Storing Data with HDFS

Overview

Understanding the components of HDFS

Moving files in and out of HDFS

Managing replication strategies for data nodes

Understanding failure management strategies for the name node

HDFS

Hadoop Distributed File System

HDFS

Built on commodity hardware

Highly fault tolerant, hardware failure is the norm

Suited to batch processing - data access has high throughput rather than low latency

Supports very large data sets

HDFS

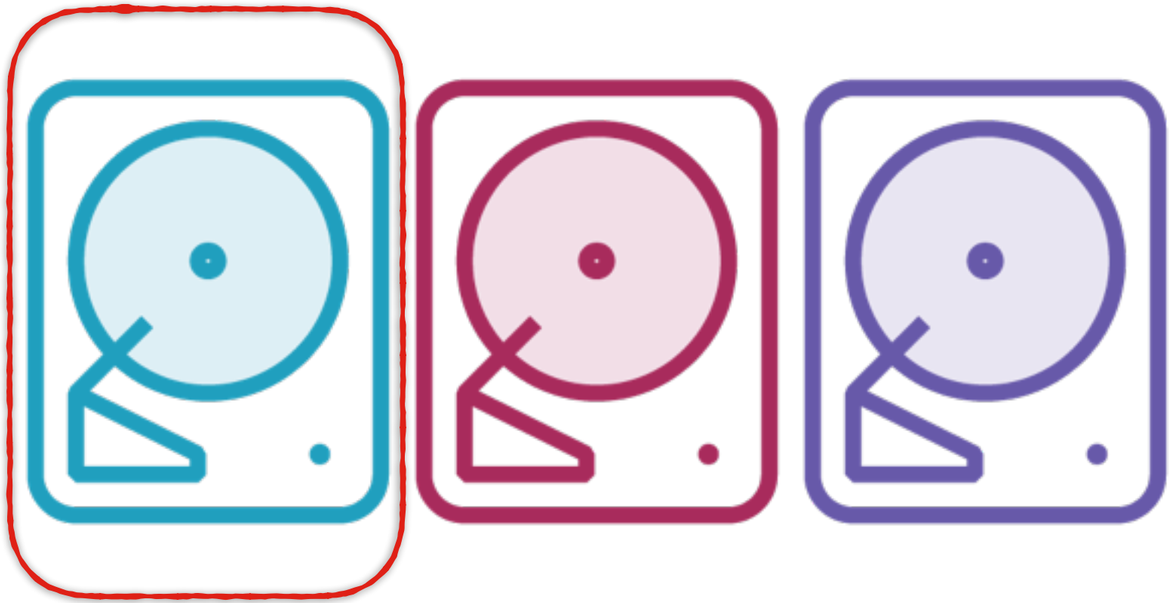
Manage file storage across multiple disks

HDFS

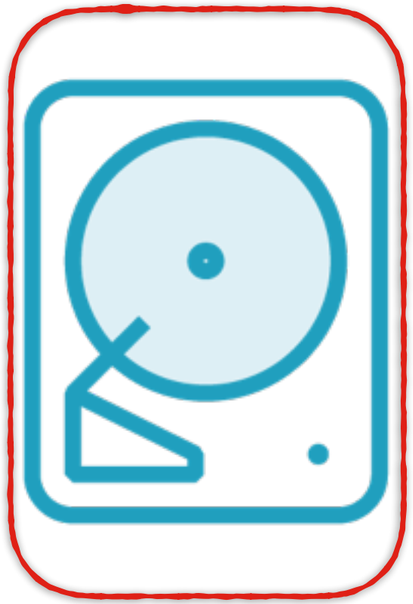
Each disk on a different machine in a cluster

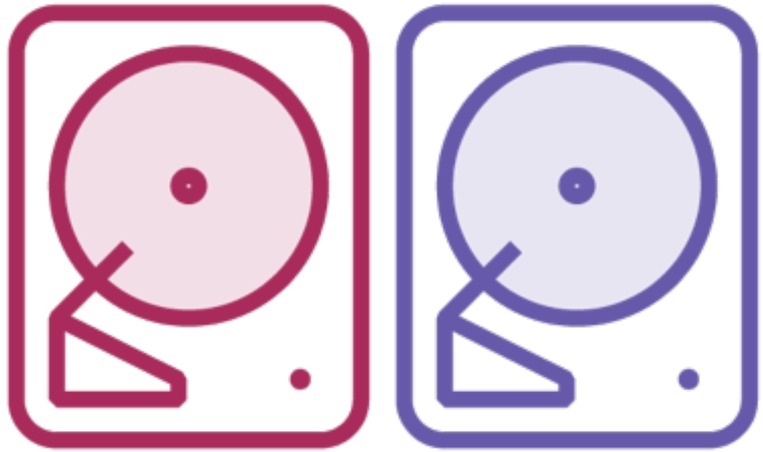
A cluster of machines

A node in the cluster



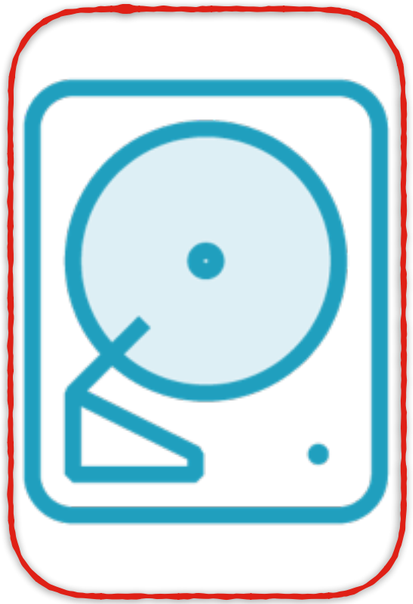
1 node is the master node

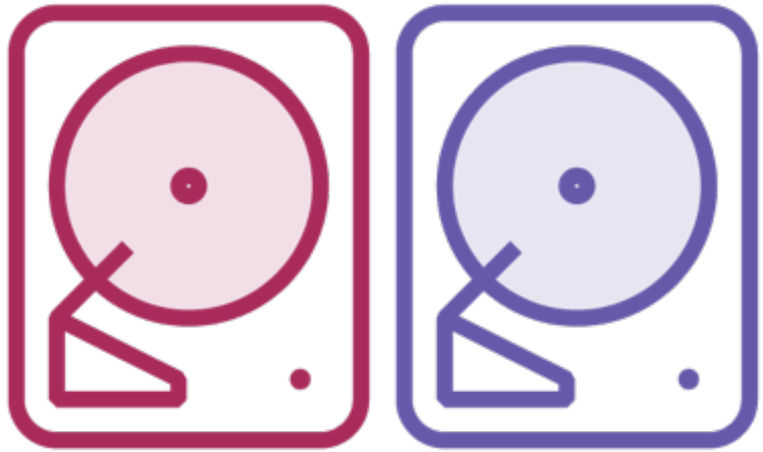




HDFS

Name node

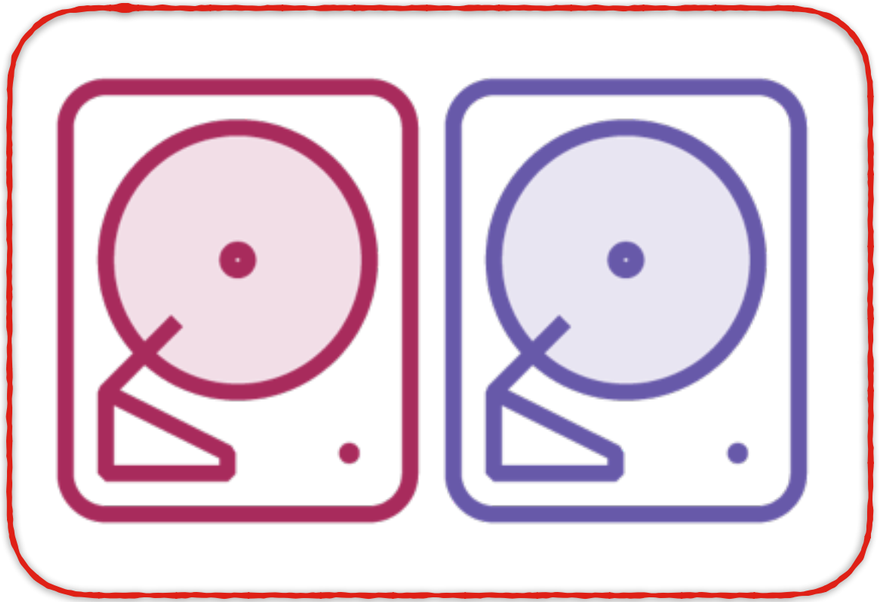




HDFS

Name node

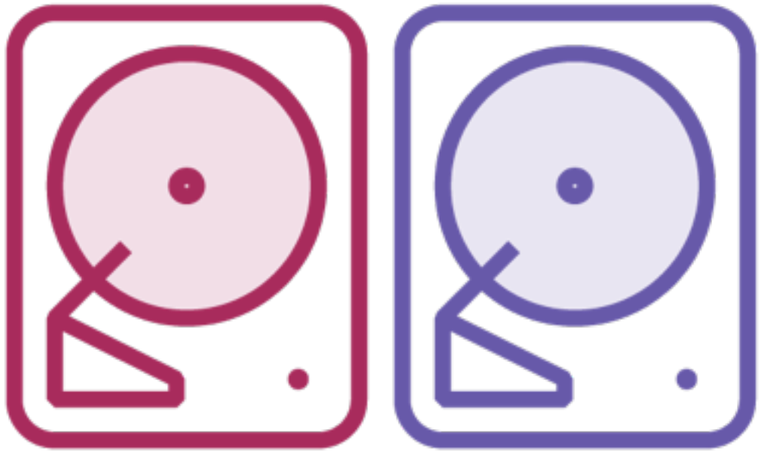
Data nodes



HDFS

Name node

Data nodes



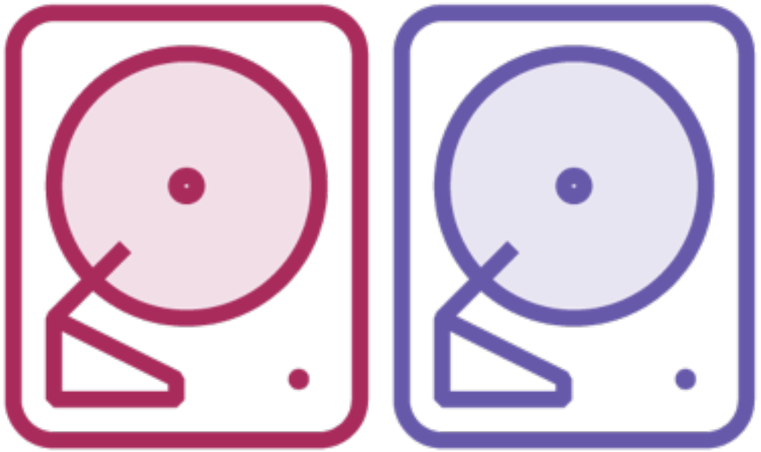
HDFS

If the data in the distributed file system is a book

Name node

The name node is the table of contents

Data nodes

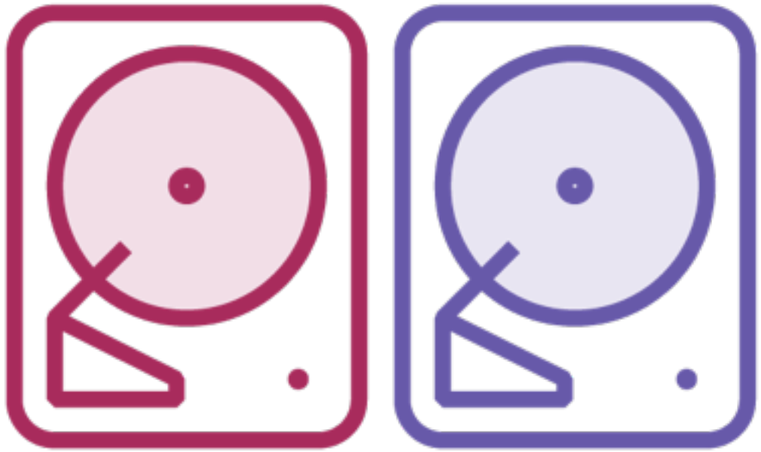


The data nodes hold the actual text in each page

HDFS

Name node

Data nodes



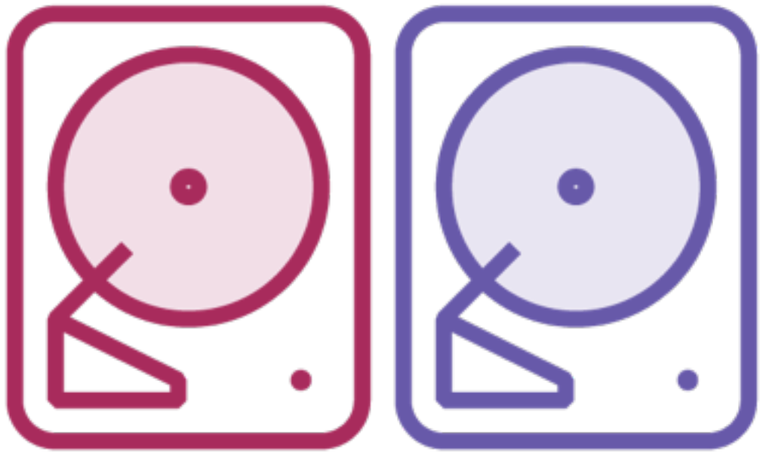
Name node

Manages the overall file system

Stores

- The directory structure
- Metadata of the files

Data nodes



Physically stores the data in the files

Action in HDFS

Create Files

Append Files

Read Files

Delete Files

pluralsight

Storing a File in HDFS

Distributed indexing

Collections are often so large that we cannot perform index construction efficiently on a single machine. This is particularly true of the World Wide Web for which we need large computer clusters [*]to construct any reasonably sized web index. Web search engines, therefore, use distributed indexing algorithms for index construction. The result of the construction process is a distributed index that is partitioned across several machines - either according to term or according to document. In this section, we describe distributed indexing for a
term-partitioned index . Most large search engines prefer a document-partitioned index (which can be easily generated from a term-partitioned index). We discuss this topic further in Section 20.3 (page [*]).

The distributed index construction method we describe in this section is an application of MapReduce , a general architecture for distributed computing. MapReduce is designed for large computer clusters. The point of a cluster is to solve large computing problems on cheap commodity machines or nodes that are built from standard parts (processor, memory, disk) as opposed to on a supercomputer with specialized hardware. Although hundreds or thousands of machines are available in such clusters, individual machines can fail at any time. One requirement for robust distributed indexing is, therefore, that we divide the work up into chunks that we can easily assign and - in case of failure - reassign. A master node directs the process of assigning and reassigning tasks to individual worker nodes.

The map and reduce phases of MapReduce split up the computing job into chunks that standard machines can process in a short time. The various steps of MapReduce are shown in Figure 4.5 and an example on a collection consisting of two documents is shown in Figure 4.6 . First, the input data, in our case a collection of web pages, are split into n splits where the size of the split is chosen to ensure that the work can be distributed evenly (chunks should not be too large) and efficiently (the total number of chunks we need to manage should not be too large); 16 or 64 MB are good sizes in distributed indexing. Splits are not preassigned to machines, but are instead assigned by the master node on an ongoing basis: As a machine finishes processing one split, it is assigned the next one. If a machine dies or becomes a laggard due to hardware problems, the split it is working on is simply reassigned to another machine.

Figure 4.5: An example of distributed indexing with MapReduce. Adapted from Dean and Ghemawat (2004).
\includegraphics[width=11.5cm]{art/mapreduce2.eps}
In general, MapReduce breaks a large computing problem into smaller parts by recasting it in terms of manipulation of key-value pairs . For indexing, a key-value pair has the form (termID,docID). In distributed indexing, the mapping from terms to termIDs is also distributed and therefore more complex than in single-machine indexing. A simple solution is to maintain a (perhaps precomputed) mapping for frequent terms that is copied to all nodes and to use terms directly (instead of termIDs) for infrequent terms. We do not address this problem here and assume that all nodes share a consistent term $\rightarrow$ termID mapping.

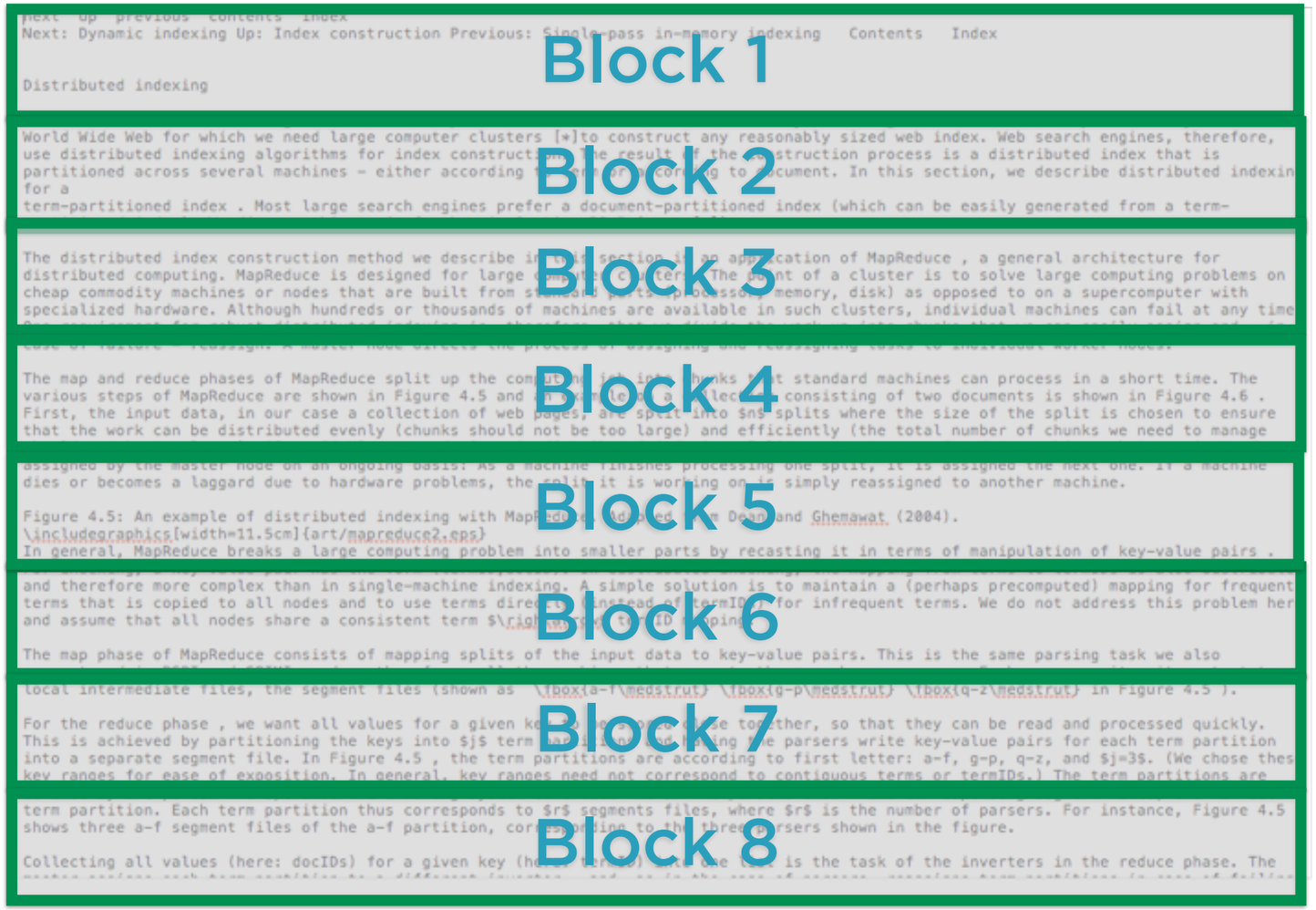
The map phase of MapReduce consists of mapping splits of the input data to key-value pairs. This is the same parsing task we also encountered in BSBI and SPIMI, and we therefore call the machines that execute the map phase parsers . Each parser writes its output to local intermediate files, the segment files (shown as \fbox{a-f\medstrut} \fbox{g-p\medstrut} \fbox{q-z\medstrut} in Figure 4.5).

For the reduce phase , we want all values for a given key to be stored close together, so that they can be read and processed quickly. This is achieved by partitioning the keys into j term partitions and having the parsers write key-value pairs for each term partition into a separate segment file. In Figure 4.5 , the term partitions are according to first letter: a-f, g-p, q-z, and $j=3$. (We chose these key ranges for ease of exposition. In general, key ranges need not correspond to contiguous terms or termIDs.) The term partitions are defined by the person who operates the indexing system (Exercise 4.6). The parsers then write corresponding segment files, one for each term partition. Each term partition thus corresponds to r segments files, where r is the number of parsers. For instance, Figure 4.5 shows three a-f segment files of the a-f partition, corresponding to the three parsers shown in the figure.

Collecting all values (here: docIDs) for a given key (here: termID) into one list is the task of the inverters in the reduce phase. The

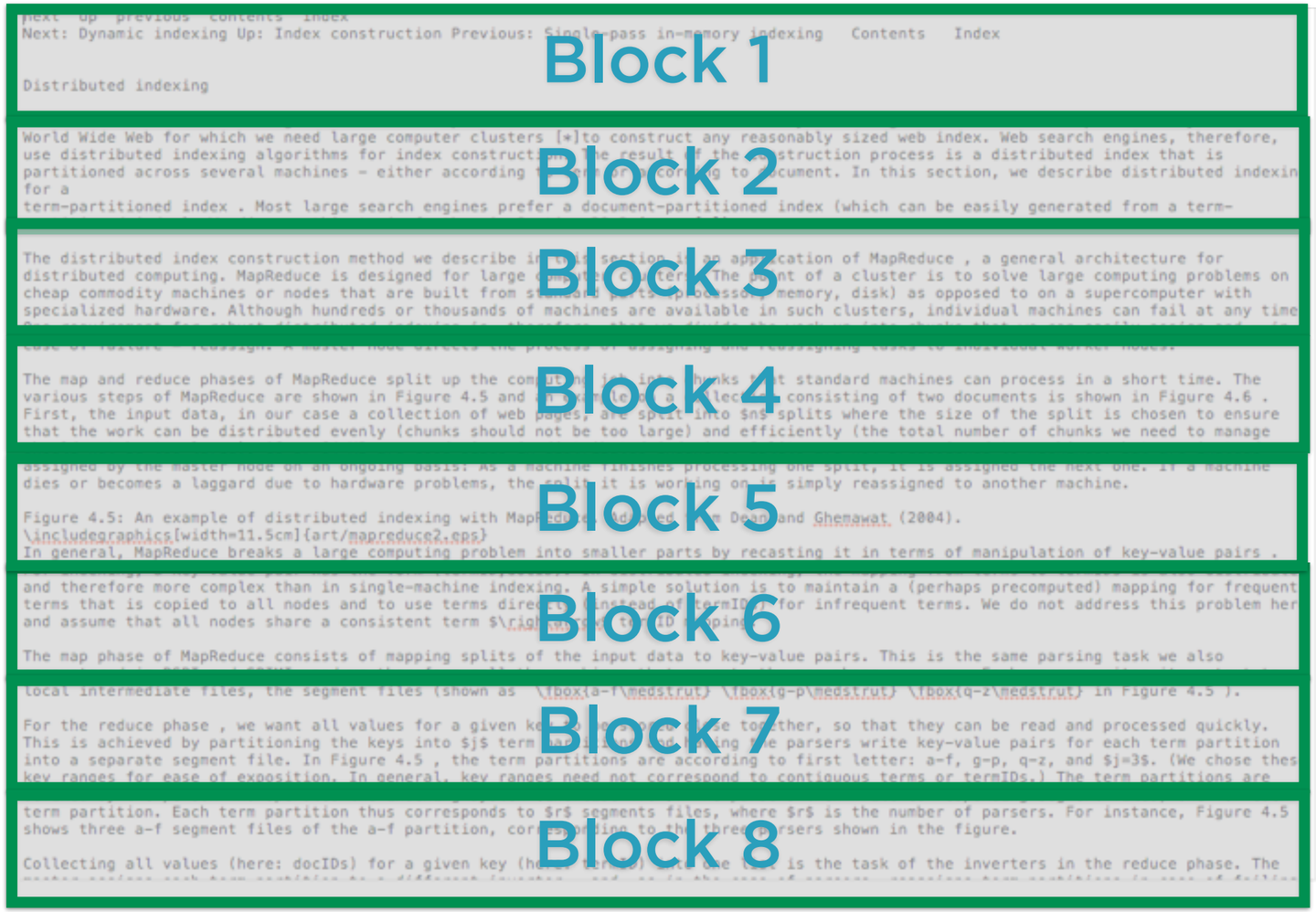
A large text file

Storing a File in HDFS



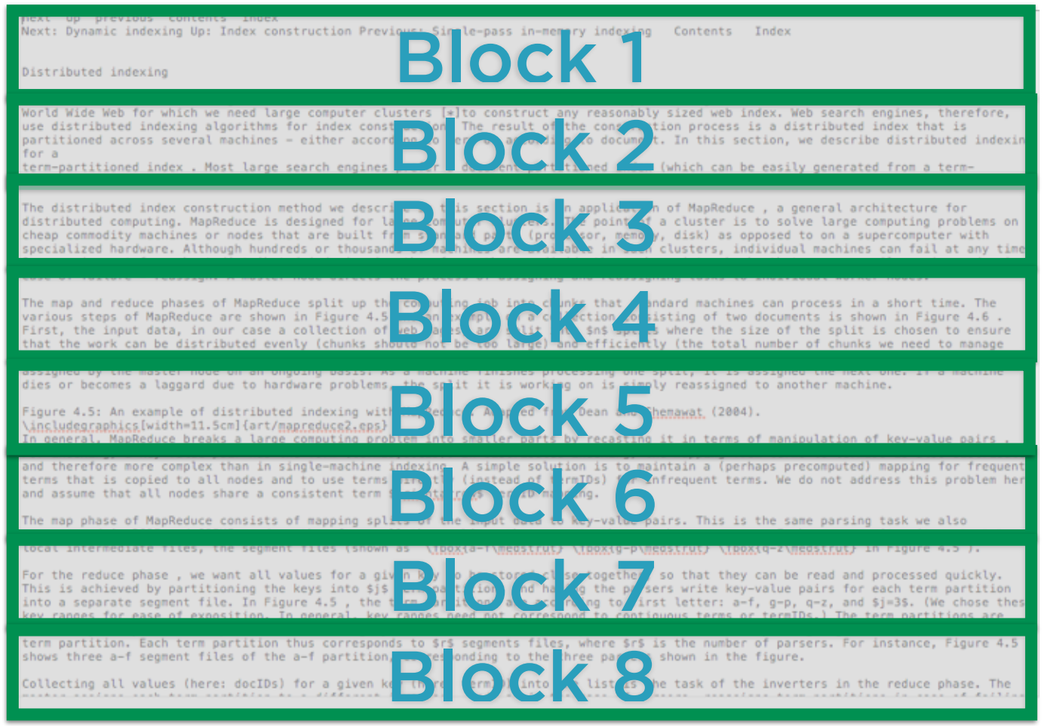
Break the data into blocks

Storing a File in HDFS



Break the data into blocks

Storing a File in HDFS



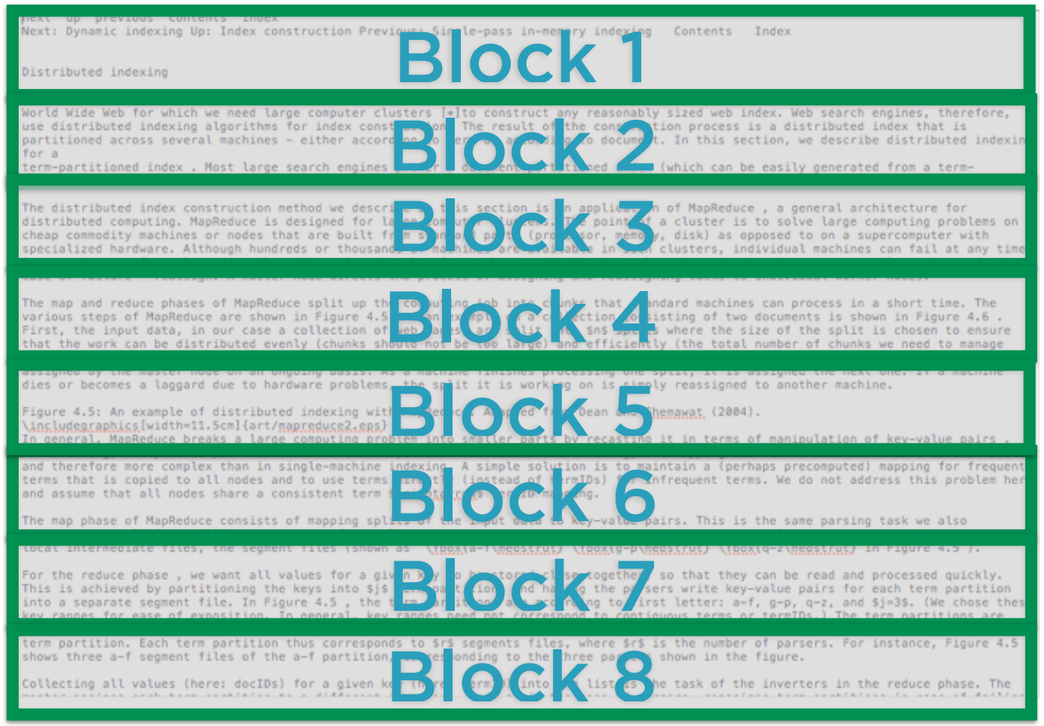
Break the data into blocks

Different length files are treated the same way

Storage is simplified

Unit for replication and fault tolerance

Storing a File in HDFS



The blocks are of size 128 MB

Storing a File in HDFS

size 128 MB

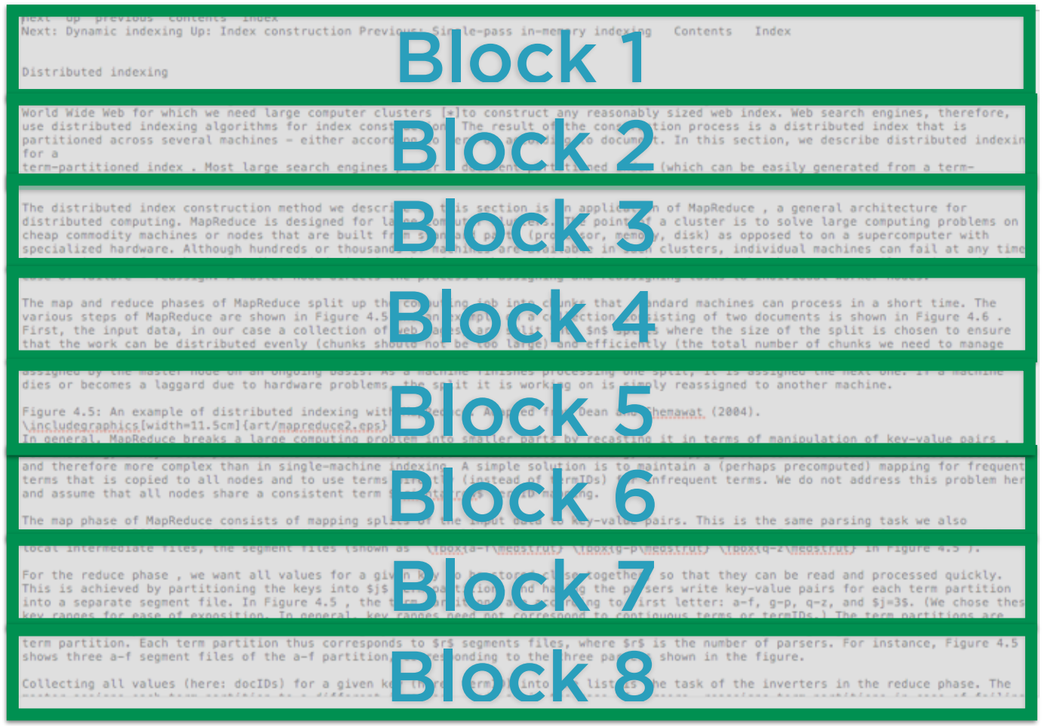
Block size is a trade off

Storing a File in HDFS

size 128 MB

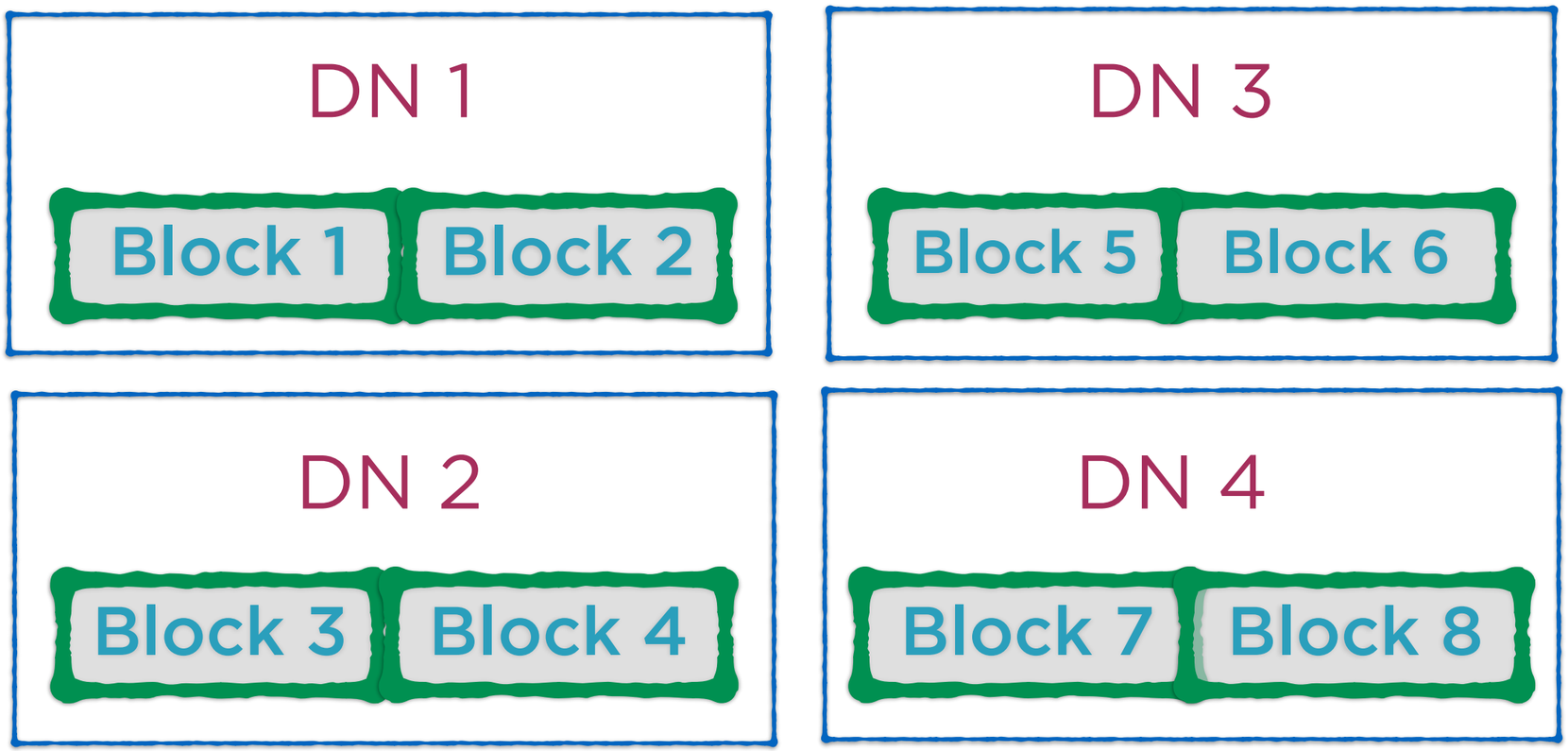
This size helps minimize the time taken to seek to the block on the disk

Storing a File in HDFS



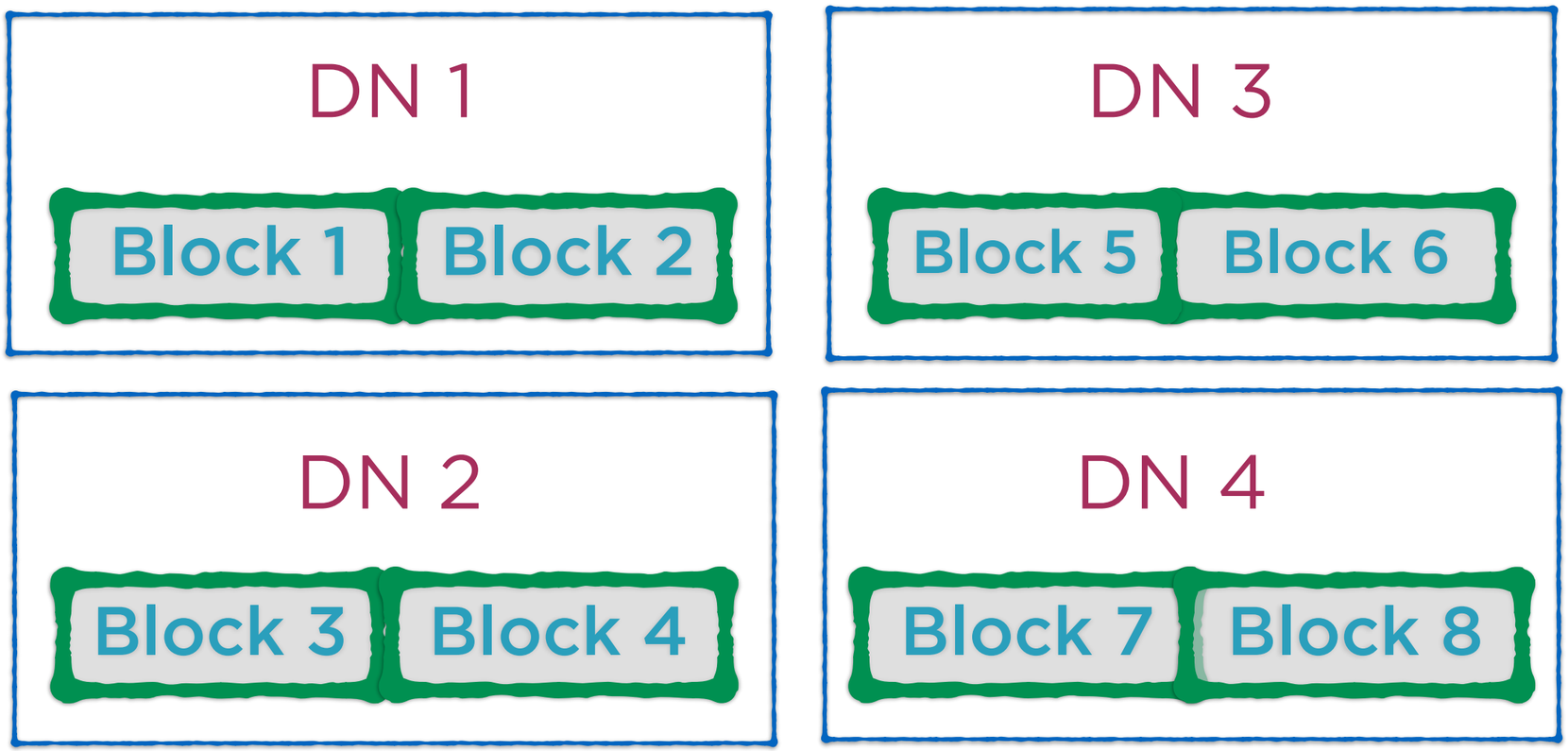
Store the blocks across the data nodes

Storing a File in HDFS



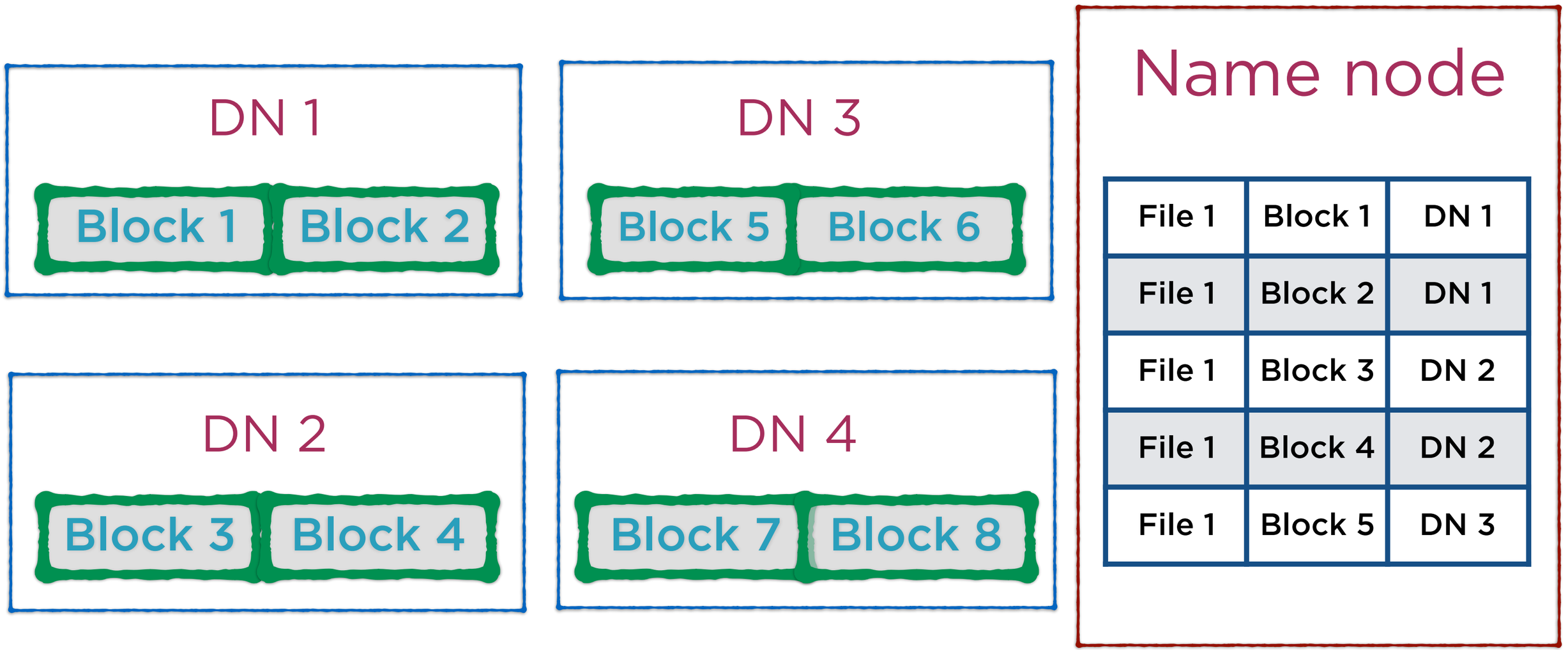
Each node contains a partition or a split of data

Storing a File in HDFS



How do we know where the splits of a particular file are?

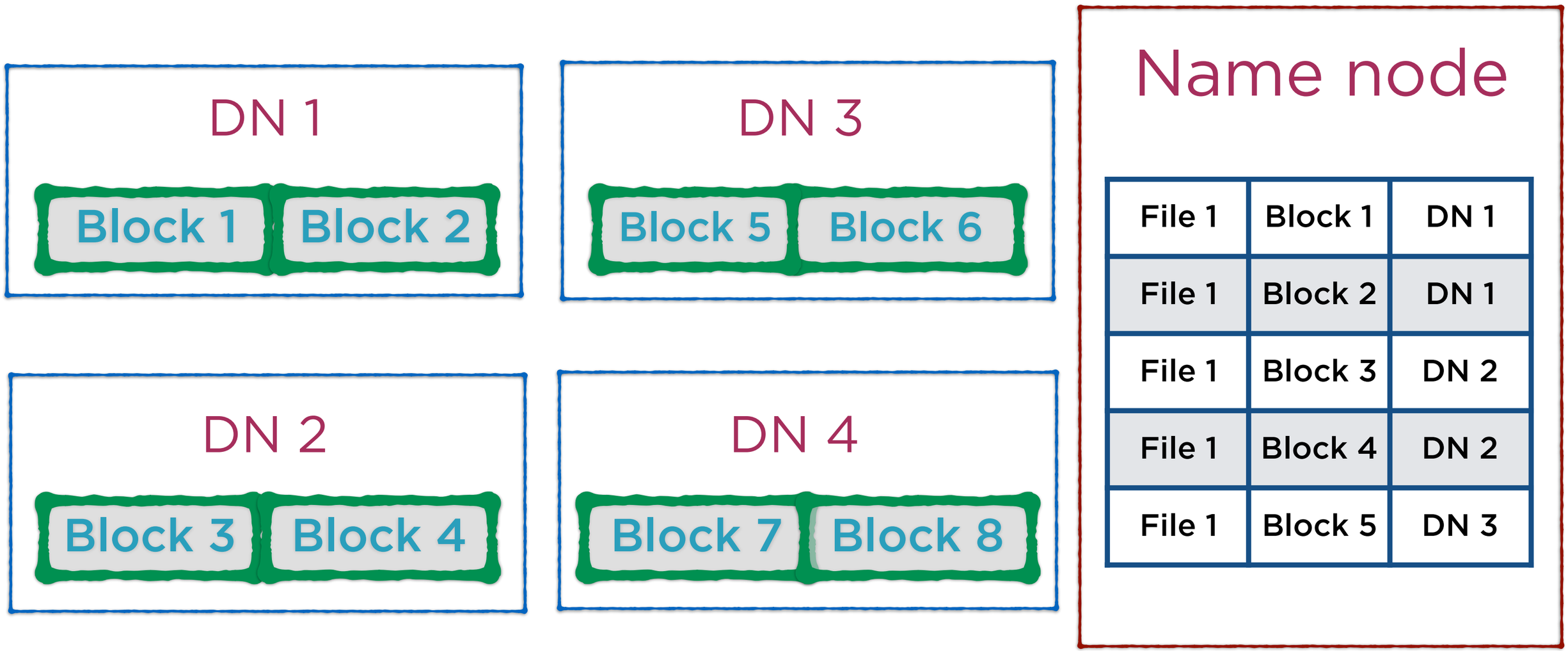
Storing a File in HDFS



Reading a File in HDFS

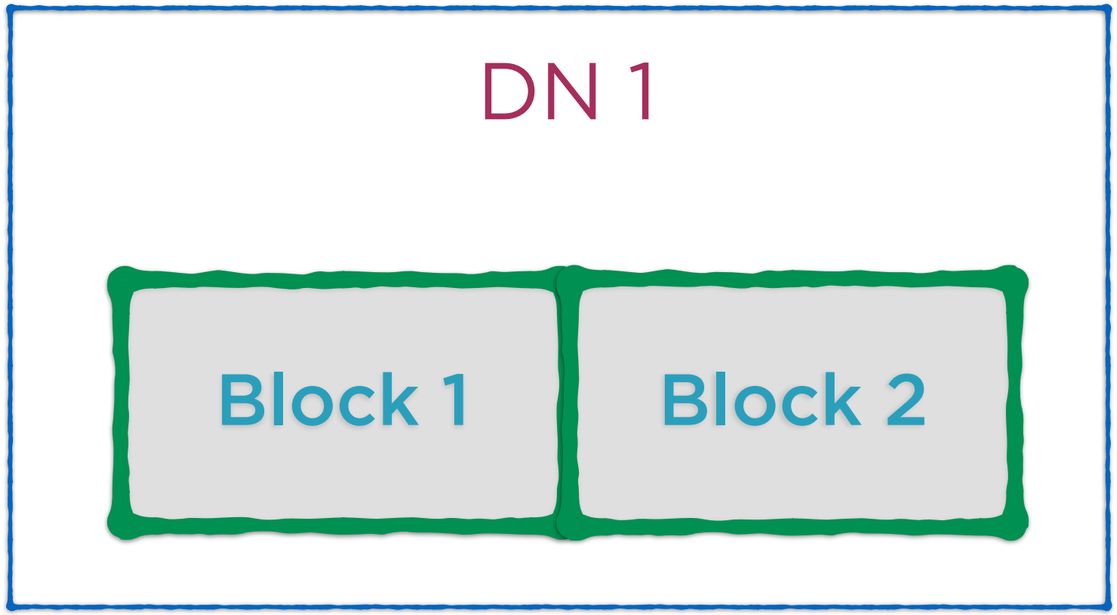
1. Use metadata in the name node to look up block locations
2. Read the blocks from respective locations

Reading a File in HDFS



Reading a File in HDFS

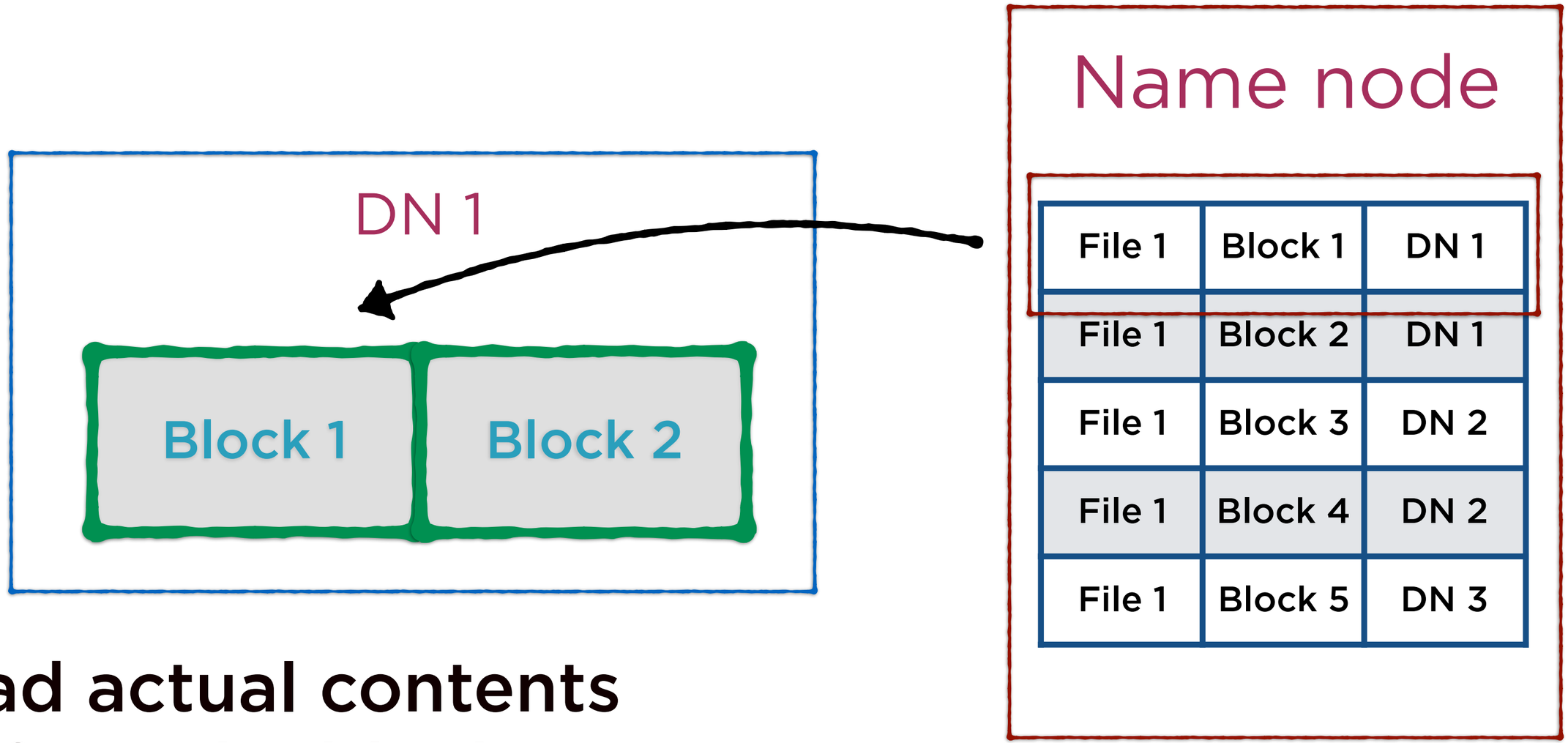
Request to the name node



Name node

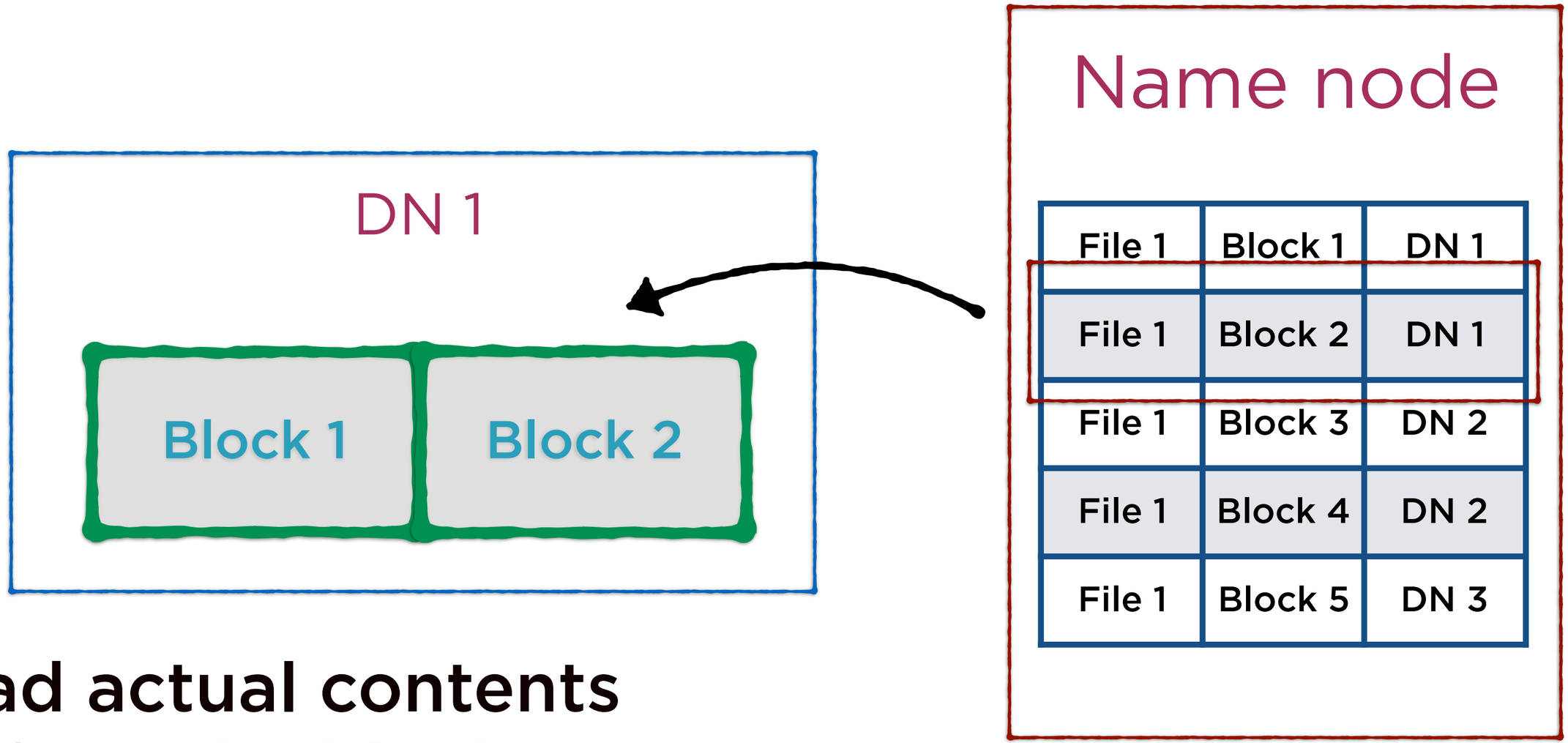
File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

Reading a File in HDFS



Read actual contents from the block

Reading a File in HDFS



Read actual contents from the block

Demo

Interacting with the HDFS command line interface

- Creating new directories
- Listing files and directories

Demo

Moving files from the local file system to HDFS and vice versa

- copyFromLocal and copyToLocal
- put and get
- Viewing the contents of a file

HDFS DFS or Hadoop FS?

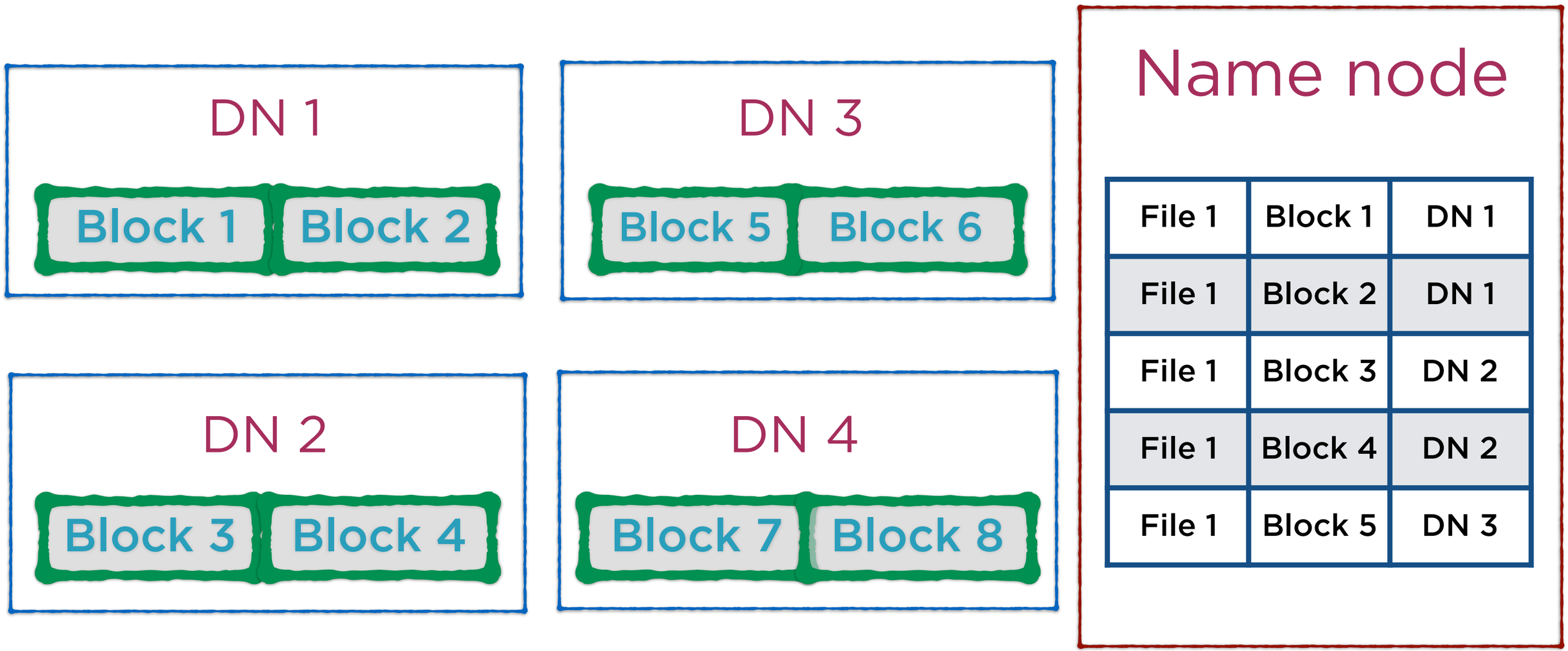
```
$ hdfs dfs – [some command]

$ hadoop fs – [some command]
```

hdfs dfs –ls = Hadoop fs –ls

pluralsight

A File Stored in HDFS

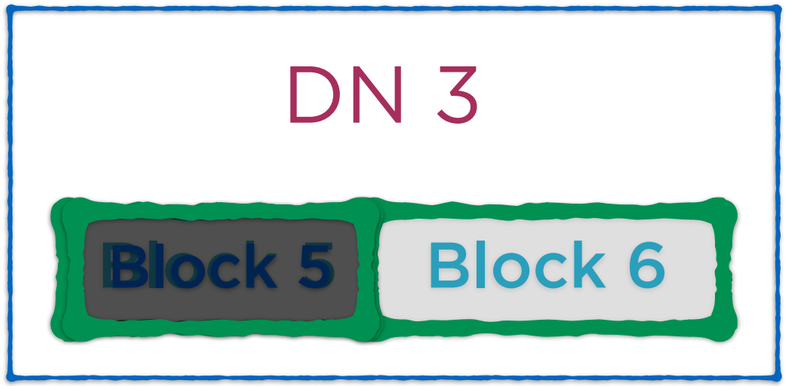


Challenges of Distributed Storage

Failure management in the data nodes

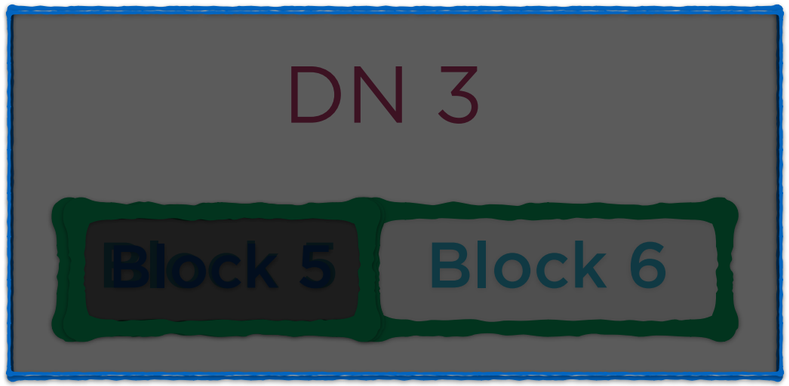
Failure management for the name node

A File Stored in HDFS



What if one of the blocks gets corrupted?

A File Stored in HDFS

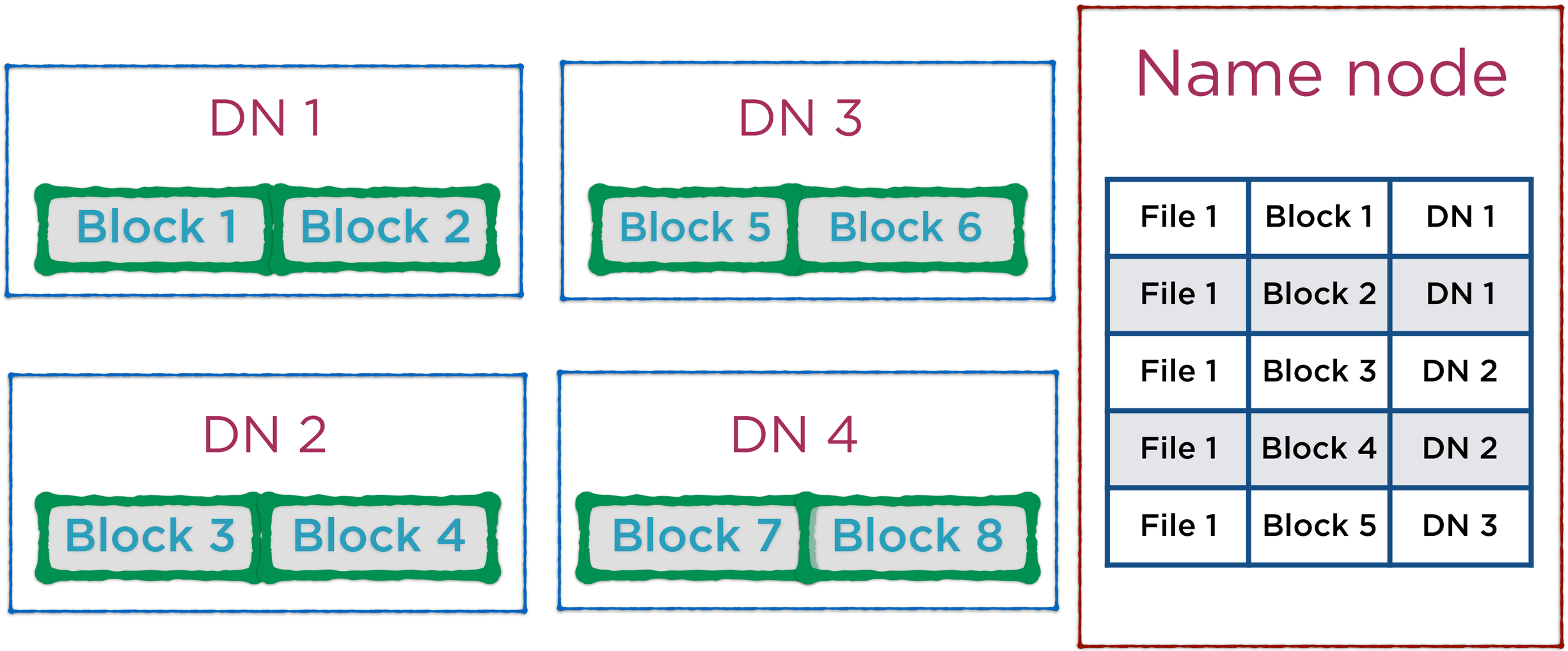


What if a data node containing some blocks crashes?

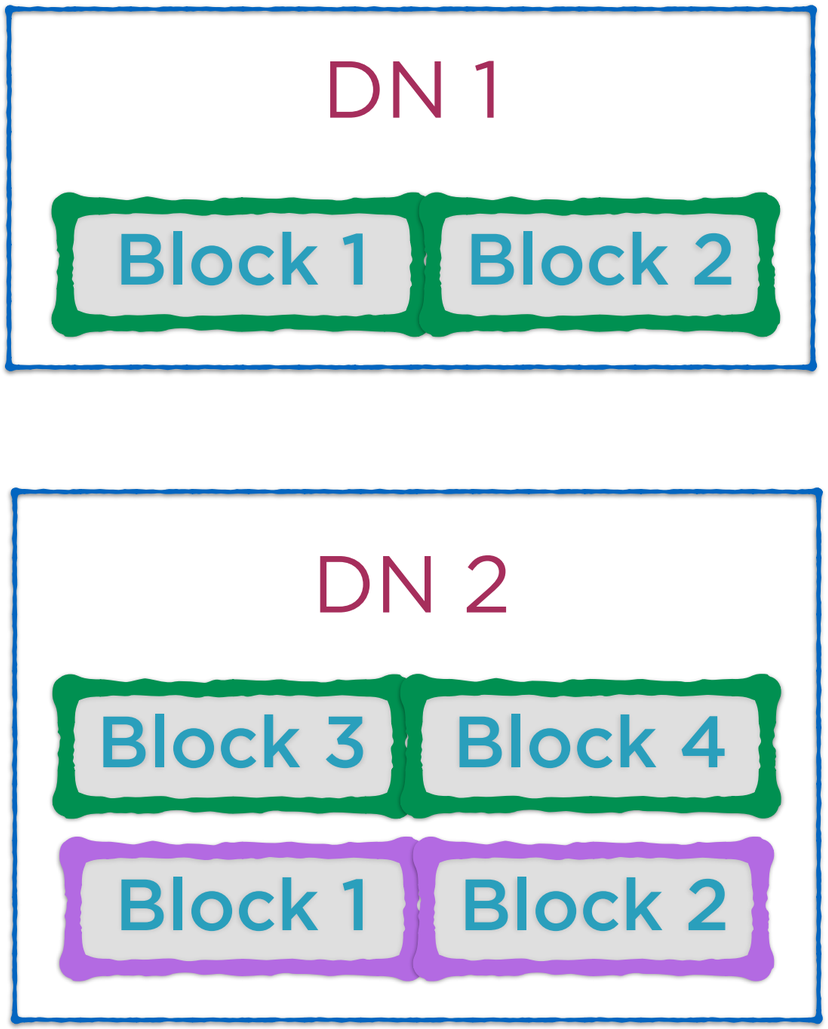
Managing Failures in Data Nodes

Define a replication factor

A File Stored in HDFS



Replication



1. Replicate blocks based on the replication factor
2. Store replicas in different locations

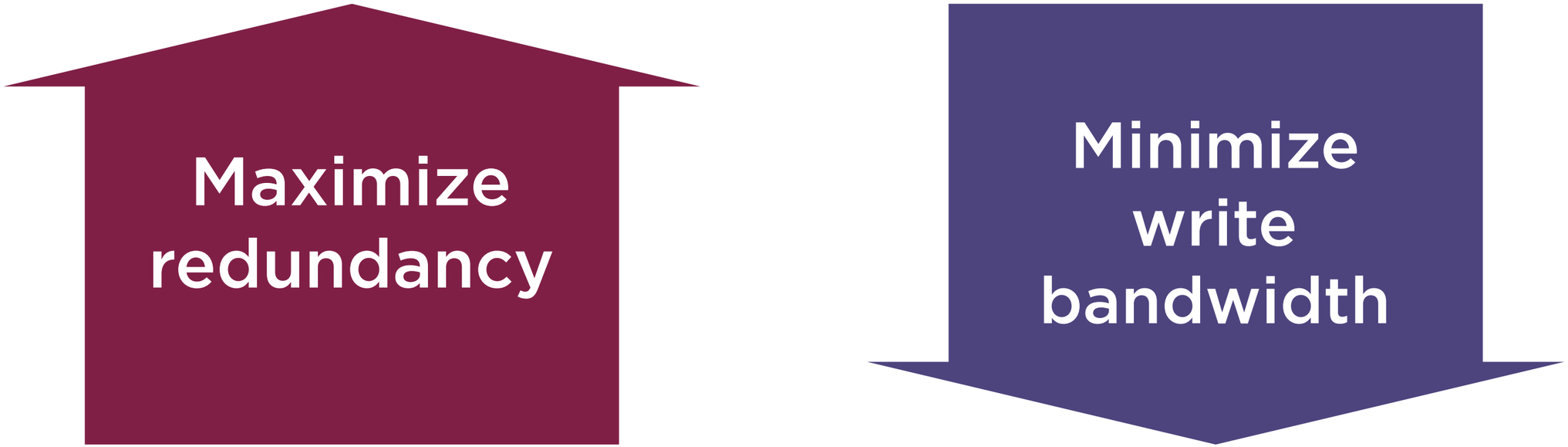
Replication

The replica locations are also stored in the name node

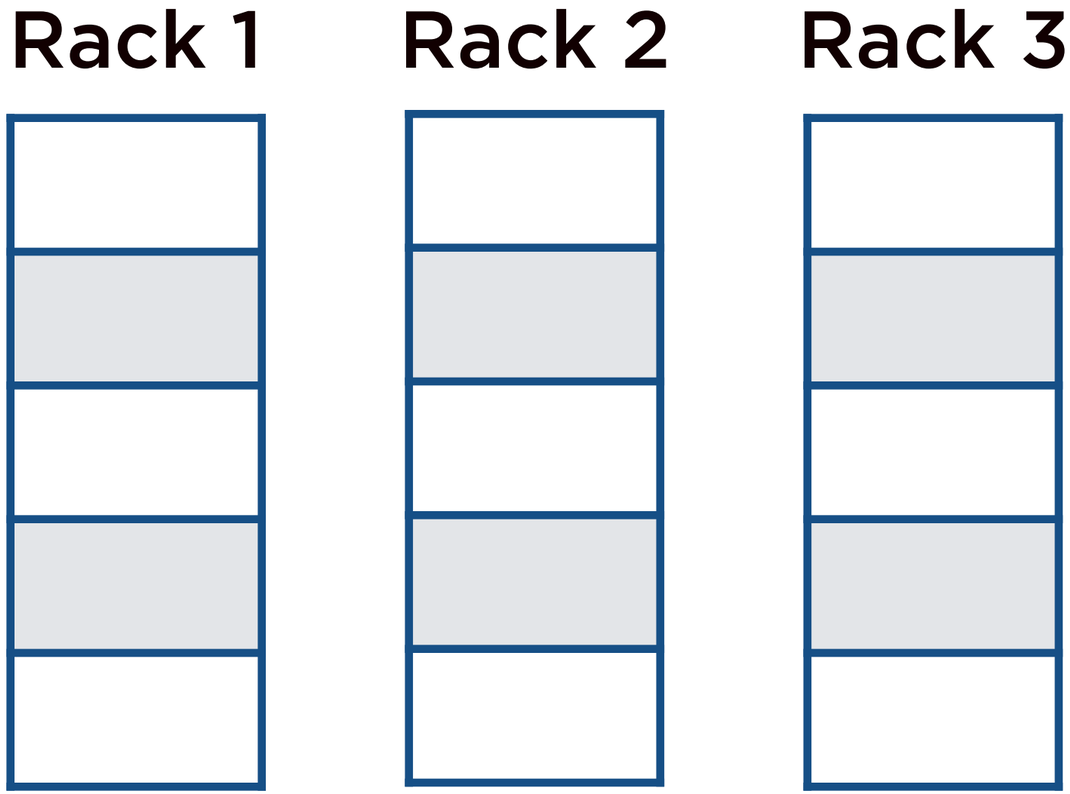
Name node

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3
File 1	Block 1	DN 2
File 1	Block 2	DN 2

Choosing Replica Locations

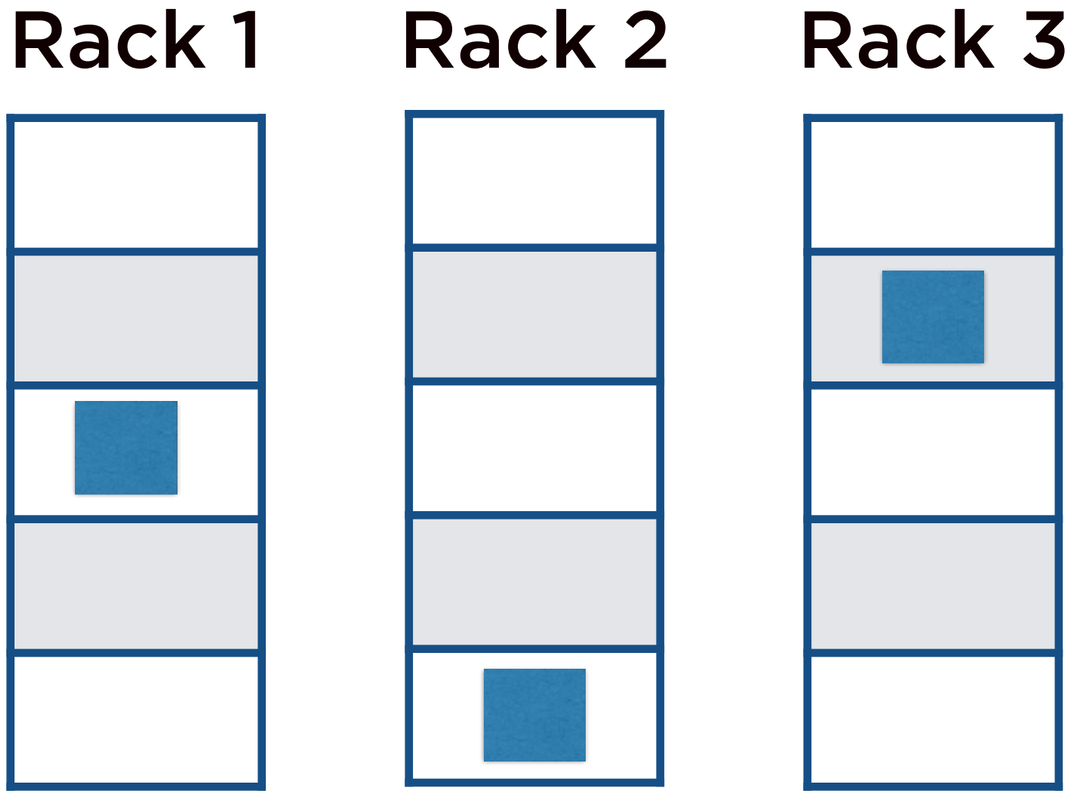


Maximize redundancy



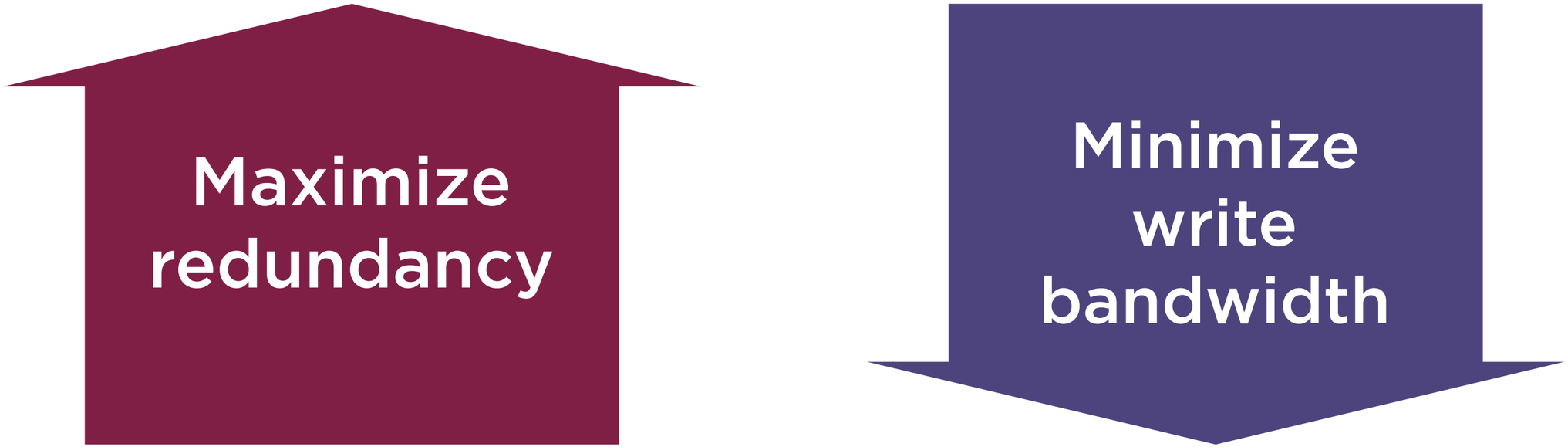
Servers in a data center

Maximize redundancy



Store replicas “far away”
i.e. on different nodes

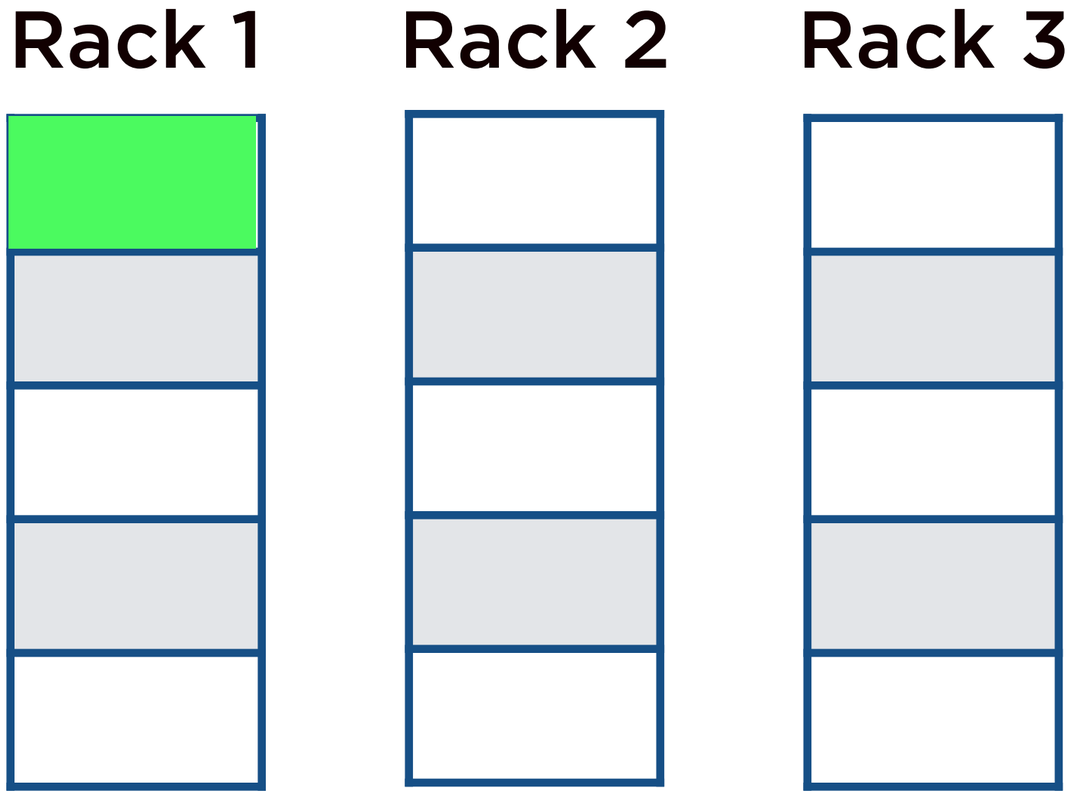
Choosing Replica Locations



Minimize write bandwidth

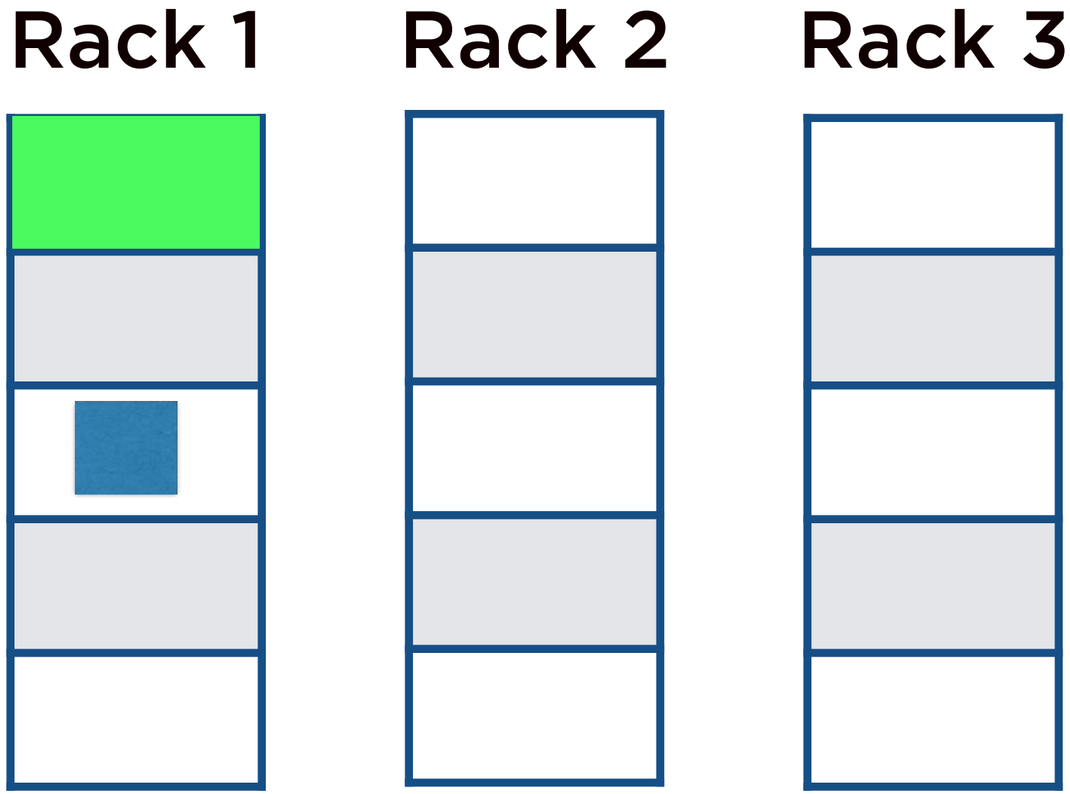
This requires that replicas be stored close to each other

Minimize write bandwidth



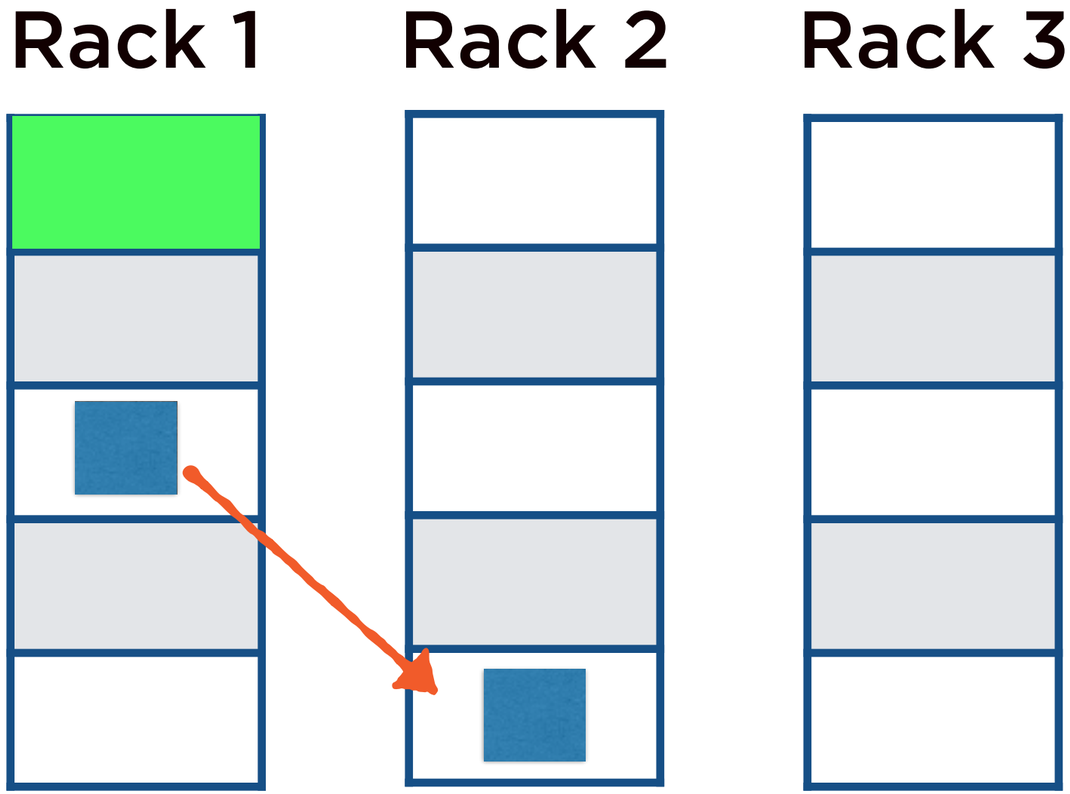
Node that runs the replication pipeline

Minimize write bandwidth



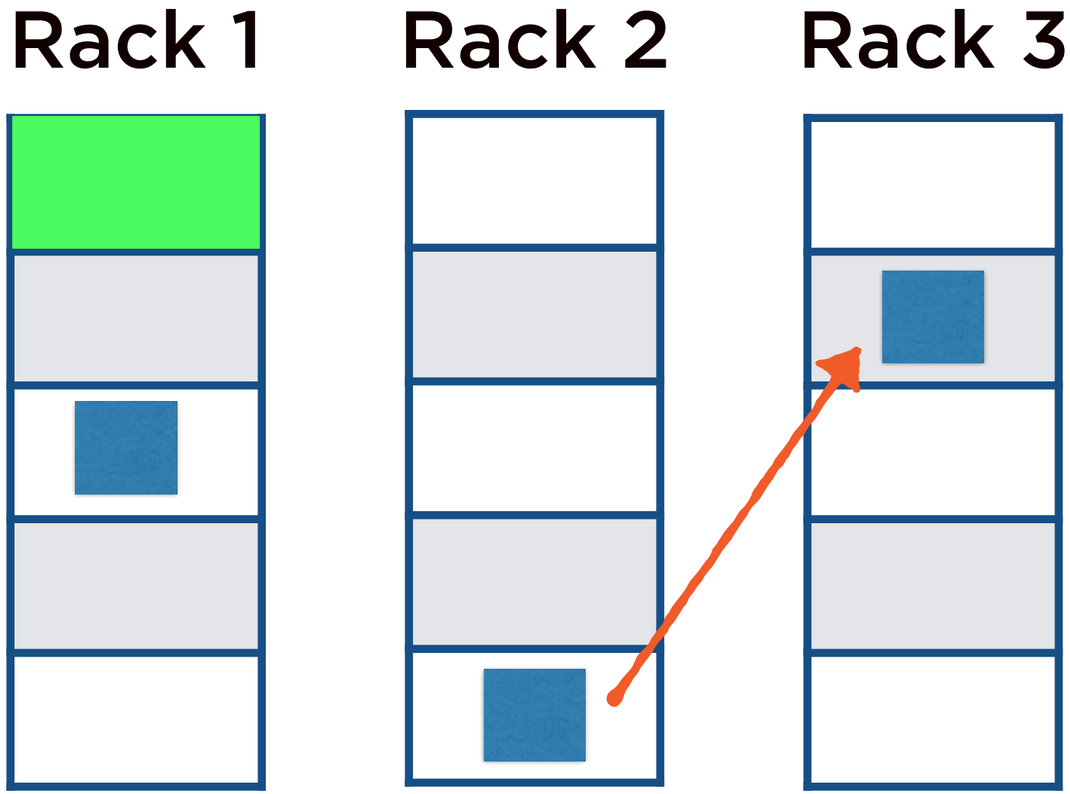
This node chooses the location for the first replica

Minimize write bandwidth



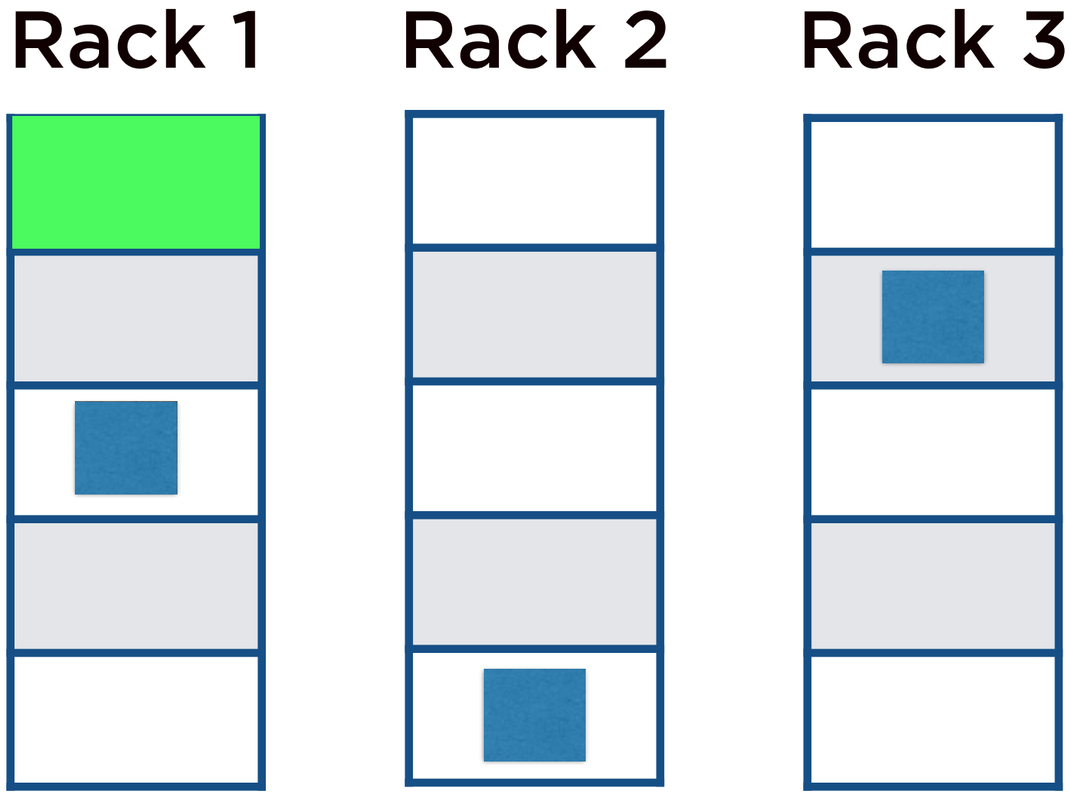
Data is forwarded from here to the next replica location

Minimize write bandwidth



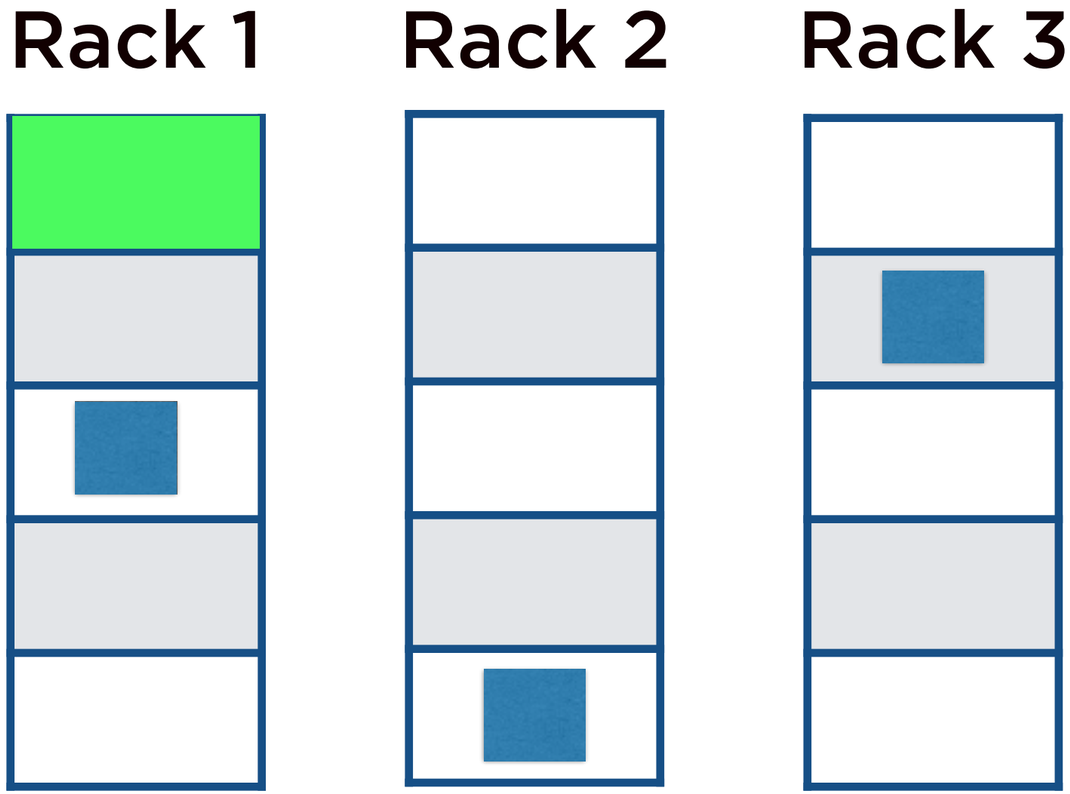
Forwarded further to the next replica location

Minimize write bandwidth



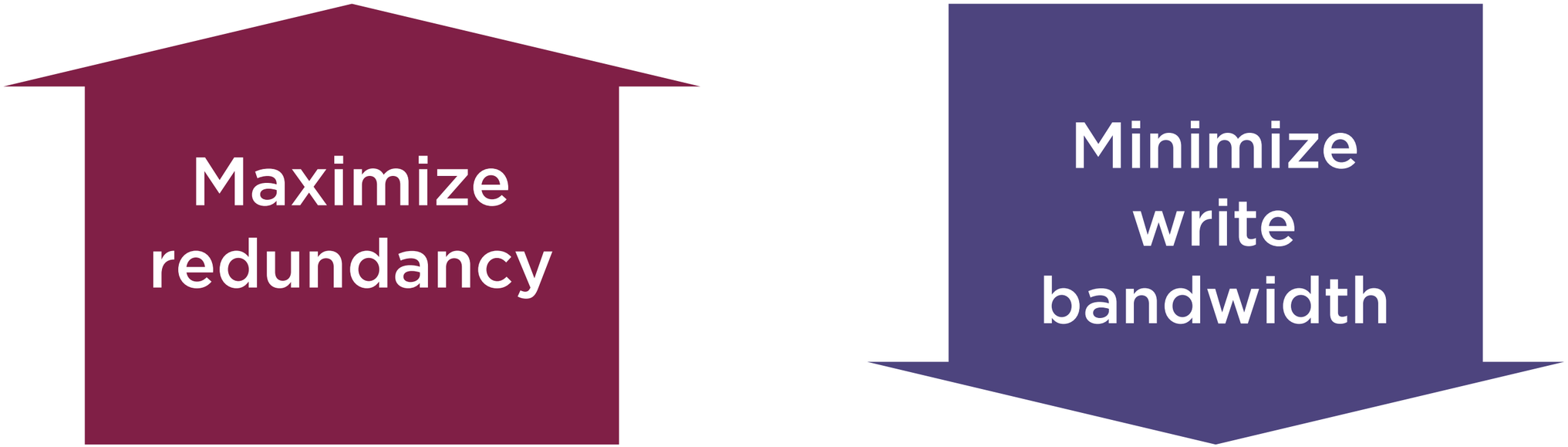
Forwarding requires a large amount of bandwidth

Minimize write bandwidth



Increases the cost of write operations

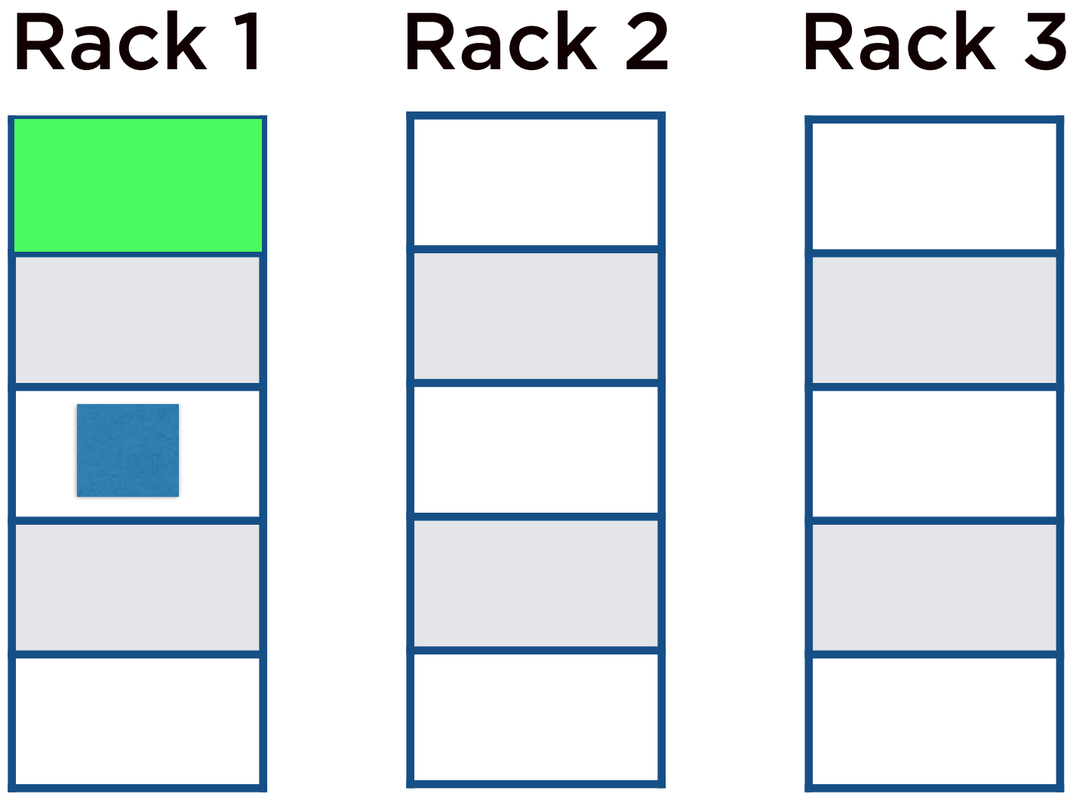
Default Hadoop Replication Strategy



Balancing both needs

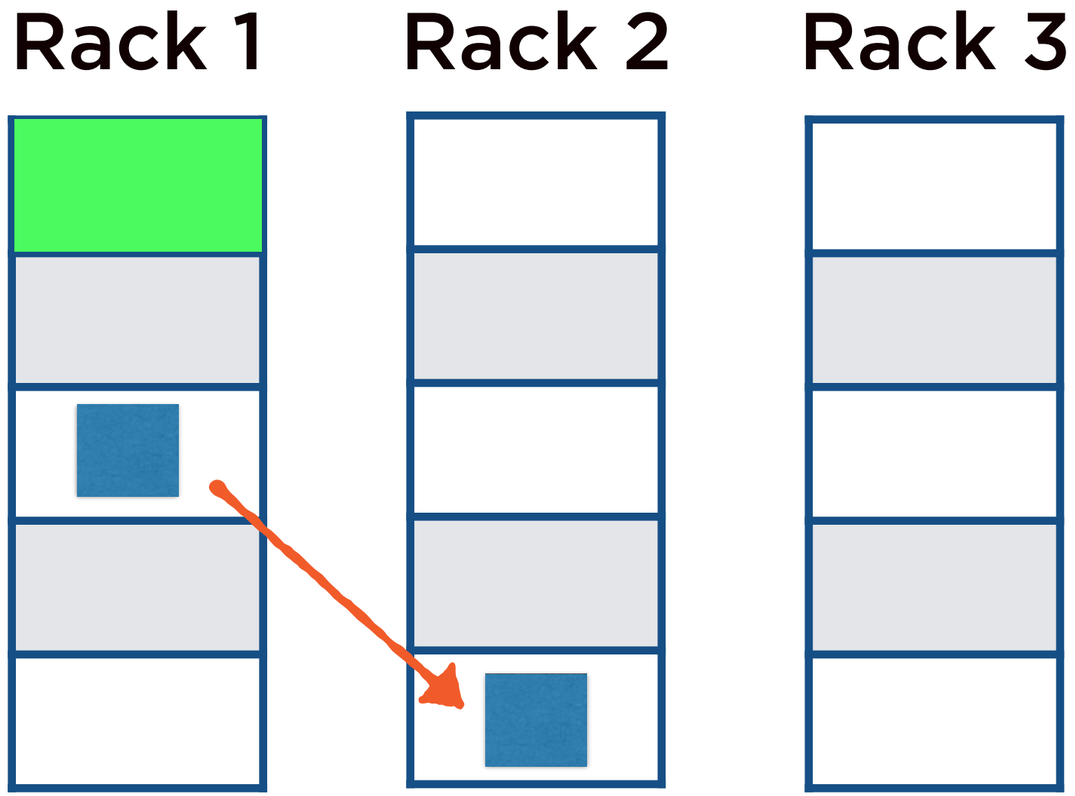
Default Hadoop Replication Strategy

First location chosen at random



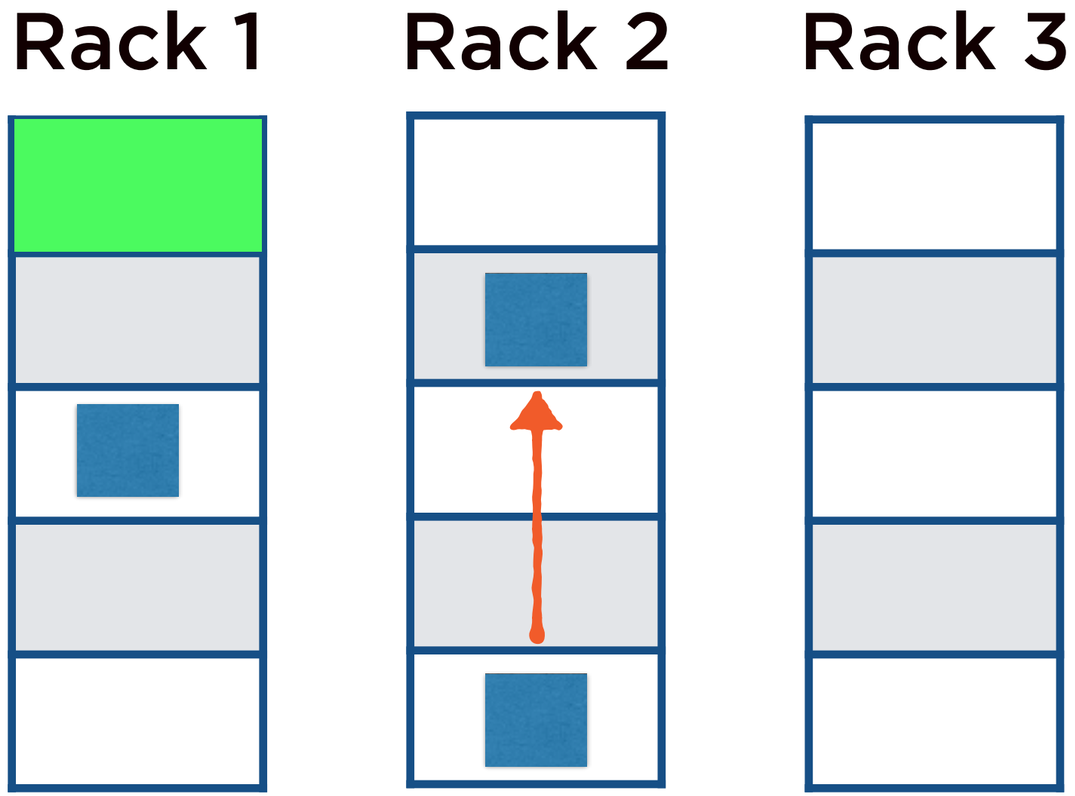
Default Hadoop Replication Strategy

Second location has to be on a different rack (if possible)



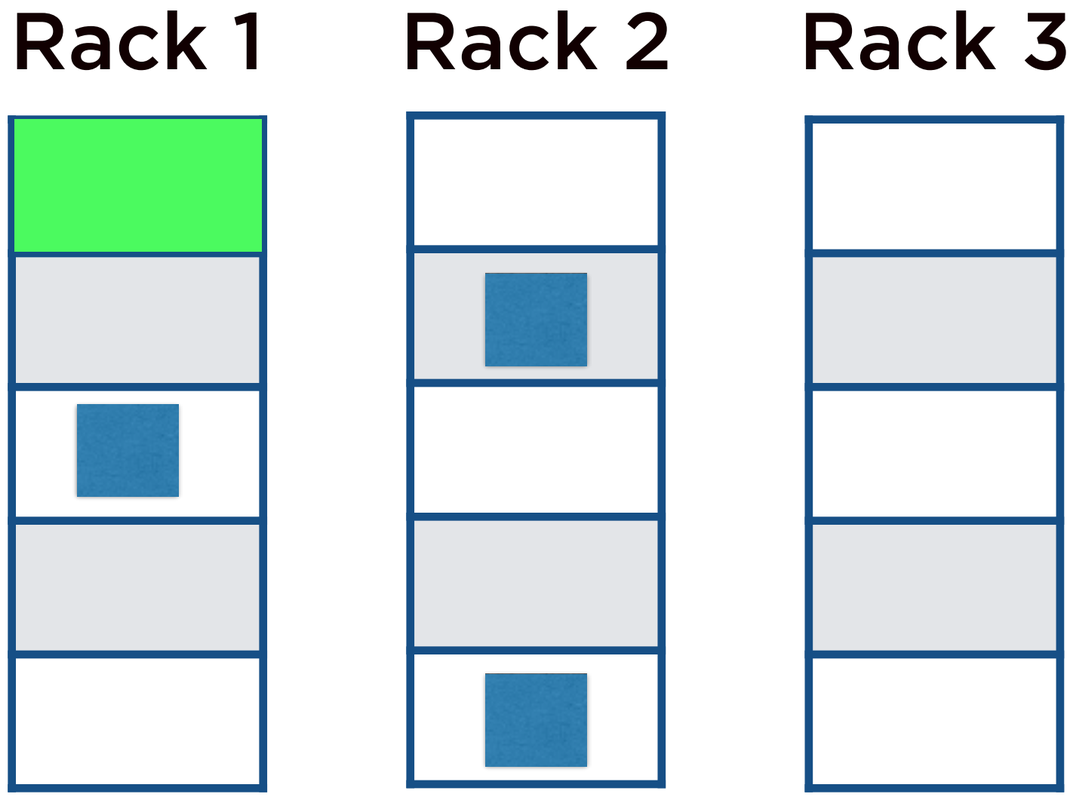
Default Hadoop Replication Strategy

Third replica is on the same rack as the second but on different nodes



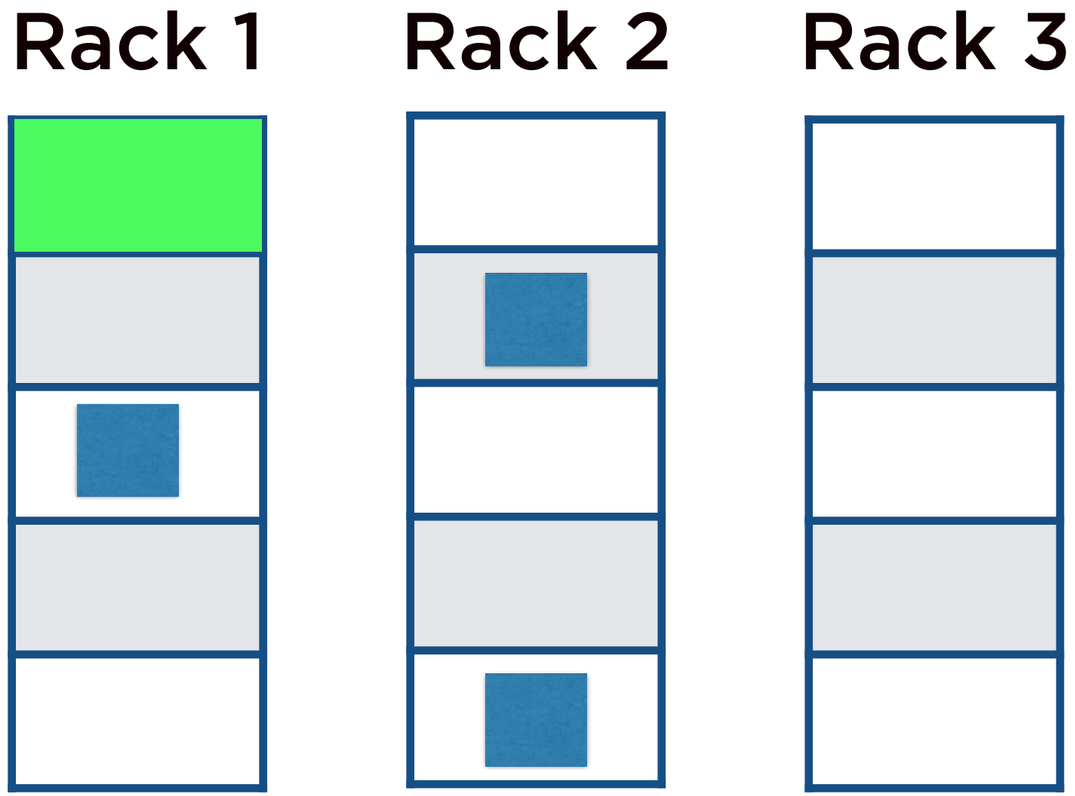
Default Hadoop Replication Strategy

Reduces inter-rack traffic and improves write performance



Default Hadoop Replication Strategy

Read operations are sent to the rack closest to the client



Setting the Replication Factor

Defined in the configuration file hdfs-site.xml

Setting the Replication Factor

`dfs.replication`

3

This is the default in fully-distributed mode

Setting the Replication Factor

`dfs.replication`

1

The pseudo-distributed mode has just one node so the replication factor cannot be >1

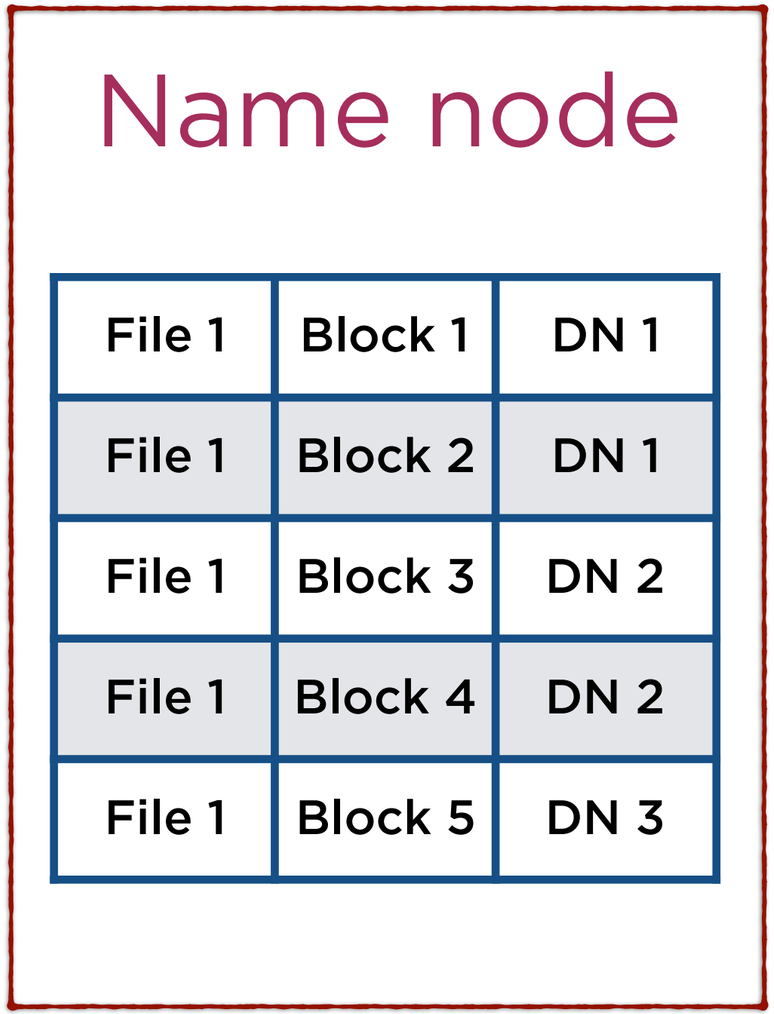
Challenges of Distributed Storage

Failure management in the data nodes

Failure management for the name node

Name Node Failures

The name node is the heart of HDFS

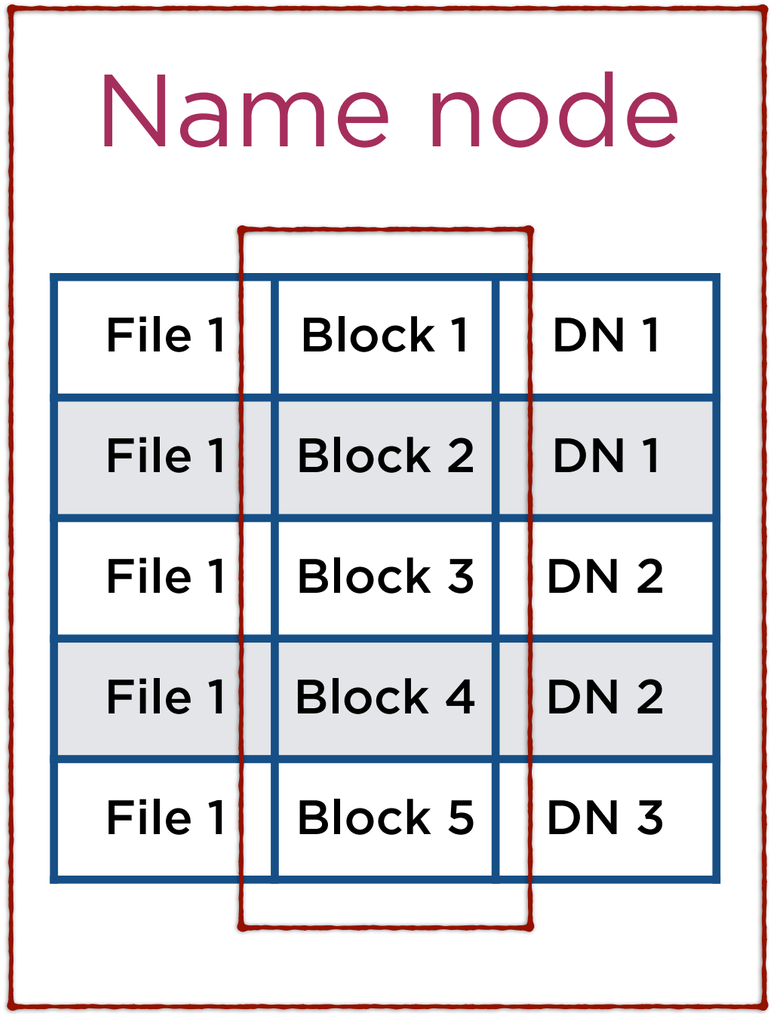


Name Node Failures

Block locations are not persistent

i.e. they are stored in memory

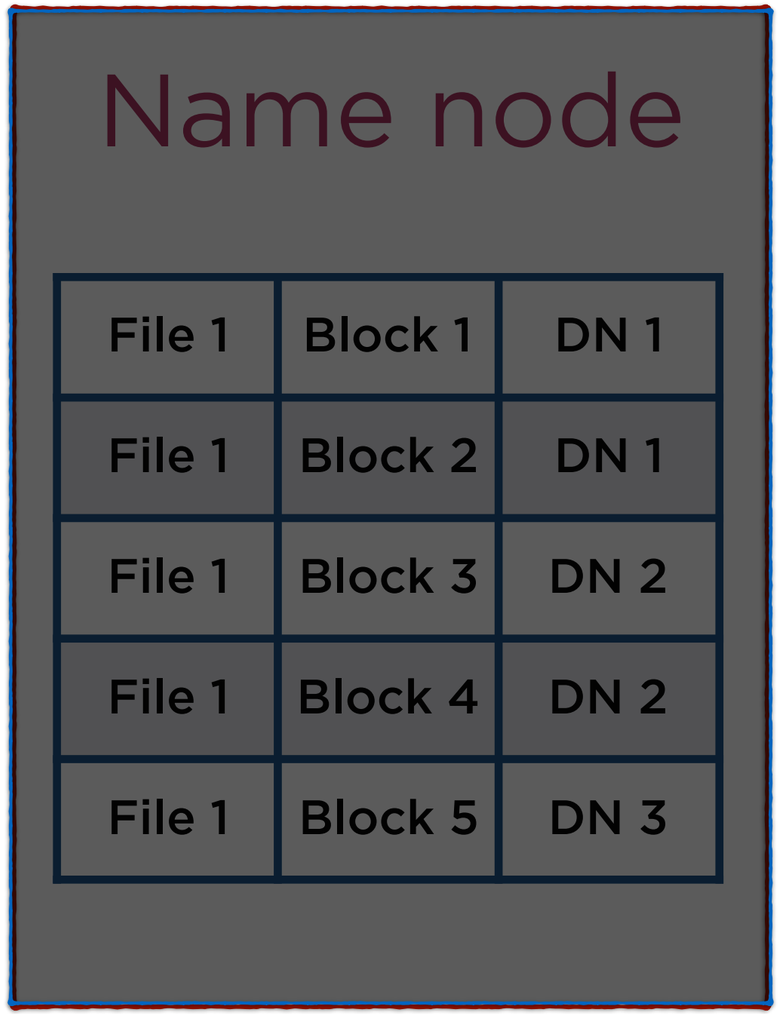
block caching



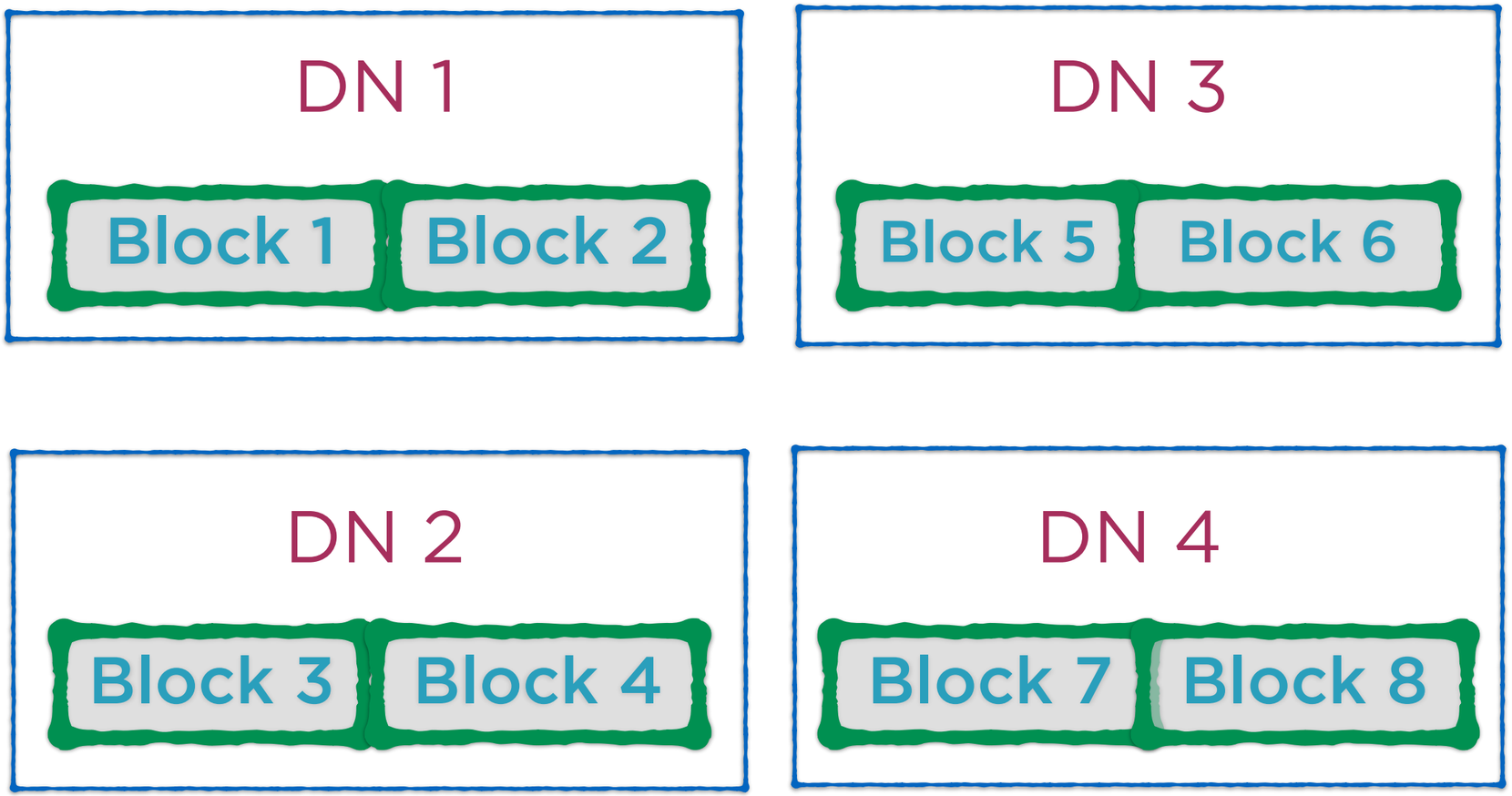
Name Node Failures

If the name node fails

File-Block Location mapping is lost!



Name Node Failures



This data is worthless without the name node

Managing Name Node Failures

Metadata Files

Secondary Name Node

Metadata Files

fsimage
edits

Two files that store the filesystem metadata

fsimage

A snapshot of the complete file system at start up

Loaded into memory

edits

A log of all in-memory edits to the file system

Metadata Files

`fsimage`

`edits`

These together can help reconstruct a name node

Metadata Files

`fsimage`

`edits`

Default backup location

Name node
local file system

Metadata Files

`fsimage`

`edits`

Alternative backup location

A remote drive

Configuring the Backup Location

Set the property

`dfs.namenode.name.dir`

in hdfs-site.xml

Configuring the Backup Location

`dfs.namenode.name.dir`

`$PATH_1,$PATH_2,$PATH_3`

A comma separated list of paths

Configuring the Backup Location

`dfs.namenode.name.dir`

$PATH_1,$PATH_2,$PATH_3

Each can be a different host

Configuring the Backup Location

`dfs.namenode.name.dir`

$PATH_1,$PATH_2,$PATH_3

Metadata files will be backed up to each path

Metadata Files

fsimage edits

- Merging these 2 files is very compute heavy
- Bringing a system back online could take a long time

Managing Name Node Failures

Metadata Files

Secondary Name Node

Secondary Name Node

Name Node

fsimage

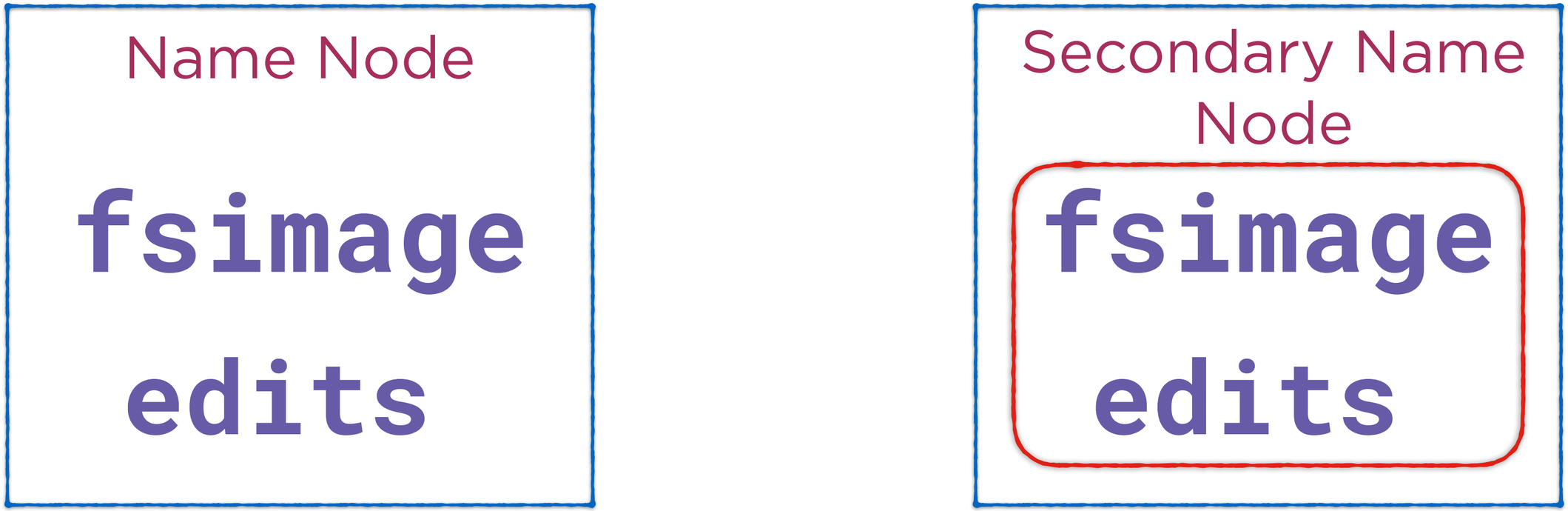
edits

Secondary Name Node

fsimage

edits

Checkpointing



Checkpointing

Name Node

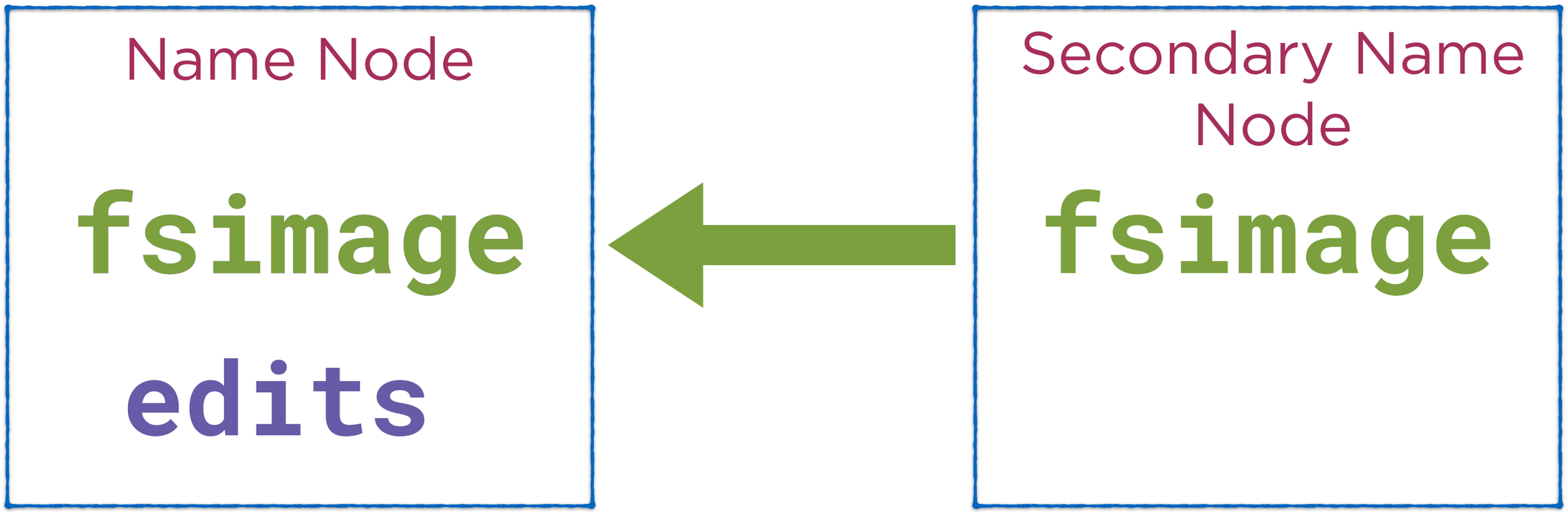
fsimage

edits

Secondary Name Node

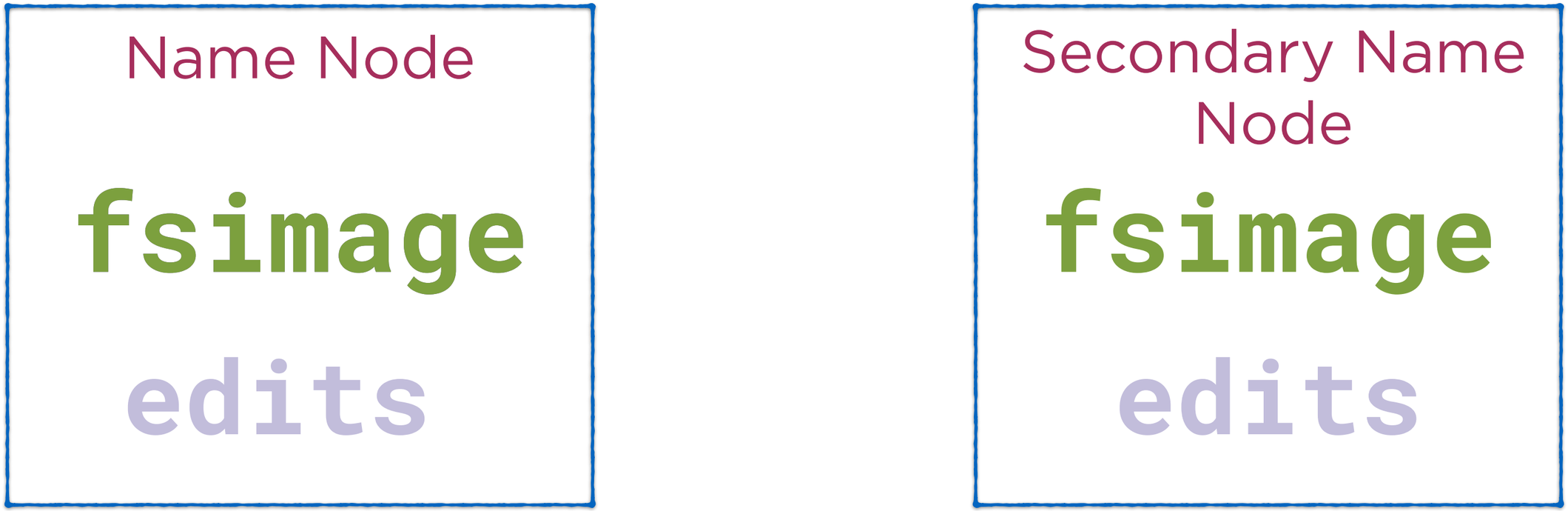
fsimage

Checkpointing



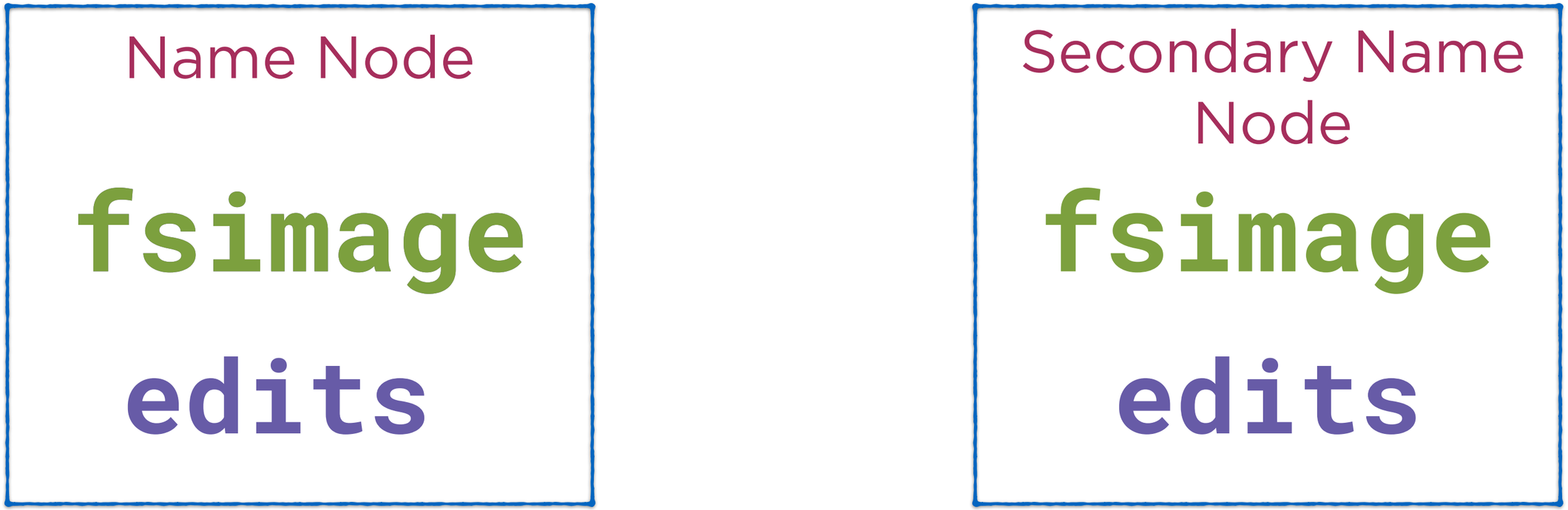
Copy to name node

Checkpointing



Reset the edits file to empty on both nodes

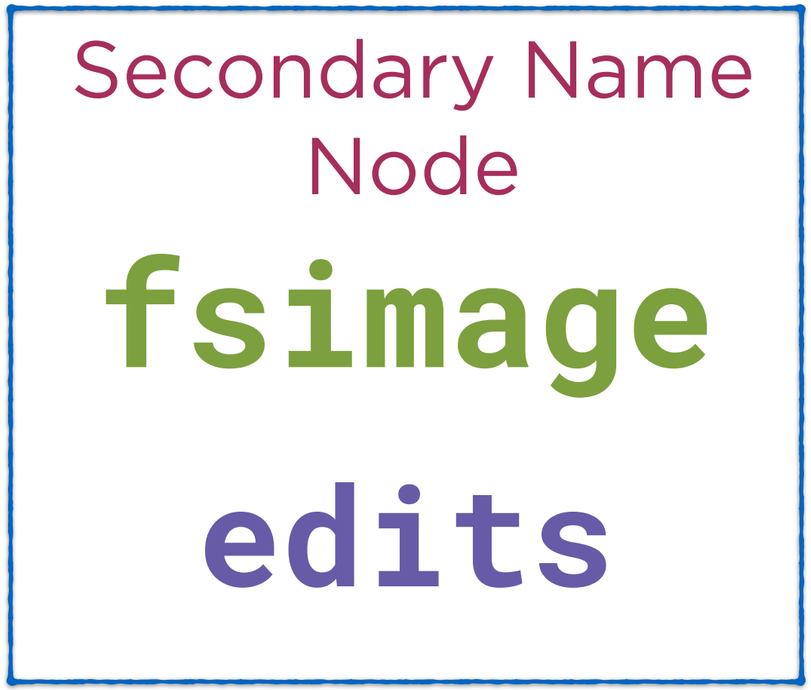
Checkpointing



Checkpointing is done at a specified frequency

Failure Management

If there is a failure



This becomes the name node

Configuring the Checkpoint Frequency

Set properties in hdfs-site.xml

Configuring the Checkpoint Frequency

`dfs.namenode.checkpoint.period`

The number of seconds between each checkpoint

Configuring the Checkpoint Frequency

`dfs.namenode.checkpoint.check.period`

The period when the secondary name node polls the name node for uncheckpointed transactions

Configuring the Checkpoint Frequency

`dfs.namenode.checkpoint.txns`

The number of transactions (edits to the file system) before checkpointing

Summary

Understood the components of HDFS

Moved files in and out of HDFS

Understood replication strategies for data nodes

Understood failure management strategies for the name node