MapReduce

- Programming model and implementation developed at Google for processing and generating large datasets
- Many real world applications can be expressed in this model
- Parallelism: same computation performed at different cpus on different pieces of input dataset
- Programs are automatically parallelized and executed on large cluster of machines

Motivation

- Before MapReduce, Google developers implemented hundreds of special-purpose computations to process large amounts of data
  - mostly simple computations
  - input data so large that it must be distributed across hundreds of thousands of machines
  - developers had to figure out how to parallelize computation, distribute data, deal with hardware failures, ...
- MapReduce: abstraction that allows programmers to write simple computations while hiding the details of:
  - parallelization
  - data distribution
  - load balancing
  - fault tolerance

run-time system/
MapReduce library

MapReduce Programming Model

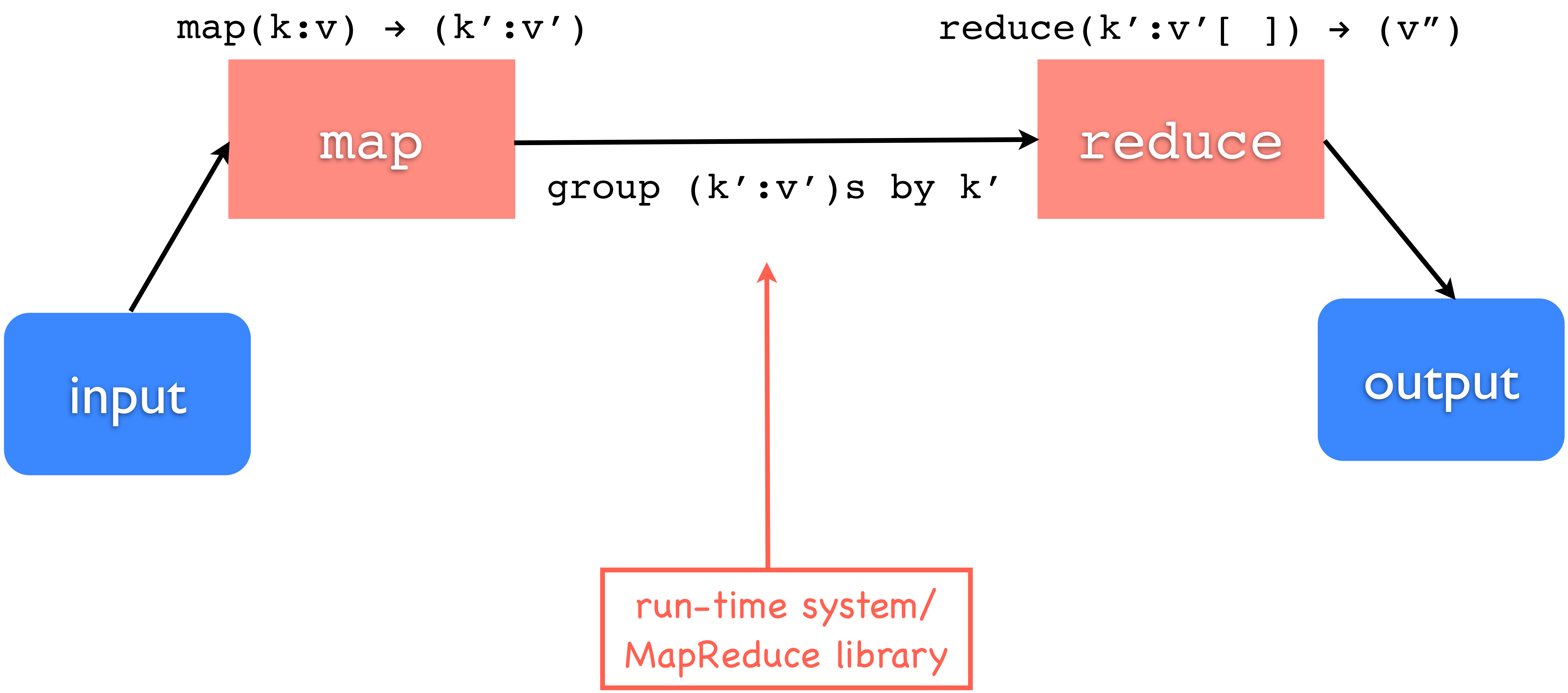
- Inspired✣ by the map and reduce primitives of functional programming languages such as Lisp
    - map: takes as input a function and a sequence of values and applies the function to each value in the sequence
    - reduce: takes as input a sequence of values and combines all values using a binary operator

✣ but not equivalent!

MapReduce Programming Model

- Computation:
  - takes a set of input <key, value> pairs and produces a set of output <key, value> pairs
- map (written by user)
  - takes a input <key, value> pair
  - produces a set of intermediate <key, value> pairs
- MapReduce library
  - groups all intermediate values associated with same intermediate key I
  - sort intermediate values by key
- reduce (written by user)
  - takes as input an intermediate key I and a set of values for that key (<key, v1, v2, ..., vn>)
  - merges values together to form a smaller set of values
  - typically produces one output value

MapReduce execution model



Example: Word Count

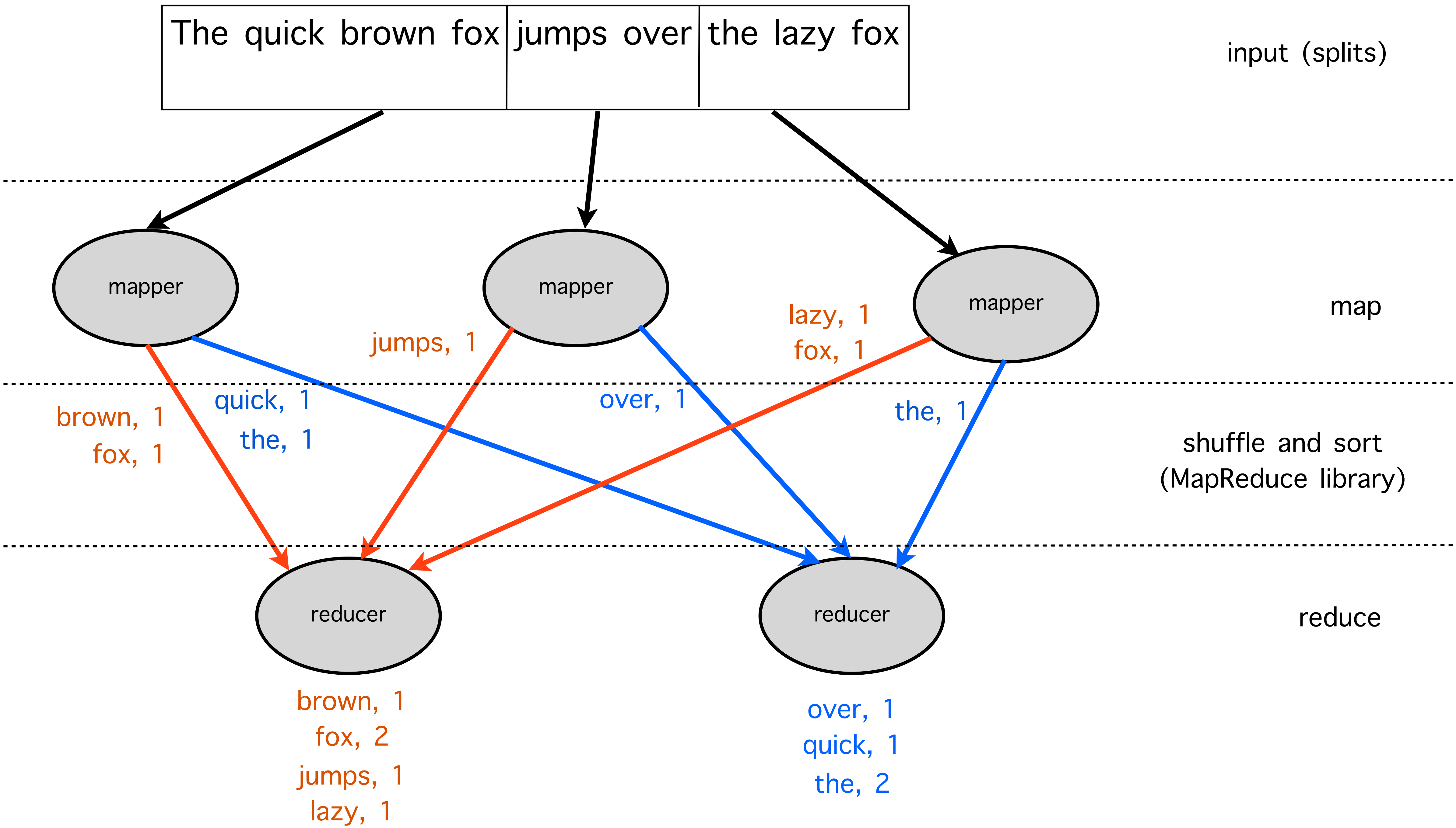
- Count the number of occurrences of a word in a large collection of documents:

```
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));
```

- User also writes code to fill in a MapReduce specification object with
  - names of input and output files
  - optional tuning parameters
- User code is linked with the MapReduce library

Execution example



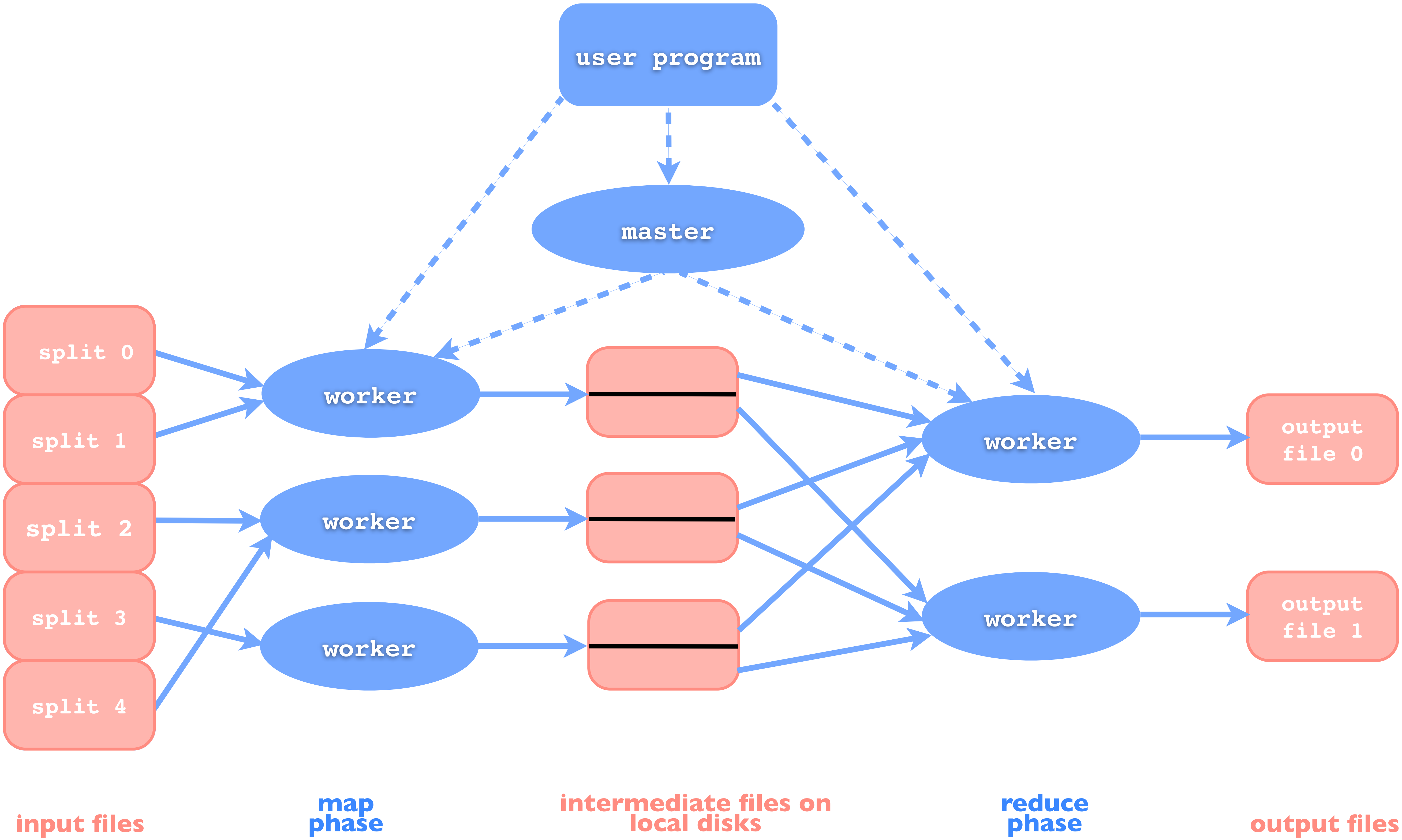
More examples

- Distributed **grep**
  - map: emits a line if it matches a supplied pattern
  - reduce: identity function (copies intermediate data to output)
- Count of URL access frequency:
  - map: processes logs of web page requests and emits **`<URL,1>`**
  - reduce: adds together all values for same URL and emits **`<URL,total_count>`** pair
- Reverse Web-Link Graph
  - map: emits **`<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 and emits **`<target,list(source)>`**

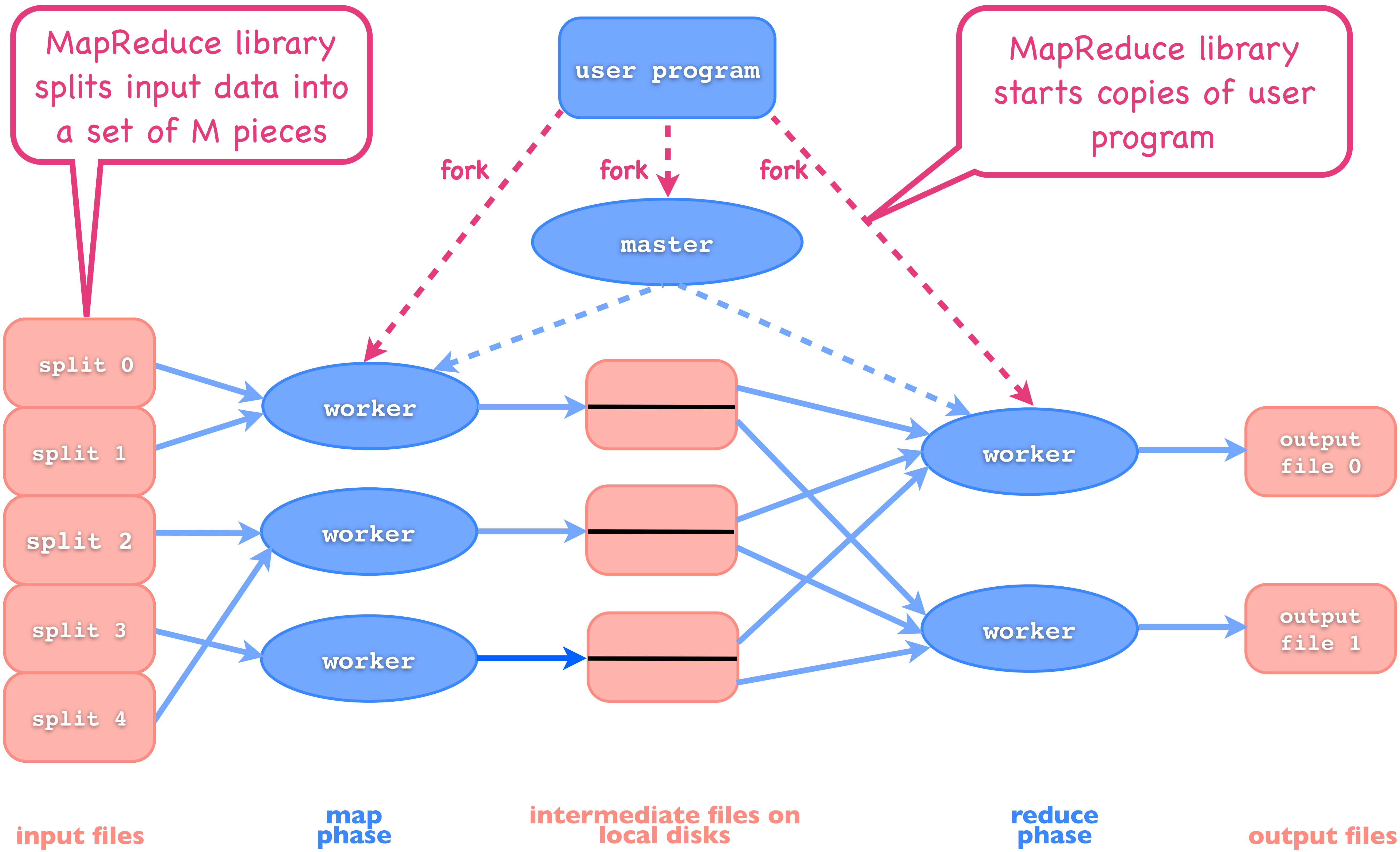
MapReduce implementation targeted to execution environment

- Google:
  - Large clusters of commodity PCs connected by Ethernet
  - A cluster has hundreds of thousands of machines: machine failures are common
  - Storage: inexpensive disks attached directly to individual machines. In-house distributed file system
  - Jobs (set of tasks) mapped by scheduler to available machines within a cluster
- Different implementations depend on environment

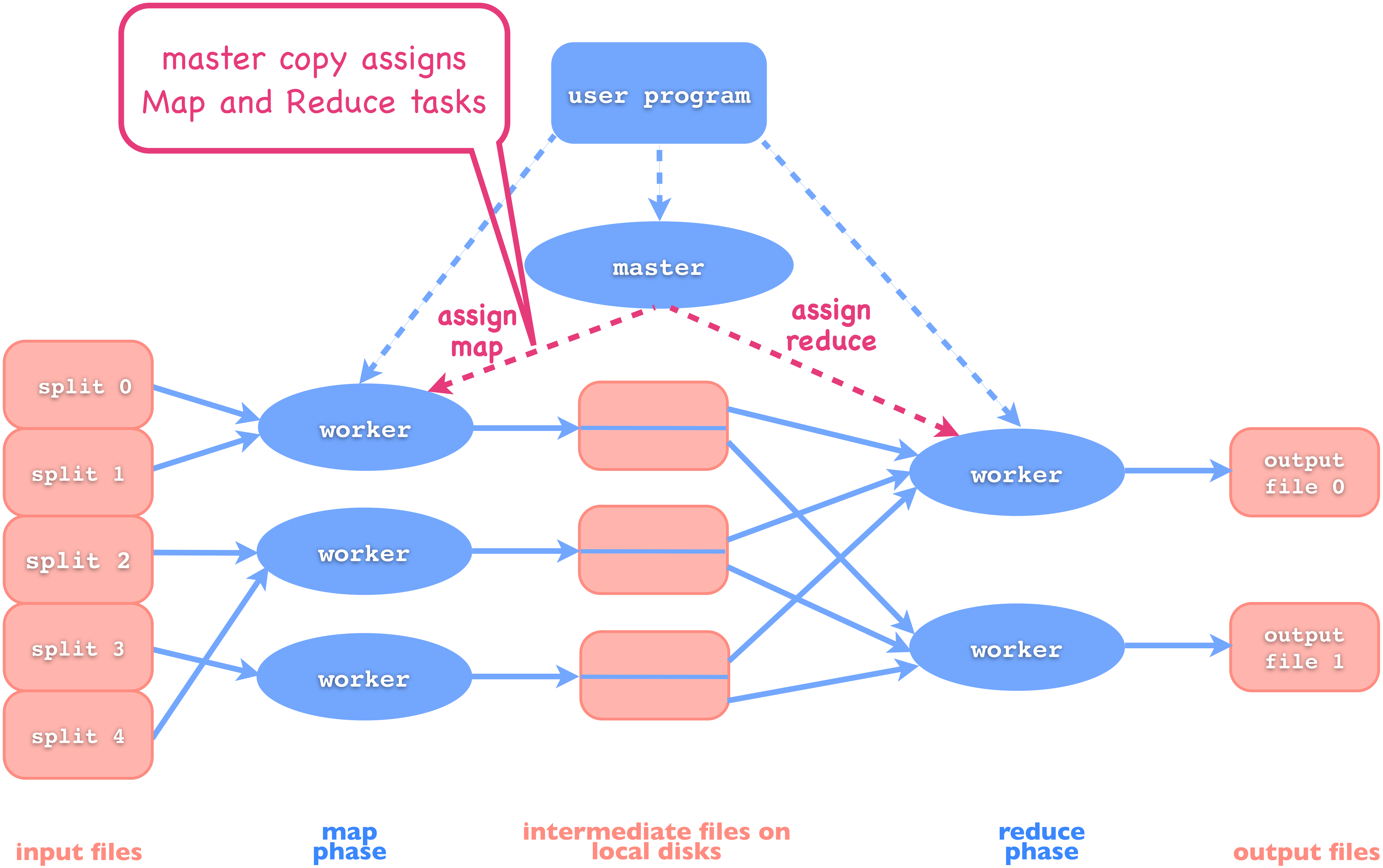
Execution


user program
master
split 0
split 1
split 2
split 3
split 4
worker
worker
worker
worker
worker
output file 0
output file 1
input files
map phase
intermediate files on local disks
reduce phase
output files

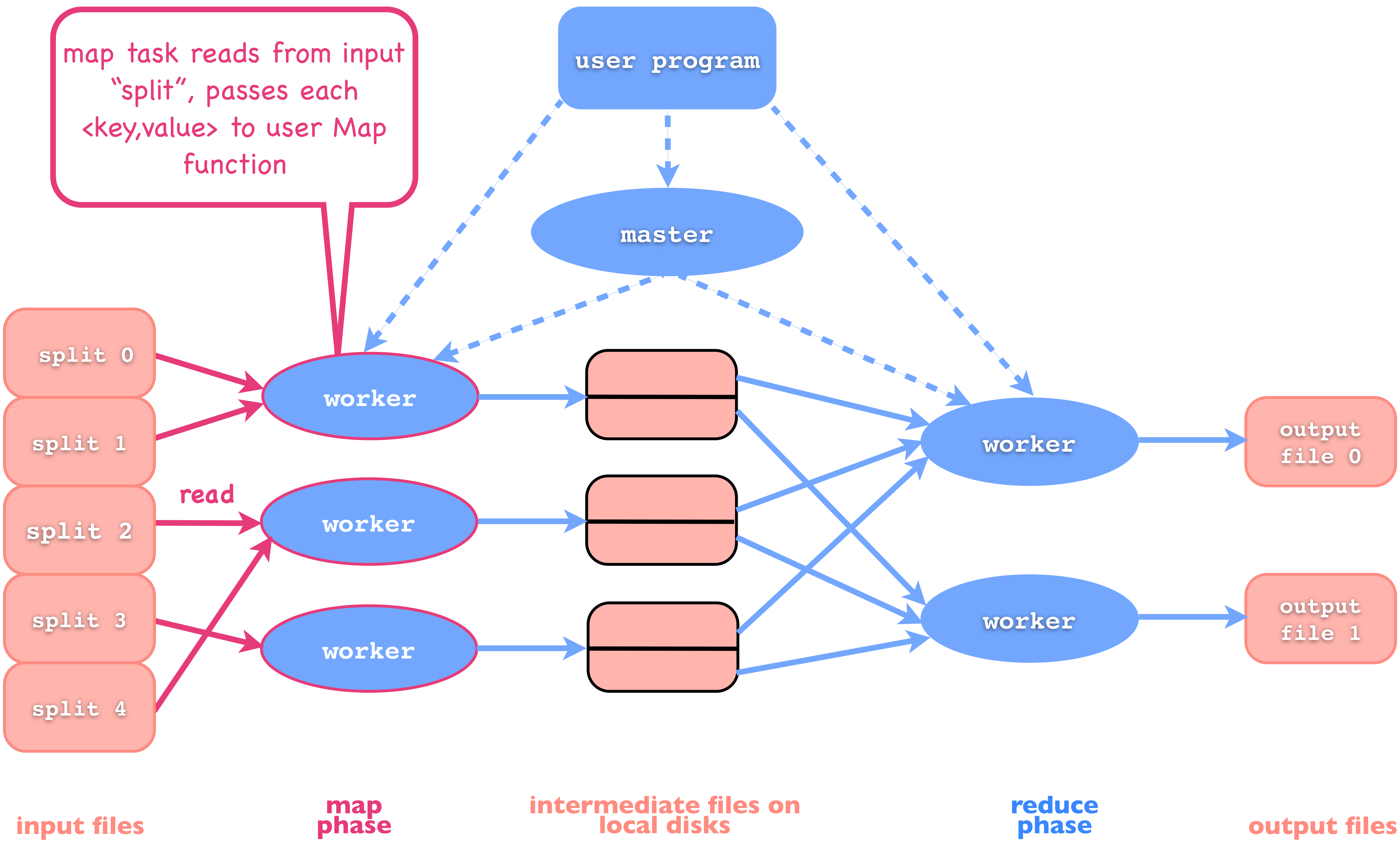
Execution


MapReduce library splits input data into a set of M pieces
user program
fork
fork
fork
MapReduce library starts copies of user program
master
split 0
split 1
split 2
split 3
split 4
worker
worker
worker
worker
worker
output file 0
output file 1
input files
map phase
intermediate files on local disks
reduce phase
output files

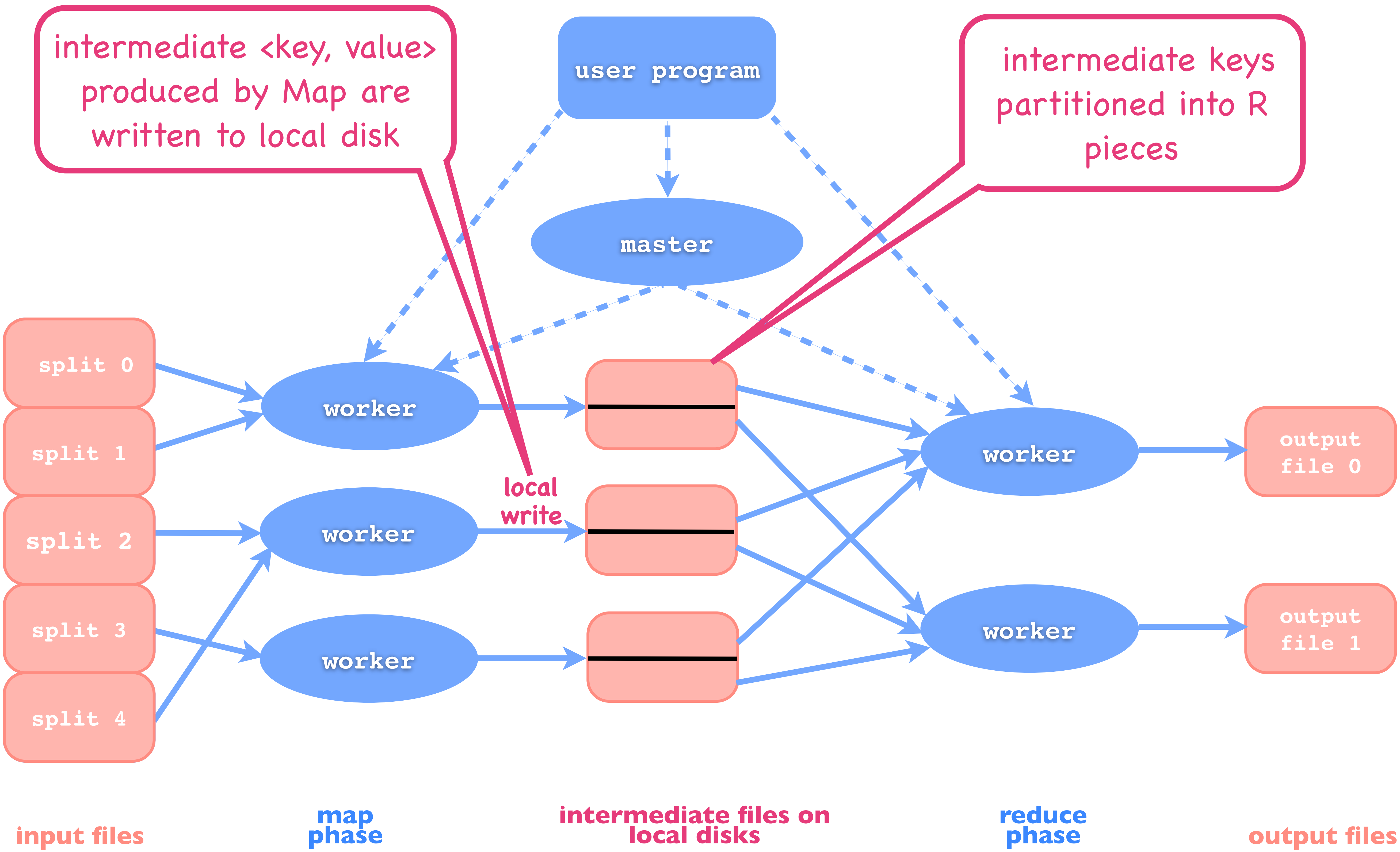
Execution


master copy assigns Map and Reduce tasks
user program
master
assign map
assign reduce
split 0
split 1
split 2
split 3
split 4
worker
worker
worker
worker
worker
output file 0
output file 1
input files
map phase
intermediate files on local disks
reduce phase
output files

Execution: map phase

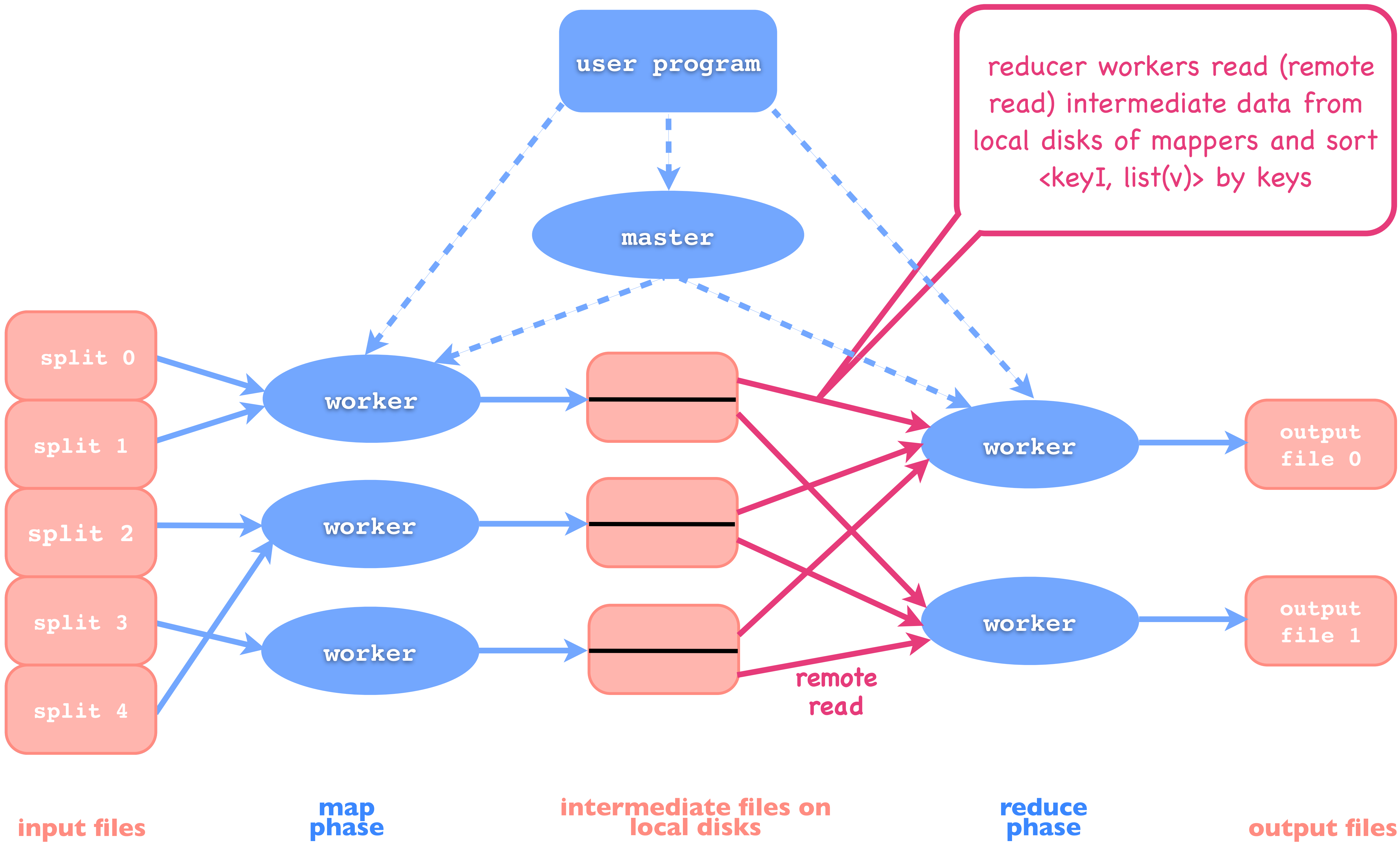


Execution

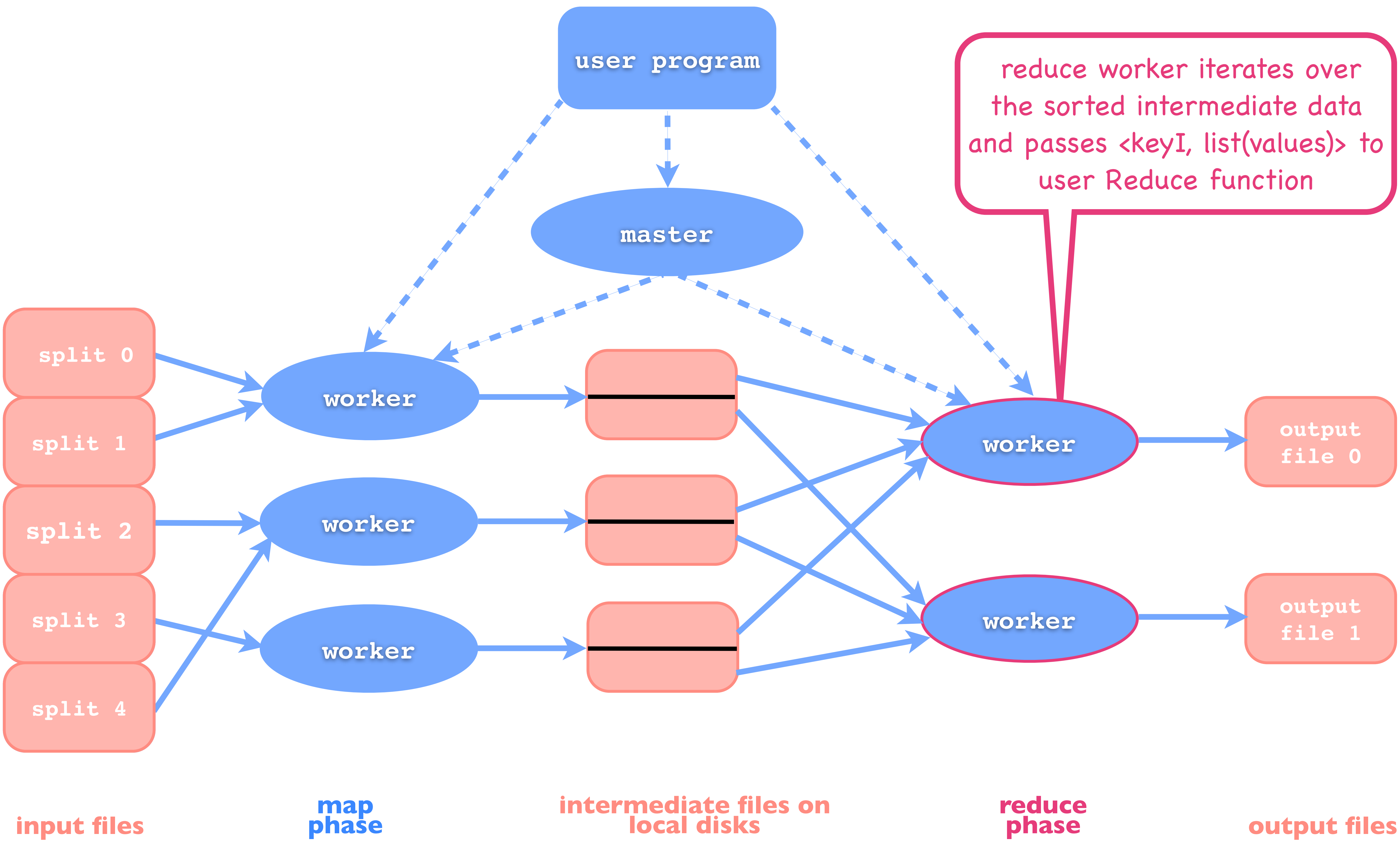


intermediate <key, value> produced by Map are written to local disk
user program
intermediate keys partitioned into R pieces
master
split 0
split 1
split 2
split 3
split 4
worker
worker
worker
local write
worker
worker
output file 0
output file 1
input files
map phase
intermediate files on local disks
reduce phase
output files

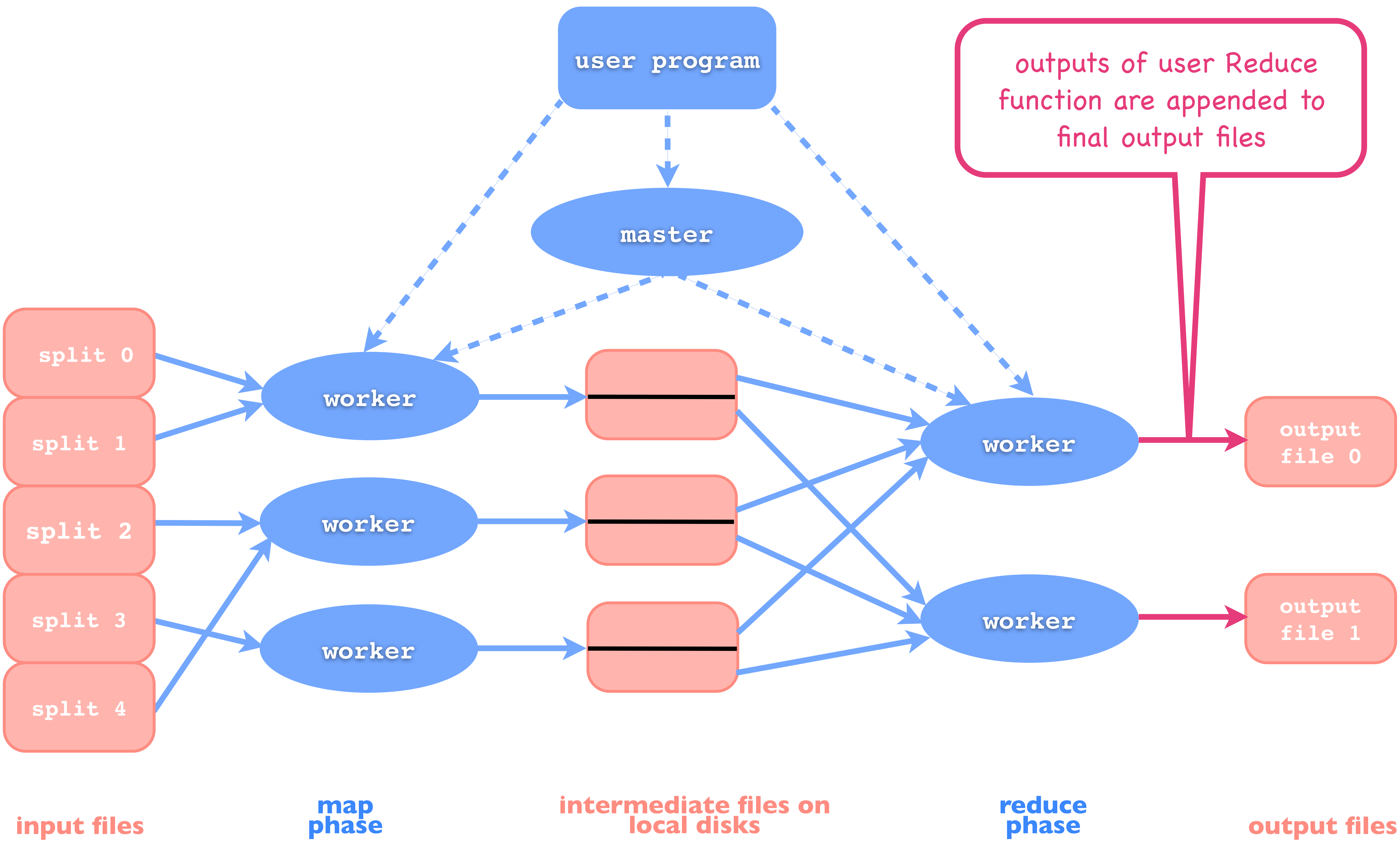
Execution: reduce



Execution: reduce phase



Execution: output



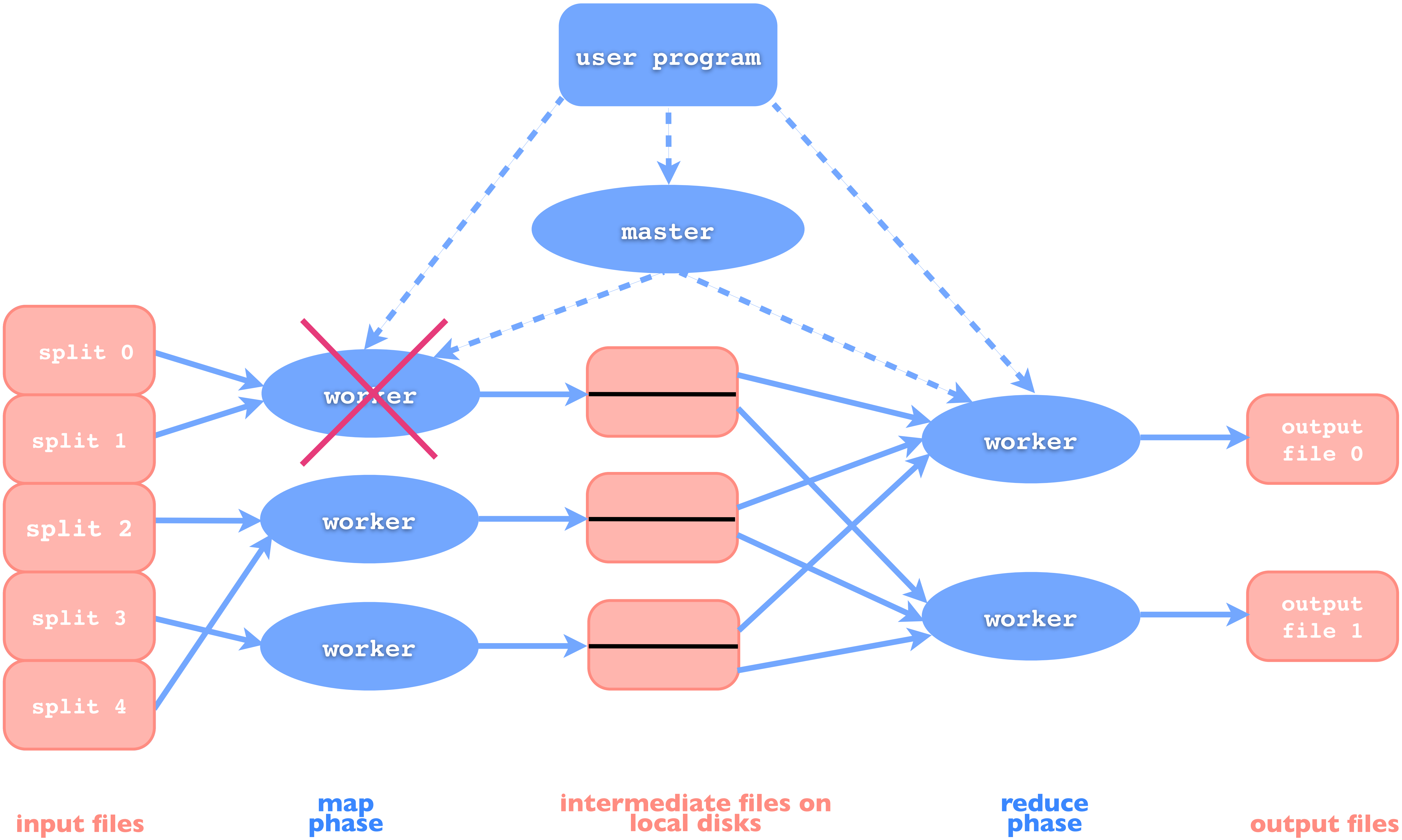
Data locality

- Input data stored in local disks of cluster machines
- Several copies of each block of data on different machines
- MapReduce master tries to assign a map task to a machine that contains a copy of the task's input data, or to a machine near that (on the same network switch)
- Most input data is read locally → consumes no bandwidth

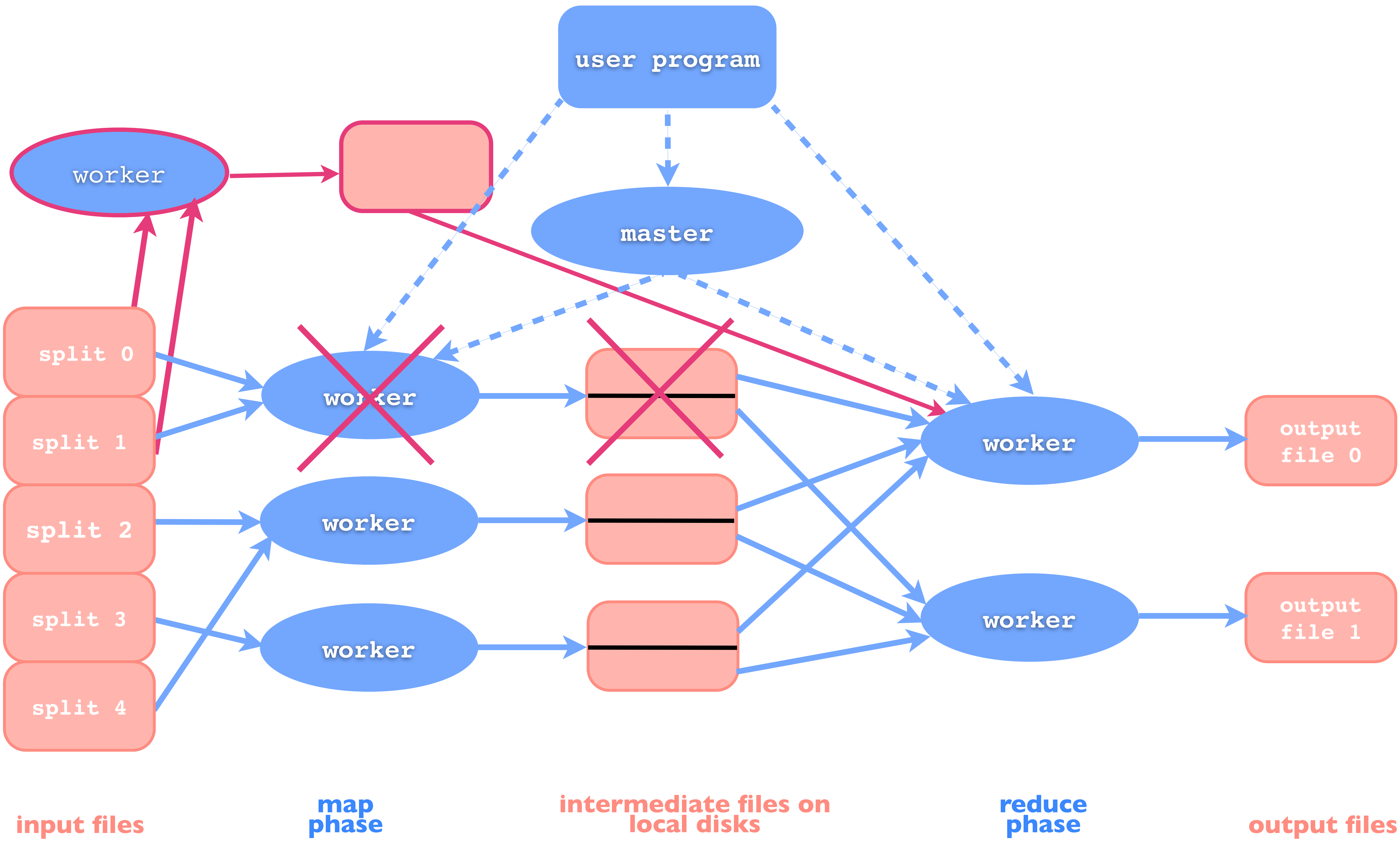
Fault tolerance

- MapReduce library designed to help process very large data → must handle machine failures
- Worker failure:
  - completed map tasks are reset to initial idle state (their output data is unavailable)
  - in-progress map and reduce tasks also reset to idle
  - idle tasks are eligible for rescheduling
  - reduce tasks notified if map task rescheduled (reads data from new worker)

Worker failure



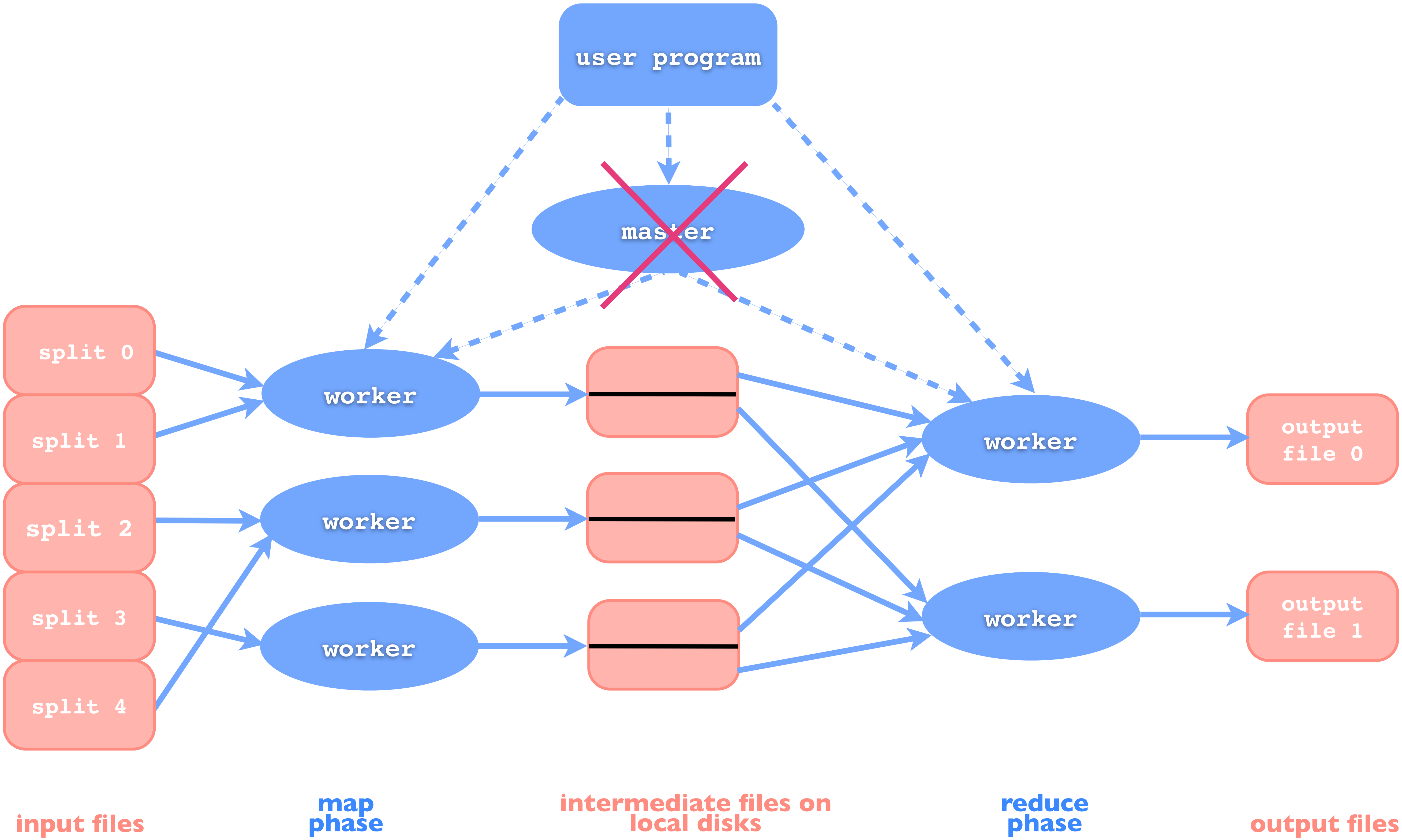
Recovery by re-execution



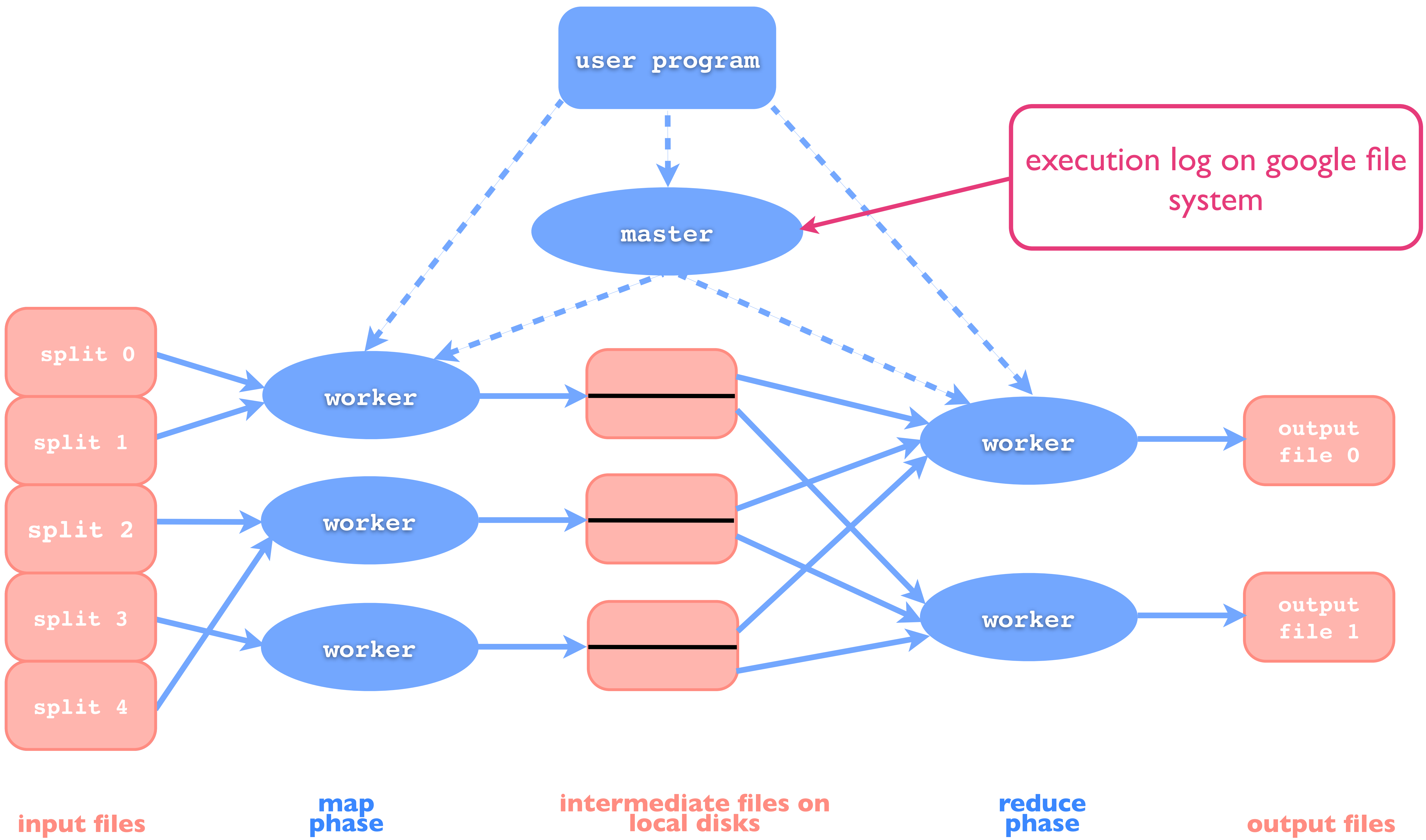
Fault tolerance

- Master failure
  - master performs periodic checkpoints of its data
  - upon failure, a new master copy can start from the checkpoint state
- Master data:
  - status of each task (idle, in-progress, complete) and machine id of non-idle tasks
  - locations and sizes of R intermediate data files generated by each map task

Master failure



Recover from master's execution log



some useful extensions: **Partitioning**

- Partitioning function
  - default partitioning function uses hashing (e.g. `hash(key) mod R`)
- Library also supports user-provided partitioning functions
  - e.g. `hash(Hostname(urlkey)) mod R` → all urls from same host end up in same output file

some useful extensions: `Combiner` function

- `Combiner`: does partial merging of data produced by a map function
  - → decreases the amount of data that needs to be read (over the network) by reduce tasks
  - e.g.: word count `Map` typically emits hundreds or thousands of pairs `<the, 1>` to be sent over the network and added by a `Reduce` function
  - `Combiner` function is executed on each machine which performs a `Map`
    - output stored in intermediate files
- Speedups some classes of MapReduce computations

Example: Word frequency

- Input: Large number of text documents
- Task: Compute word frequency across all documents
  - Frequency is calculated using the total word count
- A naive solution with basic MapReduce model requires two MapReduces
  - MR1: count number of all words in these documents
    - Use combiners
  - MR2: count number of each word and divide it by the total count from MR1

Word frequency

- Can we do better?
- Two nice features of Google's MapReduce implementation
  - Ordering guarantee of reduce key
  - Auxiliary functionality: EmitToAllReducers(k, v)
- A nice trick: To compute the total number of words in all documents
  - Every map task sends its total world count with key " " to ALL reducer splits
  - Key " " will be the first key processed by reducer
    - Sum of its values → total number of words!

Word frequency - mapper

```
map(String key, String value):

 // key: document name, value: document contents
 int word_count = 0;
 for each word w in value:
   EmitIntermediate(w, "1");
   word_count++;
 EmitIntermediateToAllReducers("", AsString(word_count));

combine(String key, Iterator values):
// Combiner for map output
// key: a word, values: a list of counts

int partial_word_count = 0;

for each v in values:

  partial_word_count += ParseInt(v);

Emit(key, AsString(partial_word_count));
```

Word frequency - reducer

```
reduce(String key, Iterator values):

// Actual reducer
// key: a word
// values: a list of counts
if (is_first_key):
  assert("" == key);  // sanity check
  total_word_count_ = 0;
  for each v in values:
    total_word_count_ += ParseInt(v)
else:
  assert("" != key);  // sanity check
  int word_count = 0;
  for each v in values:
    word_count += ParseInt(v);
  Emit(key, AsString(word_count / total_word_count_));
```

Example: Average income in a city

- SSTable 1: (SSN, {Personal Information})

  123456:(John Smith;Sunnyvale, CA)

  123457:(Jane Brown;Mountain View, CA)

  123458:(Tom Little;Mountain View, CA)

- SSTable 2: (SSN, {year, income})

  123456:(2007,$70000),(2006,$65000),(2005,$6000),...

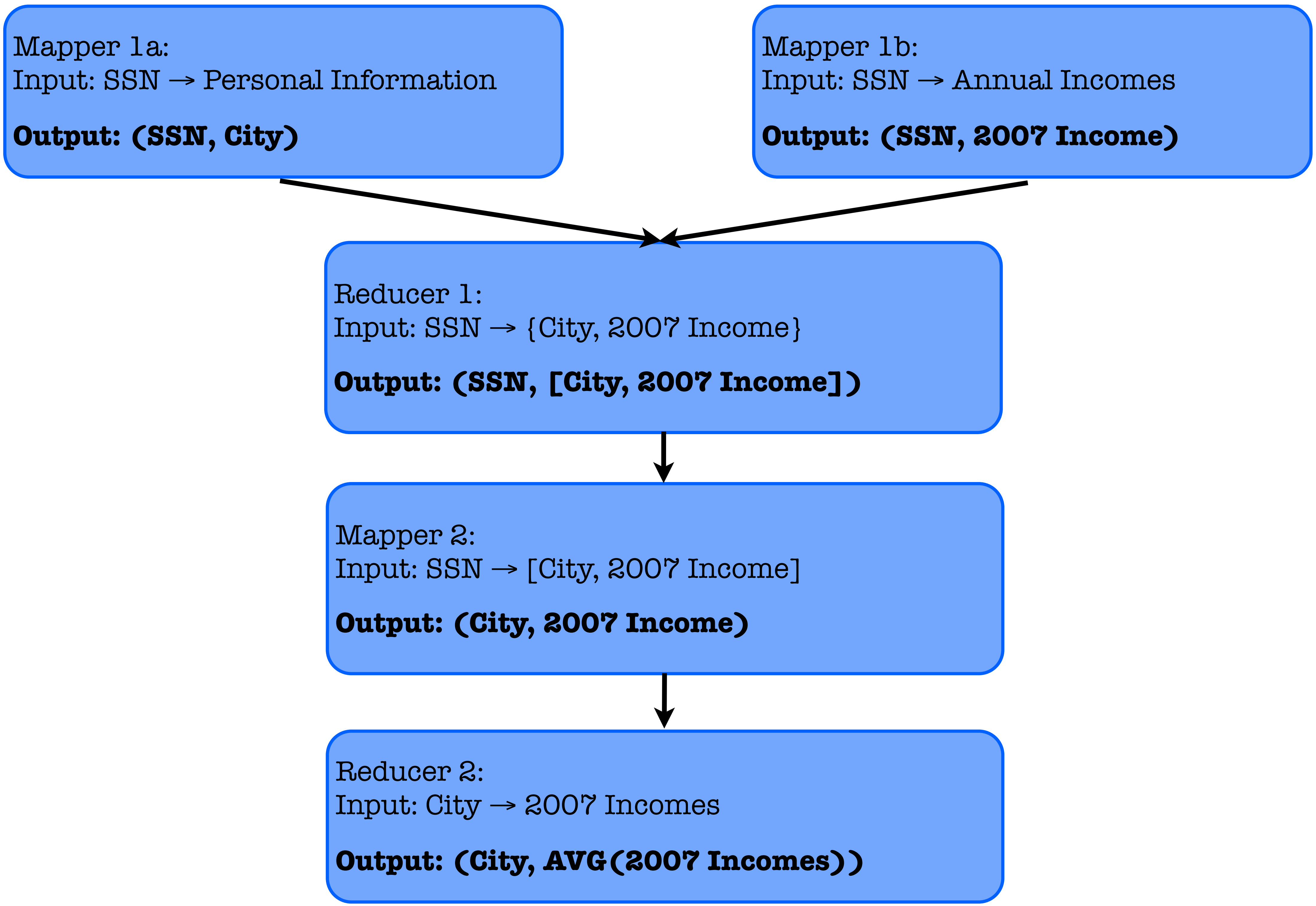
  123457:(2007,$72000),(2006,$70000),(2005,$6000),...

  123458:(2007,$80000),(2006,$85000),(2005,$7500),...

- Task: Compute average income in each city in 2007

- Note: Both inputs sorted by SSN

Average income solution



Average income joined solution

- inputs are sorted
- custom input readers

Mapper:
Input: SSN → Personal Information and Incomes

Output: (City, 2007 Income)

Reducer
Input: City → 2007 Income

Output: (City, AVG(2007 Incomes))

Summary

- MapReduce is a flexible programming framework for many applications through a couple of restricted Map()/Reduce() constructs
- Google invented and implemented MapReduce around its infrastructure to allow its engineers scale with the growth of the Internet, and the growth of Google products/services
- Open source implementations of MapReduce, such as Hadoop are creating a new ecosystem to enable large scale computing over the off-the-shelf clusters

- More examples at:

MapReduce: The Programming Model and Practice*. Jerry Zhao, Jelena Pjesivac-Grbovic. Sigmetrics tutorial, Sigmetrics 2009. *research.google.com/pubs/archive/36249.pdf

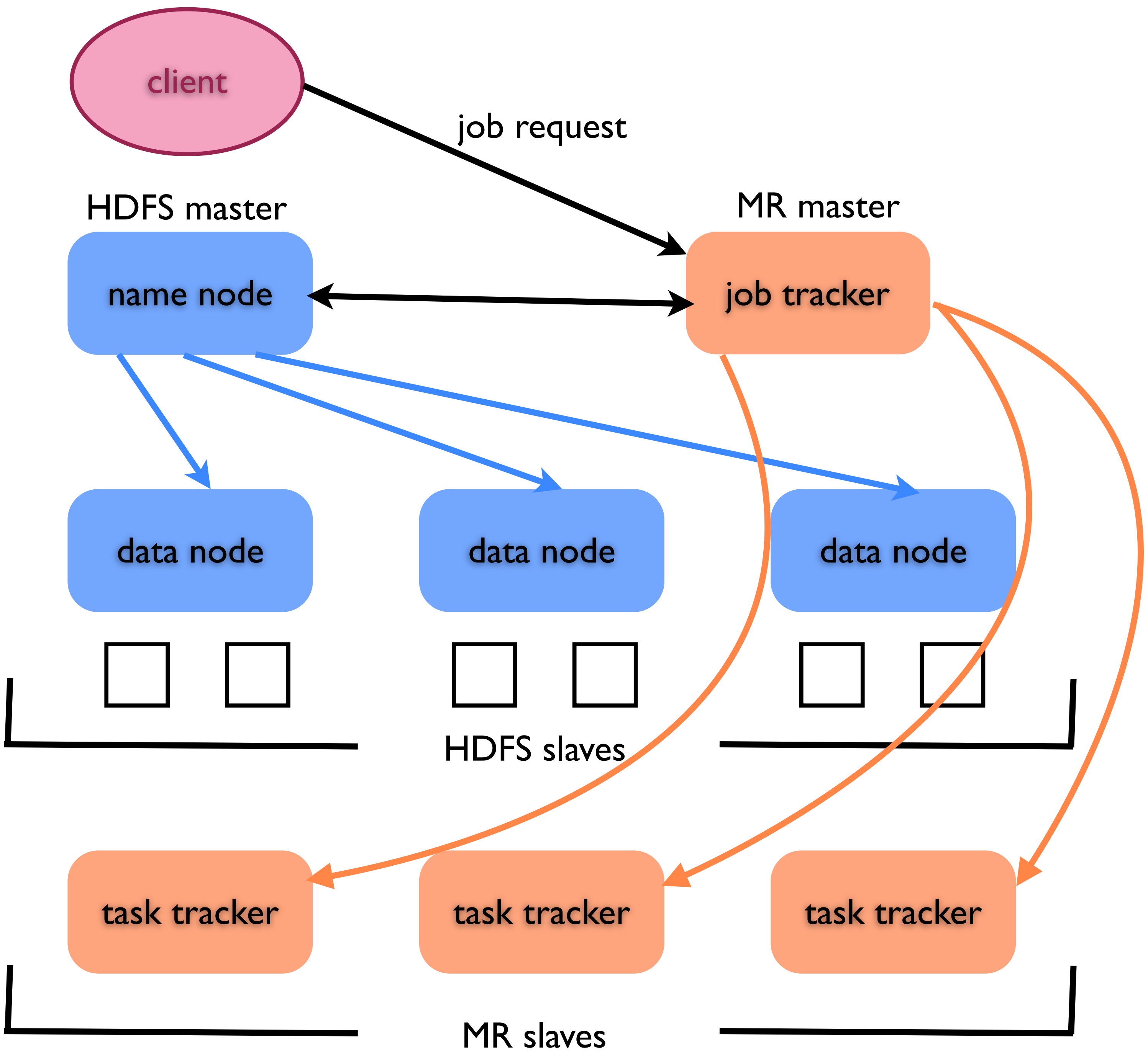
Hadoop

- Open source, top-level Apache project
- GFS $\rightarrow$ HDFS
  - HDFS (Hadoop Distributed File System) is designed to store very large files across machines in a large cluster
- Used by Yahoo, Facebook, eBay, Amazon, Twitter . . .

Hadoop

- Scalable
  - Thousands of nodes
  - Petabytes of data over 10M files
  - Single file: gigabytes to terabytes
- Economical
  - Open source
  - Commercial off-the-shelf hardware (but master nodes should be reliable)
- Well-suited to bag-of-tasks applications (many bio apps)
  - Files are split into blocks and distributed across nodes
  - High-throughput access to huge datasets

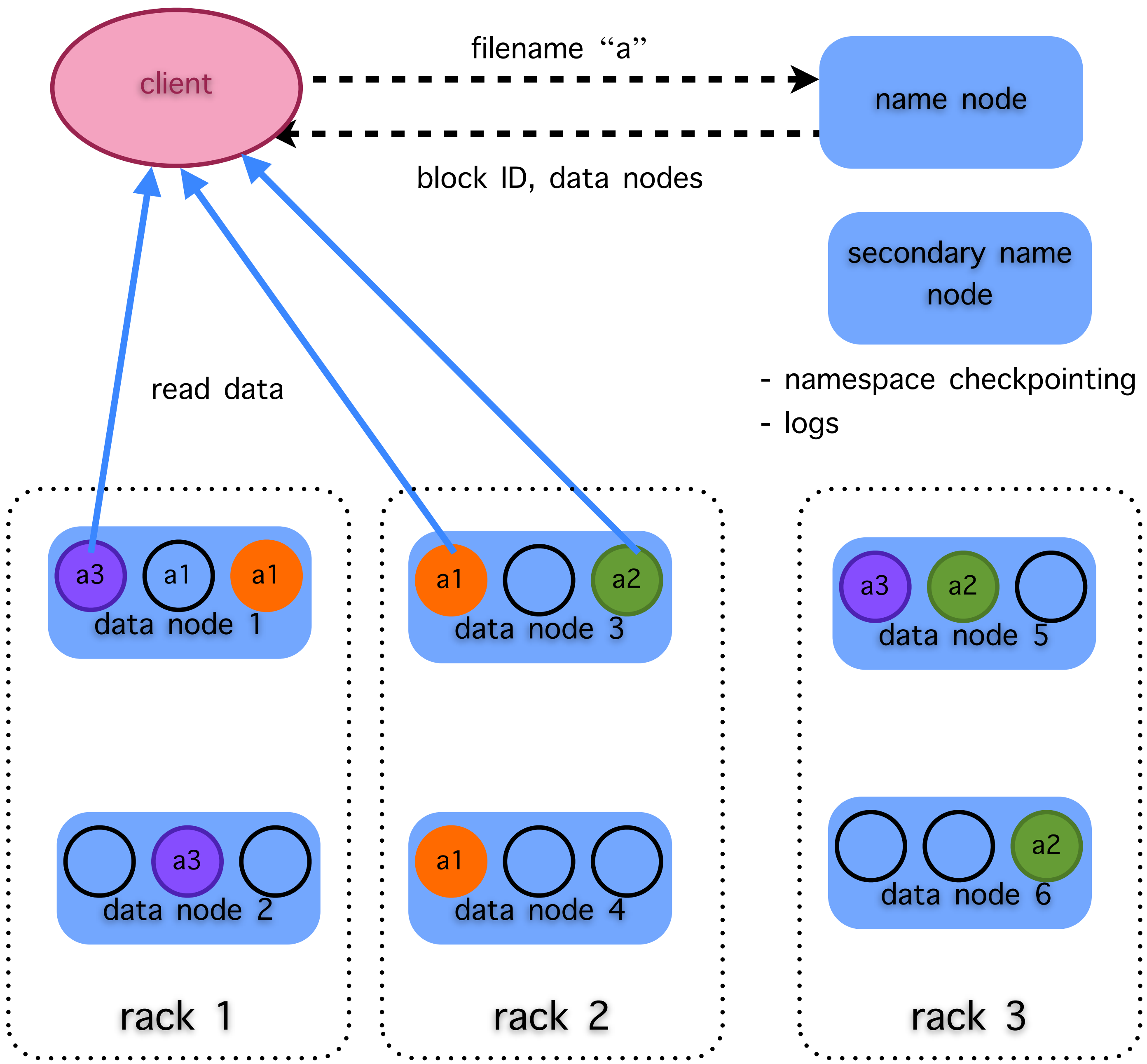
Hadoop: architecture



- client sends job request to job tracker
- job tracker queries name node about physical data block locations
- input stream is split among the desired number of map tasks
- map tasks are scheduled closest to where data reside

Slide from Simone Leo, “Python MapReduce Programming with Pydoop”, EuroPython 2011

Hadoop distributed file system



- Each block is replicated n times (3 by default)
- One replica on the same rack, the others on different racks
- User has to provide network topology

Slide from Simone Leo, "Python MapReduce Programming with Pydoop", EuroPython 2011

Other Hadoop MapReduce components

- Combiner (local Reducer)
- RecordReader
  - Translates the byte-oriented view of input files into the record-oriented view required by the Mapper
  - Directly accesses HDFS files
  - Processing unit: InputSplit (filename, offset, length)
- Partitioner
  - Decides which Reducer receives which key
  - Typically uses a hash function of the key
- RecordWriter
  - Writes key/value pairs output by the Reducer
  - Directly accesses HDFS files