Data Science at Scale: MapReduce & Spark

CSE481DS Data Science Capstone

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Thank you for sharing your feedback with us!

Group Reflection on Process & Validity
Lecture: Distributed Computing for Data Science
Agenda

- **Commodity Computing**
  Computing with thousands of failures a day

- **Map Reduce**
  Plumbing for billions of data points

- **Spark**
  A great tool for a nasty problem

- **Data Engineering in Practice**
  What to look forward to

- **Lab!**
Commodity Computing
Large-scale Computing

- **Large-scale computing for data mining problems on commodity hardware**

- **Challenges:**
  - How do you distribute computation?
  - How can we make it easy to write distributed programs?
  - Machines fail:
    - One server may stay up 3 years (1,000 days)
    - If you have 1,000 servers, expect to lose 1/day
    - With 1M machines 1,000 machines fail every day!
Storage Infrastructure

- **Problem:**
  - If nodes fail, how to store data persistently?

- **Answer:**
  - **Distributed File System**
    - Provides global file namespace

- **Typical usage pattern:**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common
Distributed File System

- **Reliable distributed file system**
- Data kept in “chunks” spread across machines
- Each chunk **replicated** on different machines
  - Seamless recovery from disk or machine failure

![Diagram of chunk servers and chunks]

**Bring computation directly to the data!**

**Chunk servers also serve as compute servers**
An Issue and a Solution

- **Issue:**
  Copying data over a network takes time

- **Idea:**
  - Bring computation to data
  - Store files multiple times for reliability

- **Map Reduce** address these problems
  - **Storage Infrastructure – File system**
    - Google: GFS. Hadoop: HDFS
  - **Programming model**
    - MapReduce
    - Spark
MapReduce is a **style of programming** designed for:

1. Easy parallel programming
2. Invisible management of hardware and software failures
3. Easy management of very-large-scale data

It has several **implementations**, including Hadoop, Spark (used in this class), Flink, and the original Google implementation just called “MapReduce”
MapReduce: Overview

3 steps of MapReduce

- **Map:**
  - Apply a user-written *Map function* to each input element
    - *Mapper* applies the Map function to a single element
      - Many mappers grouped in a *Map task* (the unit of parallelism)
    - The output of the Map function is a set of 0, 1, or more *key-value pairs*.
  - **Group by key:** Sort and shuffle
    - System sorts all the key-value pairs by key, and outputs key-(list of values) pairs
  - **Reduce:**
    - User-written *Reduce function* is applied to each key-(list of values)

Outline stays the same, *Map* and *Reduce* change to fit the problem
**Map-Reduce: A diagram**

**MAP:**
Read input and produces a set of key-value pairs

**Group by key:**
Collect all pairs with same key (Hash merge, Shuffle, Sort, Partition)

**Reduce:**
Collect all values belonging to the key and output
Example: Word Counting

Example MapReduce task:

- We have a huge text document
- Count the number of times each distinct word appears in the file

Many applications of this:

- Analyze web server logs to find popular URLs
- Statistical machine translation:
  - Need to count number of times every 5-word sequence occurs in a large corpus of documents
The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/machine partnership. "The work we're doing now -- the robotics we're doing -- is what we're going to need."
Word Count Using MapReduce

map(key, value):
# key: document name; value: text of the document
  for each word w in value:
    emit(w, 1)

reduce(key, values):
# key: a word; value: an iterator over counts
  result = 0
  for each count v in values:
    result += v
  emit(key, result)
Map-Reduce: In Parallel

All phases are distributed with many tasks doing the work
MapReduce Pattern

- **Input**
- **key-value pairs**
- **Mappers**
- **Reducers**
- **Output**
MapReduce: Environment

MapReduce environment takes care of:

- **Partitioning** the input data
- **Scheduling** the program’s execution across a set of machines
- Performing the **group by key** step
  - In practice this is the bottleneck
- Handling machine **failures**
- Managing required inter-machine **communication**
Dealing with Failures

- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle and rescheduled
  - Reduce workers are notified when map task is rescheduled on another worker

- Reduce worker failure
  - Only in-progress tasks are reset to idle and the reduce task is restarted
Spark
Problems with MapReduce

- **Two major limitations of MapReduce:**
  - Difficulty of programming directly in MR
    - Many problems aren’t easily described as map-reduce
  - Performance bottlenecks, or batch not fitting the use cases
    - Persistence to disk typically slower than in-memory work

- **In short, MR doesn’t compose well for large applications**
  - Many times one needs to chain multiple map-reduce steps
Data-Flow Systems

- **MapReduce uses two “ranks” of tasks:**
  One for Map the second for Reduce
  - Data flows from the first rank to the second

- **Data-Flow Systems generalize this in two ways:**
  1. Allow any number of tasks/ranks
  2. Allow functions other than Map and Reduce
  - As long as data flow is in one direction only, we can have the blocking property and allow recovery of tasks rather than whole jobs
Spark: Most Popular Data-Flow System

- Expressive computing system, not limited to the map-reduce model

- Additions to MapReduce model:
  - Fast data sharing
    - Avoids saving intermediate results to disk
    - Caches data for repetitive queries (e.g. for machine learning)
  - General execution graphs (DAGs)
  - Richer functions than just map and reduce

- Compatible with Hadoop
Spark: Overview

- Open source software (Apache Foundation)
- Supports **Java, Scala and Python**

- **Key construct/idea:** Resilient Distributed Dataset (RDD)

- **Higher-level APIs:** DataFrames & DataSets
  - Introduced in more recent versions of Spark
  - Different APIs for aggregate data, which allowed to introduce SQL support
Spark: RDD

Key concept **Resilient Distributed Dataset** (RDD)

- Partitioned collection of records
  - Generalizes (key-value) pairs
- Spread across the cluster, **Read-only**
- Caching dataset in memory
  - Different storage levels available
  - Fallback to disk possible

- RDDs can be created from Hadoop, or by transforming other RDDs (you can stack RDDs)
- RDDs are best suited for applications that apply the same operation to all elements of a dataset
Transformations build RDDs through deterministic operations on other RDDs:

- Transformations include `map`, `filter`, `join`, `union`, `intersection`, `distinct`

- Lazy evaluation: Nothing computed until an action requires it

Actions to return value or export data

- Actions include `count`, `collect`, `reduce`, `save`

- Actions can be applied to RDDs; actions force calculations and return values
Task Scheduler: General DAGs

- Supports general task graphs
- Pipelines functions where possible
- Cache-aware data reuse & locality
- Partitioning-aware to avoid shuffles

Tim Althoff, UW CSE481DS: Data Science Capstone, http://www.cs.washington.edu/cse481ds
DataFrame & Dataset

- **DataFrame:**
  - Unlike an RDD, data organized into named columns, e.g. a **table in a relational database**.
  - Imposes a structure onto a distributed collection of data, allowing higher-level abstraction

- **Dataset:**
  - Extension of DataFrame API which provides **type-safe, object-oriented programming interface** (compile-time error detection)

Both built on Spark SQL engine. Both can be converted back to an RDD
Spark vs. Hadoop MapReduce

- **Performance:** Spark normally faster but with caveats
  - Spark can process data in-memory; Hadoop MapReduce persists back to the disk after a map or reduce action
  - Spark generally outperforms MapReduce, but it often needs lots of memory to perform well; if there are other resource-demanding services or can’t fit in memory, Spark degrades
  - MapReduce easily runs alongside other services with minor performance differences, & works well with the 1-pass jobs it was designed for

- **Ease of use:** Spark is easier to program (higher-level APIs)
- **Data processing:** Spark is more general
Data Engineering in Practice
Data Analytics Software Stack

Spark Streaming
Stream processing

GraphX
Graph computation

MLlib
User-friendly machine learning

SparkSQL
SQL API

Hive

Storm

MPI

Spark
Fast memory-optimized execution engine (Python/Java/Scala APIs)

Tachyon
Distributed Memory-Centric Storage System

Hadoop Distributed File System (HDFS)

Mesos
Cluster resource manager, multi-tenancy
Some other technologies to keep an eye on...

**Pros**: Map Reduce with Pandas API  
**Cons**: Unstable, Not much support

**Pros**: Map Reduce via SQL, integrations  
**Cons**: Not as flexible

**Pros**: Loads of integrations, promises a lot  
**Cons**: New-ish player, lots of development ahead
5 min break 😊
Thank you for sharing your feedback with us!

Lab Part:
Intro to Spark