

# INTRO TO DATA SCIENCE

## MAP-REDUCE

**I. BIG DATA**

**II. PROGRAMMING MODEL**

**III. IMPLEMENTATION DETAILS**

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## **INTRO TO DATA SCIENCE**

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# **I. BIG DATA**

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But this is only half of the story...how would you do this?

One approach would be to get a huge supercomputer.



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But this has some obvious drawbacks:

- expensive
- difficult to maintain
- scalability is bounded

Instead of one huge machine, what if we got a bunch of regular (*commodity*) machines?

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This has obvious benefits!

- cheaper
- easier to maintain
- scalability is unbounded (just add more nodes to the *cluster*)

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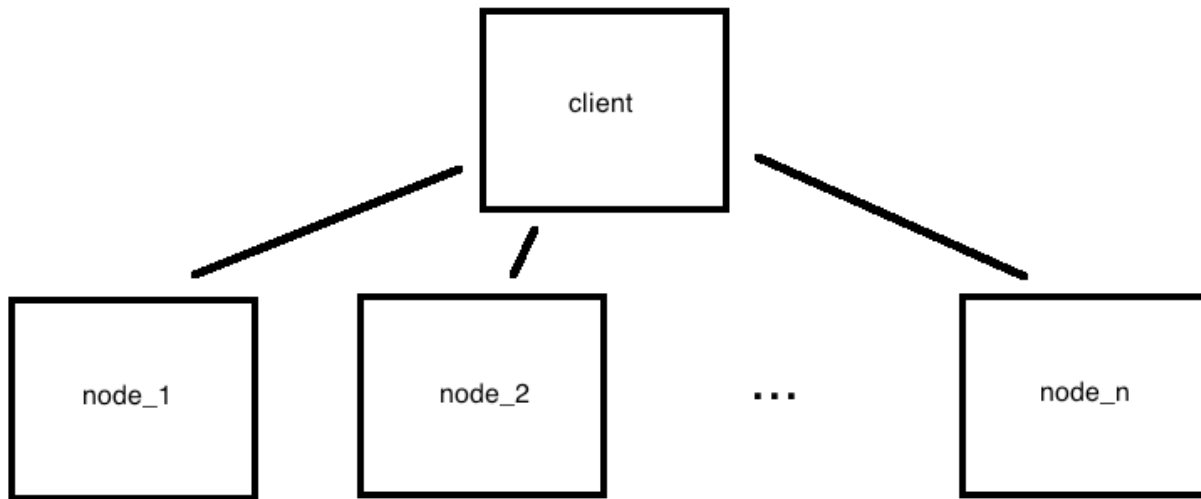
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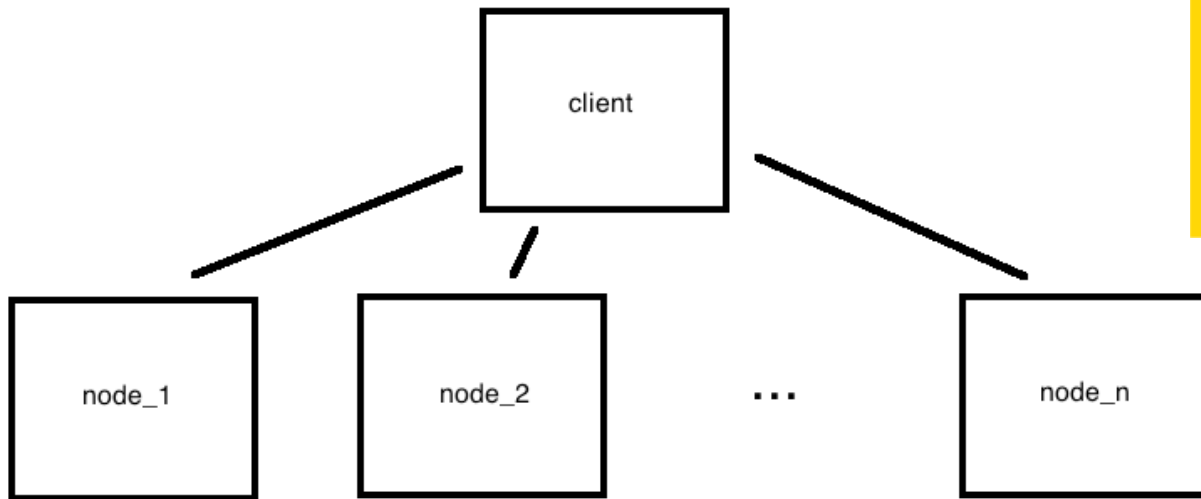
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“Scale out vs scale up!”

We can visualize this *horizontal* cluster architecture as a single client-multiple server relationship



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**NOTE**

A horizontally distributed system also has better *fault tolerance* than a single machine.



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1) move data to cores (& code)

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- SETI@home

2) move code to data (& cores)

- map-reduce → less overhead (network traffic, disk I/O)

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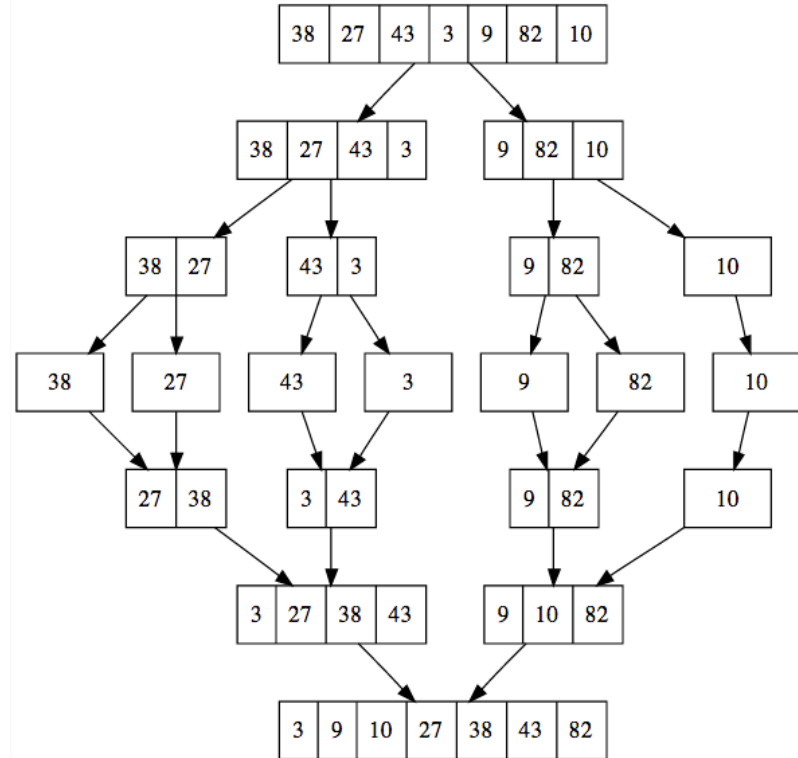
- 1) split task into subtasks
- 2) solve these subtasks *independently*
- 3) recombine the subtask results into a final result

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This is how recursive algorithms work, for example.

One famous example of divide and conquer is *merge sort*.



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In fact, running a map-reduce job with identity (eg, do-nothing) mappers and reducers is similar to merge sort!

(The similarity is approximate, because results are output in multiple sets, and data is not broken down to single-element subsets.)

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Tasks that can be *parallelized* in this way include:

- count, sum, average
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### NOTE

Parallelizing an ML algorithm can be a non-trivial exercise!

# **II. PROGRAMMING MODEL**

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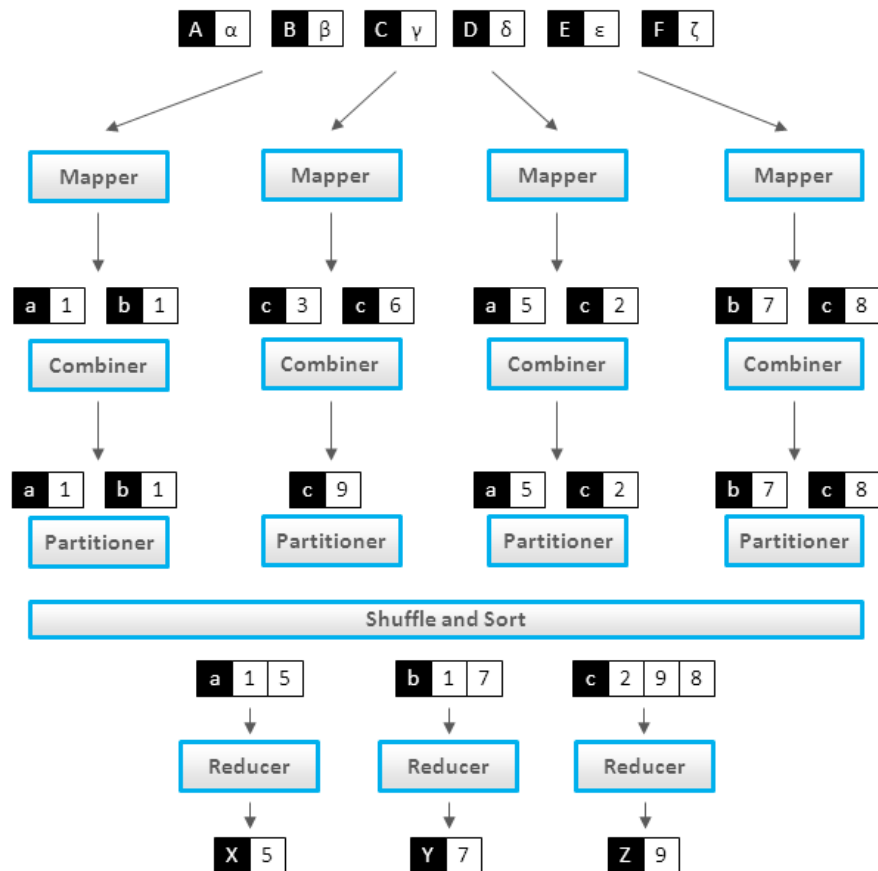
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This takes place in (*approximately*) two phases:

- 1) the **mapper** phase
- 1.5) *shuffle/sort*
- 2) the **reducer** phase



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**mappers** – filter & transform data

**reducers** – aggregate results

The functional paradigm is good at describing how to solve a problem, but not very good at describing data manipulations (eg, relational joins).

As our earlier diagram suggests, there are additional intermediate steps in a map-reduce workflow.

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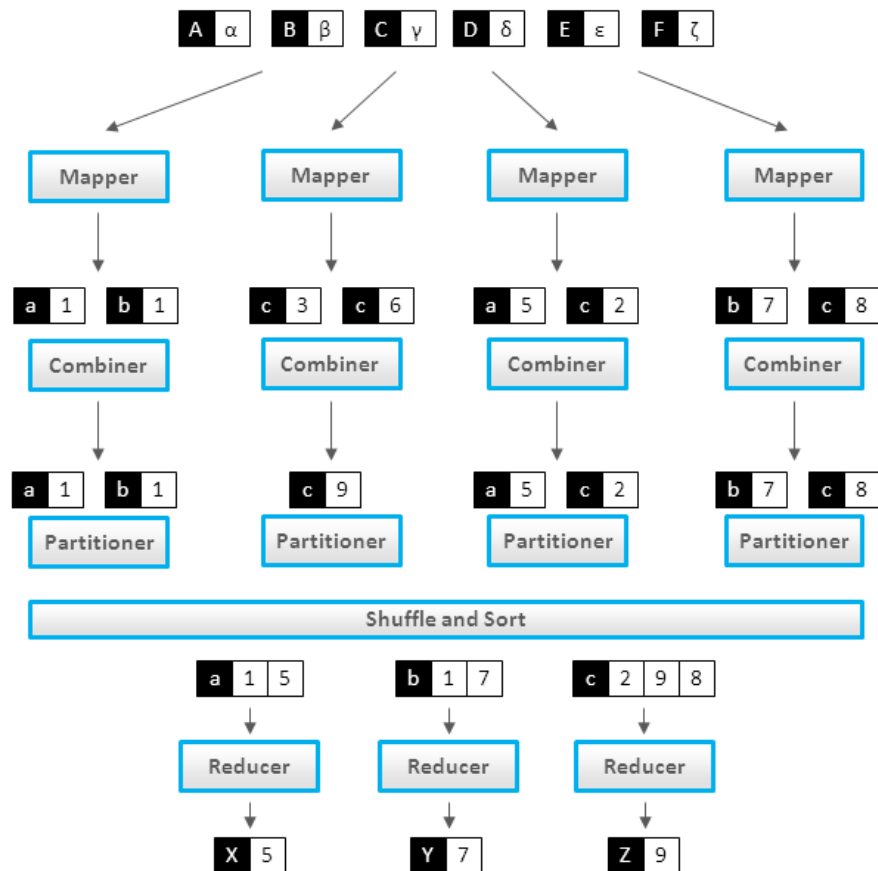
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**mappers** – filter & transform data

**combiners** – perform reducer operations on the mapper node (optional step, to reduce network traffic and disk I/O).

**partitioners** – shuffle/sort/redirect mapper output

**reducers** – aggregate results





It's possible to overlay the map-reduce framework with an additional *declarative syntax*.

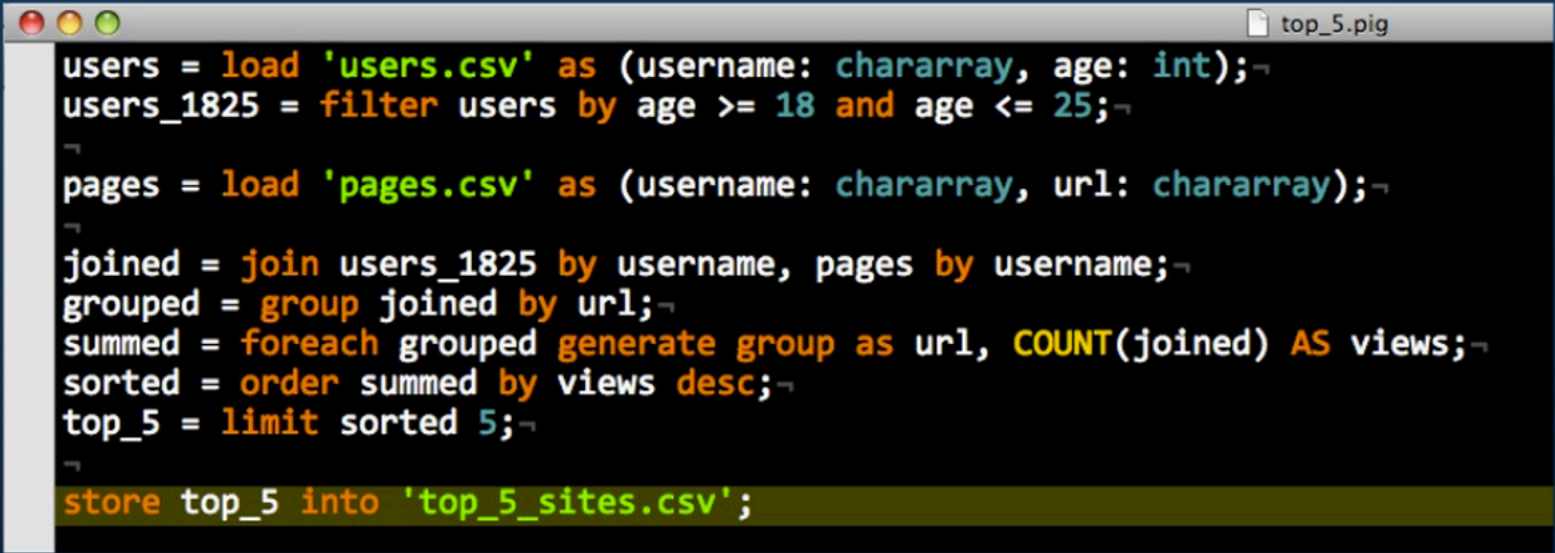
This makes operations like select & join easier to implement and less error prone.

Popular examples include Pig and Hive.

# Why Pig?

- ▶ Because I bet you can read the following script.

## A Real Pig Script



```
users = load 'users.csv' as (username: chararray, age: int);
users_1825 = filter users by age >= 18 and age <= 25;

pages = load 'pages.csv' as (username: chararray, url: chararray);

joined = join users_1825 by username, pages by username;
grouped = group joined by url;
summed = foreach grouped generate group as url, COUNT(joined) AS views;
sorted = order summed by views desc;
top_5 = limit sorted 5;

store top_5 into 'top_5_sites.csv';
```

- ▶ Now, just for fun... the same calculation in vanilla Hadoop MapReduce.

[illegible]

# **II. IMPLEMENTATION DETAILS**

The map-reduce framework handles a lot of messy details for you:

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- parallelization & distribution (eg, input splitting)
- partitioning (shuffle/sort/redirect)
- fault-tolerance (fact: tasks/nodes will fail!)
- I/O scheduling
- status and monitoring

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This (along with the functional semantics) allows you to focus on solving the problem instead of accounting & housekeeping details.



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Hadoop is written in Java, but the *Hadoop Streaming* utility allows client code to be supplied as executables (eg, written in any language).

Frequently when people say “map-reduce” they’re referring to Hadoop, but there are some exceptions:

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- many NoSQL databases support native map-reduce queries
- commercial distributions (Cloudera, MapR, etc)
- Google’s internal implementation

**That said, Hadoop has a large user base.**



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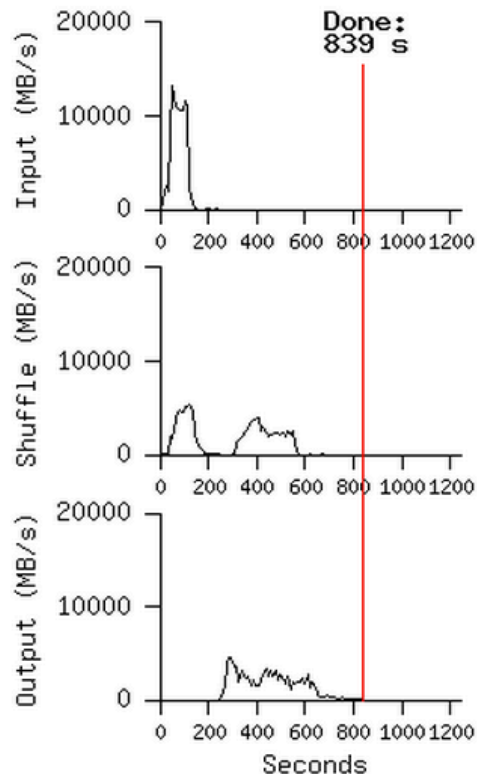
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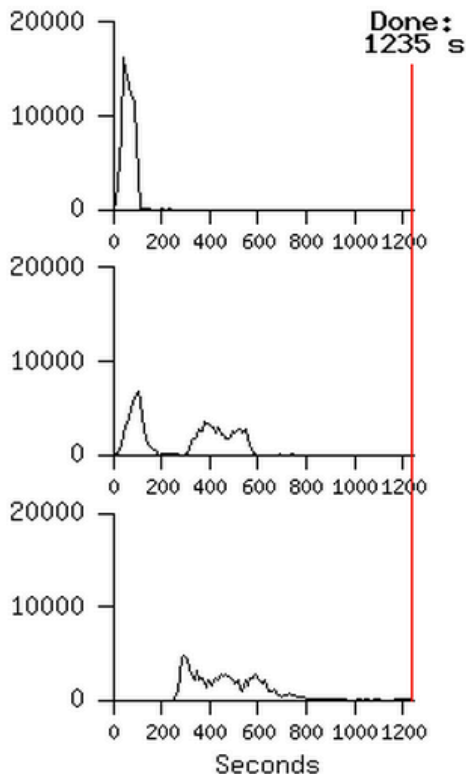
The Hadoop platform is bundled with an open-source implementation of this file system called *HDFS*.

If you use Amazon EMR, you can use Amazon S3.

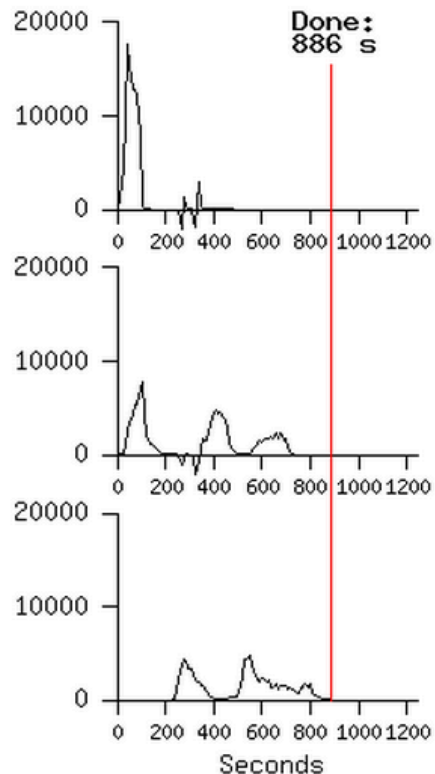
Normal



No backup tasks



200 processes killed



# **III. WORD COUNT EXAMPLE**

Map-reduce processes data in terms of *key-value pairs*:

input                       $\langle k1, v1 \rangle$

mapper                     $\langle k1, v1 \rangle \rightarrow \langle k2, v2 \rangle$

(partitioner)             $\langle k2, v2 \rangle \rightarrow \langle k2, [\text{all } k2 \text{ values}] \rangle$

reducer                    $\langle k2, [\text{all } k2 \text{ values}] \rangle \rightarrow \langle k3, v3 \rangle$



Using the following input, we can implement the “Hello World” of map-reduce: a *word count*.

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```
where  
where in  
where in the  
where in the world  
where in the world is  
where in the world is carmen  
where in the world is carmen sandiego
```

The first processing primitive is the mapper, which filters & transforms the input data, and *emits* transformed key-value pairs.

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```
mapper(k1, v1):  
    // k1 = line number  
    // v1 = line contents (eg, space-delimited string)  
  
    words = tokenize(v1)    // split string into words  
    for word in words:  
        emit (word, 1)
```

The mapper emits key-value pairs for each word encountered in the input data.

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```
where 1
where 1
in     1
where 1
in     1
the    1
...
```

The partitioner is internal to the map-reduce framework, so we don't have to write this ourselves. It shuffles & sorts the mapper output, and redirects all intermediate results for a given key to a *single* reducer.

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where	[1, 1, 1, 1, 1, 1, 1]
in	[1, 1, 1, 1, 1, 1]
the	[1, 1, 1, 1, 1]
world	[1, 1, 1, 1]
is	[1, 1, 1]
carmen	[1, 1]
sandiego	[1]



Finally, the reducer receives all values for a given key and aggregates (in this case, sums) the results.

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```
reducer(k2, k2_vals):  
    // k2 = word  
    // k2_vals = word counts  
  
    emit k2, sum(k2_vals)
```

Reducer output is aggregated...

where	7
in	6
the	5
world	4
is	3
carmen	2
sandiego	1

Reducer output is aggregated & sorted by key.

carmen	2
is	3
in	6
the	5
sandiego	1
where	7
world	4

# **IV. EXERCISE**