# Applied Data Analysis (CS401)


## Lecture 6
## Scaling up
## 2018/10/25

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Robert West

dlab


VOUS AUSSI,
VOUS ÊTES
BEAU COMME
UN CAMION.
EN 133 DY

# Announcements

- Exam: Wed, Jan 30, 8:15-11:15
- HW1 has been graded
- HW2 was due yesternight
- HW3 released today
- Tomorrow's lab session:
  - Spark (useful for HW3, projects, your love life)
  - Tutorial on good coding practices

# Announcements

Project:

- Start thinking about your topic!
- Milestone 1 due on Sun, Nov 4, 23:59
- About 20 juicy datasets available
- **Complete this form** to give us an idea of what dataset you'd like to work with (choice not yet binding)!

# Feedback

Give us feedback on this lecture here:
https://go.epfl.ch/ada2018-lec6-feedback

- What did you (not) like about this lecture?
- What was (not) well explained?
- On what would you like more (fewer) details?
- Where is Waldo?
- …

# So far in this class...

- We made one big assumption:
  - All data fits on a single machine
  - Even more, all data fits into memory on a single machine (Pandas)
- Realistic assumption for **prototyping,** but not for production code
- … and not even for all ADA projects ;)

# The big-data problem

**Data is growing faster than computation speed**

Growing data sources
» Web, mobile, sensors, ...

Cheap hard-disk storage

Stalling CPU speeds

RAM bottlenecks

# Examples

Facebook's daily logs: 60 TB

1000 Genomes project: 200 TB

Google Web index: 100+ PB

Cost of 1 TB of disk: $50

Time to read 1 TB from disk: 3 hours (100 MB/s)

# The big-data problem

Single machine can no longer store, let alone process, all the data

Only solution is to **distribute** over a large cluster of machines

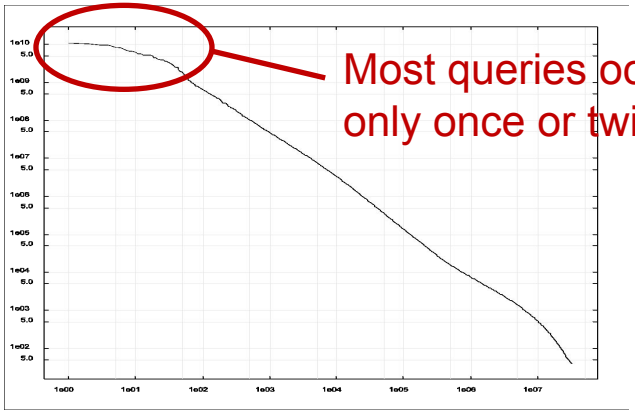
# But how much data should you get?

The answer of course depends on the question but for many applications the answer is:

## As much as you can get

Big data about people (text, Web, social media) tends to follow power law statistics.

Number of search queries [log] of freq >= x




x: search-query frequency [log]

**59% of all Web search queries are unique**
17% of all queries were made only twice
8% were made three times
[link]

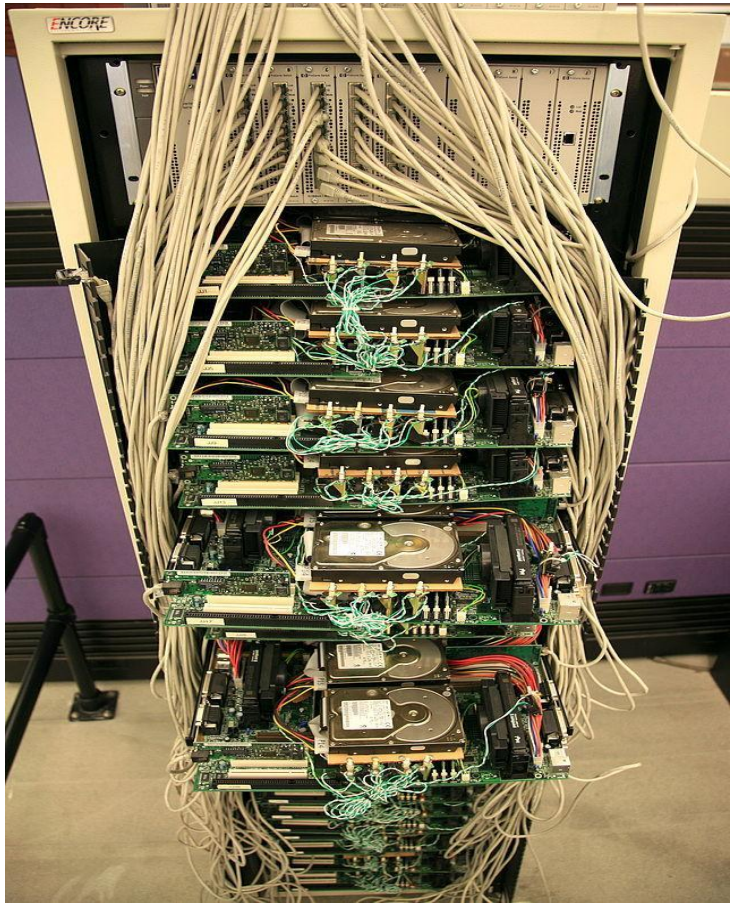
# Hardware for big data

**Budget** (a.k.a. commodity) hardware
Not "gold-plated" (a.k.a. custom)

Many low-end servers
**Easy to add capacity**
**Cheaper** per CPU/disk

**Increased complexity in software:**

- Fault tolerance
- Virtualization (e.g., distributed file systems)



Google Corkboard server: Steve Jurvetson/Flickr

# Problems with cheap hardware

**Failures**, e.g. (Google numbers)

- 1-5% hard drives/year
- 0.2% DIMMs (dual in-line memory modules)/year

**Commodity network** (1-10 Gb/s) speeds vs. RAM

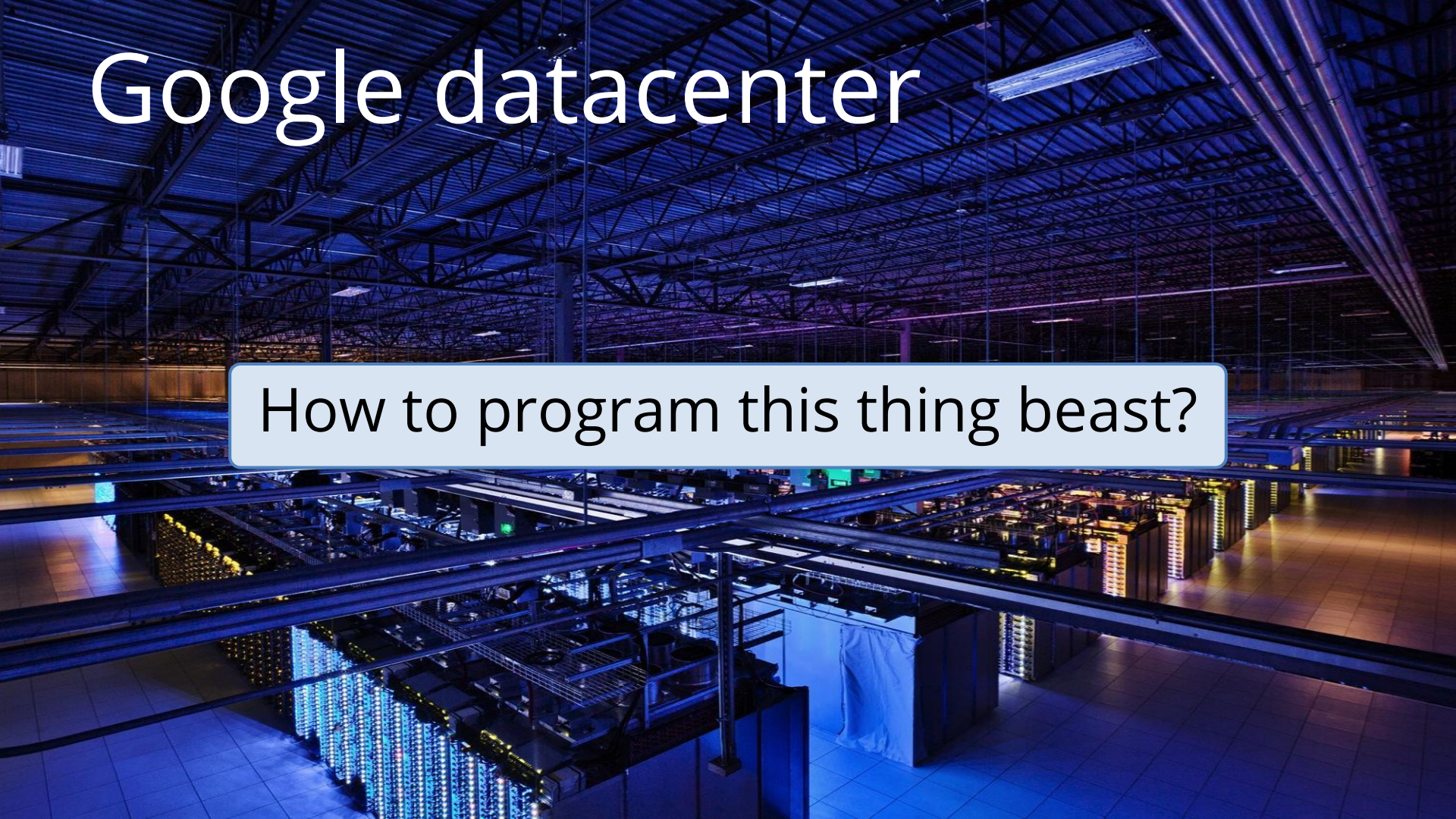
- Much more latency (100x – 100,000x)
- Lower throughput (100x-1000x)

**Uneven performance**

- Inconsistent hardware skew
- Variable network latency
- External loads

**Disclaimer: those numbers are constantly changing thanks to new technology!**

# Google datacenter



How to program this thing beast?

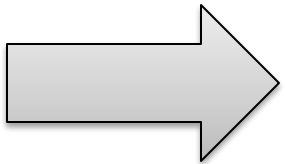
What's hard about cluster computing?

**How do we split work across machines?**

**How do we deal with failures?**

# How do you count the number of occurrences of each word in a document?

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”



I: 3
am: 3
Sam: 3
do: 1
you: 1
like: 1
…

# A hashtable (a.k.a. dict)!

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”

{}

# A hashtable!

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”

{I: 1}

# A hashtable!

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”

{I: 1,
am: 1}

# A hashtable!

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”

{I: 1,
am: 1,
Sam: 1}

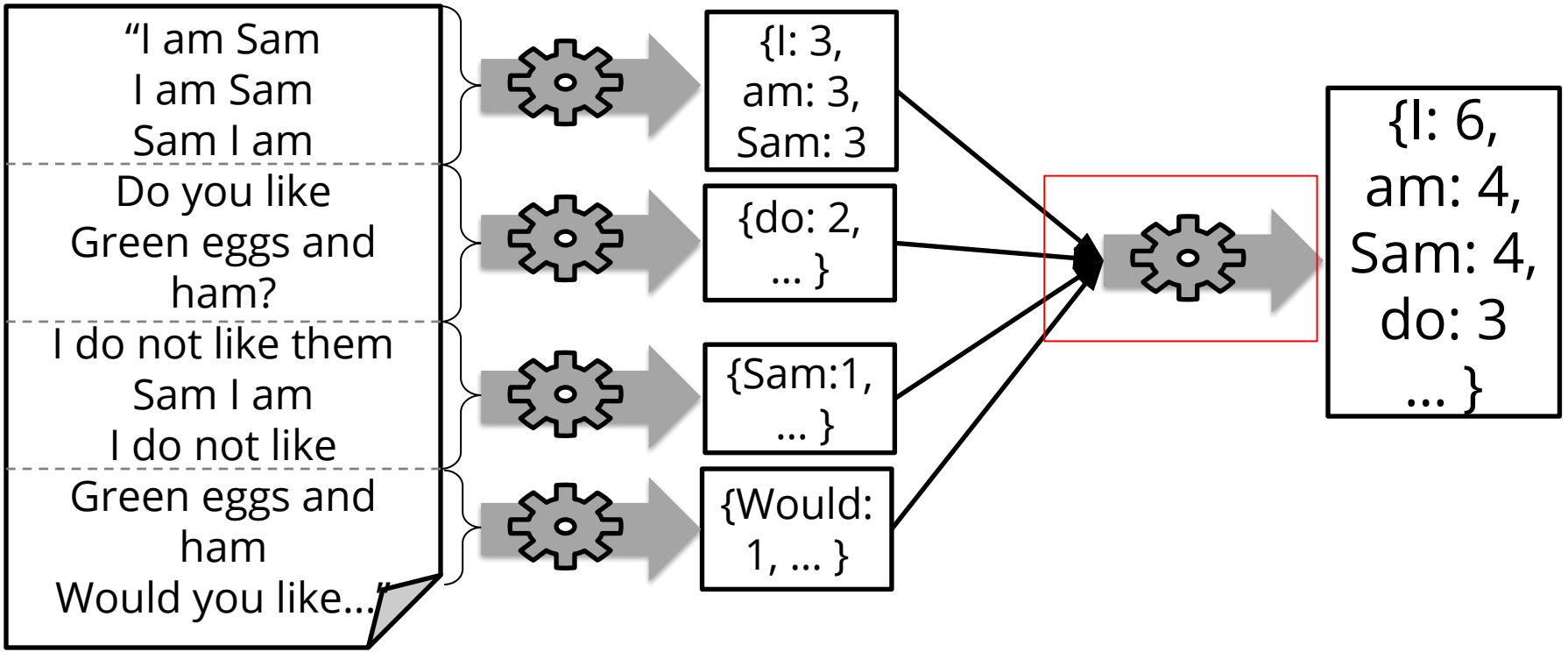
# A hashtable!

“I am Sam
I am Sam
Sam I am
Do you like
Green eggs and
ham?”

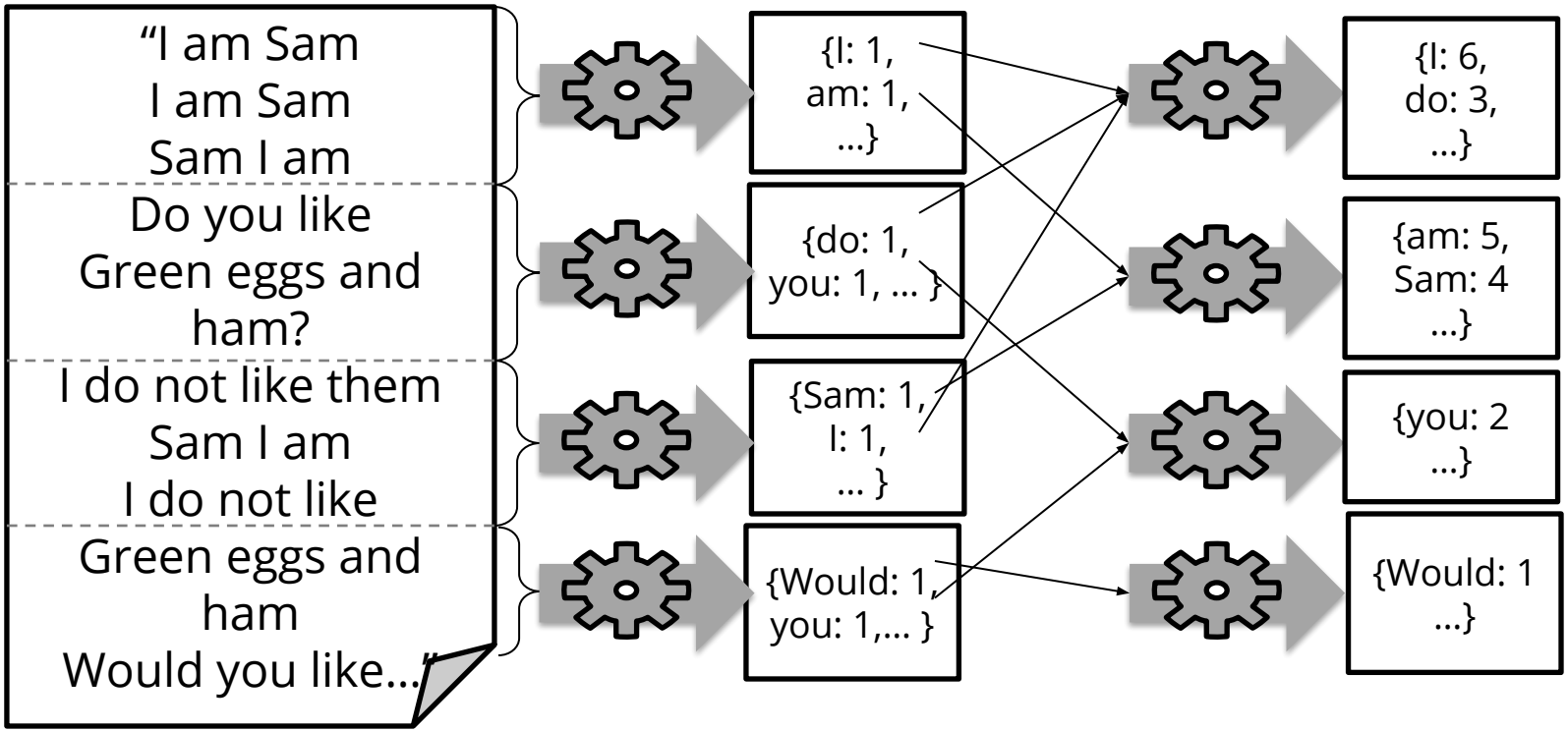
{I: 2,
am: 1,
Sam: 1}

# What if the document is really big?

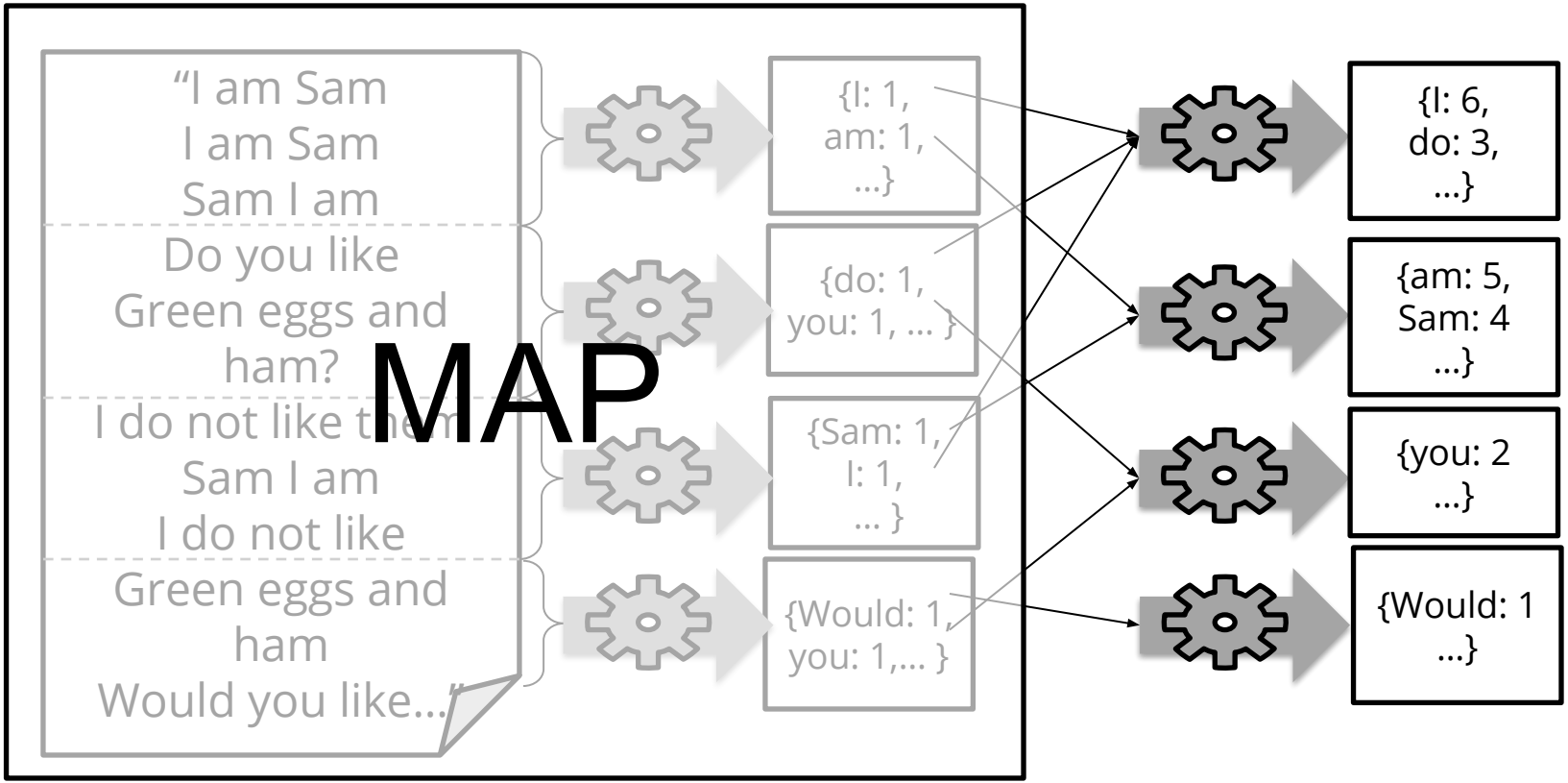
# What if the document is really big?



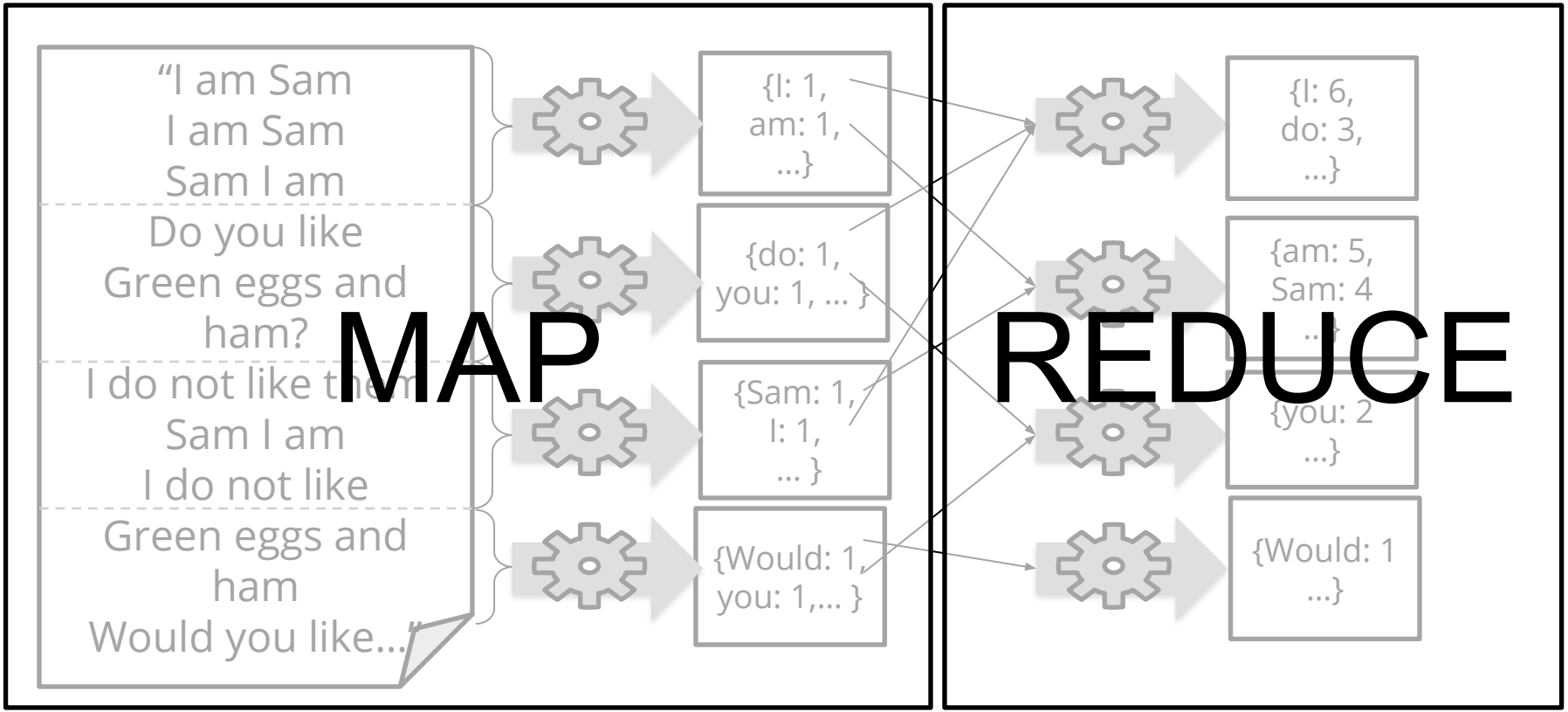
# “Divide and Conquer”



# “Divide and Conquer”



# “Divide and Conquer”



# What's hard about cluster computing?

How to divide work across machines?

- Must consider network, data locality
- Moving data may be very expensive

How to deal with failures?

- 1 server fails every 3 years => 10K nodes see 10 faults/day
- Even worse: stragglers (node is not failed, but slow)

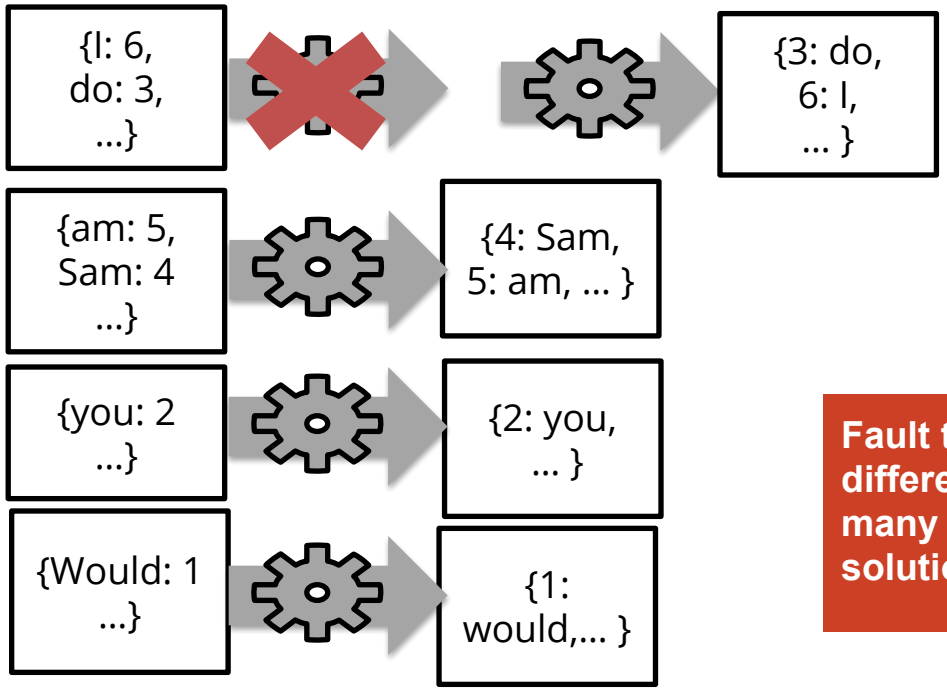
# Solution: MapReduce

Jeff Dean*

- Smart systems engineers have done all the work for you
  - Task scheduling
  - Virtualization of file system
  - Fault tolerance (incl. data replication)
  - Job monitoring
  - etc.
- “All” you do: implement Mapper and Reducer classes

* Meet Jeff in January at Applied Machine Learning Days at EPFL!

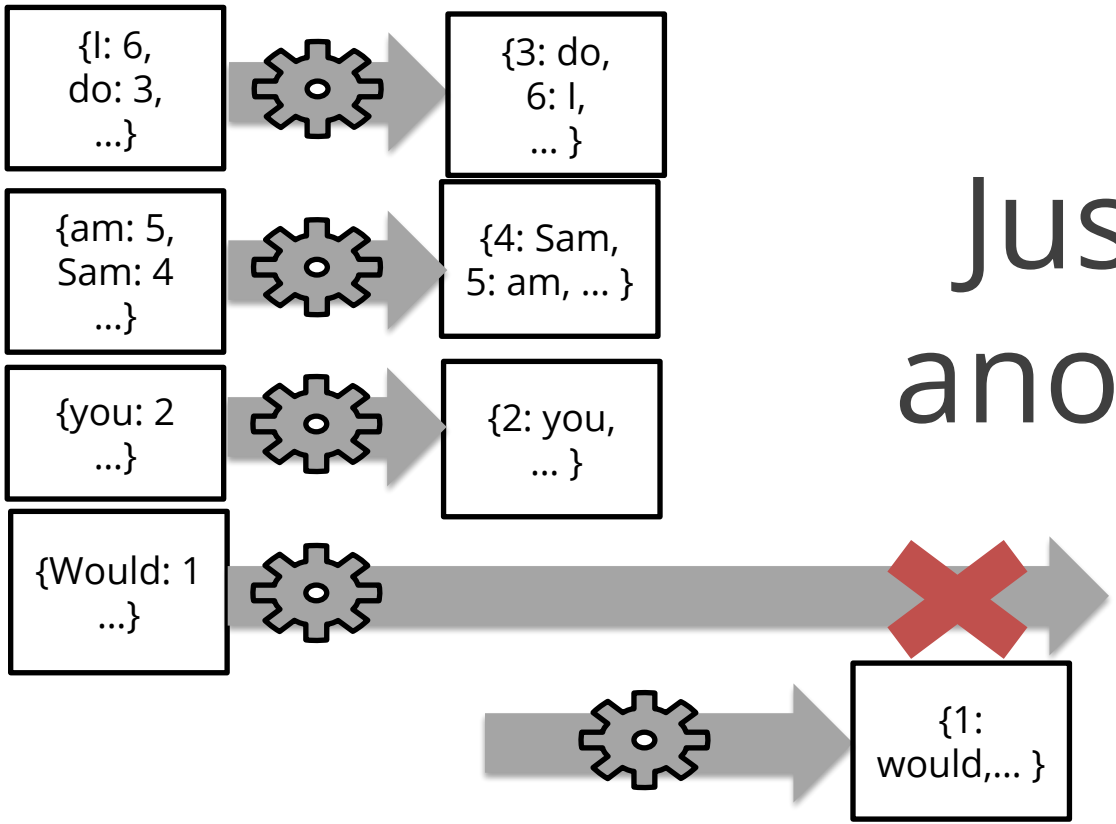
# How to deal with failures?




**Fault tolerance is a key difference compared to many Parallel Database solutions!**

Just launch another task!

# How to deal with slow tasks?




Just launch another task!

# Solution: MapReduce

Jeff Dean

- Smart systems engineers have done all the work for you
  - Task scheduling
  - Virtualization of file system
  - Fault tolerance (incl. data replication)
  - Job monitoring
  - etc.
- "All" you do: implement Mapper and Reducer classes

Need to break more complex jobs into sequence of MapReduce jobs

# Example task

Suppose you have user info in one file, website logs in another, and you need to find the top 5 pages most visited by users aged 18-25.

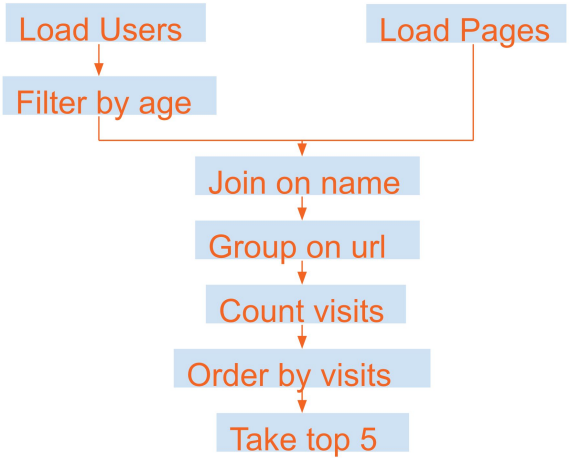



Example from http://wiki.apache.org/pig-data/attachments/PigTalksPapers/attachments/ApacheConEurope09.ppt

# In MapReduce

```
import java.io.IOException;
import java.util.ArrayList;
import java.util.Iterator;
import java.util.List;

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.io.Writable;
import org.apache.hadoop.io.WritableComparable;
import org.apache.hadoop.mapred.FileInputFormat;
import org.apache.hadoop.mapred.FileOutputFormat;
import org.apache.hadoop.mapred.JobConf;
import org.apache.hadoop.mapred.KeyValueTextInputFormat;
import org.apache.hadoop.mapred.Mapper;
import org.apache.hadoop.mapred.MapReduceBase;
import org.apache.hadoop.mapred.OutputCollector;
import org.apache.hadoop.mapred.RecordReader;
import org.apache.hadoop.mapred.Reducer;
import org.apache.hadoop.mapred.Reporter;
import org.apache.hadoop.mapred.SequenceFileInputFormat;
import org.apache.hadoop.mapred.SequenceFileOutputFormat;
import org.apache.hadoop.mapred.TextInputFormat;
import org.apache.hadoop.mapred.jobcontrol.Job;
import org.apache.hadoop.mapred.jobcontrol.JobControl;
import org.apache.hadoop.mapred.lib.IdentityMapper;

public class MRExample {
    public static class LoadPages extends MapReduceBase
        implements Mapper<LongWritable, Text, Text, Text> {

        public void map(LongWritable k, Text val,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // Pull the key out
            String line = val.toString();
            int firstComma = line.indexOf(',');
            String key = line.substring(0, firstComma);
            String value = line.substring(firstComma + 1);
            Text outKey = new Text(key);
            // Prepend an index to the value so we know which file
            // it came from.
            Text outVal = new Text("1" + value);
            oc.collect(outKey, outVal);
        }
    }
    public static class LoadAndFilterUsers extends MapReduceBase
        implements Mapper<LongWritable, Text, Text, Text> {

        public void map(LongWritable k, Text val,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // Pull the key out
            String line = val.toString();
            int firstComma = line.indexOf(',');
            String value = line.substring(firstComma + 1);
            int age = Integer.parseInt(value);
            if (age < 18 || age > 25) return;
            String key = line.substring(0, firstComma);
            Text outKey = new Text(key);
            // Prepend an index to the value so we know which file
            // it came from.
            Text outVal = new Text("2" + value);
            oc.collect(outKey, outVal);
        }
    }
    public static class Join extends MapReduceBase
        implements Reducer<Text, Text, Text, Text> {

        public void reduce(Text key,
                Iterator<Text> iter,
                OutputCollector<Text, Text> oc,
                Reporter reporter) throws IOException {
            // For each value, figure out which file it's from and
store it
            // accordingly.
            List<String> first = new ArrayList<String>();
            List<String> second = new ArrayList<String>();

            while (iter.hasNext()) {
                Text t = iter.next();
                String value = t.toString();
                if (value.charAt(0) == '1')
first.add(value.substring(1));
                else second.add(value.substring(1));
                reporter.setStatus("OK");
            }

            // Do the cross product and collect the values
            for (String s1 : first) {
                for (String s2 : second) {
                    String outval = key + "," + s1 + "," + s2;
                    oc.collect(null, new Text(outval));
                    reporter.setStatus("OK");
                }
            }
        }
    }
    public static class LoadJoined extends MapReduceBase
        implements Mapper<Text, Text, Text, LongWritable> {

        public void map(
                Text k,
                Text val,
                OutputCollector<Text, LongWritable> oc,
                Reporter reporter) throws IOException {
            // Find the url
            String line = val.toString();
            int firstComma = line.indexOf(',');
            int secondComma = line.indexOf(',', firstComma);
            String key = line.substring(firstComma, secondComma);
            // drop the rest of the record, I don't need it anymore,
            // just pass a 1 for the combiner/reducer to sum instead.
            Text outKey = new Text(key);
            oc.collect(outKey, new LongWritable(1L));
        }
    }
    public static class ReduceUrls extends MapReduceBase
        implements Reducer<Text, LongWritable, WritableComparable,
Writable> {

        public void reduce(
                Text key,
                Iterator<LongWritable> iter,
                OutputCollector<WritableComparable, Writable> oc,
                Reporter reporter) throws IOException {
            // Add up all the values we see
            long sum = 0;
            while (iter.hasNext()) {
                sum += iter.next().get();
                reporter.setStatus("OK");
            }

            oc.collect(key, new LongWritable(sum));
        }
    }
    public static class LoadClicks extends MapReduceBase
        implements Mapper<WritableComparable, Writable, LongWritable,
Text> {

        public void map(
                WritableComparable key,
                Writable val,
                OutputCollector<LongWritable, Text> oc,
                Reporter reporter) throws IOException {
            oc.collect((LongWritable)val, (Text)key);
        }
    }
    public static class LimitClicks extends MapReduceBase
        implements Reducer<LongWritable, Text, LongWritable, Text> {

        int count = 0;
        public void reduce(
                LongWritable key,
                Iterator<Text> iter,
                OutputCollector<LongWritable, Text> oc,
                Reporter reporter) throws IOException {

            // Only output the first 100 records
            while (count < 100 && iter.hasNext()) {
                oc.collect(key, iter.next());
                count++;
            }
        }
    }
    public static void main(String[] args) throws IOException {
        JobConf lp = new JobConf(MRExample.class);
        lp.setJobName("Load Pages");
        lp.setInputFormat(TextInputFormat.class);
        lp.setOutputKeyClass(Text.class);
        lp.setOutputValueClass(Text.class);
        lp.setMapperClass(LoadPages.class);
        FileInputFormat.addInputPath(lp, new
Path("/user/gates/pages"));
        FileOutputFormat.setOutputPath(lp,
                new Path("/user/gates/tmp/indexed_pages"));
        lp.setNumReduceTasks(0);
        Job loadPages = new Job(lp);

        JobConf lfu = new JobConf(MRExample.class);
        lfu.setJobName("Load and Filter Users");
        lfu.setInputFormat(TextInputFormat.class);
        lfu.setOutputKeyClass(Text.class);
        lfu.setOutputValueClass(Text.class);
        lfu.setMapperClass(LoadAndFilterUsers.class);
        FileInputFormat.addInputPath(lfu, new
Path("/user/gates/users"));
        FileOutputFormat.setOutputPath(lfu,
                new Path("/user/gates/tmp/filtered_users"));
        lfu.setNumReduceTasks(0);
        Job loadUsers = new Job(lfu);

        JobConf join = new JobConf(MRExample.class);
        join.setJobName("Join Users and Pages");
        join.setInputFormat(KeyValueTextInputFormat.class);
        join.setOutputKeyClass(Text.class);
        join.setOutputValueClass(Text.class);
        join.setMapperClass(IdentityMapper.class);
        join.setReducerClass(Join.class);
        FileInputFormat.addInputPath(join, new
Path("/user/gates/tmp/indexed_pages"));
        FileInputFormat.addInputPath(join, new
Path("/user/gates/tmp/filtered_users"));
        FileOutputFormat.setOutputPath(join, new
Path("/user/gates/tmp/joined"));
        join.setNumReduceTasks(50);
        Job joinJob = new Job(join);
        joinJob.addDependingJob(loadPages);
        joinJob.addDependingJob(loadUsers);

        JobConf group = new JobConf(MRExample.class);
        group.setJobName("Group URLs");
        group.setInputFormat(KeyValueTextInputFormat.class);
        group.setOutputKeyClass(Text.class);
        group.setOutputValueClass(LongWritable.class);
        group.setOutputFormat(SequenceFileOutputFormat.class);
        group.setMapperClass(LoadJoined.class);
        group.setCombinerClass(ReduceUrls.class);
        group.setReducerClass(ReduceUrls.class);
        FileInputFormat.addInputPath(group, new
Path("/user/gates/tmp/joined"));
        FileOutputFormat.setOutputPath(group, new
Path("/user/gates/tmp/grouped"));
        group.setNumReduceTasks(50);
        Job groupJob = new Job(group);
        groupJob.addDependingJob(joinJob);

        JobConf top100 = new JobConf(MRExample.class);
        top100.setJobName("Top 100 sites");
        top100.setInputFormat(SequenceFileInputFormat.class);
        top100.setOutputKeyClass(LongWritable.class);
        top100.setOutputValueClass(Text.class);
        top100.setOutputFormat(SequenceFileOutputFormat.class);
        top100.setMapperClass(LoadClicks.class);
        top100.setCombinerClass(LimitClicks.class);
        top100.setReducerClass(LimitClicks.class);
        FileInputFormat.addInputPath(top100, new
Path("/user/gates/tmp/grouped"));
        FileOutputFormat.setOutputPath(top100, new
Path("/user/gates/top100sitesforusers18to25"));
        top100.setNumReduceTasks(1);
        Job limit = new Job(top100);
        limit.addDependingJob(groupJob);

        JobControl jc = new JobControl("Find top 100 sites for users
18 to 25");
        jc.addJob(loadPages);
        jc.addJob(loadUsers);
        jc.addJob(joinJob);
        jc.addJob(groupJob);
        jc.addJob(limit);
        jc.run();
    }
}
```

# Enter: Spark




- A high-level API for programming MapReduce-like jobs

```
sc = SparkContext()
print “I am a regular Python program, using the pyspark lib”
users = sc.textFile(‘users.tsv’)  # user <TAB> age
          .map(lambda s: tuple(s.split(‘\t’)))
          .filter(lambda (user,age): age>=18 and age<=25)
pages = sc.textFile(‘pageviews.tsv’)  # user <TAB> url
          .map(lambda s: tuple(s.split(‘\t’)))
counts = users.join(pages)
              .map(lambda (user, age, url): (url, 1)
              .reduceByKey(add)
              .takeOrdered(5)
```

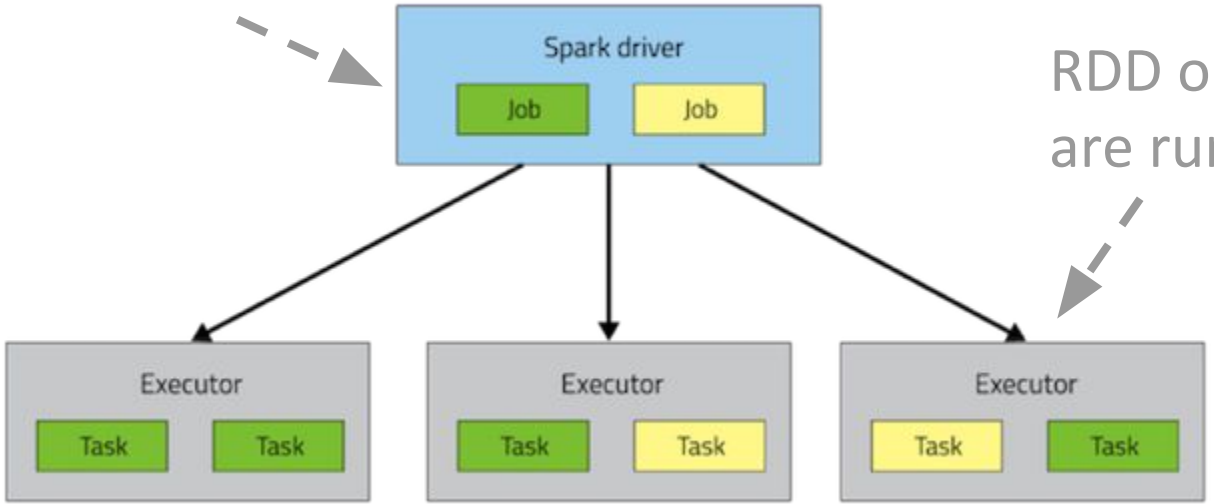

- Implemented in Scala (go, EPFL!)
- Additional APIs in
  - Python
  - Java
  - R

# RDD: resilient distributed dataset


- To programmer: looks like one single list (each element represents a “row” of a dataset)
- Under the hood: oh boy...
  - Split over several machines, replicated, etc.
  - Can be processed in parallel
  - Can be transformed to single, real list (if small...)
  - Typically read from the distributed file system (HDFS)
  - Can be written to the distributed file system

# Spark architecture

Your Python script
runs in the driver




RDD operations
are run in executors

# RDD operations


- **“Transformations”**
  - Input: RDD; output: another RDD
  - Everything remains “in the cloud”
  - Example: for every entry in the input RDD, count chars
    - RDD:[‘I’, ‘am’, ‘you’] → RDD:[1, 2, 3]
- **“Actions”**
  - Input: RDD; output: a value that is returned to the driver
  - Result is transferred “from cloud to ground”
  - Example: take a sample of entries from RDD

# Lazy execution [unrelated]

- **Transformations** (i.e., RDD→RDD operations) are not executed until it's really necessary
  (a.k.a. "lazy execution")
- Execution of transformations triggered by **actions**
- Why?
  - If you never look at the data, there's no point in manipulating it…
  - E.g., rdd2 = rdd1.map(f1)
    rdd3 = rdd2.filter(f2)
    Can be done in one go -- no need to materialize rdd2

"I have good news and bad news"

# RDD transformations [full list]

- **map**(*func*): Return a new distributed dataset formed by passing each element of the source through a function *func*
  - {1,2,3}.map(lambda x: x*2) → {2,4,6}
- **filter**(*func*): Return a new dataset formed by selecting those elements of the source on which *func* returns true
  - {1,2,3}.filter(lambda x: x <= 2) → {1,2}
- **flatMap**(*func*): Similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a list rather than a single item)
  - {1,2,3}.flatMap(lambda x: [x,x*10]) → {1,10,2,20,3,30}

# RDD transformations [full list]

- **sample**(*withReplacement?*, *fraction*, *seed*): Sample a fraction *fraction* of the data, with or without replacement, using a given random number generator *seed*
- **union**(*otherDataset*): Return a new dataset that contains the union of the elements in the source dataset and the argument.
- **intersection**(*otherDataset*): …
- **distinct**(): Return a new dataset that contains the distinct elements of the source dataset.

# RDD transformations [full list]

- **groupByKey**(): When called on a dataset of (K, V) pairs, returns a dataset of (K, Iterable<V>) pairs.
  - {(1,a), (2,b), (1,c)}.groupByKey() → {(1,[a,c]), (2,[b])}
- **reduceByKey**(*func*): When called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) => V.
  - {(1, 3.1), (2, 2.1), (1, 1.3)}.reduceByKey(lambda (x,y): x+y) → {(1, 4.4), (2, 2.1)}

# RDD transformations [full list]

- **sortByKey**(): When called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs sorted by keys
- **join**(*otherDataset*): When called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key
  - {(1,a), (2,b)}.join({(1,A), (1,X)}) ⟶ {(1, (a,A)), (1, (a,X))}
- Analogous: **leftOuterJoin**, **rightOuterJoin**, **fullOuterJoin**
- (There are several other RDD transformations, and some of the above have additional arguments; cf. tutorial)

# RDD actions [full list]

- **collect**(): Return all the elements of the dataset as an array at the driver program. This is usually useful after a filter or other operation that returns a sufficiently small subset of the data.
- **count**(): Return the number of elements in the dataset.
- **take**(*n*): Return an array with the "first" *n* elements of the dataset.
- **saveAsTextFile**(*path*): Write the elements of the dataset as a text file in a given directory in the local filesystem or HDFS.
- (There are several other RDD actions; cf. tutorial)

# Broadcast variables

- my_set = set(range(1e80))
  rdd2 = rdd1.filter(lambda x: x in my_set)
  ^ This is a bad idea: my_set needs to be shipped with every task (one task per data partition, so if rdd1 is stored in *N* partitions, the above will require copying the same object *N* times)
- Better:
  my_set = sc.broadcast(set(range(1e80)))
  rdd2 = rdd1.filter(lambda x: x in my_set.value)
  ^ This way, my_set is copied to each executor only once and persists across all tasks on the same executor
- Broadcast variables are **read-only**

# Accumulators

- def f(x): return x*2
  rdd2 = rdd1.map(f)
  ^ How can we easily know how many rows there are in rdd1 (without running a costly reduce operation)?
- Side effects via accumulators!
  counter = sc.accumulator(0)
  def f(x): counter.add(1); return x*2
  rdd2 = rdd1.map(f)
- Accumulators are **write-only** (“add-only”) for executors
- Only driver can read the value: counter.value

# RDD persistence

```
rdd2 = rdd1.map(f1)
list1 = rdd2.filter(f2).collect()
list2 = rdd2.filter(f3).collect()
```

map(f1) transformation is executed twice

---

```
rdd2 = rdd1.map(f1)
rdd2.persist()
list1 = rdd2.filter(f2).collect()
list2 = rdd2.filter(f3).collect()
```

Result of map(f1) transformation is cached and reused (can choose between memory and disk)

# Spark DataFrames


- Bridging the gap between your experience with Pandas and the need for distributed computing
- RDD = list of rows;  DataFrame = table with rows and typed columns
- Important to understand what RDDs are and what they offer, but today most of the tasks can be accomplished with DataFrames **(higher level of abstraction => less code)**
- https://databricks.com/blog/2015/02/17/introducing-dataframes-in-spark-for-large-scale-data-science.html

# Spark SQL


```
sc = SparkContext()

sqlContext = HiveContext(sc)

df = sqlContext.sql("SELECT * from table1 GROUP BY id")
```

# Spark's Machine Learning Toolkit

MLlib: Algorithms [more details]

Classification

- Logistic regression, decision trees, random forests

Regression

- Linear (with L1 or L2 regularization)

Unsupervised:

- Alternating least squares
- K-means
- SVD
- Topic modeling (LDA)

Optimizers

- Optimization primitives (SGD, L-BGFS)

# Example:
# Logistic regression with MLLib

```
from pyspark.mllib.classification \
   import LogisticRegressionWithSGD

trainData = sc.textFile("...").map(...)
testData = sc.textFile("...").map(...)
model = \
   LogisticRegressionWithSGD.train(trainData)
predictions = model.predict(testData)
```

# Remarks

- This lecture is not enough to teach you Spark!
- To use it in practice, you'll need to delve into further online material
- Tutorial in tomorrow's lab session; HW3
- You can't learn it without some frustration :(
- Projects: assess whether you'd benefit from Spark
  - Spinn3r (>1TB): yes, you'll need Spark
  - Amazon (~20GB): it depends…


# Cluster etiquette

- Develop and debug locally
  - Install Spark locally on your personal computer
  - Use a small subset of the data
- When ready, launch your script on the cluster using spark-submit
- **Never (never!) use the Spark shell (a.k.a. pyspark) -- it's hereby officially forbidden**
- Useful trench report from a dlab member: "What I learned from processing big data with Spark"

# Feedback

Give us feedback on this lecture here:
https://go.epfl.ch/ada2018-lec6-feedback

- What did you (not) like about this lecture?
- What was (not) well explained?
- On what would you like more (fewer) details?
- Where is Waldo?
- …