UNIVERSITY OF MARYLAND

UMD DATA605 - Big Data Systems

8.2: Map Reduce

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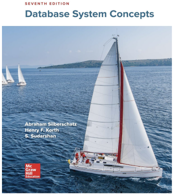
- **References**
  - Silbershatz: Chap 10
  - Ghemawat et al.: *The Google File System*, 2003
  - Dean et al.: *MapReduce: Simplified Data Processing on Large Clusters*, 2004



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
- **Sample application**
  - Analyze web server logs for popular URLs

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![1]

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)]
```

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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-d
2013/02/22 18:26:54.00EST  /exer-d
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
...
```

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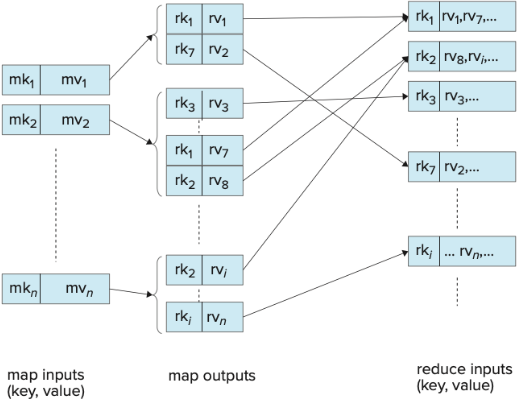
MapReduce: Interfaces

- **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: Data Flow

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

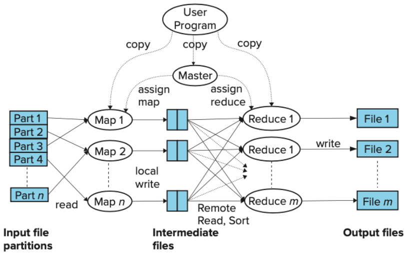


- **Input**
- **Map**
  - mki = map keys
  - mvi = map input values
- **GroupBy**
  - Shuffle / collect the data
- **Reduce**
  - rki = reduce keys
  - rvi** = reduce input values
  - Reduce outputs are not shown

Input **Map** **GroupBy** **Reduce** .

MapReduce: Parallel Data Flow

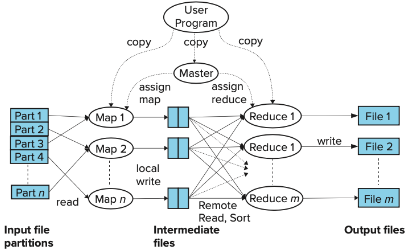
- User program specifies map/reduce code
- Input data is partitioned across multiple machines (HDFS)
- Master node sends copies of the code to all computing nodes
- Map
  - n data chunks to process
  - Functions executed in parallel on multiple k machines
  - Output data from *Map* is saved on disk
- 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 coordinates**
  - 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
- **Master node pings workers to detect failures**



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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?

- **M map tasks**
- **R reduce tasks**
- **N worker nodes**
- Rules of thumb
  - $M \gg N$
    - 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

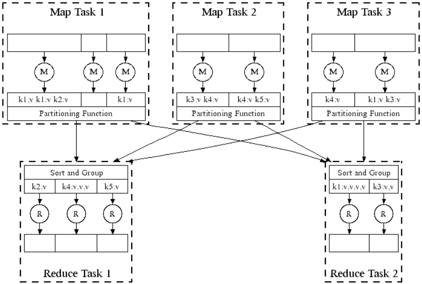
- **Problem**
  - Often a *Map* task produces many pairs for the same key *k*

`[(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*

`[k1, (v1, v2, ...), k2, ([...])]`

  - *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

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**