# CS 455: Introduction To Distributed Systems [HDFS]

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## Frequently asked questions from the previous class survey

- How is block location reconstructed on startup?
- Difference between Hadoop fs and HDFS??
- Are namenodes typically on higher quality nodes?
- HDFS block report interval: dfs.blockreport.intervalMsec = 21600000



## Topics covered in this lecture

- Hadoop Distributed File System
  - Writing Data
  - Replication
  - Data integrity
  - Parallel Copying
  - Coherency Model



## Writing Data

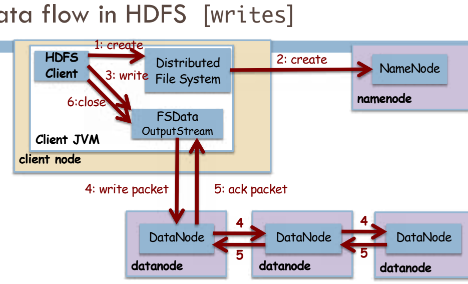


## File writes

- We will look at creating a new file and writing data to it
- File creation is done using `create()` on `DistributedFileSystem`
- `DistributedFileSystem` does an **RPC** to the namenode
  - Namenode checks existence of file and permissions
  - Creates file in the filesystem's namespace with no blocks in it



## Data flow in HDFS [writes]



## Anatomy of a file write

- `DistributedFileSystem` returns an `FSDataOutputStream` for client to write data to
- `FSDataOutputStream` wraps a `DFSOutputStream`
  - `DFSOutputStream` handles communications with the datanodes and the namenode



## As the client writes data …

- `DFSOutputStream` splits it into **packets**
  - Written to an internal queue, the **data queue**
- Data queue is consumed by the `DataStreamer`
- `DataStreamer` asks namenode to allocate new blocks
  - Pick list of suitable datanodes to store replicas
  - List of datanodes forms a **pipeline**



## Assuming a replication level of 3

- `DataStreamer` streams packets to the first datanode in the pipeline
  - 1st datanode stores the packet and forwards it to the 2nd datanode in pipeline
- The second datanode stores the packet and forwards it to the 3rd (and last) datanode in pipeline



## Managing acknowledgements

- `DFSOutputStream` maintains an internal queue of packets waiting to be ACKed by datanodes
  - This is the **ack queue**
- When is a packet removed from the ACK queue?
  - Only when it has been acknowledged by all the datanodes in the pipeline



## Handling datanode failures during writes [1/2]

- The pipeline is closed
- Any packets in the ack queue are added to the front of the data queue
  - Nodes downstream from the failed node will not miss any packets
- Current block on good datanodes is given a new identity
  - Allows *partial block on failed node* to be **deleted** if that datanode recovers later on



## Handling datanode failures during writes [2/2]

- Failed datanode is removed from the pipeline
- *Remainder* of the block's data is written to the two good datanodes in the pipeline
- Namenode **notices** block is *under-replicated*
  - Arranges for replicas to be created on another node
- Subsequent blocks are treated as normal

## It is possible that multiple datanodes fail while a block is being written

- As long as `dfs.replication.min` (default 1) replicas are written, the write will succeed
- Block is **asynchronously replicated** across cluster until its target replication factor is reached
  - `dfs.replication` (default 3)



## When a client has finished writing data

- It calls `close()` on the stream
- **Flushes** all remaining packets to the datanode pipeline
  - Wait for acknowledgements before contacting the namenode to signal that file is complete
- Namenode knows about blocks that comprise the file
  - `DataStreamer` requests block allocations
  - Client only waits for blocks to be minimally replicated



## Replica Placements



## Replica placement [1/2]

- **Trade-off** between reliability, read bandwidth, and write bandwidth
- Placing all replicas on a single node?
  - Lowest write bandwidth penalty since replication pipeline runs on a single node
  - Offers **no redundancy**



## Replica placement [2/2]

- Read bandwidth is high for off-rack reads
- Placing replicas in different data centers
  - Maximizes redundancy at the the cost of bandwidth



## Default replication strategy in Hadoop

- Place **first** replica *on the same node* as the client
  - If client runs outside the cluster, 1st node is chosen at random
- The **second** replica is placed *on a different rack* from the first
  - Chosen at random
- **Third** replica is placed *on the same rack as the second*
  - Different node is chosen at random
- **Further** replicas are placed on *random nodes* in the cluster
  - Avoid placing too many replicas on the same rack

## Default strategy balances

- **Reliability**
  - Blocks are stored on different racks
- **Write bandwidth**
  - Writes traverse a single network switch
- **Read bandwidth**
  - Choice of two racks to read from
- **Block distribution** across cluster
  - Clients write a single block on the local rack



## Once the replica locations have been chosen

- A pipeline is built
- Pipeline takes network topology into account



## Coherency Model



## A quick look at assertThat in JUnit

- Format
  - **`assertThat([value], [matcher statement]);`**
- Examples
  - `assertThat(x, is(3));`
  - `assertThat(x, is(not(4)));`
  - `assertThat(responseString, either(containsString("color")).or(containsString("colour")));`
  - `assertThat(myList, hasItem("3"));`



## Assertion syntax

- Readable
- Think in terms of **subject**, **verb**, and **object**
  - Assert "x is 3"
- Matcher statements can be negated, combined, or mapped to a collection



## Coherency Model

- For a filesystem, **coherency** *describes* data **visibility** of reads and writes to a file
- HDFS trades-off some POSIX requirements for performance

## Creation of a file

- After creation, it is visible in the file namespace

```
Path p = new Path("p");
fs.create(p);
assertThat(fs.exists(p), is(true));
```



## Contents written to the newly created file

- **Not guaranteed** to be visible
- Even if the stream is flushed
  - File may appear to have length of 0

```
Path p = new Path("p");
OutputStream out = fs.create(p);
out.write("content".getBytes("UTF-8"));
out.flush();
assertThat(fs.getFileStatus(p).getLen(), is(0L));
```



## Visibility of blocks during writes

- Once more than a block of data is written?
  - The first block is visible
- In general, the current block that is *being written to* **is not visible** to other readers



## The HDFS `sync` method

- Forces all buffers to be **synchronized** to the datanodes
- After `sync()` returns successfully?
  - All data written up to that point in the file is persisted and visible to all clients



## When to call `sync()`

- With no calls to `sync()`
  - *Possible to lose up to a block of data* due to client or system failure
- However invocations of `sync()` do have *overheads*
  - **Trade-off** between data robustness and throughput
- Frequency of `sync()` is application dependent



## Parallel Copying

## Parallel copying with `distcp`

- Enables copying large amounts of data to and from the Hadoop filesystem in **parallel**

```
% hadoop distcp hdfs://namenode1/foo hdfs://namenode2/bar
```



## `distcp` is implemented as a MapReduce job

- Copying is done by Maps that run in **parallel** across the cluster
  - There are no reducers
- Deciding the number of maps
  - Give each map sufficient data to *minimize overheads* during **task setup**
  - This is specified using the `–m` argument to `distcp`



## Keeping an HDFS cluster balanced

- HDFS works best when file blocks are **evenly spread** across the cluster
- We need to ensure that `distcp` does not disrupt this feature
- If we are transferring 1000 GB?
  - Specifying **`–m 1`** would mean that a single map would do the copy
    - Will be slow
    - The first replica of each block would reside on the node running map (till the disk fills up)



## Data Integrity



## Data Integrity

- I/O operations on disk or network carry a small chance of introducing errors
- With voluminous data movements the chances of data corruption become high
- Checksums
  - Data is **corrupt** if there is a *mismatch* between the original and the newly computed checksum
  - There is also a small chance that the checksum is corrupt



## Data integrity in HDFS

- Datanodes are responsible for **verifying** received data before storing the data and checksum
- When clients read data from the datanode, they verify the checksum
  - Compare with checksum stored at the datanode

## `DataBlockScanner`

- Each datanode runs a `DataBlockScanner` in the background **periodically**
- **Verifies all blocks** stored on the datanode
- Guards against corruption due to ***bit rot*** in the physical storage media



## Dealing with corrupted data blocks

- **Heal** corrupted blocks
  - By copying one of the good replicas to produce a new, uncorrupt replica
- When a client detects an error while reading block?
  - Report *both* the bad block and datanode it was reading from
  - Throw `ChecksumException`



## Dealing with corrupted data blocks

- Namenode marks the block replica as **corrupt**
  - Does not direct clients to it
  - Does not try to copy replica to another datanode
- **Schedules a copy** of the block to be replicated on another datanode
  - Restore replication level for the block
- Corrupt replica is then **deleted**



## Disabling checksum

- Useful if you have a corrupt file that you would like to **inspect**
- Pass `false` to `verifyChecksum()` on `FileSystem` before using `open()` to read the file
- From the shell, use the `–ignoreCrc` option with the `–get` or the `–copyToLocal` command



## Client side checksumming

- Done by the Hadoop `LocalFileSystem`
- When you write a file *filename*
  - The filesystem client creates a hidden file *.filename.crc* in the same directory
  - Contains checksums for each chunk of the file
    - Chunk size is stored in the .crc file
- Disable checksums when underlying filesystem supports this natively
  - Use `RawLocalFileSystem` instead of `LocalFileSystem`



## COMPRESSION

## Compression

- Reduces **space** needed to store files
- Speeds up data **transfers**
  - Across network
  - Disk I/O



## Compression formats that can be used with Hadoop

| Compression format | Tool | Algorithm | Filename extension | Splittable? |
|---|---|---|---|---|
| DEFLATE | N/A | DEFLATE | *.deflate* | No |
| Gzip | Gzip | DEFLATE | .gz | No |
| Bzip2 | Bzip2 | Bzip2 | .bz2 | Yes |
| LZO | Lzop | LZO | .lzo | No* |
| Snappy | N/A | Snappy | .snappy | No |


Pigeonhole principle



## Compression Algorithms

- Exhibit a **space-time** trade-off
  - Faster compression/decompression speeds usually result in smaller space savings
- Tools give some control over this trade-off at compression time
  - 9 different options
  - -1 means optimize for speed
  - -9 means optimize for space



## Compression characteristics

- gzip is a *general purpose* compressor
  - Middle of the space/time trade-off
- bzip2 compresses more effectively than gzip
  - But it is slower
  - bzip2 decompression speed is faster than its compression speed
    - But slower than other formats still
- LZO and Snappy optimize for speed
  - Order of magnitude faster but less effective compression than gzip



## A **codec** is the implementation of a compression-decompression algorithm in Hadoop

| Compression format | Hadoop CompressionCodec |
|---|---|
| DEFLATE | `org.apache.hadoop.io.compress.DefaultCodec` |
| gzip | `org.apache.hadoop.io.compress.GzipCodec` |
| bzip2 | `org.apache.hadoop.io.compress.BZip2Codec` |
| LZO | `com.hadoop.compression.lzo.LzopCodec` |
| Snappy | `org.apache.hadoop.io.compress.SnappyCodec` |



## `CompressionCodec`

- To compress data being written to an output stream
  - Use `codec.createOutputStream(OutputStream out)`
- To decompress data being read from an input stream
  - Use `codec.createInputStream(InputStream in)`

## Using compression

```
public class StreamCompressor {

    public static void main(String[] args) throws Exception {
        String codecClassname = args[0];
        Class<?> codecClass = Class.forName(codecClassname);
        Configuration conf = new Configuration();
        CompressionCodec codec = (CompressionCodec)
          ReflectionUtils.newInstance(codecClass, conf);
        CompressionOutputStream out =
             codec.createOutputStream(System.out);
        IOUtils.copyBytes(System.in, out, 4096, false);
        out.finish();
    }
}
```

Compresses data read from standard input and writes it to standard output



## Compression and input splits

- Let's look at an uncompressed file stored in HDFS
  - With an HFDS block size of 64 MB, a 1 GB file is stored as 16 blocks
  - MapReduce job will create 16 input splits
    - **Processed independently** as separate map tasks



## If the gzip compressed file is 1 GB

- HDFS stores files as 16 blocks
- Creating a split for each block does not work
  - Impossible to start reading at an *arbitrary block* in the zip stream
  - Impossible for map task to read its split *independently of others*



## Storing gzipped streams

- Gzip uses DEFLATE, which stores data as a **series** of *compressed blocks*
- The **start of each block is not distinguished** in a way that allows:
  - Reader positioned at arbitrary point in stream to advance to the beginning of the next block
    - There is **no self-synchronizing** with the stream
  - Gzip does not support splitting



## HDFS does not split `gzip` files

- Single map will process 16 HDFS blocks
- Most of these blocks will not be local to the map
  - Loss of locality
  - Job is not granular … takes much longer to run



## The same story plays out if you were dealing with LZO files, but …

- It is possible to *preprocess* LZO files using an indexer tool
- Build an **index** of split points

## Bzip2

- This does provide a **synchronization marker** between blocks
  - 48-bit approximation of pi
- The marker is used to support splitting



## Dealing with large, unbounded files [Log files]

1. Store the files uncompressed
2. Use compression format that supports
   - Splitting: Bzip2
   - Indexing to support splitting: LZO
3. Split the file into chunks in the application and compress each chunk separately
   - Choose chunk sizes such that the *compressed chunks* are approximately the size of an HDFS block



## Using compression in MapReduce

- To compress the output of MapReduce job
  - In the job config set `mapred.output.compress` property to true
  - Use `mapred.output.compression.codec` to specify the codec
- Alternatively, we can do this using the `FileOutputFormat`



## Using the FileOutputFormat

```
public class MaxTemperatureWithCompression {

   public static void main(String[] args) throws Exception {
    Job job = Job.getInstance();
    job.setJarByClass(MaxTemperature.class);
    FileInputFormat.addInputPath(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(job, new Path(args[1]));
    job.setOutputKeyClass(Text.class);
    job.setOutputValueClass(IntWritable.class);

    FileOutputFormat.setCompressOutput(job, true);
    FileOutputFormat.setOutputCompressorClass(job, GzipCodec.class);

    job.setMapperClass(MaxTemperatureMapper.class);
    job.setCombinerClass(MaxTemperatureReducer.class);
    job.setReducerClass(MaxTemperatureReducer.class);
    System.exit(job.waitForCompletion(true) ? 0 : 1);
   }

}
```



## Main reason why Hadoop does not use Java Serialization

- Deserialization creates new instance of each object being deserialized
- Writable objects can be (and are often) reused
- Large MapReduce jobs often serialize/deserialize billions of records
  - Savings from not having to allocate new objects is significant



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

- *Tom White. Hadoop: The Definitive Guide. 3rd Edition. O'Reilly Press. ISBN: 978-1-449-31152-0.* Chapters [3 and 4].
- *JUnit release notes for version 4.4 available at http://junit.sourceforge.net/doc/ReleaseNotes4.4.html*