CS 455: Introduction To Distributed Systems [Hadoop/HDFS]

Trying to have your cake and eat it too
Each phase pines for tasks with locality and their numbers on a tether
Alas within a phase, you get one, but not the other

Who gets what?
Stay tuned to find out

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Frequently asked questions from the previous class survey

- Information in auxiliary files?
- What is close to completion?
- Significant differences and implications on coding with different Hadoop versions?

Topics covered in this lecture

- Combiner Functions
- Hadoop Distributed File System

API differences

The old and new MapReduce APIs

- The new API favors abstract classes over interfaces
  - Make things easier to evolve
- New API is in `org.apache.hadoop.mapreduce` package
  - Old API can be found in `org.apache.hadoop.mapred`
- New API makes use of context objects
  - `Context` unifies roles of `JobConf`, `OutputCollector`, and `Reporter` from the old API

The old and new MapReduce APIs

- In the new API, job control is done using the `Job` class rather than using the `JobClient`
- Output files are named slightly differently
  - Old API: Both map and reduce outputs are named `part-nnnn`
  - New API: Map outputs are named `part-m-nnnn` and reduce outputs are named `part-r-nnnn`

The old and new MapReduce APIs

- The new API's `reduce()` method passes values as `Iterable` rather than as `Iterator`
  - Makes it **easier to iterate** over values using the `for-each` loop construct

```
for (VALUEIN value: values) {
  …
}
```


MapReduce tasks & Split strategies

Hadoop divides the input to a MapReduce job into fixed-sized pieces

- These are called **input-splits** or just splits
- Creates **one map task per split**
  - Runs *user-defined map function* for each **record** in the split

Split strategy: Having many splits

- Time taken to process split is small compared to processing the whole input
- Quality of **load balancing** increases as splits become *fine-grained*
  - Faster machines process proportionally more splits than slower machines
  - Even if machines are identical, this feature is desirable
    - Failed tasks get relaunched, and there are other jobs executing concurrently

Split strategy: If the splits are too small

- **Overheads** for managing splits and map task creation dominates total job execution time
- Good split size tends to be an HDFS **block**
  - This could be changed for a cluster or specified when each file is created

Scheduling map tasks

- Hadoop does its best to run a map task on the *node where input data resides* in HDFS
  - **Data locality**
- What if all three nodes holding the HDFS block replicas are busy?
  - Find free map slot on node in the same rack
  - Only when this is not possible, is an off-rack node utilized
    - Inter-rack network transfer

Why the optimal split size is the same as the block size …

- Largest size of input that can be stored on a single node
- If split size spanned two blocks?
  - Unlikely that any HDFS node has stored *both* blocks
  - Some of the split *will have to be transferred* across the network to node running the map task
    - Less efficient than operating on local data without the network movement

MANAGING OUTPUTS

Map task outputs

- Stored on the local disk
  - Not HDFS
- Once the job is complete, **intermediate map outputs are thrown away**
  - Storing in HDFS with replication is an overkill

Reduce tasks do not have the advantage of data locality

- Input to a single reduce task
  - Output from **all the mappers**
  - Sorted map outputs transferred over the network to node where reduce task is running
    - **Merged and then passed** to the reduce function
- Output of reduce task stored on HDFS
  - One replica of block is stored on local node, other replicas are stored on off-rack nodes

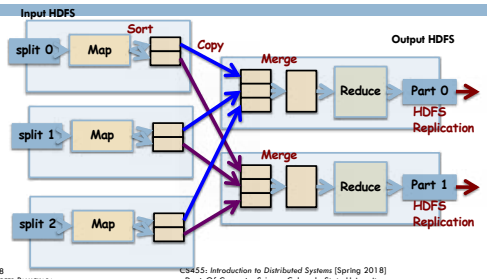
Number of reduce tasks

- Not governed by the size of the input
- Specified independently

When there are multiple reducers

- Maps **partition** their outputs
  - One partition for ***each*** reduce task
  - There can be many keys in each partition
  - Records for a given key are all in the same partition
- Partitioning controlled with a *partitioning function*
  - Default uses a hash function to bucket the key space

MapReduce Dataflow



COMBINER FUNCTIONS

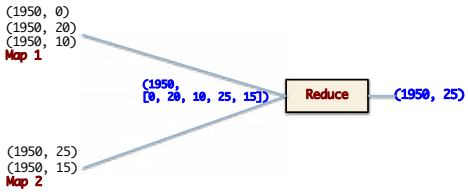
Combiner functions

- Many MapReduce jobs are limited by the available network bandwidth
  - Framework has mechanisms to *minimize the data transferred* between map and reduce tasks
- A **combiner** function is run on the map output
  - Combiner output fed to the reduce task

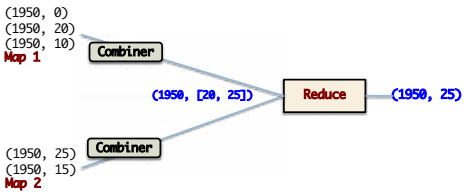
Combiner function

- No guarantees on *how many times* Hadoop will call this on a map output record
  - The combiner should, however, result in the same output from the reducer
- **Contract** for the combiner **constrains the type of function** that can be used

Combiner function: Let's look at the maximum temperature example [1/2]



Combiner function: Let's look at the maximum temperature example [2/2]



A closer look at the function calls

- `max(0, 20, 10, 25, 15) = max (max(0, 20, 10), max(25, 15)) = max (20, 25) = 25`
- Functions with this property are called **commutative** *and* **associative**
  - Commutative: Order of operands (5+2) + 1= 5 + (2+1)
    - Division and subtraction are not commutative
  - Associative: Order of operators 5 x (5x3) = (5x5)x3
    - Vector cross products are not

Not all functions posses the commutative and associative properties

- What if we were computing the mean temperatures?
- We can cannot use mean as our combiner function

```
mean(0, 20, 10, 25, 15) = 14
BUT
mean(mean(0, 20, 10), mean(25, 15)) =
   mean(10, 20) = 15
```


Combiner: Summary

- The combiner does not replace the reduce function
  - Reduce is still needed to process records from different maps
- But it is useful for cutting down traffic from maps to the reducer

Specifying a combiner function

```
public class MaxTemperatureWithCombiner {

   public static main(String[] args) throws Exception {
      Job job = Job.getInstance();
      job.setJarByClass(MaxTemperature.class);
      job.setJobName("Max temperature");

      FileInputFormat.addInputPath(job, new Path(args[0]));
      FileOutputFormat.setOutputPath(job, new Path(args[1]));

      job.setMapperClass(MaxTemperatureMapper.class);
      job.setCombinerClass(MaxTemperatureReducer.class);
      job.setReducerClass(MaxTemperatureReducer.class);

      job.setOutputKey(Text.class);
      job.setOutputValueClass(IntWritable.class);

      System.exit(job.waitForCompletion(true) ? 0: 1);

   }
}
```


HADOOP DISTRIBUTED FILE SYSTEM

Rationale

- Datasets often outgrow storage capacity of a single machine
  - Necessary to **partition** data across multiple machines
- File systems managing storage access *across* a network of machines
  - Distributed file systems

HDFS is designed for storing …

- **Very large** files
  - File sizes are in the order of 100s of GB or TB
- With **streaming data access** patterns
  - Write-once, read many times pattern
  - Each analysis involves a large portion of the dataset
    - Time to read dataset is more important than latency for the first record
- On **commodity hardware**

What is HDFS not suitable for? [1/2]

- **Low-latency** data access
- Lots of **small files**
  - Name nodes holds file system metadata in memory
  - Each file, directory and block takes about 150 bytes
    - If there were 10^6 files each of which had 1 block
      - 300 MB of memory
  - Millions of files are feasible but not billions of files

What is HDFS not suitable for? [2/2]

- **Multiple writers**, arbitrary file modifications
- HDFS does not support:
  - Multiple concurrent writers
  - Modifications at arbitrary offsets

Block

- Filesystems for a single disk, deal with data in blocks
  - Integral number of the HDD block size
- Block sizes
  - Filesystem blocks are a few KB
  - Disk blocks are normally 512 bytes

HDFS Blocks

- Has a much larger size: **128 MB** [default]
- Files are **broken** into block-sized *chunks*
  - Each chunk is stored as an independent unit
- If the last chunk is less than the HDFS block size?
  - No space is wasted because the blocks are themselves stored as files

Why is the block-size so big?

- **Time to transfer** data from disk can be made significantly larger than the time to seek first block
- If the seek time is 10 ms and transfer rate is 100 MB/sec?
  - To make seek time 1% of the transfer time, block size should be 100 MB
- Must be careful not to overdo block size increase
  - Since tasks operate on blocks, the number of tasks could reduce.

Benefits of the block abstraction in distributed file systems

- File can be **larger than any single disk** in the cluster
- Simplifies the storage subsystem
  - File metadata (including permissions) handled by another subsystem and not stored with the block

Blocks and replication

- Each block is replicated on a small number of **physically separate** machines
- If a block becomes unavailable?
  1. Copy *read from another location* transparently
  2. That block is also *replicated from its alternative locations* to other live machines
     - Bring replication factor back to the desired level

HDFS' fsck command

- List blocks that make up each file in the filesystem

```
% hadoop fsck / -files -blocks
```


Nodes in the HDFS

- Namenode {master}
- Datanode {worker}

Namenode

- Manages filesystem **namespace**
- Maintains filesystem tree and metadata
  - For all files and directories in the tree
- Information stored persistently on local disk in two files
  - **Namespace image** and the **edit log**

Tracking location of blocks comprising files

- Namenode knows about datanodes on which all blocks of a file are located
- The locations of the blocks are not stored persistently
  - Information **reconstructed** from datanodes during start up

Interacting with HDFS

- HDFS presents a **POSIX-like** file system interface
- Client code does not need to know about the namenode and datanode to function

Datanodes

- Store and retrieve blocks
  - Initiated by the client or the namenode
- **Periodically reports** back to the namenode with the *list of blocks* that they store

Failure of the namenode

- Decimates the filesystem
- **All files on the filesystem are lost**
  - No way of knowing how to reconstitute the files from the blocks

Guarding against namenode failures

- **Backup** files comprising the persistent state of the **filesystem metadata**
  - Hadoop can be configured so that the namenode writes its persistent state to multiple filesystems
    - Writes are synchronous and atomic
- Run a **secondary** namenode
  - Does not act as a namenode
  - Periodically merges namespace image with edit log

Secondary namenode

- Runs on a separate physical machine
  - Requires as much memory as the namenode to perform the merge operation
- Keeps a copy of the merged namespace image
  - Can be used if the namenode fails
- However, the secondary namenode **lags** the primary
  - Data loss is almost certain

HDFS Federation (introduced in 0.23)

- On large clusters with many files, memory is a limiting factor for scaling
- HDFS federation allows scaling with the addition of namenodes
  - Each manages a portion of the filesystem namespace
    - For e.g., one namenode for `/user` and another for `/share`

HDFS Federation [1/2]

- Each namenode manages a namespace volume
  - Metadata for the namespace and block pool
- Namespace volumes are **independent** of each other
  - No communications between namenodes
  - Failure of one namenode does not affect availability of another

HDFS Federation [2/2]

- Block pool storage is **not partitioned**
- Datanodes register with each namenode in the cluster
  - Store blocks from multiple blockpools

Recovering from a failed namenode [1/2]

- Admin starts a new primary namenode
  - With one of the filesystem metadata replicas
  - Configure datanodes and clients to use this namenode
- New namenode unable to serve requests until:
  1. Namespace image is **loaded** into memory
  2. **Replay** of edit log is complete
  3. Received enough **block reports** from datanodes to leave safe mode

Recovering from a failed namenode [2/2]

- Recovery can be really long
  - On large clusters with many files and blocks this can be about 30 minutes
- This also impacts routine maintenance

HDFS High Availability has features to cope with this

- Pair of namenodes in active standby configuration
- During failure of active namenode, standby takes over the servicing of client requests
  - In 10s of seconds

HDFS High-Availability: Additional items to get things to work

- Namenodes use a highly-available **shared storage** to store the *edit log*
- Datanodes must send block reports to **both** namenodes
  - Block mappings stored in memory not disk
- Clients must be configured to handle namenode failover

HDFS HA: Dealing with ungraceful failovers

- Slow network or a network partition can trigger failover transition
  - Previously active namenode thinks it is ***still*** the active namenode
- The HDFS HA tries to avoid this situation using **fencing**
  - Previously active namenode should be prevented from causing corruptions

Fencing mechanisms: To shutdown previously active namenode

- Kill the namenode's process
- Revoking access to the shared storage directory
- Disabling namenode's network port
  - Using the remote management command
- STONITH
  - Use specialized power distribution unit to forcibly power down the host machine

The contents of this slide set are based on the following references

- *Tom White. Hadoop: The Definitive Guide. 3rd Edition. Early Access Release. O'Reilly Press. ISBN: 978-1-449-31152-0.* Chapters [2 and 3].