CS 425 / ECE 428 Distributed Systems Fall 2022

Indranil Gupta (Indy)

Lecture 4: Mapreduce and Hadoop

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]

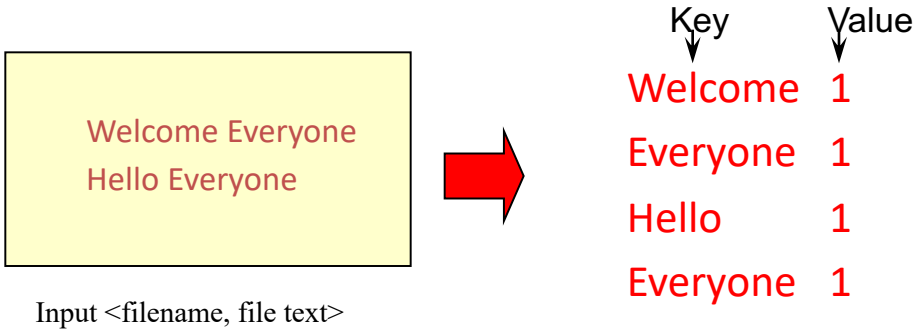
- (reduce + '(1 4 9 16))
  - (+ 16 (+ 9 (+ 4 1)))
  - Output: 30

  [processes set of all records in batches]

- Let's consider a sample application: Wordcount
  - You are given a huge 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

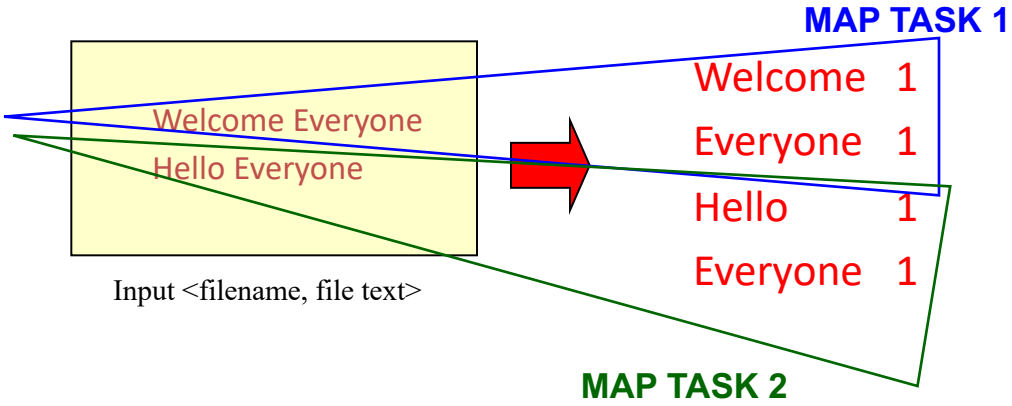
- Process individual records to generate intermediate key/value pairs.



Input <filename, file text>

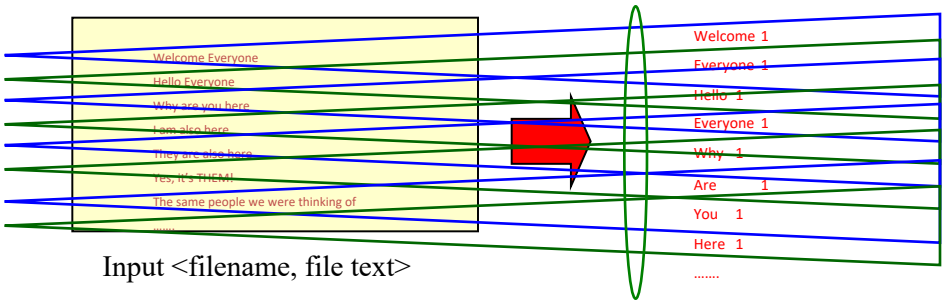
Map

- 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.

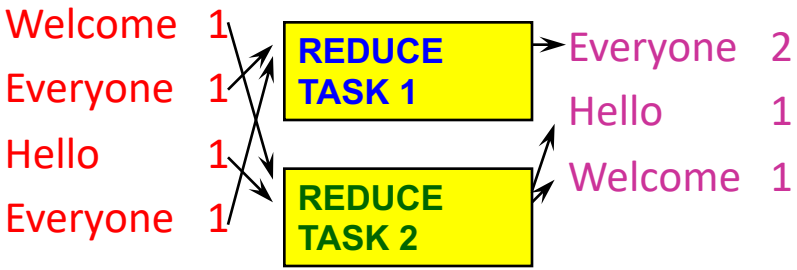


Reduce

- Reduce processes and merges all intermediate values associated per key

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)

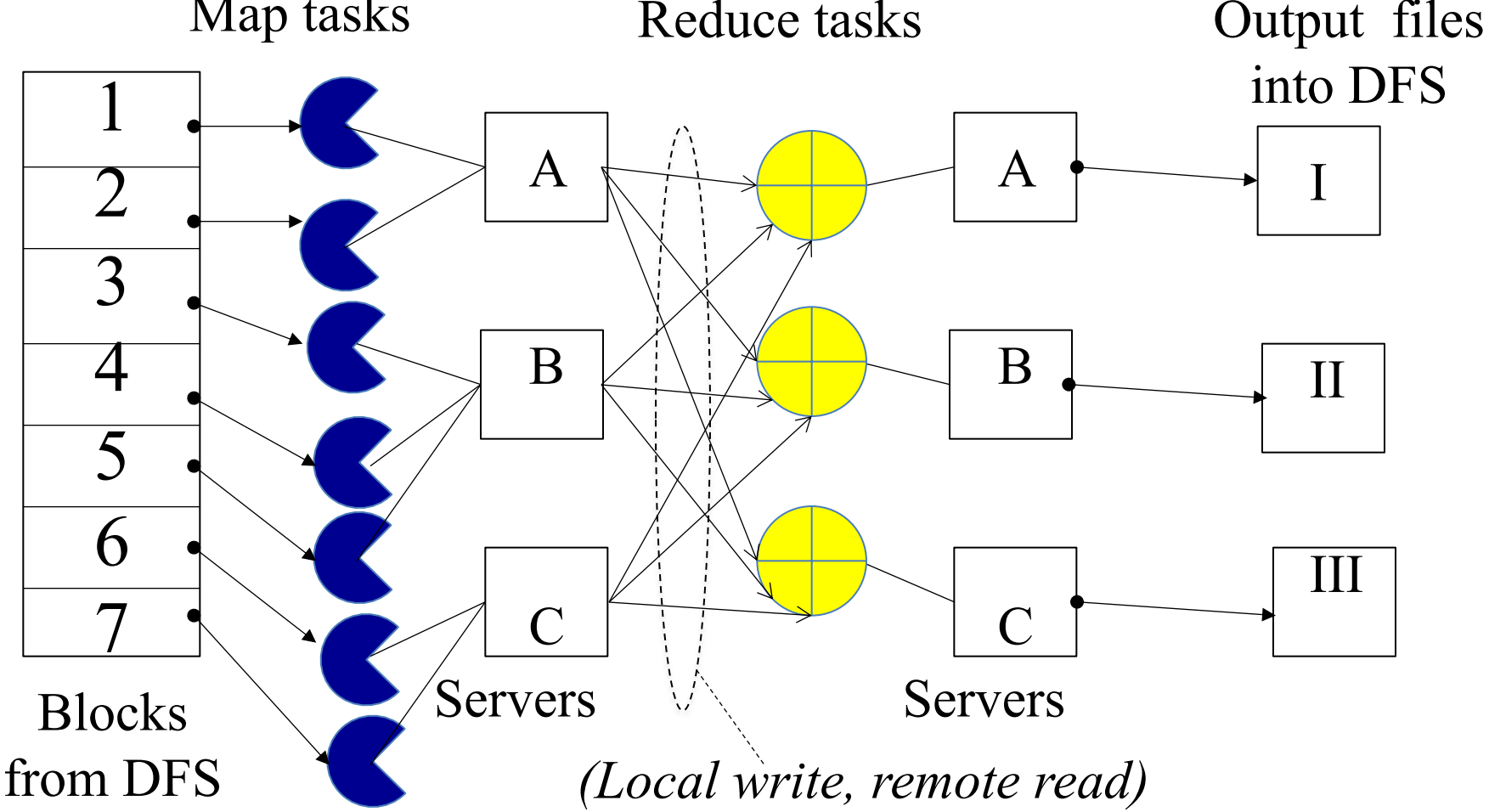
Inside MapReduce

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)

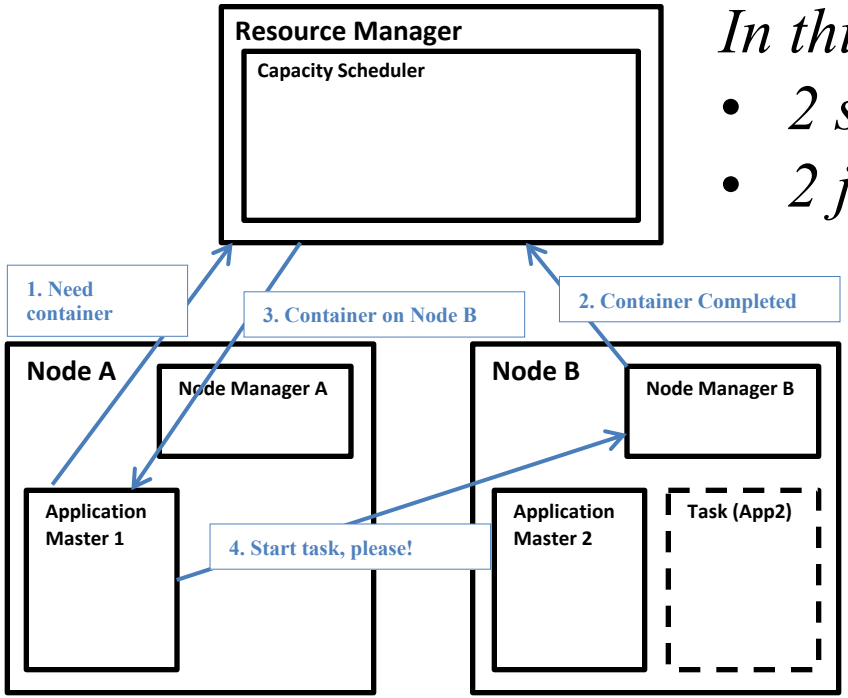


Resource Manager (assigns maps and reduces to servers)

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

- 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.

Barrier at the end of Map phase!

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

Further MapReduce Exercises

Exercise 1

1. (MapReduce) You are given a symmetric social network (like Facebook) where a is a friend of b implies that b is also a friend of a. The input is a dataset D (sharded) containing such pairs (a, b) – note that either a or b may be a lexicographically lower name. Pairs appear exactly once and are not repeated. Find the last names of those users whose first name is “Kanye” and who have at least 300 friends. You can chain Mapreduces if you want (but only if you must, and even then, only the least number). You don’t need to write code – pseudocode is fine as long as it is understandable. Your pseudocode may assume the presence of appropriate primitives (e.g., “firstname(user_id)”, etc.). The Map function takes as input a tuple (key=a,value=b).

Exercise 1: Solution

- M1 (a,b):
  - if (firstname(a)==Kanye) then output (a,b)
  - if (firstname(b)==Kanye) then output (b,a)
    - // note that second if is NOT an else if, so a single M1 function may be output up to 2 KV pairs!
- R1 (x, V):
  - if |V| >= 300 then output (lastname(x), -)

Exercise 2

2. For an asymmetrical social network, you are given a dataset D where lines consist of (a,b) which means user a follows user b. Write a MapReduce program (Map and Reduce separately) that outputs the list of all users U who satisfy the following three conditions simultaneously: i) user U has at least 2 million followers, and ii) U follows fewer than 20 other users, and iii) all the users that U follows, also follow U back.

Exercise 2: Solution

- M1(a,b):
  - Output (key=a, value=(OUT,b))
  - Output (key=b, value=(IN,a))
    - // Note that a single M1 function outputs TWO KV pairs
- R1(key=x, V):
  - Collect Sout = set of all (OUT,*) value items from V
  - Collect Sin = set of all (IN,*) value items from V
  - if (|Sout| < 20 AND |Sin| >= 2M AND all items in Sout are also present in Sin) // third term via nested for loops
    - then output (x,-_)

Exercise 3

3. For an asymmetrical social network, you are given a dataset D where lines consist of (a,b) which means user a follows user b. Write a MapReduce program (Map and Reduce separately) that outputs the list of all user *pairs* (x,y) who satisfy the following three conditions simultaneously: i) x has fewer than 100 M followers, ii) y has fewer than 100M followers, iii) x and y follow each other, and iv) *the sum* of x's followers and y's followers (double-counting common followers that follow both x and y is ok) is 100 M or more. Your output should not contain duplicates (i.e., no (x,y) and (y,x)).

Exercise 3: Solution

- M1(a,b): output (b,a)
- R1(x,V):
  - if |V| < 100M, then for all a in V, output (lexicographic_sorted_pair(x,a), |V|)
- M2(a,b): Identity
- R2(key=(a,b), value={|V1|, |V2|,…})
  - if |value|==1 output nothing
  - else if |value|==2 then add up the counts in value
    - if sum of these counts >= 100M then output (a,b)

Announcements

- **Please fill out Student Survey by 9/1 (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 11th
  - VMs being distributed now (watch Piazza)
  - Demos will be Monday Sep 12th (schedule and details will be posted next week on Piazza)
- HW1 due Sep 21st : Solve problems right after lecture covers topic!
- Check Piazza often! It's where all the announcements are at!

- (deadline passed) MP Groups DUE this week Thu Sep 1 @ 5 pm (see course webpage).
  - **Hard deadline, as Engr-IT will create and assign VMs tomorrow!**