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. 2025/26

Valeria Cardellini

Laurea Magistrale in Ingegneria Informatica

The reference Big Data stack

High-level Frameworks

Data Processing

Data Storage

Resource Management

Support / Integration

Where storage sits in Big Data stack

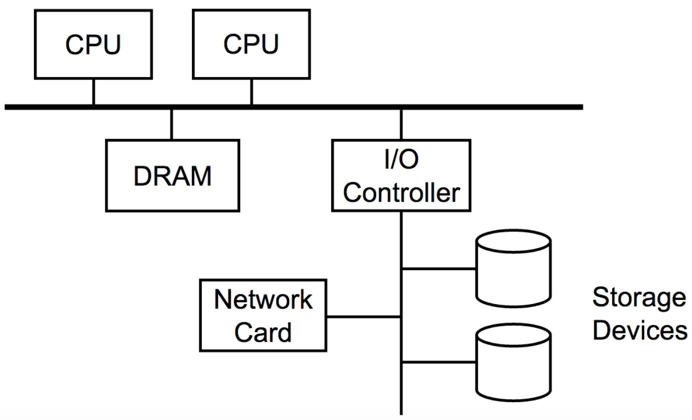
- Some frameworks and tools in a data lake architecture

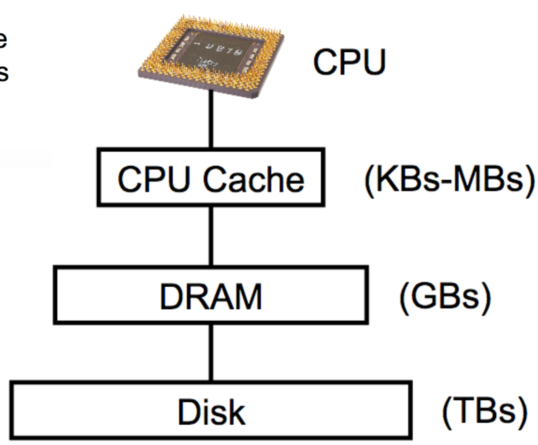
Hadoop MapReduce, Apache Spark, Flink, Presto, TensorFlow — **Processing engines**

Parquet, protobuf (Protocol Buffers), JSON (JavaScript Object Notation), Iceberg, Avro — **File formats & metadata**

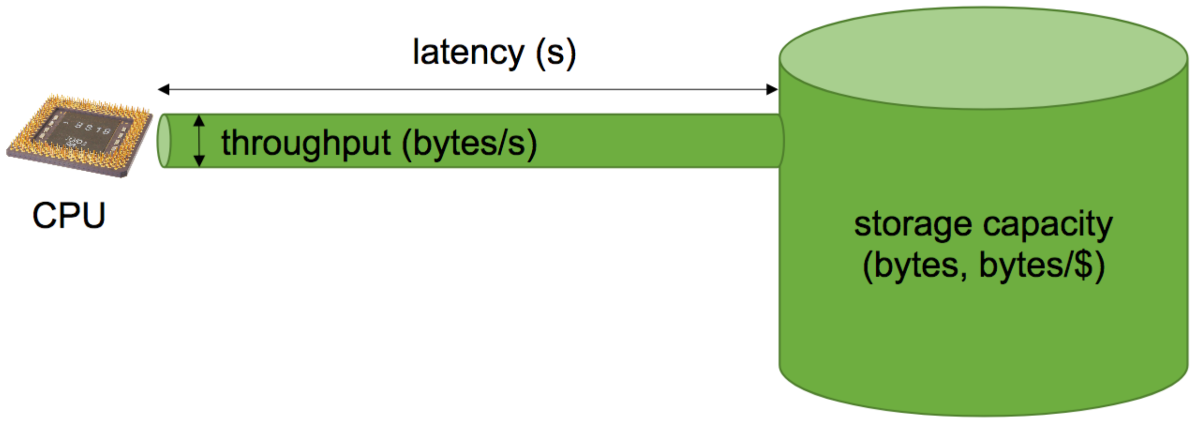
Apache Ozone™, ceph, Hadoop HDFS, Amazon S3 — **Large-scale file systems or object stores**

Typical server architecture and storage hierarchy



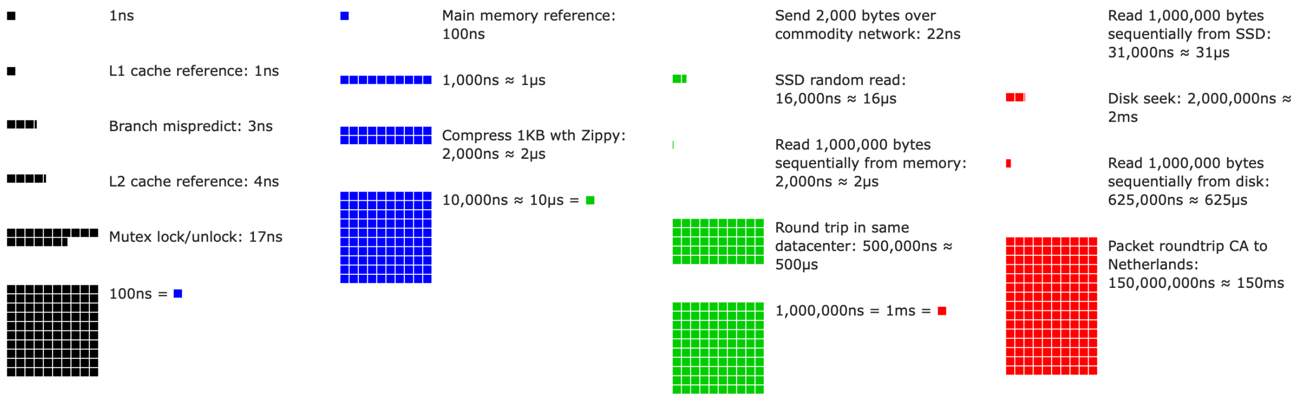


Storage performance metrics



Where to store data?

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



- Some comparisons that can surprise you:
  - RAM vs L1 cache: ~100 × slower
  - SSD vs RAM: ~1,000 × slower
  - Disk seek vs RAM: ~10,000 × slower
  - Cross-continent network vs RAM: ~1,000,000 × slower

Maximum attainable throughput

- Varies significantly by device
  - 50 GB/s for RAM
  - 10 GB/s for NVMe SSD
    - SSD: Solid State Drive
    - NVMe: Non-Volatile Memory Express
      - Storage access and transport protocol for high-speed non-volatile storage devices, especially modern flash-based SSDs; typically runs over PCI Express
  - 130 MB/s for hard disk
- Assumes large sequential reads (≫1 block)
  - Random is much slower

Hardware trends over time

- Capacity/$ grows at a fast rate (e.g., doubles every 2 years)
  - Slowed slightly in the 2020s
- Throughput grows at a slower rate (~5-10% per year), but new interconnects help
- Latency does not improve much over time
  - Because of physical limits, e.g., signal propagation, memory access time, mechanical movement

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
  - Handle continuous growth of stored data
  - Distribute storage across multiple nodes
- Ability to run on commodity hardware
  - Operate on inexpensive, widely available hardware
  - Hardware failures are the norm rather than the exception
- Reliability and fault tolerance
  - Tolerate failures without data loss
  - Transparent data replication
- Availability
  - Data should be available to serve requests when needed
  - CAP theorem: trade-off between availability and consistency

Scalable and resilient data storage solutions

Various forms of storage for Big Data

- **Distributed file systems** and **object stores**
  - Manage **large files** and **objects** across multiple nodes
  - Designed for high throughput and scalability
  - E.g., Google File System, HDFS, Ceph, Ozone, Ambry, MinIO
- **NoSQL data stores**
  - Provide flexible **non-relational** data models: key-value, column family, document, and graph
  - Designed for horizontal scalability and fault tolerance
  - E.g., Redis, BigTable, Hbase, Cassandra, MongoDB, Neo4J
  - Time-series DBs often built on NoSQL (e.g.,: InfluxDB, KairosDB)
- **NewSQL databases**
  - Add horizontal scalability and fault tolerance to **relational** model
  - E.g., VoltDB, Google Spanner, CockroachDB

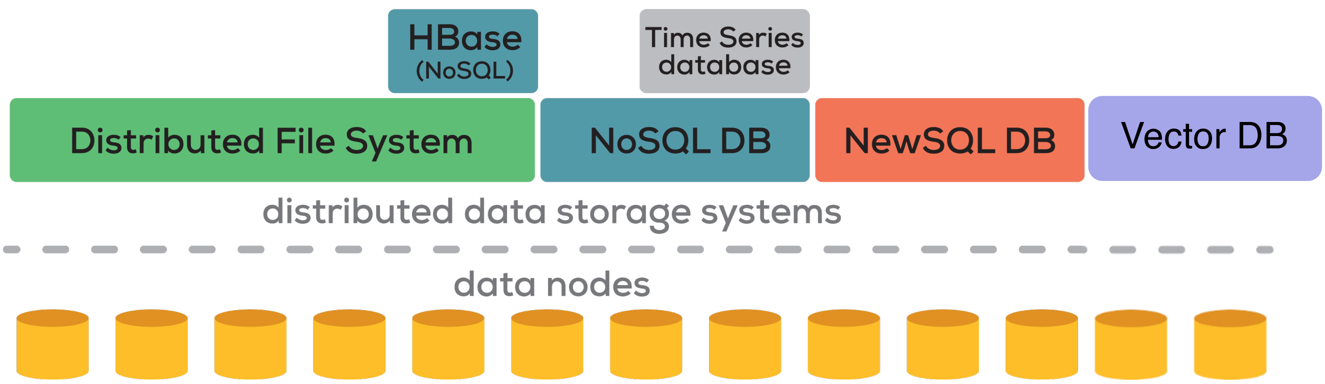
Scalable and resilient data storage solutions

Various forms of storage for Big Data

- **Vector databases**
  - Designed to store and query **high-dimensional vectors** produced by ML models
  - Vectors represent text embeddings, images, audio, user behavior patterns
  - Typical use cases: semantic search, recommendation systems, AI retrieval (RAG systems), image search
  - E.g., Milvus, Pinecon, Weaviate, Qdrant
  - Key technologies:
    - Approximate Nearest Neighbor algorithms
    - Vector indexes

Scalable and resilient data storage solutions

Whole picture of different storage solutions we consider



Cloud data storage

- Goals:
  - On-demand (elastic) scalability and geographic distribution
  - Fault tolerance
  - Durability through replicated and versioned copies
  - Simplified application development and deployment
  - Support for cloud-native apps (serverless)
- Examples of public Cloud services
  - DFSs: Amazon EFS
  - Object stores: Amazon S3, Google Cloud Storage, Azure Storage
  - Relational DBs: Amazon RDS, Google Cloud SQL, Azure SQL DB
  - NoSQL data stores: Amazon DynamoDB, Amazon DocumentDB, Google Cloud Bigtable, Google Datastore, Azure Cosmos DB, MongoDB Atlas
  - NewSQL: Google Cloud Spanner
  - Serverless DBs: Google Firestore, CockroachDB
  - Vector DBs: Weaviate Cloud, Qdrant Cloud

Distributed File Systems (DFS)

- Primary support for data management
- Manage data storage across a network of servers
  - Typically distributed within a data center, some systems support geo-distribution
- Usual interface to store data as files and later access it through read and write ops
- Several systems with different design choices
  - **GFS** and **HDFS**: batch processing of very large files
  - **Alluxio**: in-memory data access and caching layer
  - Lustre https://www.lustre.org: open-source, large-scale distributed file system used in HPC
  - Ceph https://docs.ceph.com/: open-source unified storage system supporting object, block, and file storage

Case study: Google File System (GFS)

Assumptions and motivations

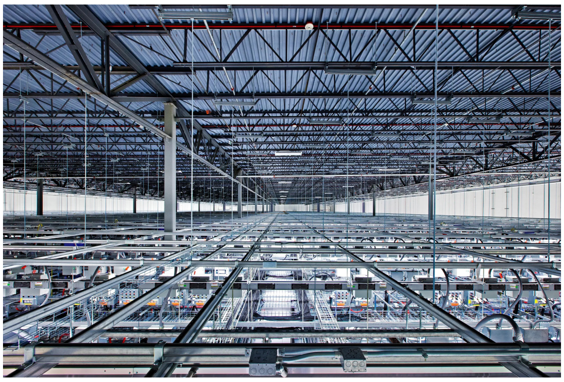
- System is built from inexpensive commodity hardware that often fails
  - 60,000 nodes, each with 1 failure per year: 7 failures per hour!
- System stores large files
- Large streaming/contiguous reads, small random reads
- Many large, sequential writes that append data
  - Concurrent clients can append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

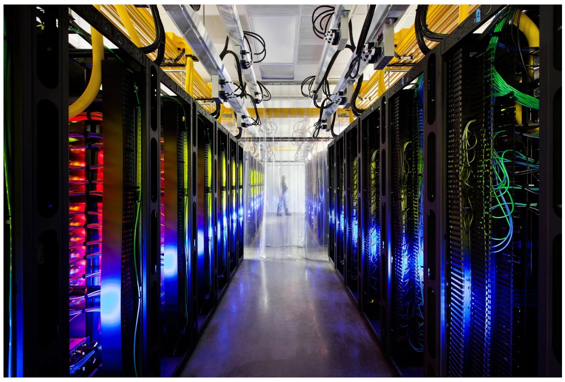
Ghemawat et al., The Google File System, *SOSP '03*

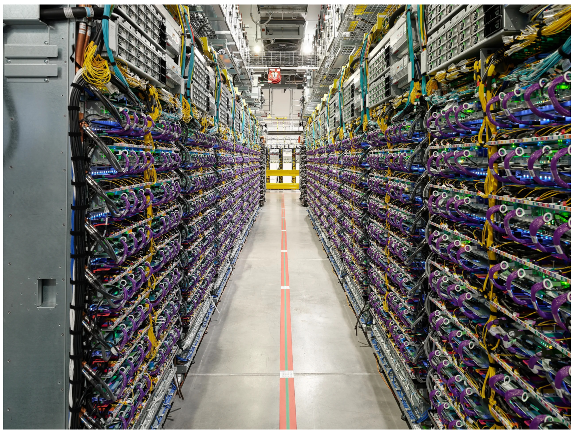
GFS: Main features

- 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

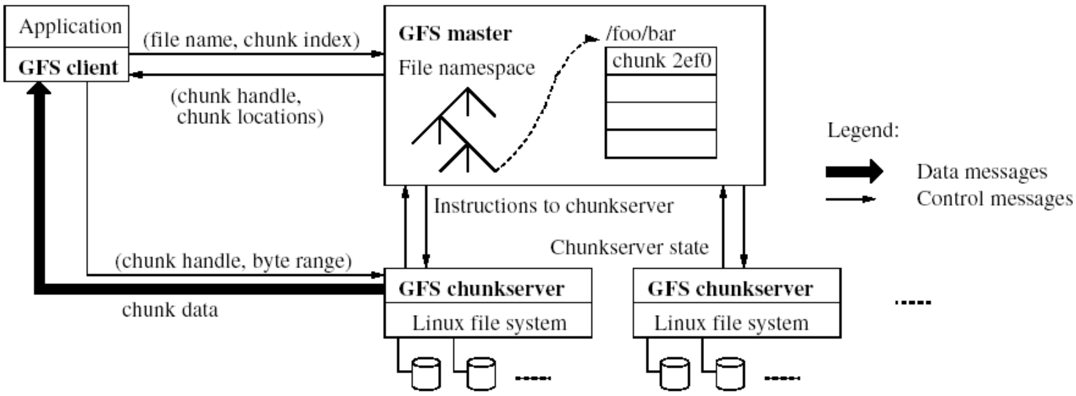
GFS: Operation environment





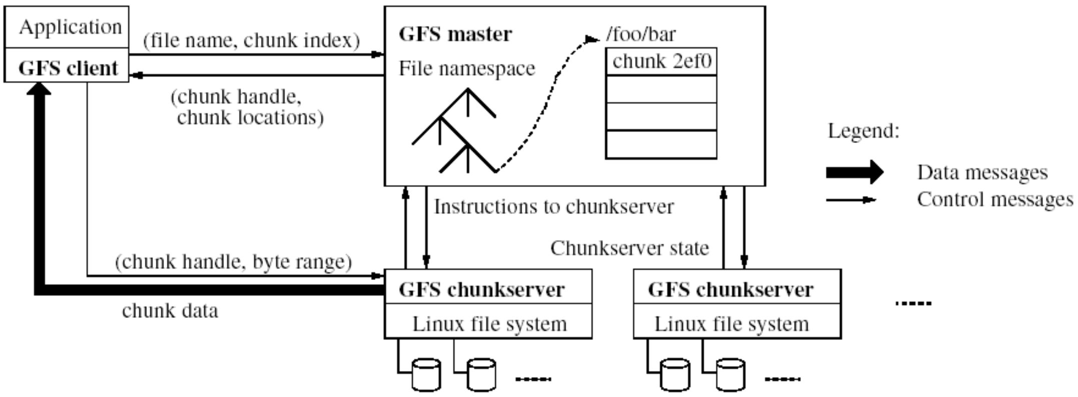


GFS: Architecture



- 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

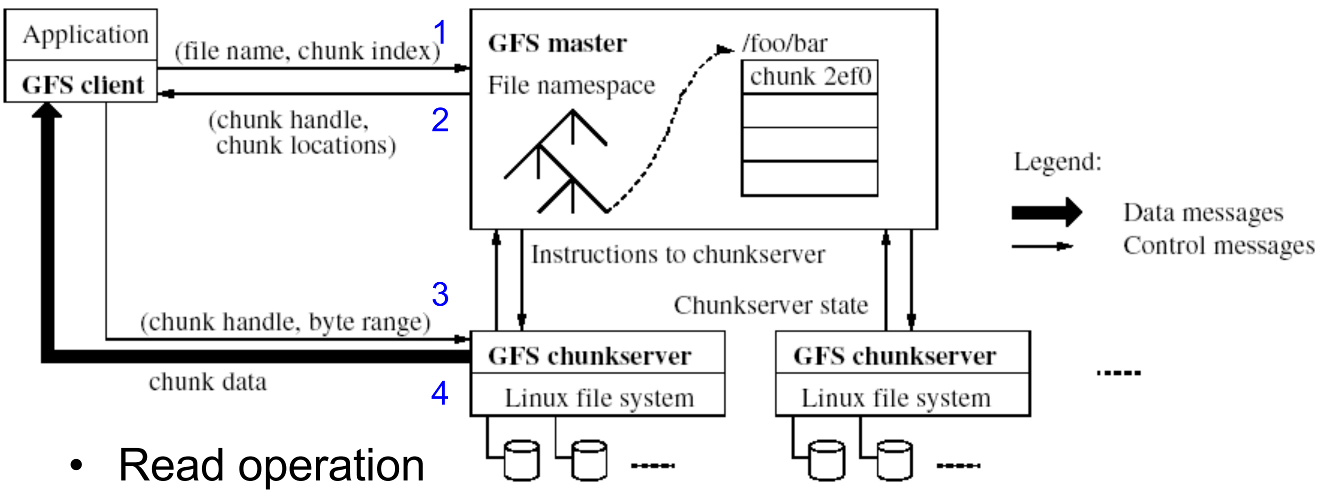
GFS: Master operations

- 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

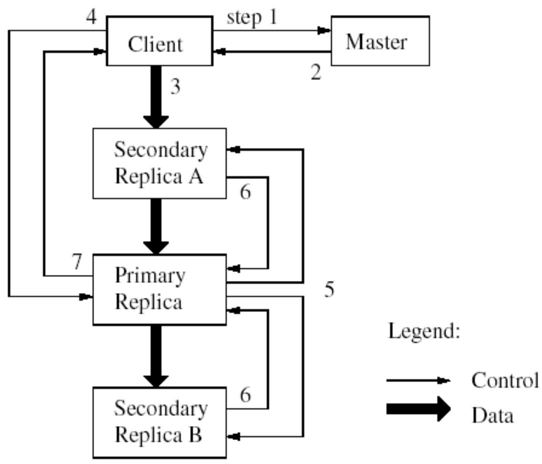
GFS: Read operation



- 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
  - Performed at all chunk's replicas in same order
- Based on *lease* mechanism
  - Goal: minimize management overhead at master
  - Master grants chunk lease to primary replica
  - Client sends command to primary (4)
  - Primary picks order for all mutations to chunk and secondaries follow order when applying them
  - Secondaries reply to primary, then primary replies to client (7)
  - Lease is 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 other replicas in a chained fashion so to fully utilize network bandwidth

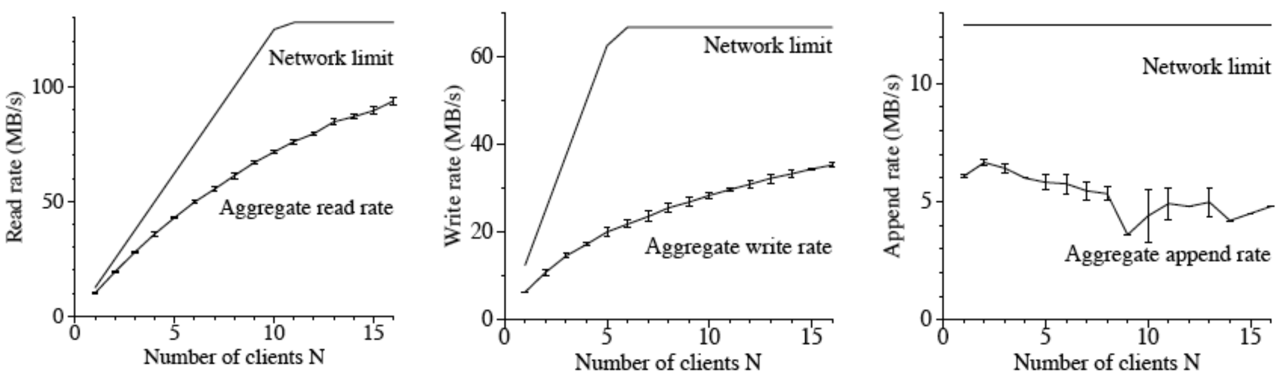
GFS: Atomic append

- Atomic append operation
- Client sends data without specifying offset
- GFS appends data *at-least-once* atomically (as one continuous sequence of bytes)
  - At offset chosen by GFS
  - Works with concurrent writers
  - At-least-once semantics: applications must handle possible duplicate data
- Append heavily used by Google use cases
  - Files often serve as multi-producer/single-consumer queues
  - Files store results merged from many clients (MapReduce)

GFS: Consistency model

- Changes to namespace (e.g., file creation, deletion) are atomic
  - Managed by GFS master with locking
- Mutation ordering is chosen by the primary replica, but failures of chunk servers can cause inconsistency
- GFS provides eventual consistency model
  - Simple and efficient to implement

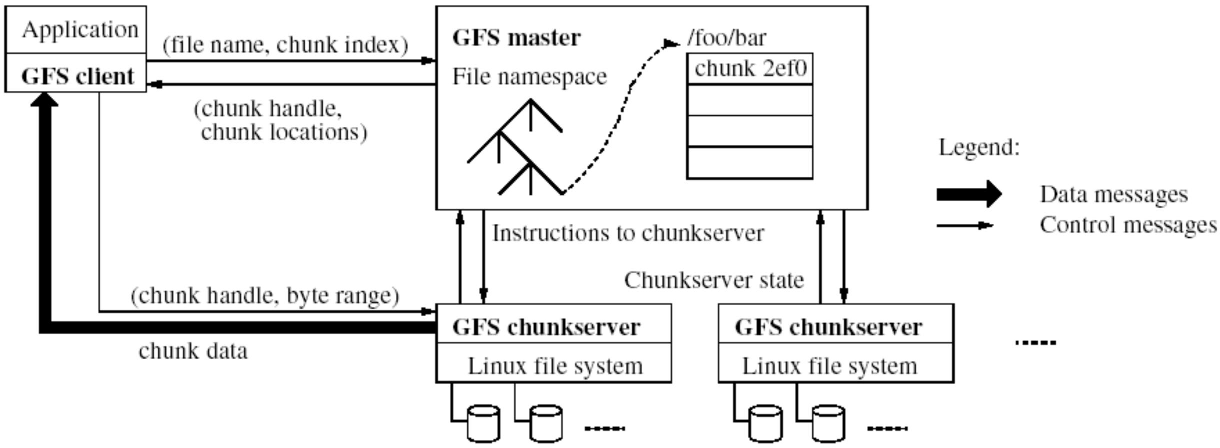
GFS performance (in 2003)



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

- Read performance is satisfactory (80-100 MB/s)
- Lower write performance (30 MB/s) and relatively inefficient (5 MB/s) in appending data

GFS problems



Main architectural problem is…

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 primary master is down
  - Overcome scalability bottleneck: by reducing interaction between master and clients
    - Master stores only metadata
    - Clients can cache metadata
    - Chunk size is large
    - Chunk lease: master delegates authority to primary replica
- Overall, simple solutions

GFS summary

- Successes
  - Supported Google Search and other services
  - High throughput by decoupling control and data planes
  - High availability on commodity hardware
  - Handles massive datasets and concurrent appends
- Limitations (besides single master)
  - Metadata stored entirely in master memory
    - “Limited” scalability: ~50M files, 10PB
  - Semantics (e.g., append behavior) not transparent to apps
  - Slow failover
    - Clients’ delay when recovering from failed chunk servers
  - Not good for all services: optimized for throughput, no guarantee on latency

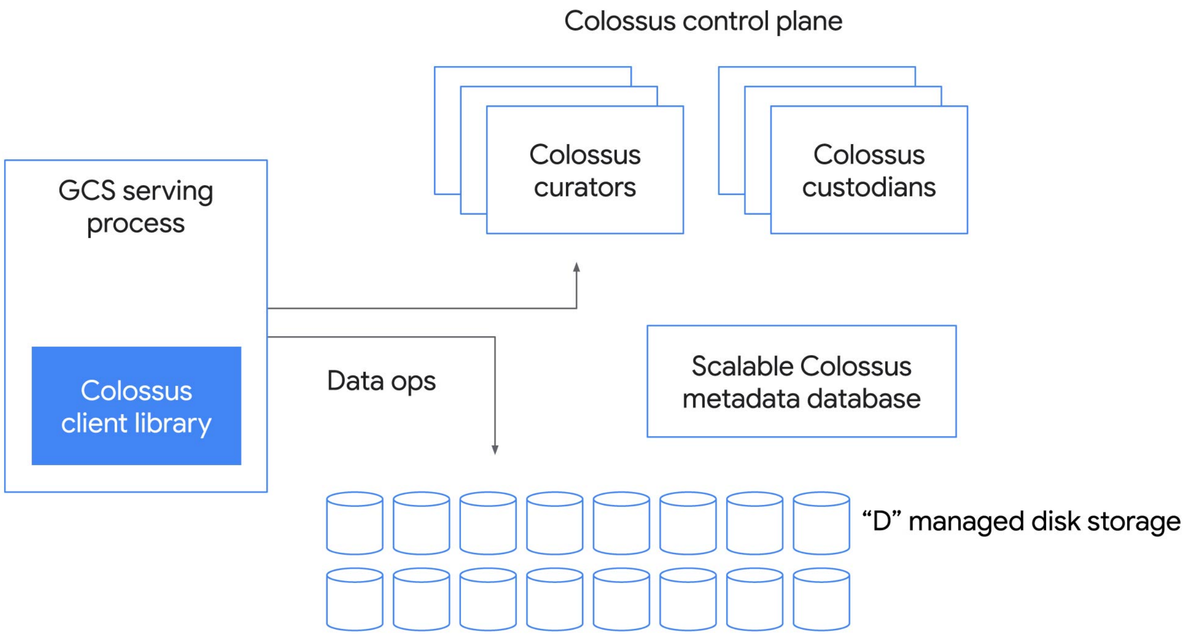
Google Colossus

- Successor to GFS (since 2010)
- Designed for a wide range of apps: YouTube, Maps, Photos, search ads
- At Google scale: EB of storage, 10K servers
- Architecture updates from GFS
  - Distributed masters, chunk servers replaced by D servers
  - Distributed metadata layer, built on top of Bigtable
  - Error-correcting codes (e.g., Reed-Solomon) to reduce storage overhead
  - Client-driven encoding and replication
  - Hardware diversity: mix of SSD and hard disks
- Google Cloud services built on top
  - Cloud Storage (object store), Cloud Firestore (NoSQL data store)

https://cloud.google.com/blog/products/storage-data-transfer/a-peek-behind-colossus-googles-file-system

https://www.youtube.com/watch?v=q4WC_6SzBz4

Colossus: key components



Hadoop Distributed File System (HDFS)

- Open-source user-level DFS https://hadoop.apache.org
- GFS clone: shares many features with GFS (including pros and cons)
  – Master/worker architecture
  – Very large files, data parallelism
  – Commodity hardware
  – Fault-tolerant and throughput-oriented
- Integrated with processing frameworks and ingestion tools, e.g., Hadoop MapReduce, Spark, Flink, NiFi

https://www.databricks.com/glossary/hadoop-distributed-file-system-hdfs

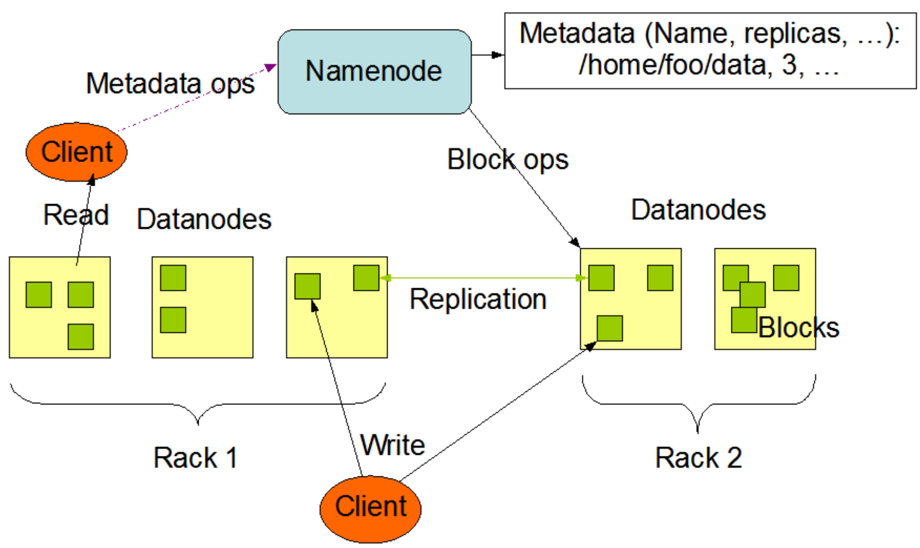
Shafer et al., The Hadoop Distributed Filesystem: Balancing Portability and Performance, *ISPASS 2010*
https://www.jeffshafer.com/publications/papers/shafer_ispass10.pdf

HDFS: Design principles

- Designed to handle large datasets
  - 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
  - Designed to work without noticeable interruption even when failures occur
- Portability across heterogeneous hardware and software platforms

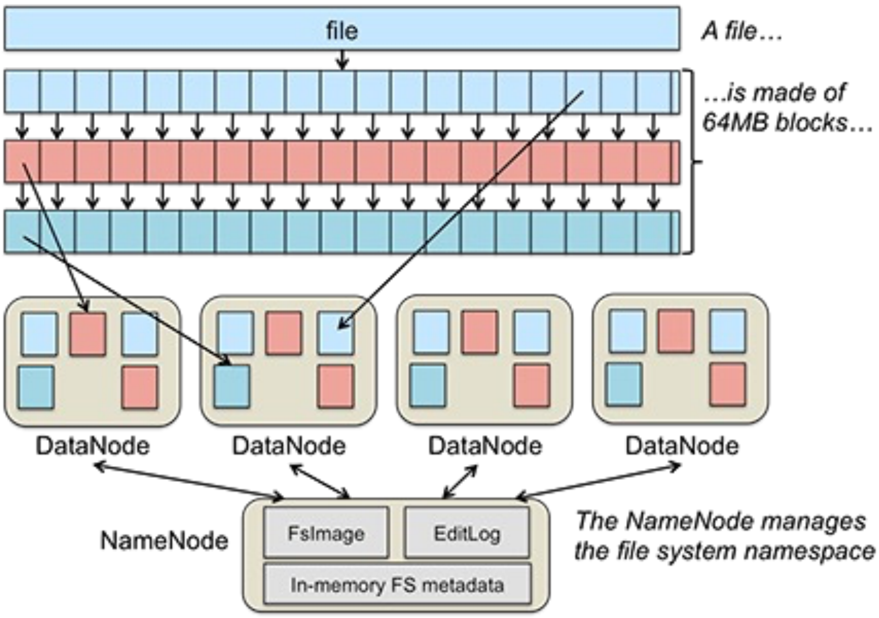
HDFS: Architecture

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



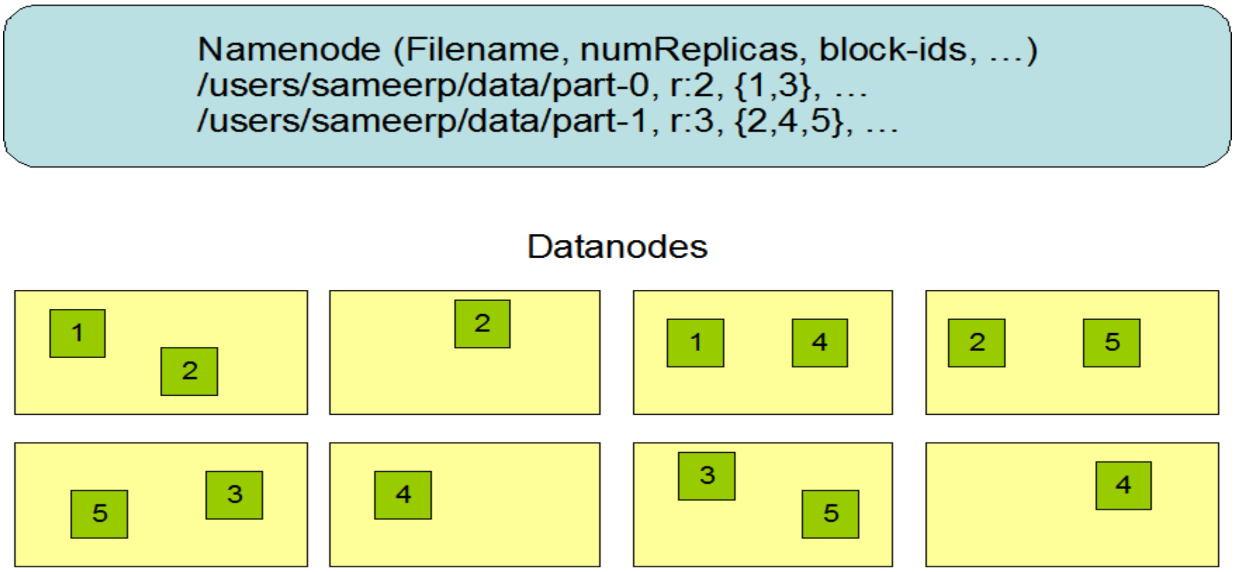
HDFS: File management

- Data parallelism: file split into blocks (GFS chunks) stored on DataNodes
- Large size blocks (default 128 MB)

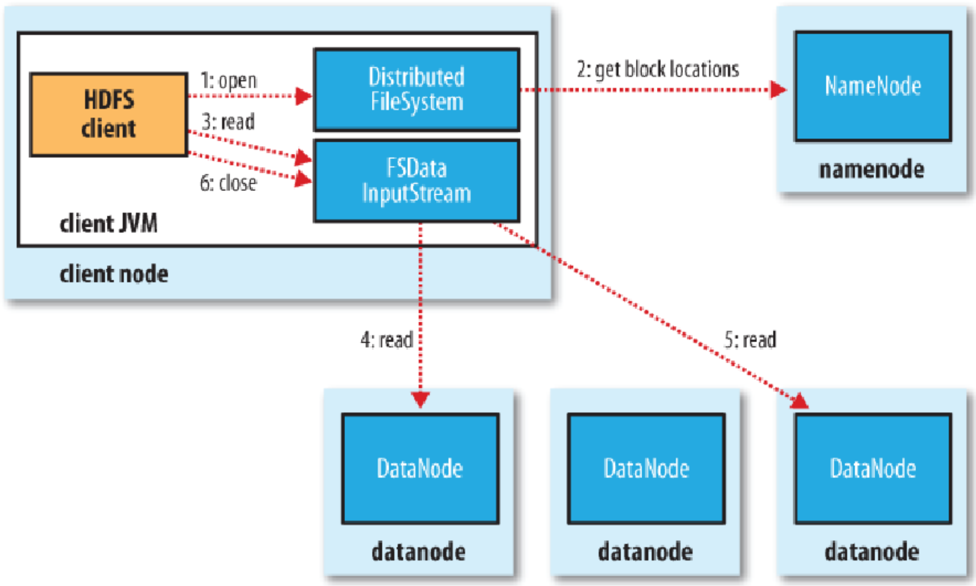


HDFS: Block replication

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



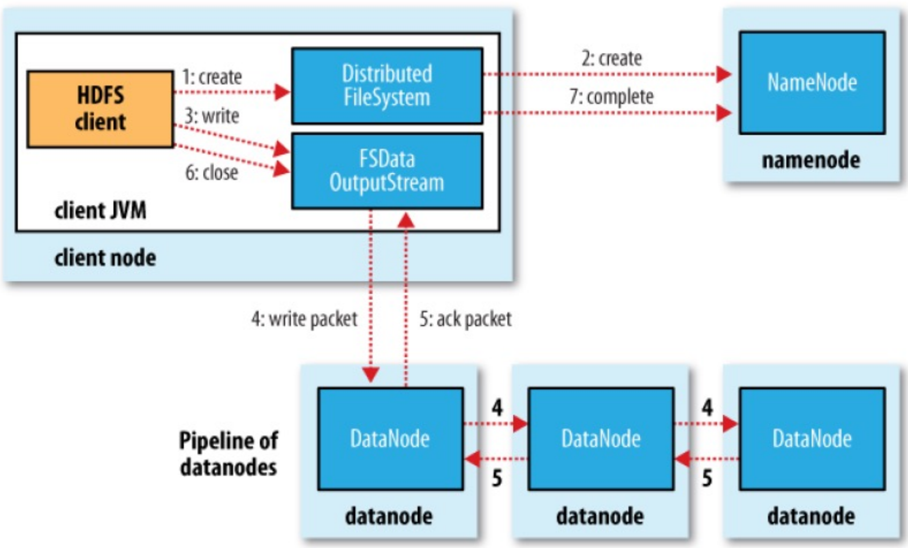
HDFS: File read



Source: "Hadoop: The definitive guide"

- NameNode returns a list of DataNodes

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 the block, then forwards it to the second, and so on

HDFS: Enhancements in 3.x

- Improved master availability
  - Multiple NameNodes with faster failover (1 active and >=1 standby)

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

- Erasure coding for storage efficiency
  - Alternative to replication for fault tolerance
  - ✓ Provides same fault tolerance with lower storage overhead: from 200% (3x replication) to 50%
  - ✗ Increases network traffic during writes and reconstruction
  - ✗ Adds CPU overhead for encoding/decoding
  - 2 codes: XOR-based and Reed-Solomon
  - Can be enabled per directory: flexibility

  https://docs.cloudera.com/runtime/7.3.1/scaling-namespaces/topics/hdfs-ec-overview.html

HDFS: security

- Early HDFS lacked robust security mechanisms
- Modern HDFS supports authentication (Kerberos, LDAP), authorization (ACLs), and encryption (data at rest and in transit)
- Integration with Apache Ranger, which provides security across Hadoop ecosystem https://ranger.apache.org
  - Centralized security administration
  - Fine-grained authorization methods (role-based AC, attribute-based AC)
  - Centralize auditing of user access and administrative actions
- Data governance can be enhanced by third-party tools, e.g., Cloudera Navigator

Distributed Object Stores

- Designed to handle large volumes of unstructured data by storing objects rather than files
- Data is stored as a whole object with unique identifier, metadata, and content
  - Object aka blob (binary large object), opaque to system
- Flat structure (buckets), no hierarchical directory structure
- Mostly read-intensive workloads
- Challenges
  - Variety of media types (photos, videos, documents, …)
  - Variety of sizes: from KBs (e.g., profile pictures) to GBs (e.g., videos) → small file efficiency
  - Volume: ever-growing number of blobs to be stored and served → cold vs. hot storage (e.g., Amazon Glacier)
  - Data consistency: cross-region distribution

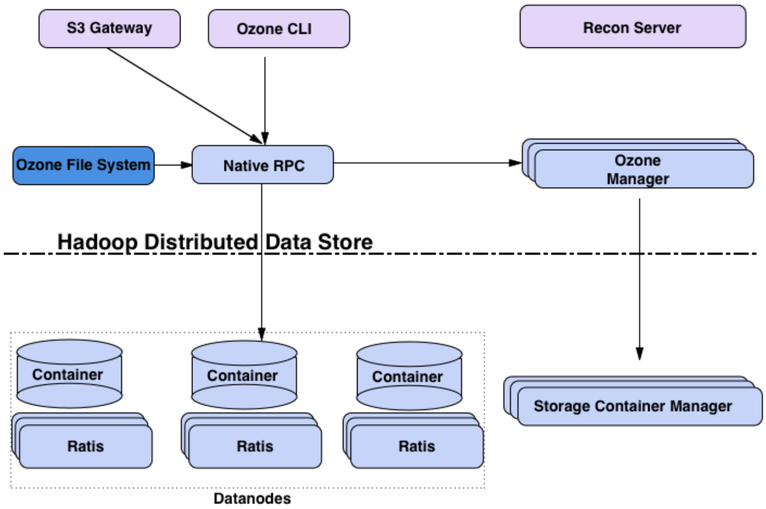
Object store: Apache Ozone

Apache Ozone™

- Highly scalable, distributed object store designed for Big Data, AI/ML, and cloud-native workloads
  https://ozone.apache.org
- Built on Hadoop Distributed Data Store, a highly available, replicated block storage layer
- Separation of metadata management layer and data storage layer
  - Scalability to billions of objects and EB of data
- Strongly consistent distributed storage thanks to Raft protocol
  - Apache Ratis https://ratis.apache.org: high-performance Java library for Raft protocol
- Secure: access control and transparent data encryption

Ozone: architecture

- Ozone Manager: handles the namespace
- Storage Container Manager: physical and data layer
  – Manages the physical “containers” (groups of blocks) and handles replication and health of data nodes
- Datanodes: store the actual data blocks
- Recon: management and monitoring interface



Object store: Ambry

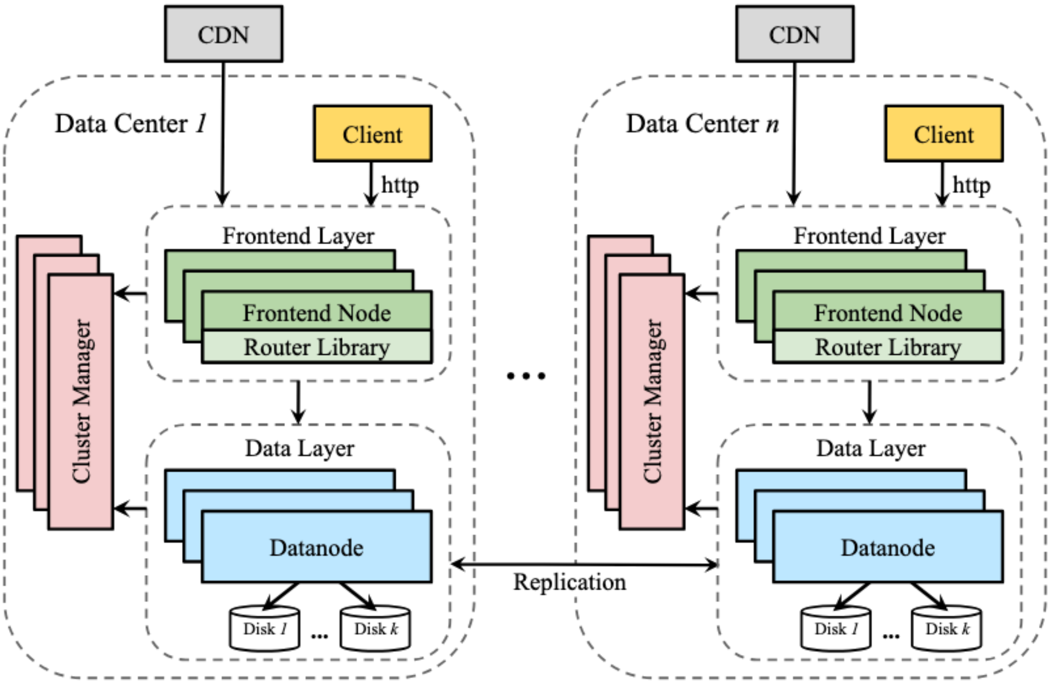
- LinkedIn’s object store for media serving
- 800M put and get ops/day (120 TB), 10K reqs/sec. (in 2016)
- Immutable objects (designed for media objects)
- Focus on low latency (media serving)
- Optimized for both small and large objects
- Geo-distributed: high durability and availability
- Decentralized, multi-master architecture
- Several techniques
  – Logical blob grouping, asynchronous replication, rebalancing mechanisms, zero-cost failure detection, and OS caching

Noghabi et al., Ambry: LinkedIn’s Scalable Geo-Distributed Object Store, *SIGMOD ’16*

Code: https://github.com/linkedin/ambry

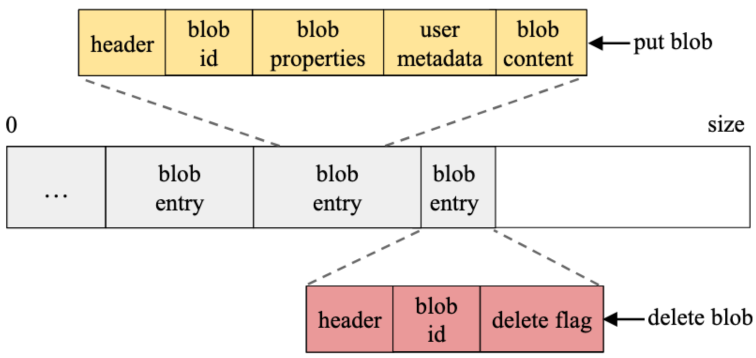
Ambry: architecture

- Decentralized multi-tenant system across geographically distributed data centers



Ambry: partitions and blobs

- Blobs are grouped in virtual units called *partitions*
  - Partition: logical grouping of a number of blobs, implemented as a large, fixed-size file, replicated on multiple Datanodes
- Physical placement of partitions on machines
- Decoupling of logical and physical placement
  - Transparent data movement (necessary for rebalancing)
  - No rehashing of data during cluster expansion



Object store: MinIO

- S3-compatible private cloud storage https://www.min.io
- Architecture: shared-nothing design
  – Unlike HDFS or Ozone, MinIO has no metadata database and no master node
  – Decentralized: every node in a MinIO cluster is identical; any node can handle any request
  – Deterministic hashing
  – Performance: optimized for NVMe drives and 100Gb networks, capable of read/write speeds exceeding 10 TB/s in large deployments
- Erasure coding based on Reed-Solomon

Storing in memory: Alluxio

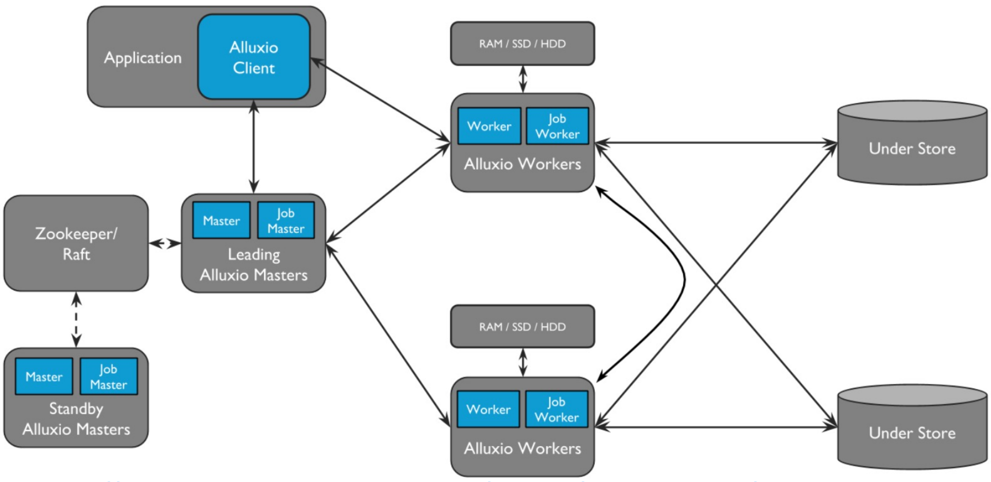
- Distributed **in-memory** storage system
  https://www.alluxio.io/
- Provides a data access layer between compute and storage
  – Decouples persistent storage (e.g., HDFS, AWS S3) and analytics/AI processing frameworks (e.g., Spark, Flink, TensorFlow)
- Goal: storage unification and data abstraction
  – Brings data from storage closer to applications for faster access
  – 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 in the cloud
- Features
  - High read/write throughput, at memory speed
  - Commonly used as distributed shared caching service
  - Addresses RAM volatility without replication using lineage-based re-computation to achieve fault tolerance
    - Only one copy of data in memory (fast)
    - Upon failure, data is re-computed from its lineage: tracks executed operations to recover lost outputs
    - Borrowed from Spark

Alluxio: Architecture

- Master-worker architecture
- Replicated masters, multiple workers
  - Passive standby approach (one active and one or more standby) to ensure master fault tolerance
  - Consensus: Zookeeper, Raft



https://documentation.alluxio.io/os-en/overview-1/architecture

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 underlying storage systems (e.g., HDFS, S3), not managed by Alluxio
  - Periodically send heartbeat to master

Alluxio: New architecture shift

- Since v. 3: shift to decentralized, master-less architecture based on consistent hashing
  - Goal: eliminates master SPOF and bottleneck, spreading metadata management across all workers
  - DORA (Decentralized Object Repository Architecture): uses consistent hashing to map file paths to a set of distributed workers
- Lineage-based re-computation deprecated
  - Replaced by simpler UFS fallback**:** if worker is unresponsive or data is missing from cache, the client automatically falls back to the Under File System (UFS) like S3 or HDFS
  - If a worker fails, the hash ring rebalances, and a new worker pulls the data from UFS
  - Benefit: the application remains functional even if the Alluxio cache layer is partially or fully unavailable

https://documentation.alluxio.io/ee-ai-en/core-concepts

Data storage so far: Summing up

- (Legacy) Distributed file systems: GFS and HDFS
  - Architecture: master/worker (single master must track every file in memory)
  - Decouple metadata from data, also control and data flows
  - Designed for batch processing of massive files (high throughput, high latency)
  - Constraint: metadata operations scale poorly
- (Next-gen) Distributed object stores: Ozone, Ambry, MinIO
  - Multi-master / cloud native
  - Decouple data control and data storage
  - Scalability: designed to handle billions of objects
- In-memory data orchestration: Alluxio
  - In-memory storage system
  - Shift from master/worker to decentralized architecture

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