CS 425 / ECE 428
Distributed Systems
Fall 2019

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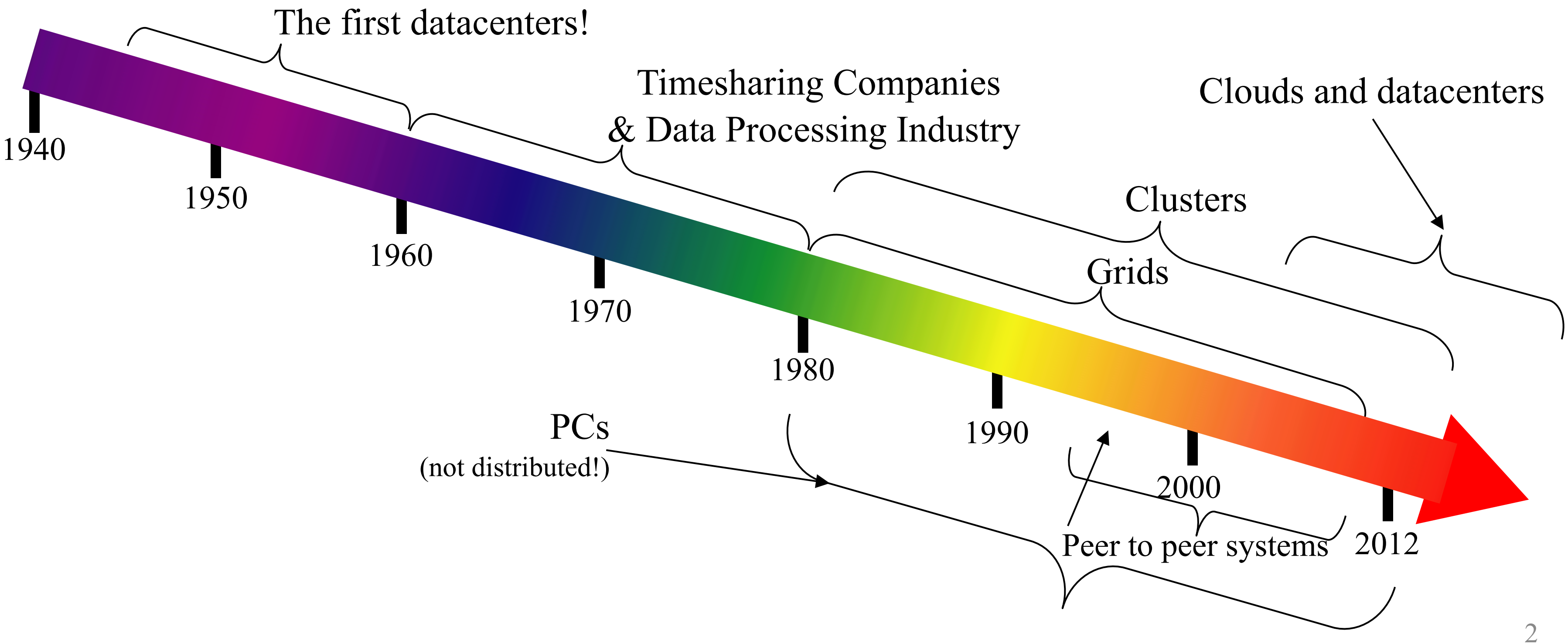
Lecture 4: Mapreduce and Hadoop

"A Cloudy History of Time"

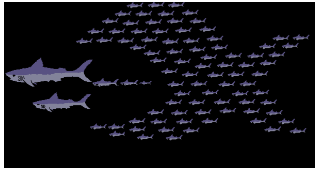


"A Cloudy History of Time"

First large datacenters: ENIAC, ORDVAC, ILLIAC
Many used vacuum tubes and mechanical relays

1940
1950
1960
1970
1980
1990
2000
2012

Berkeley NOW Project
Supercomputers
Server Farms (e.g., Oceano)

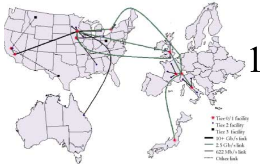


P2P Systems (90s-00s)
•Many Millions of users
•Many GB per day

Clouds

Data Processing Industry
- 1968: $70 M. 1978: $3.15 Billion

Timesharing Industry (1975):
•Market Share: Honeywell 34%, IBM 15%,
•Xerox 10%, CDC 10%, DEC 10%, UNIVAC 10%
•Honeywell 6000 & 635, IBM 370/168,
Xerox 940 & Sigma 9, DEC PDP-10, UNIVAC 1108



Grids (1980s-2000s):
•GriPhyN (1970s-80s)
•Open Science Grid and Lambda Rail (2000s)
•Globus & other standards (1990s-2000s)

Four Features New in Today's Clouds

I. Massive scale.

II. On-demand access: Pay-as-you-go, no upfront commitment.
   - And anyone can access it

III. Data-intensive Nature: What was MBs has now become TBs, PBs and XBs.
   - Daily logs, forensics, Web data, etc.
   - Humans have data numbness: Wikipedia (large) compressed is only about 10 GB!

IV. New Cloud Programming Paradigms: MapReduce/Hadoop, NoSQL/Cassandra/MongoDB and many others.
   - High in accessibility and ease of programmability
   - Lots of open-source

Combination of one or more of these gives rise to novel and unsolved distributed computing problems in cloud computing.

What is MapReduce?

- Terms are borrowed from Functional Language (e.g., Lisp)

Sum of squares:

- (map square ‘(1 2 3 4))
  - Output: (1 4 9 16)

  [processes each record sequentially and independently]

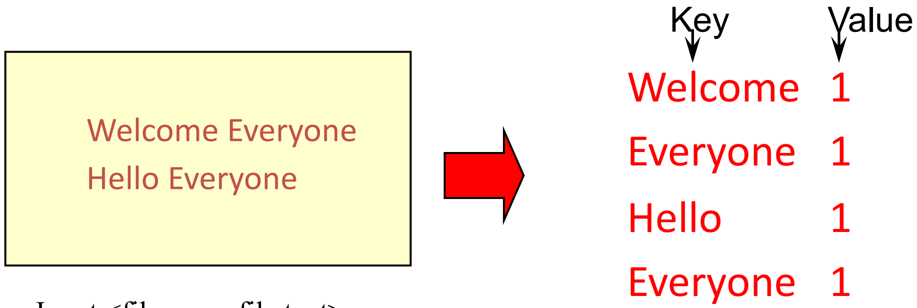
- (reduce + ‘(1 4 9 16))
  - (+ 16 (+ 9 (+ 4 1)))
  - Output: 30

  [processes set of all records in batches]

- Let’s consider a sample application: Wordcount
  - You are given a <u>huge</u> dataset (e.g., Wikipedia dump or all of Shakespeare’s works) and asked to list the count for each of the words in each of the documents therein

Map

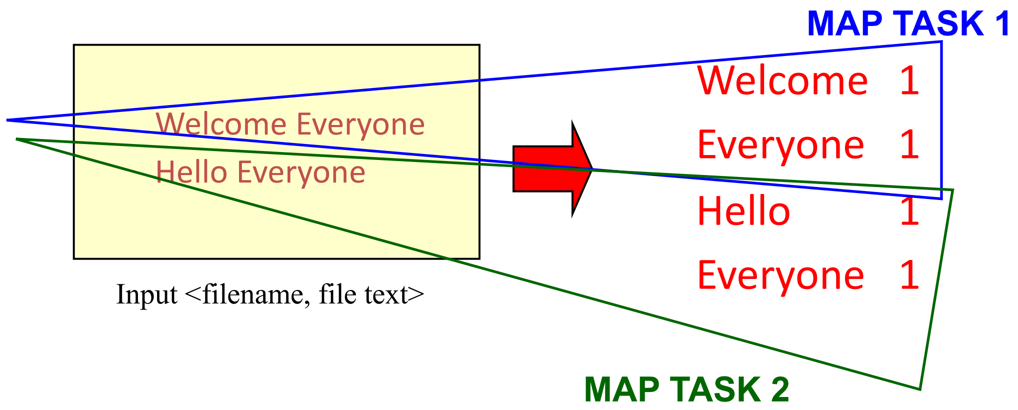
- Process individual records to generate intermediate key/value pairs.



Input <filename, file text>

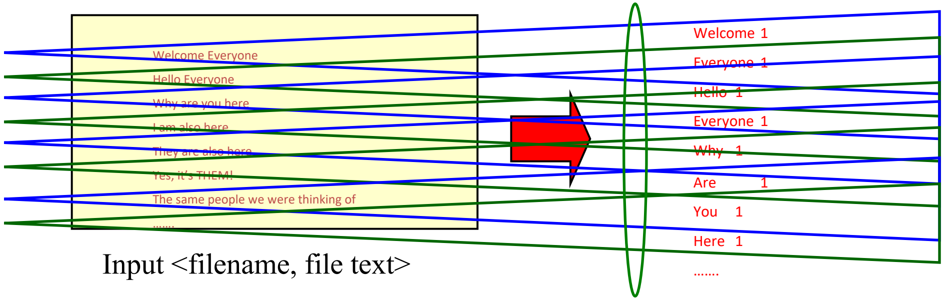
Map

- Parallelly Process individual records to generate intermediate key/value pairs.



Map

- Parallelly Process a large number of individual records to generate intermediate key/value pairs.



MAP TASKS

Reduce

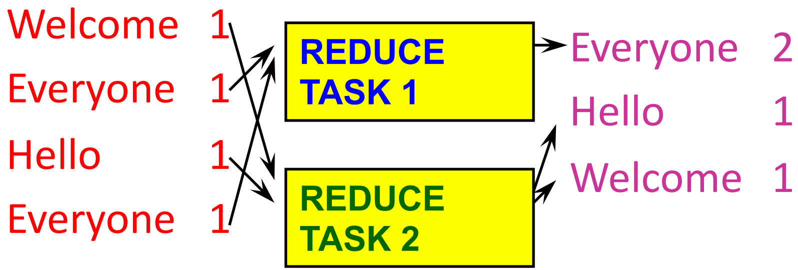
- Reduce processes and merges all intermediate values associated per key

Welcome	1
Everyone	1
Hello	1
Everyone	1

Key	Value
Everyone	2
Hello	1
Welcome	1

Reduce

- Each key assigned to one Reduce
- Parallelly Processes and merges all intermediate values by partitioning keys



- Popular: *Hash partitioning, i.e.,* key is assigned to
  - reduce # = hash(key)%number of reduce tasks

Hadoop Code - Map

```
public static class MapClass 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)
                    // key is empty, value is the line
    throws IOException {
    String line = value.toString();
    StringTokenizer itr = new StringTokenizer(line);
    while (itr.hasMoreTokens()) {
     word.set(itr.nextToken());
     output.collect(word, one);
    }
  }
} // Source: http://developer.yahoo.com/hadoop/tutorial/module4.html#wordcount
```

Hadoop Code - Reduce

```
public static class ReduceClass extends MapReduceBase  implements
Reducer<Text, IntWritable, Text, IntWritable> {
  public void reduce(
      Text key,
      Iterator<IntWritable> values,
      OutputCollector<Text, IntWritable> output,
      Reporter reporter)
     throws IOException {
           // key is word, values is a list of 1's
      int sum = 0;
      while (values.hasNext()) {
        sum += values.next().get();
      }
      output.collect(key, new IntWritable(sum));
  }
} // Source: http://developer.yahoo.com/hadoop/tutorial/module4.html#wordcount
```

Hadoop Code - Driver

```
// Tells Hadoop how to run your Map-Reduce job
public void run (String inputPath, String outputPath)
     throws Exception {
  // The job. WordCount contains MapClass and Reduce.
  JobConf conf = new JobConf(WordCount.class);
  conf.setJobName(”mywordcount");
  // The keys are words
  (strings) conf.setOutputKeyClass(Text.class);
  // The values are counts (ints)
  conf.setOutputValueClass(IntWritable.class);
  conf.setMapperClass(MapClass.class);
  conf.setReducerClass(ReduceClass.class);
  FileInputFormat.addInputPath(
     conf, newPath(inputPath));
  FileOutputFormat.setOutputPath(
     conf, new Path(outputPath));
  JobClient.runJob(conf);
} // Source: http://developer.yahoo.com/hadoop/tutorial/module4.html#wordcount
```

Some Applications of MapReduce

Distributed Grep:

- Input: large set of files
- Output: lines that match pattern

- Map – *Emits a line if it matches the supplied pattern*
- Reduce – *Copies the intermediate data to output*

Some Applications of MapReduce (2)

Reverse Web-Link Graph

- Input: Web graph: tuples (a, b) where (page a → page b)
- Output: For each page, list of pages that link *to* it

- Map – *process web log and for each input <source, target>, it outputs <target, source>*
- Reduce - *emits <target, list(source)>*

Some Applications of MapReduce (3)

Count of URL access frequency

- Input: Log of accessed URLs, e.g., from proxy server
- Output: For each URL, % of total accesses for that URL

- Map – *Process web log and outputs <URL, 1>*
- Multiple Reducers - *Emits <URL, URL_count>*

(So far, like Wordcount. But still need %)

- Chain another MapReduce job after above one
- Map – *Processes <URL, URL_count>* and outputs *<1, (<URL, URL_count>)>*
- 1 Reducer – Does two passes. In first pass, sums up all *URL_count's* to calculate overall_count. In second pass calculates %'s

Emits multiple <URL, URL_count/overall_count>

Some Applications of MapReduce (4)

Map task's output is sorted (e.g., quicksort)
Reduce task's input is sorted (e.g., mergesort)

Sort

- Input: Series of (key, value) pairs
- Output: Sorted <value>s

- Map – *<key, value> → <value, _> (identity)*
- Reducer – *<key, value> → <key, value> (identity)*
- Partitioning function – partition keys across reducers based on **ranges** (can't use hashing!)
  - Take data distribution into account to balance reducer tasks

Programming MapReduce

Externally: For user

1. Write a Map program (short), write a Reduce program (short)
2. Specify number of Maps and Reduces (parallelism level)
3. Submit job; wait for result
4. Need to know very little about parallel/distributed programming!

Internally: For the Paradigm and Scheduler

1. Parallelize Map
2. Transfer data from Map to Reduce (**shuffle data**)
3. Parallelize Reduce
4. Implement Storage for Map input, Map output, Reduce input, and Reduce output

(Ensure that no Reduce starts before all Maps are finished. That is, ensure the ***barrier*** between the Map phase and Reduce phase)

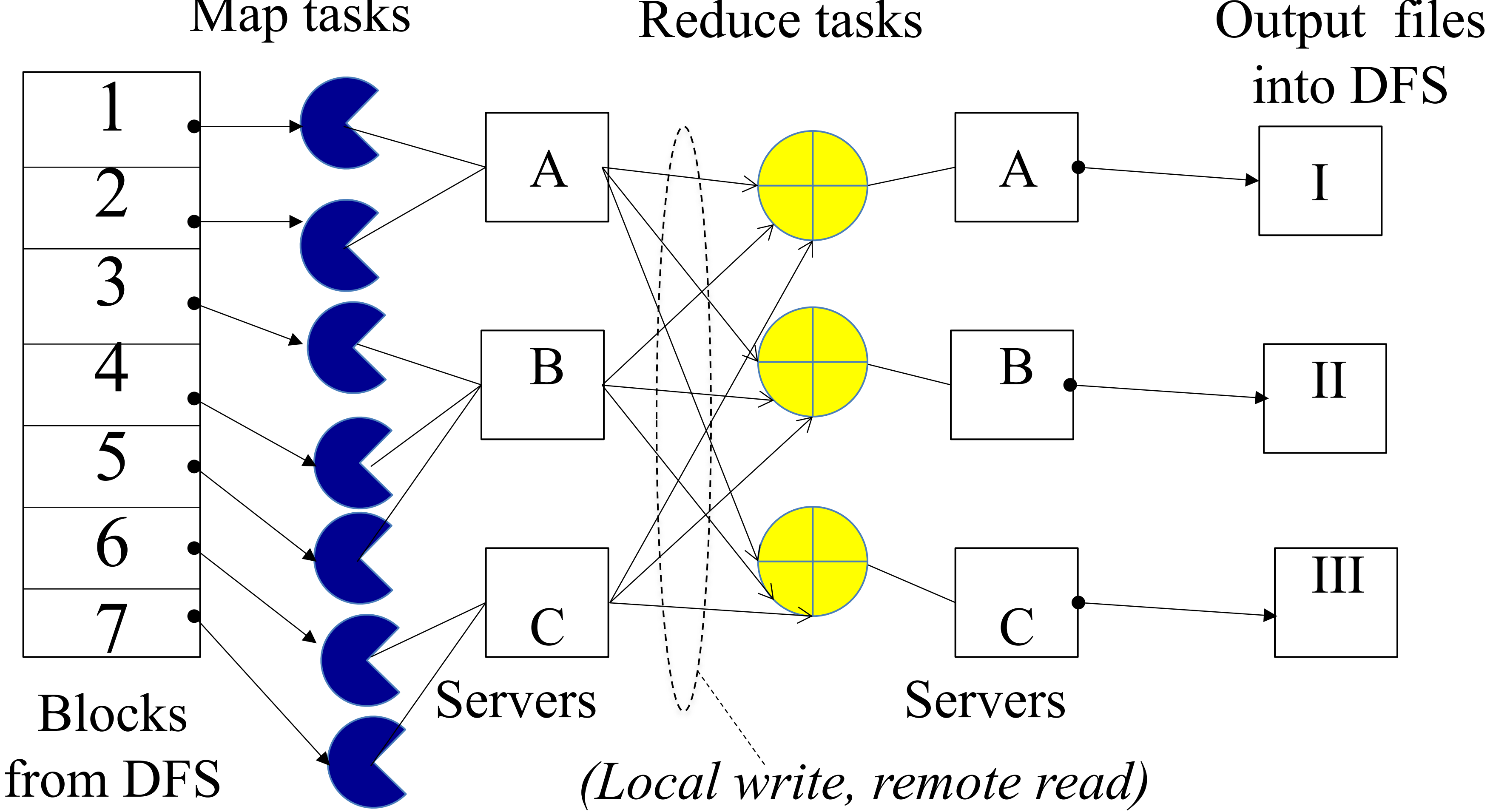
Inside MapReduce

For the cloud:

1. Parallelize Map: easy! each map task is independent of the other!
   - All Map output records with same key assigned to same Reduce
2. Transfer data from Map to Reduce:
   - Called Shuffle data
   - All Map output records with same key assigned to same Reduce task
   - use partitioning function, e.g., hash(key)%number of reducers
3. Parallelize Reduce: easy! each reduce task is independent of the other!
4. Implement Storage for Map input, Map output, Reduce input, and Reduce output
   - Map input: from distributed file system
   - Map output: to local disk (at Map node); uses local file system
   - Reduce input: from (multiple) remote disks; uses local file systems
   - Reduce output: to distributed file system

local file system = Linux FS, etc.

distributed file system = GFS (Google File System), HDFS (Hadoop Distributed File System)

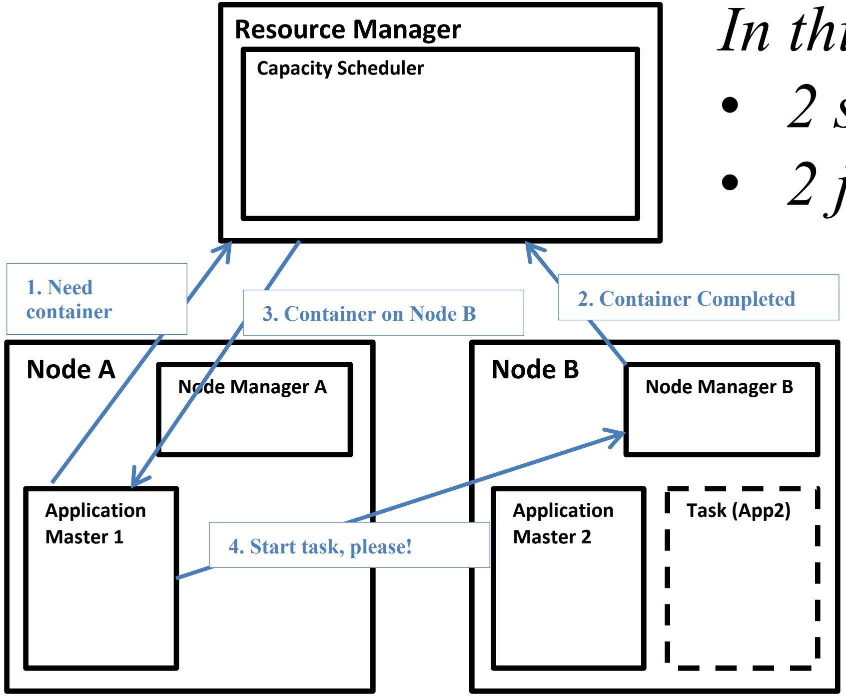


Resource Manager (assigns maps and reduces to servers)

The YARN Scheduler

- Used underneath Hadoop 2.x +
- YARN = Yet Another Resource Negotiator
- Treats each server as a collection of *containers*
  - Container = fixed CPU + fixed memory (think of Linux cgroups, but even more lightweight)
- Has 3 main components
  - Global *Resource Manager (RM)*
    - Scheduling
  - Per-server *Node Manager (NM)*
    - Daemon and server-specific functions
  - Per-application (job) *Application Master (AM)*
    - Container negotiation with RM and NMs
    - Detecting task failures of that job

YARN: How a job gets a container



In this figure

- *2 servers (A, B)*
- *2 jobs (1, 2)*

Fault Tolerance

- Server Failure
  - NM heartbeats to RM
    - If server fails: RM times out waiting for next heartbeat, RM lets all affected AMs know, and AMs take appropriate action
  - NM keeps track of each task running at its server
    - If task fails while in-progress, mark the task as idle and restart it
  - AM heartbeats to RM
    - On failure, RM restarts AM, which then syncs it up with its running tasks
- RM Failure
  - Use old checkpoints and bring up secondary RM
- Heartbeats also used to piggyback container requests
  - Avoids extra messages

Slow Servers

Slow tasks are called Stragglers

Barrier at the end of Map phase!

- The slowest task slows the entire job down (why?)
- Due to Bad Disk, Network Bandwidth, CPU, or Memory
- Keep track of "progress" of each task (% done)
- Perform proactive backup (replicated) execution of some straggler tasks
  - A task considered done when its first replica complete (other replicas can then be killed)
  - Approach called Speculative Execution.

Locality

- Locality
  - Since cloud has hierarchical topology (e.g., racks)
  - For server-fault-tolerance, GFS/HDFS stores 3 replicas of each of chunks (e.g., 64 MB in size)
    - For rack-fault-tolerance, on different racks, e.g., 2 on a rack, 1 on a different rack
  - Mapreduce attempts to schedule a map task on
    1. a machine that contains a replica of corresponding input data, or failing that,
    2. on the same rack as a machine containing the input, or failing that,
    3. Anywhere
  - Note: The 2-1 split of replicas is intended to reduce bandwidth when writing file.
    - Using more racks does not affect overall Mapreduce scheduling performance

That was Hadoop 2.x…

- Hadoop 3.x (new!) over Hadoop 2.x
  - Dockers instead of container
  - Erasure coding instead of 3-way replication
  - Multiple Namenodes instead of one (name resolution)
  - GPU support (for machine learning)
  - Intra-node disk balancing (for repurposed disks)
  - Intra-queue preemption in addition to inter-queue
  - *(From https://hortonworks.com/blog/hadoop-3-adds-value-hadoop-2/ (broken) and https://hadoop.apache.org/docs/r3.0.0/)*

Mapreduce: Summary

- Mapreduce uses parallelization + aggregation to schedule applications across clusters

- Need to deal with failure

- Plenty of ongoing research work in scheduling and fault-tolerance for Mapreduce and Hadoop

Announcements

- MP Groups **DUE this week Thu Sep 5 @ 5 pm** (see course webpage).
  - **Hard deadline, as Engr-IT will create and assign VMs tomorrow!**
- Please fill out Student Survey by 9/5 (see course webpage).
- DO NOT
  - Change MP groups unless your partner has dropped
  - Leave your MP partner hanging: Both MP partners should contribute equally (we will ask!)

- MP1 due Sep 15th
  - VMs will be distributed soon (watch Piazza)
  - Demos will be Monday Sep 16th (schedule and details will be posted before that on Piazza)
- HW1 due Sep 24th
- Check Piazza often! It's where all the announcements are at!