Data Analysis with MapReduce

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Context

- **Last week: warehouse-scale computers for implementing internet services**
  - —online services, e.g., search, mapping, email
  - —offline computations to generate data for online services
- **Today: large-scale data analysis on warehouse-scale computers**
  - —to generate data for online services
  - —analyze use of online services

Large Scale Data Processing

- **Want to process many terabytes of raw data**
  - —documents found by a web crawl
  - —web request logs
- **Produce various kinds of derived data**
  - —inverted indices
    - – e.g. mapping from words to locations in documents
  - —representations of graph structure of documents
  - —most frequent queries in a given day
  - —the number of pages crawled per host
  - —...

Problem Characteristics

- **Input data is large**
- **Need to parallelize computation so it takes reasonable time**
  - **—often need thousands of CPUs**

What Application Developers Want

- Automatic parallelization & distribution of computation
- Fault tolerance
- Clean and simple programming abstraction
  - —parallel programming for the masses …
- Monitoring and status tools
  - —monitor computation progress
  - —adjust resource provisioning, if necessary

Solution: MapReduce Programming Model

- Inspired by map and reduce primitives in Lisp
  - —mapping a function f over a sequence x y z yields f(x) f(y) f(z)
  - —reduce function combines sequence of elements using a binary op
- Many data analysis computations can be expressed as
  - —applying a map operation to each logical input record
    - – produce a set of intermediate (key, value) pairs
  - —applying a reduce to all intermediate pairs with the same key
- Simple programming model using an application framework
  - —user supplies map and reduce operators
  - —framework handles complex implementation details
    - – parallelization
    - – fault tolerance
    - – data distribution
    - – load balance

Example: Count Word Occurrences

Pseudo Code

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

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

(output_key, value)

Supports lists of values too large to fit in memory

Applying the Framework

- Fill in a MapReduce specification object with
  - —names of input and output files
  - —map and reduce operators
  - —optional tuning parameters
- Invoke the MapReduce framework to initiate the computation
  - —pass the specification object as an argument

Benefits of the MapReduce Framework

- **Functional model**
  - —simple and powerful interface
  - —automatic parallelization and distribution of computations
  - —enables re-execution for fault tolerance
- **Implementation achieves high performance**

What about Data Types?

- Conceptually, map and reduce have associated types
  - —map (k1, v1) ➔ list(k2, v2)
  - —reduce(k2, list(v2)) ➔ list(v2)
- Input keys and values
  - —drawn from a different domain than output keys and values
- Intermediate keys and values
  - —drawn from the same domain as output keys and values
- Google MapReduce C++ implementation
  - —passes strings to all user defined functions: simple and uniform
  - —have user convert between strings and appropriate types

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Input (key, value) pair

Output (key, value) pair

Output (key, list of values)

list of values; output key is implicit

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Interpret values as integers

MapReduce Examples - I

- Distributed “grep” (pattern search)
  - —map: emits <document id, line> if it matches a supplied pattern
  - —reduce: identity function - copies intermediate data to the output
- Count of URL access frequency
  - —map: processes logs of web page requests, outputs a sequence of <URL, 1> tuples
  - —reduce: adds together all values for the same URL and emits a <URL, total count> pair
- Reverse web-link graph
  - —map: outputs <target, source> pairs for each link to a target URL found in a page named source
  - —reduce: concatenates the list of all source URLs associated with a given target URL
    - – emits the pair: <target, list of sources>
      (an adjacency list representation of the graph)

MapReduce Examples - II

- **Term-vector per host**

  summarize the most important words that occur in a document or a set of documents as a list of <word, frequency> pairs

  —map: emits a <hostname, term vector> pair for each input document
  - extracts hostname from the URL of the document

  —reduce: passed all per-document term vectors for a given host
  - adds term vectors together
  - throws away infrequent terms; emits a <hostname, term vector> pair

- **Inverted Index**

  —map: parses each document, emits a sequence of <word, document ID> pairs

  —reduce: accepts all pairs for a given word, sorts the corresponding document IDs, emits a <word, list(document IDs)>

  —set of all output pairs forms a simple inverted index

  —easy to augment this to keep track of word positions

MapReduce Examples - III

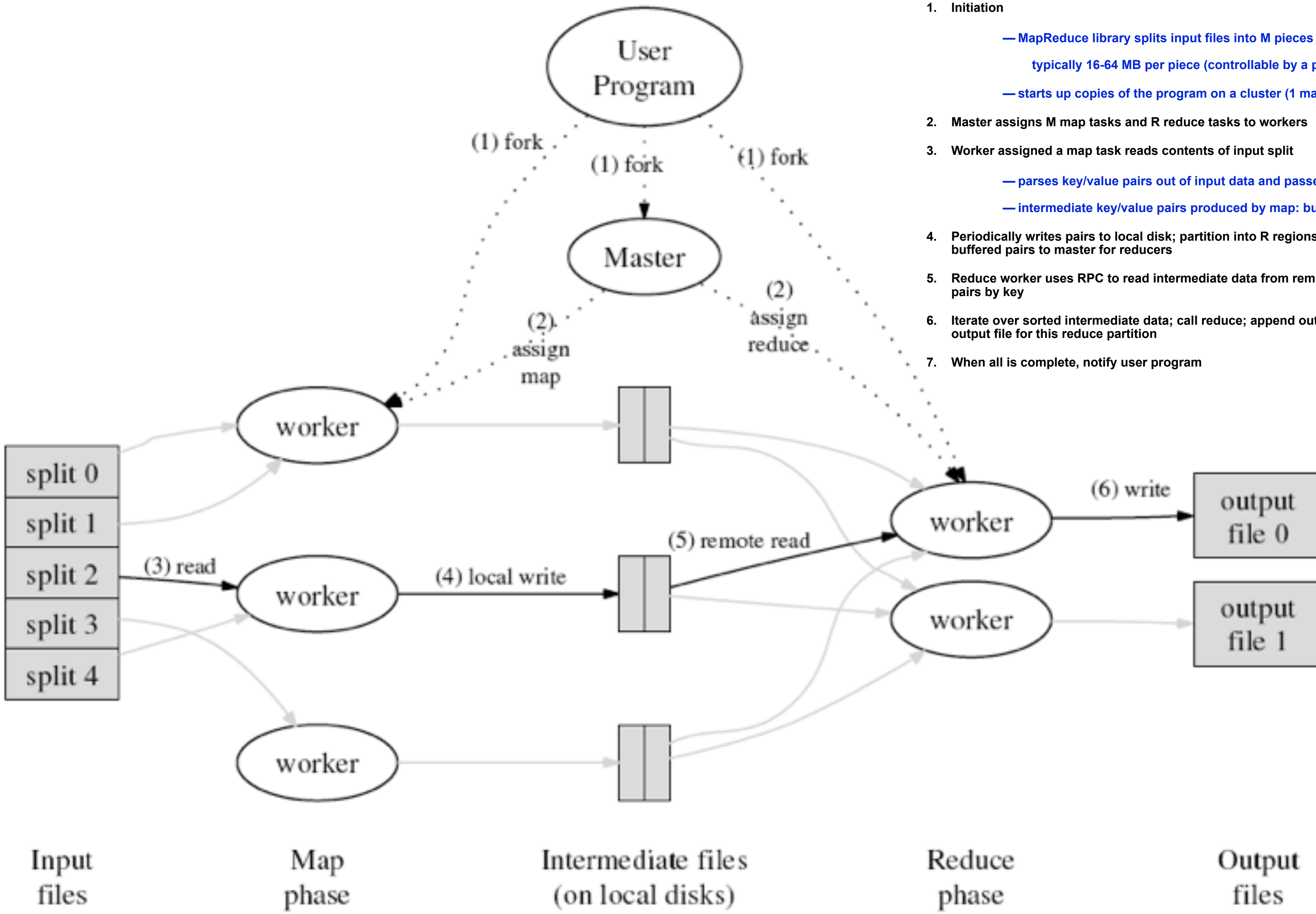
- **Distributed sort**
  - —**map**: extracts key from each record; emits a <key, record> pair
  - —**reduce**: emits all pairs unchanged
    - —resulting pairs will be in sorted order
      - —this property depends upon partitioning facilities and ordering properties guaranteed by the MapReduce framework

Implementation Considerations

- Many different implementations are possible
- Right choice depends on environment, e.g.
  - —small shared memory machine
  - —large NUMA multiprocessor
  - —larger collection of networked machines
- Google environment (2004)
  - —dual-processor x86, Linux, 2-4GB memory
  - —commodity network: 100Mb/1Gb Ethernet per machine
    - – much less than full bisection bandwidth
  - —thousands of machines: failure common
  - —storage:
    - – inexpensive disks attached directly to machines
    - – distributed file system to manage data on these disks

      replication provides availability and reliability on unreliable h/w

Execution Overview

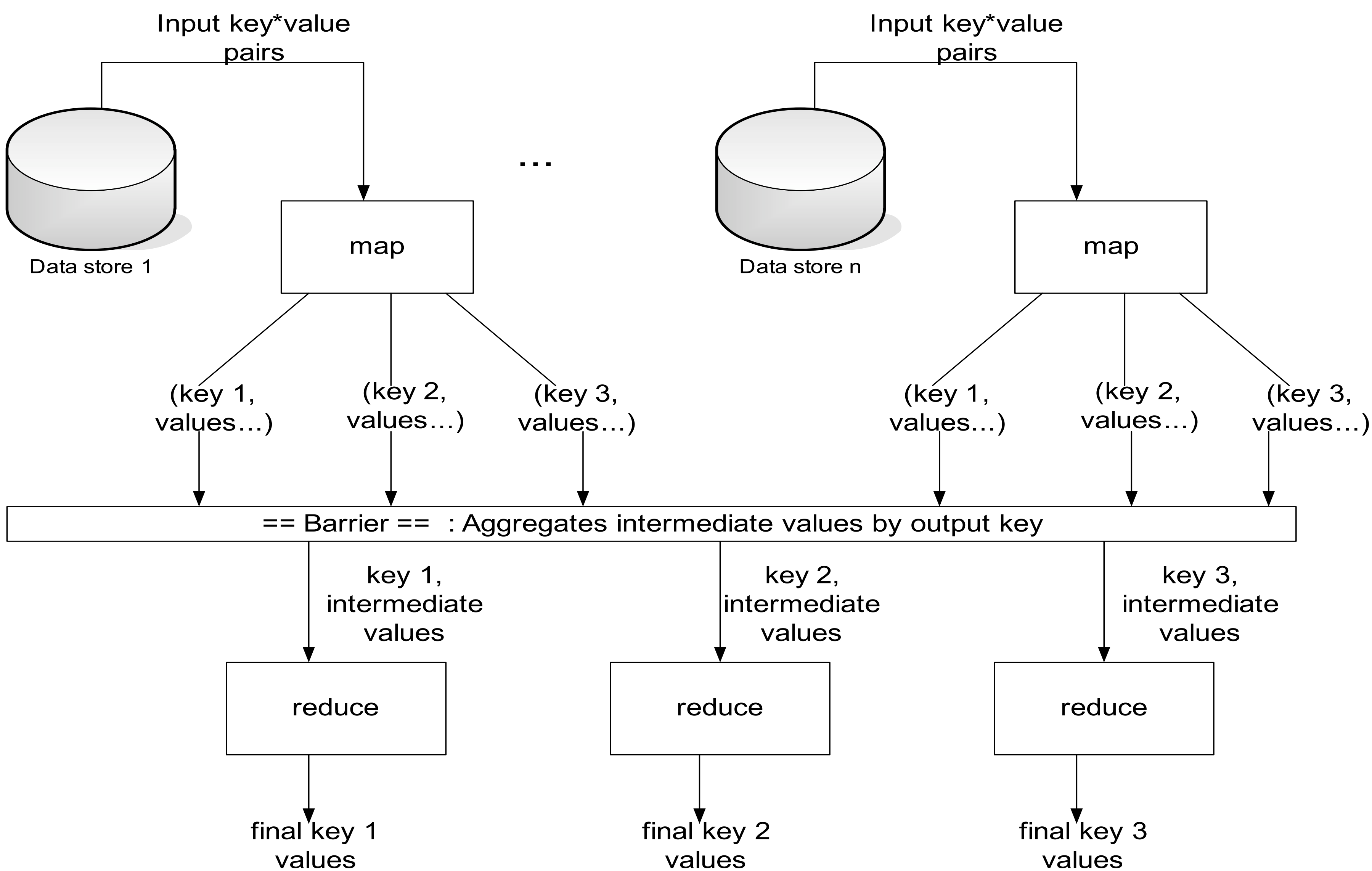


1. Initiation
   - — MapReduce library splits input files into M pieces
     typically 16-64 MB per piece (controllable by a parameter)
   - — starts up copies of the program on a cluster (1 master + workers)
2. Master assigns M map tasks and R reduce tasks to workers
3. Worker assigned a map task reads contents of input split
   - — parses key/value pairs out of input data and passes them to map
   - — intermediate key/value pairs produced by map: buffer in memory
4. Periodically writes pairs to local disk; partition into R regions; pass locations of buffered pairs to master for reducers
5. Reduce worker uses RPC to read intermediate data from remote disks; sort pairs by key
6. Iterate over sorted intermediate data; call reduce; append output to final output file for this reduce partition
7. When all is complete, notify user program

Master Data Structures

- For each map and reduce task, store
  - —state (idle, in-progress, completed)
  - —identity of worker machine (for non-idle tasks)
- For each completed map task
  - —store locations and sizes of R intermediate files produced by map
  - —information updated as map tasks complete
  - —map results are pushed incrementally to workers that have in-progress reduce tasks

Logical Overview of Execution



Logical Execution

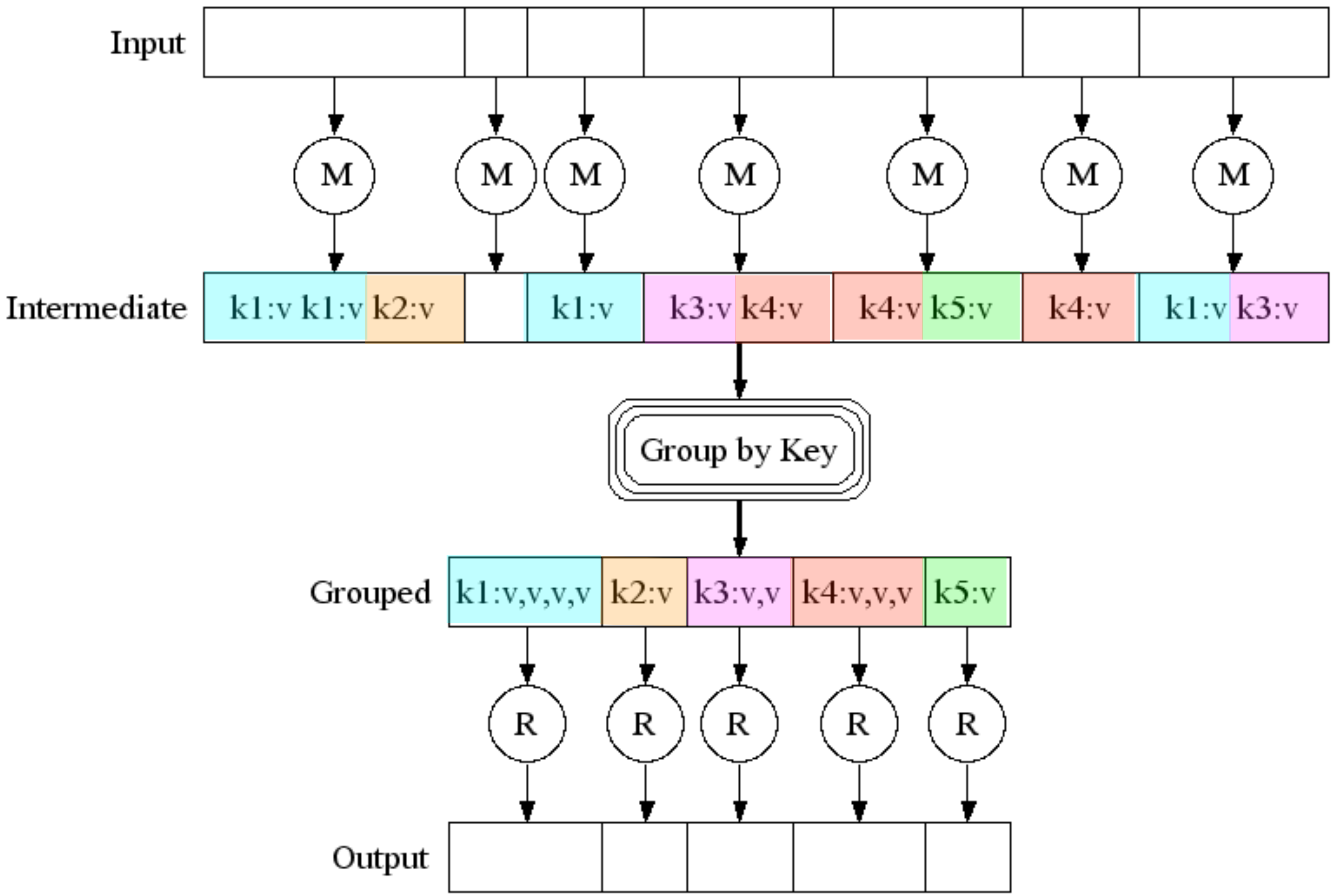
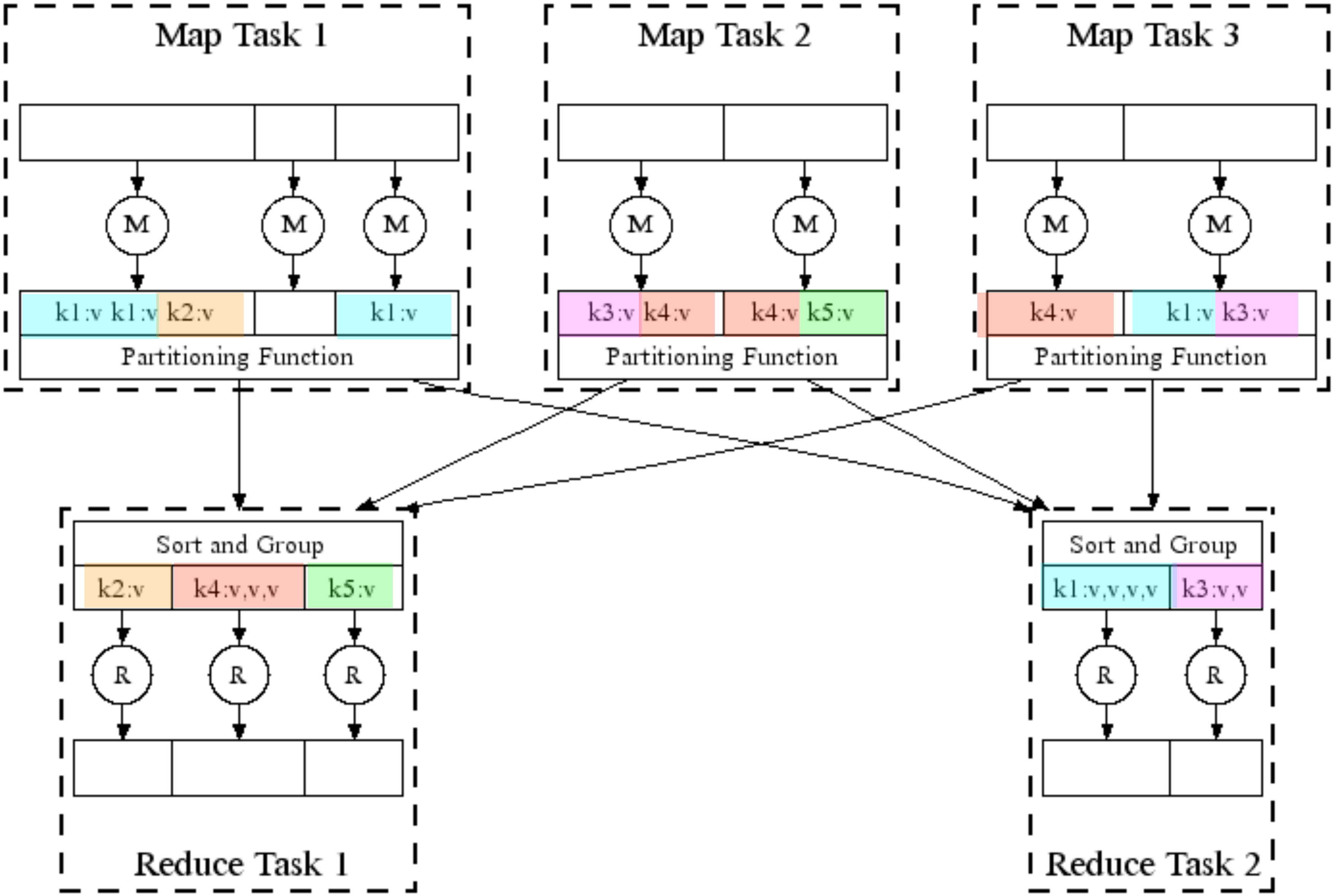


Figure credit: http://labs.google.com/papers/mapreduce-osdi04-slides/index-auto-0007.html

Execution Realization



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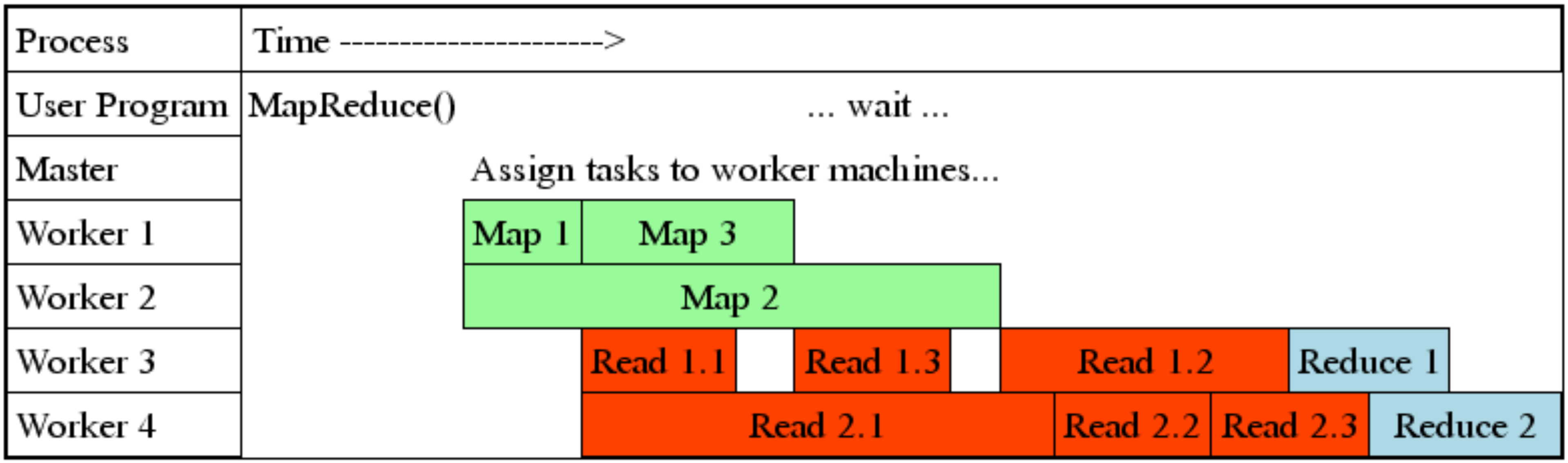
Execution Timeline

- **Many more tasks than machines**
- **Pipeline data movement with map execution**



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Fault Tolerance: Worker Failure

- **Detecting failure**
  - —master pings worker periodically
  - —if no answer after a while, master marks worker as failed
- **Coping with failure**
  - —any map tasks for worker reset to *idle* state may be rescheduled
  - —worker's completed map tasks re-execute on failure
    - – data on local disk of failed worker is inaccessible
    - – any reducers attempting to read notified of the re-execution

Fault tolerance anecdote from Google:

- —network maintenance on a cluster caused groups of 80 machines at a time to become unreachable for several minutes
- —master simply re-executed work for unreachable machines and continued to make forward progress

What about Master Failure?

- Master could periodically write checkpoints of master data structures
- If master dies, another could be recreated from checkpointed copies of its state
- In practice
  - —only a single master
  - —failure would be rare
  - —implementation currently aborts MapReduce if master fails
  - —client could check this condition and retry the computation

Exploiting Locality

- **Network bandwidth is a scarce commodity**
- **Data is stored on local disks of machines**
  - —GFS divides files into 64MB blocks
  - —stores several copies (typically 3) on different machines
- **MapReduce master**
  - —attempts to map worker onto a machine that contains a replica of input data
  - —if impossible, attempts to map task near a replica
    - – on machine attached to same network switch

Locality management anecdote from Google:

—when running large MapReduce operations on a significant fraction of machines in a cluster, most input data is local and consumes no network bandwidth

Task Granularity

- Divide map phase into M pieces; reduce phase into R pieces
- Ideally, M and R much larger than number of worker machines
- Dynamically load balance tasks onto workers
- Upon failure
  - —the many map tasks performed by a worker can be distributed among other machines
- How big are M and R?

Task granularity in practice

—e.g., M = 200K, R=5K, using 2000 worker machines

Coping with “Stragglers”

- **Problem: a slow machine at the end of the computation could stall the whole computation**
- **When a MapReduce is nearing completion, schedule redundant “backup” executions of in-progress tasks**

Backup task execution in practice

—significantly reduces time for large MapReduce computations

—a sorting example took 44% longer without backup tasks

Combiner

- When there is significant repetition in intermediate keys
  - —e.g. instances of <the, 1> in word count output

  it is useful to partially merge data locally before sending it across the network to a reducer
- Combiner
  - —function executed on each machine that performs a map task
  - —typically the same code as the reducer
- Significantly speeds up MapReduce operations with significant repetition in intermediate keys

Input and Output Types

- Can supply a "reader" for new input type
  - —e.g. reader interface might read records from a database
- Output types can produce outputs in different formats as well

Refinements

- Partitioning function
  - —typically hash(key) mod R
    - – tends to give balanced partitions
  - —user can supply their own if certain properties desired
    - – hash(Hostname(URL)) mod R: all URLs from same host end up in same output file
- Ordering guarantees
  - —within a given partition, all intermediate values processed in order: simplifies creating sorted output
- Real world issues
  - —skip "bad records"
  - —side effects - write extra files "atomically" and idempotently
  - —master provides status pages via HTTP
    - – enables users to predict run time, decide to add more resources, gain insight into performance issues

MapReduce at Google (2004)

- Large-scale machine learning and graph computations
- Clustering problems for Google News
- Extraction of data to produce popular queries (Zeitgeist)
- Extracting properties of web pages
  - e.g. geographical location for localized search
- Large-scale indexing
  - 2004: indexing crawled documents
    - data size > 20 TB
    - runs indexing as a sequence of 5-10 MapReduce operations
  - experience
    - applications smaller than ad-hoc indexing by 4x
    - readily modifiable because programs are simple
    - performance is good: keep conceptually distinct thing separate rather than forcing them together
    - indexing is easy to operate: e.g. fault tolerant; easy to improve performance by adding new machines
- Hundreds of thousands of MapReduce calculations/day!

MapReduce Examples at Google

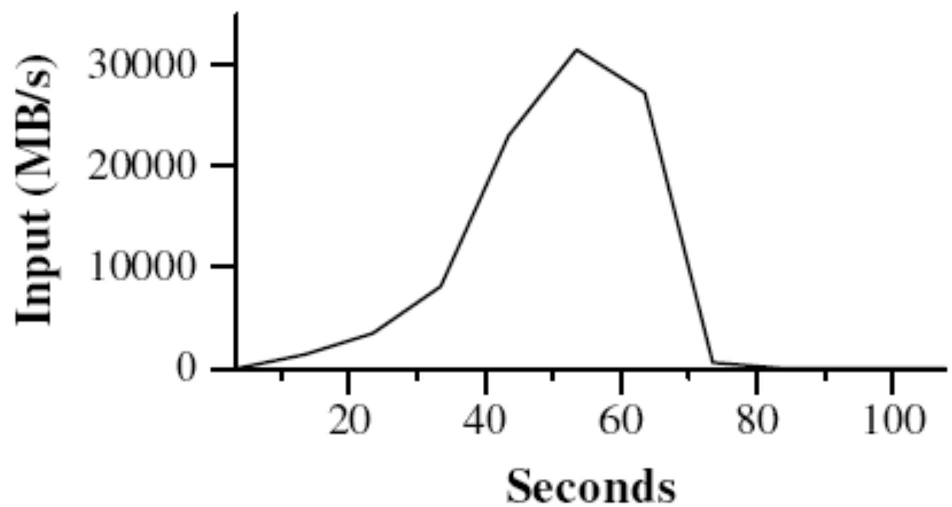
- **Extracting the set of outgoing links from a collection of HTML documents and aggregating by target document**
- **Stitching together overlapping satellite images to remove seams and to select high-quality imagery for Google Earth**
- **Generating a collection of inverted index files using a compression scheme tuned for efficient support of Google search queries**
- **Processing all road segments in the world and rendering map tile images that display these segments for Google Maps**

Performance Anecdotes I

- Cluster
  - — ~1800 nodes
    - – Two 2GHz Xeon, 4GB memory, 2 160GB IDE drives, 1Gb Ethernet
  - —network 2-level tree-shaped switched Ethernet
    - – ~100-200Gbps aggregate bandwidth at the root
- Benchmarks executed on a roughly idle cluster

grep: scan through 10^{10} 100-byte records (~1TB) for a relatively rare 3-character pattern

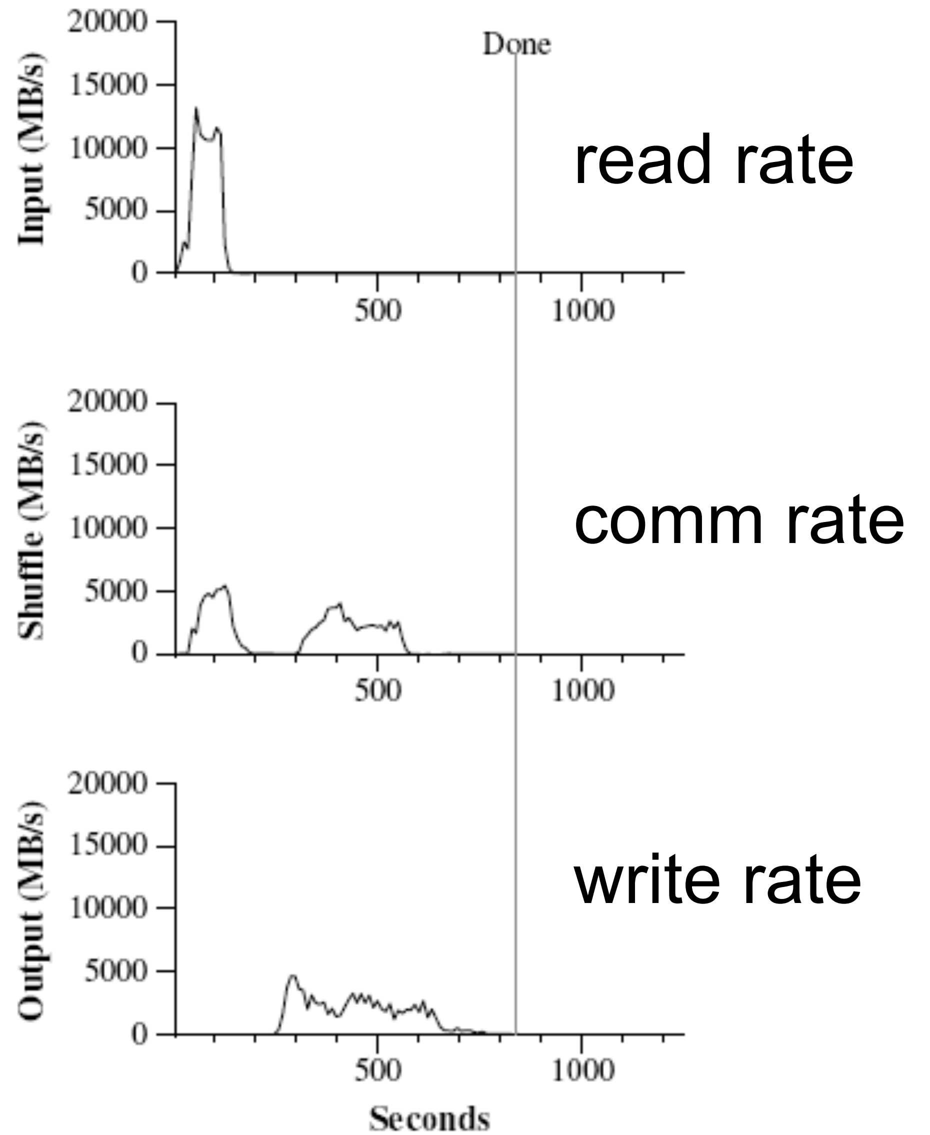
- split input into 64MB pieces, M=15000, R = 1 (one output file)
- time = ~150 seconds



Performance Anecdotes II

sort 10^{10} 100-byte records (~1TB)

- consists of < 50 lines of user code
- split input into 64MB pieces, M=15000, R=4000
- partitioning function uses initial bytes to put it into one of R pieces
- input rate higher than shuffle or output rate: on local disk
- output phase makes 2 replica for availability
- time = 891 seconds



MapReduce is a Success

- Reasons for its success
  - —easy even for users lacking experience with parallel systems
    - – insulates user from complexity
      - parallelization, fault tolerance, locality opt., load balancing
  - —large variety of computations expressible using MapReduce
    - – sorting, data mining, machine learning, etc.
  - —implementation scales to large commodity clusters
    - – makes efficient use of thousands of machines
- Lessons
  - —restricting programming model simplifies tackling parallelization, fault tolerance, distribution
  - —network bandwidth is a scarce resource
    - – locality optimizations to save network bandwidth are important
      - read data from local disk; write intermediate data to local disk
  - —redundant execution
    - – reduces impact of slow machines, machine failures, data loss

Full “Word Count” Example: Map

```
#include "mapreduce/mapreduce.h"

class WordCounter : public Mapper {
public:
    virtual void Map(const MapInput& input) {
        const string& text = input.value();
        const int n = text.size();
        for (int i = 0; i < n; ) {
            // Skip past leading whitespace
            while ((i < n) && isspace(text[i])) i++;
            // Find word end
            int start = i;
            while ((i < n) && !isspace(text[i])) i++;
            if (start < i) Emit(text.substr(start,i-start),"1");
        }
    }
};
REGISTER_MAPPER(WordCounter);
```

Full “Word Count” Example: Reduce

```
#include "mapreduce/mapreduce.h"

class Adder : public Reducer {
  virtual void Reduce(ReduceInput* input) {
    // Iterate over all entries with the
    // same key and add the values
    int64 value = 0;
    while (! input->done()) {
      value += StringToInt(input->value());
      input->NextValue();
    }
    // Emit sum for input->key()
    Emit(IntToString(value));
  }
};
REGISTER_REDUCER(Adder);
```

Full “Word Count” Example: Main Program

```
#include "mapreduce/mapreduce.h"

int main(int argc, char** argv) {
  ParseCommandLineFlags(argc, argv);
  MapReduceSpecification spec;

  // Store list of input files into "spec"
  for (int i = 1; i < argc; i++) {
    MapReduceInput* input = spec.add_input();
    input->set_format("text");
    input->set_filepattern(argv[i]);
    input->set_mapper_class("WordCounter");
  }
  // Specify the output files:
  // /gfs/test/freq-00000-of-00100
  // /gfs/test/freq-00001-of-00100
  // ...
  MapReduceOutput* out = spec.output();
  out->set_filebase("/gfs/test/freq");
  out->set_num_tasks(100);
  out->set_format("text");
  out->set_reducer_class("Adder");

  // Optional: do partial sums within map
  // tasks to save network bandwidth
  out->set_combiner_class("Adder");

  // Tuning parameters: use at most 2000
  // machines and 100 MB memory per task
  spec.set_machines(2000);
  spec.set_map_megabytes(100);
  spec.set_reduce_megabytes(100);

  // Now run it
  MapReduceResult result;
  if (!MapReduce(spec, &result)) abort();

  // Done: 'result' structure contains info
  // about counters, time taken, number of
  // machines used, etc.

  return 0;
}
```

MapReduce Evolution

- **September 2010**
  - —Google announced that its new search infrastructure "Caffeine" is no longer based on MapReduce
    - – MapReduce supported batch indexing scheme
    - – Caffeine supports incremental indexing
      - use "Bigtable" to represent WWW index
        - sparse, distributed, persistent multi-dimensional sorted map
        - (row:string, column:string, time:int64) → string
        - OSDI 2006 paper: http://bit.ly/ltB7pq
      - analyze the WWW in small pieces
      - supports incremental updates to index without entire rebuild
- **December 2011**
  - —Open source Apache Hadoop 1.0.0 - http://hadoop.apache.org
    - – Hadoop File System
    - – Hadoop MapReduce
    - – Hadoop Common - support utilities

Today: Apache Spark

- Fast and general-purpose cluster computing system
- APIs in Java, Scala, Python and R
- Optimized engine that supports general execution graphs
- Supports in-memory caching of “hot” data sets
- Simpler programming interface
  - —example: word count in Spark’s Python API

```
text_file = spark.textFile("hdfs://...")

text_file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

Figure credit: http://spark.apache.org

References - I

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