TOR VERGATA
UNIVERSITÀ DEGLI STUDI DI ROMA
Macroarea di Ingegneria
Dipartimento di Ingegneria Civile e Ingegneria Informatica

(Big) Data Storage Systems

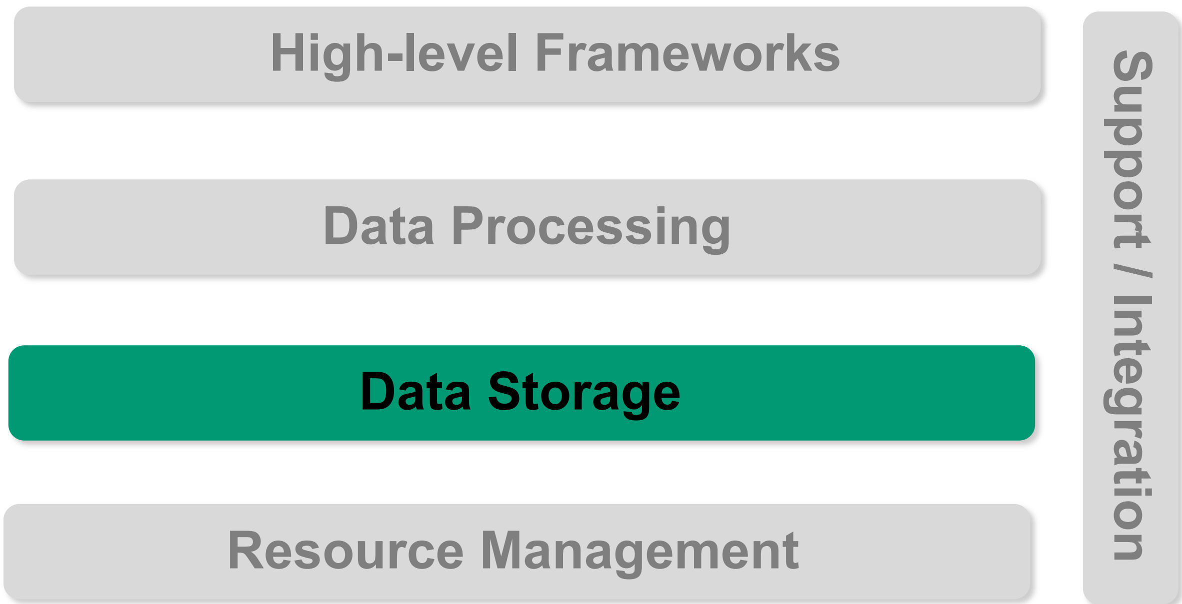
Corso di Sistemi e Architetture per Big Data

A.A. 2023/24

Valeria Cardellini

Laurea Magistrale in Ingegneria Informatica

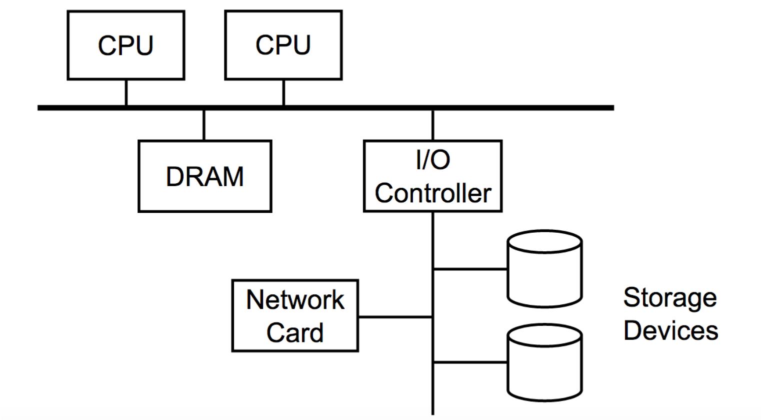
The reference Big Data stack

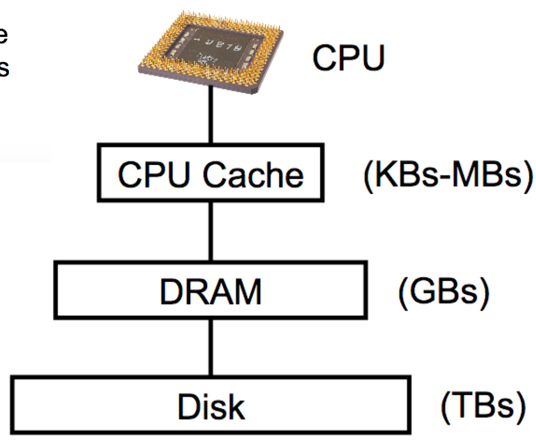


Where storage sits in the Big Data stack

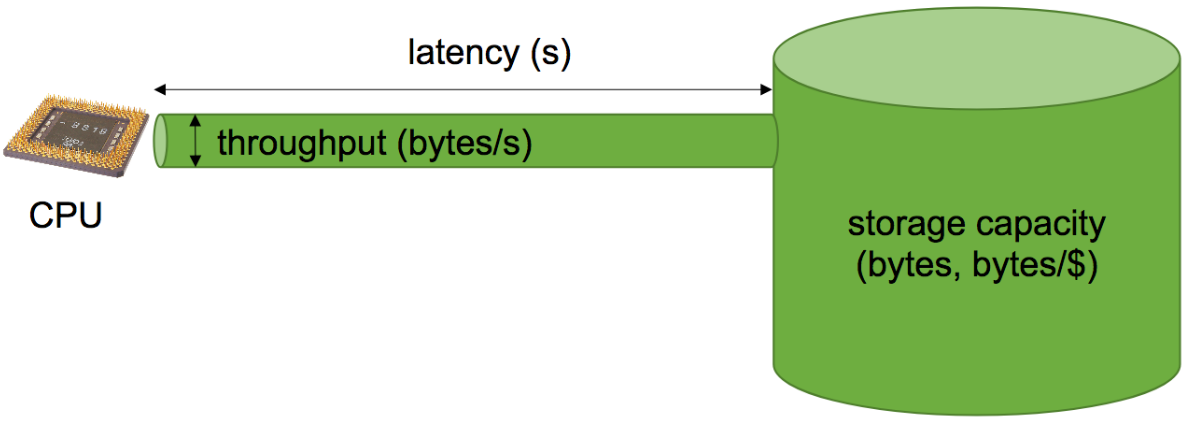
- Example of frameworks and tools in a data lake architecture

Typical server architecture and storage hierarchy



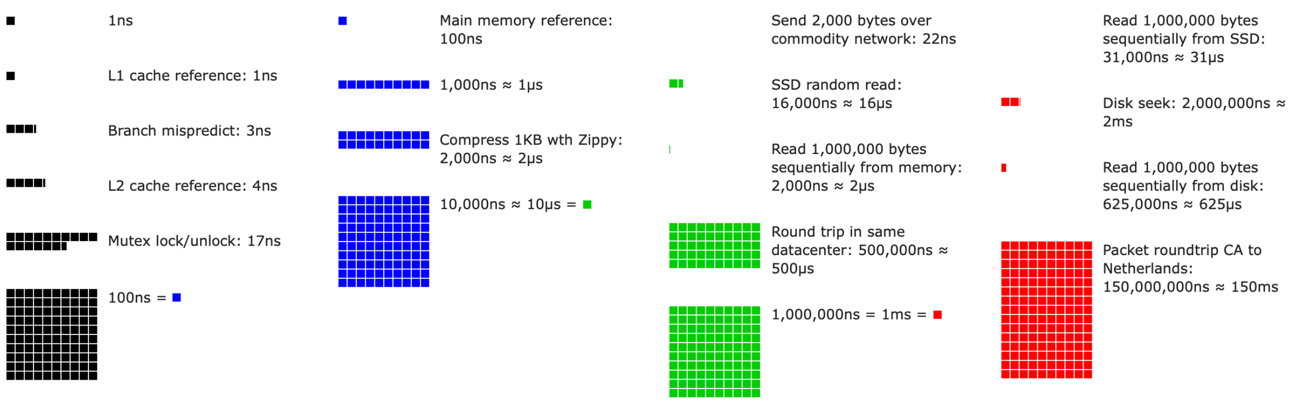


Storage performance metrics



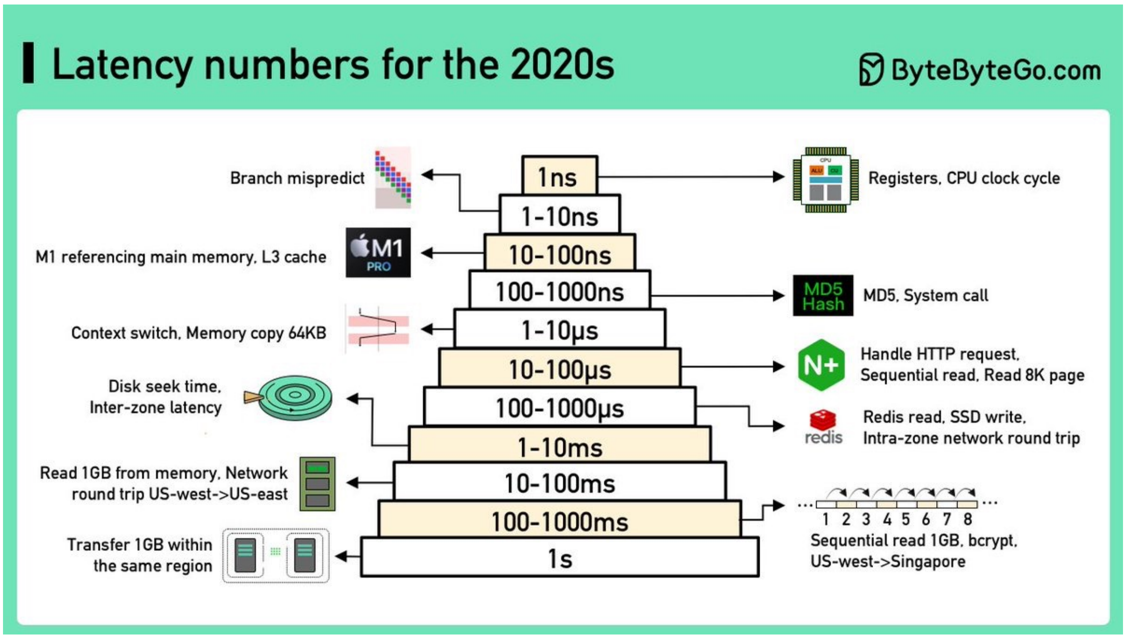
Where to store data?

- See “Latency numbers every programmer should know” (presented by Jeff Dean from Google in 2010, numbers updated in 2020)



Where to store data?

- "Latency numbers every programmer should know for the 2020s" www.youtube.com/watch?v=FqR5vESuKe0



Maximum attainable throughput

- Varies significantly by device
  - 50 GB/s for RAM
  - 3 GB/s for NVMe SSD
    - SSD: Solid State Drive
    - NVMe: Non-Volatile Memory Express
    - NVMe is a storage access and transport protocol for flash and next-generation SSDs
  - 130 MB/s for hard disk
- Assumes large reads (≫1 block)

Hardware trends over time

- Capacity/$ grows at a fast rate (e.g., doubles every 2 years)
- Throughput grows at a slower rate (~5% per year), but new interconnects help
- Latency does not improve much over time

Data storage: the classic approach

- **File**
  - Group of data, whose structure is defined by file system
- File system
  - Controls how data are structured, named, organized, stored and retrieved from disk
  - Single (logical) disk (e.g., HDD/SDD, RAID)
- **Relational database**
  - Organized/structured collection of data (e.g., entities, tables)
- Relational database management system (RDBMS)
  - Provides a way to organize and access relational data
  - Enables data definition, update, retrieval, administration

What about Big Data?

Storage capacity and data transfer rate have increased massively over the years

HDD
Capacity: ~1TB
Throughput: 250MB/s

SSD
Capacity: ~1TB
Throughput: 850MB/s

Let's consider the latency (time needed to transfer data*)

Data Size	HDD	SSD
10 GB	40s	12s
100 GB	6m 49s	2m
1 TB	1h 9m 54s	20m 33s
10 TB	?	?

* we consider no overhead

We need to scale out!

General principles for scalable data storage

- Scalability and high performance
  - Need to face continuous growth of data to store
  - Use multiple nodes to store data
- Ability to run on commodity hardware
  - But hardware failures are the norm rather than the exception
- Reliability and fault tolerance
  - Transparent data replication
- Availability
  - Data should be available to serve requests when needed
  - CAP theorem: trade-off with consistency

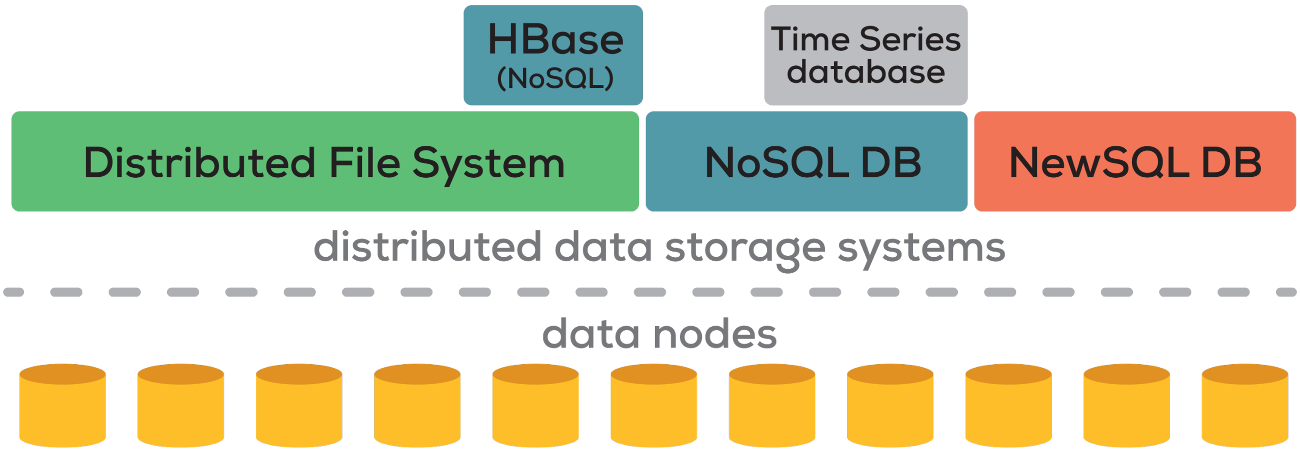
Scalable and resilient data storage solutions

Various forms of storage for Big Data:

- **Distributed file systems**
  - Manage (large) **files** on multiple nodes
  - E.g., Google File System, HDFS, GlusterFS
- **NoSQL data stores**
  - Simple and flexible **non-relational** data models: key-value, column family, document, and graph
  - Horizontal scalability and fault tolerance
  - E.g., Redis, BigTable, Hbase, Cassandra, MongoDB, Neo4J
  - Also time series databases built on top of NoSQL (e.g.,: InfluxDB, KairosDB)
- **NewSQL databases**
  - Add horizontal scalability and fault tolerance to **relational** model
  - E.g., VoltDB, Google Spanner, CockroachDB

Scalable and resilient data storage solutions

Whole picture of different storage solutions we consider



Data storage in the Cloud

- Main goals:
  - On-demand (elastic) and geographic scale
  - Fault tolerance
  - Durability (versioned copies)
  - Simplified application development and deployment
  - Support for cloud-native apps (serverless)
- Public Cloud services for data storage
  - Object stores: Amazon S3, Google Cloud Storage, Microsoft Azure Storage, …
  - Relational databases: Amazon RDS, Amazon Aurora, Google Cloud SQL, Microsoft Azure SQL Database, …
  - NoSQL data stores: Amazon DynamoDB, Amazon DocumentDB, Google Cloud Bigtable, Google Datastore, Microsoft Azure Cosmos DB, MongoDB Atlas, …
  - NewSQL databases: Google Cloud Spanner, …
  - Serverless databases: Google Firestore, CockroachDB, …

Distributed File Systems (DFS)

- Primary support for data management
- Manage data storage across a network of machines
  - Usually locally distributed, in some case geo-distributed
- Provide an interface whereby to store information in the form of files and later access them for read and write operations
- Several solutions with different design choices
  - **GFS**, **HDFS** (GFS open-source clone): designed for batch applications with large files
  - **Alluxio**: in-memory (high-throughput) storage system
  - **GlusterFS**: scalable network file system
  - Lustre: open-source, large-scale distributed file system
  - Ceph: open-source, distributed object store with Ceph File System on top

Case study: Google File System (GFS)

Assumptions and motivations

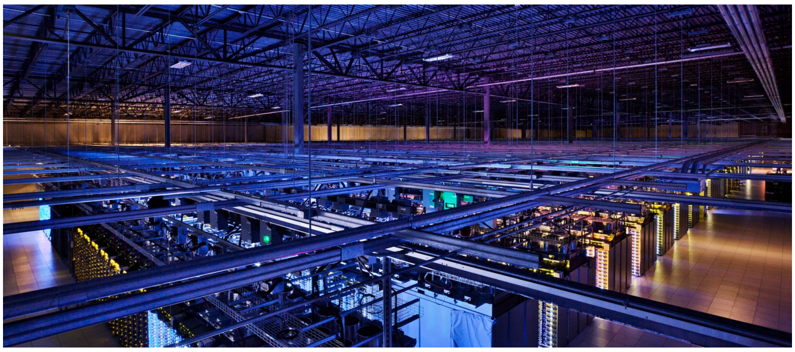
- System is built from inexpensive commodity hardware that often fails
  - 60,000 nodes, each with 1 failure per year: 7 failures per hour!
- System stores large files
- Large streaming/contiguous reads, small random reads
- Many large, sequential writes that append data
  - Concurrent clients can append to same file
- High sustained bandwidth is more important than low latency

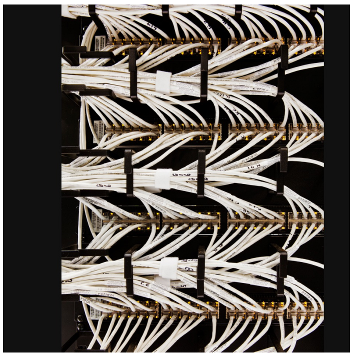
Ghemawat et al., The Google File System, *Proc. ACM SOSP '03*

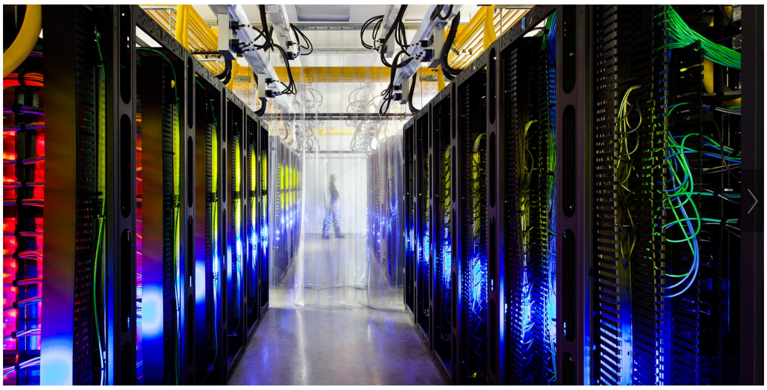
GFS: Main features

- Distributed file system implemented in user space
- Manages (very) large files: usually multi-GB
- **Data parallelism** using *divide et impera* approach: file split into fixed-size chunks
- ***Chunk***:
  - Fixed size (either 64MB or 128MB)
  - Transparent to users
  - Stored as plain file on chunk servers
- Write-once, read-many-times pattern
  - Efficient *append* operation: appends data at the end of file *atomically at least once* even in the presence of concurrent operations (minimal synchronization overhead)
- Fault tolerance and high availability through chunk replication, no data caching

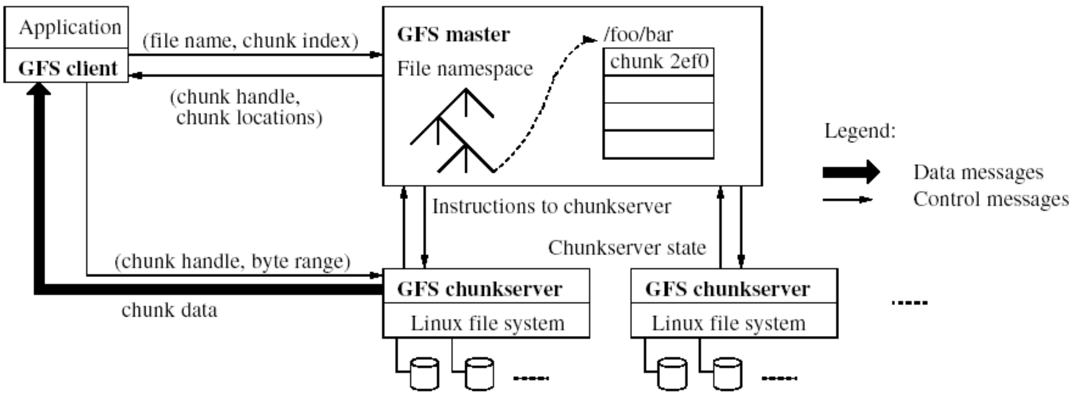
GFS: Operation environment





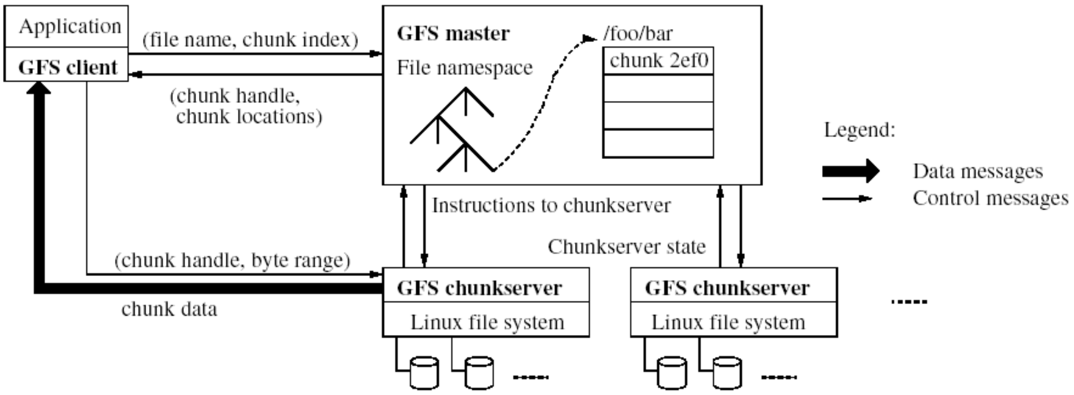


GFS: Architecture



- Master
  - Single, centralized entity (to simplify the design)
  - Manages file metadata (stored in memory)
    - Metadata: access control information, mapping from files to chunks, locations of chunks
  - Does not store data (i.e., chunks)
  - Manages operations on chunks: create, replicate, load balance, delete

GFS: Architecture



- Chunk servers (100s – 1000s)
  - Store chunks as files
  - Spread across cluster racks
- Clients
  - Issue *control* (metadata) requests to GFS master
  - Issue *data* requests to GFS chunkservers
  - Cache metadata, do not cache data (simplifies system design)

GFS: Metadata

- Master stores 3 major types of metadata:
  - File and chunk namespace (directory hierarchy)
  - Mapping from files to chunks
  - Current locations of chunks
- Metadata are stored in memory (64B per chunk)
  - ✓ Fast, easy and efficient to scan the entire state
  - ✗ Number of chunks is limited by amount of master's memory
    "The cost of adding extra memory to the master is a small price to pay for the simplicity, reliability, performance, and flexibility gained"
- Master also keeps an operation log where metadata changes are recorded
  - Log is persisted on master's disk and replicated for fault tolerance
  - Master can recover its state by replaying operation log
  - Checkpoints for fast recovery

GFS: Chunk size

- Chunk size is either 64 MB or 128 MB
  - Much larger than typical block sizes
- Why? Large chunk size reduces:
  - Number of interactions between client and master
  - Size of metadata stored on master
  - Network overhead (persistent TCP connection to chunk server)
- Each chunk is stored as a plain Linux file
- Cons
  - ✗ Wasted space due to internal fragmentation
  - ✗ "Small" files consist of a few chunks, which get lots of traffic from concurrent clients (can be mitigated by increasing replication factor)

GFS: Fault tolerance and replication

- Master controls and maintains the replication of each chunk on several chunk servers
  - At least 3 replicas on different chunk servers
  - Replication based on primary-backup schema
  - Replication degree > 3 for highly requested chunks
- Multi-level placement of replicas
  - Different machines, same rack + availability and reliability
  - Different machines, different racks + aggregated bandwidth
- Data integrity
  - Chunk divided in 64KB blocks; 32B checksum for each block
  - Checksum kept in memory
  - Checksum checked every time app reads data

GFS: Master operations

- Stores metadata
- Manages and locks namespace
  - Namespace represented as a lookup table
  - Read lock on internal nodes and read/write lock on leaves: read lock allows concurrent mutations in the same directory and prevents deletion, renaming or snapshot
- Communicates periodically with each chunk server using RPC
  - Sends instructions and collects chunk server state (*heartbeat* messages)
- Creates, re-replicates and rebalances chunks
  - Balances chunk servers' disk space utilization and load
  - Distributes replicas among racks to increase fault tolerance
  - Re-replicates a chunk as soon as the number of its available replicas falls below the replication degree

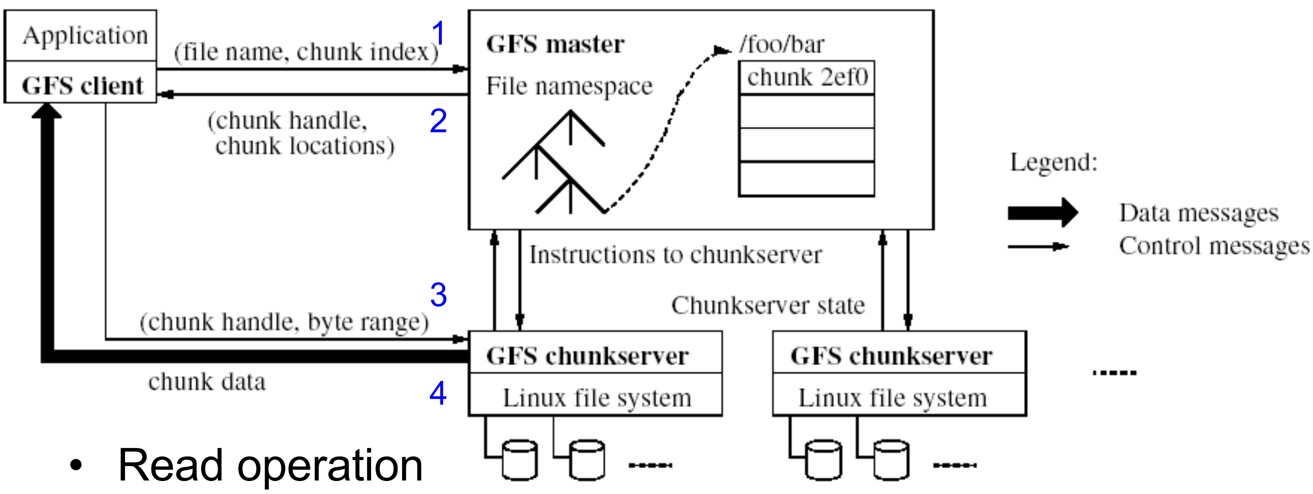
GFS: Master operations

- Garbage collection
  - File deletion logged by master
  - Deleted file is renamed to a hidden name with deletion timestamp, so that real deletion is postponed and file can be easily recovered in a limited timespan
- Stale replica detection
  - Chunk replicas may become stale if a chunk server fails or misses updates to chunk
  - For each chunk, the master keeps a chunk version number
  - Chunk version number updated at each chunk mutation
  - Master removes stale replicas during garbage collection

GFS: Interface

- Files are organized in directories
  - But no data structure to represent directory
- Files are identified by their pathname
  - Bu no alias support
- GFS supports traditional file system operations (but not Posix-compliant)
  - **create**, **delete**, **open**, **close**, **read**, and **write**
- Supports also 2 special operations:
  - **snapshot**: makes a copy of file or directory tree at low cost (based on copy-on-write techniques)
  - **record append**: allows multiple clients to append data to the same file concurrently, without overwriting one another's data

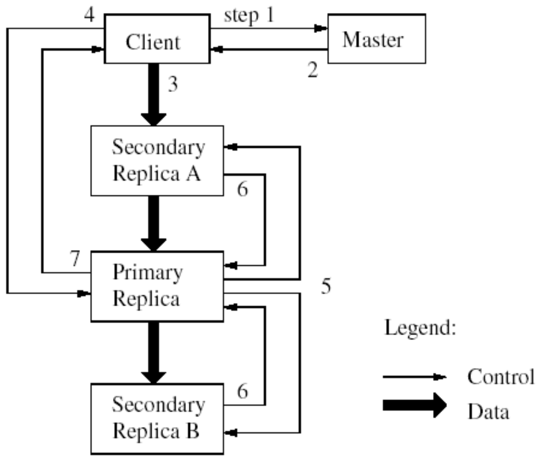
GFS: Read operation



- Read operation
  - Data flow is decoupled from control flow
  1) Client sends read(file name, chunk index) to master
  2) Master replies with *chunk handle* (globally unique ID of chunk), chunk version number (to detect stale replica), and chunk locations
  3) Client sends read(chunk handle, byte range) to the closest chunk server among those serving the chunk
  4) Chunk server replies with chunk data

GFS: Mutation operation

- Mutations are `write` or `append`
  - Mutations are performed at all chunk's replicas in the same order
- Based on *lease* mechanism:
  - Goal: minimize management overhead at master
  - Master grants chunk lease to primary replica
  - Primary picks a serial order for all mutations to chunk
  - All replicas follow this order when applying mutations
  - Primary replies to client, see 7)
  - Leases renewed using periodic heartbeat messages between master and chunk servers



- Data flow is decoupled from control flow
- Client sends data to *any* of the chunk servers identified by master, which in turn pushes data to the other chunk servers in a chained fashion so to fully utilize network bandwidth

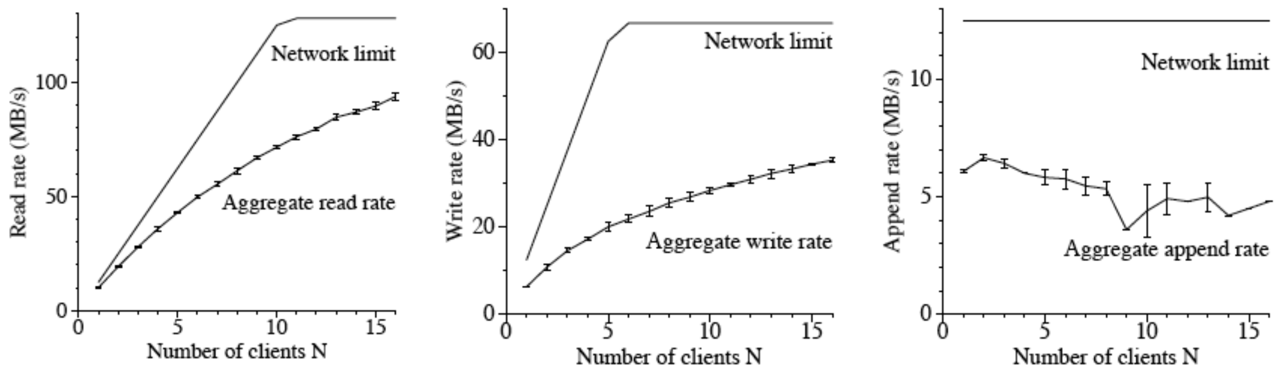
GFS: Atomic append

- Client sends only data (without specifying offset)
- GFS appends data to file *at least once* atomically (i.e., as one continuous sequence of bytes)
  - At offset chosen by GFS
  - Works with multiple concurrent writers
  - At least once: applications must cope with possible duplicates
- Append operations heavily used by Google's distributed apps
  - E.g., files often serve as multiple-producers/single-consumer queue or contain results merged from many clients (MapReduce)

GFS: Consistency model

- Changes to namespace (e.g., file creation) are atomic
  - Managed exclusively by GFS master with locking guarantee
- Changes to data are ordered as chosen by primary replica, but chunk server failures can cause inconsistency
- GFS has a “relaxed” model for data: eventual consistency
  - Simple and efficient to implement

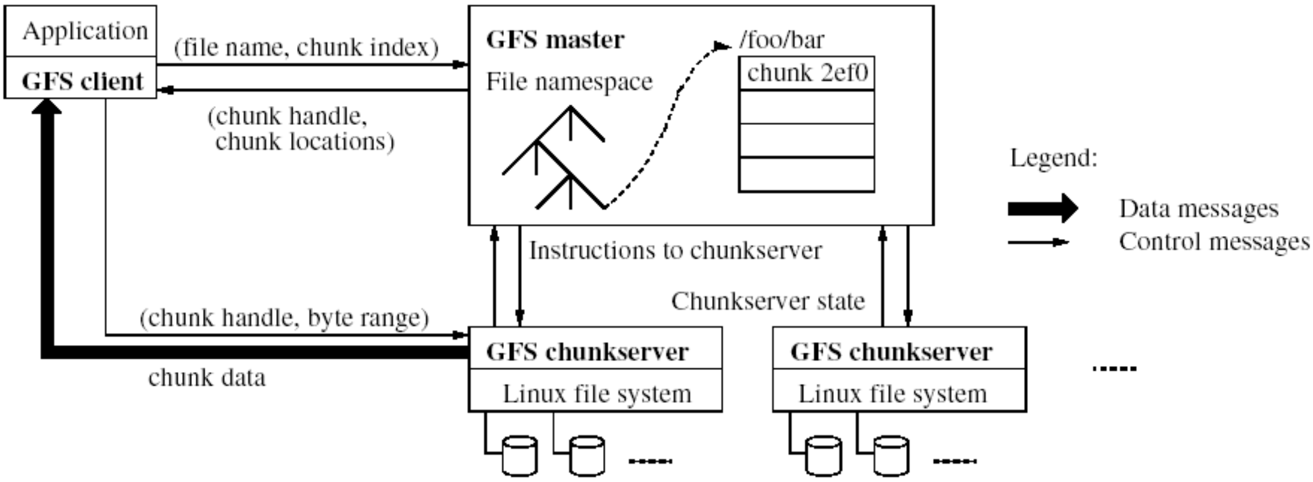
GFS performance (in 2003)



(a) Reads (b) Writes (c) Record appends

- Read performance is satisfactory (80-100 MB/s)
- But reduced write performance (30 MB/s) and relatively slow (5 MB/s) in appending data to existing files

GFS problems



Main problem with GFS architecture?

Single master → Single point of failure (SPOF)
Scalability bottleneck

GFS problems: Single master

- Solutions adopted to overcome issues related to single master
  – Overcome SPOF: by having multiple “shadow” masters that provide read-only access when the primary master is down
  – Overcome scalability bottleneck: by reducing interaction between master and clients
    - Master stores only metadata (not data)
    - Clients can cache metadata
    - Large chunk size
    - Chunk lease: master delegates the authority of coordinating the mutations to primary replica
- Overall, simple solutions

GFS summary

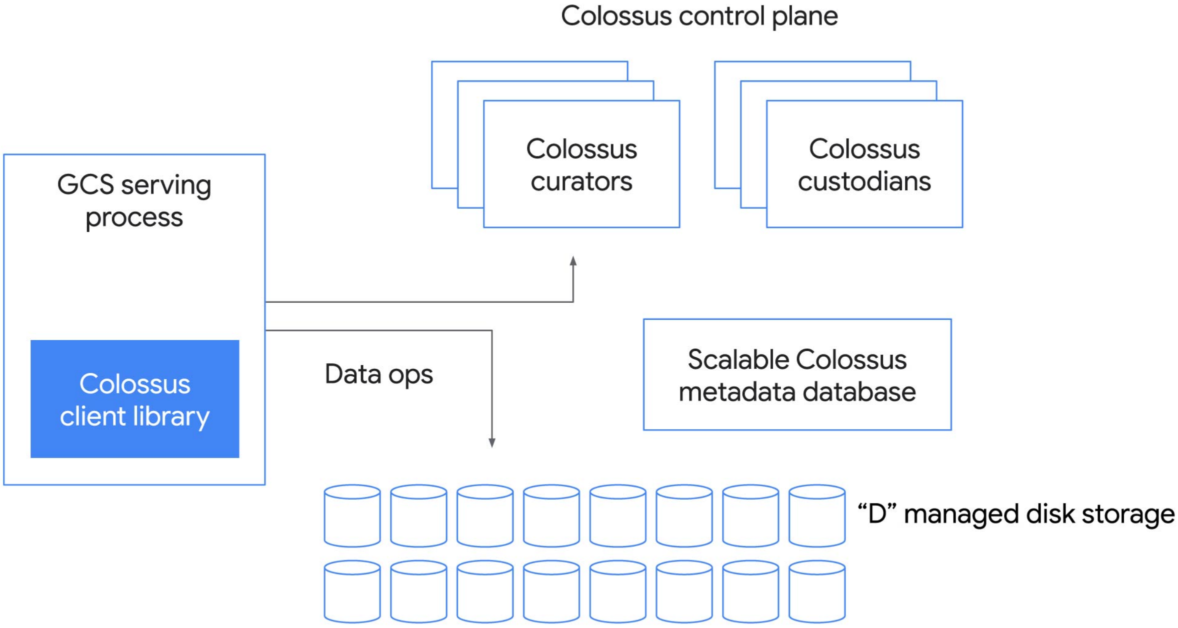
- GFS success
  - Used by Google to support search service and other services
  - Availability and recoverability on commodity hardware
  - High throughput by decoupling control and data
  - Supports massive data sets and concurrent appends
- GFS problems (besides single master)
  - All metadata stored in master memory
    - "Limited" scalability: approximately 50M files, 10PB
  - Semantics not transparent to apps
  - Slow automatic failover (~ 10 sec.)
  - Client's delay when recovering from a failed chunk server
  - Performance not good for all services
    - GFS designed for high throughput but not appropriate for latency-sensitive services like Gmail

Colossus: successor of GFS

- Next-generation Google DFS (since 2010)
- Designed for a wide variety of Google services (YouTube, Maps, Photos, search ads, …)
- Can handle EB of storage, tens of thousands of servers
- Distributed masters, chunk servers replaced by D servers
- Scalable metadata layer, built on top of Bigtable
- Error-correcting codes (e.g., Reed-Solomon)
- Mix of high-speed flash memory and disks for storage
- Client-driven encoding and replication
- Google Cloud services built on top of Colossus
  - Cloud Storage (object store) and Cloud Firestore (NoSQL data store)

Colossus under the hood: a peek into Google's scalable storage system, 2021.
www.youtube.com/watch?v=q4WC_6SzBz4

Colossus: key components



HDFS

- **Hadoop Distributed File System (HDFS)**
  – Open-source user-level distributed file system
  – Written in Java
  – GFS clone: shares many features with GFS (including pros and cons!)
    - Master/worker architecture
    - Large files, data parallelism
    - Commodity, low-cost hardware
    - Highly fault tolerant and throughput oriented
  – Integrated with processing frameworks and ingestion tools, e.g., Hadoop MapReduce, Spark, Flink, NiFi

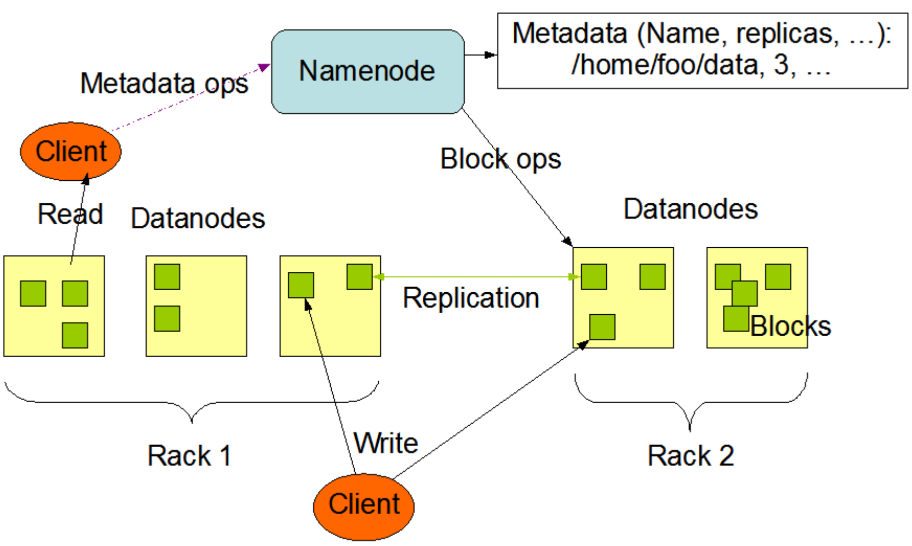
Shafer et al., The Hadoop Distributed Filesystem: Balancing Portability and Performance, *Proc. ISPASS 2010*

HDFS: Design principles

- Large data sets: typical file size is GBs or TBs
- Write-once, read-many-times access pattern to files
  - E.g., MapReduce apps, web crawlers
- Commodity, low-cost hardware
  - HDFS is designed to work without noticeable interruption to users even when failures occur
- Portability across heterogeneous hardware and software platforms

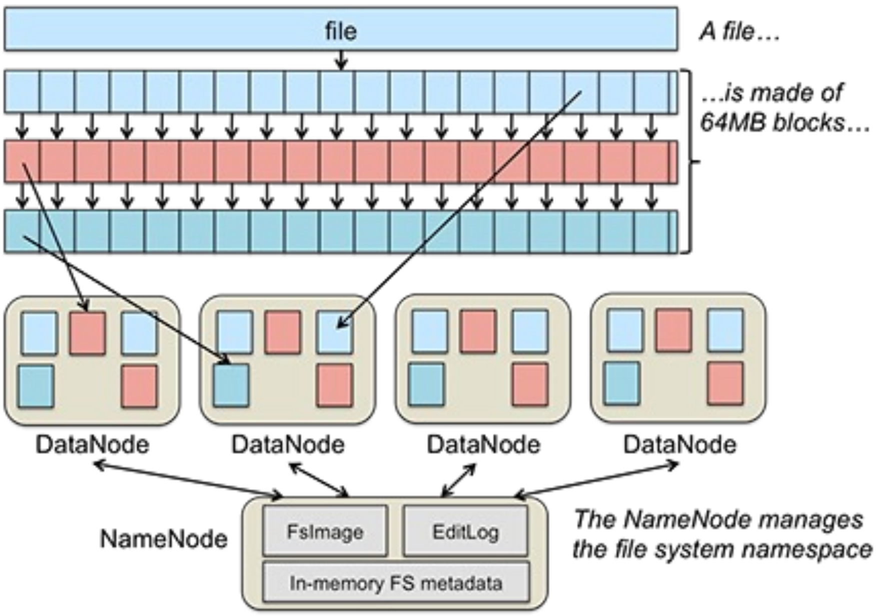
HDFS: Architecture

- Master/workers, nodes in a HDFS cluster:
  - One *NameNode* (master in GFS)
  - Multiple *DataNodes* (chunk servers in GFS)



HDFS: File management

- Data parallelism: each file is split into blocks (chunks in GFS) which are stored on DataNodes
- Large size blocks (default 64 MB), we know why

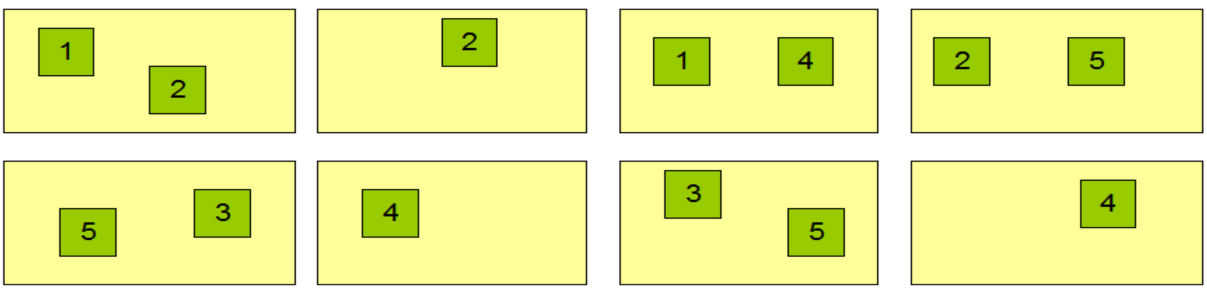


HDFS: Block replication

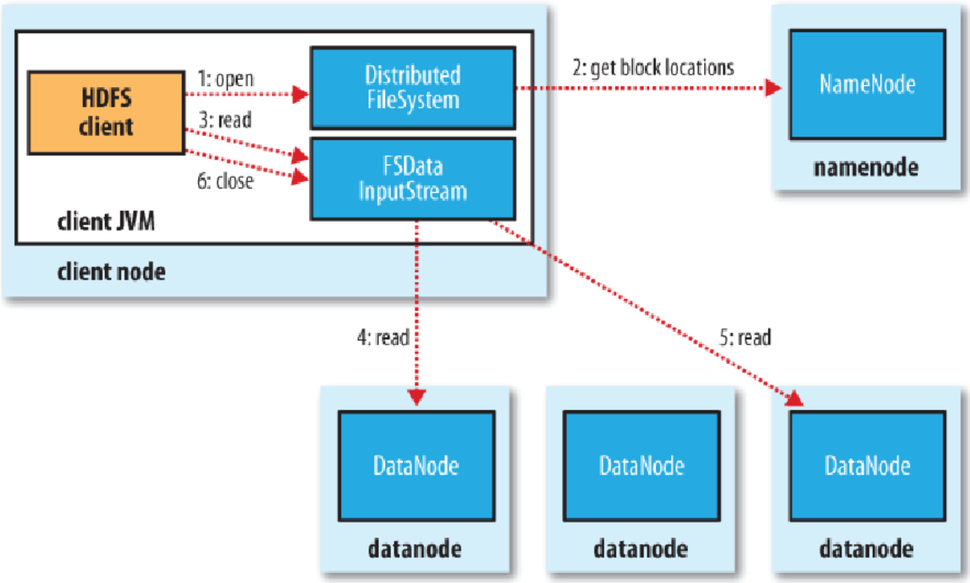
- NameNode periodically receives heartbeat and blockreport from each DataNode
  - Blockreport: list of all blocks on a given DataNode

Namenode (Filename, numReplicas, block-ids, …)
/users/sameerp/data/part-0, r:2, {1,3}, …
/users/sameerp/data/part-1, r:3, {2,4,5}, …

Datanodes



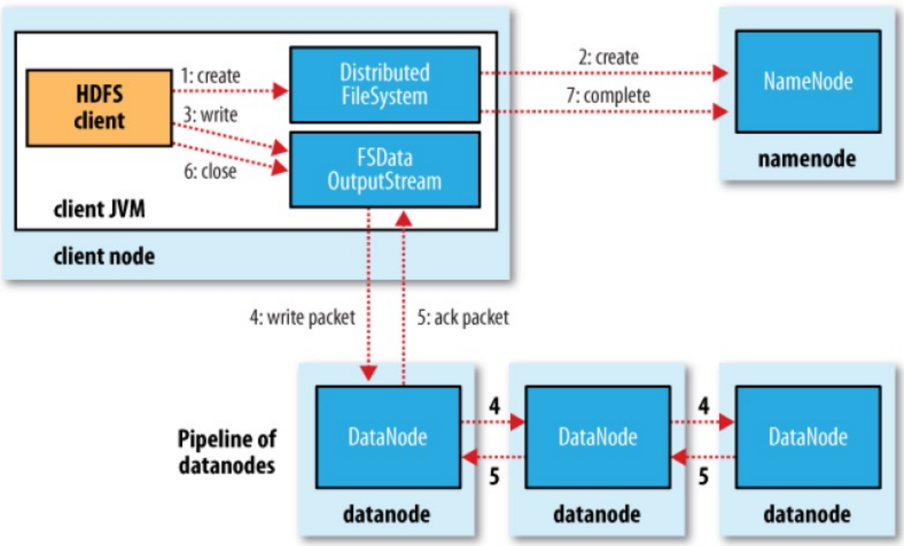
HDFS: File read



Source: "Hadoop: The definitive guide"

- NameNode is used to get block location

HDFS: File write



Source: "Hadoop: The definitive guide"

- Clients ask NameNode for a list of suitable DataNodes
- This list forms a chain: first DataNode stores a copy of the block, then forwards it to the second, and so on

Enhancements in HDFS 3.x

- High availability
  - Single NameNode is SPOF: added support for >= 2 NameNodes (1 active and >=1 standby)

  hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-hdfs/HDFSHighAvailabilityWithNFS.html

- Erasure coding can be used as alternative storage strategy to replication in order to provide fault tolerance
  - ✓ Same level of fault tolerance with less storage overhead: from 200% with replication degree equal to 3 to 50%
  - ✗ Increase in network and processing overhead
  - Two codes available: XOR and Reed-Solomon
  - Erasure coding can be enabled on a per directory basis

  blog.cloudera.com/introduction-to-hdfs-erasure-coding-in-apache-hadoop/

HDFS: security

- HDFS initially lacked robust security mechanisms
- Recent versions have introduced features like authentication (based on Kerberos and LDAP), authorization (based on ACLs), and encryption (both data at rest and data in transit)
- Can be integrated with Apache Ranger, which provides comprehensive security across Hadoop ecosystem
  - Centralized security administration
  - Fine-grained authorization
  - Support for different authorization methods (role-based AC, attribute-based AC, etc.)
  - Centralize auditing of user access and administrative actions
- Data governance can be provided by third-party tools, e.g., Cloudera Navigator

Another distributed file system: GlusterFS

- Linux-based, open source distributed file system www.gluster.org
- Designed to be highly scalable
  – Scaling to several PB (up to 72 brontobytes!)
    - Brontobyte = 10^{27} or 2^{90} bytes

GlusterFS: Features

- Global namespace
  – Issue: metadata is a bottleneck
  – Solution: avoid centralized metadata server
    - No special node(s) with special knowledge of where files are or should be
  – Solution: use consistent hashing (similarly to Chord)
    - Benefits of distributed hashing (robustness, load balancing, …)
- Clustered and highly available storage
- Built-in replication and geo-replication
- Self-healing
- Ability to re-balance data

GlusterFS: Architecture

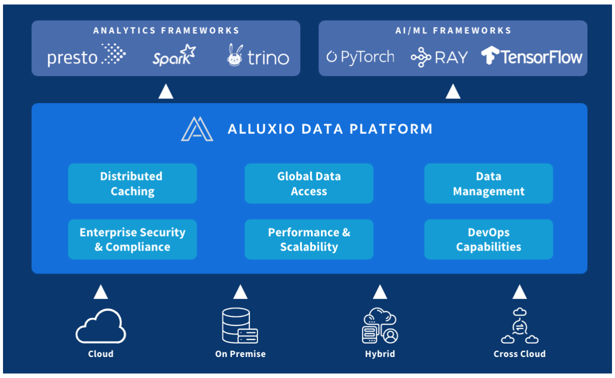
- Four main concepts:
  - **Trusted Storage Pool**: trusted network of servers that will host storage resources
  - **Bricks**: storage units which consist of a server and directory path (i.e., server:/export)
    - Bricks correspond to Chord's nodes
    - Files are mapped to bricks by calculating a hash
  - **Volumes**: collection of bricks with a common redundancy requirement
  - **Translators**: modules that are chained together to move data from point *a* to point *b*
    - Translator converts requests from users into requests for storage

A layer of indirection

- Motivations
  - Write throughput is limited by disk and network bandwidth
  - Fault tolerance by replicating data across servers, but synchronous replication slows down write ops
  - Performance and cost trend: RAM is key to fast data processing and gets cheaper over time
- Idea
  - Add a layer of indirection between computation and storage
  - Store data in RAM: faster than DFS and object stores, decoupling computation and storage
    - ✗ RAM is volatile

Alluxio

- Distributed **in-memory** storage system www.alluxio.io
- Adds a data access layer between storage and computation
  – Interposed between persistent storage layer (e.g., HDFS, AWS S3, …) and processing frameworks for analytics and AI (e.g., Spark, Flink, TensorFlow, …)
- Goal: storage unification and abstraction
  – Brings data from storage closer to applications
  – Enables applications to connect to different storage systems through a common interface and a global namespace

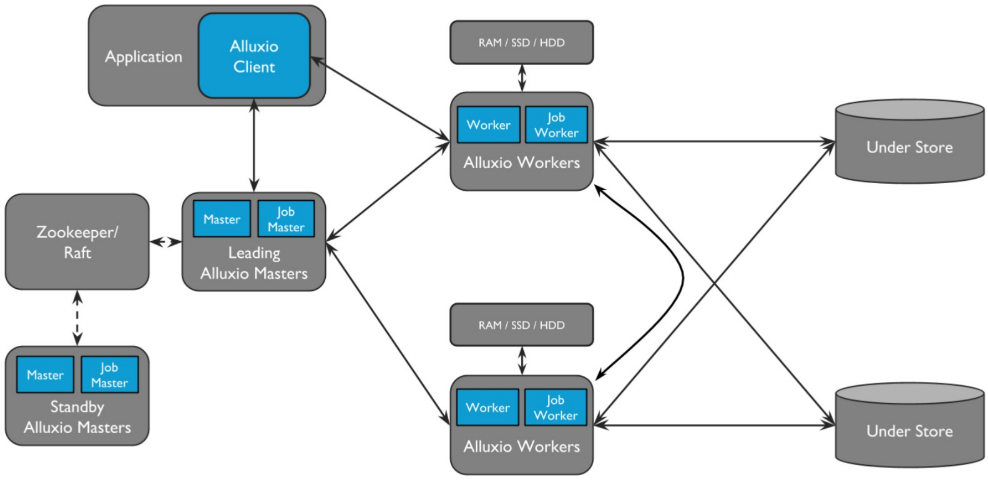


Alluxio

- History
  – Originated from Tachyon project at AMPLab (UC Berkeley)
  – Evolved as data orchestration technology for analytics and AI for the cloud
- Features
  – High read/write throughput, at memory speed
  – Commonly used as distributed shared caching service
  – How to address RAM volatility? Avoid replication and use re-computation (**lineage**) to achieve fault tolerance
    - One copy of data in memory (fast)
    - Upon failure, re-compute data using lineage: keep track of executed ops and, in case of failure, recover lost output by re-executing ops that created the output
    - Borrowed from Spark

Alluxio: Architecture

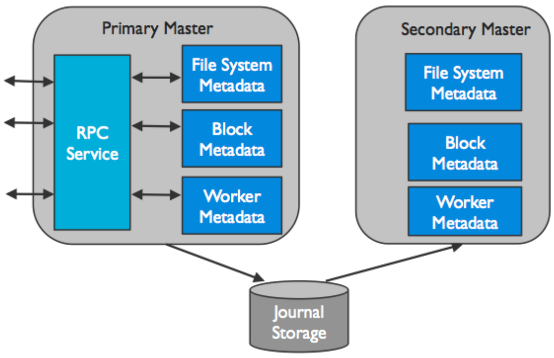
- Master-worker architecture (like GFS, HDFS)
- Replicated masters, multiple workers
  - Passive standby approach to ensure master fault tolerance
  - Consensus: Zookeeper, Raft



Alluxio: Architecture

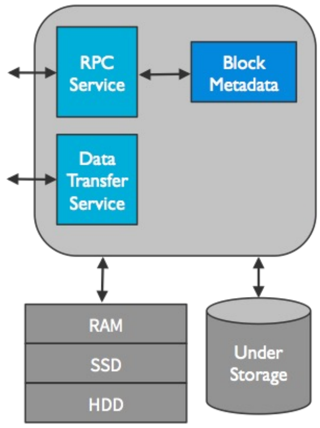
Master

- Stores metadata of storage system
- Responds to client requests
- Tracks lineage information
- Computes checkpoint order
- Secondary master(s) for fault tolerance



Workers

- Manage local storage (RAM, SSD, HDD)
- Access to “under storage” (e.g., HDFS, S3), not managed by Alluxio
- Periodically heartbeat to primary master



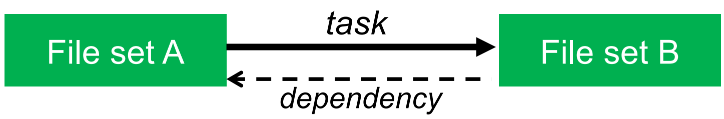
docs.alluxio.io/os/user/stable/en/overview/Architecture.html

Alluxio: Lineage and persistence

Alluxio consists of two (logical) layers:

- **Lineage layer**: tracks the sequence of operations that have created a particular data output
  - Write-once semantics: data is immutable once written
  - Frameworks using Alluxio *track* data dependencies and *recompute* them when a failure occurs
  - API for managing and accessing lineage information

Task reads file set A and writes file set B



- **Persistence layer**: persists data onto storage, used to perform asynchronous checkpoints
  - Efficient checkpointing algorithm
    - Avoids checkpointing temporary files
    - Checkpoints hot files first (i.e., the most read files)
    - Bounds re-computation time

Data storage so far: Summing up

- Google File System and HDFS
  - Master/worker architecture
  - Decouples metadata from data
  - Single master (bottleneck): limits interactions and file system size
  - Designed for batch applications: large chunks, no data caching
- GlusterFS
  - No centralized metadata server
  - Consistent hashing
- Alluxio
  - In-memory storage system
  - Master/worker architecture
  - No replication: tracks changes (lineage), recovers data using checkpoints and re-computations

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