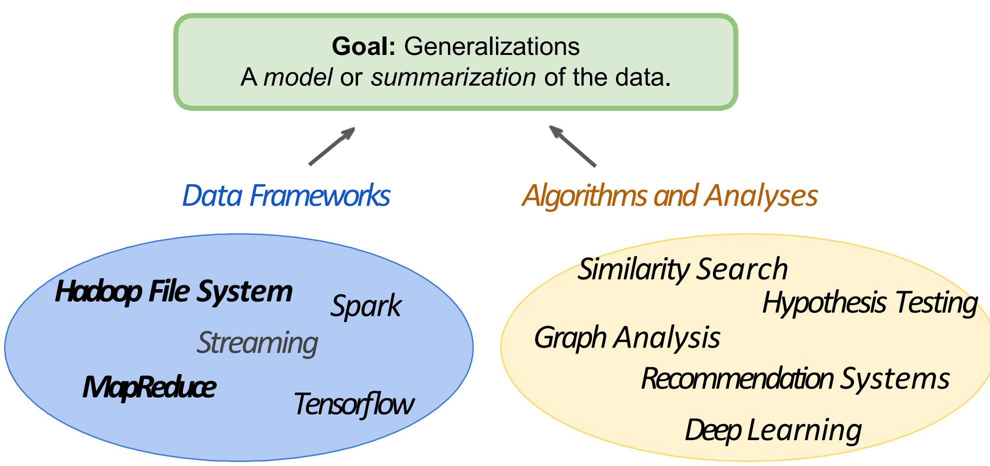
“Hadoop”:

A Distributed Architecture, FileSystem, & MapReduce

1

Big Data Analytics, The Class



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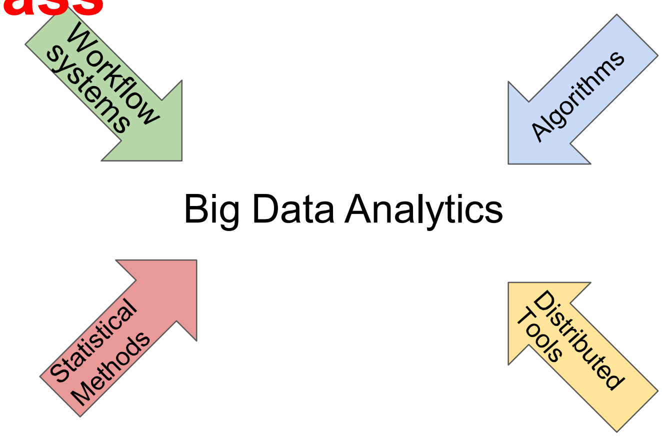

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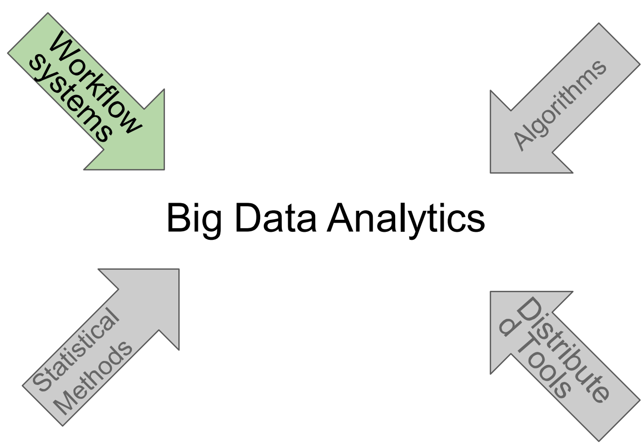

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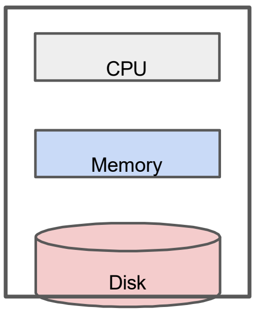
Classical Data Analytics



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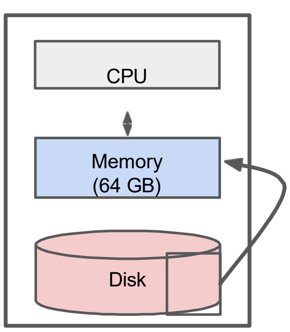

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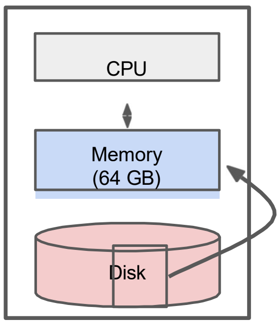
Classical Data Analytics



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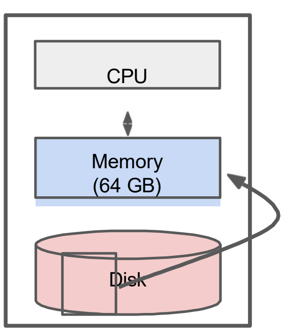
Classical Data Analytics

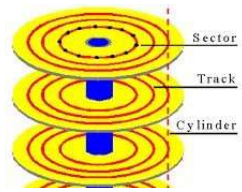


8

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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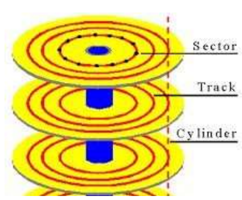

IO Bound: biggest performance bottleneck is reading / writing to disk.

starts around 100 GBs: ~10 minutes just to read

200 TBs: ~20,000 minutes = 13 days

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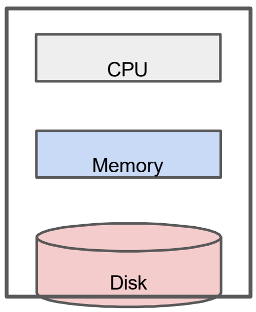
Classical Big Data



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

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

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Classical Big Data

How to solve?

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

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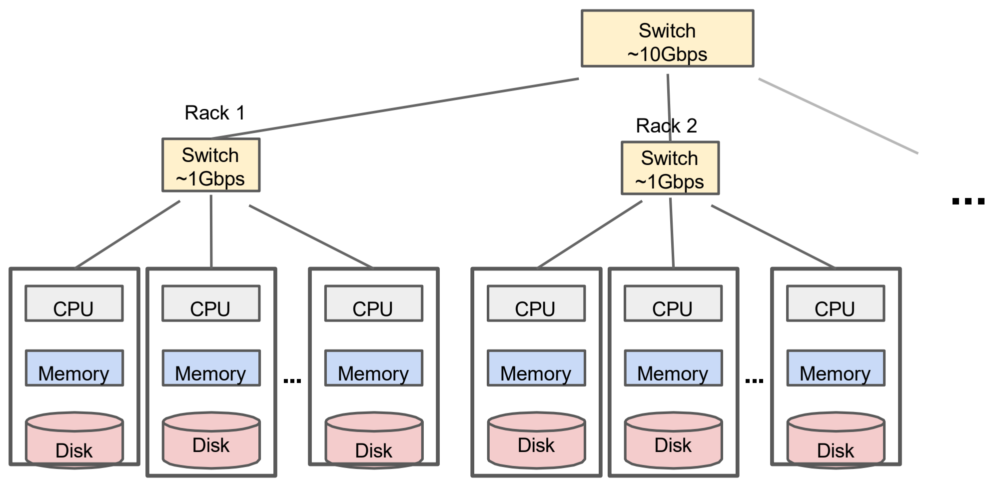
Distributed Architecture



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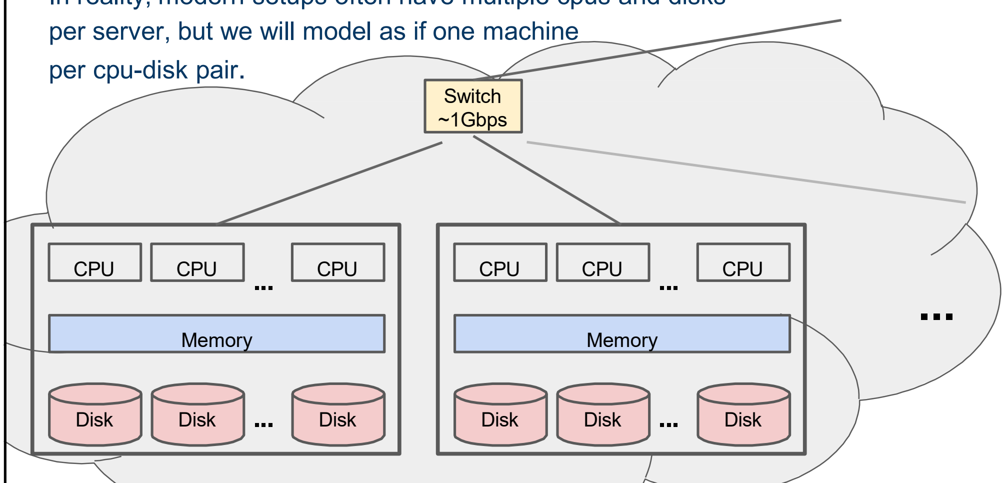
Distributed Architecture

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



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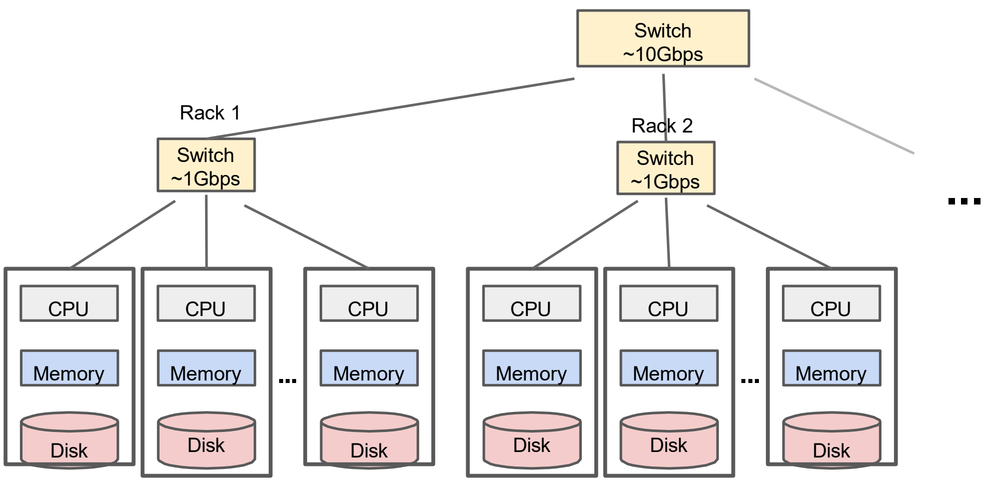
Distributed Architecture (Cluster)



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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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Distributed Architecture (Cluster)

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   Stipulate a programming system that can easily be distributed

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HDFS with MapReduce accomplishes all!

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Distributed Filesystem

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

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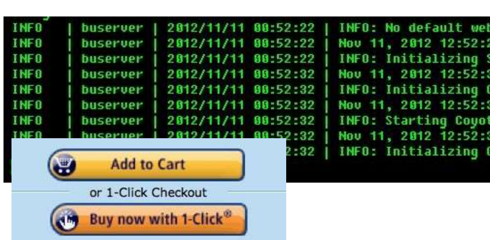
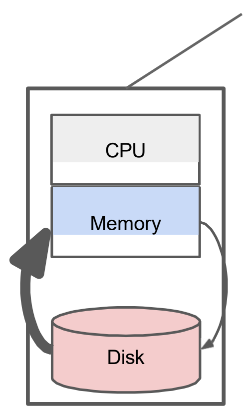
Distributed Filesystem

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)





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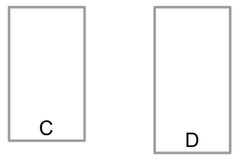
Distributed Filesystem

(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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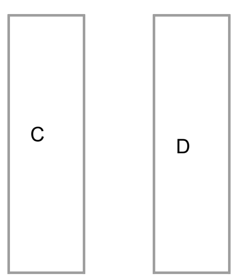
Distributed Filesystem

"Hadoop" was named after a toy elephant belonging to Doug Cutting's son. Cutting was one of Hadoop's creators.

(e.g. Apache **Hadoop**DFS, GoogleFS, EMRFS)

C, D: Two different files



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Distributed Filesystem

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

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

C_0	D_0
C_1	D_1
C_2	D_2
C_3	D_3
C_4	D_4
C_5	D_5

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Distributed Filesystem

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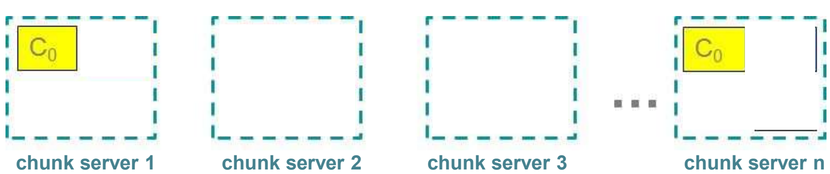

(Leskovec at al., 2014; http://www.mmds.org/)

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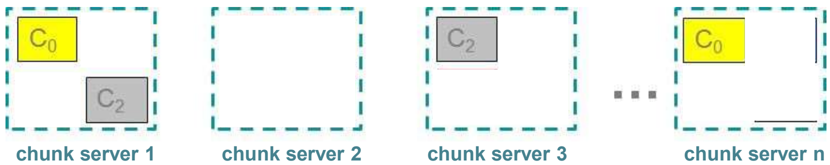

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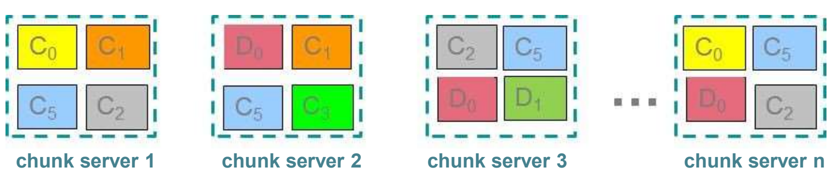

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Distributed Filesystem

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

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

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Components of a Distributed Filesystem

Chunk servers (on Data Nodes)

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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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Name node (aka master node)

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

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

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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

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

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E.g. counting words:

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

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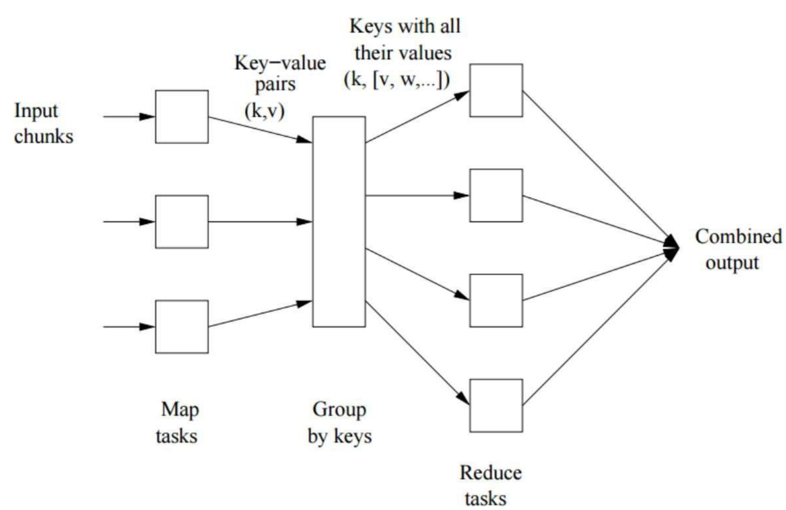
What is MapReduce



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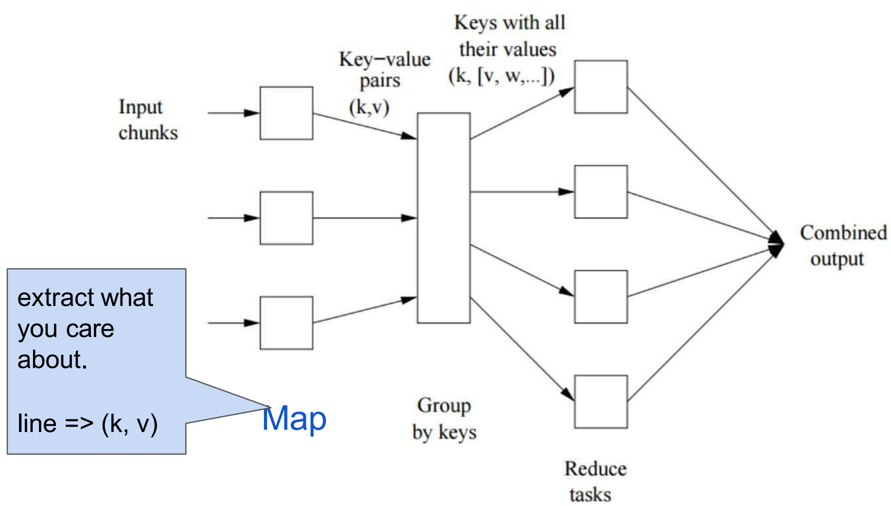

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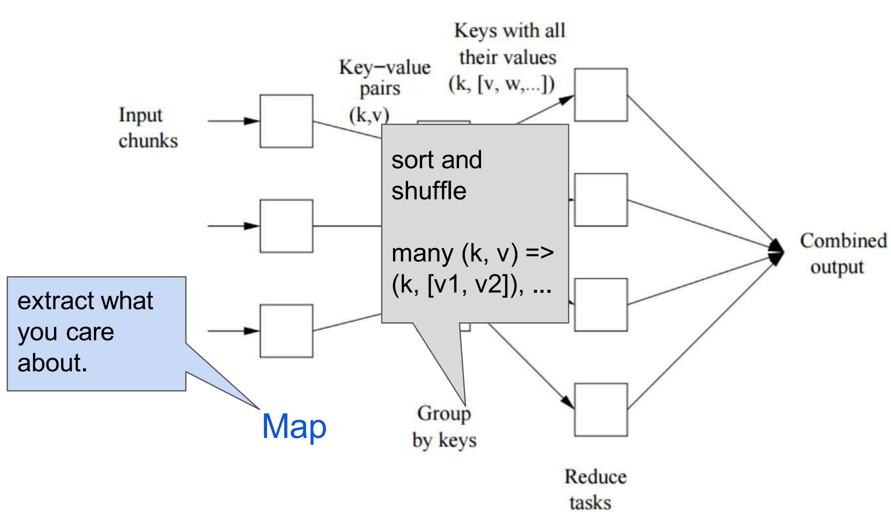

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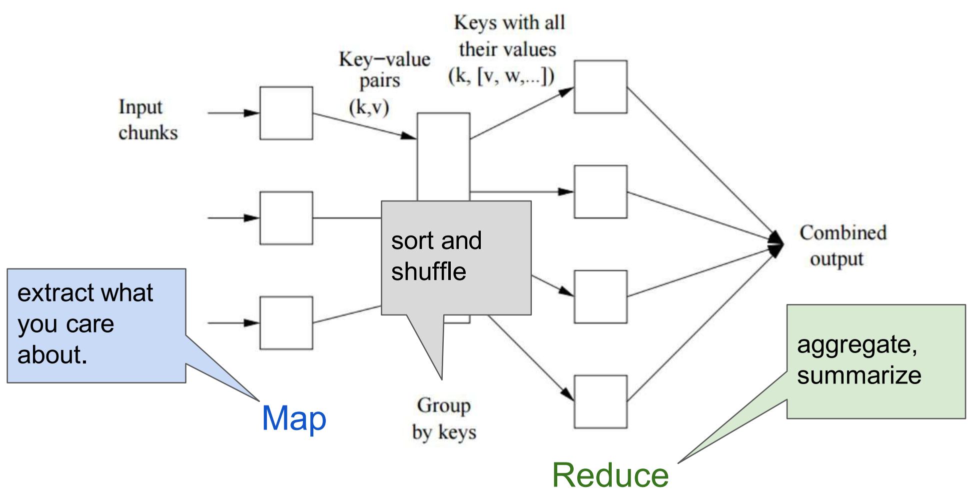

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What is MapReduce

Easy as 1, 2, 3!

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

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What is MapReduce

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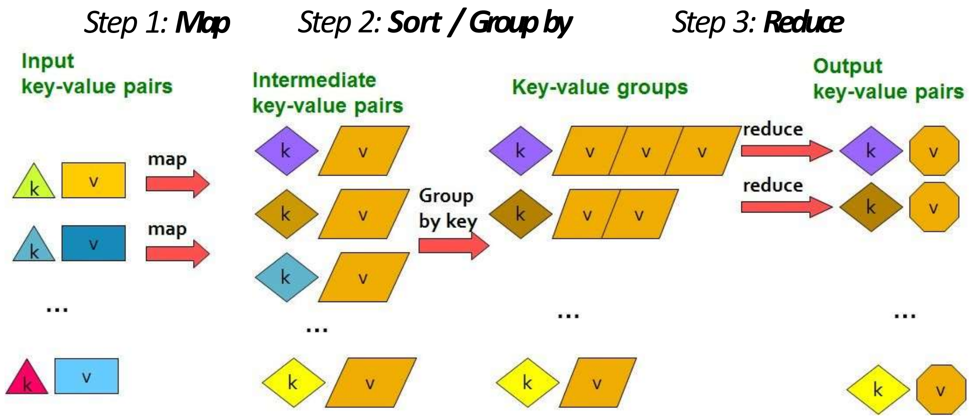

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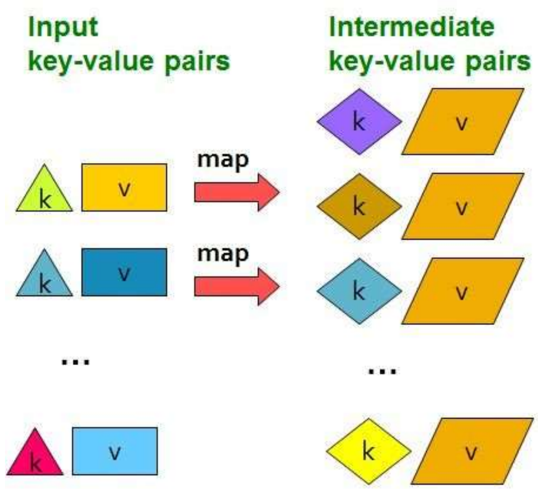
(1) The *Map* Step



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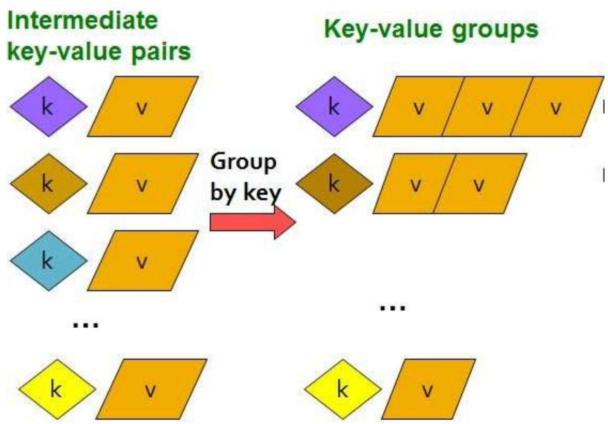
(2) The *Sort / Group-by* Step



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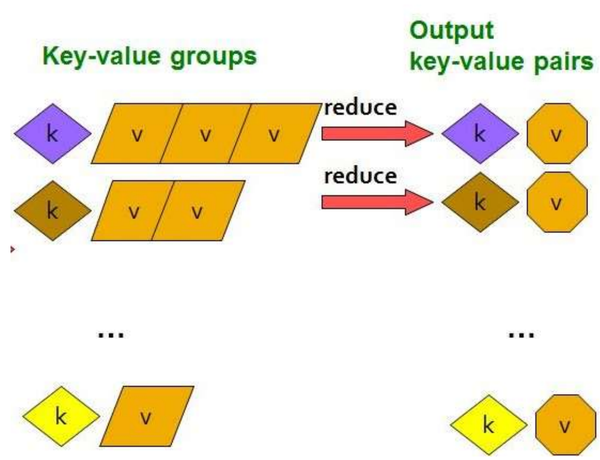
(3) The *Reduce* Step



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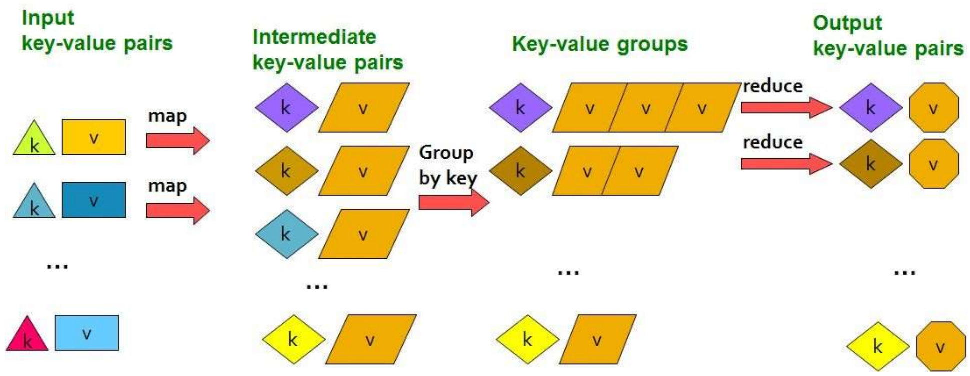

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What is MapReduce

Map: (k,v) -> (k', v')*
(Written by programmer)

Group by key: (k_1', v_1'), (k_2', v_2'), ... -> (k_1', (v_1', v', …),
(system handles) (k_2', (v_1', v', …), …

Reduce: (k', (v_1', v', …)) -> (k', v'')*
(Written by programmer)

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Example: Word Count

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

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Example: Word Count

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

Map: extract what you care about.

sort and shuffle

Reduce: aggregate, summarize

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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/)

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Provided by the programmer

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

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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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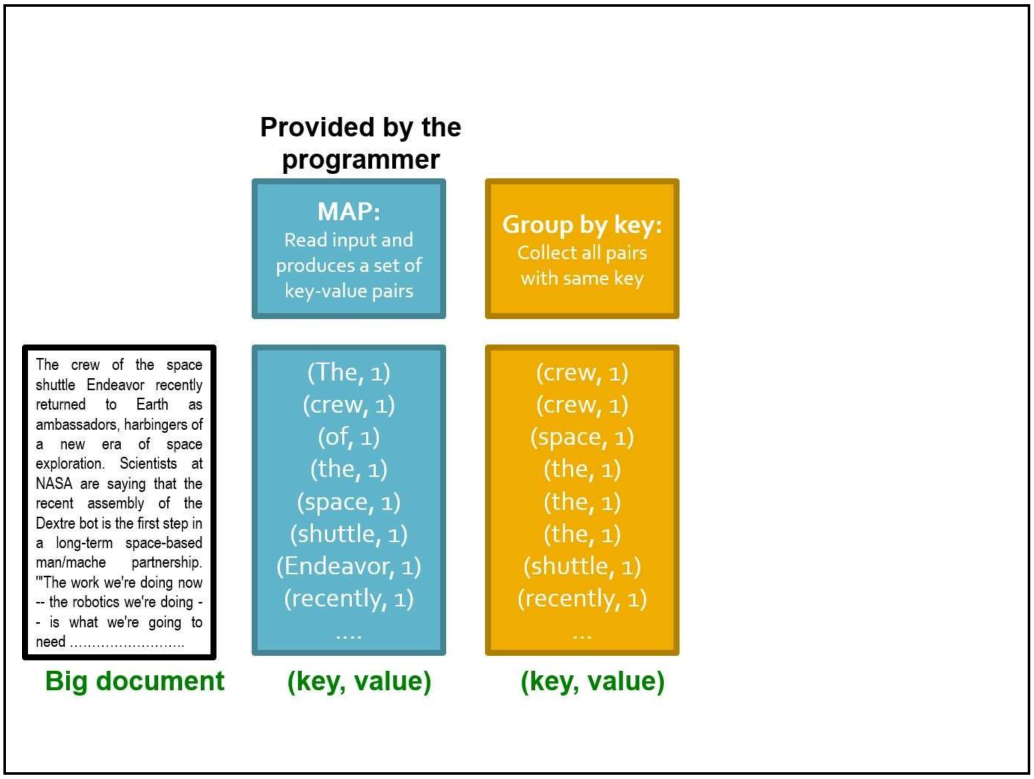
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MAP:
Read input and produces a set of key-value pairs
Group by key:
Collect all pairs with same key
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Big document
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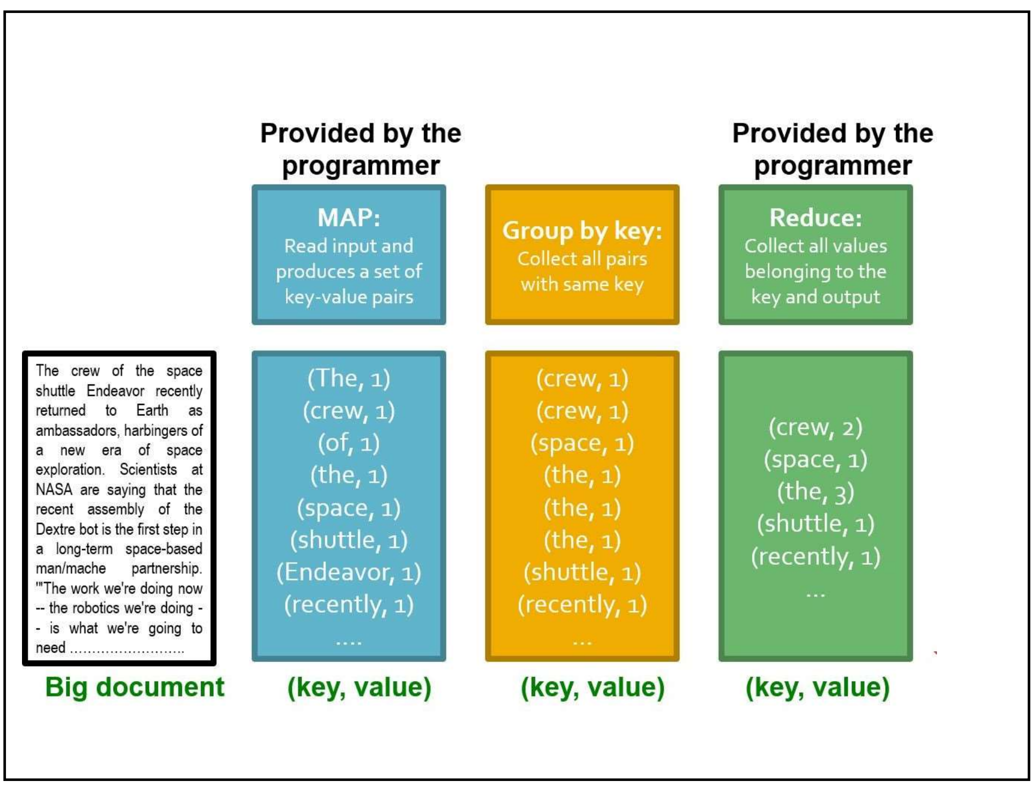
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MAP:
Read input and produces a set of key-value pairs
Group by key:
Collect all pairs with same key
Reduce:
Collect all values belonging to the key and output
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(key, value)
(key, value)

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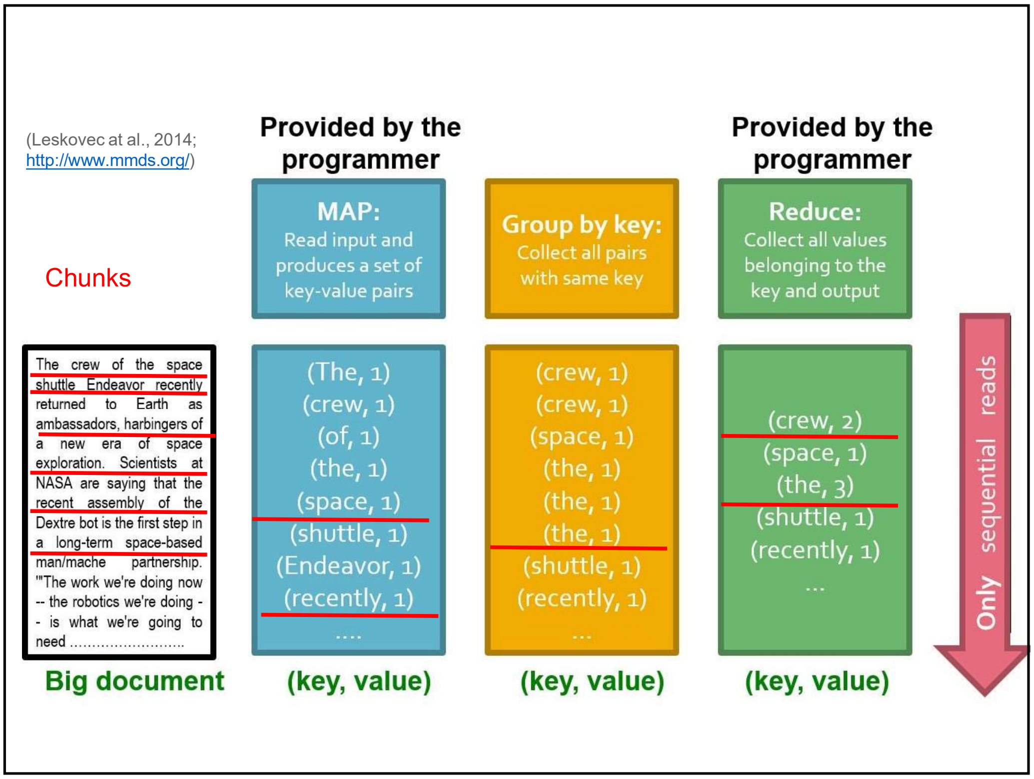

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Example: Word Count

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


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

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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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Example: Word Count (v1)

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

```
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):
```

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

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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
```

counts each word within the chunk
(try/except is faster than
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    for item in counts.iteritems():
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```

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

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

sum of counts from different chunks

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Distributed Architecture (Cluster)

Challenges for IO Cluster Computing

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   1 in 1000 nodes fail a day
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Example: Relational Algebra

Select

Project

Union, Intersection, Difference

Natural Join

Grouping

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Example: Relational Algebra

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Example: Relational Algebra

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

return only those attribute tuples where condition C is true

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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: [(...,), (...,), ...]
    r = []
    for t in v:
        if t satisfies C:
            r += [(t, t)]
    return r
```

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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: [(...,), (...,), ...]
    r = []
    for t in v:
        if t satisfies C:
            r += [(t, t)]
    return r
                def reduce(k, vs):
                  r = []
                  for each v in vs:
                    r += [(k, v)]
                  return r
```

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Example: Relational Algebra

Select

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

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    for t in v:
        if t satisfies C:
            yield (t, t)

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

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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 #B are matched attributes
```

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

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Example: Relational Algebra

Natural Join

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        return (b,('R1',a))
    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
```

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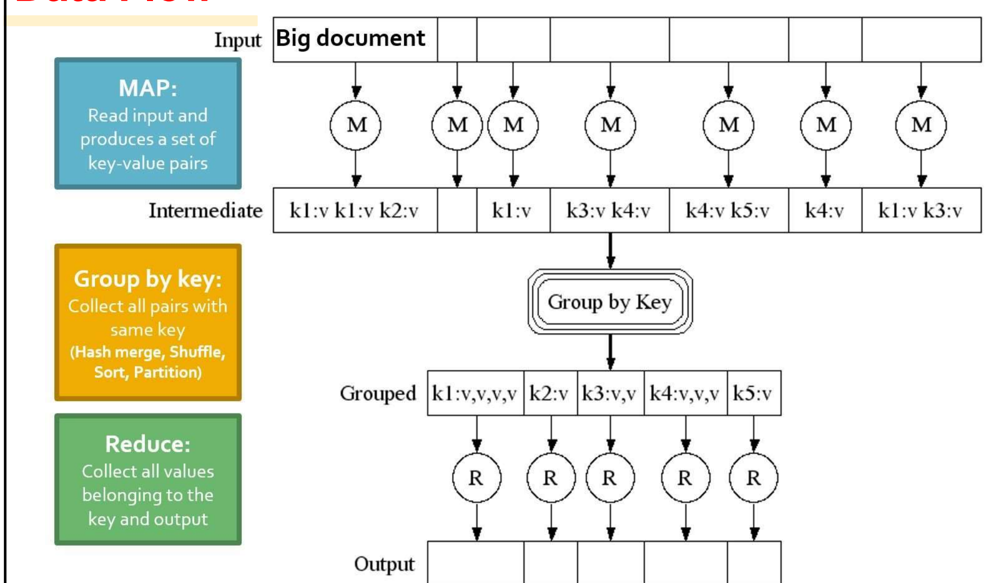
Data Flow



J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org 21

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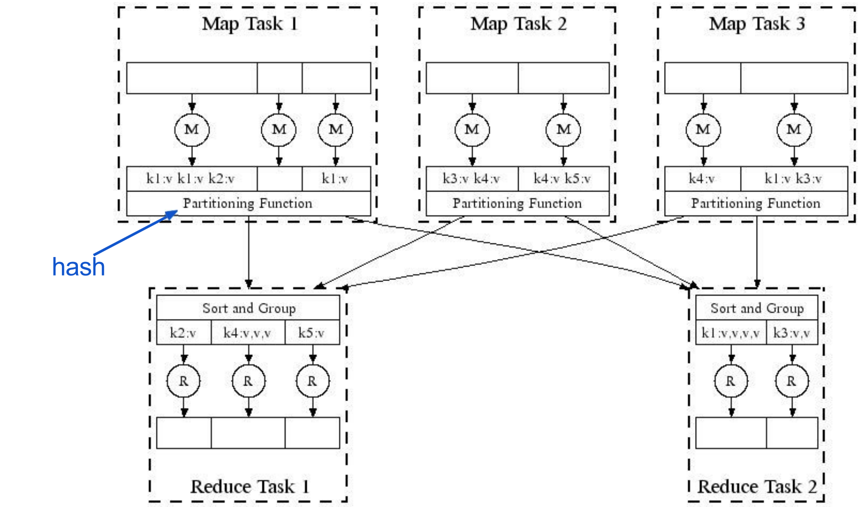
Data Flow



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

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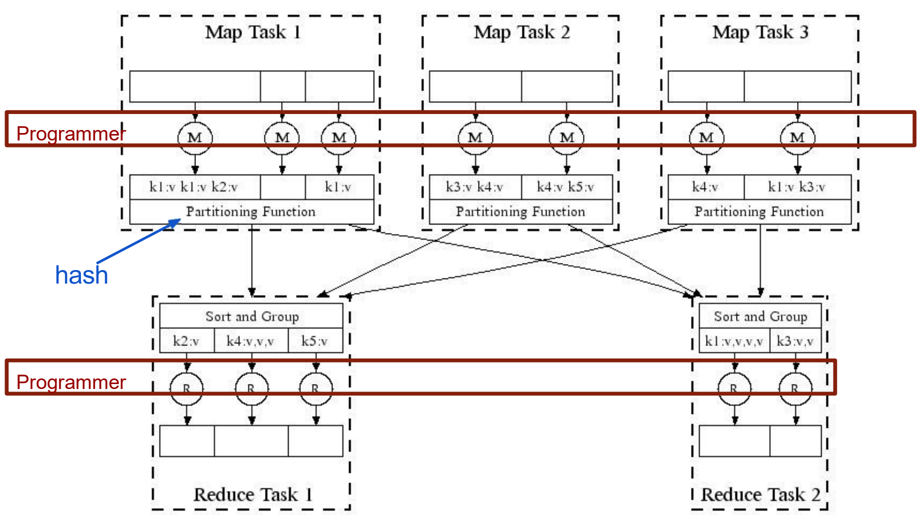
Data Flow



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

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Data Flow

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

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Data Flow

MapReduce system handles:

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

- Restarts from node failures
- Inter-machine communication

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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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Data Flow

DFS → MapReduce → DFS

- Schedule map tasks near physical storage of chunk
- 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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Data Flow

DFS ⇨ MapReduce ⇨ DFS

- Schedule map tasks near physical storage of chunk
- Intermediate results stored locally
- Master / Name Node coordinates
    - Task status: idle, in-progress, complete
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DFS ⇨ MapReduce ⇨ DFS ⇨ MapReduce ⇨ DFS

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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

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Data Flow

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

M: map tasks, *R:* reducer tasks

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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)

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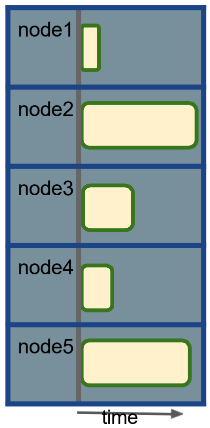
Data Flow

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)

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Data Flow

Reduce Task

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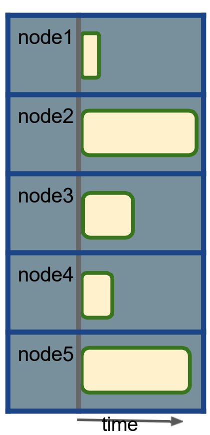
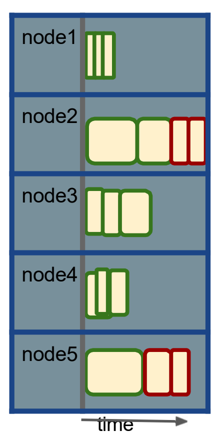


Reduce tasks represented by
time to complete task
(some tasks take much longer)

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



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

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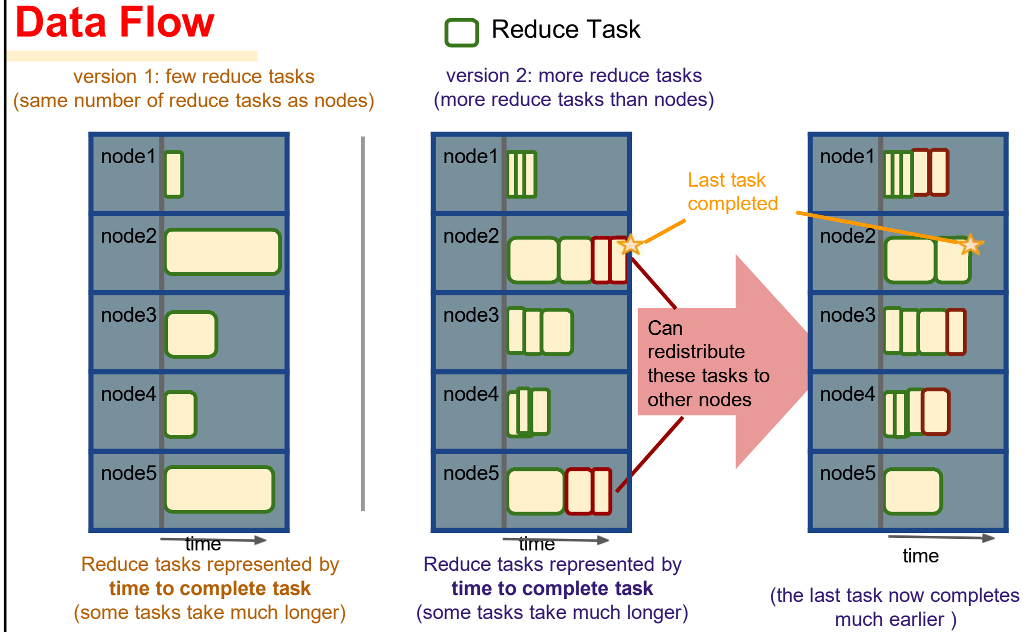
Data Flow



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Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

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

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Communication Cost Model

How to assess performance?

(1) Computation: Map + Reduce + System Tasks

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

Ultimate Goal: wall-clock Time.

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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.

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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;

Ultimate Goal: wall-clock Time

HD read: 50-150 giga**bytes** per sec

- Even reading from disk to memory typically takes longer than operating on the data.

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Communication Cost Model

How to assess performance?

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

(2) Communication: Moving key, value pairs

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Ultimate Goal: wall-clock Time

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Communication Cost Model

How to assess performance?

Communication Cost =	input size + (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

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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)

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)

```
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
```

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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
        yield (b,(R1,a))
    if k=="R2":
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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.

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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))`

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