Map/Reduce

Based on original presentation by
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Functional Programming Review

- Functional operations do not modify data structures: They always create new ones
- Original data still exists in unmodified form
- Data flows are implicit in program design
- Order of operations does not matter

Functional Programming Review

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)
```

Order of sum() and mul(), etc does not matter – they do not modify *l*

Functional Updates Do Not Modify Structures

```
fun append(x, lst) =
  let lst' = reverse lst in
    reverse ( x :: lst' )
```

The append() function above reverses a list, adds a new element to the front, and returns all of that, reversed, which appends an item.

But it *never modifies lst*!

Functions Can Be Used As Arguments

```
fun DoDouble(f, x) = f (f x)
```

It does not matter what f does to its argument; DoDouble() will do it twice.

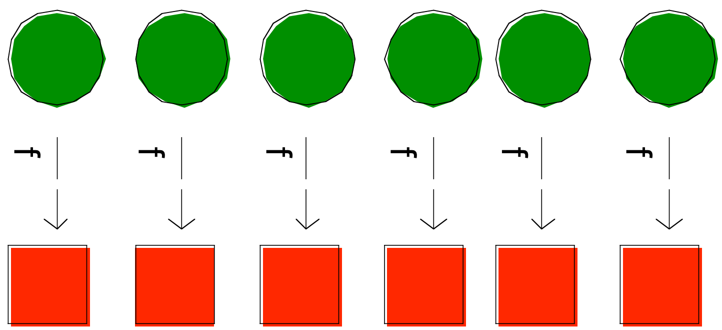
What is the type of this function?

Map

map f a [] = f(a)

map f (a:as) = list(f(a), map(f, as))

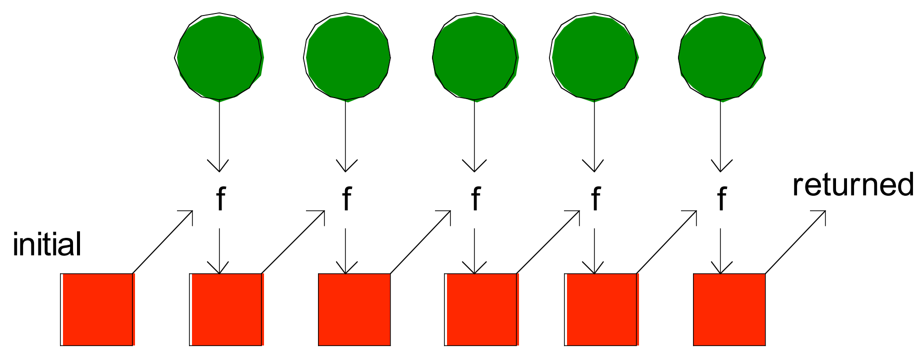
Creates a new list by applying f to each element of the input list; returns output in order.



Fold

fold f x_0 lst: ('a*'b->'b)->'b->('a list)->'b

Moves across a list, applying *f* to each element plus an *accumulator*. f returns the next accumulator value, which is combined with the next element of the list



fold left vs. fold right

- Order of list elements can be significant
- Fold left moves left-to-right across the list
- Fold right moves from right-to-left

SML Implementation:

```
fun foldl f a []      = a
  | foldl f a (x::xs) = foldl f (f(x, a)) xs

fun foldr f a []      = a
  | foldr f a (x::xs) = f(x, (foldr f a xs))
```

Example

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)
```

How can we implement this?

Example (Solved)

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)

fun sum(lst) = foldl (fn (x,a)=>x+a) 0 lst
fun mul(lst) = foldl (fn (x,a)=>x*a) 1 lst
fun length(lst) = foldl (fn (x,a)=>1+a) 0 lst
```

A More Complicated Fold Problem

- Given a list of numbers, how can we generate a list of partial sums?

e.g.: [1, 4, 8, 3, 7, 9] →

[0, 1, 5, 13, 16, 23, 32]

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fun partialsum(lst) = foldl(fn(x,a) => list(a (last(a) + x))) 0 lst

A More Complicated Map Problem

- Given a list of words, can we: reverse the letters in each word, and reverse the whole list, so it all comes out backwards?

[“my”, “happy”, “cat”] -> [“tac”, “yppah”, “ym”]

A More Complicated Map Problem

- Given a list of words, can we: reverse the letters in each word, and reverse the whole list, so it all comes out backwards?

[“my”, “happy”, “cat”] -> [“tac”, “yppah”, “ym”]

fun reverse2(lst) = foldr(fn(x,a)=>list(a, reverseword(x))) [] lst

map Implementation

```
fun map f []       = []
  | map f (x::xs) = (f x) :: (map f xs)
```

- This implementation moves left-to-right across the list, mapping elements one at a time
- … But does it need to?

Implicit Parallelism In Map

- In a purely functional setting, elements of a list being computed by map cannot see the effects of the computations on other elements
- If order of application of f to elements in list is *commutative*, we can reorder or parallelize execution
- This is the insight behind MapReduce

Motivation: Large Scale Data Processing

- Want to process lots of data (> 1 TB)
- Want to parallelize across hundreds/thousands of CPUs
- … Want to make this easy
  - Hide the details of parallelism, machine management, fault tolerance, etc.

Sample Applications

- Distributed Greo
- Count of URL Access Frequency
- Reverse Web-Lijk Graph
- Inverted Index
- Distributed Sort

MapReduce

- Automatic parallelization & distribution
- Fault-tolerant
- Provides status and monitoring tools
- Clean abstraction for programmers

Programming Model

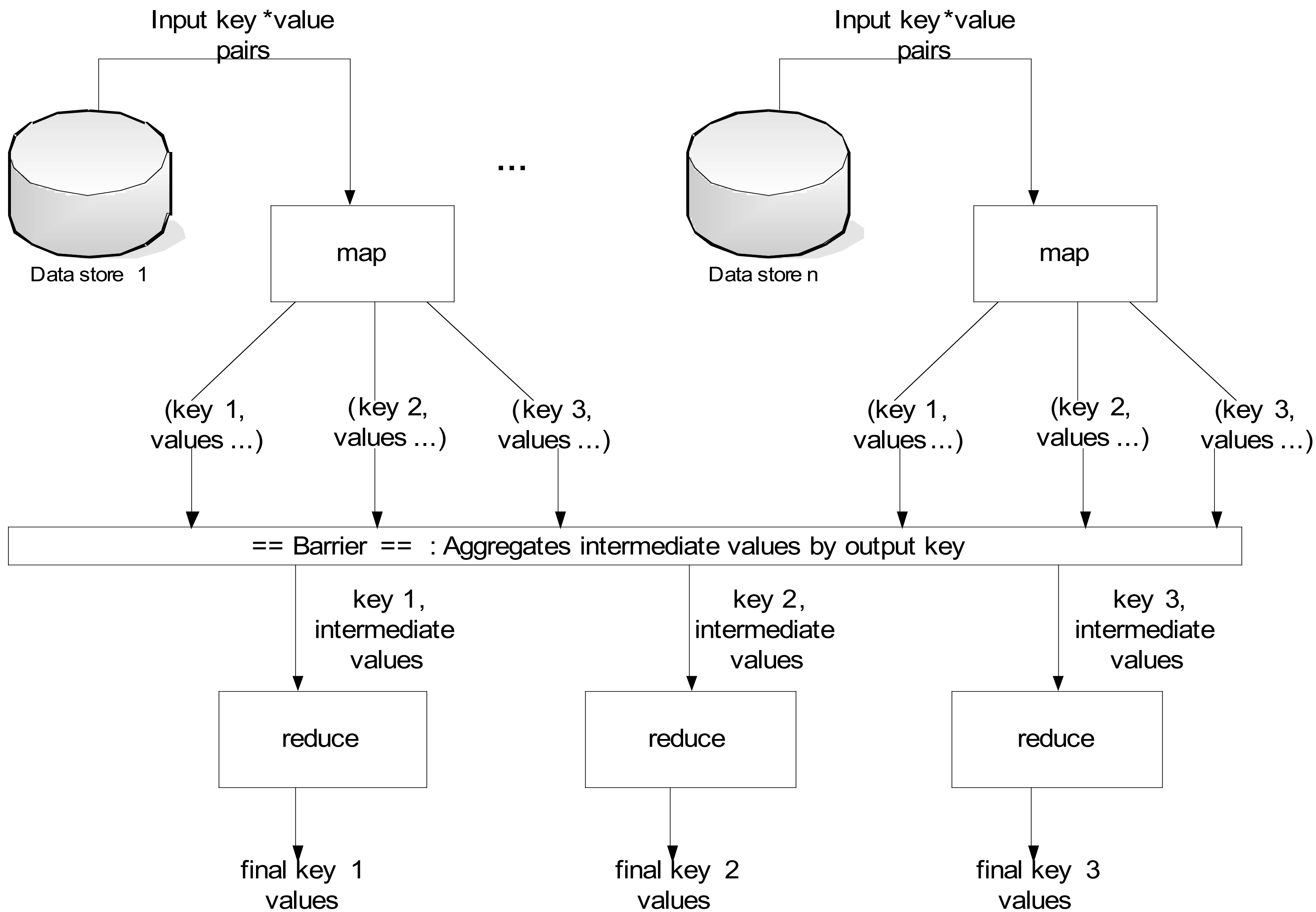
- Borrows from functional programming
- Users implement interface of two functions:
  - `map (in_key, in_value) -> (out_key, intermediate_value) list`
  - `reduce (out_key, intermediate_value list) -> out_value list`

Map

- Records from the data source (lines out of files, rows of a database, etc) are fed into the map function as key*value pairs: e.g., (filename, line)
- map() produces one or more *intermediate* values along with an output key from the input
- Buffers intermediate values in memory before periodically writing to local disk
- Writes are split into *R* regions based on intermediate key value (e.g., *hash(key) mod R*)
    - Locations of regions communicated back to master who informs reduce tasks of all appropriate disk locations

Reduce

- After the map phase is over, all the intermediate values for a given output key are combined together into a list
  - RPC over GFS to gather all the keys for a given region
  - Sort all keys since the same key can in general come from multiple map processes
- reduce() combines those intermediate values into one or more *final values* for that same output key
- Optional combine() phase as an optimization


Input key *value pairs
Data store 1
map
...
Input key*value pairs
Data store n
map
(key 1, values ...)
(key 2, values ...)
(key 3, values ...)
(key 1, values ...)
(key 2, values ...)
(key 3, values ...)
== Barrier == : Aggregates intermediate values by output key
key 1, intermediate values
key 2, intermediate values
key 3, intermediate values
reduce
reduce
reduce
final key 1 values
final key 2 values
final key 3 values

Parallelism

- map() functions run in parallel, creating different intermediate values from different input data sets
- reduce() functions also run in parallel, each working on a different output key
- All values are processed *independently*
- Bottleneck: reduce phase cannot start until map phase completes

Example: Count word occurrences

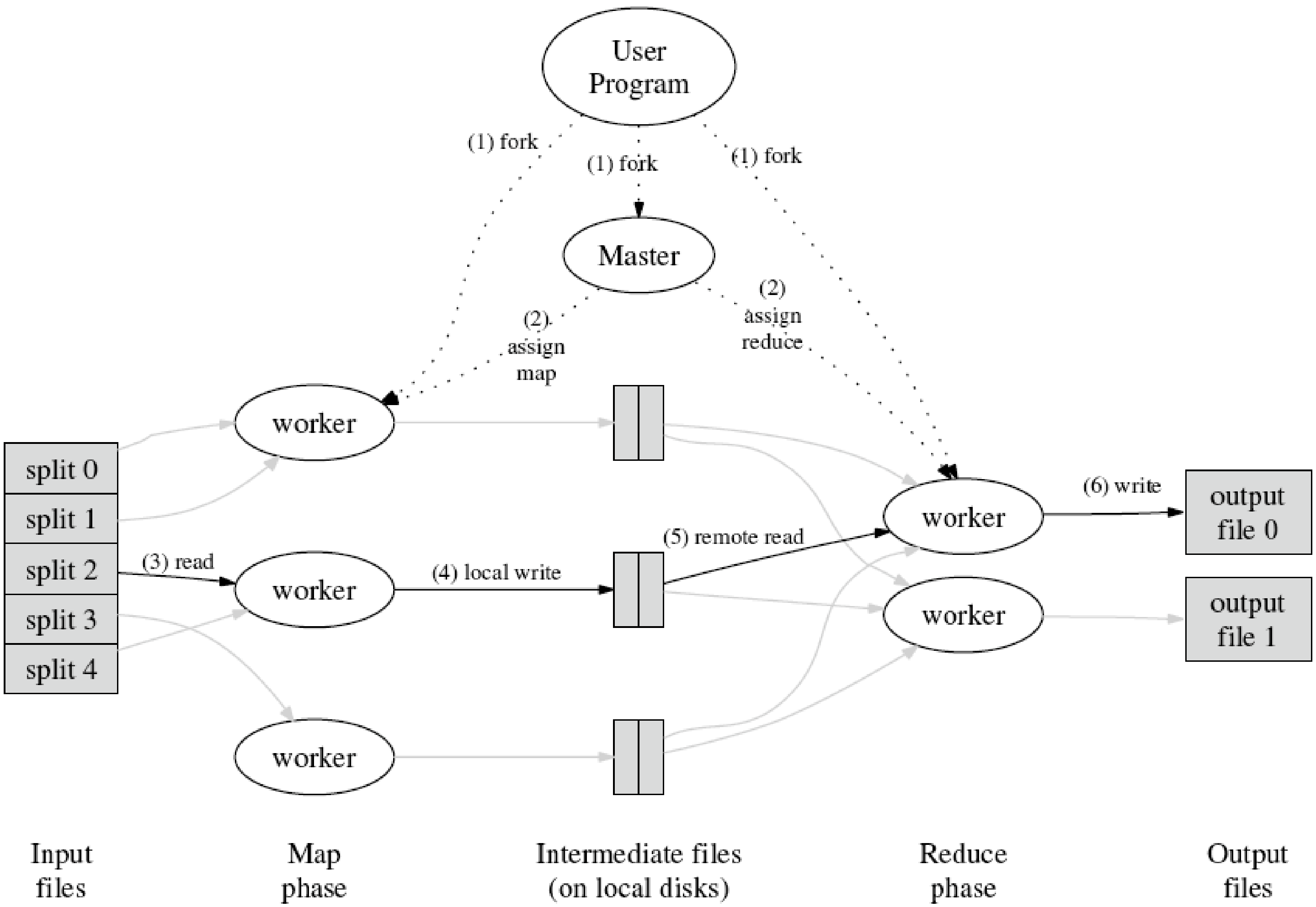
```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, "1");

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

Example vs. Actual Source Code

- Example is written in pseudo-code
- Actual implementation is in C++, using a MapReduce library
- Bindings for Python and Java exist via interfaces
- True code is somewhat more involved (defines how the input key/values are divided up and accessed, etc.)

Implementation



Locality

- Master program divides up tasks based on location of data: tries to have map() tasks on same machine as physical file data
  - Failing that, on the same switch where bandwidth is relatively plentiful
  - Datacenter communications architecture?
- map() task inputs are divided into 64 MB blocks: same size as Google File System chunks

Fault Tolerance

- Master detects worker failures
  - Re-executes completed & in-progress map() tasks
  - Re-executes in-progress reduce() tasks
  - Importance of deterministic operations
- Data written to temporary files by both map() and reduce()
  - Upon successful completion, map() tells master of file names

    Master ignores if already heard from another map on same task
  - Upon successful completion, reduce() atomically renames file
- Master notices particular input key/values cause crashes in map(), and skips those values on re-execution.
  - Effect: Can work around bugs in third-party libraries

Optimizations

- No reduce can start until map is complete:
  - A single slow disk controller can rate-limit the whole process
- Master redundantly executes "slow-moving" map tasks; uses results of first copy to finish

Why is it safe to redundantly execute map tasks? Wouldn't this mess up the total computation?

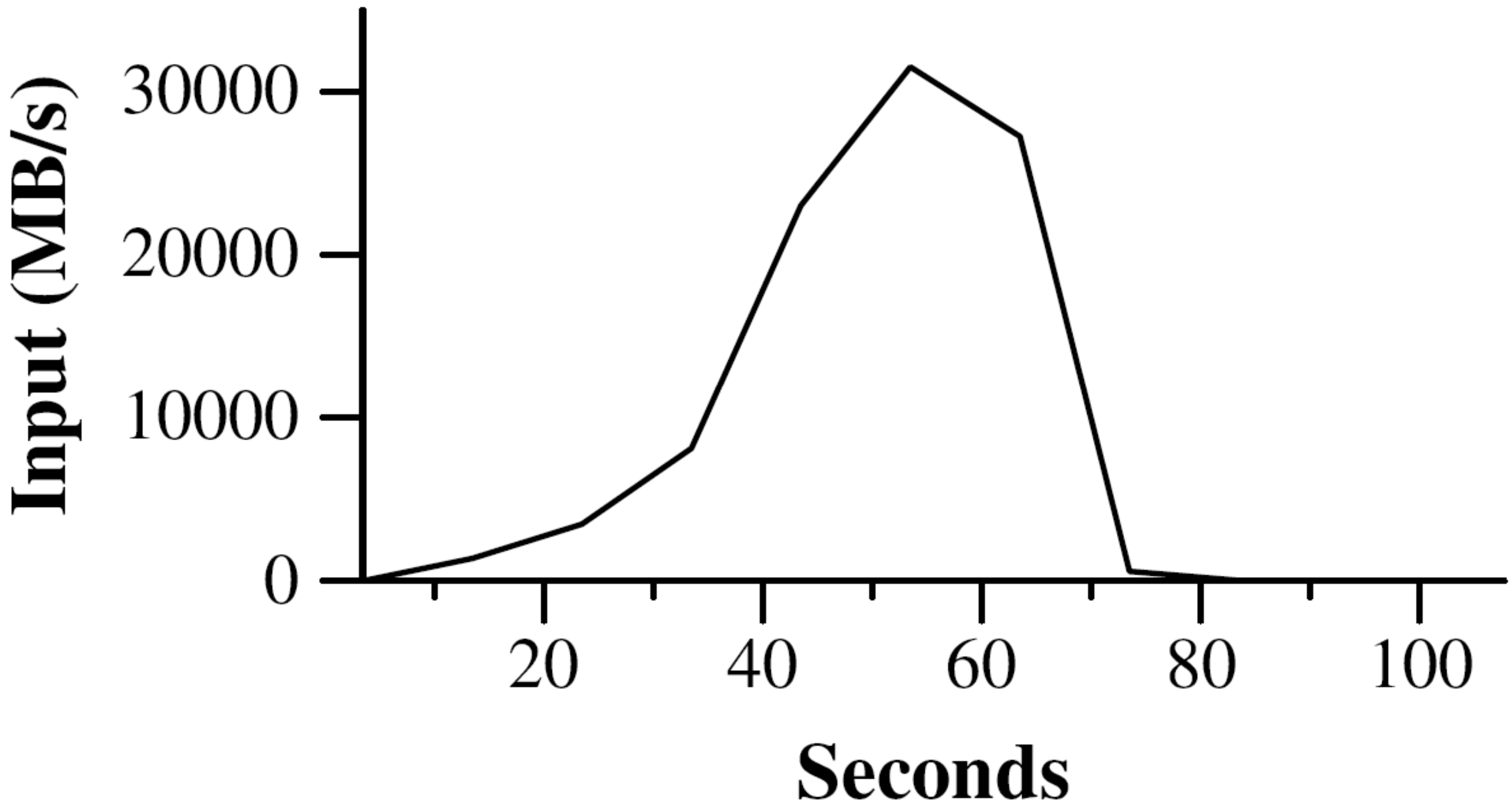
Optimizations

- "Combiner" functions can run on same machine as a mapper
- Causes a mini-reduce phase to occur before the real reduce phase, to save bandwidth

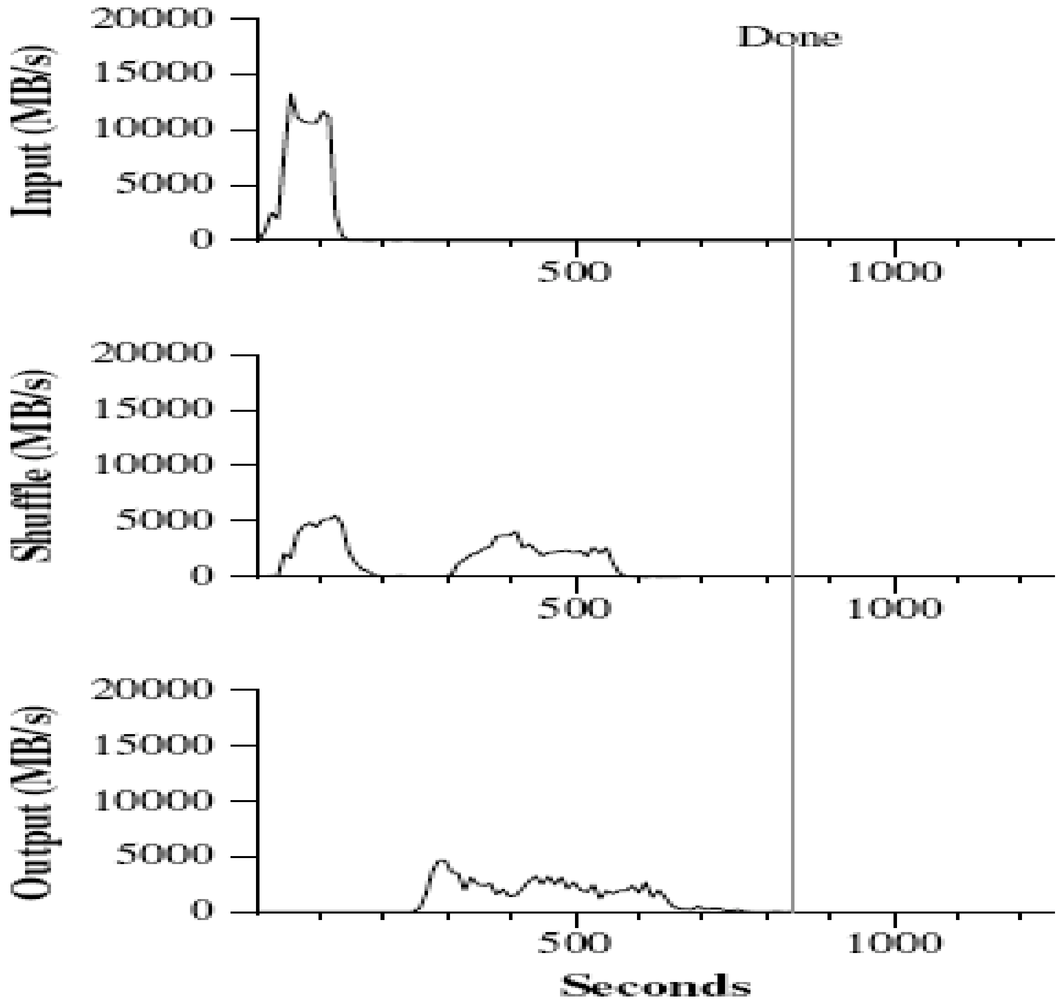
Performance Evaluation

- 1800 Machines
  - Gigabit Ethernet Switches
  - Two level tree hierarchy, 100-200 Gbps at root
  - 4GB RAM, 2Ghz dual Intel processors
  - Two 160GB drives
- Grep: 10^10 100 byte records (1 TB)
  - Search for relatively rare 3-character sequence
- Sort: 10^10 100 byte records (1 TB)

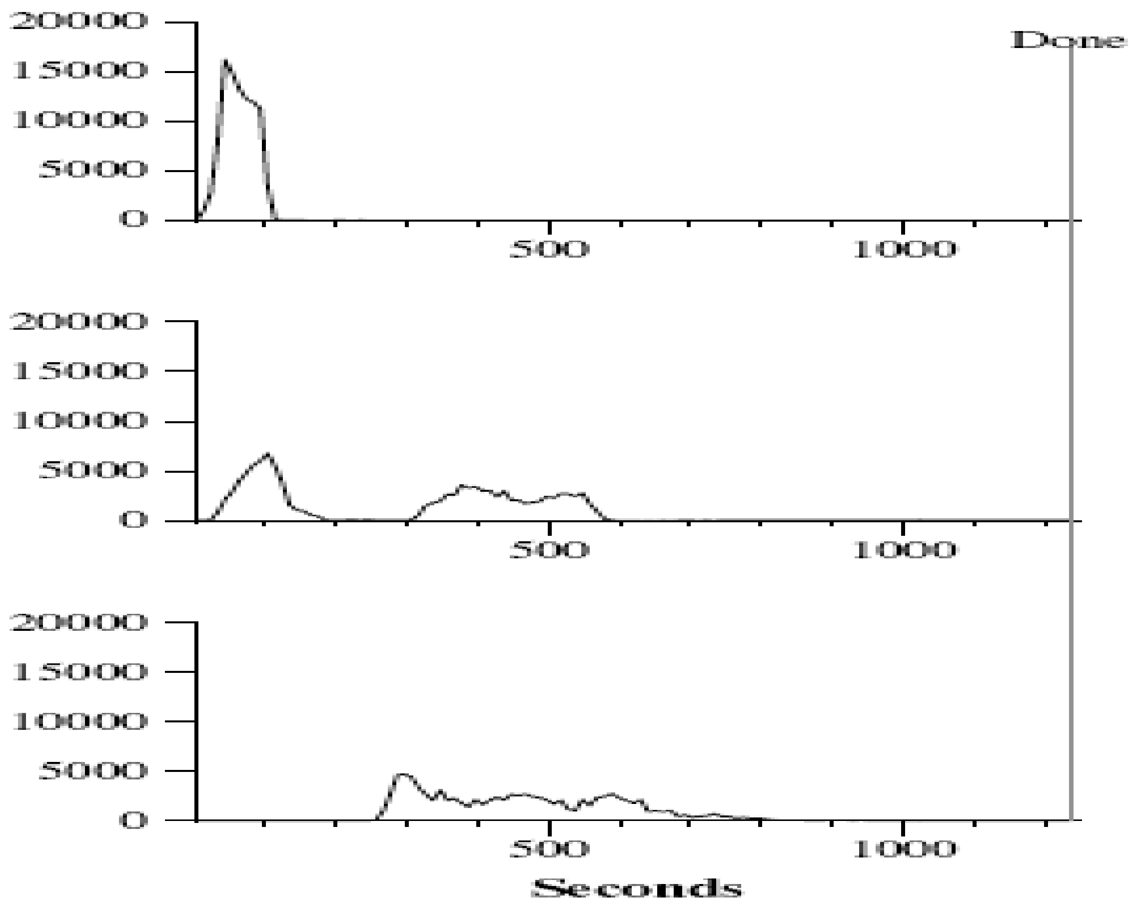
Grep Data Transfer Rate



Sort: Normal Execution



Sort: No Backup Tasks



MapReduce Conclusions

- MapReduce has proven to be a useful abstraction
- Greatly simplifies large-scale computations at Google
- Functional programming paradigm can be applied to large-scale applications
- Focus on problem, let library deal w/ messy details