PROFINIT

(Big) Data in Time

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Agenda

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1. Motivation
2. A Little Bit of History
3. A Little Bit of Theory
4. Conclusion

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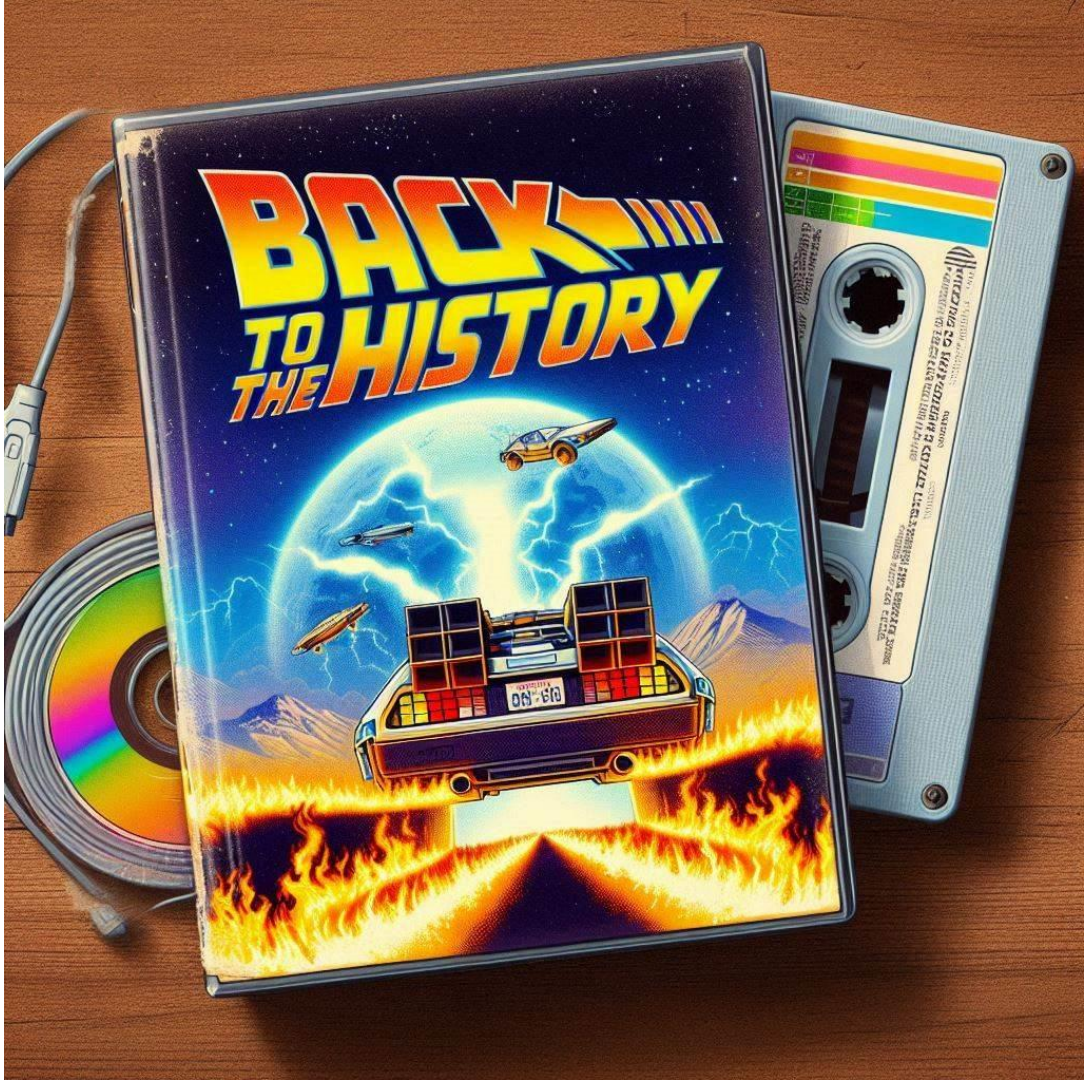

Motivation

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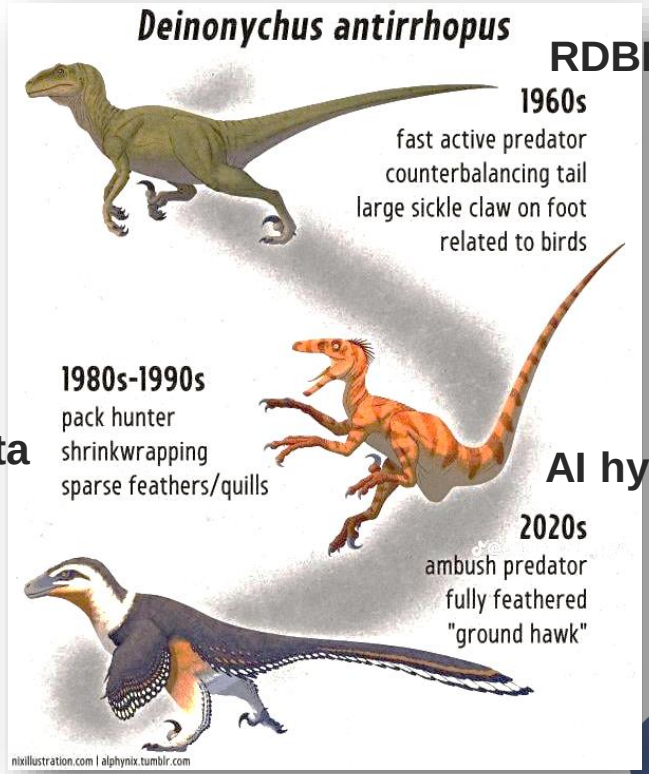
- Brief history and brief introduction to big data concepts will show
  - Money are important
  - Every technology has its rise, peak and decline
  - Key concept remains
  - Take the best and fix issues

  - Let’s go through data dinosaur land.



RDBMS

BigData

AI hype

A Little Bit of History

1950s–1980s: Foundations of Data Processing

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- **1950s–1960s:** Early developments in database management systems (DBMS) like hierarchical databases and IBM's Information Management System (IMS). File systems etc.
- **1970:** Edgar F. Codd invented the **relational database model**, laying the foundation for modern databases. He was working in IBM. Codd's rules applied. SQL development.
- **1980s:** Parallel database systems emerge, offering methods for scaling and distributing data workloads across multiple machines.
- **1989:** The term "**Big Data**" was first used in relation to the challenge of managing and processing massive datasets, especially in scientific computing.

1990s: WWW and Search Engines - this is where it really started

- **1990s:** The explosion of the web leads to a growing need for handling unstructured data at a larger scale. NoSQL databases appeared.
- **1994:** Companies like Yahoo! and Altavista create search engines, bringing forth the need to process massive amounts of data.
  - Altavista 1998 ~13 millions queries/day, 2000 ~80millions queries each day
- **1997:** Michael Cox and David Ellsworth publish a paper *Application-controlled demand paging for out-of-core visualization (NASA, Intel, Nvidia Research)*, using the term "Big Data" to describe the challenges of visualizing **large datasets**.

1 Introduction

Visualization provides an interesting challenge for computer systems: data sets are generally quite large, taxing the capacities of main memory, local disk, and even remote disk. We call this the problem of *big data*. When data sets do not fit in main memory (*in core*), or when they do not fit even on local disk, the most common solution is to acquire more resources. This *write-a-check* algorithm

2000s: Pre-Hadoop Google Big data Era

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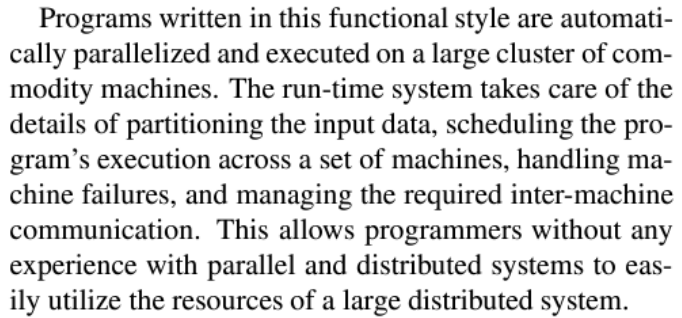
- **2003:** Google introduces the *Google File System (GFS)*, a distributed file system designed to support large-scale data processing.
- **2004:** Google's paper on *MapReduce: Simplified Data Processing on Large Clusters* is published. This paradigm **revolutionized** how distributed data is processed by simplifying parallel computing.
- **2004:** Google introduces *Bigtable paper*, a distributed storage system for managing structured data. Google is still using it.

Not Open Source

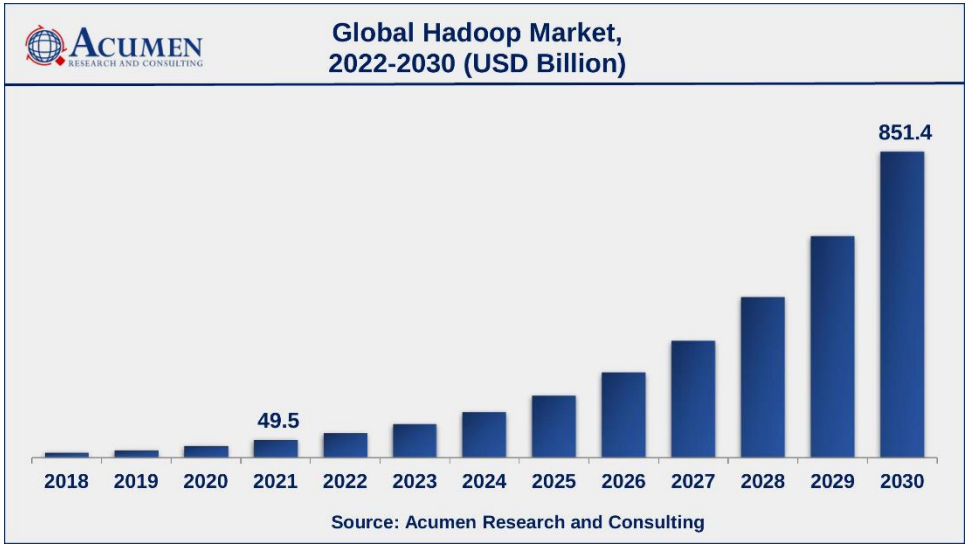
MapReduce paper



Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program's execution across a set of machines, handling machine failures, and managing the required inter-machine communication. This allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed system.

2006: Open-Source Hadoop Era

- **2006:** *Apache Hadoop* release as OS project.
  - First Hadoop = HDFS + MapReduce
- **2007:** Yahoo! adopts Hadoop for its web search engine, and Hadoop starts gaining significant momentum in industry.



Bright future ahead predicted…

2010s: BigData = Hadoop for a while...

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- **2010:** ***Apache Hive*** emerge, providing higher-level abstractions for querying large datasets in Hadoop “something like database”
- New SQL databases (noSQL with ACID) , cloud databases.
- **2011:** Commercial fight: Cloudera, Hortonworks, and MapR - making it accessible for enterprises.
- **2012:** Apache releases *Hadoop 2.0* with YARN (Yet Another Resource Negotiator), enabling Hadoop to support non-MapReduce applications and ushering in a more flexible resource management framework.
- **2012: Spark**, originally developed by UC Berkeley's AMPLab, is released as a **faster, in-memory alternative** to MapReduce for distributed data processing.

Late 2010s–now: Peak and decline of Hadoop, Bigdata still on

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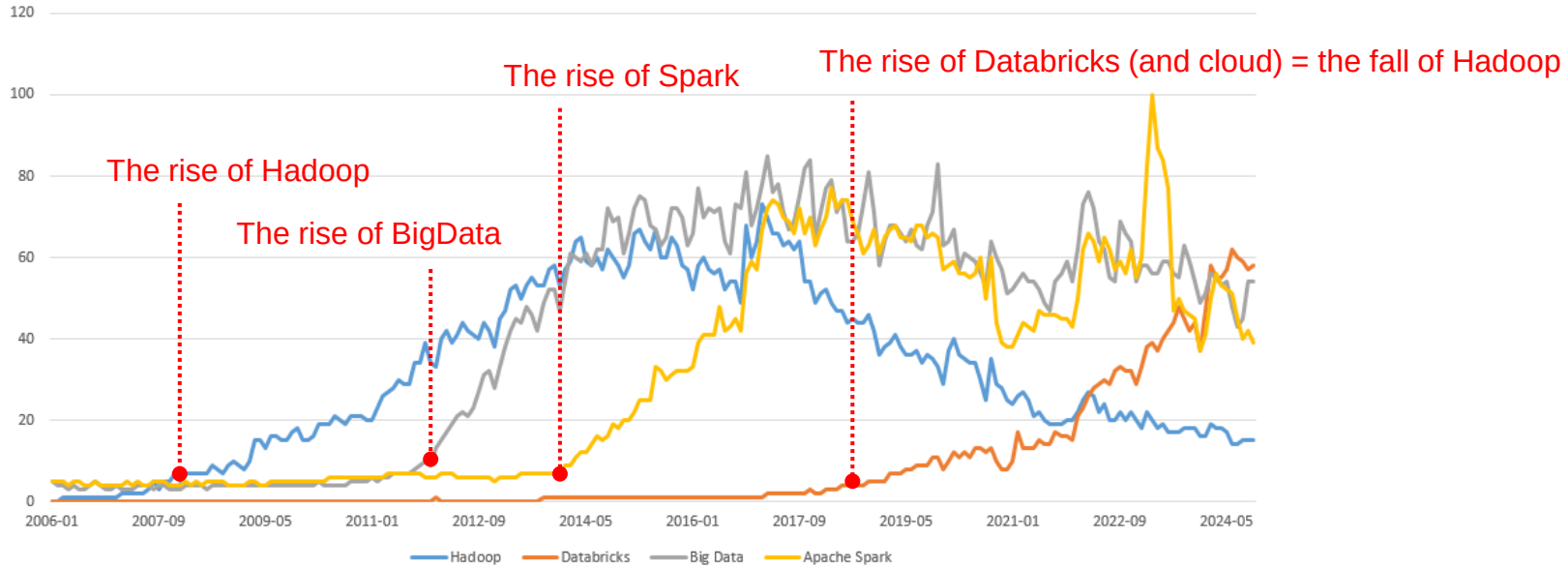
Google trends. Do you remember where it all started?



- **2018:** Hadoop's dominance starts to decline in favor of cloud-native platforms and frameworks such as Apache Kafka, Apache Flink, and more containerized, microservice-based architectures.

2020s: Rise of AI, Streaming, and Modern Data Platforms

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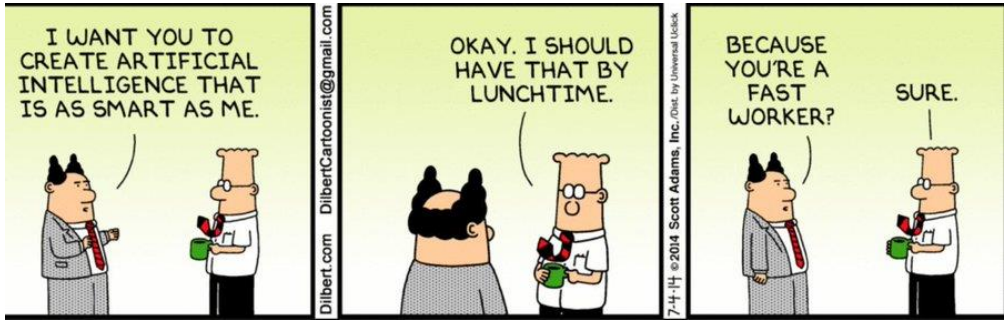
- **2020:** Modern data platforms like *Databricks*, *Snowflake*, and *Google BigQuery* gain traction due to their scalability, simplicity, and cloud-native architectures.
- **2023–2024:** Boom started with ChatGPT (OpenAI release 2022). The AI, generative AI and machine (earlier known as Data Science ☺). Everyone is integrating big data with AI/ML pipelines, moving towards more real-time analytics and AI-powered decision-making.



- **2024:** Hadoop is still alive but mostly for on-premise solution (e.g. Cloudera) = cloud-based data platforms won the war (new era is

A Little Bit of Theory

Motivation for Paralell (Data) Processing

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- Solve real life problems
  - **Complexicity** - Problems that are difficult to solve sequentially can often be broken down into smaller, parallel tasks
  - **Efficiency and Speed** - By breaking down large tasks into smaller, concurrent processes, parallel processing significantly reduces the time required to complete data-intensive tasks.
  - **Optimization**: Parallel processing makes better use of available resources. By distributing tasks across multiple processors, it maximizes the use of computational power and minimizes idle time
- Examples
  - SETI - Search for Extra-Terrestrial Intelligence
  - Financial Modeling
  - Recommendations (Netflix)
  - Big Data in enterprise

Key Principles

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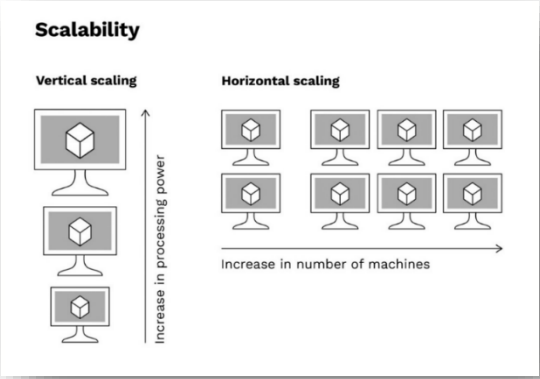
- **Decomposition**
  - Tasks being spread across multiple nodes to work in parallel
- **Load Balancing**
  - Distributing tasks evenly across compute (workers)
- **Synchronization & Communication**
  - Coordinating the execution of parallel tasks to ensure they work together correctly.
- **Scalability**
  - Ensuring that the parallel processing system can handle increasing amounts of data and processing power without significant performance degradation



Typical Architecture

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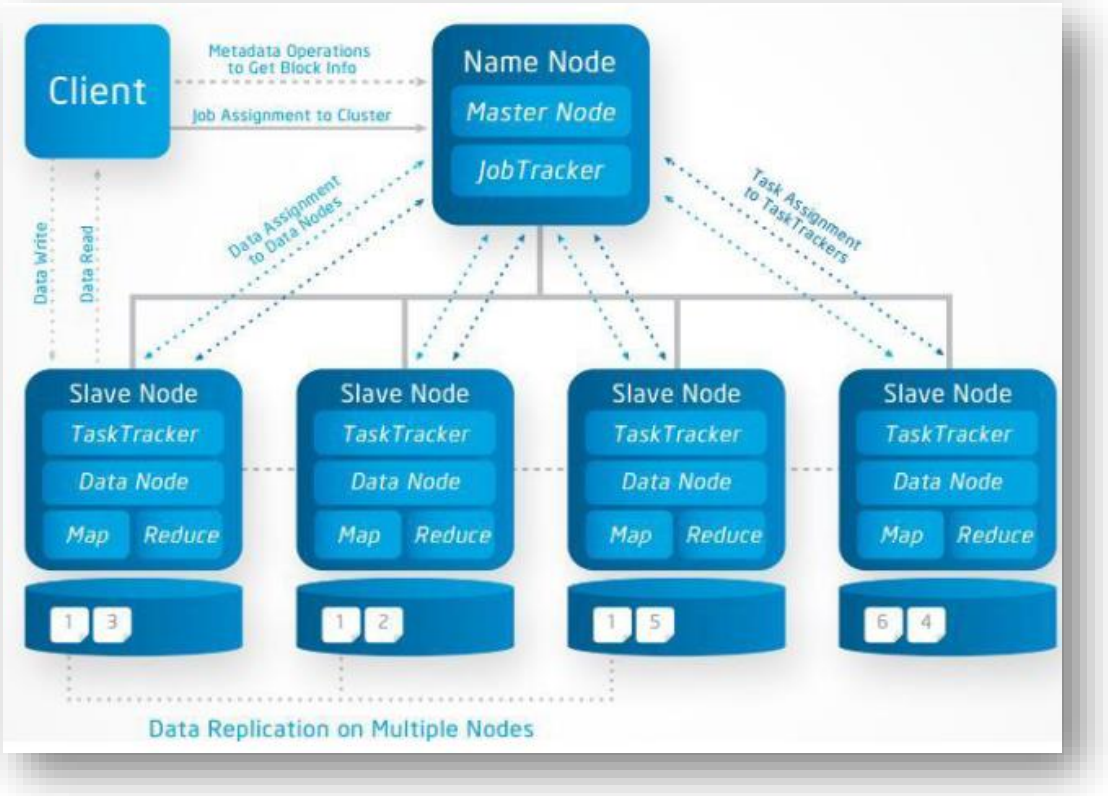

Key Principles

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- Decomposition of
  - Data – leads to **distributed storage** (HDFS, ADLS, S3)
  - Compute – leads to **distributed compute** (MapReduce, Spark)
- Data and Compute separation (cloud data platforms)
  - By decoupling storage and compute, organizations can scale each component independently.
    - Storage is cheap
    - Compute is expensive
  - A lot of data ≠ $$$, if you don’t process them
  - A small amount of data ≠ $, if you process them real-time (e.g. streaming)

Distributed Storage

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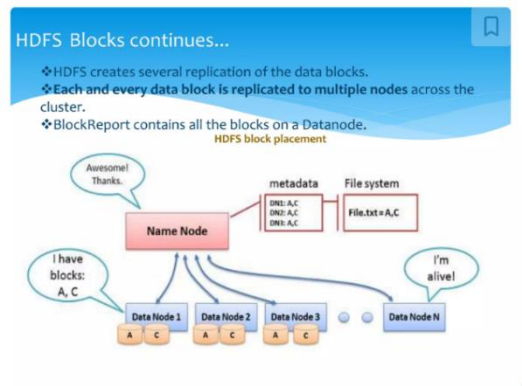
Distributed File System (DFS)

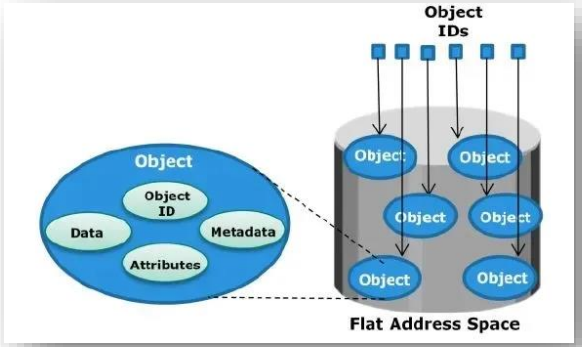
- HDFS (Hadoop Distributed File System)



- Traditional FS with directories and subdirectories (hierarchy)
- Data are split to blocks that are distributed
- Support random writes anywhere ☺
- Tightly coupled with compute (deployed alongside compute nodes) ☹

Object-Based Storage (OBS)

- ADLS (Azure Data Lake Storage)
- AWS S3 (Simple Storage Service)



- Flat address space, where each object contains the data, a unique identifier, and metadata
- No random writes within objects (read and write whole object) ☹
- Loosely coupled with compute ☺

Storage formats

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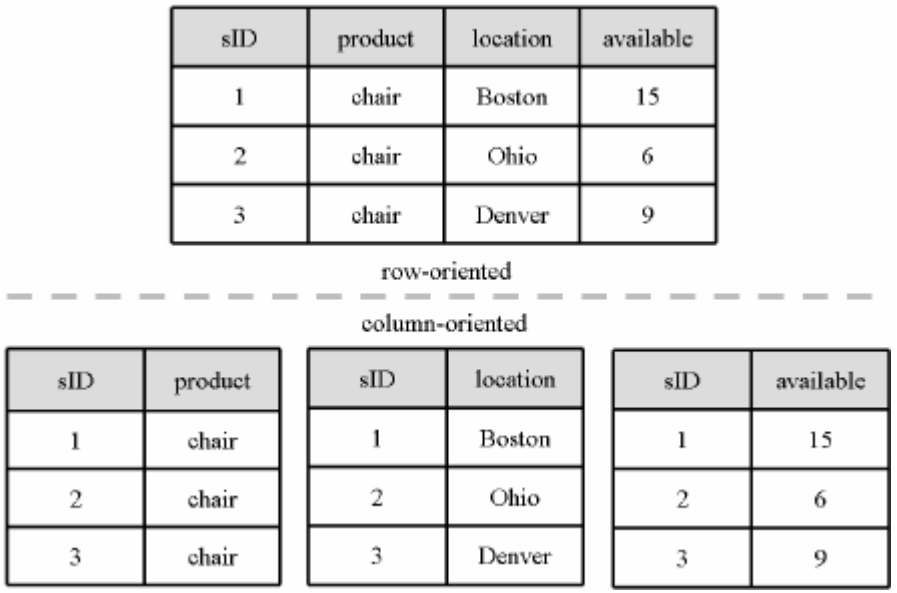
- **Parquet:** Columnar, highly efficient for analytics. Great for Spark and Fabric.
- **Avro:** Row-based, schema evolution friendly. Common in Kafka pipelines.
- **Delta:** Adds ACID, versioning, time travel and schema evolution to Parquet. Ideal for Lakehouse architecture.
- **Iceberg:** Similar to Delta but open standard. Supports hidden partitioning and time travel.
- **JSON/CSV:** Human-readable but inefficient. Best for small data or interoperability.



sID	product	location	available
1	chair	Boston	15
2	chair	Ohio	6
3	chair	Denver	9

row-oriented

column-oriented

sID	product
1	chair
2	chair
3	chair

sID	location
1	Boston
2	Ohio
3	Denver

sID	available
1	15
2	6
3	9

Storage formats

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Format	Compression	Schema Evolution	ACID Transactions	Partitioning	Read Performance	Write Performance	Typical Use Cases
	✅ Excellent	✅ Limited	❌ No	✅ Yes	✅ Fast	✅ Fast	Analytics, ML
	✅ Good	✅ Full	❌ No	✅ Yes	✅ Good	✅ Good	Streaming, Kafka
	✅ Excellent	✅ Full	✅ Yes	✅ Yes	✅ Very Fast	✅ Fast	Lakehouse, CDC
	✅ Excellent	✅ Full	✅ Yes	✅ Yes	✅ Very Fast	✅ Fast	Lakehouse, versioning
	❌ Poor	❌ Manual	❌ No	❌ No	❌ Slow	✅ Easy	Logs, APIs
	❌ None	❌ Manual	❌ No	❌ No	❌ Slow	✅ Easy	Legacy, simple ETL

Distributed Compute

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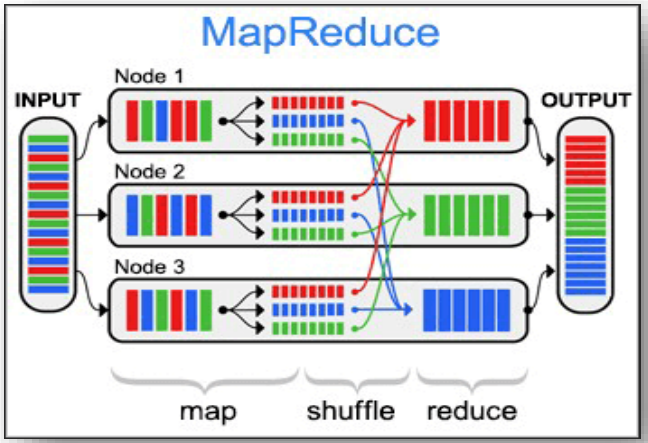
- MapReduce = programming paradigm



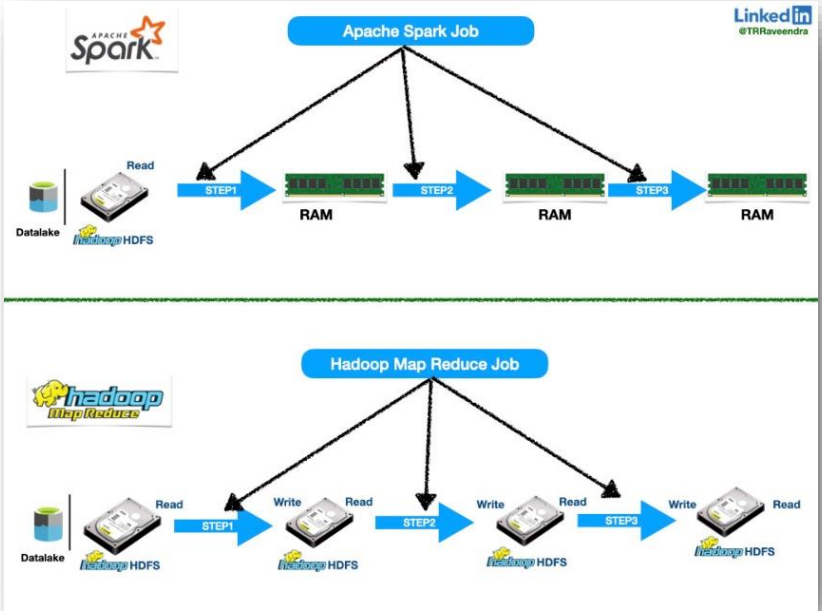
- Map - each node applies the mapping function to its data portion, filtering and sorting it according to parameters.
- Shuffle - mapped data is redistributed to other nodes on the system so that each node contains groups of key-similar data
- Reduce - Data is processed in parallel, per node, per key

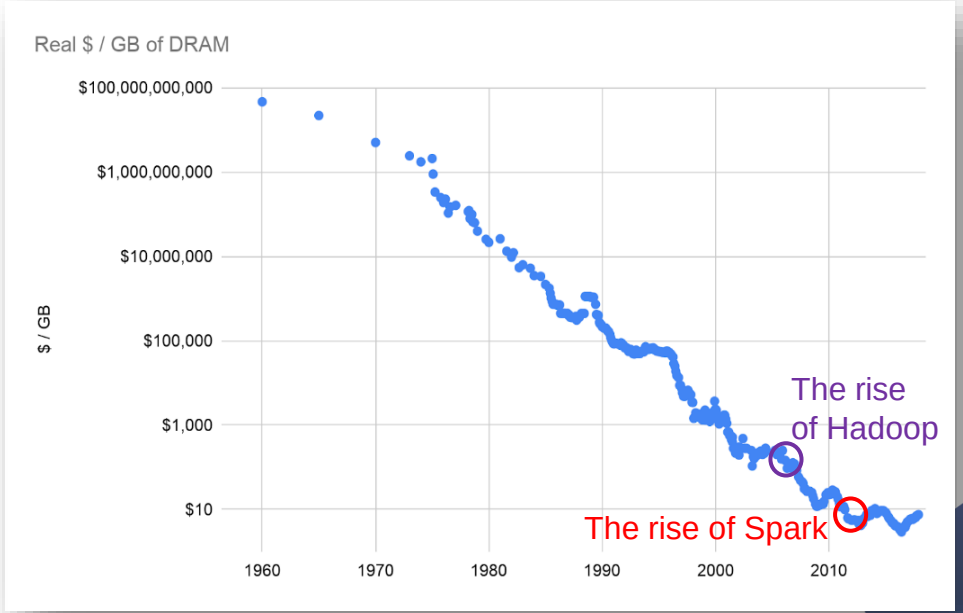
- hadoop MapReduce = implementation of MapReduce paradigm on Hadoop platform


APACHE
Spark

- Does the same thing but more efficiently and conveniently
  - **Processing speed:** Apache Spark is much faster than Hadoop MapReduce (100x).
  - **Data processing paradigm:** Hadoop MapReduce is designed for batch processing, while Apache Spark is more suited for real-time data processing and iterative analytics (but handles batch as well).
  - **Ease of use:** Apache Spark has a more user-friendly programming interface and supports multiple languages, while Hadoop MapReduce requires developers to write code in Java.
  - **Fault tolerance:** Apache Spark's Resilient Distributed Datasets (RDDs) offer better fault tolerance than Hadoop MapReduce's Hadoop Distributed File System (HDFS).
  - **Integration:** Apache Spark has a more extensive ecosystem and integrates well with other big data tools, while Hadoop MapReduce is primarily designed to work with Hadoop Distributed File System (HDFS).

- So, are there any cons?
  - It's all about the RAM
  - RAM used to be expensive but the world has changed…





What Caused Hadoop's Decline (Some of)

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- Complex setup, skilled administrators and developers.
- MapReduce (Java based) is slow and not sufficient for ML or RT processing → Spark
- HDFS is optimal for big data files and not flexible.
- Horizontal scalling lead to huge onprem clusters => hard and expensive to maintain.
- Numerous tools → difficult to make and maintain cohesive data pipelines.
- Weak bult-in governance and security tools => hard to be complient with regulations.
- Developers heavy, not user friendly.

CAP Theorem

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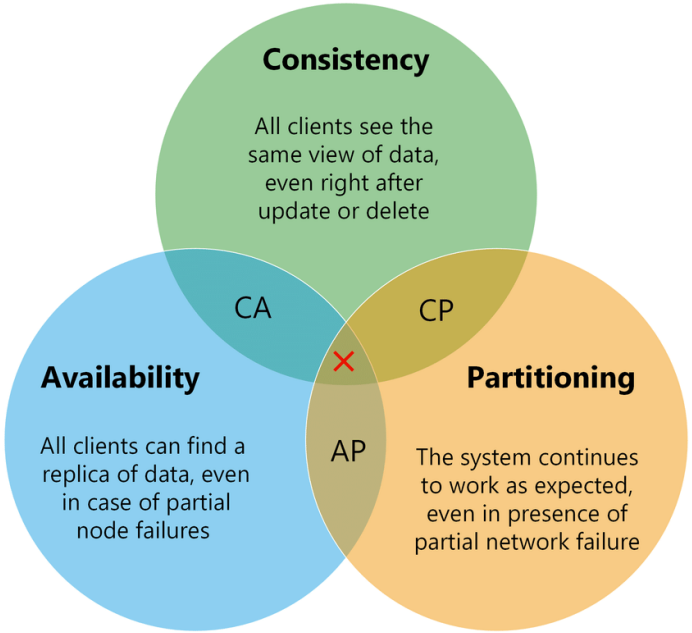
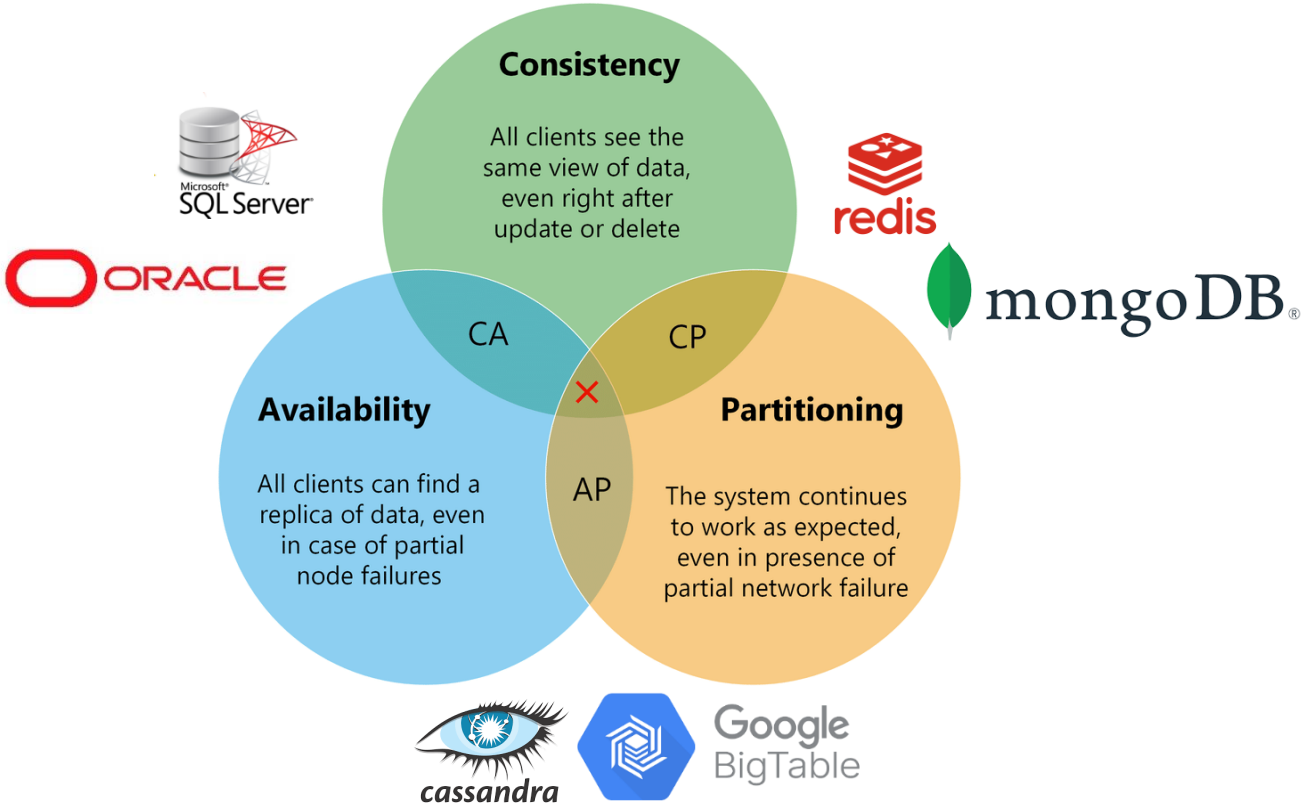
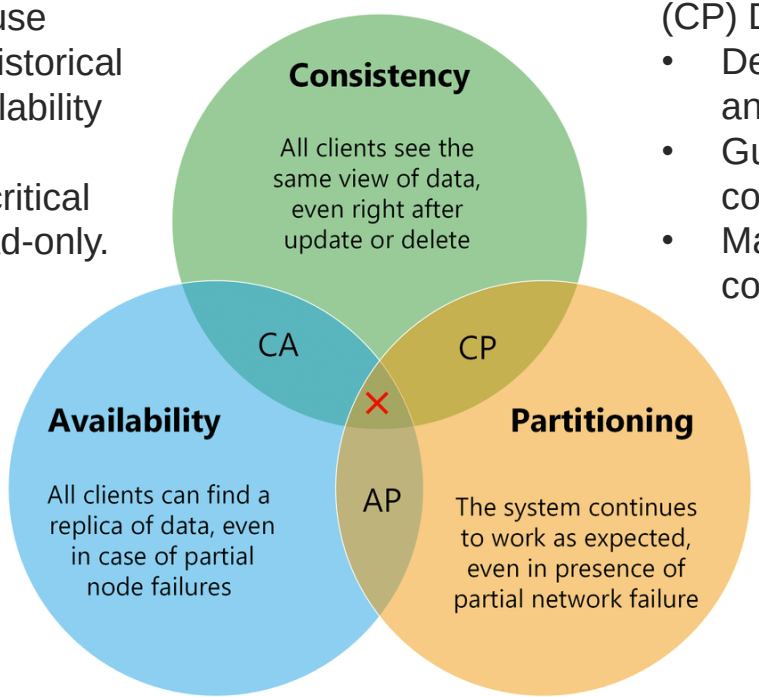
- What of CAP theorem is applicable to Relational Databases?
  - **CA**
- What of CAP theorem is applicable to BigData systems?
  - **CP or AP**
  - **Fault or Consistency tolerant**




Consistency
All clients see the same view of data, even right after update or delete
Availability
All clients can find a replica of data, even in case of partial node failures
Partitioning
The system continues to work as expected, even in presence of partial network failure
CA
CP
AP
Microsoft SQL Server
ORACLE
redis
mongoDB
cassandra
Google BigTable

(CA) Databricks SQL Warehouse

- For analytical queries on historical data, consistency and availability are prioritized.
- Partition tolerance is less critical since queries are often read-only.



(CP) Delta Lake

- Delta Lake uses ACID transactions and a transaction log (DeltaLog).
- Guarantees consistency across concurrent reads/writes.
- May sacrifice availability during write conflicts or schema enforcement.

(AP) Structured Streaming

- Prioritizes availability and low-latency processing.
- May tolerate temporary inconsistencies (e.g., late-arriving data, out-of-order events).

Conclusion

Conslusion

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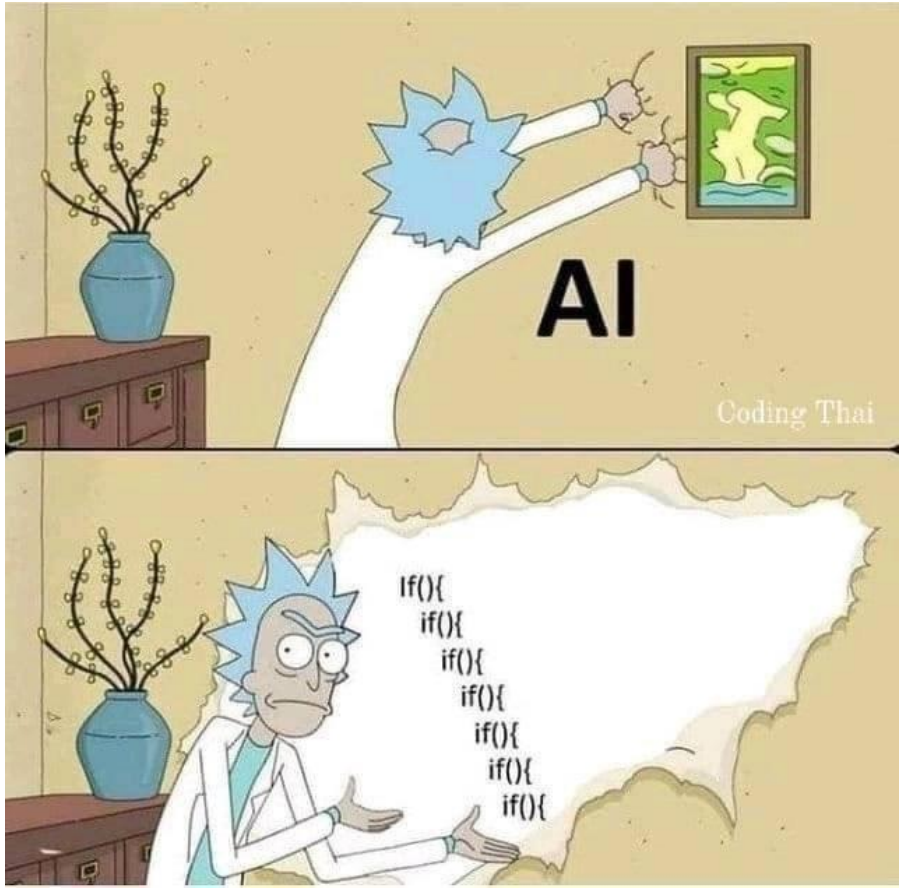
- Brief history and brief introduction to big data concepts will show
  - Money are important – GOOGLE, Yahoo, Microsoft, IBM, Linkedin…
    - Open Source developers need to eat too ☺
  - Every technology has its rise, peak and decline (Gartner hype cycle)
    - Datawarehouse, Hadoop, TV ☺, even gen AI started to decline
  - Key concept remains – distributed data, distributed processing, fault tolerancy etc.
  - **Take the best and fix issues** – modern data platforms offer security, governance, stream and batch processing, wide integration, great UI, support etc.


AI
Coding Thai
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Děkujeme za pozornost

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