Basics of Cloud Computing – Lecture 5

MapReduce Algorithms

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Some material adapted from slides by Jimmy Lin, 2008 (licensed under Creation Commons Attribution 3.0 License)
Outline

• MapReduce algorithms
• How to write MR algorithms
Shuffle and Sort: aggregate values by keys

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Hadoop Usage Patterns

• Extract, transform, and load (ETL)
  – Perform aggregations, transformation, normalizations on the data (e.g. Log files) and load into RDBMS/ data mart

• Reporting and analytics
  – Run ad-hoc queries, analytics and data mining operations on large data

• Data processing pipelines

• Machine learning & Graph algorithms
  – Implement machine learning algorithms on huge data sets
  – Traverse large graphs and data sets, building models and classifiers
MapReduce Examples

• Distributed Grep
• Count of URL Access Frequency
• Reverse Web-Link Graph
• Term-Vector per Host
• Inverted Index
• Distributed Sort
MapReduce Jobs

• Tend to be very short, code-wise
  – IdentityReducer is very common
• “Utility” jobs can be composed
• Represent a data flow, more so than a procedure
Count of URL Access Frequency

• Processing web access logs
• Very similar to word count
• Map
  – processes logs of web page requests and outputs <URL, 1>
• Reduce
  – adds together all values
  – emits a <URL, total count> pairs
Distributed Grep

• Map
  – Emits a line if it matches a supplied pattern

• Reduce
  – Identity function
  – Just copies the supplied intermediate data to the output
Reverse Web-Link Graph

• Map
  – Outputs <target, source> pairs
  – for each link to a target URL found in a page named source.

• Reduce
  – Concatenates the list of all source URLs
  – Returns <target, list(source)>
Sort: Inputs

- A set of files, one value per line.
- Mapper key is file name, line number
- Mapper value is the contents of the line
Sort Algorithm

• Takes advantage of reducer properties:
  - (key, value) pairs are processed in order by key; reducers are themselves ordered

• Mapper: Identity function for value
  \[(k, v) \rightarrow (v, \_)]

• Reducer: Identity function \[(k', \_) \rightarrow (k', \"\")\]
Sort: The Trick

• (key, value) pairs from mappers are sent to a particular reducer based on hash(key)

• Must pick the hash function for your data such that
  – K1 < K2 => hash(K1) < hash(K2)

• Used as a test of Hadoop’s raw speed
Inverted Index: Inputs

• A set of files containing lines of text

• Mapper key is file name, line number

• Mapper value is the contents of the line
Inverted Index Algorithm

• Mapper: For each word in (file, words), map to (word, file)

• Reducer: Identity function
Index MapReduce

• map(pageName, pageText):
  foreach word w in pageText:
    emit Intermediate(w, pageName);
  Done

• reduce(word, values):
  foreach pageName in values:
    AddToOutputList(pageName);
  Done
  emitFinal(FormattedPageListForWord);
Index: Data Flow

Page A

This page contains so much of text

A map output

This: A
page: A
contains: A
so: A
much: A
of: A
text: A

B map output

This: B
page: B
too: B
contains: B
some: B
text: B

Reduced output

This: A, B
page: A, B
too: B
contains: A, B
so: A
much: A
of: A
text: A, B
some: B
Let us focus much bigger problems
Managing Dependencies

• Remember: Mappers run in isolation
  – You have no idea in what order the mappers run
  – You have no idea on what node the mappers run
  – You have no idea when each mapper finishes

• Tools for synchronization:
  – Ability to hold state in reducer across multiple key-value pairs
  – Sorting function for keys
  – Partitioner
  – Cleverly-constructed data structures
Motivating Example

• Term co-occurrence matrix for a text collection
  – $M = N \times N$ matrix ($N = $ vocabulary size)
  – $M_{ij}$: number of times $i$ and $j$ co-occur in some context
    (for concreteness, let’s say context = sentence)

• Why?
  – Distributional profiles as a way of measuring semantic distance
  – Semantic distance useful for many language processing tasks

“You shall know a word by the company it keeps” (Firth, 1957)
MapReduce: Large Counting Problems

• Term co-occurrence matrix for a text collection = specific instance of a large counting problem
  – A large event space (number of terms)
  – A large number of events (the collection itself)
  – Goal: keep track of interesting statistics about the events

• Basic approach
  – Mappers generate partial counts
  – Reducers aggregate partial counts

How do we aggregate partial counts efficiently?
First Try: “Pairs”

• Each mapper takes a sentence:
  – Generate all co-occurring term pairs
  – For all pairs, emit \((a, b) \rightarrow \text{count}\)
• Reducers sums up counts associated with these pairs
• Use combiners!
“Pairs” Analysis

• Advantages
  – Easy to implement, easy to understand

• Disadvantages
  – Lots of pairs to sort and shuffle around (upper bound?)
Another Try: “Stripes”

• Idea: group together pairs into an associative array
  
  (a, b) → 1  a → { b: 1, c: 2, d: 5, e: 3, f: 2 }
  (a, c) → 2
  (a, d) → 5
  (a, e) → 3
  (a, f) → 2

• Each mapper takes a sentence:
  – Generate all co-occurring term pairs
  – For each term, emit a → { b: count_b, c: count_c, d: count_d ... }

• Reducers perform element-wise sum of associative arrays
  
  a → { b: 1, d: 5, e: 3 }  
  +  
  a → { b: 1, c: 2, d: 2, f: 2 }  
  
  a → { b: 2, c: 2, d: 7, e: 3, f: 2 }
“Stripes” Analysis

• Advantages
  – Far less sorting and shuffling of key-value pairs
  – Can make better use of combiners

• Disadvantages
  – More difficult to implement
  – Underlying object is more heavyweight
  – Fundamental limitation in terms of size of event space
Efficiency comparison of approaches to computing word co-occurrence matrices

Cluster size: 38 cores
Data Source: Associated Press Worldstream (APW) of the English Gigaword Corpus (v3), which contains 2.27 million documents (1.8 GB compressed, 5.7 GB uncompressed)
Conditional Probabilities

• How do we compute conditional probabilities from counts?

\[ P(B \mid A) = \frac{\text{count}(A, B)}{\text{count}(A)} = \frac{\text{count}(A, B)}{\sum_{B'} \text{count}(A, B')} \]

• How do we do this with MapReduce?
\( P(B|A): \text{“Pairs”} \)

\[
\begin{align*}
(a, *) &\rightarrow 32 \\
(a, b_1) &\rightarrow 3 \\
(a, b_2) &\rightarrow 12 \\
(a, b_3) &\rightarrow 7 \\
(a, b_4) &\rightarrow 1 \\
&\ldots
\end{align*}
\]

Reducer holds this value in memory

\[
\begin{align*}
(a, b_1) &\rightarrow 3/32 \\
(a, b_2) &\rightarrow 12/32 \\
(a, b_3) &\rightarrow 7/32 \\
(a, b_4) &\rightarrow 1/32 \\
&\ldots
\end{align*}
\]

For this to work:

- Must emit extra \((a, *)\) for every \(b_n\) in mapper
- Must make sure all \(a\)'s get sent to same reducer (use Partitioner)
- Must make sure \((a, *)\) comes first (define sort order)
P(B|A): “Stripes”

\[ a \to \{b_1:3, b_2:12, b_3:7, b_4:1, \ldots \} \]

• Easy!
  – One pass to compute (a, *)
  – Another pass to directly compute P(B|A)
Synchronization in Hadoop

• Approach 1: turn synchronization into an ordering problem
  – Sort keys into correct order of computation
  – Partition key space so that each reducer gets the appropriate set of partial results
  – Hold state in reducer across multiple key-value pairs to perform computation
  – Illustrated by the “pairs” approach

• Approach 2: construct data structures that “bring the pieces together”
  – Each reducer receives all the data it needs to complete the computation
  – Illustrated by the “stripes” approach
Issues and Tradeoffs

- Number of key-value pairs
  - Object creation overhead
  - Time for sorting and shuffling pairs across the network
- Size of each key-value pair
  - De/serialization overhead
- Combiners make a big difference!
  - RAM vs. disk and network
  - Arrange data to maximize opportunities to aggregate partial results
Complex Data Types in Hadoop

• How do you implement complex data types?
• The easiest way:
  – Encoded it as Text, e.g., (a, b) = “a:b”
  – Use regular expressions to parse and extract data
  – Works, but pretty hack-ish
• The hard way:
  – Define a custom implementation of WritableComparable
  – Must implement: readFields, write, compareTo
  – Computationally efficient, but slow for rapid prototyping
This week in lab

• MapReduce for data analysis
• Writing better MapReduce algorithms
Next Lecture

• Platform as a Service
  – Google AppEngine
References


• Data-Intensive Text Processing with MapReduce Authors: Jimmy Lin and Chris Dyer


Pages 50-57: Pairs and Stripes problem