

# Large Scale Data Processing

## MapReduce intro

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## What is MapReduce?

MapReduce is a programming model for data processing introduced by Google (2004) to support parallel and fault-tolerant computations over large data sets on clusters of computers. It provides an abstraction that hides many system-level details from the programmer.

## Big ideas behind MapReduce

- 1 Scale “out”, not “up”.
- 2 Assume failures are common.
- 3 Move processing to the data.
- 4 Process data sequentially and avoid random access.
- 5 Hide system-level details from the application developer.
- 6 Seamless scalability.

(1) **Scale “out”, not “up”**. There is evidence to conclude that a cluster of low-end servers approaches the performance of the equivalent cluster of high-end servers. The small performance gap is insufficient to justify the price premium of the high-end servers.

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MapReduce is an scale out approach that provides *equitable distribution* and *independence*

(2) **Assume failures are common.** Large-scale services distributed across a large cluster must cope with failures as an **intrinsic aspect of its operation.**

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MapReduce implementations cope with failures through automatic restart and replication.

(3) **Move processing to the data.** In high-performance computing processing nodes and storage nodes are linked together by a high-capacity interconnect. However, a bottleneck in the network is created when data-intensive workloads are not very processor-demanding.

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MapReduce takes advantage of data locality by running code on the processor where the block of data we need resides.



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In MapReduce all the computations are organized into long streaming operations that take advantage of the aggregated bandwidth of many disks in cluster. Mapreduce trades latency for throughput.

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MapReduce addresses the challenges of distributed programming by providing an abstraction that isolates the developer from system-level details.

MapReduce maintains a separation of **what** computations are to be performed and **how** those computations are actually carried out on a cluster of machines.

(6) **Seamless scalability.** If running an algorithm on a particular dataset takes 100 machine hours, then we should be able to finish in an hour on a cluster of 100 machines, or use a cluster of 10 machines to complete the same task in ten hours.

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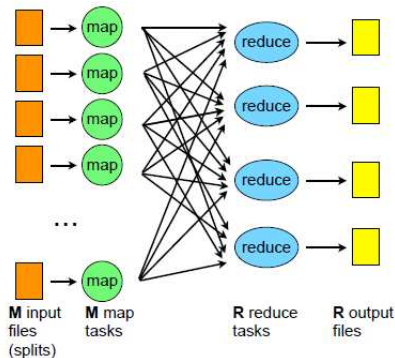
With MapReduce, this isn't so far from the truth, at least for some applications.

MapReduce is not the first model of parallel computation. However:

- it has changed the way we organize computations at a massive scale.
- it made certain large-data problems easier, but suffers from limitations as well.

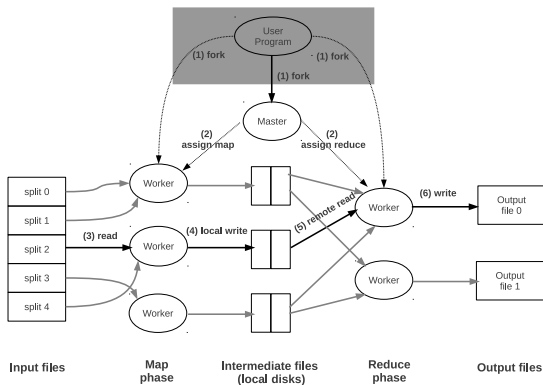
# MapReduce: logical view

- The input to a MapReduce job is divided into fixed-sized pieces called **splits**.
- A recommended split size is the size of an GDFS/HDFS block (64MB by default). However, this can be changed when each file is created.
- Splits are processed in parallel by different machines.
- The output ends up in R files on the distributed file system, where R is the number of reducers.



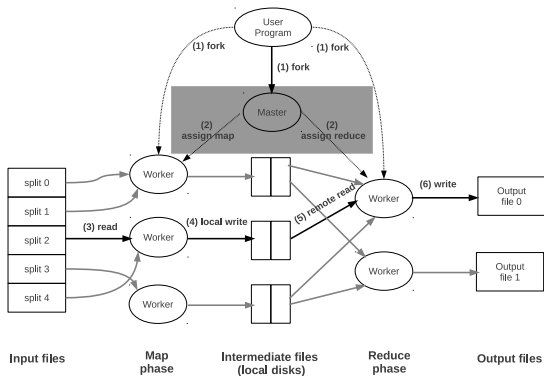


# MapReduce: execution overview

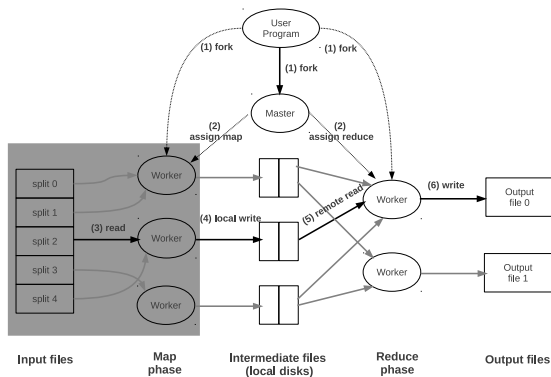


- Mapreduce splits input files into M pieces
- Many copies of the user program are started on the cluster

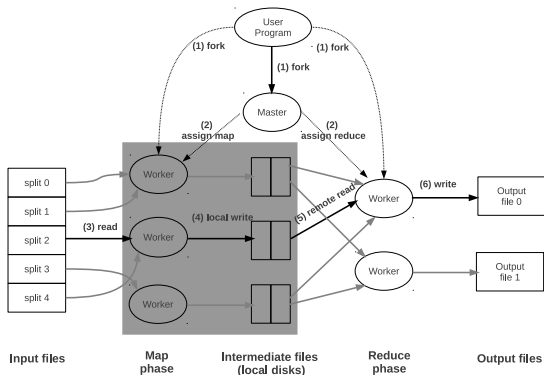
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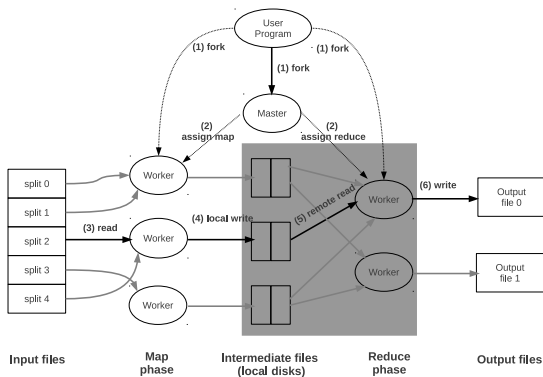
- Master node assigns map or reduce tasks to idle workers.



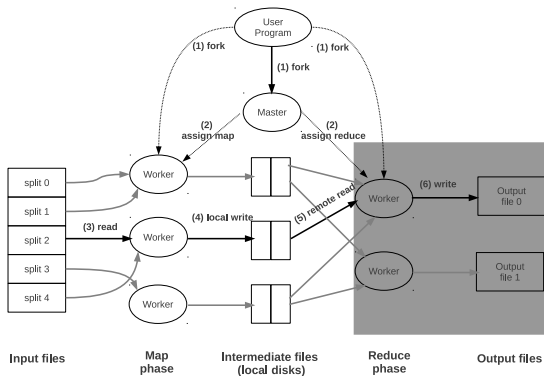
- Workers doing map tasks read a corresponding split
- Intermediate results are buffered in memory



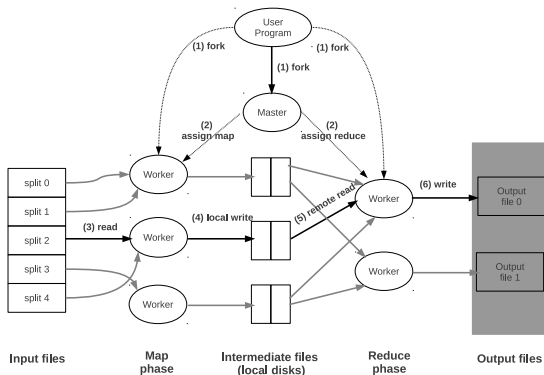
- Periodically, intermediate results are written to local disk.
- These results are partitionated in  $R$  regions.
- Locations of these partitions are published to master node.



- Reducers read all input data.
- When reducer has read all input data, it sorts data by intermediate keys.



- Each reducer iterates over sorted intermediate data.
- Output of the reduce function is appended to a final output file.



- The output is available in R output files.
- Typically these files are not combined. They could be kept for an application that is able to handle partitioned data.

- *Data-Intensive Text Processing with MapReduce*. Jimmy Lin and Chris Dyer. Pre-production manuscript book, April 2011.