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MapReduce with Apache Spark

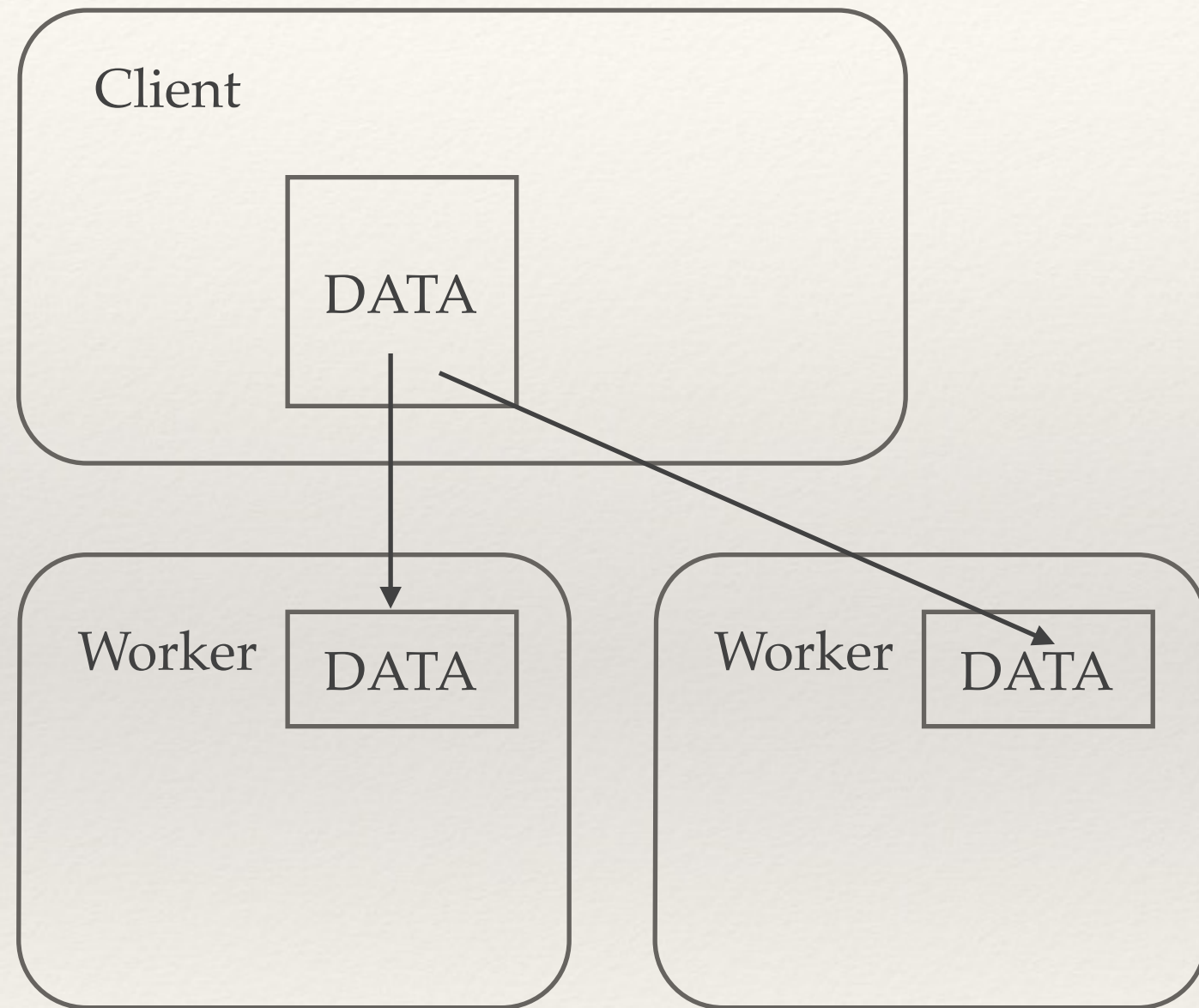
Stats 290

March 11, 2015

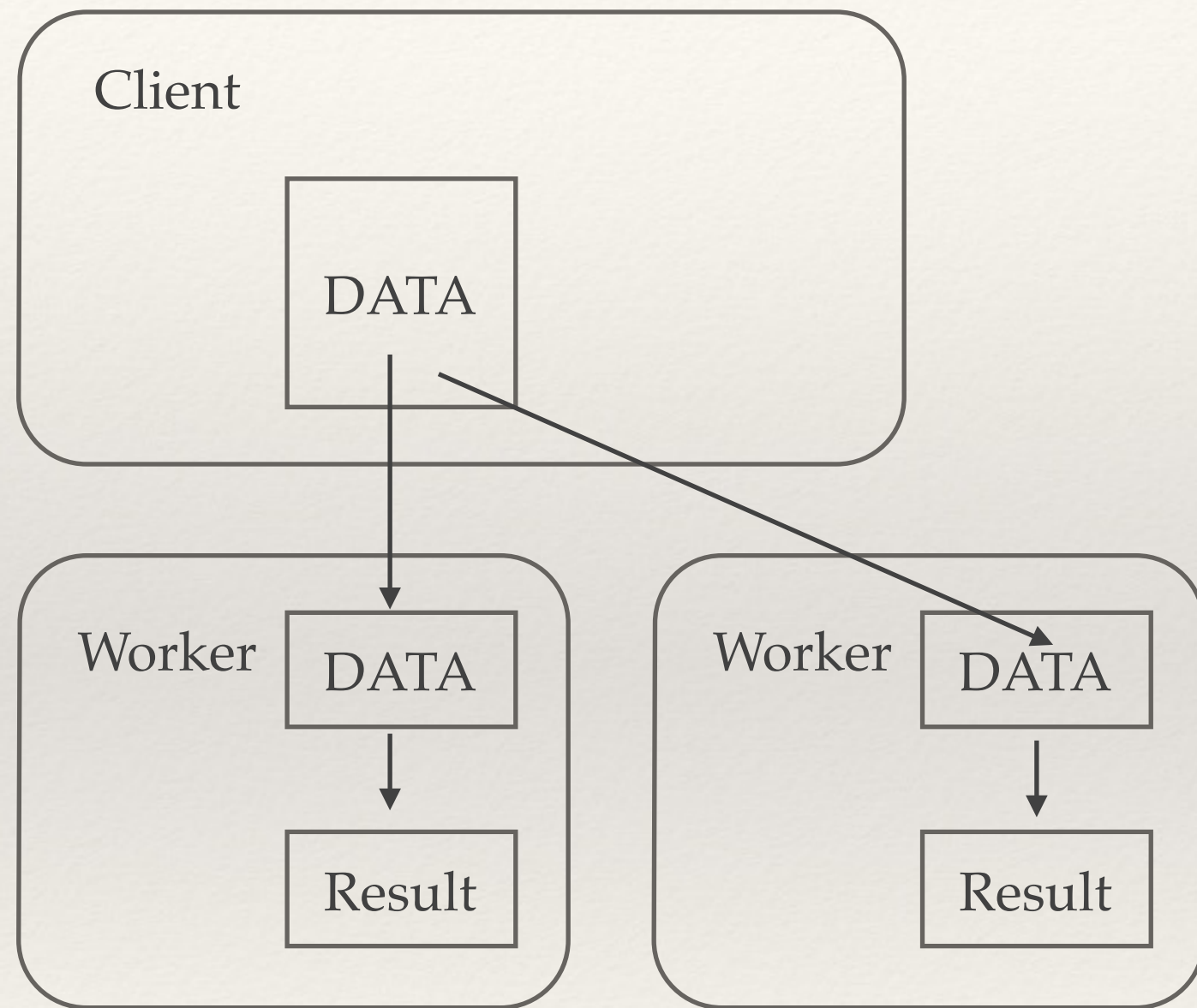
Review of Parallel/Distributed Computing

- ❖ Physical speed limit for sequential computing
- ❖ Only choice: parallelization
- ❖ Types of parallelization:
 - ❖ Multi-core on the same computer (multicore)
 - ❖ Simple network of workstations (snow)
 - ❖ Cluster computing (batch)

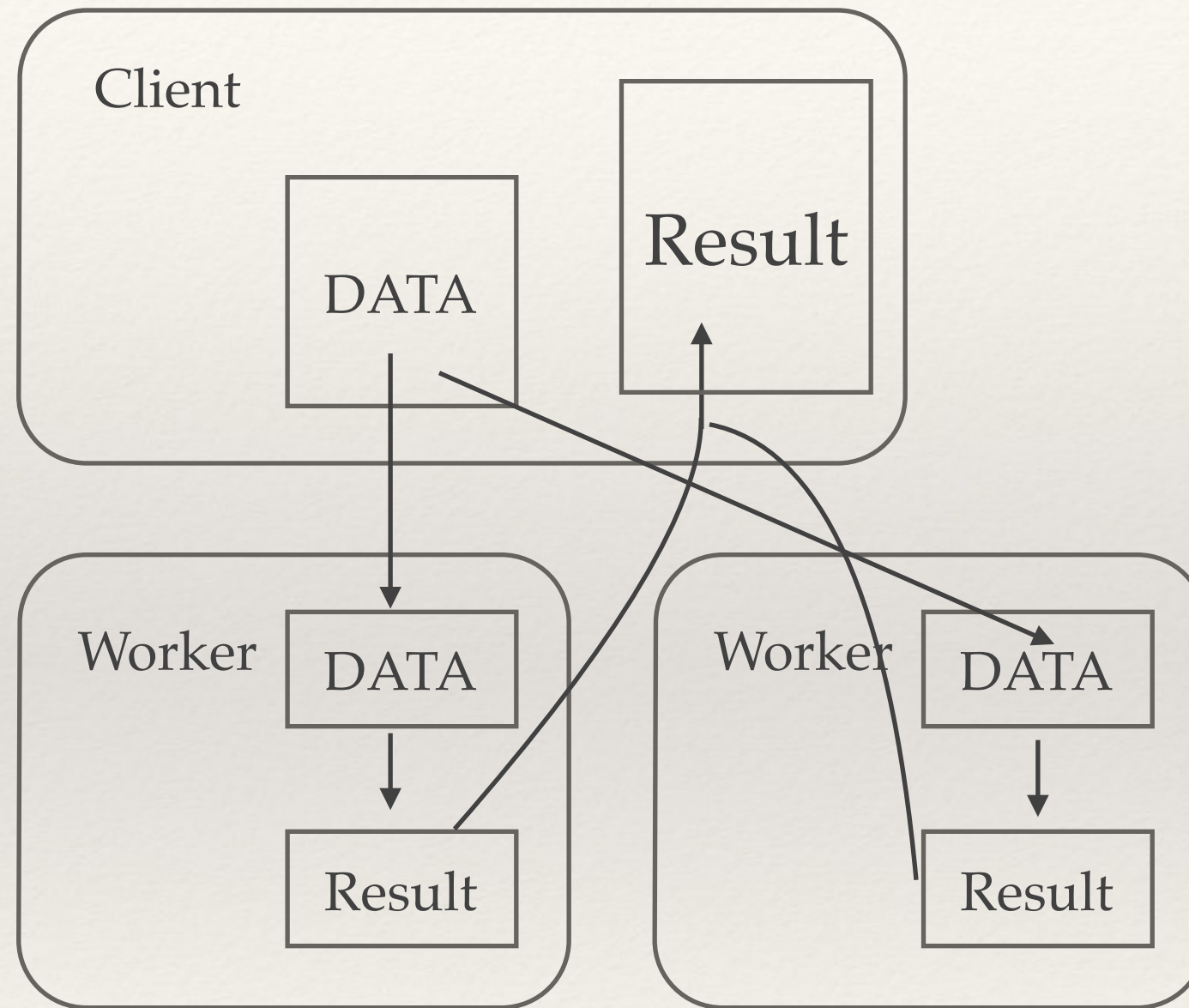
Typical Cluster Workflow



Typical Cluster Workflow



Typical Cluster Workflow



How could this be improved?

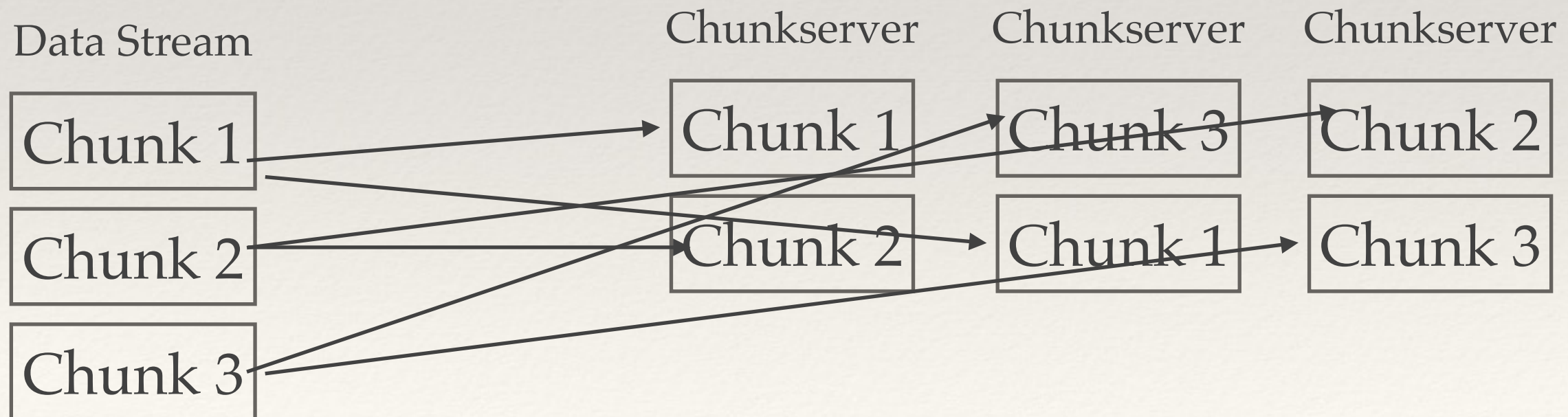
- ❖ Possible bottleneck if data / results have to be transferred to a central location
- ❖ What about tasks which require iterations?
 - ❖ Option 1. Aggregate results on a central node (slow)
 - ❖ Option 2. Use MPI (complicated)
- ❖ The basic mechanics of splitting, transferring and combining files could be abstracted

The MapReduce Framework

- ❖ A framework with two components:
- ❖ 1. A distributed file system
- ❖ 2. A “master node” which handles file splitting and assigning tasks to “worker nodes”
- ❖ Both the file system and computation are robust to individual machine failures

Distributed File System

- ❖ Files consist of many *records* (lines)
- ❖ Records are grouped into 64 MB *chunks*
- ❖ Multiple copies of each chunk spread across servers
- ❖ Master keeps track of addresses

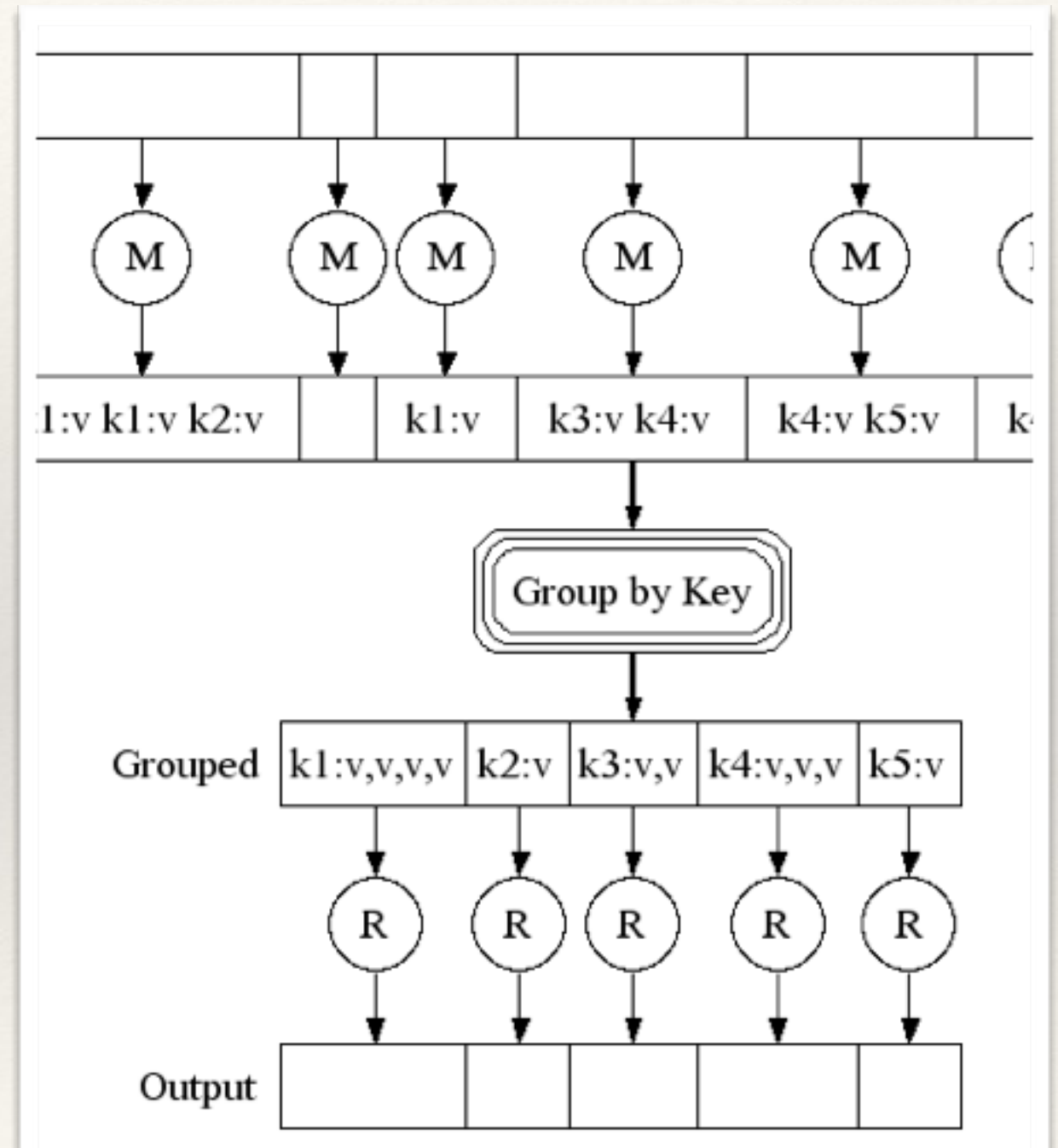


Computation: Map, Reduce

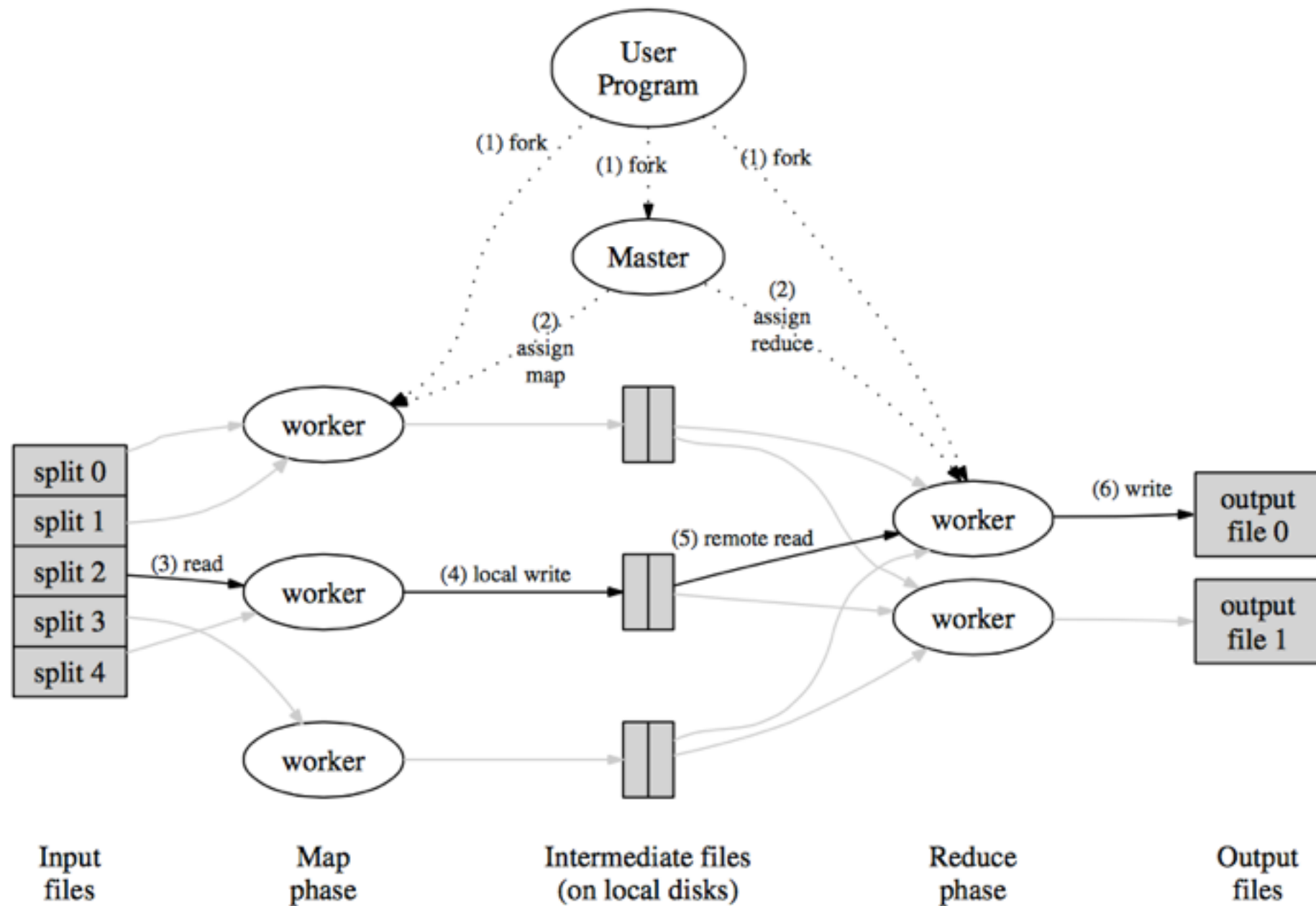
- ❖ Map (*FlatMap*): Apply the same operation to each record and produce key, value pairs
- ❖ Reduce (*Reduce by key*): Collect all values for a given key and aggregate them. Then write to file
- ❖ Master node assigns map or reduce task to workers
 - ❖ Mappers usually work on local chunks

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The MapReduce Framework



MapReduce Implementations

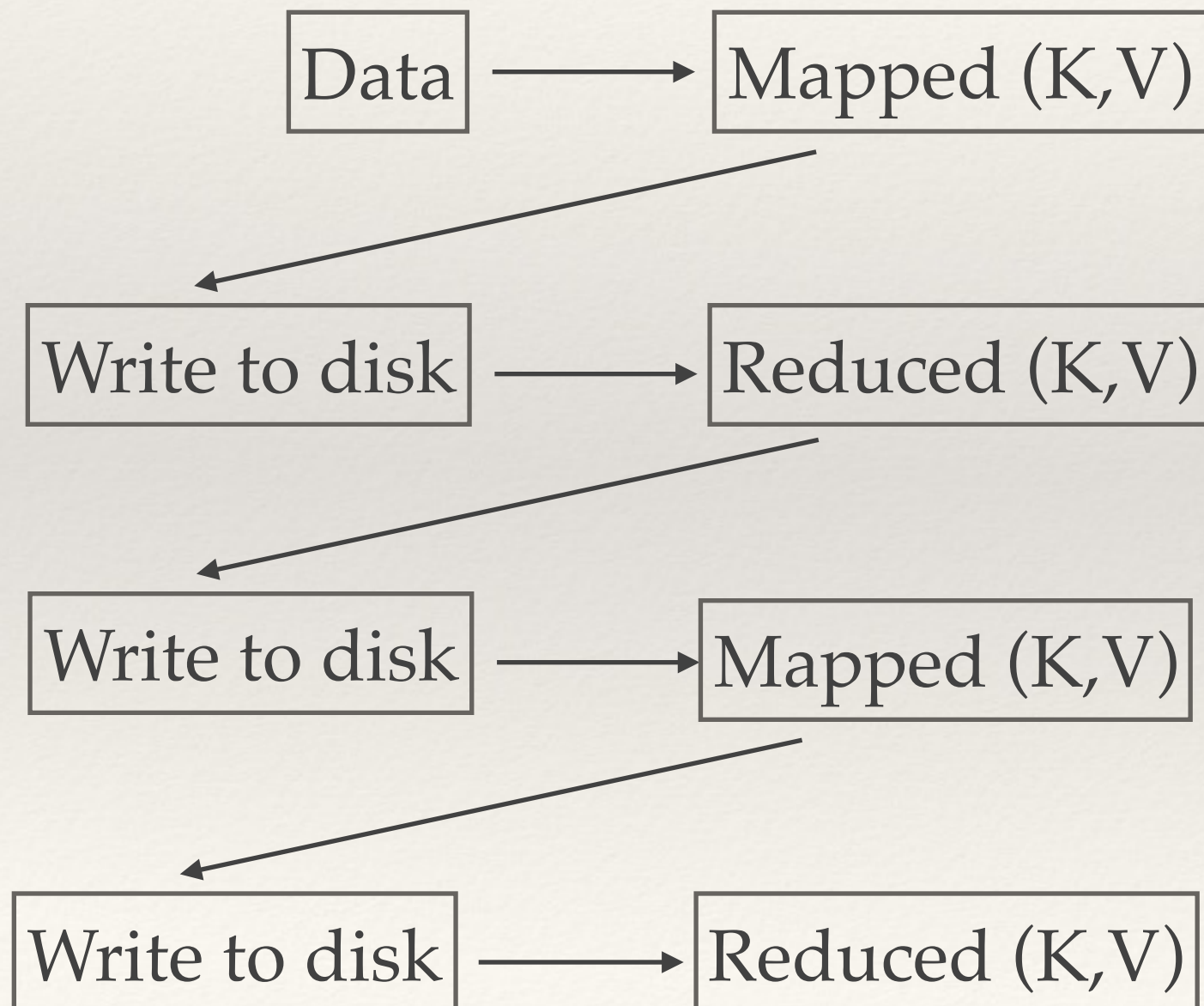
- ❖ Google in-house implementation
- ❖ Apache Hadoop
 - ❖ Based on Google's implementation
- ❖ Apache Spark
 - ❖ An extension of Hadoop
 - ❖ Optimized for iterative processes (10x speedup)

Spark Examples

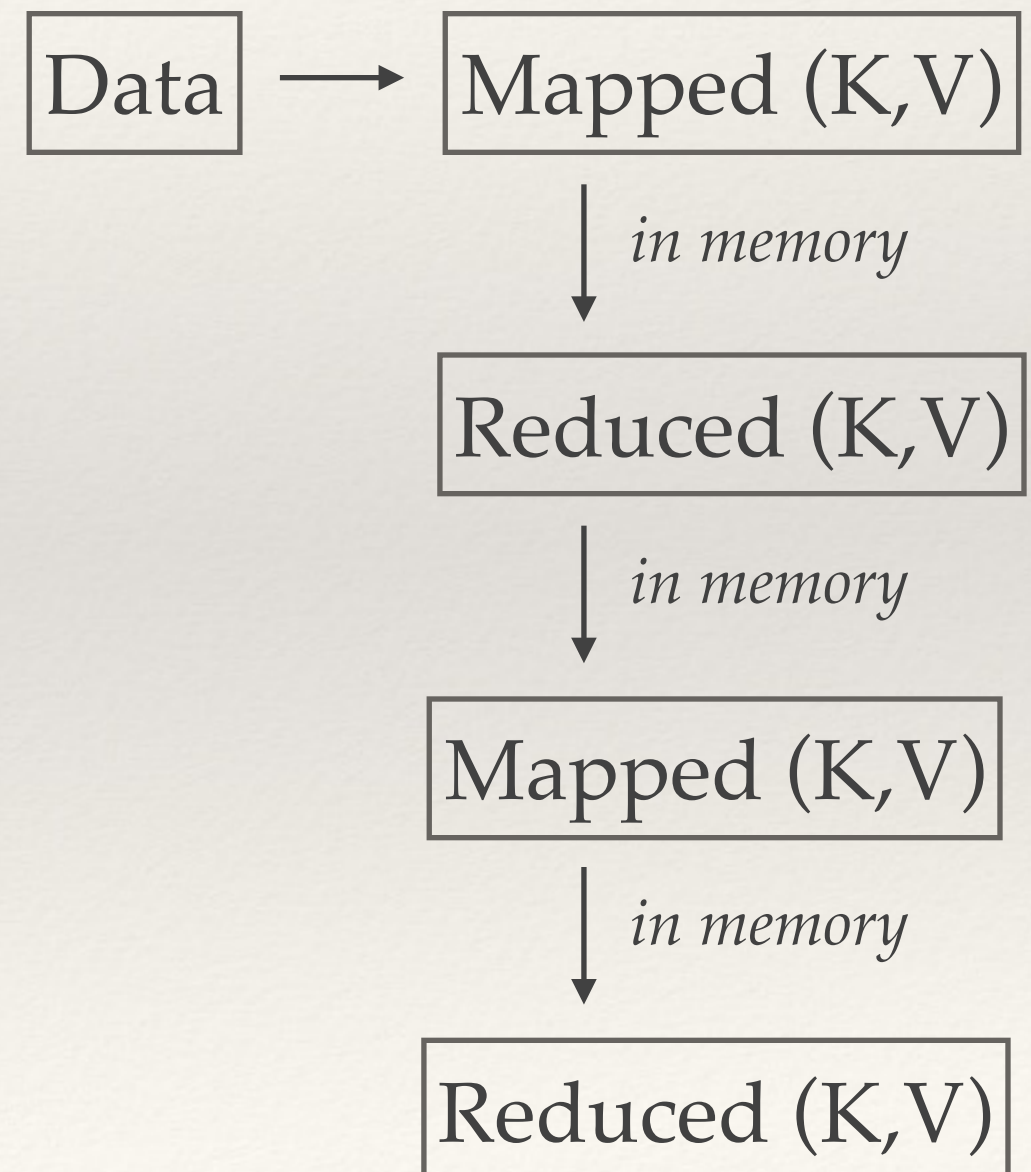
(see html files)

Hadoop vs Spark

Hadoop



Spark



Advantages of Spark

- ❖ 10x faster for machine learning
- ❖ APIs for Java, Scala, Python, and R
- ❖ Speedup enables *interactive* exploration and analysis

Interfaces for Interactive Computing

- ❖ One option: Handle GUI on client side
 - ❖ E.g. Get results of computation from Rserve, then display in R
- ❖ Other option: Web sockets
 - ❖ Launch a web application from the cloud, then access it locally
 - ❖ RStudio server, IPython notebook, 0xdata (demos)

What can interactivity do for you?

- ❖ Adjust your experiments on the fly
 - ❖ Video: Spark streaming for neuroscience
- ❖ Scale up exploratory data analysis
- ❖ Probe for weaknesses in your methods using simulations
- ❖ [Your startup idea here]

Conclusions

- ❖ *MapReduce Framework*
 - ❖ Removes need to collect data in central node, and associated bottlenecks
 - ❖ More flexible than batch computing while remaining much simpler than MPI
- ❖ *Apache Spark implementation of MapReduce*
 - ❖ Faster iterations by using memory
 - ❖ Offers APIs in Java, Scala, Python and R

References

- ❖ Ghemawat, Gobioff, and Leung (Google). “The Google File System.” *SOSP 2003*
- ❖ Dean and Ghemawat (Google). “MapReduce: Simplified Data Processing on Large Clusters.” *OSDI 2004*
- ❖ Zaharia *et al* (UC Berkeley). “Spark: Cluster Computing with Working Sets.” *HotCloud 2010*

Friday's lecture: Spark tutorial

- ❖ You will be given access to a Spark cluster on Amazon Elastic Compute Cloud
- ❖ Learn how to
 - ❖ use the Hadoop filesystem
 - ❖ launch IPython notebooks
 - ❖ run Spark jobs from your browser