Semantics with Failures

- If map and reduce are deterministic, then output identical to non-faulting sequential execution
  – For non-deterministic operators, different reduce tasks might see output of different map executions
- Relies on atomic commit of map and reduce outputs
  – In-progress task writes output to private temp file
  – Mapper: on completion, send names of all temp files to master (master ignores if task already complete)
  – Reducer: on completion, *atomically* rename temp file to final output file (needs to be supported by distributed file system)

Practical Considerations

- Conserve network bandwidth (“Locality optimization”)
  – Schedule map task on machine that already has a copy of the split, or one “nearby”
- How to choose M (#map tasks) and R (#reduce tasks)
  – Larger M, R: smaller tasks, enabling easier load balancing and faster recovery (many small tasks from failed machine)
  – Limitation: O(M+R) scheduling decisions and O(M·R) in-memory state at master; too small tasks not worth the startup cost
  – Recommendation: choose M so that split size is approx. 64 MB
  – Choose R a small multiple of number of workers; alternatively choose R a little smaller than #workers to finish reduce phase in one “wave”
- Create backup tasks to deal with machines that take unusually long for the last in-progress tasks (“stragglers”)

Refinements

- User-defined partitioning functions for reduce tasks
  - Use this for partitioning sort
  - Default: assign key K to reduce task *hash(K) mod R*
  - Use *hash(Hostname(urlkey)) mod R* to have URLs from same host in same output file
  - We will see others in future lectures
- Combiner function to reduce mapper output size
  - Pre-aggregation at mapper for reduce functions that are commutative and associative
  - Often (almost) same code as for reduce function

Careful With Combiners

- Consider Word Count, but assume we only want words with count > 10
  - Reducer computes total word count, only outputs if greater than 10
  - Combiner = Reducer? No. Combiner should not filter based on its local count!
- Consider computing average of a set of numbers
  - Reducer should output average
  - Combiner has to output (sum, count) pairs to allow correct computation in reducer

Experiments

- 1800 machine cluster
  - 2 GHz Xeon, 4 GB memory, two 160 GB IDE disks, gigabit Ethernet link
  - Less than 1 msec roundtrip time
- Grep workload
  - Scan 10^{10} 100-byte records, search for rare 3-character pattern, occurring in 92,337 records
  - M=15,000 (64 MB splits), R=1

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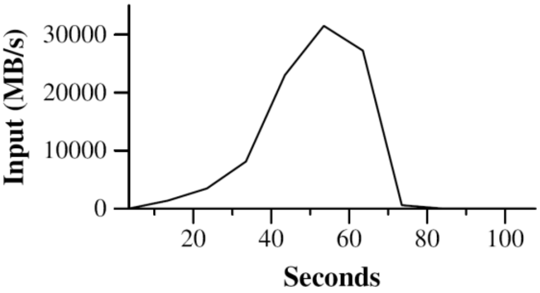
Grep Progress Over Time



- Rate at which input is scanned as more mappers are added
- Drops as tasks finish, done after 80 sec
- 1 min startup overhead beforehand
  - Propagation of program to workers
  - Delays due to distributed file system for opening input files and getting information for locality optimization

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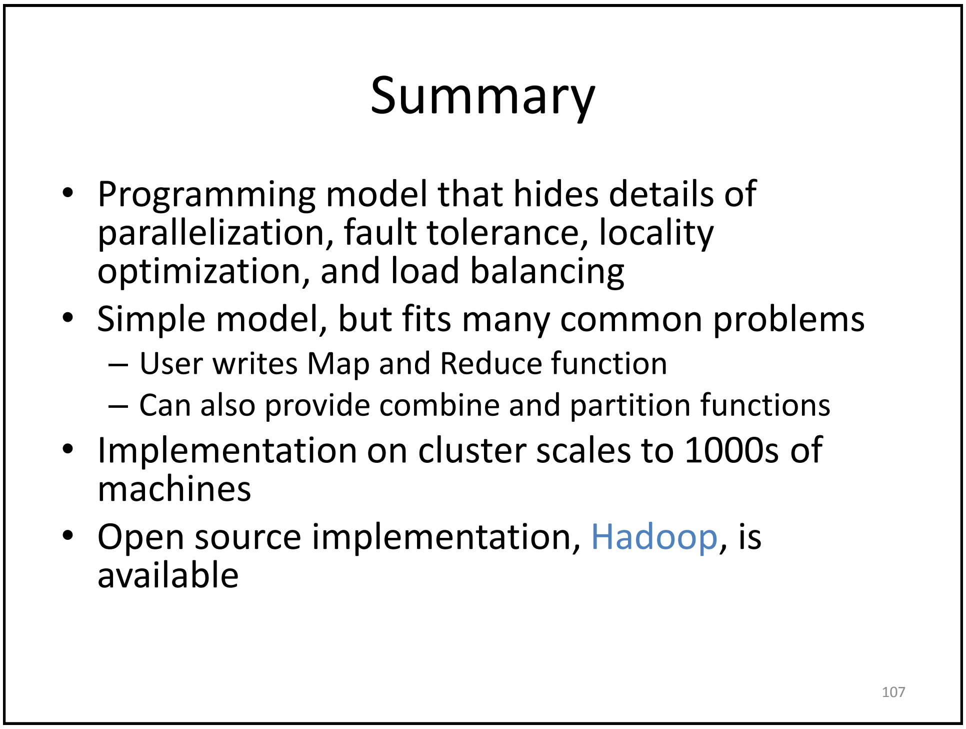
Sort

- Sort 10^{10} 100-byte records (~1 TB of data)
- Less than 50 lines user code
- M=15,000 (64 MB splits), R=4000
- Use key distribution information for intelligent partitioning
- Entire computation takes 891 sec
  - 1283 sec without backup task optimization (few slow machines delay completion)
  - 933 sec if 200 out of 1746 workers are killed several minutes into computation

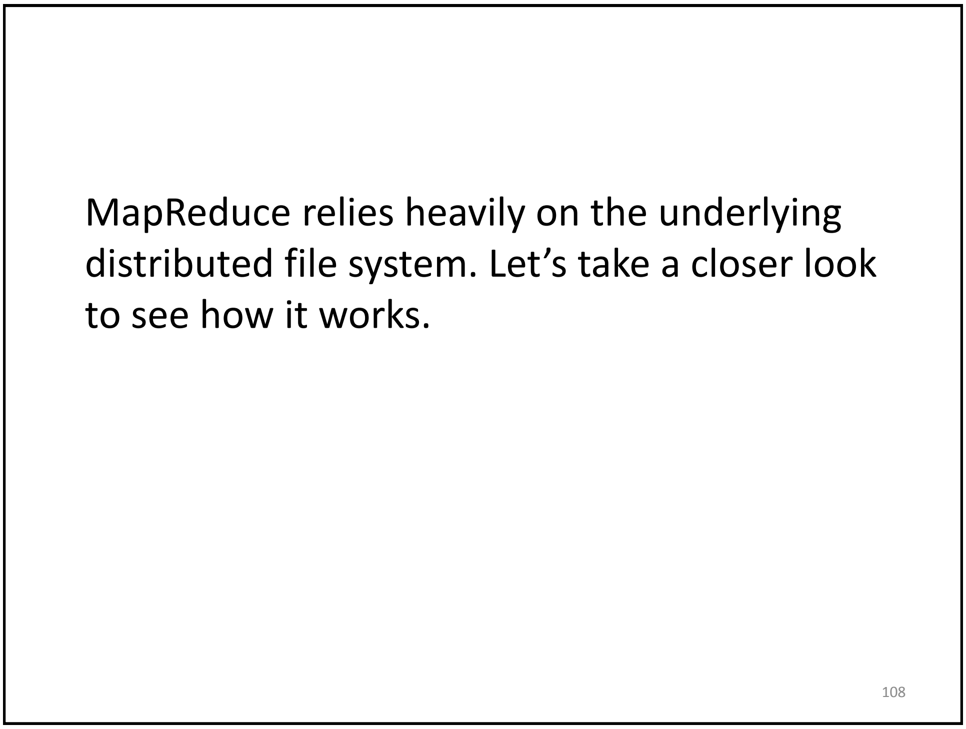
MapReduce at Google (2004)

- Machine learning algorithms, clustering
- Data extraction for reports of popular queries
- Extraction of page properties, e.g., geographical location
- Graph computations
- Google indexing system for Web search (>20 TB of data)
  - Sequence of 5-10 MapReduce operations
  - Smaller simpler code: from 3800 LOC to 700 LOC for one computation phase
  - Easier to change code
  - Easier to operate, because MapReduce library takes care of failures
  - Easy to improve performance by adding more machines

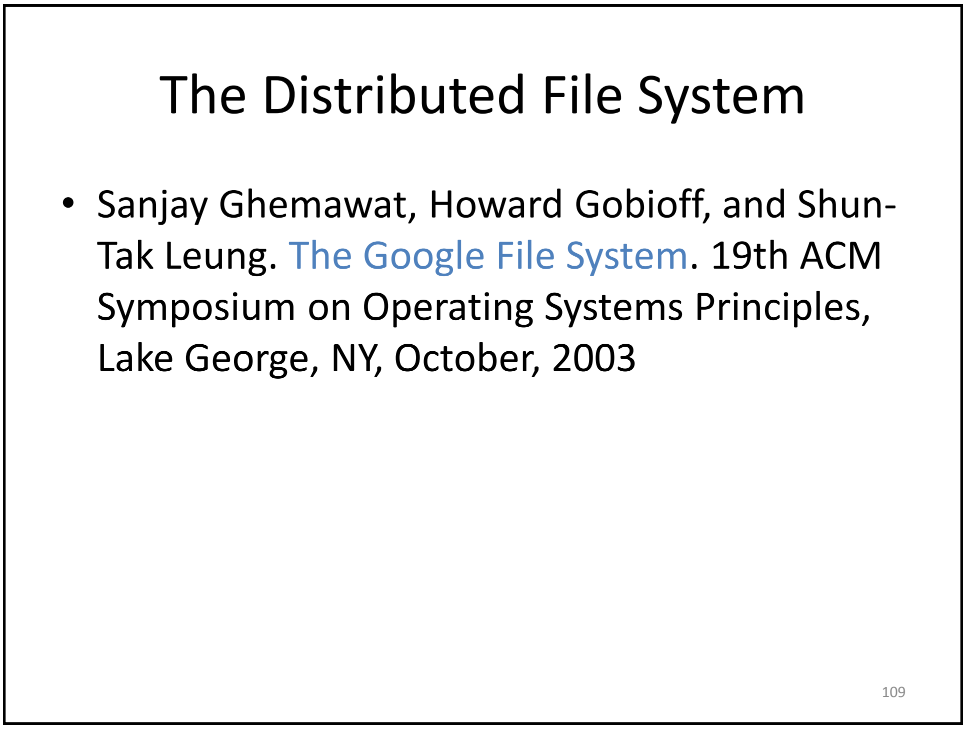


Summary

- Programming model that hides details of parallelization, fault tolerance, locality optimization, and load balancing
- Simple model, but fits many common problems
  - User writes Map and Reduce function
  - Can also provide combine and partition functions
- Implementation on cluster scales to 1000s of machines
- Open source implementation, Hadoop, is available

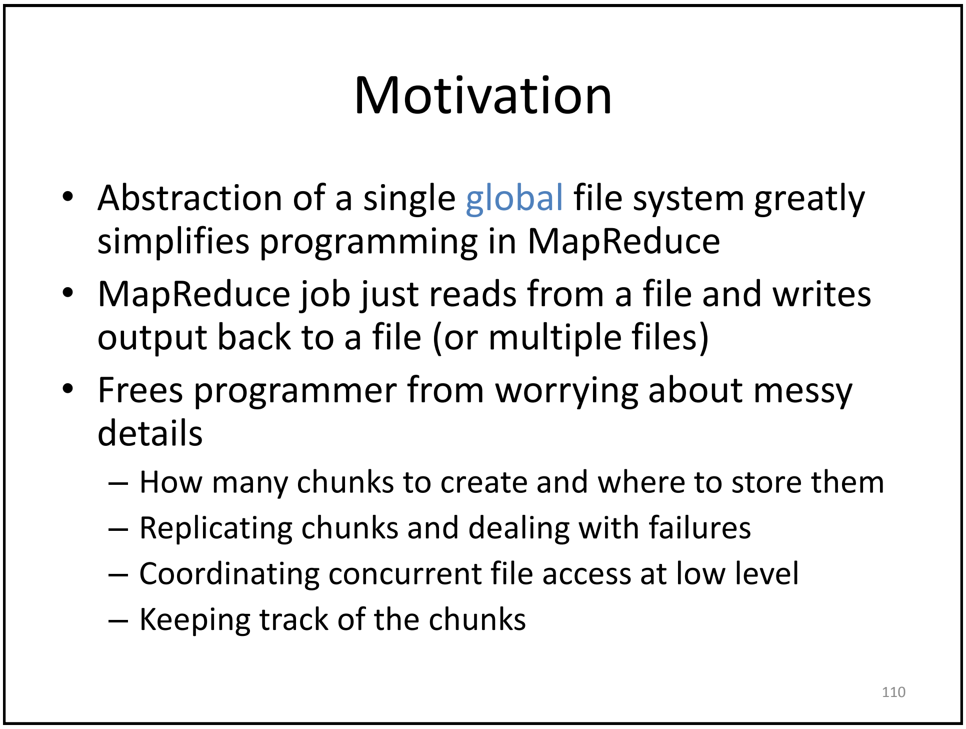


MapReduce relies heavily on the underlying distributed file system. Let’s take a closer look to see how it works.



The Distributed File System

- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung. The Google File System. 19th ACM Symposium on Operating Systems Principles, Lake George, NY, October, 2003



Motivation

- Abstraction of a single global file system greatly simplifies programming in MapReduce
- MapReduce job just reads from a file and writes output back to a file (or multiple files)
- Frees programmer from worrying about messy details
  - How many chunks to create and where to store them
  - Replicating chunks and dealing with failures
  - Coordinating concurrent file access at low level
  - Keeping track of the chunks

Google File System (GFS)

- GFS in 2003: 1000s of storage nodes, 300 TB disk space, heavily accessed by 100s of clients
- Goals: performance, scalability, reliability, availability
- Differences compared to other file systems
  - Frequent component failures
  - Huge files (multi-GB or even TB common)
  - Workload properties
    - Design system to make important operations efficient

Data and Workload Properties

- Modest number of large files
  - Few million files, most 100 MB+
  - Manage multi-GB files efficiently
- Reads: large streaming (1 MB+) or small random (few KBs)
- Many large sequential append writes, few small writes at arbitrary positions
- Concurrent append operations
  - E.g., Producer-consumer queues or many-way merging
- High sustained bandwidth more important than low latency
  - Bulk data processing

File System Interface

- Like typical file system interface
  - Files organized in directories
  - Operations: create, delete, open, close, read, write
- Special operations
  - Snapshot: creates copy of file or directory tree at low cost
  - Record append: concurrent append guaranteeing atomicity of each individual client’s append

Architecture Overview

- 1 master, multiple chunkservers, many clients
  - All are commodity Linux machines
- Files divided into fixed-size chunks
  - Stored on chunkservers’ local disks as Linux files
  - Replicated on multiple chunkservers
- Master maintains all file system metadata: namespace, access control info, mapping from files to chunks, chunk locations

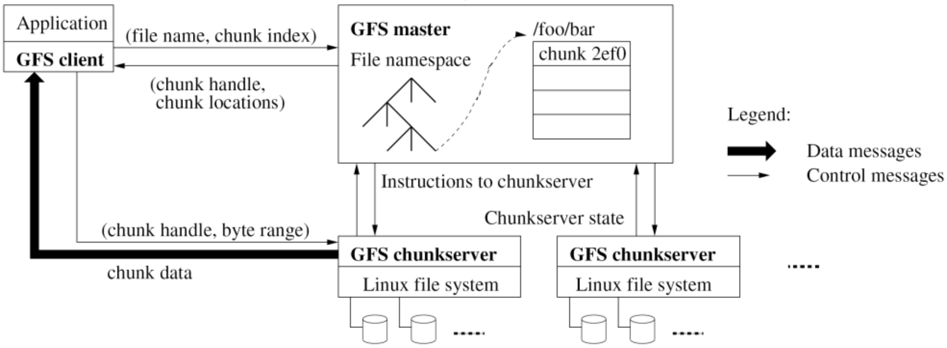
Why a Single Master?

- Simplifies design
- Master can make decisions with global knowledge
- Potential problems:
  - Can become bottleneck
    - Avoid file reads and writes through master
  - Single point of failure
    - Ensure quick recovery

High-Level Functionality

- Master controls system-wide activities like chunk lease management, garbage collection, chunk migration
- Master communicates with chunkservers through HeartBeat messages to give instructions and collect state
- Clients get metadata from master, but access files directly through chunkservers
- No GFS-level file caching
  - Little benefit for streaming access or large working set
  - No cache coherence issues
  - On chunkserver, standard Linux file caching is sufficient

Read Operation



- Client: from (file, offset), compute chunk index, then get chunk locations from master
  - Client buffers location info for some time
- Client requests data from nearby chunkserver
  - Future requests use cached location info
- Optimization: batch requests for multiple chunks into single request

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Chunk Size

- 64 MB, stored as Linux file on a chunkserver
- Advantages of large chunk size
  - Fewer interactions with master (recall: large sequential reads and writes)
  - Smaller chunk location information
    - Smaller metadata at master, might even fit in main memory
    - Can be cached at client even for TB-size working sets
  - Many accesses to same chunk, hence client can keep persistent TCP connection to chunkserver
- Disadvantage: fewer chunks => fewer options for load balancing
  - Fixable with higher replication factor
  - Address hotspots by letting clients read from other clients

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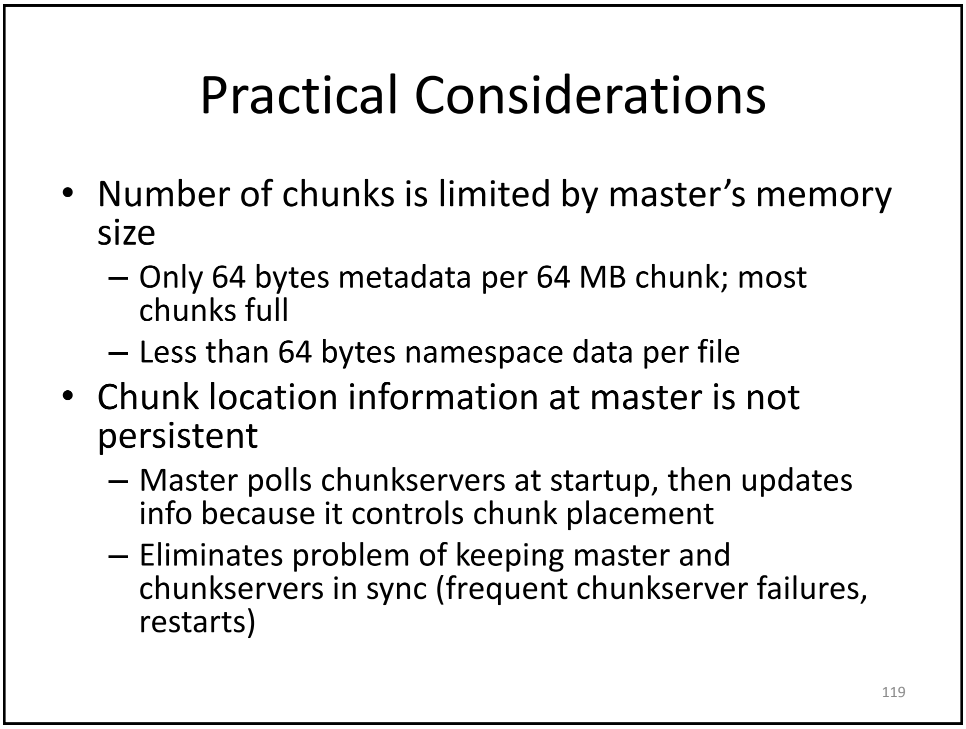
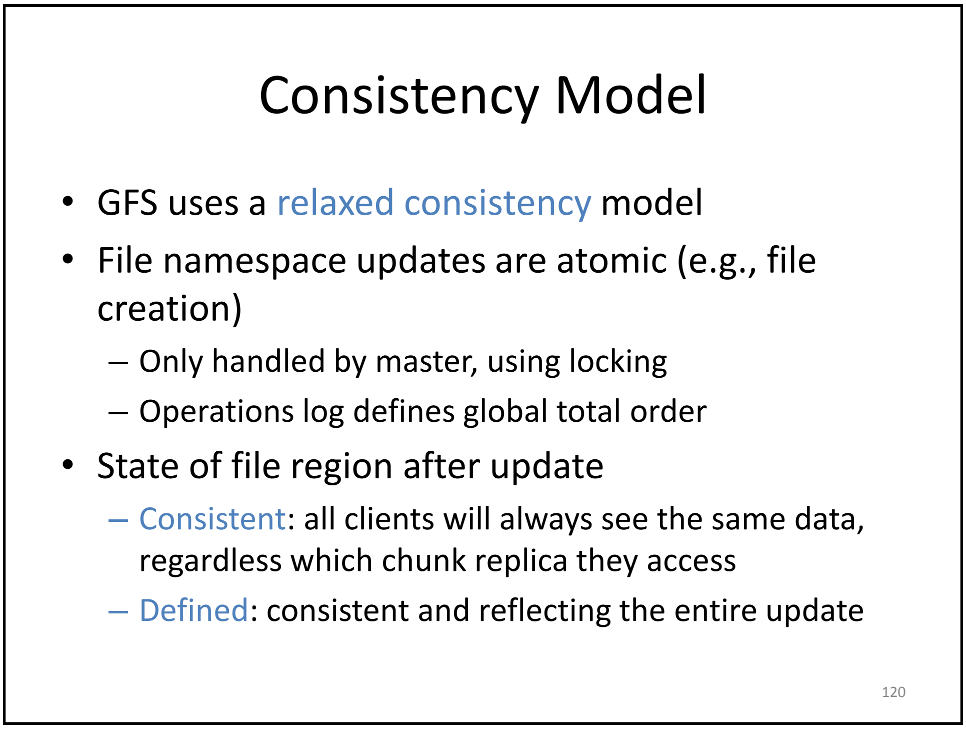


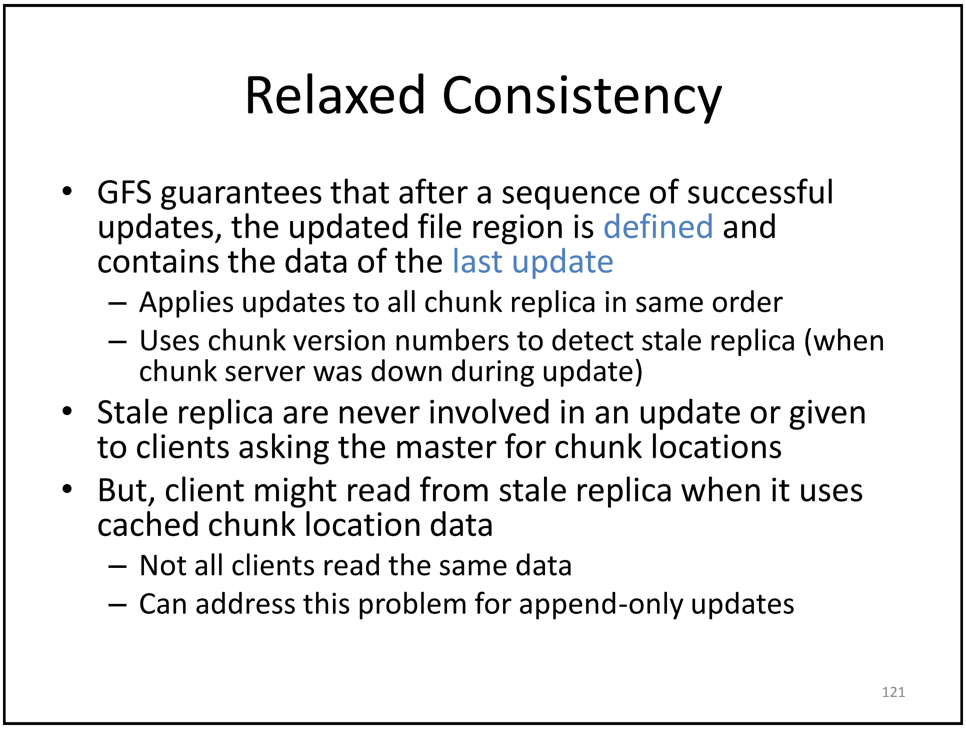
Practical Considerations

- Number of chunks is limited by master’s memory size
  - Only 64 bytes metadata per 64 MB chunk; most chunks full
  - Less than 64 bytes namespace data per file
- Chunk location information at master is not persistent
  - Master polls chunkservers at startup, then updates info because it controls chunk placement
  - Eliminates problem of keeping master and chunkservers in sync (frequent chunkserver failures, restarts)



Consistency Model

- GFS uses a relaxed consistency model
- File namespace updates are atomic (e.g., file creation)
  - Only handled by master, using locking
  - Operations log defines global total order
- State of file region after update
  - Consistent: all clients will always see the same data, regardless which chunk replica they access
  - Defined: consistent and reflecting the entire update



Relaxed Consistency

- GFS guarantees that after a sequence of successful updates, the updated file region is defined and contains the data of the last update
  - Applies updates to all chunk replica in same order
  - Uses chunk version numbers to detect stale replica (when chunk server was down during update)
- Stale replica are never involved in an update or given to clients asking the master for chunk locations
- But, client might read from stale replica when it uses cached chunk location data
  - Not all clients read the same data
  - Can address this problem for append-only updates

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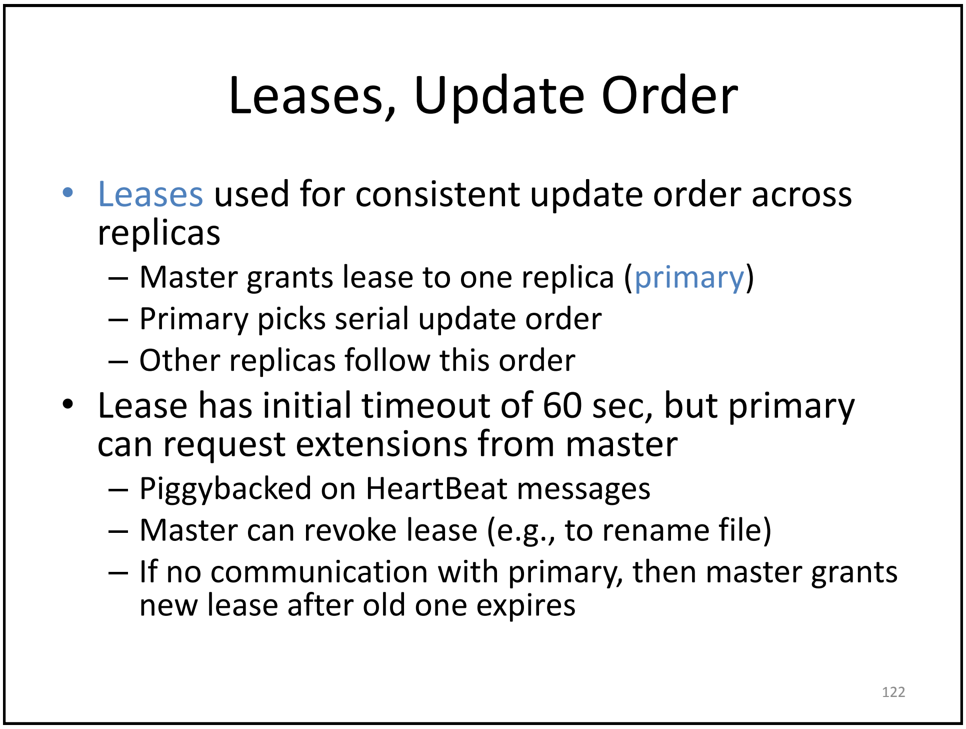

Leases, Update Order

- Leases used for consistent update order across replicas
  - Master grants lease to one replica (primary)
  - Primary picks serial update order
  - Other replicas follow this order
- Lease has initial timeout of 60 sec, but primary can request extensions from master
  - Piggybacked on HeartBeat messages
  - Master can revoke lease (e.g., to rename file)
  - If no communication with primary, then master grants new lease after old one expires

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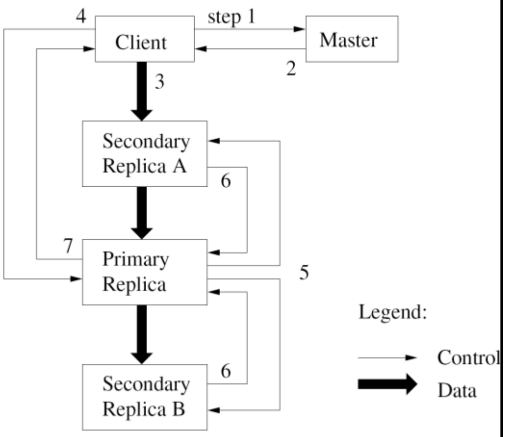
Updating a Chunk

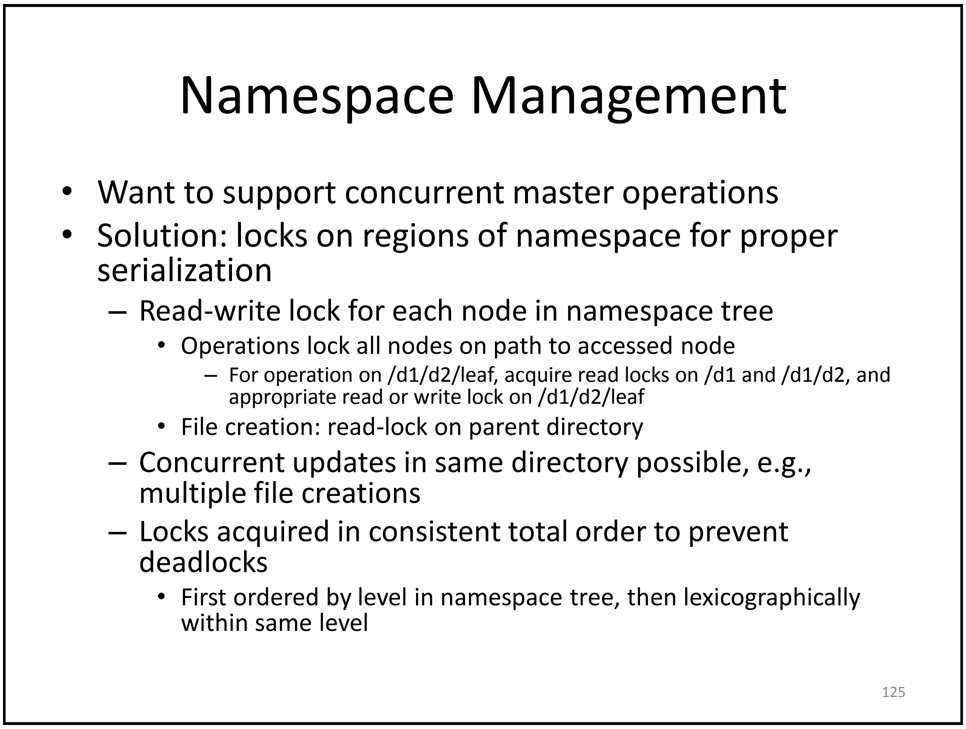
1. Who has lease?
2. Identity of primary and secondary replicas
3. Push data to all replicas
4. After receiving all acks, send write request to primary who assigns it a serial number
5. Primary forwards write request to all other replicas
6. Secondaries ack update success
7. Primary replies to client
   1. Also reports errors
   2. Client retries steps 3-7 on error

- Large writes broken down into chunks



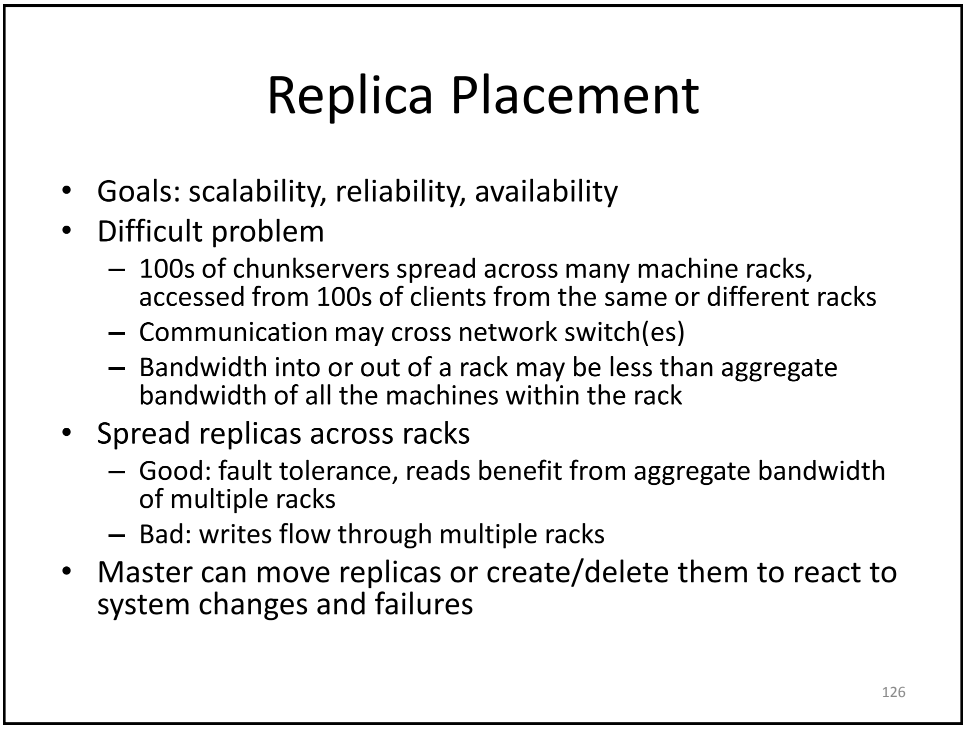
Data Flow

- Decoupled from control flow for efficient network use
- Data pipelined linearly along chain of chunkservers
  - Full outbound bandwidth for fastest transfer (instead of dividing it in non-linear topology)
  - Avoids network bottlenecks by forwarding to “next closest” destination machine
  - Minimizes latency: once chunkserver receives data, it starts forwarding immediately
    - Switched network with full-duplex links
    - Sending does not reduce receive rate
    - 1 MB distributable in 80 msec



Namespace Management

- Want to support concurrent master operations
- Solution: locks on regions of namespace for proper serialization
  - Read-write lock for each node in namespace tree
    - Operations lock all nodes on path to accessed node
      - For operation on /d1/d2/leaf, acquire read locks on /d1 and /d1/d2, and appropriate read or write lock on /d1/d2/leaf
    - File creation: read-lock on parent directory
  - Concurrent updates in same directory possible, e.g., multiple file creations
  - Locks acquired in consistent total order to prevent deadlocks
    - First ordered by level in namespace tree, then lexicographically within same level



Replica Placement

- Goals: scalability, reliability, availability
- Difficult problem
  - 100s of chunkservers spread across many machine racks, accessed from 100s of clients from the same or different racks
  - Communication may cross network switch(es)
  - Bandwidth into or out of a rack may be less than aggregate bandwidth of all the machines within the rack
- Spread replicas across racks
  - Good: fault tolerance, reads benefit from aggregate bandwidth of multiple racks
  - Bad: writes flow through multiple racks
- Master can move replicas or create/delete them to react to system changes and failures

Lazy Garbage Collection

- File deletion immediately logged by master, but file only renamed to hidden name
  - Removed later during regular scan of file system namespace
  - Batch-style process amortizes cost and is run when master load is low
- Orphaned chunks identified during regular scan of chunk namespace
- Chunkservers report their chunks to master in HeartBeat messages
- Master replies with identities of chunks it does not know
  - Chunkserver can delete them
- Simple and reliable: lost deletion messages (from master) and failures during chunk creation no problem
- Disadvantage: difficult to finetune space usage when storage is tight, e.g., after frequent creation/deletion of temp files
  - Solution: use different policies in different parts of namespace

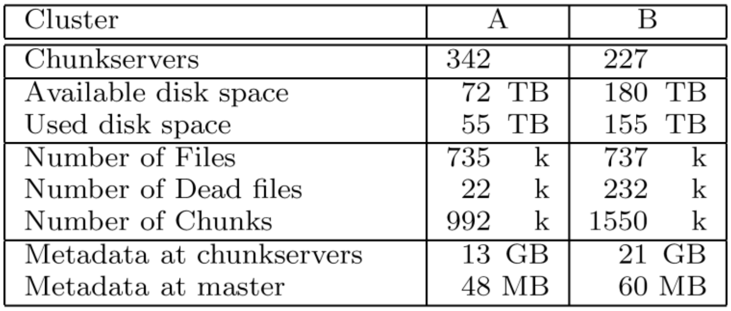
Stale Replicas

- Occur when chunkserver misses updates while it is down
- Master maintains chunk version number
  - Before granting new lease on chunk, master increases its version number
  - Informs all up-to-date replicas of new number
    - Master and replicas keep version number in persistent state
  - This happens before client is notified and hence before it can start updating the chunk
- When chunkservers report their chunks, they include version numbers
  - Older than on master: garbage collect it
  - Newer than on master: master must have failed after granting lease; master takes higher version to be up-to-date
- Master also includes version number in reply to client and chunkserver during update-process related communication

Achieving High Availability

- Master and chunkservers can restore state and start in seconds
- Chunk replication
- Master replication, i.e., operation log and checkpoints
- But: only one master process
  - Can restart almost immediately
  - Permanent failure: monitoring infrastructure outside GFS starts new master with replicated operation log (clients use DNS alias)
- Shadow masters for read-only access
  - May lag behind primary by fraction of a sec

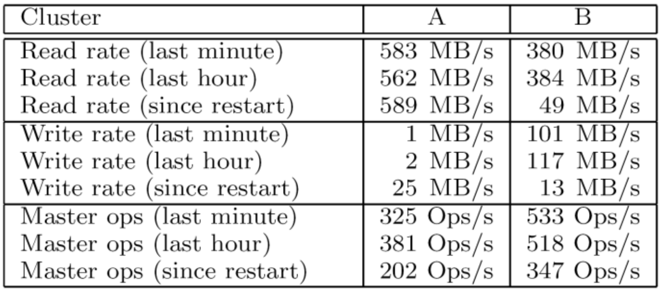
Experiments



Cluster	A	B
Chunkservers	342	227
Available disk space	72 TB	180 TB
Used disk space	55 TB	155 TB
Number of Files	735 k	737 k
Number of Dead files	22 k	232 k
Number of Chunks	992 k	1550 k
Metadata at chunkservers	13 GB	21 GB
Metadata at master	48 MB	60 MB

- Chunkserver metadata mostly checksums for 64 KB blocks
  - Individual servers have 50-100 MB of metadata
  - Reading this from disk during recovery is fast

Results



Cluster	A	B
Read rate (last minute)	583 MB/s	380 MB/s
Read rate (last hour)	562 MB/s	384 MB/s
Read rate (since restart)	589 MB/s	49 MB/s
Write rate (last minute)	1 MB/s	101 MB/s
Write rate (last hour)	2 MB/s	117 MB/s
Write rate (since restart)	25 MB/s	13 MB/s
Master ops (last minute)	325 Ops/s	533 Ops/s
Master ops (last hour)	381 Ops/s	518 Ops/s
Master ops (since restart)	202 Ops/s	347 Ops/s

- Clusters had been up for 1 week at time of measurement
- A’s network configuration has max read rate of 750 MB/s
  - Actually reached sustained rate of 580 MB/s
- B’s peak rate is 1300 MB/s, but applications never used more than 380 MB/s
- Master not a bottleneck, despite large number of ops sent to it

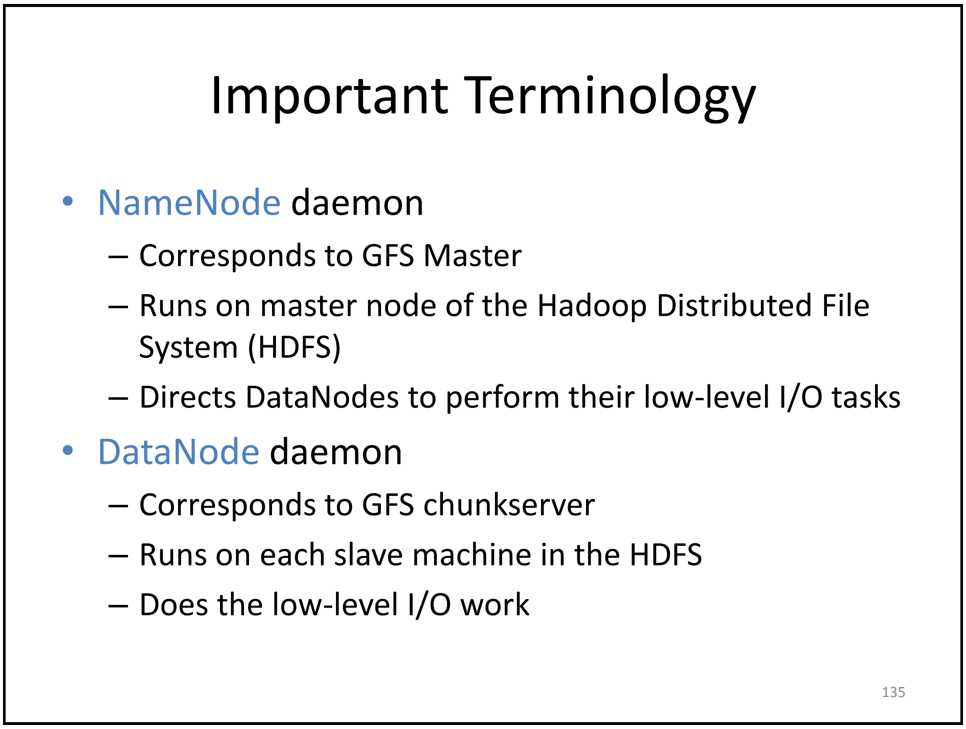
Summary

- GFS supports large-scale data processing workloads on commodity hardware
- Component failures treated as norm, not exception
  - Constant monitoring, replicating of crucial data
  - Relaxed consistency model
  - Fast, automatic recovery
- Optimized for huge files, appends, large sequential reads
- High aggregate throughput for concurrent readers and writers
  - Separation of file system control (through master) from data transfer (between chunkservers and clients)

Now that we covered the basics of MapReduce, let's look at some Hadoop specifics.

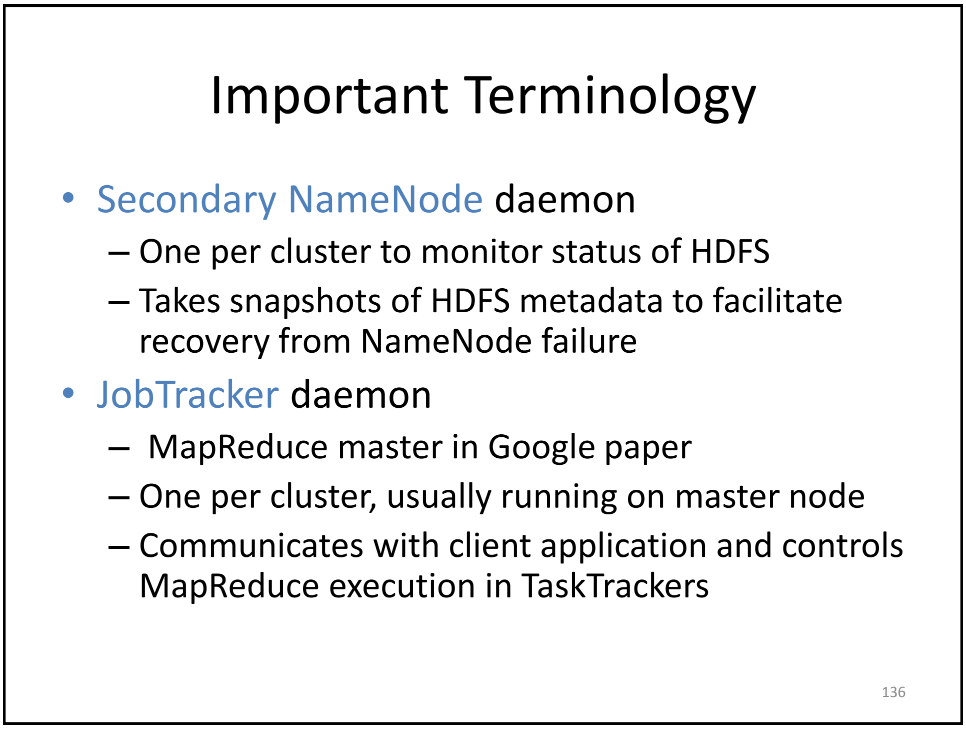
Working With Hadoop

- Mostly based on Tom White's book "Hadoop: The Definitive Guide", 2nd edition
- Note: We will use the old org.apache.hadoop.mapred API
  - New API, org.apache.hadoop.mapreduce, seems to be incomplete and less tested at this time
  - Cluster has Hadoop 0.20.2 installed



Important Terminology

- NameNode daemon
  - Corresponds to GFS Master
  - Runs on master node of the Hadoop Distributed File System (HDFS)
  - Directs DataNodes to perform their low-level I/O tasks
- DataNode daemon
  - Corresponds to GFS chunkserver
  - Runs on each slave machine in the HDFS
  - Does the low-level I/O work



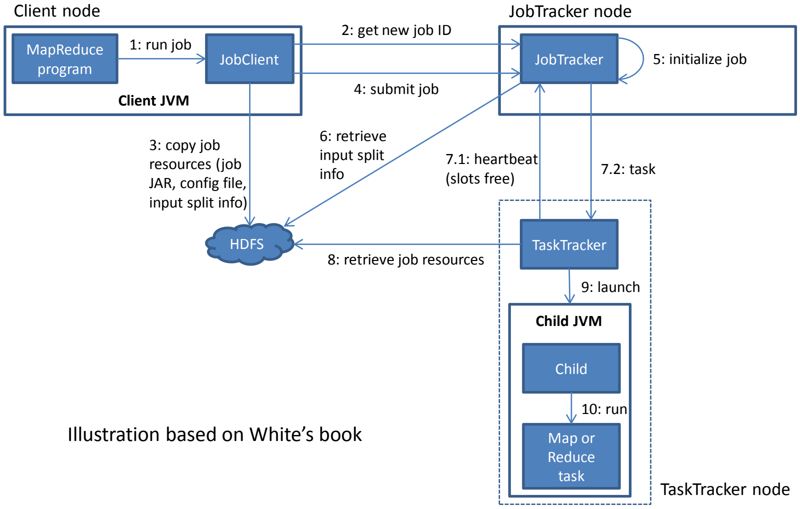
Important Terminology

- Secondary NameNode daemon
  - One per cluster to monitor status of HDFS
  - Takes snapshots of HDFS metadata to facilitate recovery from NameNode failure
- JobTracker daemon
  - MapReduce master in Google paper
  - One per cluster, usually running on master node
  - Communicates with client application and controls MapReduce execution in TaskTrackers

Important Terminology

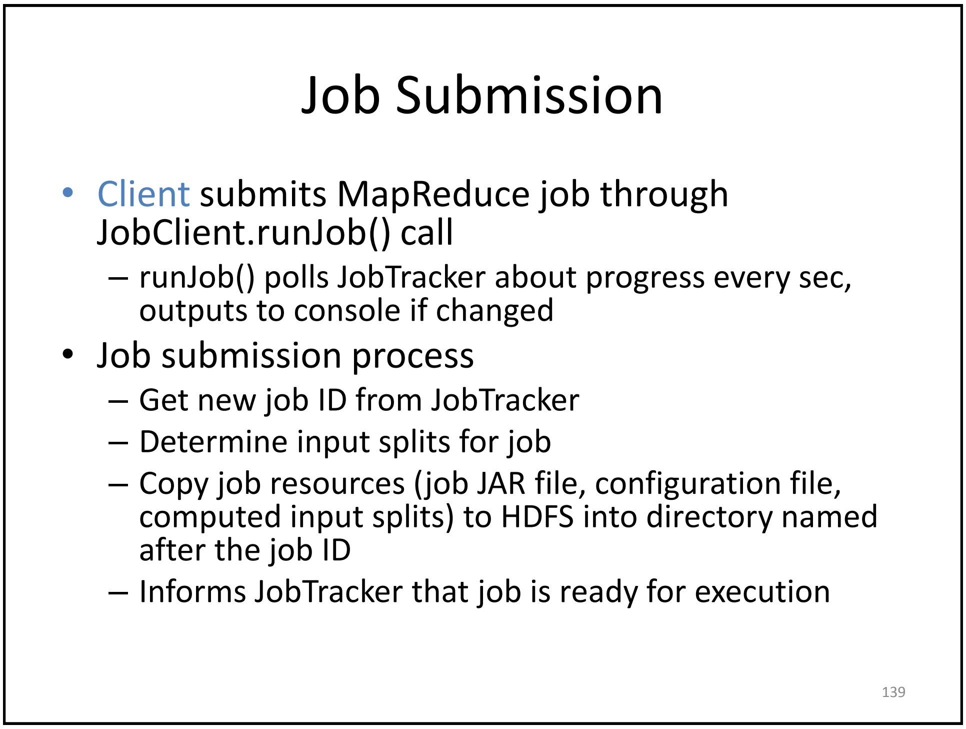
- TaskTracker daemon
  - MapReduce worker in Google paper
  - One TaskTracker per slave node
  - Performs actual Map and Reduce execution
  - Can spawn multiple JVMs to do the work
- Typical setup
  - NameNode and JobTracker run on cluster head node
  - DataNode and TaskTracker run on all other nodes
  - Secondary NameNode runs on dedicated machine or on cluster head node (usually not a good idea, but ok for small clusters)

Anatomy of MapReduce Job Run



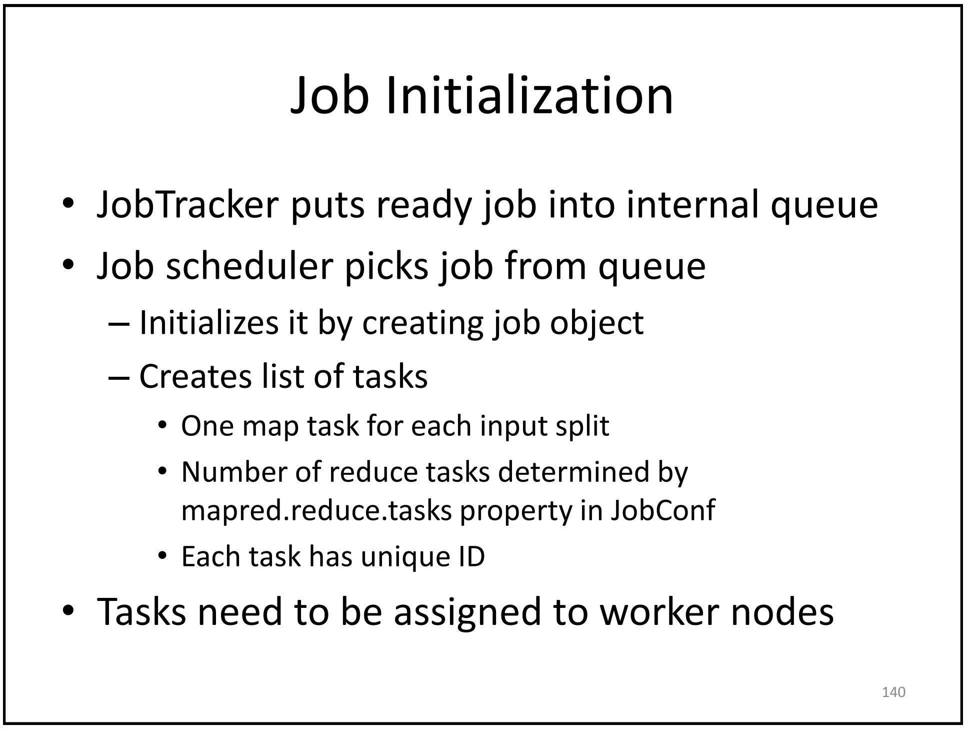
Client node
MapReduce program
1: run job
JobClient
Client JVM
2: get new job ID
4: submit job
JobTracker node
JobTracker
5: initialize job
3: copy job resources (job JAR, config file, input split info)
6: retrieve input split info
7.1: heartbeat (slots free)
7.2: task
HDFS
8: retrieve job resources
TaskTracker
9: launch
Child JVM
Child
10: run
Map or Reduce task
TaskTracker node

Illustration based on White’s book



Job Submission

- Client submits MapReduce job through JobClient.runJob() call
  - runJob() polls JobTracker about progress every sec, outputs to console if changed
- Job submission process
  - Get new job ID from JobTracker
  - Determine input splits for job
  - Copy job resources (job JAR file, configuration file, computed input splits) to HDFS into directory named after the job ID
  - Informs JobTracker that job is ready for execution



Job Initialization

- JobTracker puts ready job into internal queue
- Job scheduler picks job from queue
  - Initializes it by creating job object
  - Creates list of tasks
    - One map task for each input split
    - Number of reduce tasks determined by mapred.reduce.tasks property in JobConf
    - Each task has unique ID
- Tasks need to be assigned to worker nodes

Task Assignment

- TaskTrackers send heartbeat to JobTracker
  - Indicate if ready to run new tasks
  - Number of “slots” for tasks depends on number of cores and memory size
- JobTracker replies with new task
  - Chooses task from first job in priority-queue
    - Chooses map tasks before reduce tasks
    - Chooses map task whose input split location is closest to machine running the TaskTracker instance
      - Ideal case: data-local task
  - Could also use other scheduling policy

Task Execution

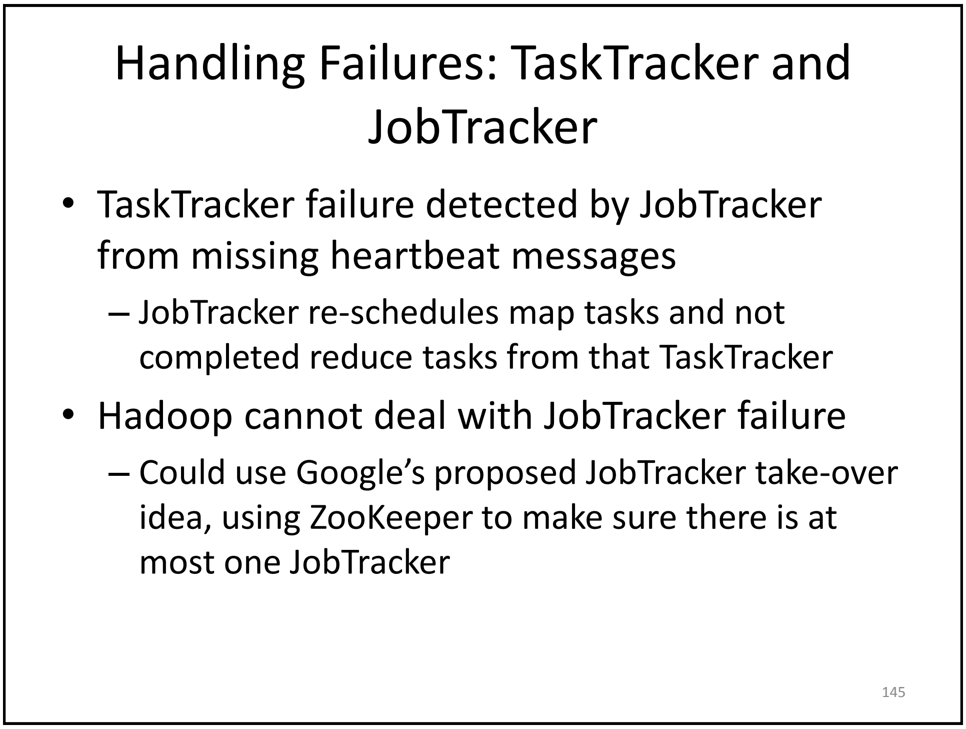
- TaskTracker copies job JAR and other configuration data (e.g., distributed cache) from HDFS to local disk
- Creates local working directory
- Creates TaskRunner instance
- TaskRunner launches new JVM (or reuses one from another task) to execute the JAR

Monitoring Job Progress

- Tasks report progress to TaskTracker
- TaskTracker includes task progress in heartbeat message to JobTracker
- JobTracker computes global status of job progress
- JobClient polls JobTracker regularly for status
- Visible on console and Web UI

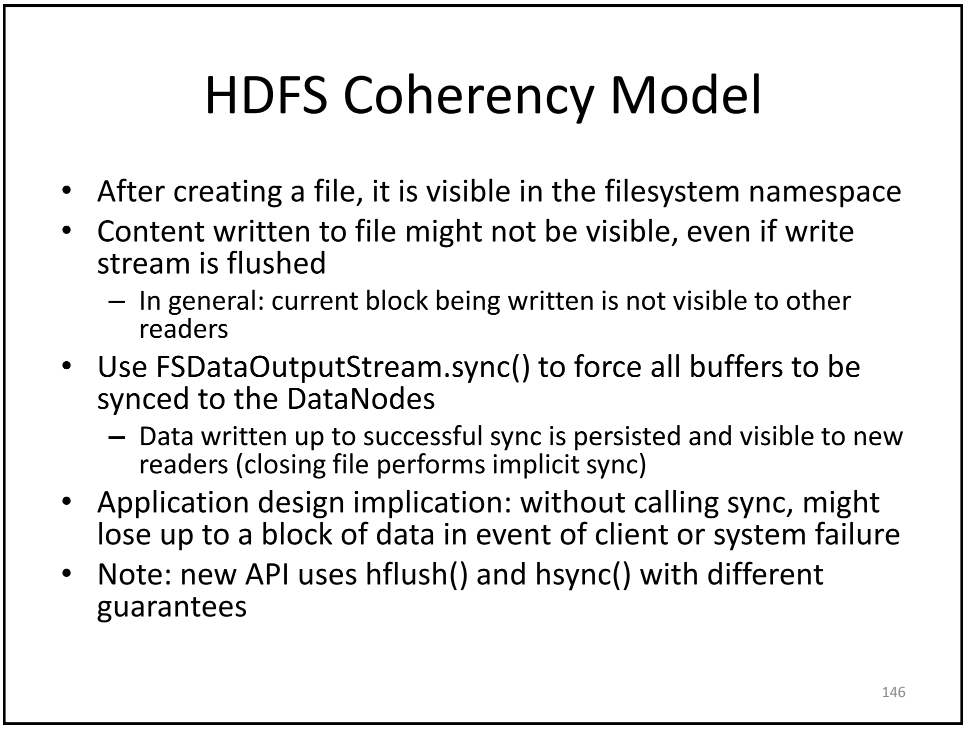
Handling Failures: Task

- Error reported to TaskTracker and logged
- Hanging task detected through timeout
- JobTracker will automatically re-schedule failed tasks
  - Tries up to mapred.map.max.attempts many times (similar for reduce)
  - Job is aborted when task failure rate exceeds mapred.max.map.failures.percent (similar for reduce)



Handling Failures: TaskTracker and JobTracker

- TaskTracker failure detected by JobTracker from missing heartbeat messages
  - JobTracker re-schedules map tasks and not completed reduce tasks from that TaskTracker
- Hadoop cannot deal with JobTracker failure
  - Could use Google’s proposed JobTracker take-over idea, using ZooKeeper to make sure there is at most one JobTracker



HDFS Coherency Model

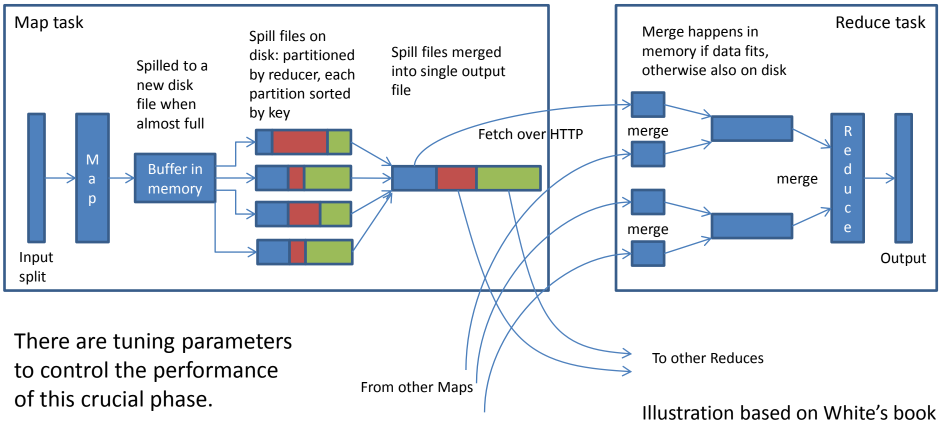
- After creating a file, it is visible in the filesystem namespace
- Content written to file might not be visible, even if write stream is flushed
  - In general: current block being written is not visible to other readers
- Use FSDataOutputStream.sync() to force all buffers to be synced to the DataNodes
  - Data written up to successful sync is persisted and visible to new readers (closing file performs implicit sync)
- Application design implication: without calling sync, might lose up to a block of data in event of client or system failure
- Note: new API uses hflush() and hsync() with different guarantees

Moving Data From Mappers to Reducers

- Shuffle and sort phase = synchronization barrier between map and reduce phase
- Often one of the most expensive parts of a MapReduce execution
- Mappers need to separate output intended for different reducers
- Reducers need to collect their data from all mappers and group it by key
- Keys at each reducer are processed in order

Shuffle and Sort Overview

Reduce task starts copying data from map task as soon as it completes. Reduce cannot start working on the data until all mappers have finished and their data has arrived.


Map task
Spilled to a new disk file when almost full
Spill files on disk: partitioned by reducer, each partition sorted by key
Spill files merged into single output file
Map
Buffer in memory
Input split
Fetch over HTTP
Merge happens in memory if data fits, otherwise also on disk
Reduce task
merge
merge
merge
Reduce
Output
To other Reduces
From other Maps

There are tuning parameters to control the performance of this crucial phase.

Illustration based on White's book

NCDC Weather Data Example

- Raw data has lines like these (year, temperature in **bold**)
  - 0067011990999991**1950**051507004+68750+023550FM-12+038299999V0203301N00671220001CN9999999N9**+0000**1+99999999999
  - 0043011990999991**1950**051512004+68750+023550FM-12+038299999V0203201N00671220001CN9999999N9**+0022**1+99999999999
- Goal: find max temperature for each year
  - Map: emit (year, temp) for each year
  - Reduce: compute max over temp from (year, (temp, temp,…)) list

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Map

- Implements Hadoop’s Mapper interface
  - Org.apache.hadoop.mapred.Mapper
- Parameters: input key type, input value type, output key type, and output value type
  - Input key: line’s offset in file (irrelevant)
  - Input value: line from NCDC file
  - Output key: year
  - Output value: temperature
- Data types are optimized for network serialization
  - Found in org.apache.hadoop.io package
- Work is done by the map() method

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Map() Method

- Input: input key type, input value type
  - Line of text from NCDC file
  - Converted to Java String type, then parsed to get year and temperature
- Output: OutputCollector instance
  - Uses output key and value types
- Only write (year, temp) pair if the temperature is present and quality indicator reading is OK

```
import java.io.IOException;

import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapred.MapReduceBase;
import org.apache.hadoop.mapred.Mapper;
import org.apache.hadoop.mapred.OutputCollector;
import org.apache.hadoop.mapred.Reporter;

public class MaxTemperatureMapper extends MapReduceBase implements Mapper<LongWritable, Text, Text, IntWritable> {

  private static final int MISSING = 9999;

  public void map(LongWritable key, Text value, OutputCollector<Text, IntWritable> output, Reporter reporter)
      throws IOException {

    String line = value.toString();
    String year = line.substring(15, 19);
    int airTemperature;
    if (line.charAt(87) == '+') { // parseInt doesn't like leading plus signs
      airTemperature = Integer.parseInt(line.substring(88, 92));
    } else {
      airTemperature = Integer.parseInt(line.substring(87, 92));
    }
    String quality = line.substring(92, 93);
    if (airTemperature != MISSING && quality.matches("[01459]")) {
      output.collect(new Text(year), new IntWritable(airTemperature));
    }
  }
}
```

Reduce

- Implements org.apache.hadoop.mapred.Reducer
- Input key and value types must match Mapper output key and value types
- Work is done by reduce() method
  - Input values passed as Iterator
  - Goes over all temperatures to find the max
  - Result pair is passed to OutputCollector instance
    - Writes result to HDFS, Hadoop's distributed file system

```
import java.io.IOException;
import java.util.Iterator;

import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapred.MapReduceBase;
import org.apache.hadoop.mapred.OutputCollector;
import org.apache.hadoop.mapred.Reducer;
import org.apache.hadoop.mapred.Reporter;

public class MaxTemperatureReducer extends MapReduceBase
  implements Reducer<Text, IntWritable, Text, IntWritable> {

  public void reduce(Text key, Iterator<IntWritable> values,
      OutputCollector<Text, IntWritable> output, Reporter reporter)
      throws IOException {

    int maxValue = Integer.MIN_VALUE;
    while (values.hasNext()) {
      maxValue = Math.max(maxValue, values.next().get());
    }
    output.collect(key, new IntWritable(maxValue));
  }
}
```

Job Configuration

- Create JobConf object to set options to control how job is run
- Specify data input path with addInputPath()
  - Can be single file, directory (to use all files there), or file pattern
  - Can be called multiple times to add multiple paths
- Specify output path
  - Single output path, which is a directory for all output files
  - Directory should not exist before running the job!
- Set mapper and reducer class to be used
- Set output key and value classes for map and reduce functions
  - For reducer: setOutputKeyClass(), setOutputValueClass()
  - For mapper (omit if same as reducer): setMapOutputKeyClass(), setMapOutputValueClass()
- Can set input types similarly (default is TextInputFormat)
- JobClient.runJob() submits job and waits for it to finish

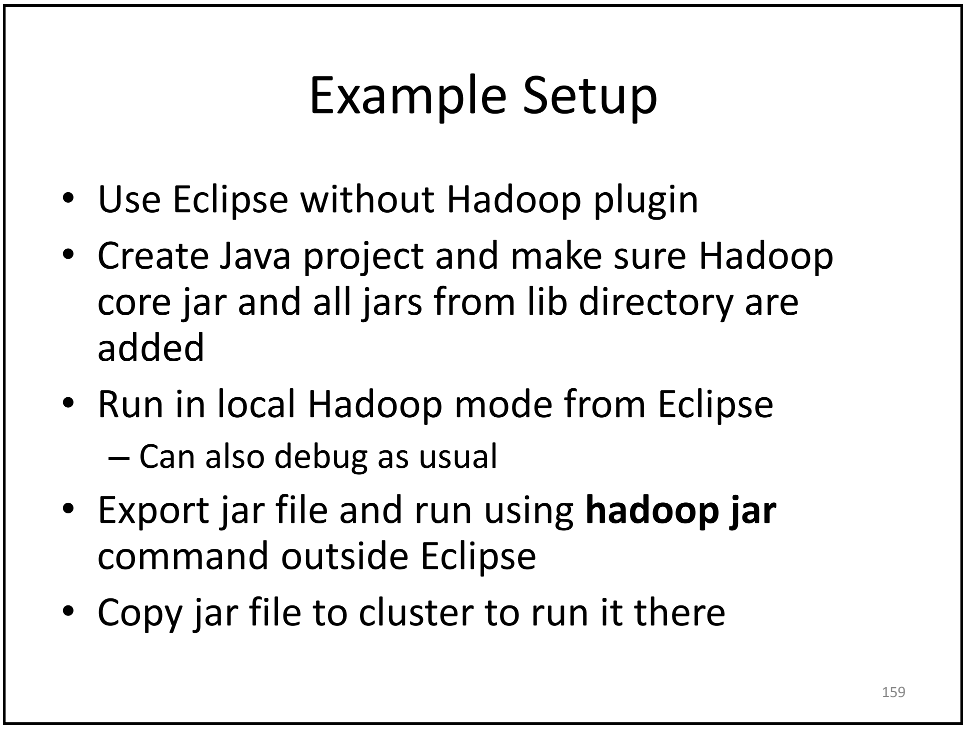
```
import java.io.IOException;

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapred.FileInputFormat;
import org.apache.hadoop.mapred.FileOutputFormat;
import org.apache.hadoop.mapred.JobClient;
import org.apache.hadoop.mapred.JobConf;

public class MaxTemperature {

  public static void main(String[] args) throws IOException {
    if (args.length != 2) {
      System.err.println("Usage: MaxTemperature <input path> <output path>");
      System.exit(-1);
    }

    JobConf conf = new JobConf(MaxTemperature.class);
    conf.setJobName("Max temperature");

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

    conf.setMapperClass(MaxTemperatureMapper.class);
    conf.setReducerClass(MaxTemperatureReducer.class);

    conf.setOutputKeyClass(Text.class);
    conf.setOutputValueClass(IntWritable.class);

    JobClient.runJob(conf);
  }
}
```

MapReduce Development Steps

1. Write Map and Reduce functions
   - Create unit tests
2. Write driver program to run a job
   - Can run from IDE with small data subset for testing
   - If test fails, use IDE for debugging
   - Update unit tests and Map/Reduce if necessary
3. Once program works on small test set, run it on full data set
   - If there are problems, update tests and code accordingly
   - IsolationRunner helps debugging cluster implementation
4. Fine-tune code, do some profiling

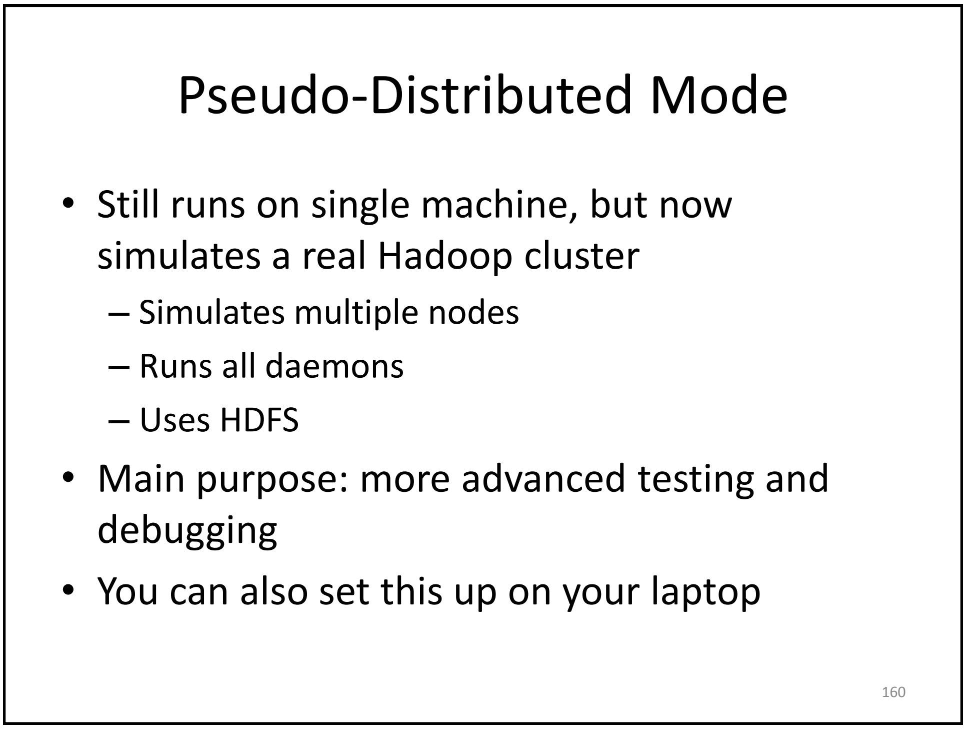
Local (Standalone) Mode

- Runs same MapReduce user program as cluster version, but does it sequentially
- Does not use any of the Hadoop daemons
- Works directly with local file system
  - No HDFS, hence no need to copy data to/from HDFS
- Great for development, testing, initial debugging
- Get Hadoop 0.20.2 and Java 1.6 to match the current cluster installation



Example Setup

- Use Eclipse without Hadoop plugin
- Create Java project and make sure Hadoop core jar and all jars from lib directory are added
- Run in local Hadoop mode from Eclipse
  - Can also debug as usual
- Export jar file and run using **hadoop jar** command outside Eclipse
- Copy jar file to cluster to run it there



Pseudo-Distributed Mode

- Still runs on single machine, but now simulates a real Hadoop cluster
  - Simulates multiple nodes
  - Runs all daemons
  - Uses HDFS
- Main purpose: more advanced testing and debugging
- You can also set this up on your laptop

Fully Distributed Mode

- Already set up for you on a cluster
- Connect to head node at 129.10.112.225
  - Copy files from/to other machines using scp
  - Copy file to HDFS using hadoop fs commands
  - Run job jar file
- Can view HDFS status though Web UI
  - Go to 129.10.112.225:50070 (only works from inside CCIS)

More Details About The Cluster

- Make sure hadoop command is found
  - Can add /usr/local/hadoop/bin to PATH
- Typical commandline call on cluster
  - hadoop jar myJar.jar myPackagePath.WordCount -D mapred.reduce.tasks=10 InputDir OutputDir
  - Make sure JAR file is in path found by Java
- View MapReduce stats at 129.10.112.225:50030 (only works from inside CCIS)