Programming at Scale: Dataflow

cs378h
Today

Questions?

Administrivia
• Project Proposal Due Soon!

Agenda:
• MPI Wrapup
• Dataflow
Review: Scale: Goal
Review: Design Space

- Throughput
- Latency
- Internet
- Private data center
- Shared nothing
- Shared something
Review: Design Space
Review: Design Space

Throughput vs. Latency

Internet vs. Private data center

Shared nothing vs. Shared something

Transaction

Grid
Review: Design Space

- Throughput
- Latency

- Internet
- Private data center

- Shared nothing
- Shared something

- Grid

Diagram showing the relationship between throughput, latency, and different types of data centers.
Review: Design Space

- Throughput
- Latency

- Internet
- Private data center

- Shared nothing
- Shared something

- Search
- Transaction
- Spark
- Dryad
- Grid

- MapReduce
Review: Design Space

- Throughput
- Latency

Internet

Private data center

Shared nothing

Shared something

Transaction

Search

MapReduce

Spark

Dryad

Grid

HPC MPI
You are an engineer at: Hare-brained-scheme.com
You are an engineer at:
Hare-brained-scheme.com

Your boss, 

comes to your office and says:

“We’re going to be super rich! We just need a program to search for strings in text files...”
You are an engineer at:
Hare-brained-scheme.com

Your boss, , comes to your office and says:

“We’re going to be super rich! We just need a program to search for strings in text files…”

Input: <search_term>, <files>
You are an engineer at: 
Hare-brained-scheme.com

Your boss, comes to your office and says:

“We’re going to be super rich! We just need a program to search for strings in text files...”

Input: <search_term>, <files>
Output: list of files containing <search_term>
public class StringFinder {
    int main(...) {
        foreach(File f in getInputFiles()) {
            if(f.contains(searchTerm)) {
                results.add(f.getFileName());
            }
        }
        System.out.println("Files:" + results.toString());
    }
}
Infrastructure is hard to get right
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1. How do we distribute the searchable files on our machines?
Infrastructure is hard to get right

1. How do we distribute the searchable files on our machines?
2. What if our webserver goes down?
Infrastructure is hard to get right

1. How do we distribute the searchable files on our machines?
2. What if our webserver goes down?
3. What if a StringFinder machine dies? How would you know it was dead?
Infrastructure is hard to get right

1. How do we distribute the searchable files on our machines?
2. What if our webserver goes down?
3. What if a StringFinder machine dies? How would you know it was dead?
4. What if marketing comes and says, “well, we also want to show pictures of the earth from space too! Ooh..and the moon too!”
StringFinder was the easy part!

You really need general infrastructure.
Many different tasks
Want to use hundreds or thousands of PC’s
Continue to function if something breaks
Must be easy to program...
Dataflow Engines

Programming model + infrastructure
Write programs that run on lots of machines
Automatic parallelization and distribution
Fault-tolerance
I/O and jobs Scheduling
Status and monitoring
Dataflow Engines

Programming model + infrastructure
Write programs that run on lots of machines
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 Status and monitoring

Key Ideas:
All modern “big data” platforms are dataflow engines!

Differences:
1. what graph structures are allowed?
2. How does this impact programming model?
MapReduce

• Input & Output: sets of <key, value> pairs

• Programmer writes 2 functions:

  map (in_key, in_value) -> list(out_key, intermediate_value)
  • Processes <k,v> pairs
  • Produces intermediate pairs

  reduce (out_key, list(interm_val)) -> list(out_value)
  • Combines intermediate values for a key
  • Produces a merged set of outputs
Indexing (1)

```java
public void map() {
    String line = value.toString();
    StringTokenizer itr = new StringTokenizer(line);
    if(itr.countTokens() >= N) {
        while(itr.hasMoreTokens()) {
            word =(itr.nextToken())+"|"+key.getFileName();
            output.collect(word, 1);
        }
    }
    Input: a line of text, e.g. "mistakes were made" from myfile.txt
    Output:
    mistakes|myfile.txt
    were|myfile.txt
    made|myfile.txt
```
public void reduce() {
    int sum = 0;
    while(values.hasNext()) {
        sum += values.next().get();
    }
    output.collect(key, sum);
}

Input: a <term, filename> pair, list of occurrences (e.g. {1, 1,..1})
Output:
    mistakes | myfile.txt  10
    were      | myfile.txt  45
    made      | myfile.txt  2
Review: K-Means

```java
public void kmeans() {
    while(...) {
        for each point
            find_nearest_center(point);
        for each center
            compute_new_center(center)
    }
}
```
Review: K-Means

```java
public void kmeans() {
    while(...) {
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Review: K-Means

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    }
}
```
Example: K-Means Mapper

```java
/*
 * Map: find minimum distance center for point, emit to reducer
 */
@override
public void map(LongWritable key, Text value,
     OutputCollector<DoubleWritable, DoubleWritable> output,
     Reporter reporter) throws IOException {
    String line = value.toString();
    double point = Double.parseDouble(line);
    double min1, min2 = Double.MAX_VALUE, nearest_center = mCenters.get(0);
    // Find the minimum center from a point
    for (double c : mCenters) {
        min1 = c - point;
        if (Math.abs(min1) < Math.abs(min2)) {
            nearest_center = c;
            min2 = min1;
        }
    }
    // Emit the nearest center and the point
    output.collect(new DoubleWritable(nearest_center),
                  new DoubleWritable(point));
}
```
/*
 * Reduce: collect all points per center and calculate
 * the next center for those points
 */
@override
public void reduce(
    DoubleWritable key, Iterator<DoubleWritable> values,
    OutputCollector<DoubleWritable, Text> output, Reporter reporter)
    throws IOException {
    double newCenter;
    double sum = 0;
    int no_elements = 0;
    String points = "";
    while (values.hasNext()) {
        double d = values.next().get();
        points = points + " " + Double.toString(d);
        sum = sum + d;
        ++no_elements;
    }
    // We have a new center now
    newCenter = sum / no_elements;
    // Emit new center and point
    output.collect(new DoubleWritable(newCenter), new Text(points));
}
How Does Parallelization Work?

INPUT FILE(s)

User Program

(1) fork
(1) fork
(1) fork

Master

(2) assign map
(2) assign reduce

worker

split 0
split 1
split 2
split 3
split 4

(3) read
(4) local write

worker

(5) remote read

worker

(6) write

output file 0
output file 1

Input files
Map phase
Intermediate files (on local disks)
Reduce phase
Output files
Execution

Key idea $\rightarrow$ shuffle $\equiv$ sort!
Task Granularity And Pipelining

| map tasks | >> | machines | -- why?
Task Granularity And Pipelining

| map tasks | >> | machines | -- why? 
Minimize fault recovery time 
Pipeline map with other tasks 
Easier to load balance dynamically
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Your boss, comes to your office and says:
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“I can’t believe you used MapReduce!!!"
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Your boss, comes to your office and says:

“I can’t believe you used MapReduce!!!
*You’re fired...*”
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“I can’t believe you used MapReduce!!! You’re fired…”

Why might he say this?
MapReduce: A major step backwards | The Database Column

on Jan 17 in Database architecture, Database history, Database innovation posted by DeWitt

[Note: Although the system attributes this post to a single author, it was written by David J. DeWitt and Michael Stonebraker]

On January 8, a Database Column reader asked for our views on new distributed database research efforts, and we’ll begin here with our views on MapReduce. This is a good time to discuss it, since the recent trade press has been filled with news of the revolution of so-called “cloud computing.” This paradigm entails harnessing large numbers of (low-end) processors working in parallel to solve a computing problem. In effect, this suggests constructing a data center by lining up a large number of “jelly beans” rather than utilizing a much smaller number of high-end servers.

For example, IBM and Google have announced plans to make a 1,000 processor cluster available to a few select universities to teach students how to program such clusters using a software tool called MapReduce [1]. Berkeley has gone so far as to plan on teaching their freshman how to program using the MapReduce framework.

As both educators and researchers, we are amazed at the hype that the MapReduce proponents have spread about how it represents a paradigm shift in the development of scalable, data-intensive applications. MapReduce may be a good idea for writing certain types of general-purpose computations, but to the database community, it is:

1. A giant step backward in the programming paradigm for large-scale data intensive applications
Why is MapReduce backwards?
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Backwards step in programming paradigm
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Sub-optimal: brute force, no indexing
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Not novel: 25 year-old ideas from DBMS lit
  It’s just a group-by aggregate engine
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Missing most DBMS features
   Schema, foreign keys, ...
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Incompatible with most DBMS tools
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So why is it such a big success?
MapReduce and Dataflow
MapReduce and Dataflow

- MR is a *dataflow* engine
MapReduce and Dataflow

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MapReduce and Dataflow

• MR is a *dataflow* engine
• Lots of others
  • Dryad
  • DryadLINQ
  • Dandelion
  • CIEL
  • GraphChi/Pregel
  • Spark
MapReduce and Dataflow

• MR is a *dataflow* engine
• Lots of others
  • Dryad
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  • GraphChi/Pregel
  • Spark
MapReduce vs Dryad (and others...)

- DAG instead of BSP
- Interface variety
  - Memory FIFO
  - Disk
  - Network
- Flexible Modular Composition
Dryad (2007): 2-D Piping

- Unix Pipes: 1-D
  
grep | sed | sort | awk | perl
Dryad (2007): 2-D Piping

- Unix Pipes: 1-D
  ```
grep | sed | sort | awk | perl
  ```

- Dryad: 2-D
  ```
grep^{1000} | sed^{500} | sort^{1000} | awk^{500} | perl^{50}
  ```
Dataflow Engines
Dataflow Job Structure

**Input files**

1. grep
2. grep
3. grep

**Vertices (processes)**

1. sed
2. sed

**Channels**

1. grep
2. grep
3. grep

**Stage**

1. sort
2. sort
3. sort

**Output files**

1. awk
2. awk
3. perl
Dataflow Job Structure

Input files

Vertices (processes)

Channels

Stage

Output files

How to implement?
Channels

Finite streams of items

- distributed filesystem files (persistent)
- SMB/NTFS files (temporary)
- TCP pipes (inter-machine)
- memory FIFOs (intra-machine)
Finite streams of items

- distributed filesystem files (persistent)
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Key idea:
Encapsulate data movement behind channel abstraction → gets programmer out of the picture
Spark (2012) Background

Commodity clusters: important platform

**In industry:** search, machine translation, ad targeting, ...

**In research:** bioinformatics, NLP, climate simulation, ...

Cluster-scale models (e.g. MR) de facto standard

Fault tolerance through replicated durable storage

Dataflow is the common theme
Commodity clusters: important platform

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Dataflow is the common theme

**Multi-core**

**Iteration**
Motivation

Programming models for clusters transform data flowing from stable storage to stable storage

E.g., MapReduce:
Motivation

Programming models for clusters transform data flowing from stable storage to stable storage.

E.g., MapReduce:

Benefits of data flow: runtime can decide where to run tasks and can automatically recover from failures.
Iterative Computations: PageRank

1. Start each page with a rank of 1
2. On each iteration, update each page’s rank to
   \[ \sum_{i \in \text{neighbors}} \frac{\text{rank}_i}{|\text{neighbors}_i|} \]

```scala
links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
    ranks = links.join(ranks).flatMap {
        (url, (links, rank)) =>
        links.map(dest => (dest, rank/links.size))
    }.reduceByKey(_ + _)
}
```
Iterative Computations: PageRank

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        links.map(dest => (dest, rank / links.size))
    }
    reduceByKey(_ + _)
}

**Solution:** augment data flow model with “resilient distributed datasets” (RDDs)
Programming Model

• Resilient distributed datasets (RDDs)
  • Immutable collections partitioned across cluster that can be rebuilt if a partition is lost
  • Created by transforming data in stable storage using data flow operators (map, filter, group-by, ...)
  • Can be cached across parallel operations
Programming Model

• Resilient distributed datasets (RDDs)
  • Immutable collections partitioned across cluster that can be rebuilt if a partition is lost
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• Parallel operations on RDDs
  • Reduce, collect, count, save, ...
Programming Model

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  • Can be *cached* across parallel operations

• Parallel operations on RDDs
  • Reduce, collect, count, save, ...

• Restricted shared variables
  • Accumulators, broadcast variables
Example: Log Mining

• Load error messages from a log into memory, then interactively search for various patterns
Example: Log Mining

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lines = spark.textFile("hdfs://...")
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Example: Log Mining

• Load error messages from a log into memory, then interactively search for various patterns

```python
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split(\'t\')(2))
```
Example: Log Mining

• Load error messages from a log into memory, then interactively search for various patterns

```python
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('\t')(2))
cachedMsgs = messages.cache()
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```scala
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('t')(2))
cachedMsgs = messages.cache()
cachedMsgs.filter(_.contains("foo")).count
```
Example: Log Mining

• Load error messages from a log into memory, then interactively search for various patterns

```scala
text = spark.textFile("hdfs://...")
errors = text.filter(_.startsWith("ERROR"))
messages = errors.map(_.split('t')(2))
cachedMsgs = messages.cache()
cachedMsgs.filter(_.contains("foo")).count
```
Example: Log Mining

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cachedMsgs.filter(_.contains("foo")).count
cachedMsgs.filter(_.contains("bar")).count
```
Example: Log Mining

- Load error messages from a log into memory, then interactively search for various patterns

```python
lines = spark.textFile("hdfs://...")
errors = lines.filter(_.startsWith("ERROR"))
messages = errors.map(_.split(\\t\n')(2))
cachedMsgs = messages.cache()

cachedMsgs.filter(_.contains("foo")).count
cachedMsgs.filter(_.contains("bar")).count
```
Example: Log Mining

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cachedMsgs.filter(_.contains("bar")).count
...
```
Example: Log Mining

• Load error messages from a log into memory, then interactively search for various patterns

```python
cachedMsgs = messages.cache()```

cachedMsgs.filter(_.contains("foo")).count

cachedMsgs.filter(_.contains("bar")).count

Result: full-text search of Wikipedia in <1 sec (vs 20 sec for on-disk data)
RDD Fault Tolerance

• RDDs maintain *lineage* information that can be used to reconstruct lost partitions

• Ex:

```scala
cachedMsgs = textFile(...).filter(_.contains("error"))
  .map(_.split('t')(2))
  .persist()
```

![Diagram showing RDD transformations](image-url)
Data-Parallel Computation Systems

- Application
- Language
- Execution
- Storage
Data-Parallel Computation Systems

Application

Language

Execution

Parallel Databases

Storage

SQL
Data-Parallel Computation Systems

- Application
- Language
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- Storage

SQL

Parallel Databases

Map-Reduce

GFS

BigTable
Data-Parallel Computation Systems

Application

Language

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Sawzall

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GFS

BigTable

```
count: table sum of int;
total: table sum of float;
sum_of_squares: table sum of float;
x: float = input;
emit count <- 1;
emit total <- x;
emit sum_of_squares <- x * x;
```
Data-Parallel Computation Systems

Application

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SQL

Sawzall

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Parallel Databases

Map-Reduce

GFS

Storage

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Sawzall
Data-Parallel Computation Systems

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Map-Reduce

GFS

BigTable

Hadoop

HDFS

S3
Data-Parallel Computation Systems

- Application
  - SQL
  - Sawzall
  - ≈SQL
- Language
  - Parallel Databases
    - Map-Reduce
    - GFS
    - BigTable
- Execution
  - Hadoop
- Storage
  - S3
lines = LOAD '/user/hadoop/HDFS_File.txt' AS (line:chararray);
words = FOREACH lines GENERATE FLATTEN(TOKENIZE(line)) as word;
grouped = GROUP words BY word;
wordcount = FOREACH grouped GENERATE group, COUNT(words);
DUMP wordcount;
Data-Parallel Computation Systems

Application

Language

Execution

Storage

Parallel Databases

- Map-Reduce
- GFS
- BigTable

Sawzall

- SQL
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Pig, Hive

Hadoop

HDFS

S3
Data-Parallel Computation Systems

- Application
  - SQL
  - Sawzall
  - Pig, Hive
  - DryadLINQ
    - Scope
  - Dryad
  - Cosmos
    - Azure
    - SQL Server
- Language
  - ≈SQL
  - Map-Reduce
  - Hadoop
  - GFS
    - BigTable
  - HDFS
    - S3
- Execution
- Storage
  - SQL
Data-Parallel Computation Systems

- Application
- Language
- Execution
- Storage

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<th>SQL</th>
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Data-Parallel Computation Systems

Application

Language

Execution

Storage

Parallel Databases

Sawzall

Map-Reduce

GFS

BigTable

Pig, Hive

Hadoop

HDFS

S3

DryadLINQ

Spark

Dryad

Sawzall

≈SQL

LINQ, SQL

SQL

≈SQL
Summary

Dataflow key enabler for cluster-scale parallelism

Key issues become runtime’s responsibility
  - Data movement
  - Scheduling
  - Fault-tolerance
Example: Counting Words...

```java
map(String input_key, String input_value):
    // input_key: document name
    // input_value: document contents
    for each word w in input_value:
        EmitIntermediate(w, "1");

reduce(String output_key, Iterator intermediate_values):
    // output_key: a word
    // output_values: a list of counts
    int result = 0;
    for each v in intermediate_values:
        result += parseInt(v);
    Emit(AsString(result));
```

*MapReduce handles all the other details!*
Redundant Execution

Slow worker can throttle performance: why?
What makes a worker slow?

Solution:
Redundant Execution

Slow worker can throttle performance: why?

What makes a worker slow?
- Other Jobs on machine (how could we fix)
- Bad disks, soft errors
- Exotica (processor caches disabled!)

Solution: spawn backups near end of phase
MapReduce is sub-optimal
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Modern DBMSs: hash + B-tree indexes to accelerate data access.
   Indexes are user-defined
   Could MR do this?
MapReduce is sub-optimal

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No query optimizer! (oh my, terrible...but good for researchers! 😊)
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   E.g. “the” more common than “zyzzyva”
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Materializing splits
  N=1000 mappers \( \rightarrow \) M=500 keys = 500,000 local files
  500 reducer instances “pull” these files
  DBMSs push splits to sockets (no local temp files)
MapReduce: novel && feature-poor
MapReduce: !novel && feature-poor

- Partitioning data sets (map) == Hash join
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Absent features:
- Indexing
- Update operator
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- Integrity constraints, referential integrity
- Views
DryadLINQ = LINQ + Dryad

```csharp
Collection<T> collection;
bool IsLegal(Key k);
string Hash(Key);

var results = from c in collection
              where IsLegal(c.key)
              select new { Hash(c.key), c.value};
```
DryadLINQ = LINQ + Dryad

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Query plan (Dryad job)
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Vertex code

Data

Query plan (Dryad job)

C#

C#

C#

C#

collection

results
Programming Model
Programming Model

Where
Programming Model

Where
Programming Model

Where

Select
Programming Model

Where

Select
Programming Model

Where
Select
GroupBy
Programming Model

Where
Select
GroupBy
Programming Model

Where
Select
GroupBy
OrderBy
Programming Model

Where
Select
GroupBy
OrderBy
Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Programming Model

Where
Select
GroupBy
OrderBy
Aggregate
Join
Programming Model

Where
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Where
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Where
Select
GroupBy
OrderBy
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Materialize
Programming Model

Where
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GroupBy
OrderBy
Aggregate
Join
Apply
Materialize
public static IQueryable<Pair> Histogram(IQueryable<LineRecord> input, int k)
{
    var words = input.SelectMany(x => x.line.Split(' '));
    var groups = words.GroupBy(x => x);
    var counts = groups.Select(x => new Pair(x.Key, x.Count()));
    var ordered = counts.OrderByDescending(x => x.count);
    var top = ordered.Take(k);
    return top;
}

"A line of words of wisdom"

["A", "line", "of", "words", "of", "wisdom"]

[["A"], ["line"], ["of", "of"], ["words"], ["wisdom"]]

[{"A", 1}, {"line", 1}, {"of", 2}, {"words", 1}, {"wisdom", 1}]

[{"of", 2}, {"A", 1}, {"line", 1}, {"words", 1}, {"wisdom", 1}]

[{"of", 2}, {"A", 1}, {"line", 1}]
Example: Histogram

```csharp
public static IQueryable<Pair> Histogram(
    IQueryable<LineRecord> input, int k)
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    var counts = groups.Select(x => new Pair(x.Key, x.Count()));
    var ordered = counts.OrderByDescending(x => x.count);
    var top = ordered.Take(k);
    return top;
}
```

"A line of words of wisdom"

```json
[ "A", "line", "of", "words", "of", "wisdom"]

[ ["A"], ["line"], ["of", "of"], ["words"], ["wisdom"]]

[ ["A", 1], ["line", 1], ["of", 2], ["words", 1], ["wisdom", 1]]

[ ["of", 2], ["A", 1], ["line", 1], ["words", 1], ["wisdom", 1]]

[ ["of", 2], ["A", 1], ["line", 1]]
```
RDDs

- Immutable, partitioned, logical collection of records
  - Need not be materialized
  - Contains information to rebuild a dataset
- Partitioning can be based on a key
- Built using bulk transformations on other RDDs
- Can be cached for future reuse
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Transformations (define a new RDD)
map
filter
col
union
groupByKey
reduceByKey
join
persist/cache
...
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Parallel operations (return a result to driver)
- reduce
- collect
- count
- save
- lookupKey
- ...
...
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  count
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  ...
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<td>Fine-grained</td>
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<td>Writes</td>
<td>Bulk transformations</td>
<td>Fine-grained</td>
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<td>Consistency</td>
<td>Trivial (immutable)</td>
<td>Up to app / runtime</td>
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<td>Fault recovery</td>
<td>Fine-grained and low-overhead using lineage</td>
<td>Requires checkpoints and program rollback</td>
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<td>Straggler mitigation</td>
<td>Possible using speculative execution</td>
<td>Difficult</td>
</tr>
<tr>
<td>Work placement</td>
<td>Automatic based on data locality</td>
<td>Up to app (but runtime aims for transparency)</td>
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Review: What is GroupBy?
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Group a collection by key
Review: What is GroupBy?

Group a collection by key
Lambda function maps elements → key
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```
foreach (T elem in ints)
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  group = GetGroup(key);
  group.Add(elem);
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Why is MapReduce backwards?

Map == group-by
Reduce == aggregate
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```
SELECT job, COUNT(*) as "numemps"
FROM employees
WHERE salary > 1000
GROUP BY job;
```
Why is MapReduce backwards?

Map == group-by
Reduce == aggregate

```sql
SELECT job, COUNT(*) as "numemps"
FROM employees
WHERE salary > 1000
GROUP BY job;
```

• Where is the aggregate in this example?
• Is the DBMS analogy clear?
Why is MapReduce backwards?
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Schemas are good (what’s a schema?)
Why is MapReduce backwards?

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Separation of schema from app is good (why?)
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