Processing of massive data: MapReduce

1. Introduction to MapReduce

Origins: the Problem

- Google faced the problem of analyzing *huge* sets of data (order of petabytes)
- E.g. *pagerank*, web access logs, etc.
- Algorithm to process data can be reasonable simple
- But to finish it in an acceptable amount of time the task must be split and forwarded to potentially thousands of machines



Origins: the Problem (2)

- Programmers were forced to develop the sw that:
  - Splits data
  - Forwards data and code to participant nodes
  - Checks nodes state to react to errors
  - Retrieves and organizes results
- Tedious, error-prone, time-consuming... and had to be done for each problem

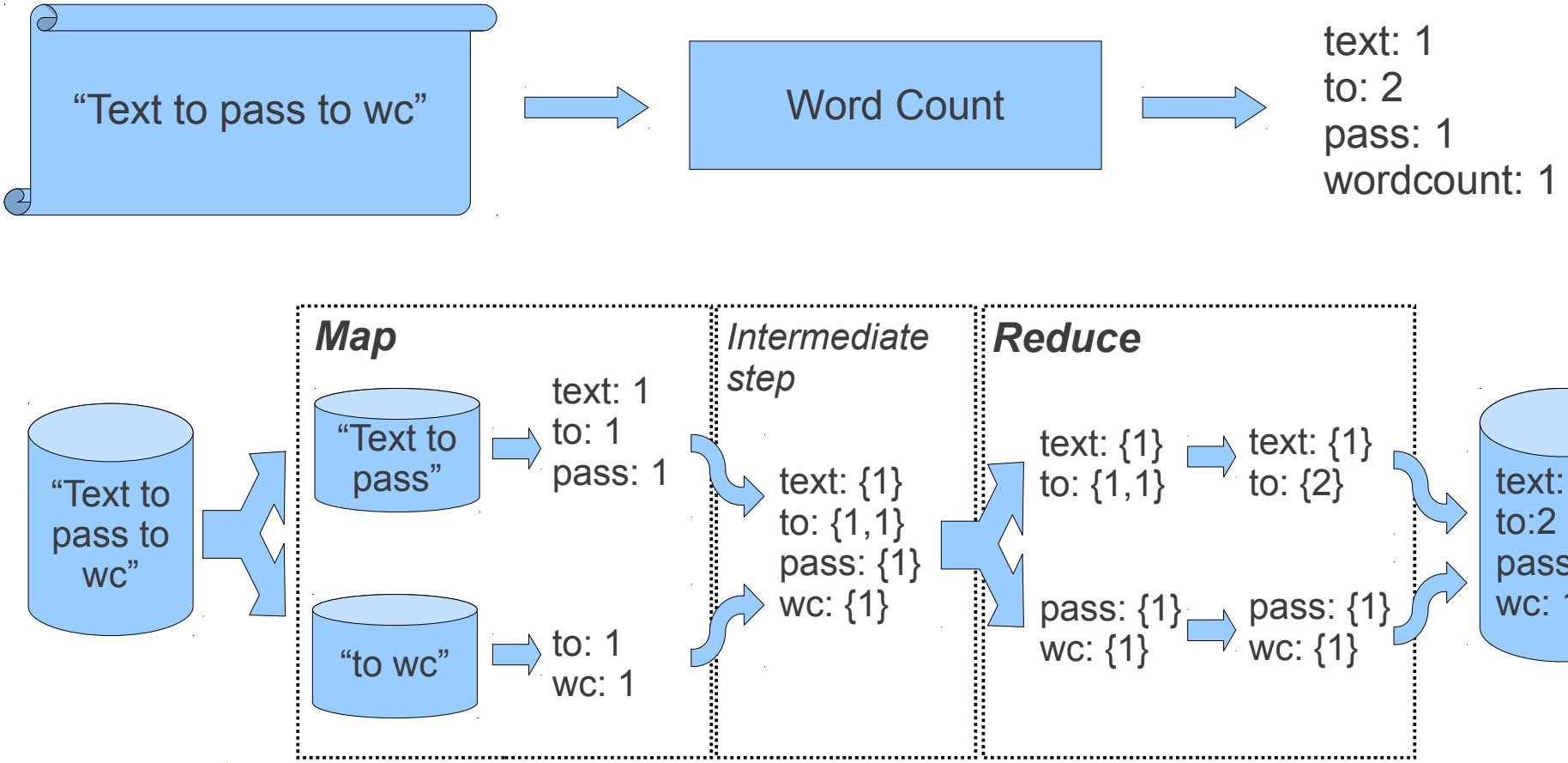
The Solution: MapReduce

- MapReduce is an abstraction to organize parallelizable tasks
- Algorithm has to be adapted to fit MapReduce's main two steps.
  1) **Map**: data processing (collecting/grouping/distribution intermediate step)
  2) **Reduce**: data collection and digesting
- The MapReduce framework will take care of data/code transport, nodes coordination, etc.



Example: Word Count

- Given a text, get the number of times each word in the text appears



Map Definition

- **Map function** signature:
  - takes as input a `(T_k1:key, T_v1:value)` pair
  - generates list of `(T_k2:key, T_v2:value)` pairs

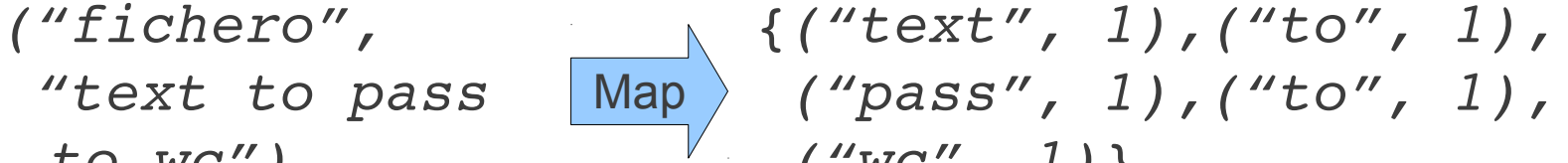
`map(T_k1:k1,T_v1:v1) → list(T_k2:k2,T_v2:v2)`

- Note that
  - Input and output types can be different
  - In the output list the same key can be repeated

Word Count Example – Map Func.

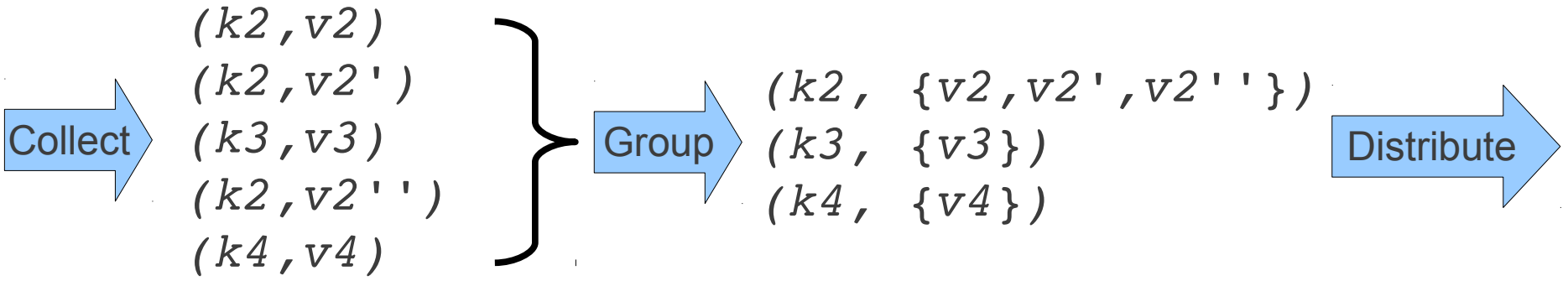
- In the Word Count example, the Map function could be programmed as follows:

```
map(String key, String value) {
  // key: doc name, value: doc text
  for each word w in value:
    EmitIntermediate(w, "1");
}
```



Intermediate Step

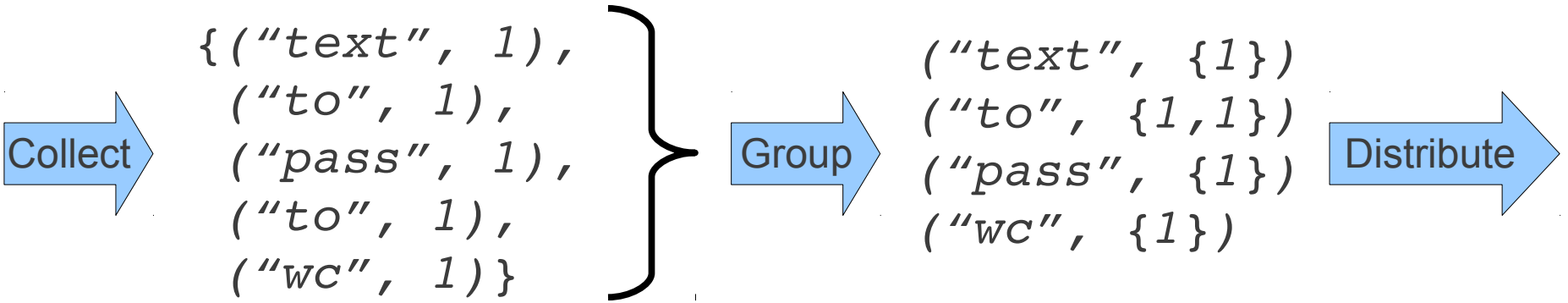
- The MapReduce software will:
  1) collect all results from nodes running Map step
  2) group the pairs `(T_k2:key, T_v2:value)` by `key`
  3) distribute keys among nodes running Reduce step



- This step does not depend on the algorithm implementation passed to MapReduce

Word Count Example – Interm Step

- Intermediate results processing would look like:



Reduce Definition

- **Reduce function** signature:
  - takes as input *(T_k2:key, list(T_v2:value))*
  - generates another list of *(T_v2:value)* values

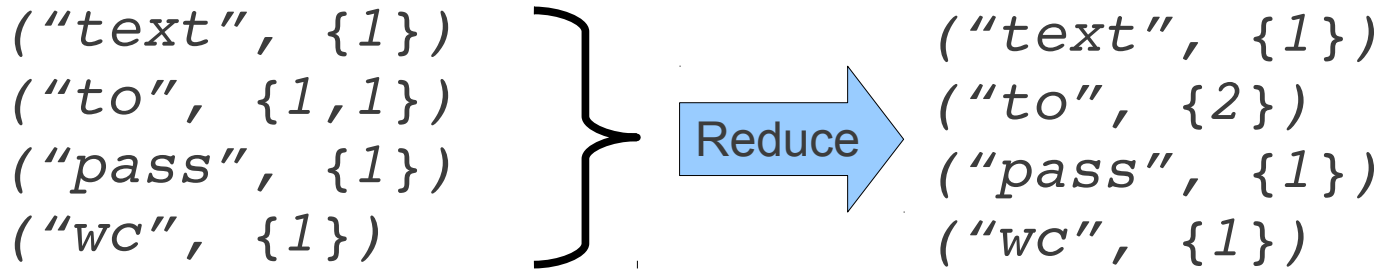
reduce(T_k2:k2,list(T_v2:v2))→(T_k2:k2,list(T_v2:v2))

- Note that
  - Processing of each key is independent
  - Typically the resulting list has one element

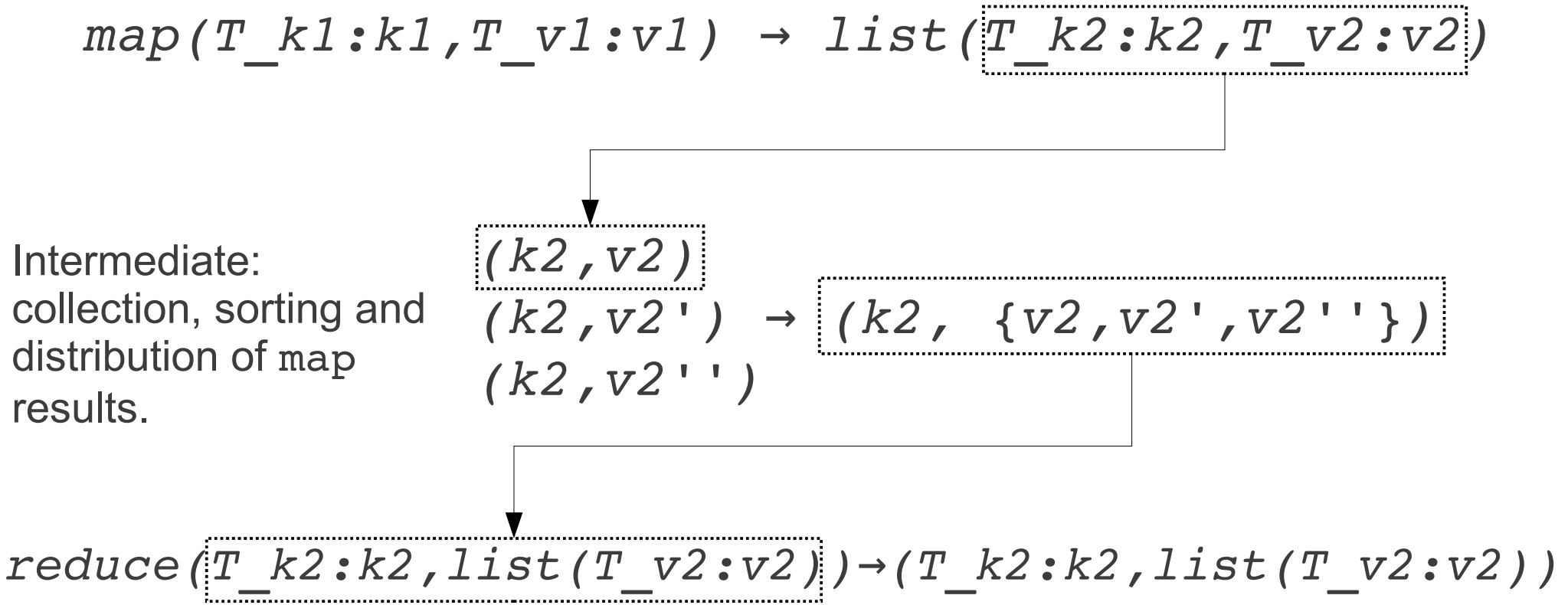
Word Count Example – Reduce Func

- The Reduce function could be coded as follows:

```
reduce(String key, List values) {
 // key: word, value: list of counts
 int result = 0;
 for each v in values:
  result +=ParseInt(v);
 Emit(key, result);
}
```



Summing Up Map and Reduce Defs



The Combiner function

- It is an *optional* step right after Map
- Typically, consists on applying the Reduce function locally in the Map node before sending the results
- It can reduce the bandwidth and disk space consumed by the Map output data
- Applicable if the reduce function is commutative and associative
  - In the previous wordcount example it can be applied

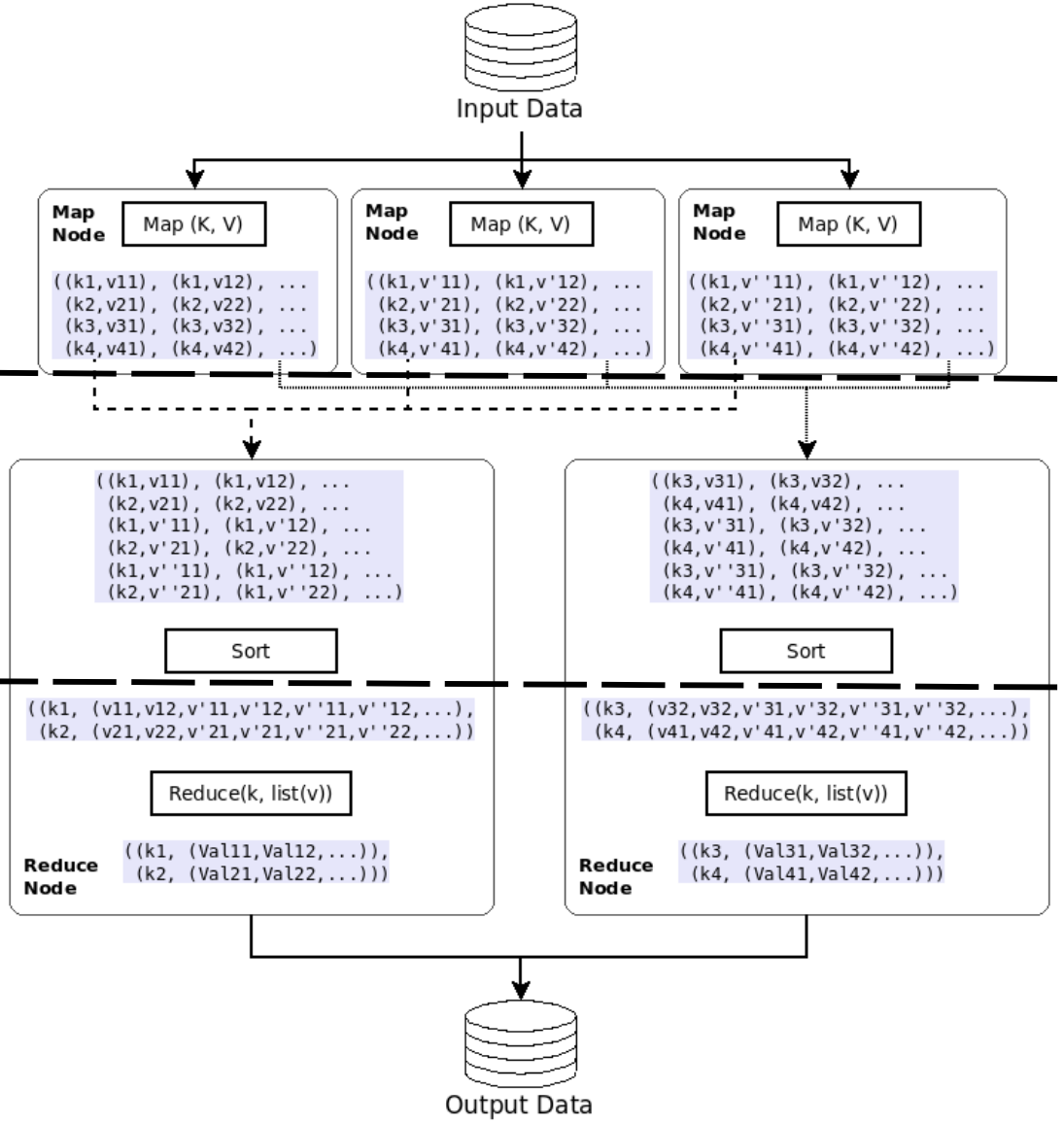


Distributed MapReduce

Map process, distributed among **Map Nodes**

Intermediate process
1) collects values by key
2) sorts by key

Reduce process, distributed among **Reduce Nodes**



Distributed Implementations Hints

- In “big data” jobs is more efficient moving code than moving data
- Map (and Reduce) nodes work independently
- A special *master* node plans the distribution of tasks
  - It also monitors nodes, who periodically report their status
  - Failure tolerance is simple: if some node fails the master can replace it immediately (the rest do not need to be notified about it)
- Map tasks can run in parallel, and Reduce tasks can work in parallel (but, *can Reduce tasks work at the same time than Map tasks?*)

Distributed Implementations Hints (2)

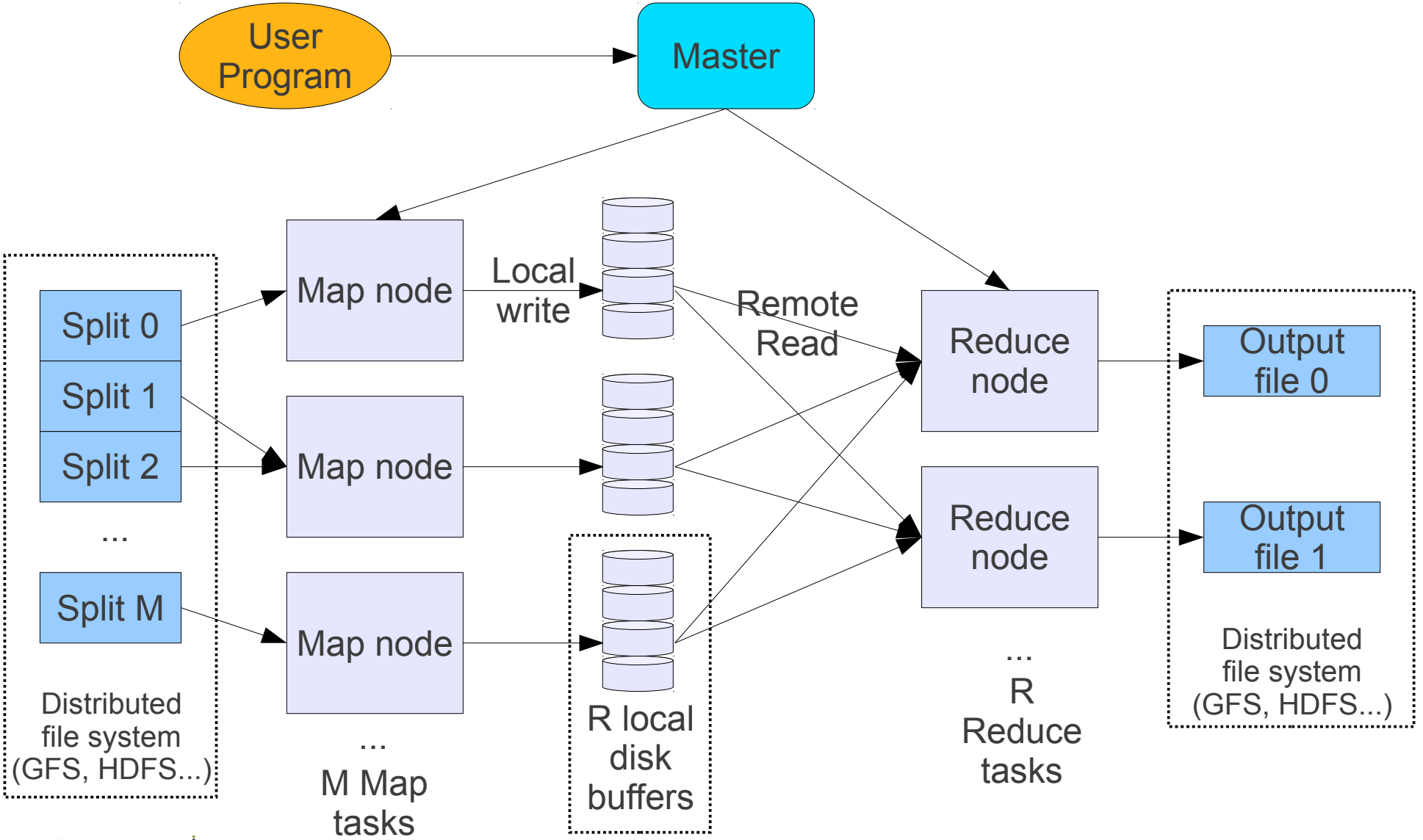
- User specifies:
  - **M**: Number of slots or *pieces* the input data is split into (i.e., number of Map tasks to run)
  - **R**: Number of pieces the intermediate data is split into (i.e., number of Reduce tasks to run)
    - To assign intermediate data to Reduce nodes some function must be used. For example:

      ```
      hash(k2) mod R
      ```

      That function usually balances data fairly among Reduce partitions
- Typical Google job: **M**=200.000; **R**=5.000; 2.000 machines



Distributed Implementation Schema



More MapReduce Examples

- Grep (distributed): look for lines that match a pattern
  - Map → Checks text line by line, it emits matching lines
  - Reduce → Identity
- Count of URL access frequency: count in web request logs how many times each URL has been accessed
  - Map → Each time an `URL` appears, emit `<URL, 1>`
  - Reduce → Add together all values, emit `<URL, sum>`
- Pages that link to a certain URL (reverse web graph)
  - Map → For each `URL` in some page, emit `<URL, page>`
  - Reduce → Identity

Applications of MapReduce

- Three main areas:
  - Text tokenization, indexing, and search
  - Creation of other kinds of data structures (e.g., graphs)
  - Data mining and machine learning
- By sector:
  - Originally developed and used by web companies: Google, Facebook, Yahoo!, Ebay, Adobe, Twitter, Last.fm, LinkedIn...
  - The scientific community is also applying it to large datasets:
    - Statistical algorithms (k-means, linear regression...); image processing; genetic sequences search
- Check http://wiki.apache.org/hadoop/PoweredBy !

Beyond MapReduce

- MapReduce has a 'low semantic interface'
  - I.e.: Map and Reduce operations are too simple
  - Complex manipulation of data is cumbersome (for example, compared with the flexibility of SQL)
- Higher level languages have been proposed
  - They work on top of MapReduce, transforming queries into MapReduce operations
  - Examples: DryadLINQ, Sawzall, PygLatin, Hive

```
hive> CREATE TABLE pokes (foo INT, bar STRING);
hive> SELECT a.foo FROM pokes WHERE a.bar='test';
```



Bibliography

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(Example with Hadoop)