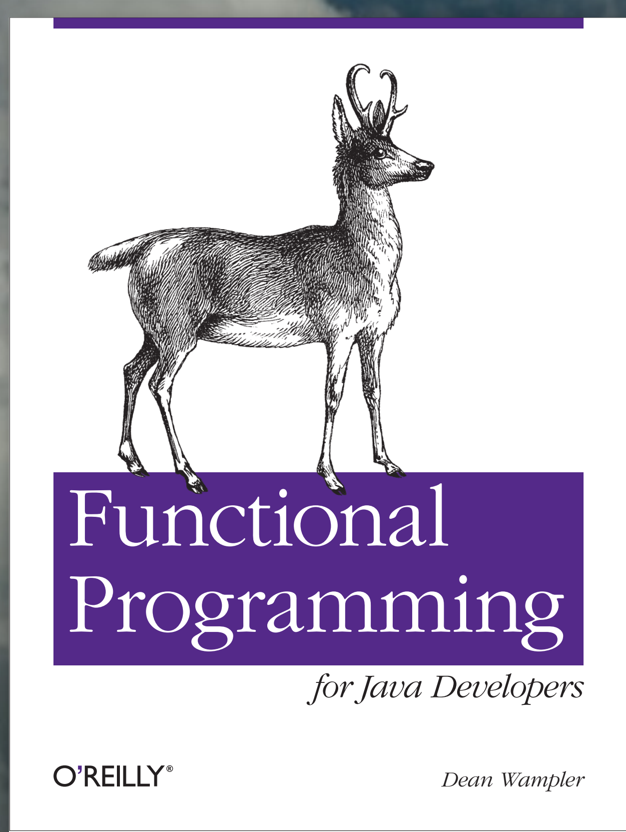
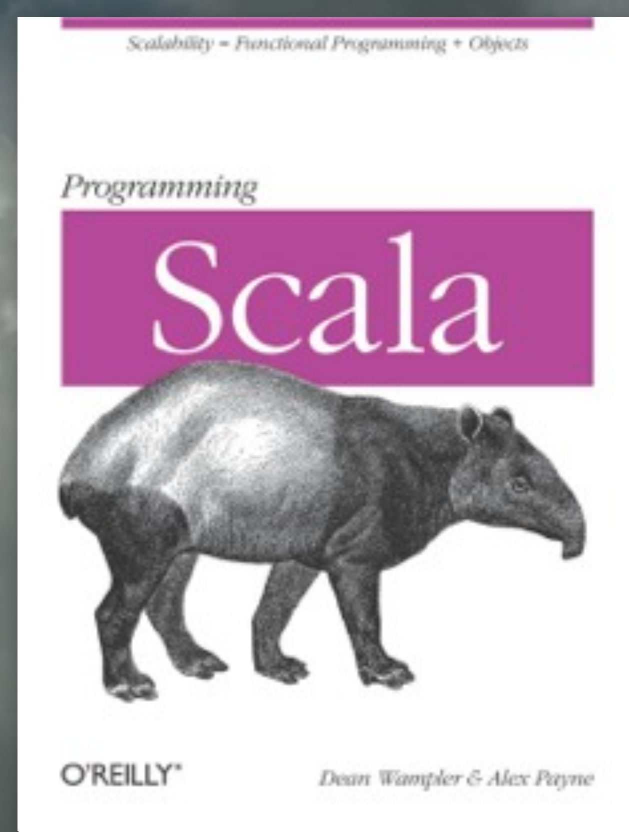
Thursday, April 11, 13

Using Scalding to leverage Cascading to write MapReduce jobs. Some prior exposure to Cascading is useful, but not assumed.

About Me...

dean@deanwampler.com@deanwampler
@deanwampler
github.com/deanwampler





My books and contact information.

My Sessions

Talks:

Beyond MapReduce

Scalding for Hadoop

Tutorials

Hadoop Data Warehousing with Hive

Crash Course in Machine Learning

A busy conference for me!!

How many of you have *all the time in the world* to get your work *done*?

How many of you have *all the time in the world* to get your work *done*?

Then why are you doing *this*:

```
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapred.*;
import java.util.StringTokenizer;

class WCMapper extends MapReduceBase
    implements Mapper<LongWritable, Text, Text, IntWritable> {

  static final IntWritable one  = new IntWritable(1);
  static final Text word = new Text;   // Value will be set in a non-thread-safe way!

  @Override
  public void map(LongWritable key, Text valueDocContents,
      OutputCollector<Text, IntWritable> output, Reporter reporter) {
    String[] tokens = valueDocContents.toString.split("\\s+");
    for (String wordString: tokens) {
      if (wordString.length > 0) {
        word.set(wordString.toLowerCase);
        output.collect(word, one);
      }
    }
  }
}

class Reduce extends MapReduceBase
    implements Reducer[Text, IntWritable, Text, IntWritable] {

  public void reduce(Text keyWord, java.util.Iterator<IntWritable> valuesCounts,
            OutputCollector<Text, IntWritable> output, Reporter reporter) {
    int totalCount = 0;
    while (valuesCounts.hasNext) {
      totalCount += valuesCounts.next.get;
    }
    output.collect(keyWord, new IntWritable(totalCount));
  }
}
```

The “simple” *Word Count* algorithm

Thursday, April 11, 13

This is intentionally too small to read and we’re not showing the main routine, which roughly doubles the code size. The “Word Count” algorithm is simple, but the Hadoop MapReduce framework is in your face. It’s very hard to see the actual “business logic”. Plus, your productivity is terrible. Yet, many Hadoop developers insist on working this way...

The main routine I’ve omitted contains boilerplate details for configuring and running the job. This is just the “core” MapReduce code. In fact, Word Count is not too bad, but when you get to more complex algorithms, even conceptually simple ideas like relational-style joins and group-bys, the corresponding MapReduce code in this API gets very complex and tedious very fast!

Notice the green, which I use for all the types, most of which are infrastructure types we don’t really care about. There is little yellow, which are function calls that do work. We’ll see how these change...

```
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapred.*;
import java.util.StringTokenizer;

class WCMapper extends MapReduceBase
    implements Mapper<LongWritable, Text, Text, IntWritable> {

  static final IntWritable one  = new IntWritable(1);
  static final Text word = new Text;   // Value will be set in a non-thread-safe way!

  @Override
  public void map(LongWritable key, Text valueDocContents,
      OutputCollector<Text, IntWritable> output, Reporter reporter) {
    String[] tokens = valueDocContents.toString.split("\\s+");
    for (String wordString: tokens) {
      if (wordString.length > 0) {
        word.set(wordString.toLowerCase);
        output.collect(word, one);
      }
    }
  }
}

class Reduce extends MapReduceBase
    implements Reducer[Text, IntWritable, Text, IntWritable] {

  public void reduce(Text keyWord, java.util.Iterator<IntWritable> valuesCounts,
           OutputCollector<Text, IntWritable> output, Reporter reporter) {
    int totalCount = 0;
    while (valuesCounts.hasNext)
      totalCount += valuesCounts.
    }
    output.collect(keyWord, new I
  }
}
```

Green types.

Yellow operations.

This is intentionally too small to read and we're not showing the main routine, which roughly doubles the code size. The "Word Count" algorithm is simple, but the Hadoop MapReduce framework is in your face. It's very hard to see the actual "business logic". Plus, your productivity is terrible. Yet, many Hadoop developers insist on working this way...

The main routine I've omitted contains boilerplate details for configuring and running the job. This is just the "core" MapReduce code. In fact, Word Count is not too bad, but when you get to more complex algorithms, even conceptually simple ideas like relational-style joins and group-bys, the corresponding MapReduce code in this API gets very complex and tedious very fast!

Notice the green, which I use for all the types, most of which are infrastructure types we don't really care about. There is little yellow, which are function calls that do work. We'll see how these change...

Your tools should:

Minimize *boilerplate* by exposing the *right abstractions*.

We would like a "domain-specific language" (DSL) for data manipulation and analysis.

Your tools should:

Maximize *expressiveness* and *extensibility*.

Thursday, April 11, 13

Expressiveness – ability to tell the system what you need done.
Extensibility – ability to add functionality to the system when it doesn't already support some operation you need.

Thursday, April 11, 13

Cascading is a Java library that provides higher-level abstractions for building data processing pipelines with concepts familiar from SQL such as a joins, group-bys, etc. It works on top of Hadoop's MapReduce and hides most of the boilerplate from you.
See http://cascading.org.

```java
import org.cascading.*;
...
public class WordCount {
  public static void main(String[] args) {
    Properties properties = new Properties();
    FlowConnector.setApplicationJarClass( properties, WordCount.class );

    Scheme sourceScheme = new TextLine( new Fields( "line" ) );
    Scheme sinkScheme = new TextLine( new Fields( "word", "count" ) );
    String inputPath  = args[0];
    String outputPath = args[1];
    Tap source = new Hfs( sourceScheme, inputPath );
    Tap sink   = new Hfs( sinkScheme, outputPath, SinkMode.REPLACE );

    Pipe assembly = new Pipe( "wordcount" );

    String regex = "(?<!\\pL)(?=\\pL)[^ ]*(?<=\\pL)(?!\\pL)";
    Function function = new RegexGenerator( new Fields( "word" ), regex );
    assembly = new Each( assembly, new Fields( "line" ), function );
    assembly = new GroupBy( assembly, new Fields( "word" ) );
    Aggregator count = new Count( new Fields( "count" ) );
    assembly = new Every( assembly, count );

    FlowConnector flowConnector = new FlowConnector( properties );
    Flow flow = flowConnector.connect( "word-count", source, sink, assembly);
    flow.complete();
  }
}
```


Here is the Cascading Java code. It's cleaner than the MapReduce API, because the code is more focused on the algorithm with less boilerplate, although it looks like it's not that much shorter. HOWEVER, this is all the code, where as previously I omitted the setup (main) code. See http://docs.cascading.org/cascading/1.2/userguide/html/ch02.html for details of the API features used here; we won't discuss them here, but just mention some highlights.

Note that there is still a lot of green for types, but now they are almost all domain-related concepts and less infrastructure types. The infrastructure is less "in your face." There is still little yellow, because Cascading has to wrap behavior in Java classes, like GroupBy, Each, Count, etc. Also, the API emphasizes composing behaviors together in an intuitive and powerful way.

```java
import org.cascading.*;
...
public class WordCount {
  public static void main(String[] args) {
    Properties properties = new Properties();
    FlowConnector.setApplicationJarClass( properties, WordCount.class );

    Scheme sourceScheme = new TextLine( new Fields( "line" ) );
    Scheme sinkScheme = new TextLine( new Fields( "word", "count" ) );
    String inputPath  = args[0];
    String outputPath = args[1];
    Tap source = new Hfs( sourceScheme, inputPath );
    Tap sink   = new Hfs( sinkScheme, outputPath, SinkMode.REPLACE );

    Pipe assembly = new Pipe( "wordcount" );

    String regex = "(?<!\\pL)(?=\\pL)[^ ]*(?<=\\pL)(?!\\pL)";
    Function function = new RegexGenerator( new Fields( "word" ), regex );
    assembly = new Each( assembly, new Fields( "line" ), function );
    assembly = new GroupBy( assembly, new Fields( "word" ) );
    Aggregator count = new Count( new Fields( "count" ) );
    assembly = new Every( assembly, count );

    FlowConnector flowConnector = new FlowConnector( properties );
    Flow flow = flowConnector.connect( "word-count", source, sink, assembly);
    flow.
  }
}
```

“Flow” setup.

Input and output taps.

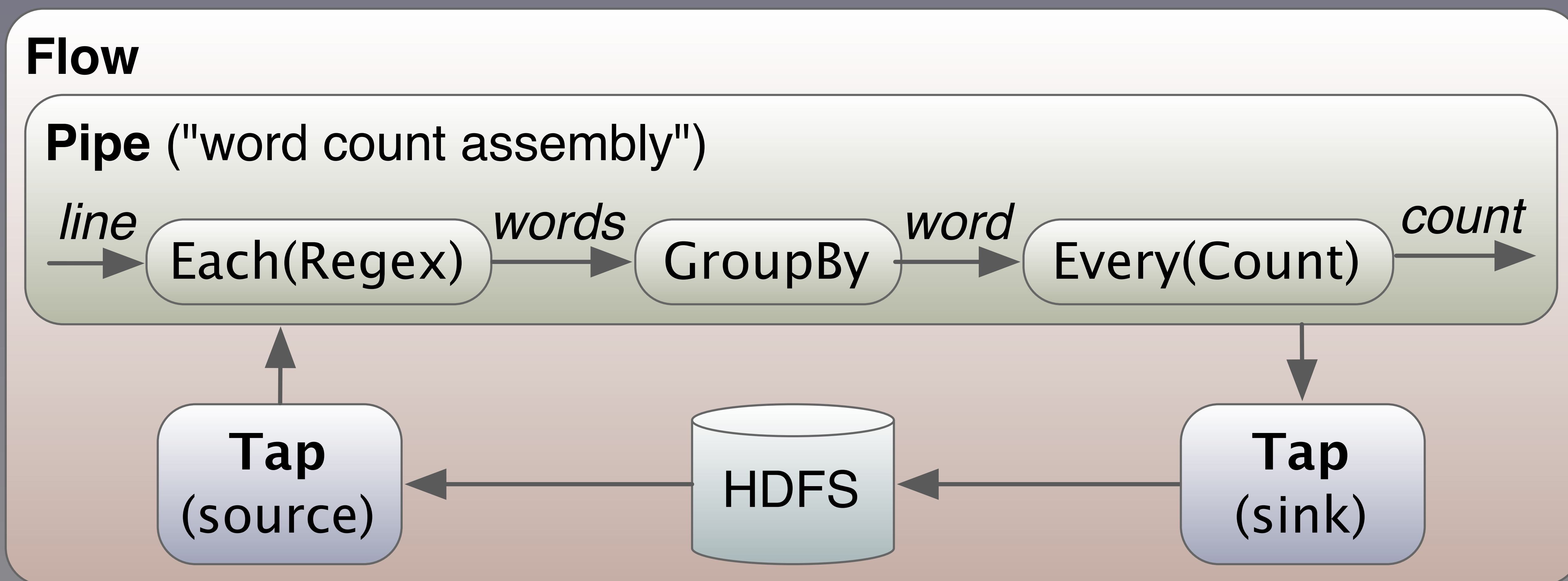
Assemble pipes.

Thursday, April 11, 13

Here is the Cascading Java code. It’s cleaner than the MapReduce API, because the code is more focused on the algorithm with less boilerplate, although it looks like it’s not that much shorter. HOWEVER, this is all the code, where as previously I omitted the setup (main) code. See http://docs.cascading.org/cascading/1.2/userguide/html/ch02.html for details of the API features used here; we won’t discuss them here, but just mention some highlights.

Note that there is still a lot of green for types, but now they are almost all domain-related concepts and less infrastructure types. The infrastructure is less “in your face.” There is still little yellow, because Cascading has to wrap behavior in Java classes, like GroupBy, Each, Count, etc. Also, the API emphasizes composing behaviors together in an intuitive and powerful way.

Word Count



Thursday, April 11, 13

Schematically, here is what Word Count looks like in Cascading. See http://docs.cascading.org/cascading/1.2/userguide/html/ch02.html for details.

Scalding is a Scala “DSL” (domain-specific language) that wraps Cascading providing an even more intuitive and more boilerplate-free API for writing MapReduce jobs. https://github.com/twitter/scalding

Scala is a new JVM language that modernizes Java’s object-oriented (OO) features and adds support for functional programming, as we’ll describe shortly.

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

That’s it!!

This Scala code is almost pure domain logic with very little boilerplate. There are a few minor differences in the implementation. You don’t explicitly specify the “Hfs” (Hadoop Distributed File System) taps. That’s handled by Scalding implicitly when you run in “non-local” model. Also, I’m using a simpler tokenization approach here, where I split on anything that isn’t a “word character” [0-9a-zA-Z_].

There is much less green, in part because Scala infers types in many cases, but also because fewer infrastructure types are required. There is a lot more yellow for the functions that do real work!

What if MapReduce, and hence Cascading and Scalding, went obsolete tomorrow? This code is so short, I wouldn’t care about throwing it away! I invested little time writing it, testing it, etc.

```sql
CREATE EXTERNAL TABLE docs (line STRING)
LOCATION '/path/to/corpus';

CREATE TABLE word_counts
AS SELECT word, count(1) AS count FROM
(SELECT explode(split(line, '\s')) AS word
 FROM docs) w GROUP BY word
ORDER BY word;
```

Hive

Thursday, April 11, 13

Here is the Hive equivalent (more or less, we aren't splitting into words using a sophisticated regular expression this time). Note that Word Count is a bit unusual to implement with a SQL dialect (we'll see more typical cases later), and we're using some Hive SQL extensions that we won't take time to explain (like ARRAYs), but you get the point that SQL is wonderfully concise… when you can express your problem in it!!

```
inpt = load '/path/to/corpus'
  using TextLoader as (line: chararray);
words = foreach inpt generate
  flatten(TOKENIZE(line)) as word;
grpd = group words by word;
cntd = foreach grpd generate group, COUNT(words);
dump cntd;
```

Pig

Pig is more expressive for non-query problems like this.


What Is
Scala?
18

Scala is a *modern*, *concise*, *object-oriented* and *functional* language for the *JVM*.

http://scala-lang.org

Thursday, April 11, 13

I'll explain what I mean for these terms in the next few slides.

Modern.

Reflects the *20 years* of *language evolution* since *Java's invention*.

Thursday, April 11, 13

Java was a good compromise of ideas for the state-of-the-art in the early 90's, but that was ~20 years ago! We've learned a lot about language design and effective software development techniques since then.

Concise.

Type *inference*, syntax for *common* OOP and FP *idioms, APIs*.

Thursday, April 11, 13

Briefly, type inference reduces “noise”, allowing the logic to shine through. Scala has lots of idioms to simplify class definition and object creation, as well as many FP idioms, such as anonymous functions. The collection API emphasizes the important data transformations we need...

Object-Oriented Programming.

Fixes *flaws* in Java's *object model*.

Composition/reuse through *traits*.

Thursday, April 11, 13

Scala fixes flaws in Java's object model, such as the essential need for a mix-in composition mechanism, which Scala provides via traits. For more on this, see Daniel Spiewak's keynote for NEScala 2013: "The Bakery from the Black Lagoon".

"

Functional

Programming.

Most *natural fit*

for *data*!

Robust, scalable.

Thursday, April 11, 13

It may not look like it, but this is actually the most important slide in this talk; FP is the most appropriate tool for data, since everything we do with data is mathematics. FP also gives us the idioms we need for robust, scalable concurrency.

JVM.

Designed for the *JVM*. *Interoperates* with all *Java* software.

Thursday, April 11, 13

But Scala is a JVM language. It interoperates with any Java, Clojure, JRuby, etc. libraries.

What Is Scalding?

Scalding is a *Scala* Big Data library based on *Cascading*, developed by *Twitter*.

https://github.com/twitter/scalding

I say “based on” Cascading, because it isn’t just a thin Scala veneer over the Java API. It adds some different concepts, hiding some Cascading API concepts (e.g., IO specifics), but not all (e.g., groupby function <=> GroupBy class).

Scalding adds a *Matrix API* useful for *graph* and *machine-learning algorithms*.

Thursday, April 11, 13

I'll show examples.

Note: *Cascalog* is a *Clojure* alternative for *Cascading*. Also adds *Logic-Programming* based on *Datalog*.

https://github.com/nathanmarz/cascalog

Thursday, April 11, 13

For completeness, note that Cascalog is a Clojure alternative. It is also notable for its addition of Logic-Programming features, adapted from Datalog. Cascalog was developed by Nathan Marz, now at Twitter, who also invented Storm.

Note: *PyCascading* is a *Python* alternative for *Cascading*. Also from Twitter. Uses *Jython*.

https://github.com/twitter/pycascading

Thursday, April 11, 13

Twitter also developed a Python API for Cascading. In fact, there are many language bindings. See cascading.org.

Moar Scalding!

More examples, starting with a deeper look at our first example.

Returning to our first example.

```
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Import the library.

Let’s walk through the code to get the “gist” of what’s happening.
First, import the Scalding API.

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
        line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Create a "Job" class.

Thursday, April 11, 13

Wrap the logic in a class (OOP!) that extends the Job abstraction.

```
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
        line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Open the user-specified input as text.

Thursday, April 11, 13

The “args” holds the user-specified arguments used to invoke the job. “--input path” specifies the source of the text. Similarly, “--output path” is used to specify the output location for the results.

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Split each 'line into 'words, a collection and flatten the collections.

Thursday, April 11, 13

A flatMap iterates through a collection, calling a function on each element, where the function "converts" each element into a collection. So, you get a collection of collections. The "flat" part flattens those nested collections into one larger collection. The "line: String => line …("\\W+")" expression is the function called by flatMap on each element, where the argument to the function is a single string variable named line and the body is to the right-hand side of the =>.
The output word field is called "word", from the first argument to flatMap: "'line -> 'word".

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Group by each 'word and determine the size of each group.

Now we group the stream of words by the word value, then count the size of each group. Give the output field the name “count”, rather than the default name “size” (if no argument is passed to size()).

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Write tab-separated
words and counts.

Finally, we write the tab-separated words and counts to the output location specified using “--output path”.

```scala
import com.twitter.scalding._

class WordCountJob(args: Args) extends Job(args) {
  TextLine( args("input") )
    .read
    .flatMap('line -> 'word) {
      line: String =>
          line.trim.toLowerCase.split("\\W+")
    }
    .groupBy('word) { group => group.size('count) }
  }
  .write(Tsv(args("output")))
}
```

Profit!!

Thursday, April 11, 13

For all you South Park fans out there...

Thursday, April 11, 13

An example of doing a simple inner join between stock and dividend data.

```scala
import com.twitter.scalding._

class StocksDivsJoin(args: Args) extends Job(args){
  val stocksSchema = ('symd, 'close, 'volume)
  val divsSchema = ('dymd, 'dividend)
  val stocksPipe = new Tsv(args("stocks"), stockSchema)
    .read
    .project('symd, 'close)
  val divsPipe = new Tsv(args("dividends"), divsSchema)
    .read

  stocksPipe
    .joinWithTiny('symd -> 'dymd, dividendsPipe)
    .project('symd, 'close, 'dividend)
    .write(Tsv(args("output")))
```

Load stocks and dividends data in separate pipes for a given stock, e.g., IBM.

```scala
import com.twitter.scalding._

class StocksDivsJoin(args: Args) extends Job(args){
  val stocksSchema = ('symd, 'close, 'volume)
  val divsSchema = ('dymd, 'dividend)
  val stocksPipe = new Tsv(args("stocks"), stockSchema)
    .read
    .project('symd, 'close)
  val divsPipe = new Tsv(args("dividends"), divsSchema)
    .read

  stocksPipe
    .joinWithTiny('symd -> 'dymd, dividendsPipe)
    .project('symd, 'close, 'dividend)
    .write(Tsv(args("output")))
}
```

Capture the schema as values.

"symd" is "stocks year-month-day" and similarly for dividends. Note that Scalding requires unique names for these fields from the different tables.

```
import com.twitter.scalding._

class StocksDivsJoin(args: Args) extends Job(args){
  val stocksSchema = ('symd, 'close, 'volume)
  val divsSchema = ('dymd, 'dividend)
  val stocksPipe = new Tsv(args("stocks"), stockSchema)
    .read
    .project('symd, 'close)
  val divsPipe = new Tsv(args("dividends"), divsSchema)
    .read

  stocksPipe
    .joinWithTiny('symd -> 'dymd, dividendsPipe)
    .project('symd, 'close, 'dividend)
    .write(Tsv(args("output")))
}
```

Load the stock and dividend records into separate pipes, project desired stock fields.

```scala
import com.twitter.scalding._

class StocksDivsJoin(args: Args) extends Job(args){
  val stocksSchema = ('symd, 'close, 'volume)
  val divsSchema = ('dymd, 'dividend)
  val stocksPipe = new Tsv(args("stocks"), stockSchema)
    .read
    .project('symd, 'close)
  val divsPipe = new Tsv(args("dividends"), divsSchema)
    .read

  stocksPipe
    .joinWithTiny('symd -> 'dymd, dividendsPipe)
    .project('symd, 'close, 'dividend)
    .write(Tsv(args("output")))
}
```

Join stocks with smaller dividends on dates, project desired fields.

```
# Invoking the script (bash)
scald.rb StocksDivsJoins.scala \
  --stocks    data/stocks/IBM.txt \
  --dividends data/dividends/IBM.txt \
  --output output/IBM-join.txt


# Output (not sorted!)
2010-02-08      121.88  0.55
2009-11-06      123.49  0.55
2009-08-06      117.38  0.55
2009-05-06      104.62  0.55
2009-02-06      96.14   0.5
2008-11-06      85.15   0.5
2008-08-06      129.16  0.5
2008-05-07      124.14  0.5
...
```

NGrams

Compute ngrams in a corpus...

```scala
import com.twitter.scalding._

class ContextNGrams(args: Args) extends Job(args) {
  val ngramPrefix =
    args.list("ngram-prefix").mkString(" ")
  val keepN = args.getOrElse("count", "10").toInt
  val ngramRE = (ngramPrefix + """\s+(\w+)""").r

  // Sort (phrase,count) by count, descending.
  val countReverseComparator =
    (tuple1:(String,Int), tuple2:(String,Int))
      => tuple1._2 > tuple2._2
  ...
```

Find, count, sort, all "I love _" in Shakespeare's plays...

Thursday, April 11, 13

1st half of this example (our longest).

```scala
  ...
  val lines = TextLine(args("input"))
    .read
    .flatMap('line -> 'ngram) { text: String =>
      ngramRE.findAllIn(text).toIterable }
    .discard('num, 'line)
    .groupBy('ngram) { g => g.size('count) }
    .groupAll { g =>
      g.sortWithTake[(String,Int)](
       ('ngram, 'count) -> 'sorted_ngrams, keepN)(
       countReverseComparator)
    }
    .write(Tsv(args("output")))
}
```


Thursday, April 11, 13

2nd half.

```scala
import com.twitter.scalding._

class ContextNGrams(args: Args) extends Job(args) {
  val ngramPrefix =
    args.list("ngram-prefix").mkString(" ")
  val keepN = args.getOrElse("count", "10").toInt
  val ngramRE = (ngramPrefix + """\s+(\w+)""").r

  // Sort (phrase,count) by count, descending.
  val countReverseComparator =
    (tuple1:(String,Int), tuple2:(String,Int))
      => tuple1._2 > tuple2._2
  ...
```

From user-specified args, the ngram prefix ("I love"), the # of ngrams desired, a matching regular expression.

Thursday, April 11, 13

Now walking through it...

```scala
import com.twitter.scalding._

class ContextNGrams(args: Args) extends Job(args) {
  val ngramPrefix =
    args.list("ngram-prefix").mkString(" ")
  val keepN = args.getOrElse("count", "10").toInt
  val ngramRE = (ngramPrefix + """\s+(\w+)""").r

  // Sort (phrase,count) by count, descending.
  val countReverseComparator =
    (tuple1:(String,Int), tuple2:(String,Int))
      => tuple1._2 > tuple2._2
  ...
```

A function "value" we'll use to sort ngrams by frequency, descending.

Thursday, April 11, 13

This is a function that is a "normal" value. We'll pass it to another function as an argument in the 2nd half of the code.

```
  ...
  val lines = TextLine(args("input"))
    .read
    .flatMap('line -> 'ngram) { text: String =>
      ngramRE.findAllIn(text).toIterable }
    .discard('num, 'line)
    .groupBy('ngram) { g => g.size('count) }
    .groupAll { g =>
      g.sortWithTake[(String,Int)](
       ('ngram, 'count) -> 'sorted_ngrams, keepN)(
       countReverseComparator)
    }
    .write(Tsv(args("output")))
}
```

Read, find desired ngram phrases, project desired fields, then group by ngram.

Thursday, April 11, 13

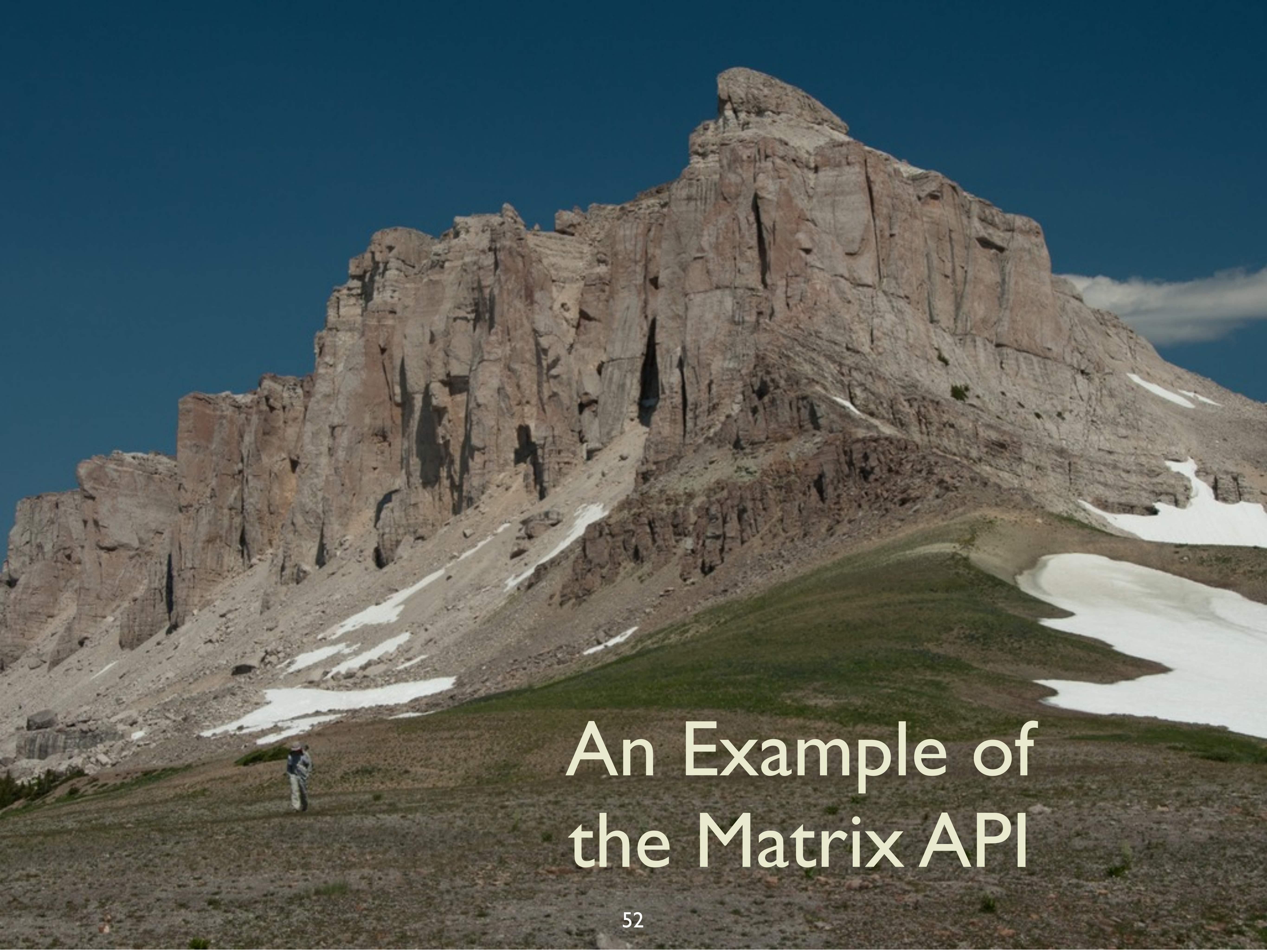
Discard is like the opposite of project(). We don't need the line number nor the whole line anymore, so toss 'em.

```
...
val lines = TextLine(args("input"))
  .read
  .flatMap('line -> 'ngram) { text: String =>
    ngramRE.findAllIn(text).toIterable }
  .discard('num, 'line)
  .groupBy('ngram) { g => g.size('count) }
  .groupAll { g =>
    g.sortWithTake[(String,Int)](
     ('ngram, 'count) -> 'sorted_ngrams, keepN)(
     countReverseComparator)
  }
  .write(Tsv(args("output")))
}
```

Group all (ngram,count) tuples together and sort descending by count. Write...

```
# Invoking the script (bash)
scald.rb ContextNGrams.scala \
  --input  data/shakespeare/plays.txt \
  --output output/context-ngrams.txt \
  --ngram-prefix "I love" \
  --count 10

# Output (reformatted)
(I love thee,44),
(I love you,24),
(I love him,15),
(I love the,9),
(I love her,8),
...,
(I love myself,3),
...,
(I love Valentine,1),
...,
(I love France,1), ...
```



Thursday, April 11, 13

From Scalding's own Matrix examples, "MatrixTutorial4", compute the cosine of every pair of vectors. This is a similarity measurement, useful, e.g., for for recommending movies and other stuff to one user based on the preferences of similar users.

```scala
import com.twitter.scalding._
import com.twitter.scalding.mathematics.Matrix

// Load a directed graph adjacency matrix where:
// a[i,j] = 1 if there is an edge from a[i] to b[j]
// and computes the cosine of the angle between
// every two pairs of vectors.
class MatrixCosine(args: Args) extends Job(args) {
  import Matrix._
  val schema = ('user1, 'user2, 'relation)
  val adjacencyMatrix = Tsv(args("input"), schema)
    .read
    .toMatrix[Long,Long,Double](schema)
  val normMatrix = adjacencyMatrix.rowL2Normalize

  // Inner product is equivalent to the cosine:
  //   AA^T/(||A||*||A||)
  (normMatrix * normMatrix.transpose)
  .write(Tsv(args("output")))
}
```

```scala
import com.twitter.scalding._
import com.twitter.scalding.mathematics.Matrix

// Load a directed graph adjacency matrix where:
// a[i,j] = 1 if there is an edge from a[i] to b[j]
// and computes the cosine of the angle between
// every two pairs of vectors.
class MatrixCosine(args: Args) extends Job(args) {
  import Matrix._
  val schema = ('user1, 'user2, 'relation)
  val adjacencyMatrix = Tsv(args("input"), schema)
    .read
    .toMatrix[Long,Long,Double](schema)
  val normMatrix = adjacencyMatrix.rowL2Normalize

  // Inner product is equivalent to the cosine:
  //   AA^T/(||A||*||A||)
  (normMatrix * normMatrix.transpose)
  .write(Tsv(args("output")))
}
```

Import matrix library.

Thursday, April 11, 13

Scala lets you put imports anywhere! So, you can scope them to just where they are needed.

```scala
import com.twitter.scalding._
import com.twitter.scalding.mathematics.Matrix

// Load a directed graph adjacency matrix where:
// a[i,j] = 1 if there is an edge from a[i] to b[j]
// and computes the cosine of the angle between
// every two pairs of vectors.
class MatrixCosine(args: Args) extends Job(args) {
  import Matrix._
  val schema = ('user1, 'user2, 'relation)
  val adjacencyMatrix = Tsv(args("input"), schema)
    .read
    .toMatrix[Long,Long,Double](schema)
  val normMatrix = adjacencyMatrix.rowL2Normalize

  // Inner product is equivalent to the cosine:
  //   AA^T/(||A||*||A||)
  (normMatrix * normMatrix.transpose)
  .write(Tsv(args("output")))
}
```

Load into a matrix.

```scala
import com.twitter.scalding._
import com.twitter.scalding.mathematics.Matrix

// Load a directed graph adjacency matrix where:
// a[i,j] = 1 if there is an edge from a[i] to b[j]
// and computes the cosine of the angle between
// every two pairs of vectors.
class MatrixCosine(args: Args) extends Job(args) {
  import Matrix._
  val schema = ('user1, 'user2, 'relation)
  val adjacencyMatrix = Tsv(args("input"), schema)
    .read
    .toMatrix[Long,Long,Double](schema)
  val normMatrix = adjacencyMatrix.rowL2Normalize

  // Inner product is equivalent to the cosine:
  //   AA^T/(||A||*||A||)
  (normMatrix * normMatrix.transpose)
  .write(Tsv(args("output")))
}
```

Normalize: sqrt(x^2+y^2)

Thursday, April 11, 13

L2 norm is the usual Euclidean distance: sqrt(a*a + b*b + …)

```scala
import com.twitter.scalding._
import com.twitter.scalding.mathematics.Matrix

// Load a directed graph adjacency matrix where:
// a[i,j] = 1 if there is an edge from a[i] to b[j]
// and computes the cosine of the angle between
// every two pairs of vectors.
class MatrixCosine(args: Args) extends Job(args) {
  import Matrix._
  val schema = ('user1, 'user2, 'relation)
  val adjacencyMatrix = Tsv(args("input"), schema)
    .read
    .toMatrix[Long,Long,Double](schema)
  val normMatrix = adjacencyMatrix.rowL2Normalize

  // Inner product is equivalent to the cosine:
  //   AA^T/(||A||*||A||)
  (normMatrix * normMatrix.transpose)
  .write(Tsv(args("output")))
}
```

Compute cosine!

Thursday, April 11, 13

L2 norm is the usual Euclidean distance: sqrt(a*a + b*b + …)
(I won't show an example invocation here.)

Scalding vs. *Hive* vs. *Pig*

Thursday, April 11, 13

Some concluding thoughts on Scalding (and Cascading) vs. Hive vs. Pig, since I've used all three a lot.

Thursday, April 11, 13

SQL is about as concise as it gets when asking questions of data and doing “standard” analytics. A great example of a “purpose-built” language. It’s great at what it was designed for. Not so great when you need to do something it wasn’t designed to do.

Thursday, April 11, 13

Pig is great for data flows, such as sequencing transformations typical of ETL (extract, transform, and load). As you might expect for a purpose-built language, it is very concise for these purposes, but writing extensions is a non-trivial step (same for Hive).

Thursday, April 11, 13

Scalding can do everything you can do with these other tools (more or less), but it gives you the full flexible power of a Turing-complete language, so it's easier to adapt to non-trivial, custom scenarios.

For more on *Scalding*:

github.com/twitter/scalding
github.com/ThinkBigAnalytics/scalding-workshop
github.com/Cascading/Impatient/tree/master/part8

All pictures © Dean Wampler, 2005-2013. The rest of the presentation is free to reuse, but attribution is appreciated. Hire us!!