

Big Data and Functional Programming

Jim Baker

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Overview

Big Data and
Functional
Programming

Jim Baker

- What is “Big Data”?

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- Why is PoPL - a theory course - one of the most pragmatic courses in the CS curriculum?

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- Explore Big Data and FP, especially by thinking about functions and how they combine

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- Specific approaches like MapReduce and the Lambda architecture

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- Why is PoPL - a theory course - one of the most pragmatic courses in the CS curriculum?
- A: functional programming
- Explore Big Data and FP, especially by thinking about functions and how they combine
- Specific approaches like MapReduce and the Lambda architecture
- Embracing failure and supporting scale free computation
- FP as the foundation of such companies as GOOG (\$357B market cap), FB (\$143B), TWTR (\$24B)

About me

Big Data and
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- Racker working on auto scaling, scalable real time architectures, and OpenStack

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- Formerly, part of original developer team of Ubuntu Juju - lots of experience with ZooKeeper

Internship available

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- Still not too late!

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- Work on Scala and Big Data problems in Austin this summer

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- Talk to me during lunch if you're interested

Lunch plans?

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- Lunch today on the *practice of computer science*

Lunch plans?

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- Lunch today on the *practice of computer science*
 - Meet at WHEN in C4C lobby

Lunch plans?

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- Lunch today on the *practice of computer science*
 - Meet at WHEN in C4C lobby
 - WHEN + 0:05 - sit together on the west side of C4C

Lunch plans?

- Lunch today on the *practice of computer science*
 - Meet at WHEN in C4C lobby
 - WHEN + 0:05 - sit together on the west side of C4C
- So WHEN should we meet?

What is “Big Data” anyway?

- Many definitions in common play

What is “Big Data” anyway?

- Many definitions in common play
- Useful summary paper on the these definitions -
“Undefined By Data: A Survey of Big Data Definitions”,
Jonathan Stuart Ward and Adam Barker,
<http://arxiv.org/pdf/1309.5821v1.pdf>

3 Vs of Big Data:

- Volume
 - Velocity
 - Variety
-
- Could equally be true of previous efforts in data warehousing, business intelligence

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- Could equally be true of previous efforts in data warehousing, business intelligence
 - Still valid for the business case
 - A bit of a leap to a CS definition

Big data combines

- Relational database
- New types of data sources - cited as unstructured, but generally have some structure
- Need new tools to help with this combination

Plays with Oracle's preeminence as a proprietary RDBMS vendor

- Focus on volume
- “Generating a median of 300 terabytes (TB) of data weekly”

Intel helpfully sells hardware to process this data

Big data is the term increasingly used to describe the process of applying serious computing power - the latest in machine learning and artificial intelligence - to seriously massive and often highly complex sets of information.

Ward & Barker

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Big data is a term describing the storage and analysis of large and or complex data sets using a series of techniques including, but not limited to: NoSQL, MapReduce and machine learning.

Still puzzled?

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- Ward & Barker capture some key ideas

Still puzzled?

- Ward & Barker capture some key ideas
- Still unsatisfying

Still puzzled?

- Ward & Barker capture some key ideas
- Still unsatisfying
- Another approach: family of related computational models that support *scale free computing* on data

Scale free computing

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- Inherently functional idea, goes back to the original idea of MapReduce

Scale free computing

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- Intuitive idea: I can run the same program on my laptop as I do on 1000 node compute cluster

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- Intuitive idea: I can run the same program on my laptop as I do on 1000 node compute cluster
- Expect to see (near) linear scale-up in some useful way - size of problem, response time, or both
- Every day evidence of scale free at work - think Google Search

MapReduce

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What is this MapReduce idea?

- Map - or sometimes `flatMap`

MapReduce

What is this MapReduce idea?

- Map - or sometimes `flatMap`
- Reduce - might also call this `fold`

Map

Related to such ideas as

- Scatter in scatter/gather
- Divide & conquer
- Problem partition

Data is consistently mapped to the same node in a given cluster

Reduce

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Word count problem

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- What is the word count problem?

Word count problem

- What is the word count problem?
- Vs how we usually say it - “wordcount”

Scalding

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- High-level domain specific language (DSL) in Scala for writing map-reduce jobs

Scalding

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Scalding

- High-level domain specific language (DSL) in Scala for writing map-reduce jobs
- Runs on top of Cascalog
- Expect to see more of Scalding in this class
- Or perhaps your future work!

Word count in Scalding

```
import com.twitter.scalding._

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

Word count in Summingbird

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```
def wordCount(  
  source: Iterable[String],  
  store: MutableMap[String, Long]) =  
source.flatMap {  
  sentence =>  
    toWords(sentence).map(_ -> 1L)  
  }.foreach {  
    case (k, v) =>  
      store.update(k, store.get(k) + v) }  
}
```

Why is it classic?

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- Actually useful

Why is it classic?

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- N grams

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- Machine translation of natural language

Why is it classic?

- Actually useful
- N grams
- Machine translation of natural language
- Historical usage of words and phrases

Ranking followers with PageRank

```
val sc = new SparkContext(...)
val users = sc
    .textFile("hdfs://user_attributes.tsv")
    .map(line => line.split)
    .map( parts => (parts.head, parts.tail))
val followerGraph = Graph.textFile(sc, ...)
val graph = followerGraph.outerJoinVertices(users){
    case (uid, deg, Some(attrList)) => attrList
    case (uid, deg, None) => Array.empty[String] }
val pagerankGraph = Analytics.pagerank(graph)
val userInfoWithPageRank =
    graph.outerJoinVertices(pagerankGraph.vertices) {
        case (uid, attrList, Some(pr)) => (pr, attrList)
        case (uid, attrList, None) => (pr, attrList)
    }
println(userInfoWithPageRank.top(5))
```

Why functional programming?

- Scala is not just a convenient language to write code

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- Could also write such programs in Python or your favorite language
- But something deeper - use how functions combine to support scale free
- Can also rewrite our functions in certain cases - query optimization

Function properties

Some possible properties:

- The object f we call a function is in fact a function!

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- Idempotence

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- Any other properties?
- Idempotence
- Referential transparency

Referential transparency

- Captures an idea that a given function f is a black box

Referential transparency

- Captures an idea that a given function f is a black box
- But one that's not capturing some state

Referential transparency

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Definition: e is *referentially transparent* if we can replace e with its v in **all usages**

Associativity

$$f(f(x, y), z) = f(x, f(y, z))$$

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- \Rightarrow certainly anything with side effects!

Monoids

- Totality (closed over an operation), associative for operation (“plus”), identity (“zero”)

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- What does this look like?

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- What does this look like?
- \Rightarrow folds!
- Remember the definition of `foldLeft`

Twitter's Algebird

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- Blog post announcing Algebird

Twitter's Algebird

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- Blog post announcing Algebird
- Algebird source

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- Foundation of Summingbird, Scalding

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- Most monads we have seen, we are interested in sequencing composable operations, taking advantage of associativity
- Back to this later! Let's explore one interesting detail. . .

At scale, sequencing is expensive!

- Local sequencing is fairly cheap

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At scale, sequencing is expensive!

- Local sequencing is fairly cheap
- Maintaining order requires communication
- Communication proceeds no faster than the speed of light
- Unless we have ansibles ;)

Question

How far does light in a vacuum approximately travel in one **nanosecond**?

- A - 1 kilometer
- B - 1 meter
- C - 1 foot
- D - 1 cm
- E - 1 mm

An interesting unit: light-foot

- Useful unit: a *light-foot* \approx 1.0167 nanoseconds

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 - No specifics about velocity factor on USB cables I could find
 - But gives some insight into what a nanosecond really is

Data center design

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- It's all about the locality, to minimize communication hops and distance

Data center design

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- It's all about the locality, to minimize communication hops and distance
- Same core, same chip, same board, same unit, same rack, same aisle, same data center. . .

Data center design

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- It's all about the locality, to minimize communication hops and distance
- Same core, same chip, same board, same unit, same rack, same aisle, same data center. . .
- Design focused on communication latency as much as it's storage, computation

Data centers, illustrated

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- Google streetview in the datacenter

Multidata center coordination

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- Big problem because of communication bottlenecks

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- Big problem because of communication bottlenecks
- Bigger problem because of data center connection reliability

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- These issues are **related!**

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- Big problem because of communication bottlenecks
- Bigger problem because of data center connection reliability
- These issues are **related!**
- Datacenters are now distributed around the world
- Observations of ping time between cities by one network provider
- What could possibly go wrong?!!

Special relativity and programming

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- Good intro/reminder of special relativity

Special relativity and programming

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- Einstein and clocks in Bern, Switzerland in 1905

Special relativity and programming

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 - Established principle since Galileo of the relativity of frames of reference

Special relativity and programming

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- Einstein and clocks in Bern, Switzerland in 1905
- Einstein was pondering the implication of two things:
 - Established principle since Galileo of the relativity of frames of reference
 - The speed of light (c) is constant, as established by the then recent Michelson-Morley experiment

Einstein's analysis

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- Einstein showed the relativity of simultaneity

Einstein's analysis

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- We cannot make statements about the whether two spatially-separated events are truly simultaneous

Einstein's analysis

- Einstein showed the relativity of simultaneity
- We cannot make statements about the whether two spatially-separated events are truly simultaneous
- We can only say something about causality - that A depends on B , which depends on C

Causality and coordination

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- Agreement protocols depend on exchanging messages

Causality and coordination

- Agreement protocols depend on exchanging messages
- Could explore this in a future CS course - Paxos and related coordination protocols

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- Support such ideas as *leader election*, *distributed transactions*, and *distributed counters*

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Causality and coordination

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- Could explore this in a future CS course - Paxos and related coordination protocols
- Support such ideas as *leader election*, *distributed transactions*, and *distributed counters*
- Can we avoid coordination costs?
- \Rightarrow yes! (at least sometimes)

Commutativity

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Eventual consistency

- Operations can be re-ordered

Eventual consistency

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- Example: Amazon shopping cart

Eventual consistency

- Operations can be re-ordered
- Example: Amazon shopping cart
- Databases includign Cassandra, Riak, Dynamo

Shopping cart, with commutative operations

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...

Restoring strong consistency across data centers

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- Start with high precision time

Restoring strong consistency across data centers

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- Start with high precision time
- Local atomic clocks for *precision*, GPS for *accuracy*

Restoring strong consistency across data centers

- Start with high precision time
- Local atomic clocks for *precision*, GPS for *accuracy*
- Network Time Protocol → Precision Time Protocol for submicrosecond accuracy

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Restoring strong consistency across data centers

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- Add time versioned databases

Restoring strong consistency across data centers

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- Google's Spanner database implements this idea

Restoring strong consistency across data centers

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- Google's Spanner database implements this idea
- Q: how does this avoid violating the relativity of simultaneity?