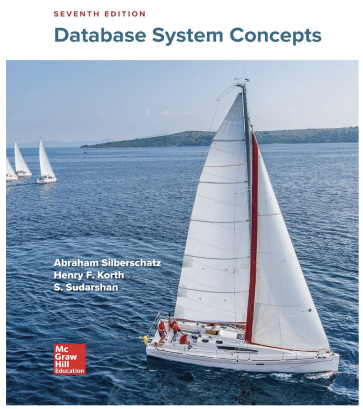
UNIVERSITY OF MARYLAND

UMD DATA605 - Big Data Systems

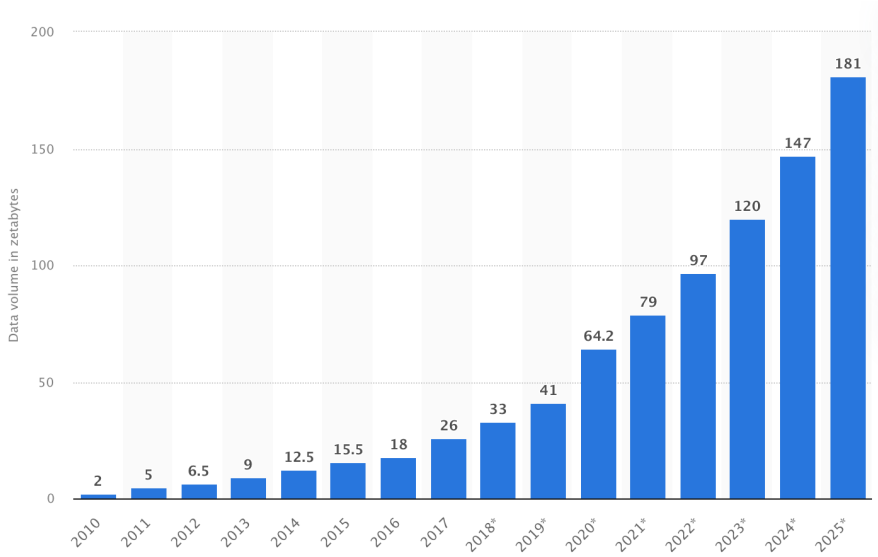
8.1: Cluster Architecture

- **Instructor**: Dr. GP Saggese, gsaggese@umd.edu
- **References**:
  - Silbershatz: Chap 10



SCIENCE ACADEMY

Big Data: Storing and Computing

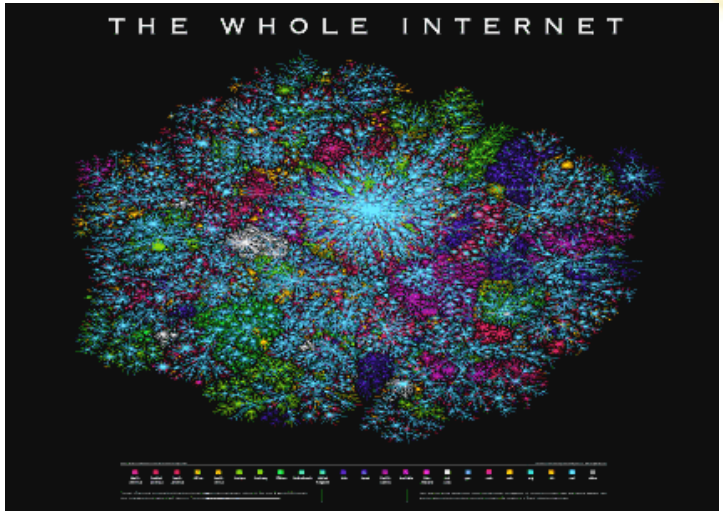


Volume of data in the world

- **Big data needs 10k-100k machines**
- **Two problems**
  - Storing big data
  - Processing big data
- **Need to solve problems together and efficiently**
  - One slow phase slows entire system

Processing the Web: Example

- Web contains (in 2024):
  - 20+ billion pages
  - 5M TBs of content
- **Storing the web**
  - Need 1M 5TB hard drives
    - $100/HDD -> $100M in total
    - Not bad
  - Wait, one computer reads 300 MB/sec
    - 4,500 years to read web serially!
- **Processing the web**
  - Much larger time / cost needed!



How to Store Big Data?

- **Many different solutions to storing big data**
  1. *Distributed file systems*
  2. *Sharding across multiple DBs*
  3. *Parallel and distributed DBs*
  4. *Key-value stores*

1) Distributed File Systems

- **Files stored across machines yet single file-system view to clients**
  - E.g.,
    - Google File System (GFS)
    - Hadoop File System (HDFS)
    - AWS S3
  - Files are:
    - Broken into blocks
    - Blocks partitioned across machines
    - Blocks often replicated
- **Goals**
  - Store data not fitting on one machine
  - Increase performance
  - Increase reliability/availability/fault tolerance

2) Sharding Across Multiple DBs

- **Sharding**: Partition records across multiple DBs or machines
  - Shard keys, aka partitioning keys / partition attributes
  - Range partition (e.g., timeseries)
  - Hash partition
- **Pros**
  - Scale beyond centralized DB for more users, storage, processing speed
- **Cons**
  - Replication needed for failures
  - Ensuring consistency is challenging
  - Relational DBs struggle with constraints (e.g., foreign key) and transactions on multiple machines

3) Parallel and Distributed DBs

- **Store and process data on multiple machines (cluster)**
- **Pros**
  - From programmer viewpoint
    - Traditional relational DB interface
    - Appears as a single-machine DB
  - Approach scales to 10s-100s of machines
  - Data replication enhances performance and reliability
    - Frequent failures with 100s of machines
    - Queries can restart on different machines
- **Cons**
  - Incremental query execution is complex
  - Scalability limits

4) (Parallel) Key-value Stores

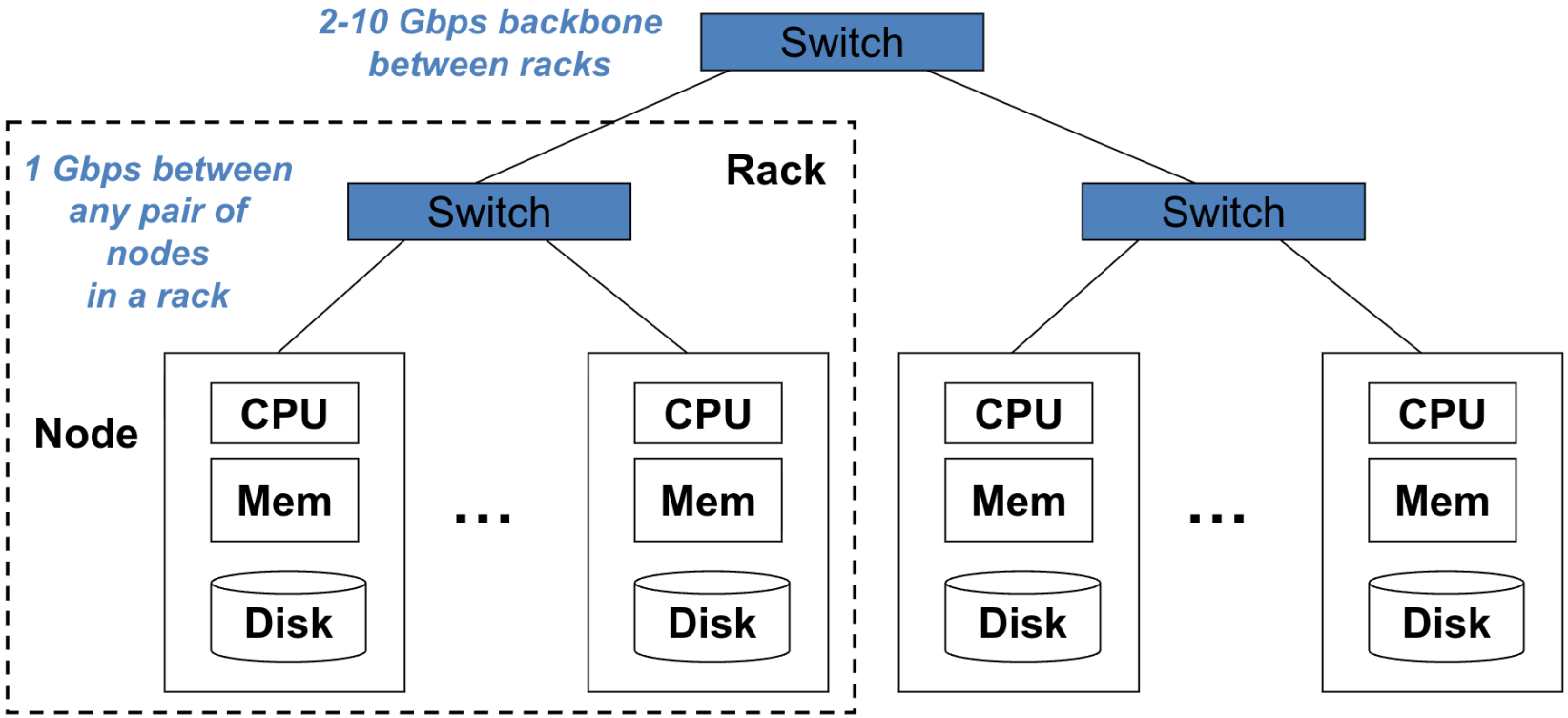
- **Problem**
  - Applications store billions of small records
  - Relational DBs lack multi-machine constraints and transactions
- **Solution**
  - Key-value stores / Document / NoSQL systems
  - E.g.,
    - Redis
    - Apache HBase (open source of Google BigTable)
    - ...
    - AWS Dynamo, S3
    - Azure cloud storage (Microsoft)
    - MongoDB cluster
- **Pros**
  - Partition data across machines
  - Support replication and consistency
  - Balance workload, add machines
- **Cons**
  - Sacrifice features for scalability
    - Declarative querying
    - Transactions
    - Non-key attribute retrieval

How to Compute with Big Data?

- **Challenges**
  - Distribute computation
  - Simplify writing distributed programs
    - Distributed/parallel programming is hard
  - Store data in a distributed system
  - Survive failures
    - One server lasts ~3 years (1,000 days)
    - With 1,000 servers, expect 1 failure/day
    - E.g., 1M machines (Google in 2011) $\rightarrow$ 1,000 machines fail daily
- **MapReduce**
  - Solve problems for specific computations
  - Elegant way to work with big data
  - Originated as Google's data manipulation model
    - Not an entirely new idea

Cluster Architecture

- **Standard architecture for big data computation**
  - Cluster of commodity Linux nodes
  - Commodity network (typically Ethernet) to connect nodes
  - 2011: Google ~1M machines
  - 2025: ~10-15M (?)



- Each rack contains 16-64 nodes

Cluster Architecture

Cluster Architecture: Network Bandwidth

- **Problems**
  - Data on different machines
  - Network data transfer delays
- **Solutions**
  - Bring computation to data
  - Store files multiple times for reliability/performance
- **MapReduce**
  - Addresses these problems
  - Storage: distributed file system
    - Google GFS, Hadoop HDFS
  - Programming model: MapReduce

Storage Infrastructure

- **Problem**
  - Store data persistently and efficiently despite node failures
- **Typical data usage pattern**
  - Huge files (100s of GB to 1TB)
  - Common operations: reads and appends
  - Rare in-place updates
- **Solution**
  - Distributed file system
  - Store files across multiple machines
  - Files are:
    - Broken into blocks
    - Partitioned across machines
    - Replicated across machines
  - Provide a single file-system view to clients

Distributed File System

- **Reliable distributed file system**
  - Data in "chunks" across machines
  - Each chunk replicated on different machines
  - Seamless recovery from disk or machine failure
- **Bring computation directly to the data**
  - "Chunk servers" also serve as "compute servers"
- Hadoop and HDFS implement all these ideas