Introduction to
Data Science

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MapReduce Overview

- Sometimes a single computer cannot process data or takes too long – traditional serial programming is not always enough
  - Processor constraints
  - Storage constraints
  - Memory Constraints

- But when resources are pooled, it may be possible – break task into parts and execute concurrently on multiple processors
  - Challenge: What can run concurrently? How to parallelize?

- **MapReduce**: a programming paradigm to process large data sets
History

- Original research done at Google (2004, Dean & Ghemawat)
- Now Apache Software Foundation provides Hadoop MapReduce implementation
- Amazon version and others also exist
Map-Reduce Overview

- First invented by Dean and Ghemawat in 2004
- Use (key, value) pairs (Inspired by Lisp)
  - \((\text{length}, [(9) (7 3) () (4,6,8)])\) gives \((1 2 0 3)\)
  - \((\text{sum}, [2 7 1 5 0 3])\) gives 18
- Scalable parallel programming paradigm to address big data processing
  - \(\text{Map}\) \((fM, \text{SetOfValues})\)
  - \(\text{Reduce}\) \((fR, \text{SetOfValues})\)
- Programmer provides \textbf{Map} and \textbf{Reduce} and system handles rest
Map-Reduce

- Ranking (e.g., PageRank) requires iterated matrix-vector multiplication with matrix containing millions of rows and columns
- Computing with social networks involves graphs with hundreds of millions of nodes and billions of edges
- Map-Reduce is a parallel programming paradigm, a software-stack that will help to address big data processing
  - Distributed file system with redundancy (e.g., Google FS, Hadoop DFS, CloudStore)
  - Network of racks of processors forming a cluster
MapReduce

- Framework used by writing 2 procedures – Map and Reduce

- Map
  - Input is broken into chunks and each Map task is given one or more chunks
  - Output of Map task: (key, value) pairs. Master controller sorts by keys
  - Reduce task works on all pairs with same key and combines values as defined
MapReduce Execution Overview

**Fig. 1. Execution overview.**
MapReduce Example

- **Input**: repository of documents
- **Output**: word Frequencies (want freq of word in a collection of docs)
- **Input element**: one document
- **Map task**: For each document, for each of its words, output pair \((w,1)\)
- **Master Controller** groups pairs by keys into a list, then merges into a file
- **Reduce task**: “Combines” items related to a word getting frequency of single word
  - If Combine is associative & commutative, can move work between map/reduce
MapReduce Subtleties

- One document assigned to one Map task (many docs to same Map)
- Tradeoff between Map-Reduce: Map could do part of combine and decrease work for Reduce, i.e., it could return \((w, m)\) count of number of occurrences of word \(w\) in one document
- Master Controller uses a hash function to distribute work into \(r\) tasks, since it knows \# of Reduce nodes. One bucket \(\rightarrow\) one file for Reduce. This helps to distribute work randomly among Reduce tasks/nodes.
- One word assigned to one Reduce task (many words to same Reduce)
Skew

- Imbalance in workload to different tasks and their compute nodes
  - More tasks means more overhead of creating tasks
  - More tasks means greater ability to balance out load
  - More documents and words than nodes
  - Number of documents and their sizes may be known beforehand
Node Failures

- Compute node failure: Restart
- Map node failure: Master node monitors, reassigns, and restarts task; all Reduce tasks informed of new task/location and to discard old task/location
- Reduce node failure: Master node monitors, reassigns and restarts task
Matrix-Vector Multiplication

- Same vector in MM of every node
- Matrix $M$: $n \times n$
- Vector $v$: length $n$
- Map step: focus on one element of $M$
- Output contribution by one element:
- Reduce step: Sum up all entries for key $i$ to get result $x_i$

$$x_i = \sum_{j=1}^{n} m_{i,j} v_j$$

$$(i, m_{i,j} v_j)$$
Matrix Vector Multiplication

Matrix M

Vector v

Map <i,j>

Reduce <i>

((i,j), m_{ij})

(j, v_j)

((i,j), v_j)

(i, m_{ij} \times v_j)

x_i
Matrix-Vector Multiplication

- Matrix M can be thought of as a relation with tuples \((i, j), m_{ij}\)
- Vector v can be thought of as a relation \((j, v_j)\) generating tuples \((i, j), v_j\)
- Map process gets these tuples and outputs
  - Relation \((i, m_{ij} \times v_j)\)
  - Can also be thought of as a 2-step map process, a join and a multiply
- Reduce: Grouping and aggregation produces \(M \times v\)
  - aggregates all tuples of the form \((i, Z)\) and stores in cell \(i\)
Map Reduce Sample Code

What if vector is too large for MM

Figure 2.4: Division of a matrix and vector into five stripes
Matrix-Matrix Multiplication

- Matrix M can be thought of as a relation with tuples \(((i, j), m_{ij})\)
- Matrix N can be thought of as a relation with tuples \(((j, k), n_{jk})\)
- Map: Join of M and N brings us closer to \(M \times N\) by creating:
  - Relation \((i, j, k, m_{ij} \times n_{jk})\) creates tuple \(((i, k), m_{ij} \times n_{jk})\)
- Grouping and aggregation produces \(M \times N\)
  - Reduce operation: aggregates all tuples with \(((i, k), Z)\) and outputs \(X_{ik}\)
Relational DB operations using MapReduce

- Selection
- Projection
- Union, Intersection & Difference
- Natural Join
- Grouping and aggregation
Example: Paths of length 2 in network

- If we want to know if there is a path of length 2 in a directed network from vertex $u$ to $v$, then we need to find a vertex $w$ such that $(u,w)$ and $(w,v)$ are directed edges in the network.

- Imagine that the directed network is given as a relation $G$ with 2 columns `source` and `destination`.

- This can be written as a join of 2 relations. **How?**
  - Join $G$ with $G$ joining `destination` in the first $G$ with the `source` in the second $G$

- This can also be written as a matrix multiplication of 2 adjacency matrices of a network/graph. **How?**
  - Now we can implement using a MapReduce framework
Paths of length 2 in network

- This can also be written as a matrix multiplication of 2 adjacency matrices of a network/graph. **How?**
  - Multiplication of a row and a column
    - $\text{Sum}(\text{product} \text{ of corresponding entries})$
  - Reachable in 2 steps
    - $\text{OR}(\text{AND} \text{ of corresponding entries})$
  - Replace $\text{product}$ with $\text{and}$ operation; replace $\text{sum}$ with $\text{or}$
More complex example: Arbitrage

Assume currency exchange rates as follows:

- EUR/CAD: 0.664 (1 CAD buys you 0.664 EUR)
- USD/EUR: 1.234
- CAD/USD: 1.398

If you start with 10,000 CAD, then use it to buy

- 6,640 EUR
- 6,640 \times 1.234 \text{ USD}
- 6,640 \times 1.234 \times 1.398 \text{ CAD} = 11,454.87 \text{ CAD}

Profit of 1,454.87 CAD or 14.5%. Not bad!
Arbitrage using MapReduce

- Process currency market quotes
- Look for uncompleted offers to make the 3 currency exchanges
  - Find all offers to BUY EUR with CAD, BUY USD with EUR, and BUY CAD with USD
- Find a triple that makes you a profit
- Now read this blog article that explains how to do it in Python/Hadoop
Running MapReduce

- Need **Map** code
- Need **Reduce** code
- Need **Hadoop** set up
  - Hadoop Distributed File System (HDFS)
  - Parallel Processing environment
- Blog tells you in detail how to set it up and run the MapReduce code
Many more examples ...

- https://datascienceguide.github.io/map-reduce
General MapReduce Steps

- Record Reader – split data & prepare for Map
- Map
- Combiner (Optional) – aggregates based on intermediate keys
- Partitioner – applies hash function & dispatches for Reduce
- Shuffle and Sort – groups keys on Reduce to simplify work
- Reduce
- Output Format