Introduction to Hadoop, MapReduce and HDFS for Big Data Applications

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Nice Systems
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You Will Learn About:

- Hadoop history and general information
- Hadoop main components and architecture
- How to work with HDFS
- MapReduce and how it works
Chapter 1: Introduction to Hadoop

- The amount of data processing in today’s life
- What Hadoop is why it is important
- Hadoop comparison with traditional systems
- Hadoop history
- Hadoop main components
There is Lots of Data out There!

Real Facts:

- New York Stock Exchange generates 1TB/day
- Google processes 700PB/month
- Facebook hosts 10 billion photos taking 1PB of storage
Amount of Data will Only Grow!

- Machine/System Logs
- Retail transaction logs
- Vehicle GPS traces
- Social Data (Facebook, Twitter, etc….)
Importance of Data

Business Success today heavily depends on:

- Ability to Store and Analyze large data sets…
  - Netflix – Folks who purchased movie A are more likely to also purchase movie B and C
- Ability to extract other organizations’ data…
  - Amazon Web Services
  - Mashup Applications
Netflix paid 1 million dollars to solve big data problem !!!!
Data Storage and Analysis – Problem #1

- **Problem #1: Read/Write to disk is slow**
  - 1TB drives are the norm, transfer speed is still at 100Mb/sec

- **Solution: Use multiple disks for parallel reads**
  - 1HD = 100Mb/sec
  - 100HD = 10Gb/sec
Data Storage and Analysis – Problem #2

Problem #2: Hardware Failure

- Single machine failure
- Single disk failure

Solution:

- Keep multiple copies of Data
- RAID or HDFS
Problem #3: How do you merge data from different reads?

- Only complete results need to be taken into consideration and results of the failed jobs will be ignored.
- Data needs to be in compressed format for network transmission.

Solution: Distributed Processing or Hadoop MapReduce.
High Performance Computing (HPS) and Grid Computing

- Large-scale data processing has been done for years
- Distribute work across cluster of machines with shared filesystem
- Example: DNA sequencing, stock market predictions, etc.
Grid Computing Challenges

- Works well for process-intensive jobs
  - (Monte-Carlo simulation, DNA sequencing, etc.)
- Problematic accessing large data volumes
- Network bandwidth can be a bottleneck, causing nodes to become idle
- Coordinating processes and node failures is a challenge
Hadoop Main Components: HDFS and MapReduce

- Hadoop provides a reliable shared storage and analysis system for large-scale data processing
  - Storage provided by **HDFS**
  - Analysis provided by **MapReduce**
## Hadoop MapReduce vs RDMS

<table>
<thead>
<tr>
<th></th>
<th>Traditional RDMS</th>
<th>Hadoop MapReduce</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data size</strong></td>
<td>Gigabytes</td>
<td>Petabytes</td>
</tr>
<tr>
<td><strong>Access</strong></td>
<td>Interactive</td>
<td>Batch</td>
</tr>
<tr>
<td><strong>Updates</strong></td>
<td>Read and Write many times</td>
<td>Write once, Read many times</td>
</tr>
<tr>
<td><strong>Structure</strong></td>
<td>Static schema</td>
<td>Dynamic schema</td>
</tr>
<tr>
<td><strong>Integrity</strong></td>
<td>High</td>
<td>Low in simple setup, can be improved with additional servers</td>
</tr>
<tr>
<td><strong>Scaling</strong></td>
<td>Non-linear</td>
<td>Linear(up to 10,000 machines as of Dec 2012)</td>
</tr>
</tbody>
</table>
Hadoop MapReduce vs RDMS…
cont.

- MapReduce fits well to analyze whole dataset in a batch fashion
- RDMS is for real-time data retrieval with low-latency and small data sets
Hadoop Origin

- Created by Doug Cutting, part of Apache project
- 2004: Google publishes GFS paper
- 2005: Nutch (open source web search) uses MapReduce
- 2008: Becomes Apache top-level project, was Lucene sub-project before.
- 2009: Yahoo used Hadoop to sort 1TB in 62 sec.
- 2013: Hadoop is used by hundreds of the companies
Hadoop Components

- **HDFS** – Distributed Filesystem
- **MapReduce** – Distributed Data Processing Model
Hadoop Components... cont.

- **Hive** – Distributed Data Warehouse, provides SQL-based query language
- **HBase** – Distributed column-based database
- **Pig** – Data Flow Language and execution environment
Summary

In this chapter we have covered:

- What Hadoop is and why it is important
- Hadoop comparison with traditional systems
- Hadoop origin
- Hadoop main components

Questions?
Chapter 2:
Hadoop Distributed File System (HDFS)

- HDFS Overview and Design
- HDFS Architecture
- HDFS File Storage
- Component Failures and Recoveries
- Block Placement
- Balancing the Cluster
HDFS Overview

- Based on Google’s GFS (Google File System)
- Provides redundant storage of massive amounts of data
  - Using commodity hardware
- Data is distributed across all nodes at load time
  - Provides for efficient Map Reduce processing (discussed later)
HDFS Design

- Runs on commodity hardware
  - Assumes high failure rates of the components
- Works well with lots of large files
  - Hundreds of Gigabytes or terabytes in size
- Built around the idea of “write-once, read-many-times”
- Large streaming reads
  - Not random access
- High throughput is more important than low latency
HDFS Architecture

- Operates on top of an existing filesystem
- Files are stored as ‘Blocks’
  - Block’s default size – 64MB
- Provides reliability through replication
  - Each Block is replicated across several Data Nodes
- NameNode stores metadata and manages access
- No data caching due to large datasets
HDFS Architecture Diagram

Metadata ops

Namenode

/home/foo/data, 3, ...

Block ops

Datanodes

Replication

Blocks

Client

Read

Write

Rack 1

Rack 2
HDFS File Storage

- **NameNode**
  - Stores all metadata: filenames, locations of each block on DataNodes, file attributes, etc…
  - Keeps metadata in RAM for fast lookup
  - Filesystem metadata size is limited to the amount of available RAM on NameNode

- **DataNode**
  - Stores file contents as blocks
  - Different blocks of the same file are stored on different DataNodes
  - Same block is replicated across several DataNodes for redundancy
  - Periodically sends a report of all existing blocks to the NameNode
DataNode Failure and Recovery

- DataNodes exchange heartbeats with NameNode
- If no heartbeat received within a certain time period – DataNode is assumed to be lost
  - NameNode determines which blocks were on the lost node
  - NameNode finds other copies of these ‘lost’ blocks and replicates them to other nodes
  - Block replication is actively maintained
NameNode Failure

- Losing a NameNode is equivalent to losing all the files on the filesystem
- Hadoop provides two options:
  - Back up files that make up the persistent state of the filesystem (local or NFS mount)
  - Run a Secondary NameNode
Secondary NameNode

- Is not a failover NameNode
  - A real HA solution still needed
- Performs memory-intensive administrative functions
  - NameNode keeps metadata in memory and writes changes to an Editlog.
  - Secondary NameNode periodically combines a prior filesystem snapshot and Editlog into a new snapshot
  - New snapshot is sent back to the NameNode
- Recommended to run on a separate machine
  - It requires as much RAM as the primary NameNode
Block Placement

- **Default strategy:**
  - One replica on local node
  - Second replica on a node in the remote rack
  - Third replica on the same node in the remote rack
  - Additional replicas are random

- **Clients always read from nearest node**
Block Placement ... cont.

- Client retrieves a list of DataNodes on which to place replicas of a block
- Client writes block to the first DataNode
- The first DataNode forwards the data to the next DataNode in the Pipeline
- When all replicas are written, the Client moves on to write the next block in file
- Please, note that multiple machines are involved in writing one files and they could be different machines
Balancing Hadoop Cluster

- Hadoop works best when blocks are evenly spread out
- Goal: Have % Disk Full on DataNodes at the same level
- Balancer – Hadoop daemon
  - `% start-balancer.sh`
  - Re-distributes blocks from over-utilized to under-utilized DataNodes
  - Run it when new DataNodes are added
  - Runs in the background and can be throttled to avoid network congestion/negative cluster impact
Summary

In this chapter we have covered:
- HDFS Overview and Design
- HDFS Architecture
- HDFS File Storage
- Component Failures and Recoveries
- Block Placement
- Balancing the Cluster

Questions?
Chapter 3: Working with HDFS

- Ways of accessing data in HDFS
- Common HDFS operations and commands
- Different HDFS commands
- Internals of a file read in HDFS
- Data copying with ‘distcp’
Ways of Accessing Data in HDFS

Data can be accessed with the following methods:

- Programmatically via Java API
- Via command line
- Via web-interface
Most Common HDFS Operations

- Creating directory
- Removing directory
- Copying files to/from HDFS
- List content of the directory
- Display file content
- Analyze space allocation
- Check permissions/write ability
- Set replication for specific directory
Commands

- `hadoop dfs -mkdir <path>`
  - Create a directory in specified location

- `hadoop dfs -rmdir <src>`
  - Remove all directories which match the specified file pattern

- `hadoop -put <localsrc> ... <dst>`
  - copy files from the local file system into fs
Commands… cont.

- hadoop dfs -copyFromLocal <localsrc> ... <dst>
  - Identical to the -put command

- hadoop dfs -moveFromLocal <localsrc> ... <dst>
  - Same as -put, except that the source is deleted after it's copied.
- **ls <path>**
  - List the contents that match the specified file pattern

- **lsr <path>**
  - Recursively list the contents that match the specified file pattern

- **cat <src>:**
  - Fetch all files that match the file pattern <src> and display their content on stdout
Commands… cont.

- **df [<path>]**
  - Shows the capacity, free and used space of the filesystem

- **du <path>**
  - Show the amount of space, in bytes, used by the files that match the specified file pattern

- **touchz <path>**
  - Create empty file at <path>
Internals of a File Read in HDFS
Internals of a File Read… cont.

- Client is guided by the NameNode to the best DataNode for each block
- Client contacts DataNodes directly to retrieve data
- NameNode only services block locations requests
- This design allows HDFS to scale to large number of clients
Parallel Copying with distcp

- Hadoop comes with a useful program called distcp for copying large amounts of data to and from Hadoop filesystems in parallel
- `hadoop distcp <src> <dst>`
- distcp is implemented as a MapReduce job where the copying is done by the maps that run in parallel across the cluster
Summary

In this chapter we have covered:

- Ways of accessing data in HDFS
- Common HDFS operations and commands
- Different HDFS commands
- Internals of a file read in HDFS
- Data copying with ‘distcp’

Questions?
Chapter 4: Map Reduce Abstraction

- What MapReduce is and why it is popular
- The Big Picture of the MapReduce
- MapReduce process and terminology
- MapReduce components failures and recoveries
What Is MapReduce?

- MapReduce is a method for distributing a task across multiple nodes.
- Each node processes data stored on that node.
- Consists of two phases:
  - Map
  - Reduce
- Map: \((K1, V1) \rightarrow (K2, V2)\)
- Reduce: \((K2, \text{list}(V2)) \rightarrow \text{list}(K3, V3)\)
Why Map Reduce is So Popular?

- Automatic parallelization and distribution (The biggest advantage!!! )
- Fault-tolerance (individual tasks can be retried)
- Hadoop comes with standard status and monitoring tools
- A clean abstraction for developers
- MapReduce programs are usually written in Java (possibly in other languages using streaming)
MapReduce: The Big Picture

Input key-value pairs

Data store 1

map

(key 1, values...)

(key 2, values...)

(key 3, values...)

... 

Data store n

map

(key 1, values...)

(key 2, values...)

(key 3, values...)

== Barrier == : Aggregates intermediate values by output key

key 1, intermediate values

reduce

final key 1 values

key 2, intermediate values

reduce

final key 2 values

key 3, intermediate values

reduce

final key 3 values
Map Process

\[
\text{map (in\_key, in\_value) -> (out\_key, out\_value)}
\]
Reduce Process

\[ \text{reduce} \ (\text{out\_key}, \ \text{out\_value\ list}) \rightarrow (\text{final\_key}, \ \text{final\_value}) \ \text{list} \]
MapReduce: Word Count Example

Map

// assume input is a
// set of text files
// k is a line offset
// v is the line for that offset

let map(k, v) =
foreach word in v:
    emit(word, 1)

Reduce

// k is a word
// vals is a list of 1s

let reduce(k, vals) =
    emit(k, vals.length())
Input/Output for Map Reduce Job

File1.txt
California is a great place

File2.txt
Los_Angeles is the biggest city in California

- California 2
- great 1
- place 1
- Los_Angeles 1
- biggest 1
- city 1
- is 2
- a 1
- in 1
Word Count Mapper

California is a great place

<table>
<thead>
<tr>
<th>Key</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>1</td>
</tr>
<tr>
<td>is</td>
<td>1</td>
</tr>
<tr>
<td>a</td>
<td>1</td>
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<td>great</td>
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<td>Los_Angeles</td>
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<td>California</td>
<td>1</td>
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</tbody>
</table>
### Word Count Mapper Reducer Transition

#### Mapper to Reducer

<table>
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<tr>
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<tbody>
<tr>
<td>California</td>
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<tbody>
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<th>Value</th>
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<tbody>
<tr>
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<td>1</td>
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<td>city</td>
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<td>in</td>
<td>1</td>
</tr>
<tr>
<td>California</td>
<td>1</td>
</tr>
</tbody>
</table>
Word Count Input to Reducer

<table>
<thead>
<tr>
<th>Key</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>{1,1}</td>
</tr>
<tr>
<td>Los_Angeles</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key</th>
<th>Values</th>
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<tbody>
<tr>
<td>a</td>
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<td>great</td>
<td>1</td>
</tr>
<tr>
<td>place</td>
<td>1</td>
</tr>
</tbody>
</table>
public static class Map extends MapReduceBase implements Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(LongWritable key, Text value,
                    OutputCollector<Text,IntWritable> output,
                    Reporter reporter) throws IOException {
        String line = value.toString();
        StringTokenizer tokenizer = new StringTokenizer(line);
        while (tokenizer.hasMoreTokens()) {
            word.set(tokenizer.nextToken());
            output.collect(word, one);
        }
    }
}
Let’s take a look how we can put together code to drive this data flow:

```java
public void map(LongWritable key, Text value, Context context) throws
IOException, InterruptedException {
    String line = value.toString();
    StringTokenizer tokenizer = new StringTokenizer(line);
    while (tokenizer.hasMoreTokens()) {
        word.set(tokenizer.nextToken());
        context.write(word, one);
    }
}
```

Key – bytes offset from the beginning of the data file
Value – line of the data file
Context – is an object that collects output and has other reporting capabilities
### Word Count Reducer Output

<table>
<thead>
<tr>
<th>Key</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>2</td>
</tr>
<tr>
<td>Los_Angeles</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key</th>
<th>Values</th>
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</thead>
<tbody>
<tr>
<td>a</td>
<td>1</td>
</tr>
<tr>
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</tr>
<tr>
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<tr>
<td>place</td>
<td>1</td>
</tr>
</tbody>
</table>
```java
public static class Reduce extends MapReduceBase implements Reducer<Text, IntWritable, Text, IntWritable> {
    public void reduce(Text key, Iterator<IntWritable> it, OutputCollector<Text, IntWritable> output, Reporter reporter) throws IOException {
        int sum = 0;
        while (it.hasNext()) {
            sum += it.next().get();
        }
        output.collect(key, new IntWritable(sum));
    }
}
```
Terminology

- The client program submits a job to Hadoop
  - The job consists of a mapper, a reducer, and a list of inputs
- The job is sent to the JobTracker process on the Master Node
- Each Slave Node runs a process called the TaskTracker
- The JobTracker instructs TaskTrackers to run and monitor tasks
- A Map or Reduce over a piece of data is a single task
- A task attempt is an instance of a task running on a slave node
MapReduce: High Level
MapReduce Failure Recovery

- Task processes send heartbeats to the TaskTracker!
- TaskTrackers send heartbeats to the JobTracker!
- Any task that fails to report in 10 minutes is assumed to have failed – its JVM is killed by the TaskTracker!
- Any task that throws an exception is said to have failed!
- Failed tasks are reported to the JobTracker by the TaskTracker!
- The JobTracker reschedules any failed tasks – it tries to avoid rescheduling the task on the same TaskTracker where it previously failed!
- If a task fails more than 4 times, the whole job fails
Task Tracker Recovery

- Any TaskTracker that fails to report in 10 minutes is assumed to have crashed
  - All tasks on the node are restarted elsewhere
  - Any TaskTracker reporting a high number of failed tasks is blacklisted, to prevent the node from blocking the entire job
  - There is also a “global blacklist”, for TaskTrackers which fail on multiple jobs!

- The JobTracker manages the state of each job – partial results of failed tasks are ignored
Summary

In this chapter we have covered:

- What MapReduce is and why it is popular
- The Big Picture of the MapReduce
- MapReduce process and terminology
- MapReduce components failures and recoveries

Questions?
The SNIA Education Committee thanks the following individuals for their contributions to this Tutorial.

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October 2013

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