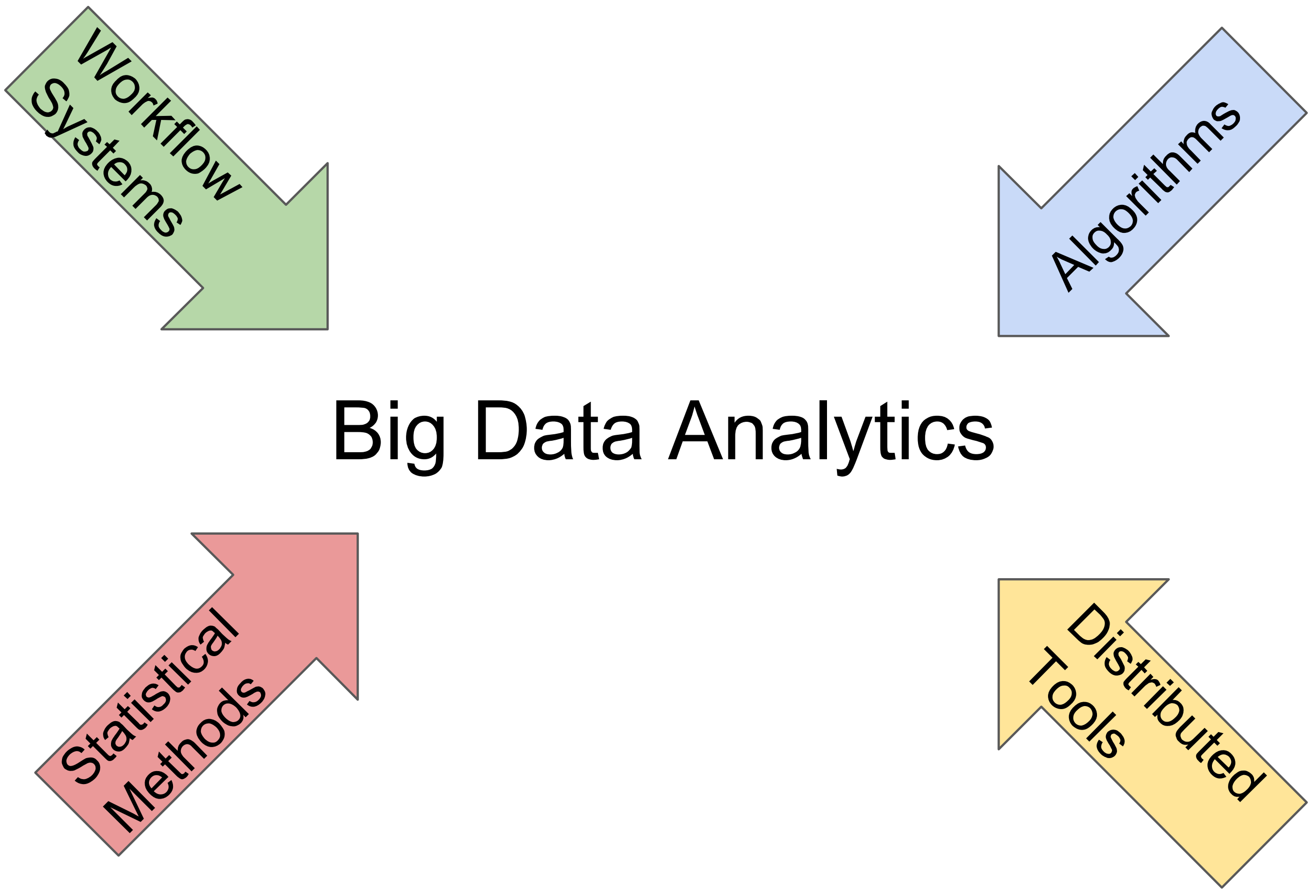
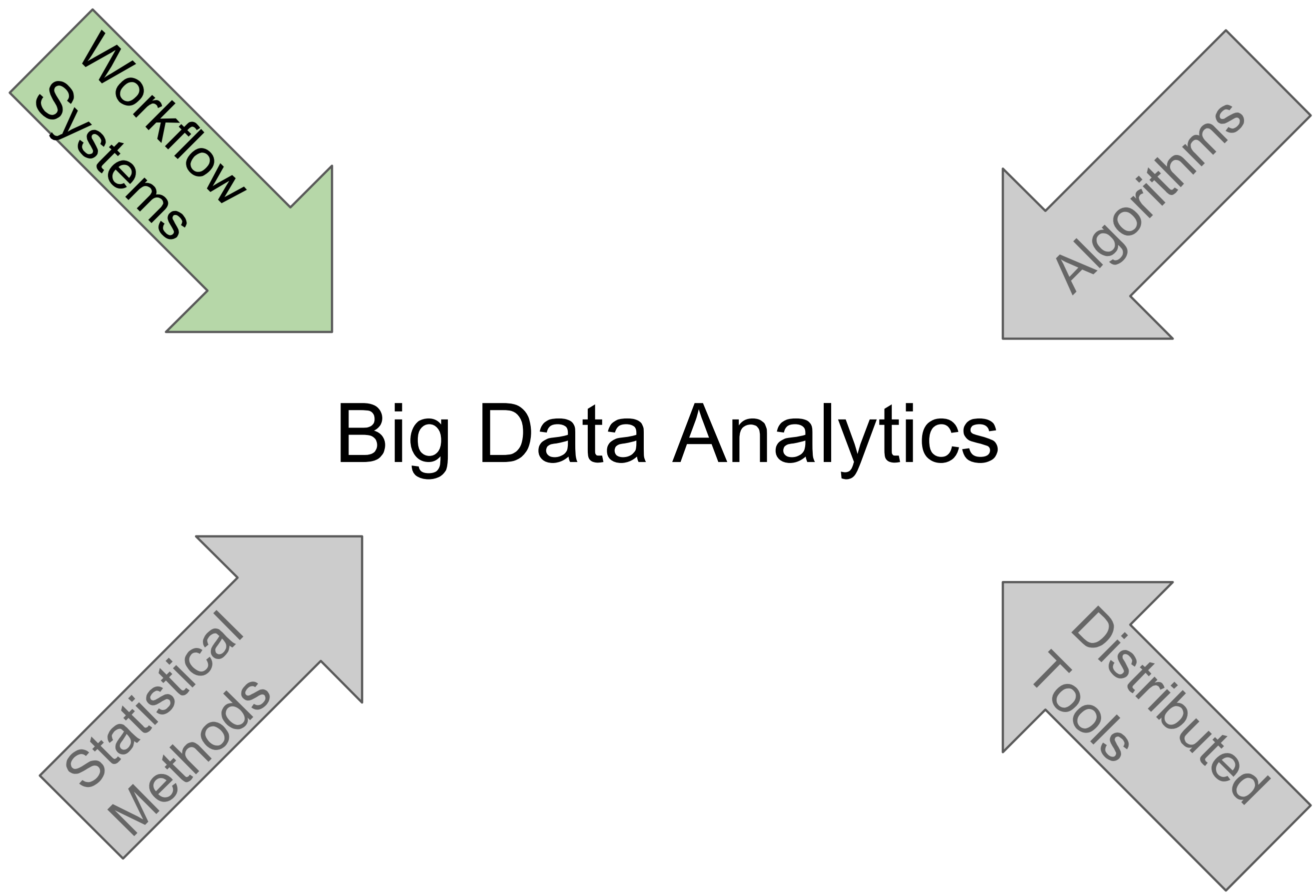
“Hadoop”: A Distributed Architecture, FileSystem, & MapReduce

Stony Brook University
CSE545 - Spring 2019


Workflow Systems
Algorithms
Big Data Analytics
Statistical Methods
Distributed Tools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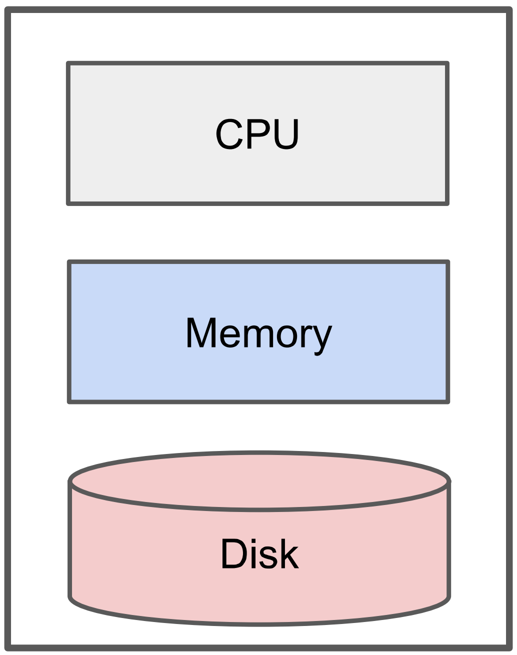
Classical Data Mining



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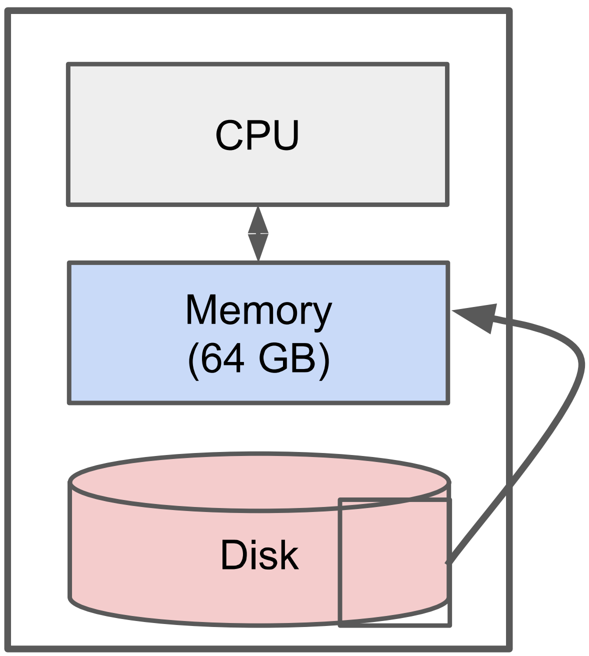

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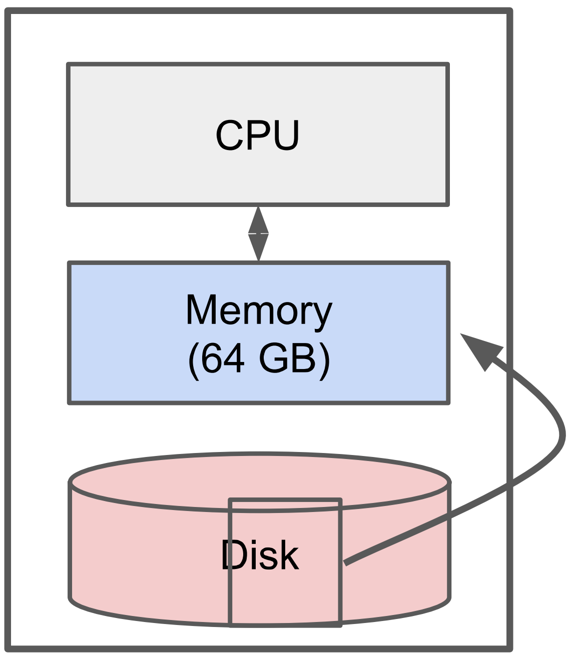

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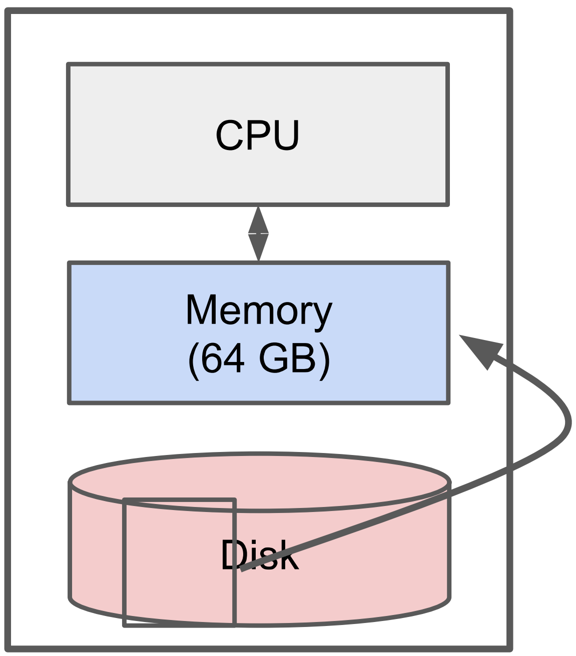
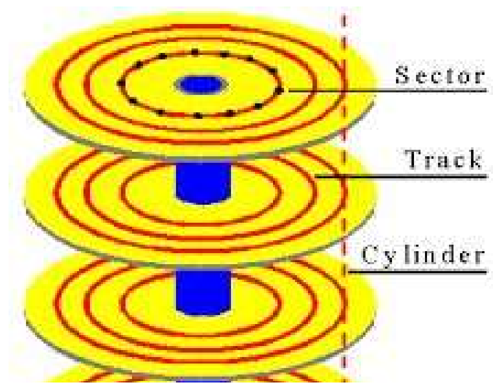


IO Bounded

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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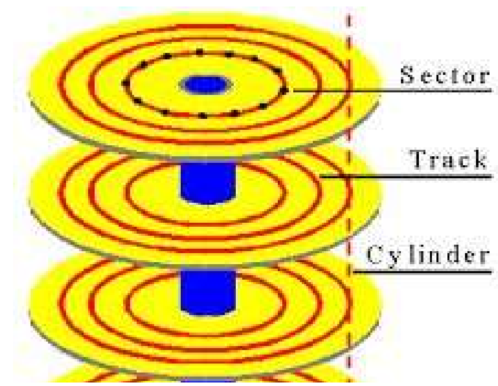
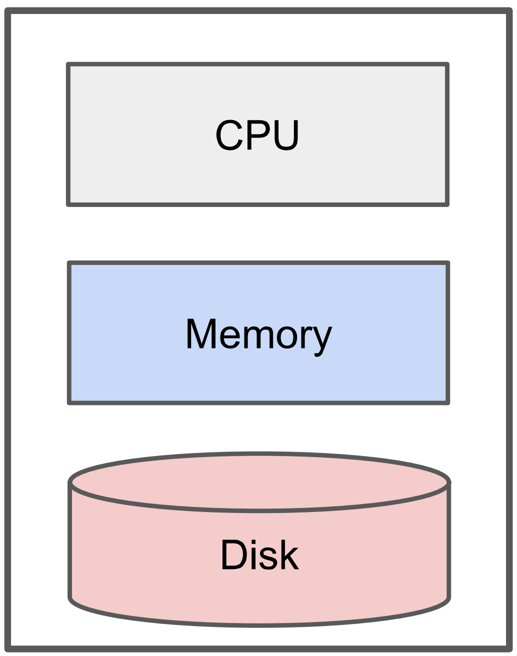


IO Bound: biggest performance bottleneck is reading / writing to disk.

starts around 100 GBs: ~10 minutes just to read

200 TBs: ~20,000 minutes = 13 days

Classical Big Data Analysis



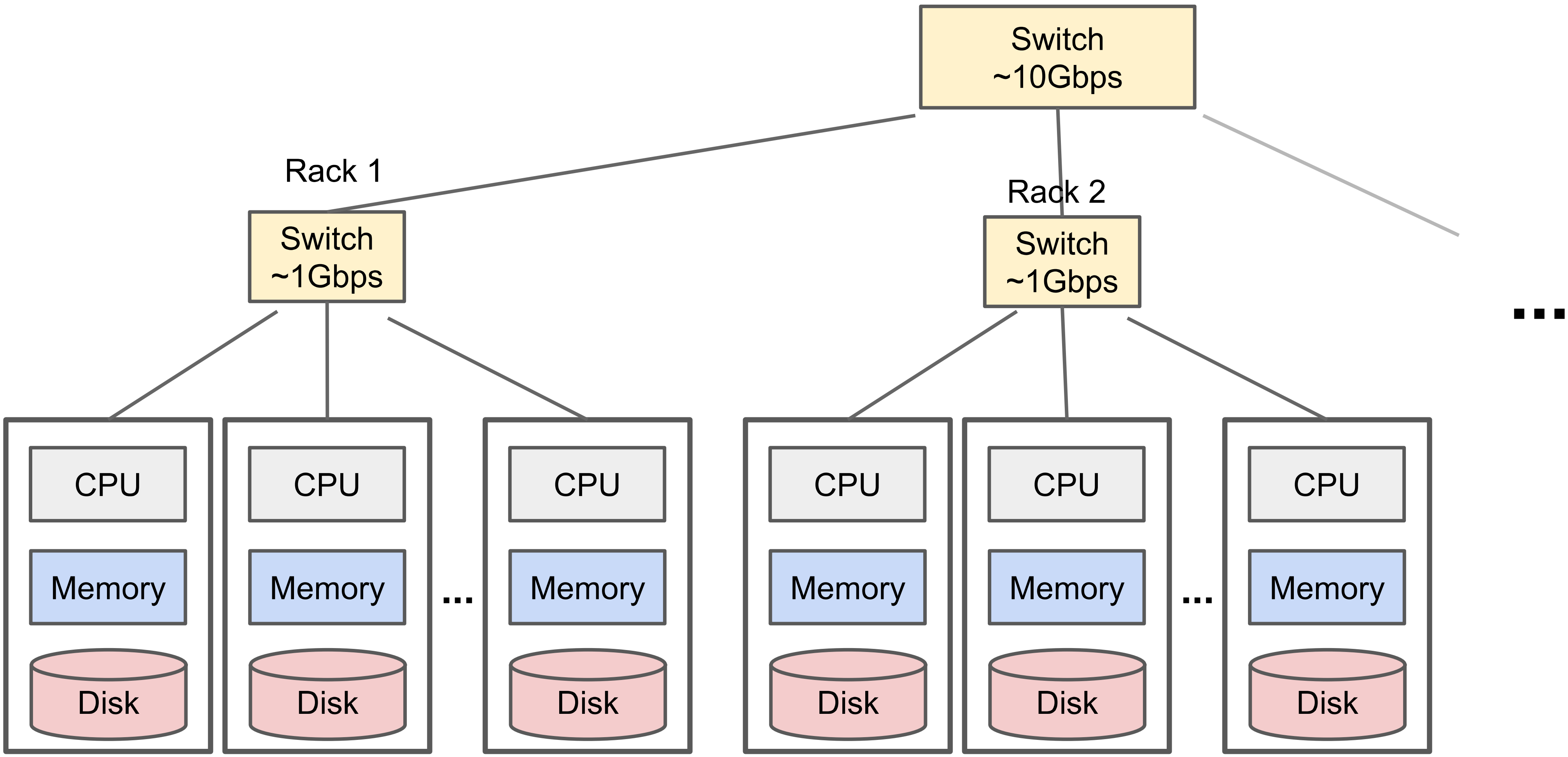
Classical focus: efficient use of disk.
e.g. Apache Lucene / Solr

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

IO Bound

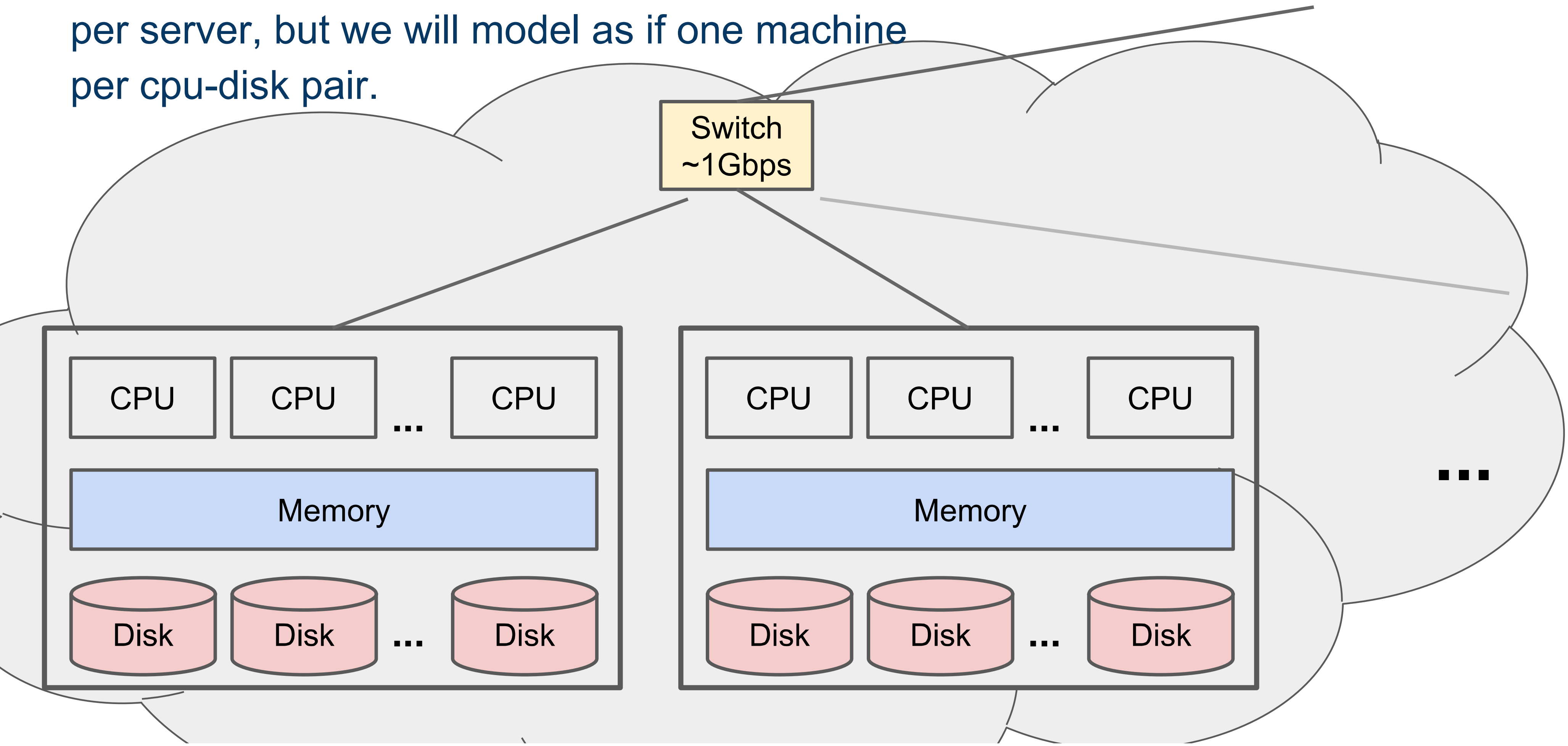
How to solve?

Distributed Architecture (Cluster)



Distributed Architecture (Cluster)

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



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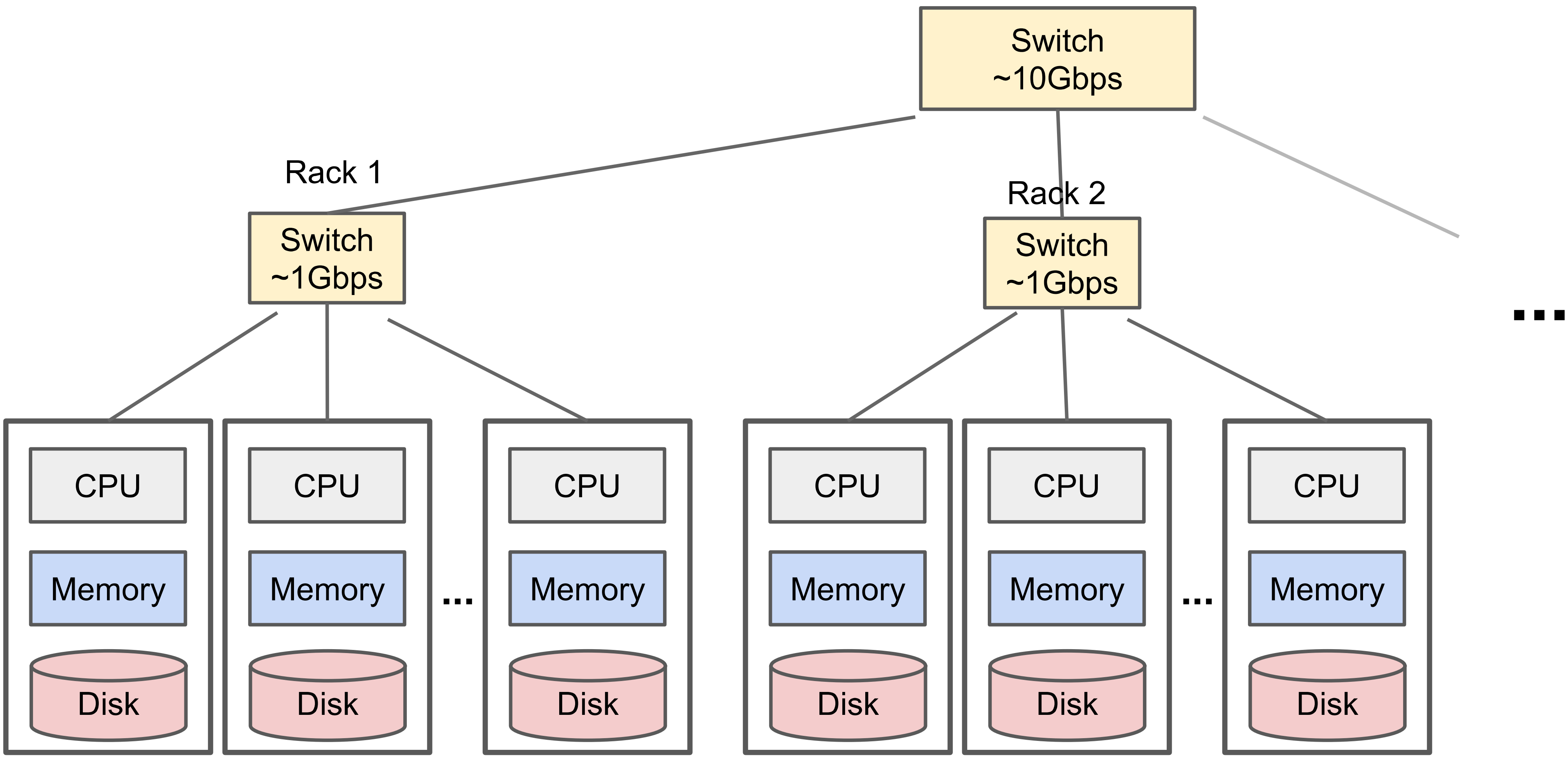

Challenges for IO Cluster Computing

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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   Stipulate a programming system that can easily be distributed

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MapReduce Accomplishes

Distributed File System

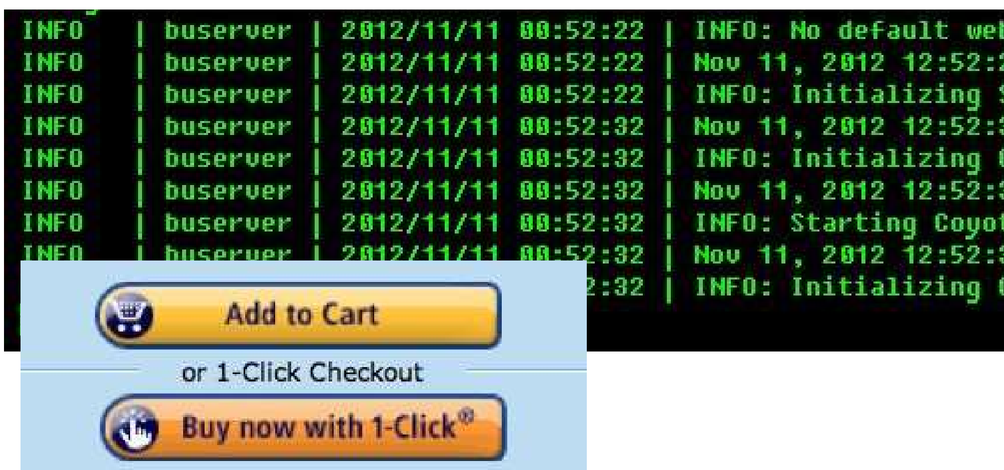
The effectiveness of MapReduce is in part simply due to use of a distributed filesystem!

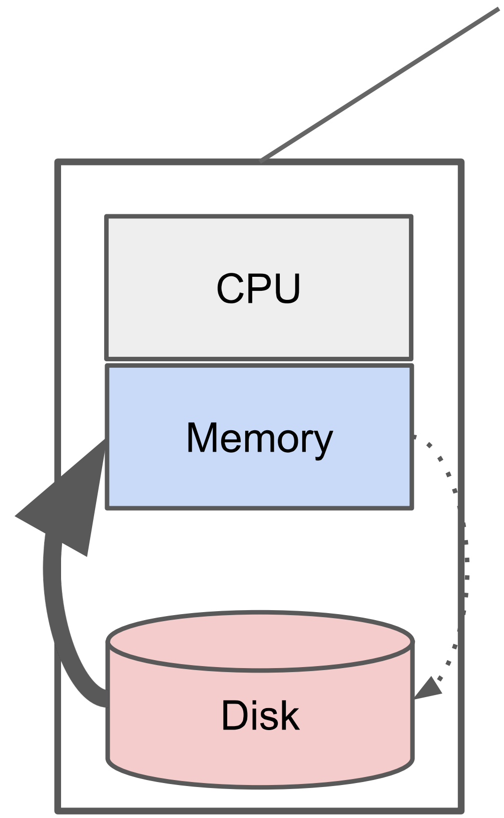
Characteristics for Big Data Tasks

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

Reads are most common

No need to update in place
(append preferred)

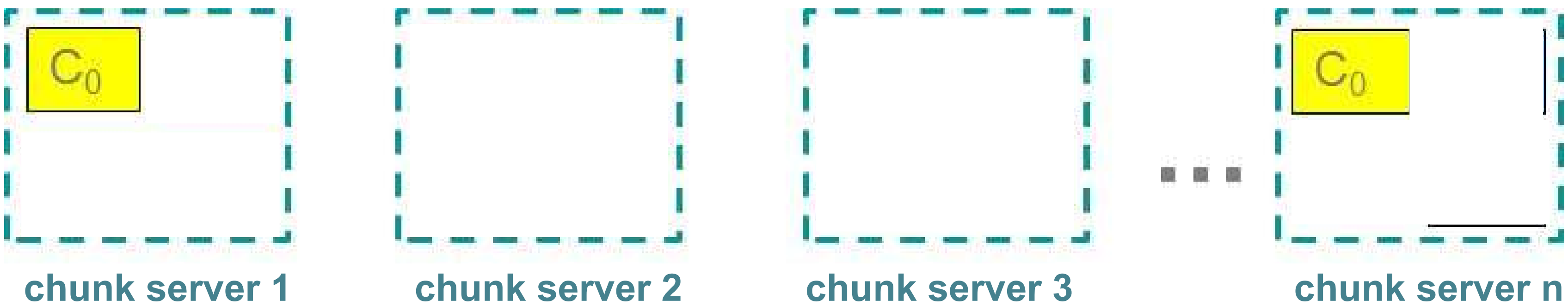




Distributed File System

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

C, D: Two different files



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

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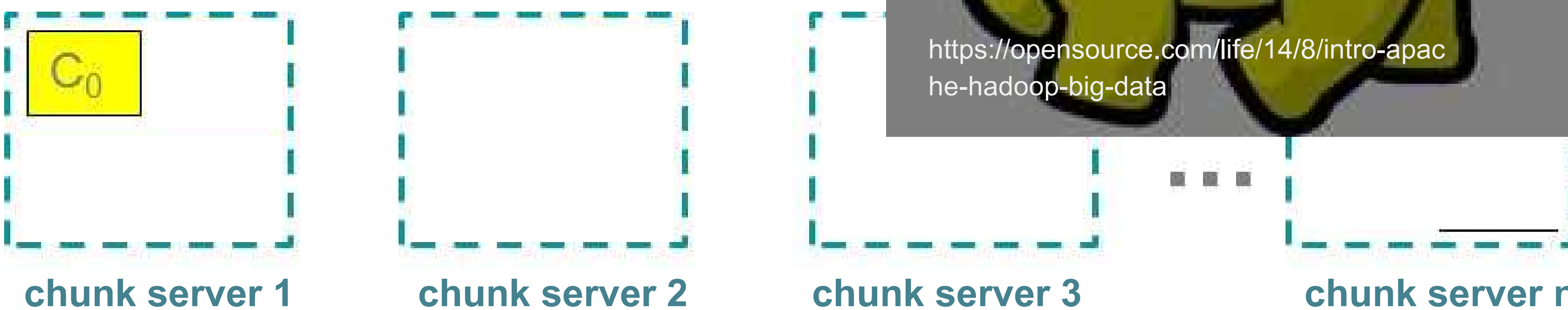

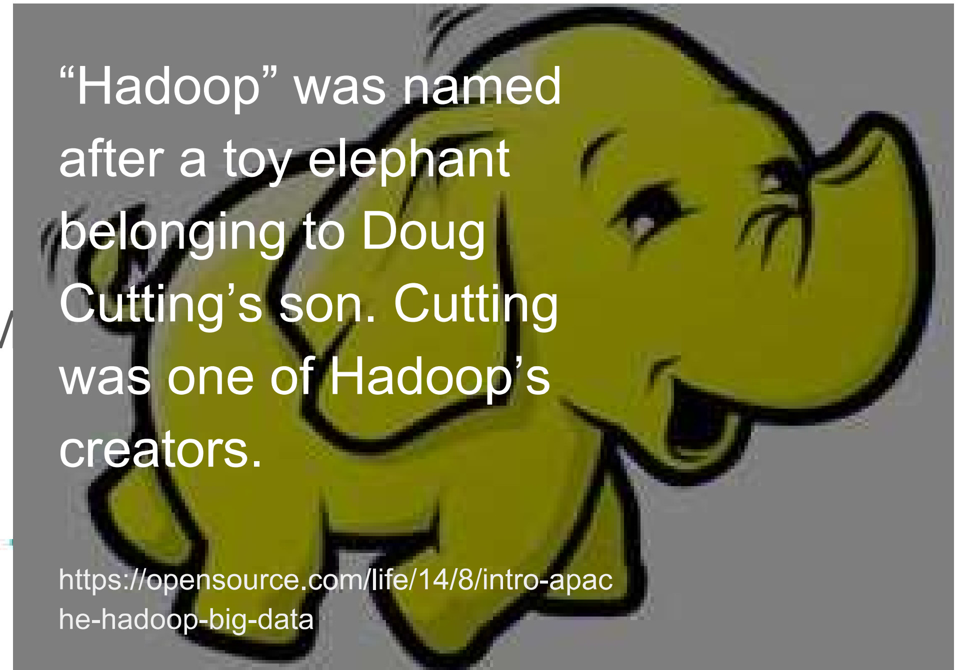

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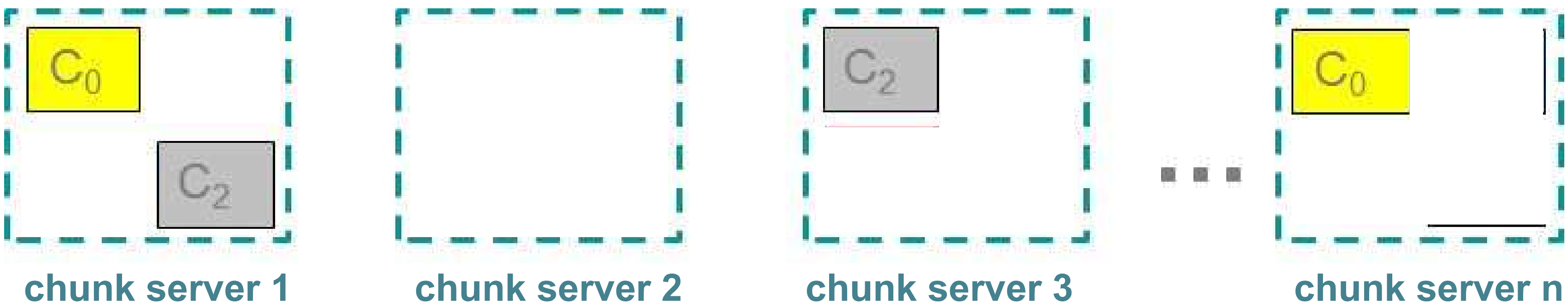

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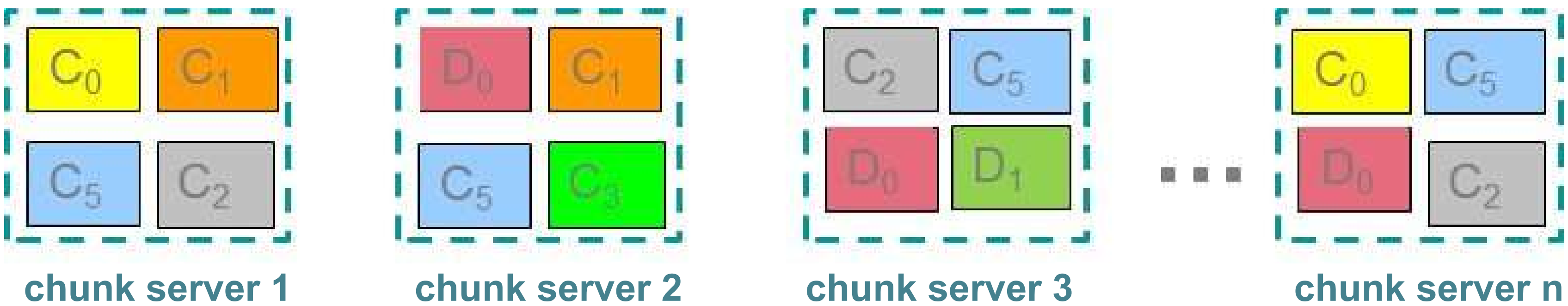

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Components of a Distributed File System

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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Name node (aka master node)

- Stores metadata about where files are stored
- Might be replicated or distributed across data nodes.

Client library for file access

- Talks to master to find chunk servers
- Connects directly to chunk servers to access data

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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.

E.g. counting words:

```
tokenize(document) | sort | uniq -c
```

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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)

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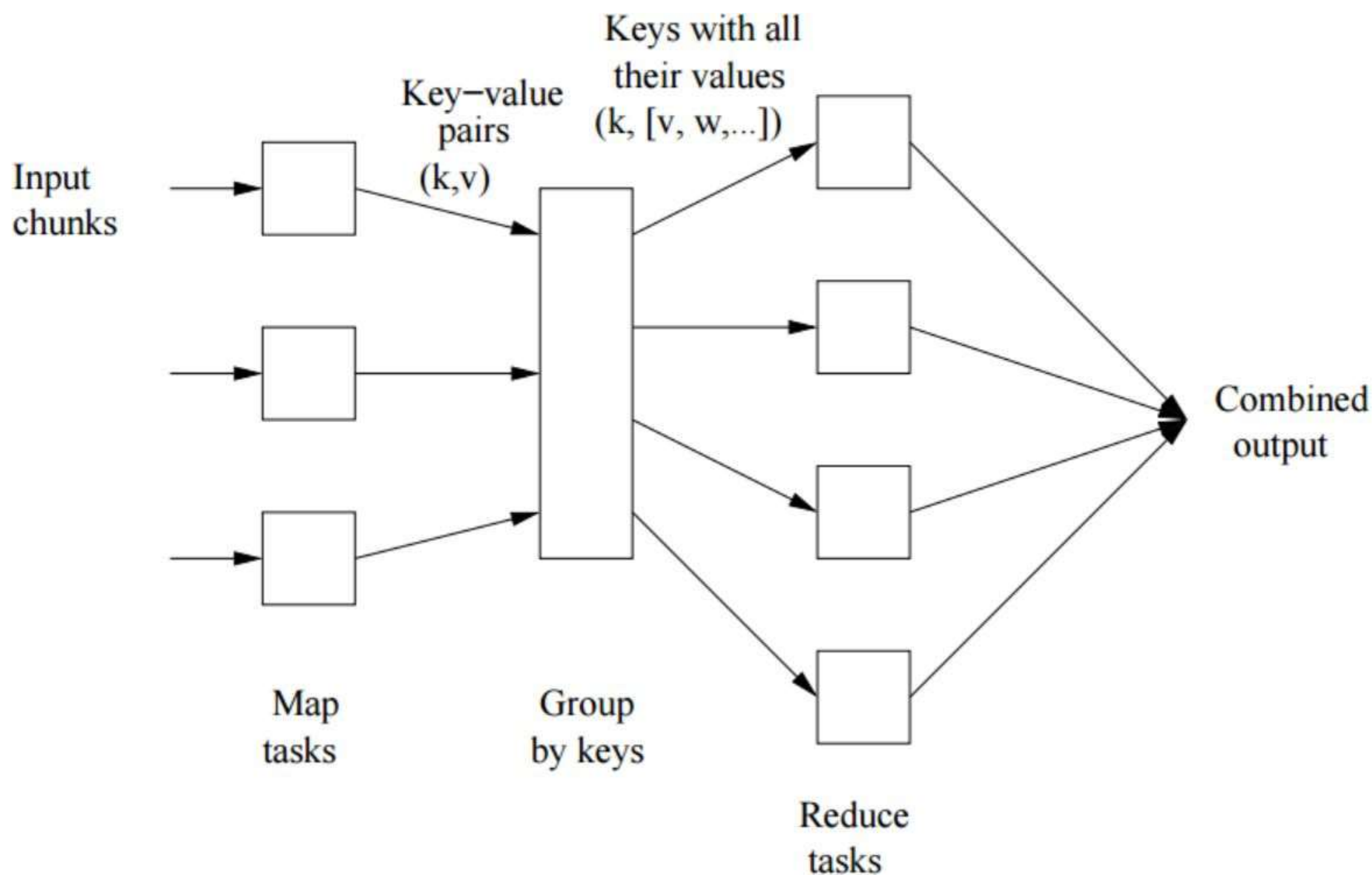

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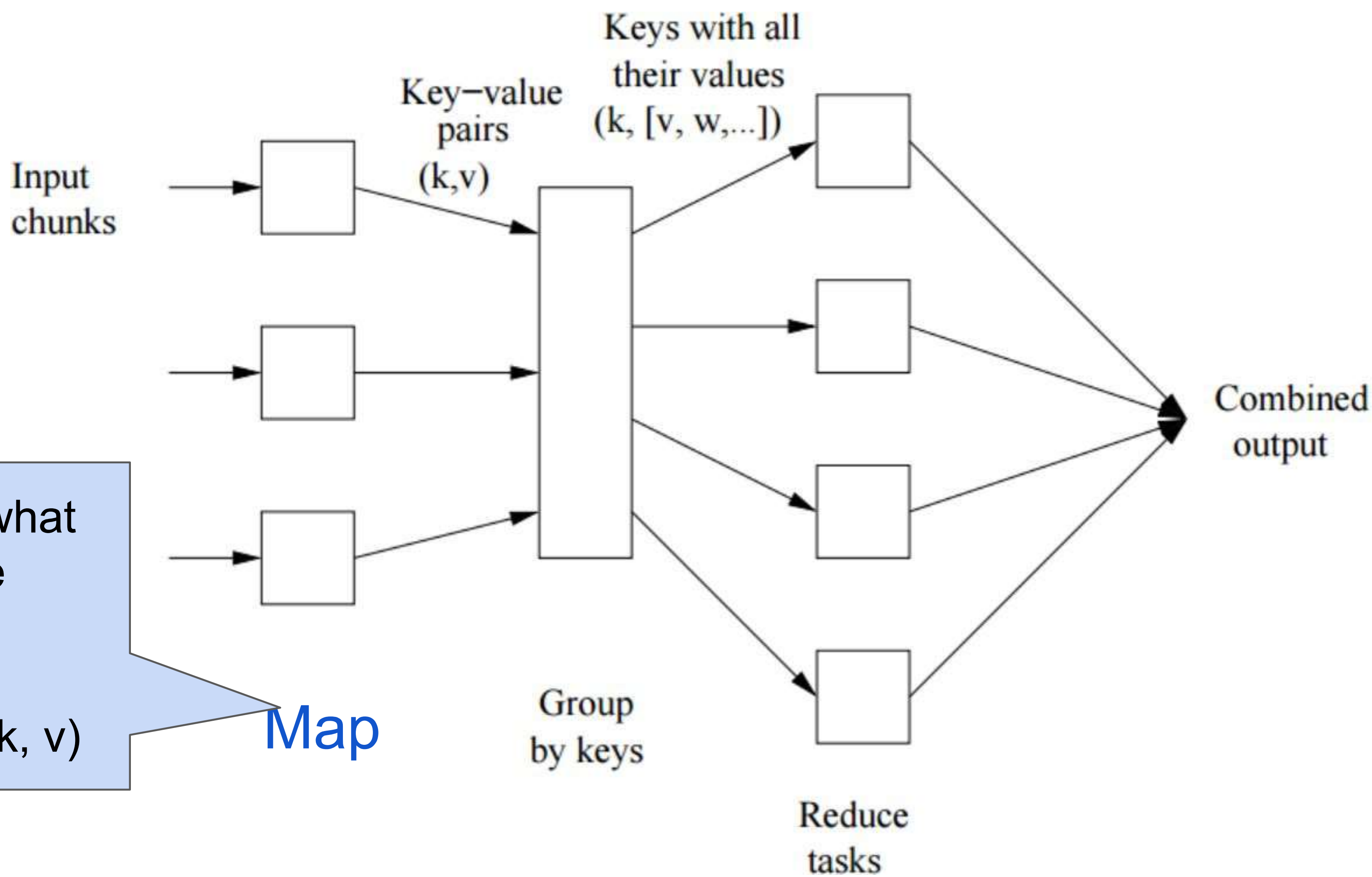
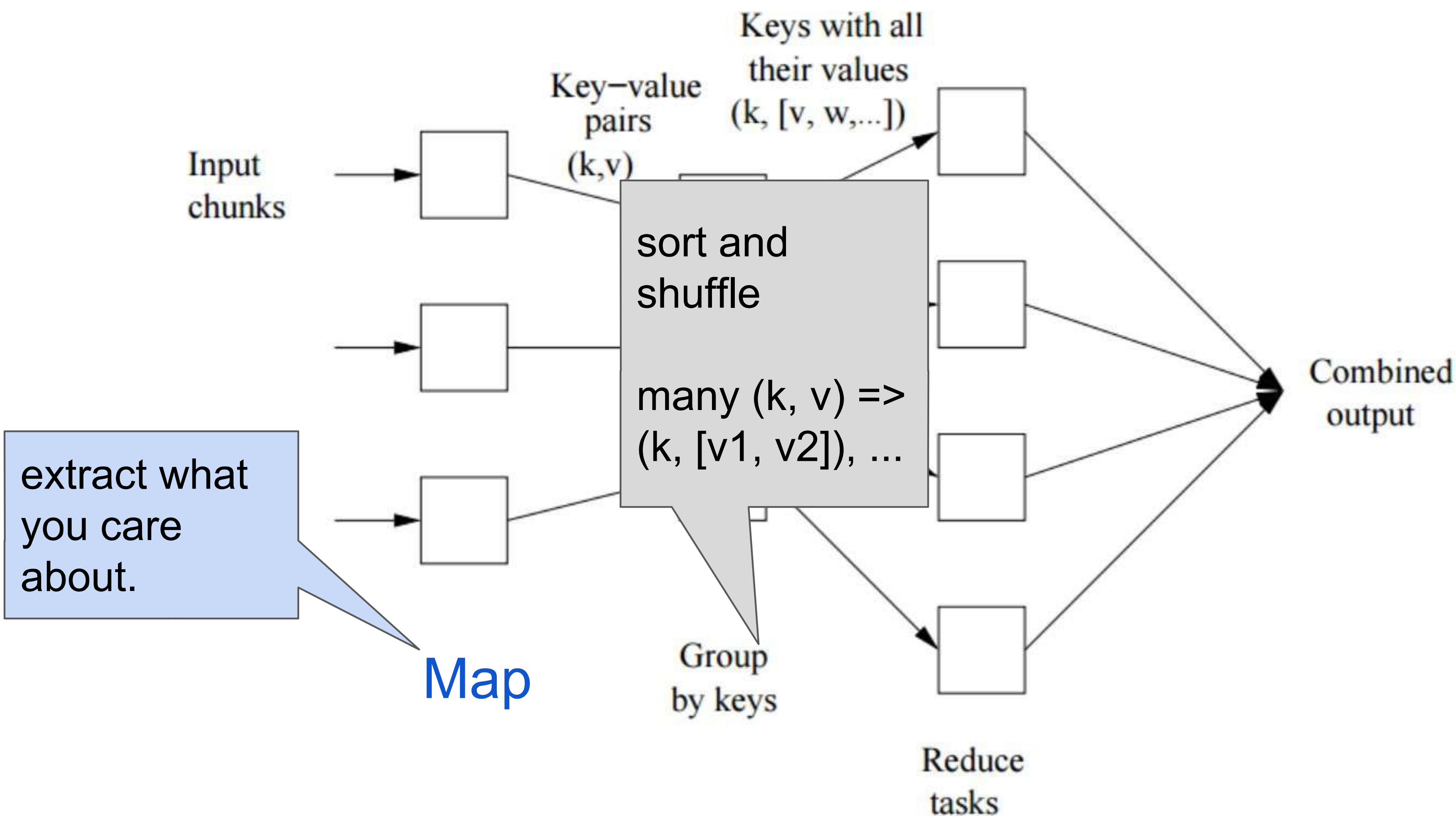


extract what you care about.

line => (k, v)

Map

What is MapReduce?



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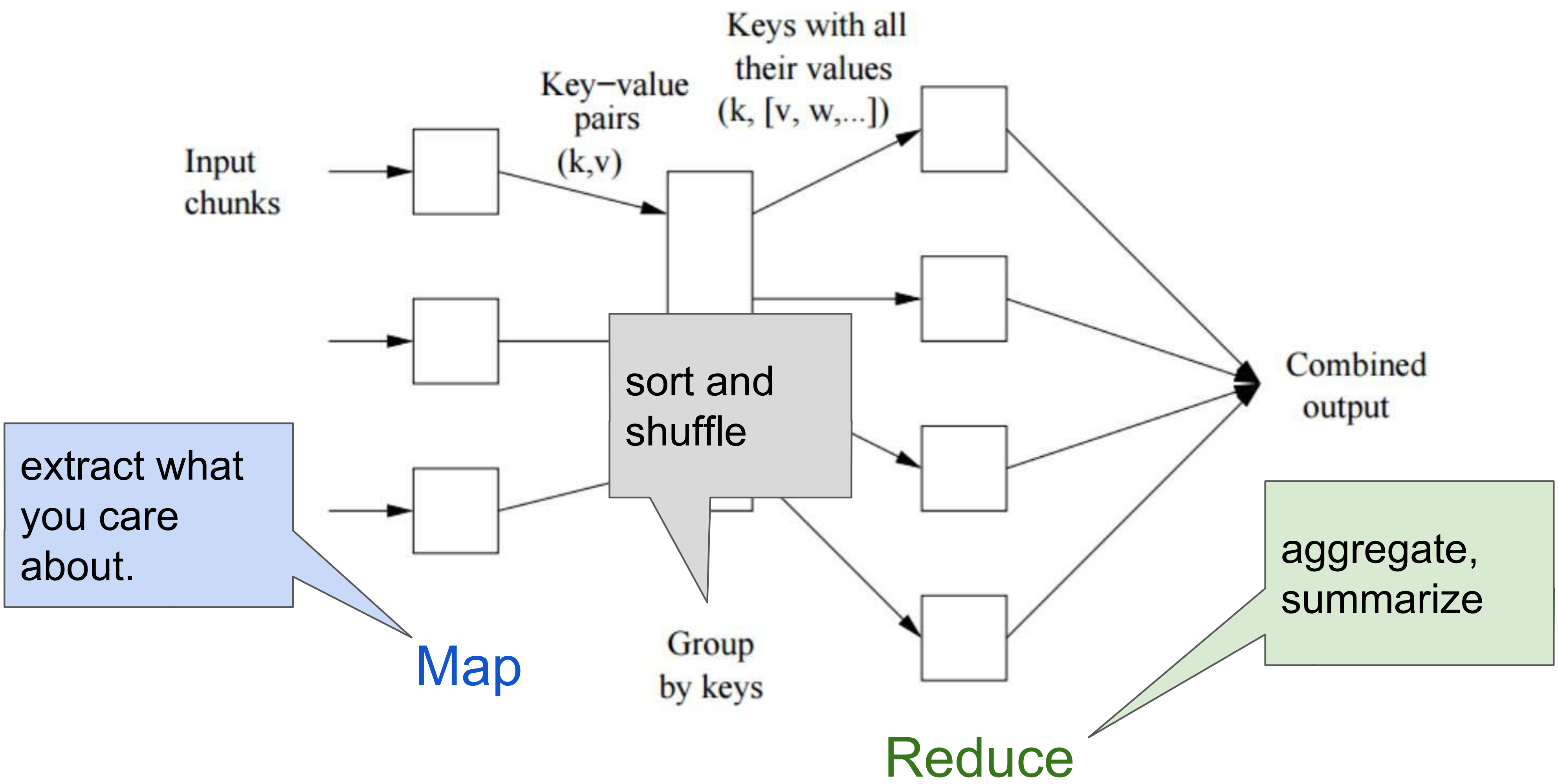

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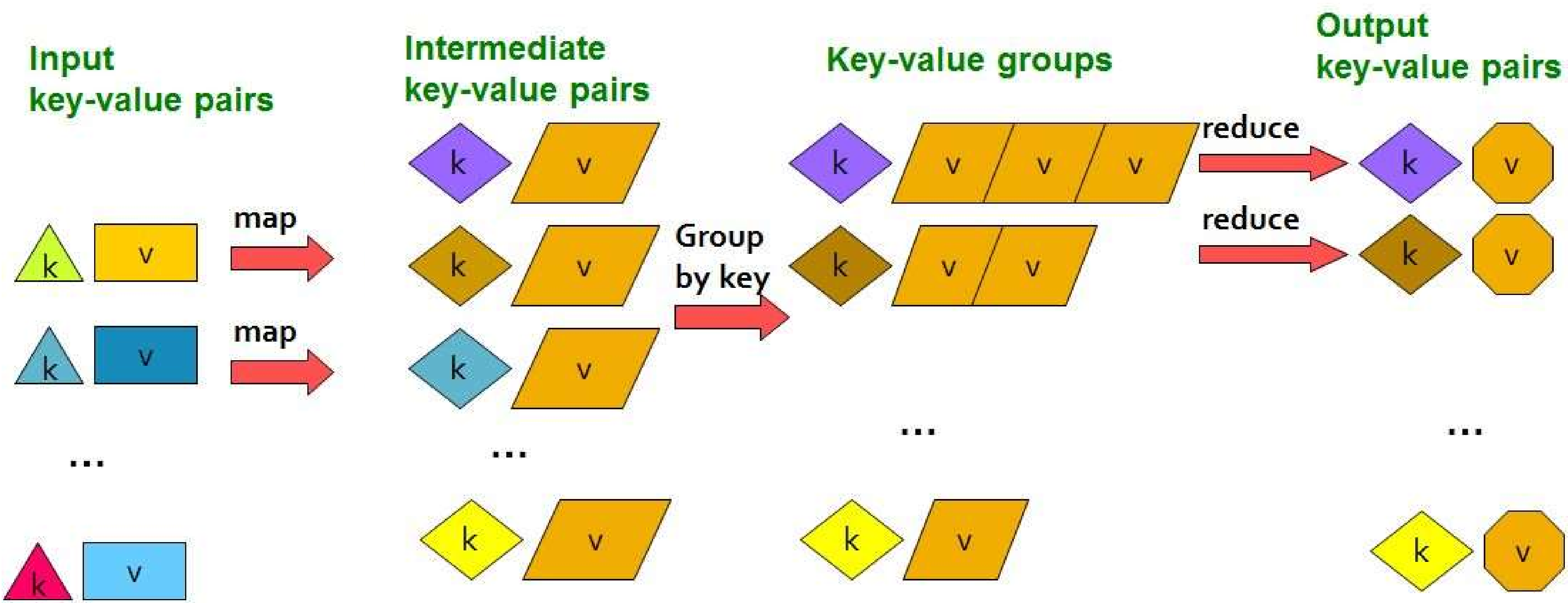

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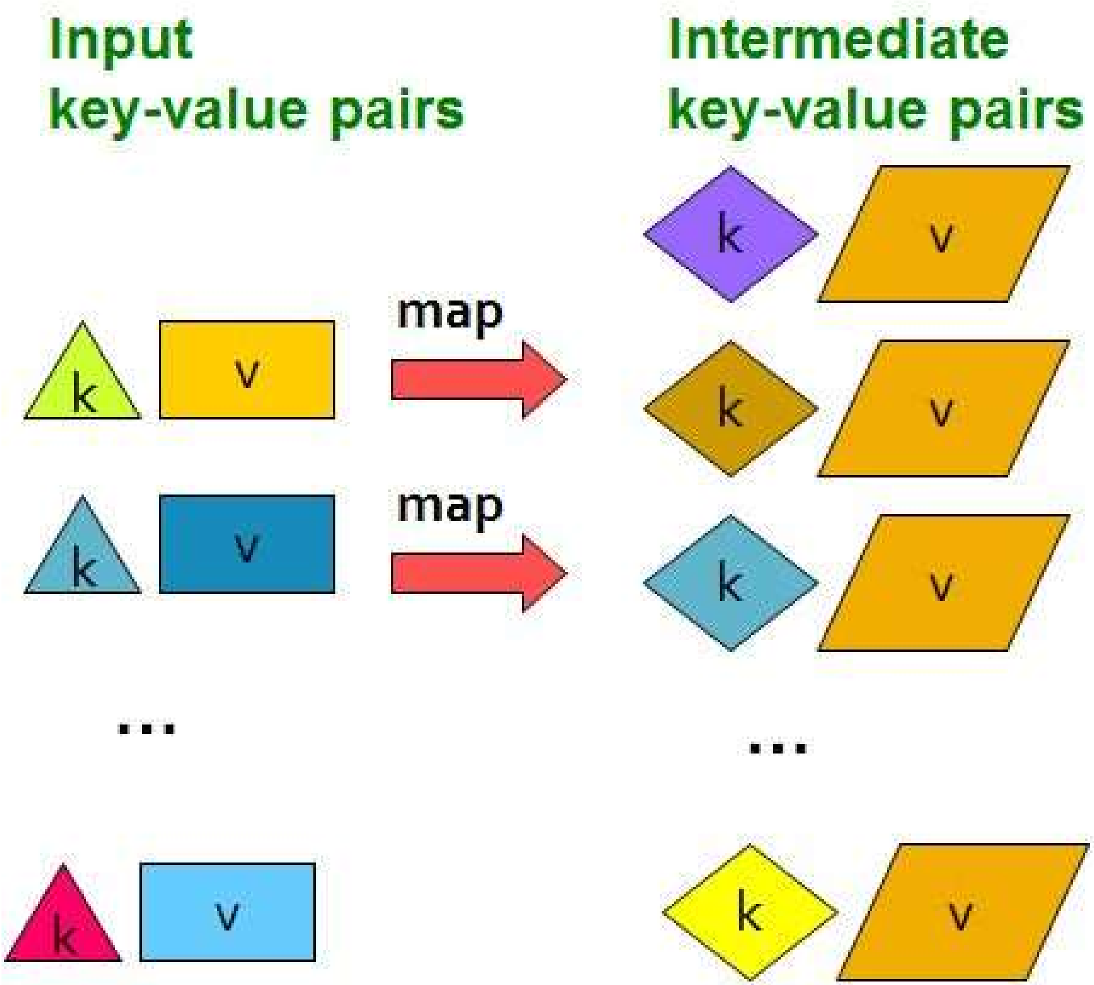
The Map Step



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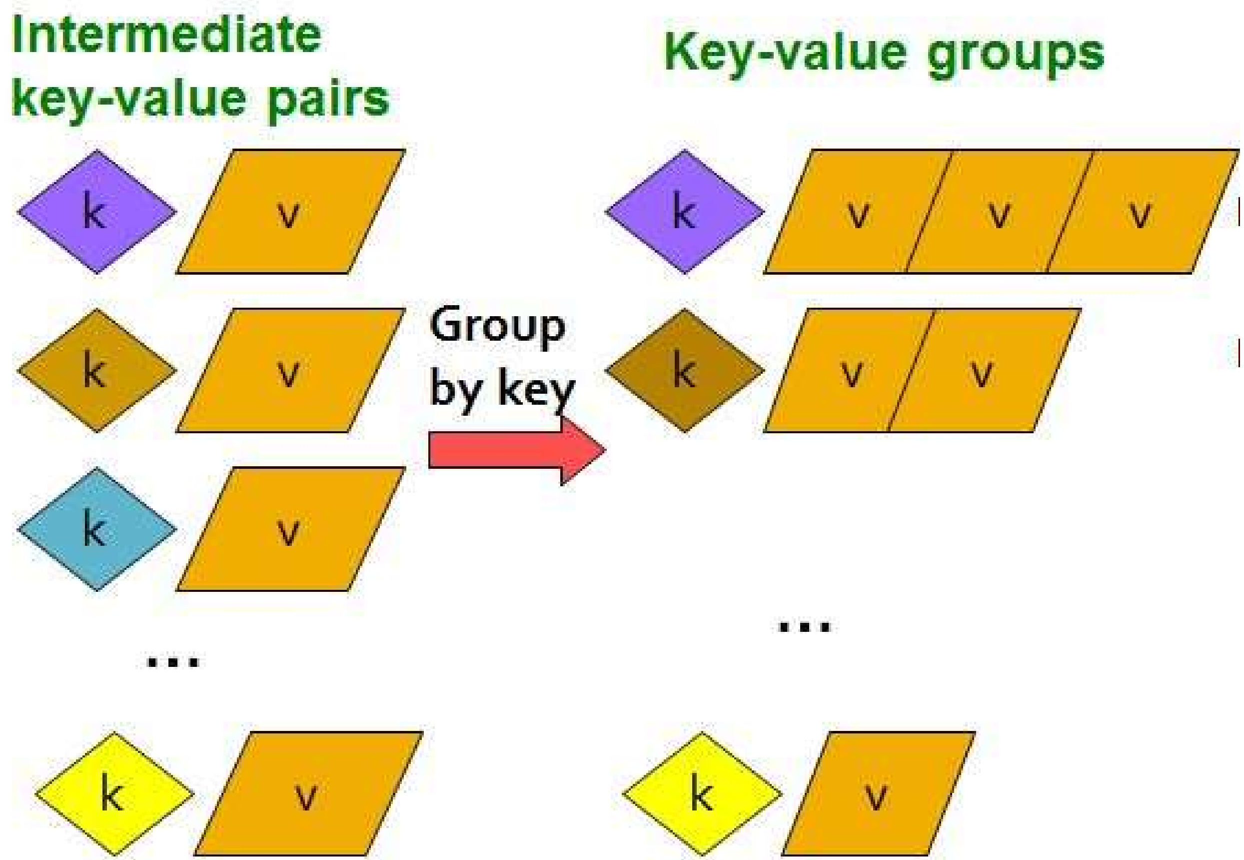
The Sort / Group By Step



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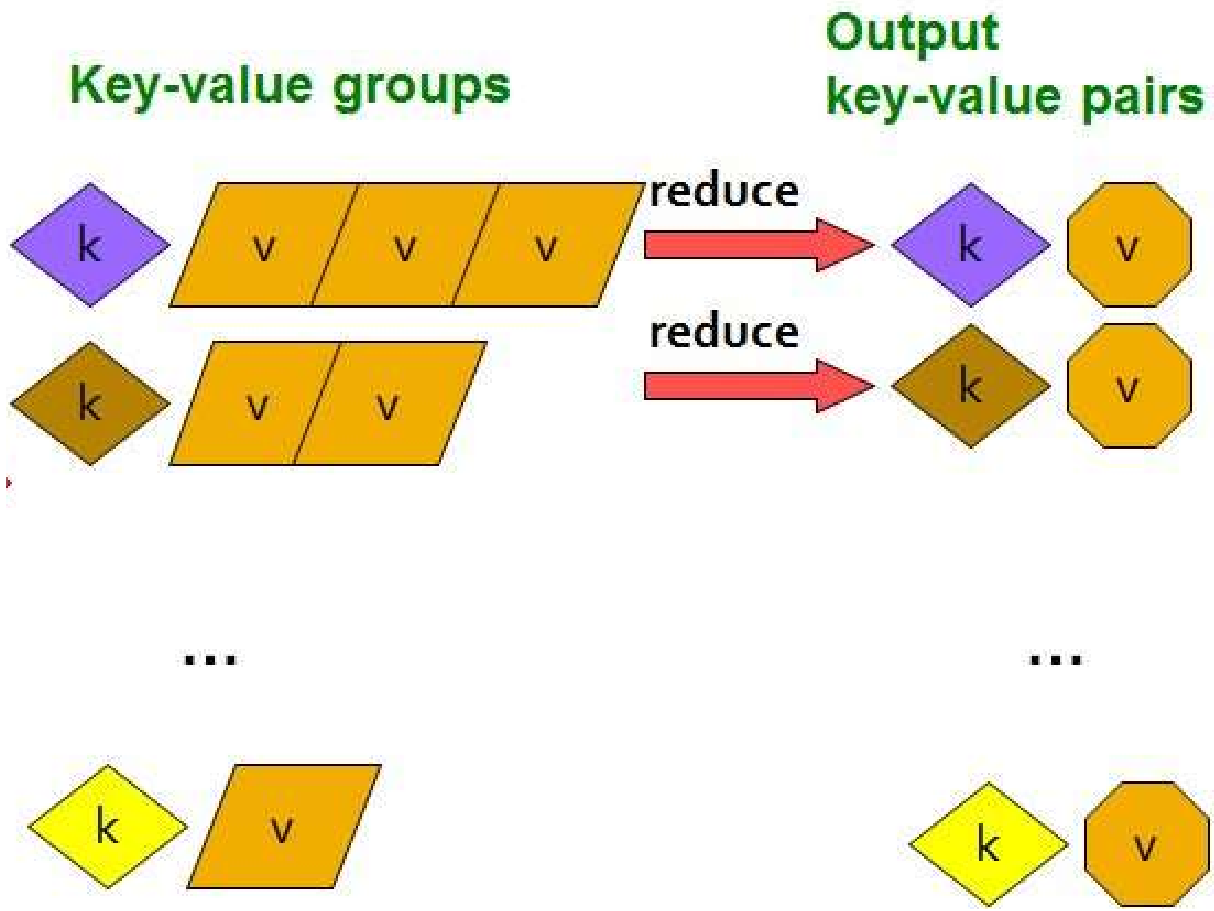
The Reduce Step



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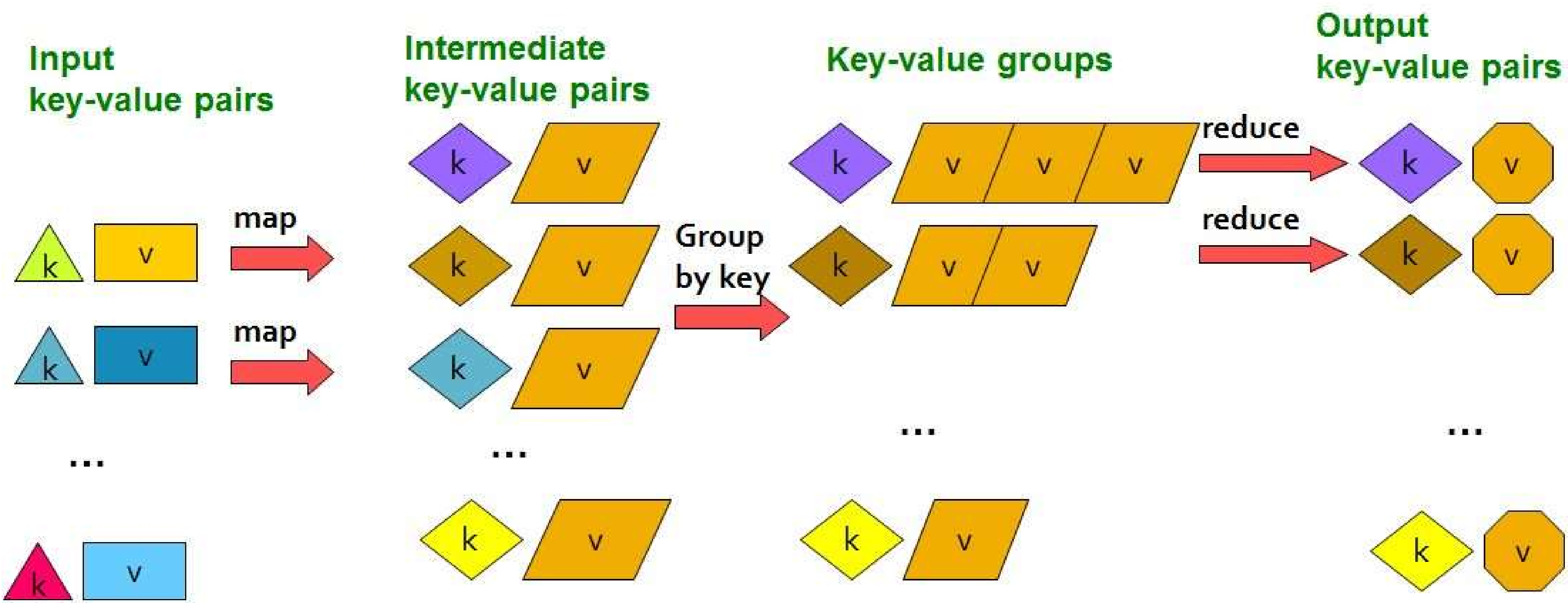

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What is MapReduce?

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: $(k', (v_1', v', \ldots)) \rightarrow (k', v'')^*$
(Written by programmer)

Example: Word Count

```
tokenize(document) | sort | uniq -C
```

Example: Word Count

```
tokenize(document) | sort | uniq -C
```

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

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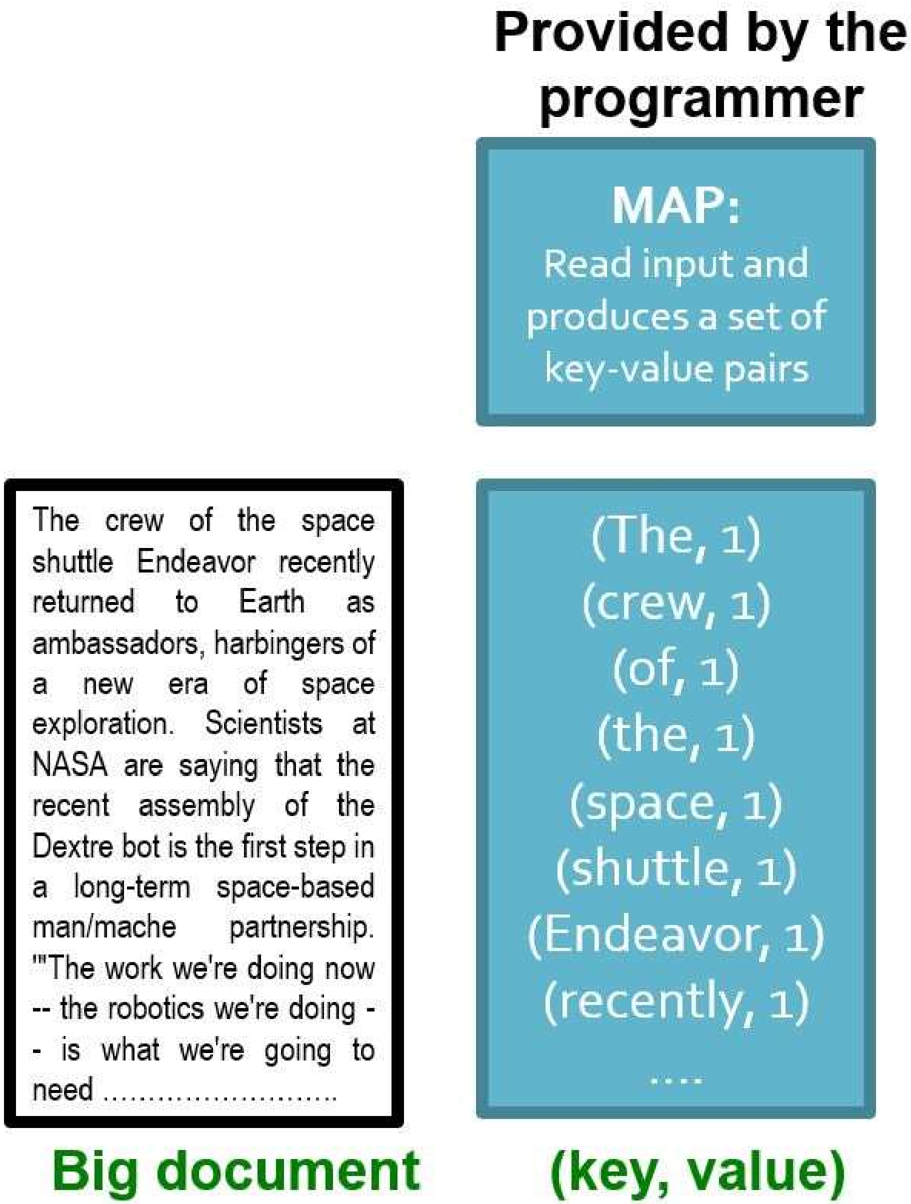
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(The, 1)
(crew, 1)
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently, 1)
....
Big document
(key, value)

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Group by key:
Collect all pairs with same key

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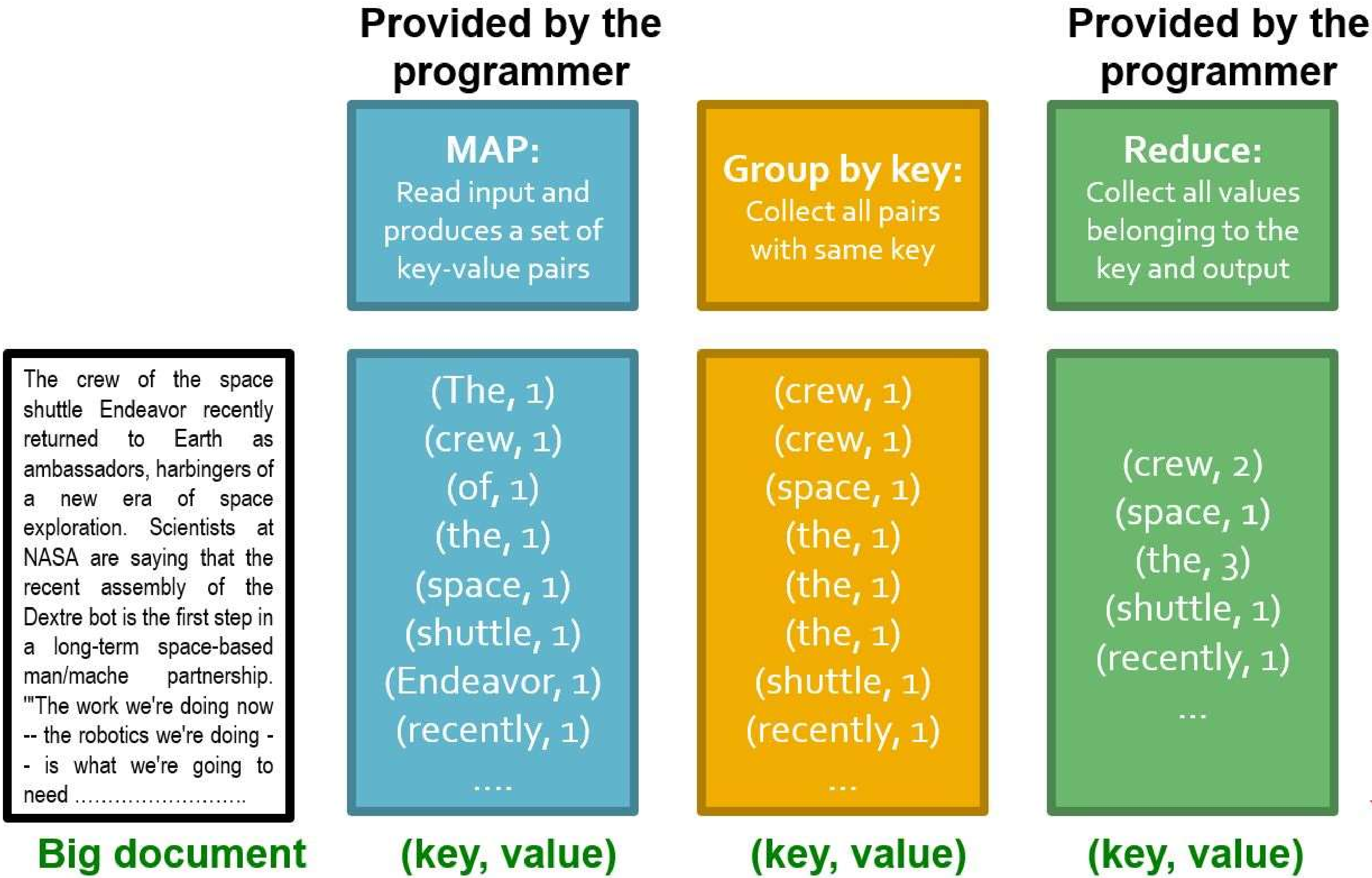
...

Big document | **(key, value)** | **(key, value)**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Big document
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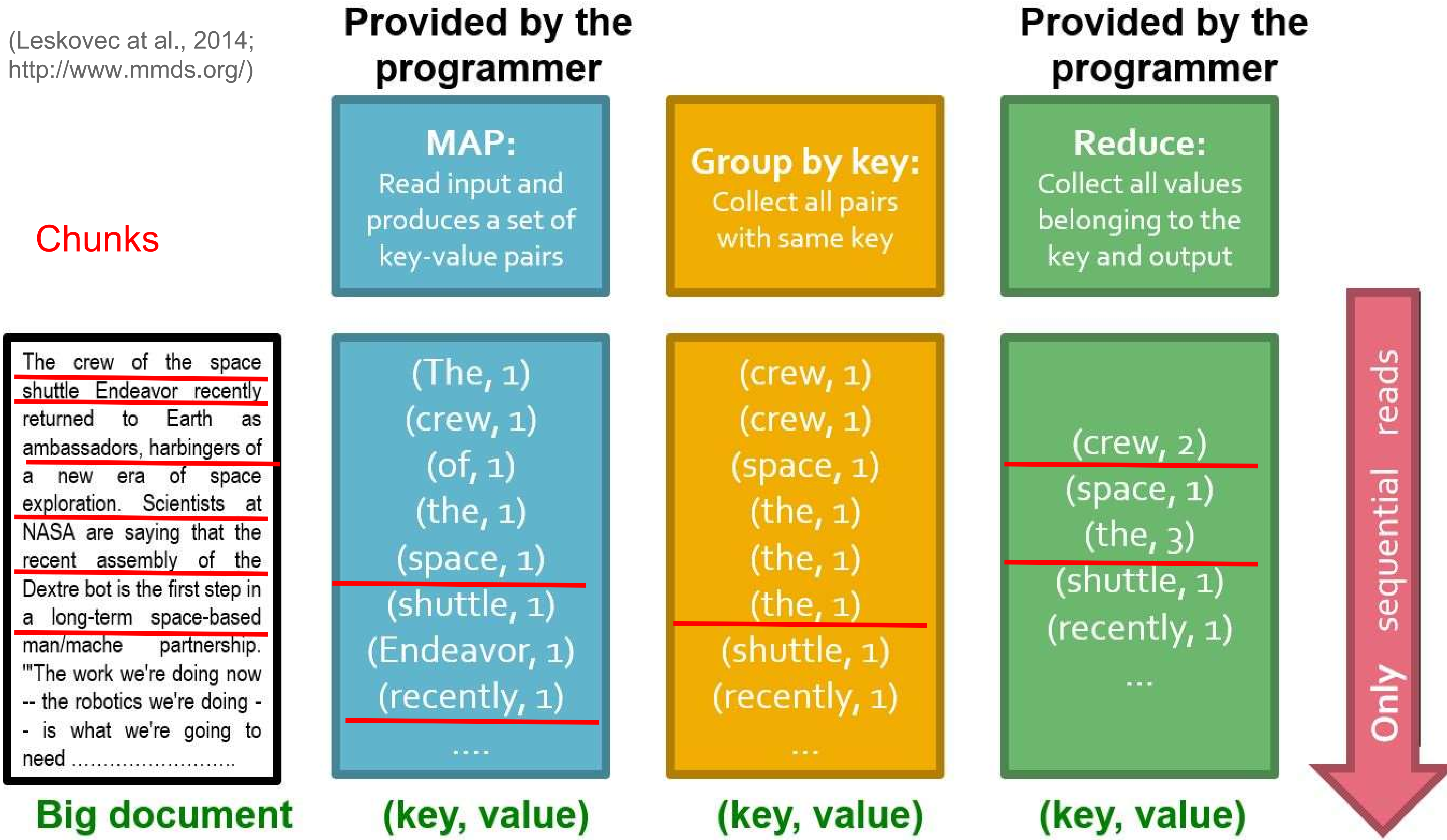
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Provided by the programmer
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Chunks
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...
Only sequential reads
Big document
(key, value)
(key, value)
(key, value)

Example: Word Count

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

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

Example: Word Count (version 1)

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


def reduce(k, vs):
    return len(vs)
```

Example: Word Count (version 1)

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def map(k, v):
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```

```
def tokenize(s):
    #simple version
    return s.split(‘ ‘)
```

```
def reduce(k, vs):
    return len(vs)
```

Example: Word Count (version 2)

```
def map(k, v):
    counts = dict()
    for w in tokenize(v):
        try:
            counts[w] += 1
        except KeyError:
            counts[w] = 1
    for item in counts.iteritems():
        yield item
```

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

```
def reduce(k, vs):
    return sum(vs)
```

sum of counts from different chunks

Challenges for IO Cluster Computing

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   Duplicate Data (Distributed FS)
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Example: Relational Algebra

Select

Project

Union, Intersection, Difference

Natural Join

Grouping

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return only those attribute tuples where condition C is true

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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

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```

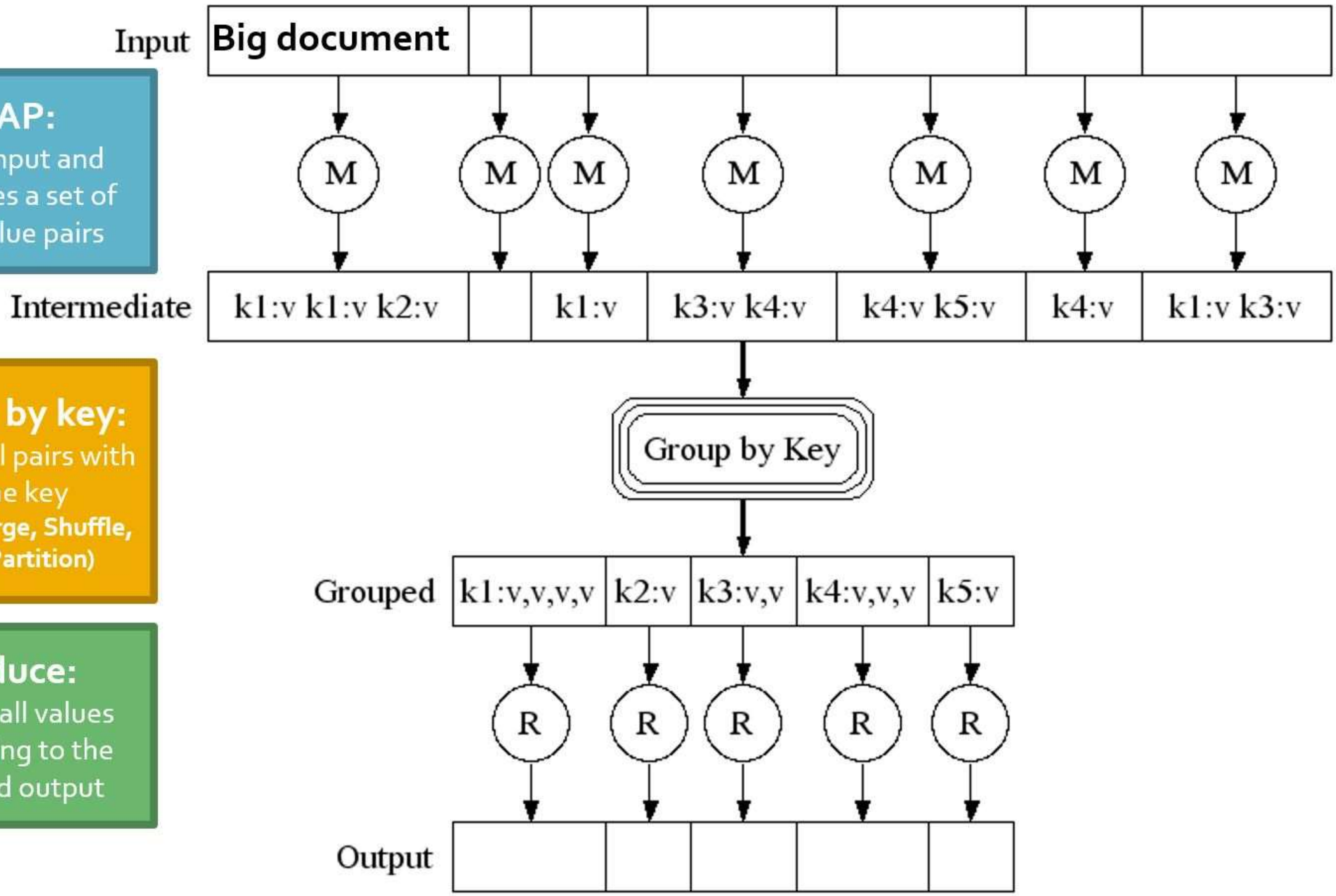
```
def reduce(k, vs):
    r1, r2 = [], []
    for (S, x) in vs: #separate rs
        if S == r1: r1.append(x)
        else: r2.append(x)
    for a in r1: #join as tuple
        for each c in r2:
            yield (Rjoin', (a, k, c)) #k is
```

Data Flow

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

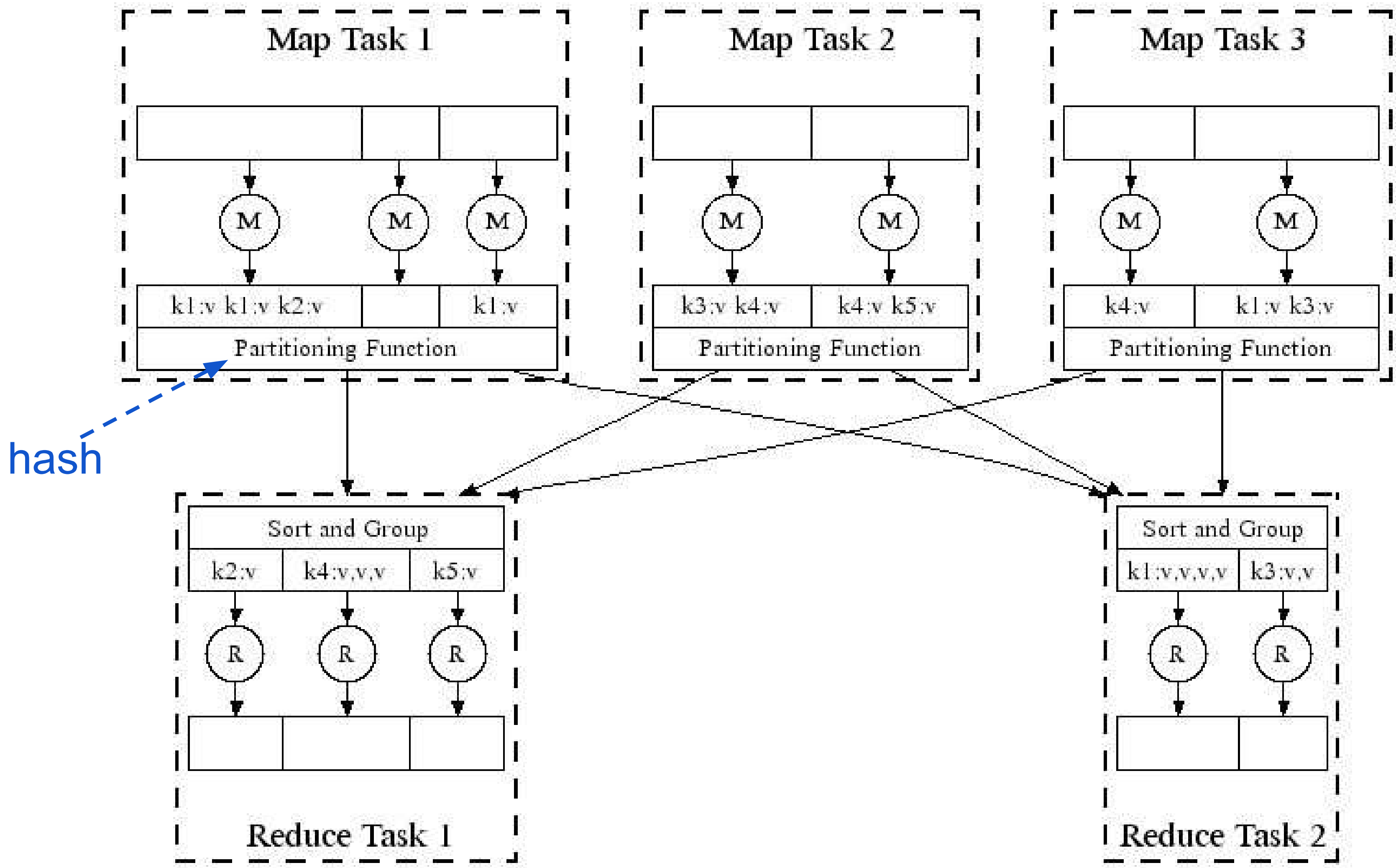
Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

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: In Parallel



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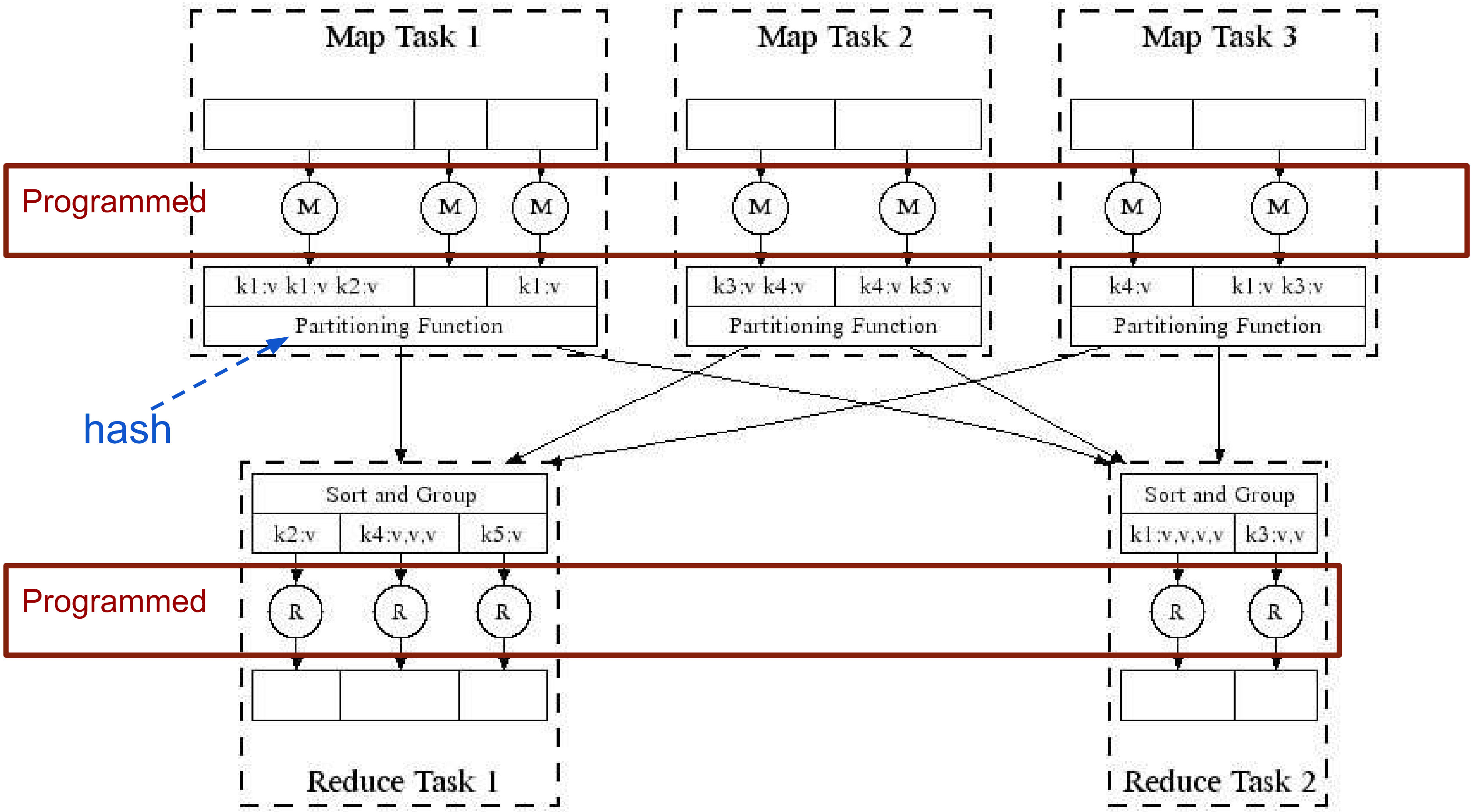

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Data Flow

DFS ⇨ Map ⇨ Map's Local FS ⇨ Reduce ⇨ DFS

Data Flow

MapReduce system handles:

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

- Restarts from node failures
- Inter-machine communication

Data Flow

DFS ⇒ MapReduce ⇒ 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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- 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 >> |nodes| ≈≈ |cores|

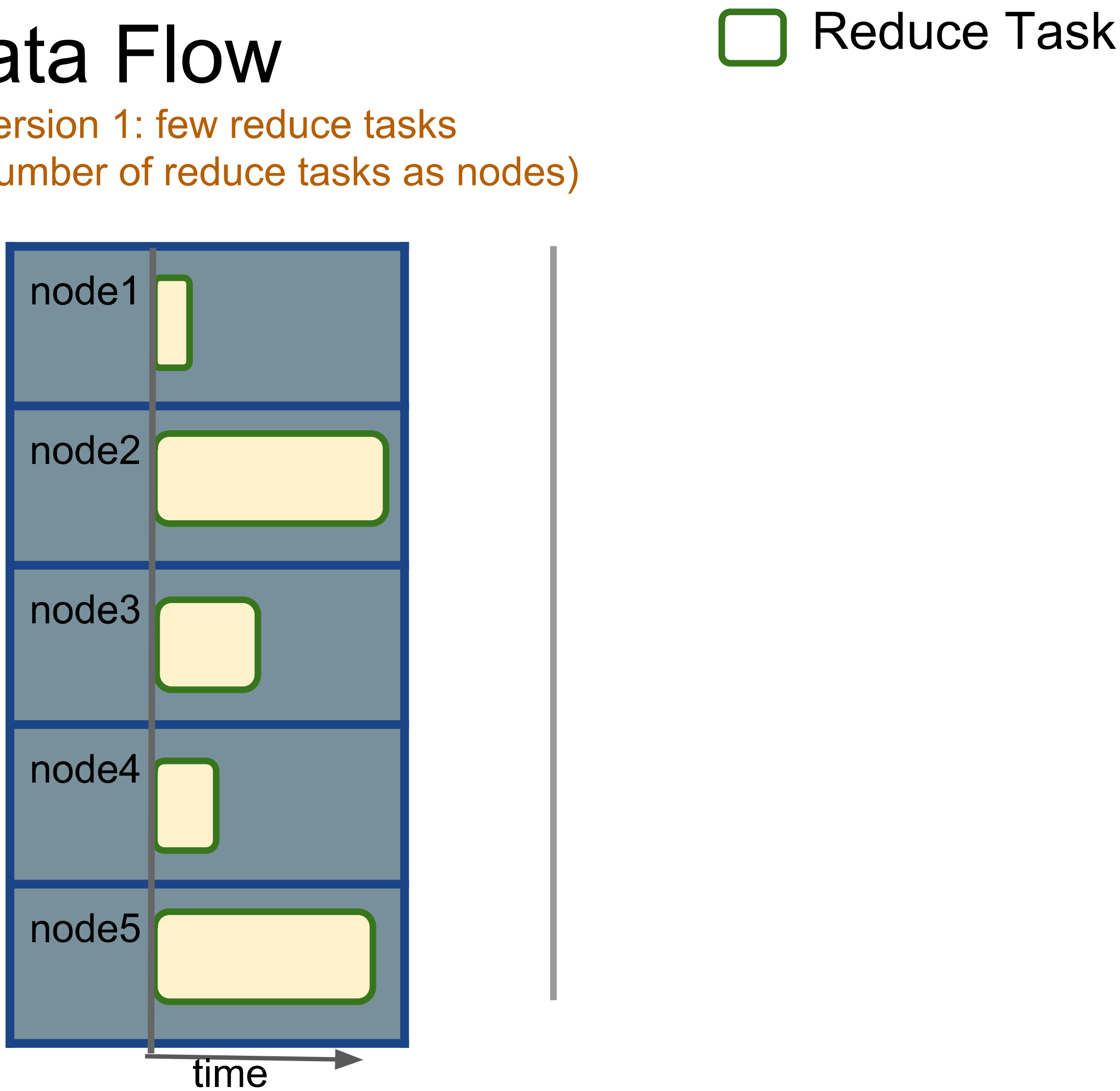
(better handling of node failures, better load balancing)

$R < M$

(reduces number of parts stored in DFS)

Data Flow

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

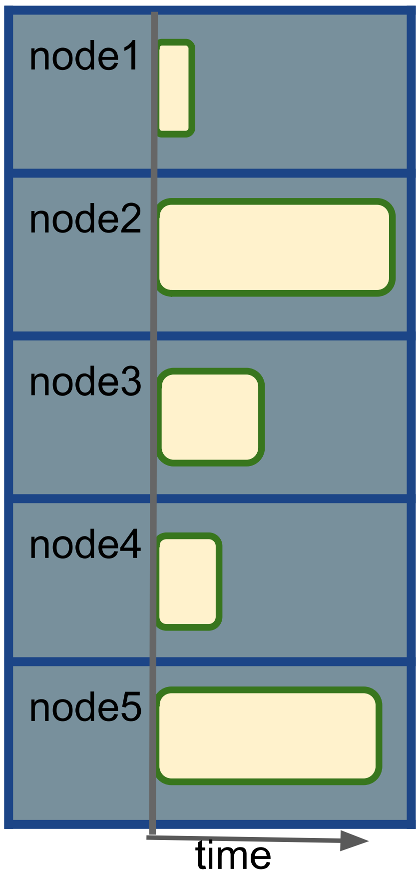


Reduce tasks represented by
time to complete task
(some tasks take much longer)

Data Flow

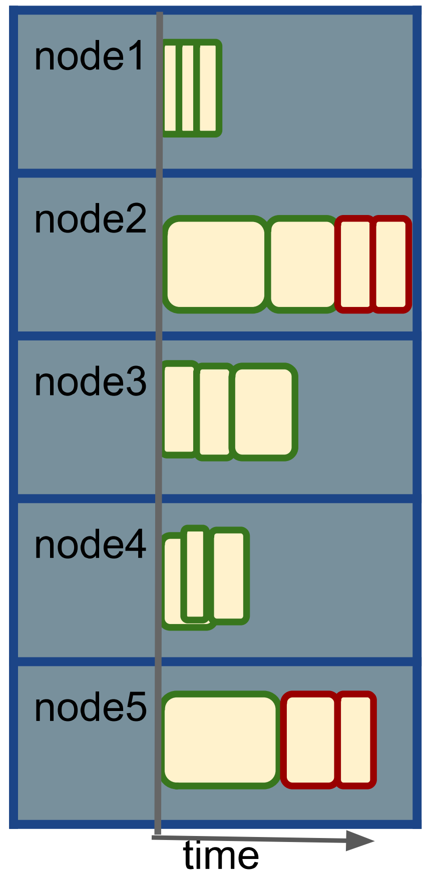
Reduce Task

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



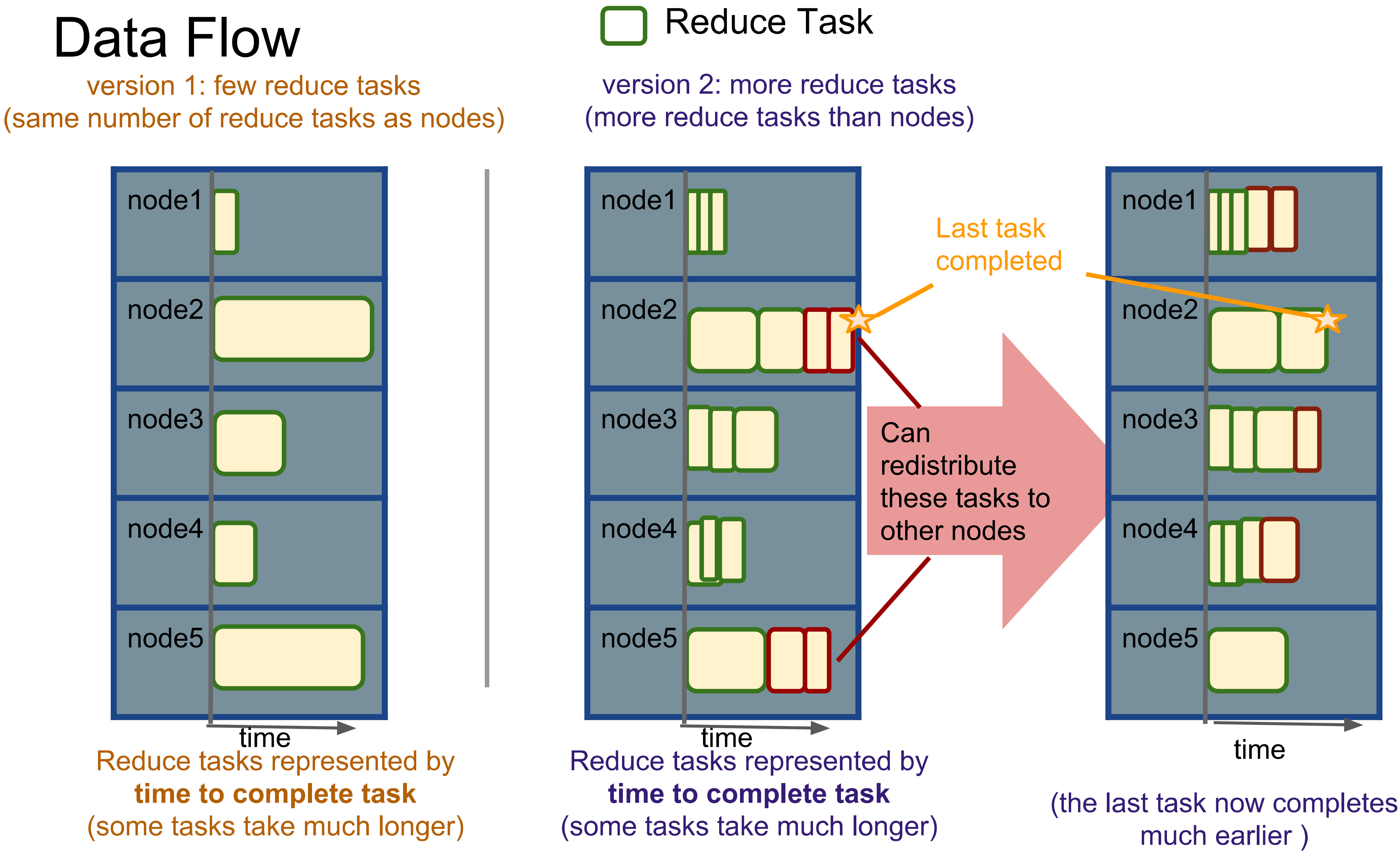
Reduce tasks represented by
time to complete task
(some tasks take much longer)

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

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

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

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

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.

Ultimate Goal: wall-clock Time

Communication Cost Model

How to assess performance?

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

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(sum of size of all map-to-reducer files)

(2) Communication: Moving key, value pairs

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.

Ultimate Goal: wall-clock Time

Example: 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 ⇨ ?

Example: Natural Join

R, S: Relations (Tables)   *R(A, B)* ⋈ *S(B, C)*

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

```
def map(k, v):
    if k=="R1":
        (a, b) = v
        yield (b,(R1,a))
    if k=="R2":
        (b,c) = v
        yield (b,(R2,c))
```

```
def reduce(k, vs):
    r1, r2 = [], []
    for (rel, x) in vs: #separate rs
        if rel == 'R': 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
```

Example: Natural Join

R, S: Relations (Tables)   *R(A, B)* ⋈ *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)

Last Notes: Further Considerations for MapReduce

- Performance Refinements:
  - Backup tasks (aka speculative tasks)
    - Schedule multiple copies of tasks when close to the end to mitigate certain nodes running slow.

  - Combiners (like word count version 2 but done via reduce)
    - Run reduce right after map from same node before passing to reduce
    - Reduces communication cost

  - Override partition hash function

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