GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 15: MAP-REDUCE

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

EXERCISE:
V. MAP-REDUCE USING PYTHON & MRJOB

I. BIG DATA

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

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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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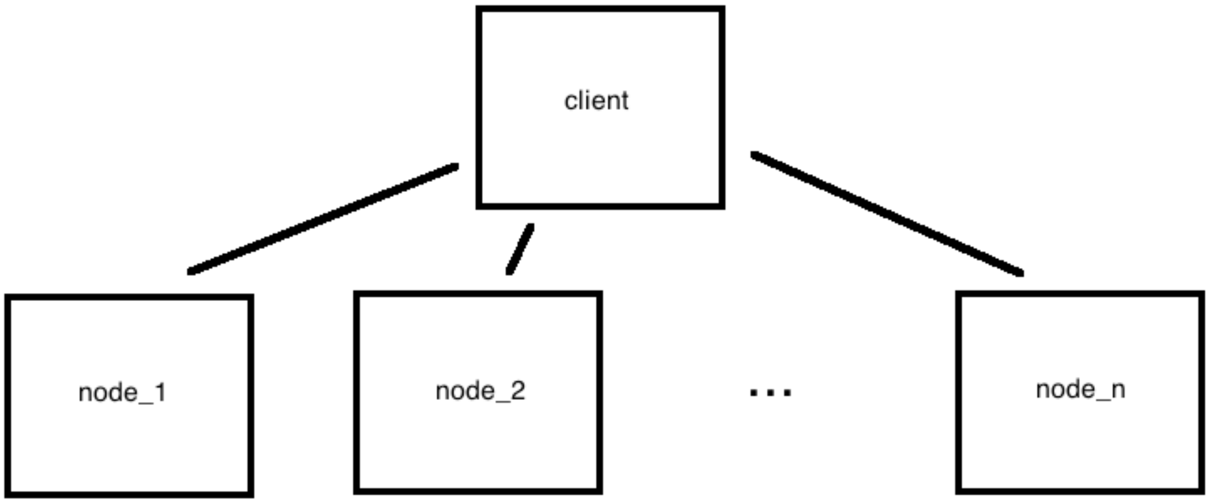
"Scale out vs scale up"

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



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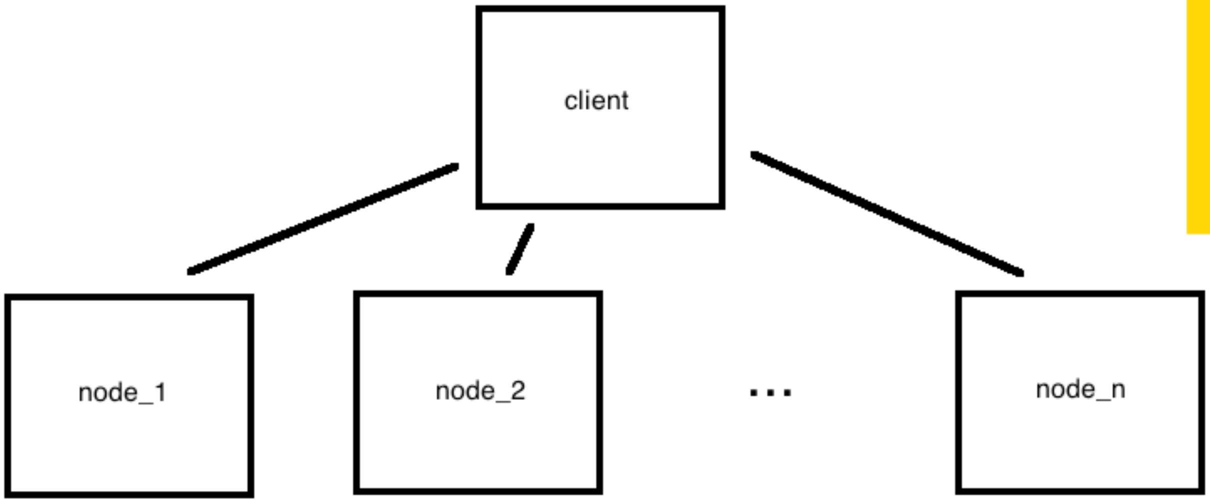

NOTE

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

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

2) *move code to data*

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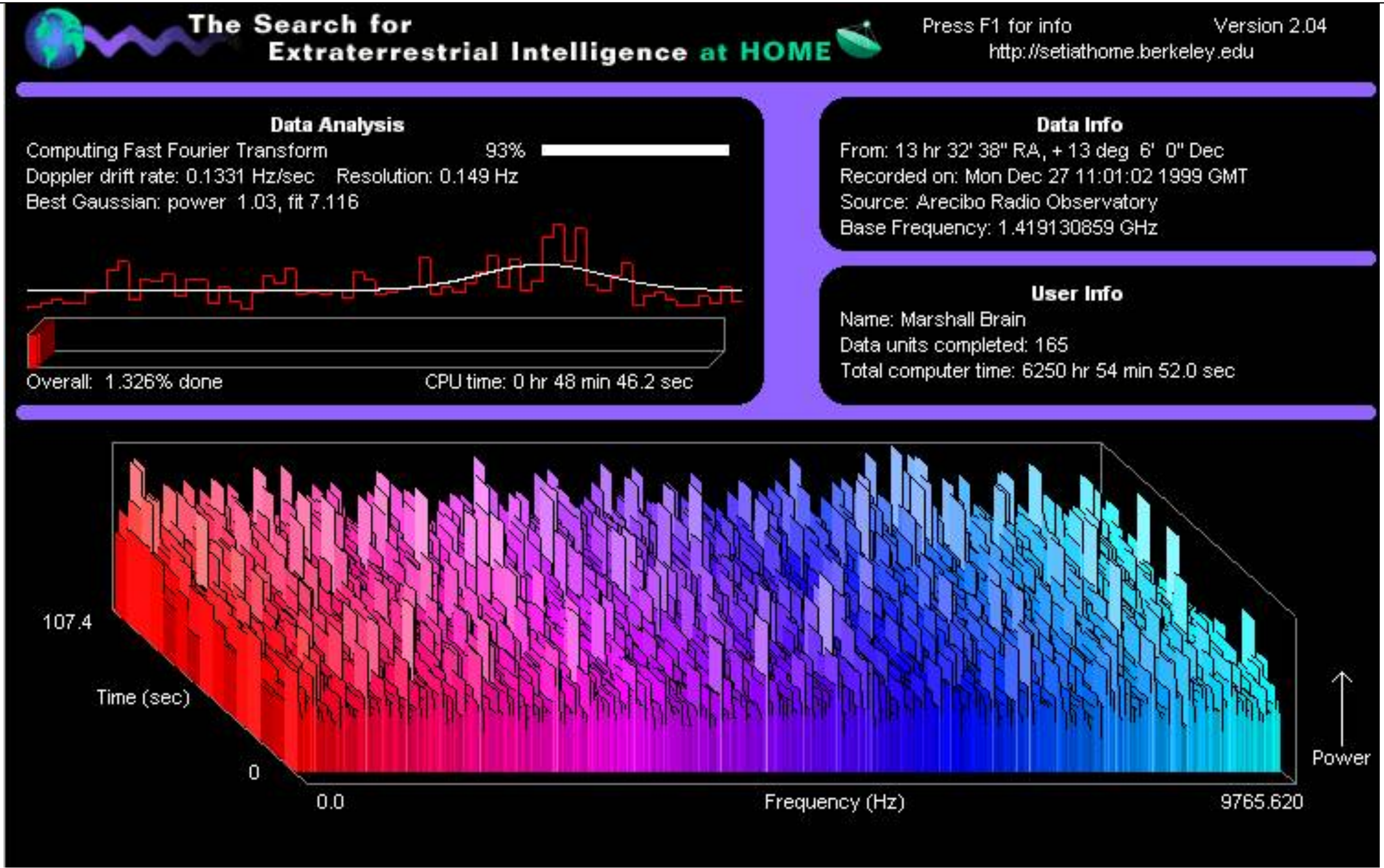
1) *move data to code (& processing power)*
   - *SETI, Folding@Home*

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

"Computing nodes are the same as storage nodes."


The Search for Extraterrestrial Intelligence at HOME
Press F1 for info
Version 2.04
http://setiathome.berkeley.edu
Data Analysis
Computing Fast Fourier Transform 93%
Doppler drift rate: 0.1331 Hz/sec Resolution: 0.149 Hz
Best Gaussian: power 1.03, fit 7.116
Overall: 1.326% done
CPU time: 0 hr 48 min 46.2 sec
Data Info
From: 13 hr 32' 38" RA, + 13 deg 6' 0" Dec
Recorded on: Mon Dec 27 11:01:02 1999 GMT
Source: Arecibo Radio Observatory
Base Frequency: 1.419130859 GHz
User Info
Name: Marshall Brain
Data units completed: 165
Total computer time: 6250 hr 54 min 52.0 sec
107.4
Time (sec)
0
0.0
Frequency (Hz)
9765.620
Power

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

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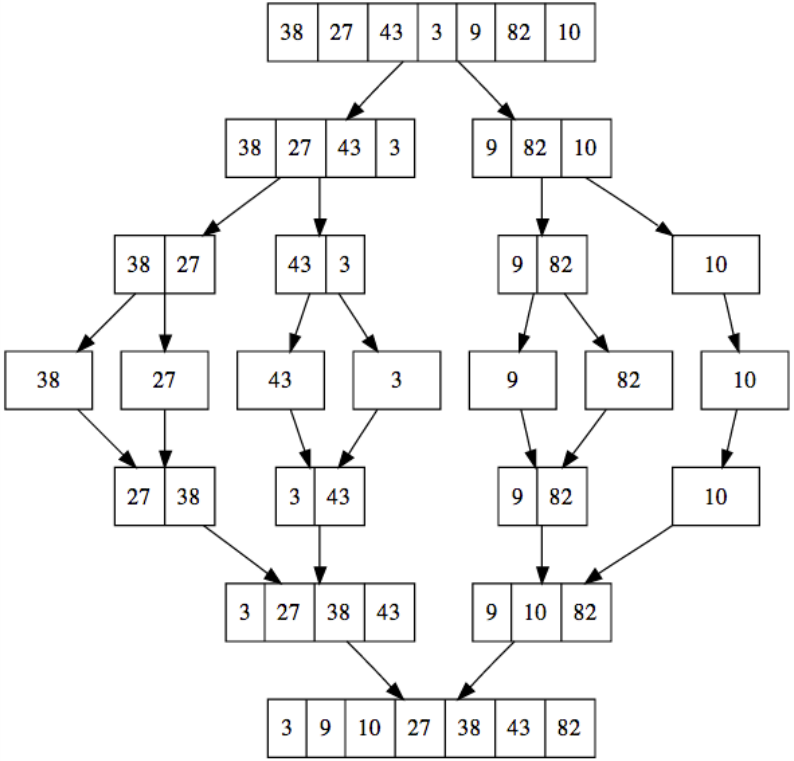
This is how recursive algorithms work, for example.

One famous example of divide and conquer is merge sort.



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(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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- *graph traversals, some ML algorithms*

NOTE

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

II. PROGRAMMING MODEL

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This takes place in (approximately) two phases:

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

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

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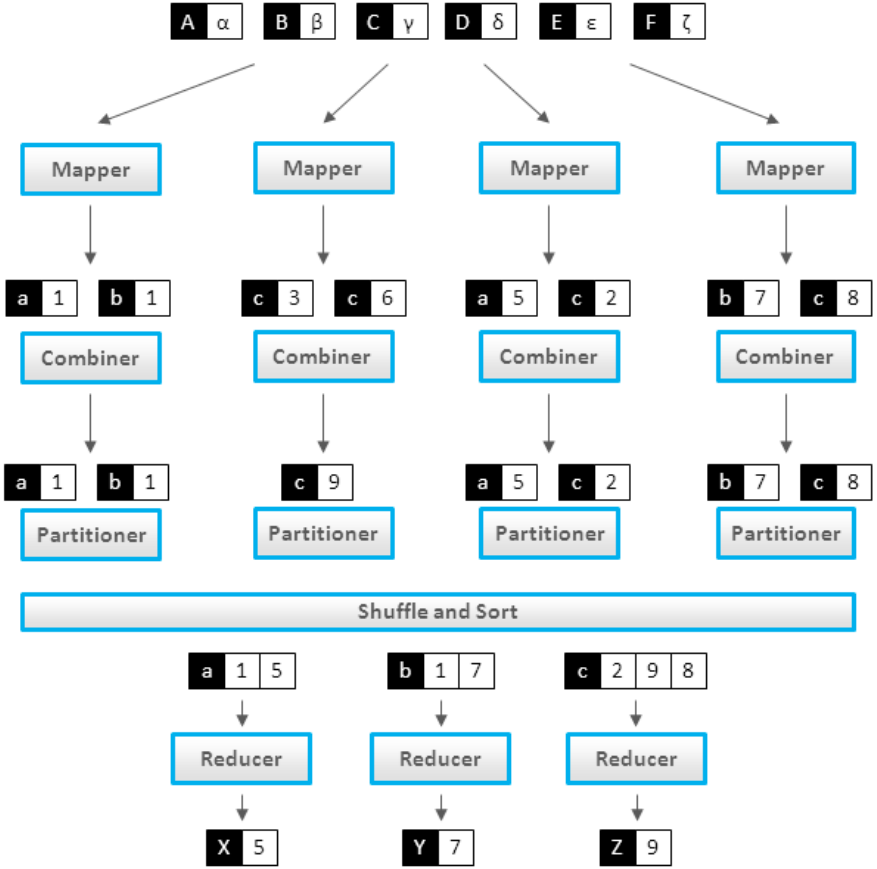
mappers – *filter & transform data*
combiners – *perform reducer operations on the mapper node (optional step, to reduce network traffic and disk I/O).*
partitioners – *shuffle/sort/redirect mapper output*
reducers – *aggregate results*

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

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

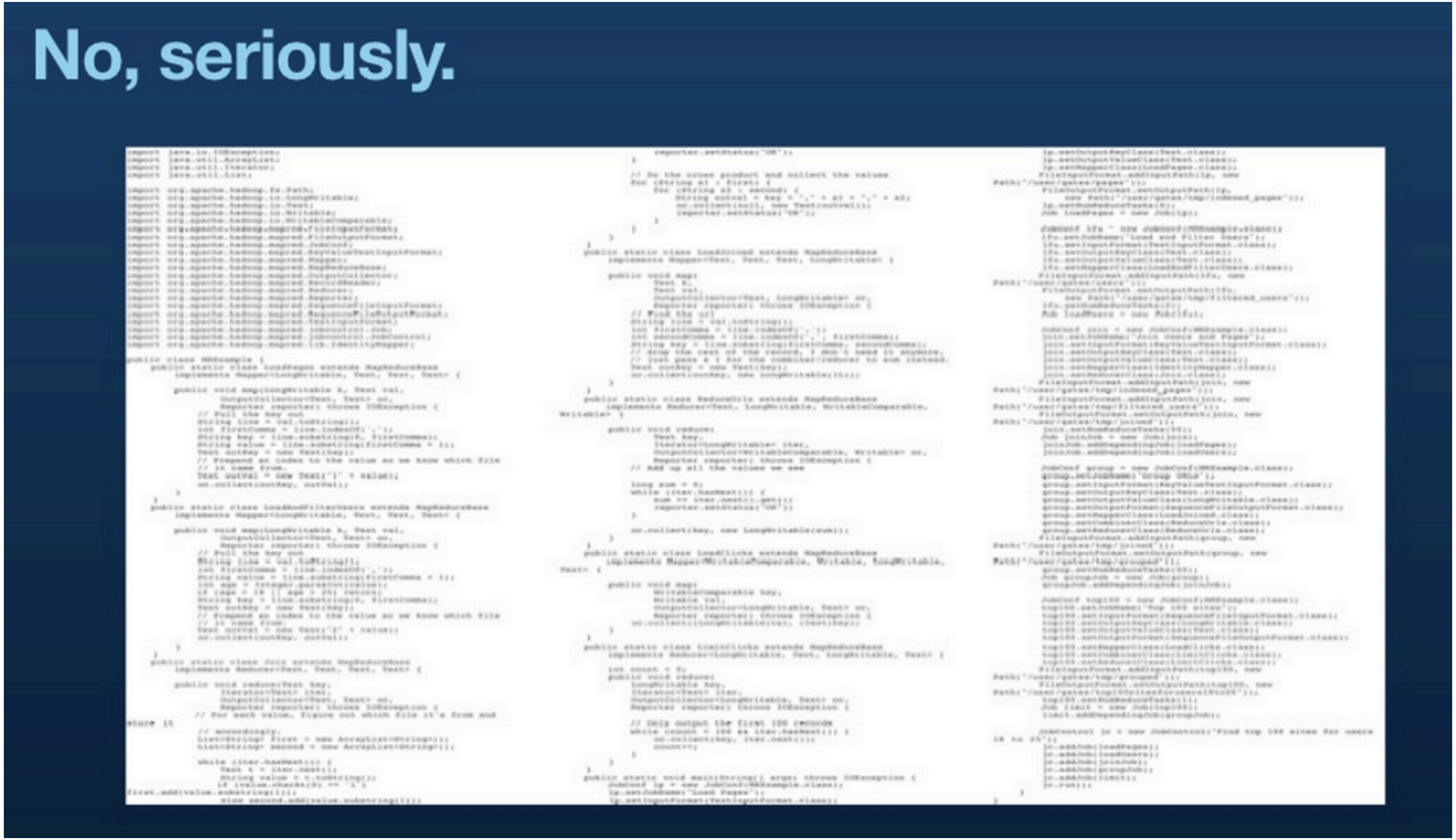
```
users = load 'users.csv' as (username: chararray, age: int);
users_1825 = filter users by age >= 18 and age <= 25;

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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- 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.

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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:

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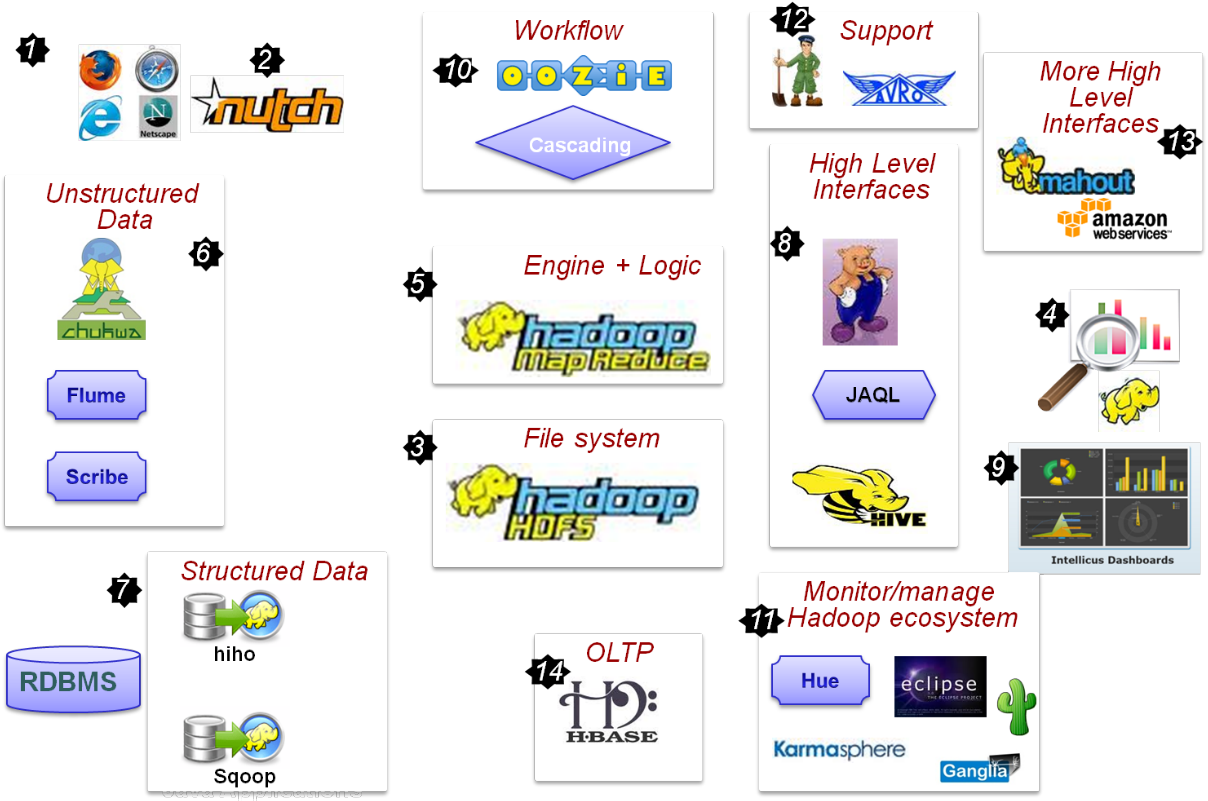
If you use Amazon EMR, you can use their file system (Amazon S3) as well.

Hadoop Ecosystem Map



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
```