# MapReduce:

## Simplified Data Processing on Large Clusters

J. Dean, S. Ghemawat, OSDI, 2004.

# Motivation: Large scale data processing

We want to:

- Extract data from large datasets
- Run on big clusters of computers
- Be easy to program

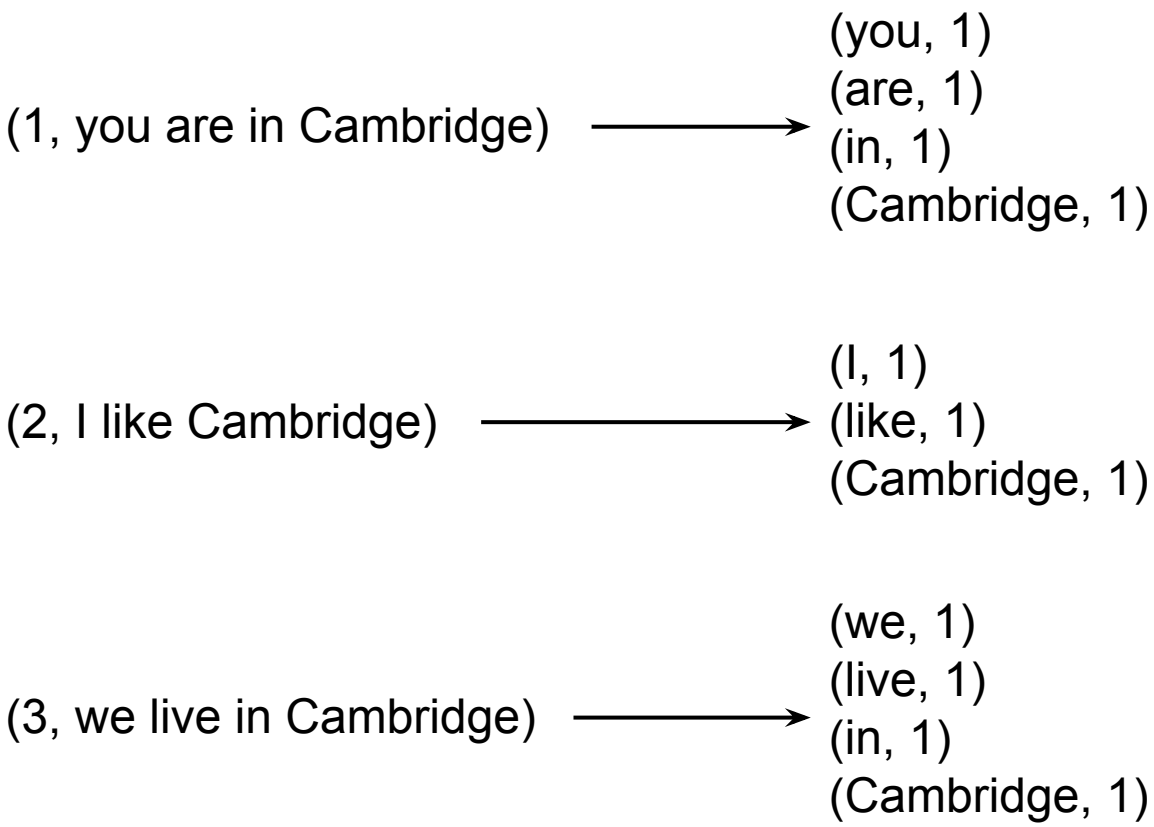
# Solution: MapReduce

A new programming model: Map & Reduce

Provides:

- Automatic parallelization and distribution
- Fault tolerance
- I/O scheduling
- Status and monitoring

# Map



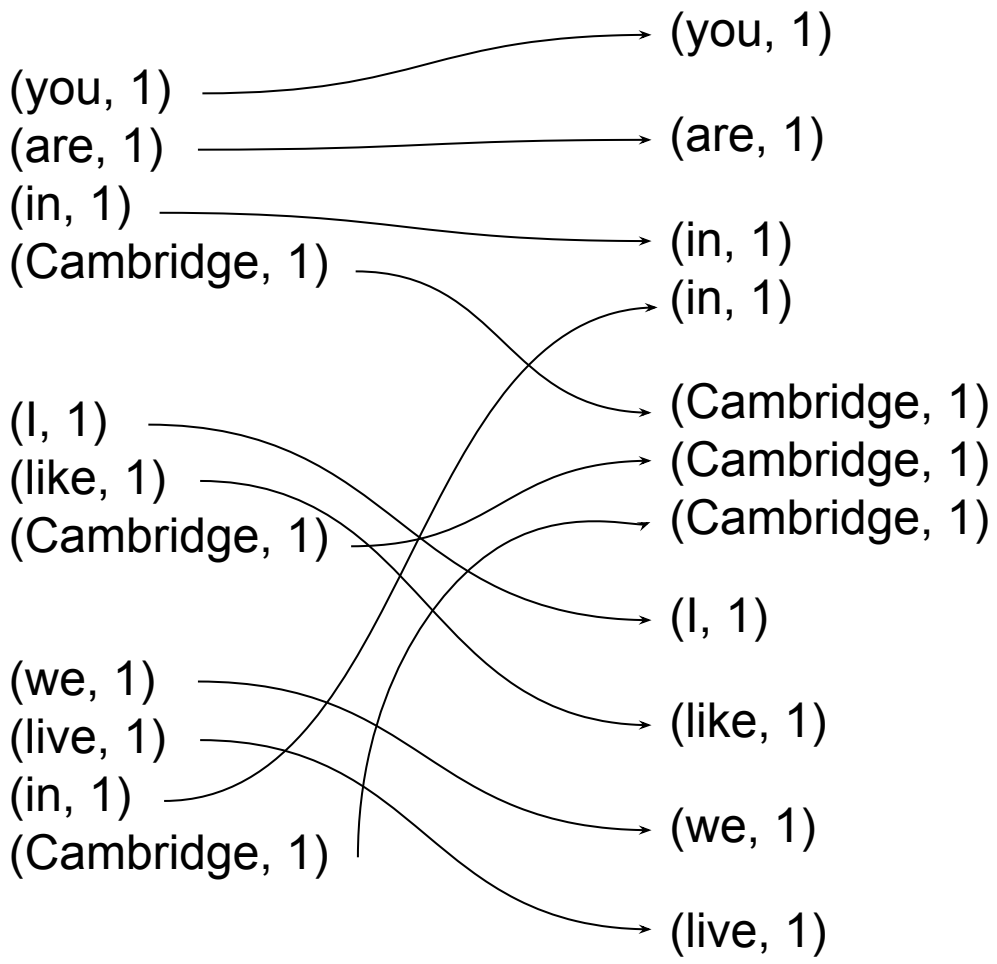

map (in_key, in_value) → list(out_key, intermediate_value)

(you, 1)
(are, 1)
(in, 1)
(Cambridge, 1)

(I, 1)
(like, 1)
(Cambridge, 1)

(we, 1)
(live, 1)
(in, 1)
(Cambridge, 1)

# Partition


(you, 1)
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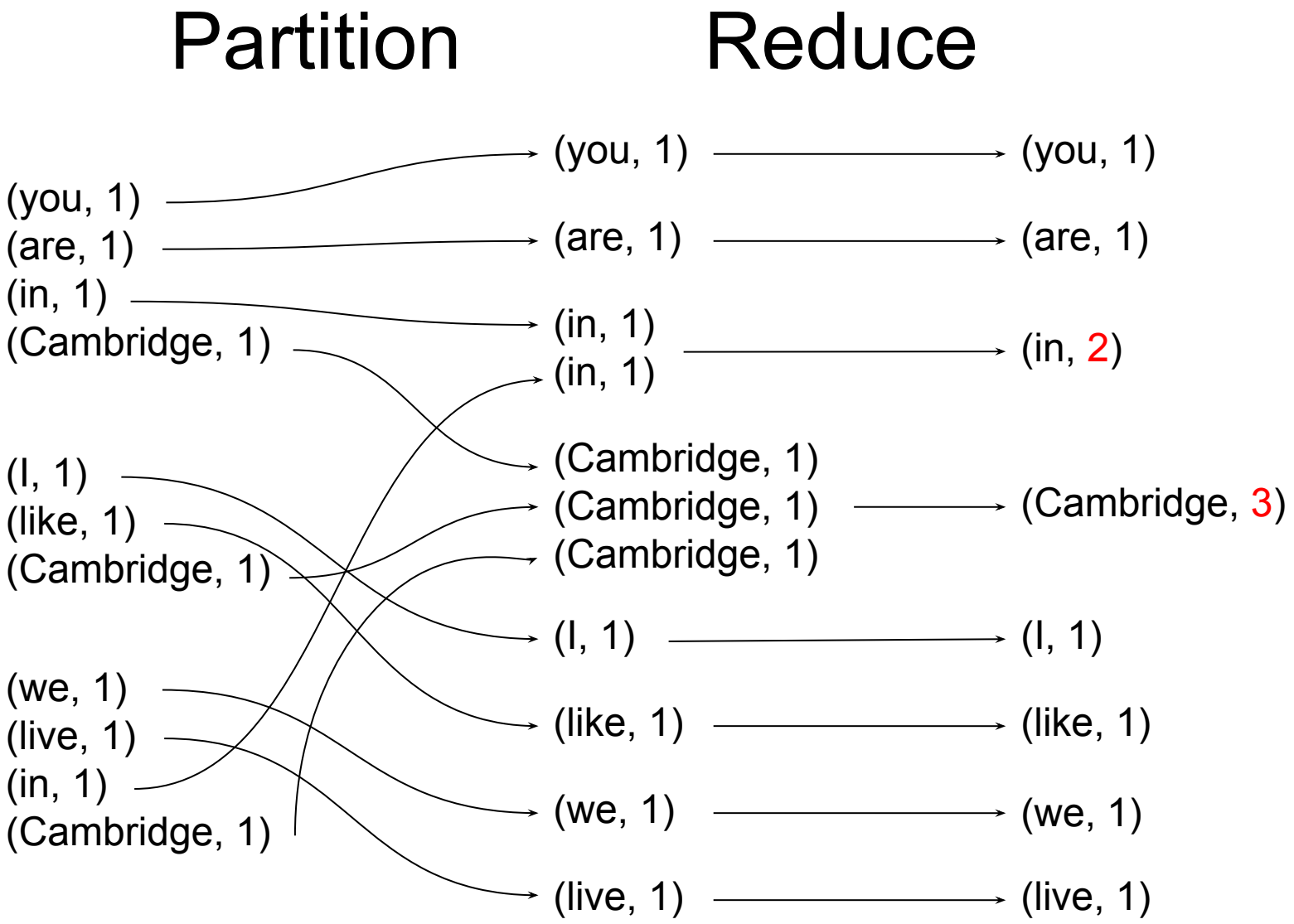
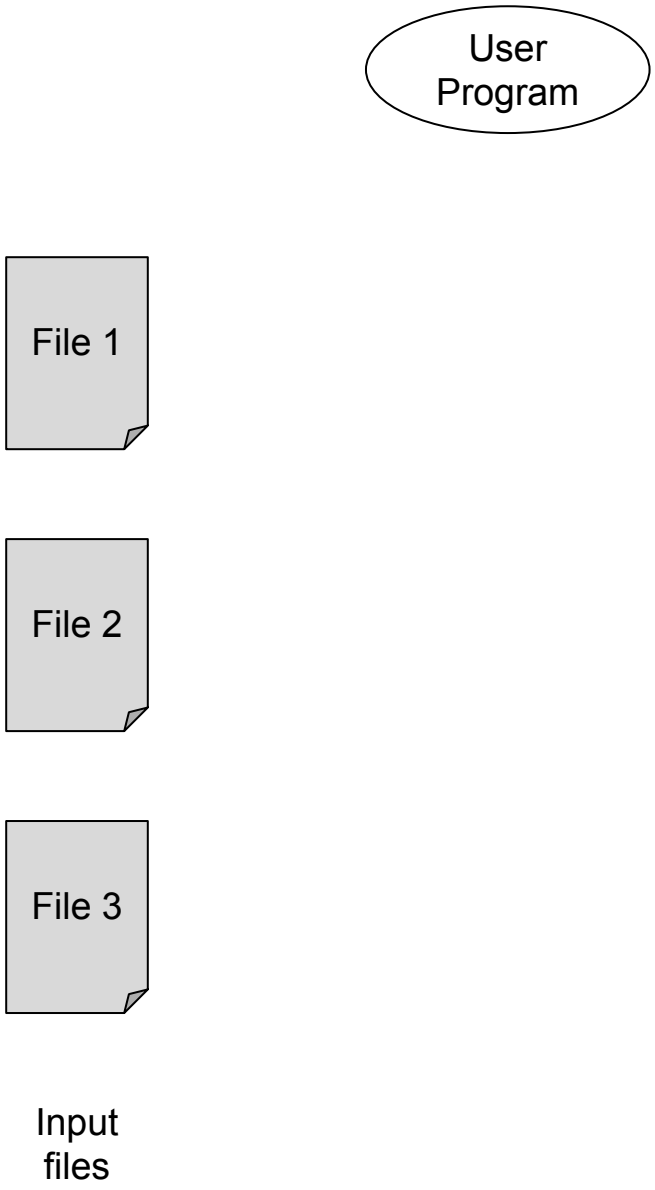
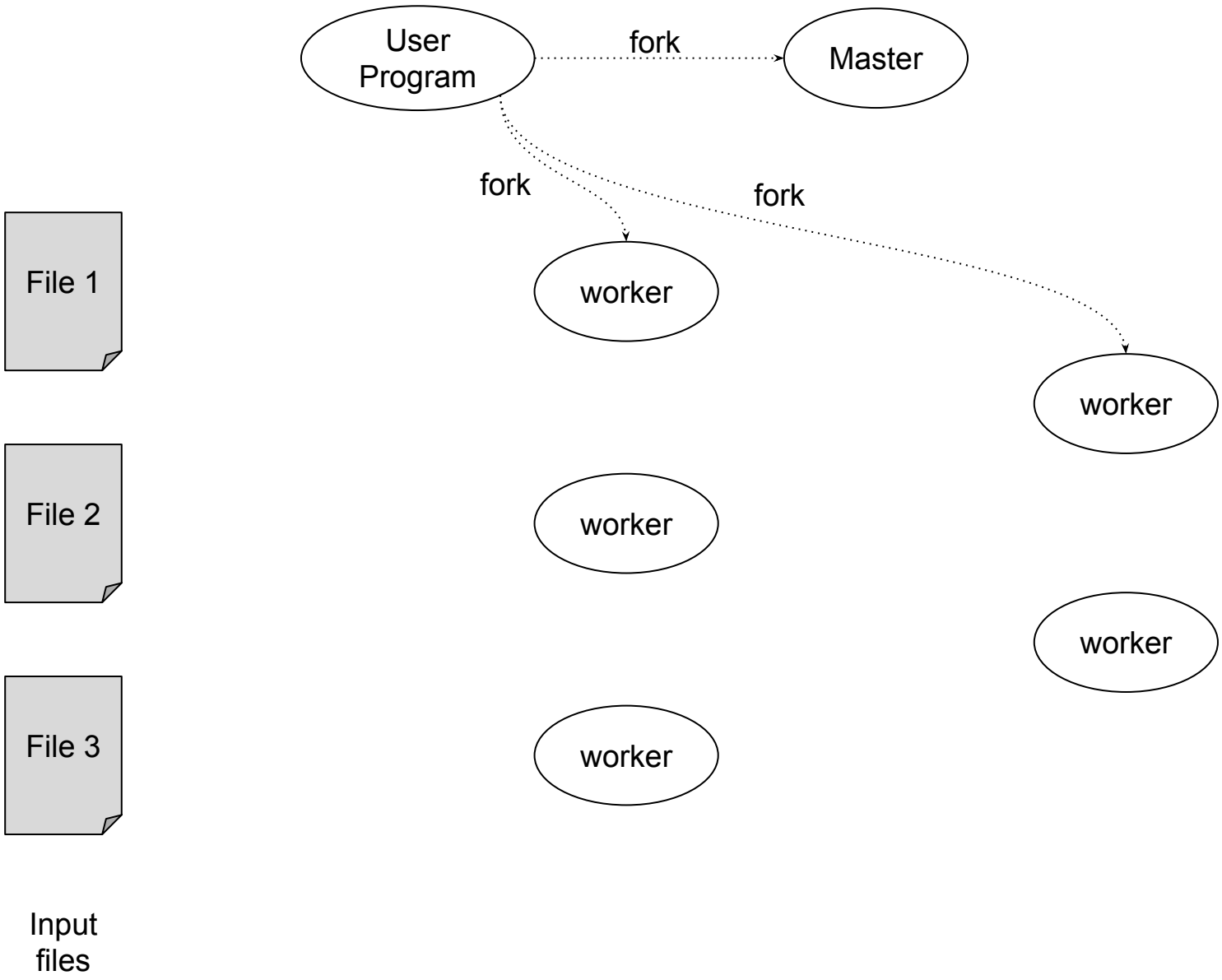
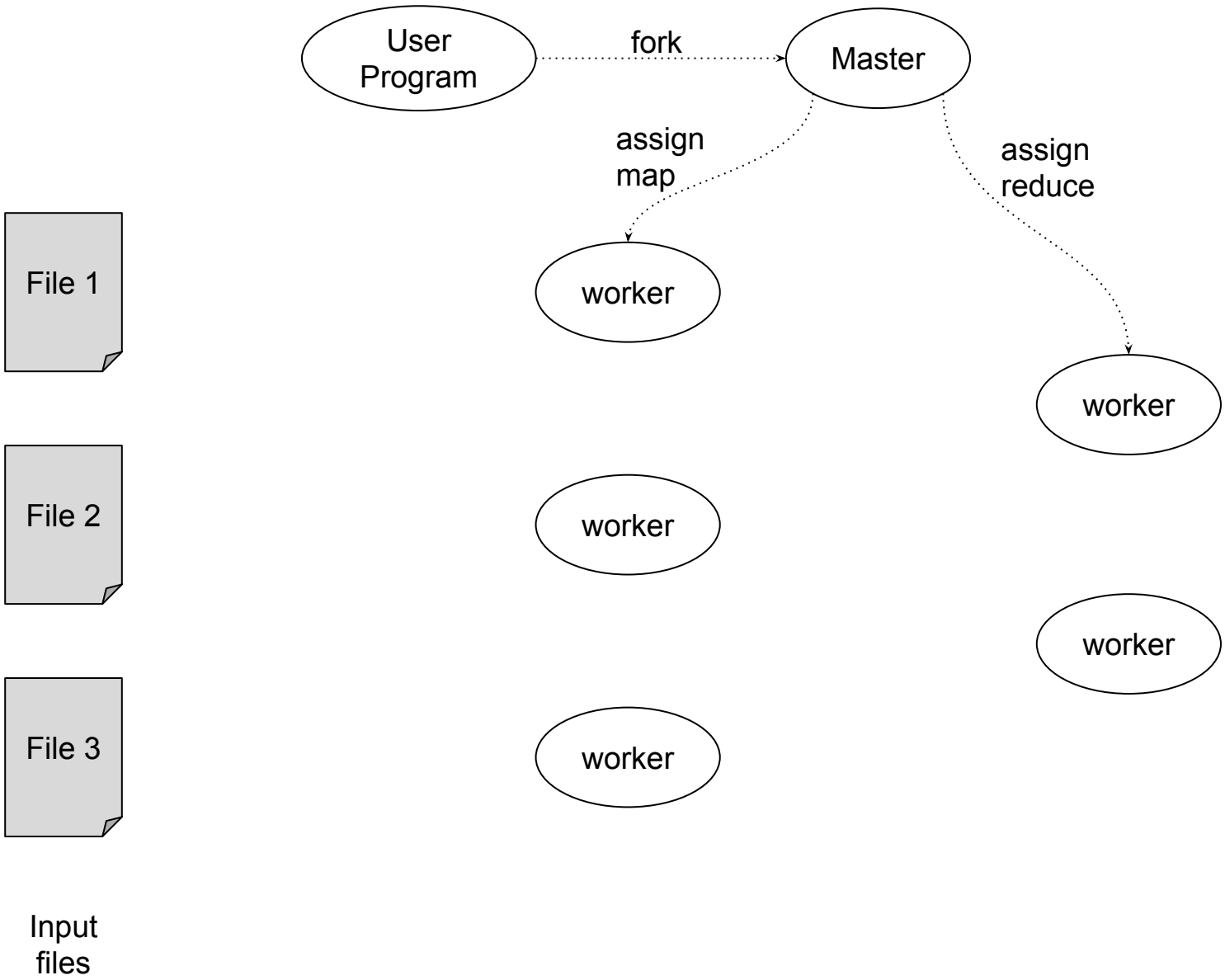
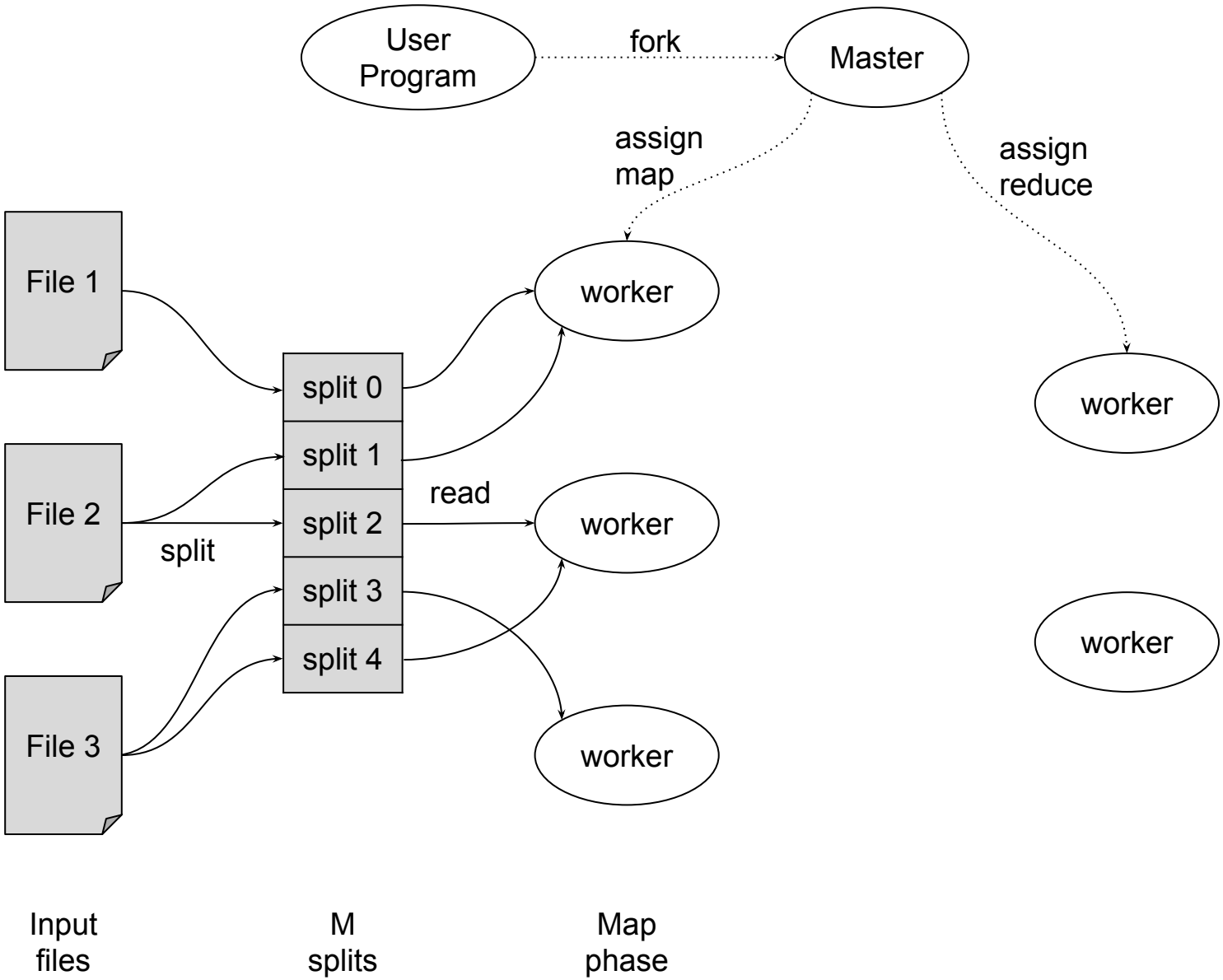


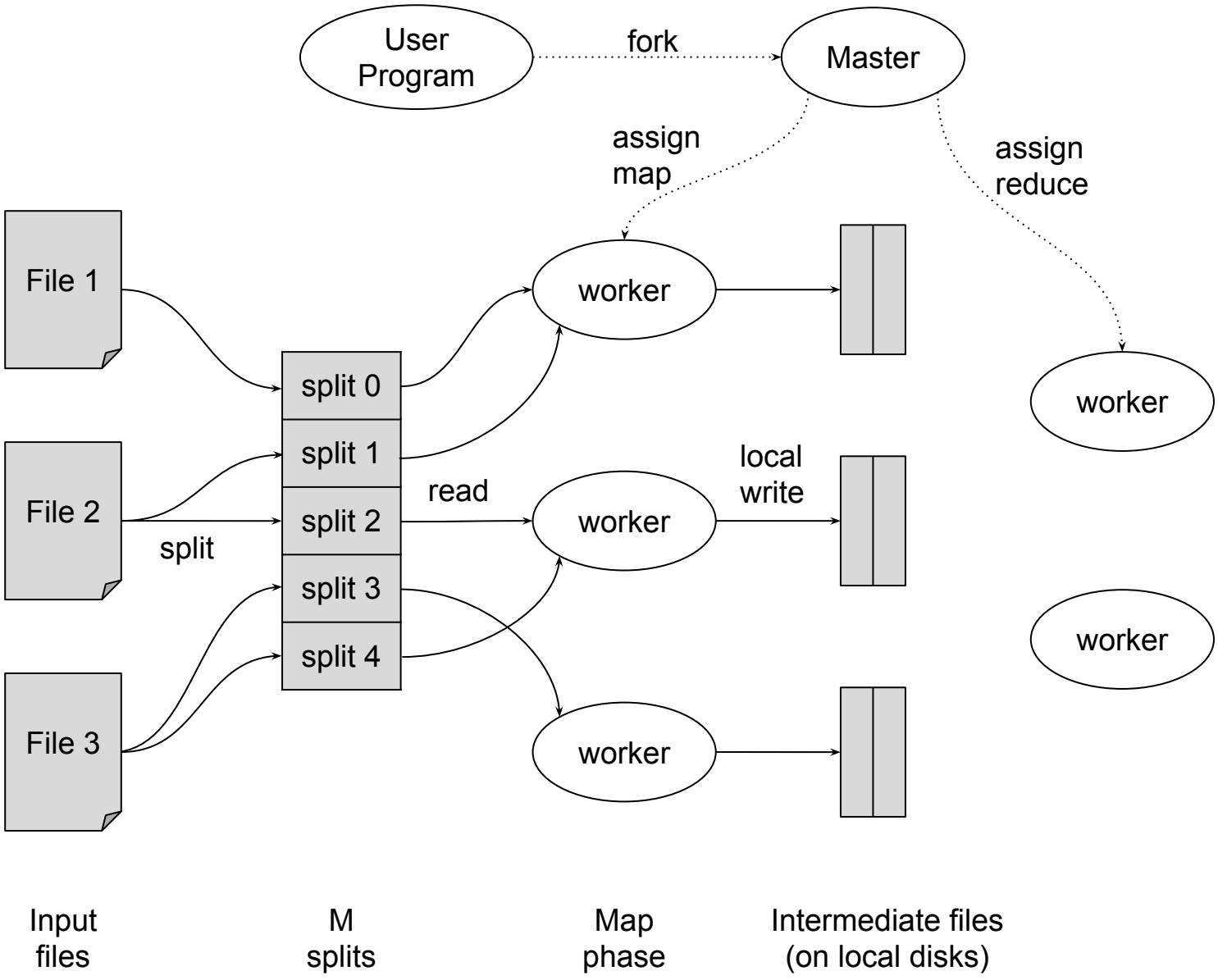

reduce (out_key, list(intermediate_value)) -> list(out_value)


User Program
File 1
File 2
File 3
Input files


User Program
fork
Master
fork
fork
worker
worker
worker
worker
worker
File 1
File 2
File 3
Input files


User Program
fork
Master
assign map
assign reduce
File 1
File 2
File 3
worker
worker
worker
worker
worker
Input files


User Program
fork
Master
assign map
assign reduce
File 1
File 2
File 3
split
split 0
split 1
split 2
split 3
split 4
read
worker
worker
worker
worker
worker
Input files
M splits
Map phase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File 1
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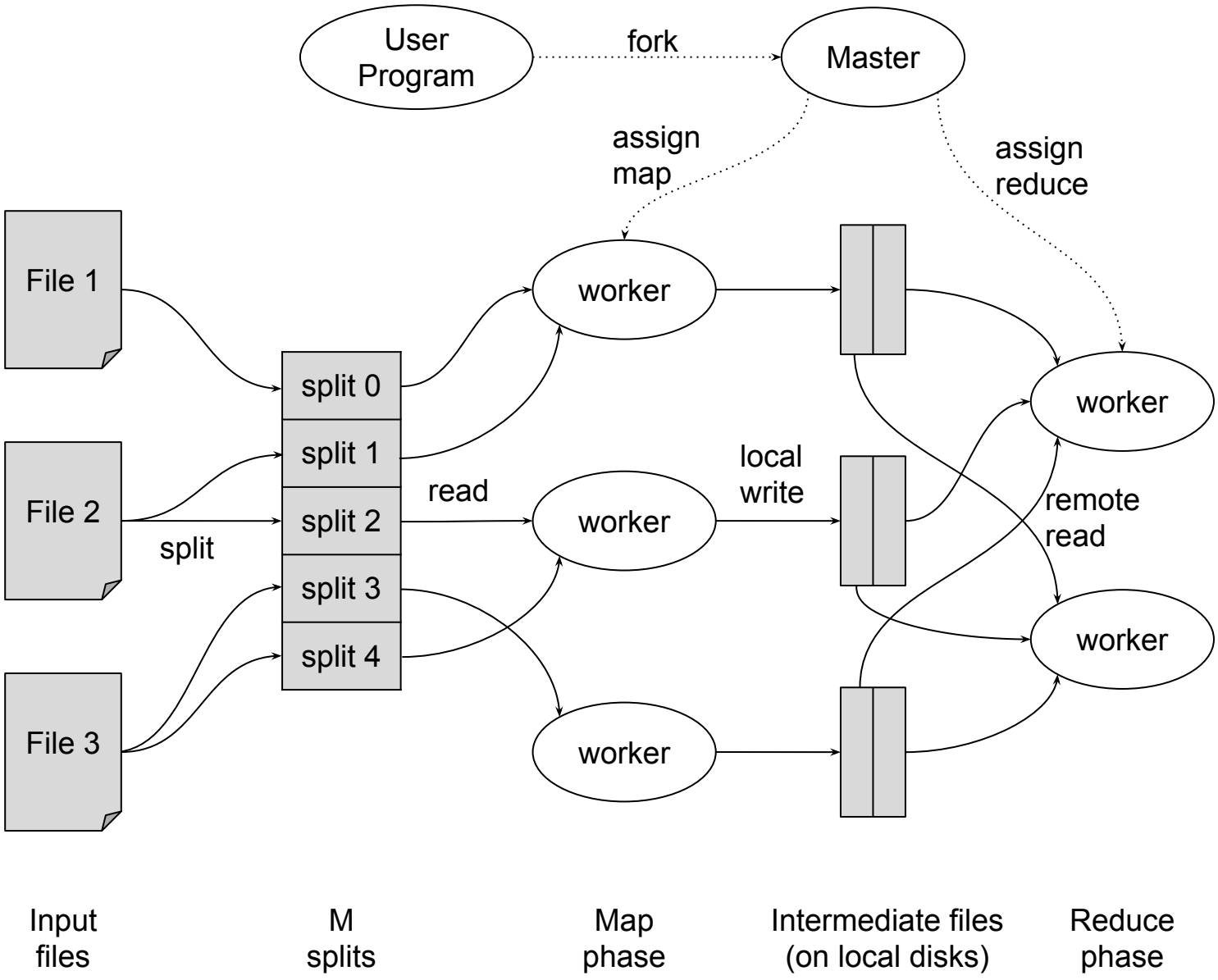
split 1
split 2
split 3
split 4
read
worker
worker
worker
worker
worker
local write
Input files
M splits
Map phase
Intermediate files (on local disks)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File 3
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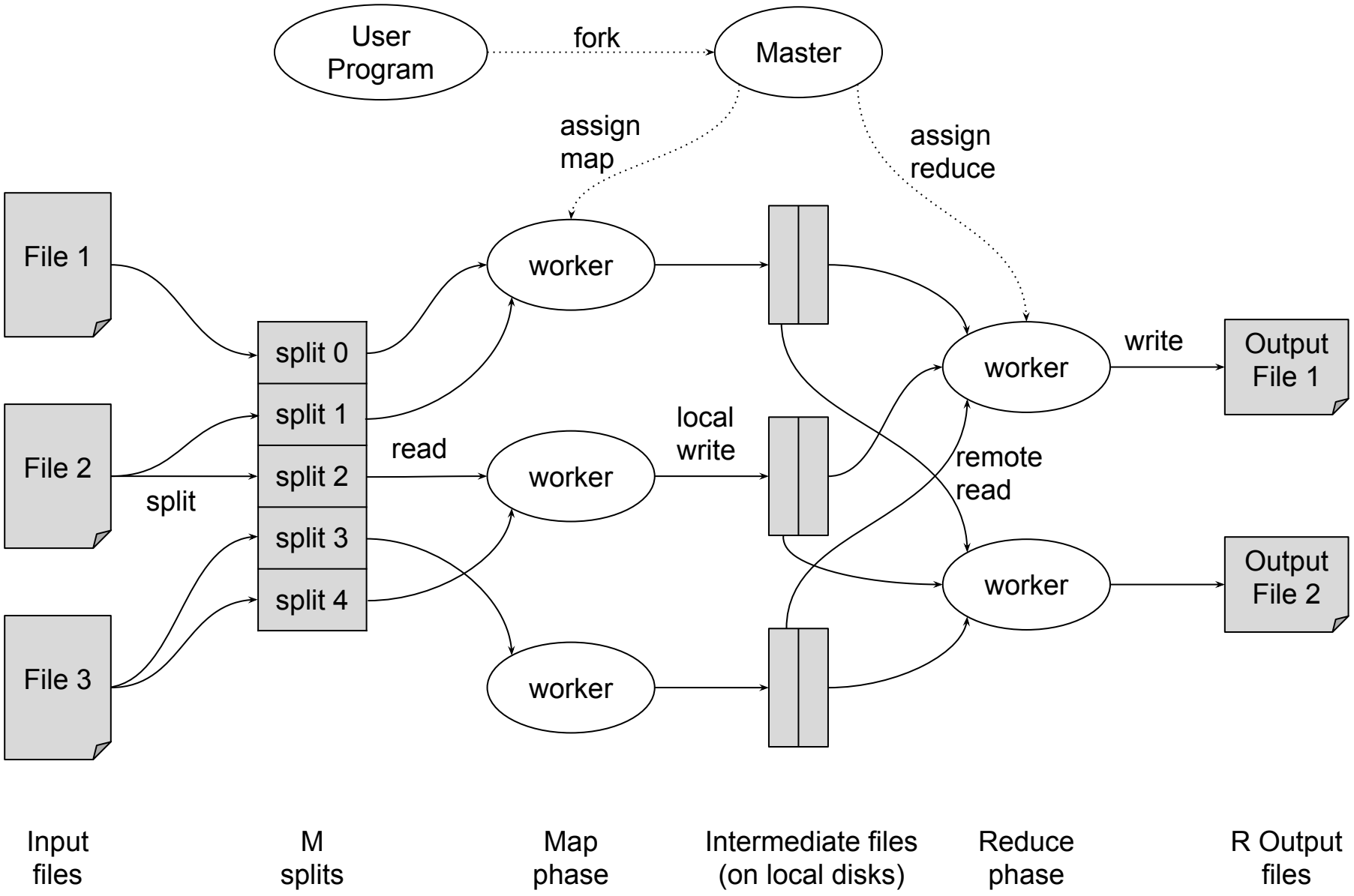
split 4
read
worker
worker
worker
local write
worker
worker
remote read
Input files
M splits
Map phase
Intermediate files (on local disks)
Reduce phase


User Program
fork
Master
assign map
assign reduce
File 1
File 2
File 3
split
split 0
split 1
split 2
split 3
split 4
read
worker
worker
worker
local write
worker
worker
write
remote read
Output File 1
Output File 2
Input files
M splits
Map phase
Intermediate files (on local disks)
Reduce phase
R Output files

# Fine task granularity

M so that data is between 16MB and 64MB

R is small multiple of workers

E.g. M = 200,000, R = 5,000 on 2,000 workers

Advantages:

- dynamic load balancing
- fault tolerance

# Fault tolerance

## Workers:

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

## Master:

- Not handled - failure unlikely

# Refinements

Locality optimization

Backup tasks

Ordering guarantees

Combiner function

Skipping bad records

Local execution

# Performance

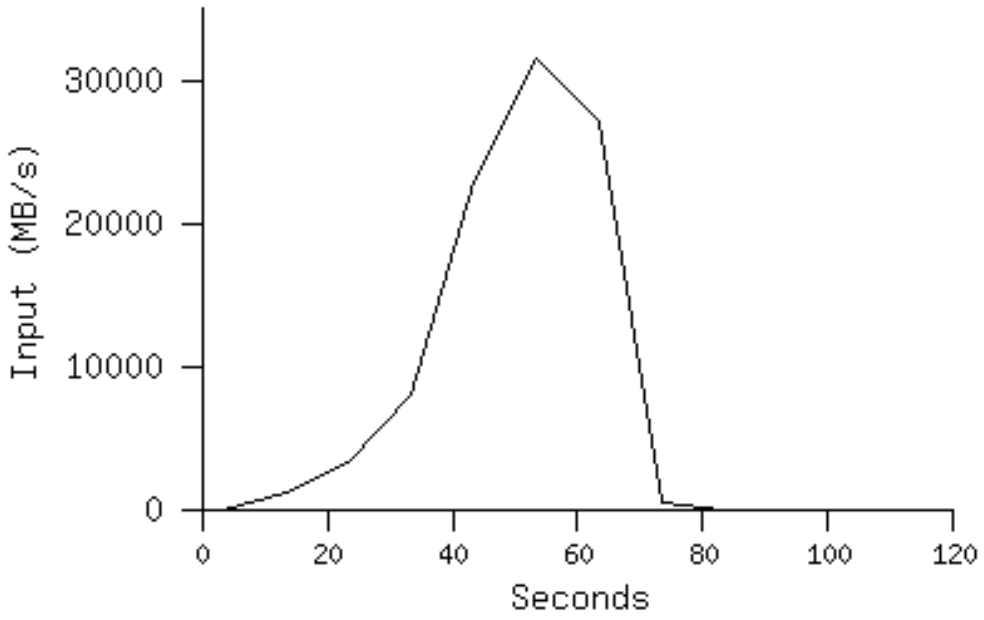
Tests run on 1800 machines:

- Dual 2GHz Intel Xeon processors
  with Hyper-Threading enabled
- 4GB of memory
- Two 160GB IDE disks
- Gigabit Ethernet link

2 Benchmarks:

| | |
|---|---|
| MR_Grep | $10^{10}$ x 100 byte entries, 92k matches |
| MR_Sort | $10^{10}$ x 100 byte entries |

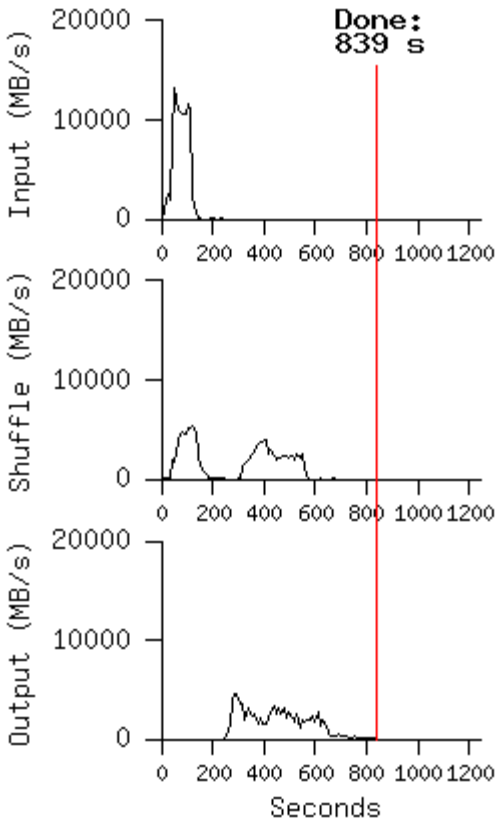
# MR_Grep



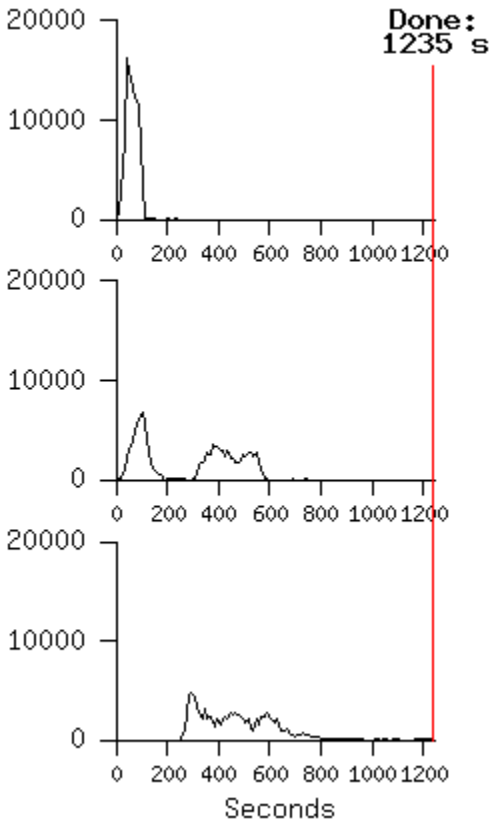

150 seconds run (startup overhead of ~60 seconds)

# MR_Sort

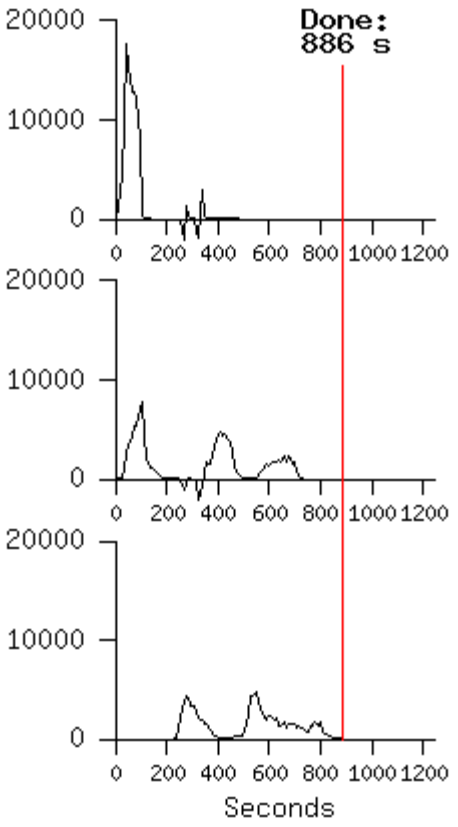
Normal execution




No backup tasks




200 tasks killed



# Experience

Rewrite of the indexing system
for Google web search

Large scale machine learning

Clustering for Google News

Data extraction for Google Zeitgeist

Large scale graph computations

# Conclusions

MapReduce:

- useful abstraction
- simplifies large-scale computations
- easy to use

However:

- expensive for small applications
- long startup time (~1 min)
- chaining of map-reduce phases?