GENERAL ASSEMBLY

INTRO TO DATA SCIENCE:
MAP-REDUCE

AGENDA

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

EXERCISE:
V. MAP-REDUCE USING PYTHON

I. BIG DATA

As you have probably heard, **big data** *is a hot topic these days.*

As you have probably heard, **big data** *is a hot topic these days.*

Q: What does "big data" actually refer to?

As you have probably heard, **big data** *is a hot topic these days.*

Q: What does "big data" actually refer to?

A: Scalability; in particular, storing & processing web-scale (multi-terabyte) datasets...

As you have probably heard, **big data** *is a hot topic these days.*

Q: What does "big data" actually refer to?

A: Scalability; in particular, storing & processing web-scale (multi-terabyte) datasets...

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

One approach would be to get a huge supercomputer.

One approach would be to get a huge supercomputer.

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?

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

This has obvious benefits!

- cheaper

- easier to maintain

- scalability is unbounded (just add more nodes to the cluster)

Now we can give a complete answer to our earlier question.

Q: What does "big data" actually refer to?

Now we can give a complete answer to our earlier question.

Q: What does "big data" actually refer to?

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

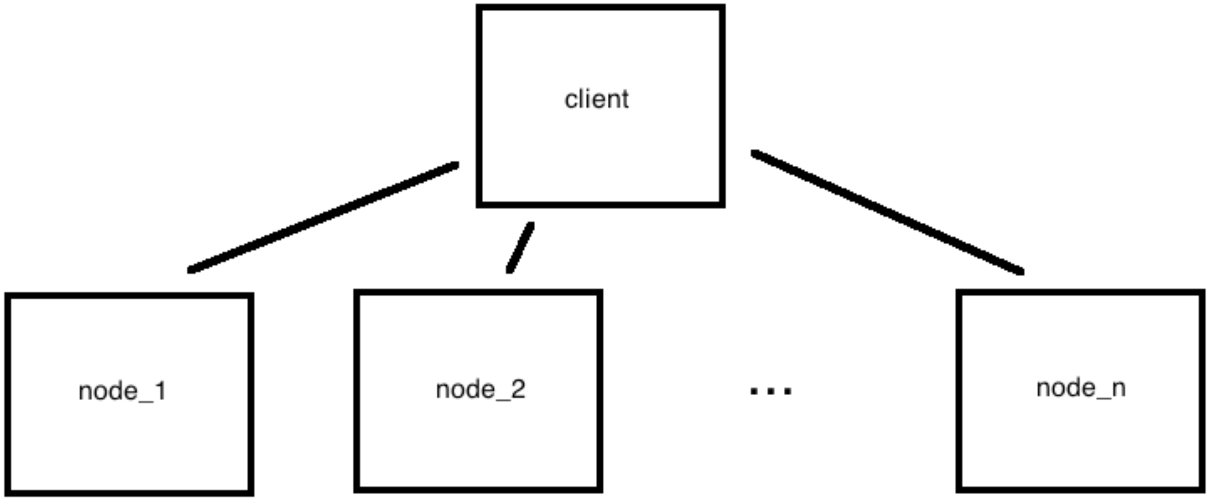
Now we can give a complete answer to our earlier question.

Q: What does "big data" actually refer to?

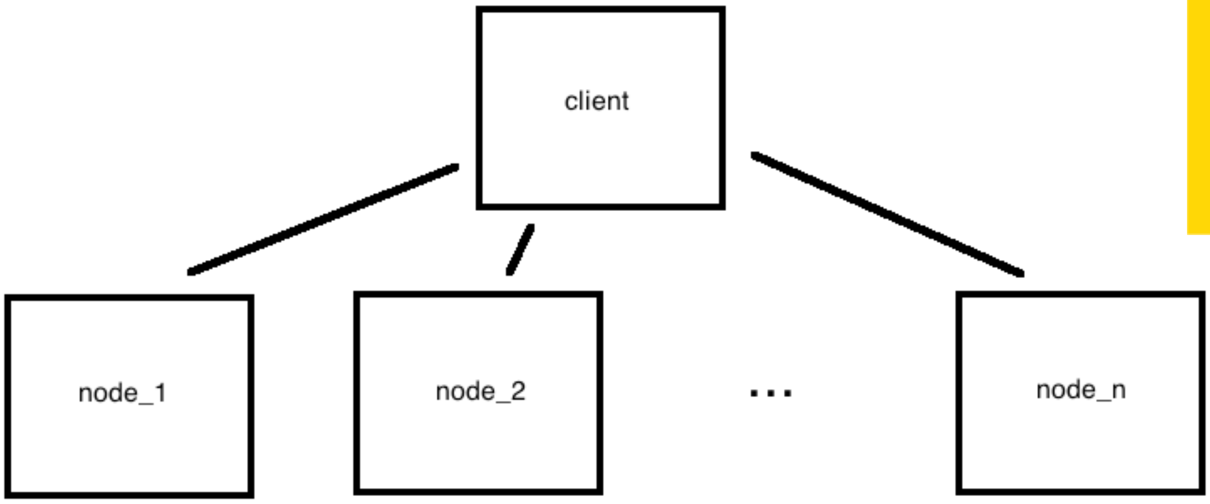
A: Scalability; in particular, storing & processing web-scale (multi-terabyte) datasets using clusters of multiple computing nodes.

"Scale out vs scale up!"

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



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



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)*

2) *move code to data*

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

1) *move data to code (& processing power)*
   - *SETI*

2) *move code to data*
   - *map-reduce → less overhead (network traffic, disk I/O)*

"Computing nodes are the same as storage nodes."

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

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

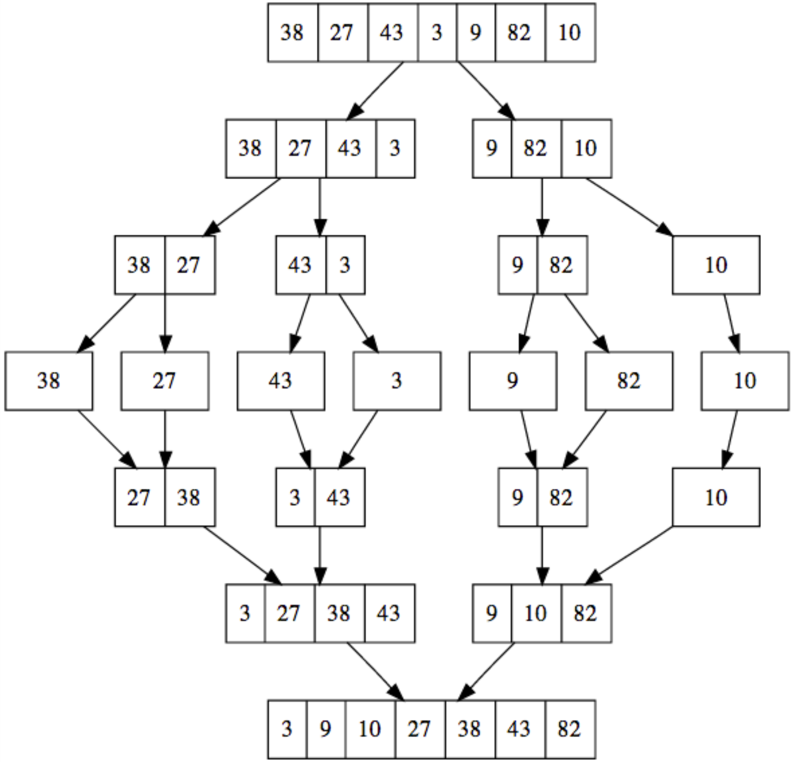
1) *split task into subtasks*
2) *solve these subtasks independently*
3) *recombine the subtask results into a final result*

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

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

This is how recursive algorithms work, for example.

One famous example of divide and conquer is merge sort.



Map-reduce leverages the divide and conquer approach by splitting a large dataset into several smaller datasets and performing a computation on each of these in parallel.

Map-reduce leverages the divide and conquer approach by splitting a large dataset into several smaller datasets and performing a computation on each of these in parallel.

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

Map-reduce leverages the divide and conquer approach by splitting a large dataset into several smaller datasets and performing a computation on each of these in parallel.

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.)

The defining characteristic of a problem that is suitable for the divide and conquer approach is that it can be broken down into independent subtasks.

The defining characteristic of a problem that is suitable for the divide and conquer approach is that it can be broken down into independent subtasks.

Tasks that can be parallelized in this way include:

- count, sum, average

- grep, sort, inverted index

- graph traversals, some ML algorithms

The defining characteristic of a problem that is suitable for the divide and conquer approach is that it can be broken down into independent subtasks.

Tasks that can be parallelized in this way include:
- count, sum, average
- grep, sort, inverted index
- graph traversals, some ML algorithms

NOTE

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

II. PROGRAMMING MODEL

As we've discussed, the map-reduce approach involves splitting a problem into subtasks and processing these subtasks in parallel.

As we've discussed, the map-reduce approach involves splitting a problem into subtasks and processing these subtasks in parallel.

This takes place in two phases:

As we've discussed, the map-reduce approach involves splitting a problem into subtasks and processing these subtasks in parallel.

This takes place in two phases:

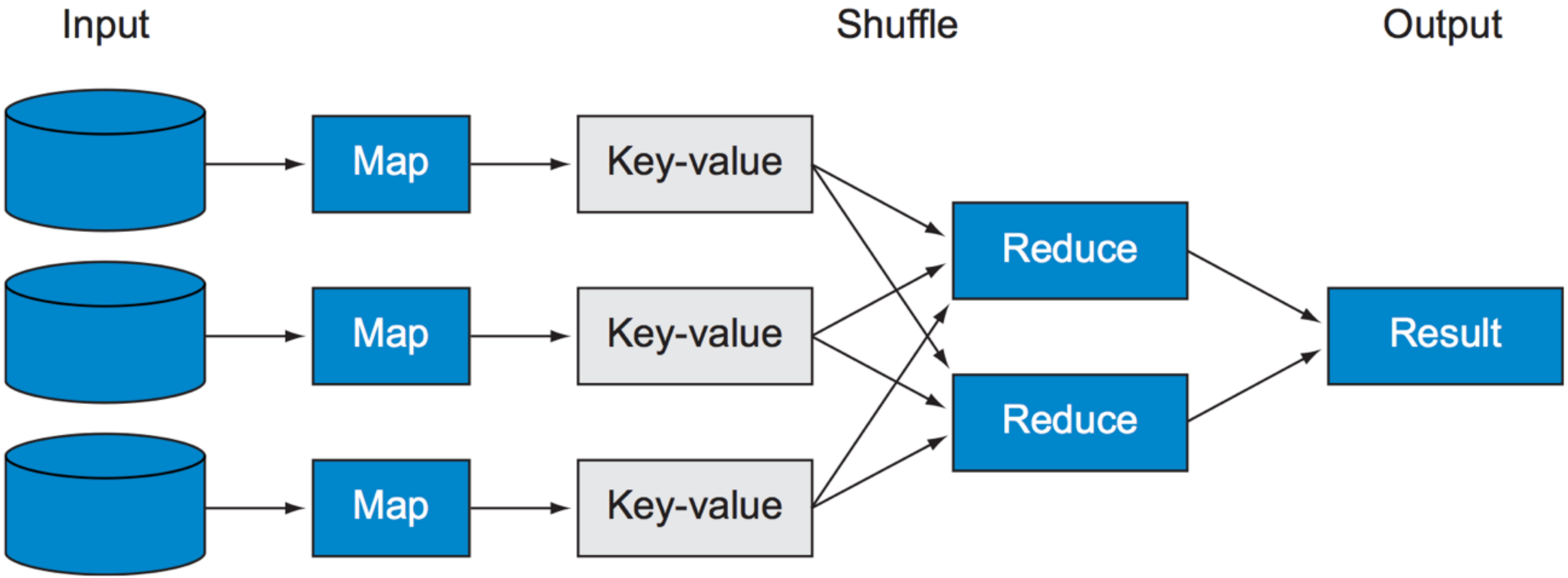
1) *the* **mapper** *phase*
2) *the* **reducer** *phase*

As we've discussed, the map-reduce approach involves splitting a problem into subtasks and processing these subtasks in parallel.

This takes place in (approximately) two phases:

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

Map-reduce uses a functional programming paradigm. The data processing primitives are mappers and reducers, as we've seen.

Map-reduce uses a functional programming paradigm. The data processing primitives are mappers and reducers, as we've seen.

mappers – *filter & transform data*
reducers – *aggregate results*

Map-reduce uses a functional programming paradigm. The data processing primitives are mappers and reducers, as we've seen.

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.

mappers – *filter & transform data*
reducers – *aggregate results*

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

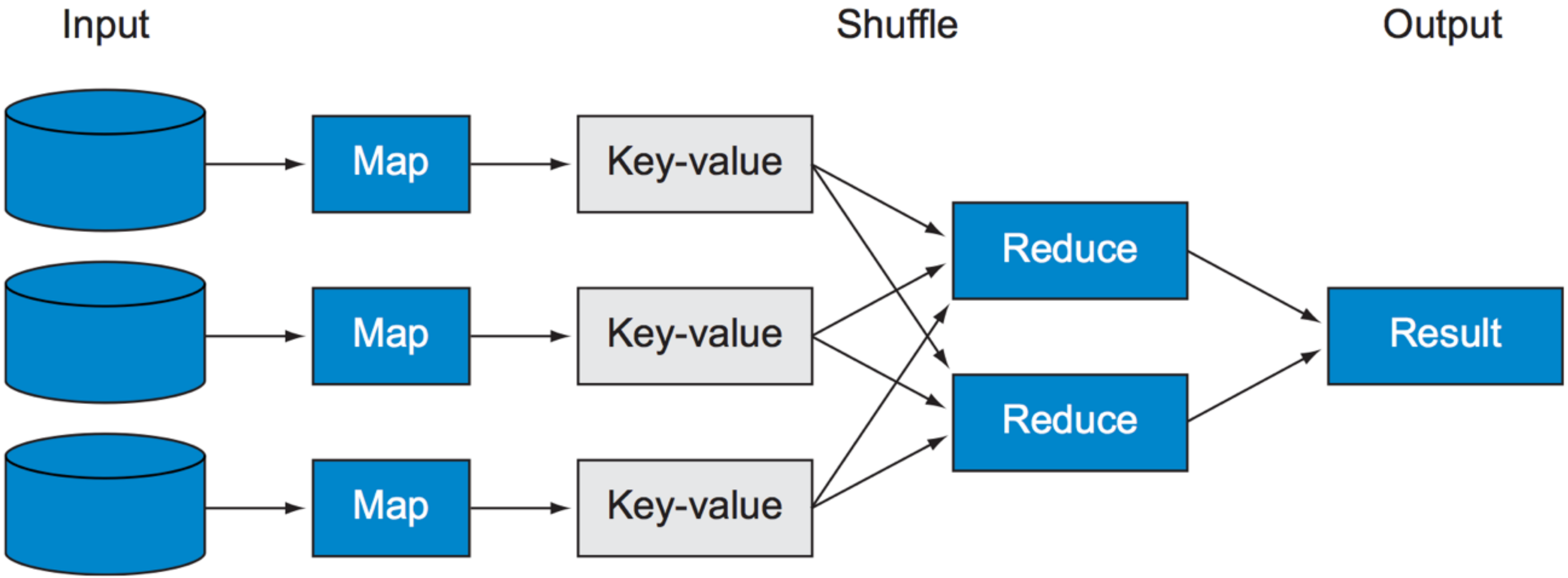
mappers – *filter & transform data*

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

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

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

- parallelization & distribution (eg, input splitting)

- partitioning (shuffle/sort/redirect)

- fault-tolerance (fact: tasks/nodes will fail!)

- I/O scheduling

- status and monitoring

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

- parallelization & distribution (eg, input splitting)

- partitioning (shuffle/sort/redirect)

- fault-tolerance (fact: tasks/nodes will fail!)

- I/O scheduling

- status and monitoring

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

Hadoop *is a popular open-source Java-based implementation of the map-reduce framework (including file storage for input/output).*

Hadoop *is a popular open-source Java-based implementation of the map-reduce framework (including file storage for input/output).*

You can download Hadoop and configure a set of machines to operate as a map-reduce cluster, or you can run it as a service via Amazon's Elastic Map-Reduce.

Hadoop *is a popular open-source Java-based implementation of the map-reduce framework (including file storage for input/output).*

You can download Hadoop and configure a set of machines to operate as a map-reduce cluster, or you can run it as a service via Amazon's Elastic Map-Reduce.

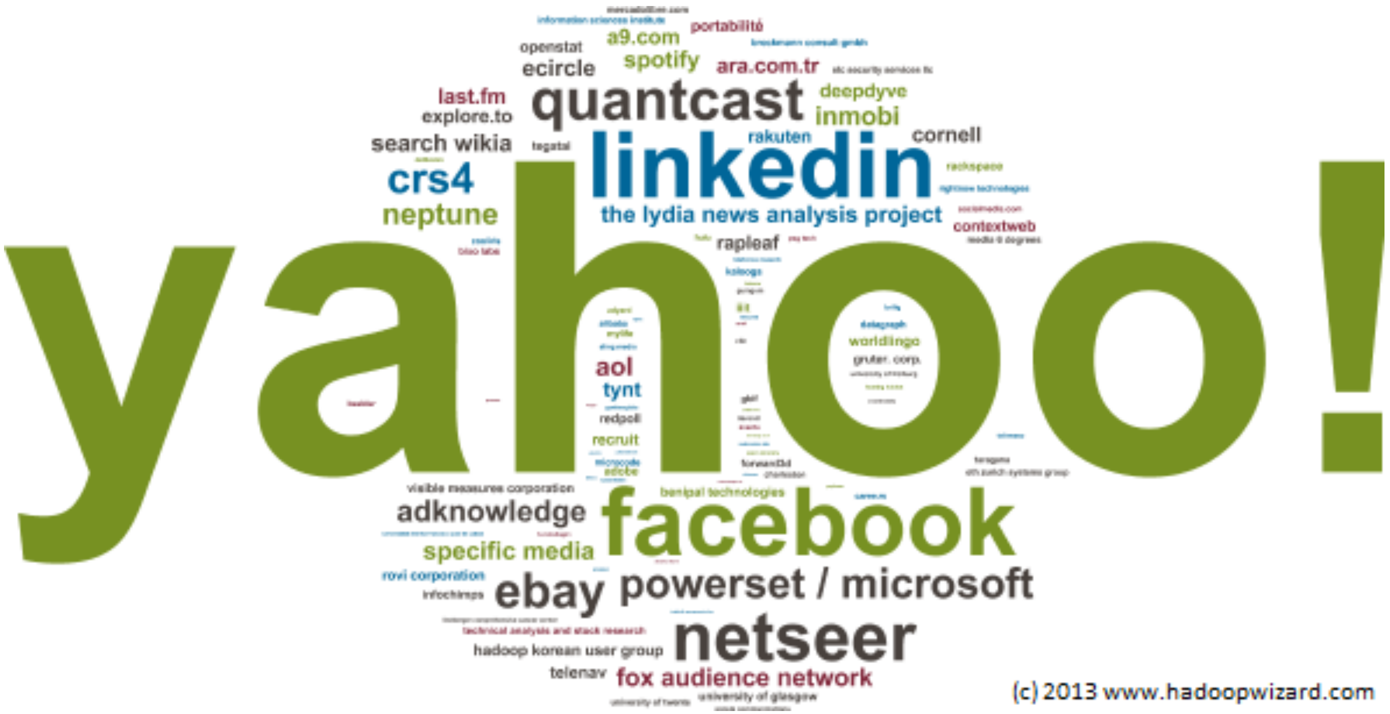
Hadoop is written in Java, but the Hadoop Streaming utility allows client code to be supplied as executables (eg, written in any language).

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

Frequently when people say "map-reduce" they're referring to Hadoop, but there are some exceptions:

- 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/

Data is replicated in the (distributed) file system across several nodes.

Data is replicated in the (distributed) file system across several nodes.

This permits locality optimization (and fault tolerance) by allowing the mapper tasks to run on the same nodes where the data resides.

Data is replicated in the (distributed) file system across several nodes.

This permits locality optimization (and fault tolerance) by allowing the mapper tasks to run on the same nodes where the data resides.

So we move code to data (instead of data to code), thus avoiding a lot of network traffic and disk I/O.

Data is replicated in the (distributed) file system across several nodes

This permits locality optimization (and fault tolerance) by a
mapper tasks to run on the same nodes where the data re

NOTE

"Compute nodes are the same as storage nodes."

So we move code to data (instead of data to code), thus avoiding a lot of network traffic and disk I/O.

The Google File System (GFS) was developed alongside map-reduce to serve as the native file system for this type of processing.

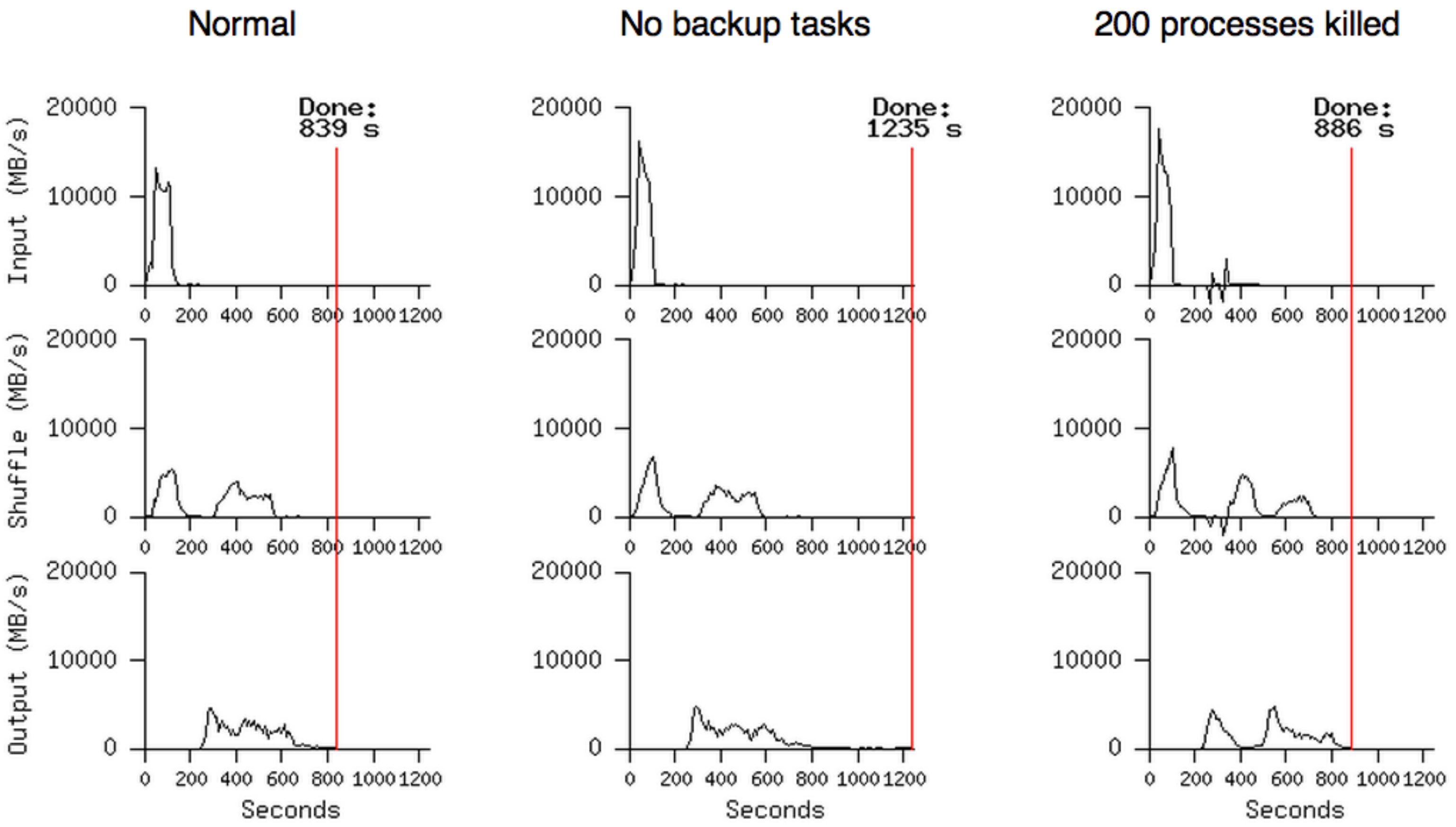
The Google File System (GFS) was developed alongside map-reduce to serve as the native file system for this type of processing.

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

The Google File System (GFS) was developed alongside map-reduce to serve as the native file system for this type of processing.

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

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.

MAP-REDUCE EXAMPLE: MAPPER INPUT

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

```
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.

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

```
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.

MAP-REDUCE EXAMPLE: MAPPER OUTPUT

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

```
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.

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.

```
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.

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

```
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
```

Reduced output is aggregated & sorted by key.

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