GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 10: MAP-REDUCE

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DAT5 SF // April 9, 2014

LAST TIME:

- K-MEANS CLUSTERING
- K-MEANS IN PYTHON
- Q&A SESSION FOR HW4 ON LOGISTIC REGRESSION

QUESTIONS?

I. BIG DATA
II. PROGRAMMING MODEL
III. IMPLEMENTATION DETAILS
IV. WORD COUNT EXAMPLE

EXERCISE:
V. MAP-REDUCE USING PYTHON

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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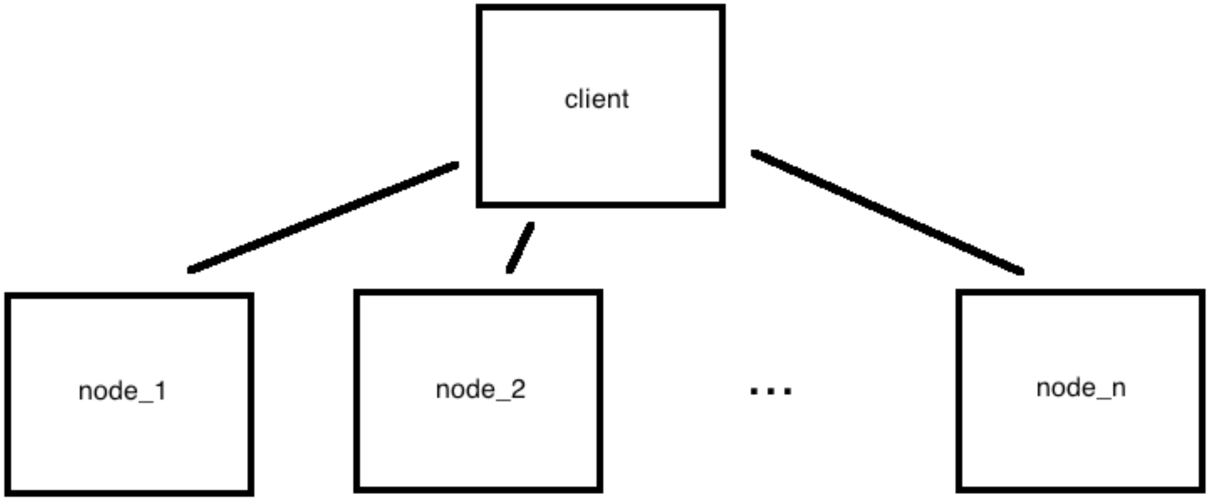
"Scale out vs scale up!"

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



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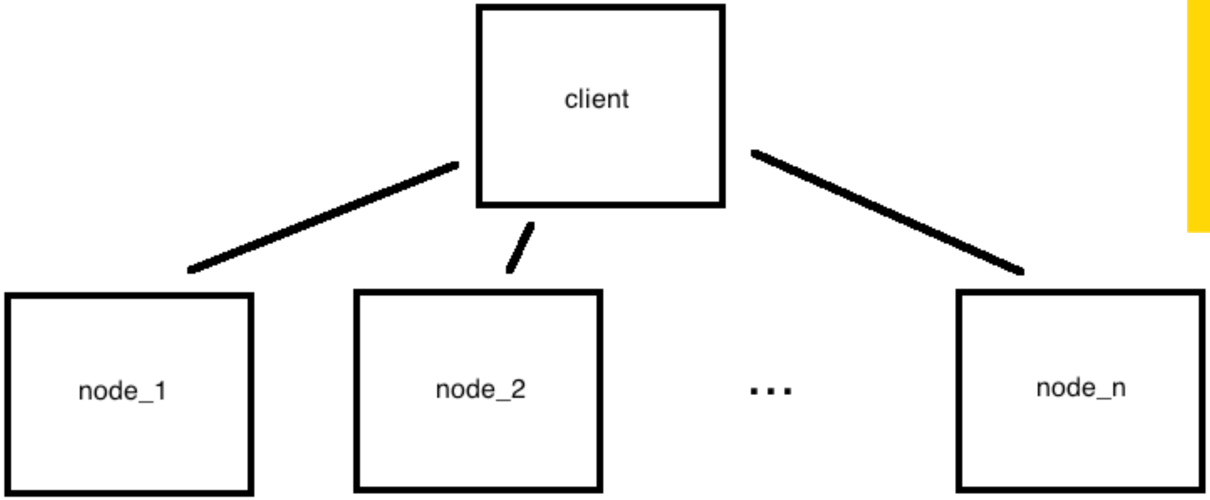

NOTE

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

There are two ways to process data in a distributed architecture:

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)*

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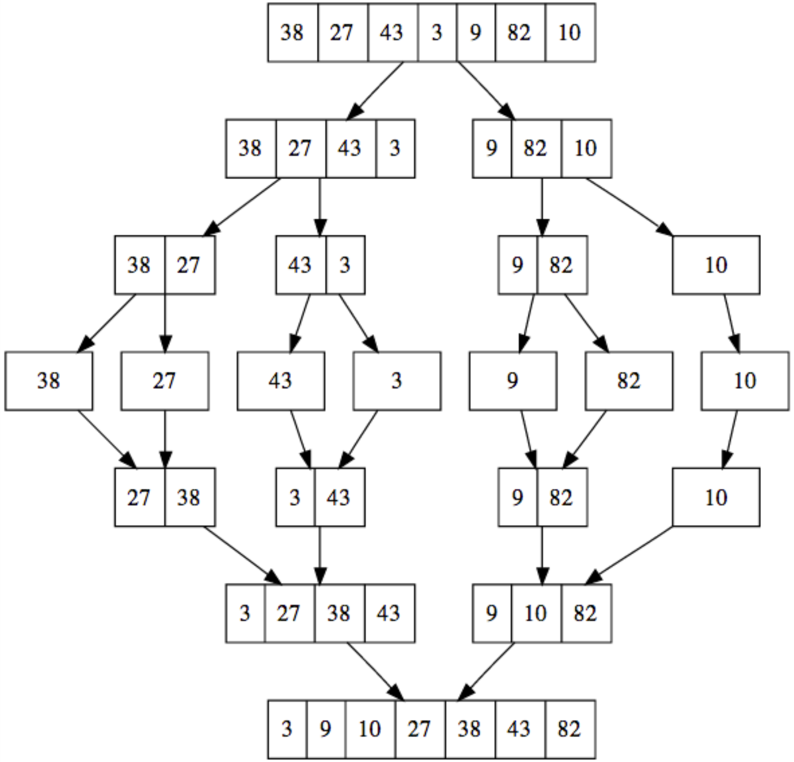
This is how recursive algorithms work, for example.

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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- count, sum, average

- grep, sort, inverted index

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NOTE

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

II. PROGRAMMING MODEL

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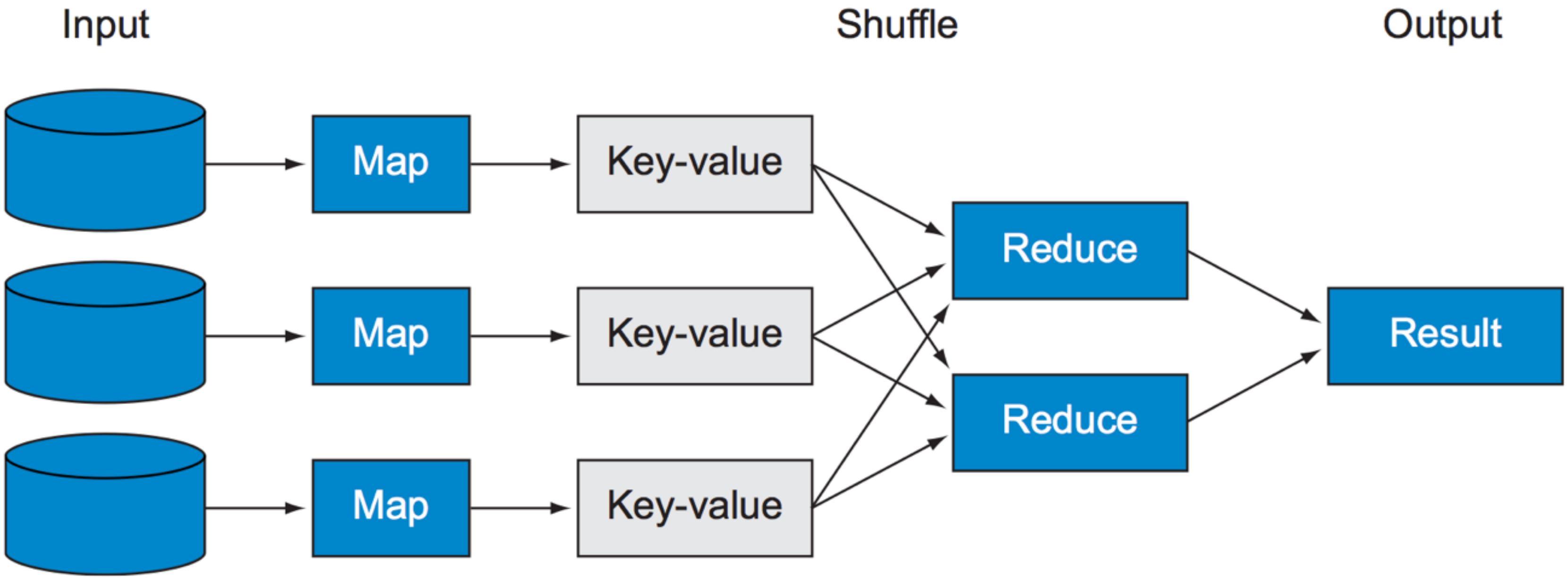
1) *the* **mapper** *phase*
1.5) *shuffle/sort*
2) *the* **reducer** *phase*

MAP-REDUCE


Input
Shuffle
Output
Map
Map
Map
Key-value
Key-value
Key-value
Reduce
Reduce
Result

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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.

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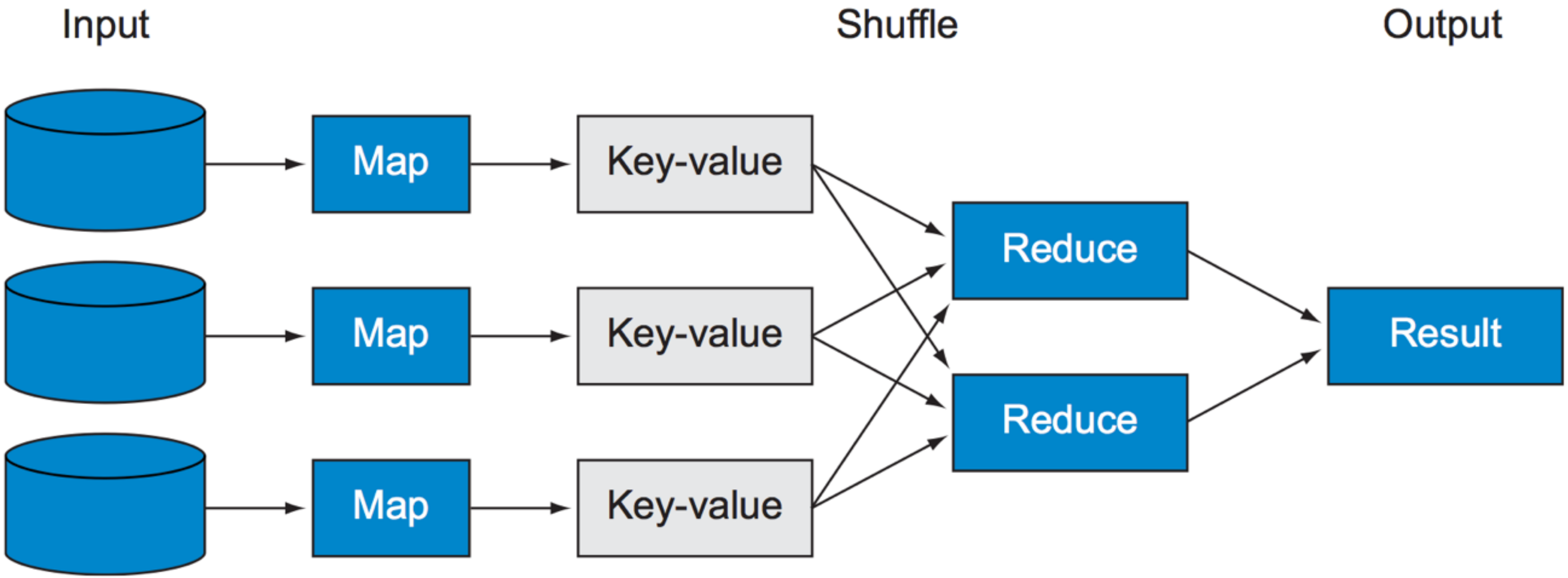
As our earlier diagram suggests, there are additional intermediate steps in a map-reduce workflow.

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*

MAP-REDUCE


Input
Shuffle
Output
Map
Map
Map
Key-value
Key-value
Key-value
Reduce
Reduce
Result

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.

source: http://www.slideshare.net/kevinweil/hadoop-pig-and-twitter-nosql-east-2009

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.

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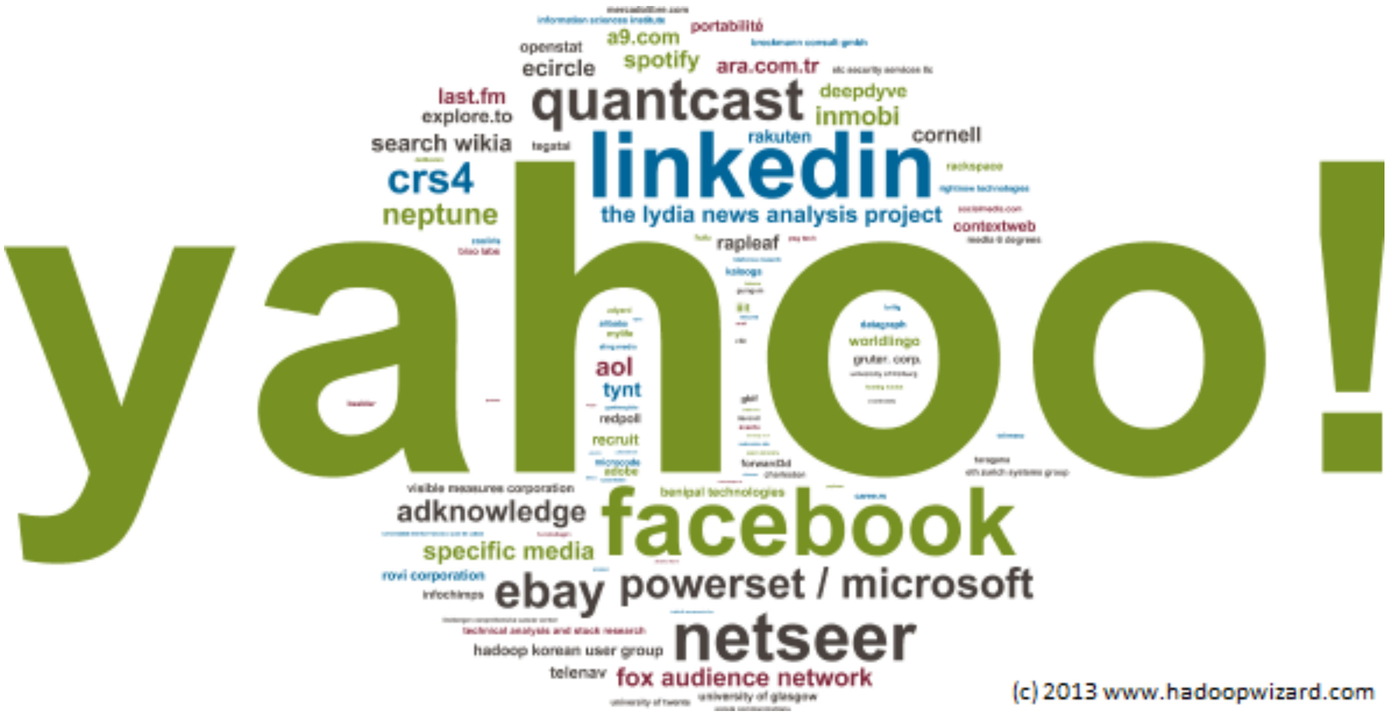
- many NoSQL databases support native map-reduce queries
- commercial distributions (Cloudera, MapR, etc)
- Google's internal implementation

That said, Hadoop has a large user base.



source: http://www.hadoopwizard.com/which-big-data-company-has-the-worlds-biggest-hadoop-cluster/

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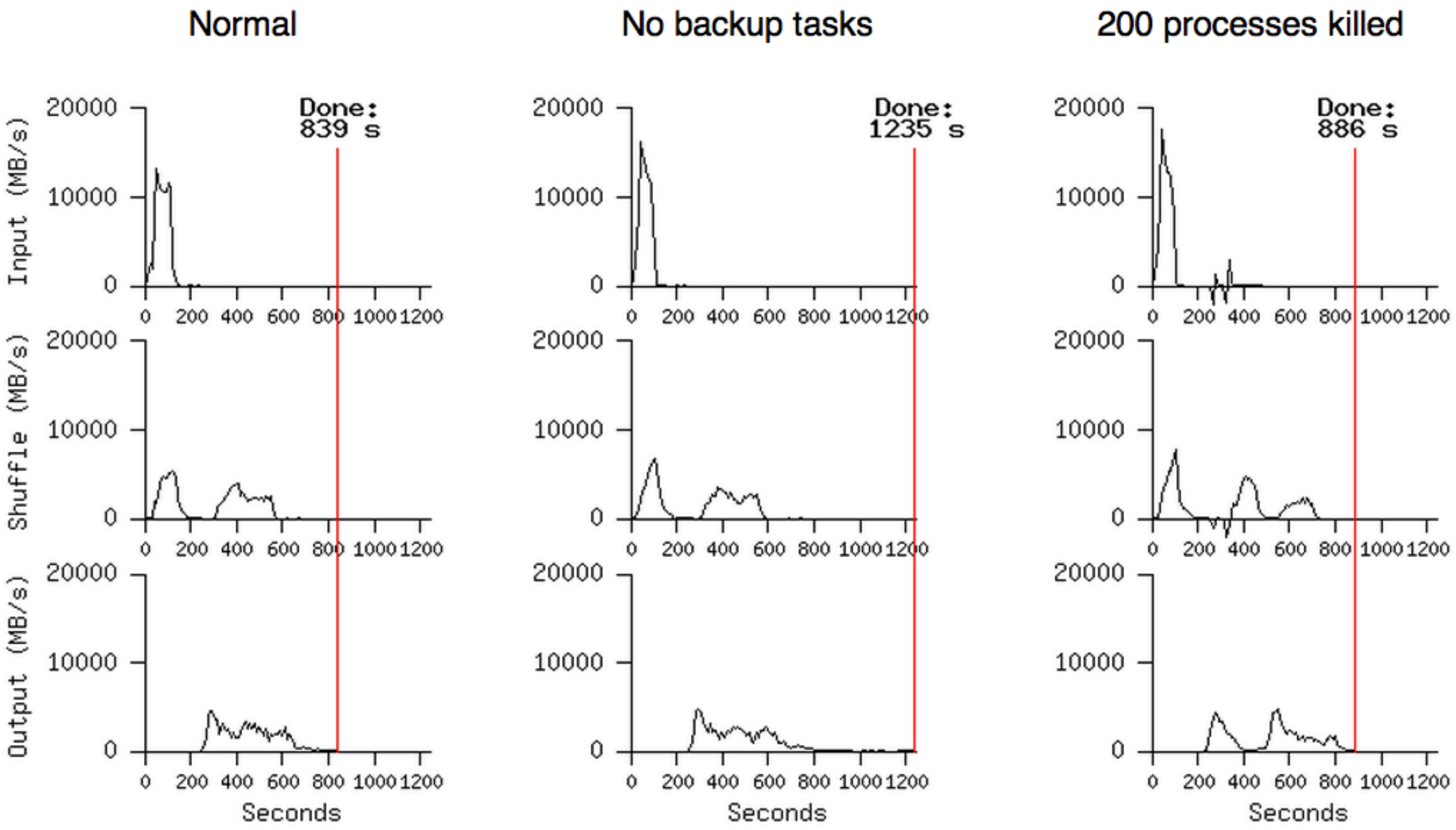
If you use Amazon EMR, you can use their file system (Amazon S3) as well.


Normal
No backup tasks
200 processes killed
Done: 839 s
Done: 1235 s
Done: 886 s
Input (MB/s)
Shuffle (MB/s)
Output (MB/s)
20000
10000
0
0 200 400 600 800 1000 1200
Seconds

III. WORD COUNT EXAMPLE

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

```
input            <k1, v1>
mapper           <k1, v1> → <k2, v2>
(partitioner)    <k2, v2> → <k2, [all k2 values]>
reducer          <k2, [all k2 values]> → <k3, v3>
```

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
```

MAP-REDUCE EXAMPLE: MAPPER

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)
```

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
...
```

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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
```

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
```