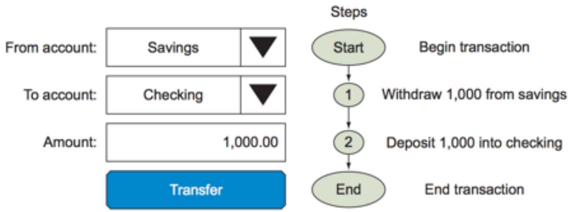
GENERAL ASSEMBLY

# INTRO TO DATA SCIENCE

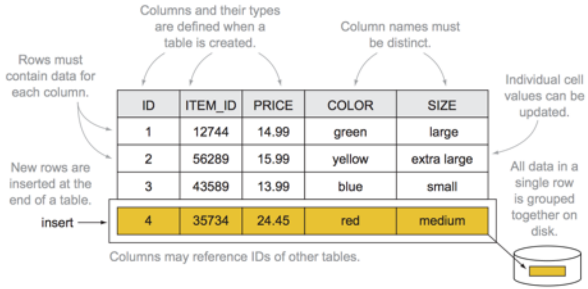
## MAP REDUCE

# 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)*

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

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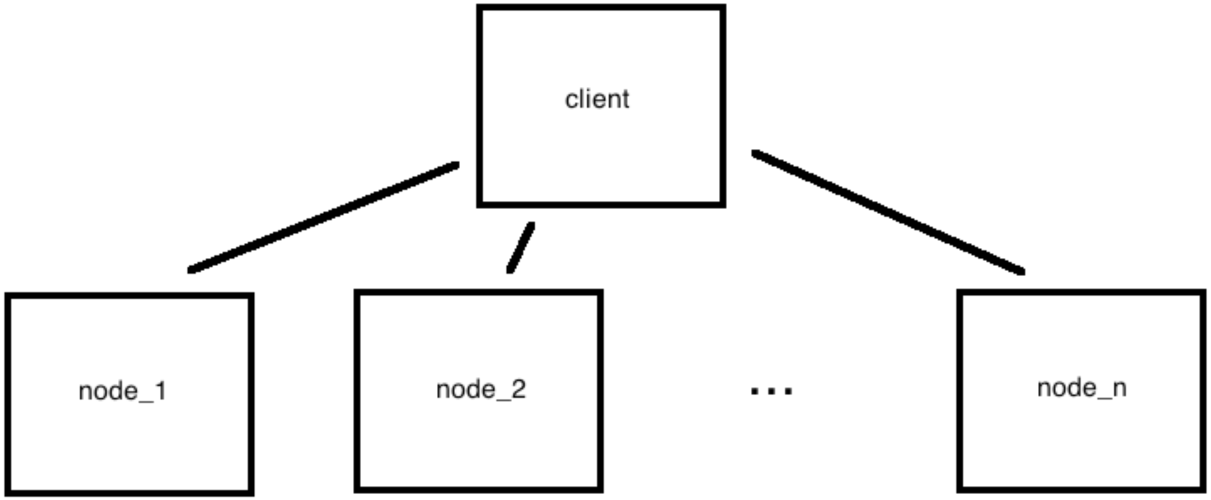
*A: Scalability; in particular, storing & processing web-scale (multi-terabyte) datasets using clusters of multiple computing nodes.*

*"Scale out vs scale up!"*

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



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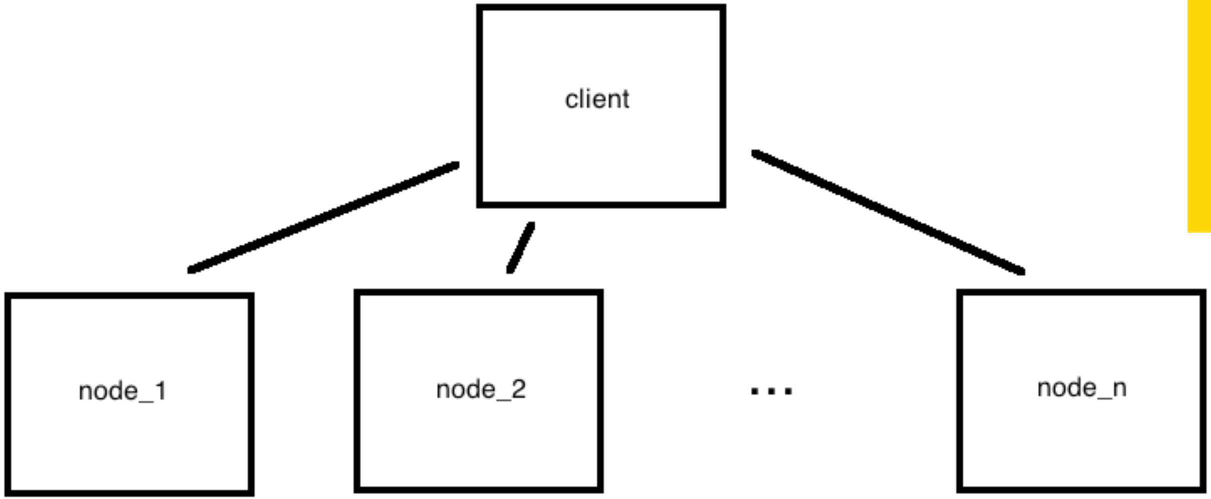


**NOTE**

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

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

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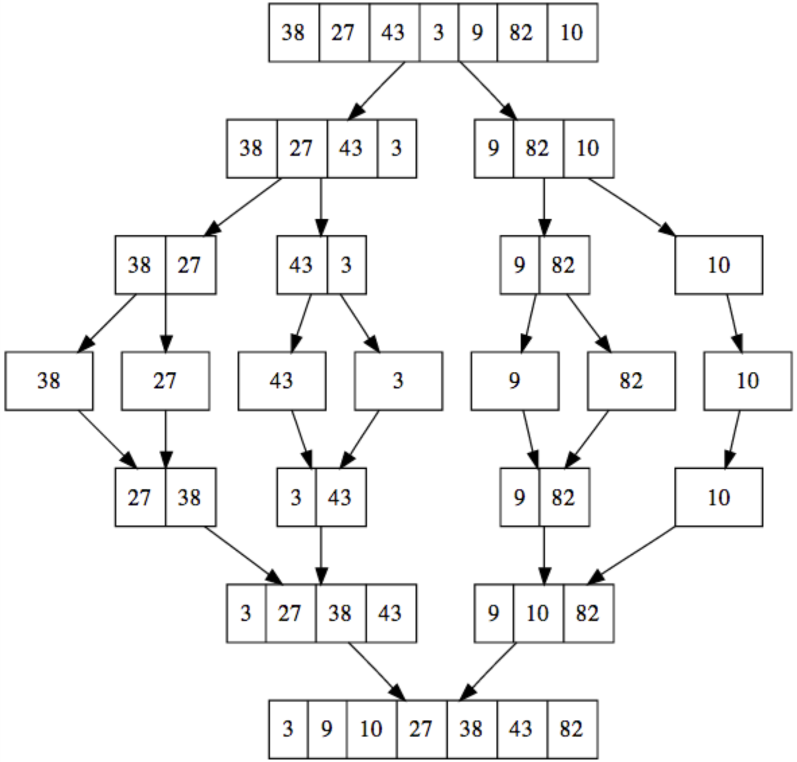
*This is how recursive algorithms work, for example.*

*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!*

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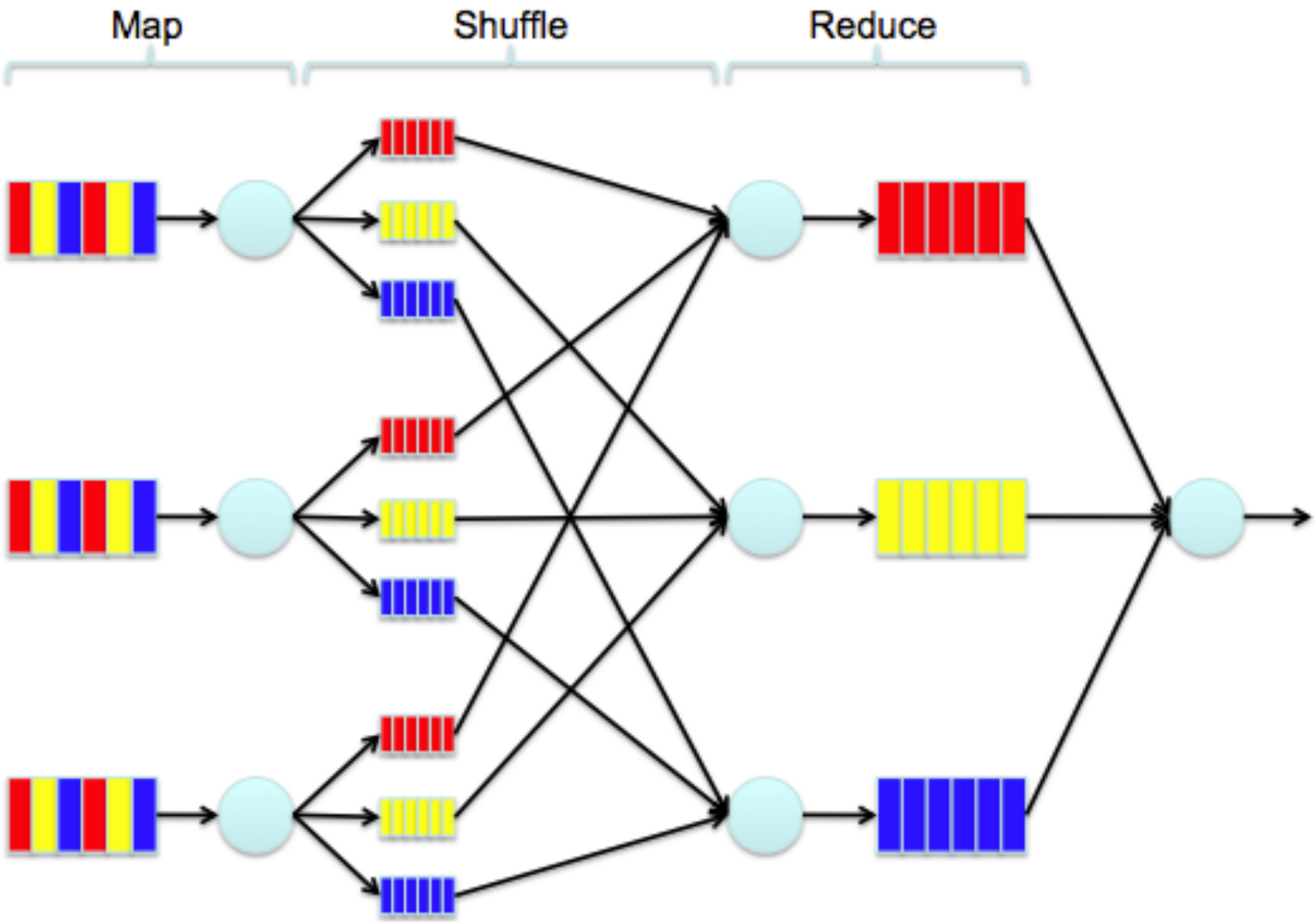
1) *the* mapper *phase*
1.5) *shuffle/sort*
2) *the* reducer *phase*


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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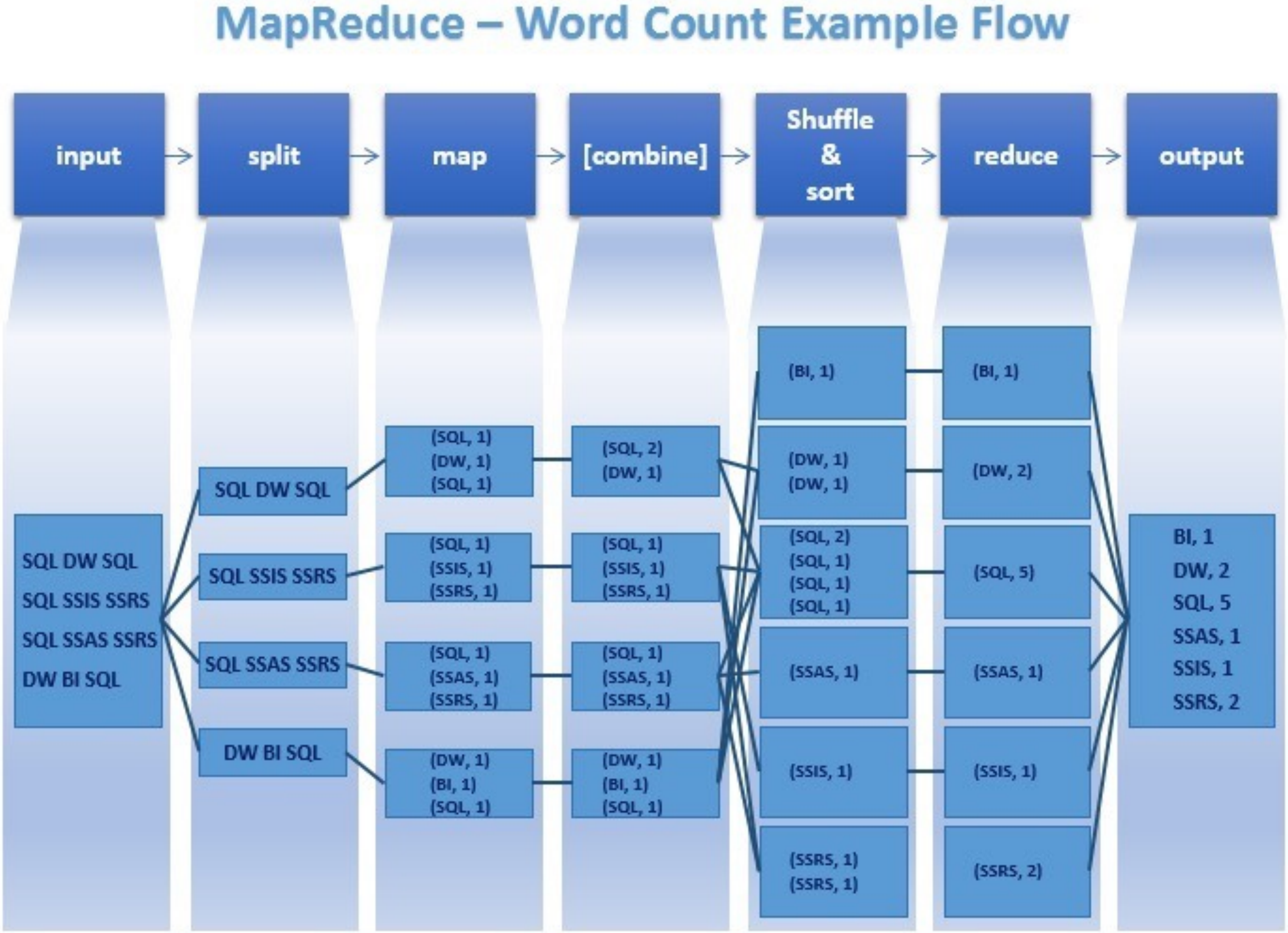
mappers – *filter & transform data*
combiners – *perform reducer operations on the mapper node (optional*
*step, to reduce network traffic and disk I/O).*
partitioners – *shuffle/sort/redirect mapper output*
reducers – *aggregate results*


MapReduce – Word Count Example Flow
input
split
map
[combine]
Shuffle & sort
reduce
output
SQL DW SQL
SQL SSIS SSRS
SQL SSAS SSRS
DW BI SQL
SQL DW SQL
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(SQL, 1) (DW, 1) (SQL, 1)
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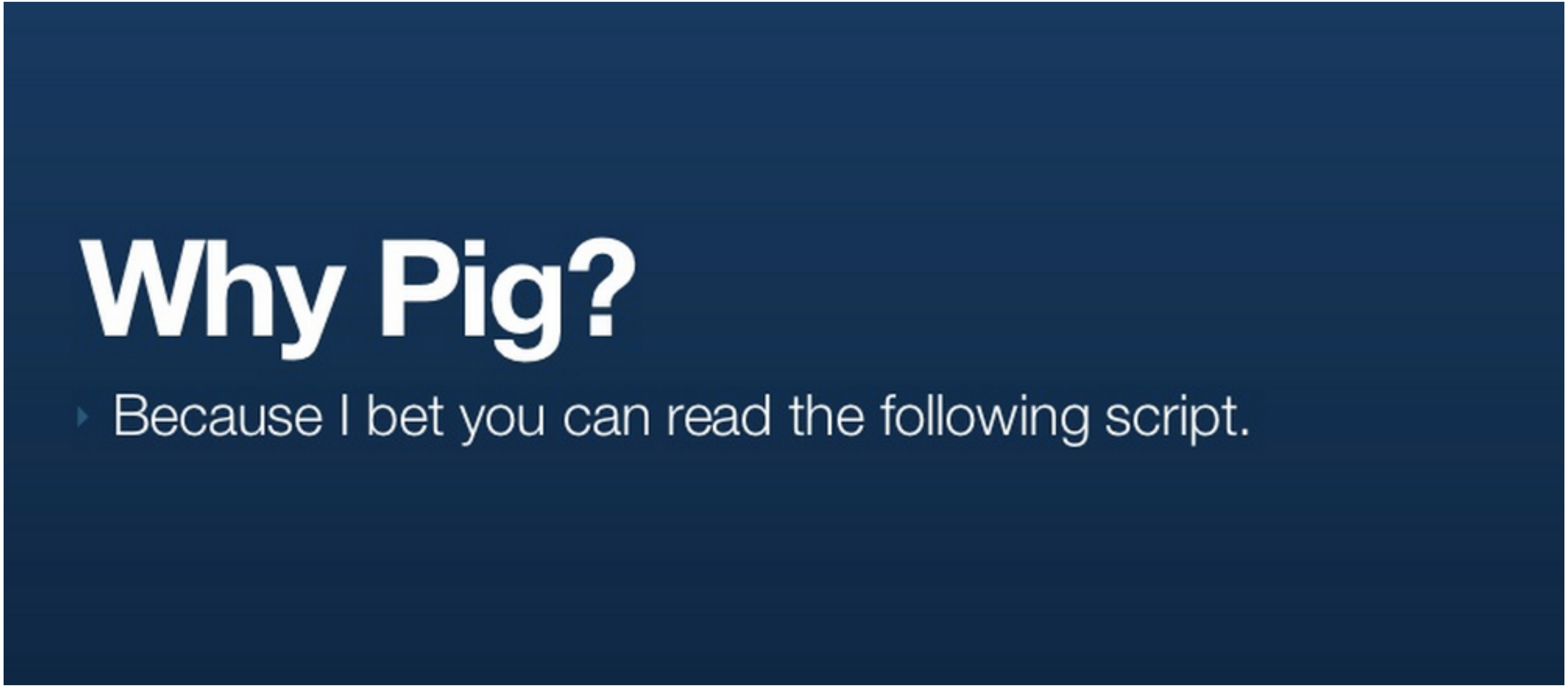
(SSRS, 1) (SSRS, 1)
(BI, 1)
(DW, 2)
(SQL, 5)
(SSAS, 1)
(SSIS, 1)
(SSRS, 2)
BI, 1
DW, 2
SQL, 5
SSAS, 1
SSIS, 1
SSRS, 2

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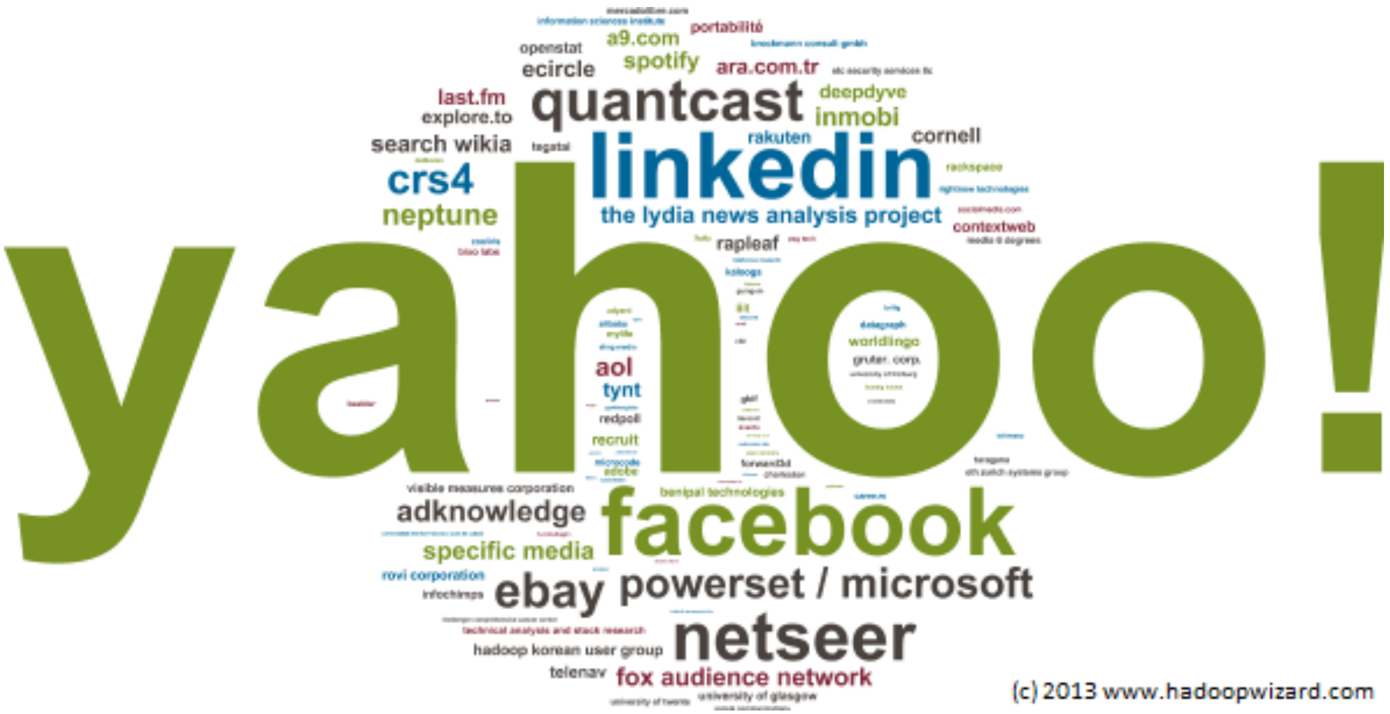
*- many NoSQL databases support native map-reduce queries*
*- commercial distributions (Cloudera, MapR, etc)*
*- Google's internal implementation*

*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.*

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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
```

*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
...
```

*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.*

## MAP-REDUCE EXAMPLE: REDUCER

*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)
```

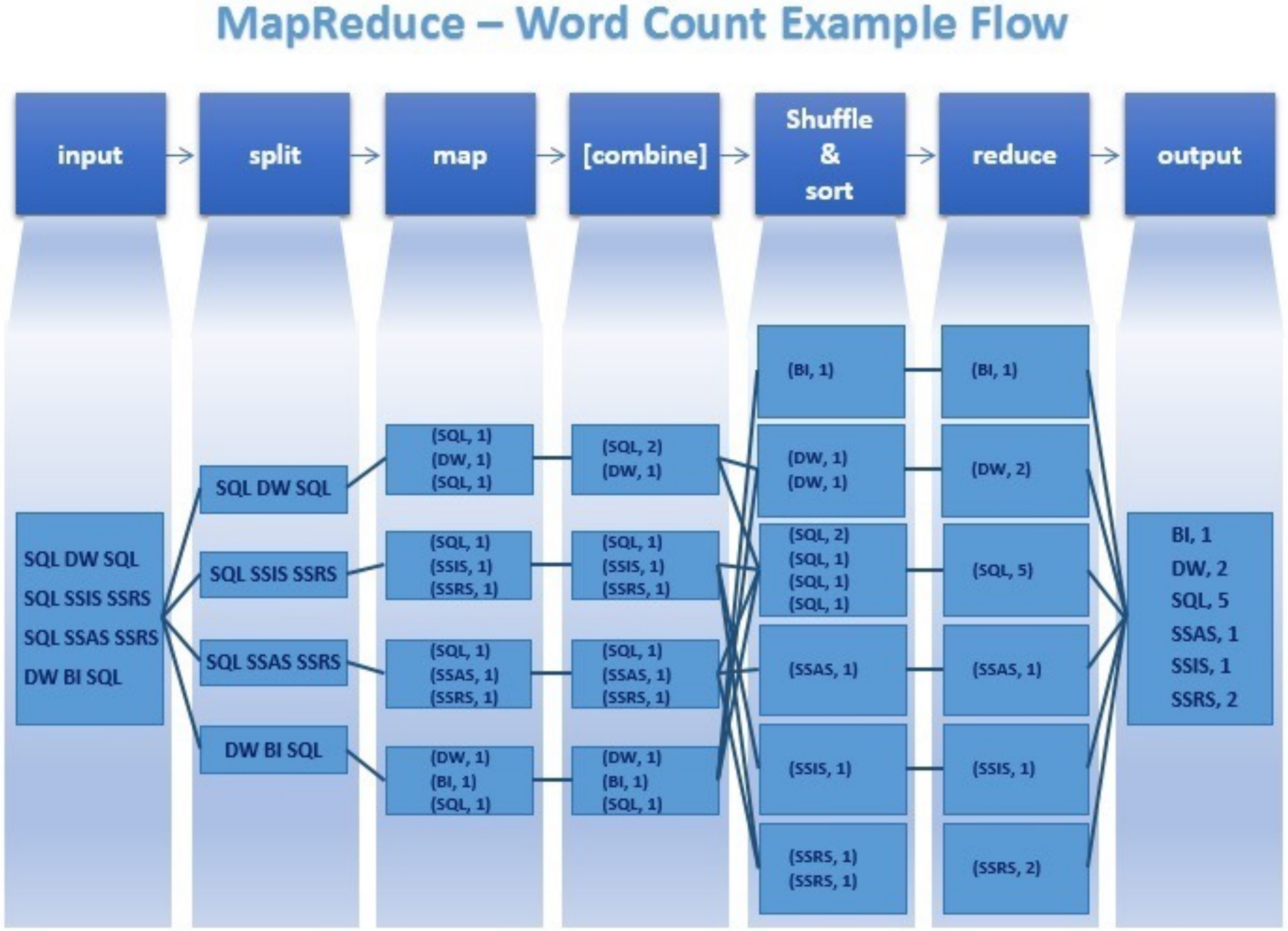
*Reducer output is aggregated…*

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

*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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# EXERCISE & DISCUSSION