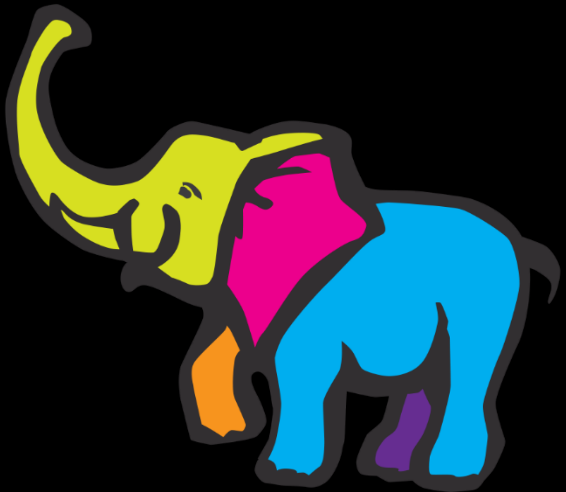
EECS4415: Big Data Systems



Processing Platforms

Big Data Technology & Analytics

Data Ingestion
ETL, Distcp, Kafka, OpenRefine, …

Query & Exploration
SQL, Search, Cypher, …

Stream Processing Platforms
Storm, Spark, ..

Batch Processing Platforms
MapReduce, SparkSQL, BigQuery, Hive, Cypher, …

Data Definition
SQL DDL, Avro, Protobuf, CSV

Storage Systems
HDFS, RDBMS, Column Stores, Graph Databases

Data Serving
BI, Cubes, RDBMS, Key-value Stores, Tableau, …

Computing Platforms
Distributed Commodity, Clustered High-Performance, Single Node

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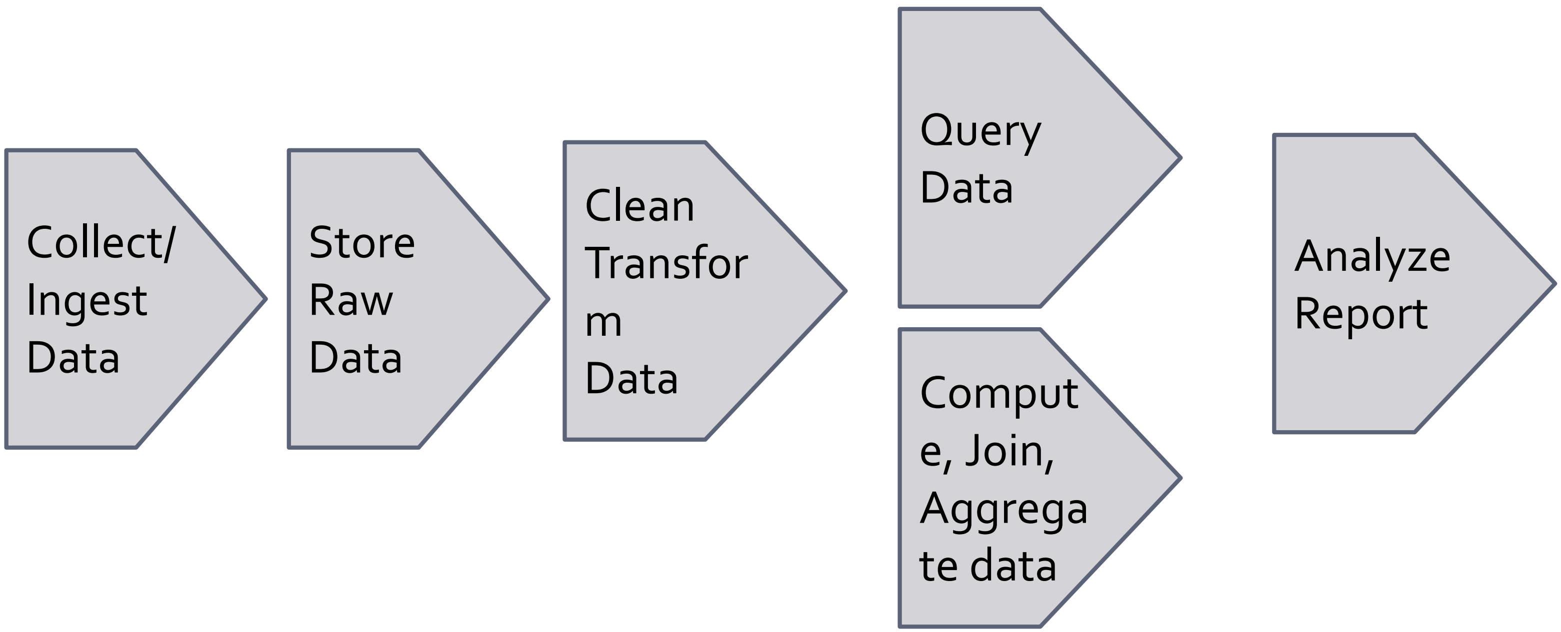
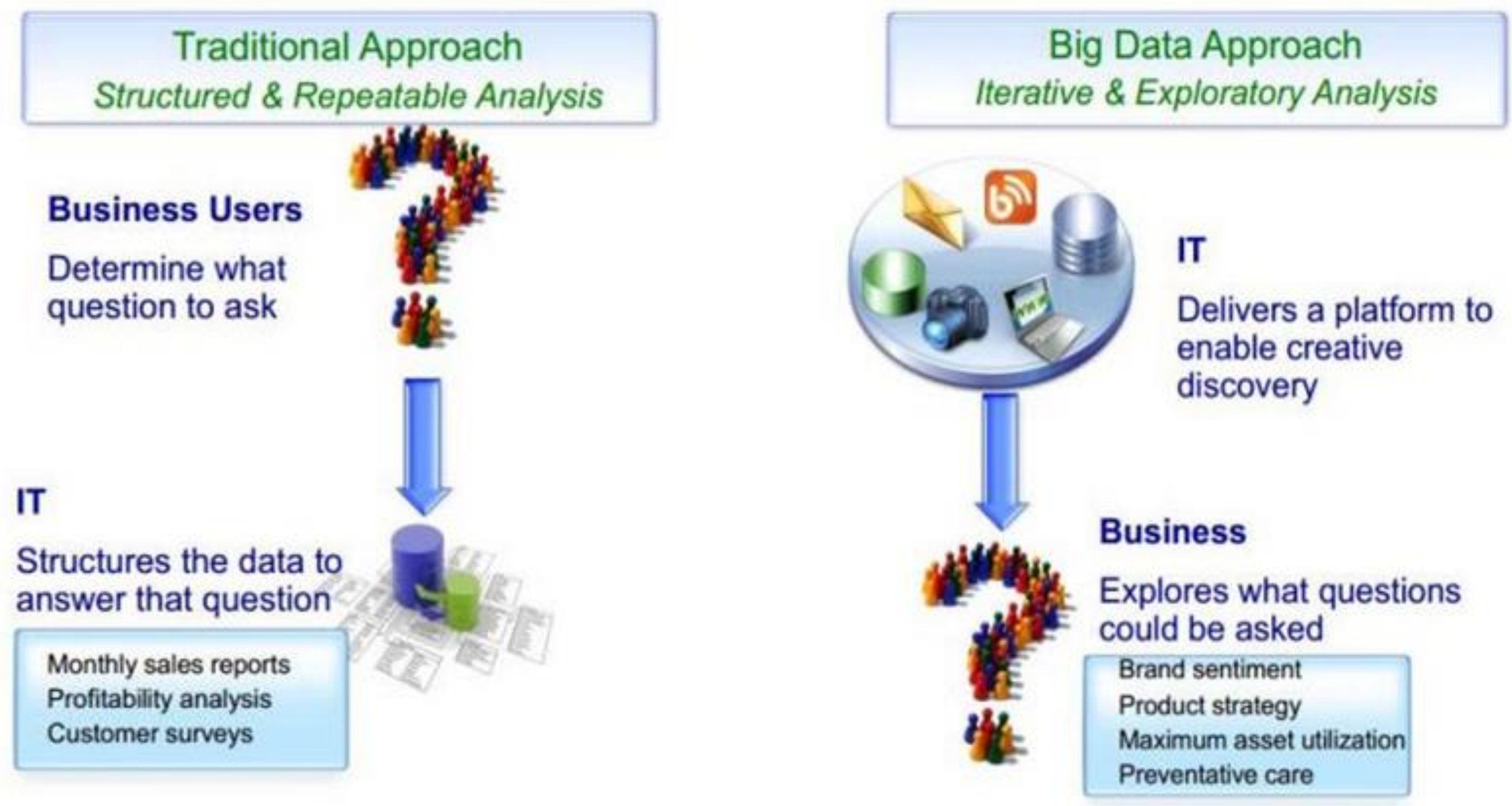
Big Data Architectures

Elements of DAV Architecture

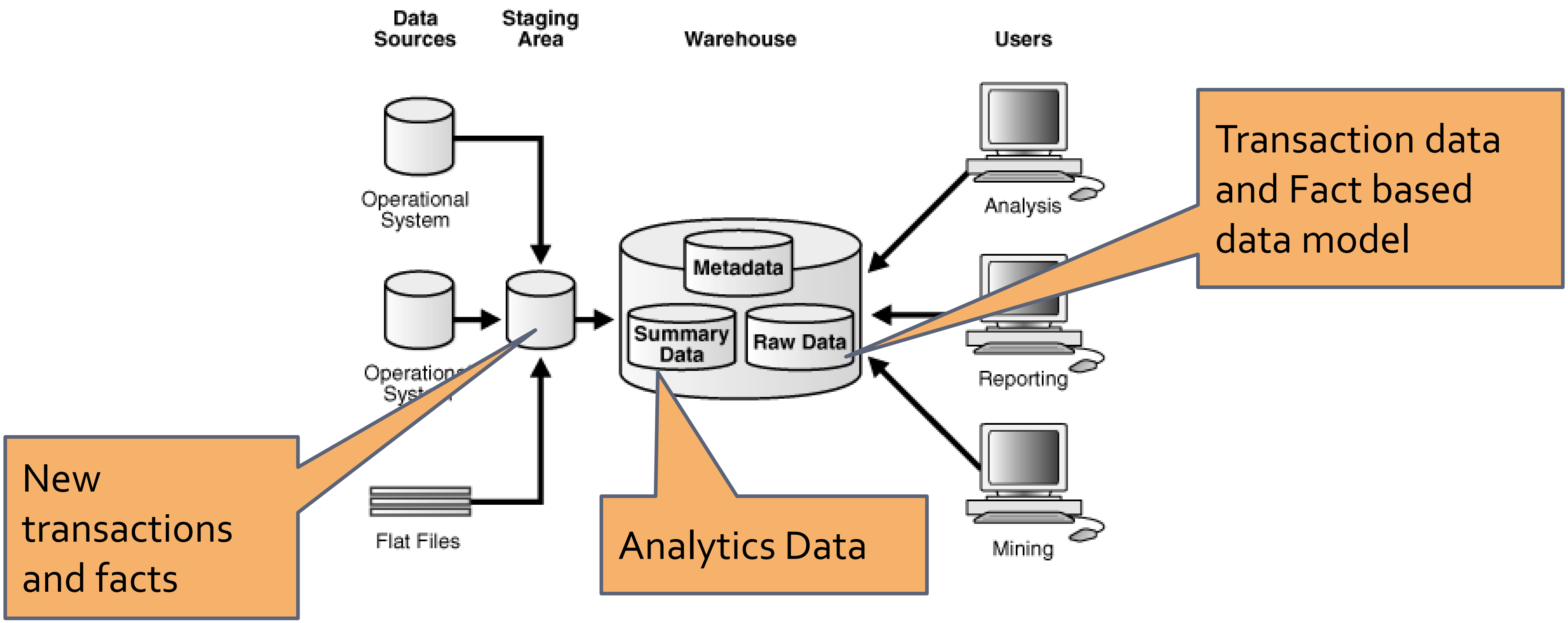


Difference in Approach



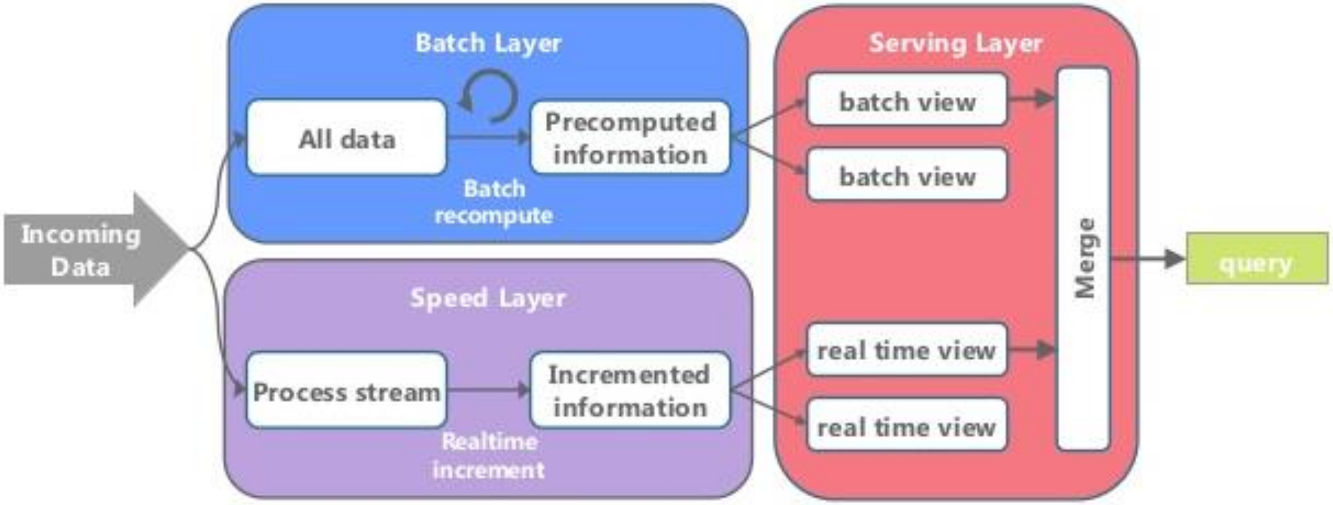
Notice the difference!

Traditional Business Warehouse



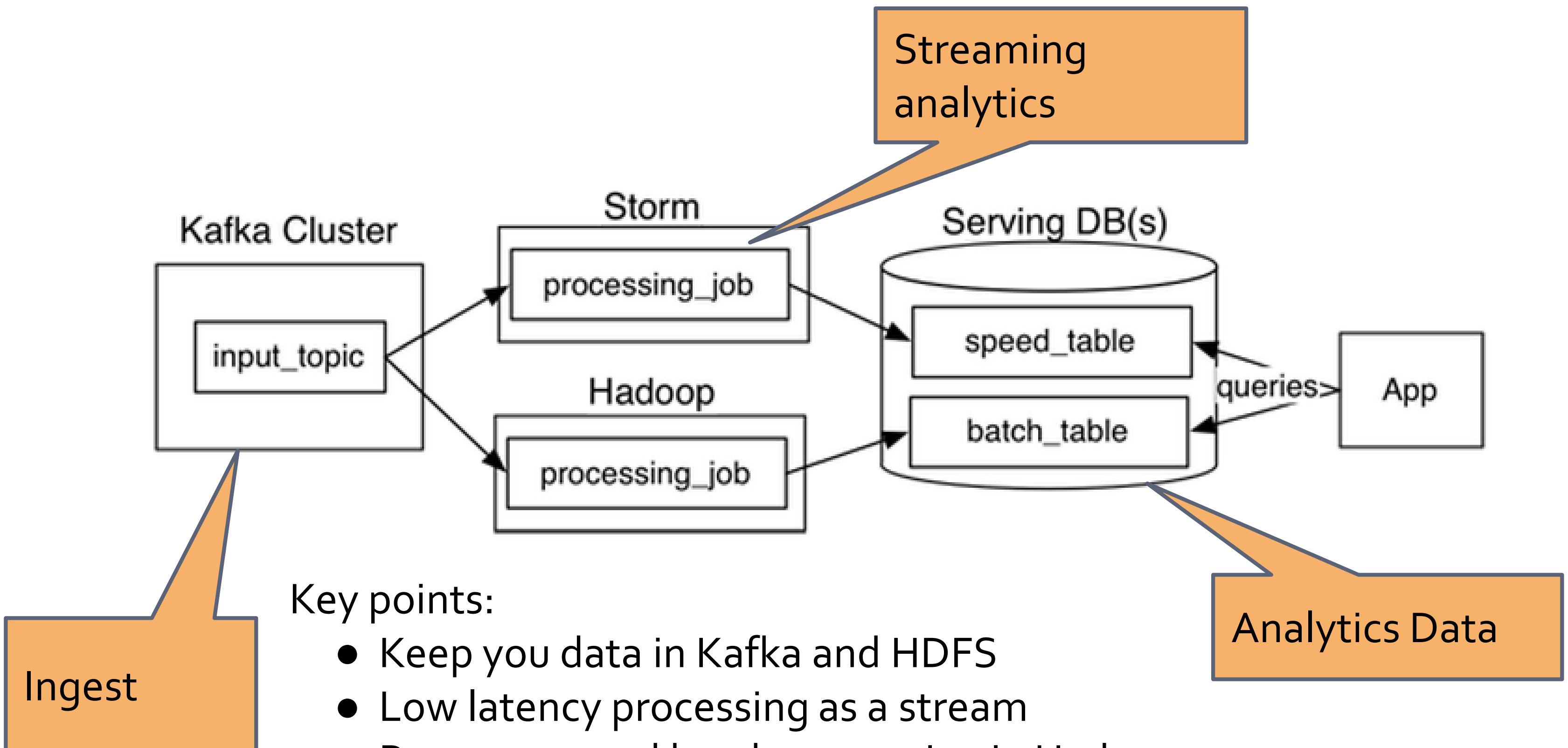
Big Data Analytics Architecture

Example:
Lambda Architecture



Other examples:
Kappa Architecture
Netflix Architecture

Lambda Architecture

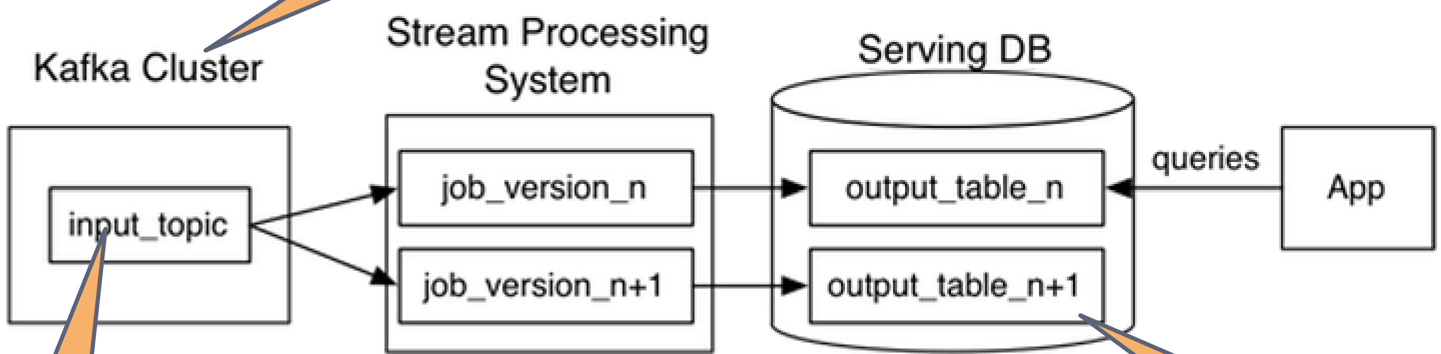


Key points:

- Keep you data in Kafka and HDFS
- Low latency processing as a stream
- Re-process and batch processing in Hadoop

Kappa Architecture

Transaction data and Fact based data model



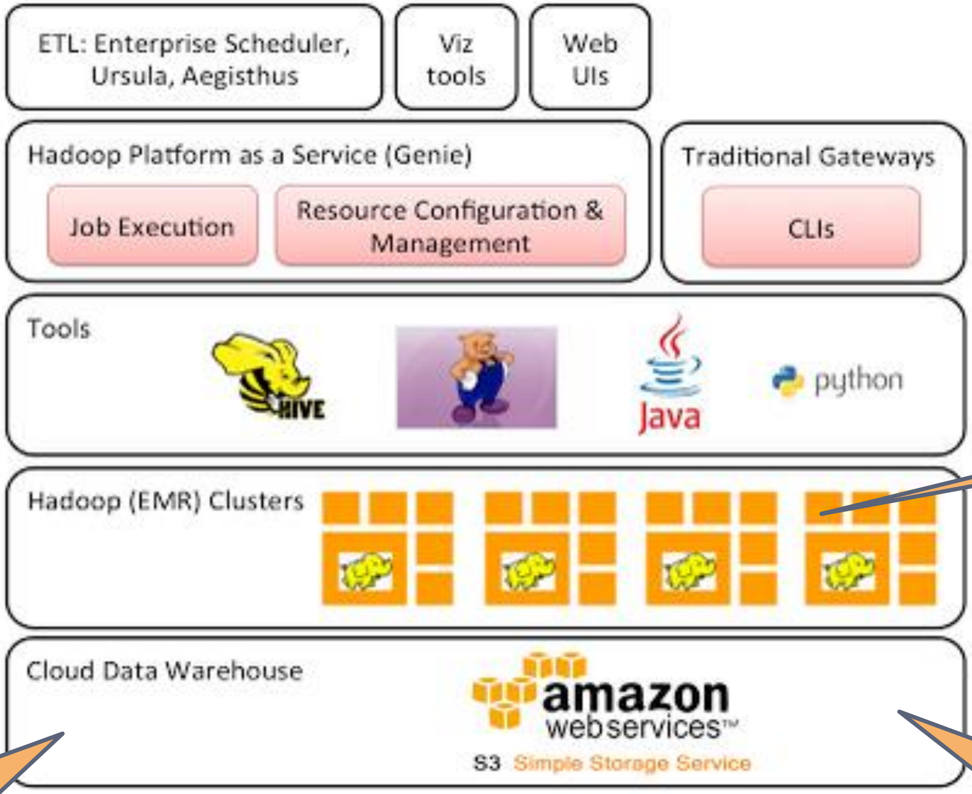
New transaction s and facts

Analytics Data

Key points:

- Keep you data in Kafka
- Treat everything as a Stream
- Re-process stream by resetting offset
- Advantage: simplified architecture, everything is a stream

Netflix Architecture



Analytics Data

New transactions and facts

Transaction data and Fact based data model

MapReduce, Spark, BigQuery, …

Processing Platforms

Processing Platforms

- Batch Processing
  - Google GFS/MapReduce (2003)
  - Apache Hadoop HDFS/MapReduce (2004)
- SQL
  - BigQuery (based on Google Dremel, 2010)
  - Apache Hive (HiveQL) (2012)
- Streaming Data
  - Apache Storm (2011) / Twitter Huron (2015)
- Unified Engine (Streaming, SQL, Batch, ML)
  - Apache Spark (2012)

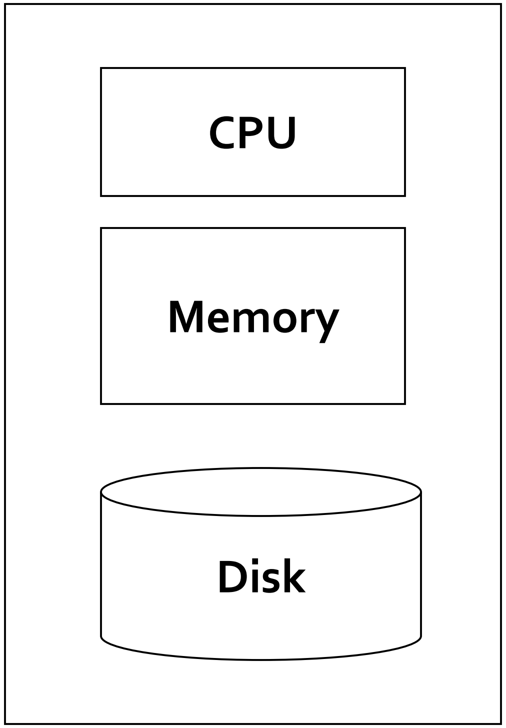
Map-Reduce and the New Software Stack

Mining of Massive Datasets

Jure Leskovec, Anand Rajaraman, Jeff Ullman
Stanford University

http://www.mmds.org

Single Node Architecture



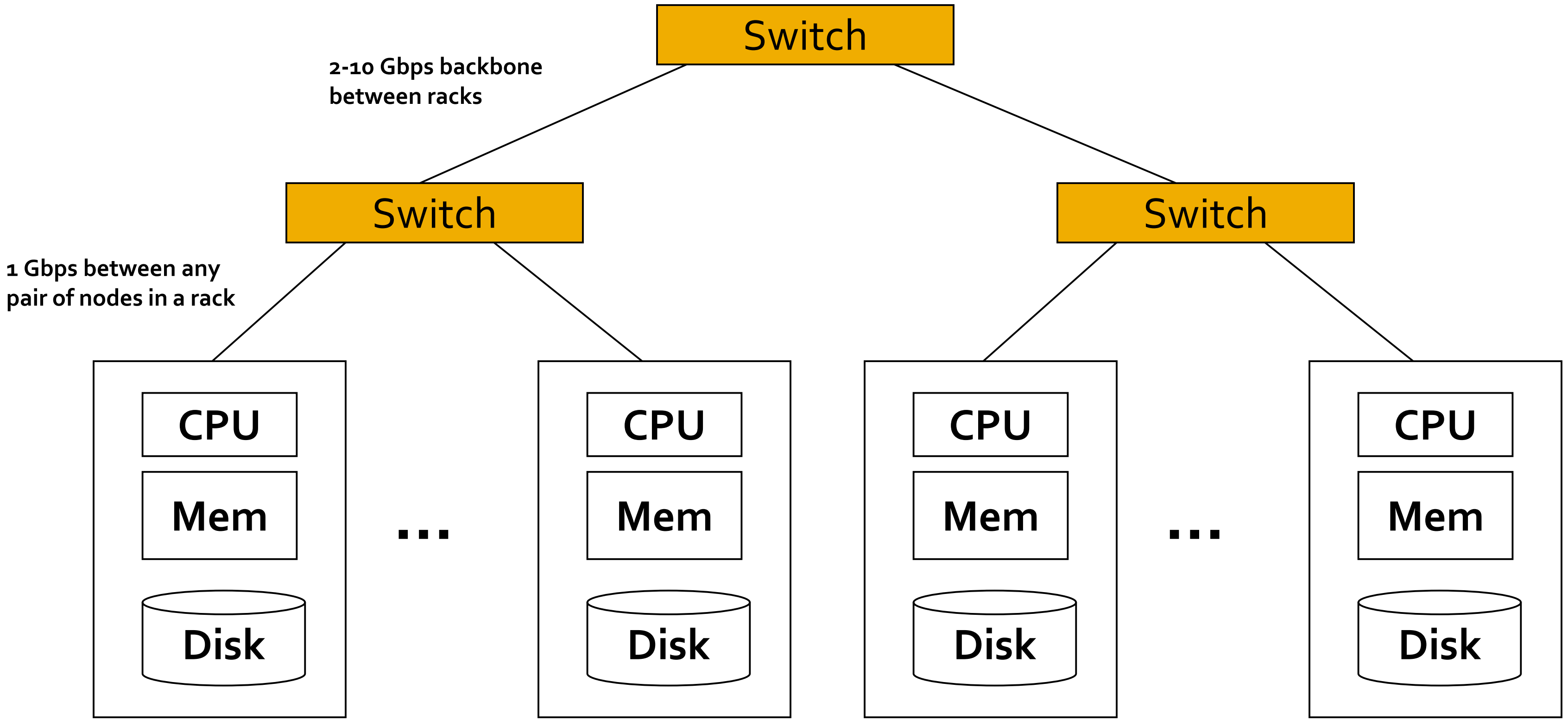
Machine Learning, Statistics

"Classical" Data Mining

Motivation: Google Example

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web
- ~1,000 hard drives to store the web
- Takes even more to **do** something useful with the data!
- **Today, a standard architecture for such problems is emerging:**
  - Cluster of commodity Linux nodes
  - Commodity network (ethernet) to connect them

Cluster Architecture



Each rack contains 16-64 nodes

In 2011 it was guestimated that Google had 1M machines, http://bit.ly/Shh0RO

Large-scale Computing

- **Large-scale computing** for **data mining** problems on **commodity hardware**
- **Challenges:**
  - **How do you distribute computation?**
  - **How can we make it easy to write distributed programs?**
  - **Machines fail:**
    - One server may stay up 3 years (1,000 days)
    - If you have 1,000 servers, expect to loose 1/day
    - People estimated Google had ~1M machines in 2011
      - 1,000 machines fail every day!

Idea and Solution

- **Issue: Copying data over a network takes time**
- **Idea:**
  - Store files multiple times for reliability
  - Bring computation close to the data
- **Storage Infrastructure: Distributed File system**
  - Google: GFS. Hadoop: HDFS
- **Programming Model: Map-Reduce**
  - Google's computational/data manipulation model
  - Elegant way to work with big data

Storage Infrastructure

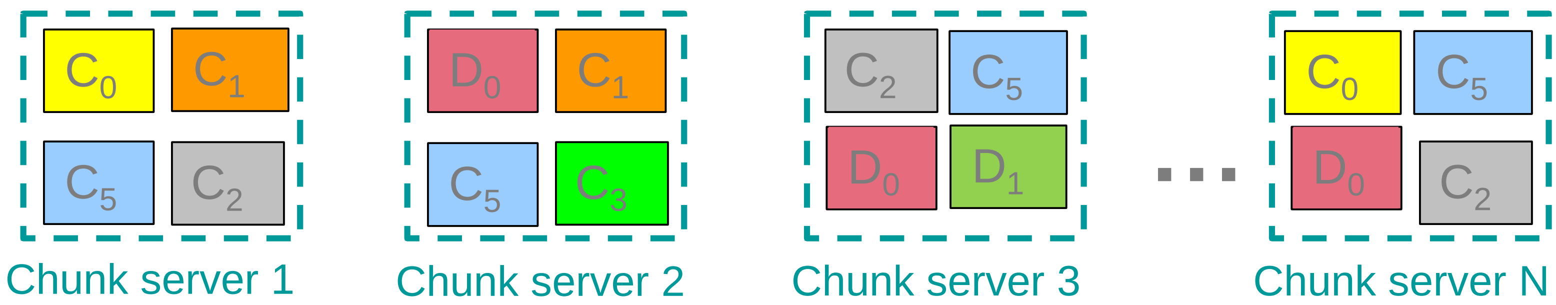
- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System:**
    - Provides global file namespace
    - Google GFS; Hadoop HDFS;
- **Typical usage pattern**
  - Huge files (100s of GB to TB)
  - Data *reads* and *appends* are common
  - Data is rarely *updated* in place

Distributed File System

- Chunk servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Node in Hadoop's HDFS
  - Stores metadata about where files are stored
  - Might be replicated
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

Distributed File System

- **Reliable distributed file system**
- Data kept in “chunks” spread 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

Programming Model: MapReduce

Warm-up task:

- We have a huge text document
- Count the number of times each distinct word appears in the file
- **Sample application:**
  - Analyze web server logs to find popular URLs

Task: Word Count

Case 1:

- File too large for memory, but all `<word, count>` pairs fit in memory

Case 2:

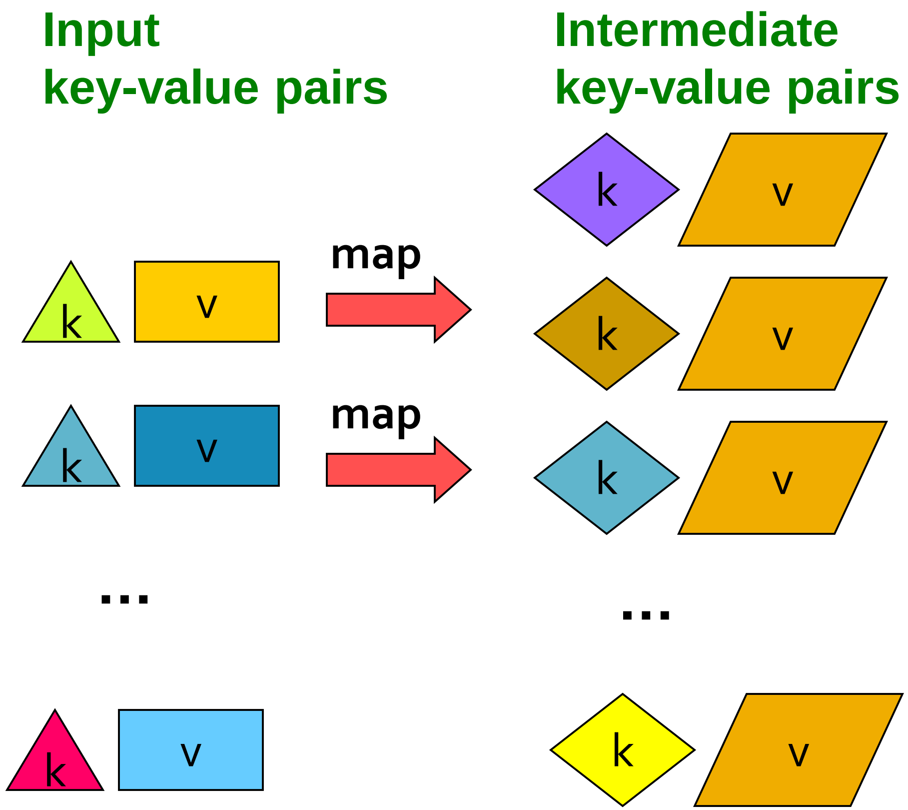
- Count occurrences of words:
  - `words(doc.txt) | sort | uniq -c`
    - where `words` takes a file and outputs the words in it, one per a line
- Case 2 captures the essence of **MapReduce**
  - Great thing is that it is naturally parallelizable

MapReduce: Overview

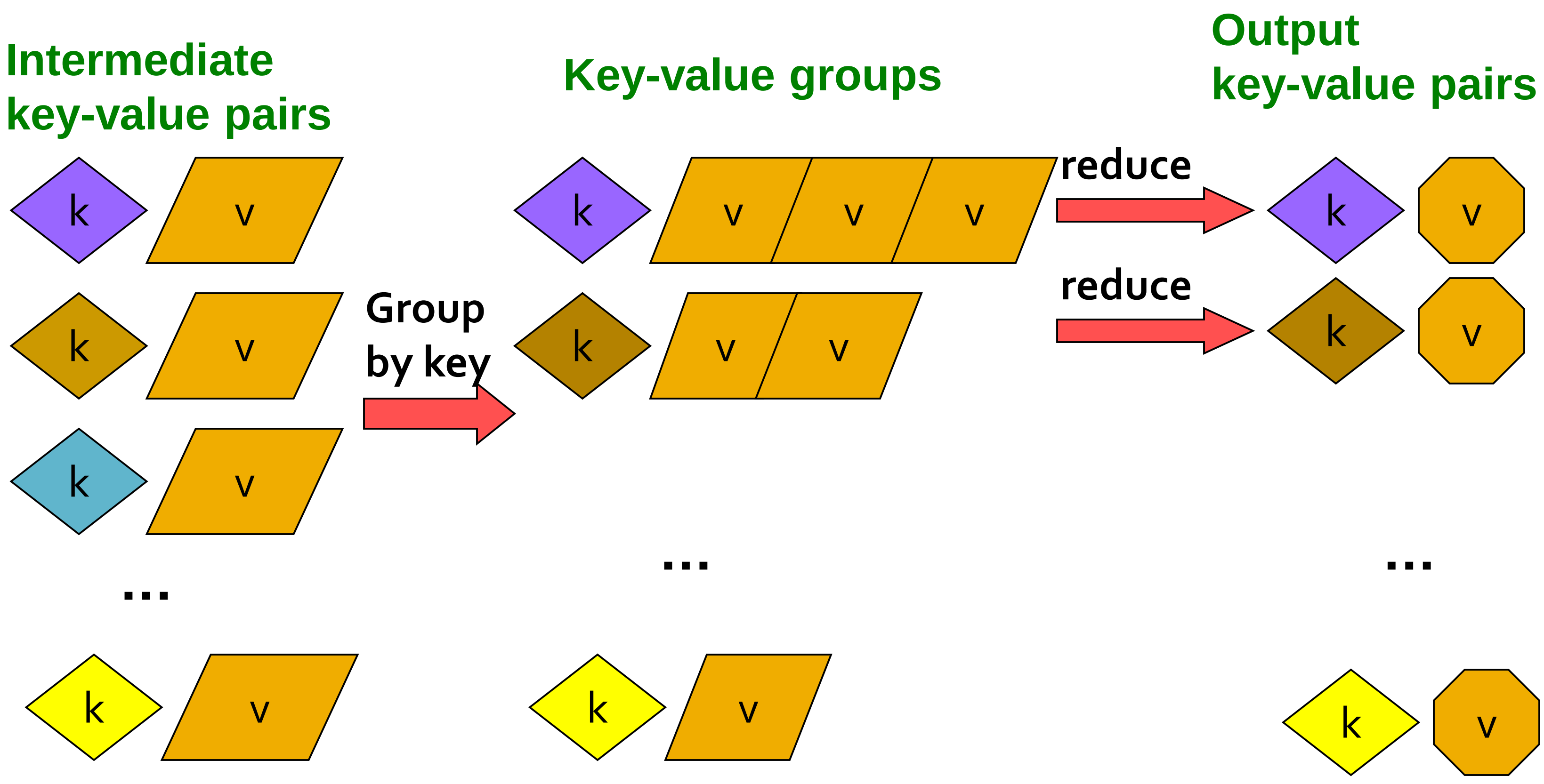
- Sequentially read a lot of data
- Map: Extract something you care about
- Group by key: Sort and Shuffle
- Reduce: Aggregate, summarize, filter or transform
- Write the result

Outline stays the same, **Map** and **Reduce** steps change to fit the problem

MapReduce: The Map Step



MapReduce: The Reduce Step



More Specifically

- **Input:** a set of key-value pairs
- Programmer specifies two methods:
  - **Map(k, v)** → <k', v'>*
    - Takes a key-value pair and outputs a set of key-value pairs
      - E.g., key is the filename, value is a single line in the file
    - There is one Map call for every *(k,v)* pair
  - **Reduce(k', <v'>*)** → <k', v''>*
    - **All values *v'* with same key *k'* are reduced together and processed in *v'* order**
    - There is one Reduce function call per unique key *k'*

MapReduce: Word Counting

Big document	Provided by the programmer		Provided by the programmer
	MAP: Read input and produces a set of **key-value** pairs	**Group by key:** Collect all pairs with same key	**Reduce:** Collect all values belonging to the key and output
The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/mache partnership. '"The work we're doing now -- the robotics we're doing - - is what we're going to need ……………………..	(The, 1) (crew, 1) (of, 1) (the, 1) (space, 1) (shuttle, 1) (Endeavor, 1) (recently, 1) ….	(crew, 1) (crew, 1) (space, 1) (the, 1) (the, 1) (the, 1) (shuttle, 1) (recently, 1) …	(crew, 2) (space, 1) (the, 3) (shuttle, 1) (recently, 1) …
Big document	**(key, value)**	**(key, value)**	**(key, value)**

Only sequential reads

Word Count Using MapReduce

```
map(key, value):
// key: document name
// value: text of the document
   for each word w in value:
      emit(w, 1)

reduce(key, values):
// key: a word
// value: an iterator over counts
      result = 0
      for each count v in values:
            result += v
      emit(key, result)
```

Map-Reduce: Environment

Map-Reduce environment takes care of:

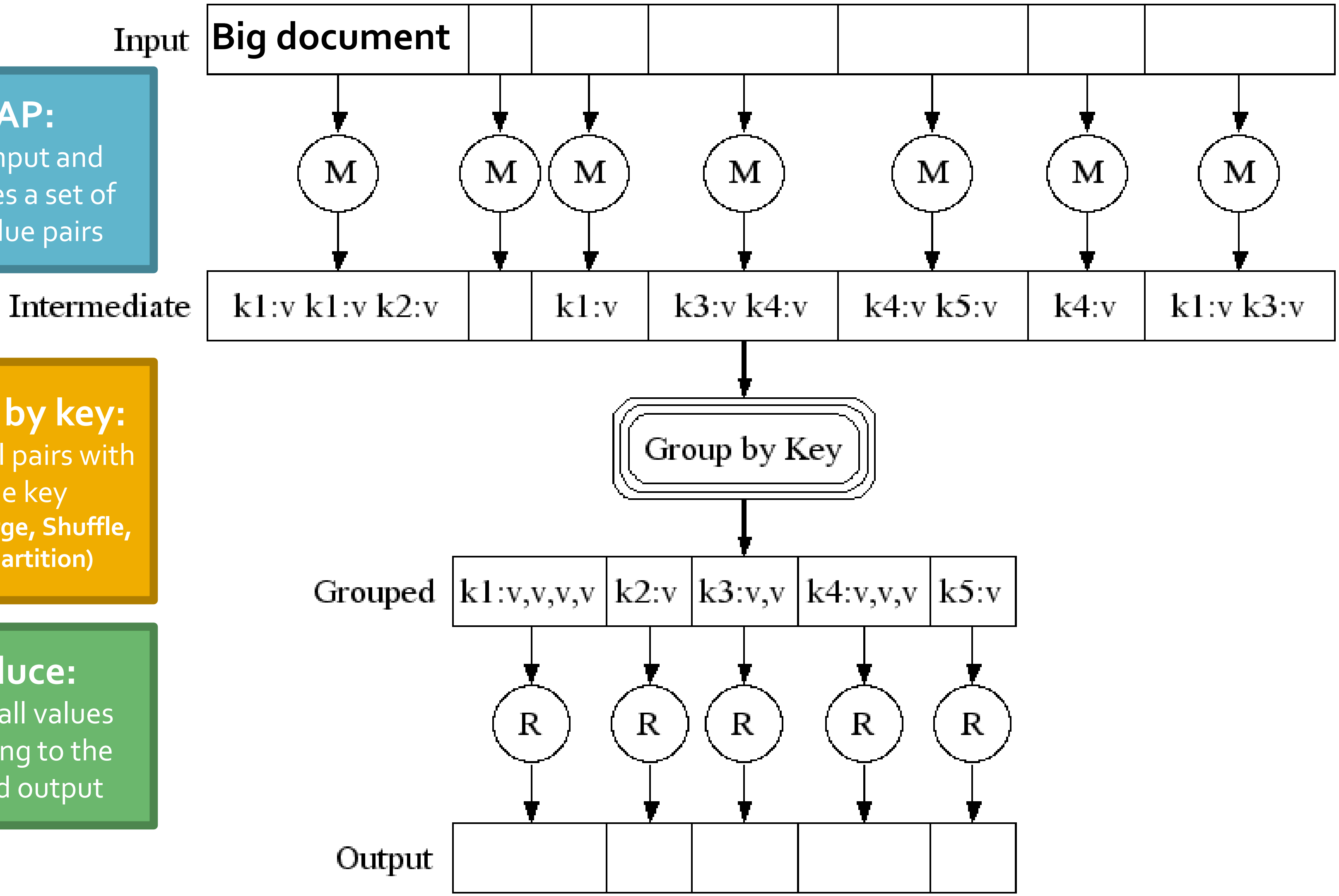
- Partitioning the input data
- Scheduling the program's execution across a set of machines
- Performing the **group by key** step
- Handling machine failures
- Managing required inter-machine communication

Map-Reduce: A diagram

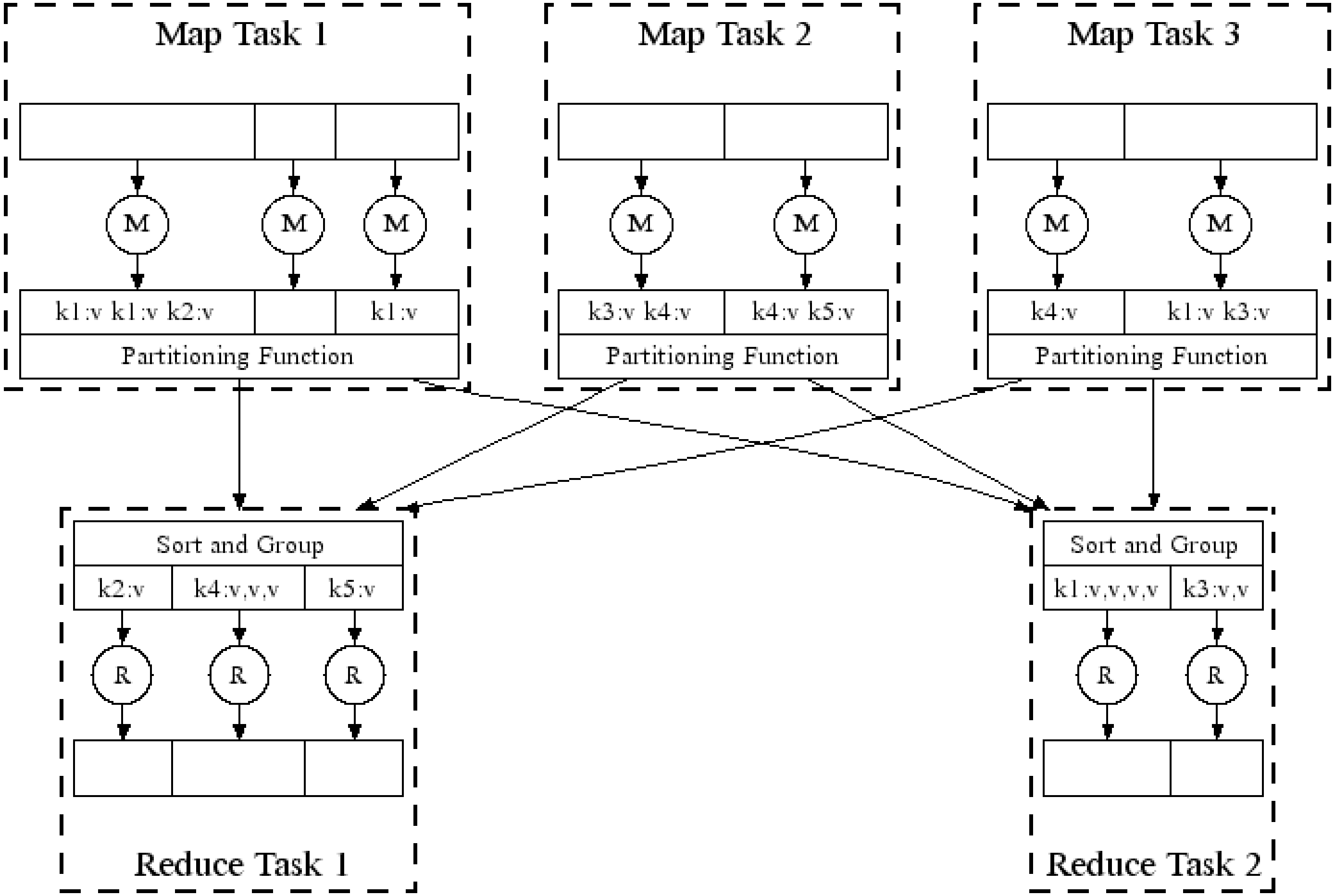
MAP:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

Reduce:
Collect all values belonging to the key and output



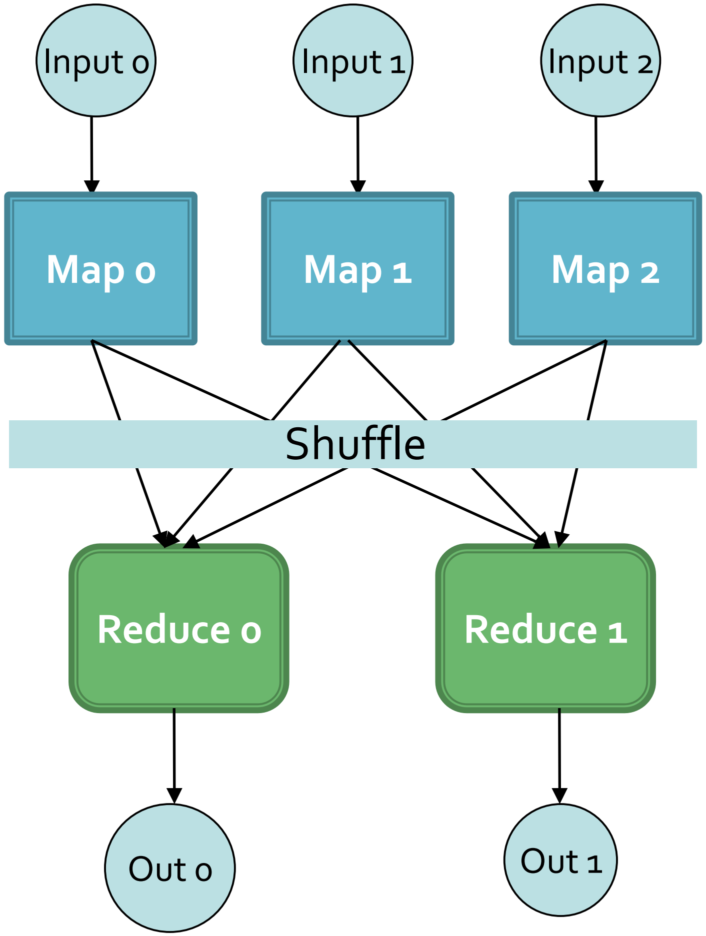
Map-Reduce: In Parallel



All phases are distributed with many tasks doing the work

Map-Reduce

- Programmer specifies:
  - Map and Reduce and input files
- **Workflow:**
  - Read inputs as a set of key-value-pairs
  - **Map** transforms input kv-pairs into a new set of k'v'-pairs
  - Sorts & Shuffles the k'v'-pairs to output nodes
  - All k'v'-pairs with a given k' are sent to the same **reduce**
  - **Reduce** processes all k'v'-pairs grouped by key into new k''v''-pairs
  - Write the resulting pairs to files
- All phases are distributed with many tasks doing the work



Data Flow

- Input and final output are stored on a distributed file system (FS):
  - Scheduler tries to schedule map tasks "close" to physical storage location of input data
- Intermediate results are stored on local FS of Map and Reduce workers
- Output is often input to another MapReduce task

Coordination: Master

- Master node takes care of coordination:
  - **Task status:** (idle, in-progress, completed)
  - **Idle tasks** get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its *R* intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

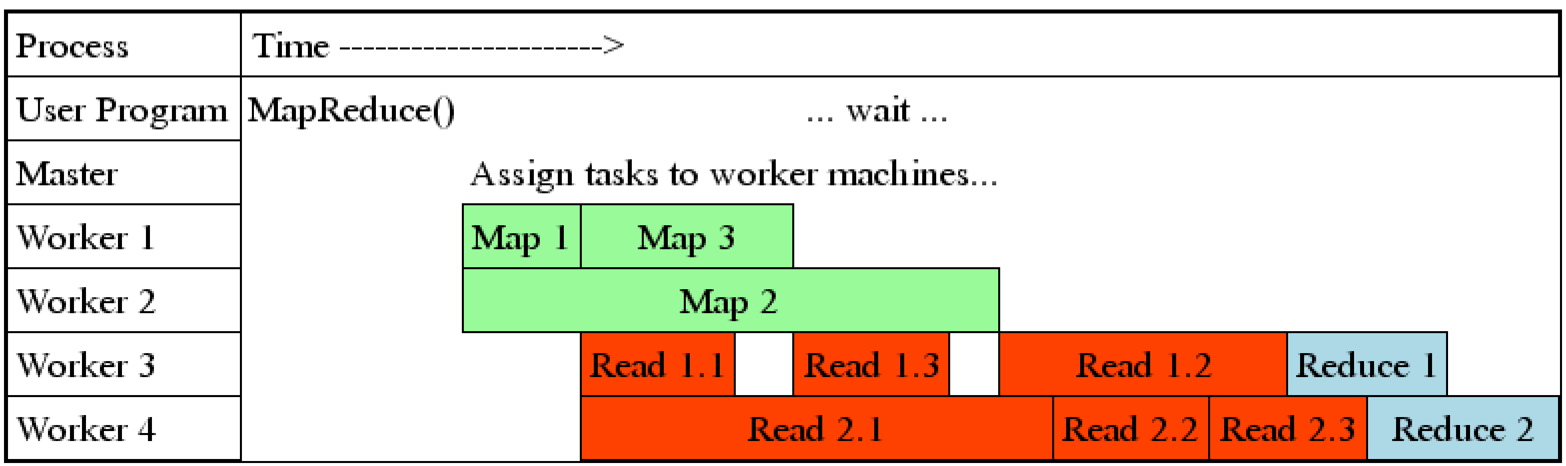
- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Only in-progress tasks are reset to idle
  - Reduce task is restarted
- Master failure
  - MapReduce task is aborted and client is notified

How many Map and Reduce jobs?

- *M* map tasks, *R* reduce tasks
- **Rule of a thumb:**
  - Make *M* much larger than the number of nodes in the cluster
  - One DFS chunk per map is common
  - Improves dynamic load balancing and speeds up recovery from worker failures
- **Usually *R* is smaller than *M***
  - Because output is spread across *R* files

Task Granularity & Pipelining

- **Fine granularity tasks:** map tasks >> machines
  - Minimizes time for fault recovery
  - Can do pipeline shuffling with map execution
  - Better dynamic load balancing

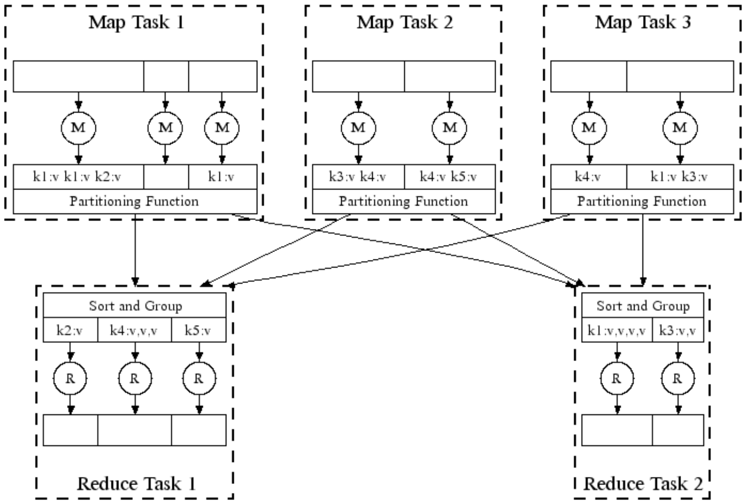


Refinements: Backup Tasks

- Problem
  - Slow workers significantly lengthen the job completion time:
    - Other jobs on the machine
    - Bad disks
    - Weird things
- Solution
  - Near end of phase, copy and run poorly performing tasks (**stragglers**) on another machine
    - Called **speculative execution** (tasks called “backup tasks”)
    - Whichever copy finishes first “wins”
- Effect
  - Dramatically shortens job completion time

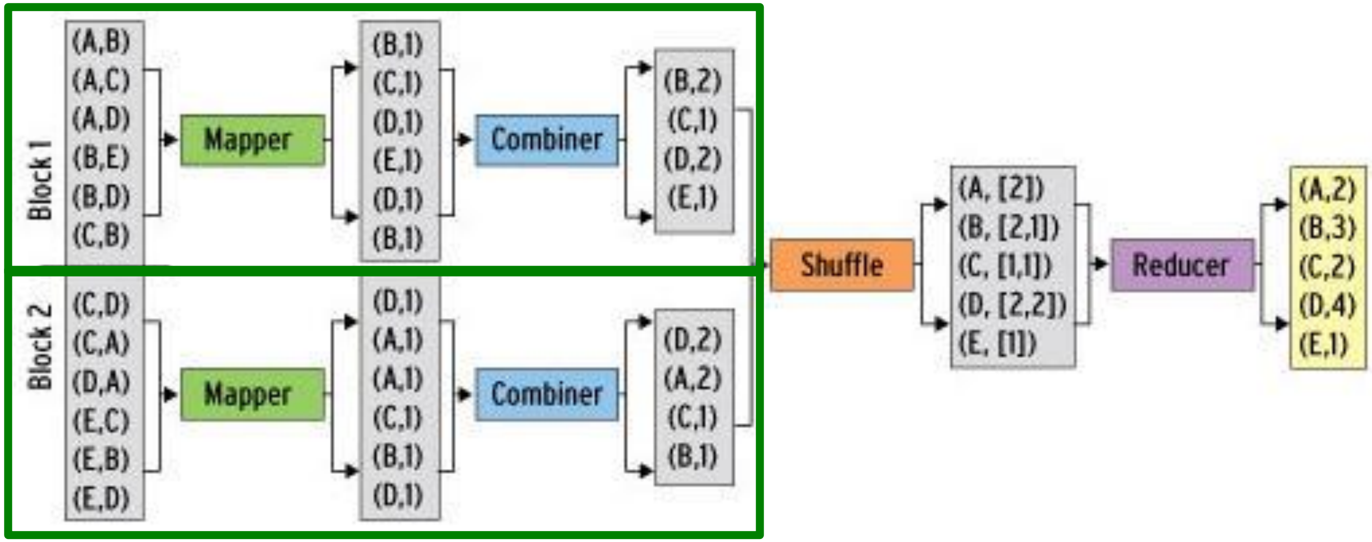
Refinement: Combiners

- Often a Map task will produce many pairs of the form *(k,v_1), (k,v_2), …* for the same key *k*
  - E.g., popular words in the word count example
- **Can save network time by pre-aggregating values in the mapper:**
  - combine(k, list(v_1)) → v_2
  - Combiner is usually same as the reduce function
- Works only if reduce function is **commutative** and **associative**



Refinement: Combiners

- **Back to our word counting example:**
  - Combiner combines the values of all keys of a single mapper (single machine):



  - Much less data needs to be copied and shuffled!

Refinement: Partition Function

- **Want to control how keys get partitioned**
  - Inputs to map tasks are created by contiguous splits of input file
  - Reduce needs to ensure that records with the same intermediate key end up at the same worker
- **System uses a default partition function:**
  - **hash(key) mod *R***
- **Sometimes useful to override the hash function:**
  - E.g., **hash(hostname(URL)) mod *R*** ensures URLs from a host end up in the same output file

Problems Suited for Map-Reduce

Example: Host size

- **Suppose we have a large web corpus**
- **For each host, find the total number of bytes**
  - That is, the sum of the page sizes for all URLs from that particular host

- **Other examples:**
  - Link analysis and graph processing
  - Machine Learning algorithms

Example: Language Model

- **Statistical machine translation:**
  - Need to count number of times every 5-word sequence occurs in a large corpus of documents
- **Very easy with MapReduce:**
  - **Map:**
    - Extract (5-word sequence, count) from document
  - **Reduce:**
    - Combine the counts

Example: Join By Map-Reduce

- **Compute the natural join *R(A,B)* ⋈ *S(B,C)***
- *R* and *S* are each stored in files
- Tuples are pairs *(a,b)* or *(b,c)*

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

R

⋈

B	C
b_2	c_1
b_2	c_2
b_3	c_3

S

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Map-Reduce Join

- **Use a hash function *h* from B-values to *1...k***
- **A Map process turns:**
  - Each input tuple *R(a,b)* into key-value pair *(b,(a,R))*
  - Each input tuple *S(b,c)* into *(b,(c,S))*
- **Map processes** send each key-value pair with key *b* to Reduce process *h(b)*
  - Hadoop does this automatically; just tell it what *k* is.
- Each **Reduce process** matches all the pairs *(b,(a,R))* with all *(b,(c,S))* and outputs *(a,b,c)*.

Cost Measures for Algorithms

- **In MapReduce we quantify the cost of an algorithm using**

1. *Communication cost* = total I/O of all processes
2. *Elapsed communication cost* = max of I/O along any path
3. (*Elapsed*) *computation cost* analogous, but count only running time of processes

Note that here the big-O notation is not the most useful (adding more machines is always an option)

Example: Cost Measures

- **For a map-reduce algorithm:**
  - **Communication cost =** input file size + 2 × (sum of the sizes of all files passed from Map processes to Reduce processes) + the sum of the output sizes of the Reduce processes.
  - **Elapsed communication cost** is the sum of the largest input + output for any map process, plus the same for any reduce process

What Cost Measures Mean

- Either the I/O (communication) or processing (computation) cost dominates
  - Ignore one or the other
- Total cost tells what you pay in rent from your friendly neighborhood cloud
- Elapsed cost is wall-clock time using parallelism

Cost of Map-Reduce Join

- **Total communication cost** $= O(|R|+|S|+|R \bowtie S|)$
- **Elapsed communication cost** = O(s)
  - We're going to pick ***k*** and the number of Map processes so that the I/O limit ***s*** is respected
  - We put a limit ***s*** on the amount of input or output that any one process can have. ***s* could be:**
    - What fits in main memory
    - What fits on local disk
- With proper indexes, computation cost is linear in the input + output size
  - So computation cost is like communication cost

Pointers and Further Reading

Implementations

- Google
  - Not available outside Google
- **Hadoop**
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://lucene.apache.org/hadoop/
- Aster Data
  - Cluster-optimized SQL Database that also implements MapReduce

Cloud Computing

- Ability to rent computing by the hour
  - Additional services e.g., persistent storage
- Amazon’s “Elastic Compute Cloud” (EC2)
- Aster Data and Hadoop can both be run on EC2

Reading

- Jeffrey Dean and Sanjay Ghemawat: MapReduce: Simplified Data Processing on Large Clusters
  - http://labs.google.com/papers/mapreduce.html
- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung: The Google File System
  - http://labs.google.com/papers/gfs.html

Resources

- Hadoop Wiki
  - Introduction
    - http://wiki.apache.org/lucene-hadoop/
  - Getting Started
    - http://wiki.apache.org/lucene-hadoop/GettingStartedWithHadoop
  - Map/Reduce Overview
    - http://wiki.apache.org/lucene-hadoop/HadoopMapReduce
    - http://wiki.apache.org/lucene-hadoop/HadoopMapRedClasses
  - Eclipse Environment
    - http://wiki.apache.org/lucene-hadoop/EclipseEnvironment
- Javadoc
  - http://lucene.apache.org/hadoop/docs/api/

Resources

- Releases from Apache download mirrors
  - http://www.apache.org/dyn/closer.cgi/lucene/hadoop/
- Nightly builds of source
  - http://people.apache.org/dist/lucene/hadoop/nightly/
- Source code from subversion
  - http://lucene.apache.org/hadoop/version_control.html

Further Reading

- Programming model inspired by functional language primitives
- Partitioning/shuffling similar to many large-scale sorting systems
  - NOW-Sort ['97]
- Re-execution for fault tolerance
  - BAD-FS ['04] and TACC ['97]
- Locality optimization has parallels with Active Disks/Diamond work
  - Active Disks ['01], Diamond ['04]
- Backup tasks similar to Eager Scheduling in Charlotte system
  - Charlotte ['96]
- Dynamic load balancing solves similar problem as River's distributed queues
  - River ['99]