CAP4770/5771
Introduction to Data Science
Fall 2016

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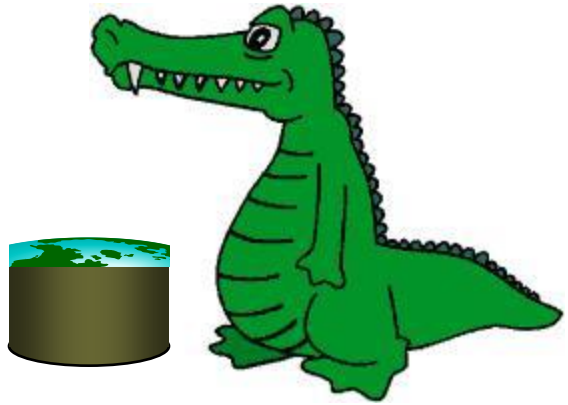


Based on notes from CS194 at UC Berkeley by Michael Franklin, John Canny, and Jeff Hammerbacher

Logistics

- Lab 4 finished, Lecture 6 this week
- Lab 5 material will be released this Friday, due Thursday 11:59pm
  - JAVA + AWS/EMR
- Lecture 7 next Monday
- Lab 5 in class next Wed.
  - Extra prep: AWS, EMR setup and tutorial
- NIST DSE Introduction + QA next Friday
- No office hour next Wed.

Review

- Machine Learning
  - Supervised
  - Unsupervised
- Supervised Learning
  - Classification and Regression
  - K-NN
  - Naïve Bayes
  - Linear/Logistic Regression
  - SVM

Supervised Learning Pipeline

1. Application Data: D
2. Training Data Annotation/Labeling: D→y_T
3. Feature Extraction D → X_T
4. Model Selection: KNN, NB, LR, LogR, SVM
5. Training: Model Fitting X_T, y_T → f(X)
6. Testing: Inference/Prediction X_t→y_t-hat
7. Evaluation: e.g., precision/recall
8. Analysis and Iterate: e.g., more labeling, features…

Main techniques

- Feature extraction from different data types, e.g., structured, logs, text, image
- Learning
  - Model: KNN, NB, LR, LogR, SVM
  - Model parameters, error function: SSE/ML, optimization: minimization/maximization
- Inference
  - For each of KNN, NB, LR, LogR, SVM
  - How to use learned model f(X) to predict new numerical or categorical values y_t-hat
- Evaluation: P-R, Type I/II error

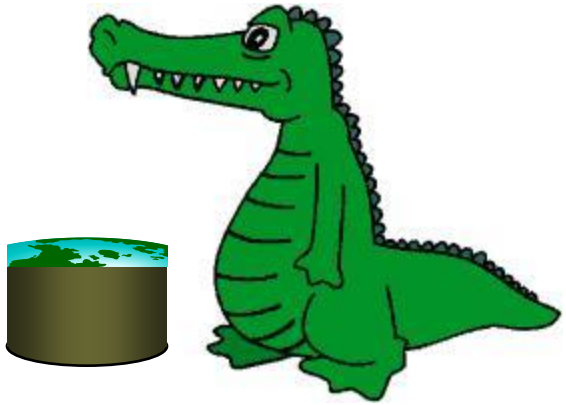
Map/Reduce: Simplified Data Processing on Large Clusters

Parallel/Distributed Computing

Distributed File System

M/R Programming Model

Parallel Analytics using M/R



Adapted Slides from Jeff Ullman, Anand Rajaraman and Jure Leskovec from Stanford

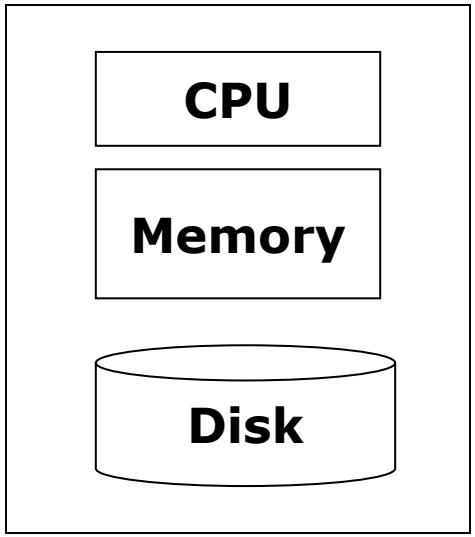
Parallel Computing

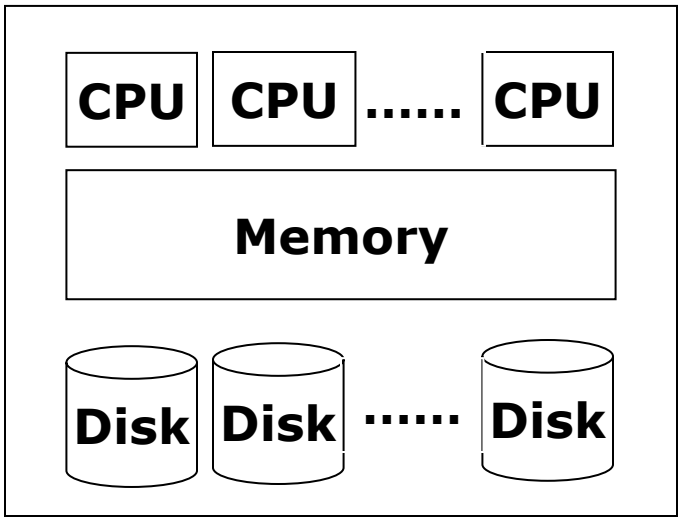
- MapReduce is designed for parallel computing
- Before MapReduce
  - Enterprise: a few super-computers, parallelism is achieved by parallel DBs (e.g., Teradata)
  - Science, HPC: MPI, openMP over commodity computer clusters or over super-computers for parallel computing, do not handle failures (i.e., Fault tolerance)
- Today:
  - Enterprise: map-reduce, parallel DBs
  - Science, HPC: openMP, MPI and map-reduce

MapReduce can apply over both multicore and **distributed environment**

Data Analysis on Single Server

- Many data sets can be very large
  - Tens to hundreds of terabytes
- Cannot always perform data analysis on large datasets on a single server (why?)
  - Run time (i.e., CPU), memory, disk space





Motivation: Google's Problem

- 20+ billion web pages * 20KB = 400+ TB
  - ~1000 hard drives to store the web
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web

- Takes even more to do something useful with the data!
  - CPU
  - Memory

Commodity Clusters

- Recently standard commodity architecture for such problems:
  - Cluster of commodity Linux nodes
  - Gigabit ethernet interconnect

- How to organize computations on this architecture?

Distributed Computing

- Challenges:
  - Distributed/parallel programming is hard
    - How to distribute Data? Computation? Scheduling? Fault Tolerant? Debugging?
  - On the software side: what is the programming model?
  - On the hardware side: how to deal with hardware failures?
- MapReduce/Hadoop addresses all of the above
  - Google's computational/data manipulation model
  - Elegant way to work with big data

Stable storage

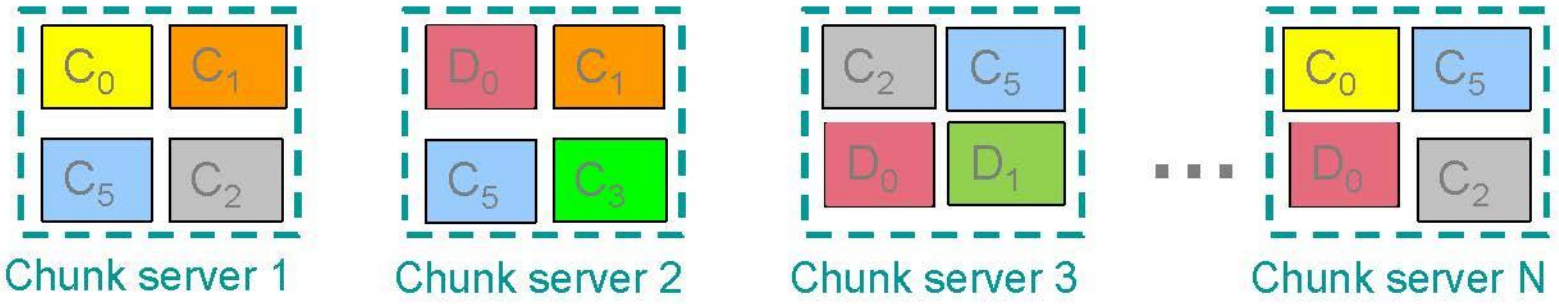
- First order problem: if nodes can fail, how can we store data persistently?
- Idea:
  - Store files multiple times for reliability
- Solution: Distributed File System
  - Provides global file namespace
  - Google GFS; Hadoop HDFS
- Typical Usage Pattern
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

Distributed File System

- Chunk Servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Nodes in HDFS
  - Stores metadata
  - Likely to be replicated as well
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

Reliable Distributed File System

- Data kept in "chunks" spread across machines
- Each chunk replicated on different machines
  - Seamless recovery from disk or machine failure



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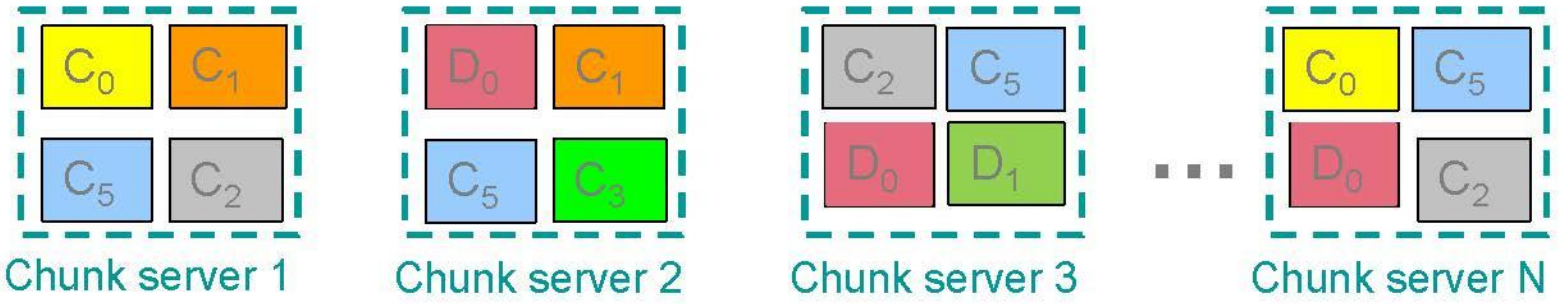

Bring computation directly to the data!

Chunk servers also serve as compute servers

Simpole Programming Model for Distributed Computing: MapReduce

- Large-Scale Data Processing
  - Want to use 1000s of CPUs, But don't want the hassle of scheduling, synchronization, etc.
- MapReduce provides
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling and synchronization
  - Monitoring & status updates

MapReduce Basics

- MapReduce
  - Programming model similar to Lisp
  - (and other functional languages)

- General pattern for parallel/distributed computing: Many problems can be phrased using Map and Reduce functions

- Simple and intuitive to implement an algorithm in MapReduce API

Example Problem: Word Count

- We have a huge text file: doc.txt or a large corpus of documents: docs/*
- Count the number of times each distinct word appears in the file..
  - Apps?
- Sample application: analyze web server logs to find popular URLs

Word Count (2)

- Case 1: File too large for memory, but all <word, count> pairs fit in memory
- Case 2: File on disk, too many distinct words to fit in memory
  - Count occurrences of words

```
words(doc.txt) | sort | uniq -c
```

  - `words` takes a file and output the words in it, one word a line
  - Naturally capture the essence of MapReduce and naturally parallelizable

3 steps of MapReduce

- Sequentially read a lot of data
- **Map:** Extract something you care about
- **Group by key:** Sort and shuffle
- **Reduce:** Aggregate, summarize, filter or transform
- Output the result

For different problems, steps stay the same,
Map and Reduce change to fit the problem

MapReduce: more detail

- Input: a set of key/value pairs
- Programmer specifies two methods
  - Map(k,v) → list(k1,v1)
    - Takes a key-value pair and outputs a set of key-value pairs (e.g., key is the file name, value is a single line in the file)
    - One map call for every (k,v) pair
  - Group by key is executed by default: Sort(list(k1,v1)) → list (k1, list(v1))
  - Reduce(k1, list(v1)) → list (k1, v2)
    - All values v1 with the same key k1 are reduced together to produce a single value v2
    - There is one reduce call per unique key k1

InputFormat → <K,V> pairs

- InputFormat: transform on-disk data representation on HDFS to in-memory key-value

- Example: InputFormat for plain text files. Files are broken into lines. Either linefeed or carriage-return are used to signal end of line.

  - TextInputFormat: Keys are the position in the file, and values are the line of text.

  - KeyValueTextInputFormat: Each line is divided into key and value parts by a separator byte. If no such a byte exists, the key will be the entire line and value will be empty.