GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 15: MAP-REDUCE

LAST TIME:

- RELATIONAL DB’S (RDBMS)

QUESTIONS?

I. BIG DATA

II. PROGRAMMING MODEL

III. IMPLEMENTATION DETAILS

EXERCISE:

V. MAP-REDUCE USING PIG

I. BIG DATA

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

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

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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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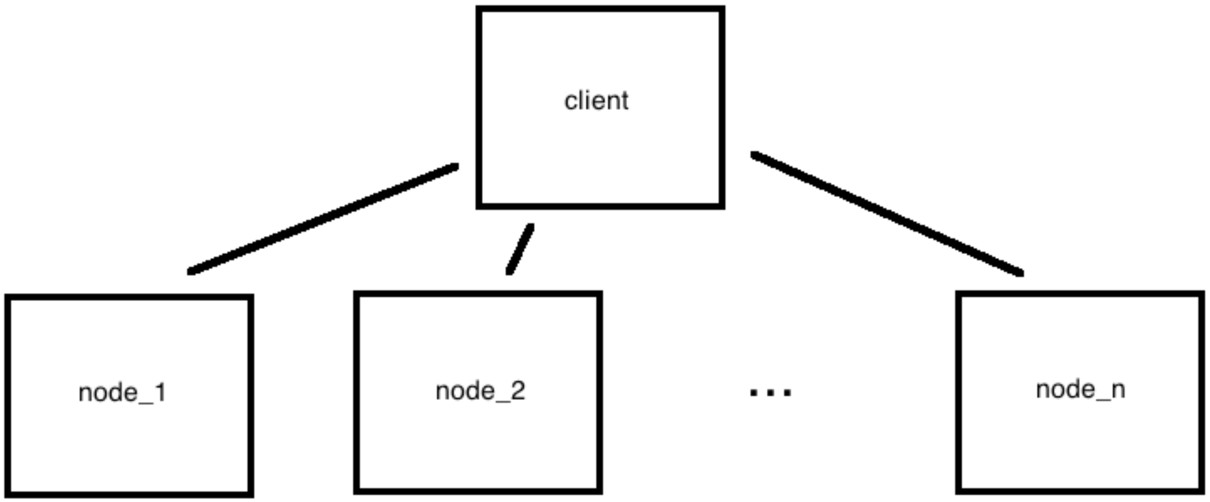
"Scale out vs scale up!"

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



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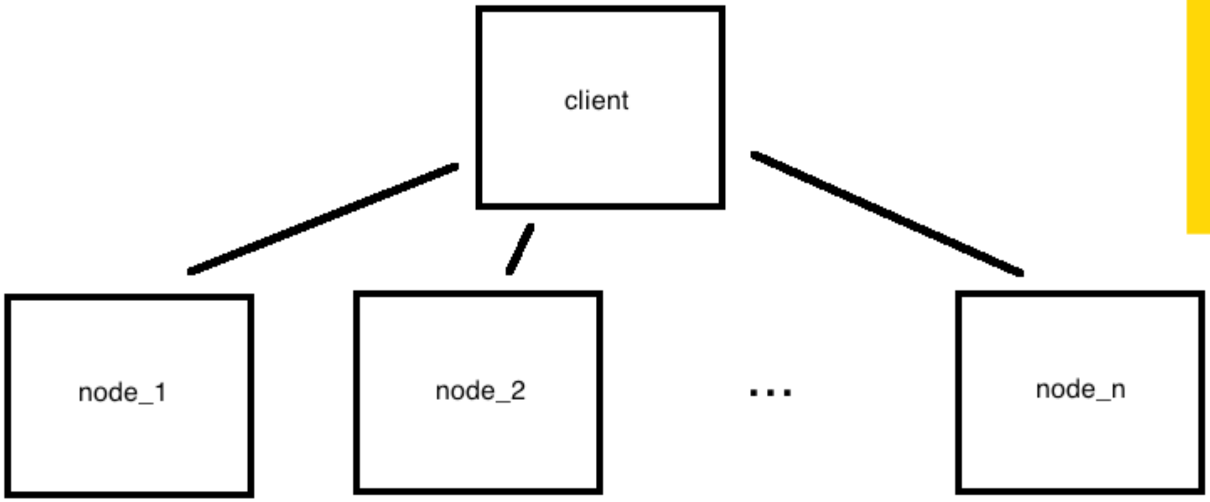
NOTE

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



How do we process data in a distributed architecture?

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

“Computing nodes are the same as storage nodes.”

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2) solve these subtasks *independently*
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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.

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- count, sum, average
- grep, sort, inverted index
- graph traversals, ***some*** ML algorithms

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NOTE

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

II. PROGRAMMING MODEL

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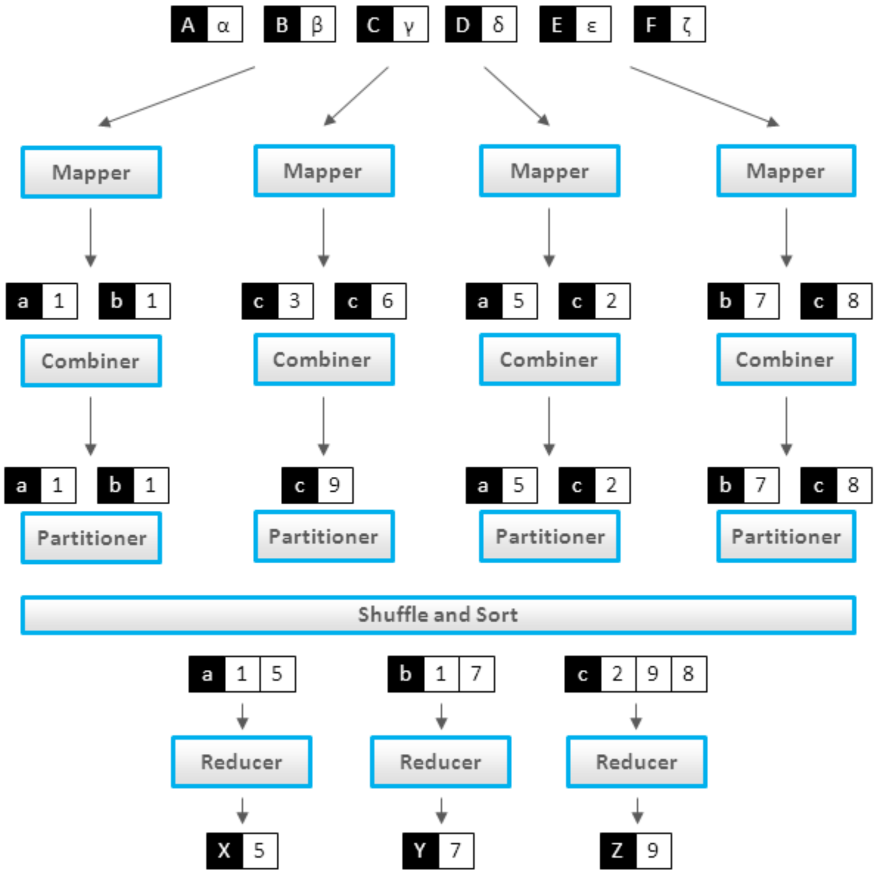
1) the **mapper** phase
1.5) *shuffle/sort*
2) the **reducer** phase

MAP-REDUCE


A α
B β
C γ
D δ
E ε
F ζ
Mapper
Mapper
Mapper
Mapper
a 1
b 1
c 3
c 6
a 5
c 2
b 7
c 8
Combiner
Combiner
Combiner
Combiner
a 1
b 1
c 9
a 5
c 2
b 7
c 8
Partitioner
Partitioner
Partitioner
Partitioner
Shuffle and Sort
a 1 5
b 1 7
c 2 9 8
Reducer
Reducer
Reducer
X 5
Y 7
Z 9

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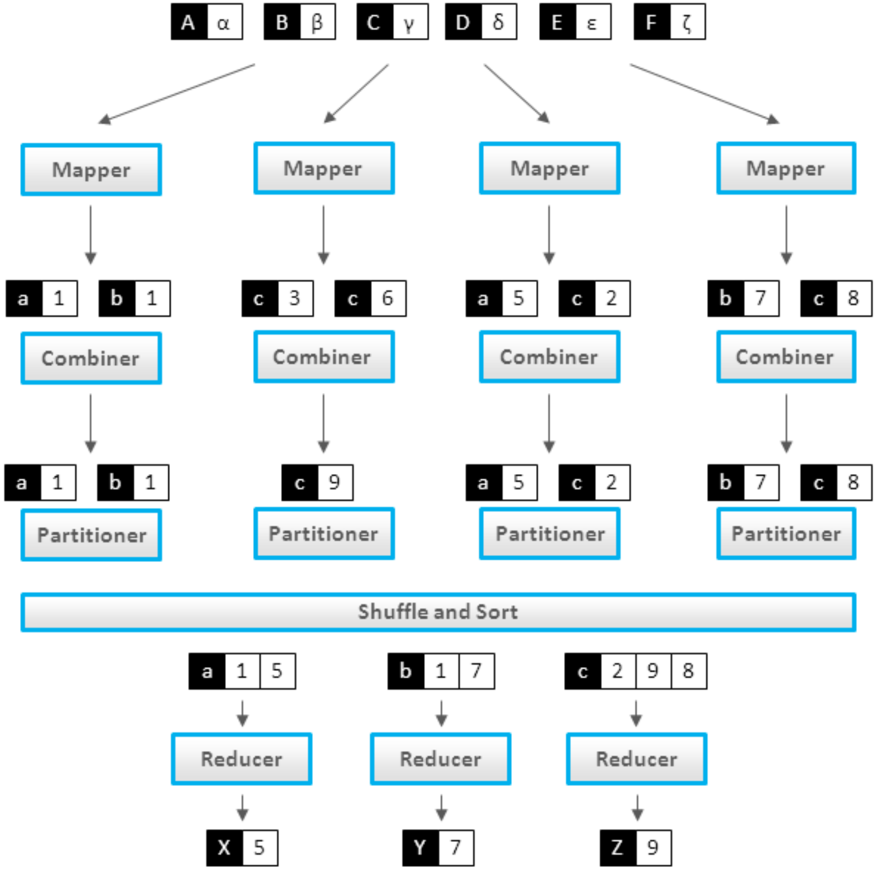
As our earlier diagram suggests, there are additional intermediate steps in a map-reduce workflow.

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


A α
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a 1
b 1
c 3
c 6
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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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- parallelization & distribution (eg, input splitting)
- partitioning (shuffle/sort/redirect)
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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

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

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

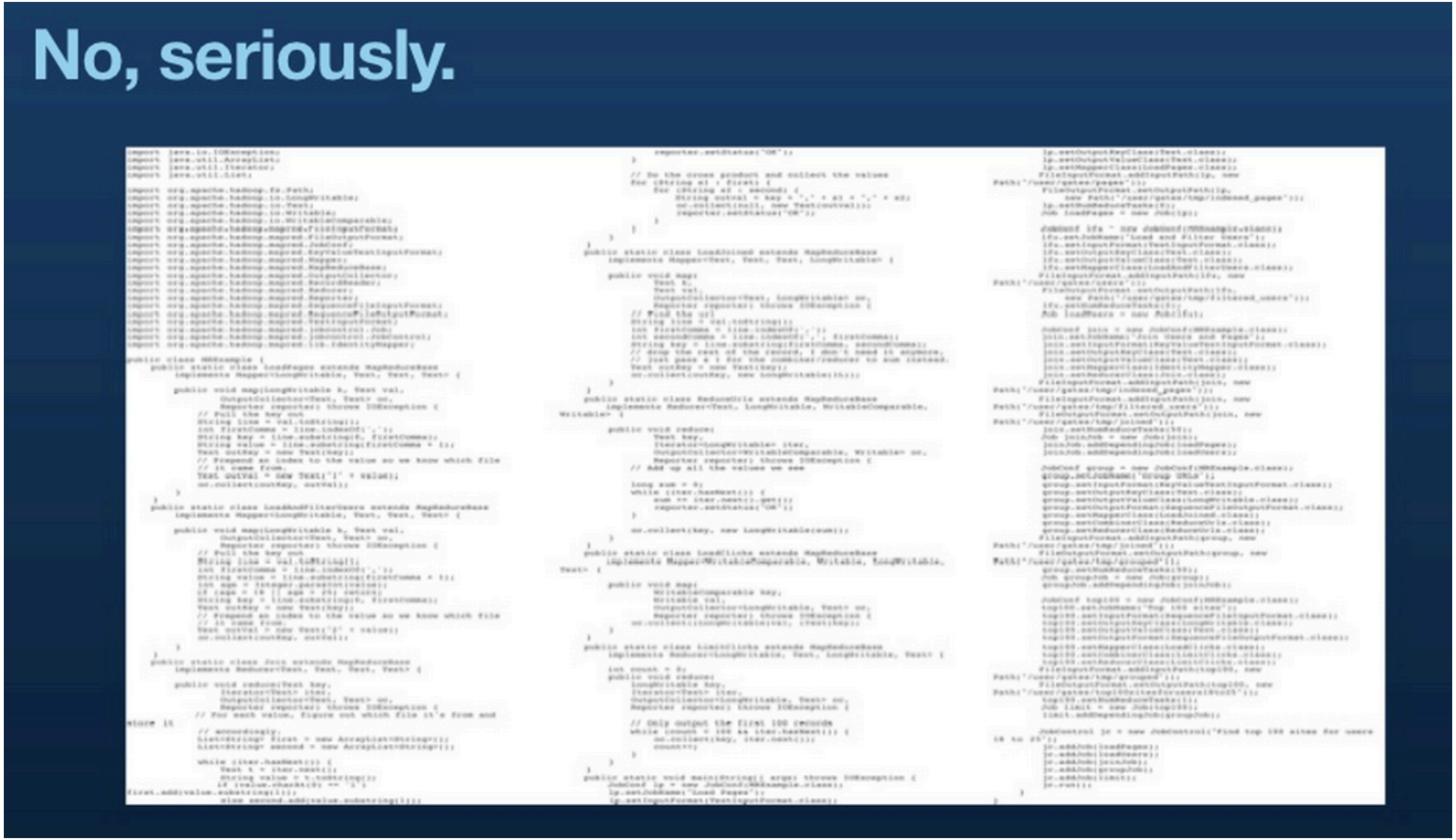
```
users = load 'users.csv' as (username: chararray, age: int);
users_1825 = filter users by age >= 18 and age <= 25;

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.

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
```

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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
```