# “Hadoop”: A Distributed Architecture, FileSystem, & MapReduce

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CSE545
Spring 2020

# Big Data Analytics, The Class

**Goal:** Generalizations
A *model* or *summarization* of the data.

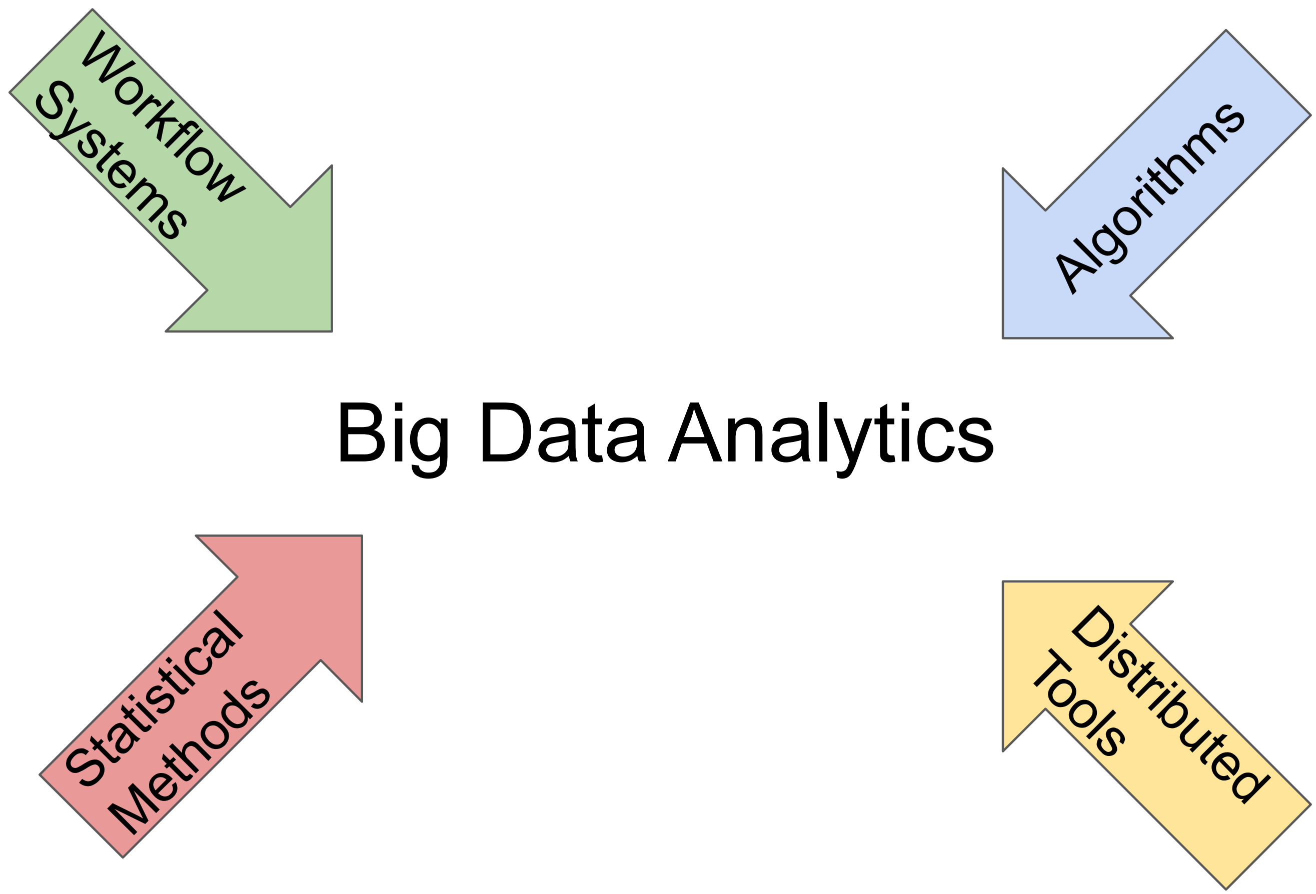
Data Frameworks

- Hadoop File System
- Spark
- Streaming
- MapReduce
- Tensorflow

Algorithms and Analyses

- Similarity Search
- Hypothesis Testing
- Graph Analysis
- Recommendation Systems
- Deep Learning

# Big Data Analytics, The Class



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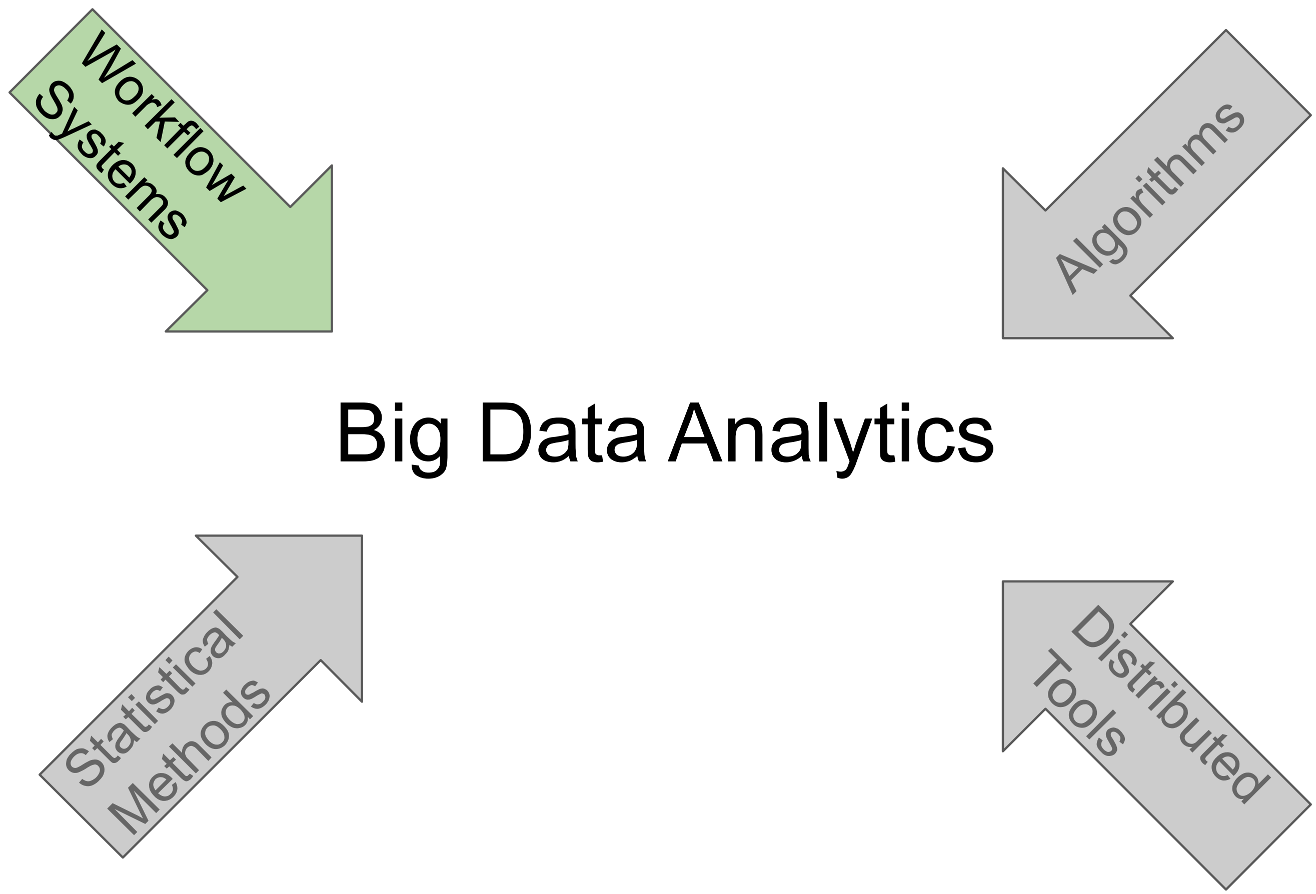
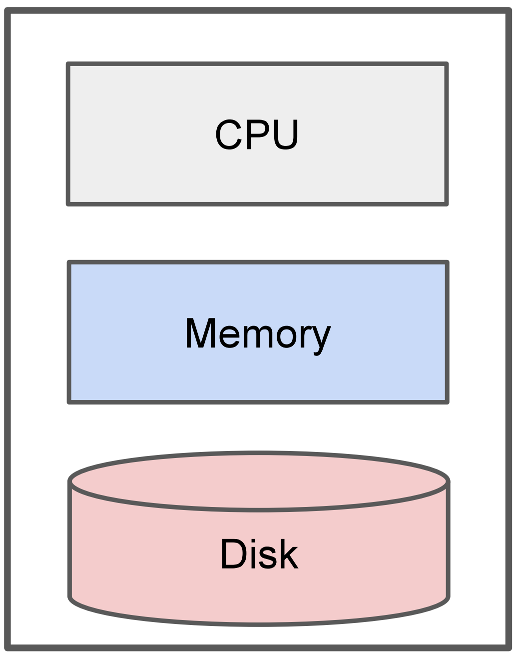


# Classical Data Mining



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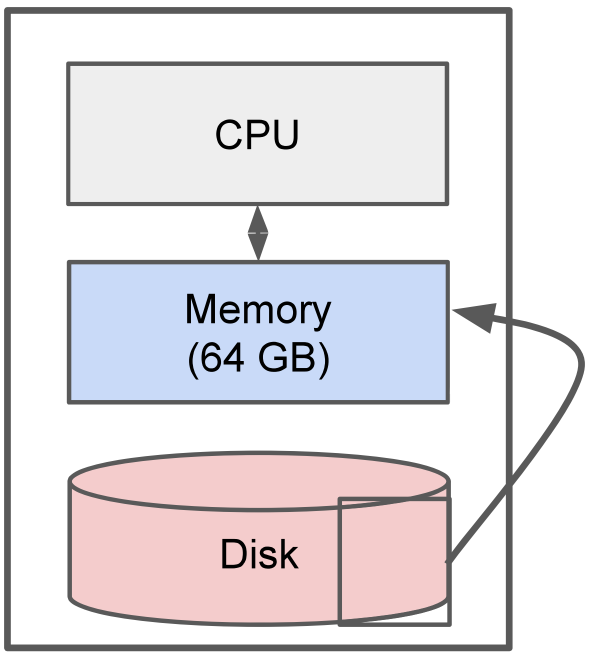

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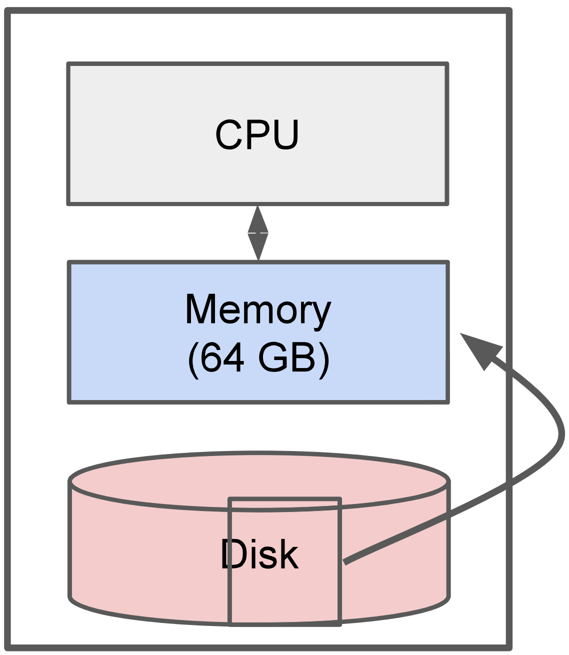

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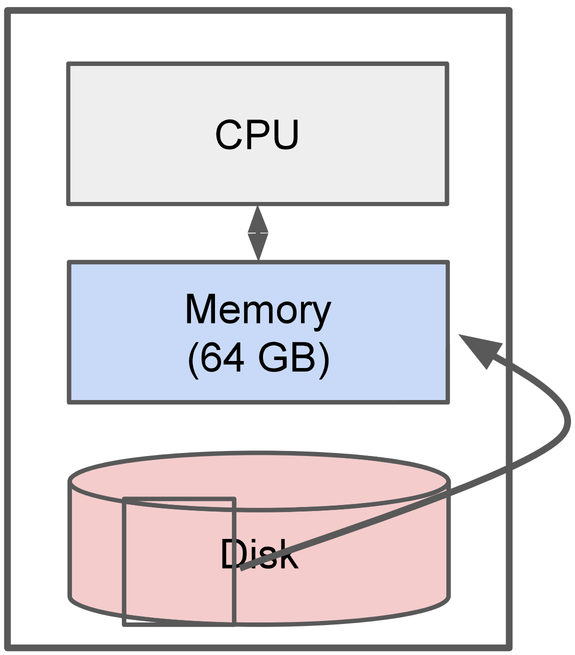
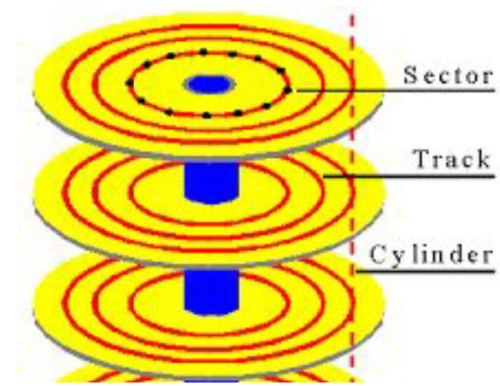


# IO Bounded

Reading a word from disk versus main memory: $10^5$ slower!

Reading many contiguously stored words
is faster per word, but fast modern disks
still only reach 150MB/s for sequential reads.



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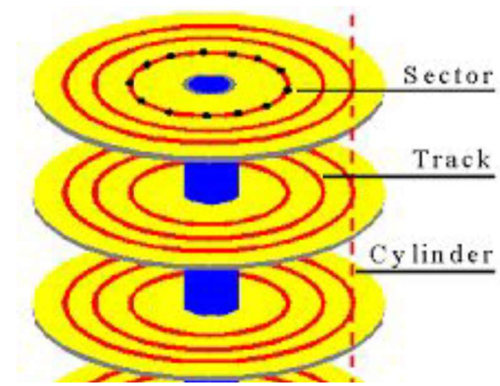
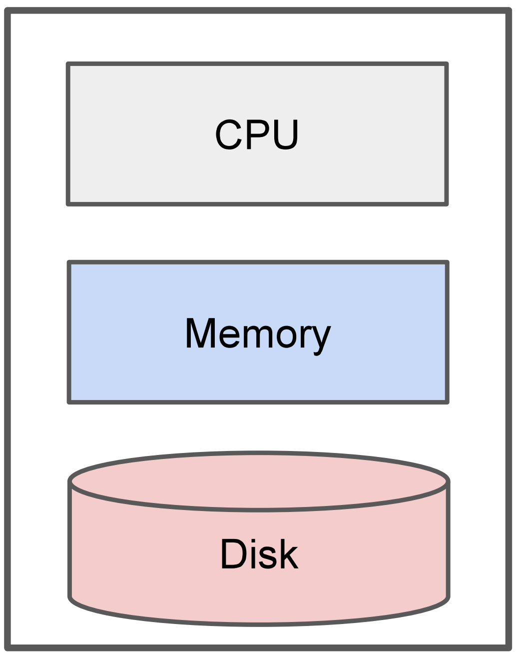



IO Bound: biggest performance bottleneck is reading / writing to disk.

*starts around 100 GBs: ~10 minutes just to read*

*200 TBs: ~20,000 minutes = 13 days*

# Classical Big Data




**Classical focus:** efficient use of disk.
e.g. Apache Lucene / Solr

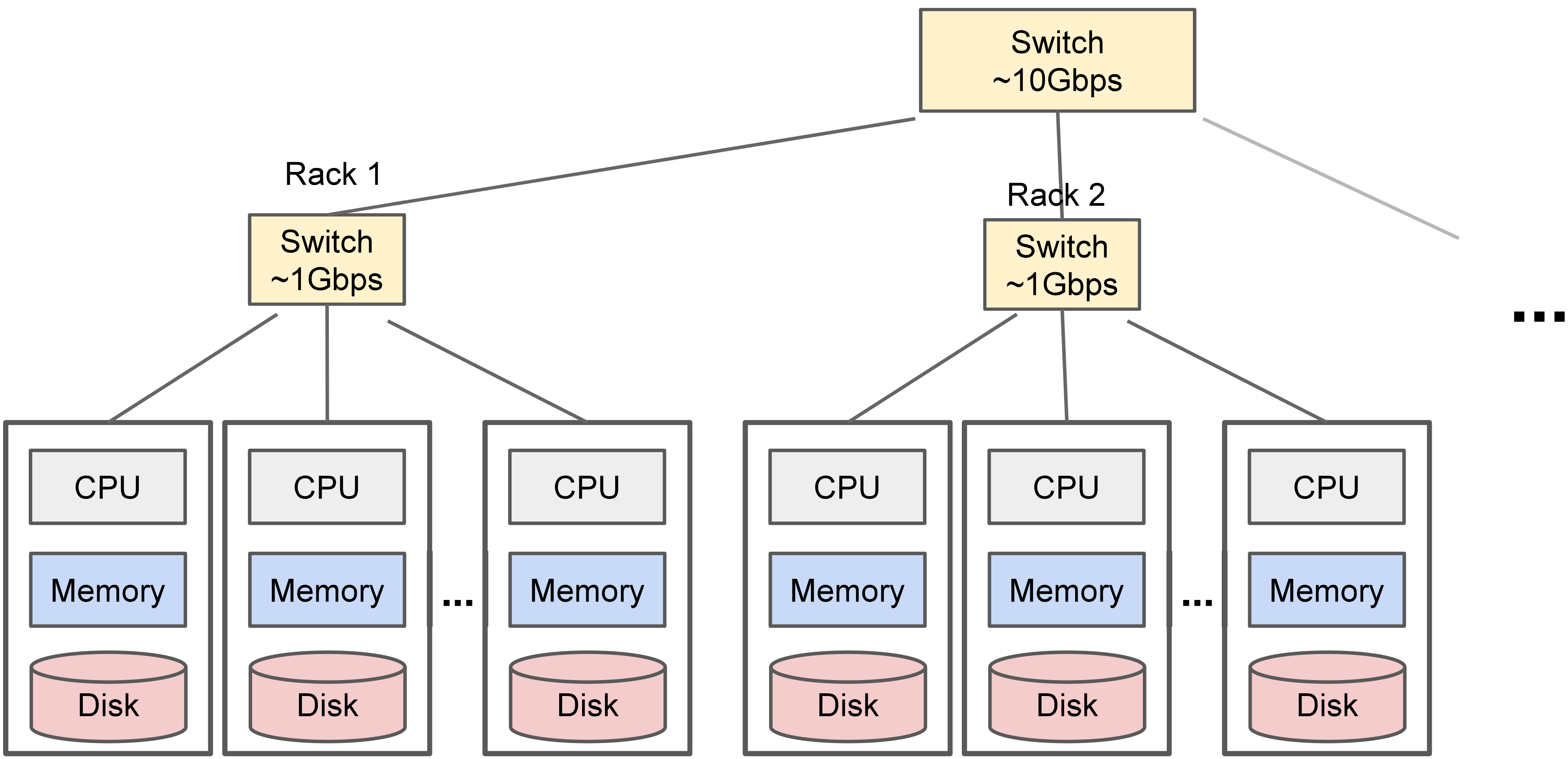
**Classical limitation:** Still bounded when needing to process all of a large file.

# Classical Big Data

*How to solve?*

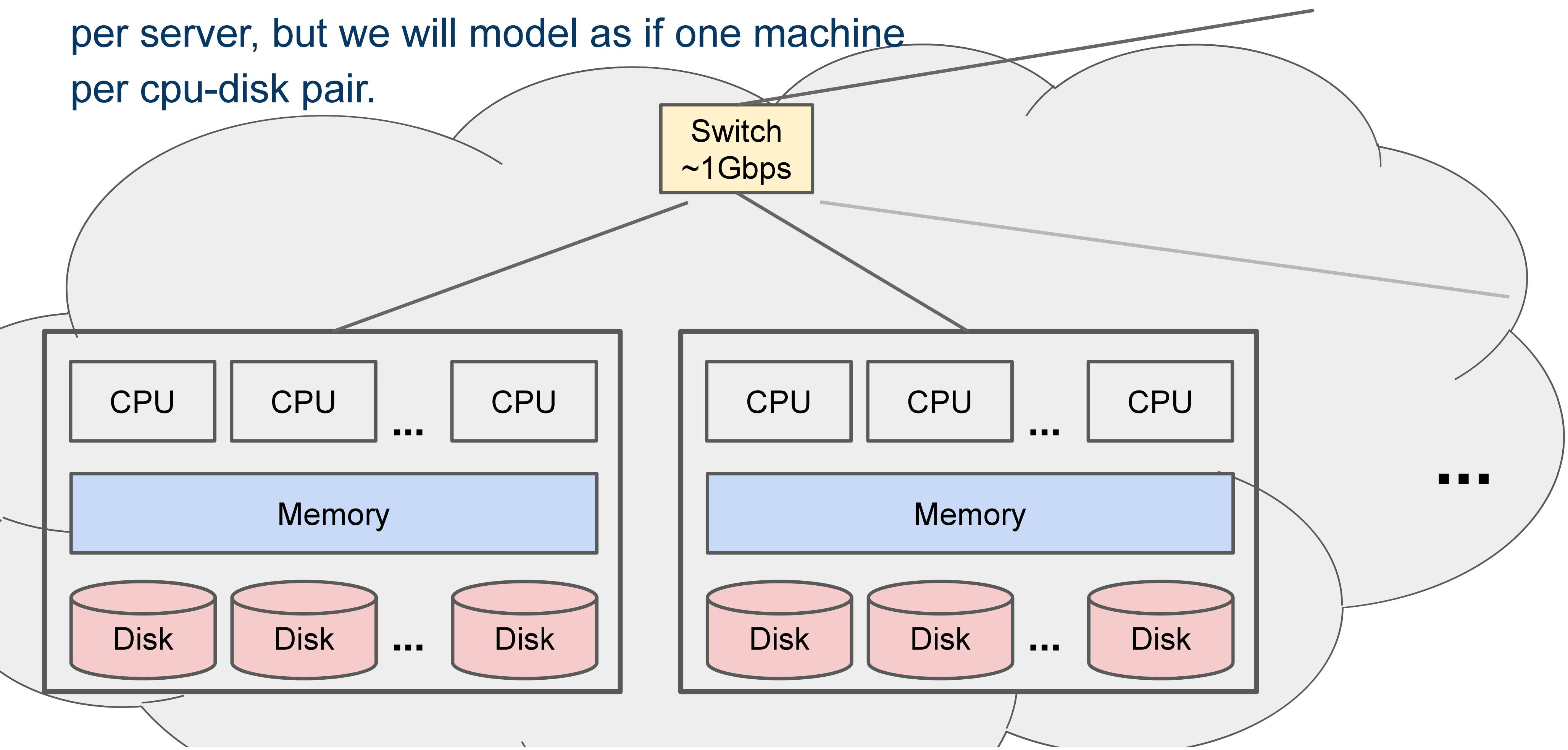
**Classical limitation:** Still bounded when needing to process all of a large file.

# Distributed Architecture

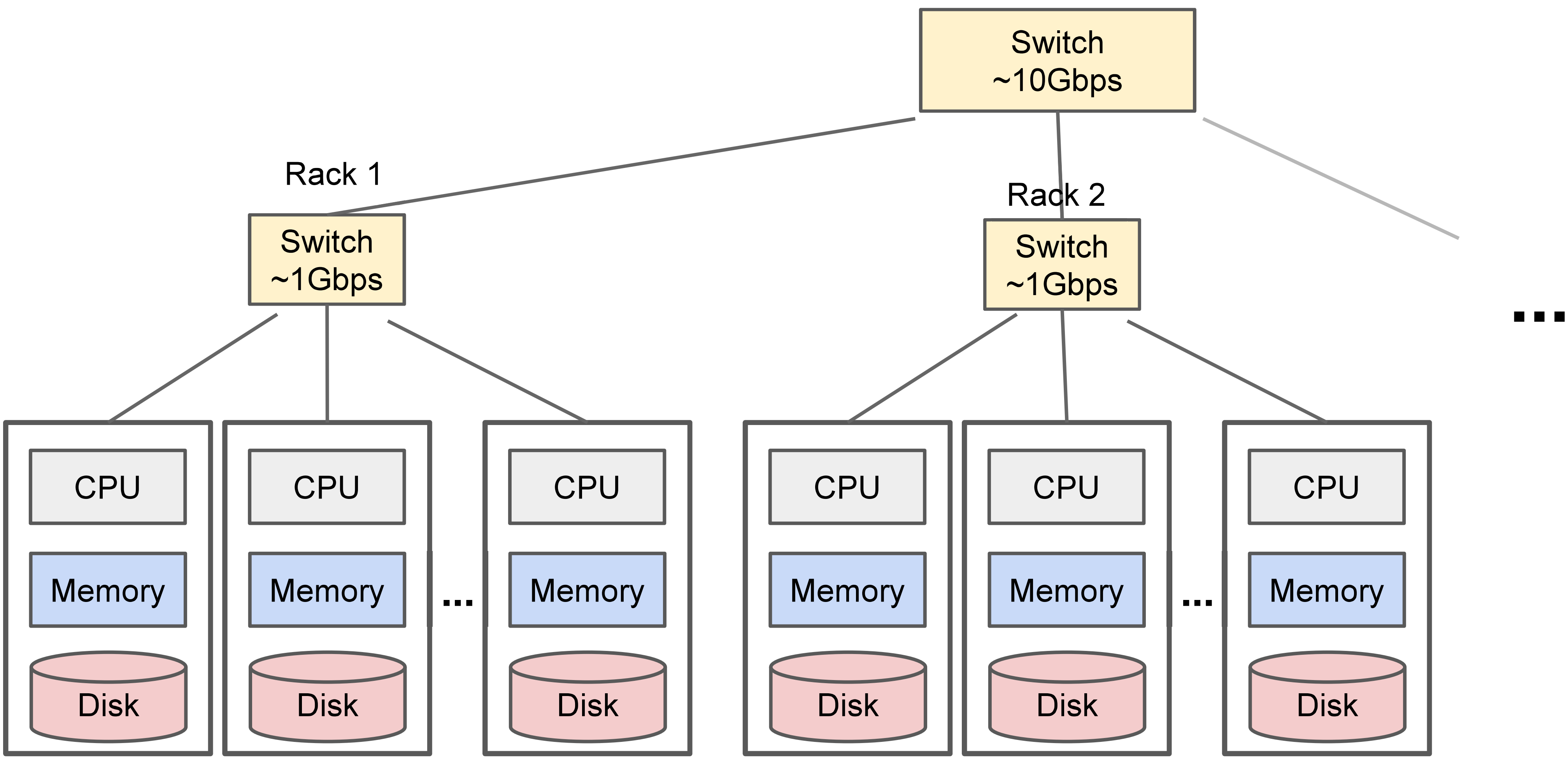


# Distributed Architecture

In reality, modern setups often have multiple cpus and disks per server, but we will model as if one machine per cpu-disk pair.



# Distributed Architecture (Cluster)



# Distributed Architecture (Cluster)

## Challenges for IO Cluster Computing

1. Nodes fail
   1 in 1000 nodes fail a day

2. Network is a bottleneck
   Typically 1-10 Gb/s throughput

3. Traditional distributed programming is
   often ad-hoc and complicated

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HDFS/
MapReduce
Accomplishes

# Distributed Filesystem

The effectiveness of MapReduce is in part simply due to use of a distributed filesystem!

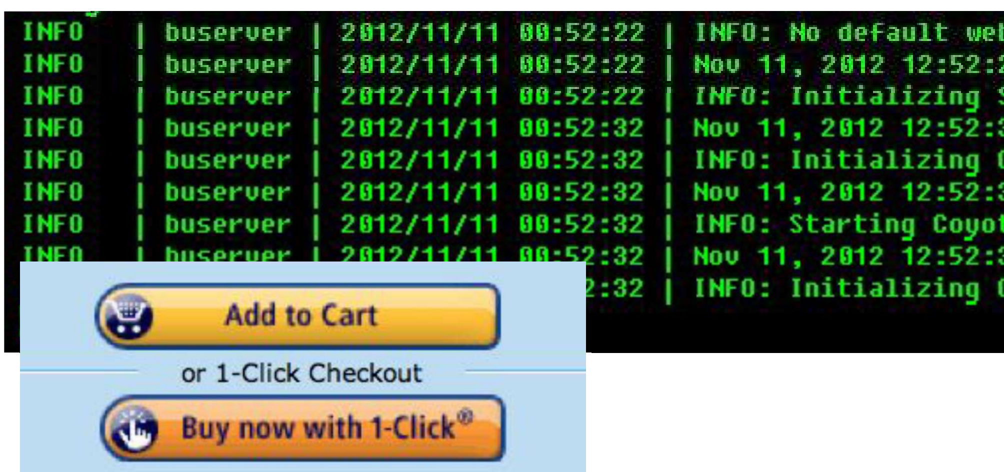
# Distributed Filesystem

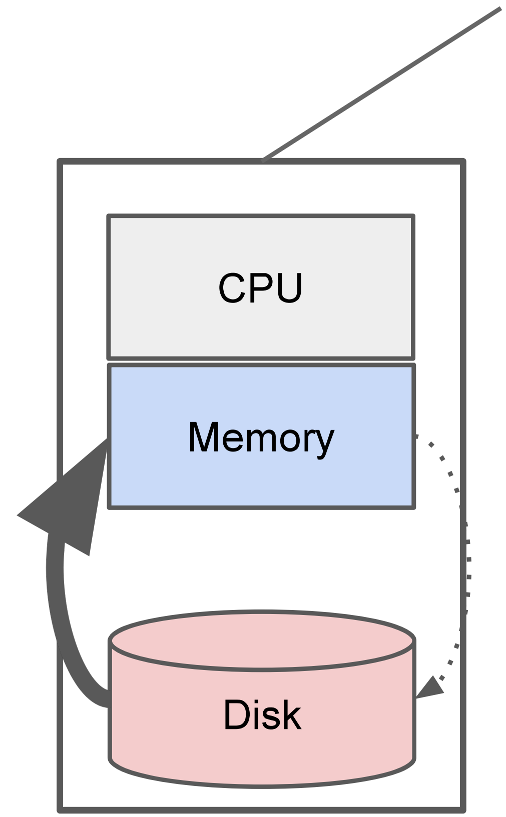
## Characteristics for Big Data Tasks

Large files (i.e. >100 GB to TBs)

Reads are most common

No need to update in place
(append preferred)

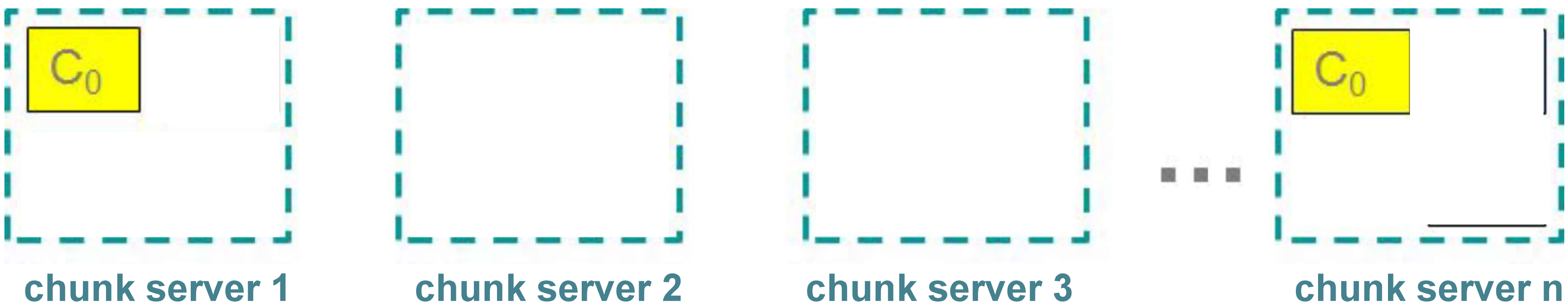


# Distributed Filesystem

(e.g. Apache HadoopDFS, GoogleFS, EMRFS)

C, D: Two different files




(Leskovec at al., 2014; http://www.mmds.org/)

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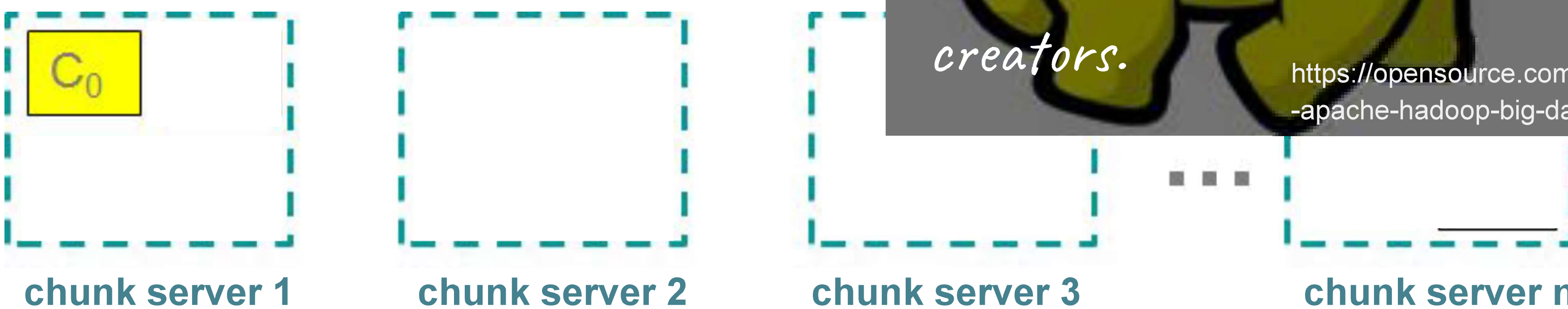


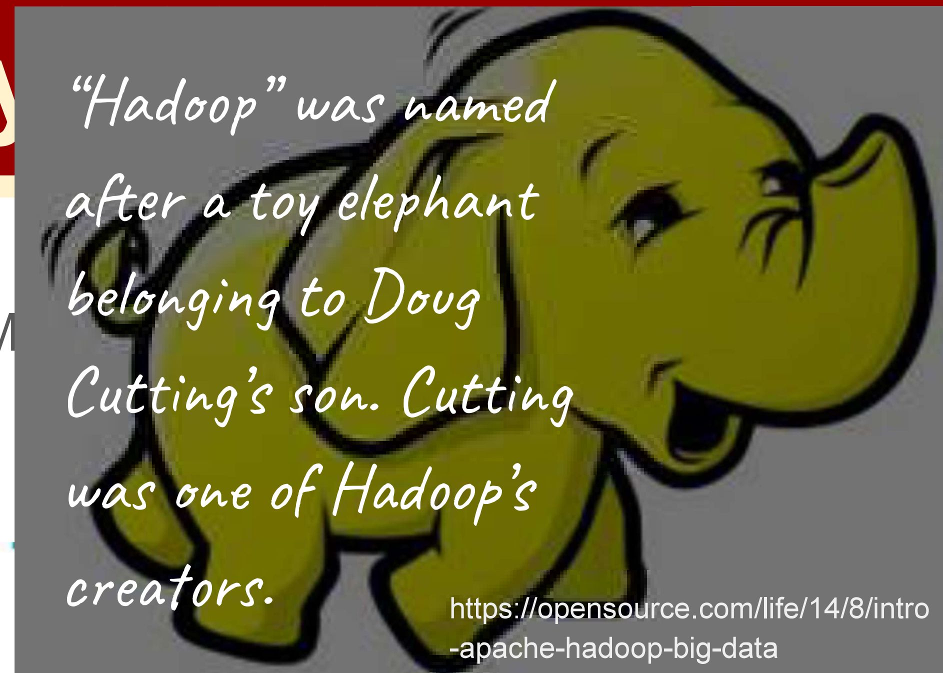


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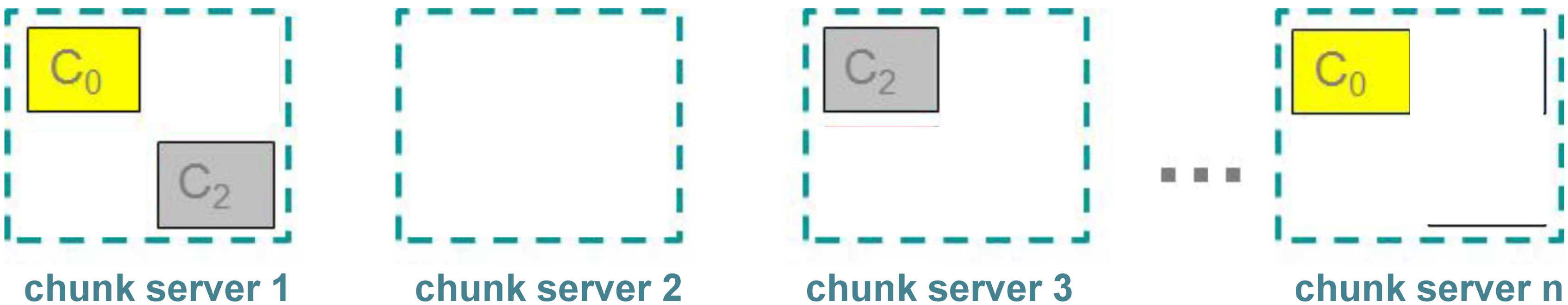


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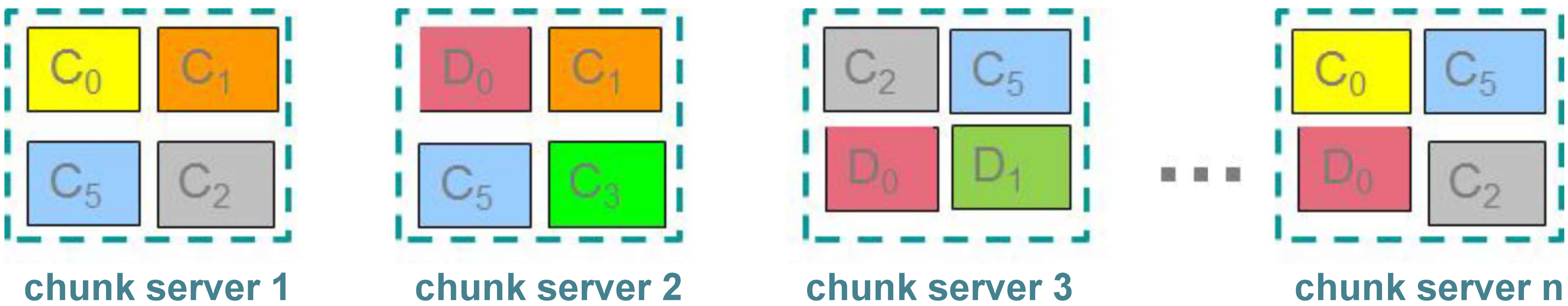


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# Distributed Filesystem

## Chunk servers (on Data Nodes)

File is split into contiguous chunks

Typically each chunk is 16-64MB

Each chunk replicated (usually 2x or 3x)

Try to keep replicas in different racks

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- Stores metadata about where files are stored
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Stores metadata about where files are stored

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## Client library for file access

Talks to master to find chunk servers

Connects directly to chunk servers to access data

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# Distributed Architecture (Cluster)

Challenges for IO Cluster Computing

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   Duplicate Data **(Distributed FS)**

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# What is MapReduce

***noun.1* - A *style of programming***

input chunks => map tasks | group_by keys | reduce tasks => output

“|” is the linux “pipe” symbol: passes stdout from first process to stdin of next.

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E.g. counting words:

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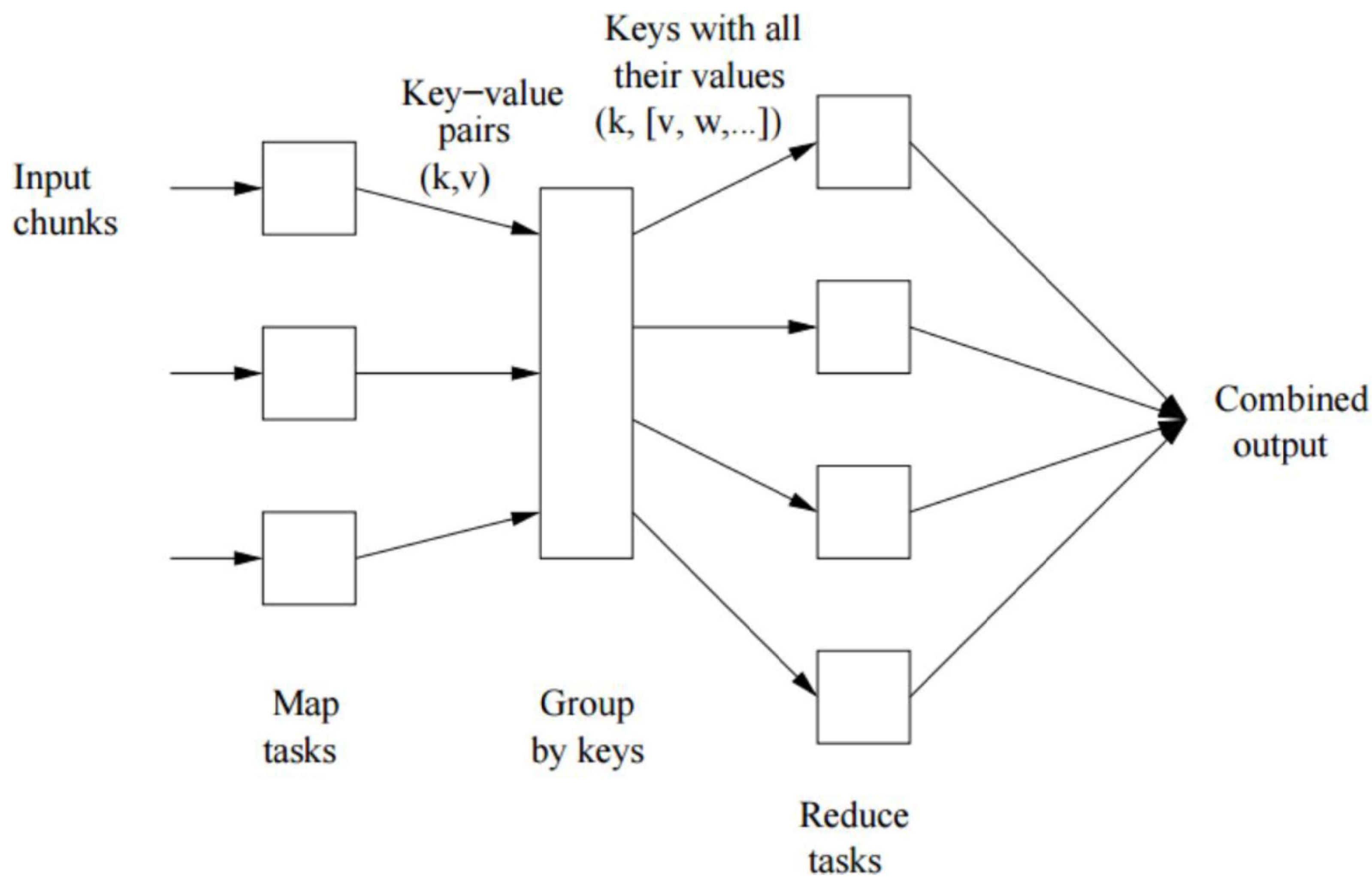
***noun.2* - A *system* that distributes MapReduce style programs across a distributed file-system.**

(e.g. Google’s internal “MapReduce” or apache.hadoop.mapreduce with hdfs)

# What is MapReduce



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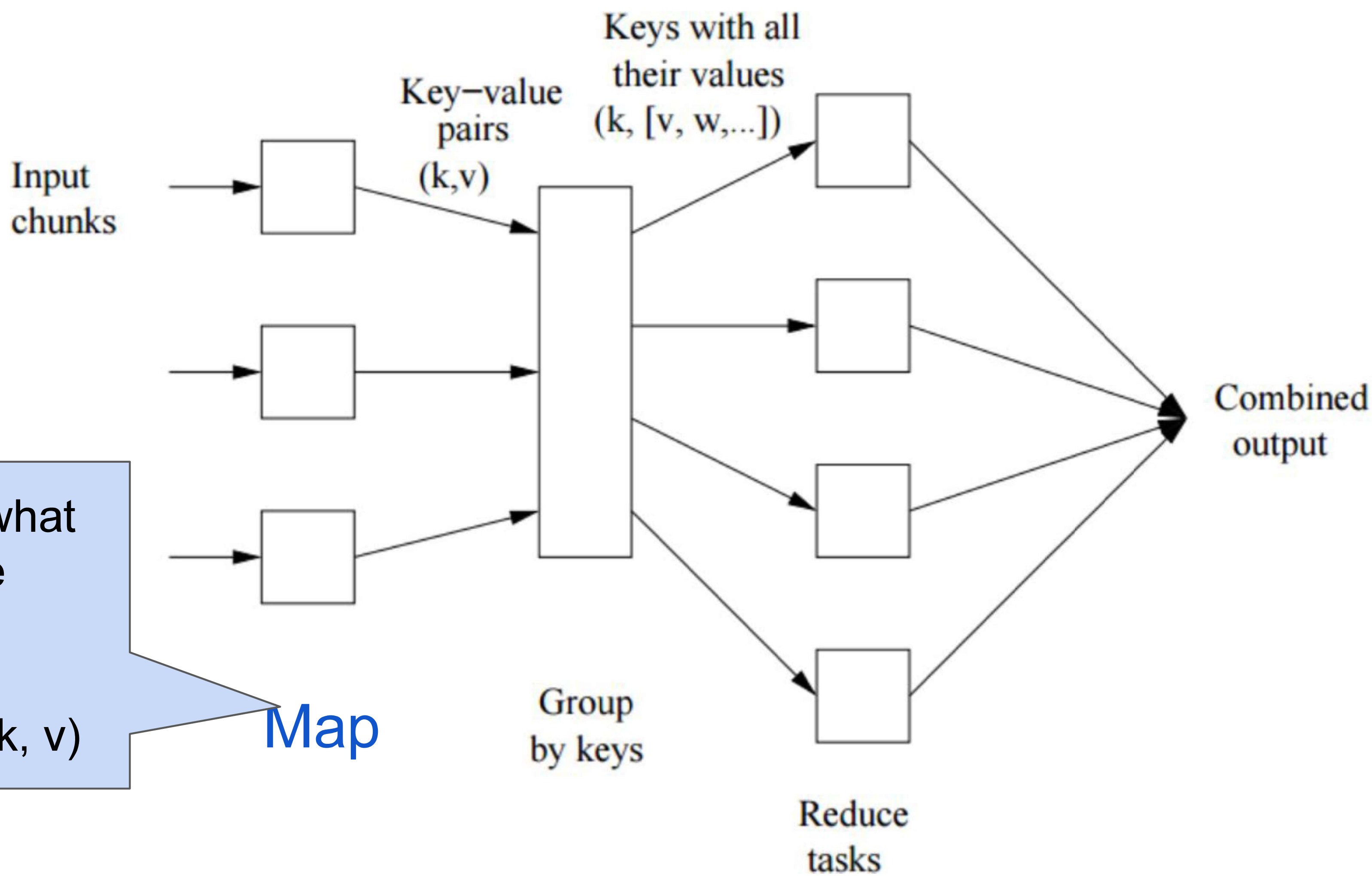
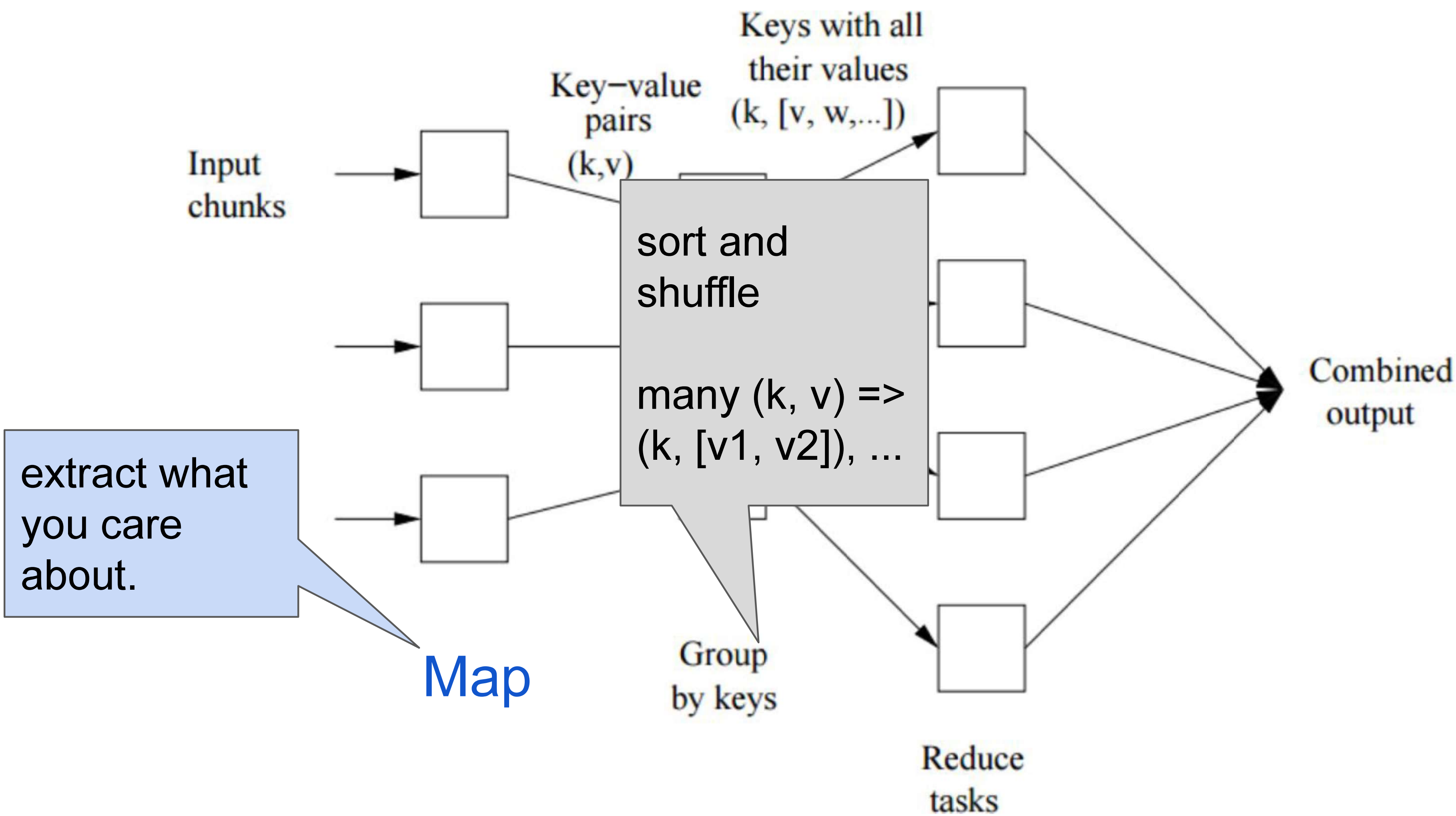



extract what you care about.

line => (k, v)

Map

# What is MapReduce



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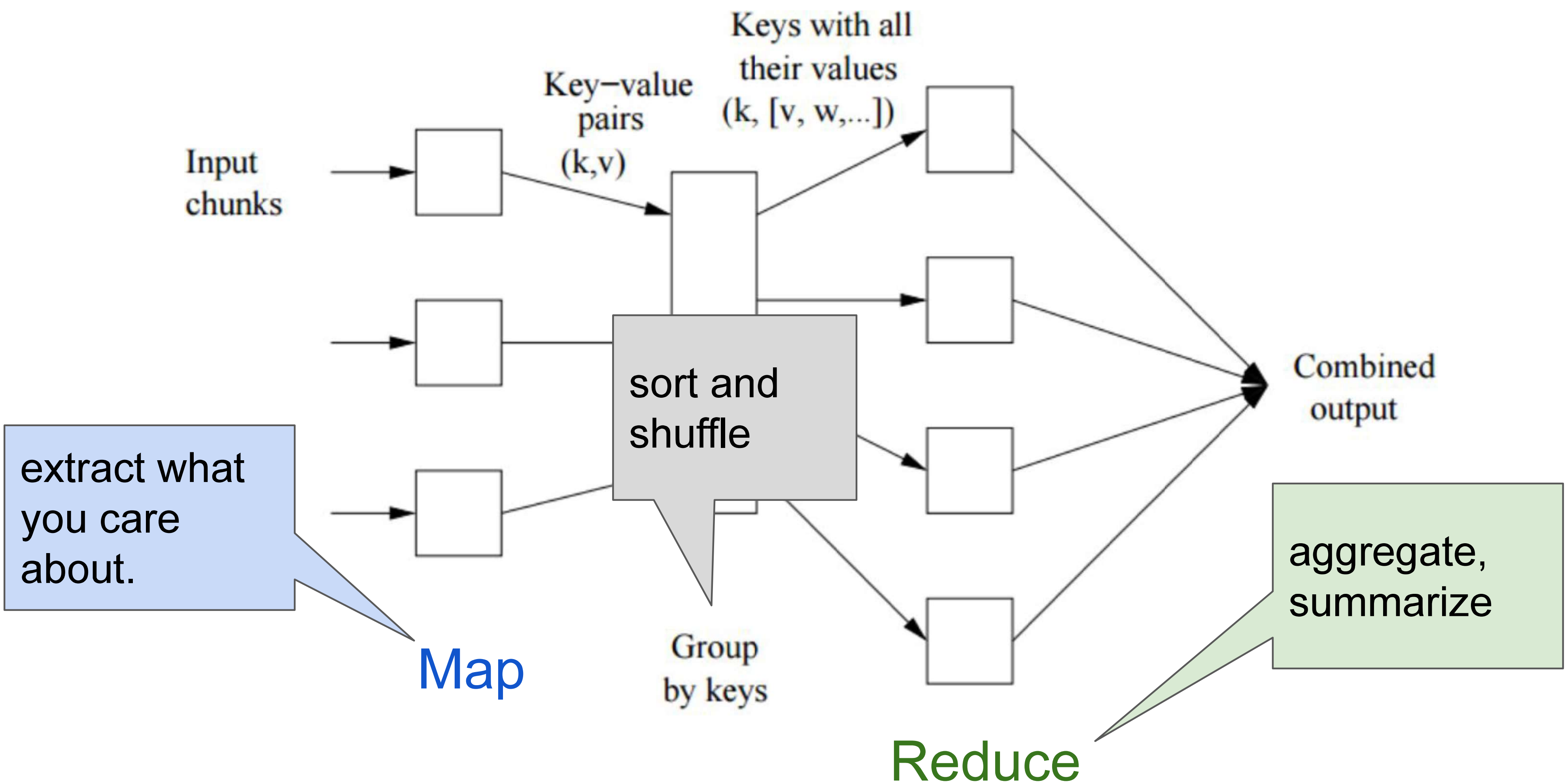

# What is MapReduce

Easy as 1, 2, 3!

Step 1: **Map** Step 2: **Sort / Group by** Step 3: **Reduce**

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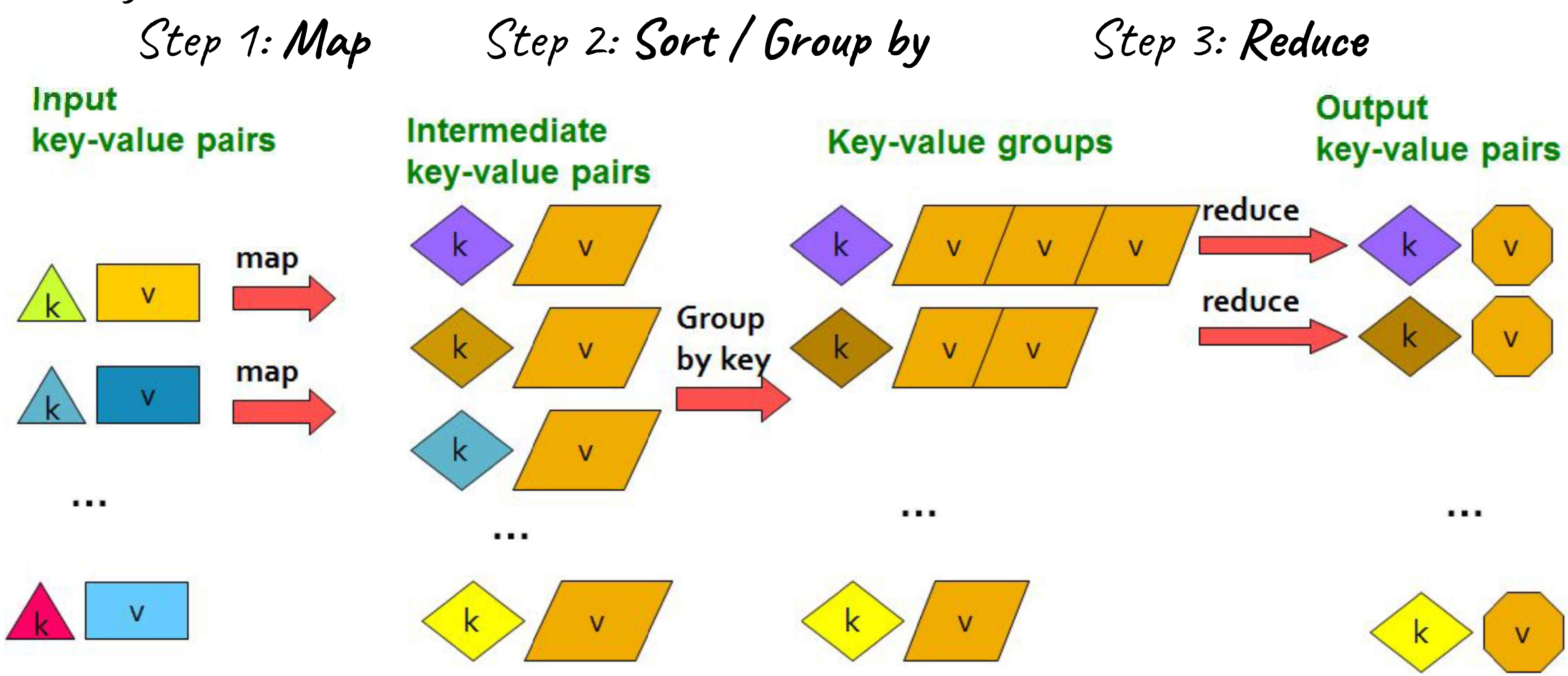


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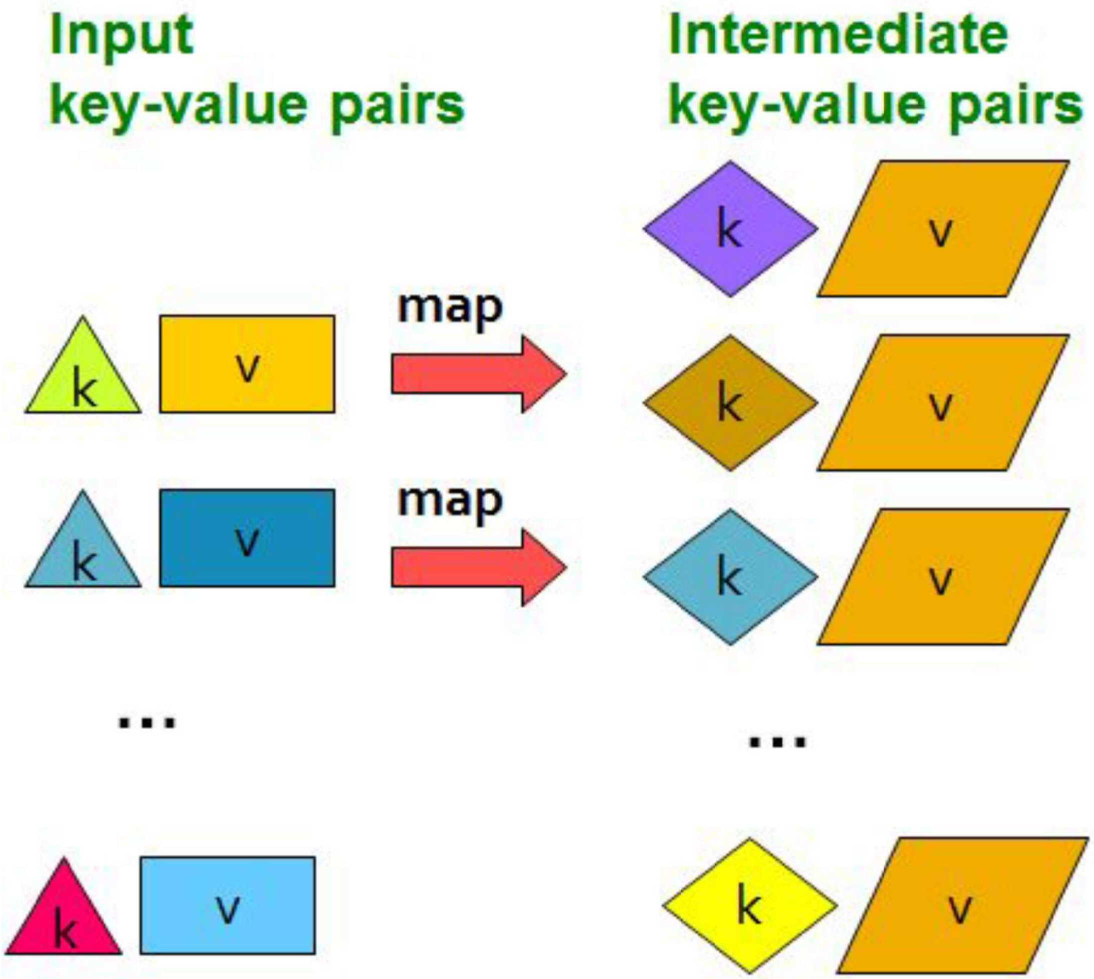
# (1) The *Map* Step

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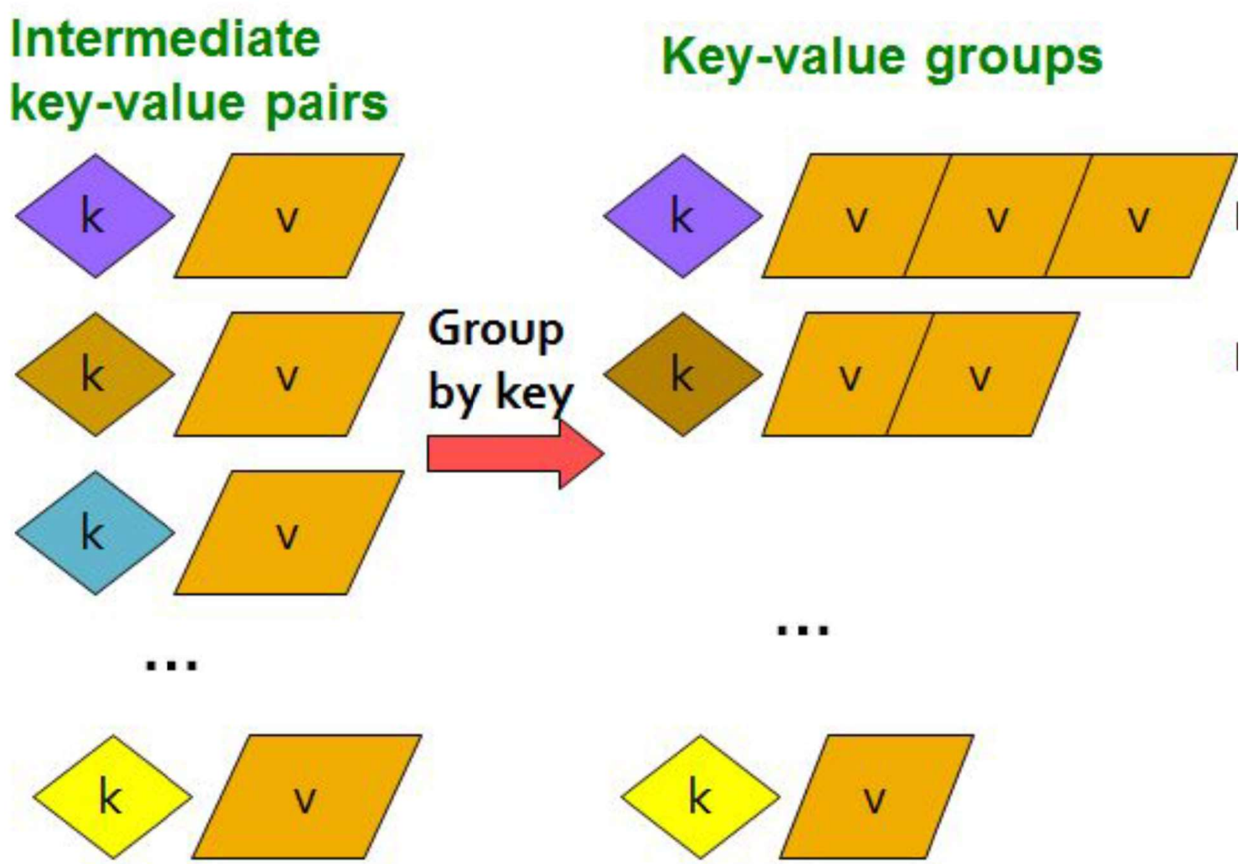
# (2) The *Sort / Group-by* Step

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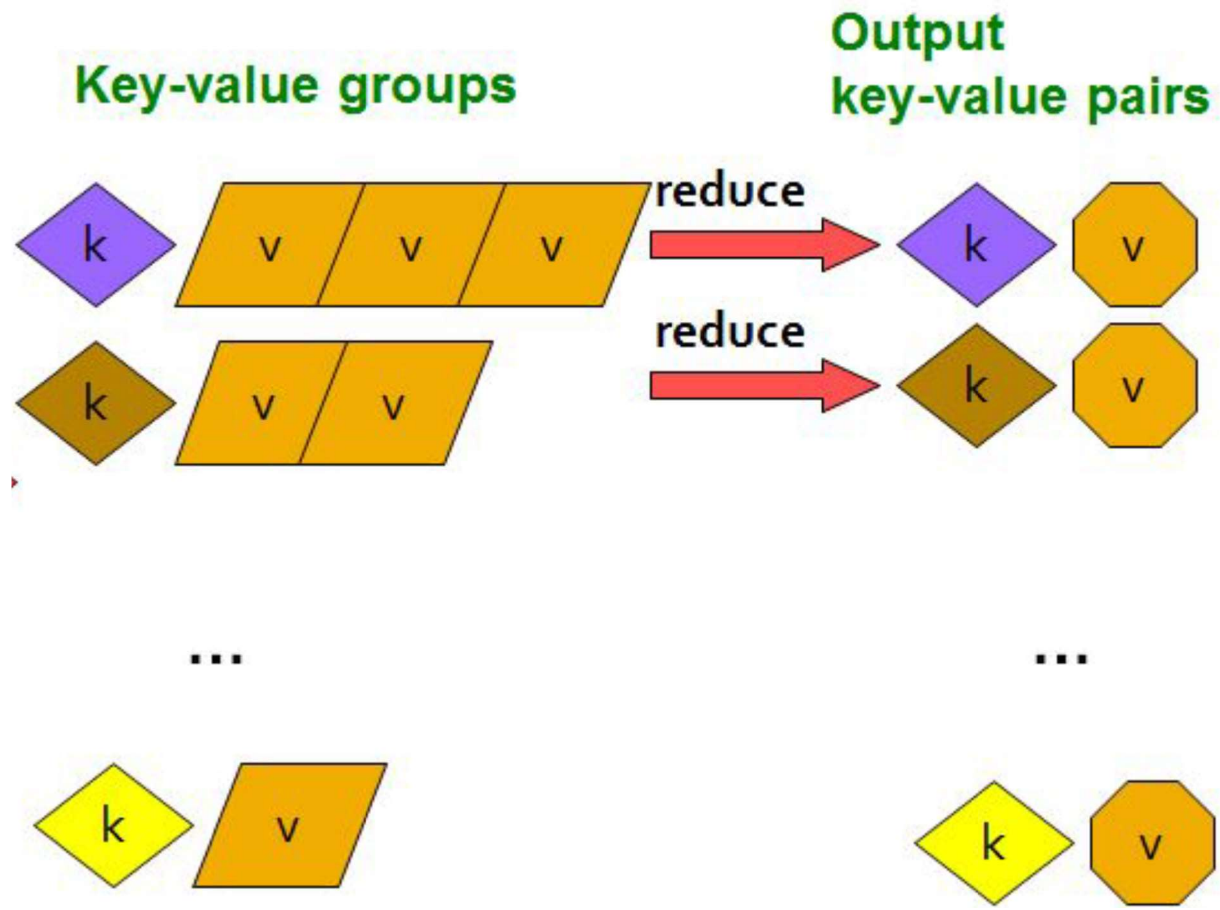
# (3) The *Reduce* Step

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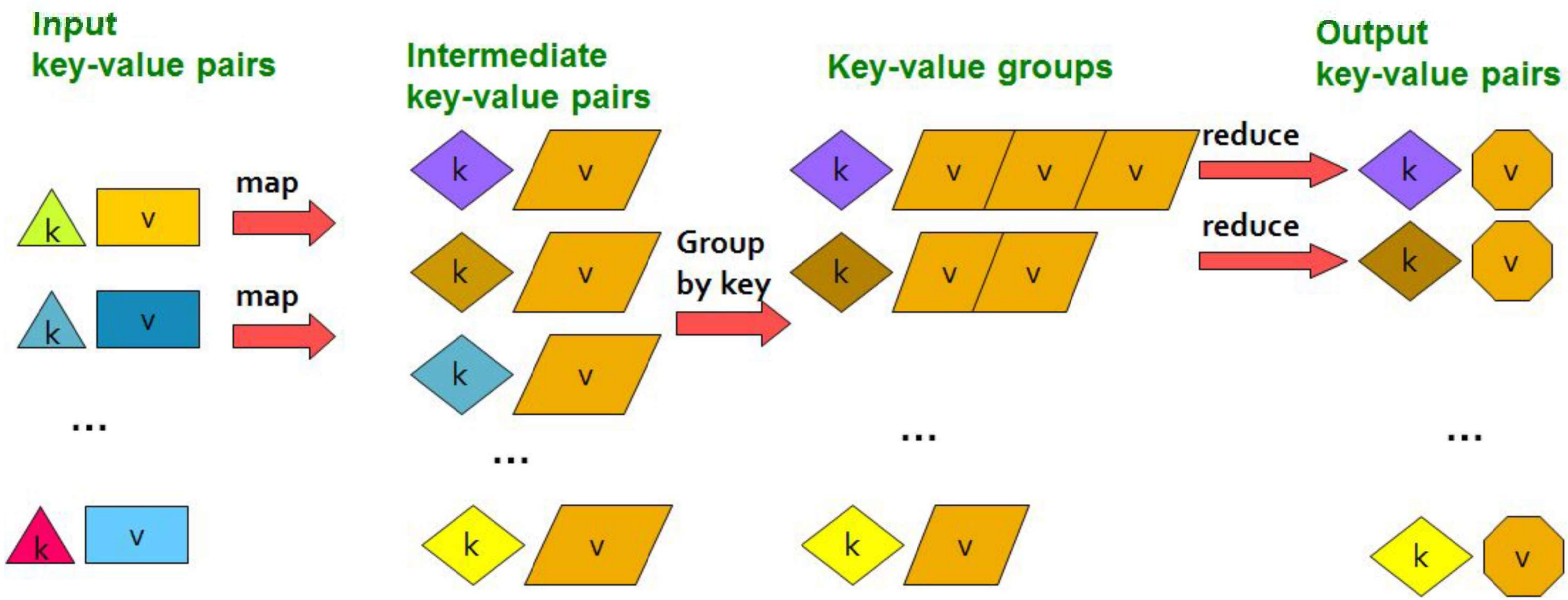


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# What is MapReduce

Map: $(k,v) \rightarrow (k', v')^*$
(Written by programmer)

Group by key: $(k_1', v_1'), (k_2', v_2'), \ldots \rightarrow (k_1', (v_1', v', \ldots)),$
(system handles) $(k_2', (v_1', v', \ldots)), \ldots$

Reduce: $(k', (v_1', v', \ldots)) \rightarrow (k', v'')^*$
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# Example: Word Count

```
tokenize(document) | sort | uniq -c
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# Example: Word Count

```
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```

Map: extract what you care about.

sort and shuffle

Reduce: aggregate, summarize

# Example: Word Count

The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/mache partnership. '"The work we're doing now -- the robotics we're doing -- is what we're going to need ..........................

**Big document**

(Leskovec at al., 2014; http://www.mmds.org/)

**Provided by the programmer**

**MAP:**
Read input and produces a set of key-value pairs

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**Big document**

(The, 1)
(crew, 1)
(of, 1)
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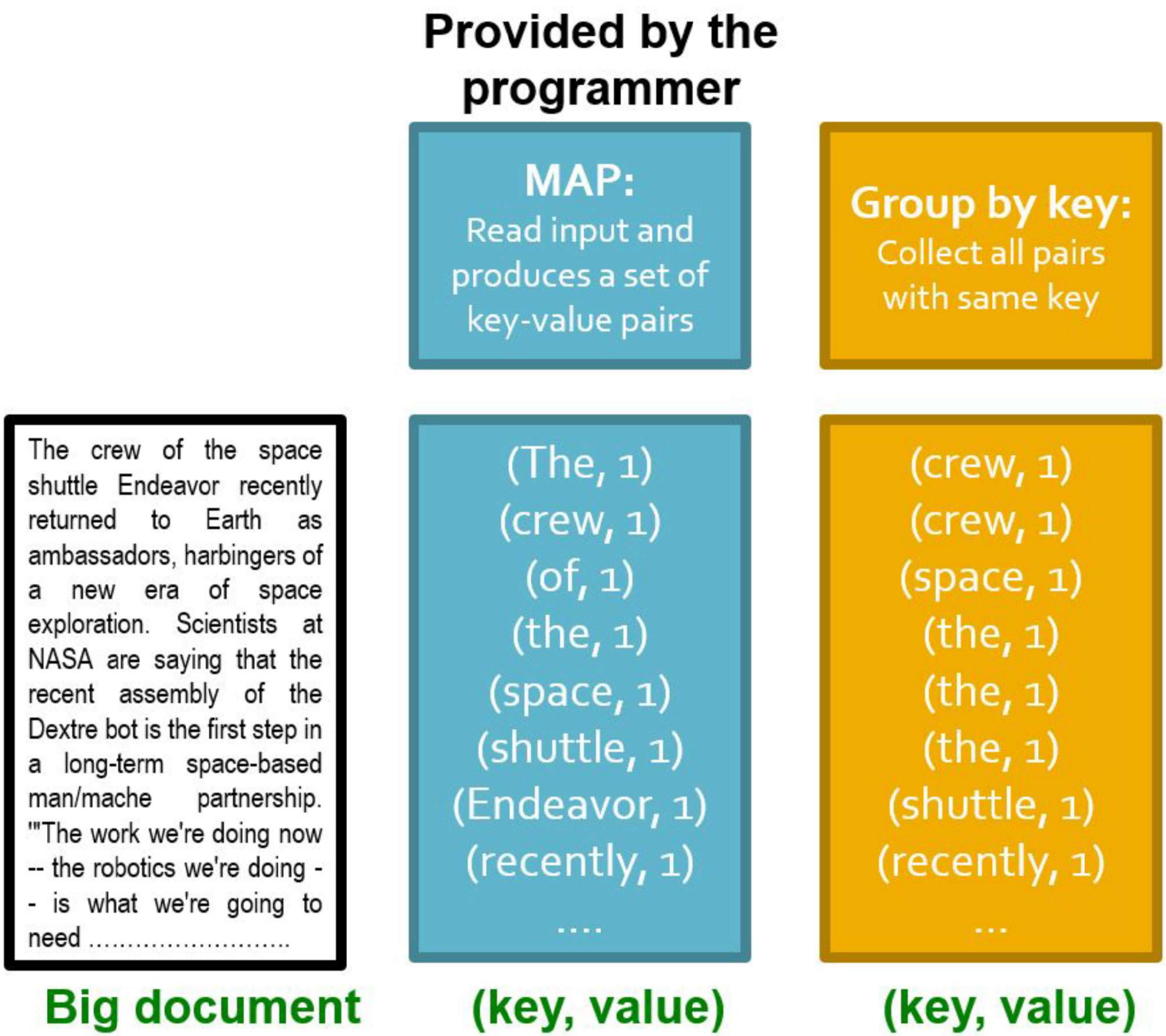
(shuttle, 1)
(Endeavor, 1)
(recently, 1)
….

**(key, value)**


Provided by the programmer
MAP:
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Group by key:
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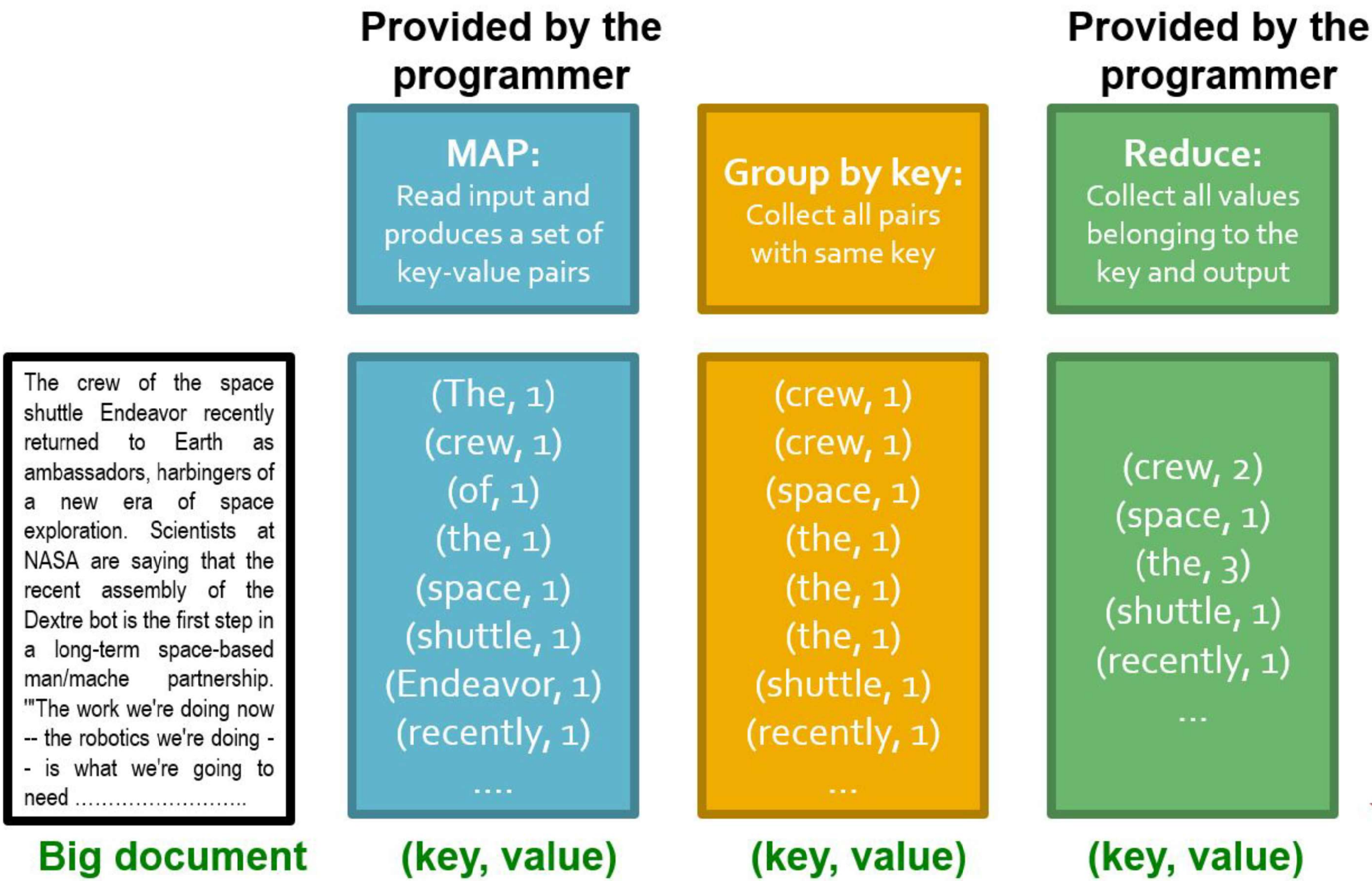
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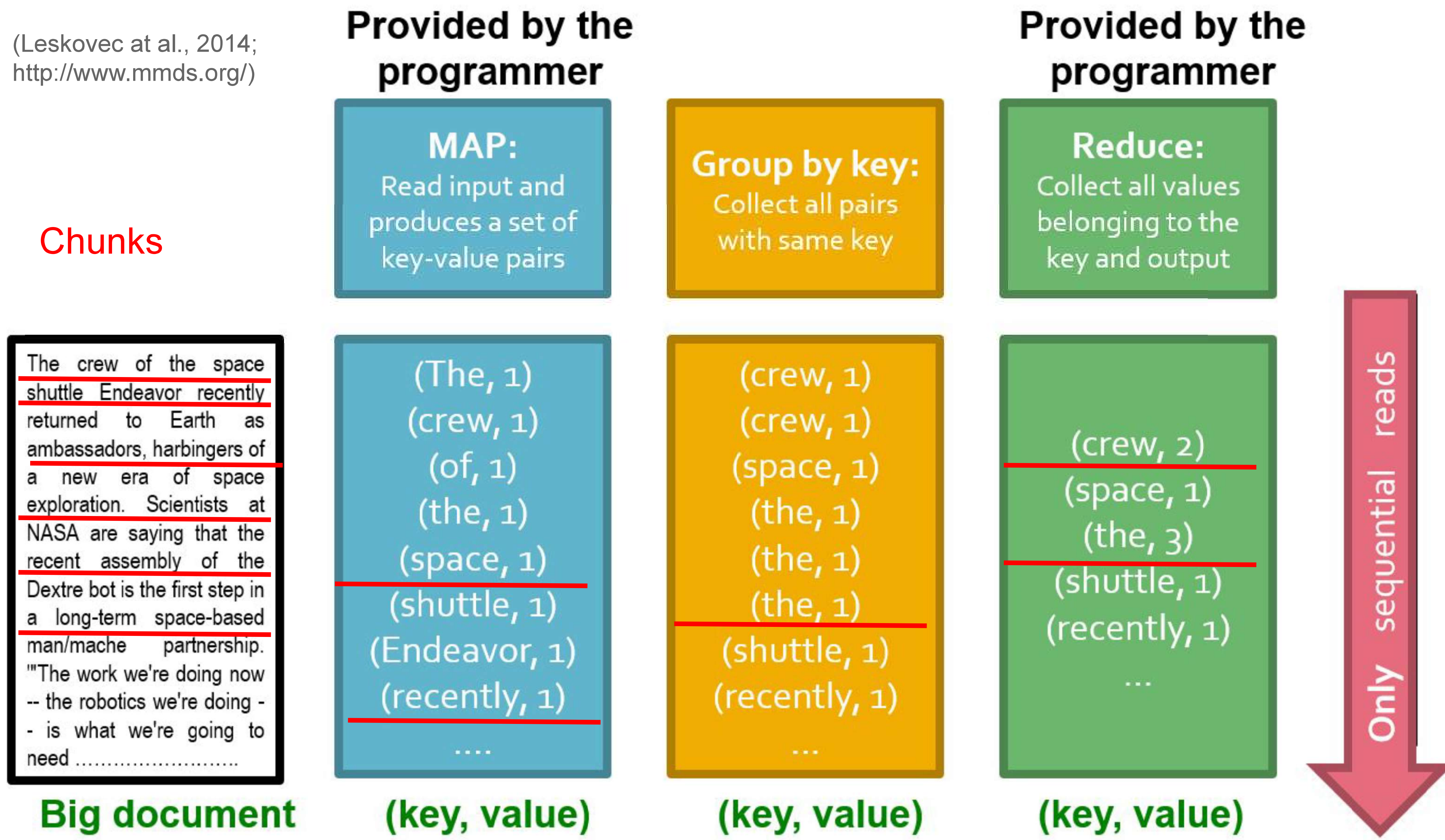
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Provided by the programmer
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Chunks
MAP:
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Big document
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# Example: Word Count

```python
@abstractmethod
def map(k, v):
    pass
```

```python
@abstractmethod
def reduce(k, vs):
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```

# Example: Word Count (v1)

```
def map(k, v):
    for w in tokenize(v):
        yield (w,1)


def reduce(k, vs):
    return len(vs)
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```python
def tokenize(s):
    #simple version
    return s.split(‘ ‘)
```

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# Example: Word Count (v2)

```
def map(k, v):
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    for w in tokenize(v):
```

counts each word within the chunk
(try/except is faster than
“if w in counts”)

# Example: Word Count (v2)

```
def map(k, v):
    counts = dict()
    for w in tokenize(v):
        try:
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        except KeyError:
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    for item in counts.iteritems():
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```
def reduce(k, vs):
    return sum(vs)
```

sum of counts from different chunks

# Distributed Architecture (Cluster)

Challenges for IO Cluster Computing

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   1 in 1000 nodes fail a day

   Duplicate Data **(Distributed FS)**

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# Example: Relational Algebra

Select

Project

Union, Intersection, Difference

Natural Join

Grouping

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$R(A_1,A_2,A_3,\ldots)$, Relation $R$, Attributes $A_*$

return only those attribute tuples where condition $C$ is true

# Example: Relational Algebra

## Select

$R(A_1,A_2,A_3,...)$, Relation $R$, Attributes $A_*$

return only those attribute tuples where condition $C$ is true

```
def map(k, v): #v is list of attribute tuples
    for t in v:
        if t satisfies C:
            yield (t, t)

def reduce(k, vs):
    For each v in vs:
        yield  (k, v)
```

# Example: Relational Algebra

## Natural Join

Given $R_1$ and $R_2$ return $R_{join}$ -- union of all pairs of tuples that match given attributes.

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def map(k, v): #k \in {R1, R2}, v is (R1=(A, B), R2=(B, C));B are matched attributes
    if k==”R1”:
        (a, b) = v
        yield (b,(R1,a))
    if k==”R2”:
        (b,c) = v
        yield (b,(R2,c))
```

# Example: Relational Algebra

## Natural Join

Given $R_1$ and $R_2$ return $R_{join}$ -- union of all pairs of tuples that match given attributes.

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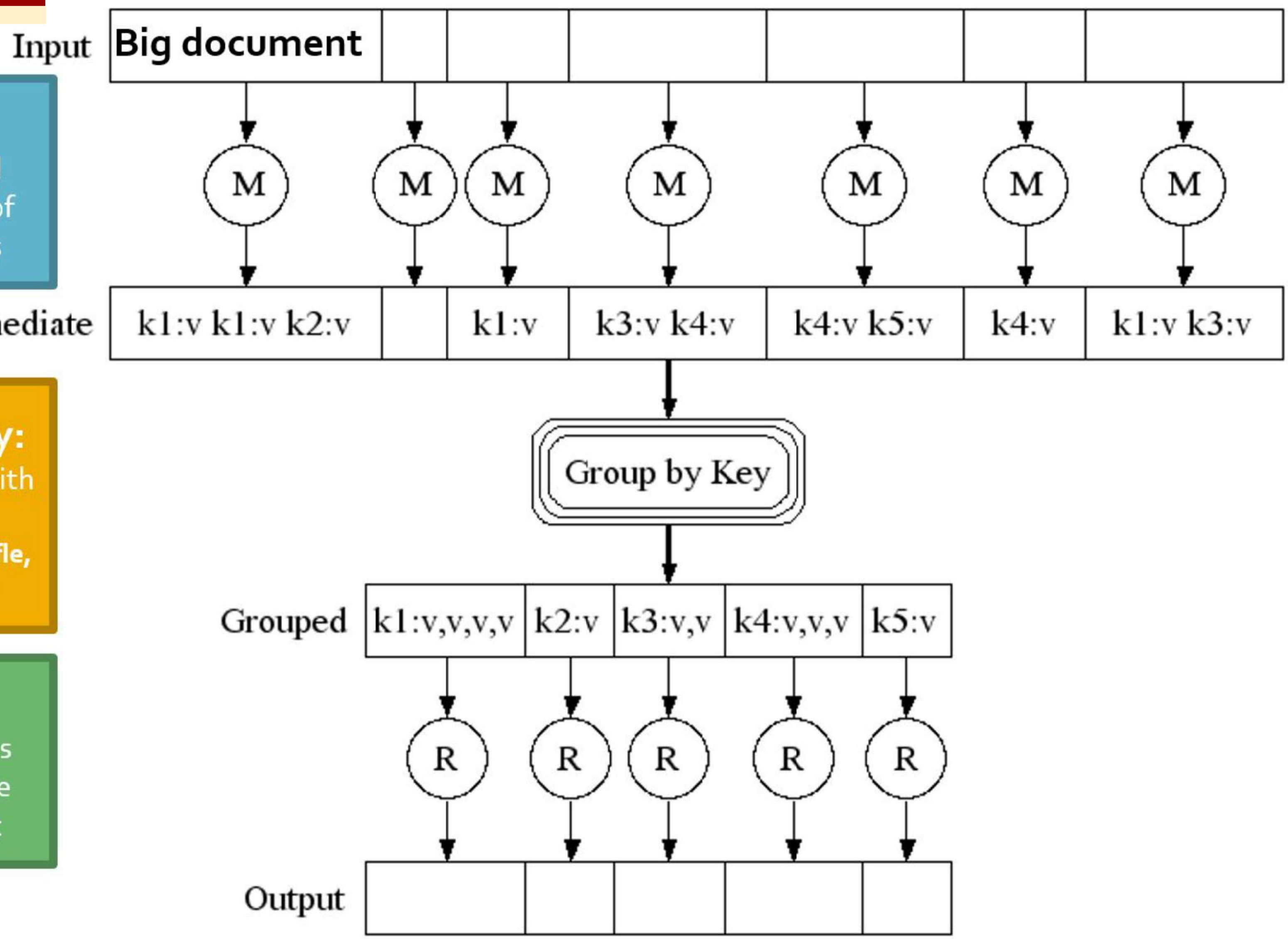
```
def reduce(k, vs):
    r1, r2 = [], []
    for (S, x) in vs: #separate rs
        if S == r1: r1.append(x)
        else: r2.append(x)
    for a in r1: #join as tuple
        for each c in r2:
            yield (Rjoin’, (a, k, c)) #k is
```

# Data Flow

**MAP:**
Read input and produces a set of key-value pairs

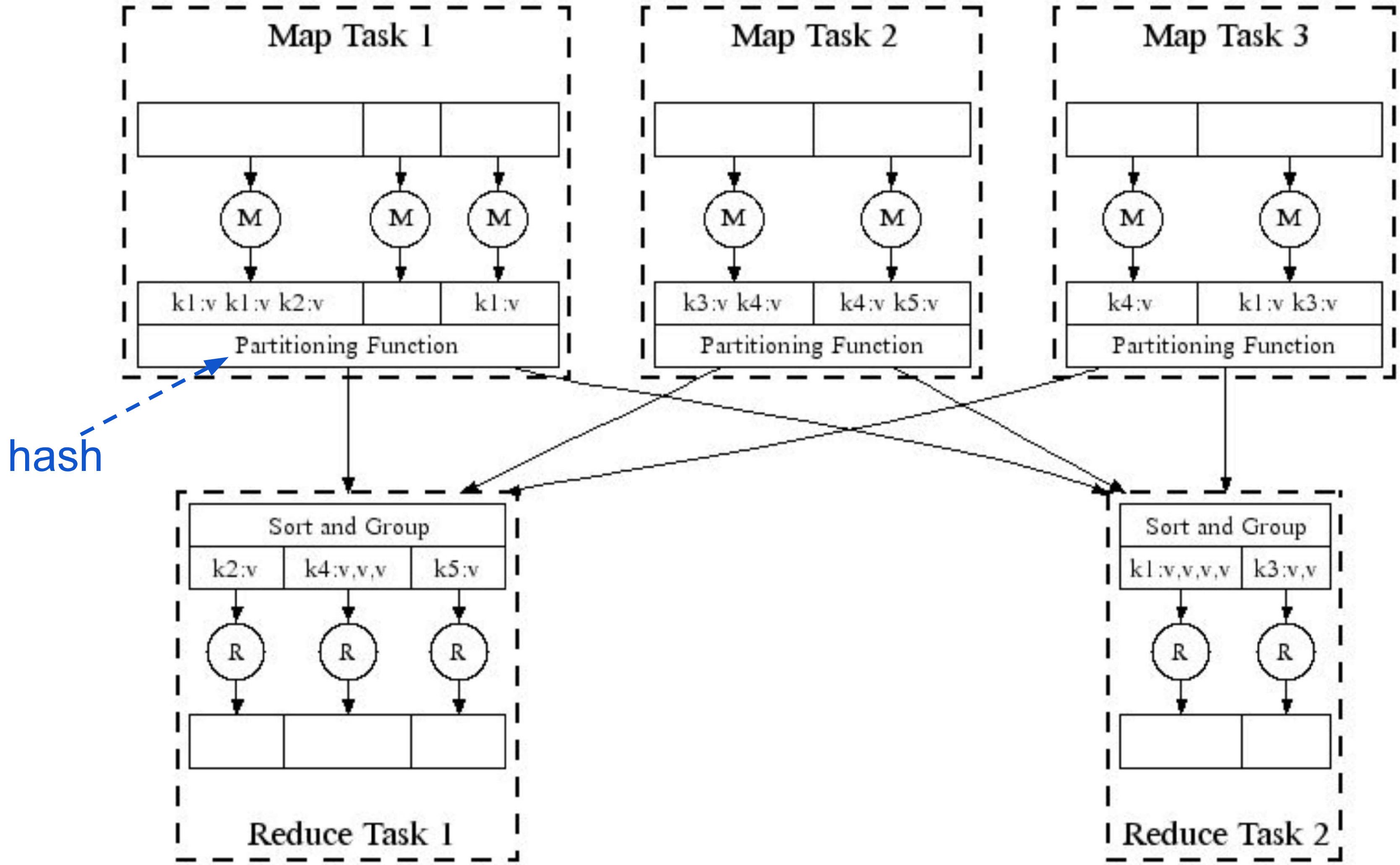
**Group by key:**
Collect all pairs with same key
**(Hash merge, Shuffle, Sort, Partition)**

**Reduce:**
Collect all values belonging to the key and output



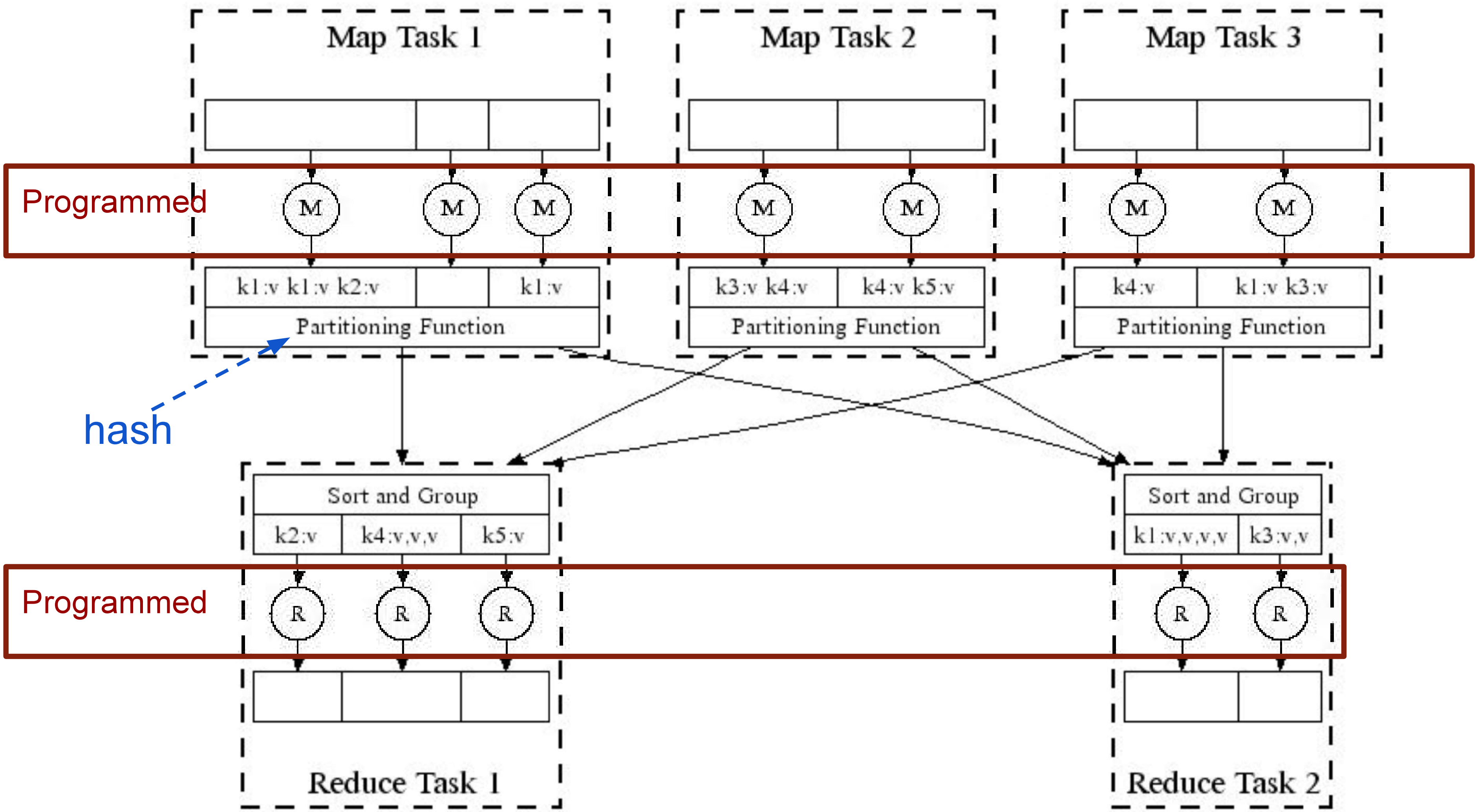

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

# Data Flow




(Leskovec at al., 2014; http://www.mmds.org/)

# Data Flow




(Leskovec at al., 2014; http://www.mmds.org/)

# Data Flow

DFS $\Rightarrow$ Map $\Rightarrow$ Map’s Local FS $\Rightarrow$ Reduce $\Rightarrow$ DFS

# Data Flow

MapReduce system handles:

- Partitioning
- Scheduling map / reducer execution
- Group by key

- Restarts from node failures
- Inter-machine communication

# Data Flow

DFS $\Rightarrow$ MapReduce $\Rightarrow$ DFS

- Schedule map tasks near physical storage of chunk
- Intermediate results stored locally
- Master / Name Node coordinates

# Data Flow

DFS → MapReduce → DFS

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- Intermediate results stored locally
- Master / Name Node coordinates
  - Task status: idle, in-progress, complete
  - Receives location of intermediate results and schedules with reducer
  - Checks nodes for failures and restarts when necessary
    - All map tasks on nodes must be completely restarted
    - Reduce tasks can pickup with reduce task failed

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DFS → MapReduce → DFS → MapReduce → DFS

# Data Flow

Skew: The degree to which certain tasks end up taking much longer than others.

Handled with:

- More reducers than reduce tasks
- More reduce tasks than nodes

# Data Flow

**Key Question:** *How many Map and Reduce jobs?*

# Data Flow

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*M:* map tasks, *R:* reducer tasks

**A:** If possible, one chunk per map task

and $M \gg |\text{nodes}| \approx |\text{cores}|$

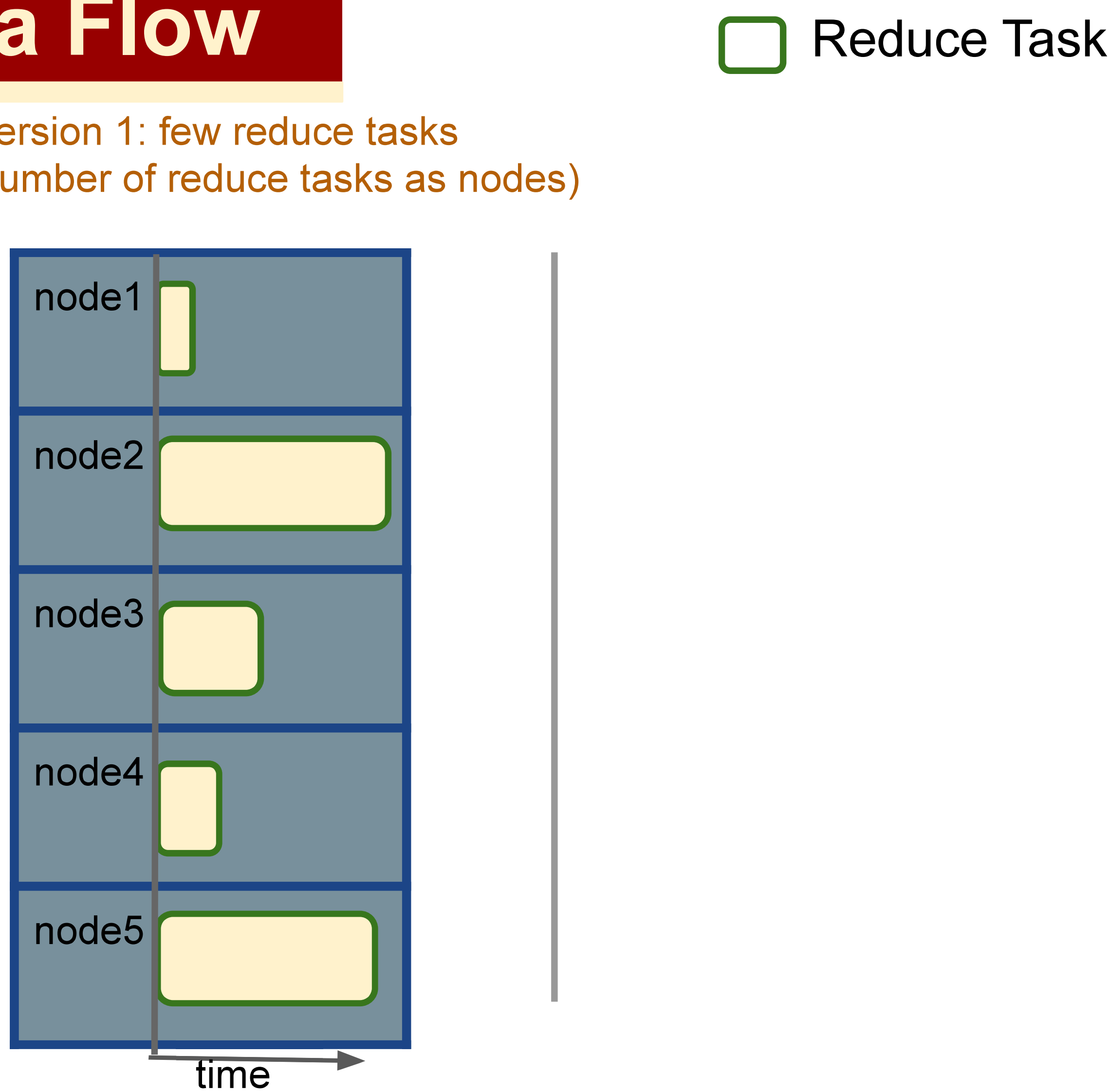
(better handling of node failures, better load balancing)

$R < M$

(reduces number of parts stored in DFS)

# Data Flow

version 1: few reduce tasks
(same number of reduce tasks as nodes)




Reduce tasks represented by
**time to complete task**
(some tasks take much longer)

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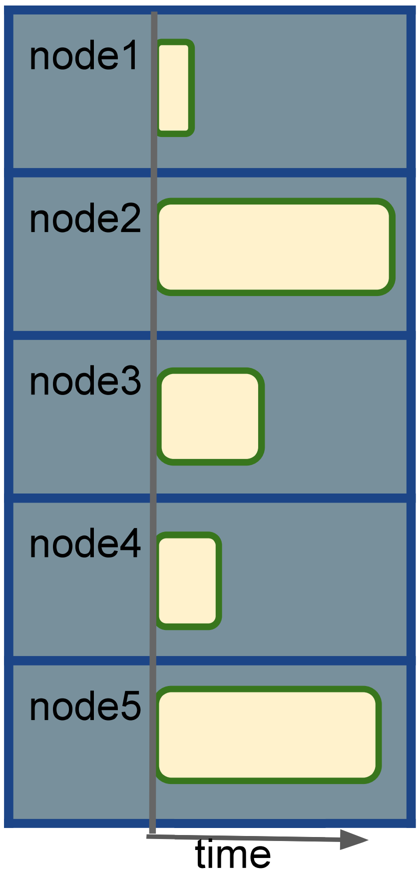
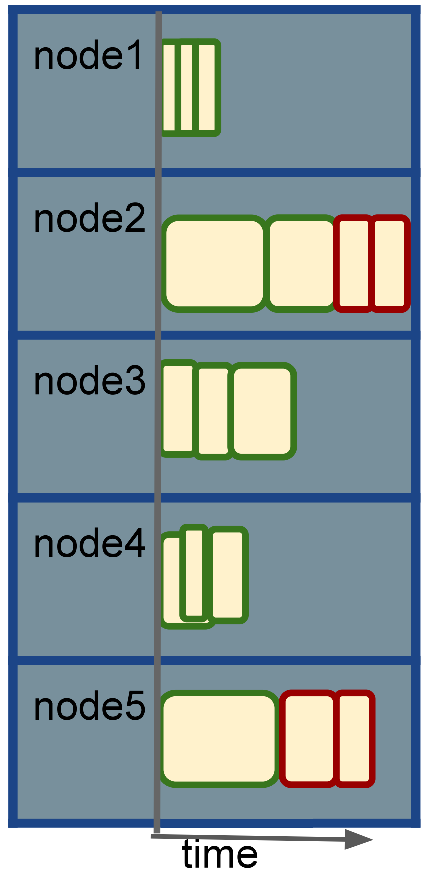


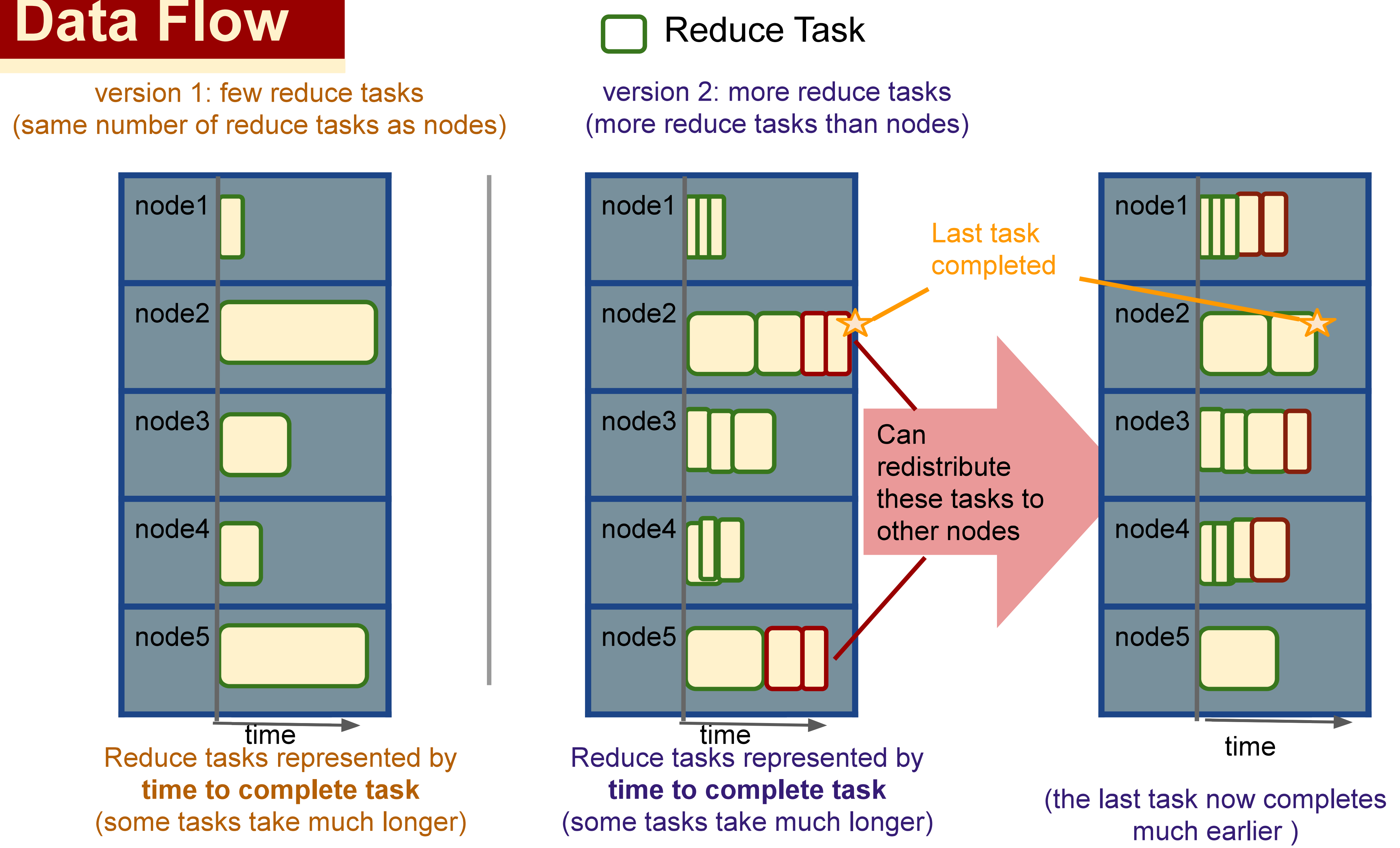

Reduce tasks represented by **time to complete task** (some tasks take much longer)

version 2: more reduce tasks
(more reduce tasks than nodes)




Reduce tasks represented by **time to complete task** (some tasks take much longer)

# Data Flow



Reduce Task
version 1: few reduce tasks
(same number of reduce tasks as nodes)
node1
node2
node3
node4
node5
time
Reduce tasks represented by
**time to complete task**
(some tasks take much longer)
version 2: more reduce tasks
(more reduce tasks than nodes)
node1
node2
node3
node4
node5
time
Reduce tasks represented by
**time to complete task**
(some tasks take much longer)
Last task completed
Can redistribute these tasks to other nodes
node1
node2
node3
node4
node5
time
(the last task now completes much earlier )

# Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

(2) Communication: Moving (key, value) pairs

# Communication Cost Model

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(1) Computation: Map + Reduce + System Tasks

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Ultimate Goal: wall-clock Time.

# Communication Cost Model

How to assess performance?

## (1) Computation: Map + Reduce + System Tasks

- Mappers and reducers often single pass O(n) within node
- System: sort the keys is usually most expensive
- Even if map executes on same node, disk read usually dominates
- In any case, can add more nodes

(2) Communication: Moving key, value pairs

Ultimate Goal: wall-clock Time.

# Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

(2) **Communication: Moving key, value pairs**

Ultimate Goal: wall-clock Time

Often dominates computation.

- Connection speeds: 1-10 giga**bits** per sec;
  HD read: 50-150 giga**bytes** per sec
- Even reading from disk to memory typically takes longer than operating on the data.

# Communication Cost Model

## How to assess performance?

**Communication Cost =** input size +
(sum of size of all map-to-reducer files)

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# Communication Cost Model

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## (2) Communication: Moving key, value pairs

Ultimate Goal: wall-clock Time

Often dominates computation.

- Connection speeds: 1-10 giga**bits** per sec;
  HD read: 50-150 giga**bytes** per sec
- Even reading from disk to memory typically takes longer than operating on the data.
- Output from reducer ignored because it’s either small (finished summarizing data) or being passed to another mapreduce job.

# Communication Cost: Natural Join

R, S: Relations (Tables)      $R(A, B) \bowtie S(B, C)$

**Communication Cost =** input size +
(sum of size of all map-to-reducer files)

DFS ⇨ Map ⇨ LocalFS ⇨ Network ⇨ Reduce ⇨ DFS ⇨ ?

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# Communication Cost: Natural Join

R, S: Relations (Tables)    $R(A, B) \bowtie S(B, C)$

**Communication Cost =** input size + (sum of size of all map-to-reducer files)

= |R1| + |R2| + (|R1| + |R2|)

= $O(|R1| + |R2|)$

```
def map(k, v):
    if k=="R1":
        (a, b) = v
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```

# Exercise:

Calculate Communication Cost for
"Matrix Multiplication with One MapReduce Step"
(see MMDS section 2.3.10)

# MapReduce: Final Considerations

- Performance Refinements:
  - Combiners (like word count version 2 but done via reduce)
    - Run reduce right after map from same node before passing to reduce (MapTask can execute)
    - Reduces communication cost
  - Backup tasks (aka speculative tasks)
    - Schedule multiple copies of tasks when close to the end to mitigate certain nodes running slow.
  - Override partition hash function to organize data

    E.g. instead of `hash(url)` use `hash(hostname(url))`