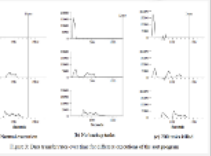
individual web pages

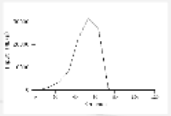
(source: Google Insights)

MR_Sort

backup tasks reduce job completion time significantly
system deals well with failures



MR_Grep



Locality optimization helps:
- 1800 machines read 1 TB of data at peak of ~31 GB/s
- Without this, rack switches would limit to 10 GB/s

Startup overhead is significant for short jobs

Performance

Tests run on cluster of 1800 machines:
- 4 GB of memory
- Dual processor 2 GHz Xeons with Hyperthreading
- Dual 160 GB IDE disks
- Gigabit Ethernet per machine
- Bisection bandwidth approximately 100 Gbps

Two benchmarks:

1. MR_Grep Scan: 10^10 100-byte records to extract records matching a rare pattern (92K matching records)

2. MR_Sort Sort: 10^10 100-byte records (modeled after TeraSort benchmark)

MapReduce: Simplified Data Processing on Large Clusters

By: Bikramdeep Singh

Motivation

130 trillion
individual web pages

(source: Google Insights)

Motivation

100 million GB
index data on google

- (source: Google Insights)

Some questions...

- What is the most frequent search query in a given day?

- How many number of pages are crawled per host?

- What is the most popular video in youtube Canada?

MapReduce provides:

- Automatic parallelization and distribution

- Fault-tolerance

- I/O scheduling

- Status and monitoring

Programming Model

Input & Output: each a set of key/value pairs
Programmer specifies two functions:

map (in_key, in_value) -> list(out_key, intermediate_value)
Processes input key/value pair
Produces set of intermediate pairs

reduce (out_key, list(intermediate_value)) -> list(out_value)
Combines all intermediate values for a particular key
Produces a set of merged output values (usually just one)

Inspired by similar primitives in LISP and other languages

See it in action...

https://goo.gl/DykPHB

Some other examples

- Distributed Grep
- Count of URL access frequency
- Reverse Web-Link Graph
- Term Vector per host
- Inverted Index
- Distributed Sort

Implementation Overview

Typical cluster:

- 100s/1000s of 2-CPU x86 machines, 2-4 GB of memory
- Limited bisection bandwidth
- Storage is on local IDE disks
- GFS: distributed file system manages data
- Job scheduling system: jobs made up of tasks, scheduler assigns tasks to machines

Implementation is a C++ library linked into user programs

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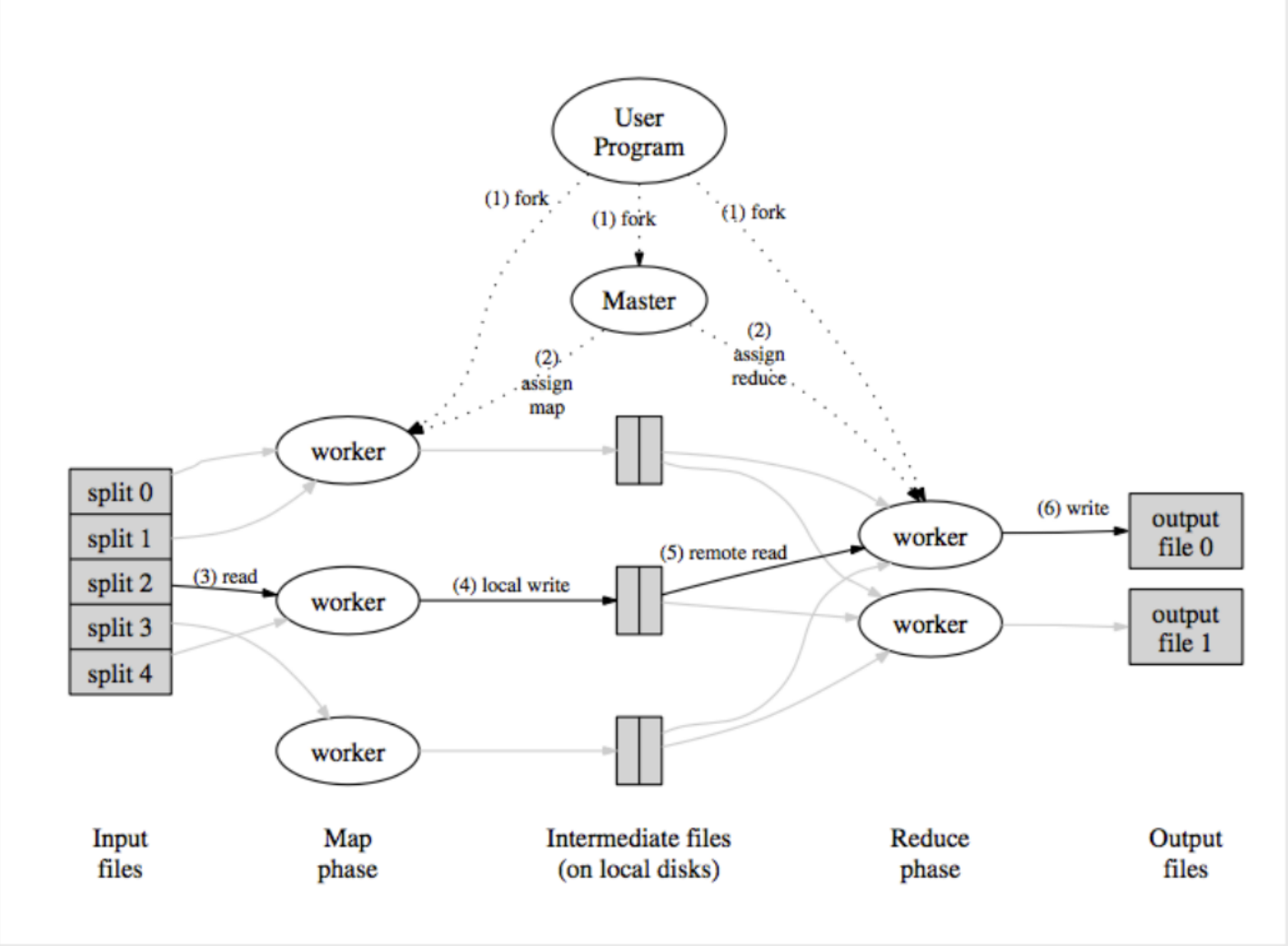
User Program
(1) fork
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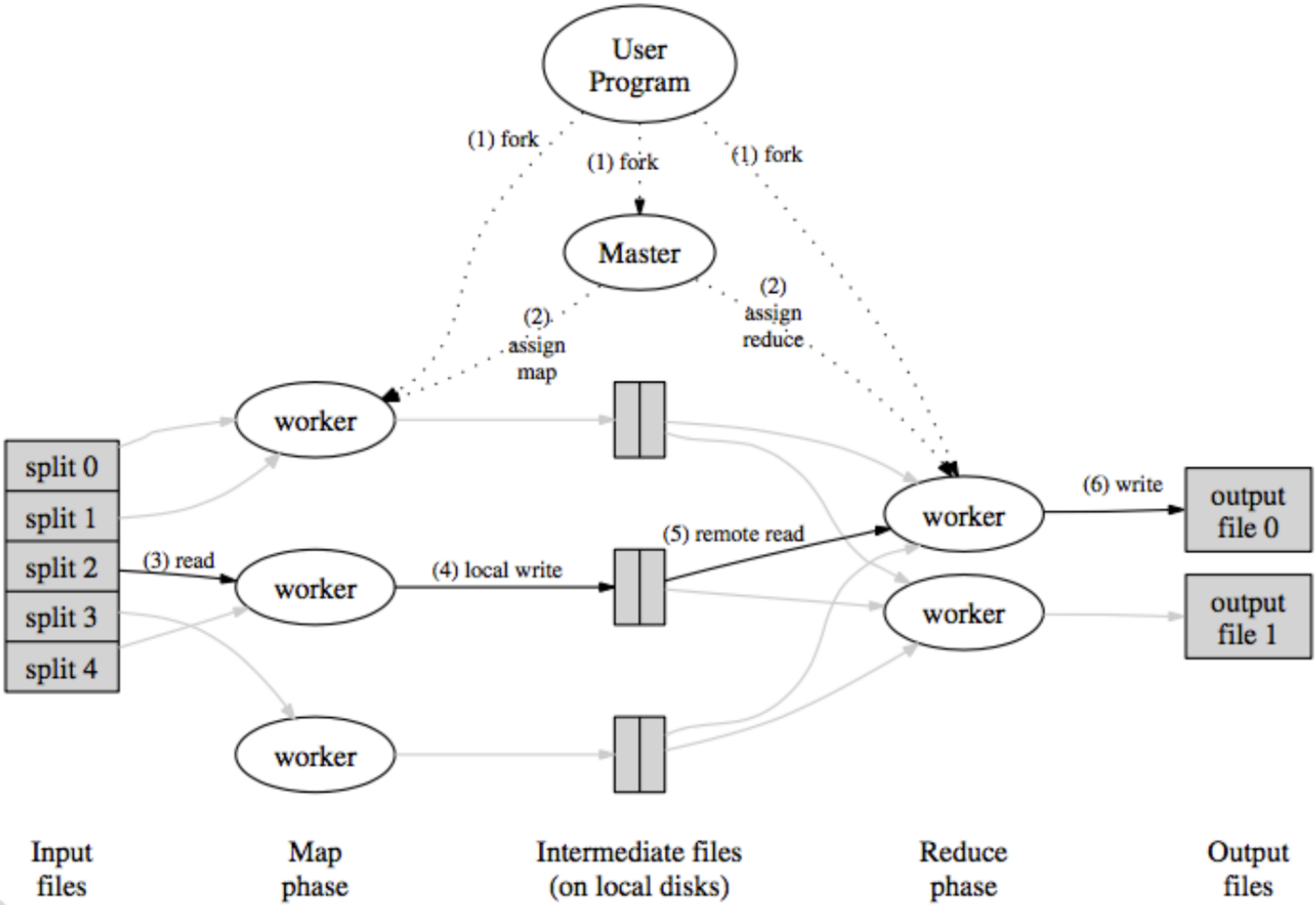
Master
(2) assign map
(2) assign reduce
worker
split 0
split 1
split 2
split 3
split 4
(3) read
worker
(4) local write
worker
(5) remote read
worker
worker
(6) write
output file 0
output file 1
Input files
Map phase
Intermediate files (on local disks)
Reduce phase
Output files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Fault Tolerance

On worker failure:

- Detect failure via periodic heartbeats
- Re-execute completed and in-progress map tasks
- Re-execute in progress reduce tasks
- Task completion committed through master

Master failure:
Could handle, but don't yet (master failure unlikely)

Robust: lost 1600 of 1800 machines once, but finished fine

Refinement: Redundant Execution

Slow workers (stragglers) significantly lengthen completion time

- Other jobs consuming resources on machine
- Bad disks with soft errors transfer data very slowly
- Processor caches disabled

Solution: Near end of phase, spawn backup copies of tasks, whichever one finishes first "wins"

Effect: Dramatically shortens job completion time

Refinement: Locality Optimization

Master scheduling policy:

- Asks GFS for locations of replicas of input file blocks
- Map tasks typically split into 64MB (== GFS block size)
- Map tasks scheduled so GFS input block replica are on same machine or same rack

Effect: Thousands of machines read input at local disk speed

Without this, rack switches limit read rate

Refinement: Skipping Bad Records

Map/Reduce functions sometimes fail for particular inputs

- Best solution is to debug & fix, but not always possible
- On seg fault:
  - Send UDP packet to master from signal handler
  - Include sequence number of record being processed
- If master sees two failures for same record:
- Next worker is told to skip the record

Effect: Can work around bugs in third-party libraries

Other Refinements

- Sorting guarantees within each reduce partition
- Compression of intermediate data
- Combiner: useful for saving network bandwidth
- Local execution for debugging/testing
- User-defined counters

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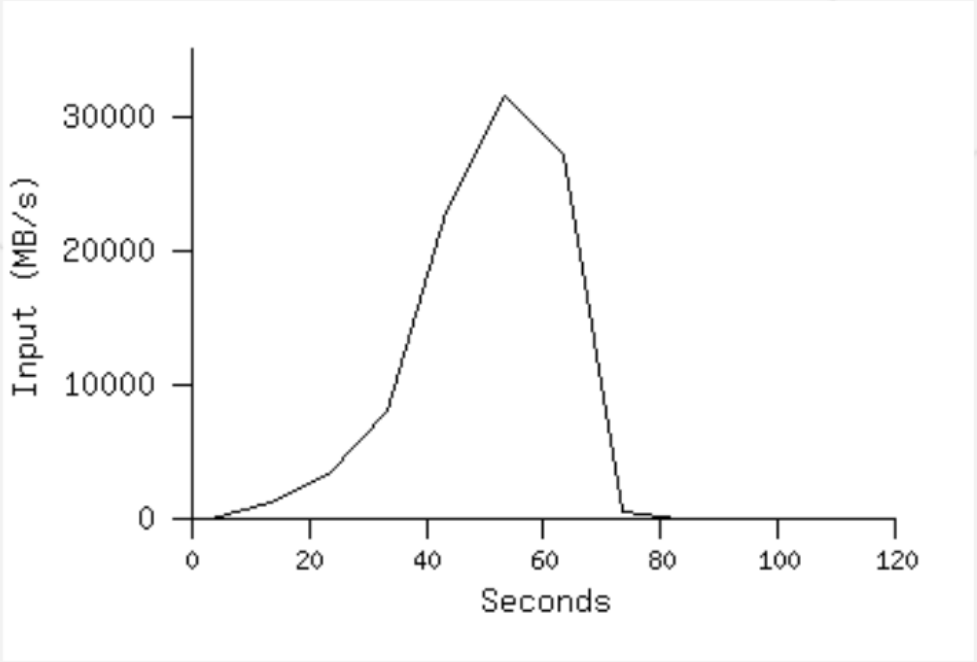

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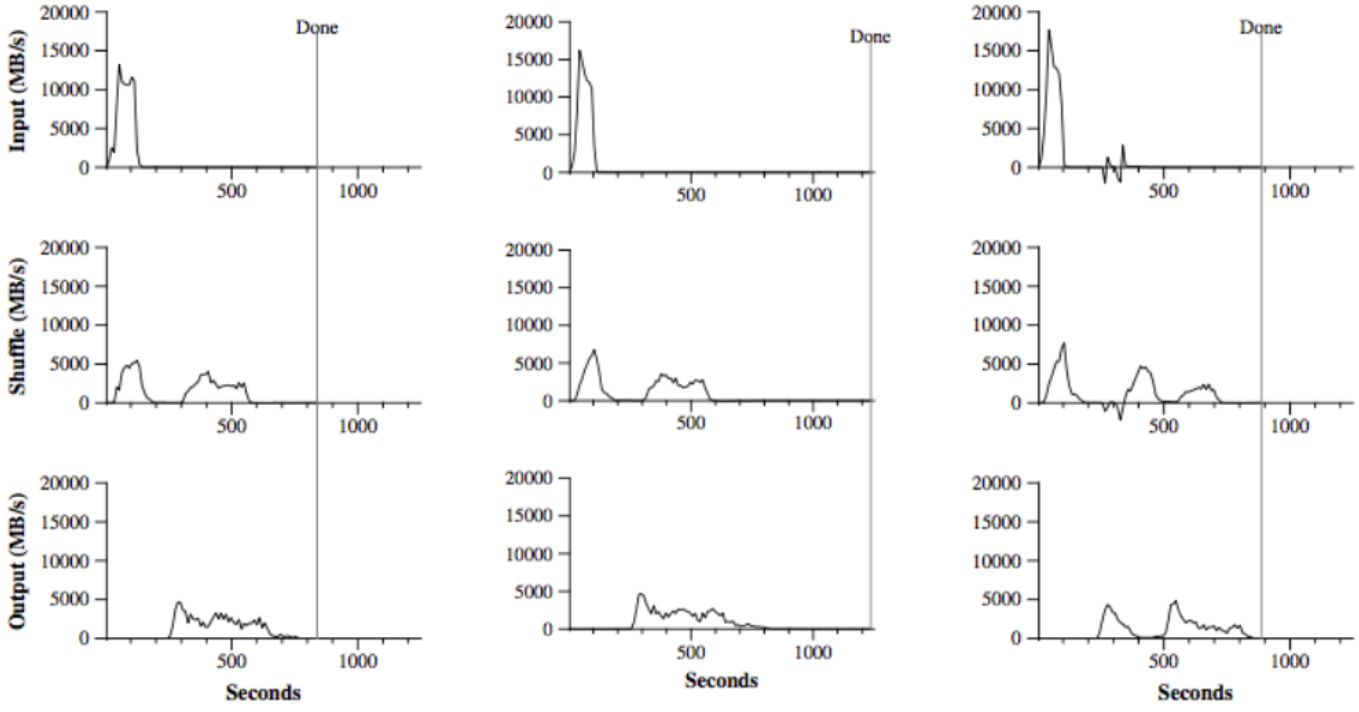
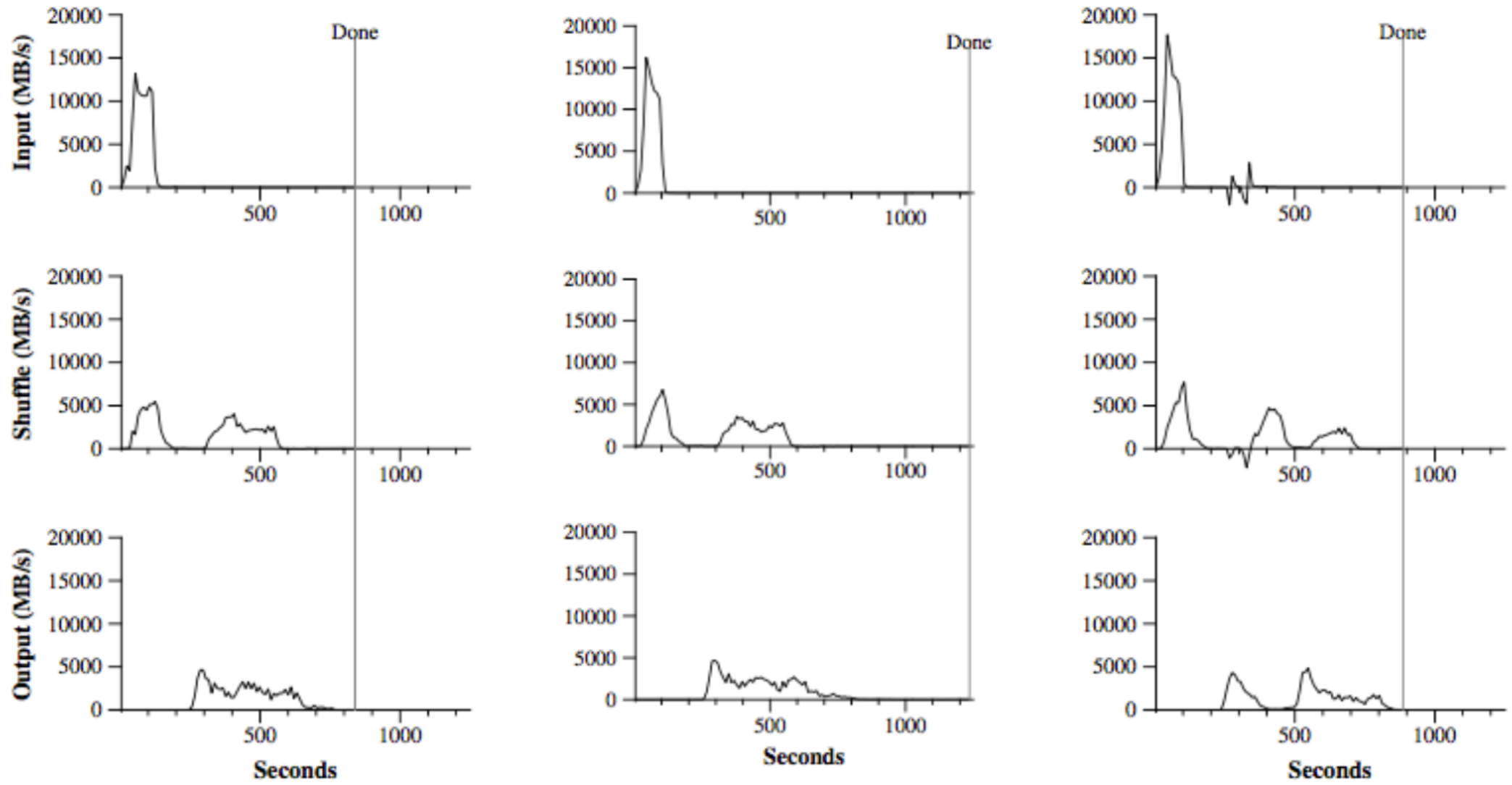


(a) Normal execution (b) No backup tasks (c) 200 tasks killed

Figure 3: Data transfer rates over time for different executions of the sort program

- System deals well with failures



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Experience

Rewrote Google's production indexing system using MapReduce

- New code is simpler, easier to understand
- MapReduce takes care of failures, slow machines
- Easy to make indexing faster by adding more machines

Conclusion

- MapReduce has proven to be a useful abstraction
- Greatly simplifies large-scale computations at Google (and the world ;))
- Fun to use: focus on problem, let library deal w/ messy details

Thank You