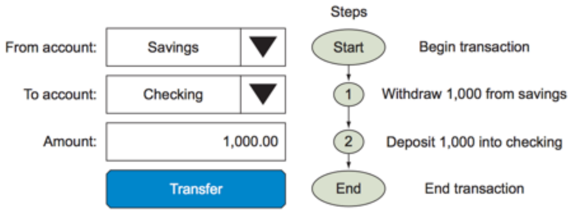
GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

MAP REDUCE

DATA SCIENCE IN THE NEWS

LAST TIME:

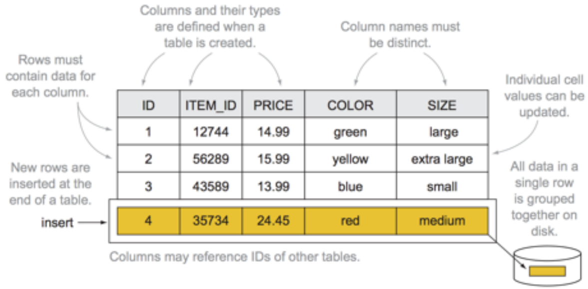


I. DATABASE EVOLUTION

II. THE NOSQL MOVEMENT

III. WORKING WITH STRUCTURED DATA (MYSQL, SQLITE)

LAB: SQL (SQLITE)



QUESTIONS?

WHAT WAS THE MOST INTERESTING THING YOU LEARNT?

WHAT WAS THE HARDEST TO GRASP?

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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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.

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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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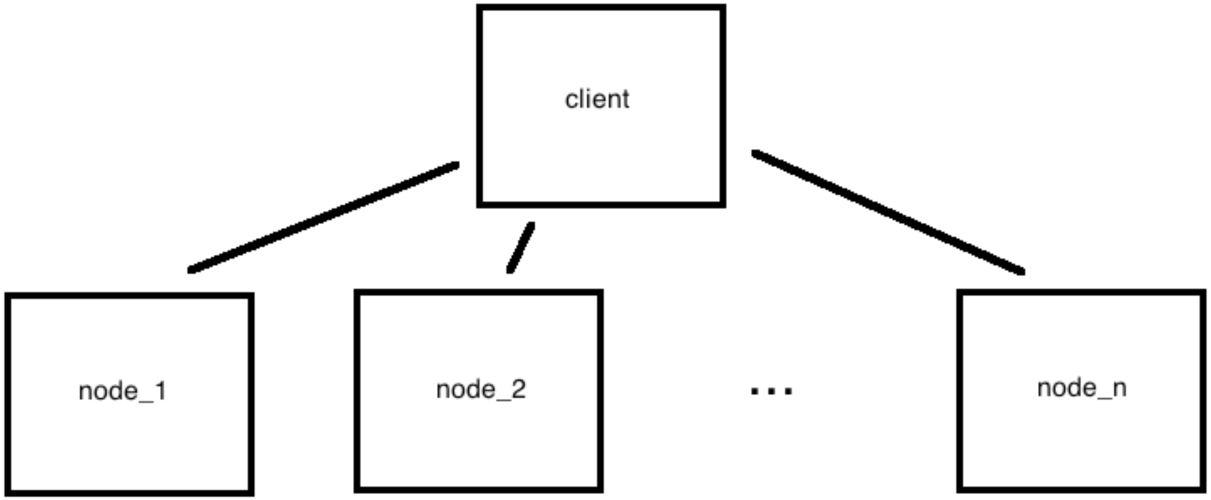
"Scale out vs scale up!"

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



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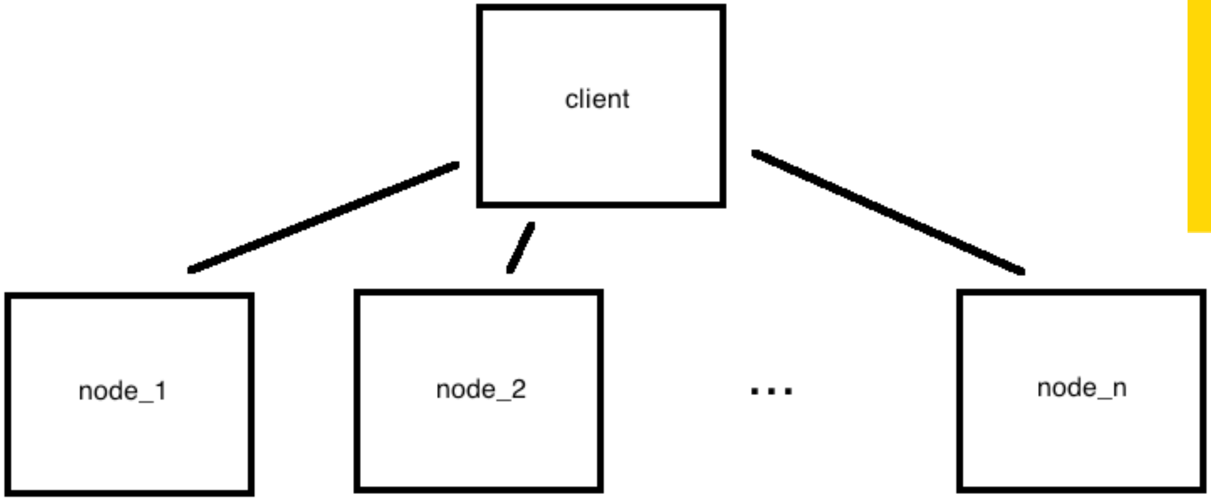

NOTE

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)*

2) *move code to data*

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- SETI

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

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

ASIDE: DIVIDE AND CONQUER ALGORITHMS

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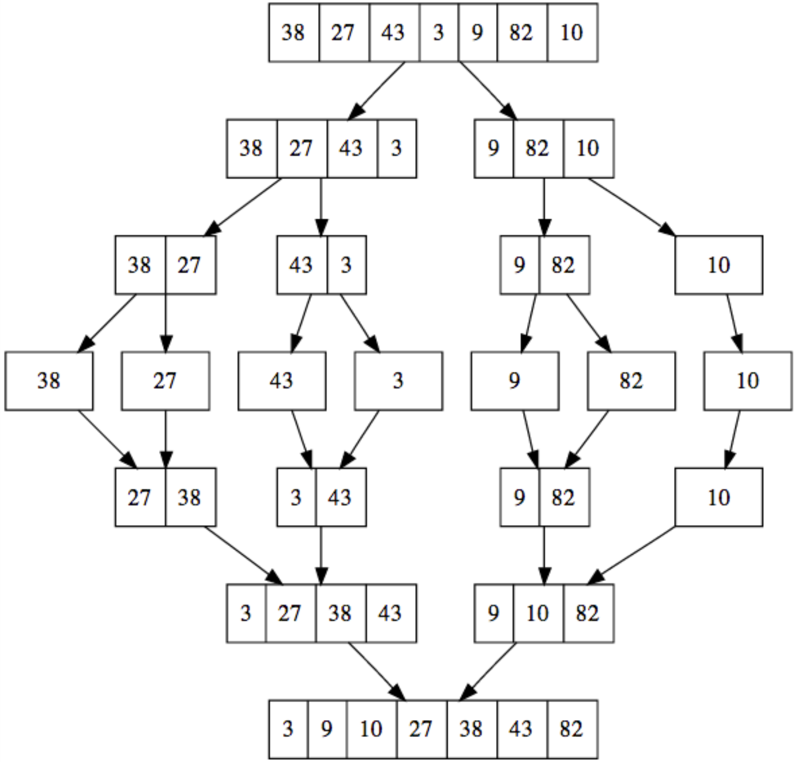
This is how recursive algorithms work, for example.

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!

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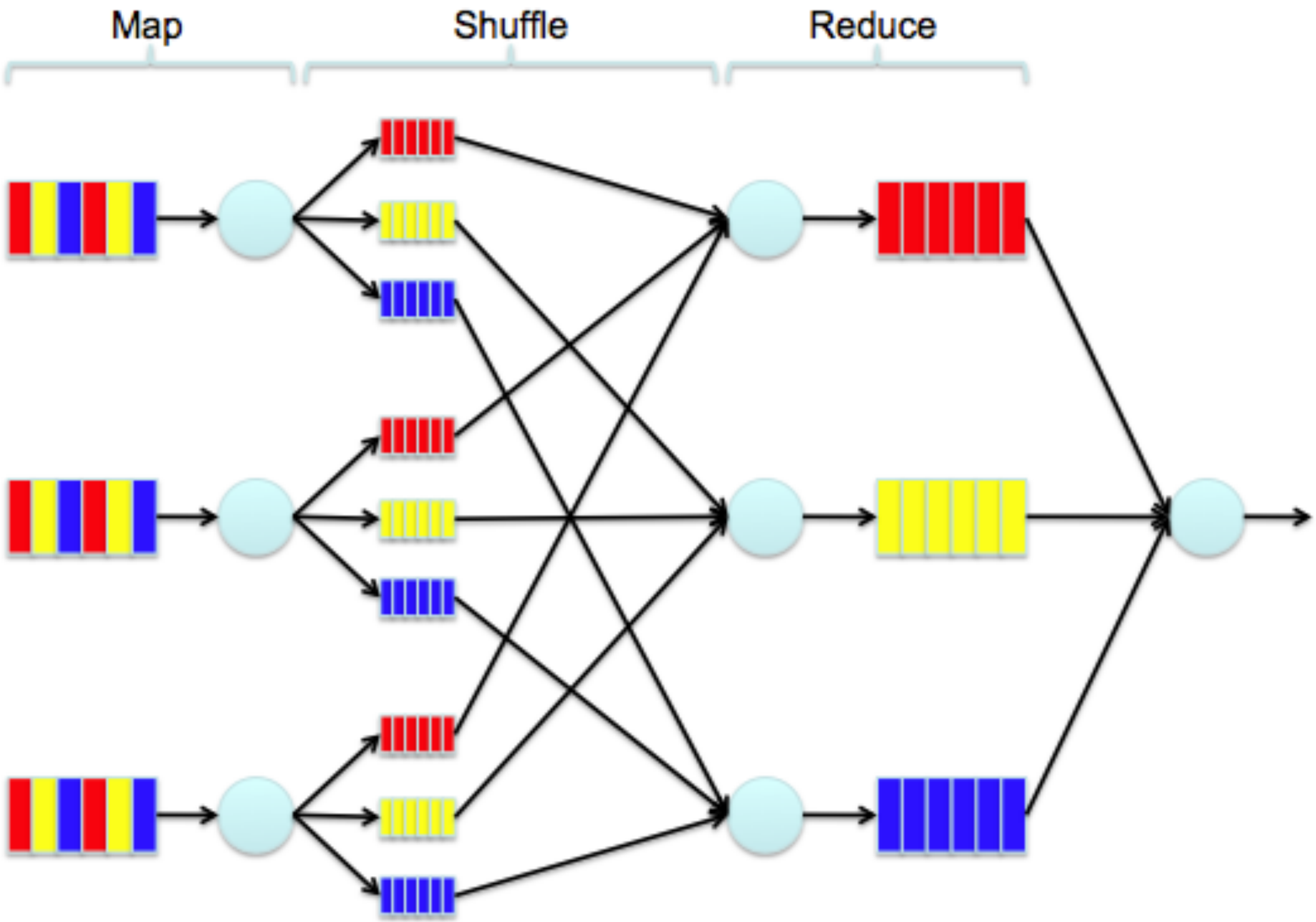
1) *the* mapper *phase*
1.5) *shuffle/sort*
2) *the* reducer *phase*


Map
Shuffle
Reduce

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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).

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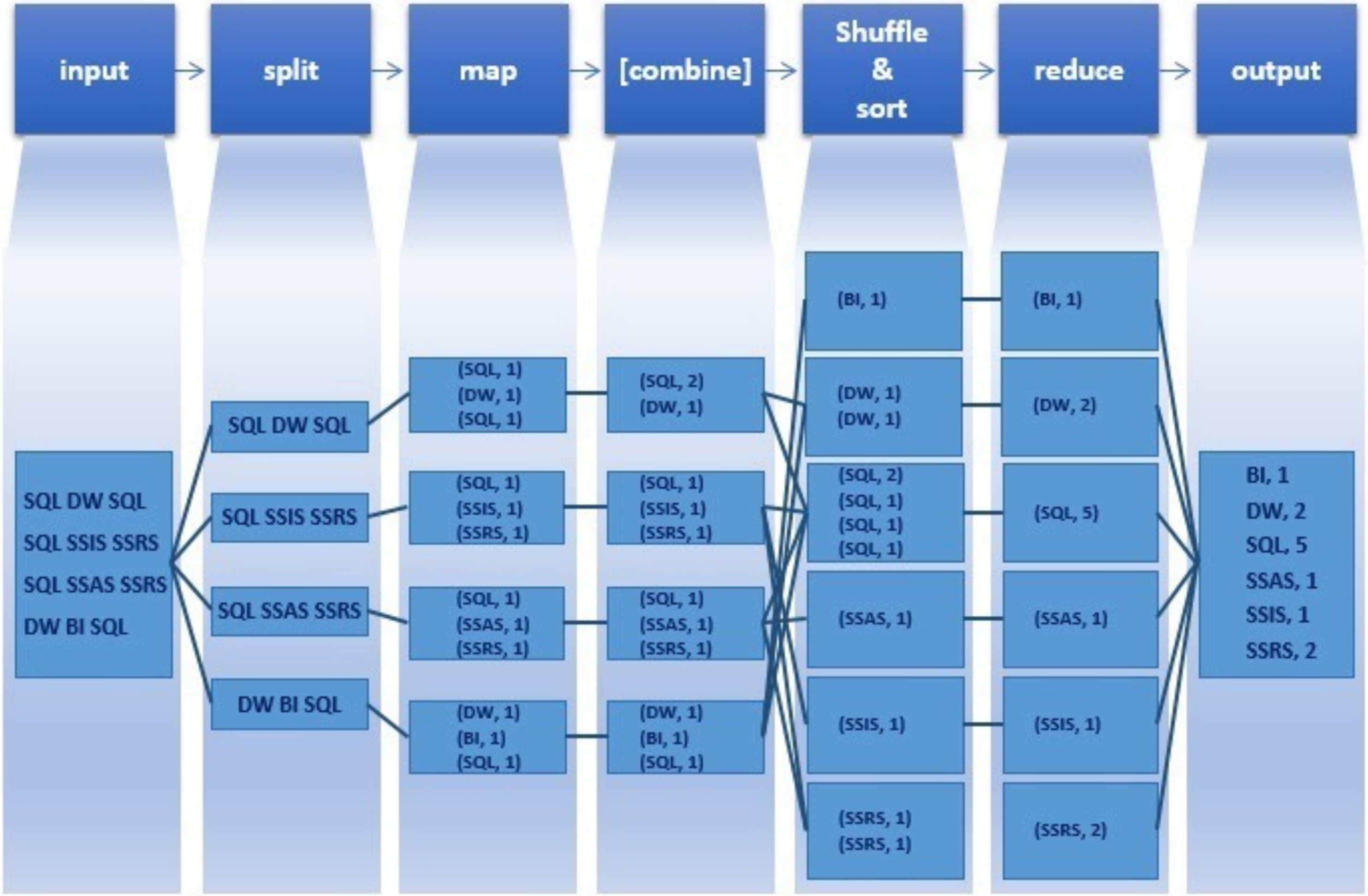
As our earlier diagram suggests, there are additional intermediate steps in a map-reduce workflow.

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*

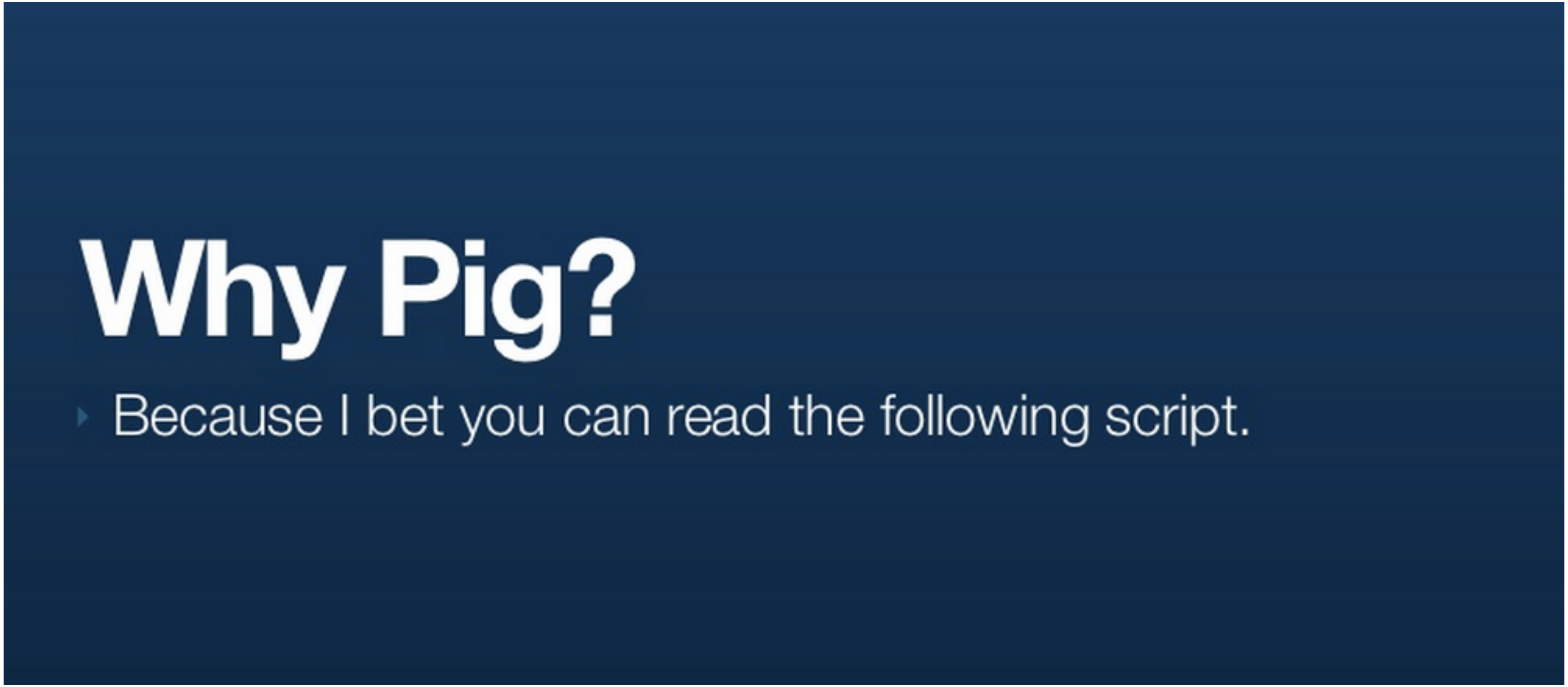
MapReduce – Word Count Example Flow



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.

MAP-REDUCE

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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).

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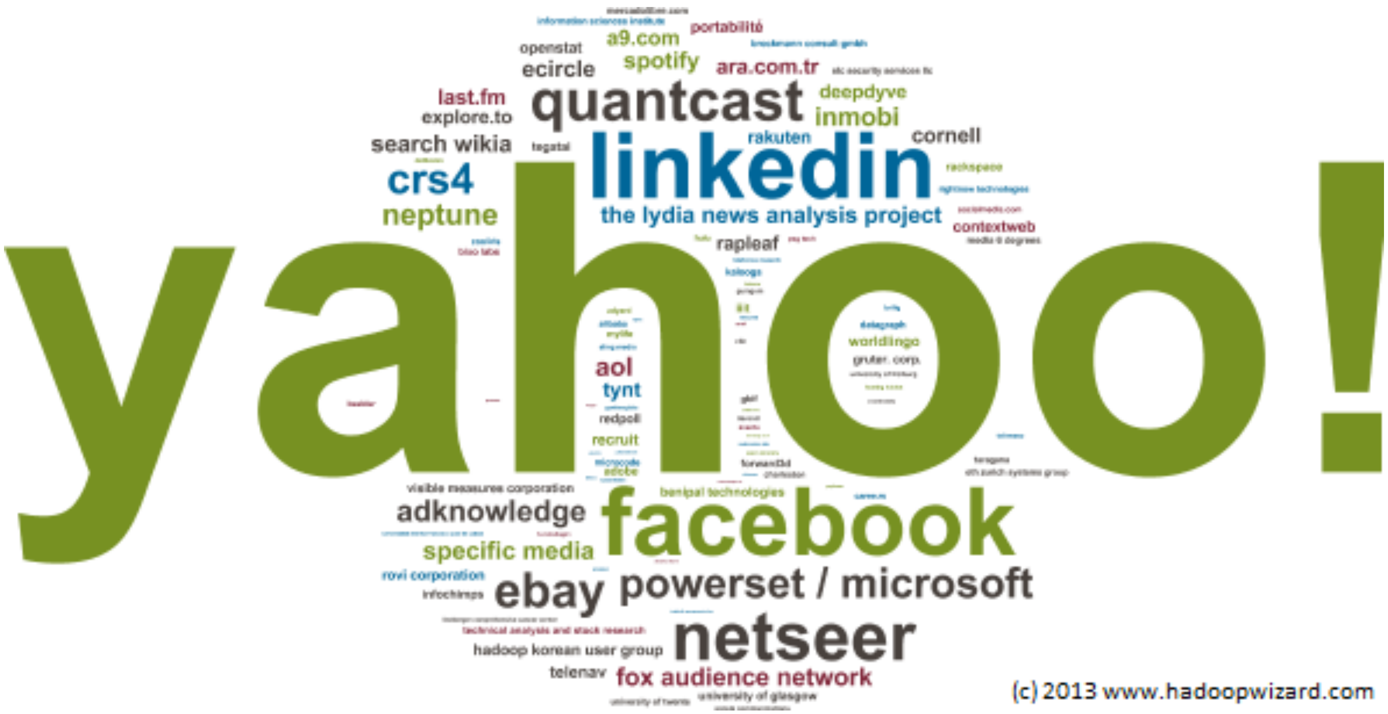
- many NoSQL databases support native map-reduce queries
- commercial distributions (Cloudera, MapR, etc)
- Google's internal implementation

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.

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

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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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MAP-REDUCE EXAMPLE: MAPPER

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.

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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.

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

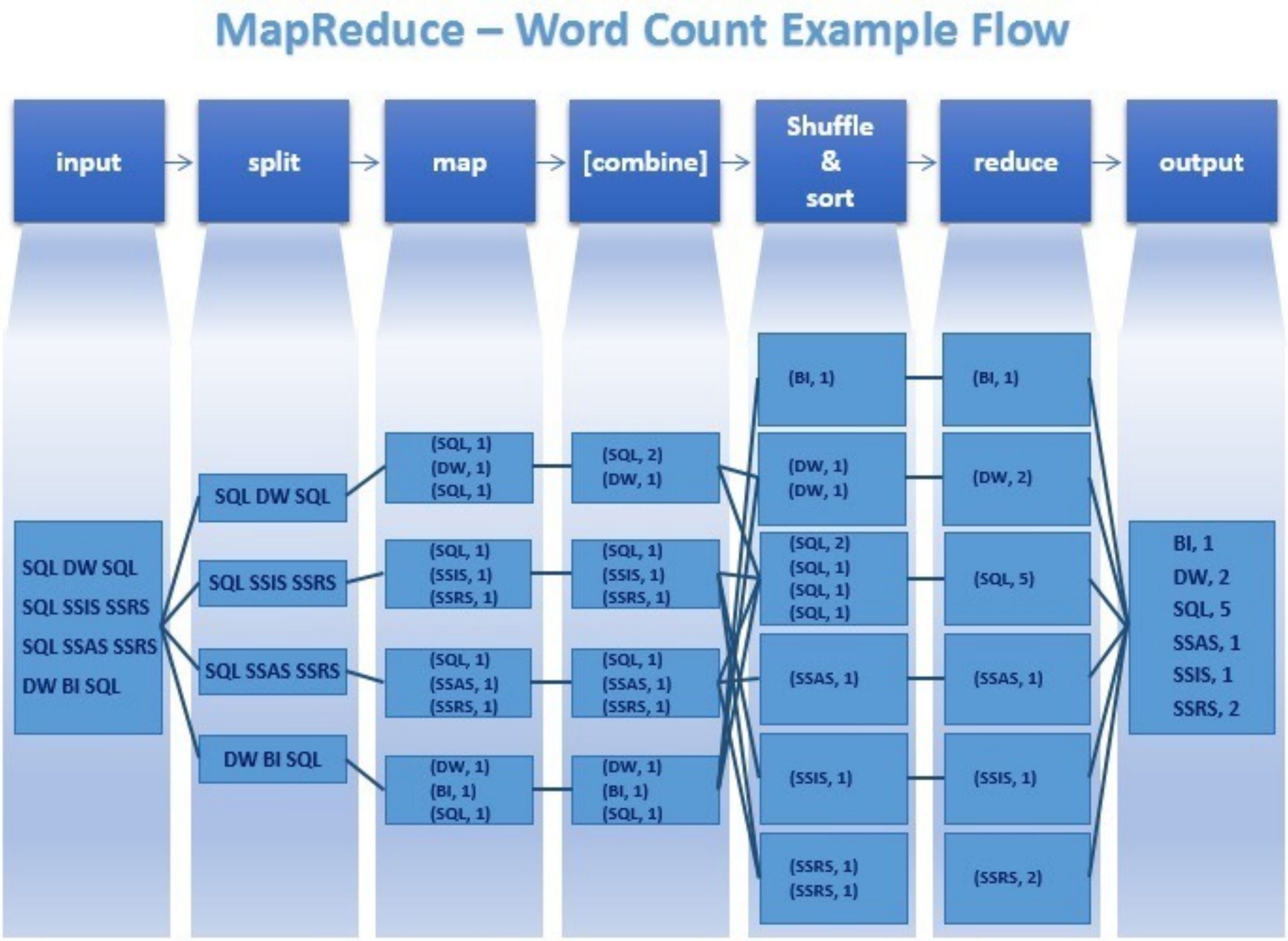
Reducer output is aggregated…

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

Reducer output is aggregated & sorted by key.

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

MAP-REDUCE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input
split
map
[combine]
Shuffle & sort
reduce
output
SQL DW SQL
SQL SSIS SSRS
SQL SSAS SSRS
DW BI SQL
SQL DW SQL
SQL SSIS SSRS
SQL SSAS SSRS
DW BI SQL
(SQL, 1) (DW, 1) (SQL, 1)
(SQL, 1) (SSIS, 1) (SSRS, 1)
(SQL, 1) (SSAS, 1) (SSRS, 1)
(DW, 1) (BI, 1) (SQL, 1)
(SQL, 2) (DW, 1)
(SQL, 1) (SSIS, 1) (SSRS, 1)
(SQL, 1) (SSAS, 1) (SSRS, 1)
(DW, 1) (BI, 1) (SQL, 1)
(BI, 1)
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(SQL, 2) (SQL, 1) (SQL, 1) (SQL, 1)
(SSAS, 1)
(SSIS, 1)
(SSRS, 1) (SSRS, 1)
(BI, 1)
(DW, 2)
(SQL, 5)
(SSAS, 1)
(SSIS, 1)
(SSRS, 2)
BI, 1
DW, 2
SQL, 5
SSAS, 1
SSIS, 1
SSRS, 2

EXERCISE & DISCUSSION