



BUILDING A RESEARCH DATA
SCIENCE PLATFORM FROM
INDUSTRIAL MACHINES

FANG (CHERRY) LIU (PACE)

DUEN HORNG (POLO) CHAU (CSE)

FU SHEN, NEIL BRIGHT, MEHMET

BELGIN CREATING THE NEXT

#### OUTLINE



- Motivations and Goals
- Challenges
- Existing Hadoop distributions
- Cloud based solutions
- Configuration tools
- Software and hardware configuration
- Validation tests
- Conclusion and ongoing project

### MOTIVATIONS AND GOAL



- Free cycles from 200 compute nodes donated by yahoo
- Deep understanding on Hadoop ecosystem from ground-up building experience
- Freedom on trying out up-to-date software to bring more research value in which existing cloud solutions don't provide
- Education platform

Turning industry machines into a high-performance research data science platform based on Hadoop facilitates computing cycle reuse.

### **CHALLENGES**



- Performance: how to get most performance from existing hardware?
- Maintenance: how to make the software upgrades and hardware maintenance minimally intrusive? -> configuration tools and software stack choice
- Sustainability: how to enable horizontal scalability to more compute nodes in future. -> hardware configuration

## **EXITING HADOOP DISTRIBUTIONS**



Hadoop distributions like Hortonworks and Cloudera have drawbacks for a research DSP:

- Vendor code less compatible with configuration tools
- Infrequent update schedules
- Limited library selection in enterprise releases
- Harder to debug proprietary libraries without fee-based consulting

Apache Hadoop gives most freedom as a research software stack as it can be tailored to meet local requirements, reduce the cost, etc.

### **CLOUD BASED SOLUTION**



- Amazon Elastic Compute Cloud (Amazon EC2) requires system administrator knowledge of software installation
- Amazon Elastic MapReduce (Amazon EMR) does not benefit from Hadoop Distributed File System (HDFS) without raising the cost
- Microsoft Azure Data Lake Analytics (DLA) and HDInsight use Hortonworks Hadoop distribution which poses some software limitation
- Google Cloud Datproc (GCD) provides higher I/O operations through SSD, but offers fewer types of machine instances

## **CLOUD BASED SOLUTION (CONT.)**



- Hadoop ecosystem as a black box
- Provides quick start on research, a lot of universities and companies adopt cloud solution
- Education usage with some costs, multiple Georgia Tech courses are using Amazon EMR, EC2 and Microsoft HDInsight for projects

## **CONFIGURATION TOOLS**



- Ansible, Puppet and Chef are software configuration tools widely used:
  - Ansible is the simplest solution, low learning curve, and employs a pushbased masterless approach
  - Chef and Puppet are pull-based approach, but with steeper learning curve without significant programming experience
- The system is configured with Puppet tool (preexisting) for machines's OS and to provision the bare metal.
- Ansible is used to configure all Hadoop related tasks:
  - Propagate the software installations
  - Create needed file folders: /dfs/hadoop, haddoop/pids, hadoop/logs, etc

### **HARDWARE**





- 200 compute nodes donated by Yahoo (in four racks)
  - Runs Red Hat Enterprise Linux 6.7
  - 2x4-core Intel xeon CPUs (2.5GHz)
  - 24GB memory
  - Service nodes use RAID 1 mirroring (2x1TB)
  - DataNodes use separate data and OS disks with 500GB each

### SOFTWARE CONFIGURE



- As paper was written, 40 nodes were online
  - 24 nodes run Hadoop (v 2.7.2) and Spark (v 1.6.1)
  - 12 nodes run Hbase (v 1.1.5) and OpenTSDB (2.2.0)
  - Other nodes run as service nodes, such as Ansible server
- As now, there are 40 more nodes are ready to be deployed to existing cluster, the goal is to:
  - 34 nodes for Hadoop cluster
  - 42 nodes for OpenTSDB cluster

## **VALIDATION AND TESTS**



### **Test data sets**

| IDs | Size  |
|-----|-------|
| Ds1 | 88GB  |
| Ds4 | 300GB |

## Test program:

- Wordcount with Ds4 (300GB)
- SparkML Linear Regression on Ds1 (88GB)

# VALIDATION AND TESTS (CONT.)



# Data size 300GB (Ds4), MapReduce Wordcount

| Map.memory.mb               | 4096 | 2048 | 1560 | 2560 |
|-----------------------------|------|------|------|------|
| Map.java.optsXmx(MB)        | 3686 | 1843 | 1400 | 2304 |
| Reduce.memory.mb            | 5120 | 2048 | 2048 | 2560 |
| Reduce.java.opts<br>Xmx(MB) | 4608 | 1843 | 1843 | 2304 |
| Runtime (Hours)             | 2.18 | 1.31 | 1.66 | 2.11 |

# VALIDATION AND TESTS (CONT.)



# Dataset size 88G (Ds1) SparkML Linear Regression

| Driver-memory       | 8G | 6G | 8G | 8G | 10G | 8G |
|---------------------|----|----|----|----|-----|----|
| Executor-<br>memory | 4G | 4G | 4G | 8G | 8G  | 4G |
| Num-executors       | 8  | 4  | 4  | 8  | 8   | 8  |
| Executor-core       | 4  | 8  | 8  | 4  | 4   | 8  |
| Runtime (mins)      | 27 | 38 | 41 | 49 | 80  | 23 |

### ONGOING PROJECT



- The interdisciplinary research involves school of industry engineering and school of computational science and engineering
- research considers a large scale settings that involves thousands of power generating assets, each equipped with hundreds of sensors to monitor its condition and performance.
- Reduce the frequency of false alarms in multi-stream
- Building a scalable analytics architecture with Data ingestion in OpenTSDB cluster, and anomaly detection (FDR) on hadoop/spark cluster

#### CONCLUSION



- The valuable ground-up building experience could be shared to other institutes:
  - Nontrivial hardware design decisions
  - Configuration tool choices
  - Node integration into existing HPC infrastructure
  - Partitioning resource to meet different application's requirement
- In-depth exiting tools comparison study gives more insights for technology adaptation
- In house big data platform gives more freedom to try out upto-date software and brings more research value in existing cloud solution won't provide