

Data-Intensive Distributed Computing

CS 431/631 451/651 (Winter 2019)

Part 1: MapReduce Algorithm Design (2/4) January 10, 2019

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These slides are available at http://roegiest.com/bigdata-2019w/



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Announcements

A0 finalized for all sections

CS 431/631 Only: If you want a challenge, you may elect to do all of the CS 451 assignments instead of the six CS 431 assignments. This is a one-way road. No switching back.

Agenda for Today

Why big data? Hadoop walkthrough

Why big data?



"big data stack"

Why big data? Science Business Society

Source: Wikipedia (Everest)

Science

Emergence of the 4th Paradigm Data-intensive e-Science





Observation of a new particle in the search for the Standard Model Higgs boson with the ATLAS detector at the LHC

The ATLAS Collaboration

(Submitted on 31 Jul 2012 (v1), last revised 31 Aug 2012 (this version, v2))

A search for the Standard Model Higgs boson in proton-proton collisions with the ATLAS detector at the LHC is presented. The datasets used correspond to integrated luminosities of approximately 4.8 fb^-1 collected at sqrt(s) = 7 TeV in 2011 and 5.8 fb^-1 at sqrt(s) = 8 TeV in 2012. Individual searches in the channels H->ZZ^(*)->IIII, H->gamma gamma and H->WW->e nu mu nu in the 8 TeV data are combined with previously published results of searches for H->ZZ^(*), WW^(*), bbbar and tau^+tau^- in the 7 TeV data and results from improved analyses of the H->ZZ^(*)->IIII and H->gamma gamma channels in the 7 TeV data. Clear evidence for the production of a neutral boson with a measured mass of 126.0 + /- 0.4(stat) + /- 0.4(sys) GeV is presented. This observation, which has a significance of 5.9 standard deviations, corresponding to a background fluctuation probability of 1.7×10^{-9} , is compatible with the production and decay of the Standard Model Higgs boson.

Comments:24 pages plus author list (38 pages total), 12 figures, 7 tables, revised author list, matches version to appear in
Physics Letters BSubjects:High Energy Physics - Experiment (hep-ex)Journal reference:Phys.Lett. B716 (2012) 1-29DOI:10.1016/j.physletb.2012.08.020Report number:CERN-PH-EP-2012-218Cite as:arXiv:1207.7214 [hep-ex]
(or arXiv:1207.7214v2 [hep-ex] for this version)

Submission history

From: Atlas Publications [view email] [v1] Tue, 31 Jul 2012 11:59:59 GMT (334kb) [v2] Fri, 31 Aug 2012 19:29:54 GMT (334kb)



Source: Wikipedia (DNA)



Subject genome



GATGCTTACTATGCGGGGCCCC CGGTCTAATGCTTACTATGC GCTTACTATGCGGGGCCCCTT AATGCTTACTATGCGGGGCCCCTT TAATGCTTACTATGC AATGCTTACTATGCGGGCCCCTT AATGCTTACTATGCGGGCCCCTT CGGTCTAGATGCTTACTATGC AATGCTTACTATGCGGGCCCCTT CGGTCTAATGCTTAGCTATGC ATGCTTACTATGCGGGCCCCTT

Reads

Human genome: 3 gbp A few billion short reads (~100 GB compressed data)

Sequencer



EPSON

Balance Inc.

855-105

3858-108

PEARLBAR

Business Intelligence

An organization should retain data that result from carrying out its mission and exploit those data to generate insights that benefit the organization, for example, market analysis, strategic planning, decision making, etc.



This is not a new idea!

In the 1990s, Wal-Mart found that customers tended to buy diapers and beer together. So they put them next to each other and increased sales of both.*

So what's changed?

More compute and storage Ability to gather behavioral data

* BTW, this is completely apocryphal. (But it makes a nice story.)

Virtuous Product Cycle



Google. Facebook. Twitter. Amazon. Uber.

data products

data science

net·flix·ing/v

1. The act of watching an entire season of a show in one sitting.

2. A totally valid excuse for avoiding social obligations.

"Sorry, I can't make it to the party tonight. I am *netflixing*."

Source: https://images.lookhuman.com/render/standard/8002245806006052/pillow14in-whi-z1-t-netflixing.png



Source: https://www.reddit.com/r/teslamotors/comments/6gsc6v/i_think_the_neural_net_mining_is_just_starting/ (June 2017)

Translate

Turn off instant translation



Google Translate for Business: Translator Toolkit Website Translator



No data like more data!



(Banko and Brill, ACL 2001) (Brants et al., EMNLP 2007)

Society Humans as social sensors Computational social science

Predicting X with Twitter



(Paul and Dredze, ICWSM 2011; Bond et al., Nature 2011)



Blacktivist

Black Panthers were dismantled by US government because they were black men and women standing up for justice and equality.

never forget that the Black Panthers, group formed to protect black people from the KKK, was dismantled by us govt but the KKK exists today



205 Comments 29K Shares



Suggested Page

Defend the 2nd

Sponsored

Source: https://www.theverge.com/2017/11/1/16593346/house-russia-facebook-ads

Facebook Enabled Advertisers to Reach 'Jew Haters'

After being contacted by ProPublica, Facebook removed several anti-Semitic ad categories and promised to improve monitoring.

by Julia Angwin, Madeleine Varner and Ariana Tobin, Sept. 14, 2017, 4 p.m. EDT



MACHINE BIAS Investigating Algorithmic Injustice

ruin the world."

Want to market Nazi memorabilia, or recruit marchers for a far-right rally? Facebook's self-service ad-buying platform had the right audience for you.

Until this week, when we asked Facebook about it, the world's largest social network enabled advertisers to direct their pitches to the news feeds of almost 2,300 people who expressed interest in the topics of "Jew hater," "How to burn jews," or, "History of 'why jews

To test if these ad categories were real, we paid \$30 to target those groups with three "promoted posts" — in which a ProPublica article or post was displayed in their news feeds. Facebook approved all three ads within 15 minutes.



C The photo you want to upload does not meet our criteria because:

Subject eyes are closed

Please refer to the technical requirements. You have 9 attempts left.

Check the photo requirements.

Read more about <u>common photo problems and</u> how to resolve them.

After your tenth attempt you will need to start again and re-enter the CAPTCHA security check.

Reference number: 20161206-81

Filename: Untitled.jpg

If you wish to <u>contact us</u> about the photo, you must provide us with the reference number given above.



The Perils of Big Data

The end of privacy Who owns your data and can the government access it?

> The echo chamber Are you seeing only what you want to see?

The racist algorithm Algorithms aren't racist, people are?

We desperately need "data ethics" to go with big data!





Tackling Big Data



* Important detail: reducers process keys in sorted order

Physical View



Adapted from (Dean and Ghemawat, OSDI 2004)

The datacenter *is* the computer!

mess

Source: Google

The datacenter *is* the computer!

It's all about the right level of abstraction Moving beyond the von Neumann architecture What's the "instruction set" of the datacenter computer?

Hide system-level details from the developers No more race conditions, lock contention, etc. No need to explicitly worry about reliability, fault tolerance, etc.

Separating the *what* from the *how* Developer specifies the computation that needs to be performed Execution framework ("runtime") handles actual execution

The datacenter *is* the computer! "Big ideas"

Scale "out", not "up" * Limits of SMP and large shared-memory machines

Assume that components will break Engineer software around hardware failures

Move processing to the data* Cluster have limited bandwidth, code is a lot smaller

Process data sequentially, avoid random access Seeks are expensive, disk throughput is good

Seek vs. Scans

Consider a 1 TB database with 100 byte records We want to update 1 percent of the records

> Scenario 1: Mutate each record Each update takes ~30 ms (seek, read, write) 10⁸ updates = ~35 days

Scenario 2: Rewrite all records

Assume 100 MB/s throughput Time = 5.6 hours(!)

Lesson? Random access is expensive!

Source: Ted Dunning, on Hadoop mailing list



So you want to drive the elephant!

Source: Wikipedia (Mahout)

So you want to drive the elephant! (Aside, what about Spark?)

EXPRESSWAY

()

A tale of two packages...

org.apache.hadoop.mapreduce org.apache.hadoop.mapred

MapReduce API*

Mapper<K_{in},V_{in},K_{out},V_{out}>

void setup(Mapper.Context context) Called once at the start of the task void map(K_{in} key, V_{in} value, Mapper.Context context) Called once for each key/value pair in the input split void cleanup(Mapper.Context context) Called once at the end of the task Reducer<K_{in},V_{in},K_{out},V_{out}>/Combiner<K_{in},V_{in},K_{out},V_{out}> void setup(Reducer.Context context) Called once at the start of the task void reduce(K_{in} key, Iterable<V_{in}> values, Reducer.Context context)

Called once for each key

void cleanup(Reducer.Context context) Called once at the end of the task

*Note that there are two versions of the API!

MapReduce API*

Partitioner<K, V>

int getPartition(K key, V value, int numPartitions) Returns the partition number given total number of partitions

Job

Represents a packaged Hadoop job for submission to cluster Need to specify input and output paths Need to specify input and output formats Need to specify mapper, reducer, combiner, partitioner classes Need to specify intermediate/final key/value classes Need to specify number of reducers (but not mappers, why?) Don't depend of defaults!

*Note that there are two versions of the API!

Data Types in Hadoop: Keys and Values

Writable **WritableComprable** IntWritable LongWritable Text ...

Defines a de/serialization protocol. Every data type in Hadoop is a Writable.

Defines a sort order. All keys must be of this type (but not values).

Concrete classes for different data types. Note that these are container objects.

SequenceFile

Binary-encoded sequence of key/value pairs.

"Hello World" MapReduce: Word Count

```
def map(key: Long, value: String) = {
  for (word <- tokenize(value)) {
    emit(word, 1)
  }
}
def reduce(key: String, values: Iterable[Int]) = {
  for (value <- values) {
    sum += value
  }
  emit(key, sum)
}</pre>
```

Word Count Mapper

private static final class MyMapper
 extends Mapper<LongWritable, Text, Text, IntWritable> {

```
private final static IntWritable ONE = new IntWritable(1);
private final static Text WORD = new Text();
```

```
@Override
public void map(LongWritable key, Text value, Context context)
  throws IOException, InterruptedException {
   for (String word : Tokenizer.tokenize(value.toString())) {
     WORD.set(word);
     context.write(WORD, ONE);
   }
}
```

Word Count Reducer

private static final class MyReducer
 extends Reducer<Text, IntWritable, Text, IntWritable> {

private final static IntWritable SUM = new IntWritable();

```
@Override
public void reduce(Text key, Iterable<IntWritable> values,
    Context context) throws IOException, InterruptedException {
    Iterator<IntWritable> iter = values.iterator();
    int sum = 0;
    while (iter.hasNext()) {
        sum += iter.next().get();
    }
    SUM.set(sum);
    context.write(key, SUM);
}
```

Three Gotchas

Avoid object creation

Execution framework reuses value object in reducer

Passing parameters via class statics doesn't work!

Getting Data to Mappers and Reducers

Configuration parameters Pass in via Job configuration object

"Side data"

DistributedCache

Mappers/Reducers can read from HDFS in setup method

Complex Data Types in Hadoop How do you implement complex data types?

The easiest way:

Encode it as Text, e.g., (a, b) = "a:b" Use regular expressions to parse and extract data Works, but janky

The hard way:

Define a custom implementation of Writable(Comprable) Must implement: readFields, write, (compareTo) Computationally efficient, but slow for rapid prototyping Implement WritableComparator hook for performance

Somewhere in the middle: Bespin (via lin.tl) offers various building blocks

Anatomy of a Job

Hadoop MapReduce program = Hadoop job Jobs are divided into map and reduce tasks An instance of a running task is called a task attempt Each task occupies a slot on the tasktracker Multiple jobs can be composed into a workflow

Job submission:

Client (i.e., driver program) creates a job, configures it, and submits it to jobtracker

That's it! The Hadoop cluster takes over...



Anatomy of a Job

Behind the scenes:

Input splits are computed (on client end) Job data (jar, configuration XML) are sent to jobtracker Jobtracker puts job data in shared location, enqueues tasks Tasktrackers poll for tasks Off to the races...





Where's the data actually coming from?





Input and Output

InputFormat

TextInputFormat KeyValueTextInputFormat SequenceFileInputFormat

OutputFormat

. . .

TextOutputFormat SequenceFileOutputFormat

...

Spark also uses these abstractions for reading and writing data!

Hadoop Workflow



You



Submit node (datasci)



Hadoop Cluster

Getting data in? Writing code? Getting data out?

Where's the actual data stored?

Debugging Hadoop

First, take a deep breath Start small, start locally Build incrementally



Code Execution Environments

Different ways to run code: Local (standalone) mode Pseudo-distributed mode Fully-distributed mode

Learn what's good for what

Hadoop Debugging Strategies

Good ol' System.out.println Learn to use the webapp to access logs Logging preferred over System.out.println Be careful how much you log!

Fail on success

Throw RuntimeExceptions and capture state

Use Hadoop as the "glue"

Implement core functionality outside mappers and reducers Independently test (e.g., unit testing) Compose (tested) components in mappers and reducers

Questions?

Source: Wikipedia (Japanese rock garden).