

# ***DATA ANALYTICS PROGRAMMING ON SPARK: PYTHON IN THE CLOUD***

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①

## 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)

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## 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

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## 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

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## 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

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## 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?

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## 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.

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## 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>

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## 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

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## 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

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## 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

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## 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

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## 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

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## 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

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## 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

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## 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

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## MapReduce Had a Huge Impact

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

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## 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

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## 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

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## 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

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## 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

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## Why Popular? (5)

- Software is free!

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## 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...

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## 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);
        TextOutputFormat.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...

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## 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

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## And API Too Restrictive

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

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## 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

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## 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...
```

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## 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...

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## 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 ???
```

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## 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
```

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## 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)
```

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## 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

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## 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

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## 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<sub>1</sub>, V<sub>2</sub>, ..., V<sub>n</sub>)*) pairs
- Use the lambda to “reduce” the list to a single value

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## 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)  
  return aggCounts.top (200, key=lambda 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

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## 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`

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## 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

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## 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...

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## 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`

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## 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...

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## 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  $x[i]$

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## 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]
  - First process “this”, giving  $x = [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]$

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- $x$  is [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  $x = [0, 0, 0, 0, 0, 1, 1, 0, 0, 0]$

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## 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]

- 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  $x = [0, 0, 1, 0, 0, 1, 1, 0, 0, 0]$

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## 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]

- 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  $x = [0, 0, 1, 1, 0, 1, 1, 0, 1, 0]$

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## 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?

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## The Classic Workflow

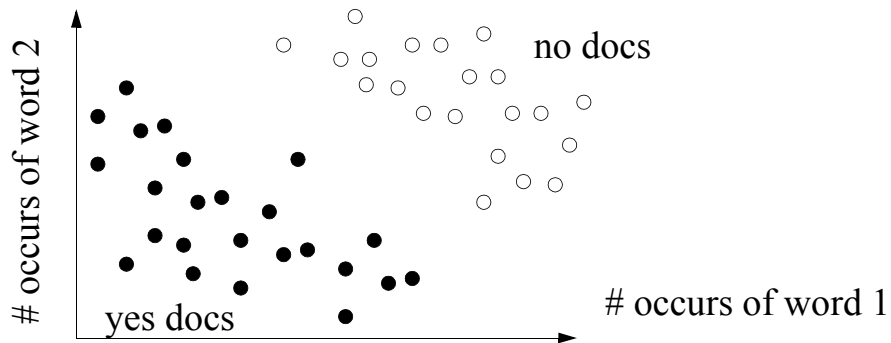
- Assume we have a set of labeled data
  - For example, check to see if the patient was billed for BC in next 6 months
- This gives a set of  $(x, \text{label})$  pairs
- Feed these as *training data* into your classifier-of-choice
- Then, when have a new record to classify
  - Convert it into a bag-of-words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

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## A Common Classifier is “KNN”

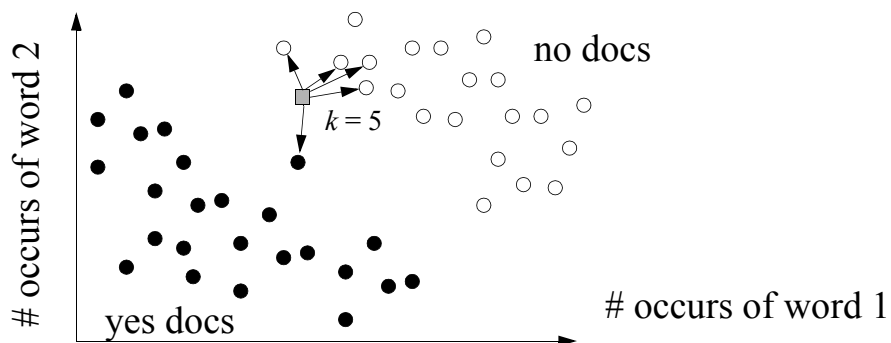
- This is the first one that you’ll be implementing on Spark
- Idea: place docs in multi-dim space



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## A Common Classifier is “KNN”

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

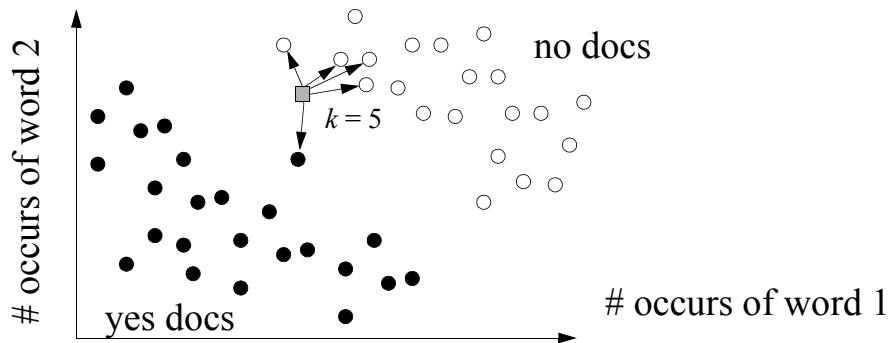


- To classify a new doc...
  - You place it in the space, and find its  $k$  nearest neighbors (hence “KNN”)

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## 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

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## 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”):

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

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

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

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## Just About Ready for Activity Two

- But first some new RDD transformations we’ll be using

— `join ()`, `groupByKey ()`, `aggregateByKey ()`

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## 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!

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## groupByKey ()

- Data must be *(Key, Value)* pairs
- Shuffle so that all *(K, V)* pairs with same *K* on same machine
- Organize into *(K, (V<sub>1</sub>, V<sub>2</sub>, ..., V<sub>n</sub>))* pairs
- Store each list as a `ResultIterable` for future processing
- Like `reduceByKey ()` but without the reduce

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## aggregateByKey ()

- Like `reduceByKey ()`
- Data must be *(Key, Value)* pairs
- Organize into  $(K, (V_1, V_2, \dots, V_n))$  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  $x_1, x_2$  and aggs them, where  $x_1$  already aggregated,  $x_2$  not
  - Lambda that takes  $x_1, x_2$  and aggs them, where both already aggregated

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## Activity Two

- KNN over bag-of-words vectors
- See [cmj4.web.rice.edu/DSDay2/kNNBasic.html](http://cmj4.web.rice.edu/DSDay2/kNNBasic.html)

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## 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

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## 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-grams*, 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

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## Activity Three

- KNN over TF-IDF bag-of-words vectors
- See [cmj4.web.rice.edu/DSDay2/kNNTFIDF.html](http://cmj4.web.rice.edu/DSDay2/kNNTFIDF.html)

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## Linear Regression

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

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# 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

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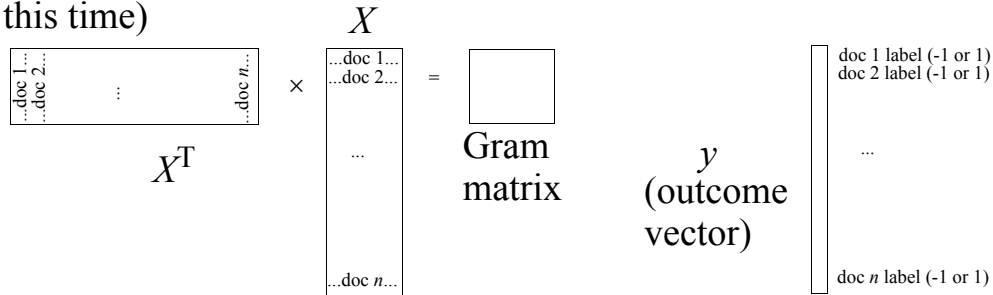
— KNN trivially extends to many classes

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## 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  $(\text{Gram matrix})^{-1} X^T y$

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## 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  $(\text{Gram mat})^{-1}$  by every data record by to get  $(\text{Gram mat})^{-1} X^T$  stored as one vec per doc
- Finally, multiply every result rec by corresponding outcome/class label and sum using `aggregate ()` to get  $(\text{Gram matrix})^{-1} X^T y$
- That's it! Well, almost...

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## 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!

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## 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 (Gram matrix) $^{-1}X^T y...$ 
  - Just multiply each data vector with  $M$
- 20,000-dimensional problem becomes 1,000 dimensional!

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## Activity Four

- LR over TF-IDF bag-of-words vectors
- Tries to classify religion vs. not
- See [cmj4.web.rice.edu/DSDay2/LinReg.html](http://cmj4.web.rice.edu/DSDay2/LinReg.html)

## That's It!

- Questions?