MapReduce: Simplified Data Processing on Large Clusters

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Outline

- Motivation & Overview
- Word Count Example & Implementation
- Structure & Execution Overview
- Fault Tolerance
- Refinements
- Performance

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Motivation

- **Large amount** of raw data to process
- Conceptually straightforward computation
- Distributed computations → Finish in reasonable time
- Problems:
    - Parallelize computations
    - Distribute data
    - Handle failures

MapReduce: Overview

- A **programming model** & an **associated implementation** for processing and generating **large data sets**.

MapReduce: Overview

- First version in 2003 by Google
- Significant growth of usage
- Applications:
  - Large-scale **machine learning** problems
  - **Clustering problems** for the Google News
  - **Extraction of data** in queries &
  - **Extraction of properties** of web pages
  - Large-scale **graph computations**
  - **…**
  - Rewrite the production **indexing system** for the Google web search service

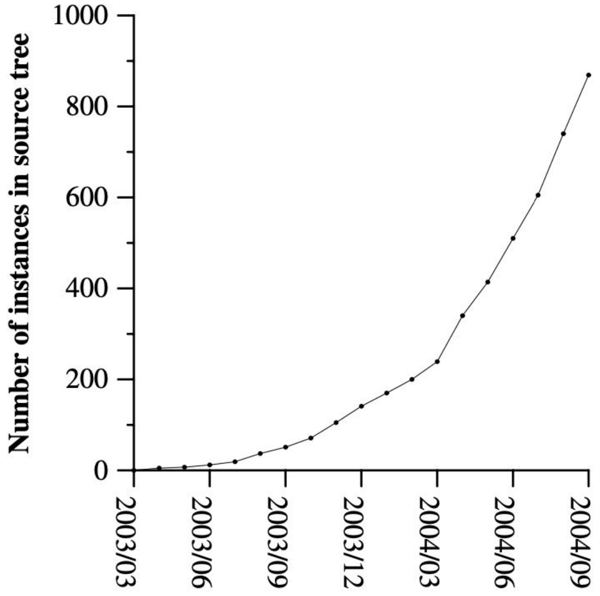


Figure 4: MapReduce instances over time

What is MapReduce

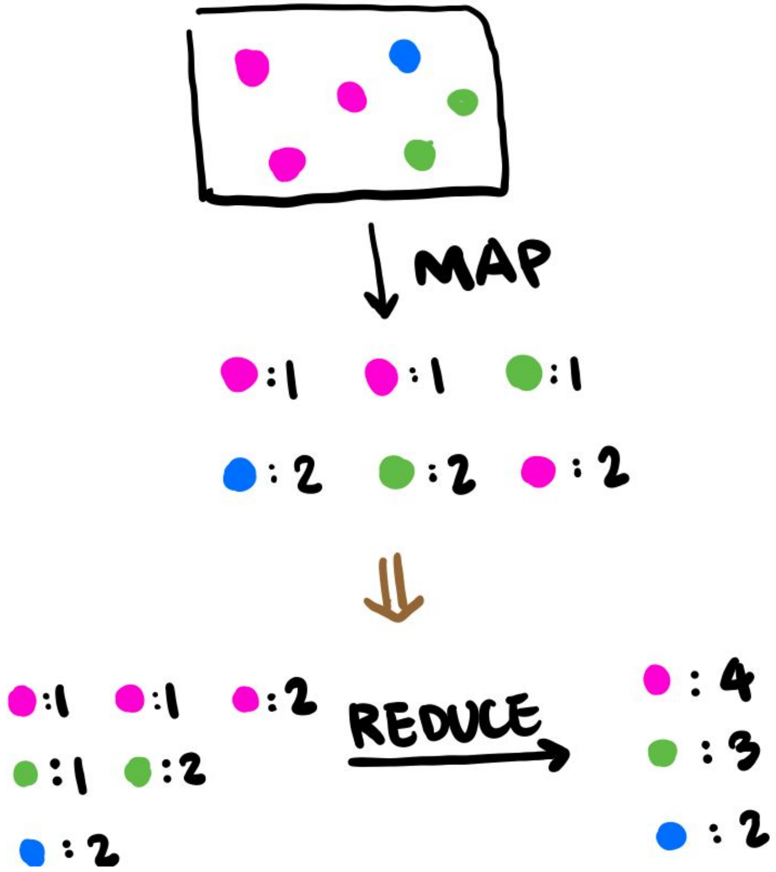
- Inspired by the ***map*** and ***reduce*** primitives
  - In Lisp & other languages

- Advantages:
  - Allow **user defined** computations
  - **Hides messy details** in a library:
    - Parallelization
    - Fault-tolerance
    - Data distribution
    - Load balancing

Main idea

- **Map** operation:
  - Each Input record → key/value pair

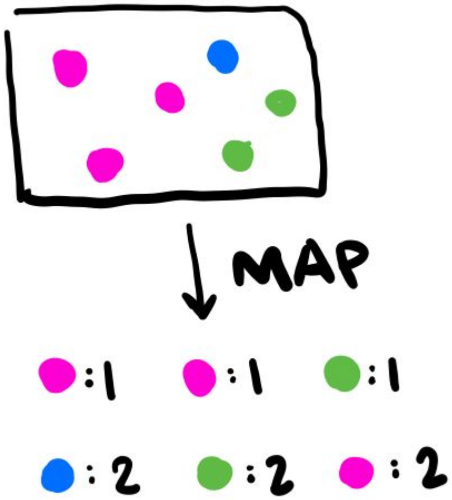
- **Reduce** operation:
  - (same key) values → Derived data



Map Function

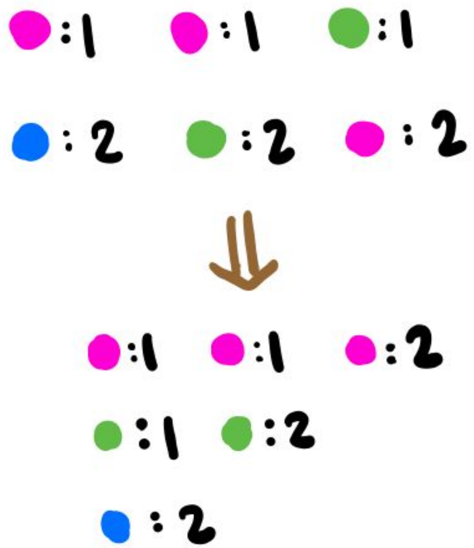
- User specified

- In: An input pair
- Out: A set of intermediate key/value pairs

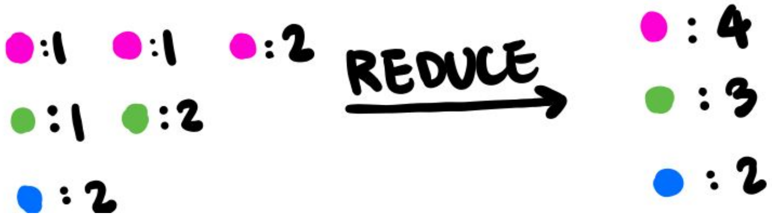


Intermediate key/value pairs

- MapReduce library **groups** intermediate values with **same key *I***



Reduce Function



- User specified

- In: Intermediate key *I* and a set of values for key *I*
- Out: Smaller set of values

- Typically 0 or 1 output value per Reduce invocation

User specification

- **Map** & **Reduce** functions
- Names of input & output files
- Optional tuning parameters

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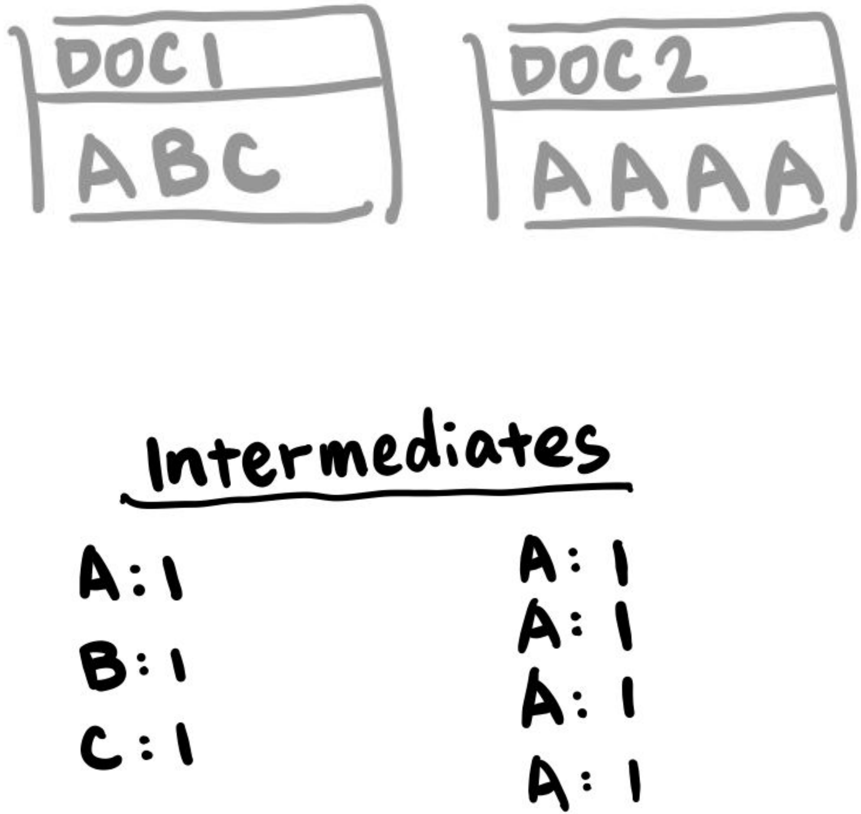
Example: Word Count

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");
```



Example: Word Count

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

Intermediates

A:1
B:1
C:1

A: 1
A: 1
A: 1
A: 1

Results:

A: 5
B: 1
C: 1

Implementation of MapReduce

- Many possible implementations depend on the environment

- Here: A MapReduce interface tailored towards Google’s cluster-based computing environment
  - Build on **Commodity PCs** connected with **switched Ethernet**
  - **Machine failures** are common

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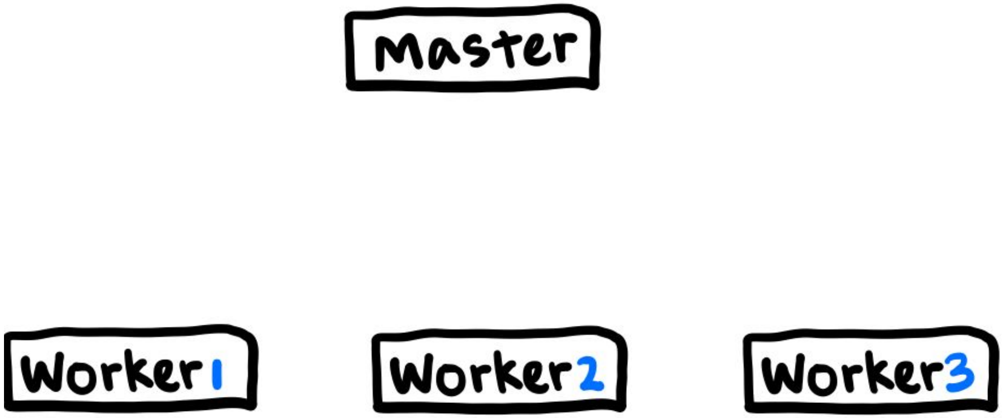
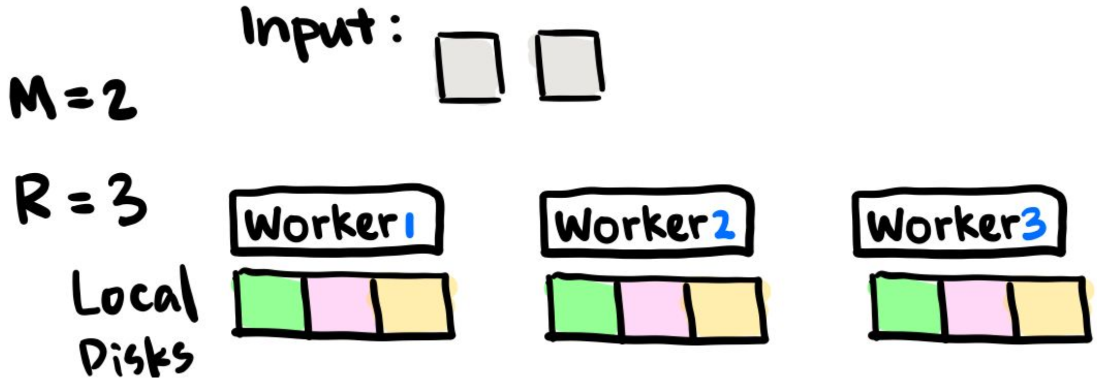
Structure

- Single master
- A set of workers



Structure

- M: Partition input data into ***M*** splits
  - Typically 16-64 MB per piece
- R: Partition intermediate key space into ***R*** pieces
  - Using a **partitioning function**
  - E.g. (hash(key) **mod** R)
- All specified by user



Execution Overview

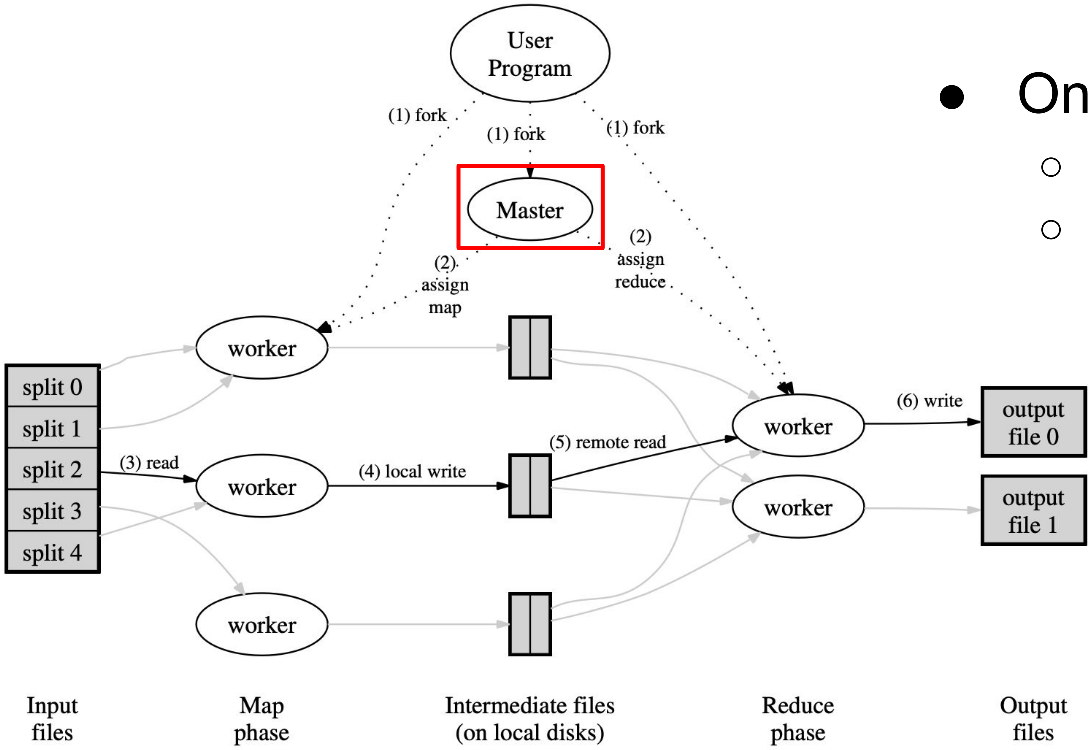


Figure 1: Execution overview

- One master program
  - The rest are workers
  - Master assign map/reduce tasks to idle workers

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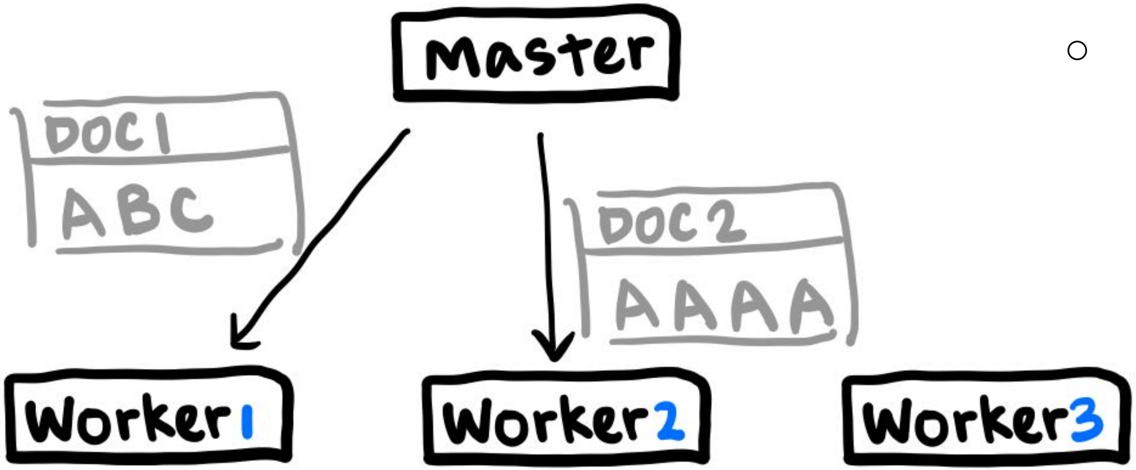

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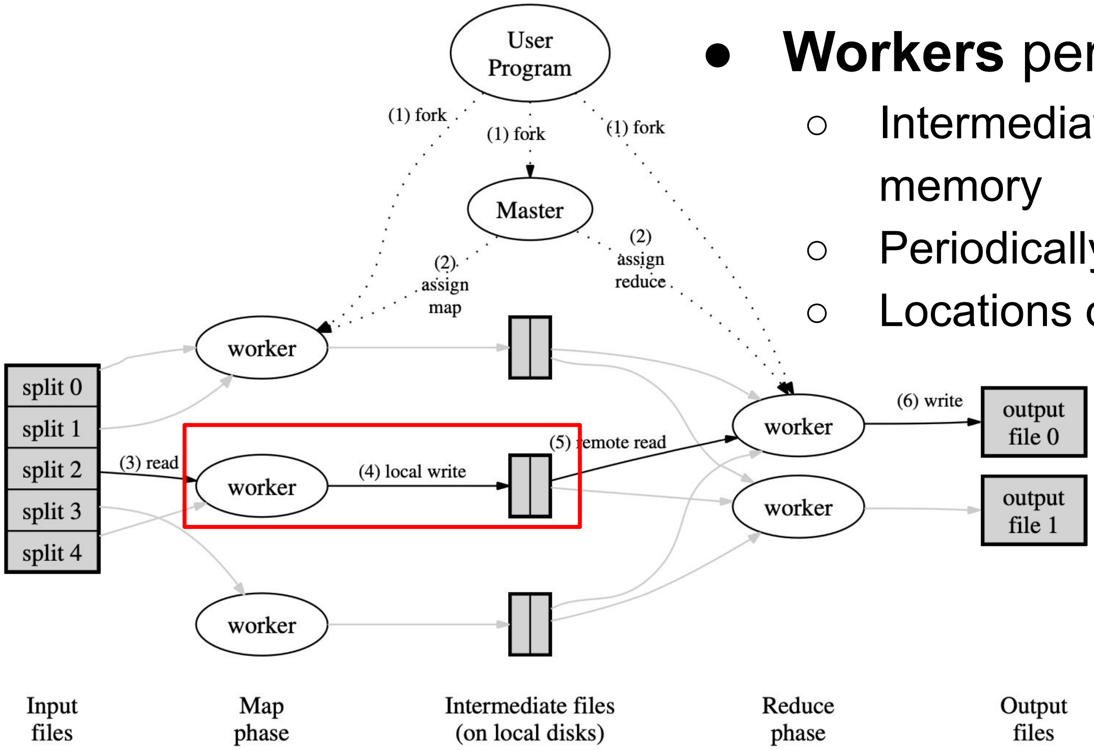

Figure 1: Execution overview

- **Workers** perform ***Map*** task
  - Intermediate key/value pairs buffered in memory
  - Periodically write buffered pairs into **local disk**
  - Locations of buffered pairs → Master

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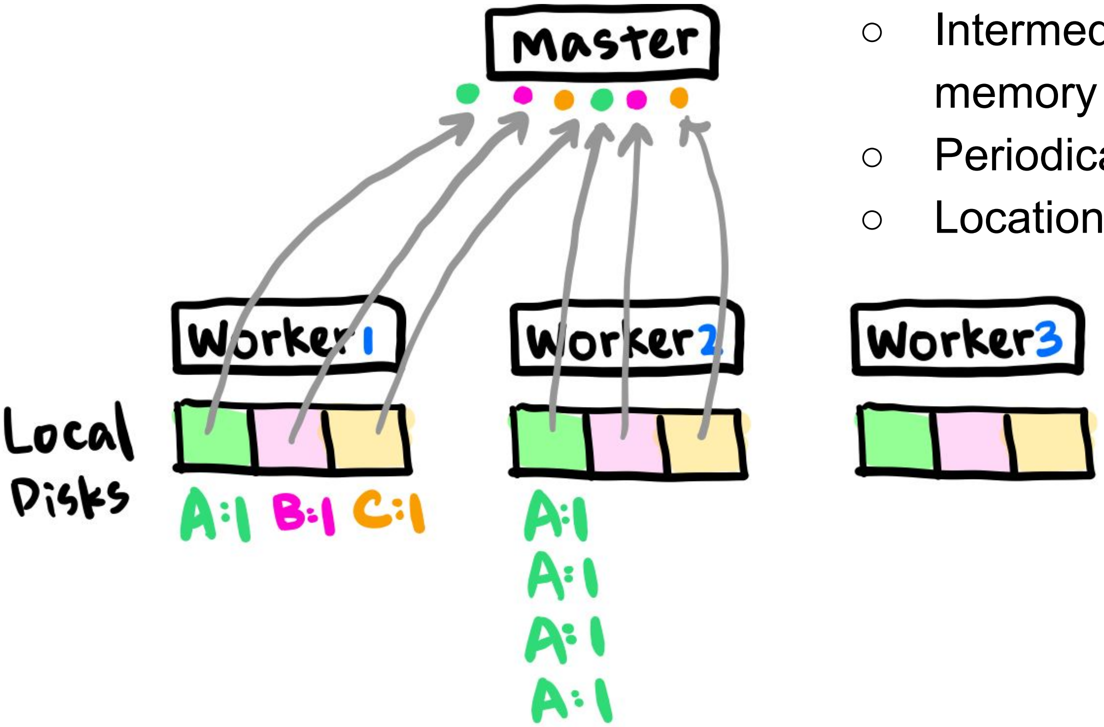

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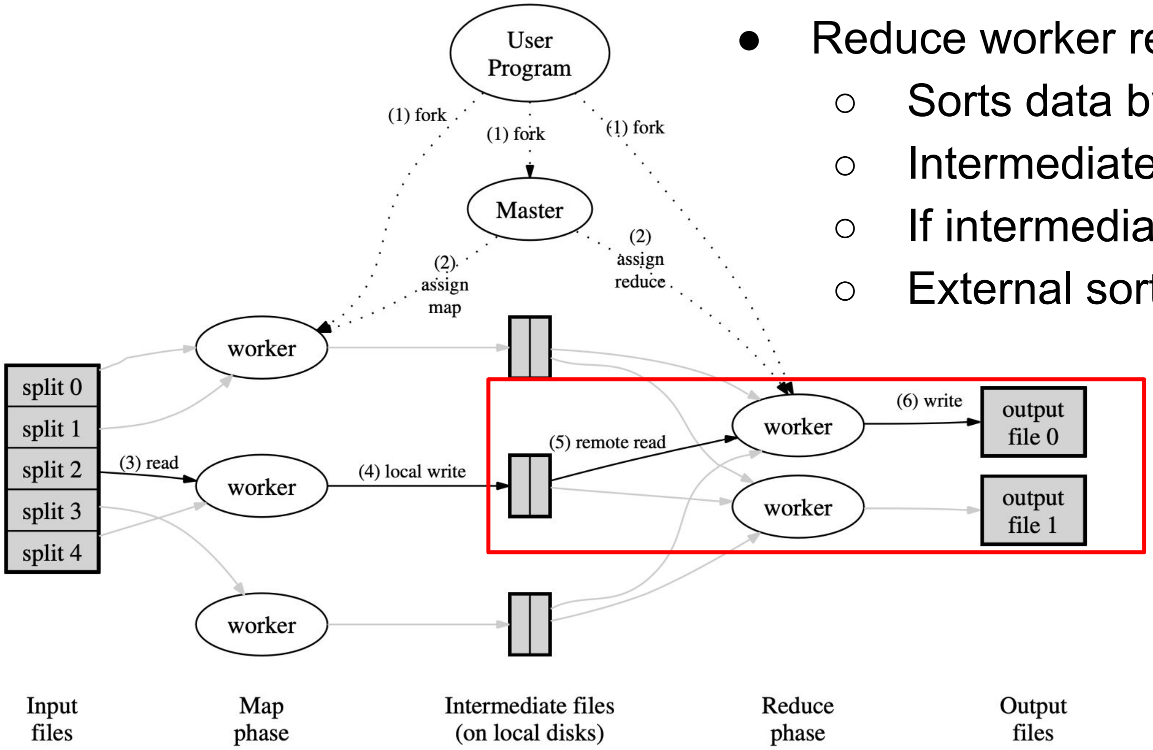
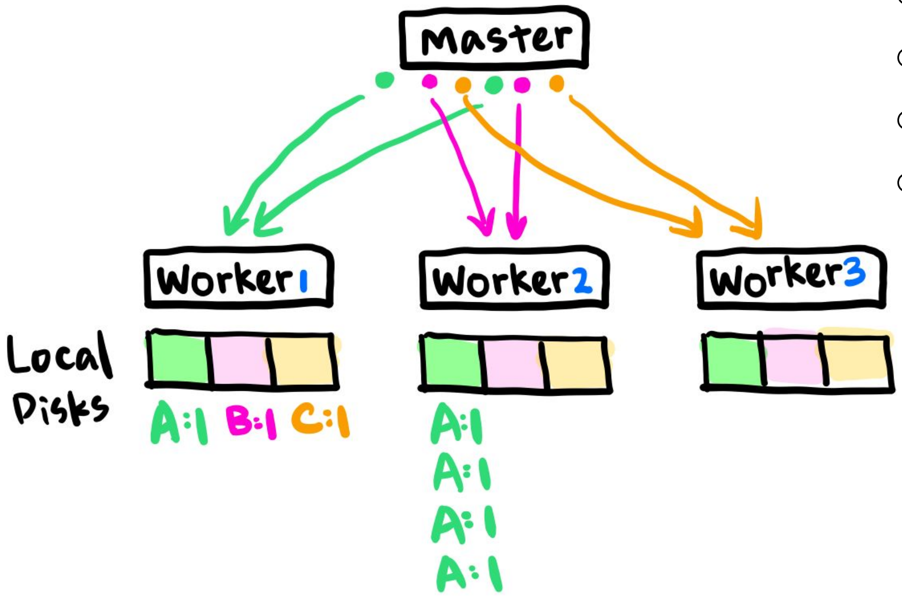


Figure 1: Execution overview

- Master sends these locations to **reduce workers**
- Reduce worker reads **intermediate data**
  - Sorts data by intermediate keys →
  - Intermediates with same key group together
  - If intermediate data too large:
  - External sort is used

- **Atomically renames** temporary output file → Final output file
- Final file system: Data from **one** execution of each reduce task
- Therefore, *R* output files

Execution Overview



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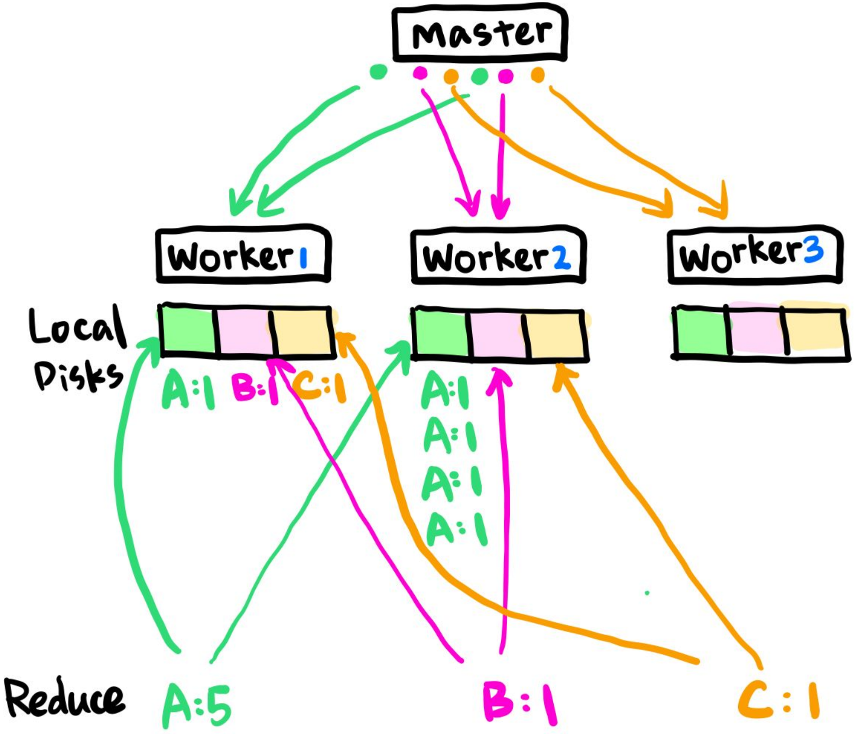

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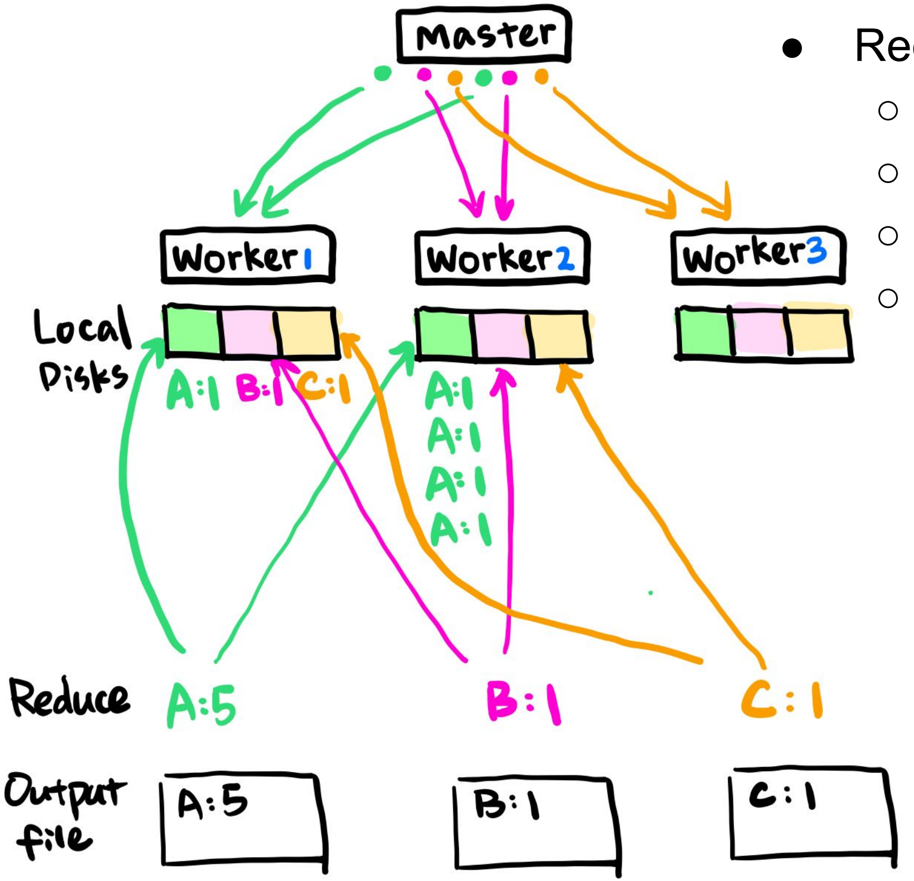

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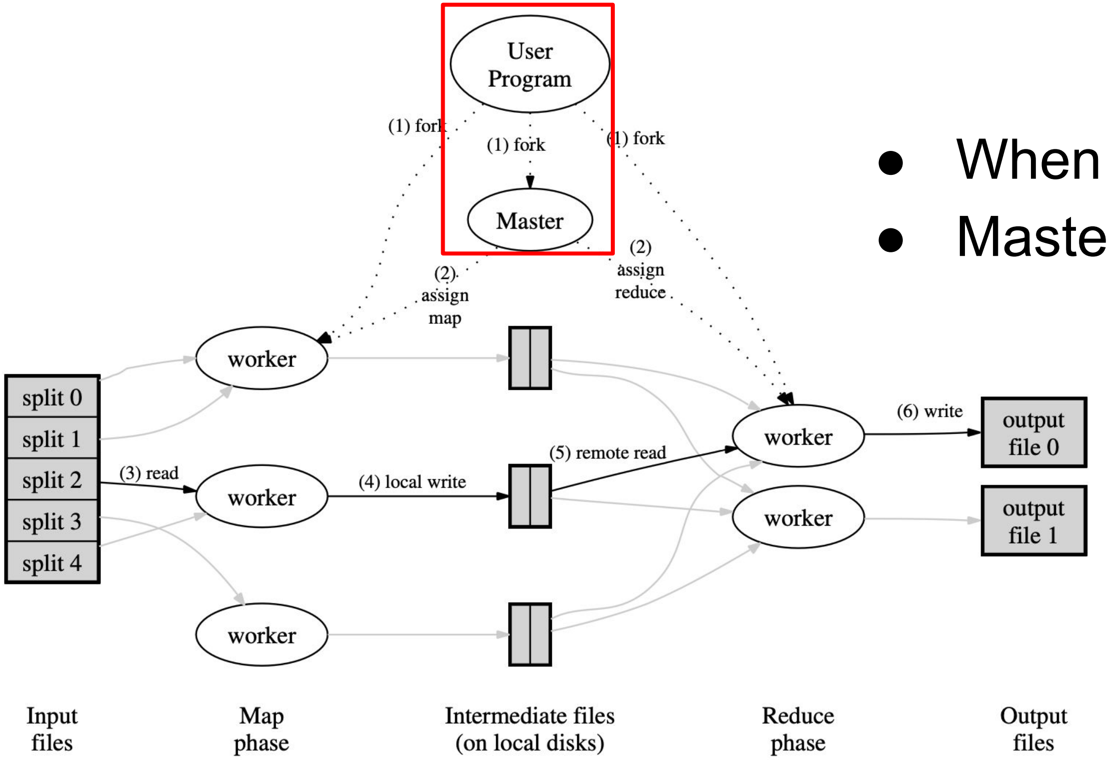

Figure 1: Execution overview

- When all tasks completed
- Master wakes up the user program

Execution Overview

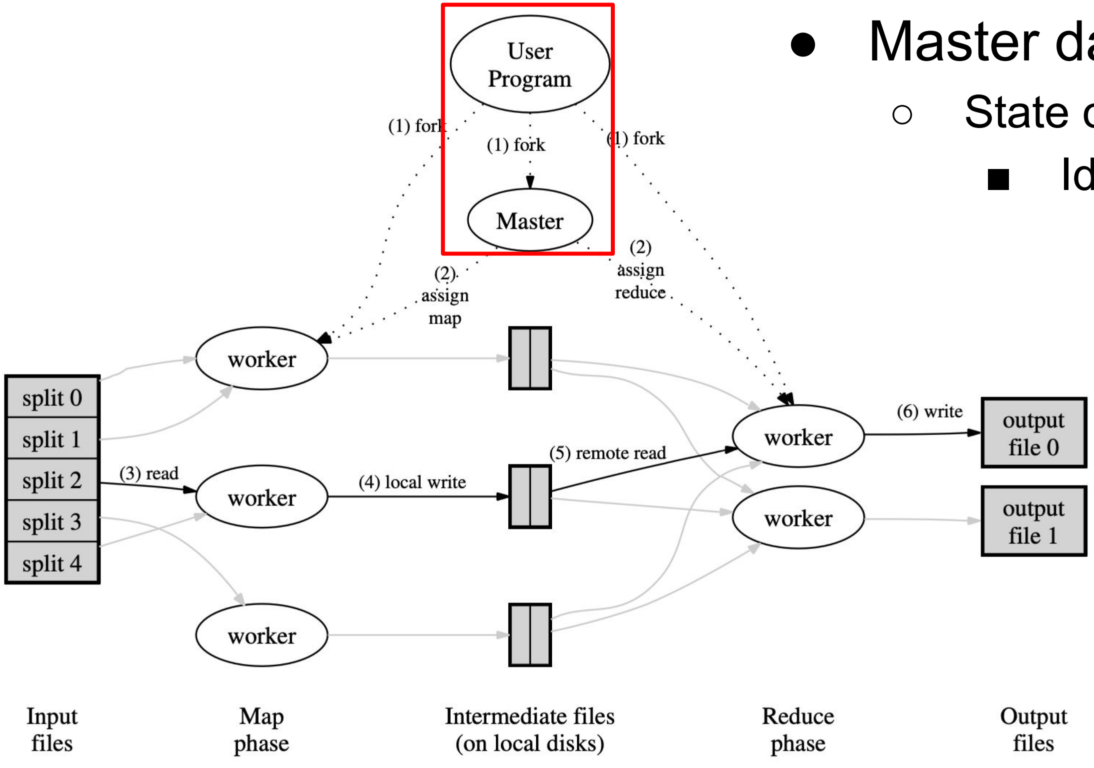

Figure 1: Execution overview

- Master data structures:
  - State of each map & reduce task:
    - Idle, in-progress, completed
  - Identity of worker machine
  - *R* intermediate file locations for each completed map task

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Fault Tolerance

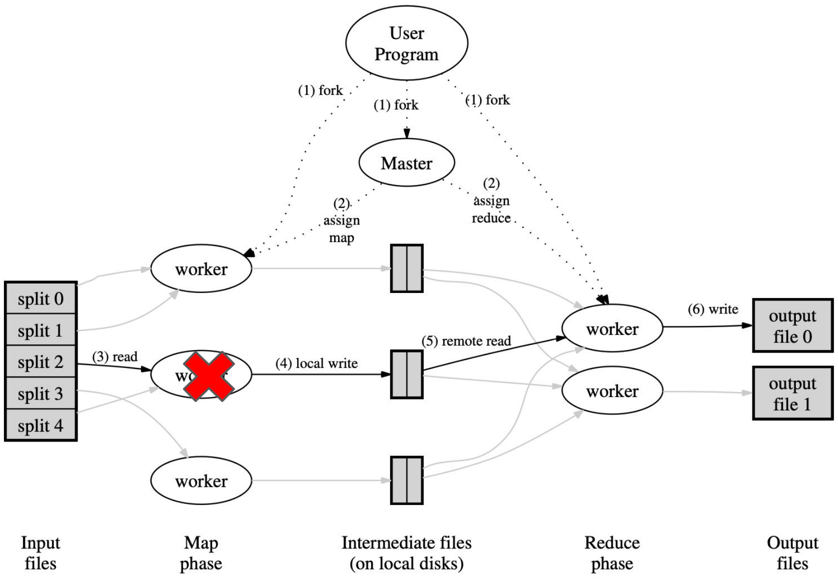
- Why important:
  - Commodity machines: Failures are common
  - Hundreds and thousands of machines: Tolerate faults gracefully
- Primary mechanism: Re-execution

- Worker Failure
- Master Failure

Fault Tolerance

Worker Failure

- Master pings worker periodically
- No response → Mark worker failed
- Reset Map task **completed** by failed worker → idle state
- Reset **in-progress** Map and Reduce tasks by failed worker → idle state
- Idle tasks → eligible for rescheduling



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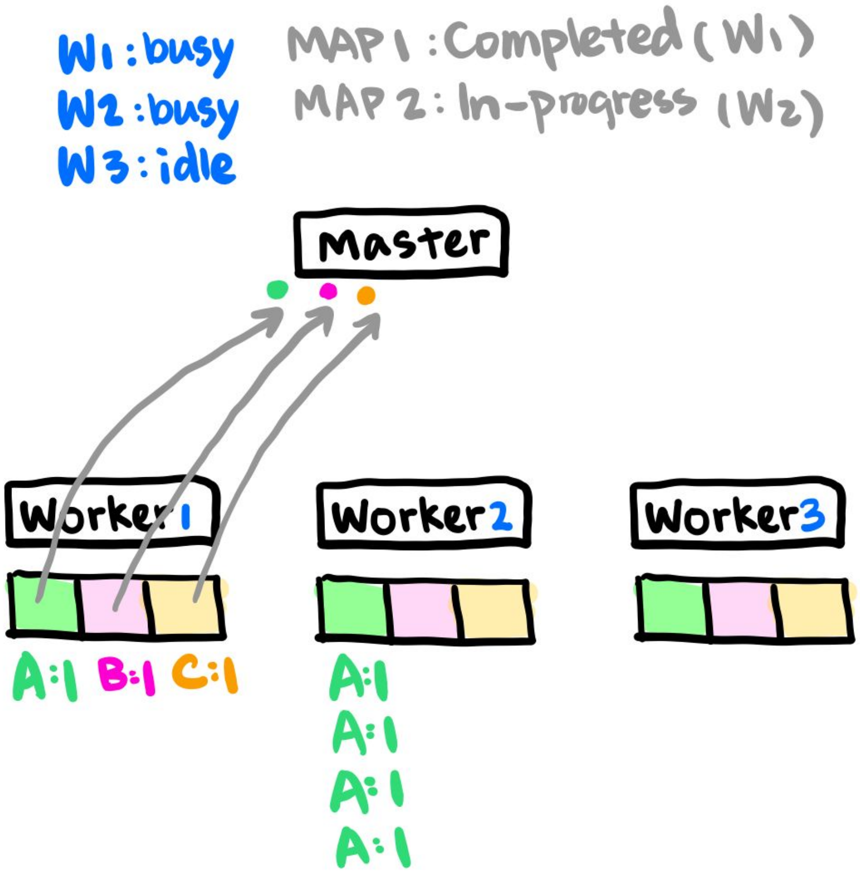

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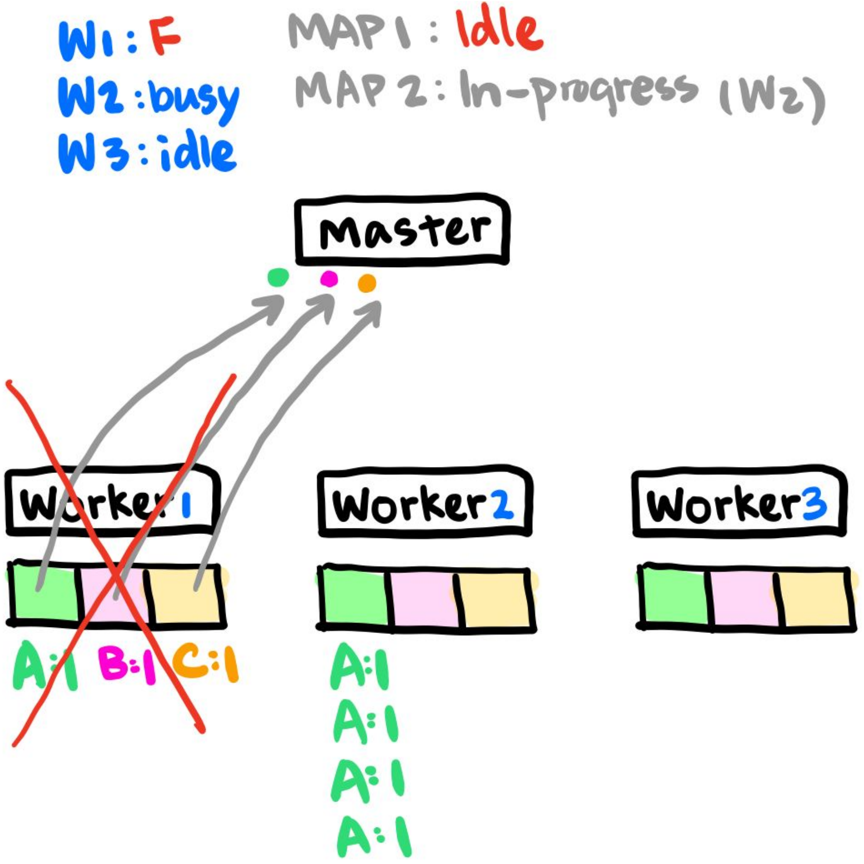

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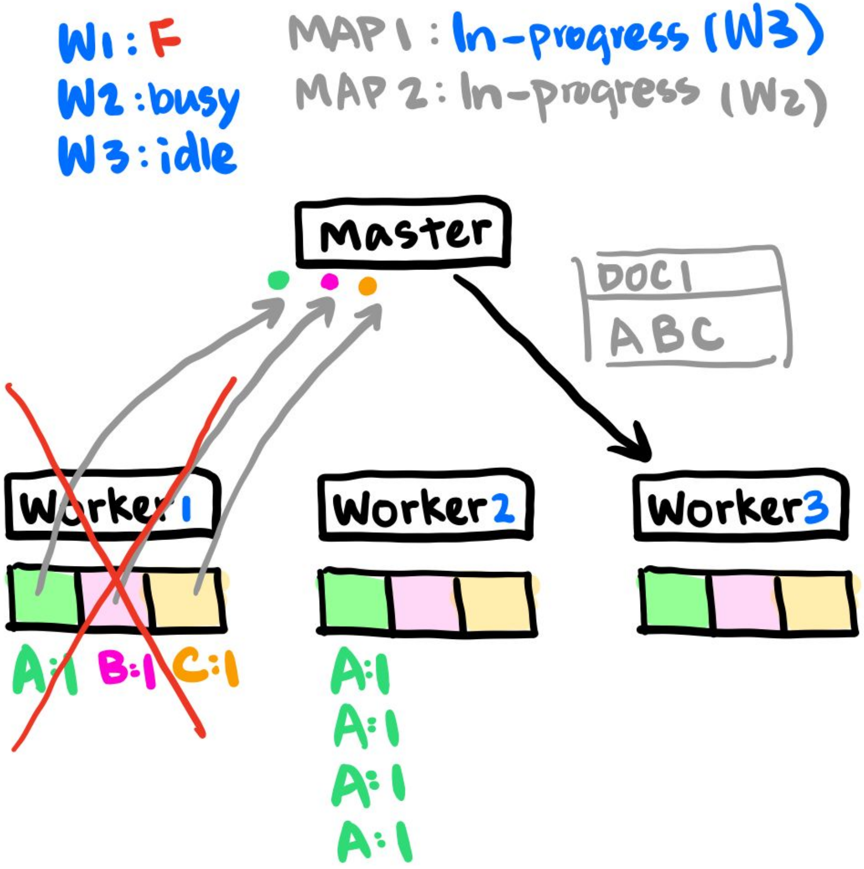
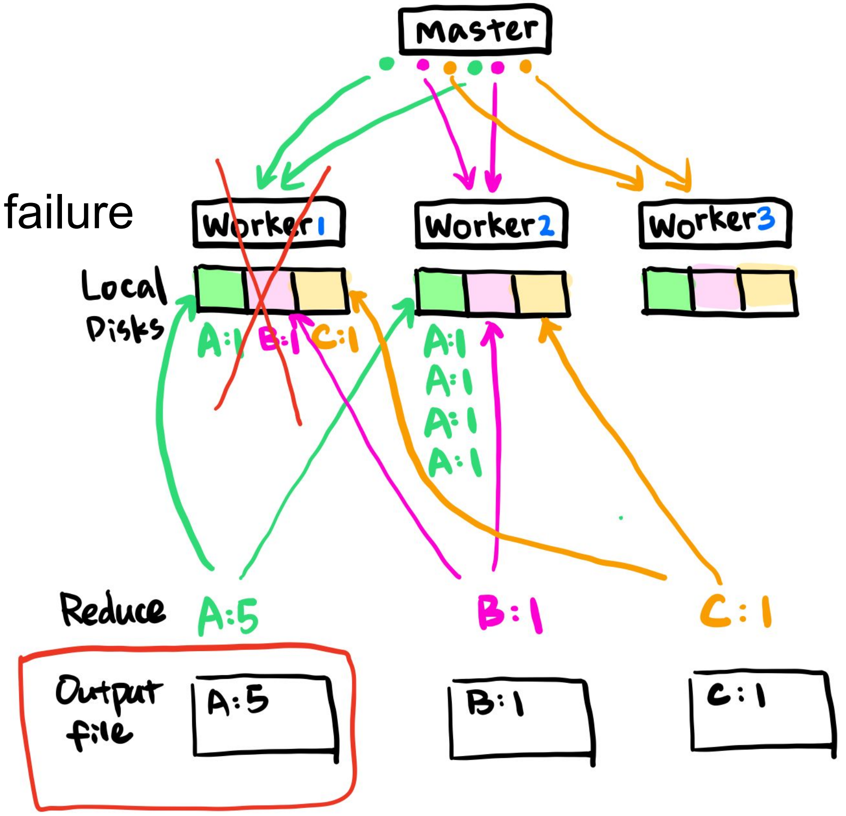


Fault Tolerance

Worker Failure

- Completed Map tasks are re-executed on failure
  - *Map* outputs: on **local disks** of workers
- Completed Reduce tasks do not need
  - *Reduce* outputs: in **global file system**
- **All the workers** will be notified of a re-execution
  - Reduce worker read data from new location
- Resilient to **large-scale worker failures**



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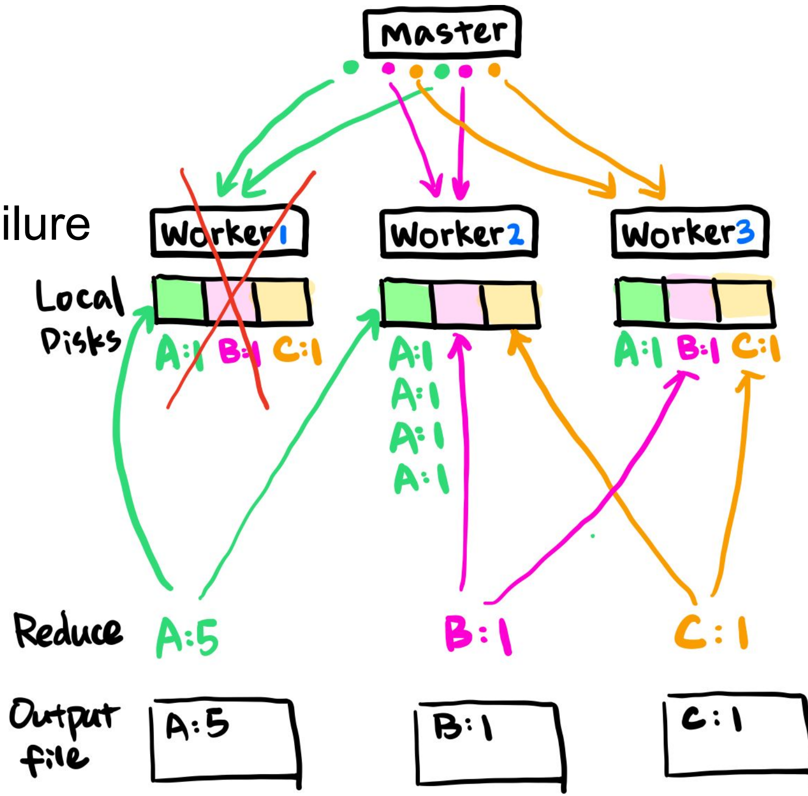

Fault Tolerance

Master Failure

- Single master, rare failure
- If master fails, aborts the MapReduce computation
- Client can retry

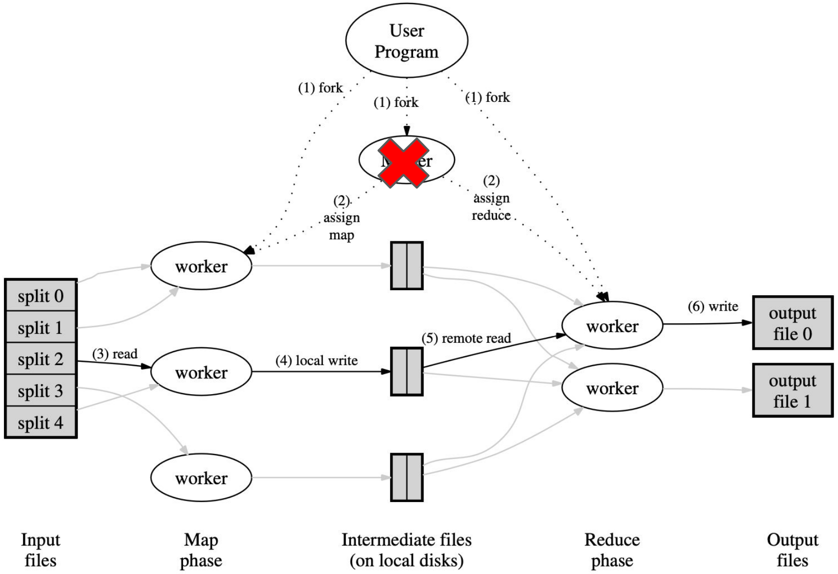

Figure 1: Execution overview

Semantics in the Presence of Failures

- Deterministic Map/Reduce Functions
  - Atomic commit task output:
    - guarantee no duplicates of *Map* results
  - Atomic rename operation:
    - guarantee no duplicates of *Reduce* results
- Non-deterministic Functions
  - Weaker but still reasonable semantics

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Locality

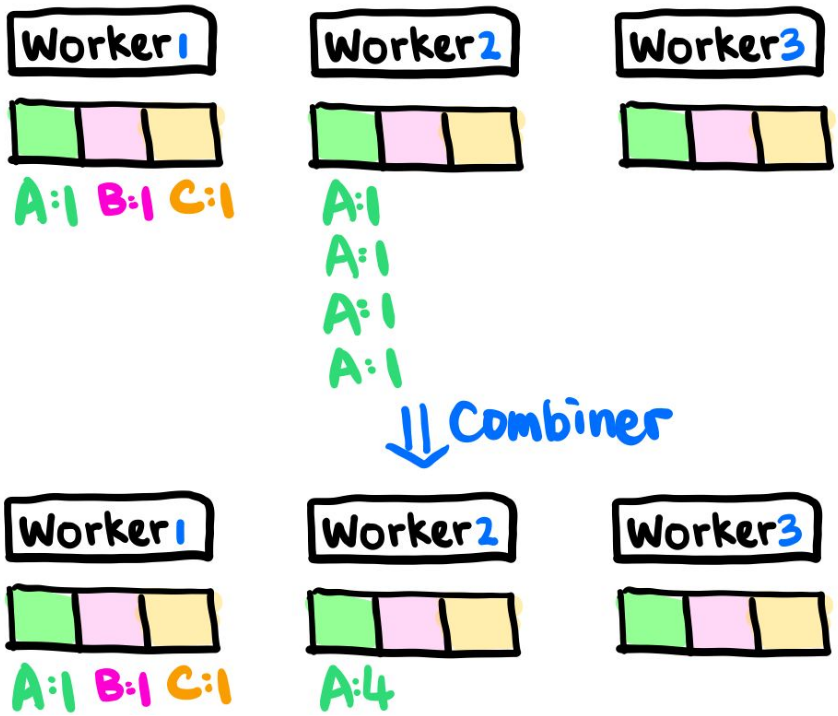
- Scarce resource: Network bandwidth
- Solution: Store input data (managed by GFS) on local disks of machines that makes up the cluster
- GFS:
  - Divides data into 64 MB blocks
  - Replicates data in different machines (usually 3)
- Master: Assign map tasks to machines **contains** the data or **close to** data locations (e.g. same network switch)

Refinements

- Customizable Partitioning Function
- Ordering Guarantees
- Input and Output Types
- Auxiliary additional outputs
- Skipping bad records
- Local Execution
- Status information
- Counters

Refinements

- Optional Combiner Function
  - Partial merging of data at the end of Map
  - Typically same code as *Reduce*
  - E.x. <the, 1> in Zipf distributed word count task



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Performance

2 computation tasks:

- Search through appx. 1 terabytes data → rare 3-character pattern (Grep)
  - Extract small amount of interesting data from large dataset
  - Input → 64 MB pieces (M = 15000)
  - Output in 1 file (R = 1)

Grep

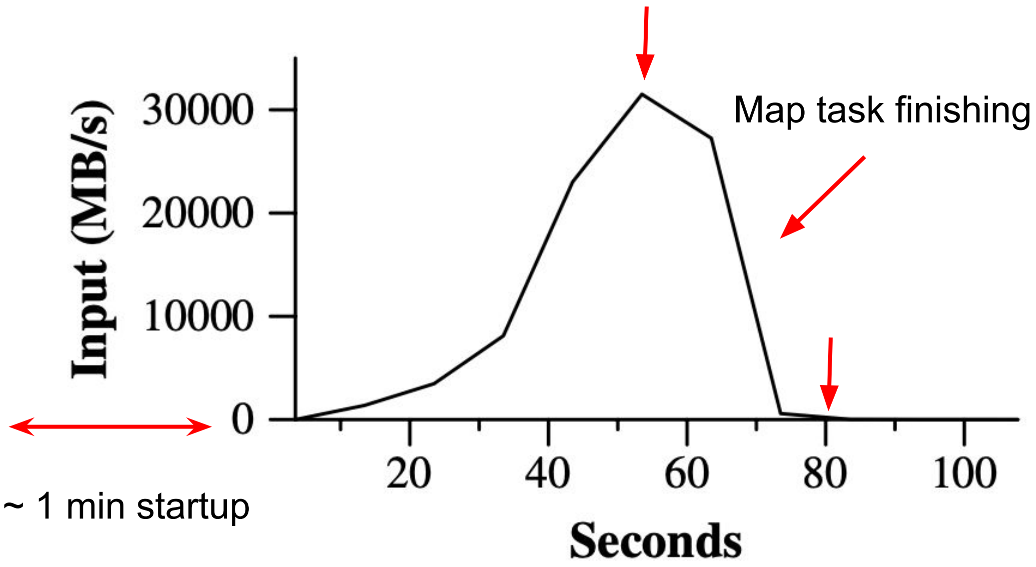
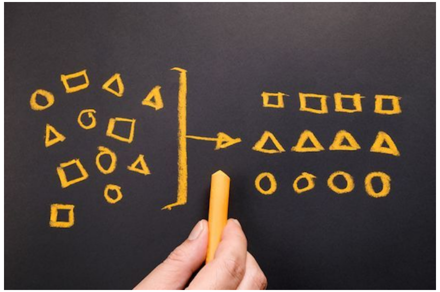


Figure 2: Data transfer rate over time

- Peaks at ~ 30 GB/s
  - 1764 Workers
- ~ 1 min startup overhead
  - Program propagation to workers
  - Delays when interacting with GFS for locality optimization

Performance

2 computation tasks:

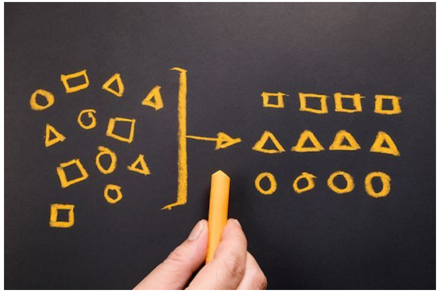


- Sort appx. 1 terabyte of data (Sort)
  - Shuffles data from one representation to another
  - Modeled after the TeraSort benchmark
  - Map → word, text line
  - Reduce → Built-in Identity function

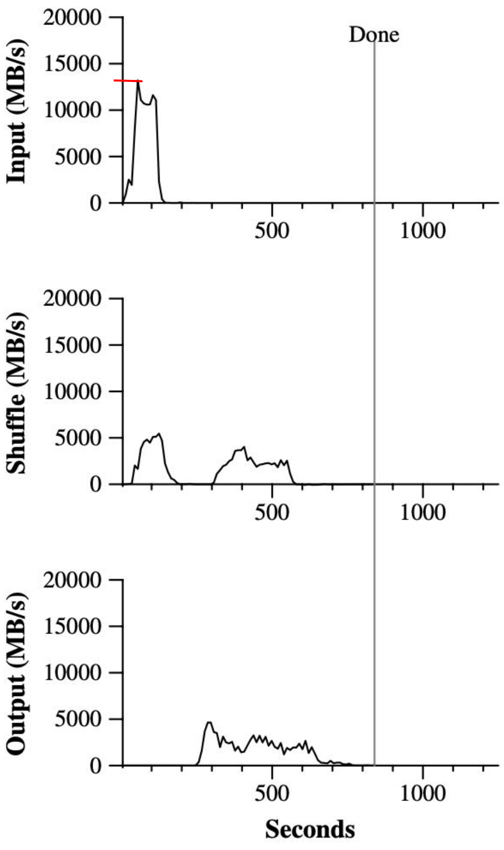
Performance

2 computation tasks:

- Sort appx. 1 terabyte of data (Sort)
  - Input → 64 MB pieces (M = 15000)
  - Final output: A set of 2-way replicated GFS files
  - R = 4000



Sort Performance

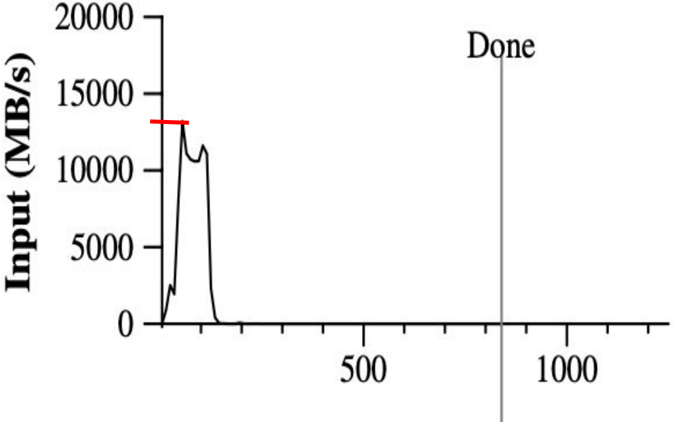


(a) Normal execution

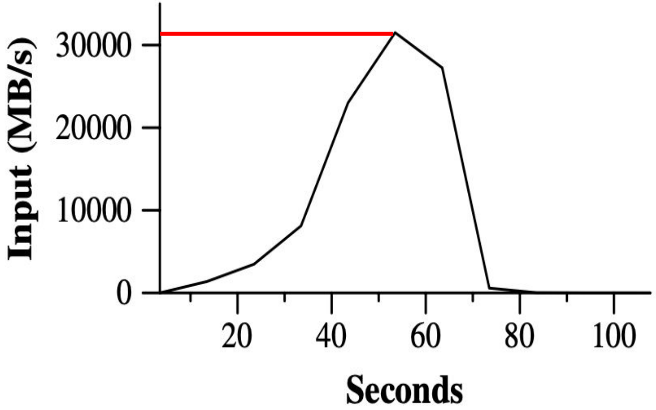
- Input rate:
  - Input is read
- Shuffle rate:
  - Data sent from map tasks to reduce tasks
- Output rate
  - Sorted data written to final output files by reduce tasks
- Higher input rate
  - Locality optimization

Sort Performance

Peaks at ~13 GB/s



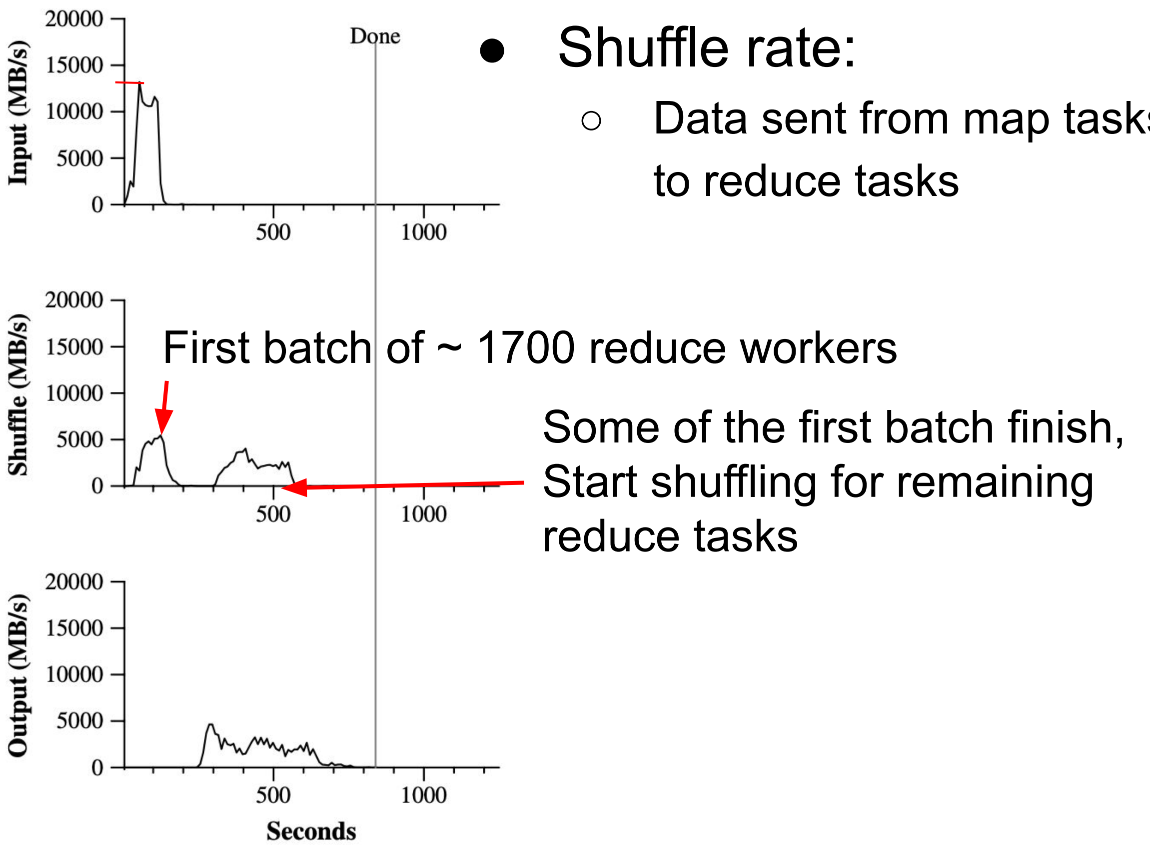
Sort input rate



Grep input rate

- Input rate less than that for grep
  - Spend half of time & bandwidth writing intermediates

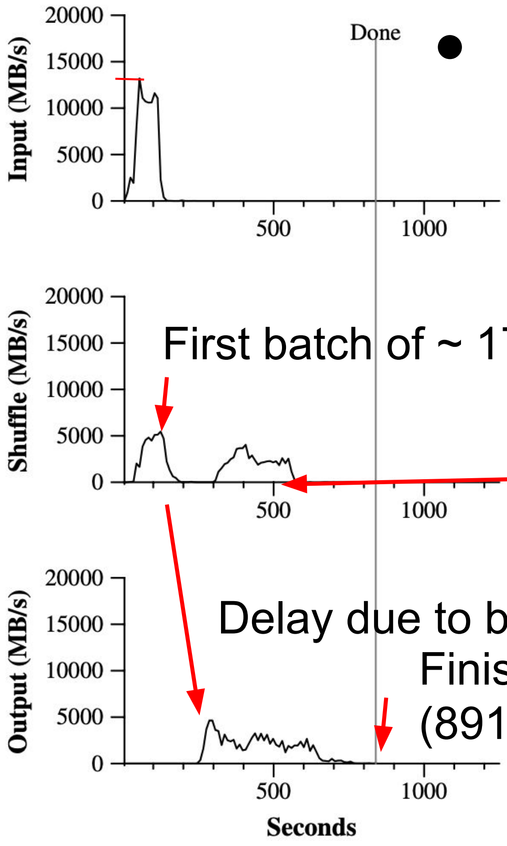
Sort Performance



(a) Normal execution

- Shuffle rate:
  - Data sent from map tasks to reduce tasks

Sort Performance



(a) Normal execution

- Output rate
  - Sorted data written to final output files by reduce tasks

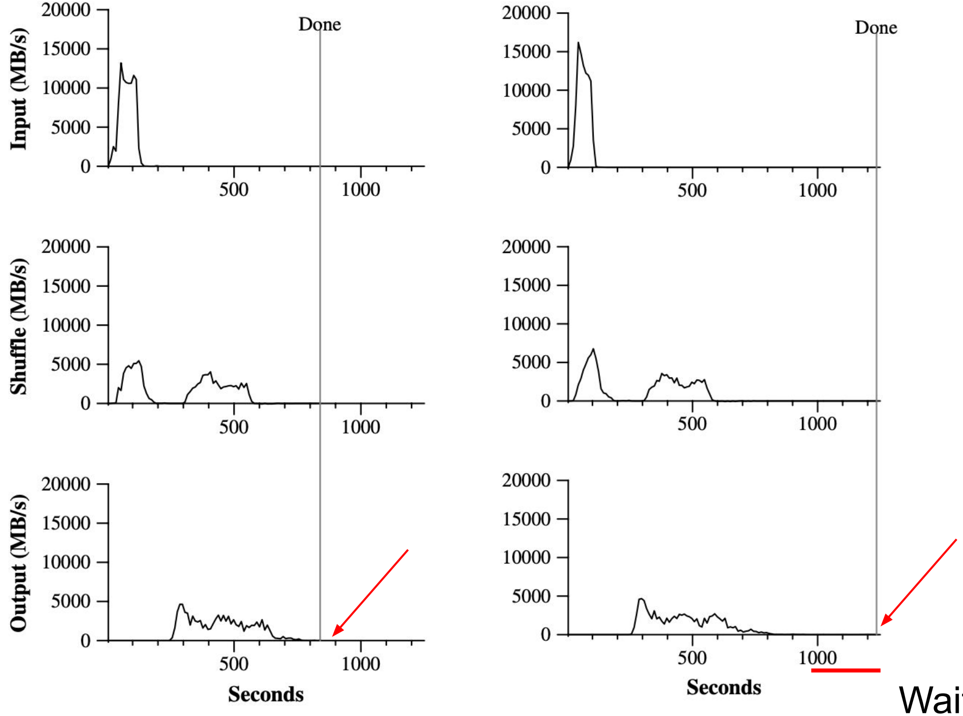
First batch of ~ 1700 reduce workers

Some of the first batch finish, Start shuffling for remaining reduce tasks

Delay due to busy sorting of intermediates

Finishes at ~850s (891s including the startup overhead)

Backup Task

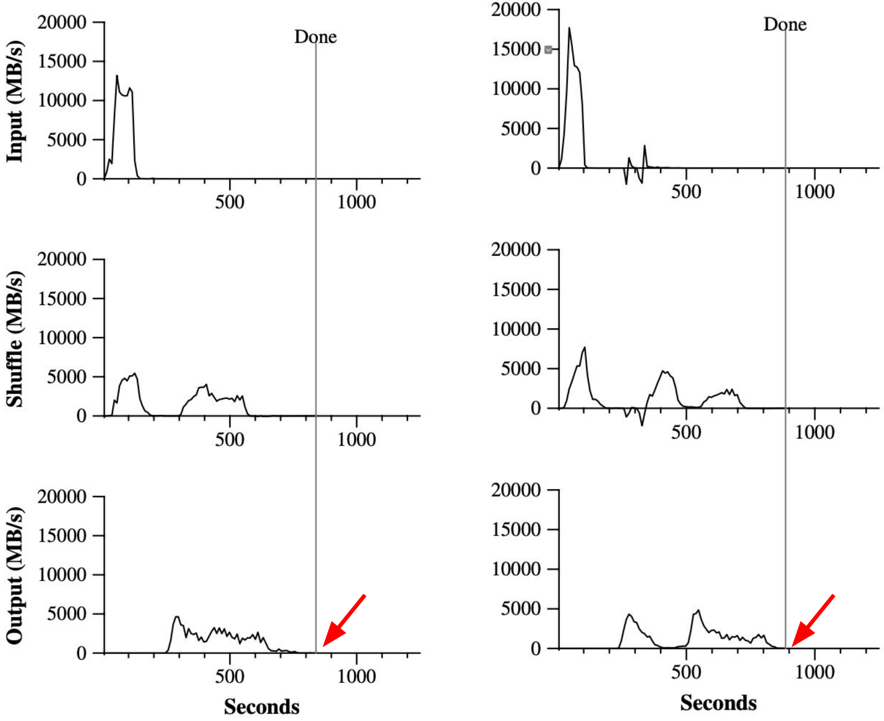


(a) Normal execution
(b) No backup tasks

Wait for 5 “stragglers” from 960s

- “Stragglers”: machines take unusually long time
- Solution:
  - *Map*/*Reduce* close to completion
  - Master schedule backups for remaining in-progress tasks
- 44% longer time when no backup tasks

Machine Failure



(a) Normal execution

(c) 200 tasks killed

- Killed 200 out of 1746 workers
  - ~ 11.5% workers
- 5% increase of execution time
- Neg values: *Map* work need to be redone in dead workers

Sort Performance

- Entire computation takes 891s
- Comparable to best reported results (1057s) for the TeraSort Benchmark

Conclusion

- Mapreduce is easy to use
  - Hides details of
    - Parallelization
    - Fault-tolerance
    - Locality optimization
    - Load balancing
- Powerful
  - A large variety of problems are expressible as MapReduce computations
- Scalable
  - Implementation of MapReduce using large cluster of machines

Thank you!

Questions?