CSE 4/587
Data Intensive Computing

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Introduction to MapReduce
Additional Reference for MapReduce


An online version of this text is also available through UB Libraries since UB subscribes to Morgan and Claypool Publishers.

Online version available at: http://lintool.github.com/MapReduceAlgorithms/index.html
Recap

- Last week we covered the Hadoop File System (HDFS)
  - Large scale distributed storage for huge files of data
  - Fault tolerance allows for reliability at scale
  - Provides the underlying backbone for a number of different technologies
How Big is Big Data?

- Man on the moon with 4K RAM, 32KB HDD (1969); my laptop has 16GB RAM (2017)
- Google collects 270PB data in a month (2007), 20PB a day (2008), 200PB a day estimated (2020)
- 2010 census data is a huge gold mine of information
- Data mining huge amounts of data collected in a wide range of domains
  - Astronomy, Healthcare, Finance, etc.
- Data is an important asset to any organization
- National Science Foundation refers to it as “data-intensive computing” and industry calls it “big-data” and “cloud computing”
Introduction (Ch 1. Lin and Dyer)

- Text Processing at large scales
  - Simple word count, cross reference, n-grams, etc
- A simpler technique on more data can beat a more sophisticated technique on less data.
- Google researchers call this "Unreasonable effectiveness of data" [1]

MapReduce

- MapReduce is a programming model and an execution framework
  - Developed by Google for operating on its large amounts of data
  - Open Source implementation in Hadoop
- Computation specified in terms of map and reduce functions
- Underlying runtime system (RTS) automatically parallelizes and coordinates the computation across a cluster of machines
  - Also handles machine failures, communication, and performance issues
- APIs originally in Java, now also supports Python, Ruby, C++, etc…
Big Ideas

- **Scale-out not scale-up**: Use a large number of commodity servers, as opposed to smaller number of high-end specialized servers
  - Part of this comes down to economies of scale and warehouse scale computing — what costs are associated with running such a warehouse?
  - High-end SMP servers will always outperform a network of commodity servers, but once data gets big, network communication becomes unavoidable — levels the playing field.
Failures are the norm — not an exception
  ○ Typical MTBF for commodity components of 1000 days — if you have 1000s in your cluster, probability of at least 1 being down at any time nears 100%
Big Ideas

- **Failures are the norm — not an exception**
  - Typical MTBF for commodity components of 1000 days — if you have 1000s in your cluster, probability of at least 1 being down at any time nears 100%

- **Move "Processing" to the Data**: Co-locate processing of the data with the data itself rather than sending data around as in HPC.
Big Ideas

- **Failures are the norm — not an exception**
  - Typical MTBF for commodity components of 1000 days — if you have 1000s in your cluster, probability of at least 1 being down at any time nears 100%

- **Move "Processing" to the Data**: Co-locate processing of the data with the data itself rather than sending data around as in HPC.

- **Process Data Sequentially vs Random Access**: Do mass analytics on large sequential build data as opposed to search for individual items
Big Ideas

- **Hide System Details from the User Application**: Programmers are bad at details (at least compared to computers). Let the RTS manage details for you.
  - ie: where is the data located, what communication is required, what is a given machine doing, etc.
Big Ideas

- **Hide System Details from the User Application:** Programmers are bad at details (at least compared to computers). Let the RTS manage details for you.
  - ie: where is the data located, what communication is required, what is a given machine doing, etc.

- **Seamless Scalability:** Machines can be added or removed without changing the algorithms.
  - Allows scaling up to process larger data sets without rethinking the entire application
Issues to Address

- How do we decompose large problems into smaller ones?
- How do we assign tasks to workers distributed across the cluster?
  - How do the workers get the data?
  - How do we synchronize among workers?
  - How do we share partial results among workers?
- How do we do all of this in the presence of faults?
Issues to Address

- How do we decompose large problems into smaller ones?
- How do we assign tasks to workers distributed across the cluster?
  - How do the workers get the data?
  - How do we synchronize among workers?
  - How do we share partial results among workers?
- How do we do all of this in the presence of faults?

As discussed last week, MR is supported by a distributed file system that provides many of these answers.
MapReduce Basics

Fundamental Concept: key-value pairs
- Key-value pairs form the basic structure of MapReduce
- Keys can be anything from simple data types to custom types
Fundamental Concept: key-value pairs

- Key-value pairs form the basic structure of MapReduce
- Keys can be anything from simple data types to custom types
- Examples:

  - `<docid, doc>`
  - `<yourName, yourLifeHistory>`
  - `<graphNode, nodeCharacteristics>`
  - `<geneNum, {pathway, geneExp, proteins}>`
  - `<yourID, yourFollowers>`
  - `<studentNum, studentDetails>`
  - `<word, numberOfOccurrences>`
  - etc...
Conceptual Example

Consider a large data collection:
{web, weed, green, sun, moon, land, part, web, green,...}

Problem: Count the occurrences of the different words in the collection.
Consider a large data collection:
{web, weed, green, sun, moon, land, part, web, green,...}

Problem: Count the occurrences of the different words in the collection.

Let's design a solution for this problem:
- We will start from scratch
- We will add and relax constraints
- We will do incremental design, improving solution as we go
Sequential Counter and Table

Diagram:

- Data
- DataCollection
- WordCounter
  - parse()
  - count()
- Main
- ResultTable

Table:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>web</td>
<td>2</td>
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<tr>
<td>weed</td>
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</table>
Sequential Counter and Table

**WordCounter**
- parse()
- count()

**DataCollection**

**Main**

**ResultTable**

**Single WordCounter is a sequential bottleneck**

<table>
<thead>
<tr>
<th>Data</th>
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<tbody>
<tr>
<td>web</td>
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</table>
Multiple Word Counters

```java
Data

Thread

DataCollection

Main

WordCounter

parse()
count()

ResultTable

<p>| | |</p>
<table>
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```
Multiple Word Counters

What additional constraints does this introduce?

<p>| | |</p>
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<tbody>
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Multiple Word Counters

- **Main**
  - parse()
  - count()
- **WordCounter**
  - parse()
  - count()
- **DataCollection**
- **ResultTable**
- **Thread**
  - 1..*

What additional constraints does this introduce?

We need a lock!

<p>| | |</p>
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</tbody>
</table>
Splitting Up Our Tasks

Data

Parser

ResultTable

Main

Thread

Word List

DataCollection

Counter

Key | web | weed | green | sun | moon | land | part | web | green | ... |
--- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
Value |     |     |       |     |      |      |      |     |     |   ...

web  2 | weed 1 | green 2 | sun 1 | moon 1 | land 1 | part 1 | web | green | ...
Splitting Up Our Tasks

Data Collection

Parser

Word List

Counter

Result Table

Main

Thread

Separate counters removes need for locks

Data

<table>
<thead>
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<th>Key</th>
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What if our Data is "Big"?

Peta-Scale Data

Main

Thread

Parser

Counter

DataCollection

Word List

ResultTable

<table>
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<th>Key</th>
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Addressing the Scale Issue

- Eventually a single machine can't hold all of our data
  - We need a distributed file system! (HDFS)
- Large number of commodity disks; ie 1000s of disks @ 1TB each
  - **Issue:** with a failure rate of 1/1000, then at least 1 of the above disks would be down at any given time
  - Failure is the norm; need reliability
    - Replication, checksum, etc
  - Bandwidth of data transfer also becomes critical at this point
- We need to exploit parallelism afforded by splitting parsing and counting
- Move these computations to where the data is
What if our Data is "Big"?

```
| Key   | web | weed | green | sun | moon | land | part | web | green | ...
<table>
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<td></td>
</tr>
</tbody>
</table>
```
Distribute the Data

Key | web | weed | green | sun | moon | land | part | web | green | ...
Value

DataCollection

Parser 1..*

Thread

Main

Counter 1..*

Word List

ResultTable
Distribute the Data

Remember!
We are dealing with WORM data

WORM data is amenable to parallelism

Data without dependencies is amenable to out-of-order processing

<table>
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</tbody>
</table>

DataCollection

ResultTable
Divide and Conquer
For our example:
1. We schedule parse tasks
2. We then schedule count
Divide and Conquer

For our example:
1. We schedule parse tasks
2. We then schedule count

Let's generalize this:

Our "parse" is a mapping operation
MAP: input →<key, value> pairs
For our example:
1. We schedule parse tasks
2. We then schedule count

Let's generalize this:

Our "parse" is a mapping operation
MAP: input → <key, value> pairs

Our "count" is a reduce operation
REDUCE: <key, value> pairs reduced
Divide and Conquer

For our example:
1. We schedule parse tasks
2. We then schedule count

Let's generalize this:

Our "parse" is a mapping operation
MAP: input →<key, value> pairs

Our "count" is a reduce operation
REDUCE: <key, value> pairs reduced

RTS adds distribution, fault tolerance, replication, monitoring, load balancing, etc...
Mapper and Reducer

MapReduceTask

Mapper
  MyMapper
  Parser

Reducer
  Counter
  MyReducer
Map Operation

Split the data to supply multiple processors

Data

Parser : Mapper

Parser : Mapper

Parser : Mapper

Parser : Mapper

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</table>
Split the data to supply multiple processors

Each mapper maps its own piece of the data

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<table>
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<tbody>
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</tbody>
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---

Parser : Mapper

---

Data
The Big Picture
MapReduce Design

- Your focus is on map, reduce, and other associated functions like combiner
  - Mapper and Reducer are classes in Java
- Configure the MR "Job" for location of these functions, location of input and output (paths), scale or size of the cluster in terms of #maps #reduces etc.
- Full job is code for the mapper, reducer, combiner, partitioner, plus job configuration. Execution framework handles everything else.
- Configuration methodology has been evolving with different versions of Hadoop
Pseudo Code

Class MAPPER

Method MAP(
    doc d)

For term t in doc d:
emit(t, count = 1)

Class REDUCER

Method REDUCE(
    term t, counts)

sum = 0

For count c in counts:
    sum = sum + c
emit(t, count = sum)
Word Count Problem Revisited

This is a cat
Cat sits on a roof
The roof is a tin roof
There is a tin can on the roof
Cat kicks the can
It rolls on the roof and falls on the next roof
The cat rolls too
It sits on the can
This is a cat
Cat sits on a roof
The roof is a tin roof
There is a tin can on the roof
Cat kicks the can
It rolls on the roof and falls on the next roof
The cat rolls too
It sits on the can
Word Count Problem: Shuffle to Reducers

Output of Mappers:
<this 1> <is 1> <a 1> <cat 1> <cat 1> <sits 1> <on 1> <a 1> <roof 1> <the 1> <roof 1> <is 1> <a 1> <tin 1> <roof 1> <there 1> <is 1> <a 1> <can 1> <on 1> <the 1> <roof 1> <cat 1> <kicks 1> <the 1> <can 1> <it 1> <rolls 1> <on 1> <the 1> <roof 1> <and 1> <falls 1> <on 1> <the 1> <next 1> <roof 1> <the 1> <cat 1> <rolls 1> <too 1> <it 1> <sits 1> <on 1> <the 1> <can 1>
Word Count Problem: Shuffle to Reducers

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Input to the Reducers: delivered sorted, by key
...
<can <1,1>>
<cat <1,1,1,1>>
...
<roof <1,1,1,1,1>>
...
Reduce (sum in this case) the values:

... <can 2> <cat 4> <roof 6> ...
More on MapReduce

- All mappers work in parallel
- Barriers enforce that all mappers complete before reducers start
- Mappers and Reducers execute on same machine
- Jobs can be configured to have other combinations besides mapper/reducer.
- Mappers and reducers can have side effects
  - Allows sharing between iterations
What is it used for?

- Google uses it (we think) for wordcount, adwords, pagerank, indexing
- Simple algorithms such as grep, text-indexing, reverse indexing
- Bayesian classification: data mining
- Facebook uses it for various things, ie demographic information
- Financial services use it for analytics
- Astronomy: Gaussian analysis for location extra-terrestrial objects
- Expected to play a critical role in semantic web and web3.0
Summary

- Very large scale WORM data (allows for parallelism)
- Map and Reduce are the main operations → simple code
- There are other supporting operations we'll look at later
- Operations are executed near the data
- Commodity hardware and storage
- RTS takes care of splitting and moving data
- Requires a distributed file system (HDFS) and runtime (Hadoop runtime)