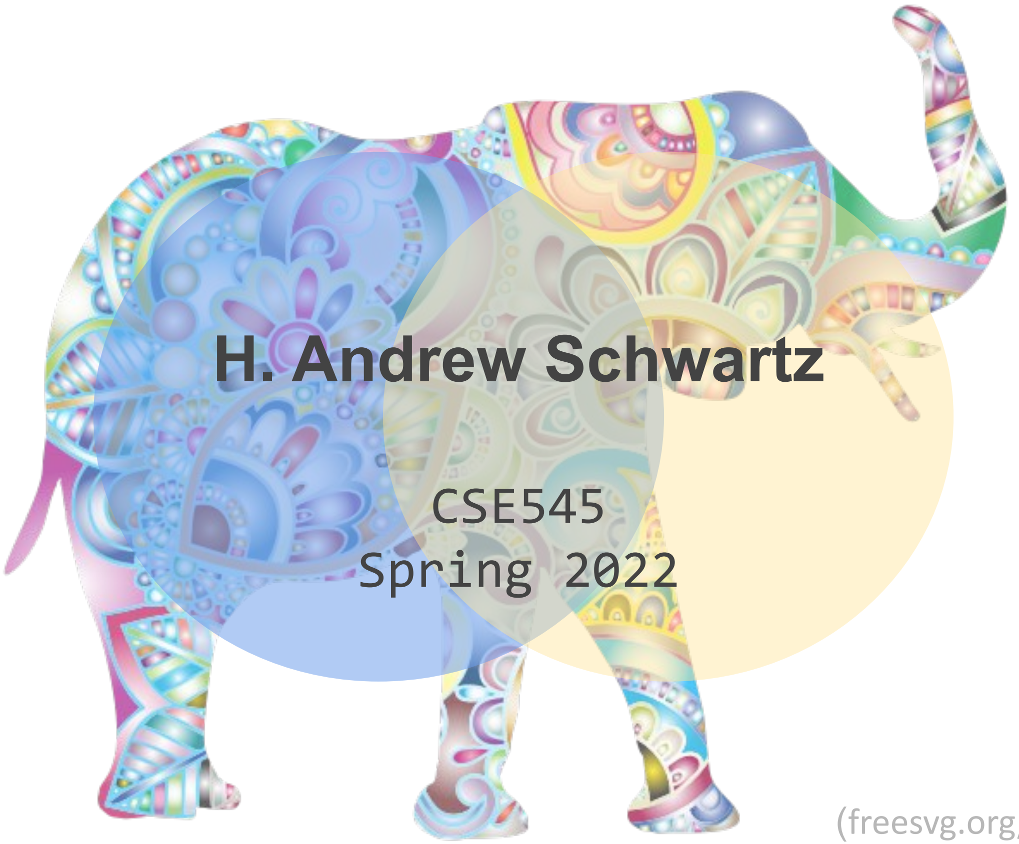
“Hadoop”:
A Distributed Architecture, FileSystem, & MapReduce



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CSE545
Spring 2022

(freesvg.org/1534373472)

Big Data Analytics, The Class

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

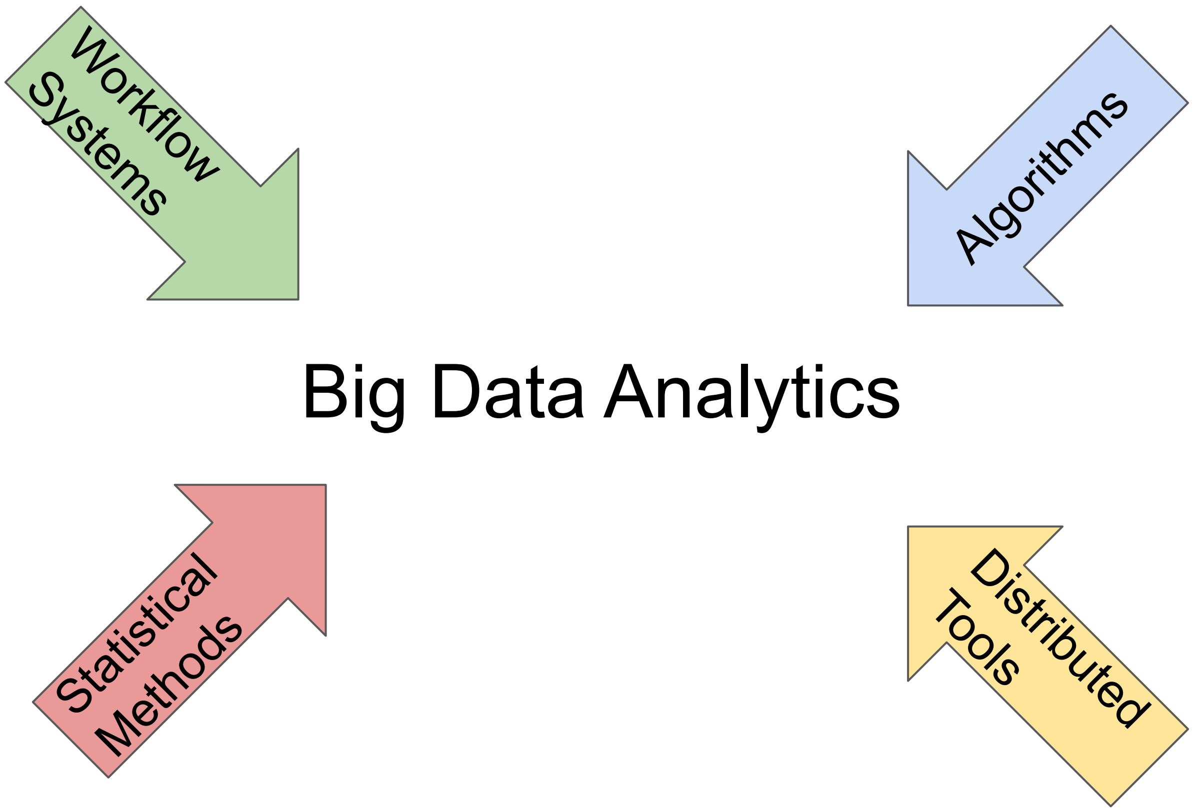
Data Frameworks

- 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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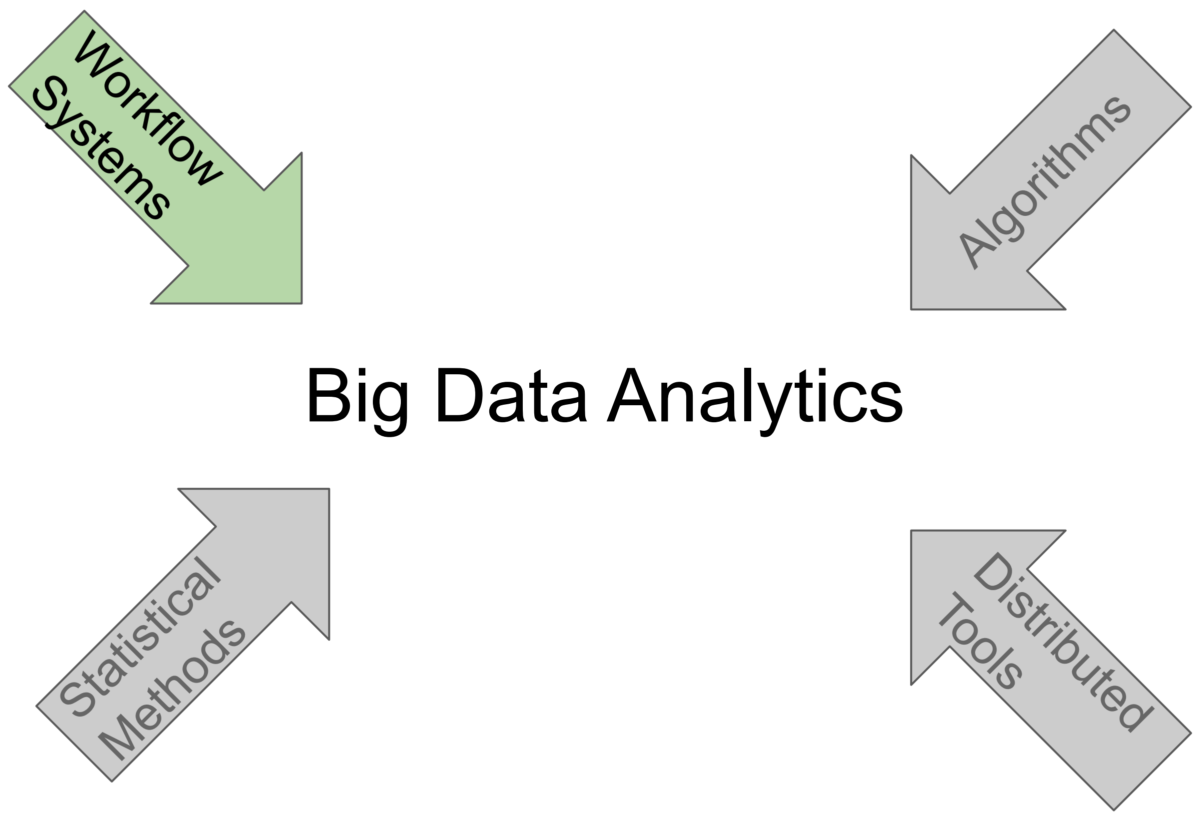
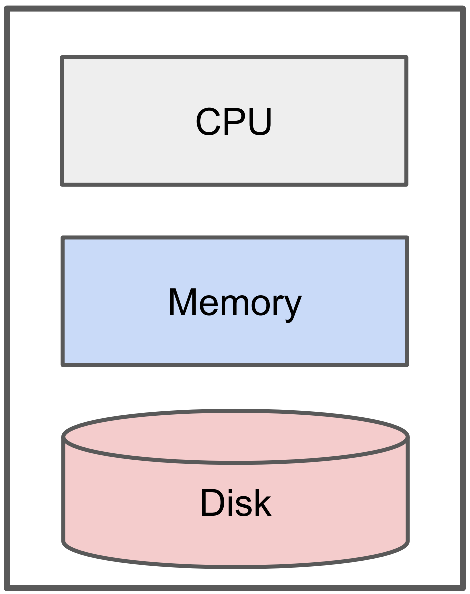


Classical Data Analytics



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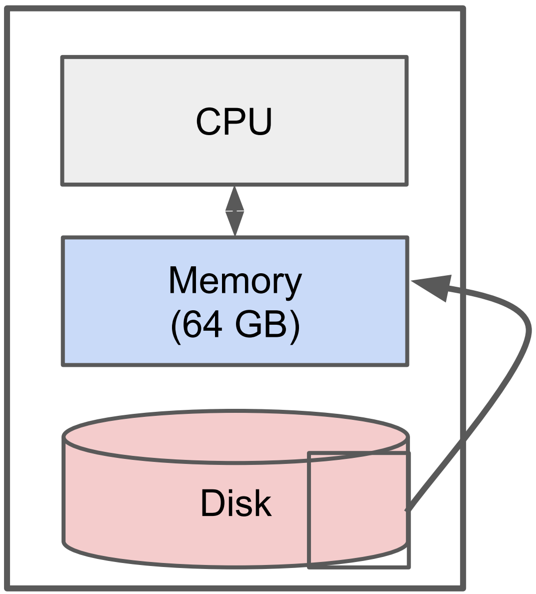

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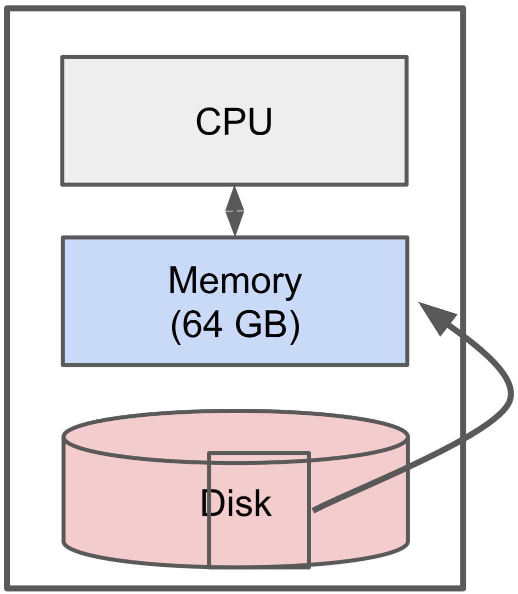

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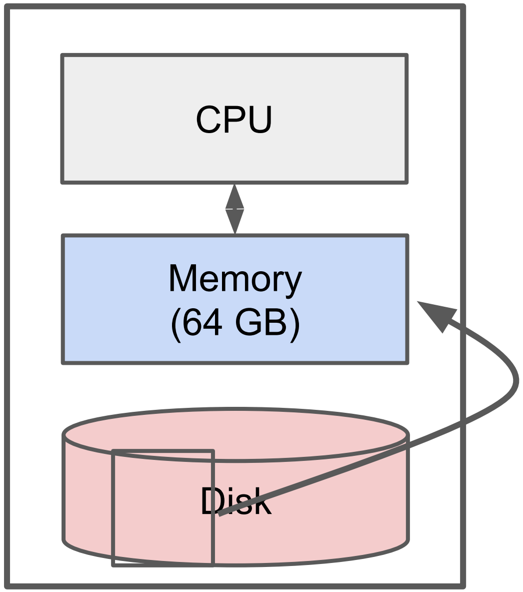
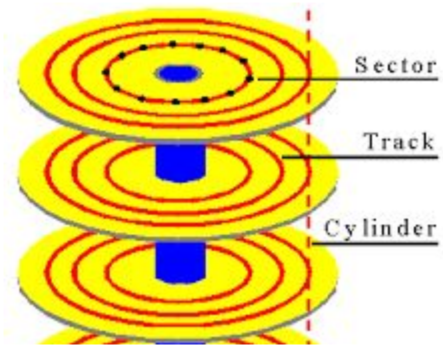


IO Bounded

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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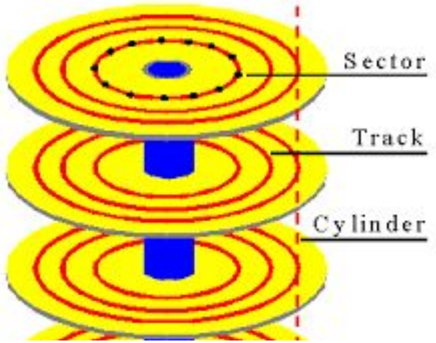
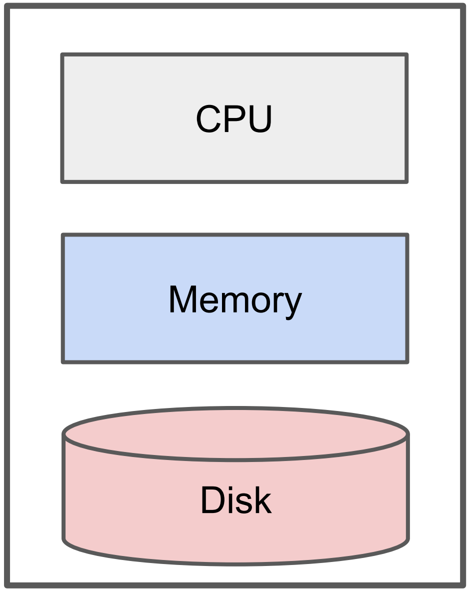


IO Bound: biggest performance bottleneck is reading / writing to disk.

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

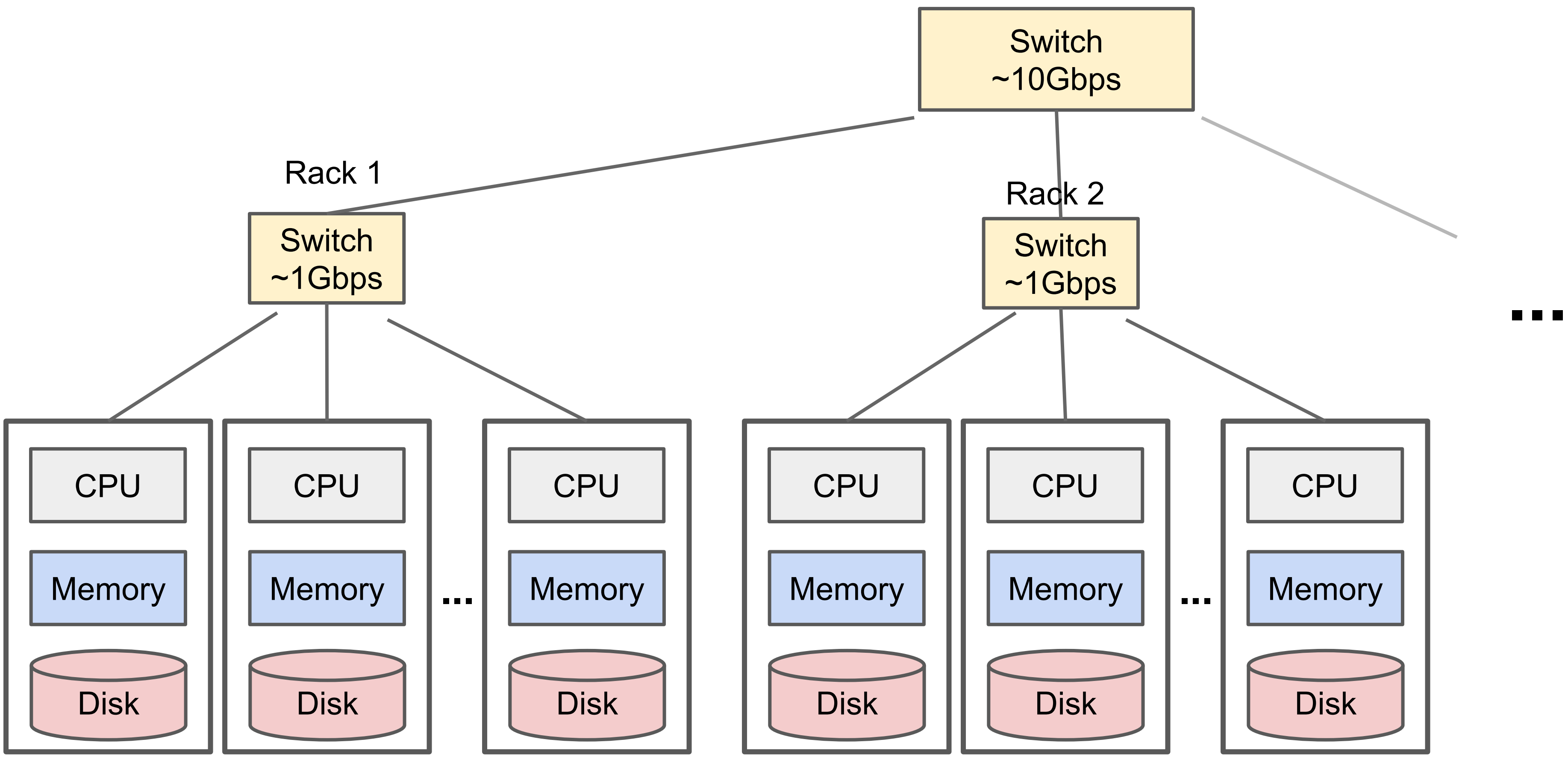
Classical limitation: Still bounded when needing to process all of a large file.

Classical Big Data

How to solve?

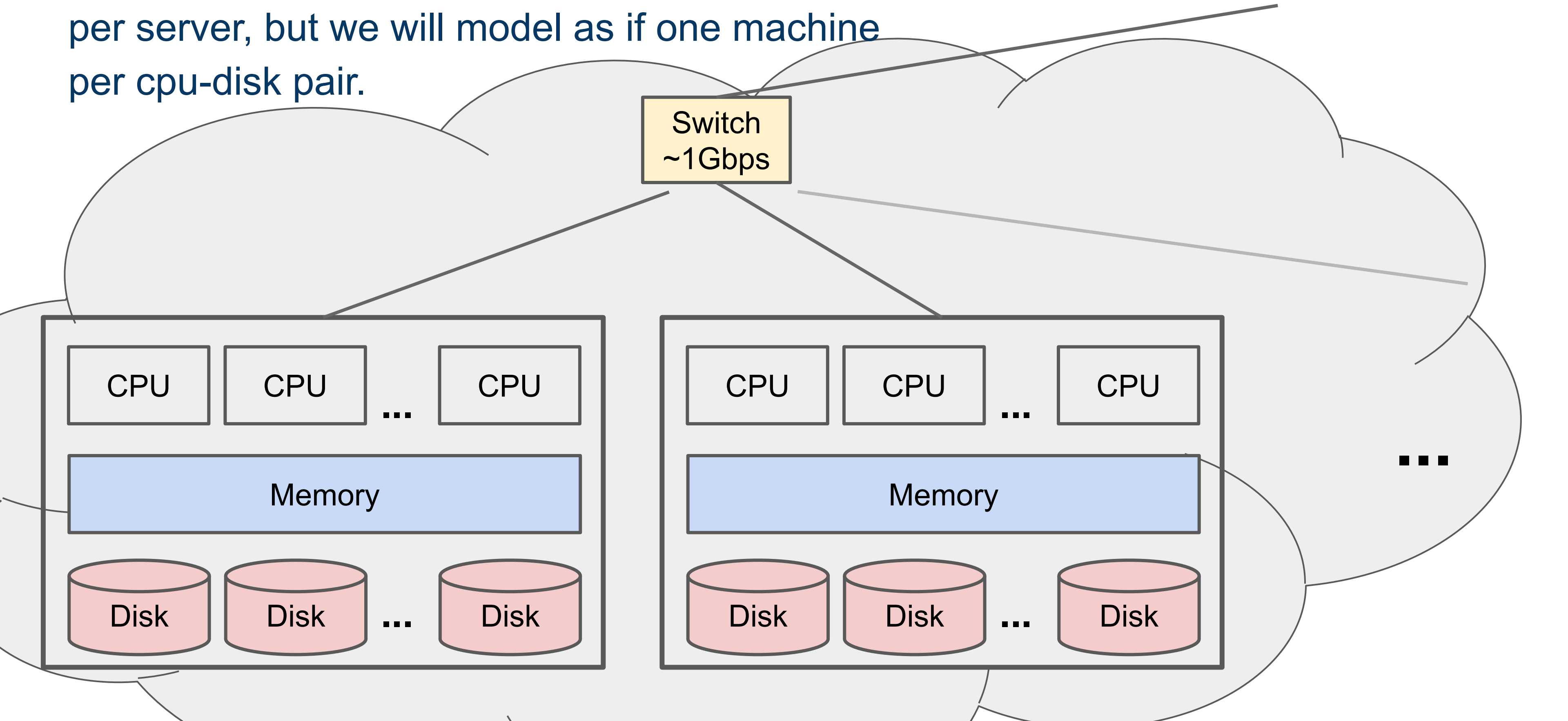
Classical limitation: Still bounded when needing to process all of a large file.

Distributed Architecture

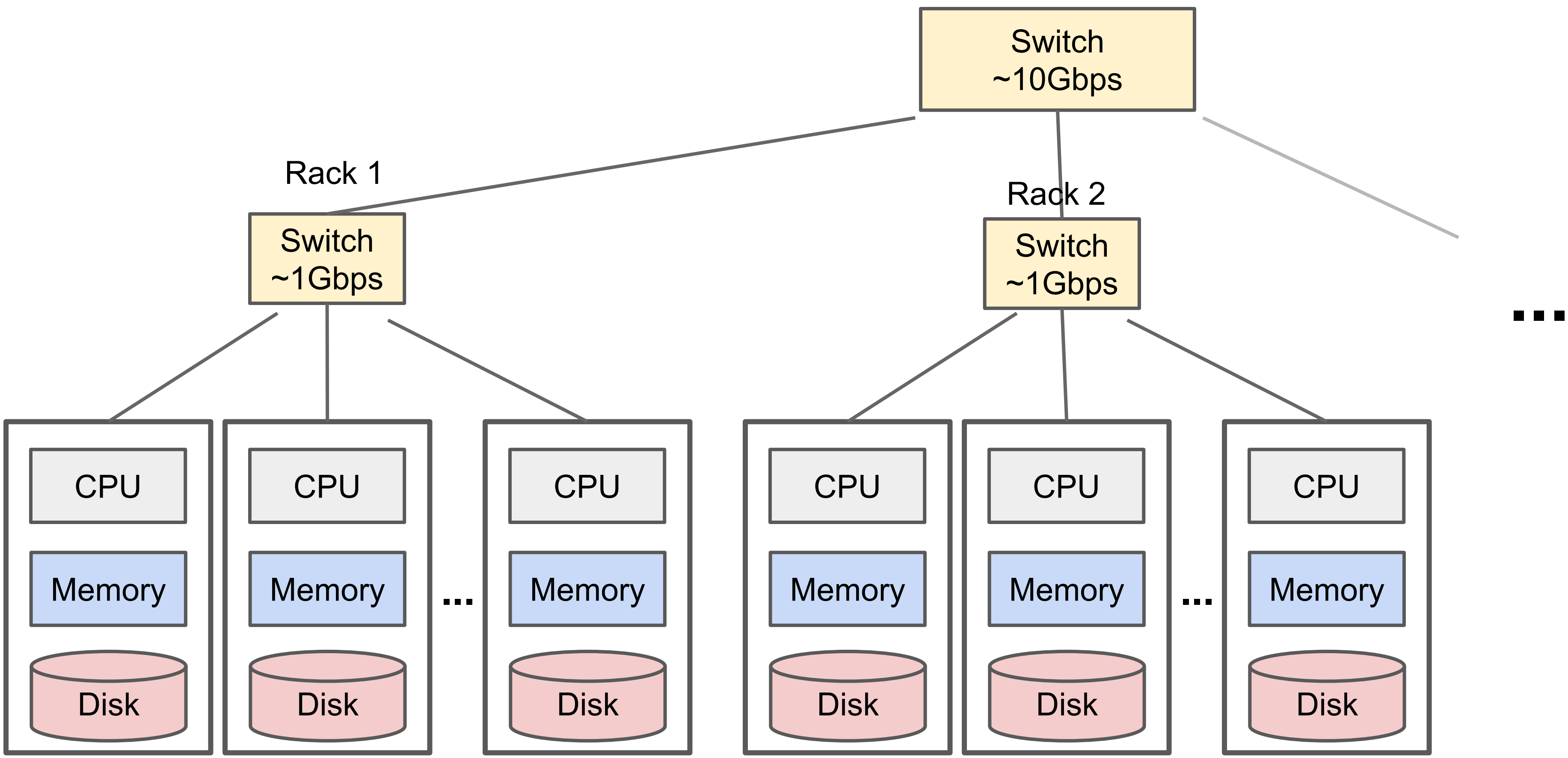


Distributed Architecture

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 with MapReduce accomplishes all!

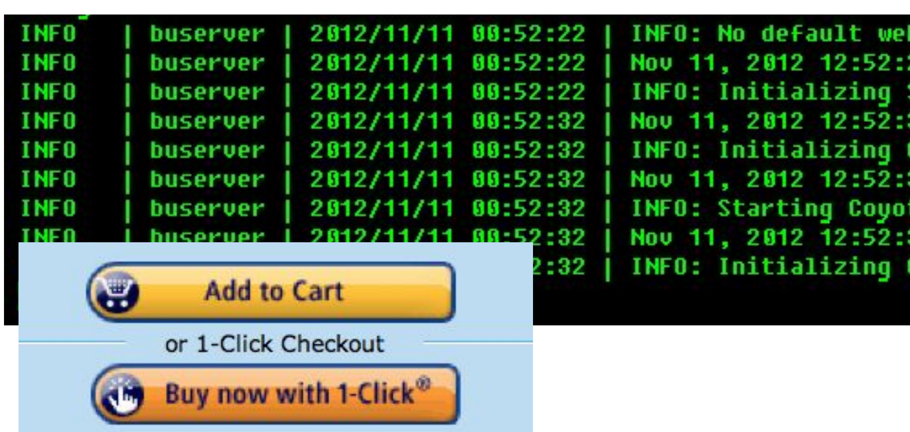
Distributed Filesystem

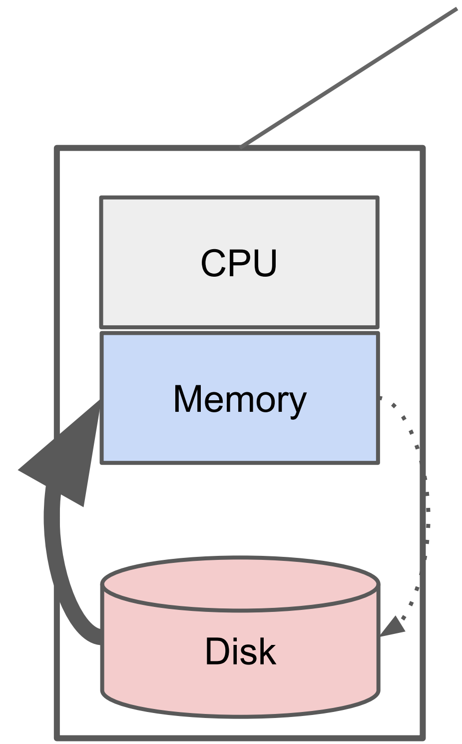
The effectiveness of MapReduce, Spark, and other distributed processing systems is in part simply due to use of a <u>distributed filesystem!</u>

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)

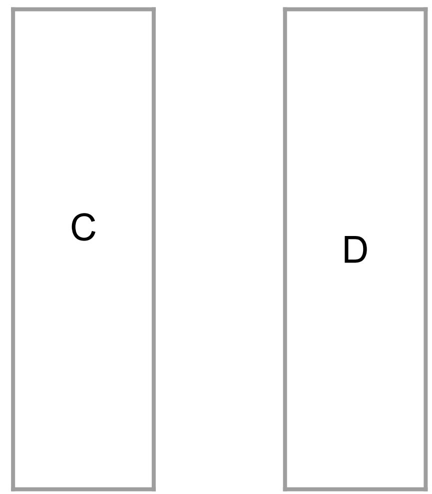




Distributed Filesystem

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

C, D: Two different files



https://opensource.com/life/14/8/intro-apache-hadoop-big-data

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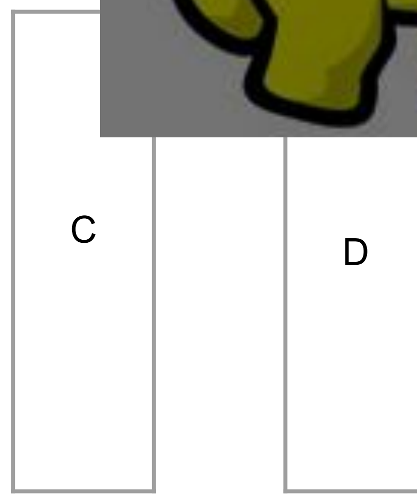

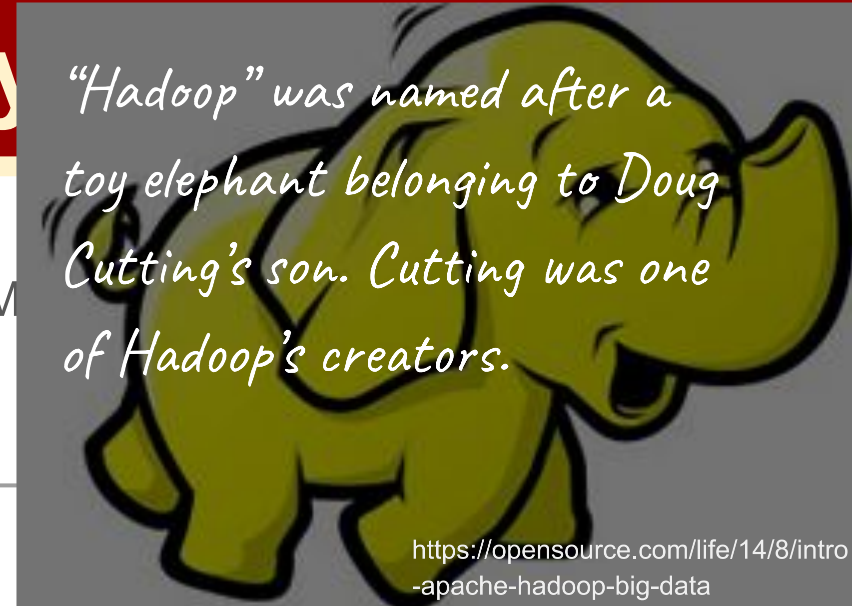

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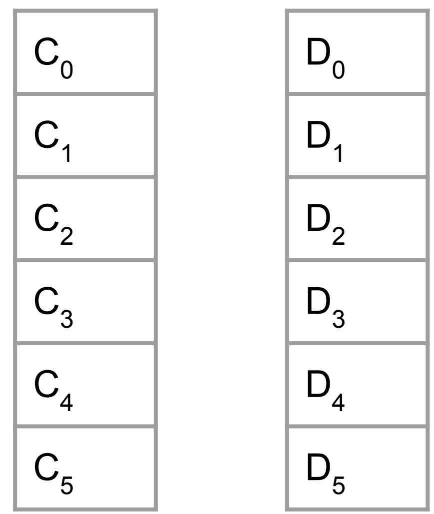
C, D: Two different files; break into chunks (or "partitions"):



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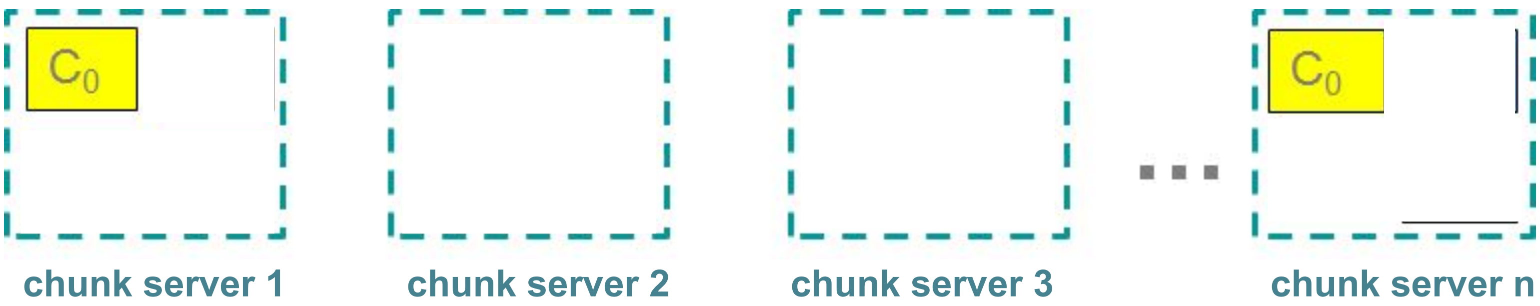

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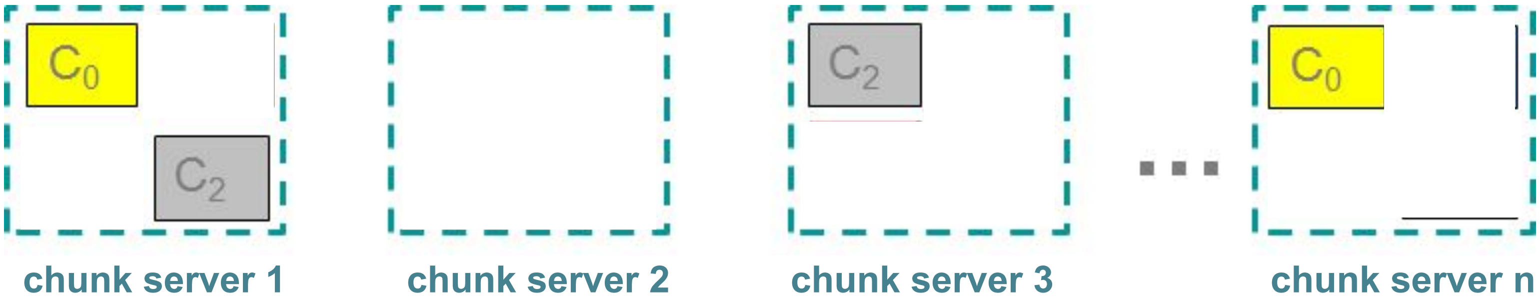

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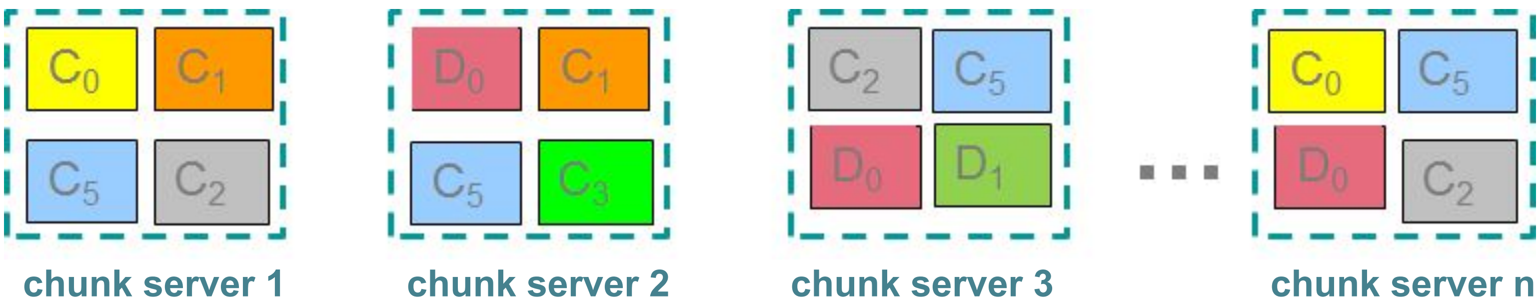

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Distributed Filesystem

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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Components of a Distributed Filesystem

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Name node (aka master node)

Stores metadata about where files are stored

Might be replicated or distributed across data nodes.

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Components of a Distributed Filesystem

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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)

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What is MapReduce

noun.1* - A *style of programming

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

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E.g. counting words:

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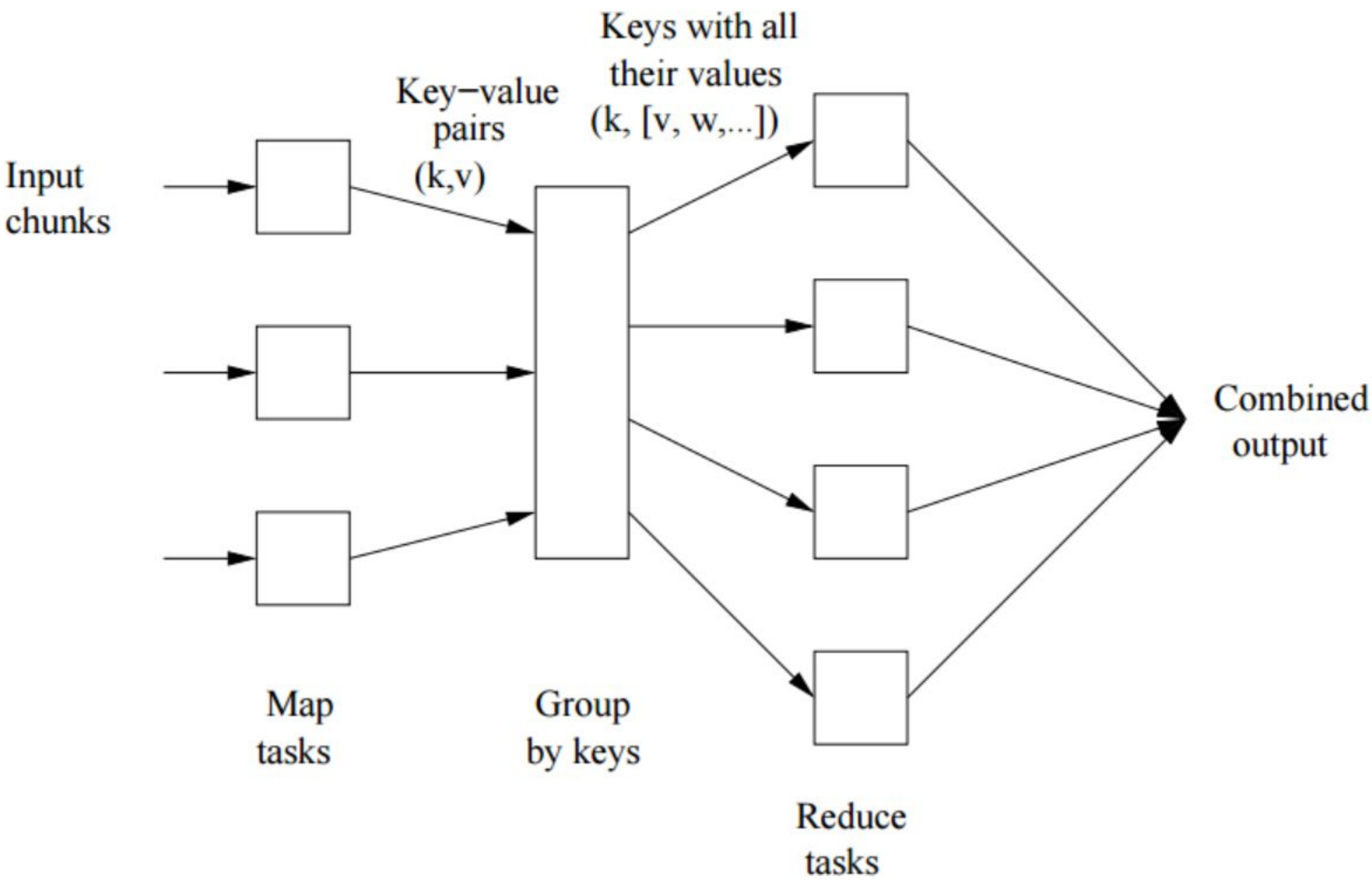
***noun.2* - A *system* that distributes MapReduce style programs across a distributed file-system.**

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

What is MapReduce



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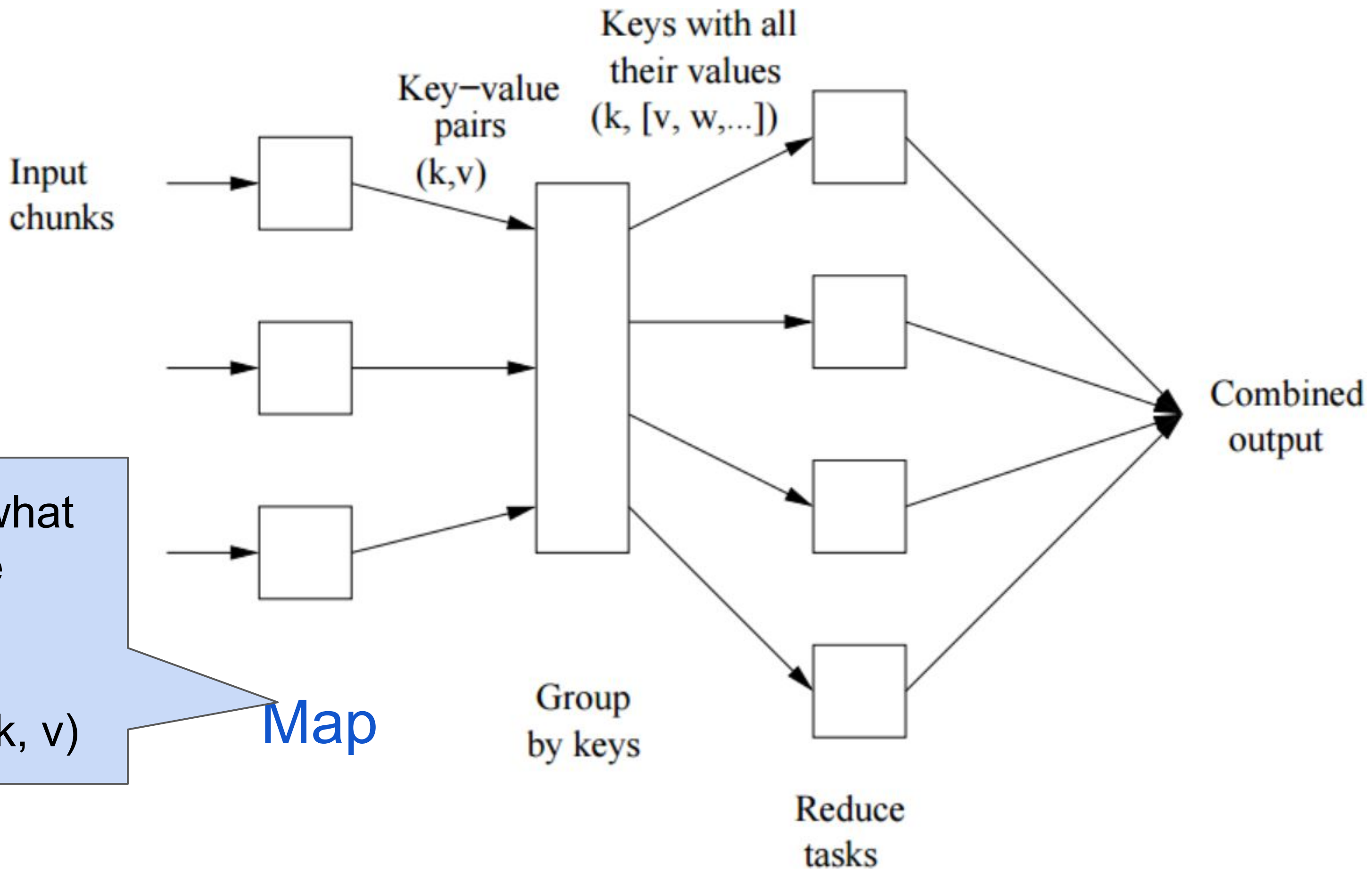
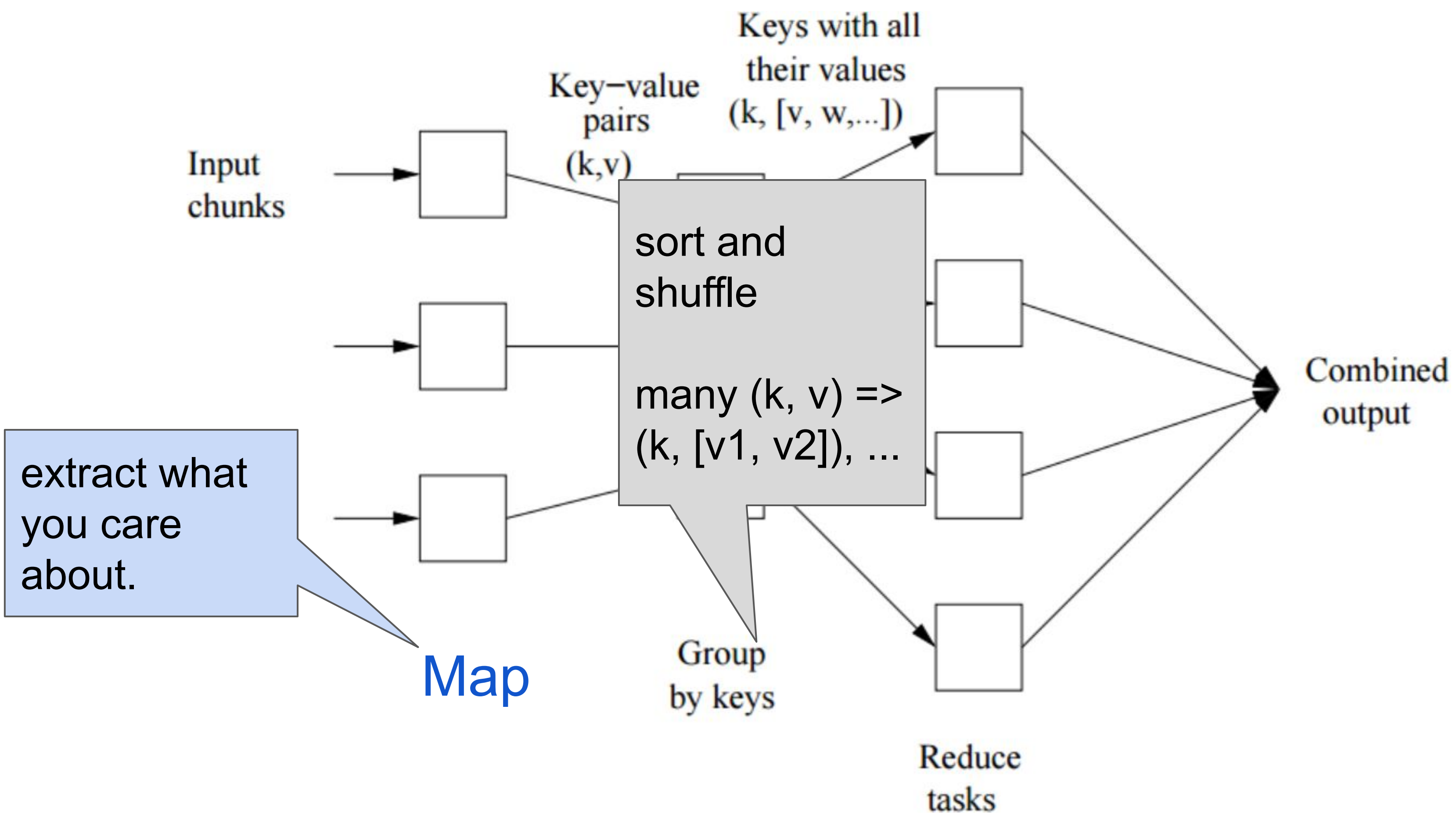


extract what you care about.

line => (k, v)

Map

What is MapReduce



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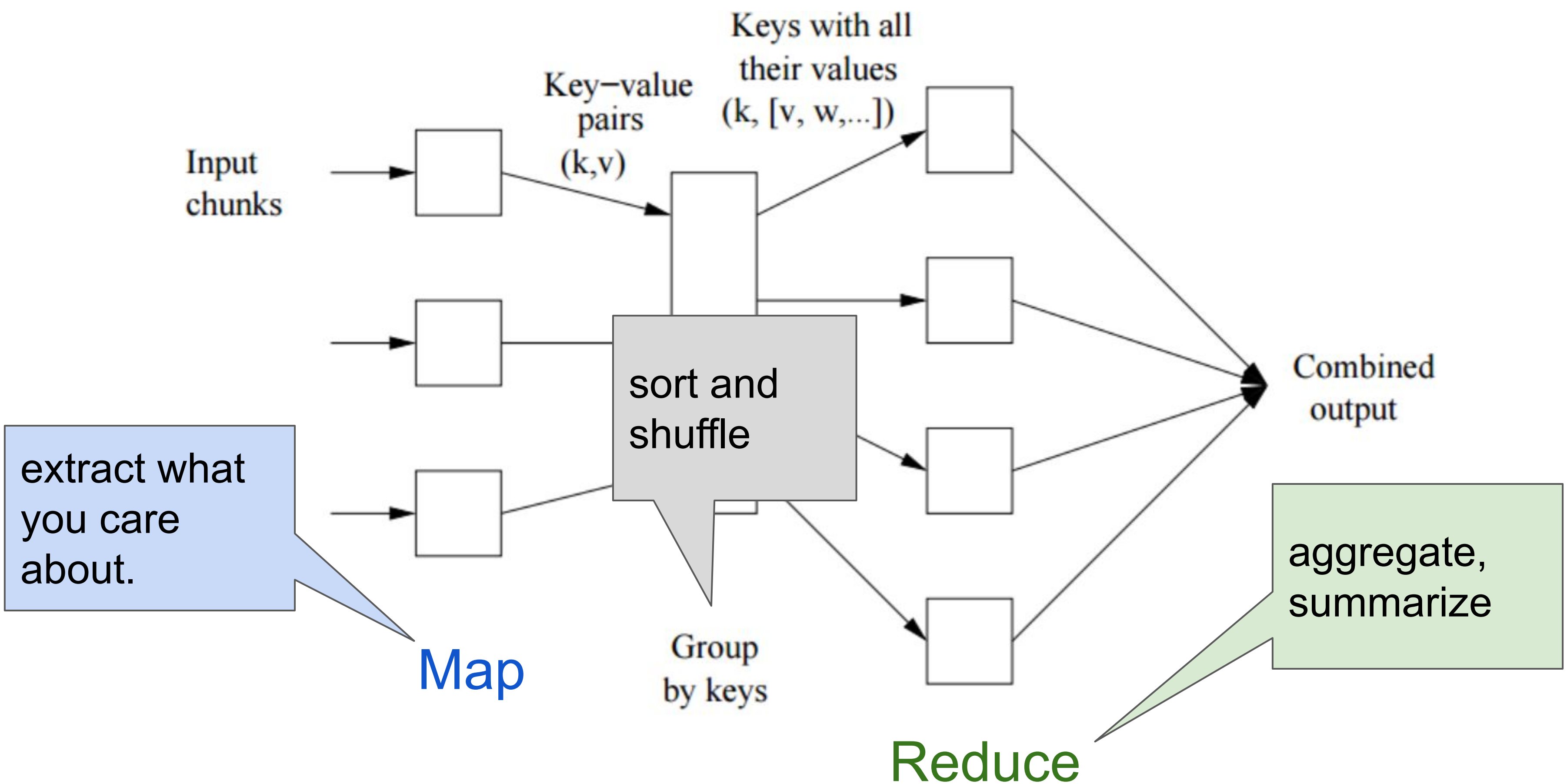

What is MapReduce

Easy as 1, 2, 3!

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

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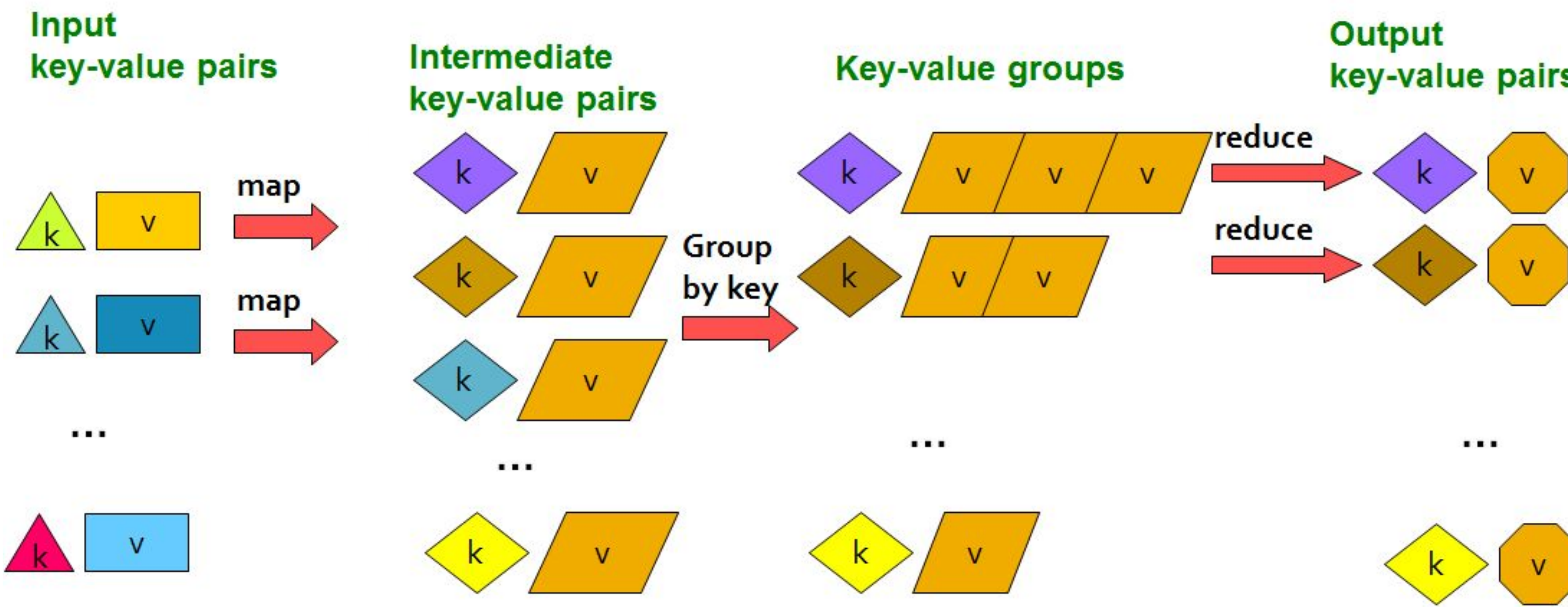

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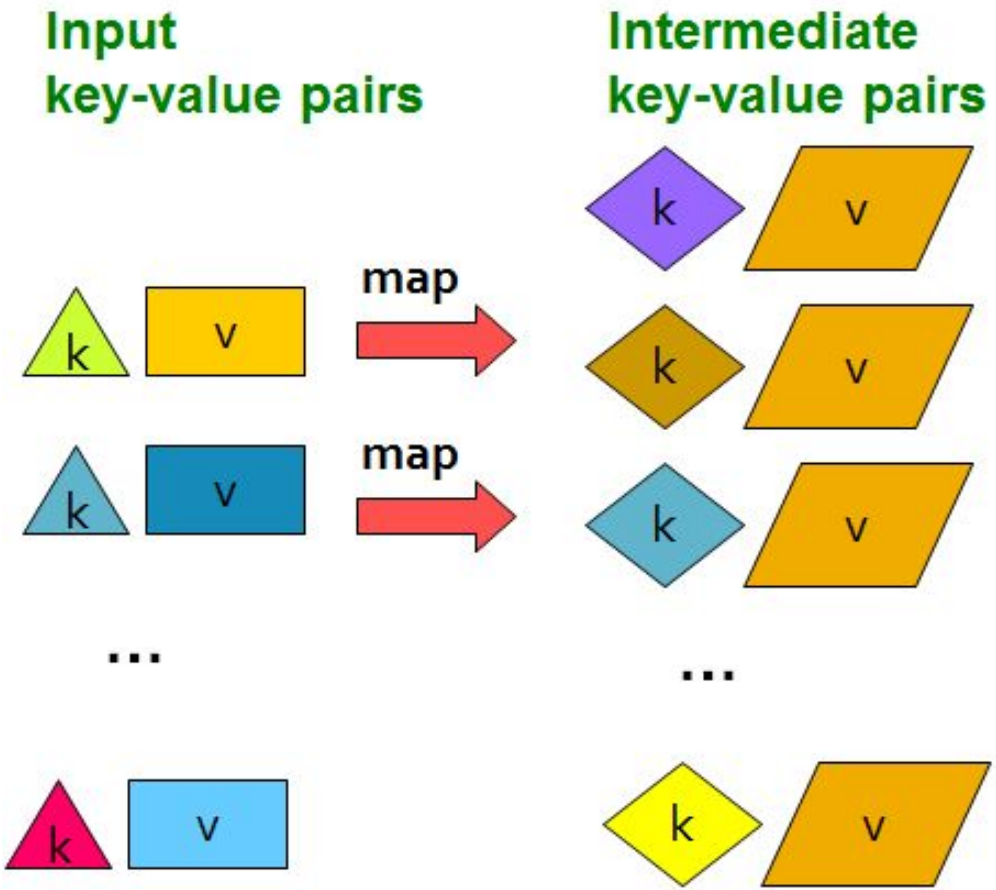
(1) The *Map* Step



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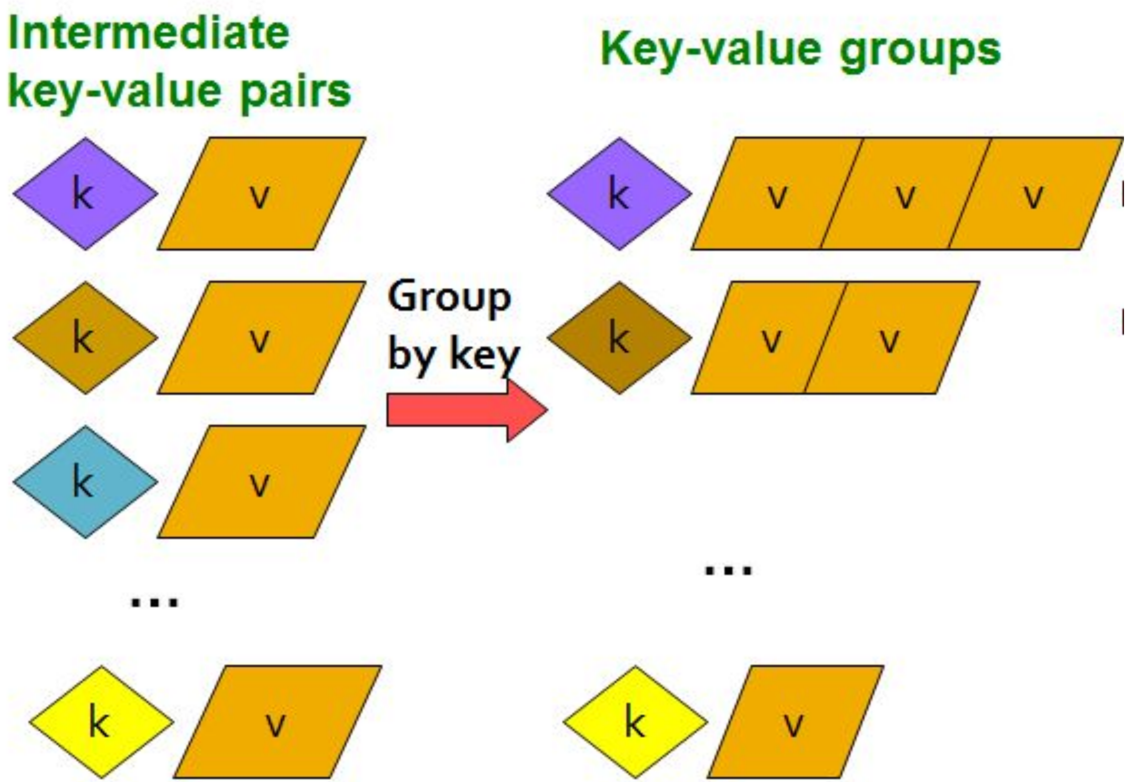
(2) The *Sort / Group-by* Step



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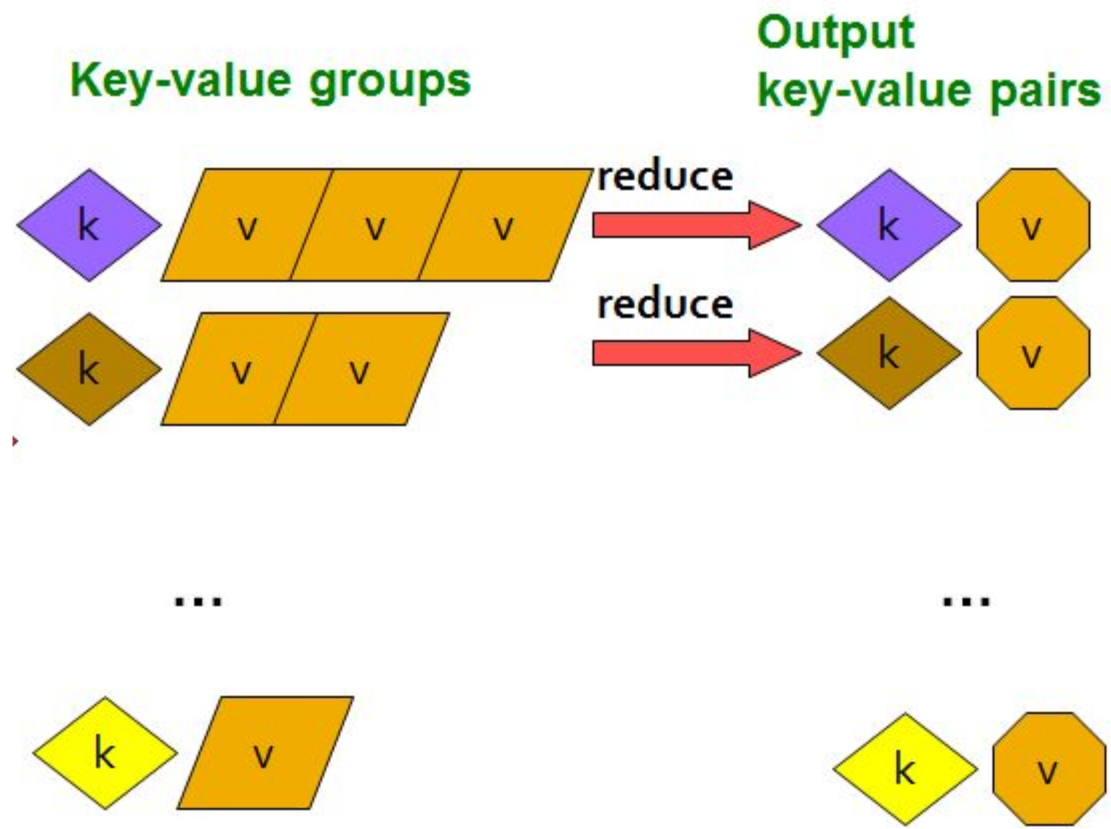
(3) The *Reduce* Step



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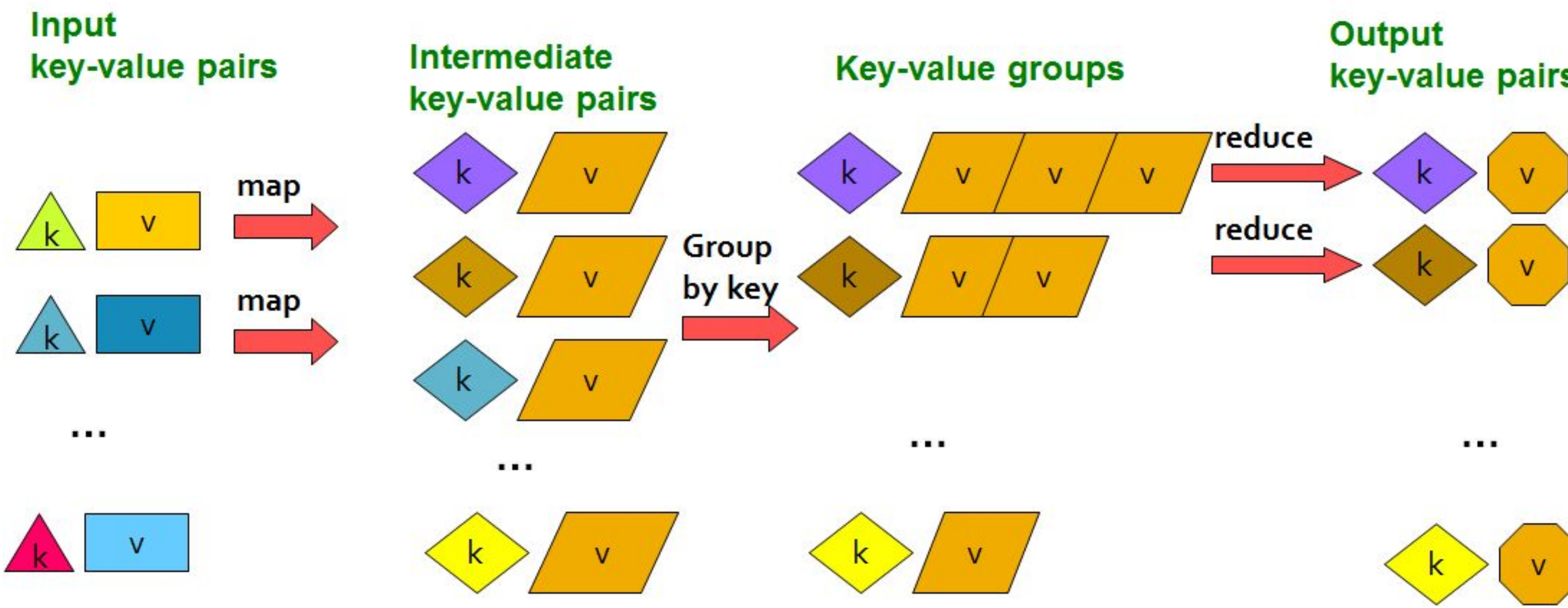

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What is MapReduce

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

Example: Word Count

```
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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

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Provided by the programmer

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Read input and produces a set of key-value pairs

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Big document

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(of, 1)
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....

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Reduce:
Collect all values belonging to the key and output

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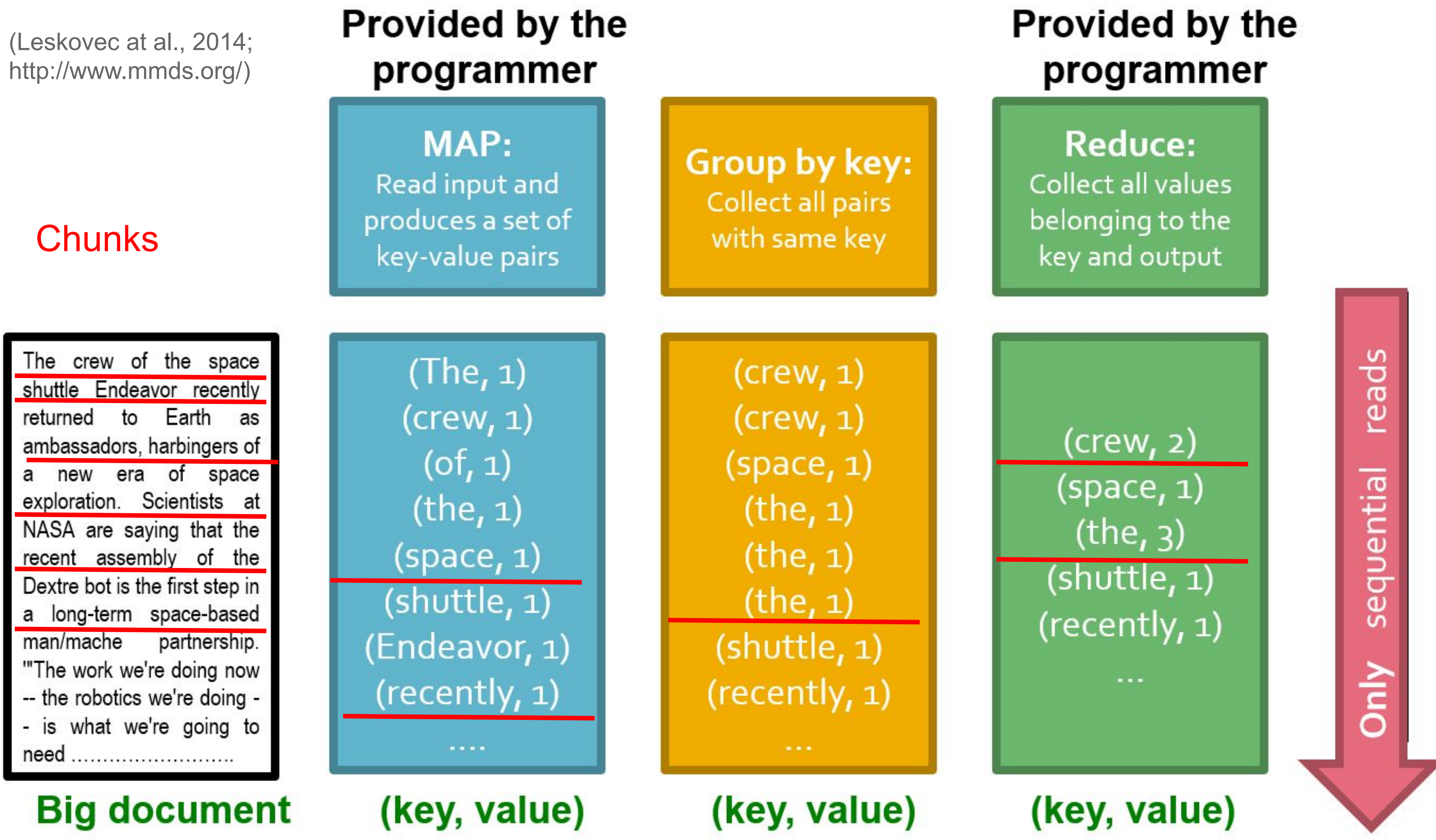

Example: Word Count

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

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

Example: Word Count (v1)

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

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

Example: Word Count (v1)

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def map(k, v):
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```
def tokenize(s):
    #simple version
    return s.split(‘ ‘)
```

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Example: Word Count (v2)

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

sum of counts from different chunks

Distributed Architecture (Cluster)

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

return only those attribute tuples where condition C is true

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return only those attribute tuples where condition C is true

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def map(k, v): #v is list of attribute tuples: [(...,), (...,), ...]
    r = []
    for t in v:
        if t satisfies C:
            r += [(t, t)]
    return r
```

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```

Example: Relational Algebra

Natural Join

Given R_1 and R_2 return R_{join}

-- union of all pairs of tuples that match given attributes.

```
def map(k, v): #k \in {R1, R2}, v is (A, B) for R1, (B, C) for R2
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Example: Relational Algebra

Natural Join

Given R_1 and R_2 return R_{join}

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    if k==’R1’:
        (a, b) = v
        return (b,(‘R1’,a))
    if k==’R2’:
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        return (b,(‘R2’,c))
```

Example: Relational Algebra

Natural Join

Given R_1 and R_2 return R_{join}

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def map(k, v): #k \in {R1, R2}, v is (A, B) for R1, (B, C) for R2
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    if k=='R2':
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        return (b,('R2',c))
```

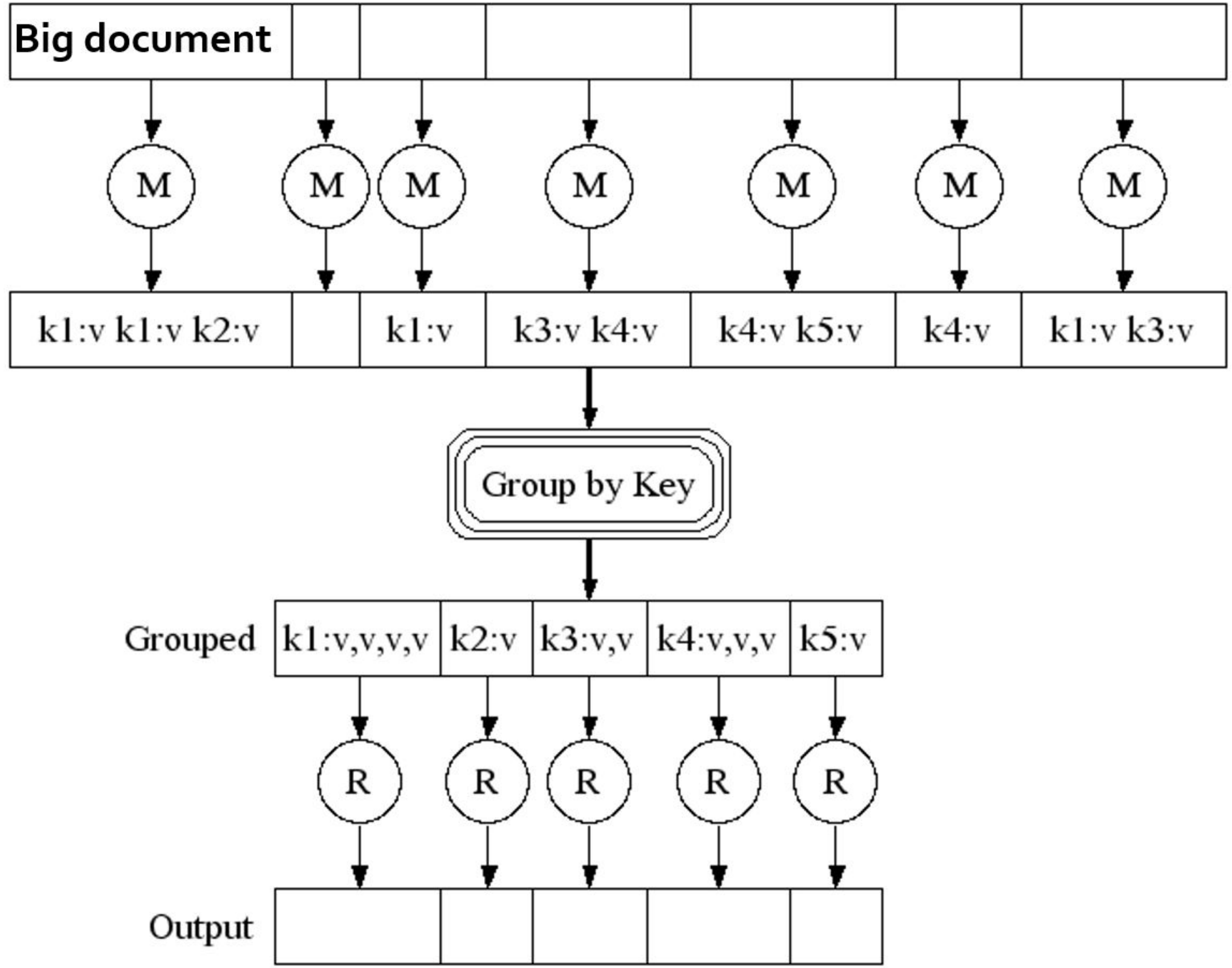
```
def reduce(k, vs):
    r1, r2, rjn = [], [], []
    for (s, x) in vs: #separate rs
      if s == 'R1': r1.append(x)
      else: r2.append(x)
    for a in r1: #join as tuple
      for each c in r2:
        rjn += ('Rjoin', (a, k, c)) #k is b
    return rjn
```

Data Flow

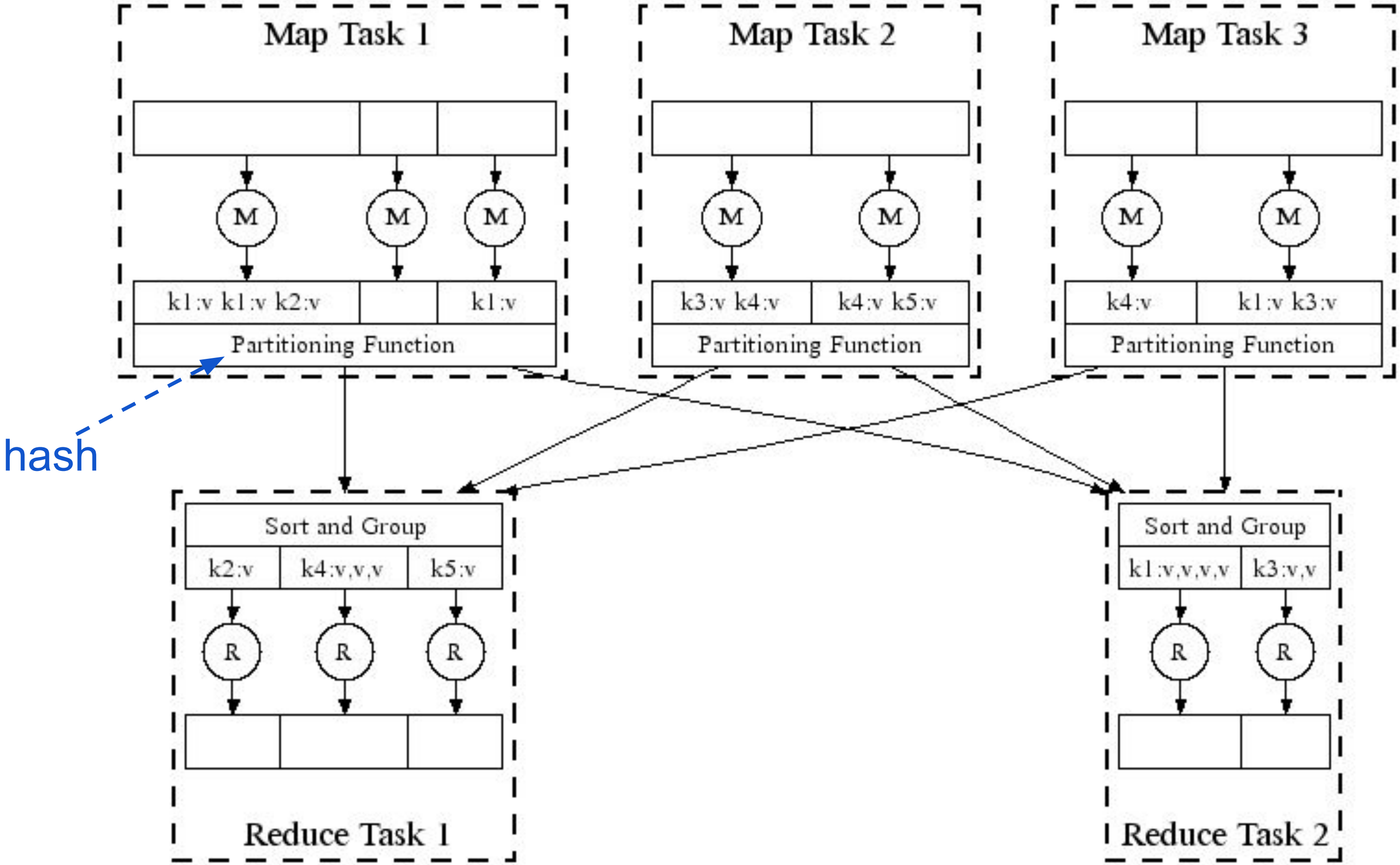
MAP:
Read input and produces a set of key-value pairs

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

Reduce:
Collect all values belonging to the key and output

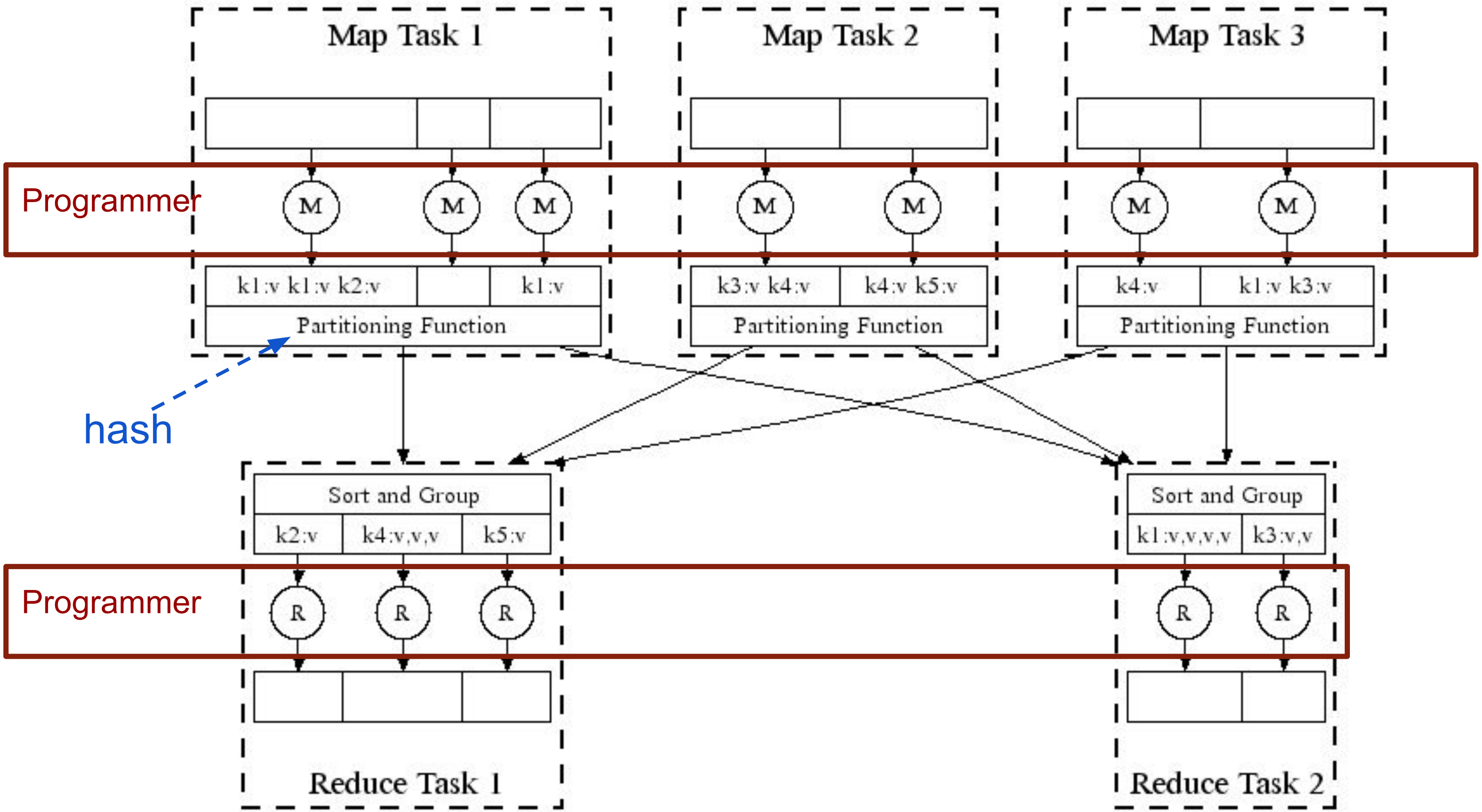


Data Flow



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

Data Flow



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

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

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  - 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?*

M: map tasks, *R:* reducer tasks

Data Flow

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

M: map tasks, *R:* reducer tasks

Answer: 1) If possible, one chunk per map task, and

2) *M* >> |nodes| ≈≈ |cores|

(better handling of node failures, better load balancing)

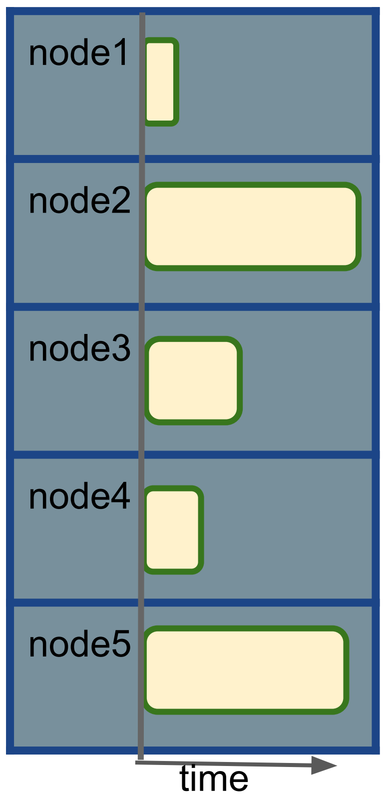
3) *R* <= *M*

(reduces number of parts stored in DFS)

Data Flow

Reduce Task

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



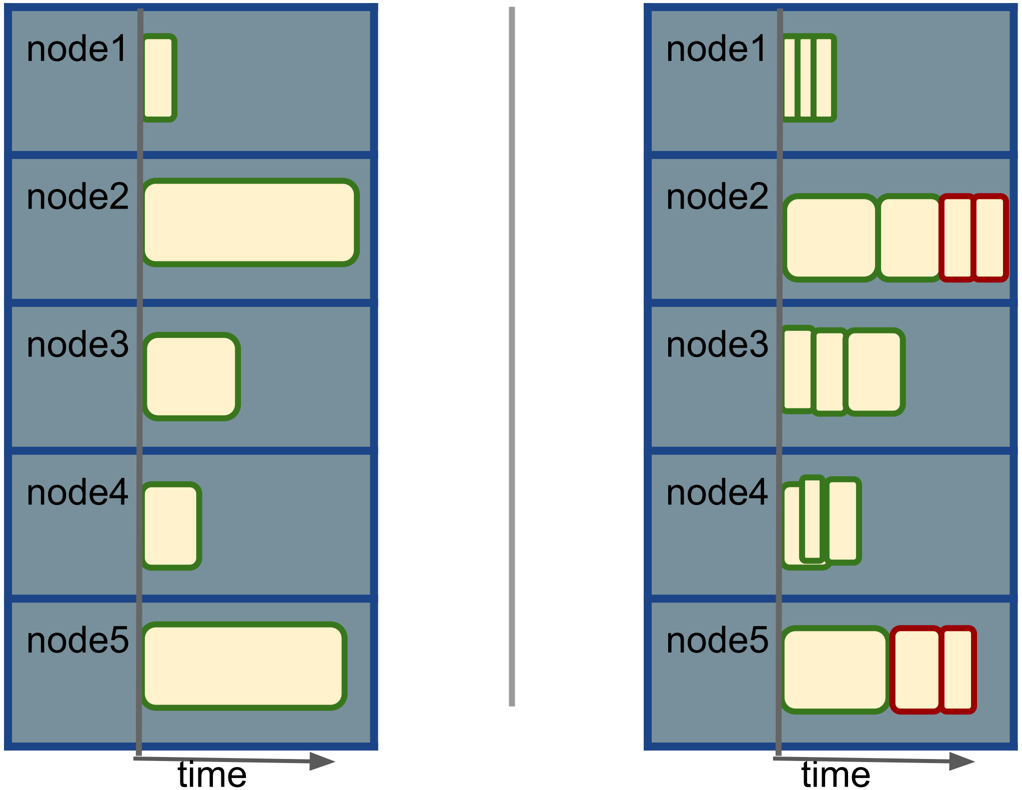
Reduce tasks represented by
time to complete task
(some tasks take much longer)

Data Flow

Reduce Task

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

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



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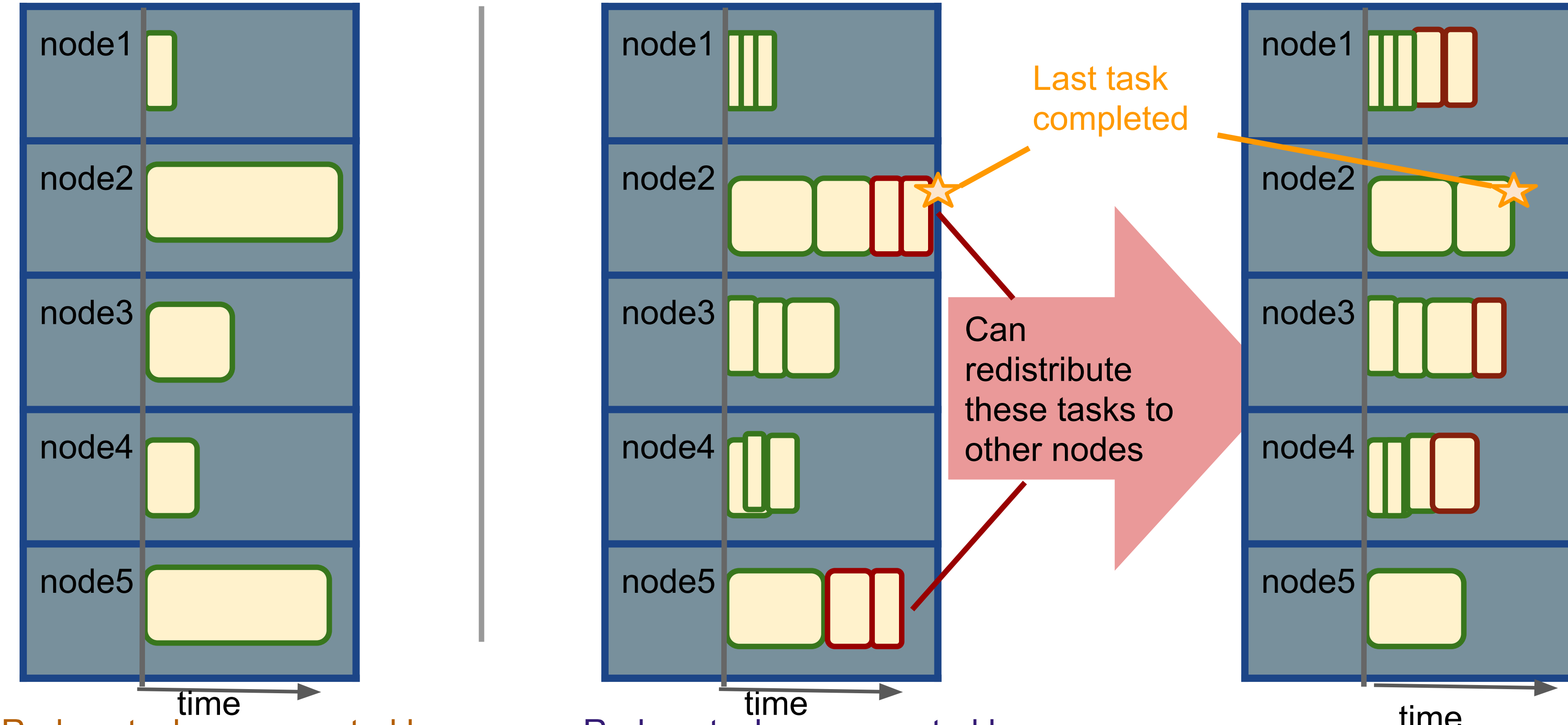

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Reduce tasks represented by
time to complete task
(some tasks take much longer)

(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

(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

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 ⇨ ?

Communication Cost: Natural Join

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def map(k, v):
    if k=="R1":
        (a, b) = v
        yield (b,(R1,a))
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        (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
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Communication Cost: 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)

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

      Requires commutative and associative reducer function.

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))`