

## 8.2: Map Reduce

- **Instructor:** Dr. GP Saggese, [gsaggese@umd.edu](mailto:gsaggese@umd.edu)
- **References**
  - Silberschatz: Chap 10
  - Ghemawat et al.: *The Google File System*, 2003
  - Dean et al.: *MapReduce: Simplified Data Processing on Large Clusters*, 2004

SEVENTH EDITION  
Database System Concepts



# MapReduce: Overview

---

- **MapReduce programming model**

- Inspired by functional programming (e.g., Lisp)
- Common pattern of parallel programming to process large number of records

- **Basic algorithm**

- Apply `map()` to each record
- Group results by key
- Apply `reduce()` to results of `map()`

- **Example**

- *Goal:* Sum length of all tuples in a document
  - E.g.,  
[(), (a,), (a, b), (a, b, c)]
- *map(function, set of values)*
  - Apply function to each value (e.g., `len`)  
`map(len, [(), (a,), (a, b), (a, b, c)])` -> [0, 1, 2, 3]
- *reduce(function, set of values)*
  - Combine values using a binary function (e.g., `add`)  
`reduce(add, [0, 1, 2, 3])` -> 6

# MapReduce: Overview

---

- **Structure of computation**

- *Read input*
  - Sequentially or in parallel
- *Map*
  - Extract / compute from records
- *Group by key*
  - Sort and shuffle
- *Reduce*
  - Aggregate, summarize, filter, transform
- *Write result*

- **Division of responsibilities**

- User specifies `map()` and `reduce()` functions to solve problem
- MapReduce framework (e.g., Hadoop, Spark) implements algorithm

# MapReduce: Word Count

---

- **Word Count**

- “Hello world” of MapReduce
- Huge text file (can’t fit in memory)
- Count occurrences of each distinct word

- **Linux solution**

```
> 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 outputs words one per line
- Unix pipeline is parallelizable in MapReduce sense

Hot cross buns!

Hot cross buns!

One a penny, two a penny,

Hot cross buns!

If you have no daughters,  
Give them to your sons.

One a penny, two a penny,  
Hot cross buns!<sup>[1]</sup>

- **Sample application**

- Analyze web server logs for popular URLs

# MapReduce: Word Count

## Action

Read input

Map:

- Invoke `map()` on each input record
- Emit 0 or more output data items

Group by key:

- Gather all outputs from `map()` stage
- Collect outputs by keys

Reduce:

- Combine the list of outputs with same keys

## Python code

```
values = read(file_name)
```

```
def map(values):
```

*# values: words in document*

```
for word in values:  
    emit(word, 1)
```

```
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)
```

## Example

"One a penny, two a penny,  
hot cross buns."

Map:

```
[("one", 1), ("a", 1),  
("penny", 1), ("two", 1),  
("a", 1), ("penny", 1),  
("hot", 1), ("cross", 1),  
("buns", 1)]
```

Group by key:

```
[("a", [1, 1]),  
("buns", [1]),  
("cross", [1]),  
("hot", [1]),  
("one", [1]),  
("penny", [1, 1]),  
("two", [1])]
```

Reduce:

```
[("one", 1),  
("a", 2),  
("penny", 2),  
("two", 1),  
("hot", 1),  
("cross", 1),  
("buns", 1)]
```

# MapReduce: Log Processing

- **Goal:**

- Log file recording access to a website with format (date, hour, filename)
- Find how many times each file is accessed during Feb 2013

- **Input**

- Read file and split into lines

- **Map**

- Parse each line into 3 fields
- If date is in the required interval  
emit(dir\_name, 1)

- **GroupBy**

- Reduce key is the filename
- Accumulate all (key, value) with the same filename

- **Reduce**

- Add values for each list of (key, value) with the same filename
- Output number of accesses to each file

- **Output**

- Write results on disk separated by

*After Input*

```
2013/02/21 10:31:22.00EST /slide-  
2013/02/21 10:43:12.00EST /slide-  
2013/02/22 18:26:45.00EST /slide-  
2013/02/22 18:26:48.00EST /exer-  
2013/02/22 18:26:54.00EST /exer-  
2013/02/22 20:53:29.00EST /slide-
```

*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*

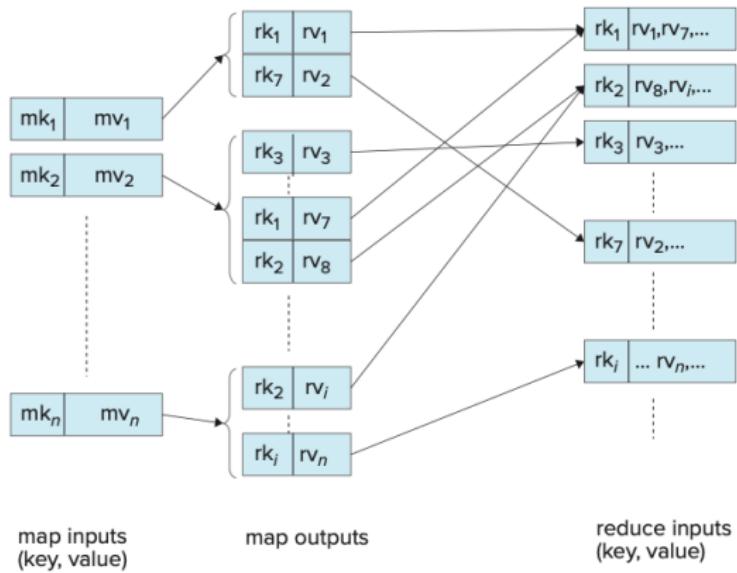
```
/slide_dir/11.ppt 1  
...  
/slide-dir/12.ppt 2  
...
```

# MapReduce: Interfaces

- **Input:** Read key-value pairs  $\text{List}[\text{Tuple}[k, v]]$
- **Programmer** specifies two methods `map` and `reduce`
- **Map**
  - $\text{Map}(\text{Tuple}[k, v]) \rightarrow \text{List}[\text{Tuple}[k, v]]$
  - 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"  $\rightarrow [("One", 1), ("a", 1), ("penny", 1)]$
  - There is one Map call for every  $(k, v)$  pair
- **GroupBy**
  - $\text{GroupBy}(\text{List}[\text{Tuple}[k, v]]) \rightarrow \text{List}[\text{Tuple}[k, \text{List}[v]]]$
  - Group and optionally sort all the records with the reduce key
- **Reduce**
  - $\text{Reduce}(\text{Tuple}[k, \text{List}[v]]) \rightarrow \text{Tuple}[k, v]$
  - All values  $v'$  with same key  $k'$  are reduced together
  - There is one Reduce call per unique key  $*k'$
- **Output:** write key-value pairs  $\text{List}[\text{Tuple}[k, v]]$

# MapReduce: Data Flow

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



- Input**

- Map**

- $mk_i$  = map keys
- $mv_i$  = map values

- GroupBy**

- Shuffle / collect the data

- Reduce**

- $rk_i$  = reduce keys
- $rv_i$  = reduce values
- Reduce outputs are not shown

Input

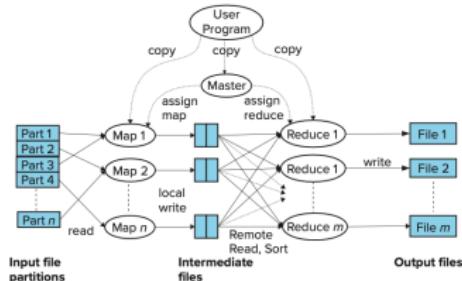
Map

GroupBy

Reduce

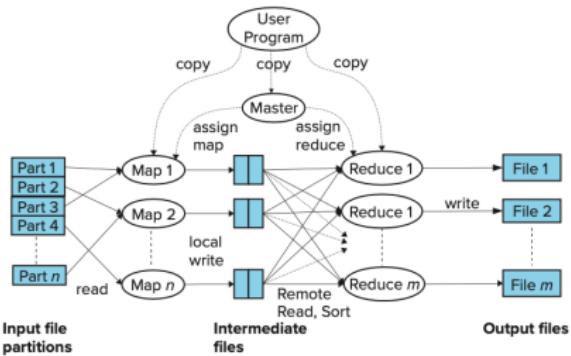
# MapReduce: Parallel Data Flow

- **User program** specifies map/reduce code
  - *MasterNode* sends code to all computing nodes
  - *Machines* reused for multiple computations (Map, Reduce) at different times
  - All operations use HDFS as storage
- **Map**
  - $n$  data chunks to process
  - Functions executed in parallel on  $k$  machines
  - Output data saved on disk
- **GroupBy / Sort**
  - Output data sorted and partitioned by reduce key
  - Files created for each Reduce task
- **Reduce**
  - Functions executed in parallel on multiple machines
  - Each works on part of the data
  - Output data saved on disk



# MasterNode Responsibilities

- MasterNode coordinates / schedule tasks
  - Task status: idle, in-progress, completed
  - Schedule idle tasks as workers become available
  - Map task completion sends location and sizes of intermediate files to Master
  - Master informs Reduce tasks
  - Schedule idle Reduce tasks
- MasterNode pings workers to detect failures
  - Heartbeat



# Dealing with Failures

---

- **Map worker failure**
  - Reset failed map tasks to idle
  - Notify reduce workers when task is rescheduled
- **Reduce worker failure**
  - Reset in-progress tasks to idle
  - Restart reduce task
- **Master failure**
  - Abort MapReduce task
  - Notify client

# How Many Map and Reduce Jobs?

---

- Number of map tasks =  $M$
- Number of reduce tasks =  $R$
- Number of worker nodes =  $N$
- Typically  $M \gg N$ 
  - Pros:
    - Improve dynamic load balancing
    - Speed up recovery from worker failures
  - Cons:
    - More communication between *MasterNode* and *WorkerNodes*
    - Lots of smaller files
- Typically  $R > N$
- 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  $k$   
 $[(k_1, v_1), (k_1, v_2), \dots]$
- 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  
 $[k_1, (v_1, v_2, \dots), k_2, ([\dots])]$
- 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**

- Users want to control key partitioning
- Inputs to Map tasks created by contiguous input file splits
- Default partition function: `hash(key) mod R`
- Ensure records with the same intermediate key go to the same worker

- **Solution**

- Override hash function:
- E.g., `hash(hostname(URL)) mod R` ensures URLs from a host end up in the same output file

# Implementations of MapReduce

---

- There are many implementations of map reduce
  - **Google**
    - Not available outside Google
  - **Hadoop**
    - Open-source in Java
    - Uses HDFS for storage
    - Hadoop Wiki: Intro, Getting Started, Map/Reduce Overview
  - **Amazon Elastic MapReduce (EMR)**
    - Hadoop MapReduce on Amazon EC2
    - Also runs Spark, HBase, Hive,
  - **Spark**
  - **Dask**