Data Analytics Programming on Spark: Python In The Cloud

Chris Jermaine
cmj4@cs.rice.edu

15 Years Ago...

- Say you had a “big” data set, wanted platform to analyze it
  - — Analysis: report generation, customer profiling, statistical modelling, etc.
- What do I mean by “big”?
  - — Too large to fit in aggregate RAM of a standard distributed/parallel system
- Big is 100GB+ in 2002, TB+ now (all the way to dozens of PB)

Hardware: Agreement on "Shared Nothing"

- Store/analyze data on a large number of commodity machines
- Local, non-shared storage attached to each of them
- Only link is via a LAN
- "Shared nothing" refers to no sharing of RAM, storage
- Why preferred?
  - — Inexpensive: built out of commodity components (same stuff as in desktop PCs)
  - — You are leveraging price/tech wars among Dell, HP, Intel, AMD, etc.
  - — Compute resources scales nearly linearly with $$
  - — Contrast this to a shared RAM machine with uniform memory access

But What About the Software?

- 15 years ago, you'd have two primary options
  - — Put your data into an SQL database, or
  - — Roll your own software stack to perform your analysis

Clearly, Building Own Software Not Desirable

- Costly, time consuming
  - — A $10M software feature might eat up most of the IT budget for a single firm
  - — But Oracle can spread those costs across 100K customers
- Requires expertise not always found in house
- Risky: high potential for failure

But People Not Happy With SQL Databases

- Also quite expensive: even today, pay $5K to $50K/year/TB
- Performance often unpredictable, or just flat out poor
  - — Only now are there systems that mortals can get to work in TB+ range
- In 2004, not a lot of options for commodity shared nothing
- Software insanely complicated to use correctly
  - — Hundreds or even thousands of “knobs” to turn
- Software stack too big/deep, not possible to unbundle
  - — If you are doing analysis, ACID not important
  - — And yet, you pay for it ($$, complexity, performance)
- Difficult to put un- or semi-structured data into an SQL DB
  - — How does an archive of 10M emails get put into a set of relations?

And, Many People Just Don't Like SQL

- It is "declarative"
  - — In some ways, very nice, since parallelism is implicit
  - — But user doesn't really know what's happening under the hood... people don't like
- Also, not easy/natural to specify important computations
  - — Such as Google's PageRank, or rule mining, or data clustering, etc.

By Early-Mid 2000's...

- The Internet companies (Google, Yahoo!, etc.)...
  - — ...had some of the largest databases in the world
- But they never used classical SQL databases for webscale data
- How'd they deal with all of the data they had to analyze?
  - — Many ways
  - — But paradigm with most widespread impact was **MapReduce**
  - — First described in a 2004 academic paper, appeared in OSDI
  - — Easy read:

    http://research.google.com/archive/mapreduce.html

What Is MapReduce?

- It is a simple data processing paradigm
- To process a data set, you have two pieces of user-supplied code:
  - A **map** code
  - And a **reduce** code
- These are run (potentially over a large compute cluster) using three data processing phases
  - A **map** phase
  - A **shuffle** phase
  - And a **reduce** phase

The Map Phase

- Assume that the input data are stored in a huge file

  This file contains a simple list of pairs of type `(key1,value1)`

- And assume we have a user-supplied function of the form

  ```
  map (key1,value1)
  ```

- That outputs a list of pairs of the form `(key2, value2)`
- In the **map** phase of the MapReduce computation
  - — this `map` function is called for every record in the input data set
  - — Instances of `map` run in parallel all over the compute cluster

The Shuffle Phase

- The **shuffle** phase accepts all of the `(key2, value2)` pairs from the **map** phase
- And it groups them together
- So that all of the pairs
  - — From all over the cluster
  - — Having the same `key2` value
  - — Are merged into a single `(key2, list <value2>)` pair
- Called a **shuffle** because this is where a potential all-to-all data transfer happens

The Reduce Phase

- Assume we have a user-supplied function of the form

```
reduce (key2,list <value2>)
```

- That outputs a list of `value2` objects
- In the **reduce** phase of the MapReduce computation
  - this `reduce` function is called for every `key2` value output by the shuffle
  - Instances of `reduce` run in parallel all over the compute cluster
  - The output of all of those instances is collected in a (potentially) huge output file

The Distributed File System

- Now MapReduce is a **compute** paradigm
- It is not a **data storage** paradigm
- But any MapReduce system must read/write data from some storage system
- As a result, the MapReduce programming paradigm is tightly integrated with the idea of a **distributed file system (DFS)**
- A DFS is a storage system that allows data to be stored/accessed across machines in a network
- And abstracts away differences between local and remote data
  - — Same mechanism to read/write data
  - — No matter where data is located in the network

Distributed File Systems for MR

- DFSs have been around for a long time
  - — First widely used DFS was Sun's NFS, first introduced in 1985
- How is a DFS for MapReduce going to be different?
- Unlike classical DFSs, it sits on top of each machine's OS
- The OS is not aware of the DFS; you can't "mount" it anywhere
  - — So the files in the DFS are not accessible from "My Computer" in Windows
- Why "on top of" rather than "in" the OS?
  - — Ease of use, portability, means no worries with a heterogeneous cluster
  - — Just start up a process on each machine in the cluster
  - — No need to tell the OS about anything
  - — Means you can have a DFS up and running on a cluster in minutes/hours

Distributed File Systems for MR

- But (in theory) they still give you most of what a classic DFS does
- Replication
  - — Put each block at n locations in the cluster
  - — That way, if a disk/machine goes down, you are still OK
- Network awareness
  - — Smart enough to try to satisfy a data request locally, or from same rack
- Easy to add/remove machines
  - — You buy 10 more machines, just tell the DFA about them, and it'll add data to 'em
  - — Can take machines off the network; no problem, DFS will realize this and handle
- Load balancing
  - — If one machine is getting hit, go to another machine that has the data

Take Home Message From Last 10 Slides

- MapReduce is a distributed programming paradigm
- Needs to run on top of some storage system--a DFS
- DFS should be lightweight, easy to install, OS agnostic
- Thus, you can expect most MR softwares to be tightly integrated with a particular DFS
  - — And that DFS will typically run **on top of** the OS of each machine

MapReduce Had a Huge Impact

- One of the key technologies in the "NoSQL movement"
- What do people like about it?

Why Popular? (1)

- Schema-less
- You write code that operates over raw data
- No need to spend time/$$ loading the data into a database system
- Really nice for unstructured/semi-structured data: text, logs, for example

Why Popular? (2)

- Easier to code than classical HPC system
- Distributed/parallel computing **very** difficult to program correctly
  - — pthreads, MPI, semaphores, monitors, condition variables...
  - — All are hard to use!
- But MapReduce is a super-simple compute model
- All communication is done during shuffle phase
- All scheduling is taken care of by the MapReduce system
- Radically reduces complexity for the programmer

Why Popular? (3)

- Much more control than an SQL database
- You write the actual code that touches the data
  - — In a standard language, such as Java
- You control what happens during the map and reduce phases
- Contrast to an SQL database
  - — Where you write SQL that can be compiled to an arbitrary execution plan

Why Popular? (4)

- Fits very nicely into the “cloud computing” paradigm
- Why? So simple, lightweight, hardware agnostic
- Need to run a MapReduce computation?
  - — Just rent a bunch of machines from Amazon
  - — Give ‘em back when you are done
- Contrast this with a multi-terabyte Oracle database
  - — Most SQL databases are NOT lightweight and simple to get going in a few mins

Why Popular? (5)

- Software is free!

By 2010, Hadoop Was Widely Used

- Open-source implementation of Google MapReduce
  - — Had Hadoop MapReduce
  - — Plus Hadoop distributed file system
- But the cracks were appearing in the edifice...

Hadoop MR Word Count Java Code

```
import java.util.*;

import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.io.IntWritable;

public class WordCount {

  public static int main(String[] args) throws Exception {

    // if we got the wrong number of args, then exit
    if (args.length != 4 || !args[0].equals ("-r")) {
      System.out.println("usage: WordCount -r <num reducers> <input> <output>");
      return -1;
    }

    // Get the default configuration object
    Configuration conf = new Configuration ();

    // now create the MapReduce job
    Job job = new Job (conf);
    job.setJobName ("WordCount");

    // we'll output text/int pairs (since we have words as keys and counts as values)
    job.setMapOutputKeyClass (Text.class);
    job.setMapOutputValueClass (IntWritable.class);

    // again we'll output text/int pairs (since we have words as keys and counts as values)
    job.setOutputKeyClass (Text.class);
    job.setOutputValueClass (IntWritable.class);

    // tell Hadoop the mapper and the reducer to use
    job.setMapperClass (WordCountMapper.class);
    job.setCombinerClass (WordCountReducer.class);
    job.setReducerClass (WordCountReducer.class);

    // we'll be reading in a text file, so we can use Hadoop's built-in TextInputFormat
    job.setInputFormatClass (TextInputFormat.class);

    // we can use Hadoop's built-in TextOutputFormat for writing out the output text file
    job.setOutputFormatClass (TextOutputFormat.class);

    // set the input and output paths
    TextInputFormat.setInputPaths (job, args[2]);
    TextOutputFormat.setOutputPath (job, new Path (args[3]));

    // set the number of reduce paths
    try {
      job.setNumReduceTasks (Integer.parseInt (args[1]));
    } catch (Exception e) {
      System.out.println("usage: WordCount -r <num reducers> <input> <output>");
      return -1;
    }

    // force the mappers to handle one megabyte of input data each
    TextInputFormat.setMinInputSplitSize (job, 1024 * 1024);
    TextInputFormat.setMaxInputSplitSize (job, 1024 * 1024);

    // this tells Hadoop to ship around the jar file containing "WordCount.class" to all of
the different
    // nodes so that they can run the job
    job.setJarByClass(WordCount.class);

    // submit the job and wait for it to complete!
    int exitCode = job.waitForCompletion (true) ? 0 : 1;
    return exitCode;
```

Not pretty!
Programmer burden too high...

Many Felt Hadoop MR Too Slow

- Data read from HDFS again for each MR job
- Bad for iterative data processing
  - — Many analytics tasks process and reprocess data

And API Too Restrictive

- Can only do Map
- Or MapReduce
- Everything else in terms of those operations... annoying!

So Hadoop MR Used Less and Less

- Issues led to other dataflow platforms to replace Hadoop MR
  - — Notable are Spark and Flink
  - — We will study Spark
- Interesting fact:
  - — While Hadoop MR is dying...
  - — Hadoop DFS is going strong
  - — De-facto standard for Big Data management
  - — Looks set to stay that way for a very long time

Apache Spark

- #1 Hadoop MR killer
- What is Spark?
  - — Platform for efficient, distributed data analytics
- Basic abstraction: **Resilient Distributed Data Set** (RDD)
- RDD is a data set buffered in RAM by Spark
  - — Distributed across machines in cluster
  - — To create and load an RDD (in Python):

```
myRDD = sc.textFile (someFileName) # sc is the Spark context
# or else...
data = [1, 2, 3, 4, 5]
myRDD = sc.parallelize (data) # or
myRDD = sc.parallelize (range (20000)) # or...
```

Computations: Series of Xforms Over RDDs

- Example: word count
  - — Count number of occurs of each distinct word in a corpus

```
def countWords (fileName):
     textFile = sc.textFile (fileName)
     lines = textFile.flatMap (lambda line: line.split(" "))
     counts = lines.map (lambda word: (word, 1))
     aggCounts = counts.reduceByKey (lambda a, b: a + b)
     retrun aggCounts.top (200, key=lamda p: p[1])
```

- What transforms do we see here?
  - — `flatMap`, `map`, `reduceByKey`, `top`
- Let's go through them...

But First... What's a Lambda?

- Basically, a function that I can pass like a variable
- Key ability: can "capture" its surroundings at creation

```
def addTwelveToResult (myLambda):
     return myLambda (3) + 12

a = 23
aCoolLambda = lambda x : x + a
addTwelveToResult (aCoolLambda) # prints 48

a = 45
addTwelveToResult (aCoolLambda) # prints ???
```

Lambdas and Comprehensions

- Lambdas can return many items

```
def sumThem (myLambda):
      tot = 0
      for a in myLambda ():
            tot = tot + a
      return tot

x = np.array([1, 2, 3, 4, 5])
iter = lambda : (j for j in x)
sumThem (iter) # prints 15
```

Lambdas and Comprehensions

- Lambdas can return many items

```
def sumThem (myLambda):
     tot = 0
     for a in myLambda ():
          tot = tot + a
     return tot

x = np.array([1, 2, 3, 4, 5])
iter = lambda : (j for j in x)
sumThem (iter) # prints 15
```

- Exercise: change `iter` so accepts param, adds to each item, then:

```
def sumThem (myLambda, addMeIn):
     tot = 0
     for a in myLambda (addMeIn):
          tot = tot + a
     return tot                    # try sumThem (iter, 5)
```

flatMap ()

```
def countWords (fileName):
     textFile = sc.textFile (fileName)
     lines = textFile.flatMap (lambda line: line.split(" "))
```

- Process every data item in the RDD
- Apply lambda to it
- Lambda argument to return zero or more results
- Each result added to resulting RDD

map ()

```
def countWords (fileName):
     textFile = sc.textFile (fileName)
     lines = textFile.flatMap (lambda line: line.split(" "))
     counts = lines.map (lambda word: (word, 1))
```

- Process every data item in the RDD
- Apply lambda to it
- But the lambda must return **exactly** one result

reduceByKey ()

```
def countWords (fileName):
     textFile = sc.textFile (fileName)
     lines = textFile.flatMap (lambda line: line.split(" "))
     counts = lines.map (lambda word: (word, 1))
     aggCounts = counts.reduceByKey (lambda a, b: a + b)
```

- Data must be (*Key, Value*) pairs
- Shuffle so that all (*K, V*) pairs with same *K* on same machine
- Organize into (K, (V_1, V_2, ..., V_n)) pairs
- Use the lambda to "reduce" the list to a single value

top ()

```
def countWords (fileName):
     textFile = sc.textFile (fileName)
     lines = textFile.flatMap (lambda line: line.split(" "))
     counts = lines.map (lambda word: (word, 1))
     aggCounts = counts.reduceByKey (lambda a, b: a + b)
     retrun aggCounts.top (200, key=lamda p: p[1])
```

- Data must be (*Key, Value*) pairs
- Takes two params... first is number to return
- Second (optional): lambda to use to obtain key for comparison
- Note: `top` **collects** an RDD, moving from cloud to local
- So result is **not** an RDD

filter ()

- Not used in example code
- But needed for first activity
- Accepts a boolean-valued lambda
- That lambda applied to each item in RDD
- Item removed from result if and only if lambda returns `false`

An Important Note

- Lazy evaluation... if I run this code:

```
textFile = sc.textFile (fileName)
lines = textFile.flatMap (lambda line: line.split(" "))
counts = lines.map (lambda word: (word, 1))
aggCounts = counts.reduceByKey (lambda a, b: a + b)
```

- Nothing happens! (Other than Spark remembers the ops)
  - — Spark does not execute until an attempt made to collect an RDD
  - — When we hit `top()`, **then** all of these are executed
- Why do this?
  - — By waiting until last possible second, opportunities for "pipelining" exploited
  - — Only ops that require a shuffle can't be pipelined

Another Important Note

- Lambda capture **by value** at a difficult-to-determine instant
  - — All referenced variables serialized and broadcast
  - — Sometime between definition of RDD transform...
  - — And lazy evaluation
  - — Very useful! Standard way of broadcasting local state to distributed computations
  - — So be careful! Never rely on side-effects...

Activity One

- Word count on Amazon EC2
  - — Word count is everyone's favorite first-big-data-computation!
- See `cmj4.web.rice.edu/DSDay2/GettingStarted.html`

Next, We'll Look at Text Analytics on Spark

- Say we have a very large database of text documents (aka a "corpus") that we want to mine...

The Classic Workflow

- First, build a *dictionary* for the corpus.
  - — Given *d* distinct words...
  - — A *dictionary* is a map from each word to an integer from 1 to *d*
- Then, process each doc to obtain a "bag of words"
  - — Start with an array/vector *x* of length *d*, initialized to all zeros
  - — Then, for each word in the doc:
    - (1) look it up in the dictionary to get its corresponding int *i*
    - (2) Increment *x*[*i*]

The Classic Workflow

- Example:
  - — Doc is “This was followed by radiotherapy.”
  - — Dictionary is: {(patient, 1), (status, 2), (followed, 3), (radiotherapy, 4), (negative, 5), (was, 6), (this, 7), (treated, 8), (by, 9), (with, 10)}
- x is [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
  - — First process “this”, giving x = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]

The Classic Workflow

- Example:
  - — Doc is “This was followed by radiotherapy.”
  - — Dictionary is: {(patient, 1), (status, 2), (followed, 3), (radiotherapy, 4), (negative, 5), (was, 6), (this, 7), (treated, 8), (by, 9), (with, 10)}
- x is [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
  - — First process “this”, giving x = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
  - — Then process “was”, giving x = [0, 0, 0, 0, 0, 1, 1, 0, 0, 0]

The Classic Workflow

- Example:
  - — Doc is “This was followed by radiotherapy.”
  - — Dictionary is: {(patient, 1), (status, 2), (followed, 3), (radiotherapy, 4), (negative, 5), (was, 6), (this, 7), (treated, 8), (by, 9), (with, 10)}
- x is [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
  - — First process “this”, giving x = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
  - — Then process “was”, giving x = [0, 0, 0, 0, 0, 1, 1, 0, 0, 0]
  - — Then process “followed”, giving x = [0, 0, 1, 0, 0, 1, 1, 0, 0, 0]

The Classic Workflow

- Example:
  - — Doc is “This was followed by radiotherapy.”
  - — Dictionary is: {(patient, 1), (status, 2), (followed, 3), (radiotherapy, 4), (negative, 5), (was, 6), (this, 7), (treated, 8), (by, 9), (with, 10)}
- x is [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
  - — First process “this”, giving x = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
  - — Then process “was”, giving x = [0, 0, 0, 0, 0, 1, 1, 0, 0, 0]
  - — Then process “followed”, giving x = [0, 0, 1, 0, 0, 1, 1, 0, 0, 0]
  - — After “by” and “radiotherapy”, have x = [0, 0, 1, 1, 0, 1, 1, 0, 1, 0]

The Classic Workflow

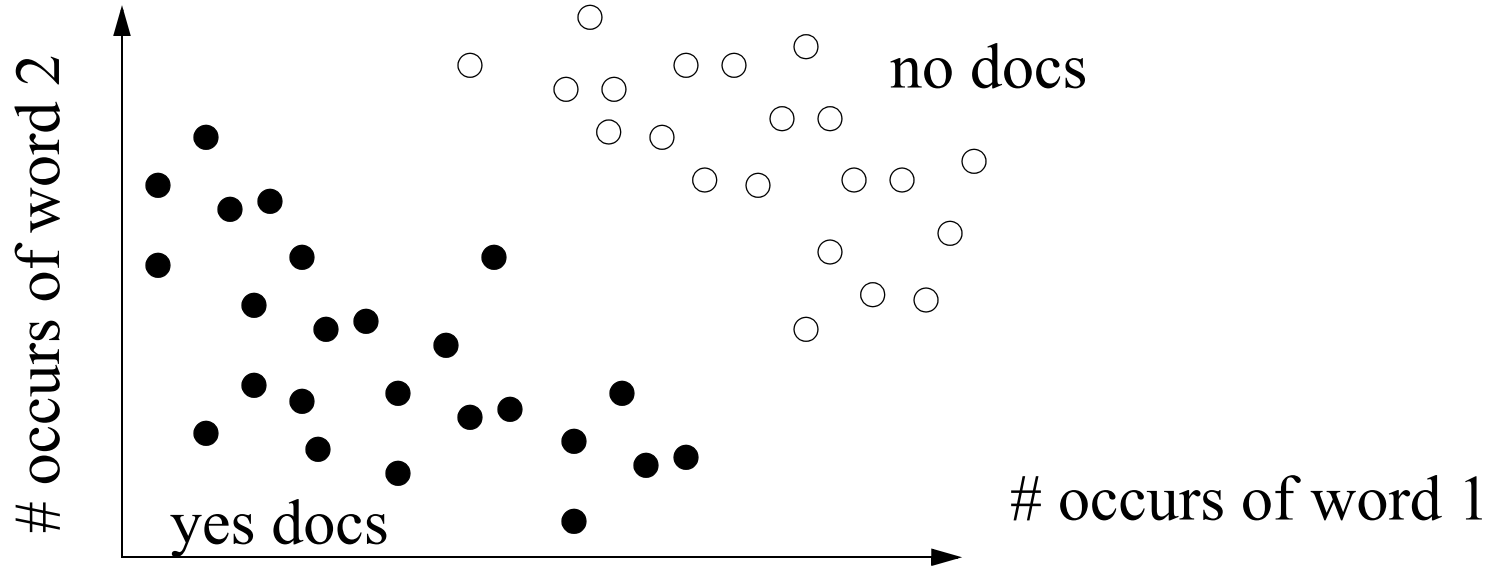
- x = [0, 0, 1, 1, 0, 1, 1, 0, 1, 0] is then treated as a *feature vector*
- Now want to figure out how to classify (label) text documents...
  - — For example: "+1: this patient had breast cancer"
  - — "-1: this patient didn't have breast cancer"
- How?

The Classic Workflow

- Assume we have a set of labeled data
  - — For example, check to see if the patient was billed for BC in next 6 months
- This gives a set of (*x*, label) pairs
- Feed these as *training data* into your classifier-of-choice
- Then, when have a new record to classify
  - — Convert it into a bag-of-words
  - — And feed it into the classifier for labeling

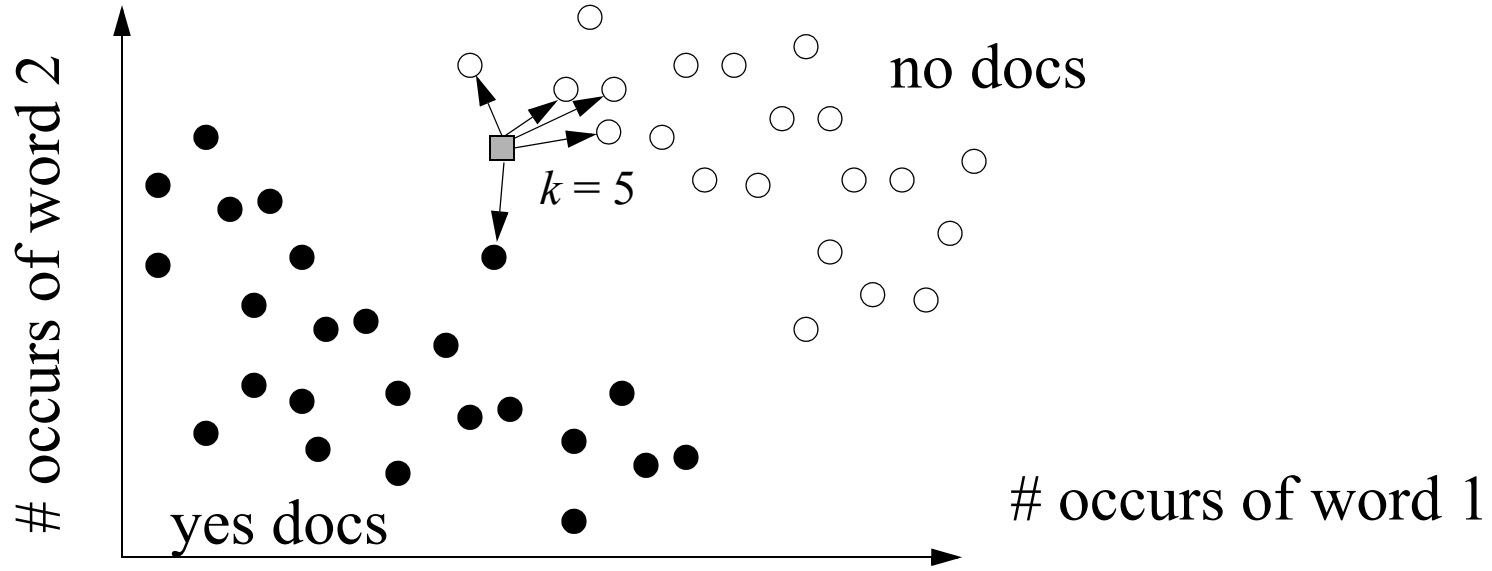
A Common Classifier is "KNN"

- This is the first one that you'll be implementing on Spark
- Idea: place docs in multi-dim space



A Common Classifier is "KNN"

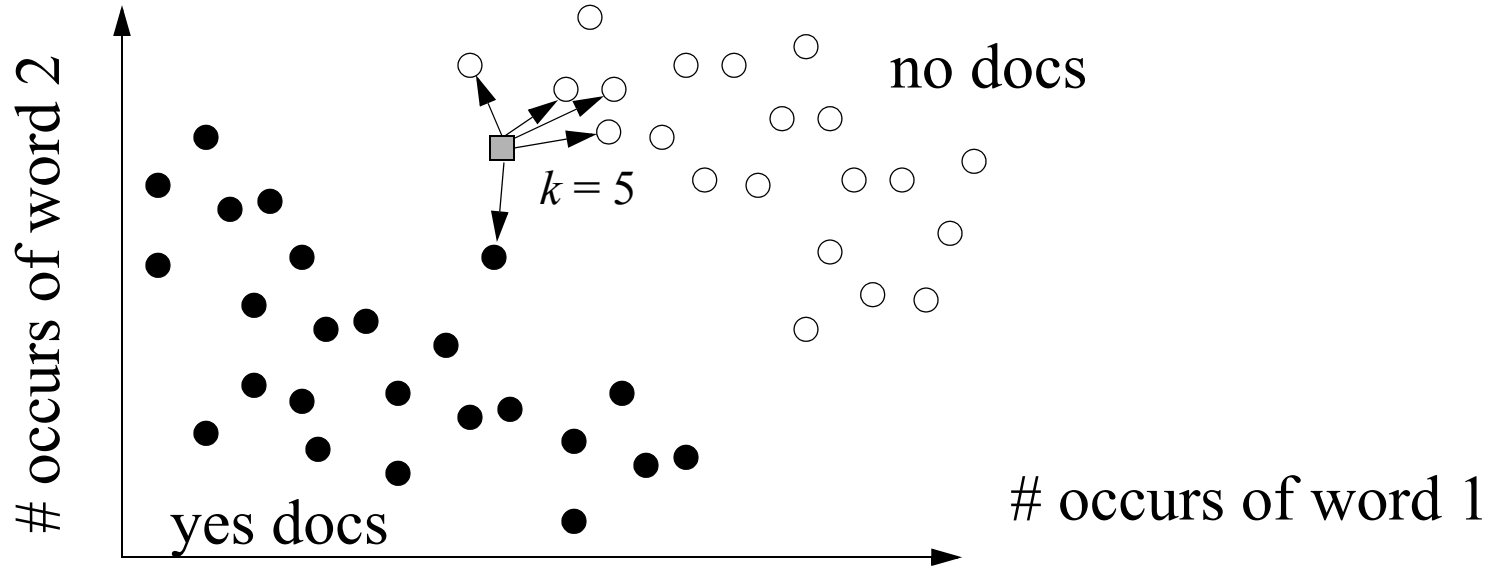
- This is the first one that you'll be implementing on Spark
- Idea: place docs in multi-dim space



- To classify a new doc...
  - — You place it in the space, and find its *k* nearest neighbors (hence "KNN")

A Common Classifier is "KNN"

- This is the first one that you'll be implementing on Spark
- Idea: place docs in multi-dim space



- To classify a new doc...
  - — You place it in the space, and find its *k* nearest neighbors (hence "KNN")
  - — And you give it the most common label of its *k* nearest neighbors

A Common Classifier is "KNN"

- This is the first one that you'll be implementing on Spark
- Idea: place docs in multi-dim space
- To classify a new doc...
  - — You place it in the space, and find its *k* nearest neighbors (hence "KNN")
  - — And you give it the most common label of its *k* nearest neighbors
- How to define distance?
  - — Often use *ED* (note: small values mean "close"):

$$ED(x_1, x_2) = \sum_{i=1}^{d} (x_1 - x_2)^2$$

— We will use **cosine similarity** (note: big values mean “close”):

$$Cos(x_1, x_2) = \sum_{i=1}^{d} x_1 \times x_2$$

Just About Ready for Activity Two

- But first some new RDD transformations we'll be using
  - `join (),groupByKey (),aggregateByKey ()`

join ()

- Given two data sets `rddOne`, `rddTwo` of (*Key, Value*) pairs
- `rddOne.join (rddTwo)` returns (*K*, (*V1, V2*)) pairs
- constructed from all (*K1, V1*) from `rddOne`, (*K2, V2*) from `rddTwo`, where *K1* == *K2*
- Can blow up RDD size if join is many-to-many
- Requires expensive shuffle!

groupByKey ()

- Data must be (*Key, Value*) pairs
- Shuffle so that all (*K, V*) pairs with same *K* on same machine
- Organize into (*K*, (V_1, V_2, ..., V_n)) pairs
- Store each list as a `ResultIterable` for future processing
- Like `reduceByKey ()` but without the reduce

aggregateByKey ()

- Like `reduceByKey ()`
- Data must be (*Key, Value*) pairs
- Organize into (K, (V_1, V_2, ..., V_n)) pairs
- Then aggregate the list, like `reduceByKey ()`
- With `reduceByKey ()` aggregate directly, can be restrictive...
  - — what if values are cities, and we want the list of unique cities?
- `aggregateByKey ()` takes three args
  - — The "zero" to init the aggregation
  - — Lambda that takes `x1`, `x2` and aggs them, where `x1` already aggregated, `x2` not
  - — Lambda that takes `x1`, `x2` and aggs them, where both already aggregated

Activity Two

- KNN over bag-of-words vectors
- See `cmj4.web.rice.edu/DSDay2/kNNBasic.html`

Some Other Tricks Are Used Mining Text

- Rather than using x...
- Use vector y, where $y[w]$ is the "TF-IDF" of the word in the doc
  - $TF(x, w) = \frac{x[w]}{\sum_{w'} x[w']}$; this is the "term frequency"
  - $IDF(w) = \log\left(\frac{\text{size of corpus}}{\sum_{x \text{ in corpus}} 1 \text{ if } (x[w] \geq 1), 0 \text{ otherwise}}\right)$, the "inverse doc freq"
  - Then $y[w] = TF(x, w) \times IDF(w)$
- Often helps cause it weights rare words more highly
- In our next activity, we use TF-IDF in our KNN classifier

Some Other Tricks Are Used Mining Text

- Remove *stop words* since they convey little meaning
  - — "the" "which" "at" "which" "on"...
- Perform *stemming* of words
  - — "running", "run", "runner", "runs" are all reduced to "run"
- Use only the top *k* most frequent words
  - — Removes obscure terms, mis-spellings, etc.
- Use *n-gram*s, not just individual words
  - — Given "This was followed by radiotherapy", 2-grams are: "This was", "was followed", "followed by", "by radiotherapy"
  - — Helps to address bag-of-words' total lack of contextual knowledge

Activity Three

- KNN over TF-IDF bag-of-words vectors
- See `cmj4.web.rice.edu/DSDay2/kNNTFIDF.html`

Linear Regression

- KNN often works well, but it's expensive
- Requires complete scan of data
- Alternative: LR

Linear Regression

- KNN often works well, but it's expensive
- Requires complete scan of data
- Alternative: LR
- In LR, compute a vector of regression weights *r*
- Then to classify TF-IDF vector *x*, compute:

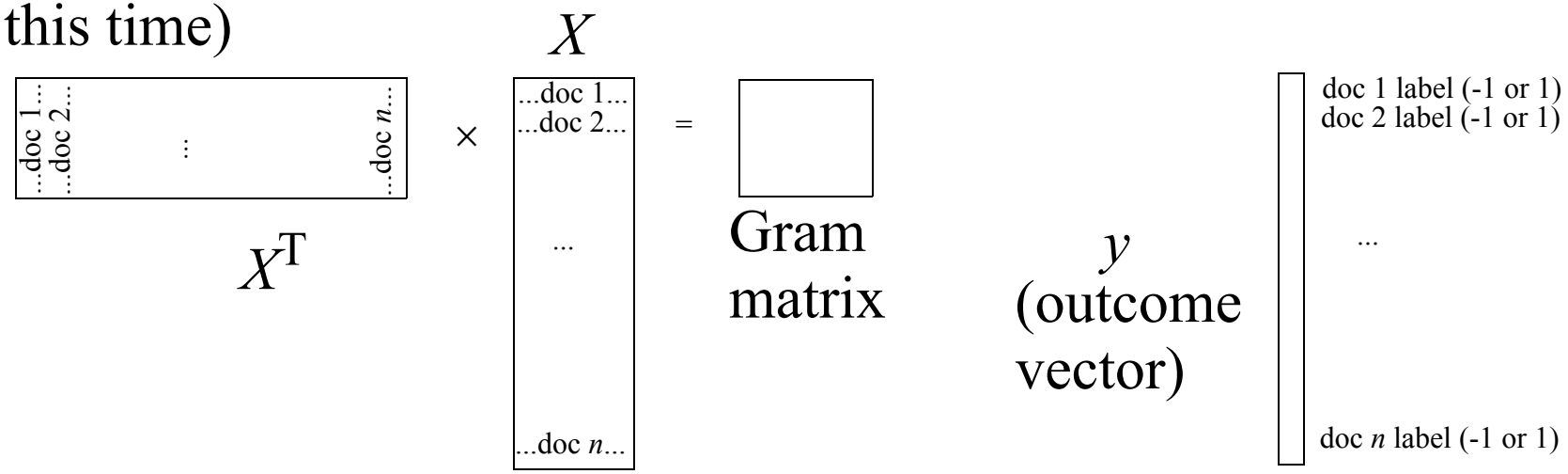
$$\sum_{w=1}^{d} x[w] \times r[w]$$

- If greater than 0, say "yes", otherwise "no"
- Drawback: simple regression only allows two classes

— KNN trivially extends to many classes

How To Compute?

- Let X be the data matrix, y the outcome vector
  - — Each row in X is a doc, column TF-IDF value for a word
- The Gram matrix is $X^T X$... we did this yesterday! (but no trimming this time)



- r is computed as (Gram matrix)$^{-1} X^T y$

How To Compute on Spark?

- Gram matrix
  - — We know matrix multiply fastest, but not feasible here
  - — Why? X is distributed in an RDD
  - — So use `map ()` that computes outer product
  - — And then use `aggregate ()` to sum them, collect locally, invert locally
  - — `aggregate ()` just like `aggregateByKey ()`, but no grouping by key
- Then, use a `map()` to multiply (Gram mat)$^{-1}$ by every data record by to get (Gram mat)$^{-1}X^{T}$ stored as one vec per doc
- Finally, multiply every result rec by corresponding outcome/class label and sum using `aggregate ()` to get (Gram matrix)$^{-1}X^{T}y$
- That's it! Well, almost...

Gram Matrix Too Expensive

- Have to sum 20,000 different 20,000 by 20,000 matrices
- Not gonna happen fast enough
- So map each 20,000-dimensional vector down to 1,000 dims
  - — Now we sum 20,000 different 1,000 by 1,000 matrices
  - — Much more reasonable!

Gram Matrix Too Expensive

- How to map?
  - — Could use something like PCA, which is classic
  - — But too expensive!
- We just use a random mapping...
  - — In practice, as good as PCA unless you map to very low dimensions
- Fill a matrix M of 1,000 columns and 20,000 rows with samples from a Normal (0, 1) distribution
- Then, before we compute $(\text{Gram matrix})^{-1} X^{T} y$...
  - — Just multiply each data vector with M
- 20,000-dimensional problem becomes 1,000 dimensional!

Activity Four

- LR over TF-IDF bag-of-words vectors
- Tries to classify religion vs. not
- See `cmj4.web.rice.edu/DSDay2/LinReg.html`

That's It!

- Questions?