UMD DATA605 - Big Data Systems

8.1: Cluster Architecture

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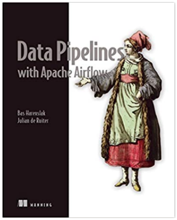
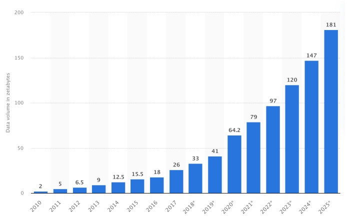
- Resources
  - Silbershatz: Chap 10



SCIENCE ACADEMY

Big Data: Sources and Applications

- **Growth of World Wide Web in 1990s and 2000s**
  - Store and query data larger than enterprise data
  - Valuable data for advertisements and marketing
  - Web server logs, web links
  - Social media
  - Mobile phone app data
  - Transaction data
  - Sensor/Internet of Things data
  - Communication metadata



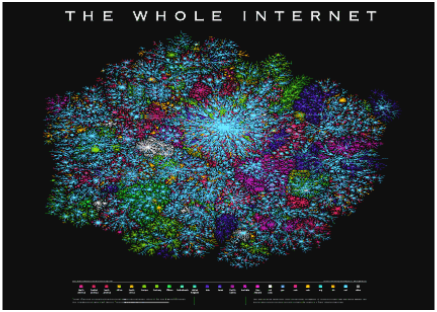
Volume of data in the world

Big Data: Storing and Computing

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

Processing the Web: Example

- Web contains:
  - 20+ billion pages
  - 5M TBs = 5 ZB
  - 1M 5TB hard drives needed
  - $100/HDD -> $100M total
- One computer reads 300 MB/sec
  - 4,433 years to read web serially
- More time needed for data processing



SCIENCE ACADEMY

Big Data: Storage Systems

- Store big data
- **Distributed file systems**
  - Store large files like log files
- **Sharding across multiple DBs**
  - Partition records based on shard key
- **Parallel and distributed DBs**
  - Store data / perform queries across machines
  - Use relational DB interface
- **Key-value stores**
  - Store/retrieve data based on a key
  - Limitations on semantics, consistency, querying
  - E.g., NoSQL DB, Mongo, Redis

1 Distributed File Systems

- **Distributed file system**
  - Files stored across machines, single file-system view to clients
    - E.g., Google File System (GFS)
    - E.g., Hadoop File System (HDFS) based on GFS
    - E.g., 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
- Attributes to partition data
  - Range partition (e.g., timeseries)
  - Hash partition
- **Pros**
  - Scale beyond a 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

- **Parallel and distributed DBs**: store and process data on multiple machines (cluster)
  - E.g., mongo
- **Pros**
  - Programmer viewpoint
    - Traditional relational DB interface
    - Appears as a single-machine DB
  - Operates on 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 Key-value Stores

- **Problem**
  - Applications store billions of small records
  - File systems can't handle so many files
  - RDBMSs lack multi-machine constraints and transactions
- **Solution**
  - Key-value stores / Document / NoSQL systems
  - Store, update, retrieve records by key
  - Operations: **put(key, value)**, **get(key)**
- **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

4 Parallel Key-value Stores

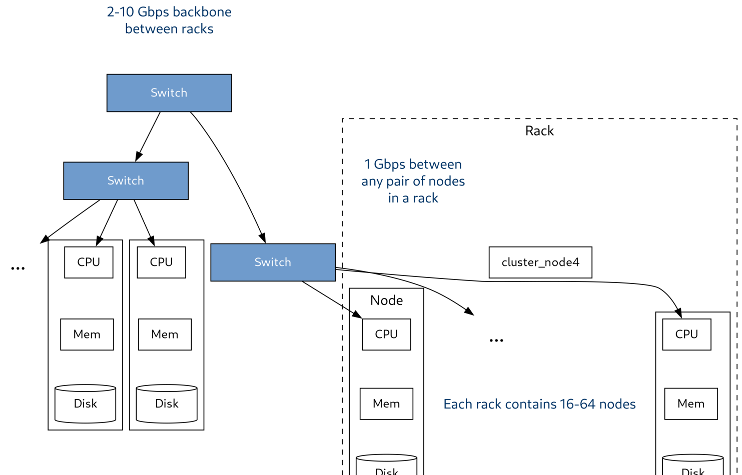
- **Parallel key-value stores**
  - BigTable (Google)
  - Apache HBase (open source BigTable)
  - Dynamo, S3 (AWS)
  - Cassandra (Facebook)
  - Azure cloud storage (Microsoft)
  - Redis
- **Parallel document stores**
  - MongoDB cluster
  - Couchbase
- **In-memory caching systems**
  - Store relations in-memory
  - Replicated or partitioned across machines
  - E.g., memcached or Redis

Big Data: Computing Systems

- **How to process Big Data?**
- **Challenges**
  - Distribute computation
  - Simplify writing distributed programs
    - Distributed/parallel programming is hard
  - Store data in a distributed system
  - Survive failures
    - One server may last 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 these 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

- Today, a standard architecture for big data computation has emerged:
  - Cluster of commodity Linux nodes
  - Commodity network (typically Ethernet) to connect them
  - In 2011 it was guesstimated that Google had 1M machines, in 2025 ~10-15M (?)


2-10 Gbps backbone between racks
Switch
Switch
Switch
...
CPU
Mem
Disk
CPU
Mem
Disk
Rack
1 Gbps between any pair of nodes in a rack
cluster_node4
Node
CPU
Mem
Disk
...
Each rack contains 16-64 nodes
CPU
Mem
Disk

Cluster Architecture

Cluster Architecture: Network Bandwidth

- **Problems**
  - Data hosted on different machines
  - Network data transfer takes time
- **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 Distributed File System

- **NameNode**
  - Store file/dir hierarchy
  - Store file metadata (location, size, permissions)
- **DataNodes**
  - Store data blocks
  - Split file into 16-64MB blocks
  - Replicate chunks (2x or 3x)
  - Keep replicas in different racks

Hadoop Distributed File System

- **Library for file access**
  - Read:
    - Contact *NameNode* for *DataNode* and block pointer
    - Connect to *DataNode* for data access
  - Write:
    - *NameNode* creates blocks
    - Assign blocks to multiple *DataNodes*
    - Client sends data to *DataNodes*
    - *DataNodes* store data
- **Client**
  - API (e.g., Python, Java) to library
  - Mount HDFS on local filesystem