NDBI040

Big Data Management and NoSQL Databases

Lecture 2. MapReduce

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MapReduce Framework

- A programming model + implementation
- Developed by Google in 2008
  - To replace old, centralized index structure
- Distributed, parallel computing on large data

> Google: "A simple and powerful interface that enables automatic parallelization and distribution of large-scale computations, combined with an implementation of this interface that achieves high performance on large clusters of commodity PCs."

- Programming model in general:
  - Mental model a programmer has about execution of application
  - Purpose: improve programmer's productivity
  - Evaluation: expressiveness, simplicity, performance

Programming Models

- Von Neumann model
  - Executes a stream of instructions (machine code)
  - Instructions can specify
    - Arithmetic operations
    - Data addresses
    - Next instruction to execute
    - …
  - Complexity
    - Billions of data locations and millions of instructions
    - Manages with:
      - Modular design
      - High-level programming languages

Programming Models

- Parallel programming models
  - Message passing
    - Independent tasks encapsulating local data
    - Tasks interact by exchanging messages
  - Shared memory
    - Tasks share a common address space
    - Tasks interact by reading and writing from/to this space
      - Asynchronously
  - Data parallelization
    - Data are partitioned across tasks
    - Tasks execute a sequence of independent operations

MapReduce Framework

- Divide-and-conquer paradigm
  - Map breaks down a problem into sub-problems
    - Processes input data to generate a set of intermediate key/value pairs
  - Reduce receives and combines the sub-solutions to solve the problem
    - Processes intermediate values associated with <u>the same</u> intermediate key
- Many real world tasks can be expressed this way
  - Programmer focuses on map/reduce code
  - Framework cares about data partitioning, scheduling execution across machines, handling machine failures, managing inter-machine communication, …

MapReduce
A Bit More Formally

- Map
  - Input: a key/value pair
  - Output: a set of intermediate key/value pairs
    - Usually different domain
  - $(k_1,v_1) \rightarrow \text{list}(k_2,v_2)$
- Reduce
  - Input: an intermediate key and a set of values <u>for that key</u>
  - Output: a possibly smaller set of values
    - The same domain
  - $(k_2,\text{list}(v_2)) \rightarrow (k_2,\text{possibly smaller list}(v_2))$

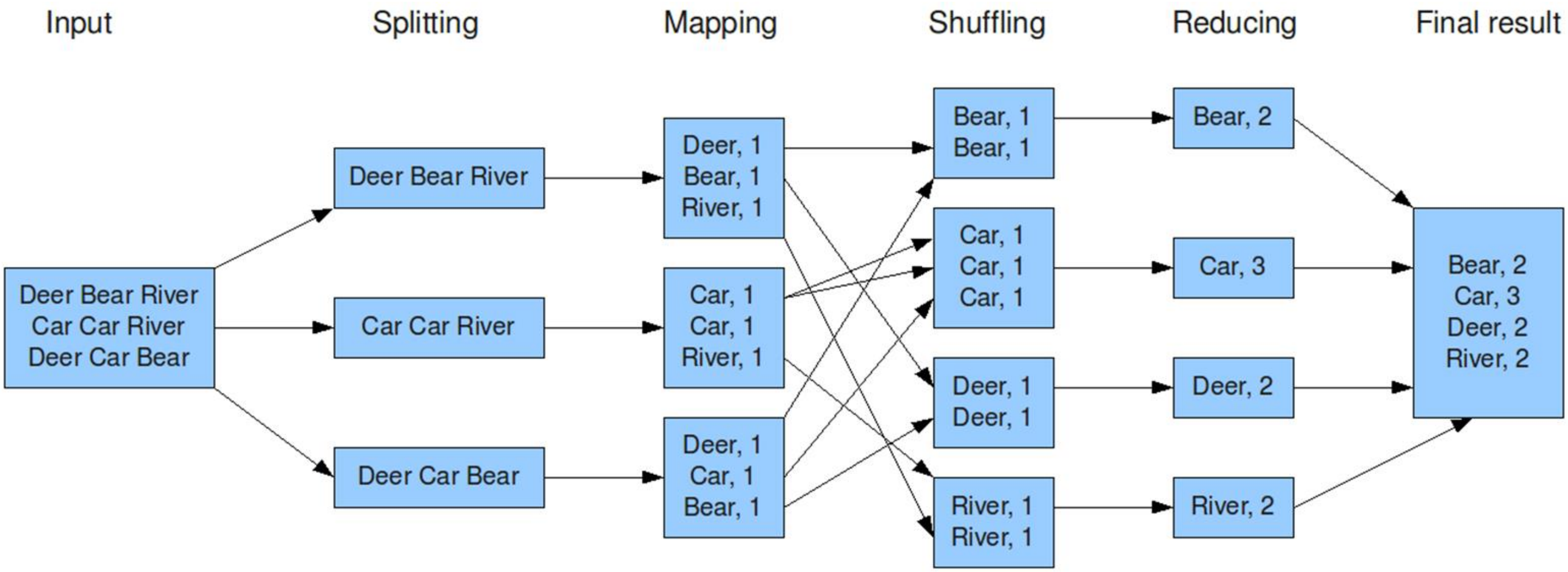
MapReduce

Example: Word Frequency

```
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(key, AsString(result));
```

MapReduce
Example: Word Frequency



MapReduce
More Examples

- distributed grep
  - Map: emits <word, line number> if it matches a supplied pattern
  - Reduce: identity
- URL access frequency
  - Map: processes web logs, emits <URL, 1>
  - Reduce: sums values and emits <URL, sum>
- reverse web-link graph
  - Map: <target, source> 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 <target, list(source)>

MapReduce
More Examples

- term vector per host
  - “Term vector” summarizes the most important words that occur in a document or a set of documents
  - Map: emits <hostname, term vector> for each input document
    - The hostname is extracted from the URL of the document
  - Reduce: adds the term vectors together, throws away infrequent terms
- inverted index
  - Map: parses each document, emits <word, document ID>
  - Reduce: sorts the corresponding document IDs, emits <word, list(document ID)>
- distributed sort
  - Map: extracts the key from each record, and emits <key, record>
  - Reduce: emits all pairs unchanged

MapReduce
Application Parts

- Input reader
  - Reads data from stable storage
    - e.g., a distributed file system
  - Divides the input into appropriate size 'splits'
  - Prepares key/value pairs
- Map function
  - <u>User-specified</u> processing of key/value pairs
- Partition function
  - Map function output is allocated to a reducer
  - Partition function is given the key (output of Map) and the number of reducers and returns the index of the desired reducer
    - Default is to hash the key and use the hash value modulo the number of reducers

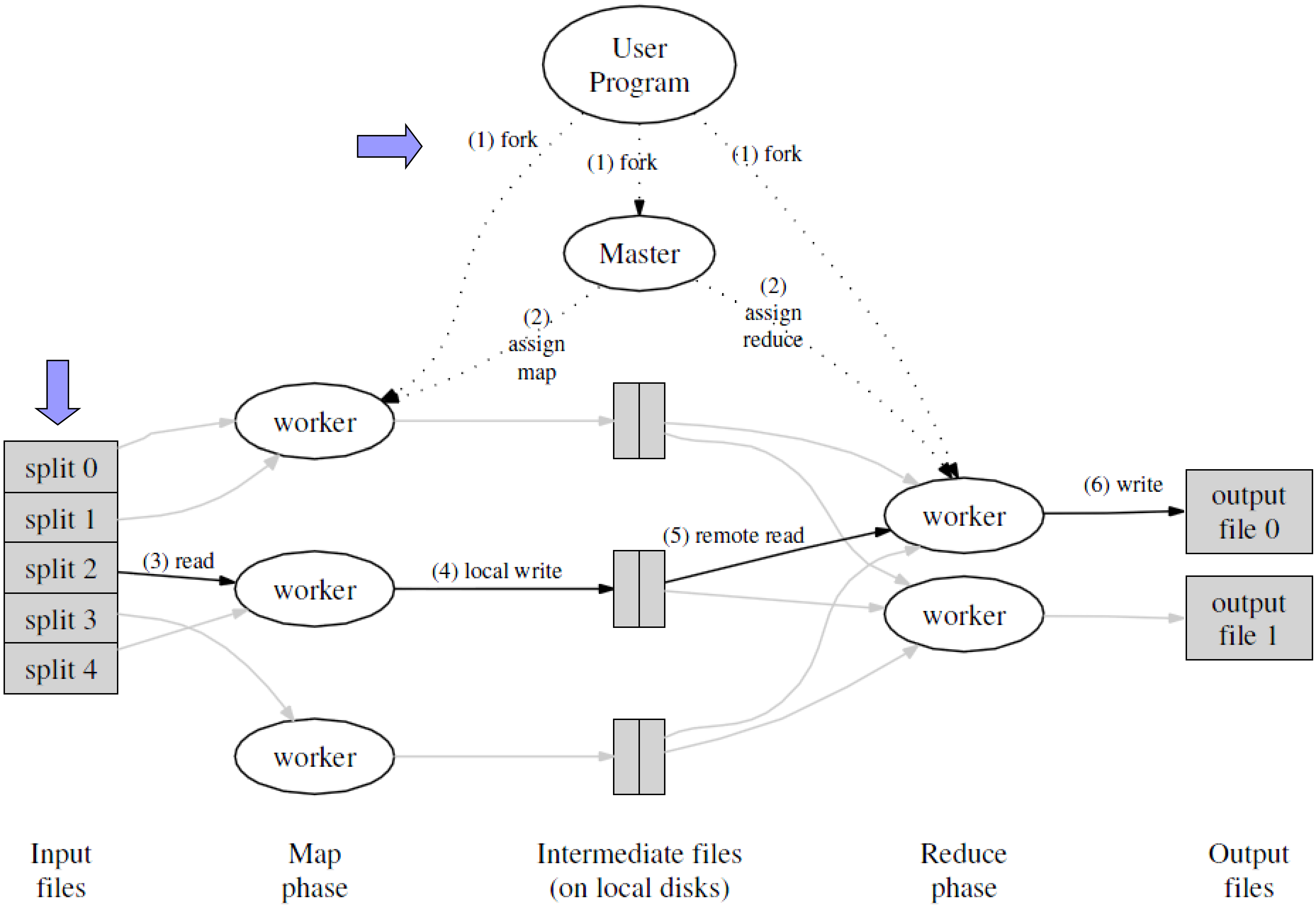
MapReduce
Application Parts

- Compare function
  - Sorts the input for the Reduce function
- Reduce function
  - User-specified processing of key/values
- Output writer
  - Writes the output of the Reduce function to stable storage
    - e.g., a distributed file system

MapReduce

Execution (Google) – Step 1

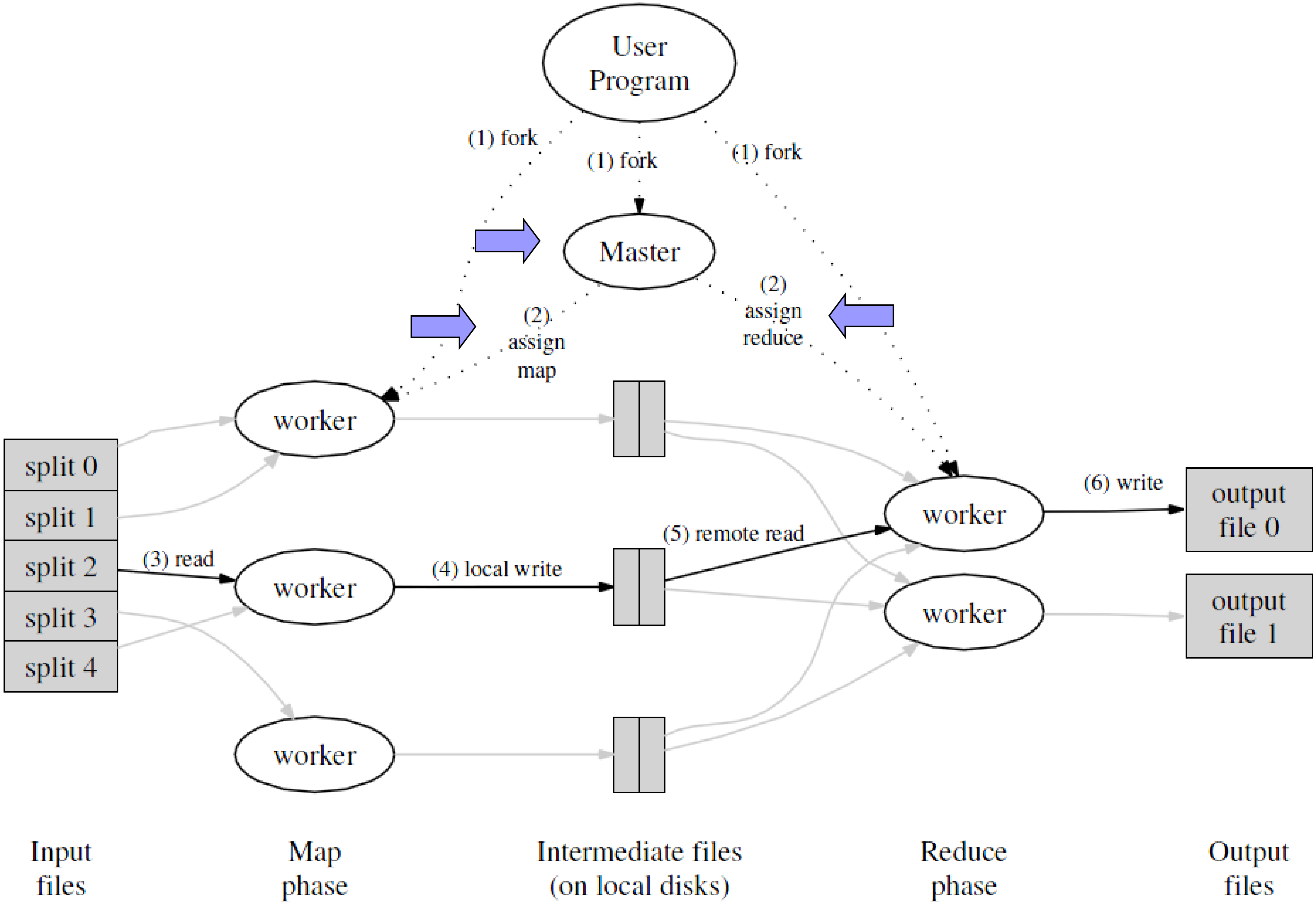
1. MapReduce library in the user program splits the input files into *M* pieces
   - Typically 16 – 64 MB per piece
   - Controllable by the user via optional parameter
2. It starts copies of the program on a cluster of machines


User Program
(1) fork
(1) fork
(1) fork
Master
(2) assign map
(2) assign reduce
worker
worker
worker
split 0
split 1
split 2
split 3
split 4
(3) read
(4) local write
(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

MapReduce

Execution – Step 2

- Master = a special copy of the program
- Workers = other copies that are assigned work by master
- *M* Map tasks and *R* Reduce tasks to assign
- Master picks idle workers and assigns each one a Map task (or a Reduce task)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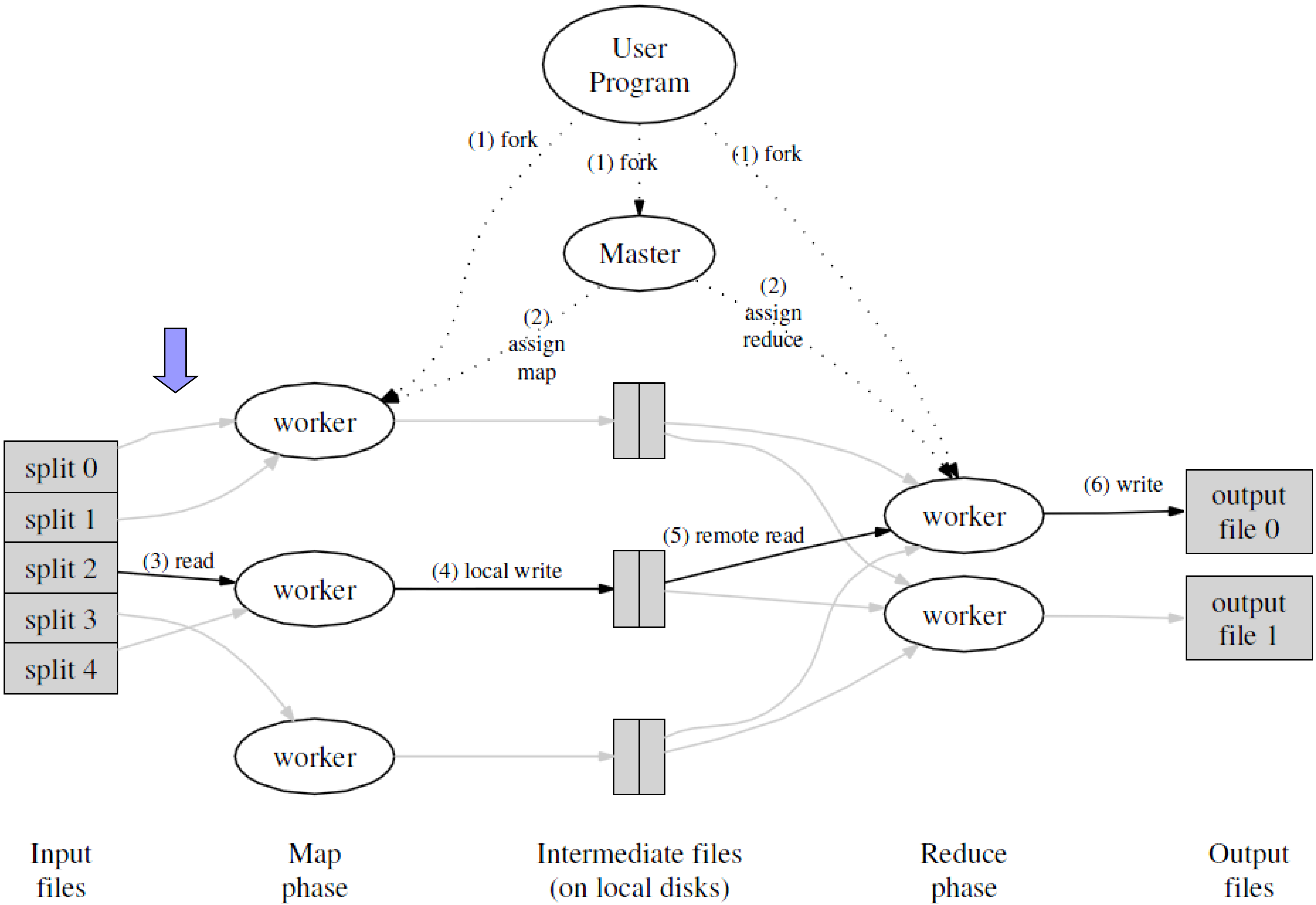
MapReduce

Execution – Step 3

- A worker who is assigned a Map task:
  - Reads the contents of the corresponding input split
  - Parses key/value pairs out of the input data
  - Passes each pair to the user-defined Map function
  - Intermediate key/value pairs produced by the Map function are buffered in memory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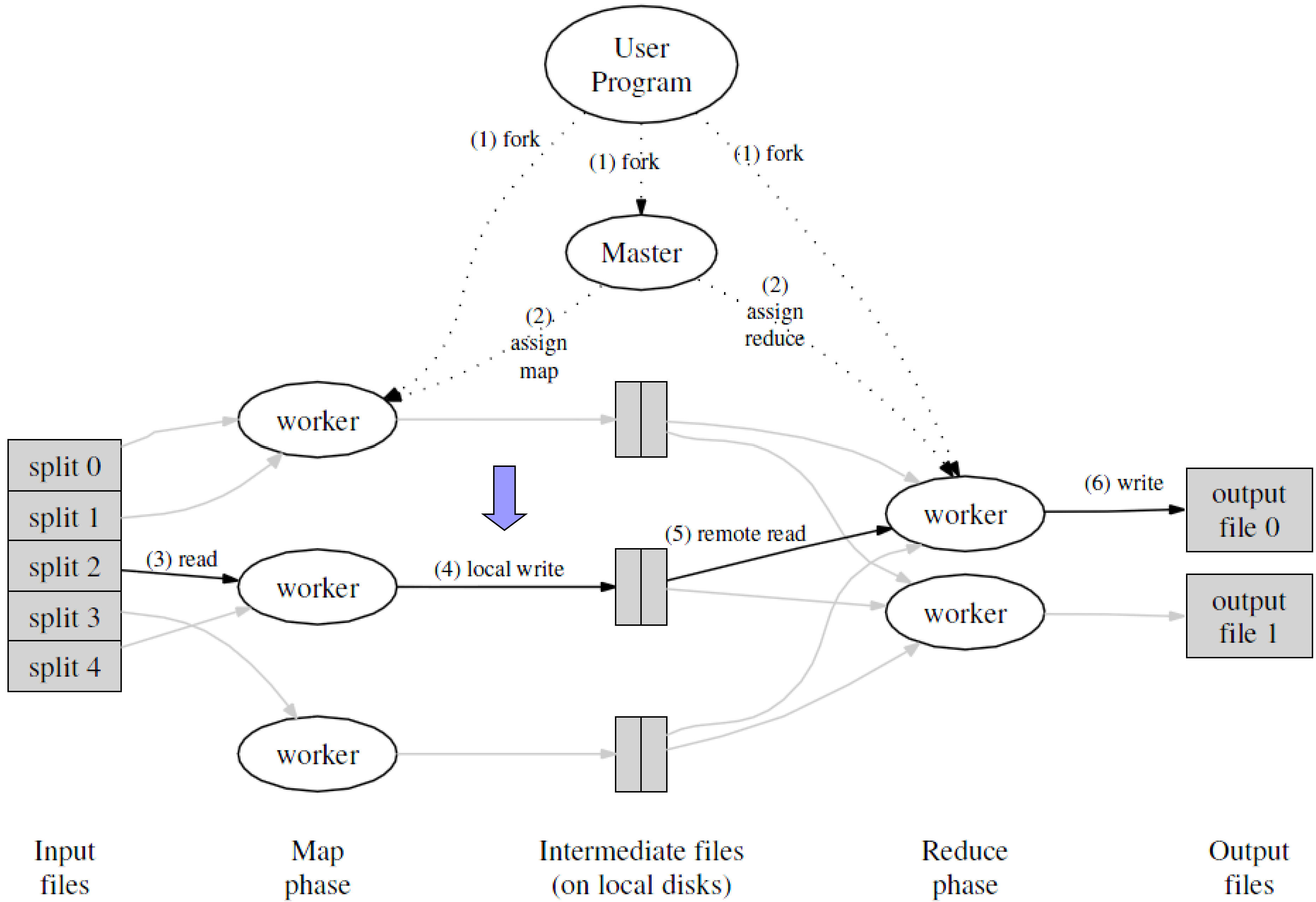
MapReduce

Execution – Step 4

- Periodically, the buffered pairs are written to local disk
  - Partitioned into *R* regions by the partitioning function
- Locations of the buffered pairs on the local disk are passed back to the master
  - It is responsible for forwarding the locations to the Reduce workers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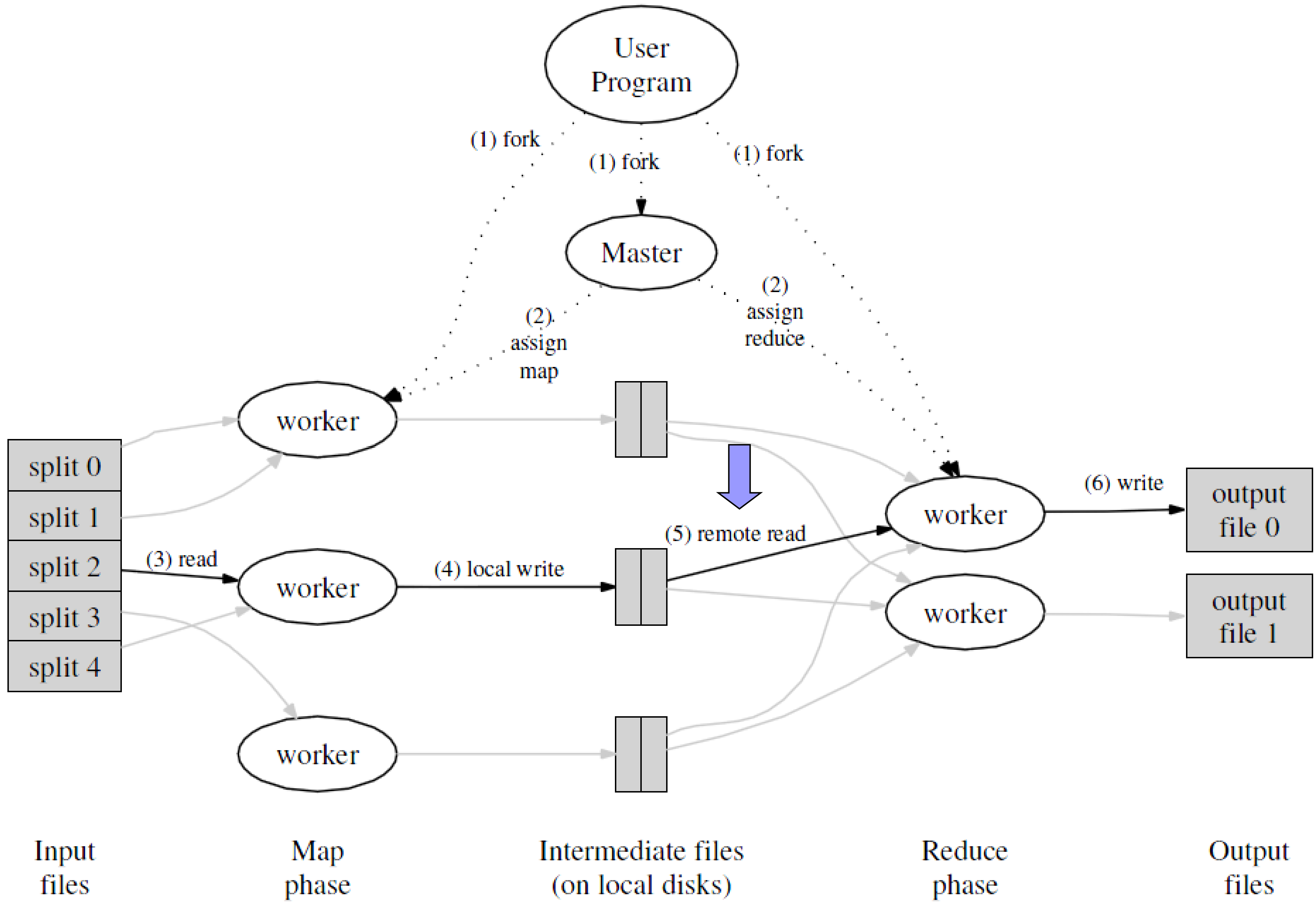
MapReduce

Execution – Step 5

- Reduce worker is notified by the master about data locations
- It uses <u>remote procedure calls</u> to read the buffered data from local disks of the Map workers
- When it has read all intermediate data, it sorts it by the intermediate keys
  - Typically many different keys map to the same Reduce task
  - If the amount of intermediate data is too large, an external sort is used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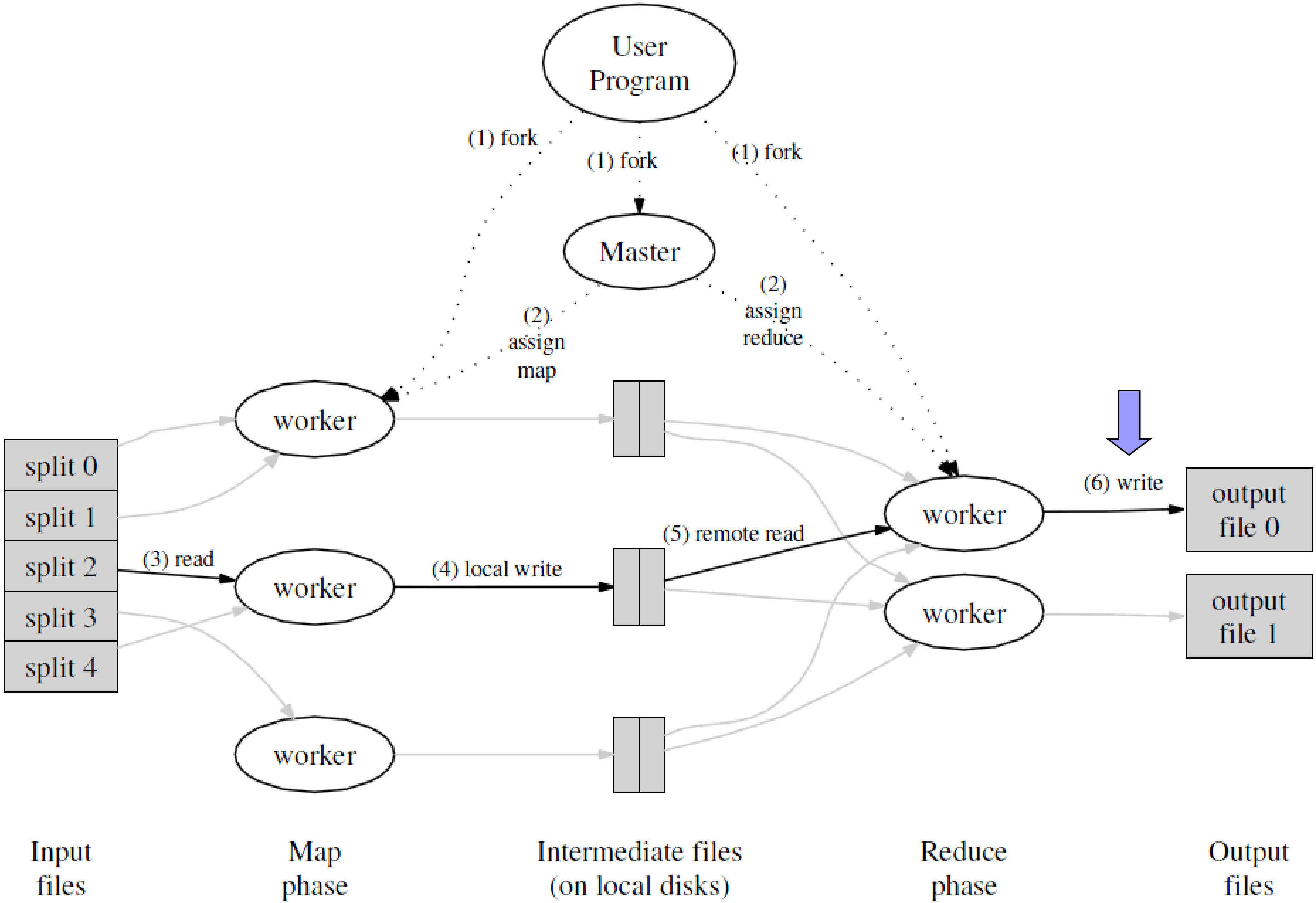
MapReduce

Execution – Step 6

- A Reduce worker iterates over the sorted intermediate data
- For each intermediate key encountered:
  - It passes the key and the corresponding set of intermediate values to the user's Reduce function
  - The output is appended to a final output file for this Reduce partition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MapReduce
Function combine

- After a map phase, the mapper transmits over the network the entire intermediate data file to the reducer
- Sometimes this file is highly compressible
- User can specify function combine
  - Like a reduce function
  - It is run by the mapper before passing the job to the reducer
    - Over local data

MapReduce

Counters

- Can be associated with any action that a mapper or a reducer does
  - In addition to default counters
    - e.g., the number of input and output key/value pairs processed
- User can watch the counters in real time to see the progress of a job

MapReduce
Fault Tolerance

- A large number of machines process a large number of data → fault tolerance is necessary
- Worker failure
  - Master pings every worker periodically
  - If no response is received in a certain amount of time, master marks the worker as failed
  - <u>All</u> its tasks are reset back to their initial <u>idle</u> state → become eligible for scheduling on other workers

MapReduce
Fault Tolerance

- Master failure
  - Strategy A:
    - Master writes periodic checkpoints of the master data structures
    - If it dies, a new copy can be started from the last checkpointed state
  - Strategy B:
    - There is only a single master → its failure is unlikely
    - MapReduce computation is simply aborted if the master fails
    - Clients can check for this condition and retry the MapReduce operation if they desire

MapReduce
Stragglers

- Straggler = a machine that takes an unusually long time to complete one of the map/reduce tasks in the computation
  - Example: a machine with a bad disk
- Solution:
  - When a MapReduce operation is close to completion, the master schedules backup executions of the remaining in-progress tasks
  - A task is marked as completed whenever either the primary or the backup execution completes

MapReduce
Task Granularity

- *M* pieces of Map phase and *R* pieces of Reduce phase
  - Ideally both much larger than the number of worker machines
  - How to set them?
- Master makes *O(M + R)* scheduling decisions
- Master keeps *O(M * R)* status information in memory
  - For each Map/Reduce task: state (idle/in-progress/completed)
  - For each non-idle task: identity of worker machine
  - For each completed Map task: locations and sizes of the *R* intermediate file regions
- *R* is often constrained by users
  - The output of each Reduce task ends up in a separate output file
- Practical recommendation (Google):
  - Choose *M* so that each individual task is roughly 16 – 64 MB of input data
  - Make *R* a small multiple of the number of worker machines we expect to use

Real-World Example (Google)
Cluster Configuration

- 1,800 machines
- Each machine:
  - 2x 2GHz Intel Xeon processor
    - With Hyper-Threading enabled
  - 4GB memory
    - Approx. 1-1.5GB reserved by other tasks
  - 2x 160GB IDE disks
  - Gigabit Ethernet link
- Arranged in a two-level tree-shaped switched network with approximately 100-200 Gbps of aggregate bandwidth available at the root

Real-World Example 1

grep

- Search through approx. 1 terabyte of data looking for a particular pattern
  - Rare three-character pattern
  - Present in 92,337 records
- M = 15,000
- R = 1
- 1,764 workers assigned
- Entire computation: 150 seconds
  - About a minute of start-up overhead

Real World Example 2

sort

- Sorting of approx. 1 terabyte of data
- Map: 3-line function
  - Extracts a 10-byte sorting key from a text line and emits the key and the original text line
- Reduce: identity
- M = 15,000
- R = 4,000
- About 1,700 workers assigned
- Entire computation: 891 seconds
  - 5 stragglers increase the time of 44%

MapReduce Criticism

David DeWitt and Michael Stonebraker – 2008

1. MapReduce is a step backwards in database access based on
   - Schema describing data structure
   - Separating schema from the application
   - Advanced query languages
2. MapReduce is a poor implementation
   - Instead of indexes is uses brute force
3. MapReduce is not novel (ideas more than 20 years old and overcome)
4. MapReduce is missing features common in DBMSs
   - Indexes, transactions, integrity constraints, views, …
5. MapReduce is incompatible with applications implemented over DBMSs
   - Data mining, business intelligence, …

End of MapReduce?

- FaceBook used MapReduce in 2010
  - Hadoop

but…

- Google has recently (June 2014) announced a shift towards: Google Cloud DataFlow
  - Based on cloud and stream data processing
  - Idea: no need to maintain complex infrastructure
    - Data can be easily read, transformed and analyzed in a cloud

http://googledevelopers.blogspot.fr/2014/06/cloud-platform-at-google-io-new-big.html

Resources

- Jeffrey Dean and Sanjay Ghemawat: MapReduce: **Simplified Data Processing on Large Clusters**, Google, Inc.
  - http://labs.google.com/papers/mapreduce.html
- Google Code: **Introduction to Parallel Programming and MapReduce**
  - code.google.com/edu/parallel/mapreduce-tutorial.html
- **Hadoop Map/Reduce Tutorial**
  - http://hadoop.apache.org/docs/r0.20.2/mapred_tutorial.html
- **Open Source MapReduce**
  - http://lucene.apache.org/hadoop/
- David DeWitt and Michael Stonebraker: **Relational Database Experts Jump The MapReduce Shark**