UMD DATA605 - Big Data Systems

Storing and Computing Big Data
MapReduce Framework
(Apache) Hadoop
Algorithms
MapReduce vs DBs

Dr. GP Saggese
gsaggese@umd.edu

with thanks to:
Alan Sussman
Amol Deshpande
Authors of www.mmds.org

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Storing and Computing Big Data

MapReduce Framework

(Apache) Hadoop

Algorithms

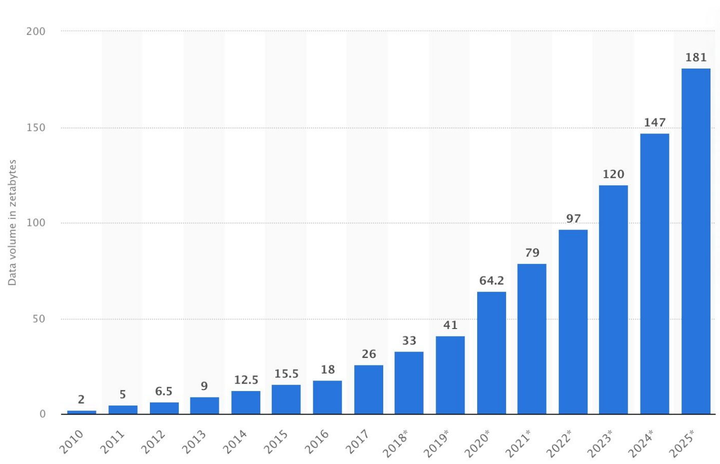
MapReduce vs DBs

Resources

- Silbershatz: Chap 10
- Seminal papers
  - Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung: The Google File System, 2003
  - Jeffrey Dean and Sanjay Ghemawat: MapReduce: Simplified Data Processing on Large Clusters, 2004

Big Data: Sources and Applications

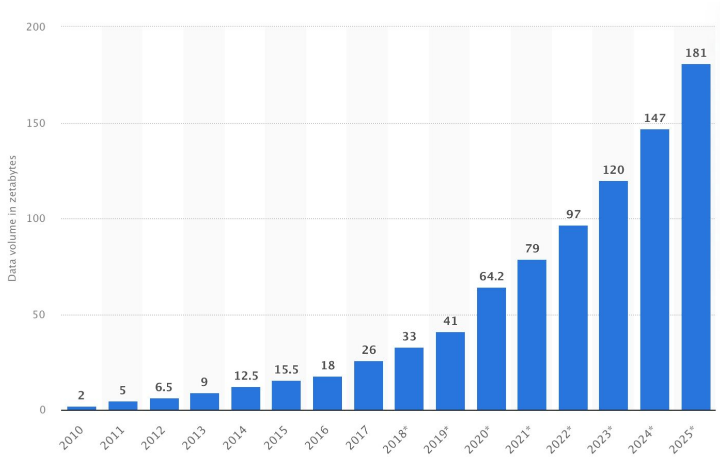
- **Growth of World Wide Web in 1990s and 2000s**
- Storing and querying data much larger than enterprise data
- Extremely valuable data to target advertisements and marketing
  - Web server logs, web links
  - Social media
  - Data from mobile phone apps
  - Transaction data
  - Data from sensors / Internet of Things
  - Metadata from communication data



Volume of data in the world

Big Data: Sources and Applications

- **Big Data characteristics**
  - Volume:
    - Amount of data to store and process is much larger than traditional DBs
    - Too big even for parallel DB systems with 10-100 machines
  - Velocity
    - Store data at very high rate, due to rate of arrival
    - Data might be processed in real-time (e.g., streaming systems)
  - Variety
    - Not all data is relational
    - E.g., semi-structured, textual, graphical data
- **Solution**: process data with 10,000-100,000 machines



Volume of data in the world

Big Data: Sources and Applications

- **Web server logs**
  - Record user interactions with web servers
  - Billions of users click on thousands links per day → TB of data / day
  - Decide what information (e.g., posts, news) to present to users to keep them "engaged"
    - E.g., what user has viewed, what other similar users have viewed
  - Understand visit patterns to optimize for users to find information
  - Determine user preferences and trends to inform business decisions
  - Decide what advertisements to show to which users
    - Maximize benefit to the advertiser
    - Websites are paid for click-through or conversion
- **Click-through rate**
  - A user clicks on an advertisement to get more information
  - It is a measure of success in getting user attention/engagement
- **Conversion rate**
  - When a user actually purchases the advertised product or service

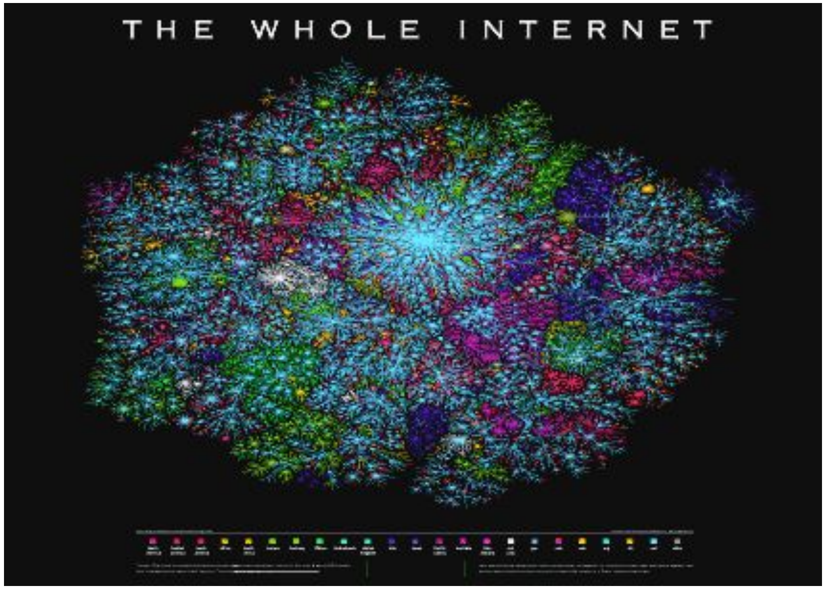
Big Data: Storing and Computing

- Big data needs 10k-100k machines
- **Two problems**
  - Storing big data
  - Processing big data
- **Need to be solved *together* and *efficiently***
  - If one phase is slow → the entire system is slow

Processing the Web: Example

- The web has:
  - 20+ billion web pages
  - Total ~5M TBs = 5 ZB
  - ~1M 5TB hard drives to store the web
- One computer reads 300 MB/sec from disk
  - 5e6 * 1024 * 1024 * 8 / 300 / 3600 / 24 / 365

    = 4,433 years to read the web serially from disk
- It takes even more to do something useful with the data!



Big Data: Storage Systems

- How to store big data?
1. **Distributed file systems**
   - E.g., store large files like log files
2. **Sharding across multiple DBs**
   - Partition records based on shard key across multiple systems
3. **Parallel and distributed DBs**
   - Store data / perform queries across multiple machines
   - Use traditional relational DB interface
4. **Key-value stores**
   - Data stored and retrieved based on a key
   - Limitations on semantics, consistency, querying with respect to relational DBs
   - E.g., NoSQL DB, Mongo, Redis

1) Distributed File Systems

- **Distributed file system**
  - Files stored across a number of machines, giving a single file-system view to clients
    - E.g., Google File System (GFS)
    - E.g., Hadoop File System (HDFS) based on GFS architecture
    - E.g., AWS S3
  - Files are:
    - Broken into multiple blocks
    - Blocks are partitioned across multiple machines
    - Blocks are often replicated across machines
  - **Goals**:
    - Store data that doesn't fit on one machine
    - Increase performance
    - Increase reliability/availability/fault tolerance

2) Sharding Across Multiple DBs

- **Sharding** = process of partitioning records across multiple DBs or machines
- Shard keys
  - Aka partitioning keys / partition attributes
- One or more attributes to partition the data
  - Range partition (e.g., timeseries)
  - Hash partition
- **Pros**
  - Scale beyond a centralized DB to handle more users, storage, processing speed
- **Cons**
  - Replication is often needed to deal with failures
  - Ensuring consistency is challenging
  - Relational DBs are not good at supporting constraints (e.g., foreign key) and transactions on multiple machines

3) Parallel and Distributed DBs

- **Parallel and distributed DBs**: store and process data running on multiple machines (aka "cluster")
  - E.g., Mongo
- **Pros**
  - Programmer viewpoint
    - Traditional relational DB interface
    - Looks like a DB running on a single machine
  - Can run on 10s-100s of machines
  - Data is replicated for performance and reliability
    - Failures are “frequent” with 100s of machines
    - A query can be just restarted using a different machine
- **Cons**
  - Run a query incrementally requires a lot of complexity
  - Limit to the scalability

4) Key-value Stores

- **Problem**
  - Many applications (e.g., web) store a very large number (billions or more) small records (few KBs to few MBs)
  - File systems can't store such a large number of files
  - RDBMSs don't support constraints and transactions on multiple machines
- **Solution**
  - Key-value stores / Document / NoSQL systems
  - Records are stored, updated, and retrieved based on a key
  - Operations are: `put(key, value)` to store, `get(key)` to retrieve data
- **Pros**
  - Partition data across multiple machines easily
  - Support replication and consistency (no referential integrity)
  - Balance workload and add more machines
- **Cons**
  - Features are sacrificed to achieve scalability on large clusters
    - Declarative querying
    - Transactions
    - Retrieval based on non-key attributes

4) Parallel Key-value Stores

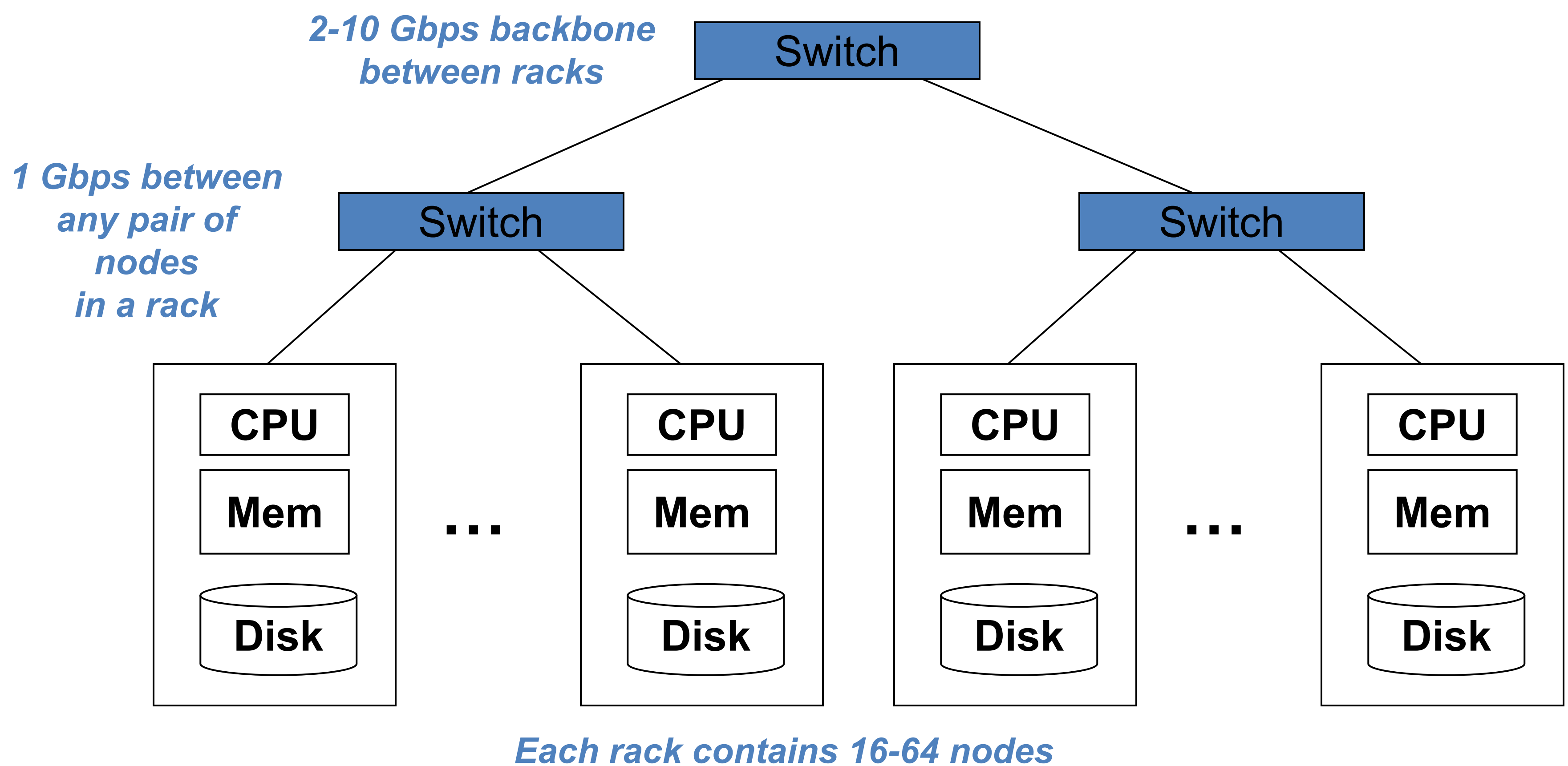
- **Parallel key-value stores**
  - BigTable (Google)
  - Apache HBase (open source version of BigTable)
  - Dynamo, S3 (AWS)
  - Cassandra (Facebook)
  - Azure cloud storage (Microsoft)
  - Redis
- **Parallel document stores**
  - MongoDB cluster
  - Couchbase
- **In-memory caching systems**
  - Store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

Big Data: Computing Systems

- **How to process Big Data?**
- **Challenges**
  - How to distribute computation?
  - How can we make it easy to write distributed programs?
    - Distributed / parallel programming is hard
  - How to store data in a distributed system?
  - How to survive failures?
    - One server may stay up 3 years (1,000 days)
    - If you have 1,000 servers, expect to lose 1 / day
    - E.g., ~1M machines (Google in 2011) → 1,000 machines fail every day!
- **MapReduce**
  - Solve these problems for certain kinds of computations
  - An elegant way to work with big data
  - Started as Google's data manipulation model
    - (But it wasn't 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, now 10M (?)



Cluster Architecture

Cluster Architecture: Network Bandwidth

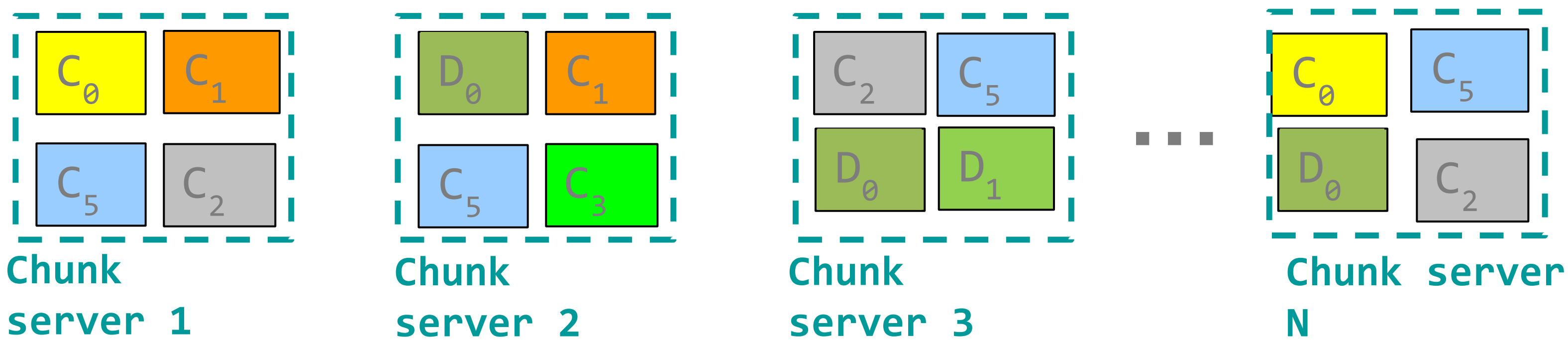
- **Problems**
  - Data is hosted on different machines in a cluster
  - Copying data over a network takes time
- **Solutions**
  - Bring computation close to the data
  - Store files multiple times for reliability/performance
- **MapReduce**
  - Addresses both these problems
  - Storage infrastructure: distributed file system
    - Google GFS, Hadoop HDFS
  - Programming model: MapReduce

Storage Infrastructure

- **Problem**
  - How to store data *persistently* and *efficiently* when nodes can fail?
- **Typical data usage pattern**
  - Huge files (100s of GB to 1TB)
  - Reads and appends are common operations
  - Data is rarely updated in place
- **Solution**
  - Distributed file system
  - Allow files to be stored across a number of machines
  - Files are:
    - Broken into multiple blocks
    - Partitioned across multiple machines
    - Typically with replication across machines
  - Give a single file-system view to clients

Distributed File System

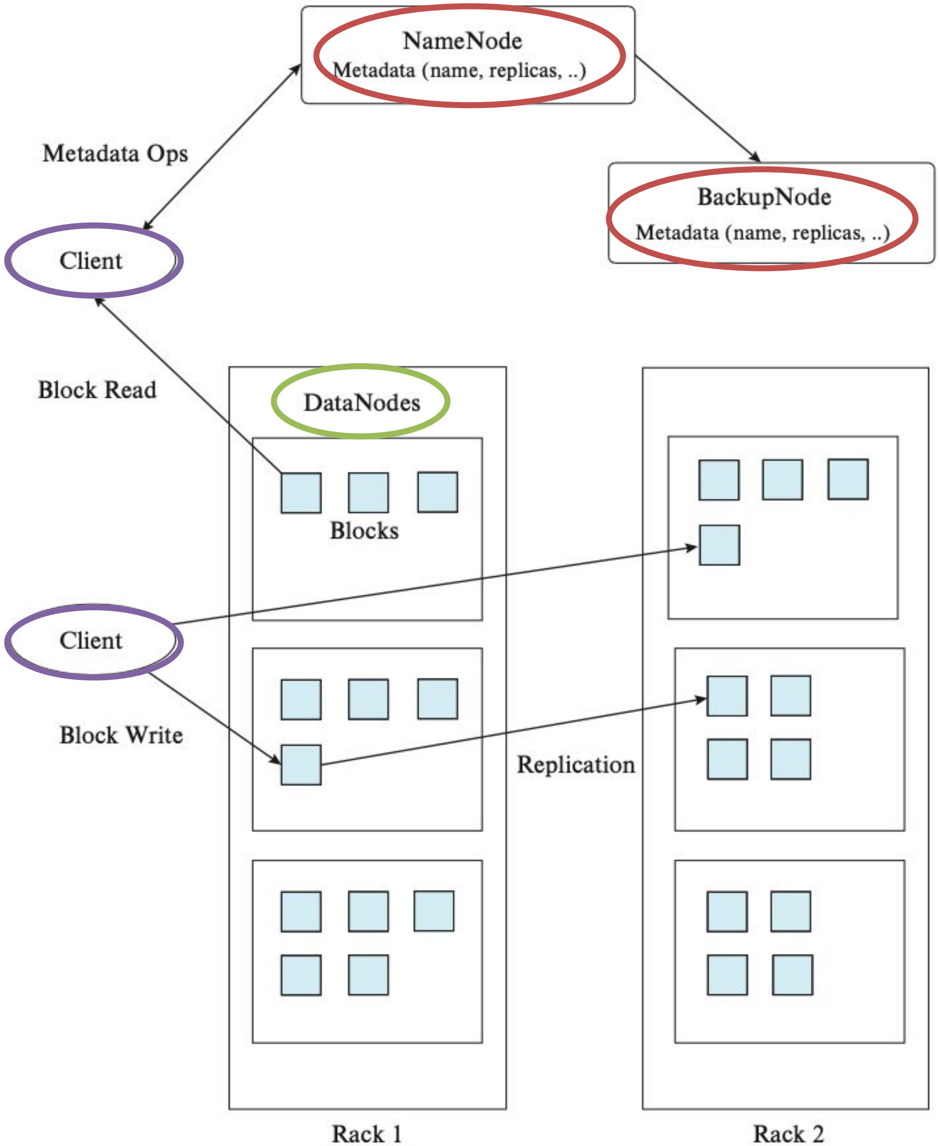
- Reliable distributed file system
  - Data kept in "**chunks**" spread across machines
  - Each chunk **replicated** on different machines
  - Seamless recovery from disk or machine failure



- Bring computation directly to the data
  - "chunk servers" also serve as "compute servers"

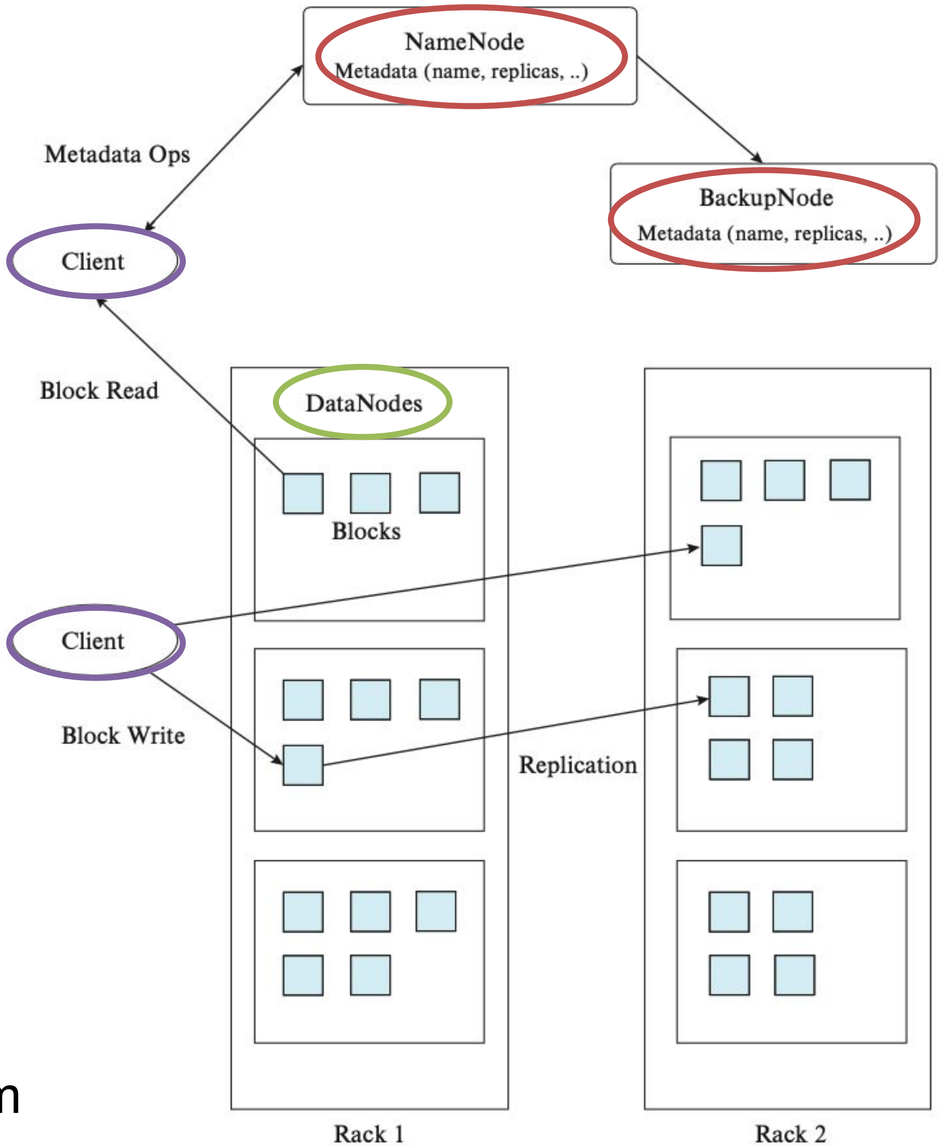
Hadoop Distributed File System

- **NameNode**
  - Store file / dir hierarchy
  - Store metadata about files (e.g., where are stored, size, permissions)
- **DataNodes**
  - Store data blocks
  - File is split into contiguous 16-64MB blocks
  - Each chunk is replicated (usually 2x or 3x)
  - Keep replicas in different server racks



Hadoop Distributed File System

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



MapReduce: Overview

- **MapReduce programming model**
  - Inspired by functional programming (e.g., Lisp)
  - Common pattern of parallel programming
  - Basic algorithm
    - Given a large number of records to process
    - The same function `map()` is applied to each record
    - Group the results by key
    - A form of aggregation `reduce()` is applied to the result of `map()`
- **Example**
  - Goal: sum the length of all the tuples in a document
    - E.g., `[() (a,) (a, b) (a, b, c)]`
  - **map**(function, set of values)
    - Apply function to each value in the set (e.g., len)
      `map(len, [(), (a), (a, b), (a, b, c))]) ⇒ [0, 1, 2, 3]`
  - **reduce**(function, set of values)
    - Combine all the values using a binary function (e.g., add)
      `reduce(add, [0, 1, 2, 3]) ⇒ 6`

MapReduce: Overview

- Structure of computation stays the same
  - **Read input**
    - Sequentially or in parallel
  - **Map**
    - Extract / compute something from records in the inputs
  - **Group by key**
    - Sort and shuffle
  - **Reduce**
    - Aggregate, summarize, filter, or transform
  - **Write the result**

- MapReduce framework (e.g., Hadoop, Spark) implements the general algorithm

- User specifies the **`map()`** and **`reduce()`** functions to solve the problem

MapReduce: Word Count

- **Word Count**
  - “Hello world” of MapReduce
  - We have a huge text file (so big you can’t keep it in memory)
  - Count the number of times each distinct word appears in the file
- **Sample application**
  - Analyze web server logs to find popular URLs
- **Linux solution**
  - Example file from https://en.wikipedia.org/wiki/Hot_Cross_Buns_(song)

```
> more doc.txt
One a penny, two a penny, hot cross buns.
> words doc.txt | sort | uniq -c
a 2
buns 1
cross 1
...
```

- `words` takes a file and outputs the words one per line
- This Unix pipeline is naturally parallelizable in a MapReduce sense

MapReduce: Word Count

Action	Python code	Example
Read input	`values = read(file_name)`	`“One a penny, two a penny, hot cross buns.”`
Map: - Invoke **`map()`** on each input record - Emit 0 or more output data items	`def map(values):` `  # values: words in document` `  for word in values:` `    emit(word, 1)`	***Map:*** `[(“one”, 1), (“a”, 1), (“penny”, 1),(“two”, 1), (“a”, 1), (“penny”, 1), (“hot”, 1), (“cross”, 1), (“buns”, 1)]`
Group by key: - Gather all outputs from **`map()`** stage - Collect outputs by keys		***Group by key:*** `[(“a”, [1, 1]), (“buns”, [1]), (“cross”, [1]), (“hot”, [1]), (“one”, [1]), (“penny”, [1, 1]), (“two”, [1])]`
Reduce: - Combine the list of outputs with same keys	`def reduce(key, values):` `  # key: a word` `  # value: a list of counts` `  result = 0` `  # result = sum(values)` `  for count in values:` `    result += count` `  emit(key, result)`	***Reduce:*** `[(“one”, 1), (“a”, 2), (“penny”, 2), (“two”, 1), (“hot”, 1), (“cross”, 1), (“buns”, 1)]`

MapReduce: Word Count

Provided by the programmer (above Map) | **Provided by the programmer** (above Reduce)

Map:
Read input
Produce 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/machine partnership. '"The work we're doing now -- the robotics we're doing -- is what we're going to need …

Big document

(The, 1)
(crew, 1)
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently, 1)
….

(key, value)

(crew, [1, 1])
(space, [1])
(the, [1, 1, 1])
(shuttle, [1])
(recently, [1])
…

(key, value)

(crew, 2)
(space, 1)
(the, 3)
(shuttle, 1)
(recently, 1)
…

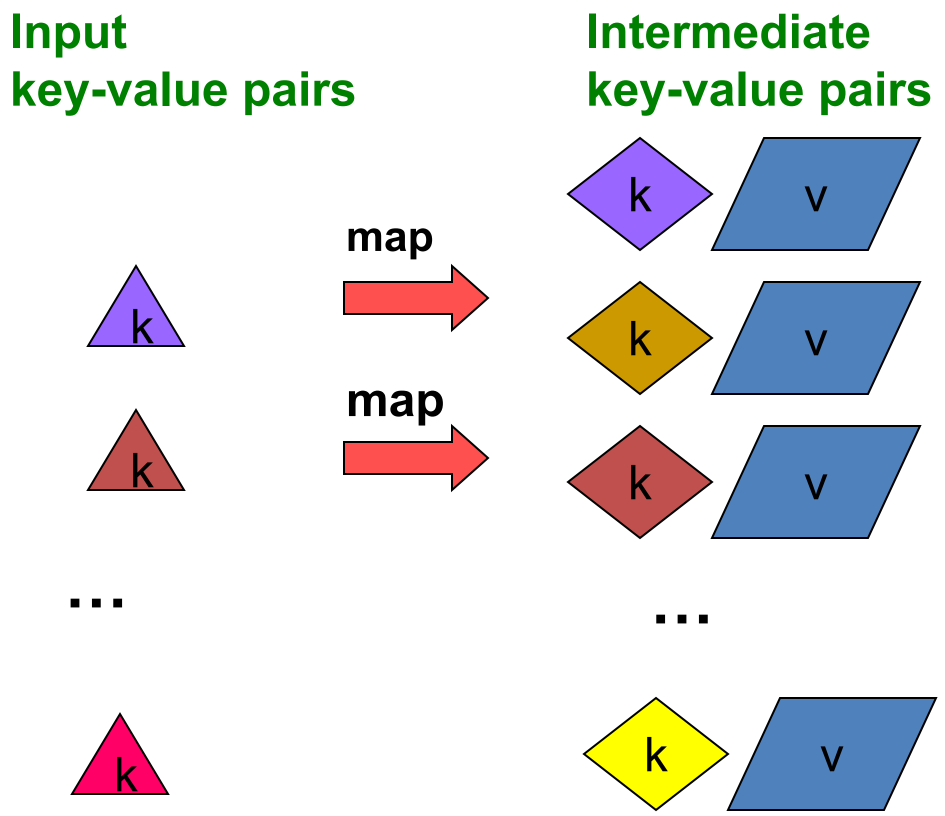
(key, value)

MapReduce: Map Step

```
map(values: List):
  # values: words in document
  for word in values:
    emit(word, 1)
```

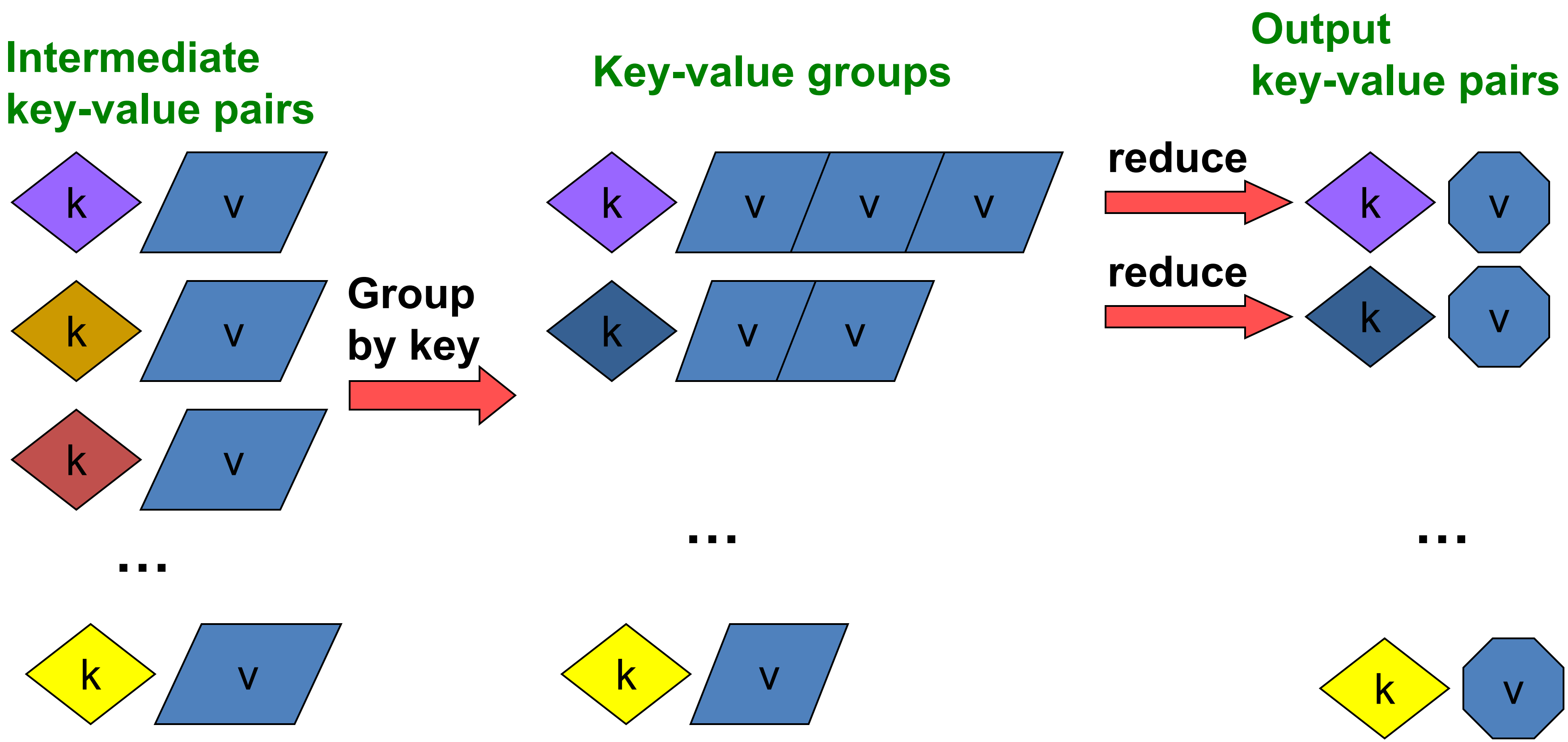
map() needs to process all the values

can output 0 or more tuples for each input



MapReduce: Reduce Step

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



MapReduce: Interfaces

- Input: read key-value pairs `List[Tuple[k, v]]`
- Programmer specifies two methods map and reduce

`Map(Tuple[k, v]) → List[Tuple[k, v]]`

- Take a key-value pair and output a set of key-value pairs
  - E.g., key is a file, value is the number of occurrences
  - "One a penny" → [("One", 1), ("a", 1), ("penny", 1)]
- There is one `Map` call for every *(k, v)* pair

`GroupBy(List[Tuple[k, v]]) → List[Tuple[k, List[v]]]`

- Group and optionally sort all the records with the reduce key

`Reduce(Tuple[k, List[v]]) → Tuple[k, v]`

- All values *v'* with same key *k'* are reduced together
- There is one `Reduce` call per unique key *k'*

- Output: write key-value pairs `List[Tuple[k, v]]`

MapReduce: Log Processing

- Log file recording access to a website with format
  `date, hour, filename`
- **Goal**: find how many times each files is accessed during Feb 2013

- Input
  - Read the file and split into lines
- Map
  - Parse each line into the 3 fields
  - If the date is in the required interval emit(dir_name, 1)
- GroupBy
  - The reduce key is the filename
  - Accumulate all the (key, value) with the same filename
- Reduce
  - Add the values for each list of (key, value) since they have the same filename
  - Output the number of access to each file
- Output
  - Write results on disk separated by newline

After Input

```
...
2013/02/21 10:31:22.00EST /slide-dir/11.ppt
2013/02/21 10:43:12.00EST /slide-dir/12.ppt
2013/02/22 18:26:45.00EST /slide-dir/13.ppt
2013/02/22 18:26:48.00EST /exer-dir/2.pdf
2013/02/22 18:26:54.00EST /exer-dir/3.pdf
2013/02/22 20:53:29.00EST /slide-dir/12.ppt
...
```

After Map

```
[(`/slide-dir/11.ppt`, 1), ...]
```

After GroupBy

```
[(`/slide_dir/11.ppt`, 1), ...,
(`/slide-dir/12.ppt`, [1, 1]), ...]
```

After Reduce

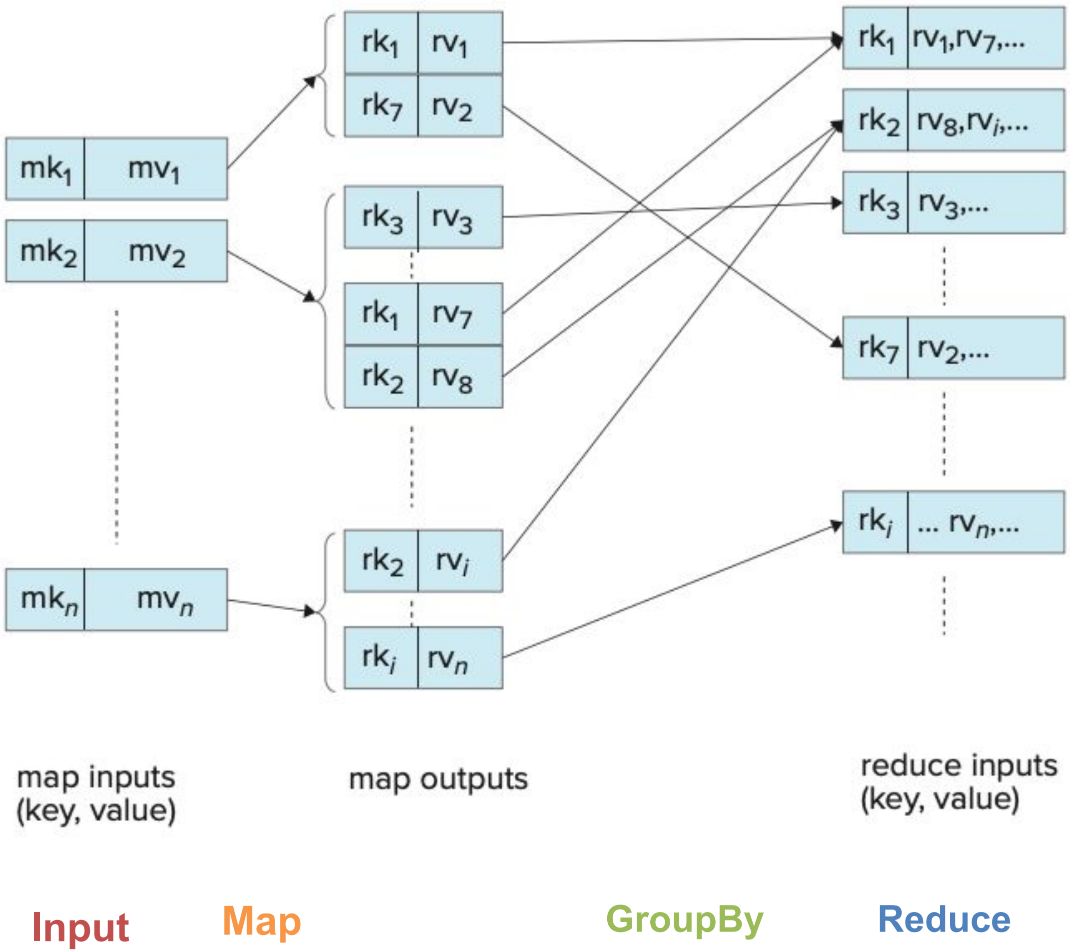
```
[(`/slide_dir/11.ppt`, 1), ...,
(`/slide-dir/12.ppt`, 2), ...]
```

Output

```
/slide_dir/11.ppt 1
...
/slide-dir/12.ppt 2
...
```

MapReduce: Data Flow

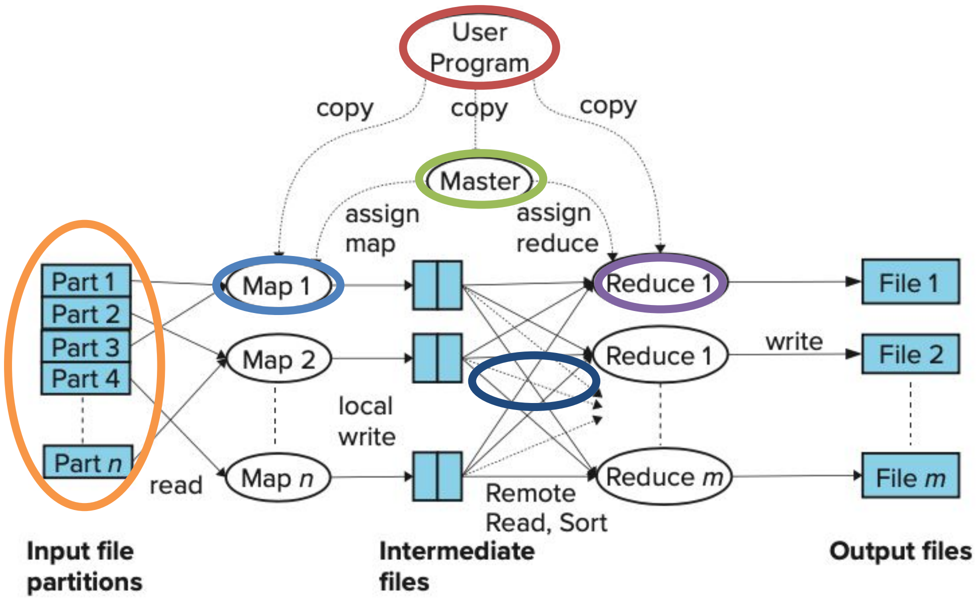
- Focusing on MapReduce functionality / flow of the data to expose the parallelism



- **Input**
- **Map**
  - mk_i = map keys
  - mv_i = map input values
- **GroupBy**
  - Shuffle / collect the data
- **Reduce**
  - rk_i = reduce keys
  - rv_i = reduce input values
  - Reduce outputs are not shown

MapReduce: Parallel Data Flow

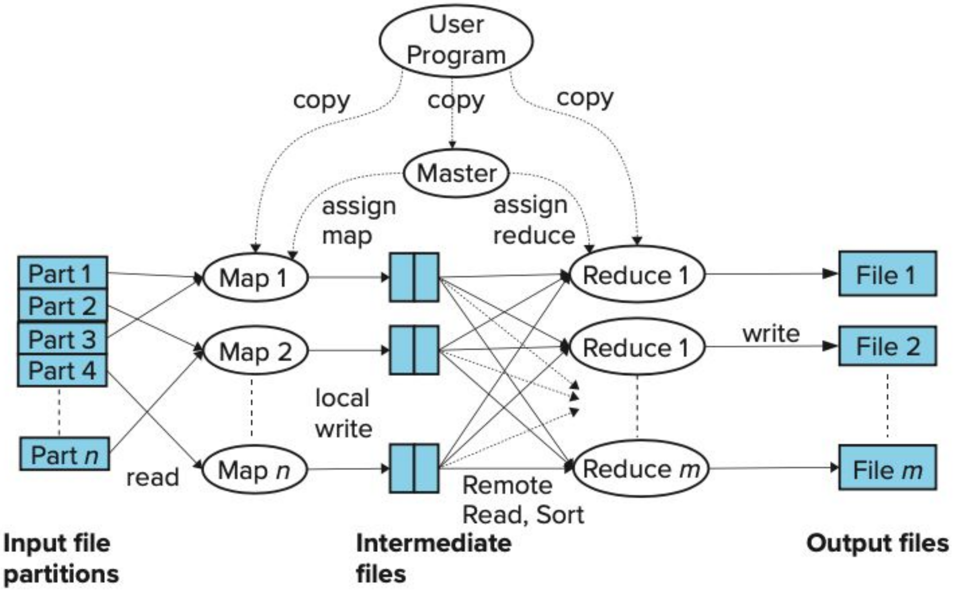
- **User program** specifies map/reduce code
- **Input data** is partitioned across multiple machines (HDFS)
- **Master** node sends copies of the code to all computing nodes
- **Map**
  - *n* data chunks to process
  - Functions executed in parallel on multiple *k* machines
  - Output data from *Map* is saved on disk
- **GroupBy / Sort**
  - Output data from *Map* is sorted and partitioned based on reduce key
  - Different files are created for each *Reduce* task
- **Reduce**
  - Functions executed in parallel on multiple machines
  - Each work on some part of the data
  - Output data from Reduce is saved on disk
- **Write to disk**



- All operations use HDFS as storage
- Machines are reused for multiple computations (Map, GroupBy, Reduce) at different times

Master Node Responsibilities

- **Master node takes care of coordination**
  - Each task has 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 intermediate files
  - Master pushes this info to *Reduce tasks*
  - Reduce tasks become idle and can get scheduled
- **Master node pings workers periodically to detect failures**



Dealing with Failures

- **Map worker failure**
  - Failed map tasks are reset to idle (i.e., back in the queue for execution)
  - 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
  - Client is notified

How many Map and Reduce jobs?

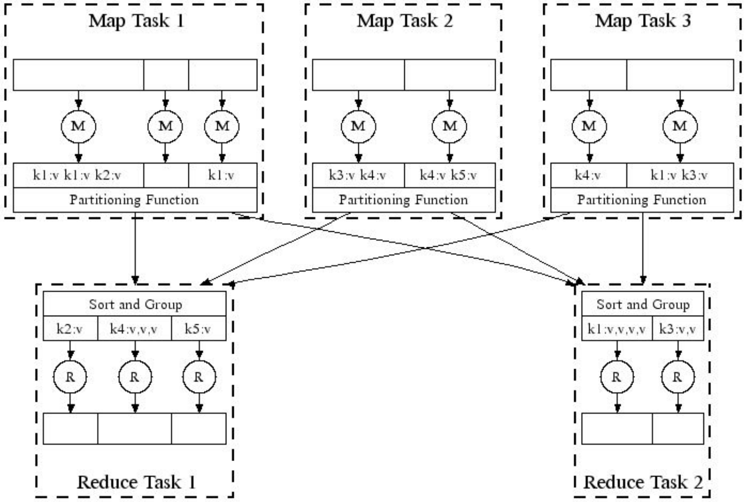
- ***M* map tasks**
- ***R* reduce tasks**
- ***N* worker nodes**
- Rules of thumb
  - $M >> N$
    - Pros
      - Improve dynamic load balancing
      - Speed up recovery from worker failures
    - Cons
      - More communication between *Master* and *Worker Nodes*
      - Lots of smaller files
  - $R > N$
    - Usually $R < M$
    - Output is spread across fewer files

Refinements: Backup Tasks

- **Problem**
  - Slow workers significantly lengthen the job completion time
  - Slow workers due to:
    - Older processor
    - Not enough RAM
    - Other jobs on the machine
    - Bad disks
    - OS thrashing / virtual memory hell
- **Solution**
  - Near the end of Map / Reduce phase
    - Spawn backup copies of tasks
    - Whichever one finishes first "wins"
- **Result**
  - Shorten job completion time

Refinement: Combiners

- **Problem**
  - Often a *Map* task produces many pairs for the same key *k*
    `[(k₁,v₁), (k₁,v₂), ...]`
  - E.g., common words in the word count example
  - Increase complexity of the GroupBy stage
- **Solution**
  - Pre-aggregate values in the *Map* with a *Combine*
    $[(k_1,(v_1,v_2, \ldots), k_2,(\ldots)]$
  - *Combine* is usually the same as the *Reduce* function
  - Works only if *Reduce* function is commutative and associative
- **Result**
  - Better data locality
  - Less shuffling and reordering
  - Less network / disk traffic



Refinement: Partition Function

- **Problem**
  - Sometimes users want to control how keys get partitioned
  - Inputs to *Map* tasks are created by contiguous splits of input file
  - MapReduce uses a default partition function

    `hash(key) mod R`
  - Reduce needs to ensure that records with the same intermediate key end up at the same worker
- **Solution**
  - 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

UMD DATA605 - Big Data Systems

MapReduce Framework

(Apache) Hadoop

Algorithms

MapReduce vs DBs

Implementations of MapReduce

- **Google**
  - Not available outside Google
- **Hadoop**
  - Website
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Hadoop Wiki
    - Introduction, Getting Started, Map/Reduce Overview
- **Amazon Elastic MapReduce (EMR)**
  - Website
  - Hadoop MapReduce running on Amazon EC2
  - Can also run Spark, HBase, Hive, …
- **Spark**
- **Dask**

MapReduce: Hadoop

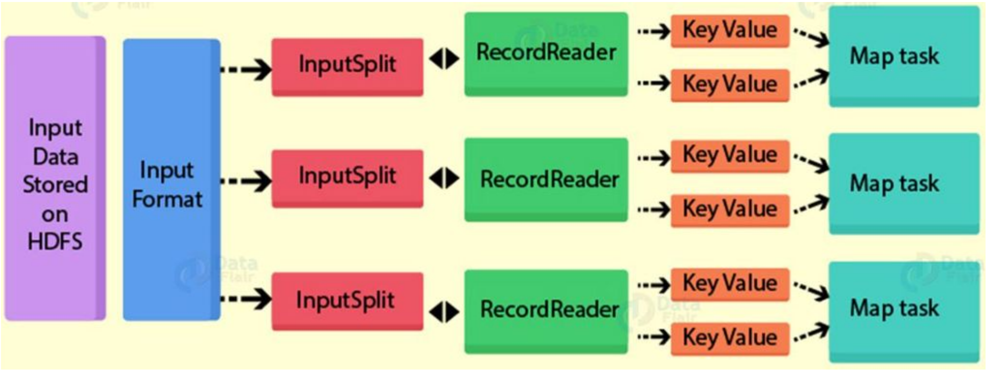
- Hadoop is an open-source implementation of MapReduce
- Functionalities
  - Partition the input data (HDFS)
  - Input adapters
    - E.g., HBase, MongoDB, Cassandra, Amazon Dynamo
  - Schedule program's execution across a set of machines
  - Handle machine failures
  - Manage inter-machine communication
  - Perform the *GroupByKey* step
  - Output adapters
    - E.g., Avro, ORC, Parquet
  - Schedule multiple *MapReduce* jobs

Data Flow

- Input, intermediate, final outputs are stored in a distributed file system (HDFS)
  - Every operation in Hadoop goes from disk to disk
- Adapters to read / partition the data in chunks
- Scheduler tries to schedule map tasks “close” to physical storage location of input data
  - Intermediate results (e.g., GroupBy) are stored on local FS of Map and Reduce workers
- Output is often input to another MapReduce task

Input Data

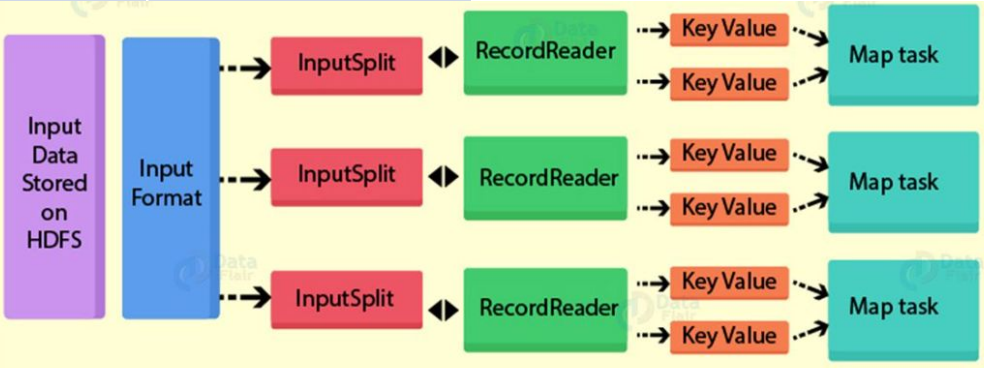
- **InputData** stores the data for a **MapTask** typically in a distributed file system (e.g., HDFS)
- The format of input data is arbitrary
  - Line-based log files
  - Binary files
  - Multi-line input records
  - Something else
    - E.g., an SQL database



InputFormat

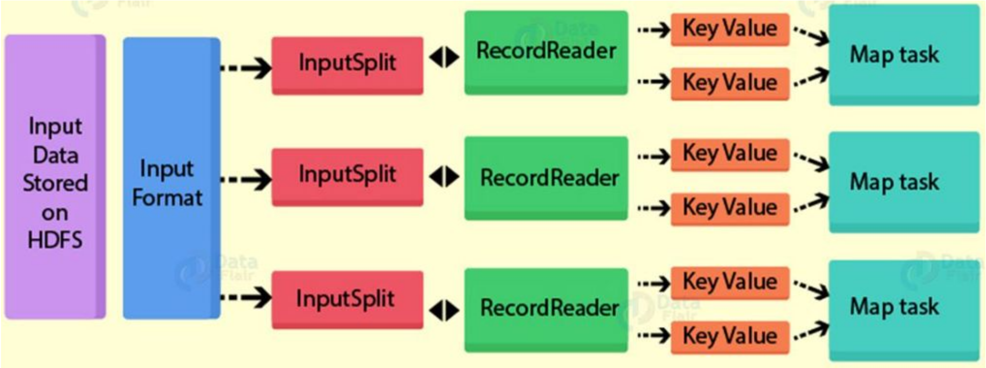
- **InputFormat** class reads and splits up the input files
  - Select the files that should be used for input
  - Defines the **InputSplits** that break a file
  - Provides a factory for **RecordReaders** objects that read the file

InputFormat	Description	Key	Value
TextInputFormat	Default format; reads lines of text files	The byte offset of the line	The line contents
KeyValueInputFormat	Parses lines into (K, V) pairs	Everything up to the first tab character	The remainder of the line
SequenceFileInputFormat	A Hadoop-specific high-performance binary format	User-defined	User-defined



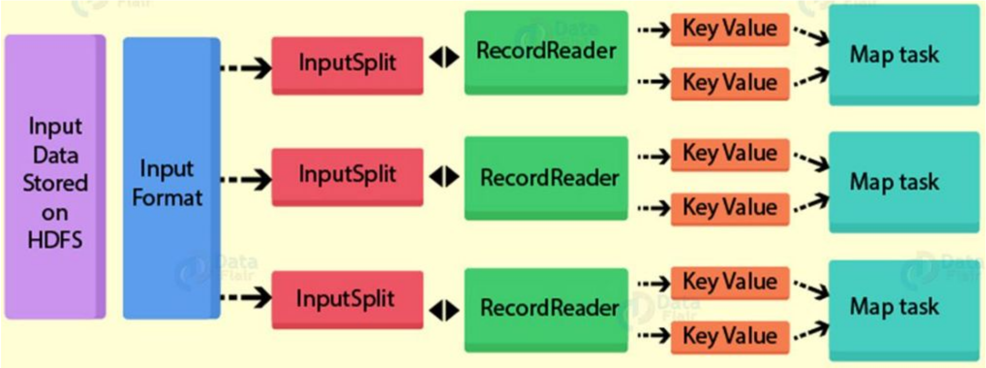
InputSplit

- **InputSplit** describes a unit of work that comprises a single **MapTask**
  - By default, the **InputFormat** breaks a file up into 64MB splits
- By dividing the file into splits
  - Each **MapTask** corresponds to a single input split
  - Several **MapTasks** to operate on a single file in parallel



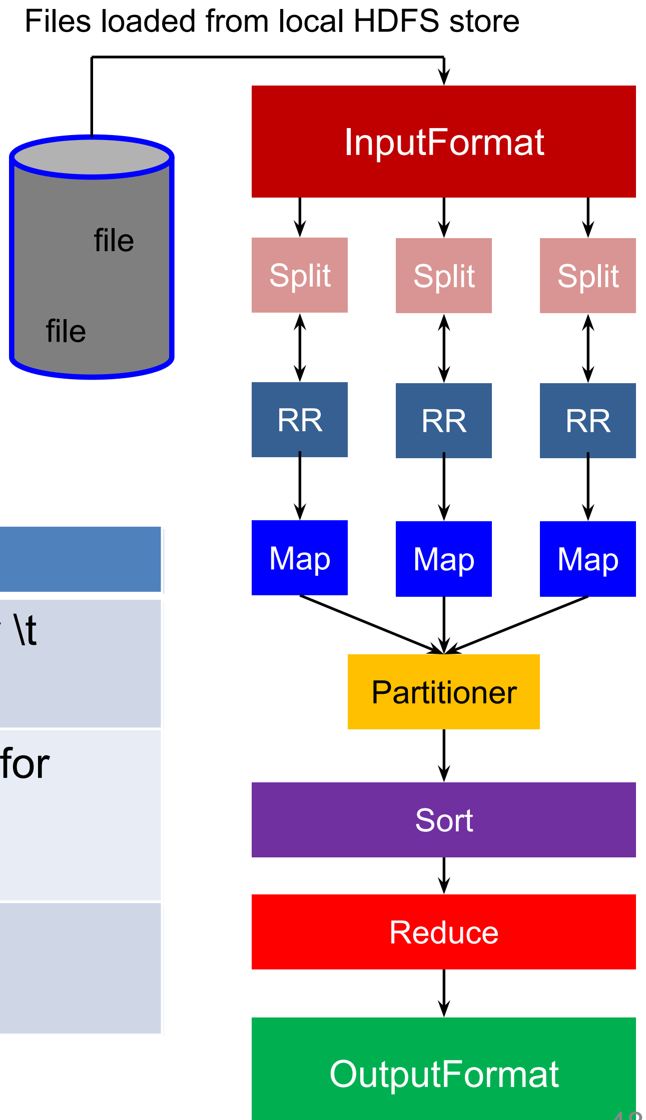
RecordReader

- The **InputSplit** defines a slice of work but does not describe how to access it
- The **RecordReader** class
  - Loads data from its source and converts it into **(K, V) pairs** suitable for reading by **MapTasks**
  - Is invoked repeatedly on the input until the entire **InputSplit** is consumed
  - Each invocation leads to a call of the map function defined by the programmer



OutputFormat

- The **OutputFormat** class
  - defines the way (K,V) pairs produced by **Reducers** are written to output files
  - write to files on the local disk or in HDFS in different formats



OutputFormat	Description
TextOutputFormat	Default; writes lines in "key \t value" format
SequenceFileOutputFormat	Writes binary files suitable for reading into subsequent MapReduce jobs
NullOutputFormat	Generates no output files

UMD DATA605 - Big Data Systems

MapReduce Framework

(Apache) Hadoop

Algorithms

MapReduce vs DBs

MapReduce: Applications

- Major classes of applications
  - Text tokenization, indexing, and search
  - Processing of large data structures
  - Data mining and machine learning
  - Link analysis and graph processing

Example: Language Model

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

Cost Measures for Distributed Algorithms

- **Quantify the cost of a parallel algorithm in terms of:**
  1. Communication cost
     - = total I/O of all processes
     - Related to disk usage as well
  2. Elapsed communication cost
     - = max I/O along any path (critical path)
  3. Elapsed computation cost
     - = end-to-end running time of algorithm
     - It is the wall-clock time using parallelism
- **Total cost**
  – = what you pay as rent to your “friendly” neighborhood cloud provider
    - CPU + disk + I/O used

  – Either CPU, disk, I/O cost dominates → ignore the others
- **In this case, the big-O notation is not the most useful**
  – The actual cost matters and not the asymptotic cost!
  – Multiplicative constant matters
  – Adding more machines is always an option

MapReduce Cost Measures

- **For a map-reduce algorithm:**
  - **Communication cost**
    - = total I/O of all processes
    - input file size
    - + 2 × (sum of the sizes of all files passed from Map processes to Reduce processes)
      - You need to write and read back the data
    - + the sum of the output sizes of the Reduce processes
  - **Elapsed communication cost**
    - = max of I/O along any path
    - sum of the largest input + output for any Map process, plus the same for any Reduce process
  - **Elapsed computation cost**
    - = end-to-end running time of algorithm
    - Ideally all Map and Reduce processes end at the same time
    - Workload is "perfectly balanced"

Example: Join By MapReduce

- Compute the natural join **R(A,B)⋈S(B,C)** joining on column **B**
- **R** and **S** are stored in files as pairs **(a, b)** or **(b, c)**
- Use a hash function *h* from B-values to *h(b)* in [1, ..., k]
- **Map task**
  - Transform an input tuple *R(a, b)* into key-value pair *(h(b), (a, R))*
  - Each input tuple *S(b, c)* → *(h(b), (c, S))*
- **GroupBy task**
  - Each key-value pair with key *b* to is sent to Reduce task *h(b)*
  - Hadoop does this automatically; just tell it what *h* is
- **Reduce task**
  - Matches all the pairs (b, (a, R)) with all (b, (c, S)) to get (a, b, c)
  - Output (a, c)

R

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

⋈

S

B	C
b_2	c_1
b_2	c_2
b_3	c_3

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Cost of MapReduce Join

- **Total communication cost**
  - = total I/O of all processes
  - = $O(|R|+|S|+|R \bowtie S|)$
  - You need to read all the data and then write the result
  - It doesn't matter how you split the computation
- **Elapsed communication cost**
  - We put a limit ***s*** on the amount of input or output that any one process can have, e.g.,
    - What fits in main memory
    - What fits on local disk
  - = $O(s)$
  - We're going to pick the number of Map and Reduce processes so that the I/O limit ***s*** is respected
- **Computation cost**
  - = $O(|R|+|S|+|R \bowtie S|)$
  - Using proper indexes there is no shuffle
  - So computation cost is like communication cost

UMD DATA605 - Big Data Systems

MapReduce Framework

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History

- Abstract ideas about MapReduce have been known before Google's MapReduce paper
- **The strength of MapReduce comes from simplicity, ease of use, and performance**
  - Declarative design
  - User specifies what is to be done, not how many machines to use, etc...
  - Many times commercial success comes from making something simple to use
- MapReduce can be implemented using user-defined aggregates in PostgreSQL quite easily
  - See MapReduce and Parallel DBMSs by Stonebraker et al., 2010
- No database system can come close to the performance of MapReduce infrastructure
  - E.g., RDBMSs
  - Can't scale to that degree
  - Are not as fault-tolerant
  - Designed to support ACID
    - Most MapReduce applications don't care about ACID consistency

History

- MapReduce
  - Is very good at doing what it was designed for
    - If the application maps well to MapReduce, one can achieve optimal theoretical speed-up
  - May not be ideal for more complex tasks
    - E.g., no notion of “query optimization”, e.g., operator order optimization
    - The sequence of MapReduce tasks makes it procedural within a single machine
  - Assumes a single input
    - E.g., joins are tricky to do, but doable
- Much work in recent years on extending the basic MapReduce functionality, e.g.,
  - Hadoop Zoo
  - E.g., Spark, Dask, Ray

Hadoop Ecosystem (aka Hadoop Zoo)

- Pig
  - High-level data-flow language and execution framework for parallel computation
- HBase
  - Scalable, distributed database
  - Supports structured data storage for large tables (like Google BigTable)
- Cassandra
  - Scalable multi-master database with no single points of failure
- Hive
  - Data warehouse infrastructure
  - Provide data summarization and ad-hoc querying
- ZooKeeper
  - High-performance coordination service for distributed applications
- YARN, Kafka, Storm, Spark, Solr, ...