Behavioral Data Mining

Lecture 7
Hadoop and MapReduce
(slides from Matei Zaharia)

Wrap-up from last time

- MCMC + Gibbs Sampling
- What it all means

Back to Inference

- **Estimation:** Given a joint distribution Pr(X, Y) on observed data Y and unobserved data X, we want to estimate X given Y. We may want:
  - MAP estimates: the mode of the posterior Pr(X | Y)
  - Condition means: E(X | Y)

  In practice it may only be possible to get a local max or mean.

- **Model Inference:** Since we cant know the true Pr(X, Y), we choose a family of models M with tractable Pr(X, Y | M) and then find a "best" model (e.g. minimum loss).
  - Most model inference formulations are not closed form, so an iteration is needed to find the best model.

MCMC

Basics:

- The expected value of a sum is the sum of expected values (no independence needed), so a random mean can be approximated as a mean of random values with the same mean.
- A Markov chain is a sequence of random values $X_0, X_1, X_2, \ldots$ such that the distribution of X_{i-1} depends only on the value of X_i

- So if you can generate a Markov chain whose stationary distribution is the posterior probability, any posterior statistics can be estimated.

MCMC

Metropolis Hastings: X_t is the current state.

1. Sample a point Y from a proposal distribution $q(.|X_t)$
2. With probability $\alpha(X, Y)$ accept the new point and set $X_{t+1} = Y$.

where

$$\alpha(X, Y) = \min\left(1, \frac{\pi(Y)q(X|Y)}{\pi(Y)q(Y|X)}\right)$$

And $\pi(.)$ is the distribution of interest, usually the posterior probability.

The stationary distribution of this sampler is $\pi(.)$ and we can estimate the statistics of any variable derived from X.

MCMC

1. Sample a point Y from a proposal distribution $q(.|X_t)$
2. With probability $\alpha(X, Y)$ accept the new point and set $X_{t+1} = Y$.

$$\alpha(X, Y) = \min\left(1, \frac{\pi(Y)q(X|Y)}{\pi(X)q(Y|X)}\right)$$

Very simple, but its not magic.

Note that the sampler will spend most time in high-probability states. If the proposed Y is too "far" from X_t it will have low probability and the chain will never move.

A very successful strategy for this is the Gibbs Sampler, which changes one variable at a time.

Gibbs Sampler

Proposal distribution is:

$$q_i(Y_i \mid X) = \pi_i(Y_i \mid X_{-i})$$

where $X_{-i} = X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n$

For this q_i , the acceptance probability is 1.

Its exceptionally simple if the X_i are binary or categorical variables. Then $q_i(Y_i \mid X)$ is simply a vector of probabilities from which we can directly sample.

Gibbs Sampler

There are lots of principled and semi-principled improvements:

1. Update independent blocks of variables in parallel.
2. Delay (mini-batch) updates to model parameters, rather than updating with every block – Smola et al. paper
3. Use collapsed inference for continuous variables where possible.
4. Draw multiple samples for each variable (skip-ahead) in one time step:
   - Bernoulli samples → Binomial samples
   - Categorical samples → Multinomial samples
   - Or approximate both with Poisson distributions

Open Problem

Gibbs sampler approaches so far have been much slower than algebraic (e.g. variational LDA) ones.

- With collapsed sampling, the number of "operations" is essentially the same.
- But implementation choices lead to huge constant factors
  - Java random numbers are quite slow
  - Updating random memory locations is very slow
- Instead, dense parametric GPU-based random number generators can do the same calculations orders of magnitude faster.

Outline

- Design patterns for Behavioral Modeling
- Stochastic Gradient Descent
- Second-Order SGD
- MCMC + Gibbs Sampling
- What it all means

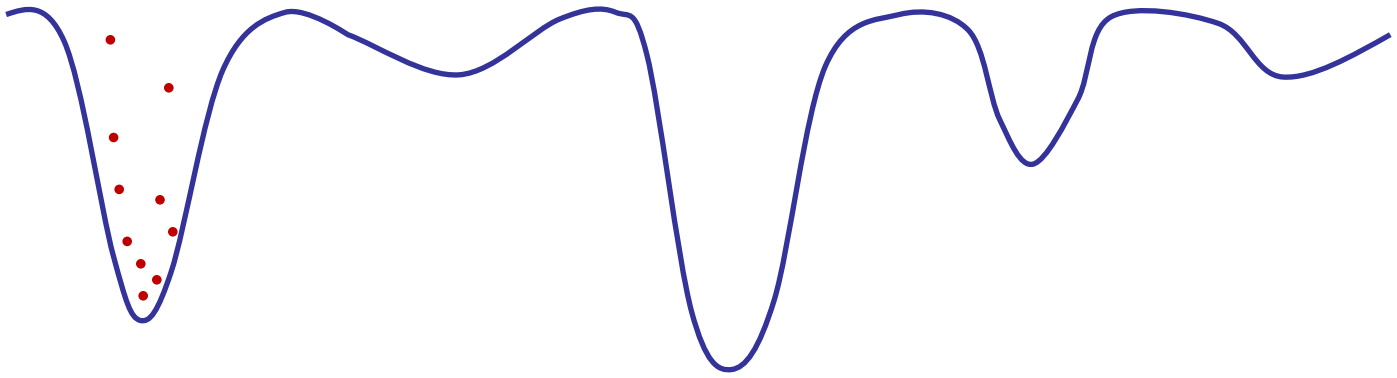
Convex vs non-Convex Optimization

- Many simple optimization problems are convex (e.g. regression), and the choice of optimization strategy affects only the rate of convergence.

- But most non-trivial models are non-convex (e.g. factor and cluster models, latent variable models), and have multiple local risk minima. The optimization strategy can have a significant affect on final accuracy.

Convex vs non-Convex Optimization

- Classical gradient descent is a "deterministic" algorithm. It will usually find a nearby local minimum of risk.
- SGD adds "randomness" to the gradient estimates. It moves both with and against the gradient, and can move away from local minima.
- Gibbs samplers in principle explore the entire posterior space, but in practice often wander only near a local minimum.



Convex vs non-Convex Optimization

- For this reason, its common to start Gibbs samplers (or other MCMC estimators) from many random initial points.
- Since some trajectories can wander far from the minima, they can be periodically pruned.
- The acceptance probability can be adjusted (down) – to reduce the "temperature" of the sampler.
- This process (called annealing) eventually causes the sampler to settle in a true local minimum.
- If the loss is a negative log probability, then the local risk minimum is a local mode of probability.

Summary

- Design patterns for Behavioral Modeling
- Stochastic Gradient Descent
- Second-Order SGD
- MCMC + Gibbs Sampling
- What it all means

What is MapReduce?

- Data-parallel programming model for clusters of commodity machines

- Pioneered by Google
  - Processes 20 PB of data per day
- Popularized by open-source Hadoop project
  - Used by Yahoo!, Facebook, Amazon, …

What is MapReduce used for?

- At Google:
  - Index building for Google Search
  - Article clustering for Google News
  - Statistical machine translation
- At Yahoo!:
  - Index building for Yahoo! Search
  - Spam detection for Yahoo! Mail
- At Facebook:
  - Data mining
  - Ad optimization
  - Spam detection

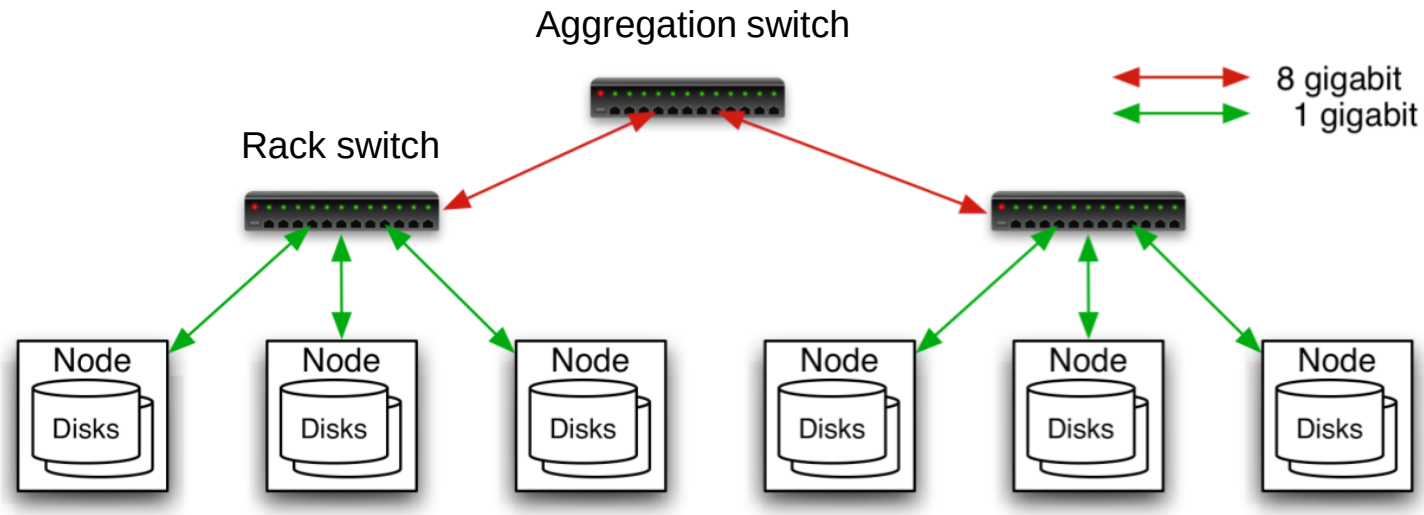
Outline

- MapReduce architecture
- Fault tolerance in MapReduce
- Sample applications
- Getting started with Hadoop

MapReduce Design Goals

1. **Scalability** to large data volumes:
   - Scan 100 TB on 1 node @ 50 MB/s = 23 days
   - Scan on 1000-node cluster = 33 minutes
2. **Cost-efficiency:**
   - Commodity nodes (cheap, but unreliable)
   - Commodity network
   - Automatic fault-tolerance (fewer admins)
   - Easy to use (fewer programmers)

Typical Hadoop Cluster



- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 GBps bandwidth in rack, 8 GBps out of rack
- Node specs (Yahoo terasort):
  8 x 2.0 GHz cores, 8 GB RAM, 4 disks (= 4 TB?)

Typical Hadoop Cluster

Image from http://wiki.apache.org/hadoop-data/attachments/HadoopPresentations/attachments/aw-apachecon-eu-2009.pdf

Challenges

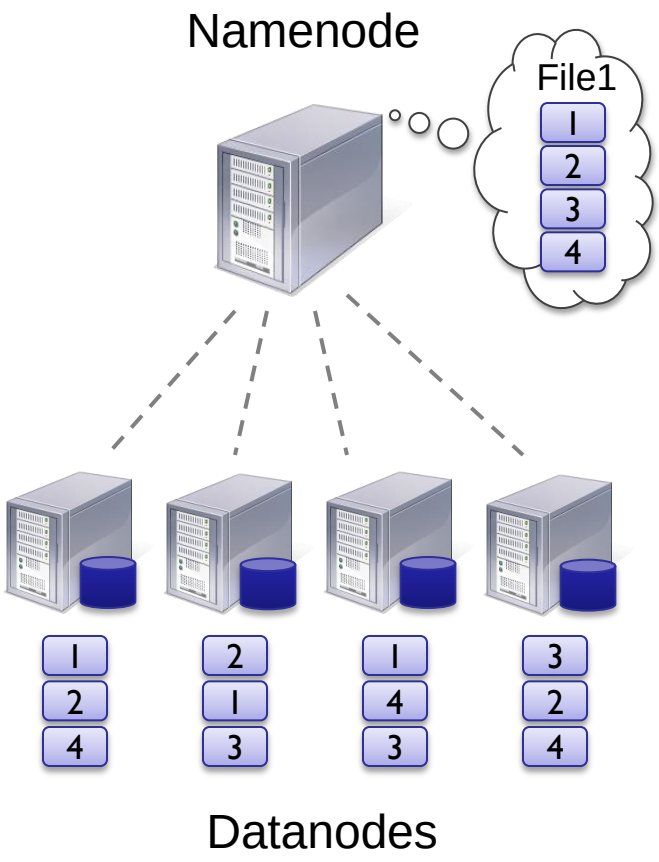
- **Cheap nodes fail, especially if you have many**
  - Mean time between failures for 1 node = 3 years
  - MTBF for 1000 nodes = 1 day
  - Solution: Build fault-tolerance into system
- **Commodity network = low bandwidth**
  - Solution: Push computation to the data
- **Programming distributed systems is hard**
  - Solution: Data-parallel programming model: users write "map" and "reduce" functions, system handles work distribution and fault tolerance

Hadoop Components

- Distributed file system (HDFS)
  - Single namespace for entire cluster
  - Replicates data 3x for fault-tolerance
- MapReduce implementation
  - Executes user jobs specified as "map" and "reduce" functions
  - Manages work distribution & fault-tolerance

Hadoop Distributed File System

- Files split into 128MB *blocks*
- Blocks replicated across several *datanodes* (usually 3)
- Single *namenode* stores metadata (file names, block locations, etc)
- Optimized for large files, sequential reads
- Files are append-only



MapReduce Programming Model

- Data type: key-value *records*

- Map function:

$$(K_{in}, V_{in}) \rightarrow \text{list}(K_{inter}, V_{inter})$$

- Reduce function:

$$(K_{inter}, \text{list}(V_{inter})) \rightarrow \text{list}(K_{out}, V_{out})$$

MapReduce Programming Model

- To map tabular data to MapReduce, use keys which are row/column tuples:
- Row-based:

$$K = (K_{row}, K_{column})$$

- Column-based:

$$K = (K_{column}, K_{row})$$

- or lumped row-based:

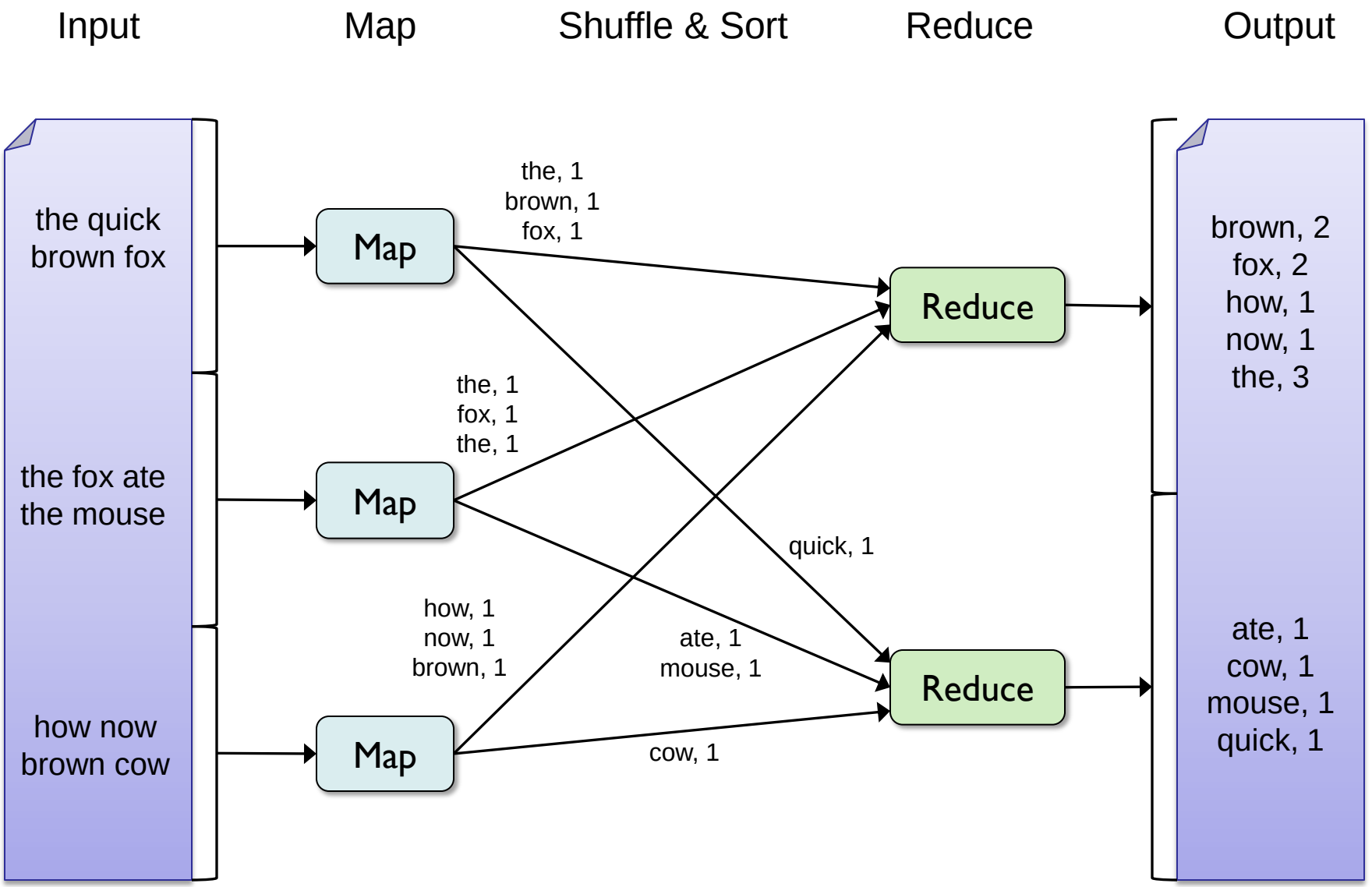
$$K = K_{row}, V = list(v_{col1}, v_{col2}, v_{col3}, \ldots)$$

Example: Word Count

```
def mapper(line):
  foreach word in line.split():
    output(word, 1)

def reducer(key, values):
  output(key, sum(values))
```

Word Count Execution



SQL analogue

Think:

```
SELECT red_fcn(cols) FROM
   SELECT map_fcn(cols) FROM data_source
GROUP BY key
```

MapReduce Execution Details

- Single *master* controls job execution on multiple *slaves* as well as user scheduling
- Mappers preferentially placed on same node or same rack as their input block
  - Push computation to data, minimize network use
- Mappers save outputs to local disk rather than pushing directly to reducers
  - Allows having more reducers than nodes
  - Allows recovery if a reducer crashes

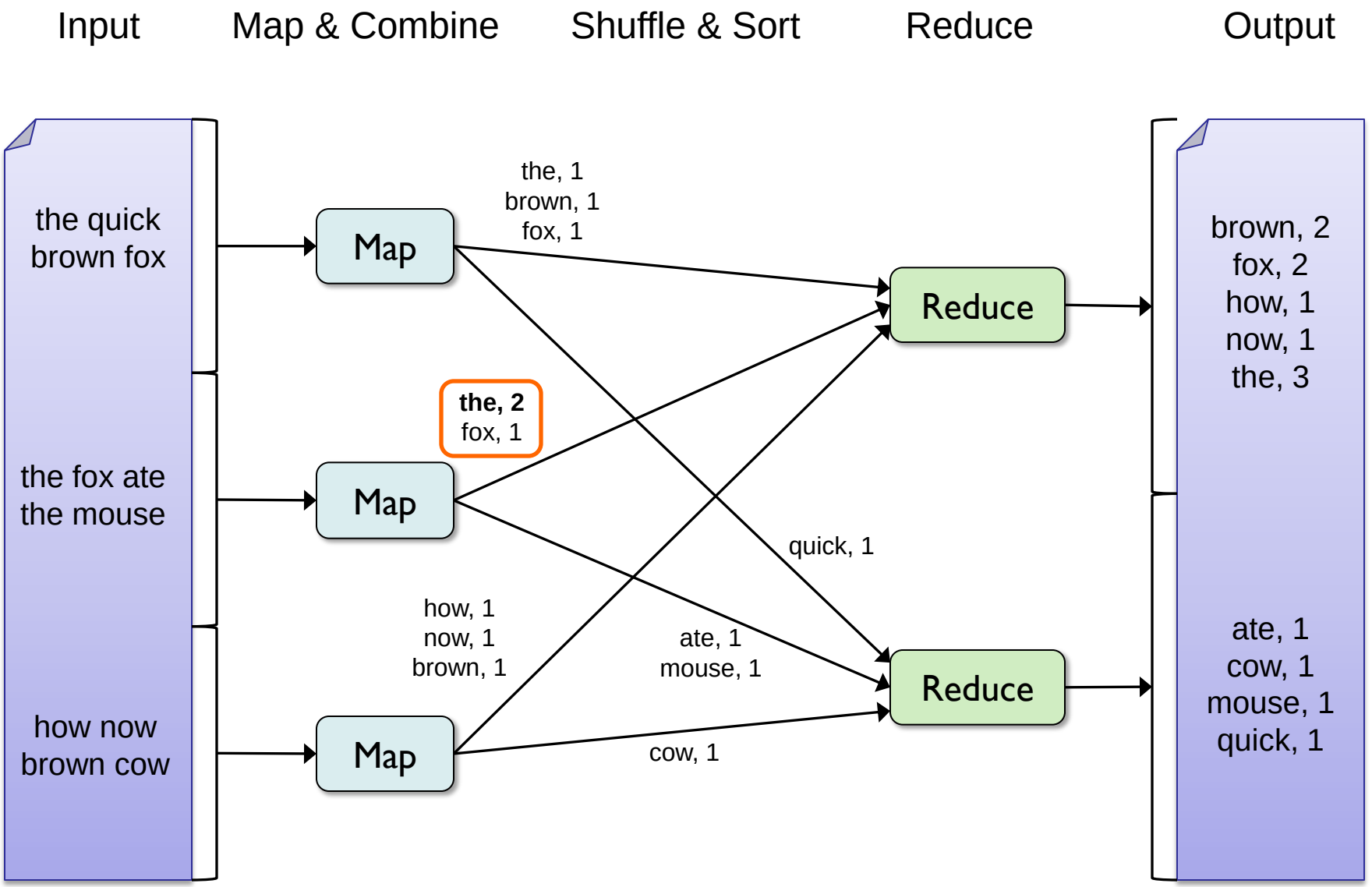
An Optimization: The Combiner

- A combiner is a local aggregation function for repeated keys produced by same map
- For associative ops. like sum, count, max
- Decreases size of intermediate data
- Very often the same function as the reducer

- Example: local counting for Word Count:

```
def combiner(key, values):
  output(key, sum(values))
```

Word Count with Combiner



Outline

- MapReduce architecture
- Fault tolerance in MapReduce
- Sample applications
- Getting started with Hadoop

Fault Tolerance in MapReduce

1. If a task crashes:
   - Retry on another node
     - Okay for a map because it had no dependencies
     - Okay for reduce because map outputs are on disk
   - If the same task repeatedly fails, fail the job or ignore that input block (user-controlled)

➢ Note: For this and the other fault tolerance features to work, *your map and reduce tasks must be side-effect-free*

Fault Tolerance in MapReduce

2. If a node crashes:
   - Relaunch its current tasks on other nodes
   - Relaunch any maps the node previously ran
     - Necessary because their output files were lost along with the crashed node

Fault Tolerance in MapReduce

3. If a task is going slowly (straggler):
   - Launch second copy of task on another node
   - Take the output of whichever copy finishes first, and kill the other one

- On behavioral data (usually power law) you will often get structural stragglers – nodes whose random share of the data is very large. These require special treatment – truncation, splitting,…

Takeaways

- By providing a data-parallel programming model, MapReduce can control job execution in useful ways:
  - Automatic division of job into tasks
  - Automatic placement of computation near data
  - Automatic load balancing
  - Recovery from failures & stragglers
- User focuses on application, not on complexities of distributed computing

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1. Search

- **Input:** (lineNumber, line) records
- **Output:** lines matching a given pattern

- **Map:**

```
if(line matches pattern):
   output(line)
```

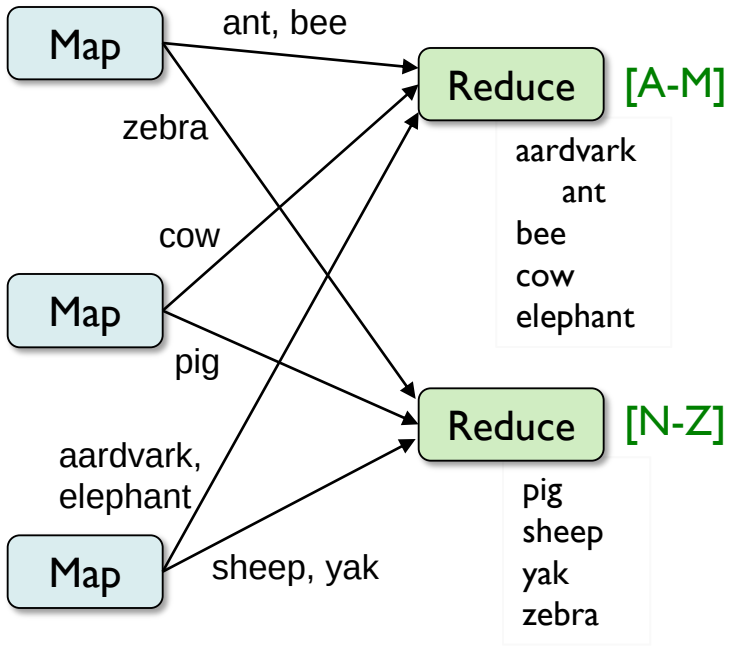
- **Reduce:** identify function
  - Alternative: no reducer (map-only job)

2. Sort

- **Input:** (key, value) records
- **Output:** same records, sorted by key

- **Map:** identity function
- **Reduce:** identify function

- **Trick:** Pick partitioning function h such that $k_1<k_2 \Rightarrow h(k_1)<h(k_2)$



3. Inverted Index

- **Input:** (filename, text) records
- **Output:** list of files containing each word

- **Map:**

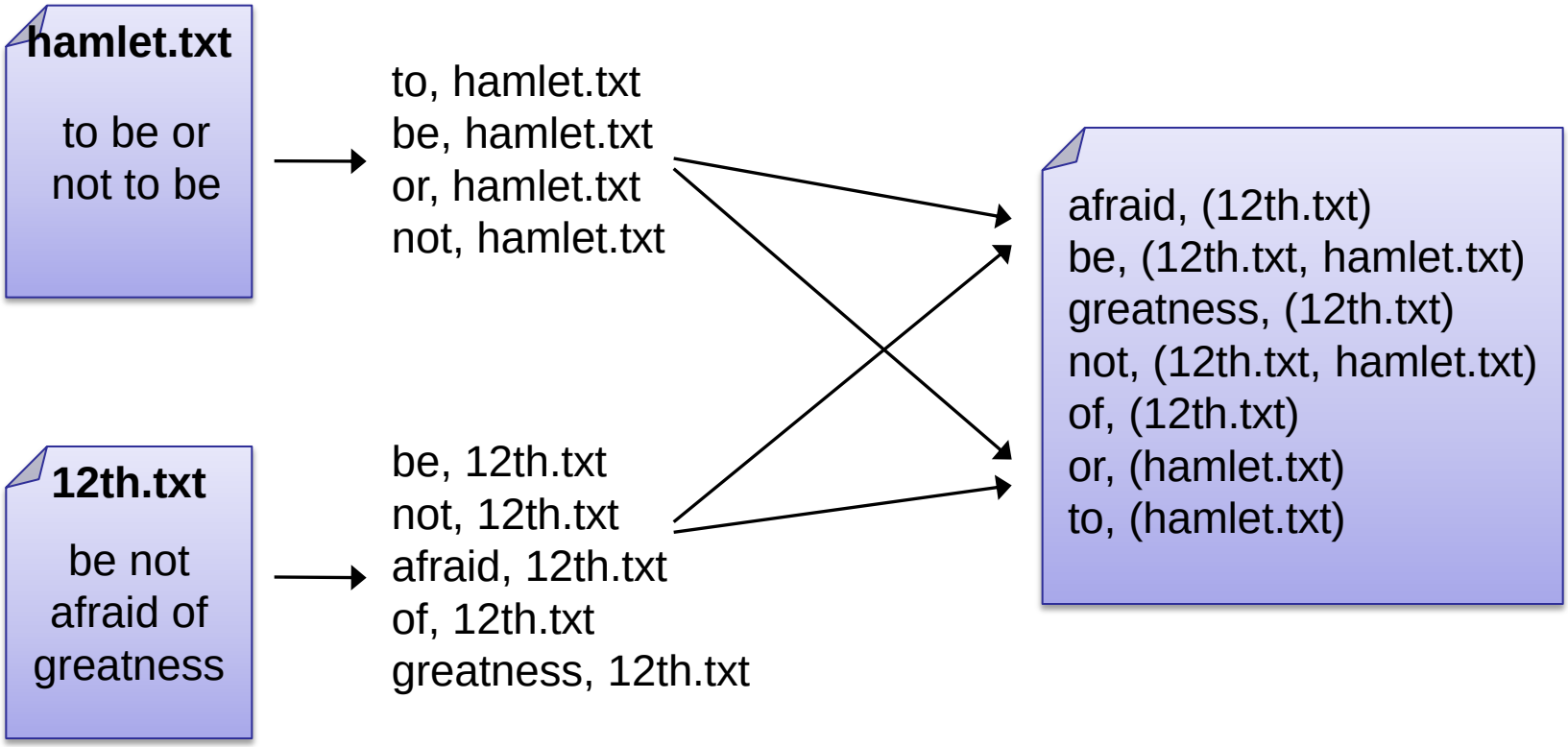
```
foreach word in text.split():
    output(word, filename)
```

- **Combine:** uniquify filenames for each word

- **Reduce:**

```
def reduce(word, filenames):
    output(word, sort(filenames))
```

Inverted Index Example



4. Most Popular Words

- **Input:** (filename, text) records
- **Output:** the 100 words occurring in most files

- Two-stage solution:
  - **Job 1:**
    - Create inverted index, giving (word, list(file)) records
  - **Job 2:**
    - Map each (word, list(file)) to (count, word)
    - Sort these records by count as in sort job

- Optimizations:
  - Map to (word, 1) instead of (word, file) in Job 1
  - Estimate count distribution in advance by sampling

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Getting Started with Hadoop

- Run jobs on icluster1.eecs.berkeley.edu

OR

- Download from hadoop.apache.org
- To install locally, unzip and set `JAVA_HOME`
- Details: hadoop.apache.org/core/docs/current/quickstart.html

- Three ½ ways to write jobs:
  - Java API
  - Hadoop Streaming (for Python, Perl, etc)
  - Pipes API (C++)
  - Write in Scala and run a jar with the runtime

Word Count in Java

```
public static class MapClass extends MapReduceBase
    implements Mapper<LongWritable, Text, Text, IntWritable> {

    private final static IntWritable ONE = new IntWritable(1);

    public void map(LongWritable key, Text value,
                    OutputCollector<Text, IntWritable> output,
                    Reporter reporter) throws IOException {
      String line = value.toString();
      StringTokenizer itr = new StringTokenizer(line);
      while (itr.hasMoreTokens()) {
        output.collect(new text(itr.nextToken()), ONE);
      }
    }
 }
```

Word Count in Java

```
public static class Reduce extends MapReduceBase
   implements Reducer<Text, IntWritable, Text, IntWritable> {

   public void reduce(Text key, Iterator<IntWritable> values,
                      OutputCollector<Text, IntWritable> output,
                      Reporter reporter) throws IOException {
     int sum = 0;
     while (values.hasNext()) {
       sum += values.next().get();
     }
     output.collect(key, new IntWritable(sum));
   }
 }
```

Word Count in Java

```
public static void main(String[] args) throws Exception {
   JobConf conf = new JobConf(WordCount.class);
   conf.setJobName("wordcount");

   conf.setMapperClass(MapClass.class);
   conf.setCombinerClass(Reduce.class);
   conf.setReducerClass(Reduce.class);

   FileInputFormat.setInputPaths(conf, args[0]);
   FileOutputFormat.setOutputPath(conf, new Path(args[1]));

   conf.setOutputKeyClass(Text.class); // out keys are words (strings)
   conf.setOutputValueClass(IntWritable.class); // values are counts

   JobClient.runJob(conf);
 }
```

Word Count in Python with Hadoop Streaming

Mapper.py:

```
import sys
for line in sys.stdin:
  for word in line.split():
    print(word.lower() + "\t" + 1)
```

Reducer.py:

```
import sys
counts = {}
for line in sys.stdin:
  word, count = line.split("\t")
    dict[word] = dict.get(word, 0) + int(count)
for word, count in counts:
  print(word.lower() + "\t" + 1)
```

The Good, the Bad, the Ugly

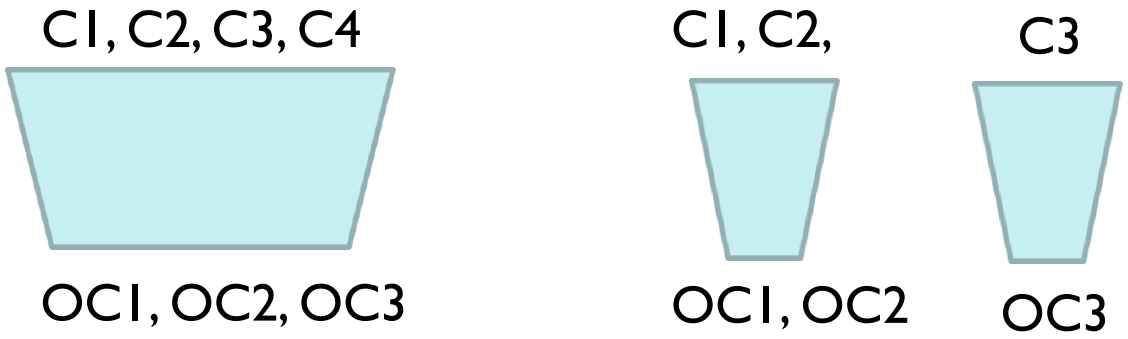
- MapReduce is extremely popular, especially since the release of Hadoop.
- Availability in cloud services (like EC2) makes it usable by just about anyone.
- While you can't do everything in Hadoop, its task coverage seems to be very high.
- Hash partitioning, the basic sort/group model, and its error recovery make it relatively simple to use as a programming model.
- Leverages Java serialization, reflection,…
- Fits well with higher-level interfaces like Hive, Pig etc.

The Good, the Bad, the Ugly

- By itself, Hadoop/MR is too low-level for large-scale programming.
- It is procedural, and doesn't support query optimization.
- Job turnaround time is high because of rigidity in the design.
- On a cluster, you don't have to do everything "well", and its easy to compensate for a weak implementation with extra cycles.

The Good, the Bad, the Ugly

- Mapper/reducer code has poor structure compared to columnar design (e.g. SQL functions).



- Hard memory partitioning in Hadoop make it a poor match for machine learning algorithms with large models.
- "stateless" mappers and reducers are also inefficient for ML algorithms that work incrementally.

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- MapReduce architecture
- Fault tolerance in MapReduce
- Sample applications
- Getting started with Hadoop
- Hadoop and machine learning

Conclusions

- MapReduce's data-parallel programming model hides complexity of distribution and fault tolerance
- Principal philosophies:
  - *Make it scale*, so you can throw hardware at problems
  - *Make it cheap*, saving hardware, programmer and administration costs (but requiring fault tolerance)
- MapReduce is not suitable for all problems, but when it works, it may save you a lot of time
- Even with many cores, data representation dominates performance. Use efficient designs with one or many CPUs.

Resources

- Hadoop: http://hadoop.apache.org/core/
- Hadoop docs: http://hadoop.apache.org/core/docs/current/
- Pig: http://hadoop.apache.org/pig
- Hive: http://hadoop.apache.org/hive
- Hadoop video tutorials from Cloudera: http://www.cloudera.com/hadoop-training