

STATS 769

High Performance Computing

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Overview

- This section of the course (two lectures) explores some more complex and larger-scale computational problems and solutions

Large Data and Parallel Computing Problems

- Data larger than mass storage (not just RAM).
- Jobs that take days (or weeks or months) to run.
- Job scheduling and load balancing (at scale).
- Fault tolerance (redundancy).
- Checkpointing.

Large Data and Parallel Computing Solutions

- Get an even bigger/faster computer
 - Supercomputers (NeSI)
 - GPUs
- Combine lots of smaller computers
 - Hadoop MapReduce
 - Apache Spark

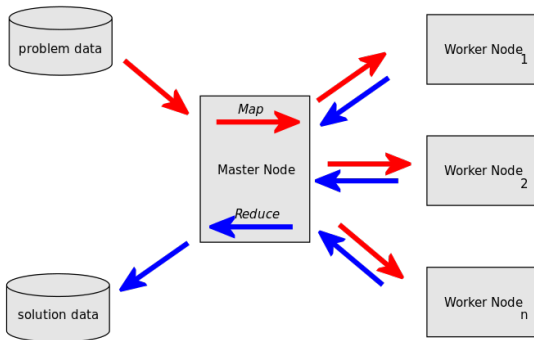
Apache Hadoop

- HPC on standard hardware.
- Fault tolerance (data replication, node monitoring)
- Distributed file system (HDFS)
- Resource management and job scheduling (YARN)
- MapReduce engine
- We are only going to look at an R interface to Hadoop.

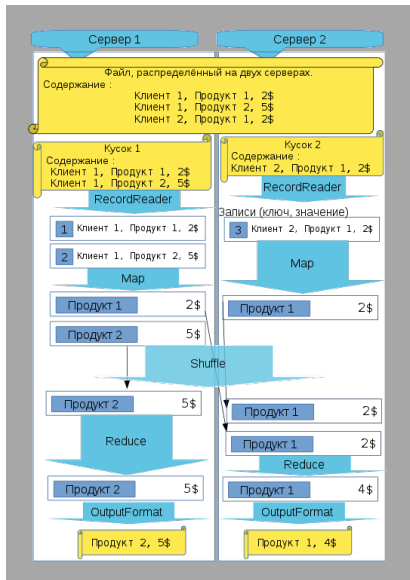
MapReduce

- Split step.
Break input into chunks.
- **Map step.**
For each chunk, generate one or more key-value pairs.
- Combine step.
Collect all key-value pairs with same key.
- Shuffle/sort step.
Transfer key-value pairs with same key to reducers.
- **Reduce step.**
For each key, generate one or more key-value pairs.
- Fast and easy for certain types of jobs; slow and difficult for others (Spark the new alternative)
- Significant set up/configuration costs

MapReduce



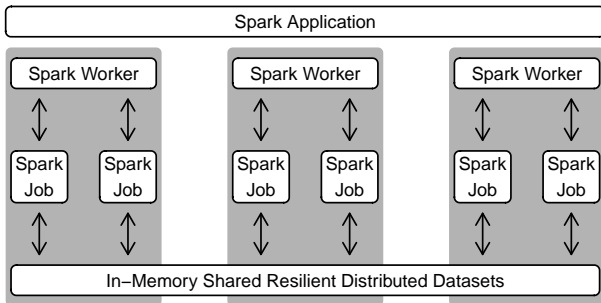
MapReduce



- The **rmr2** package provides an R interface to MapReduce (and Hadoop).
- We can define mappers and reducers in R code.
- Mapper and reducer work done in R.
- Input and output in Hadoop (disk based).
- Useful for Tidying and Transforming; harder to perform Modelling.
- `from.dfs()` to get result back to R.

- Alternative to MapReduce.
- Reuse HDFS and YARN (or alternatives).
- In-memory computation (rather than disk-based).
- Better for iterative algorithms (as used in Modelling).
- Machine Learning library provided (for Modelling).
- We are only going to look at an R interface to Spark.

Spark



- The **sparklyr** package provides an R interface to Spark.
- R is just used to direct traffic; R code is converted to Spark (SQL) code.
- Work done in Spark (RAM based).
- R code creates references to Spark DataFrames (memory is in Spark not R).
- Useful for Tidying and Transformation and Modelling.
- Use **dplyr** functions for Tidying and Transforming; dplyr code converted to Spark code.
- Use `ml_*()` functions for Modelling.
- `spark::collect()` to get result back to R.

- Mahuika:
 - Cray CS400 Cluster High Performance Computer
8,424 × 2.1 GHz Intel Broadwell cores
30 Terabytes of memory (in total)
 - Cray CS400 Virtual Labs Cluster
640 × 2.1GHz Intel Broadwell Cores
12.3 Terabytes of memory (in total)
8 Nvidia Tesla P100 GPGPUs
- Maui:
 - Cray XC50-LC Supercomputer
18,650 × 2.4GHz Intel Skylake cores
66.8 Terabytes of memory (in total)
 - Cray CS500 Virtual Labs Cluster
1,120 × 2.4GHz Intel Skylake cores
21.5 Terabytes of memory (in total)
8 Nvidia Tesla P100 GPGPUs

- Designed for BATCH computing.
- `ssh` (and `scp`) to access.
- Write R script.
- Define jobs with a SLURM script
(Simple Linux Utility for Resource Management)
- Use `sbatch` to submit SLURM script.
- Use `squeue` to view job status

- GPUs have (many) more cores than CPUs
(my desktop GPU has 1792 cores)
- GPUs can perform certain operations much faster than CPUs
- GPUs tend to have smaller RAM
(my desktop GPU has 8 GB RAM)
- Code has to be written in a special language
(e.g., CUDA for NVIDIA graphics cards, OpenCL for AMD and NVIDIA)
- The **gpuR** package provides an R interface for matrix operations via OpenCL.
- Some packages, like **keras**, automatically make use of GPUs.

- NeSI High performance computing and analytics
<https://www.nesi.org.nz/services/high-performance-computing>
- **sparklyr**
<https://spark.rstudio.com/>
- **RHadoop** (including **rmr2**)
<https://github.com/RevolutionAnalytics/RHadoop/wiki>