# CS 7172 Parallel and Distributed Computation

### **MapReduce**

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### **Outline**

- Single server vs multiple server processing
- Divide-and-conquer
- MapReduce
  - Map
  - Reduce
  - How it works
  - Fault-tolerance
  - Limitation

### Processing Data on a single Machine

- Data on file system on disk
- Simple processing flow:
  - 1. Read into memory
  - 2. Process data (apply some function)
  - 3. Write back to disk





### Why Multiple Servers?

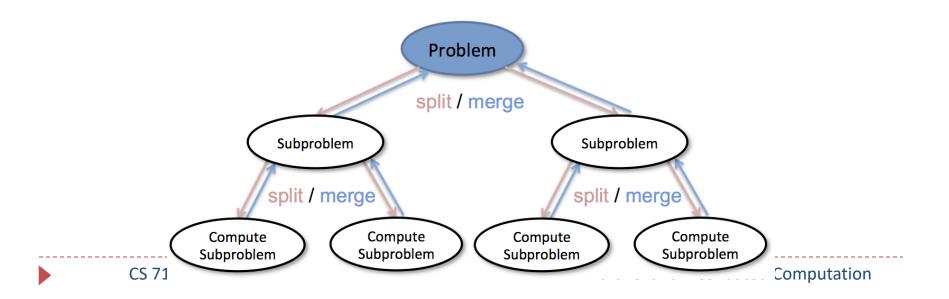
- Data size larger than disk capacity
- Sequentially processing data can be slow
  - Limited by disk read/write speeds
  - Parallel processing can significantly reduce time
- Single point of failure with a single server





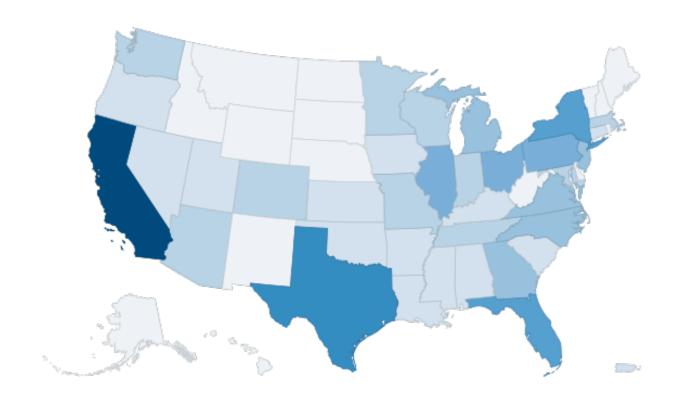
### **Divide-and-Conquer**

 A divide-and-conquer algorithm works by recursively breaking down a problem into two or more sub-problems of the same or related type, until these become simple enough to be solved directly. The solutions to the subproblems are then combined to give a solution to the original problem.



# **Divide-and-Conquer**

How to get the total population of USA?



# What kind of problem can Divide-and-Conquer solve?

#### Problem characteristics:

 The scale of the problem is large or complex, and the problem can be broken down into several smaller, simple problems of the same type to solve

The sub-problems are independent of each other

 The solutions of the sub-problems can be combined to obtain the solution of original problem

### How to Use Divide-and-Conquer

- Decompose the original problem.
  - The original problem is decomposed into several smaller, independent sub-problems that have the same form as the original problem.

- Solve subproblems.
  - If the sub-problems are small and easy to solve, solve them directly;
  - Otherwise, solve the sub-problems recursively.

- Merging solutions
  - Merge the solutions of the sub-problems into solutions of the original problem.

### MapReduce

 https://static.googleusercontent.com/media/research.google.com/en//arc hive/mapreduce-osdi04.pdf

#### MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

#### **Abstract**

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a key/value pair to generate a set of intermediate key/value

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually large and the computations have to be distributed across





Published at OSDI 2004. >25,000 citations

### Why MapReduce?

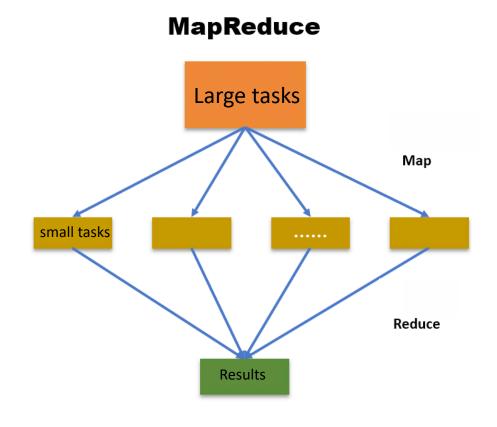
- Automated parallelization and distribution of data and processing
- Clean, powerful, well-understood abstraction (Map and Reduce)
- Fault-tolerance
- Scalability: 1000s of servers, TBs of data, ...
- Apache Hadoop: widely used open source Java implementation



### MapReduce

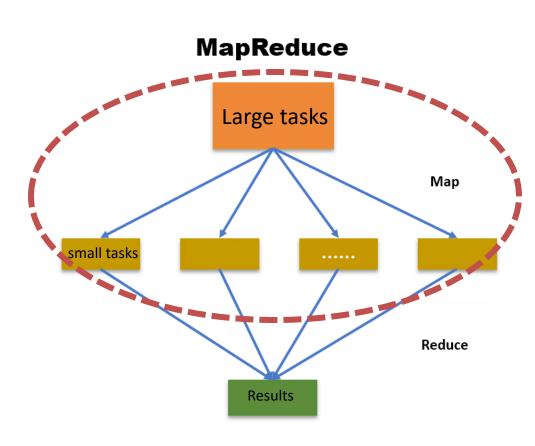
- MapReduce is divided into two core phases: Map and Reduce
- Map corresponds to "divide": complex tasks are broken down into several simple tasks for execution

 Reduce corresponds to "conquer": the results of the Map phase are summarized.



### Map

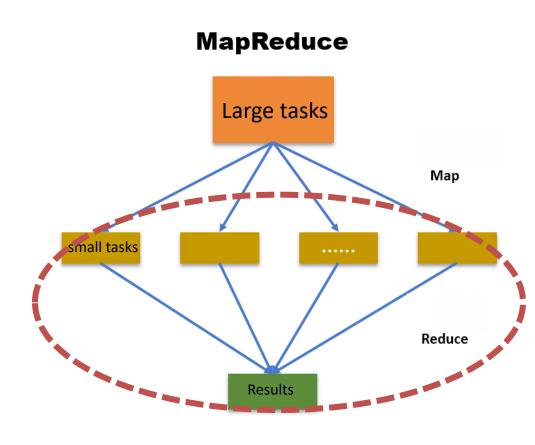
- The small tasks after map have the following characteristics:
  - Compared to the original task, the divided sub-tasks are homogeneous with the original task
  - The sub-task data size and calculation size is much smaller
  - There are no dependencies
     between different sub-tasks, which
     can run independently and run in
     parallel



### Reduce

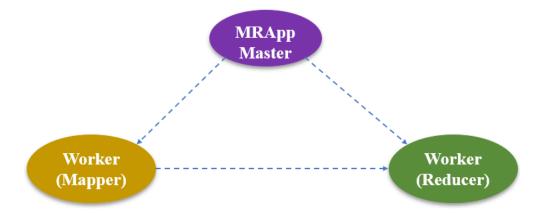
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 After the division of the sub-tasks in the first stage is completed, the calculation results of all sub-tasks are summarized to obtain the final results.



#### MapReduce includes the three components:

- Master (MRAppMaster): is responsible for assigning tasks, coordinating the operation of tasks, and assigning map function operations to Mappers, and reduce function operations to the Reducers.
- Mapper worker: is responsible for Map function and performing sub-tasks.
- Reducer worker: is responsible for Reduce function and summarizing the results of each sub-task

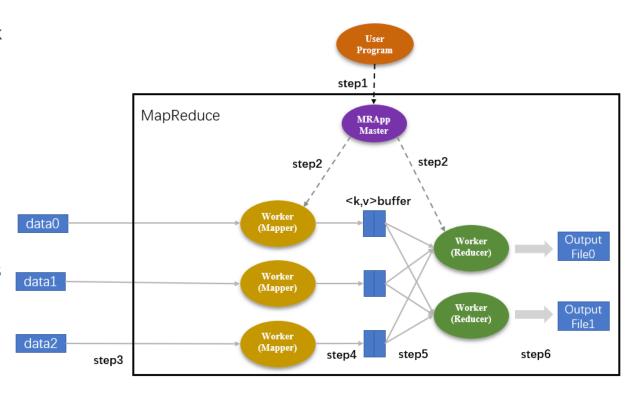


#### Workflow (step 1):

User Program sends the task to MRAppMaster. Then, MRAppMaster splits the task into M subtasks (M is a user-defined value).

Example: Assume that the MapReduce function divides the task into 5, of which there are 3 Map jobs and 2 Reduce jobs.

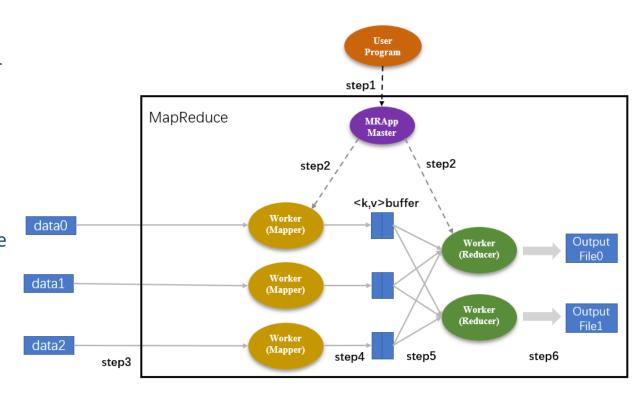
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#### Workflow (step 2):

MRAppMaster assigns Map and Reduce jobs to Mapper and Reducer, respectively.

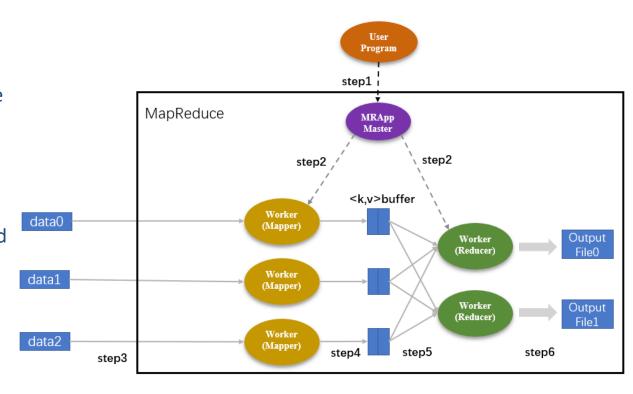
The number of Map jobs is the number of divided subtasks, which is 3; Reduce jobs are 2



#### Workflow (step 3):

The Mapper worker starts reading the input data of the subtask and extracts the <key, value> pairs from the input data.

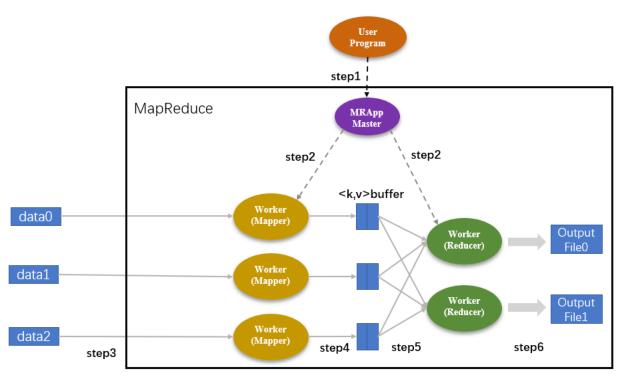
Each key-value pair is passed to the map () function as a parameter.



#### Workflow (step 4):

The output of the map () function is stored in the ring buffer <k, v>Buffer.

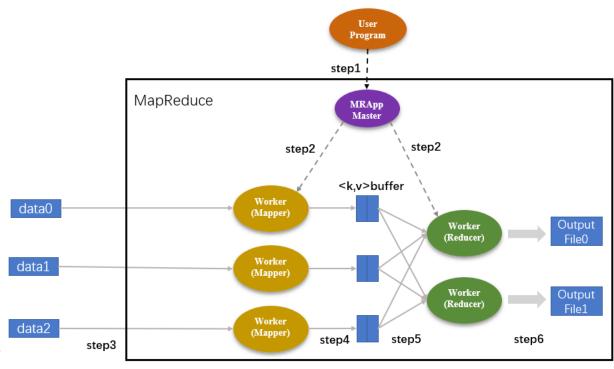
These results are periodically written to the local disk and stored in R different disk areas. Here R represents the number of Reduce jobs. In this case, R = 2. Also, the storage location of each Map result is reported to the MRAppMaster.



#### Workflow (step 5):

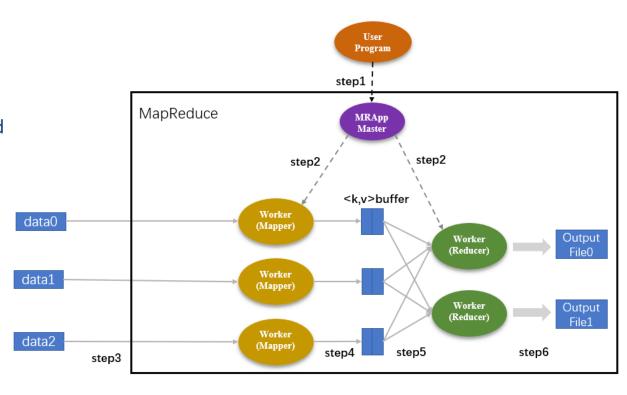
The MRAppMaster informs the Reducer which partition it is responsible for, and the Reducer remotely reads the corresponding Map result, which is the intermediate key-value pair.

After the Reducers read all the intermediate key-value pairs it is responsible for, it sorts and aggregates the keyvalue pairs of the same key value.



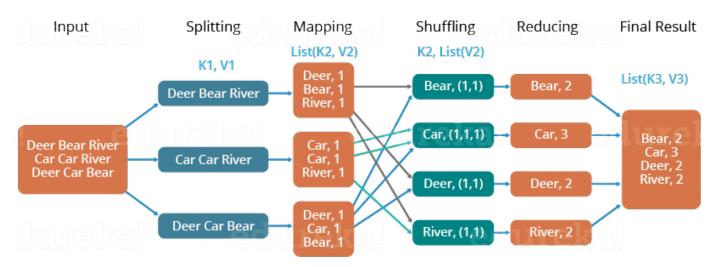
#### Workflow (step 6):

The reducer traverses the sorted key-value pairs, merges the key-value pairs with the same key value, and stores the statistical results as output files in the corresponding partition.



- The entire workflow of MapReduce can be divided into 5 parts:
  - Input, splitting, mapping, reducing and final result

#### The Overall MapReduce Word Count Process



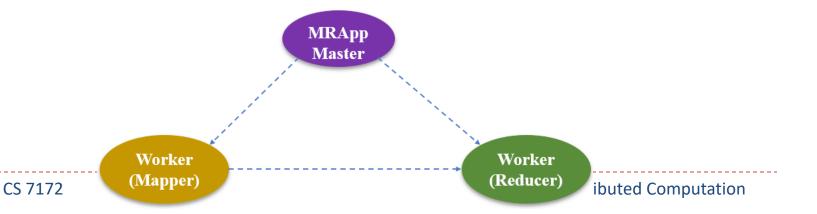
### Fault-Tolerance in MapReduce

#### Master fails

- Switch to secondary master
- Restart entire job

#### Worker fails

- If running map: restart map tasks on available/free worker nodes
- If running reduce: restart reducer tasks

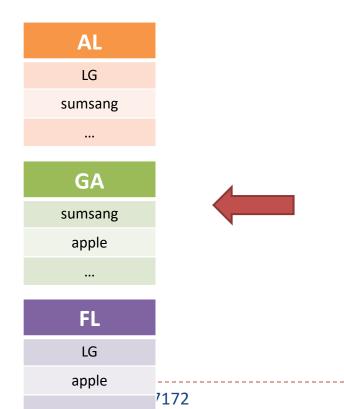


 We want to know the top 3 selling smartphones in Alabama, Georgia and Florida area

AL	GA	FL
LG	Sumsang	LG
Sumsang	apple	apple
apple	LG	Sumsang

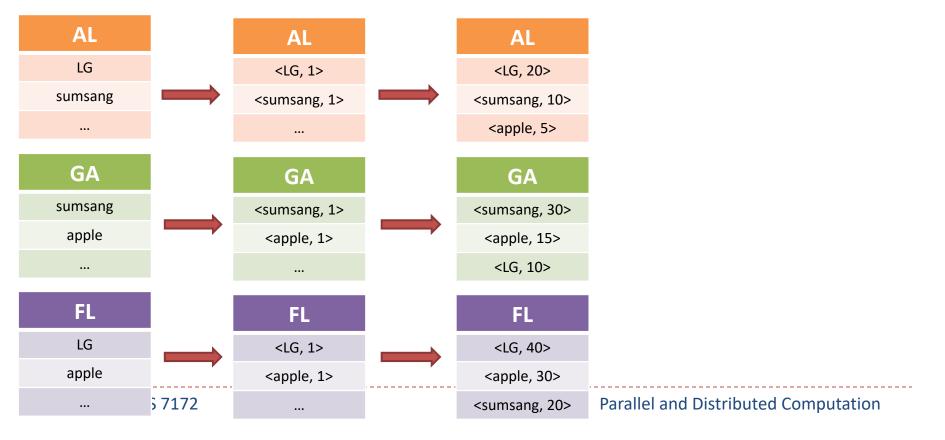


Splitting: divide the task into 3 sub-tasks

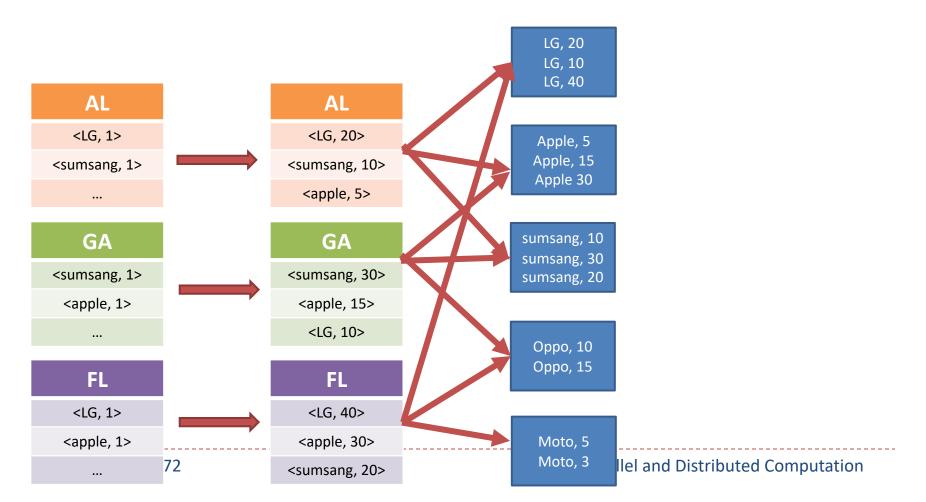


AL	GA	FL
LG	Sumsang	LG
Sumsang	apple	apple
apple	LG	Sumsang

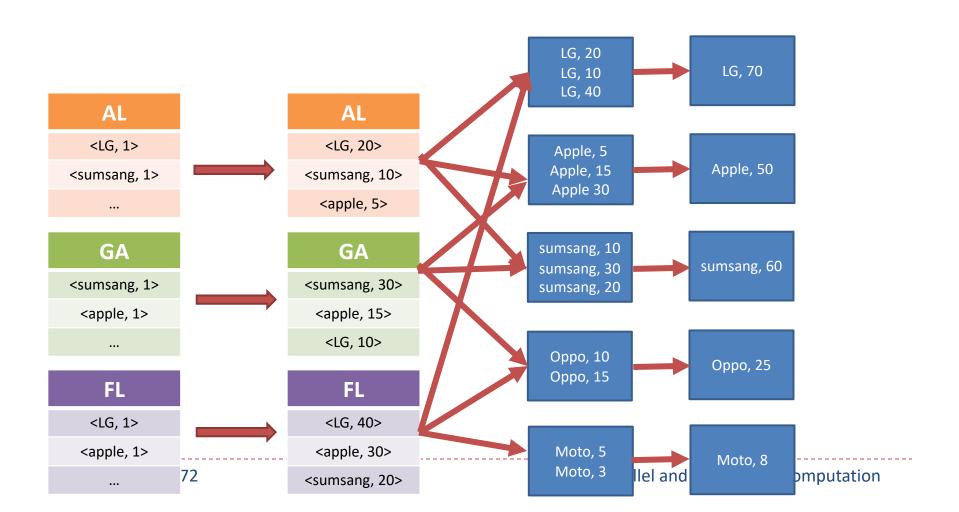
 Mapping: keep calling map() function and get the selling statistics of each smartphone brand. Here the key is the smartphone brand and value is the number



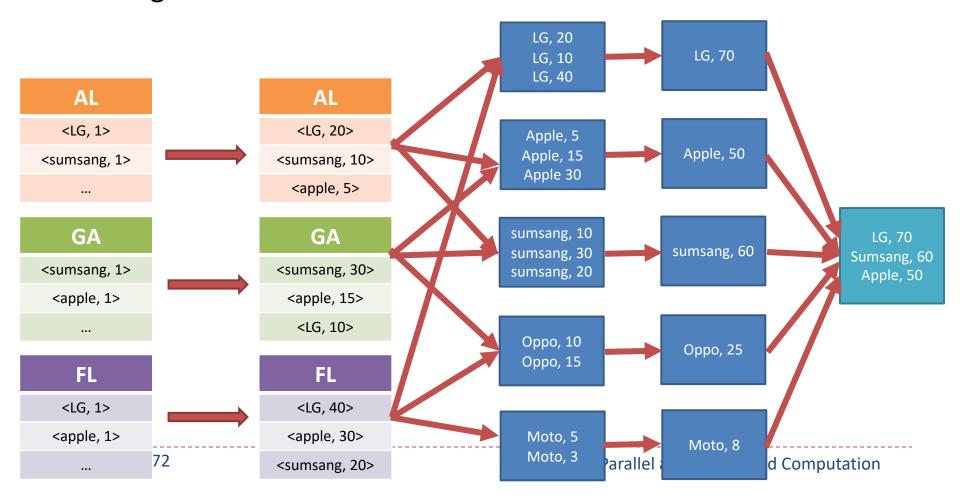
 Shuffuling: read the results of the Mapping phase and divide the different results into different areas



Reducing: merge the results of the same brand



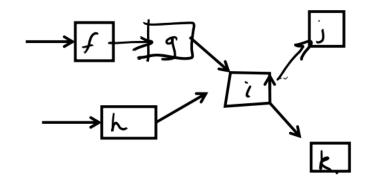
Final results: get the top 3 selling smartphones in Alabama,
 Georgia and Florida area



### **MapReduce Limitations**

#### Static data

- Restrictive programming model
- No support for dataflows (not dynamic)
- Purely batch processing (not flow)
- Jobs can take hours to complete
- No streaming, interactive analytics



- How many mappers and reducers?
- How much memory to allocate?

### When NOT To Use MapReduce

- Modern computing hardware has plenty of computing power:
  - A typical laptop: 8 cores, 16 GB RAM, 512 GB SSD (usually NVMe)
  - A typical server: 64 cores, 256 GB RAM, 2 TB SSD, ...

- Is your dataset really that large?
  - Wikipedia: 30 GB

 In many cases, an optimized non-distributed implementation beats a large cluster (!)

### Conclusion

- Single server vs multiple server processing
- Divide-and-conquer
- MapReduce
  - Map
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  - How it works
  - Fault-tolerance
  - Limitation