

INTRO to DATA SCIENCE

LECTURE 21: MAP-REDUCE

AGENDA

I. BIG DATA

II. PROGRAMMING MODEL

III. IMPLEMENTATION DETAILS

IV. WORD COUNT EXAMPLE

EXERCISE:

V. MAP-REDUCE USING PYTHON & MRJOB

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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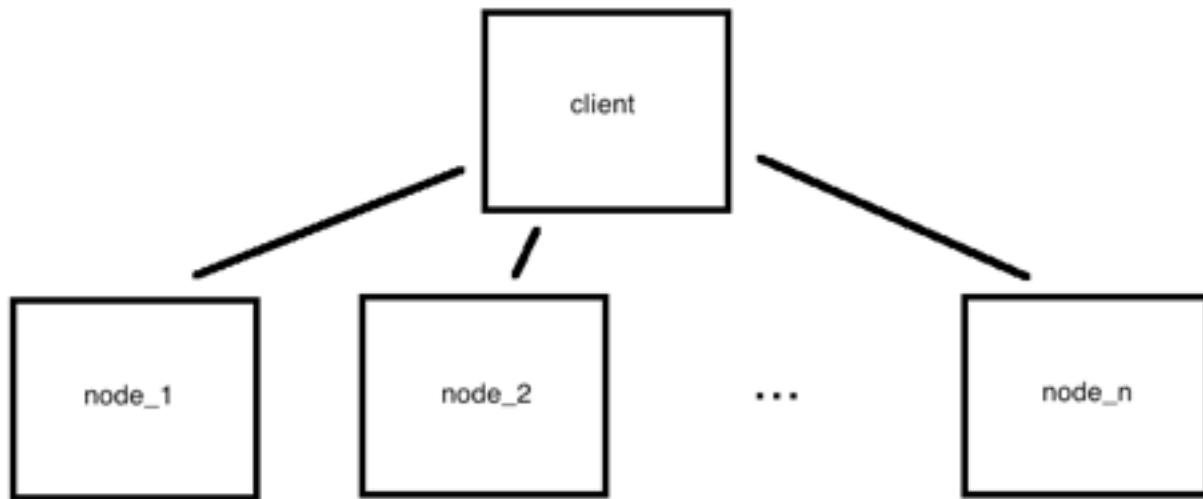
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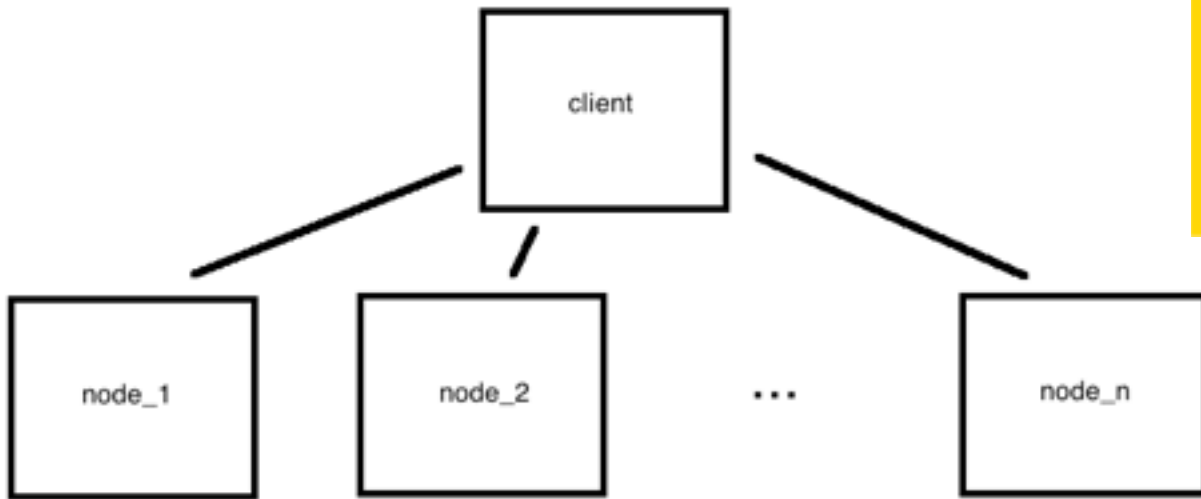
A: Scalability; in particular, storing & processing web-scale (multi-terabyte) datasets using clusters of multiple computing nodes.

“Scale out vs scale up!”

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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 code (& processing power)

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- SETI

2) move code to data

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

“Computing nodes are the same as storage nodes.”

ASIDE: DIVIDE AND CONQUER ALGORITHMS

Divide and conquer is a fundamental algorithmic technique for solving a given task, whose steps include:

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

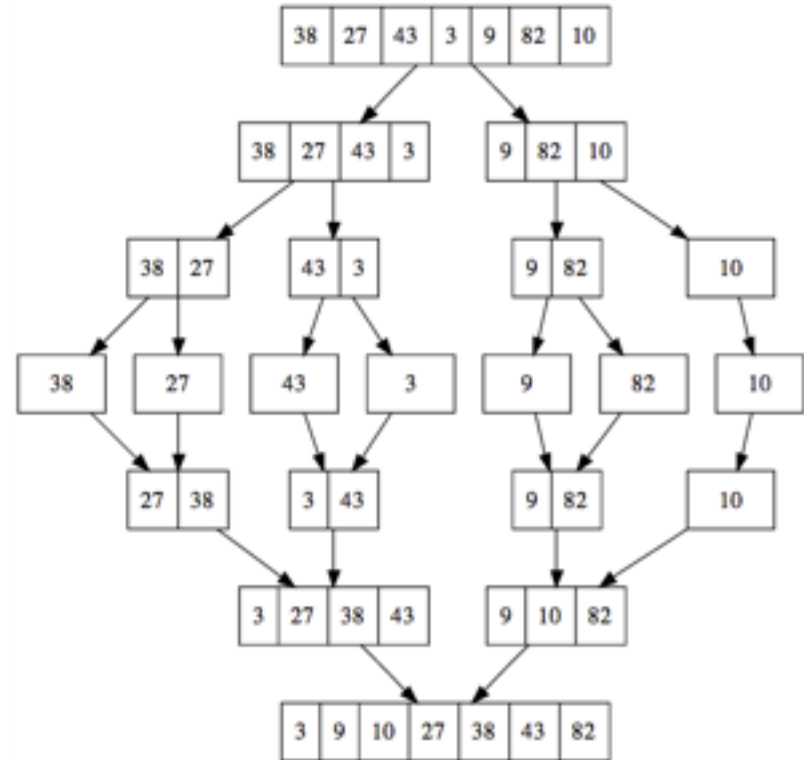
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This is how recursive algorithms work, for example.

ASIDE: DIVIDE AND CONQUER ALGORITHMS

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.)

ASIDE: DIVIDE AND CONQUER ALGORITHMS

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NOTE

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

II. PROGRAMMING MODEL

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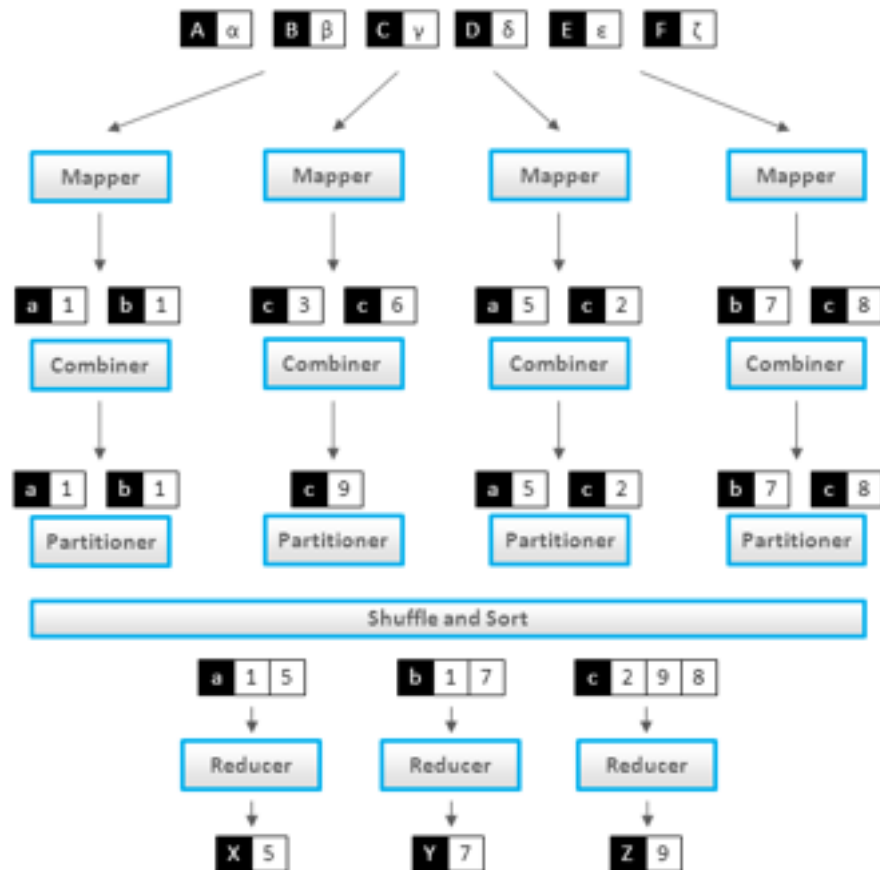
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1.5) shuffle/sort

*2) the **reducer** phase*



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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.

mappers – *filter & transform data*

reducers – *aggregate results*

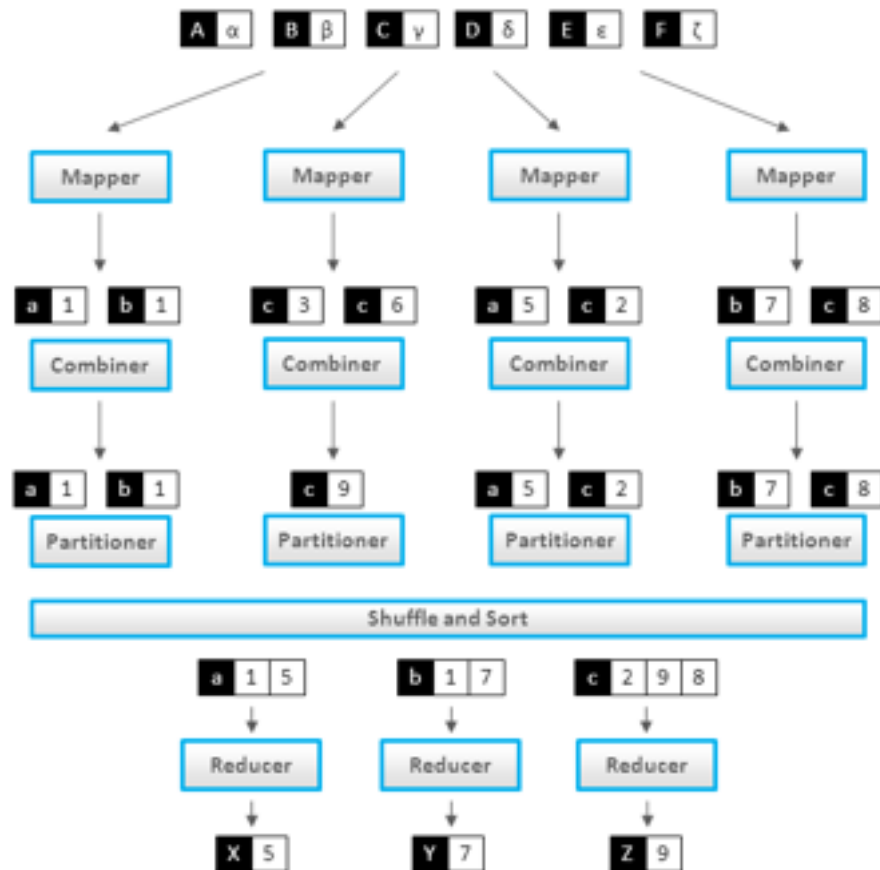
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mappers – *filter & transform data*

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

```
top_5.pig
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.

No, seriously.

[illegible]

II. IMPLEMENTATION DETAILS

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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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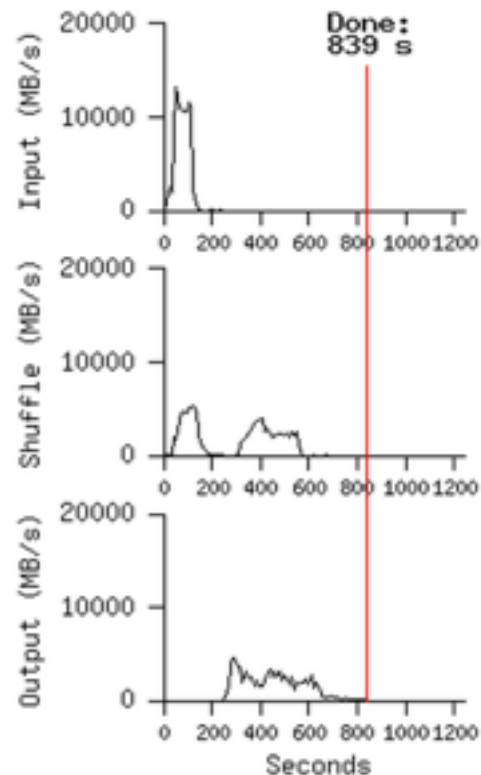
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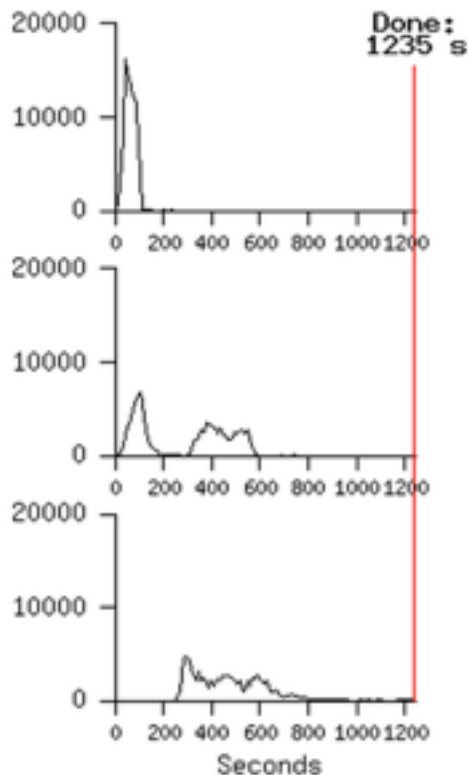
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If you use Amazon EMR, you can use their file system (Amazon S3) as well.

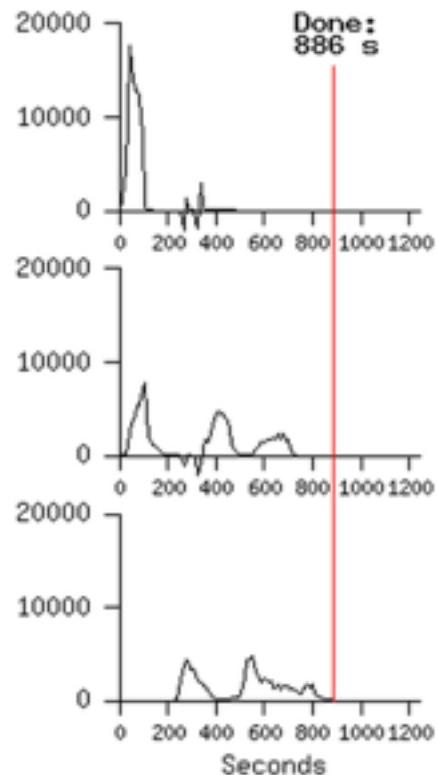
Normal



No backup tasks



200 processes killed



III. WORD COUNT EXAMPLE

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

MAP-REDUCE EXAMPLE

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

MAP-REDUCE EXAMPLE: MAPPER INPUT

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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
```

MAP-REDUCE EXAMPLE: MAPPER

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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)
```

MAP-REDUCE EXAMPLE: MAPPER OUTPUT

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
... 
```

MAP-REDUCE EXAMPLE: PARTITIONER

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.

MAP-REDUCE EXAMPLE: PARTITIONER OUTPUT

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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]

MAP-REDUCE EXAMPLE: REDUCER

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)
```

MAP-REDUCE EXAMPLE: REDUCER OUTPUT

Reducer output is aggregated...

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

MAP-REDUCE EXAMPLE: REDUCER OUTPUT

Reducer output is aggregated & sorted by key.

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