Map-Reduce

CompSci 590.04 Fall 2015
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2,095,100,000,000 searches in 2014

What do these searches say about us?

EXPLORE THE YEAR IN SEARCH

Trending Searches
1. Robin Williams
2. World Cup
3. Ebola
4. Malaysia Airlines

Trending People
1. Jennifer Lawrence
2. Kim Kardashian
3. Julie Gayet
4. Tracy Morgan

Trending Athletes
1. James Rodriguez
2. Michael Schumacher
3. Ray Rice
4. Luis Suarez
Size of the entire corpus??

131,000,000 pages mentioning Einstein

Albert Einstein
Theoretical Physicist

Albert Einstein was a German-born theoretical physicist. He developed the general theory of relativity, one of the two pillars of modern physics (alongside ...)

Hans Albert Einstein - General relativity - Religious views - Brain

Albert Einstein - Biographical - Nobelprize.org
www.nobelprize.org/nobel_prizes/physics/.../einstein-bio.htm... - Nobel Prize
Albert Einstein was born at Ulm, in Württemberg, Germany, on March 14, 1879. Six weeks later the family moved to Munich, where he later on began his ...

News for einstein

Einstein's lost theory uncovered
Nature.com - 19 hours ago
A manuscript that lay unnoticed by scientists for decades has revealed that Albert Einstein once dabbled with an alternative to the Big Bang ...

Albert Einstein's Lost Theory Resurfaces, Shows His Resistance To Big Bang ...
Huffington Post - 19 minutes ago

Albert Einstein Biography - Facts, Birthday, Life Story - Biography.com
www.biography.com » People » The Biography Channel
Biography.com offers a glimpse into the life of Albert Einstein, the most influential physicist of the 20th century, who developed the theory of relativity.
Size of the entire corpus??

http://www.worldwidewebsize.com/
Trend 1: Data centers

Trend 2: Multicore

Moore’s Law: # transistors on integrated circuits doubles every 2 years
Need to think “parallel”

- Data resides on different machines
- Split computation onto different machines/cores
But … parallel programming is hard!

Low level code needs to deal with a lot of issues …

• Failures
  – Loss of computation
  – Loss of data
• Concurrency
• …
Parallel Data Processing Paradigms

In the next few classes we will look at:

• Map Reduce
• Graph analysis under Bulk Synchronous Parallel Model
• Asynchronous processing
• Resilient Distributed Datasets
• Feed Following
Map-Reduce

**Programming Model**
- Simple model
- Programmer only describes the logic

**Distributed System**
- Works on commodity hardware
- Scales to thousands of machines
- Ship code to the data, rather than ship data to code
- Hides all the hard systems problems from the programmer
  - Machine failures
  - Data placement
  - ...
Map-Reduce Programming Model

rows of dataset

map

reduce
Map-Reduce Programming Model

map($k_1, v_1$) → list($k_2, v_2$)

reduce($k_2$, list($v_1$)) → list($k_3, v_3$)
Example 1: Word Count

• Input: A set of documents, each containing a list of words
  – Each document is a row
  – E.g., search queries, tweets, reviews, etc.

• Output: A list of pairs $<w, c>$
  – $c$ is the number of times $w$ appears across all documents.
Word Count: Map

<docid, {list of words}> ➞ {list of <word, 1>}

• The mapper takes a document d and creates n key value pairs, one for each word in the document.

• The output key is the word

• The output value is 1
  – (count of each appearance of a word)
Word Count: Reduce

\[ \text{<word, \{list of counts\}>} \rightarrow \text{<word, sum(counts)>} \]

- The reducer aggregates the counts (in this case 1) associated with a specific word.
Map-Reduce Implementation

map\((k_1, v_1) \rightarrow \text{list}(k_2, v_2)\)

reduce\((k_2, \text{list}(v_1)) \rightarrow \text{list}(k_3, v_3)\)
Map-Reduce Implementation

Split phase partitions the data across different mappers (... think different machines)

Map Phase
(per record computation)

Reduce Phase
(global computation)

Split

Shuffle
Map-Reduce Implementation

Each mapper executes user defined map code on the partitions in parallel

Map Phase
(per record computation)

Reduce Phase
(global computation)

Split

Shuffle
Map-Reduce Implementation

Data is shuffled such that there is one reducer per output key (... again think different machines)
Map-Reduce Implementation

Each reducer executes the user defined reduce code in parallel.
Map Reduce Implementation

• After every map and reduce phase, data is written onto disk
  – If machines fail during the reduce phase, then no need to rerun the mappers.

Writing to disk is slow.
Should minimize number of map-reduce phases.
Mappers, Reducers and Workers

• Physical machines are called workers
• Multiple mappers and reducers can run on the same worker.

• More workers implies …
  … more parallelism (faster computation) …
  … but more (communication) overhead …
Map Reduce Implementation

• All reducers start only after all the mappers complete.

• Straggler: A mapper or reducer that takes a long time
Back to Word Count

- **Map:**
  \[
  \langle \text{docid}, \{\text{list of words}\} \rangle \rightarrow \{\text{list of } \langle \text{word}, 1 \rangle\}\]

- **Reduce:**
  \[
  \langle \text{word}, \{\text{list of counts}\} \rangle \rightarrow \langle \text{word}, \text{sum(counts)} \rangle\]

- **Number of records output by the map phase equals the number of words across all documents.**
Map-Combine-Reduce

• Combiner is a mini-reducer within each mapper.
  – Helps when the reduce function is commutative and associative.

• Aggregation within each mapper reduces the communication cost.
Word Count … with combiner

- **Map:**
  \[<\text{docid}, \{\text{list of words}\}> \rightarrow \{\text{list of } <\text{word, 1}>\}\]

- **Combine:**
  \[<\text{word, } \{\text{list of counts}\}> \rightarrow <\text{word, sum(counts)}>\]

- **Reduce:**
  \[<\text{word, } \{\text{list of counts}\}> \rightarrow <\text{word, sum(counts)}>\]
Word Count … *in python*

```python

"""The classic MapReduce job: count the frequency of words.
"""

```
from mrjob.job import MRJob
import re

WORD_RE = re.compile(r"\w\+"

```class MRWordFreqCount(MRJob):

    def mapper(self, _, line):
        for word in WORD_RE.findall(line):
            yield (word.lower(), 1)

    def combiner(self, word, counts):
        yield (word, sum(counts))

    def reducer(self, word, counts):
        yield (word, sum(counts))

```if __name__ == '__main__':
    MRWordFreqCount.run()

One of the many MapReduce libraries for python
```
Example 2: K most frequent words

• Need multiple Map-Reduce steps

• Map:
  \(<\text{docid}, \{\text{list of words}\}\rangle \rightarrow \{\text{list of } <\text{word}, 1>\}\>

• Reduce:
  \(<\text{word}, \{\text{list of counts}\}\rangle \rightarrow \langle _, (\text{word}, \text{sum(counts)})\rangle\>

• Reduce:
  \(<_, \{\text{list of (word, count) pairs}\}\rangle \rightarrow
    \langle _, \{\text{list of words with k most frequent counts}\}\rangle\>
Example 3: Distributed Grep

• Input: String
• Output: {list of lines that match the string}

• Map:
  
  <lineid, line> → <lineid, line> // if line matches string

• Reduce:
  
  // do nothing
Example 4: Matrix Multiplication

\[ P_{ik} = \sum_{j} m_{ij} n_{jk} \]

If \( M \) is a matrix with element \( m_{ij} \) in row \( i \) and column \( j \), and \( N \) is a matrix with element \( n_{jk} \) in row \( j \) and column \( k \), then the product \( P = MN \) is the matrix \( P \) with element \( p_{ik} \) in row \( i \) and column \( k \), where

\[ p_{ik} = \sum_{j} m_{ij} n_{jk} \]
Matrix Multiplication

- Assume the input format is \( <\text{matrix id, row, col, entry}> \)
  - E.g.: \(<M, i, j, m_{ij}>\)

- Map:
  \( _<, (M, i, j, m_{ij})> \to <(i,k), (M, i, m_{ij})> \text{ ... for all } k \)
  \( _<, (N, j, k, n_{jk})> \to <(i,k), (N, k, n_{jk})> \text{ ... for all } i \)

- Reduce:
  \(<(i,k), \{(M, i, j, m_{ij}), (N, j, k, n_{jk}) \text{ ...}\}> \to \{ <(i,k), \Sigma_j m_{ij}n_{jk}>\} \)
Example 5: Join two tables

- Input: file1 and file2, with schema <key, value>
- Output: keys appearing in both files.

- Map:
  \[ (_ , (file1, key, value)) \rightarrow (key, file1) \]
  \[ (_ , (file2, key, value)) \rightarrow (key, file2) \]

- Reduce:
  \[ (key , \{list of fileids\}) \rightarrow (_, key) \]
  // if list contains both file1 and file2.
Map-side Join

• Suppose file2 is very small ...

• Map:
  \[
  \langle _, (\text{file1}, \text{key}, \text{value}, \{\text{keys in file2}\}) \rangle \rightarrow (\_, \text{key})
  \]
  
  // If key is also in file2

• Reduce: // do nothing
  \[
  \langle _, \{\text{list of keys}\} \rangle \rightarrow \langle _, \{\text{list of keys}\} \rangle
  \]
Example 5: Join 3 tables

• Input: 3 Tables
  – User (id:int, age:int)
  – Page (url:varchar, category:varchar)
  – Log (userid: int, url:varchar)

• Output: Ages of users and types of urls they clicked.
Multiway Join

• Join( Page, Join (User, Log))
  • Map:
    \(<_, (User, id, age)> \rightarrow (id, (User, key, value))\)
    \(<_, (Log, userid, url)> \rightarrow (userid, (Log, userid, url))\)
  • Reduce:
    \(<id, \{list of records\}> \rightarrow \langle _, \{records from User\} \times \{records from Log\}\rangle\)
    \(// \text{ if list contains records both from User and Log.}\)
  • Map:
    \(<_, (User, Log, id, age, userid, url)> \rightarrow (url, (User, Log, id, age, userid, url))\)
    \(<_, (Page, url, category)> \rightarrow (url, (Page, url, category))\)
  • Reduce:
    \(<url, \{list of records\}> \rightarrow \langle _, \{records from User \times Log\} \times \{records from Page\}\rangle\)
    \(// \text{ if list contains records both from User \times Log and Page.}\)
Summary

• Map-reduce is a programming model + distributed system implementation that make parallel programming easy.
  – Programmer does not need to worry about systems issues.

• Computation is a series of Map and Reduce jobs.
  – Parallelism is achieved within each Map and Reduce phase.