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)
  - (length, [(9) (7 3) () (4,6,8)]) gives (1 2 0 3)
  - (sum, [2 7 1 5 0 3]) gives 18
- Scalable parallel programming paradigm to address big data processing
  - Map (fM, SetOfValues)
  - Reduce (fR, SetOfValues)
- Programmer provides Map and 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

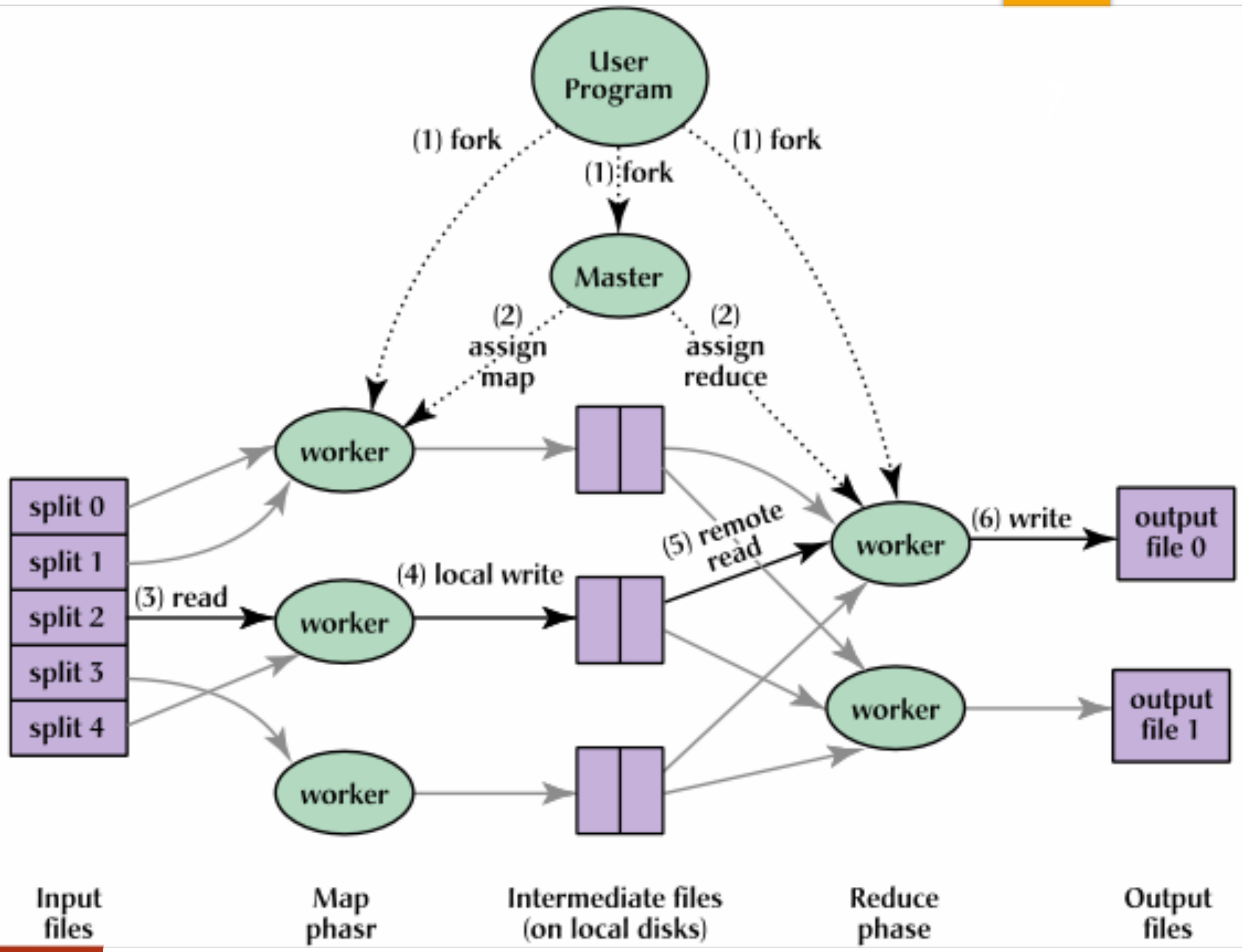


Fig. 1. Execution overview.

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 → 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

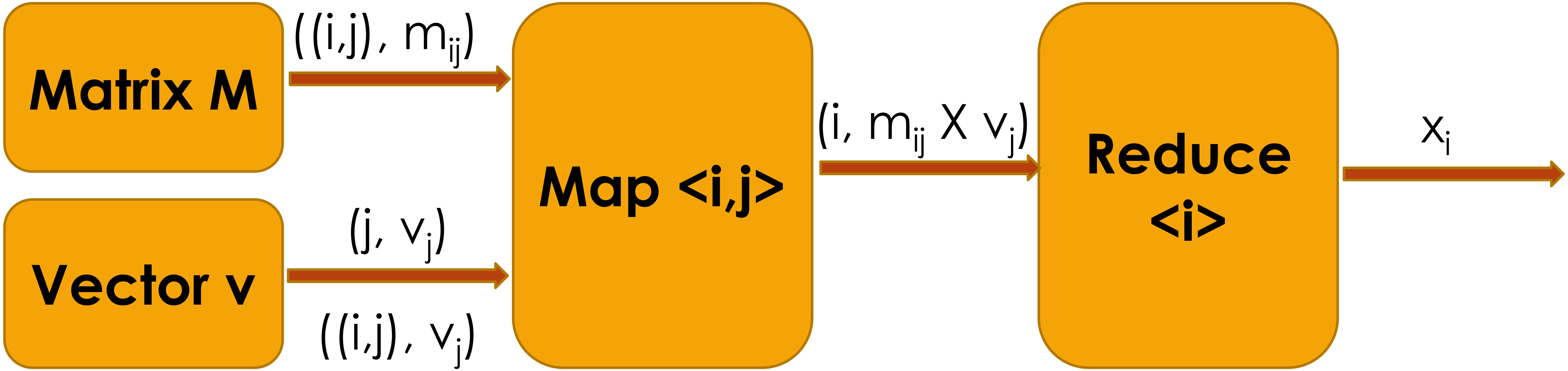
Matrix-Vector Multiplication

- Same vector in MM of every node
- Matrix M: n X 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

$$\boxed{x_i = \sum_{j=1}^{n} m_{ij} v_j}$$

$$\boxed{(i, m_{ij} v_j)}$$

Matrix Vector Multiplication



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 X v
  - aggregates all tuples of the form (i, Z) and stores in cell (i)

Map Reduce Sample Code

- https://www.michael-noll.com/tutorials/writing-an-hadoop-mapreduce-program-in-python/

What if vector is too large for MM

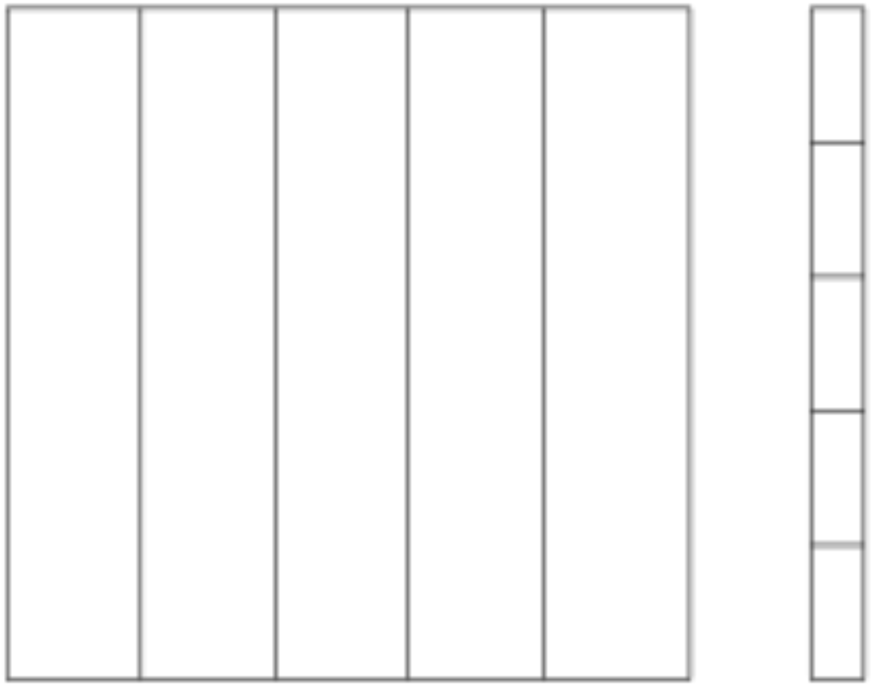


Figure 2.4: Division of a matrix and vector into five stripes

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 X N by creating:
  - Relation (i, j, k, m_{ij} X n_{jk}) creates tuple ((i, k), m_{ij} X n_{jk})
- Grouping and aggregation produces M X 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
    - **Sum**(**product** of corresponding entries)
  - Reachable in 2 steps
    - **OR**(**AND** of corresponding entries)
  - Replace **product** with **and** operation; replace **sum** with **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 * 1.234 USD
  - 6,640 * 1.234 * 1.398 CAD = 11,454.87 CAD
- **Profit** of 1,454.87 CAD or 14.5%. Not bad!

Triangular Arbitrage

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
  - https://medium.com/@rrfd/your-first-map-reduce-using-hadoop-with-python-and-osx-ca3b6f3dfe78

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
  - https://medium.com/@rrfd/your-first-map-reduce-using-hadoop-with-python-and-osx-ca3b6f3dfe78
  -

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