Storage Infrastructures for Large Data Volumes

Week 3

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DATA7201 Data Analytics at Scale

Week	Date	Lecture	Prac	Assessment
1	21-Feb	Introduction to DATA7201 - Data Analytics at Scale	-	
2	28-Feb	Supporting Infrastructures and Use Cases	-	
3	6-Mar	Storage Infrastructures for Large Data Volumes	Intro to Cluster and HDFS	
4	13-Mar	Analytics Queries for Large Data Volumes	PIG(1)	
5	20-Mar	Distributed Data Processing	PIG (2)	
6	27-Mar	Processing Large Data Streams	PySpark (1)	Quiz 1 Due (5)
7	10-Apr	Processing Large Graph Data (1) + use cases	PySpark (2)	
8	17-Apr	Processing Large Graph Data (2) + use cases	Project support	
9	24-Apr	Recommender Systems	Project support	Quiz 2 Due (5)
10	1-May	Opinion Mining + use cases	Project support	
11	8-May	Health Data Analytics (guest speaker)	Project support	
12	15-May	Large Language Models?	Project support	Report Due (45)
13	22-May	Course Revision	-	Quiz 3 Due (5)

Last Week

- Example applications and data products that can be developed using Big Data
- Infrastructures required to handle Big Data and enable Data Analytics
- Cloud computing
- Scalable architectures (e.g., MapReduce, Hadoop, Pig, HBase)
 - Volume
- Open source vs. commercial software/services

Lecture Outline

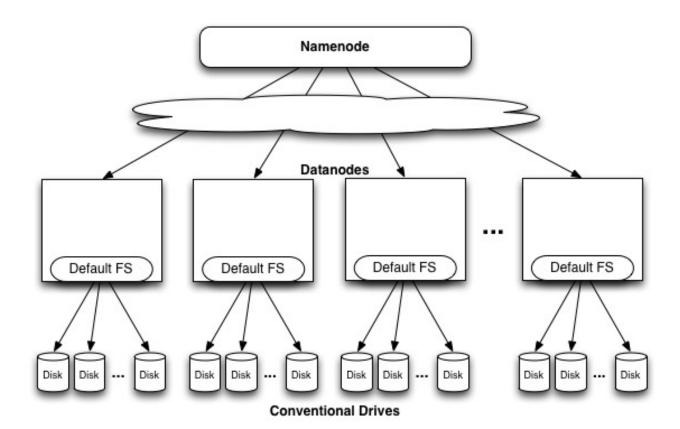
- Distributed Infrastructures
 - CAP Theorem
- Google File System
- HDFS
- Spark RDDs
- Column-stores / noSQL

Distributed Systems

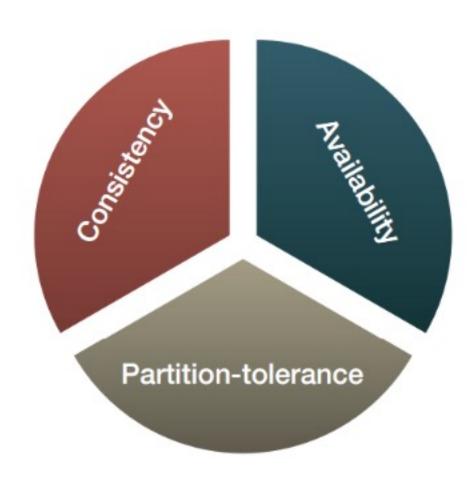
• [Wikipedia] A distributed system is a model in which components located on **networked computers** communicate and **coordinate their actions** by passing **messages**. The components interact with each other in order to achieve a **common goal**.

Distributed Systems

- Large Data Volumes
- Store them over a distributed system



CAP properties of distributed systems

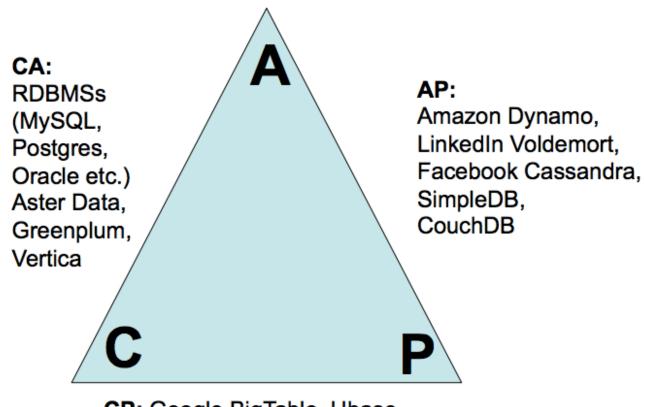


CAP Theorem

- Consistency means that each client always has the same view of the data.
- Availability means that all clients can always read and write.
- **Partition tolerance** means that the system works well across physical network partitions.

Only 2 out of 3 can be implemented

Some recent systems



CP: Google BigTable, Hbase, Berkeley DB, MemcachDB, MongoDB

Map/Reduce and Hadoop

"MapReduce is a programming model for expressing distributed computations on massive amounts of data and an execution framework for large-scale data processing on clusters of commodity servers."

-Jimmy Lin

GFS

Hadoop is an open-source implementation of the MapReduce framework.

Distributed File Systems

Google File System

- Research papers:
 - The Google file system by Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung (2003)
 - The Hadoop distributed file system by Konstantin Shvachko, Hairong Kuang, Sanjay Radia, and Robert Chansler (2010)

What is a file system?

- File systems determine how data is stored and retrieved
- **Distributed file systems** manage the storage across a network of machines
 - GFS/HDFS are distributed file systems

GFS Assumptions

- Hardware failures are common (commodity hardware)
- Files are large (GB/TB) and their number is limited (millions, not billions)
- Two main types of reads: large streaming reads and small random reads
- Workloads with sequential writes that append data to files
- Once written, files are seldom modified (!=append) again
 - Random modification in files possible, but not efficient in GFS

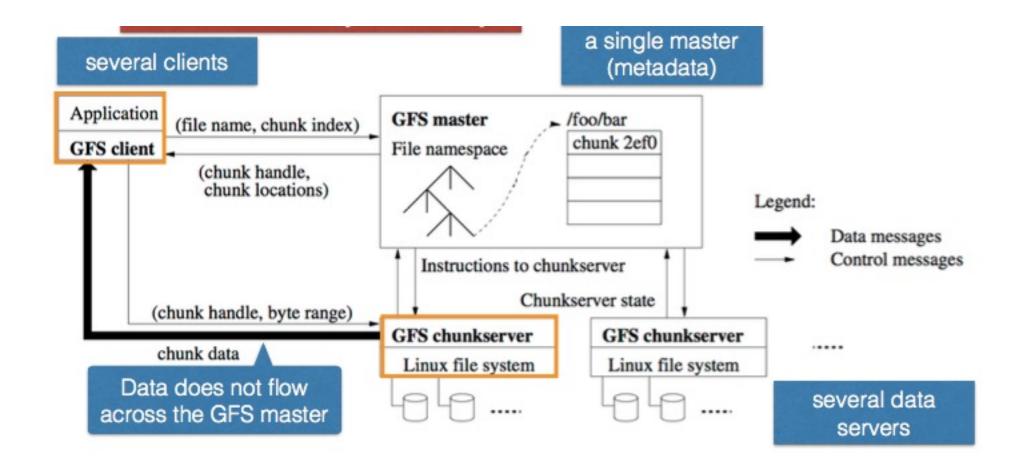
GFS is not good for

- Low latency data access (in the milliseconds range)
- Many small files
- Constantly changing data

Files in GFS

- A single file can contain many objects
- Files are divided into fixed size chunks (64MB)
 - In Hadoop 128MB
- chunkservers store chunks on local disk as "normal" files
- Files are replicated (by default 3 times) across all chunk servers
- master maintains all file system metadata
- To read/write data: client communicates with master (metadata)

GFS Architecture



Single master architecture

- Single master simplifies the design tremendously
 - Chunk placement and replication with global knowledge
- Single master in a large cluster can become a **bottleneck**

Hadoop Distributed File System (HDFS)

- Inspired by Google File System
- Scalable, distributed, portable file system written in Java for Hadoop framework
- Primary distributed storage used by Hadoop applications
- HDFS can be part of a Hadoop cluster or can be a stand-alone general purpose distributed file system
- Reliability and fault tolerance ensured by replicating data across multiple hosts
- Zookeeper for the distributed coordination

GFS vs HDFS

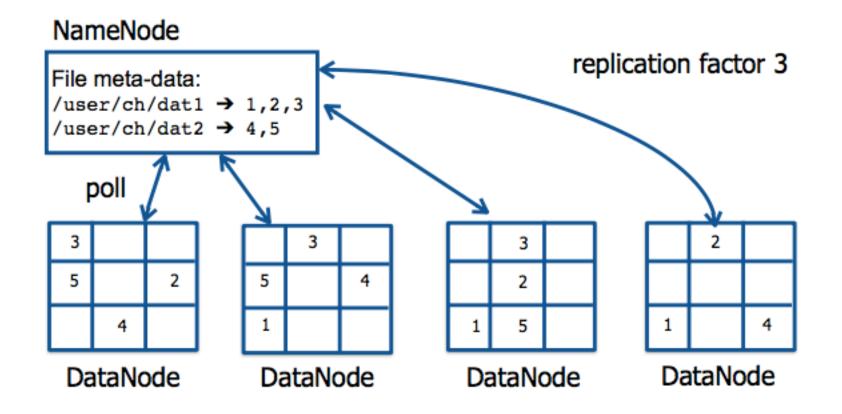
GFS	HDFS
Master	NameNode
chunkserver	DataNode
operation log	journal, edit log
chunk	block
random file writes possible	only append is possible
multiple writer, multiple reader model	single writer, multiple reader model
chunk: 64KB data and 32bit checksum pieces	per HDFS block, two files created on a DataNode: data file & metadata file (checksums, timestamp)
default block size: 64MB	default block size: 128MB

HDFS

NameNode

- Master of HDFS, directs the slave DataNode daemons to perform low-level I/O tasks
- Keeps track of file splitting into blocks, replication, block location, etc.
- Secondary NameNode: takes snapshots of the NameNode
- DataNode: each slave machine hosts a DataNode daemon

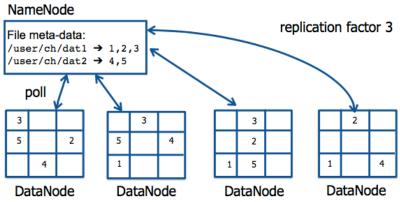
NameNodes and DataNodes



HDFS Replication

- Files divided in blocks and replicated
 - Block size and replication factors are configurable
- NameNode makes all replication decisions
 - It receives Hearbeats and Blockreport from DataNodes

- Replica placement
 - E.g., on unique racks (good for reliability, bad for latency)
 - Satisfy a read request from a replica that is closest to the reader



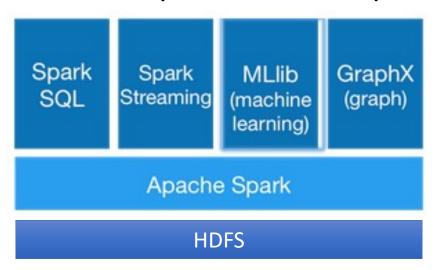
Hadoop in practice: Yahoo! (2010)

- 40 nodes/rack sharing one IP switch
- 16GB RAM per cluster node, 1-gigabit Ethernet
- 70% of disk space allocated to HDFS
- NameNode: up to 64GB RAM
- Total storage: 9.8PB -> 3.3PB net storage (replication: 3)
- 60 million files, 63 million blocks
- Cluster with 3500 nodes
 - 1-2 nodes lost per day
 - Time for cluster to re-replicate lost blocks: 2 minutes

Apache Spark Data Structures

Apache Spark

- https://spark.apache.org/ by databricks.com
- Started by students at UC Berkeley
- General system for large-scale data processing
- Faster (in-memory), interactive
- Version 3.3 released in 2022 (v3 since 2020)
 - SparkRBut also:sparklyretc.



- pyspark

Spark RDDs (Ch. 3, Spark book)

- Based on HDFS
- Resilient distributed dataset (RDD)
 - Distributed collection of elements
 - Immutable
 - Lazy evaluation
- Spark distributes data across the cluster
 - Partitions
- Operations
 - Transformations
 - Actions

In Python: https://spark.apache.org/docs/latest/api/python/

Transformations

- Generates a new RDD partition
- Lazy evaluation (computed only when needed)
- Filter: select certain rows in a log file
- Map, Filter, flatMap, Sample, Union, Intersection, Distinct, groupByKey, reduceByKey, sortByKey, Join, Cogroup, cartesian

Transformations

- Map(function): Return a new distributed dataset formed by passing each element of the source through a function
- FlatMap(function): each input item can be mapped to 0 or more output items (instead of one as for map)
- reduceByKey(function): When called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function, which must be of type (V,V) => V.

Actions

- Return a final value
- Force the evaluation of transformation operations

 Reduce, Collect, Count, First, Take, takeSample, saveAsTextFile, foreach

• Collect(): Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.

NoSQL

- Non-relational Databases: noSql
 - [Wikipedia] NoSQL is a term used to designate database management systems that differ from classic relational database management systems (RDBMS) in some way. These data stores may not require fixed table schemas, usually avoid join operations, do not attempt to provide ACID properties and typically scale horizontally.
- Distributed: scale-out

ACID Properties

- Atomicity
 - A transaction is completely executed or not at all
- Consistency
 - A DB is in a consistent state before and after a transaction is executed
- Isolation
 - A transaction execution is not affected by other concurrent transactions
- Durability
 - Changes made during a transaction are permanent

NoSQL

- Four approaches:
 - Key-value (BigTable (2004), Dynomite (2008), Voldemort (2009))
 - Column-oriented (Hbase (2007), Cassandra (2008))
 - Graph-based (Neo4j (2007), ArangoDB(2011))
 - Document-oriented (CouchDB(2005), MongoDB (2009))

Column Stores

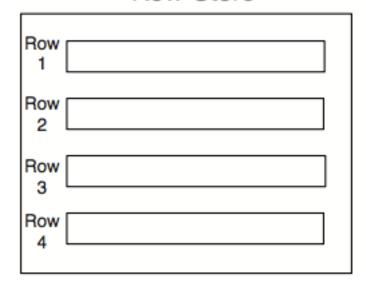
• Row store:

- Rows are stored consecutively
- Optimal for row-wise access (e.g. SELECT *)

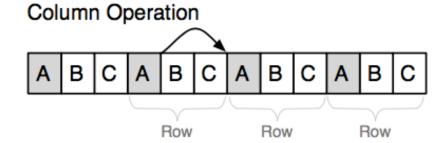
• Column store:

- Columns are stored consecutively
- Optimal for attribute focused access (e.g. SUM, GROUP BY)

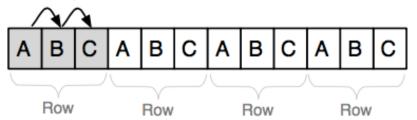
Row-Store



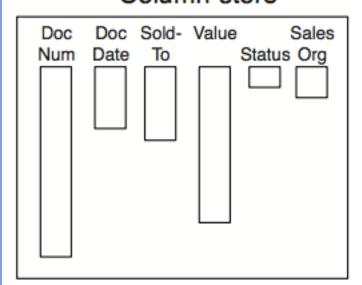
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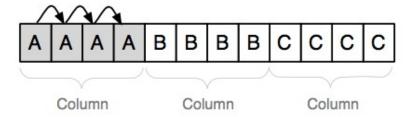
Row Operation



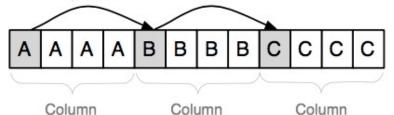
Column-store



Column Operation



Row Operation



Apache HBase

- "Apache HBase is the Hadoop database, a distributed, scalable, big data store."
- On top of HDFS
- Billions of rows * millions of columns
- Non-relational DB / NoSQL
- Column store: columns instead of tables
- Key-value cells

Apache HBase

HBase is not ACID compliant

"HBase is a **distributed column-oriented** database built on top of HDFS. HBase is the Hadoop application to use when you require **real-time** read/write **random** access to very **large** datasets." (Tom White)

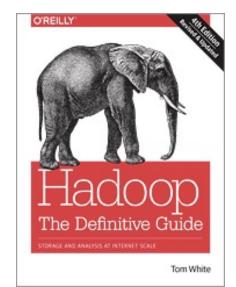
"HBase tables are like those in an RDBMS, only cells are **versioned**, rows are **sorted**, and columns can be **added on the fly...**" (Tom White)

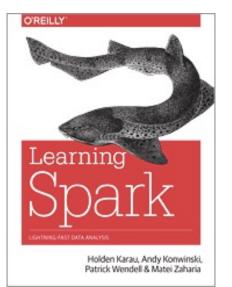
Summary

- Distributed Infrastructures
 - CAP Theorem
- Google File System
- HDFS
- Spark RDDs
- Column-stores / noSQL

References

- Tom White. *Hadoop: The Definitive Guide.* O'Reilly.
- Zaharia et al. Learning Spark. O'Reilly.
- The Google file system by Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung (2003)
- Bigtable: A Distributed Storage System for Structured Data. Fay Chang et. al. OSDI 2006





DATA7201 Cluster

- Amazon EMR set up operates the Hadoop cluster
- Student notebooks on UQcloud zones (JupyterLab, new this year)
- A VPN link joins the two systems together
- m5.4xlarge EC2 instances (each have 64 GB RAM and 16 CPU cores)
- Resizing the cluster during the semester

Time span	Instances	Compute memory [5]	Available disk
Weeks 1-6	3	128 GB	600 GB
Week 7	6	320 GB	900 GB
Week 8	9	512 GB	1.75 TB
Week 9	25	1.5 TB	4.8 TB
Weeks 10-12	49	3 TB	9.3 TB ^[3]
Weeks 12-14	9	512 GB	1.75 TB
(Base + Avg. Spot)	3 + 9.42	128 + 667 GB	600 GB + 1.77 TB

• ~\$30K AUD