



NYU

Center for  
Data Science

# Week 04.4: HDFS

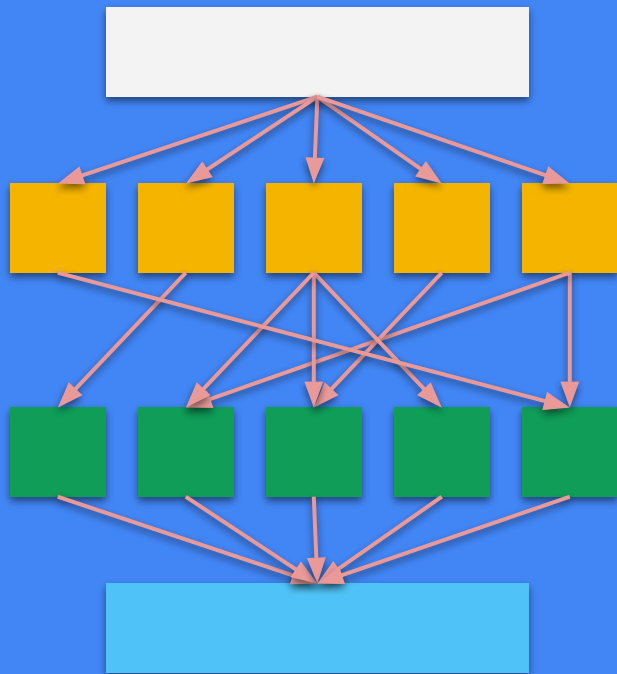
DS-GA 1004: Big Data

# Announcements



- Lab #1 (SQL/RDBMS)  
**Due (02/18)**
- Lab #2 (Map-Reduce)  
**Starts (02/16)**
- HPC accounts
- No class next week (02/21)

# Previously...



1. Introduction to Map-Reduce
2. Criticisms of Map-Reduce

# This week

1. Distributed storage
2. The Hadoop distributed file system (HDFS)

**\$ `hadoop fs -command ...`**

3. HDFS and Map-reduce

# Hadoop distributed file system

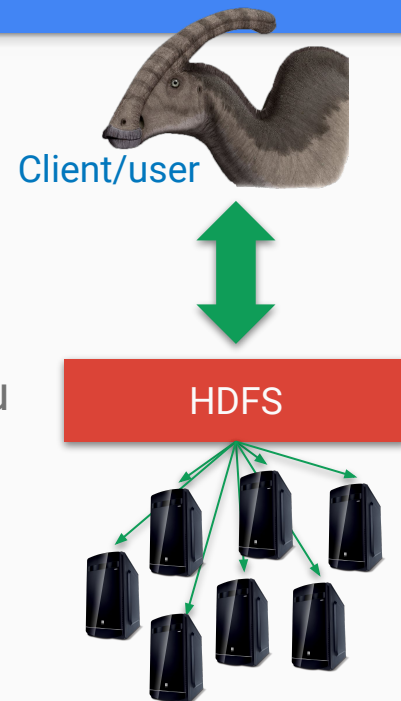
- HDFS is the storage component of Hadoop
  - Useful beyond map-reduce!
- Provides distributed, redundant storage
- Optimizes for **single-write**, **multiple-read** patterns

# RAID vs NFS vs HDFS

- RAID distributes storage over multiple disks in **one machine**
- NFS stores data on one machine, but provides access from **multiple machines**
- HDFS spreads each file across **multiple machines**
  - ~1 disk per machine with no internal redundancy
- If a disk fails, you need to take the machine offline anyway
  - Fault tolerance is at the level of **machines, not disks**
  - **Designing this way lets us tolerate other machine-level failures, not just disks!**

# Using HDFS

- HDFS is a “file system”, but we use it differently
- HDFS sits on top of the operating system’s built-in FS
- Better to think of it as an **application** that stores files for you
  - Kind of like Google Drive or Apple iCloud
  - Data can be accessed through the “**hadoop fs**” command



# Division of responsibilities

- Name nodes do not store **data**!
- Data nodes do not store **metadata** (e.g. file names)!
- Name node failure is **catastrophic**
- Data node failure can be tolerated, up to a point
  - Depends on how much replication you have





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**Why do you think the HDFS designers parallelized storage at the level of blocks instead of files?**

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# Several reasons...

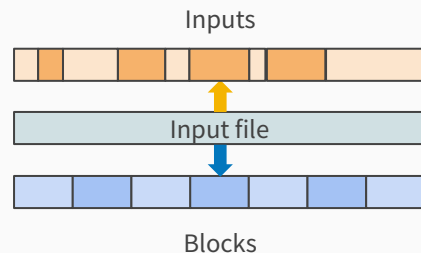
- A file can be larger than any single disk
- Map-Reduce programs typically only see small portions of a large file
- Uniform (maximum) block size makes allocation / replication easier

# HDFS isn't quite POSIX-compliant

- Updates are append-only
  - No changing old data!
  - This makes replication logic much simpler: if data is there, you can trust it
- Not all file modes are supported
  - Not all modes make sense in this limited context anyway
  - E.g., executable

# Job scheduling and input splits

- A typical map-reduce job runs over one large file
  - Each file contains an array of (independent) inputs
  - E.g., lines in text files
- MapReduce divides the input into **splits**
  - Split = unit of work assigned to a mapper, contains **multiple records**
- Each **split** maps onto one or more **blocks**
  - Try to assign work such that work for a **split** is done on a machine with its **blocks**
- HDFS exposes block layout to the application layer to make this possible



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**What do you think will happen  
if a split is spread across  
multiple HDFS blocks?**

① Start presenting to display the poll results on this slide.

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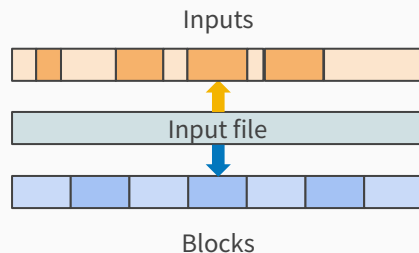


**[2] What do you think will happen if a split is spread across multiple HDFS blocks?**

① Start presenting to display the poll results on this slide.

# Splits and blocks

- **Split** = one logical division of input data for a map process
  - Each **split** typically consists of **multiple records**, e.g., rows of a CSV file
- Machine running `map()` must have access to the entire split, so **data may have to move!**
- By default, **split size** = **block size**, but some fragmentation is unavoidable



# A typical Map-Reduce work-flow

1. Upload data from UNIX filesystem to HDFS
  - a. `hadoop fs -put my_file.csv`
2. Run map-reduce program
  - a. Each mapper sees a portion of `my_file.csv`
  - b. Each mapper produces intermediate outputs as HDFS files
  - c. Shuffle stage collects intermediate outputs to give to reducers
  - d. Reducers operate on intermediates, produce final output as multiple blocks
3. Retrieve output from from HDFS
  - a. `hadoop fs -getmerge my_output_file.csv`



# Replication factors

- If we copy a block to multiple nodes, scheduling becomes easier
  - We're more likely to find a free worker that has our data
- HDFS lets you set the replication factor for each file
  - Replication isn't free: cost is multiplicative in the data size
- Typical setup: 3x replication
  - If possible, 2 nodes in one rack, +1 in a separate rack
  - This protects against both **node failure** and **rack failure**

# The CAP theorem for DFS

- **Consistency:**
  - Read always produces the most recent value
- **Availability:**
  - Requests cannot be ignored
- **Partition-tolerance:**
  - System maintains correctness during network failure



**Pick two**

(but networks always fail)

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**Which CAP property does  
HDFS sacrifice?**

① Start presenting to display the poll results on this slide.

# HDFS and CAP

- Consistency

- Centralized name node always has a consistent view of the file system
- Data can be added (appended), but **not modified!**

- Availability

- If the name node goes offline, we're out of luck

- Partition-tolerance

- Depends on network configuration and replication factor

# Wrap-up on HDFS

- Files divide into blocks, and are replicated across the cluster
- Checksums are replicated with each block
- Name node allocates blocks and directs clients
- Blocks are append-only ⇒ optimized for write-once, read-many patterns

# Next week

- Spark and Spark-SQL
  - [Zaharia et al., 2010]
  - [Armbrust et al., 2015]
- Quiz #2 (2022-02-25):  
Map-Reduce and HDFS
- No class on 2022-02-21

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# Audience Q&A Session

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