Data Parallel Frameworks

Ashvin Goel

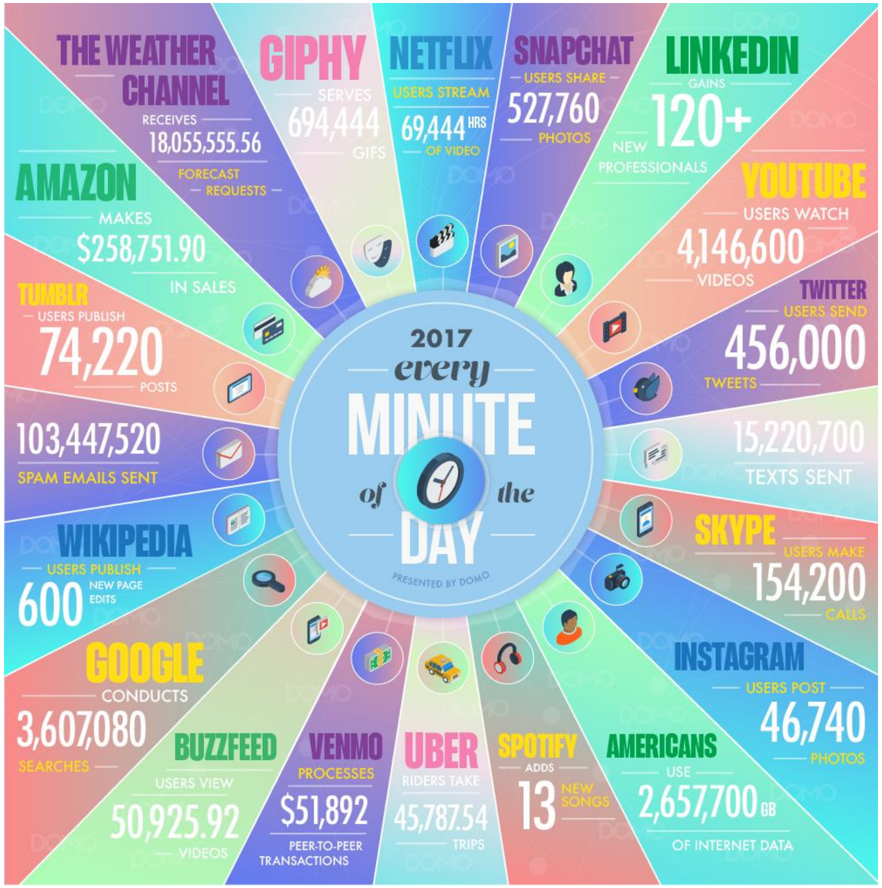
Electrical and Computer Engineering
University of Toronto

ECE1724

Some of these slides are heavily modified slides from
Prof. Ken Birman's course on Cloud Computing

What are Web-Scale Apps?

- Applications that are hosted in massive-scale computing infrastructures such as data centers



- Used by millions of geographically distributed users
  - Via web browsers, mobile clients, etc.
- Produce, store, consume massive amounts of data
  - Scale is hard to comprehend

What Kind of Data is Stored?

- Companies store data based on their business model …
  - Google, e.g., daily snapshot of all the web pages in the world
  - Amazon, e.g., current product data & price for every product
  - Facebook, e.g., social networking graph
  - …
- We have seen various types of storage systems for storing this data
  - Data is typically sharded across many machines
  - Sharded data is replicated for fault tolerance, fast read access
  - Much focus on scalability, data availability, consistency, etc.

How is the Data Used? i.e, What is "Big Data"?

- Web search (e.g., Google) needs to analyze billions of web pages to determine the most relevant pages
- Product search (e.g., Amazon) needs to analyze millions of products, who bought them, their reviews, etc.
- Recommendation systems (e.g., LinkedIn, Facebooks) need to analyze massive social graphs
- All the above can be used to generate revenue streams, e.g., smart ad placement, recommendations
  - These are restaurants you might like based on your tastes …
  - These stores have hugde Christmas sales for things you like …

A Simple Example: Web Search

- Data collection and storage
  - Collect web pages, store them
- Data analytics
  - Grep, sort, word count, e.g., extract words (or phases) from web pages
  - Index pages, e.g., associate each word with a ranked list of web pages that contain these words
  - Log analysis
- Data serving
  - When user searches for word, serve associated list of pages

Data Analytics Requirements

- Data analytics
  - Extract words (or phases) from web pages
  - Associate each word with a ranked list of web pages that contain these words
- Massive computation needs
  - Parse all pages
  - Rank all pages, similar to sorting a very large data set
    - E.g., find the "most authoritative pages" by organizing web pages in a graph, then finding the graph nodes with highest weight (rank)

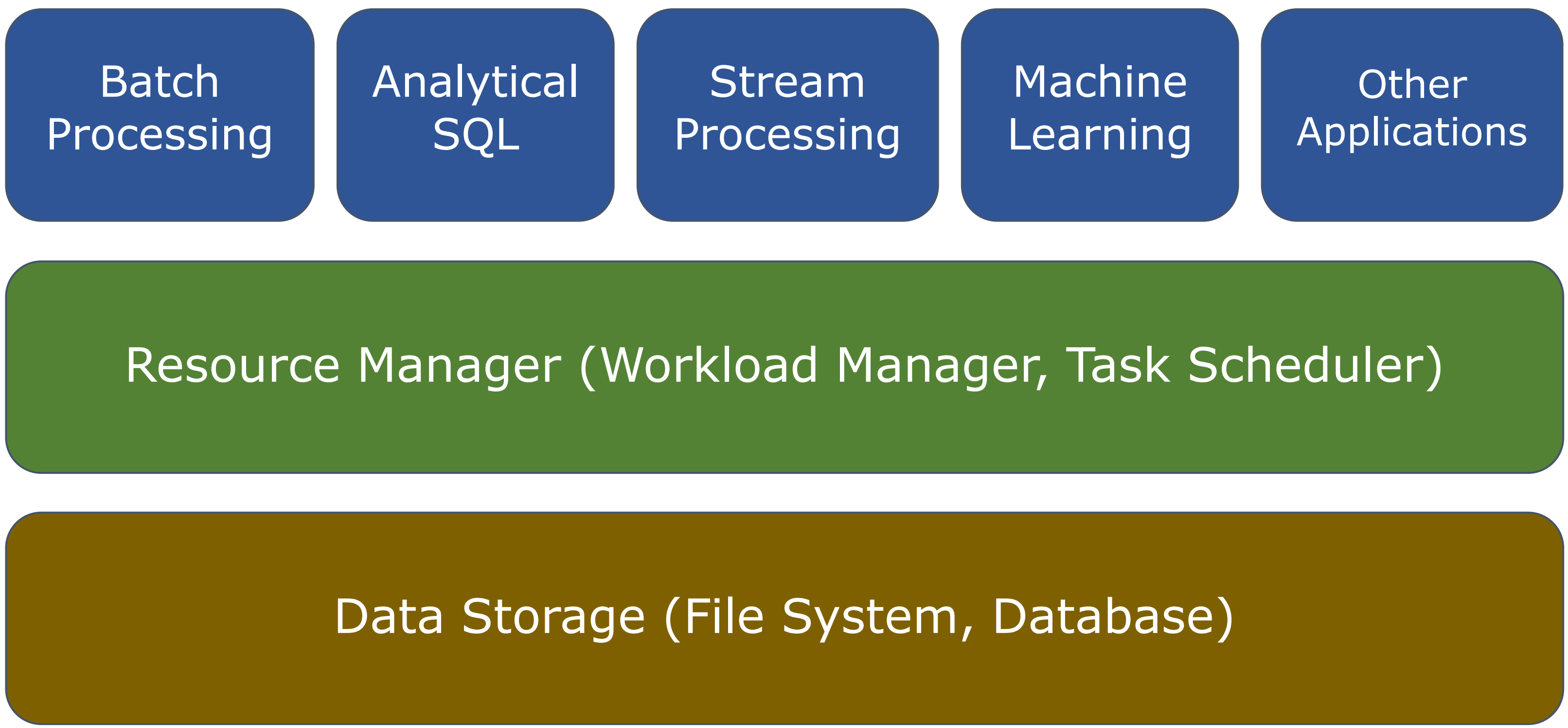
Data Analytics Challenges

- Data is massive
  - Need sharding across large numbers of machines
  - Need storage on disk
  - Need to handle storage failures
  - Need to handle updates (later)
- Computation is massive
  - Need scalable, parallel computation models
  - Need to handle massive intermediate, final results
  - Need to handle compute failures

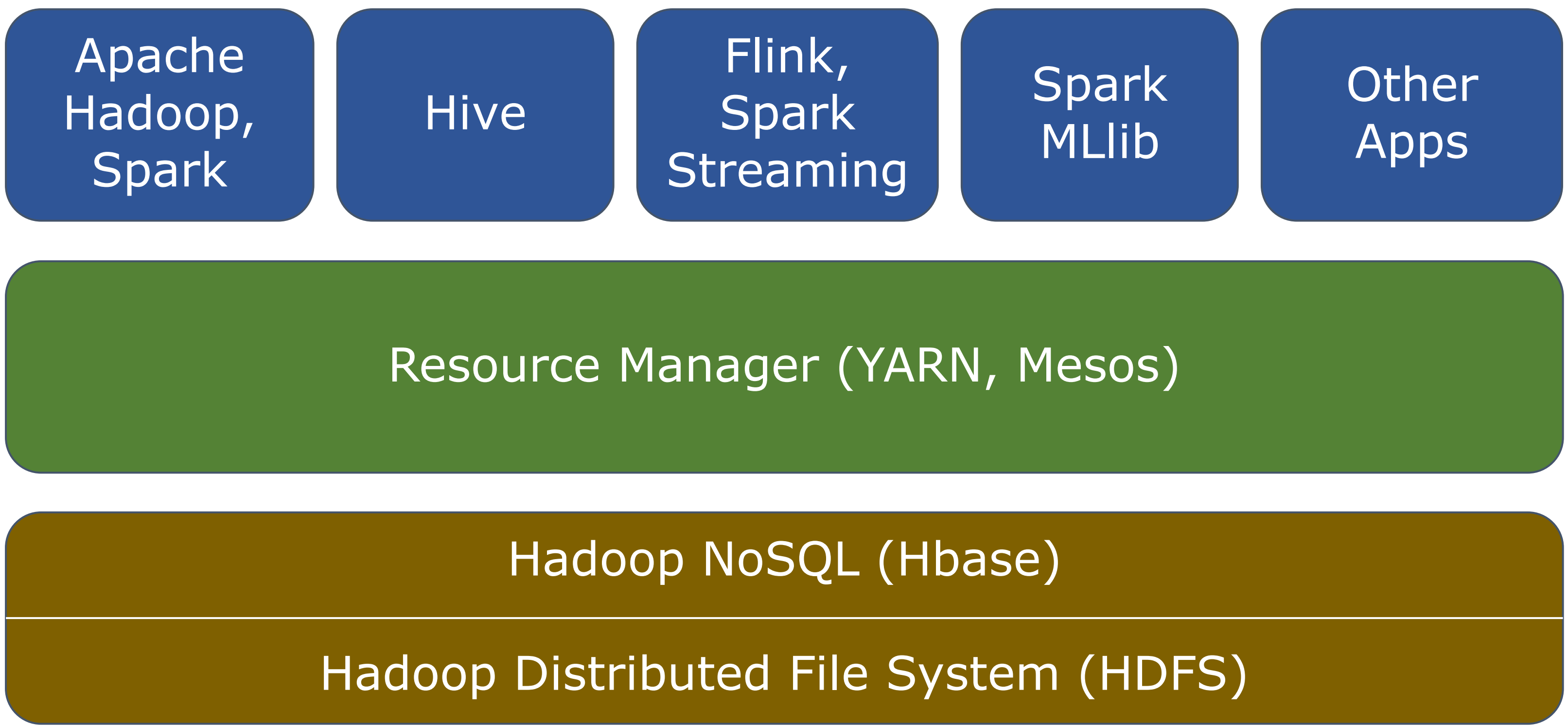
Data Analytics Frameworks

- These frameworks perform massively parallel (“always sharded”) computing efficiently
- The data starts out sharded
- Often the intermediary states and results are sharded
- Results are typically human-useful output, e.g., charts

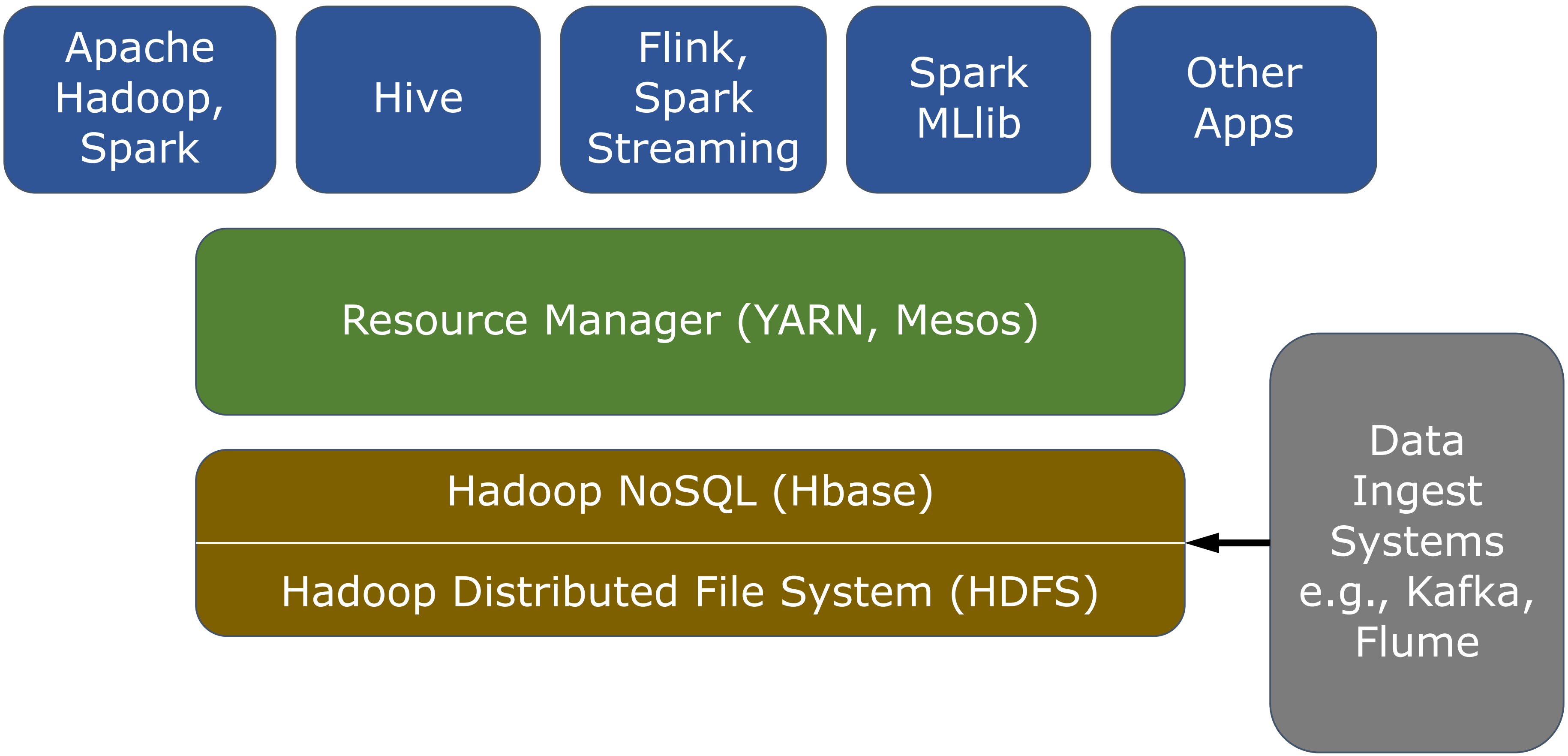
A Typical Big Data System



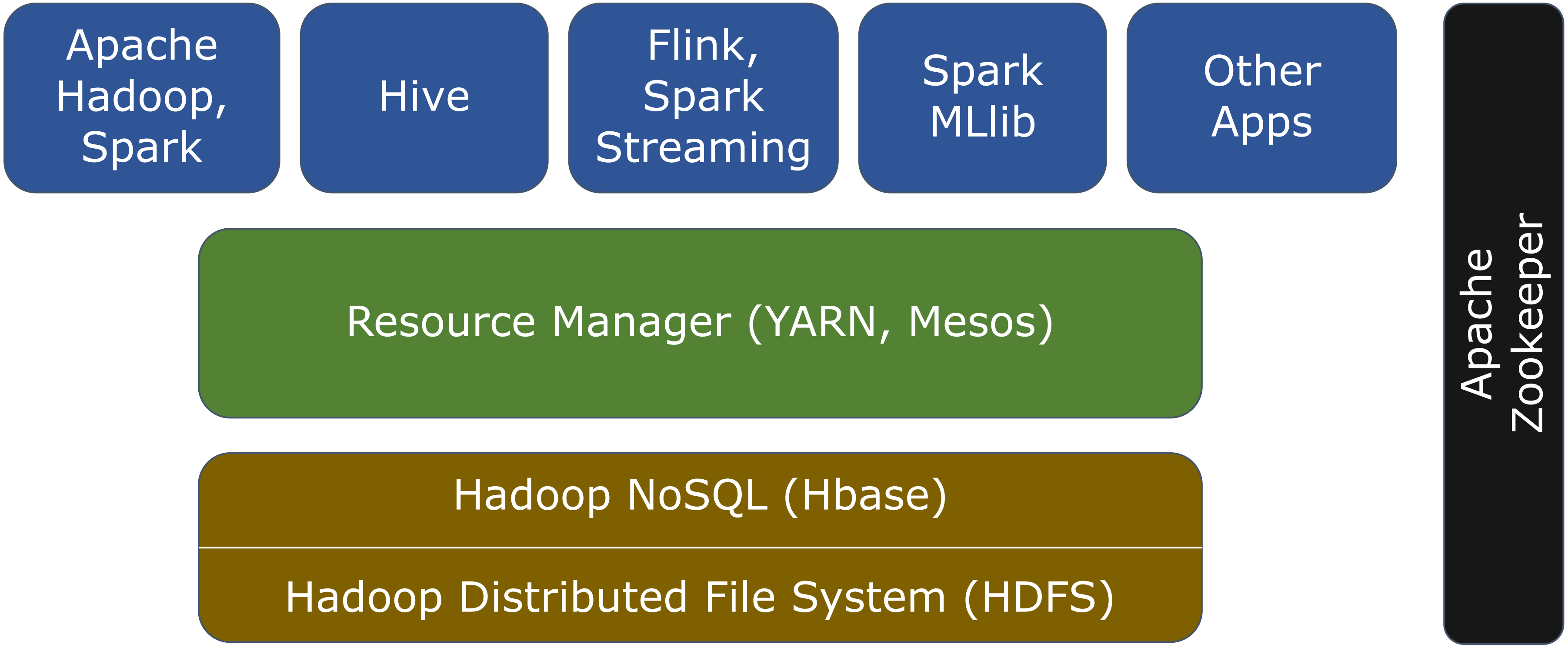
Open-Source Apache Ecosystem



Data Ingestion



Coordination

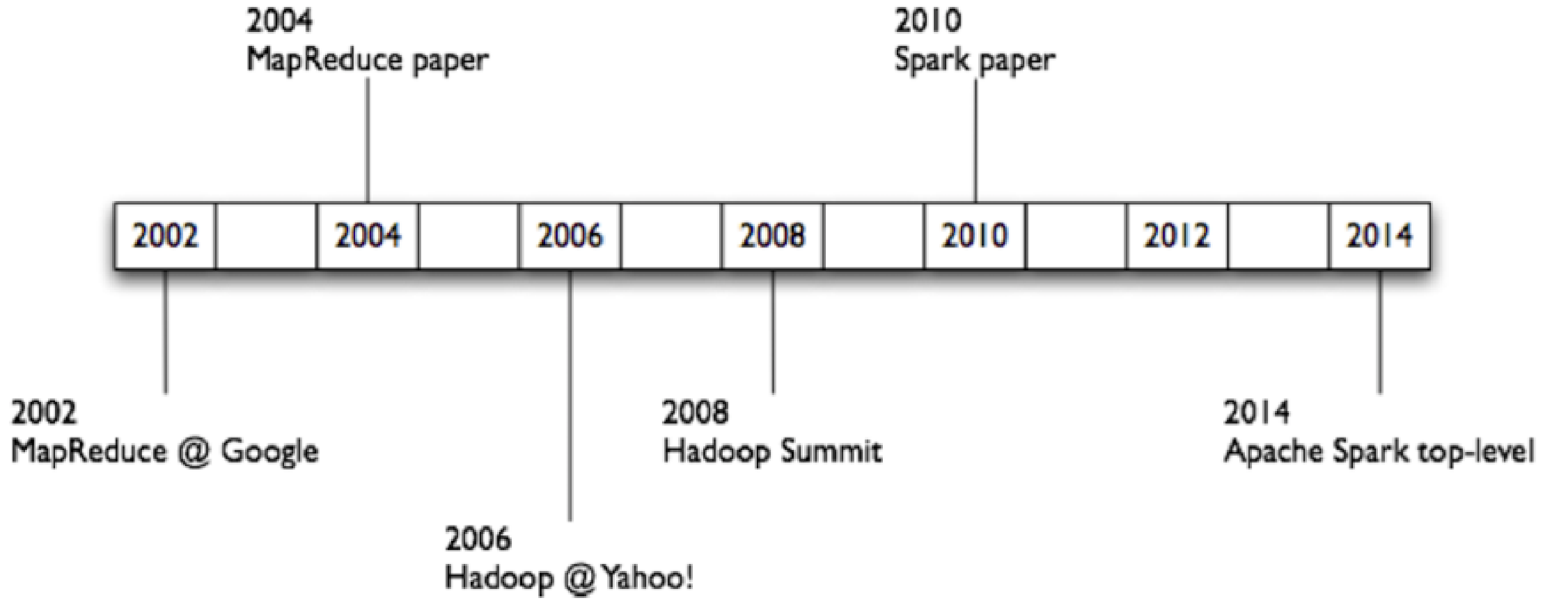


Batch Processing Frameworks

- Focus on simplifying the complexity of distributed programming
  - Developer focuses on logic for processing data
  - Framework takes care of parallelization, fault tolerance, scheduling, caching, …

- Hadoop (MapReduce)
  - Suited for individual batch (long running) jobs
- Spark
  - Also suited for iterative and interactive batch jobs

History of Hadoop and Spark



Map Reduce

- MapReduce enables distributing (parallelizing) a job across multiple nodes of a cluster
- Allows programmers to describe processing in terms of simple map and reduce functions on items
- Framework takes care of scaling, scheduling, hardware and software failures

Spark

- Same goal as Map Reduce, i.e., enable distributing (parallelizing) a job across multiple nodes of a cluster
- Allows programmers to describe processing in terms of transformations on fault-tolerant, distributed datasets
  - Datasets are nodes, transformations are edges in a graph
  - Transformations are evaluated only when needed (lazily)
- Framework takes care of caching, data locality, scaling, scheduling, hardware and software failures
- Key idea is to cache intermediate data that is reused

Challenges

- Parallelization
- Fault tolerance

Parallelization

- Key intuition
  - Often same processing is required for all items
  - Processing is independent for each item
- E.g., update count of the # of accesses to each website
  - Same operation is performed for each website
- Operation (e.g., map) can be performed in parallel
  - Like a SIMD instruction
  - However, operation works on shards on different machines
  - Produces intermediate data that is also sharded across machines

Why Batching?

- Shards are typically large, e.g., 16-64MB
  - Recall GFS chunk size
- Batch processing, i.e., processing all the data in a shard amortizes processing costs
  - Cost of processing each item is typically low, e.g., count++
  - Cost of accessing each item from storage is high
  - Batching reduces the latter cost
- However, batching requires enough data (or updates) to be available, so trades latency for efficiency

Fault Tolerance

- Why is it vital for large computations?
- Aim is to hide failures from applications
  - Provide behavior equivalent to fail-free operation
  - You will hear terms like exactly-once operation
- Both Map Reduce and Spark provide strong consistency and fault tolerance guarantees
  - Their behavior is equivalent to running a sequential computation, even in the presence of failures
  - Next, we will discuss these ideas in detail