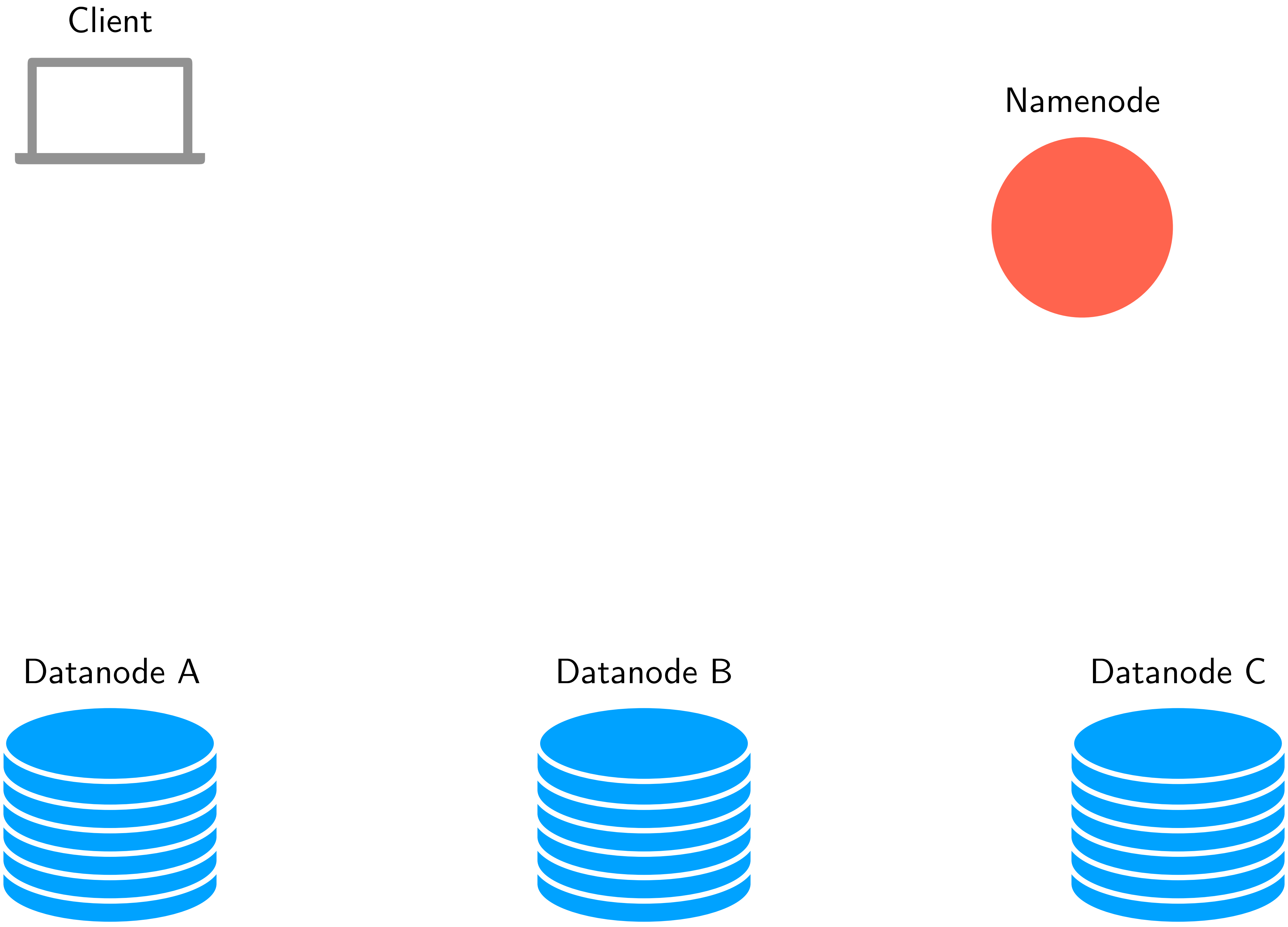
- Minimum amount of data that it can read or write
- File System Blocks are typically few KB
- Disk blocks are normally 512 bytes
- HDFS Block is much larger – 64 MB by default
  - Unlike file system the smaller file does not occupy the full 64MB block size
  - Large to minimize the cost of seeks
  - Time to transfer blocks happens at disk transfer rate
- Block abstractions allows
  - Files can be larges than block
  - Need not be stored on the same disk
  - Simplifies the storage subsystem
  - Fit well for replications
  - Copies can be read transparent to the client



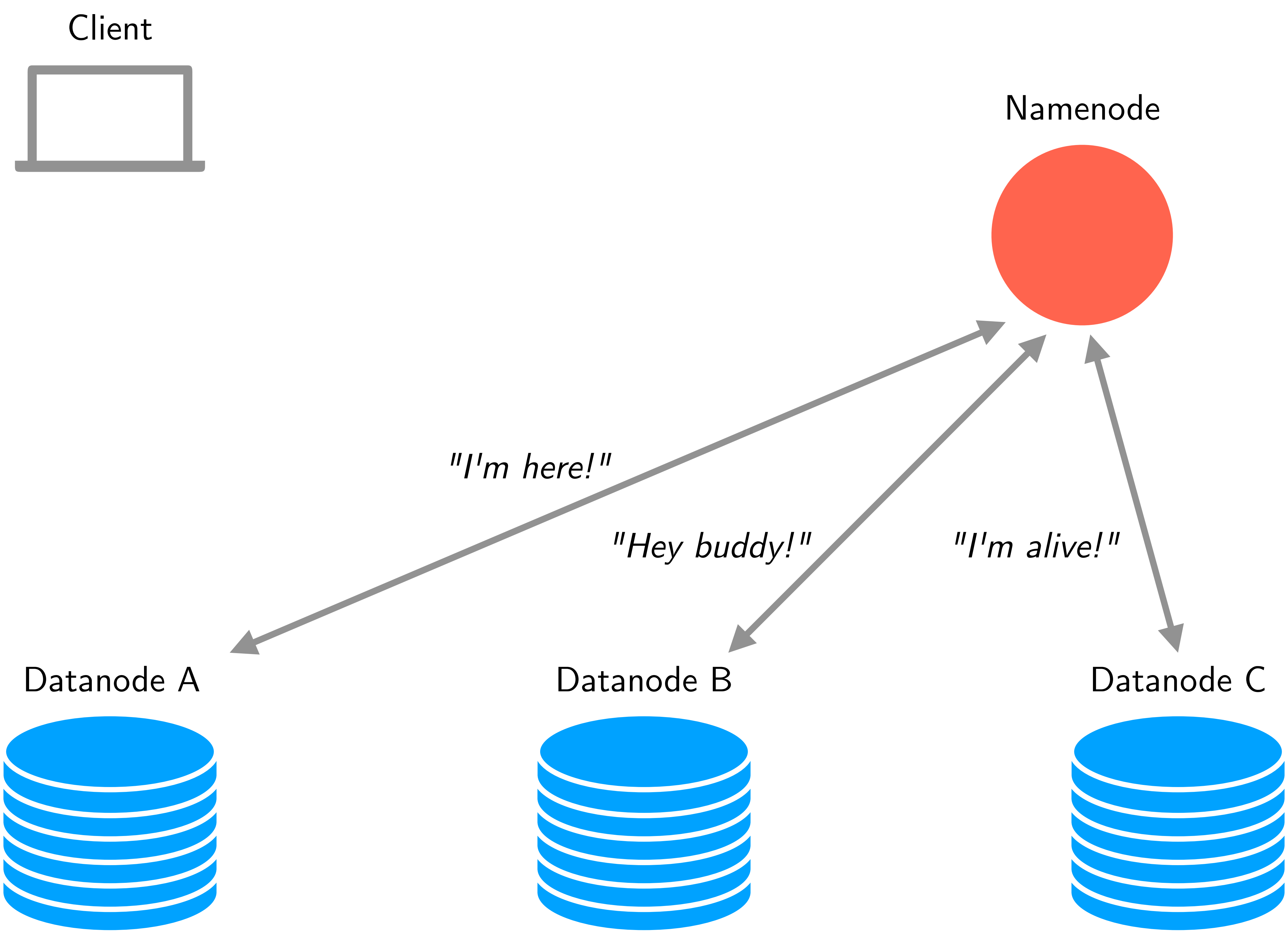
Namenodes & Datanodes

- Master/slave architecture
- DFS cluster consists of a single name node, a master server that manages the file system namespace and regulates access to files by clients.
  - Metadata
  - Directory structure
  - File-to-block mapping
  - Location of blocks
  - Access permissions
- There are a number of data nodes, usually one per node in a cluster.
  - A file is split into one or more blocks and set of blocks are stored in data nodes.
  - The data nodes manage storage attached to the nodes that they run on.
  - Data nodes serve read, write requests, perform block creation, deletion, and replication upon instruction from name node.

HDFS Architecture



HDFS Architecture



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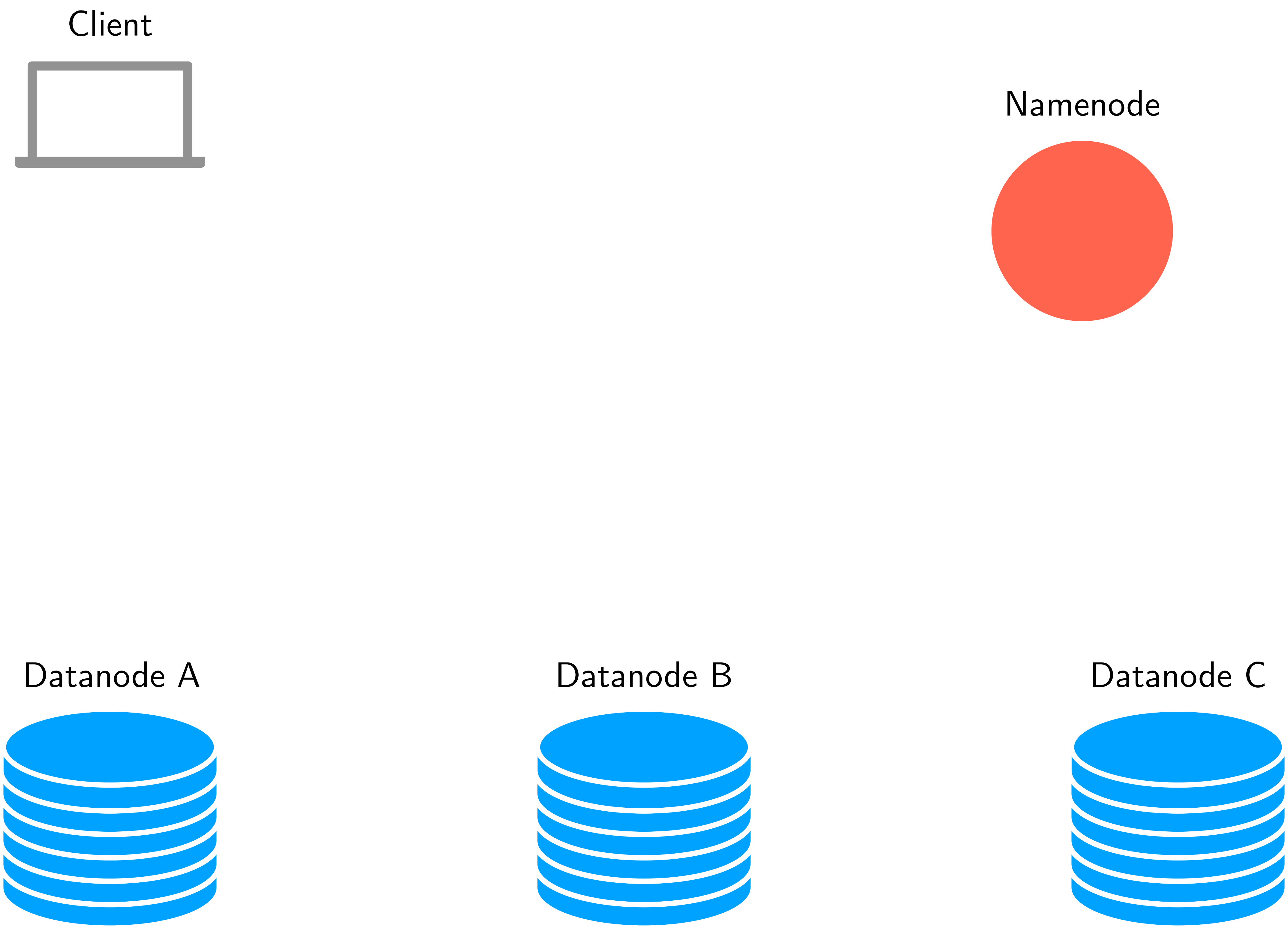

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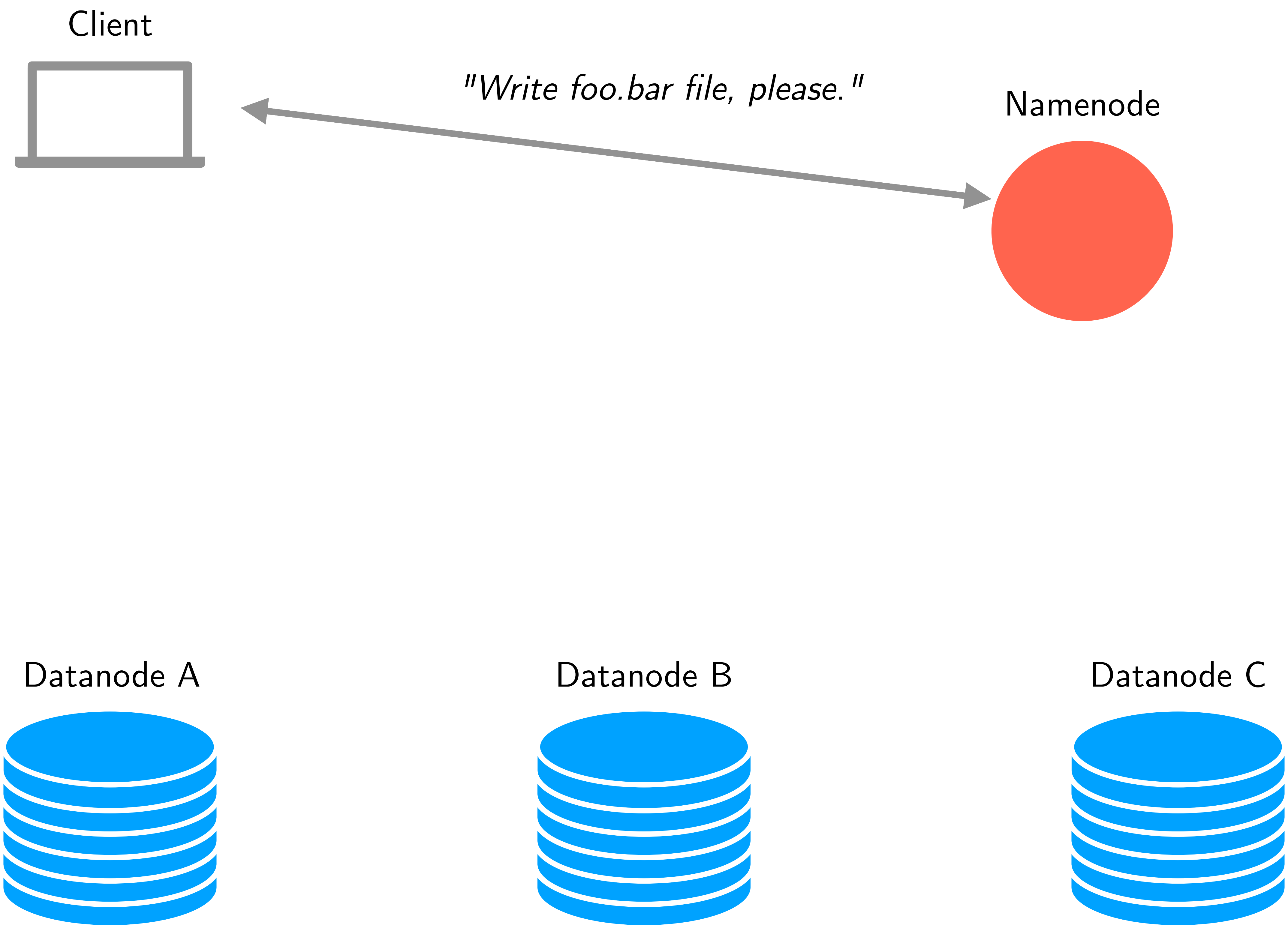

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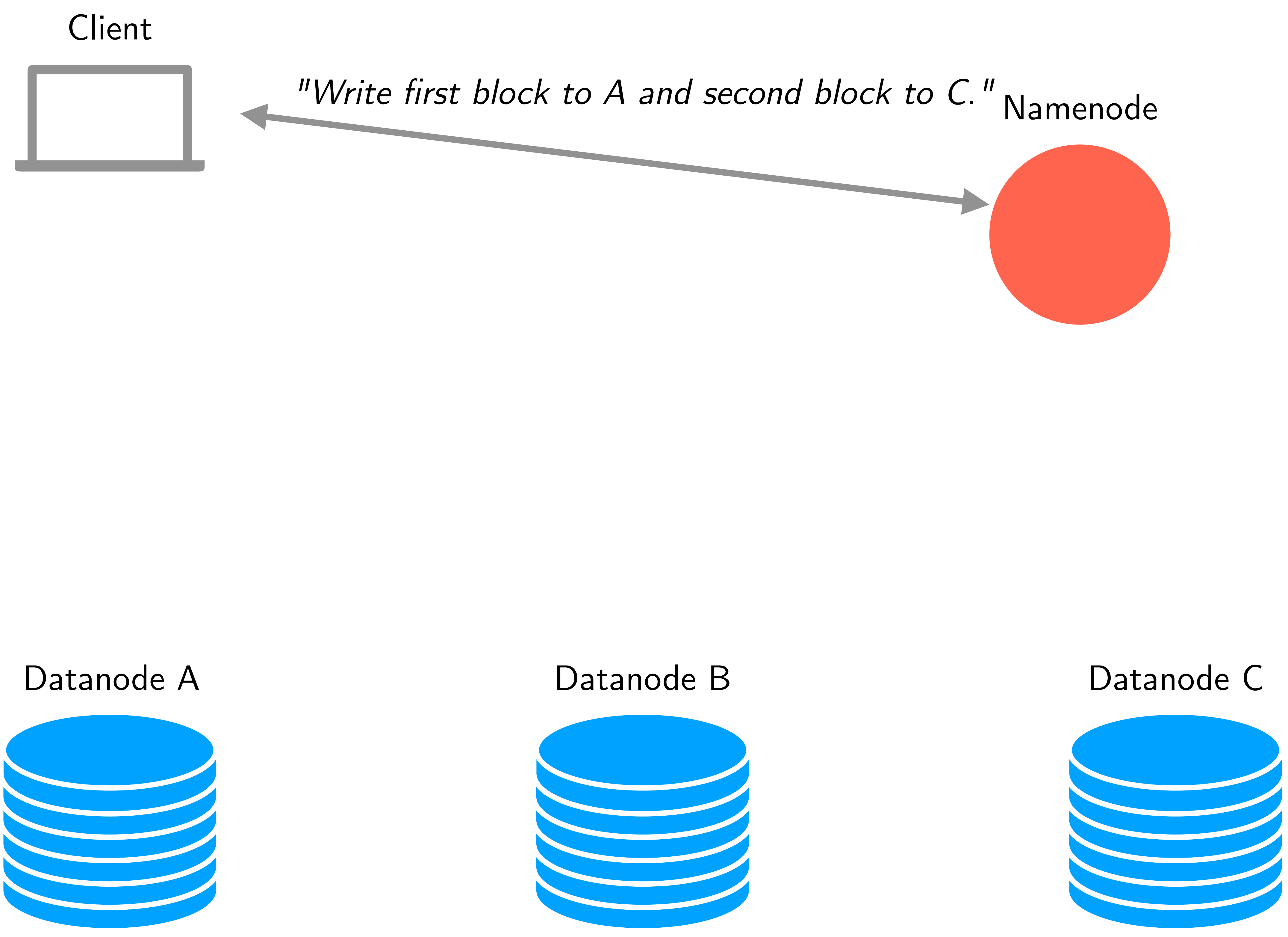

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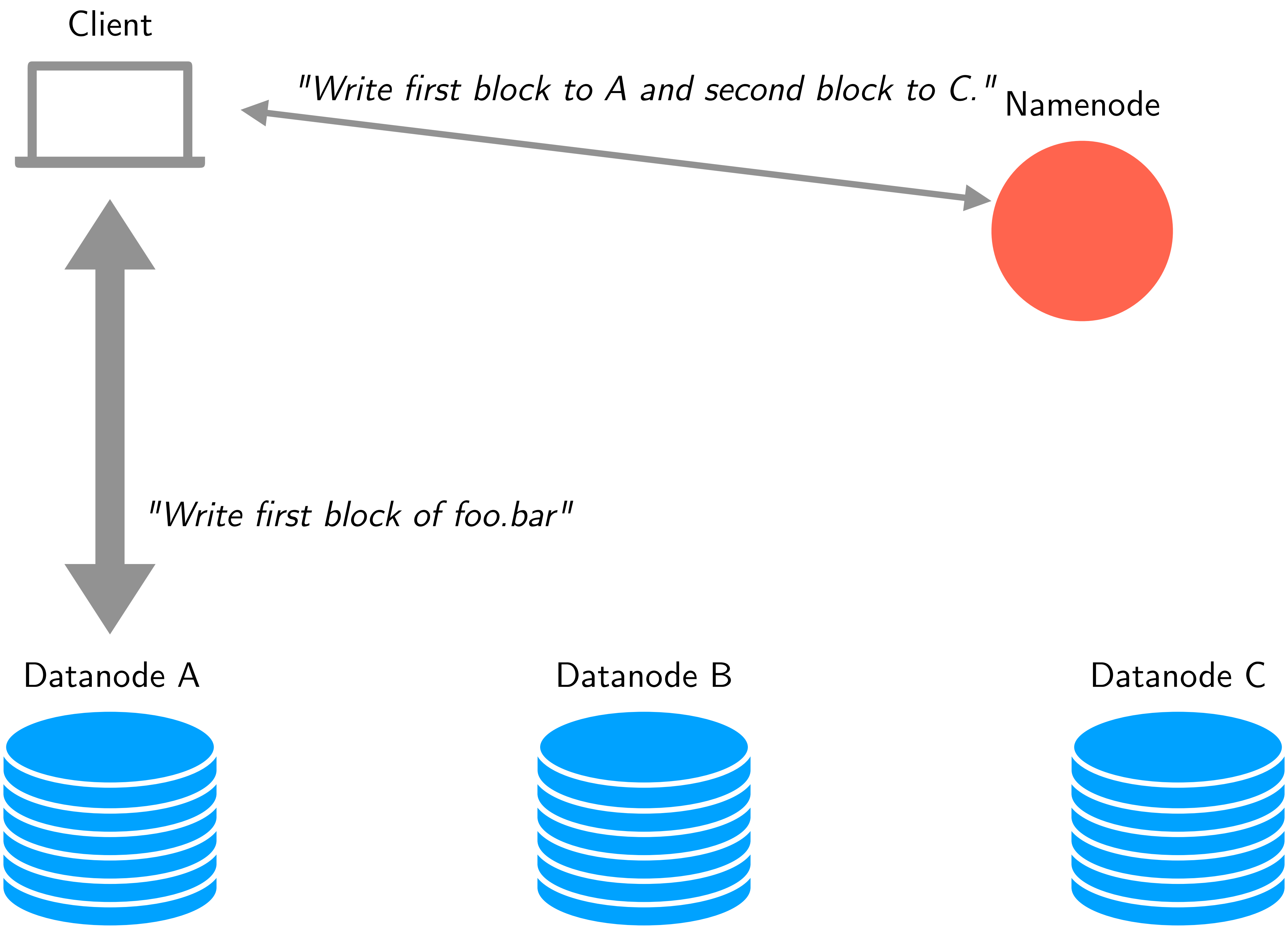

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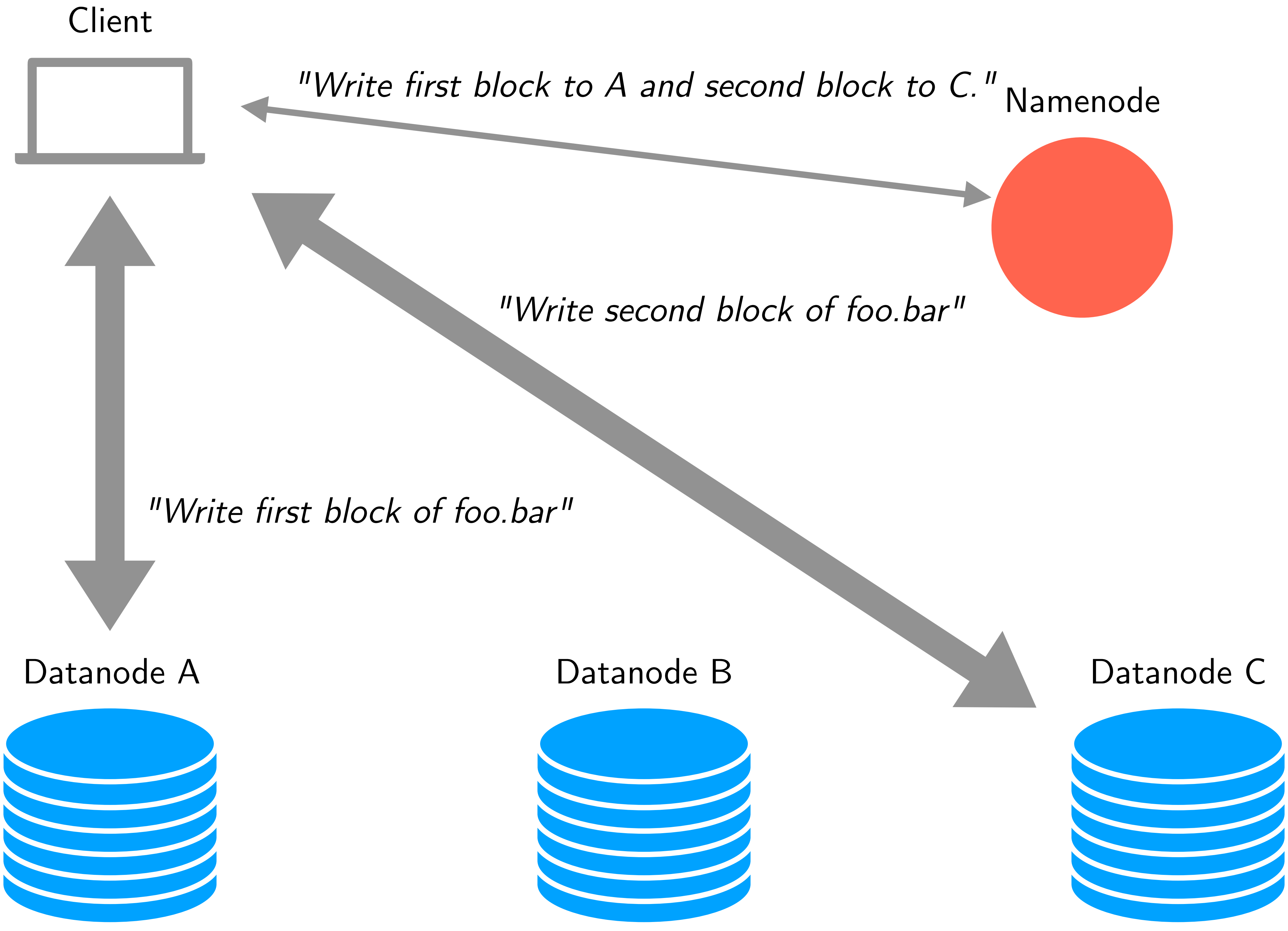
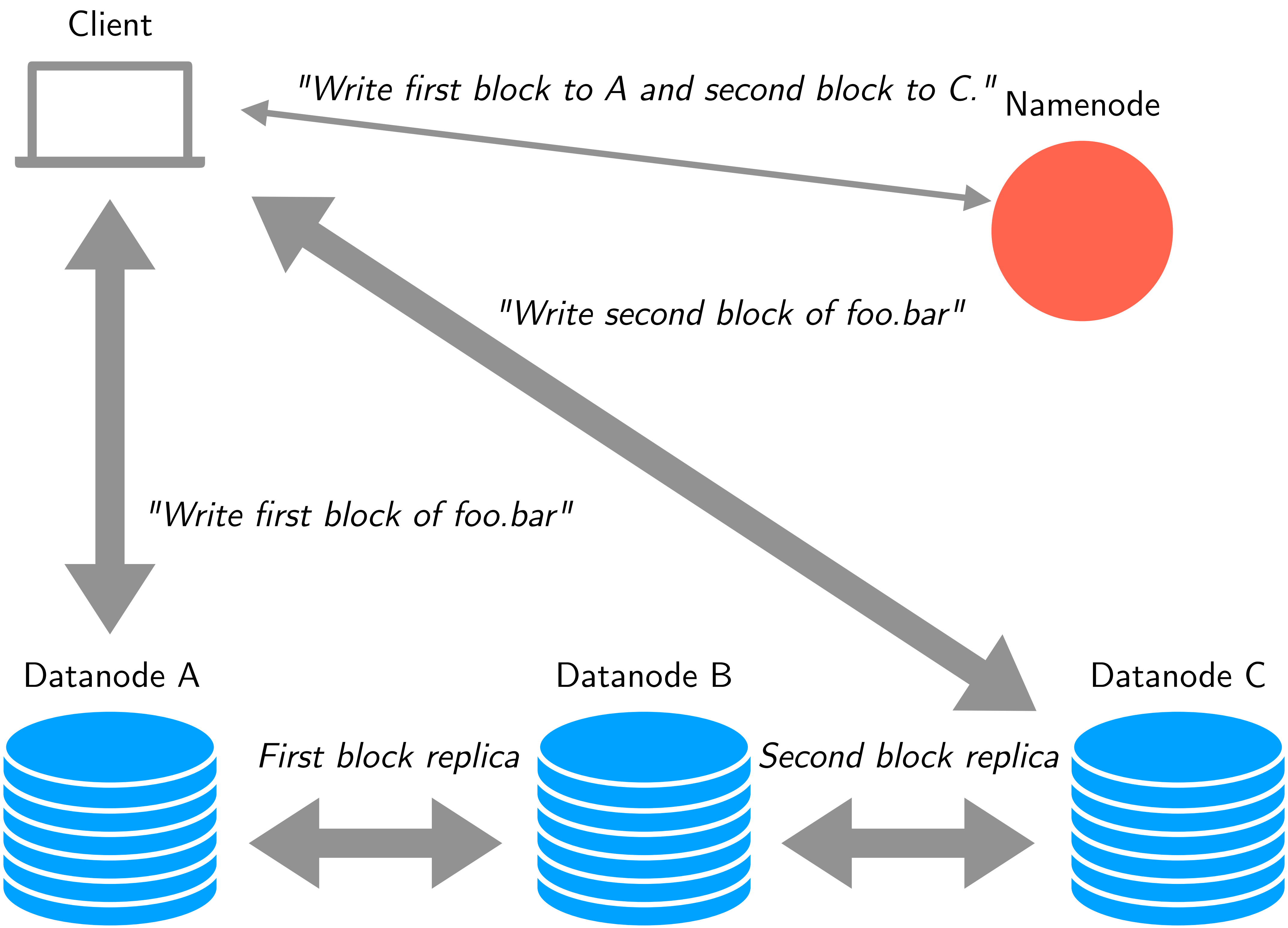
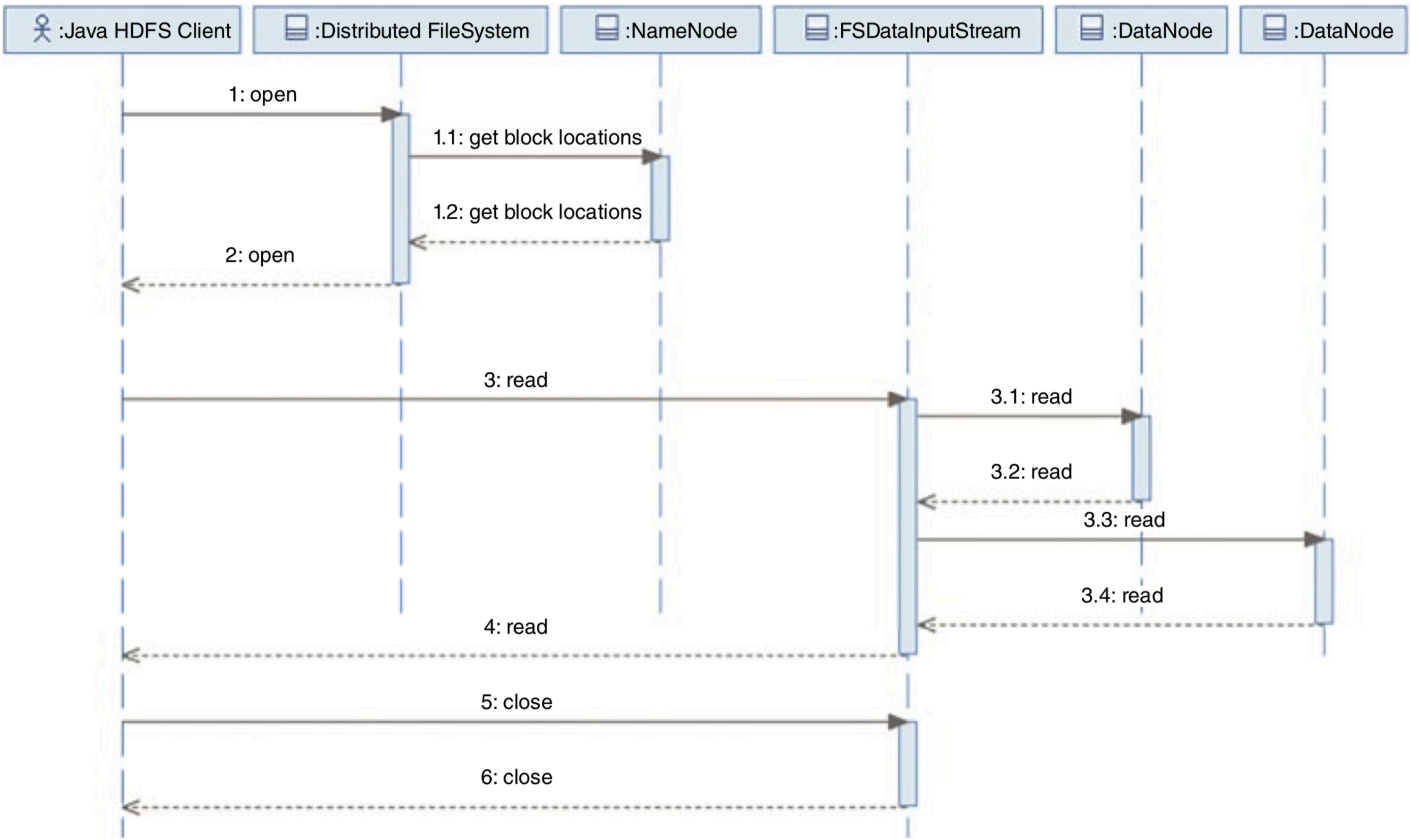


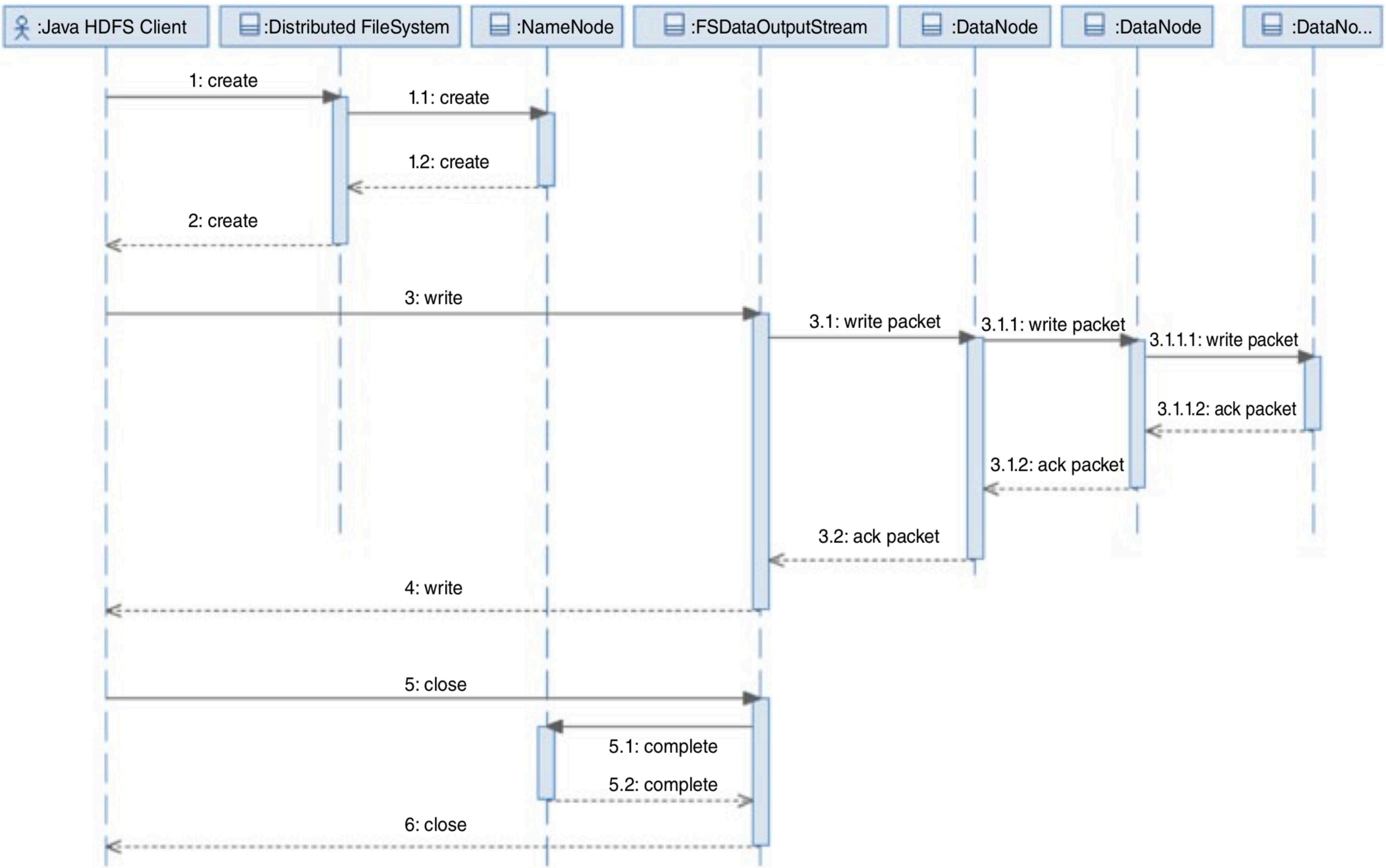
HDFS Architecture



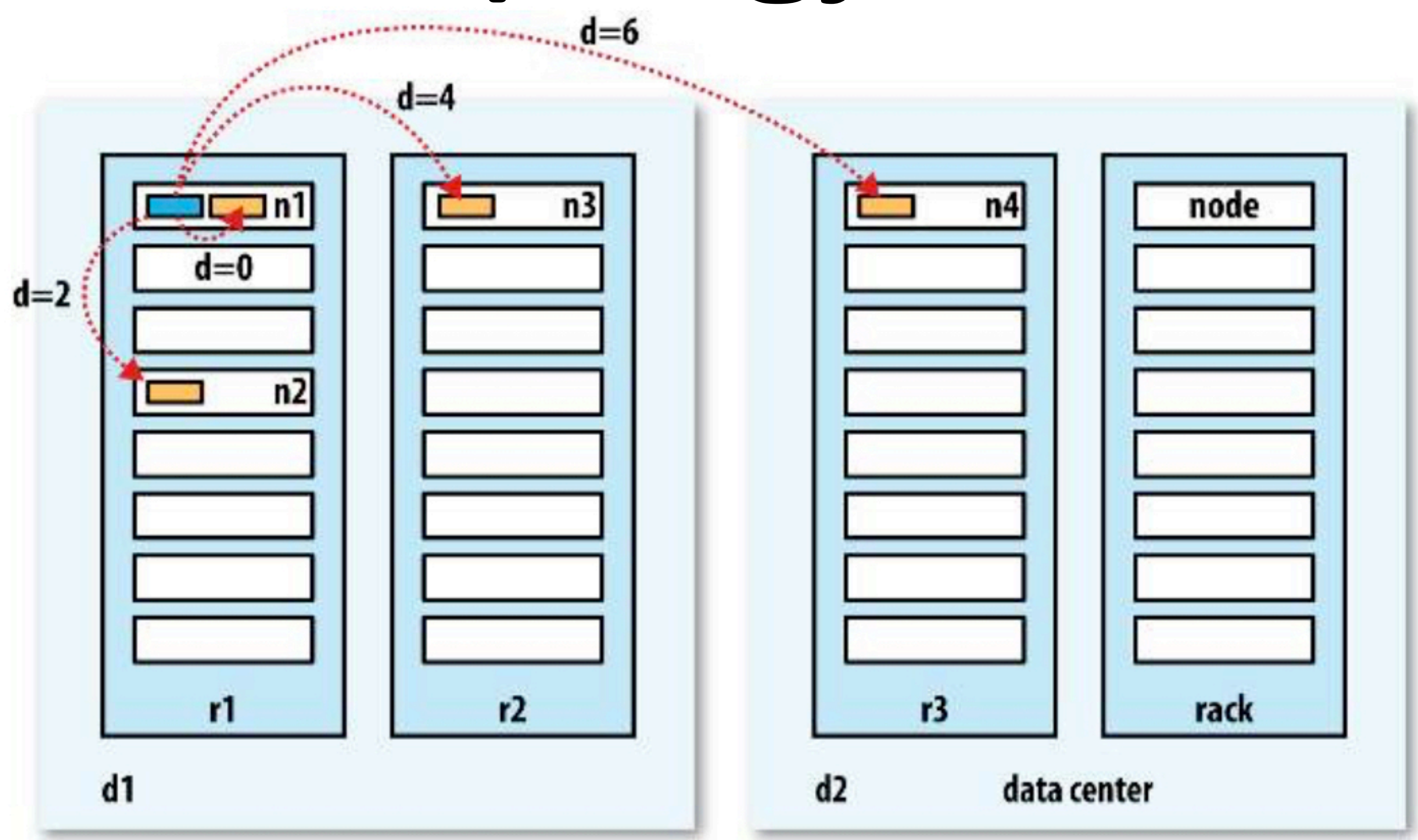
Anatomy of a read



Anatomy of a write



Network Topology and Hadoop



- **First replica** on the same node as the client
  - For clients running outside the cluster, a node is chosen at random
- **Second replica** on a different rack from the first, chosen at random
- **Third replica** on the same rack as the second, but on a different node chosen at random
- **Further replicas** are placed on random nodes in the cluster
- The system always tries to avoid placing too many replicas on the same rack/node

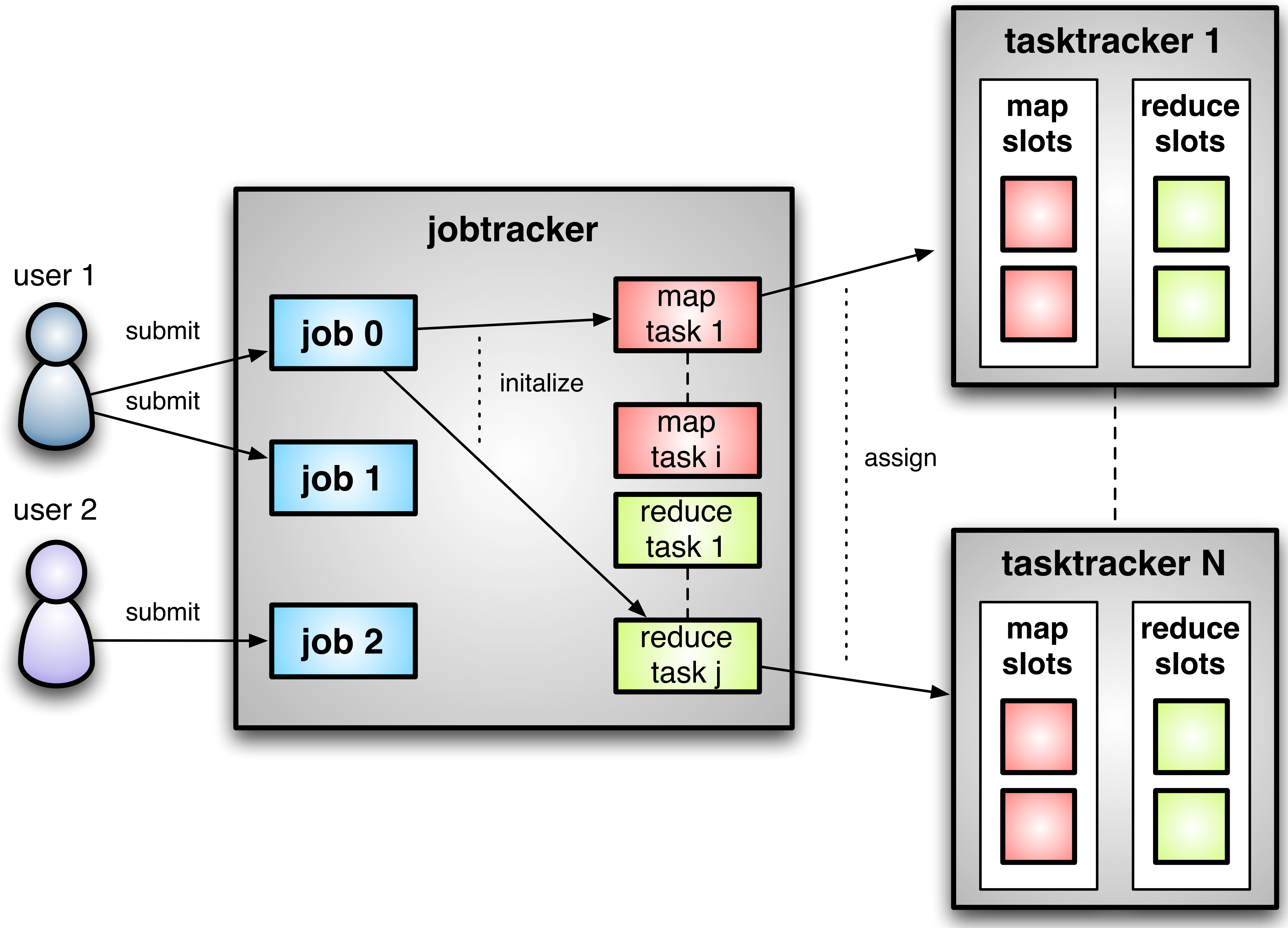
Source: Tom White, "*Hadoop - The Definitive Guide (4 ed)*", O'Reilly, 2015

Hadoop Distributed Resource Management

Hadoop 1.0

- **Job**
  - Unit of work that the client wants to be performed
- **Task**
  - Unit of work that Hadoop schedules and runs run on nodes in the cluster (map & reduce)
- **Slot**
  - Processing element for tasks (map & reduce)
- **Job Tracker**
  - Accepts jobs submitted by users
  - Creates tasks
  - Assigns map and reduce tasks to Task Trackers
  - Monitors tasks and Task Trackers status, re-executes tasks upon failure
- **Task Tracker**
  - Runs map and reduce tasks upon instruction from the Job Tracker
  - Manages storage and transmission of intermediate output

Hadoop 1.0

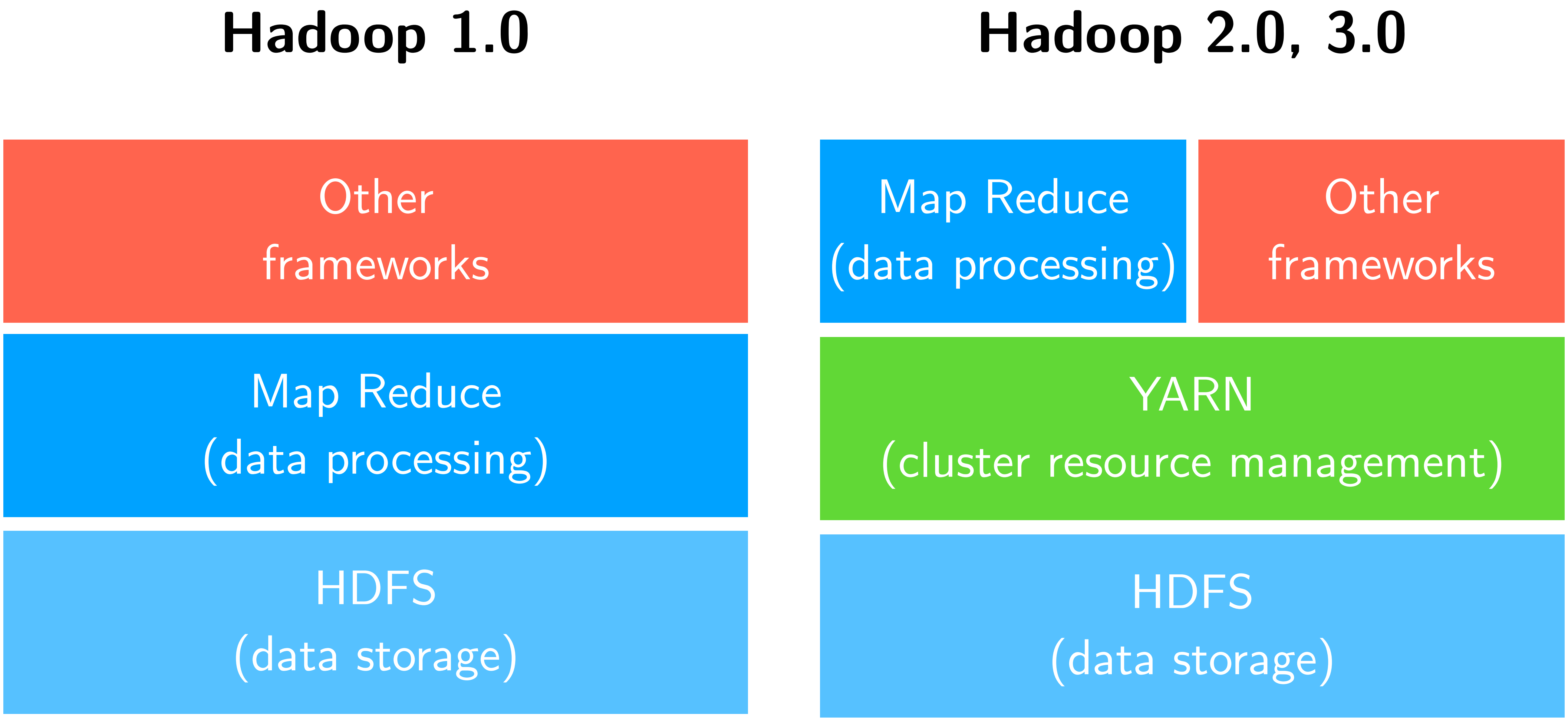


user 1
user 2
submit
submit
submit
jobtracker
job 0
job 1
job 2
initalize
map task 1
map task i
reduce task 1
reduce task j
assign
tasktracker 1
map slots
reduce slots
tasktracker N
map slots
reduce slots

Hadoop 1.0 Limitations

- Scalability
  - Due to the single job tracker, it becomes a **bottleneck**
  - No more than 4'000 nodes and 40'000 concurrent tasks
- Availability
  - Job tracker is a **single point of failure**
  - Any failure kills all queued and running jobs
  - Jobs need to be resubmitted by the users
- Resource Utilization
  - Due to the **predefined number** of map and reduce slots for each task tracker, utilization issues occur
- Limitations in running non-Hadoop applications
  - Problems in performing real-time analysis and running ad-hoc queries as Hadoop is **batch-driven**

Need of YARN


Hadoop 1.0
Other frameworks
Map Reduce (data processing)
HDFS (data storage)
Hadoop 2.0, 3.0
Map Reduce (data processing)
Other frameworks
YARN (cluster resource management)
HDFS (data storage)

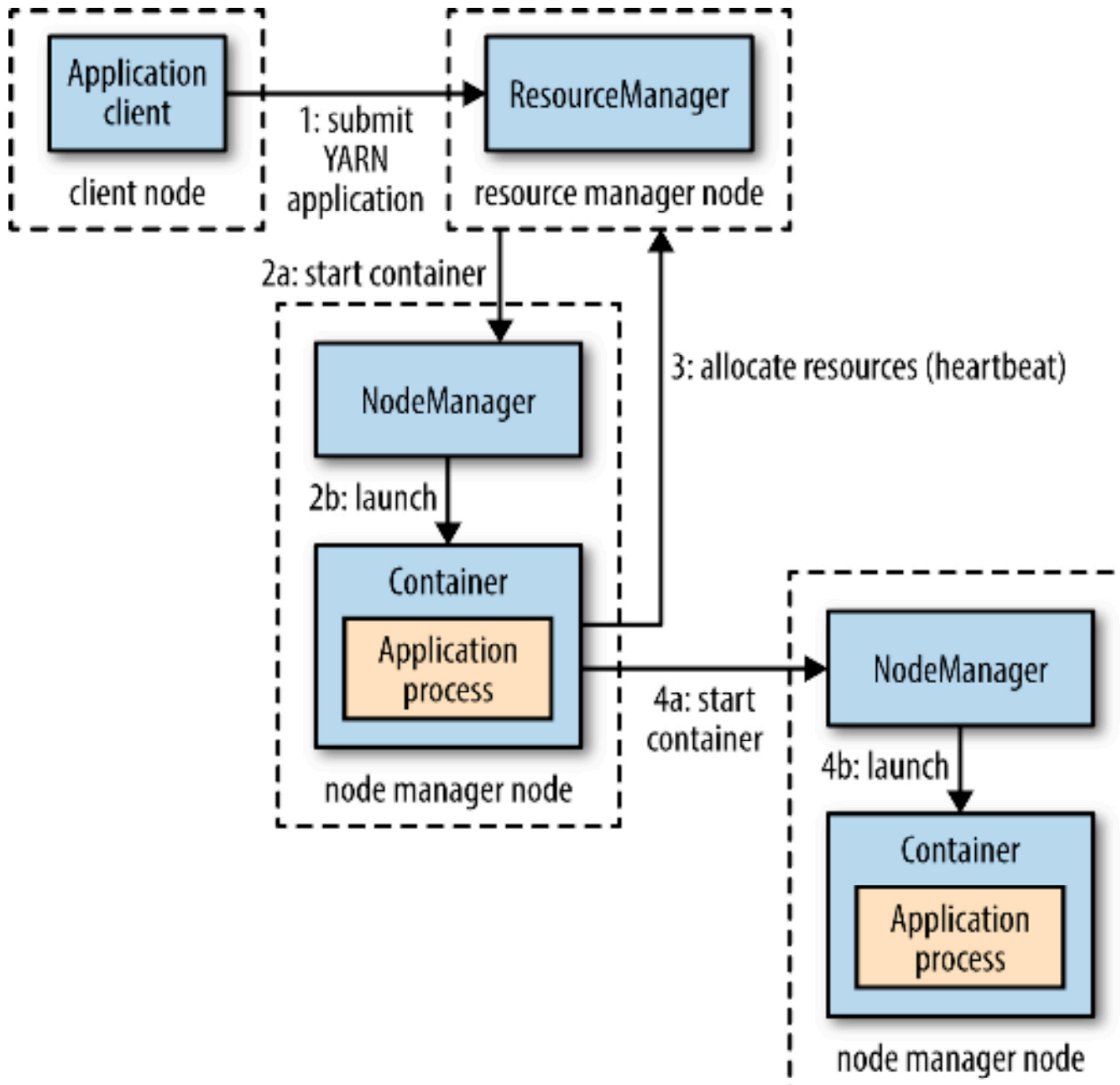
YARN Benefits

- **Scalability**
  - Cluster size of more than 10'000 nodes
  - More than 100'000 concurrent jobs
- **Compatibility**
  - Applications developed for Hadoop 1.0 runs on YARN
  - No disruption/availability issues
- **Resource Utilization**
  - Dynamic allocation of cluster resources
  - Improved use of resources
- **Multi-tenancy**
  - Can use open-source and proprietary data access engines
  - Can perform real-time analysis and execute ad-hoc queries
  - Is used in many more distributed frameworks (e.g., Spark)

YARN Components

- YARN provides its core services via two types of long-running daemon
  - a **resource manager** (one per cluster) to manage the use of resources across the cluster
  - **node managers** running (one per node in the cluster) to launch and monitor containers
- A **container** executes an application-specific process (a.k.a. **application master**) with a constrained set of resources (memory, CPU, and so on)
- A **resource request** for a set of containers can express
  - the amount of computer resources required for each container (memory and CPU)
  - locality constraints for the containers in that request.
- If the **locality constraint** cannot be met
  - no allocation is made or
  - the constraint can be loosened
- YARN itself does not provide any **communication mechanism** for the parts of the application

Anatomy of a YARN application run



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YARN Applications

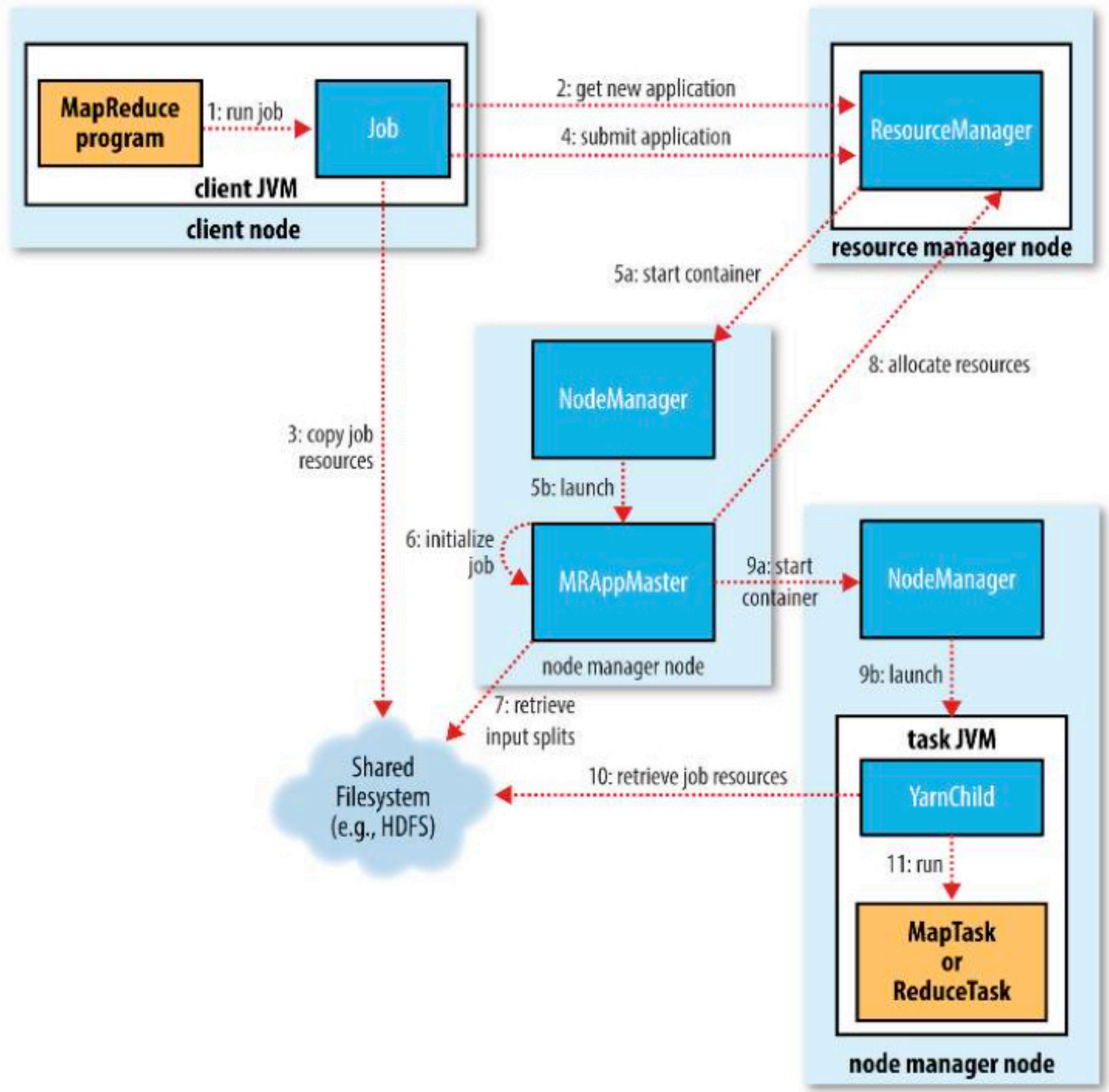
The lifespan of a YARN applications can be categorized in terms of how they map to the jobs that users run:

- First: one application per user job, e.g., MapReduce jobs
- Second: one application per workflow or user session of (possibly unrelated) jobs., e.g., Spark jobs
  - This approach can be more efficient than the first, since containers can be reused between jobs
  - There is also the potential to cache intermediate data between jobs.
- Third: long-running application that is shared by different users.
  - Such an application often acts in some kind of coordination role
  - For example, a long-running application master for launching other applications on the cluster
  - The "always on" application master means that users have very low latency

YARN Scheduling

- YARN provides a **choice of configurable schedulers**
  - Scheduling in general is a **NP-Hard** problem and there is no one "best" policy
- The **FIFO Scheduler** places applications in a **single queue** and runs them in the order of submission (first in, first out)
  - Simple to understand and no configuration needed
  - Not suitable for shared clusters. Large applications will use all the resources in a cluster, so each application has to wait its turn
- The **Capacity Scheduler** has separate **dedicated queues**, each configured to use a given fraction of the cluster capacity
  - Within a queue, applications are scheduled using FIFO scheduling
- The **Fair Scheduler** will dynamically balance resources between all running jobs
  - There is no need to reserve a set amount of capacity
- **Delay scheduling** is supported by both the Capacity Scheduler and the Fair Scheduler
  - In practice, waiting a short time (no more than a few seconds) can dramatically increase the chances of being allocated a container on the requested node, and therefore increase the efficiency of the cluster
- Every node manager in a YARN cluster periodically sends a **heartbeat request** to the resource manager
  - Heartbeats carry information about the node manager's running containers and the resources available for new containers
  - Each heartbeat is a potential **scheduling opportunity** for an application to run a container

Anatomy of a MapReduce application run



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Fault Tolerance (I)

- **Task** Failure
  - The user code in the map or reduce task throws a **runtime exception**
    - the task JVM reports the error back to its parent application master before it exits.
    - The application master marks the task attempt as failed
    - The application master frees up the container
  - **Sudden exit** of the task JVM
    - the node manager informs the application master
    - The application master marks the task attempt as failed
    - The application master frees up the container
  - **Hanging tasks**
    - The application master notices that it hasn't received a progress update for a while
    - The task JVM process will be killed automatically after this period
    - The application master marks the task as failed
  - When the application master is notified of a task attempt that has failed, it will reschedule execution of the task
  - The application master will try to avoid rescheduling the task on a node manager where it has previously failed

Fault Tolerance (II)

- **Application Master** Failure
  - The resource manager will detect the failure and start a new instance of the master running in a new container (managed by a node manager)
  - The client needs to go back to the resource manager to ask for the new application master's address (this process is transparent to the user)
  - If a MapReduce application master fails **twice** it will not be tried again and the job will fail
- **Node Manager** Failure
  - The resource manager will notice a node manager that has stopped sending heartbeats if it hasn't received one for 10 minutes
  - The resource manager will remove it from its pool of nodes to schedule containers on
  - Any task or application master running on the failed node manager will be considered failed
  - Node managers may be blacklisted if the number of failures for the application is high
  - **Blacklisting** is done by the application master

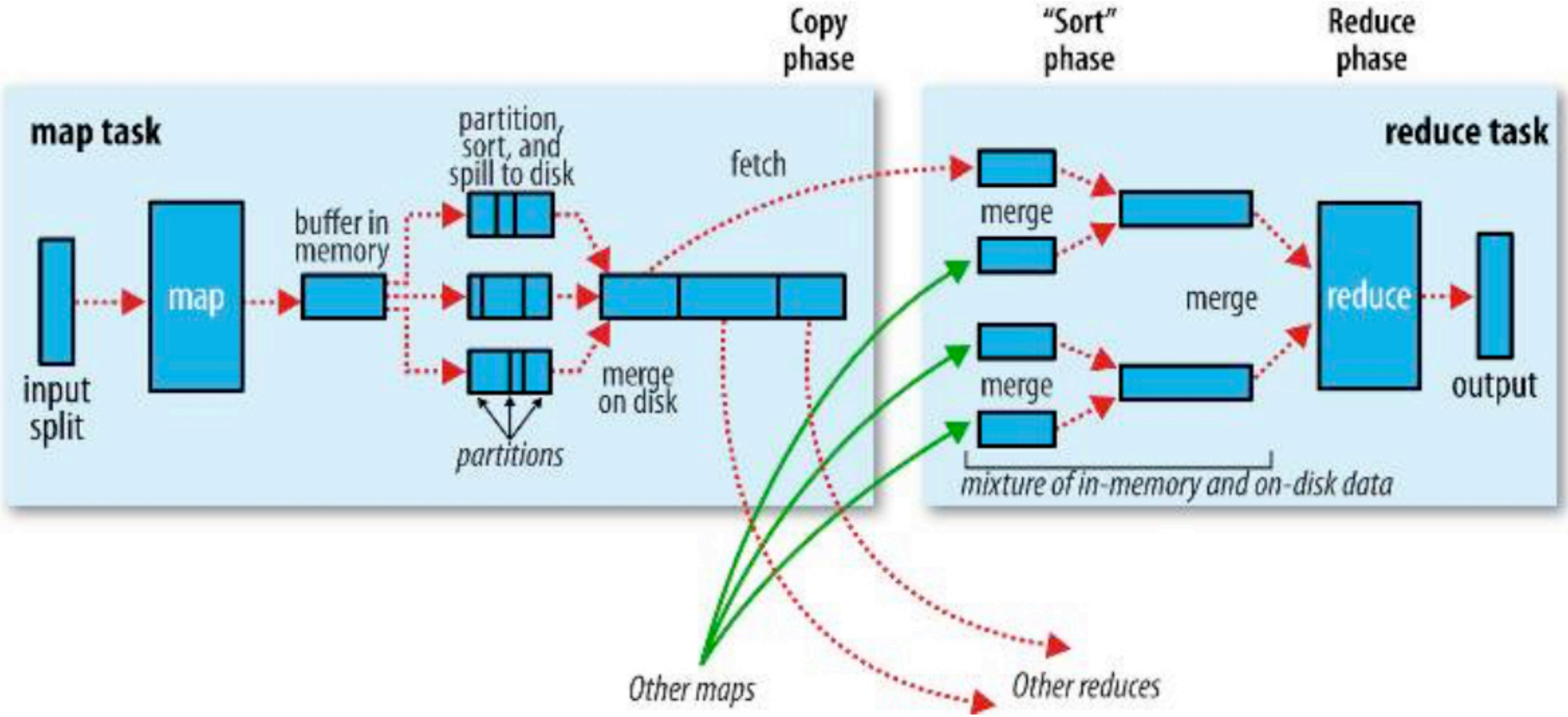
Fault Tolerance (III)

- **Resource Manager** Failure
  - In the default configuration, the resource manager is a **single point of failure**
  - To achieve **high availability**, it is necessary to run a pair of resource managers in an **active-standby** configuration
  - Information about all the running applications is stored in a highly available state store
  - The standby resource manager can recover the core state of the failed active resource manager
  - The transition of a resource manager from standby to active is handled by a **failover controller**
  - The default failover controller uses **leader election** to ensure that there is only a single active resource manager at one time

Speculative Execution

- Problem: **Stragglers** (i.e., slow workers) significantly lengthen the completion time
  - Other jobs may be consuming resources on machine
  - Bad disks with soft (i.e., correctable) errors transfer data very slowly
  - Other weird things: processor caches disabled at machine init
- Solution: Close to completion, **spawn backup copies** of the remaining in-progress tasks.
  - Whichever one finishes first, "wins"
- Additional cost: a few percent more resource usage
- Example: A sort program without backup = 44% longer

Shuffle and Sort



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