Distributed Systems

CS425/ECE428

April 23 2021

Adopted from Spring 2021

Our agenda for the next 2-3 classes

- Brief overview of key-value stores
- Distributed Hash Tables
  - Peer-to-peer protocol for efficient insertion and retrieval of key-value pairs.
- Key-value stores in the cloud
  - How to run large-scale distributed computations over key-value stores?
    - Map-Reduce Programming Abstraction
  - How to design a large-scale distributed key-value store?
    - Case-study: Facebook's Cassandra

Cloud Computing

Many Cloud Providers

- AWS: Amazon Web Services
  - EC2: Elastic Compute Cloud
  - S3: Simple Storage Service
- Microsoft Azure
- Google Cloud/Compute Engine/AppEngine
- Rightscale, Salesforce, EMC, Gigaspaces, 10gen, Datastax, Oracle, VMWare, Yahoo, Cloudera
- And many many more!

What is a cloud?

- Cloud = Lots of storage + compute cycles nearby

- Cloud services provide:
  - managed *clusters* for distributed computing.
  - managed *distributed datastores*.

What is a cloud?

- A single cloud-site (aka “Datacenter”) consists of
  - Compute nodes (grouped into racks) (2)
  - Switches, connecting racks in a hierarchical network topology.
  - Storage (backend) nodes connected to the network (3)
  - Front-end for submitting jobs and receiving client requests (1)
  - (1)-(3): Often called “three-tier architecture”

- A geographically distributed cloud consists of
  - Multiple such sites
  - Each site perhaps with a different structure and services

Features of cloud

I. Massive scale.
   - Tens of thousands of servers and cloud tenants, and hundreds of thousands of VMs.

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

III. Data-intensive nature:
   - What was MBs has now become TBs, PBs and XBs.
     - Daily logs, forensics, Web data, etc.

Must deal with immense complexity!

- Fault-tolerance and failure-handling
- Replication and consensus
- Cluster scheduling

- How would a cloud user deal with such complexity?
  - Powerful abstractions and frameworks
  - Provide easy-to-use API to users.
  - Deal with the complexity of distributed computing under the hood.

MapReduce
is one such powerful
abstraction.

MapReduce Abstraction

- Map/Reduce
  - Programming model inspired from LISP (and other functional languages).
- Expressive: many problems can be phrased as map/reduce.
- Easy to distribute across nodes.
  - High-level job divided into multiple independent “map” tasks, followed by multiple independent “reduce” tasks.
- Nice retry/failure semantics.

MapReduce Architecture

- *MapReduce programming abstraction:*
  - Easy to program distributed computing tasks.

- MapReduce programming abstraction offered by multiple open-source *application frameworks*:
  - Handle creation of “map” and “reduce” tasks.
  - *Hadoop: one of earliest map-reduce frameworks.*
  - *Spark: easier API and performance optimizations.*

- Application frameworks use *resource managers*.
  - Deal with hassle of distributed cluster management.
  - *e.g. Kubernetes, YARN, Mesos, etc.*

MapReduce Architecture

- *MapReduce programming abstraction:*
  - Easy to program distributed computing tasks.
- MapRedu… …ed by multiple c… …ks:
  - Handle… …asks.
  - *Hadoo… …neworks.*
  - *Spark:… …nizations.*
- Application frameworks use *resource managers*.
  - Deal with hassle of distributed cluster management.
  - *e.g. Kubernetes, YARN, Mesos, etc.*

- Automatic parallelization & distribution
- Fault tolerance
- Scheduling
- Monitoring & status updates

Map/Reduce in LISP

Sum of squares:

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

- (reduce + 0 ‘(1 4 9 16))
  - (+ 16 (+ 9 (+ 4 (+1 + 0))))
  - Output: 30

Map/Reduce in LISP

Sum of squares:

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

  [processes each record sequentially and independently]

Unary operator

- (reduce + 0 '(1 4 9 16))
  - (+ 16 (+ 9 (+ 4 (+1 0))))
  - Output: 30

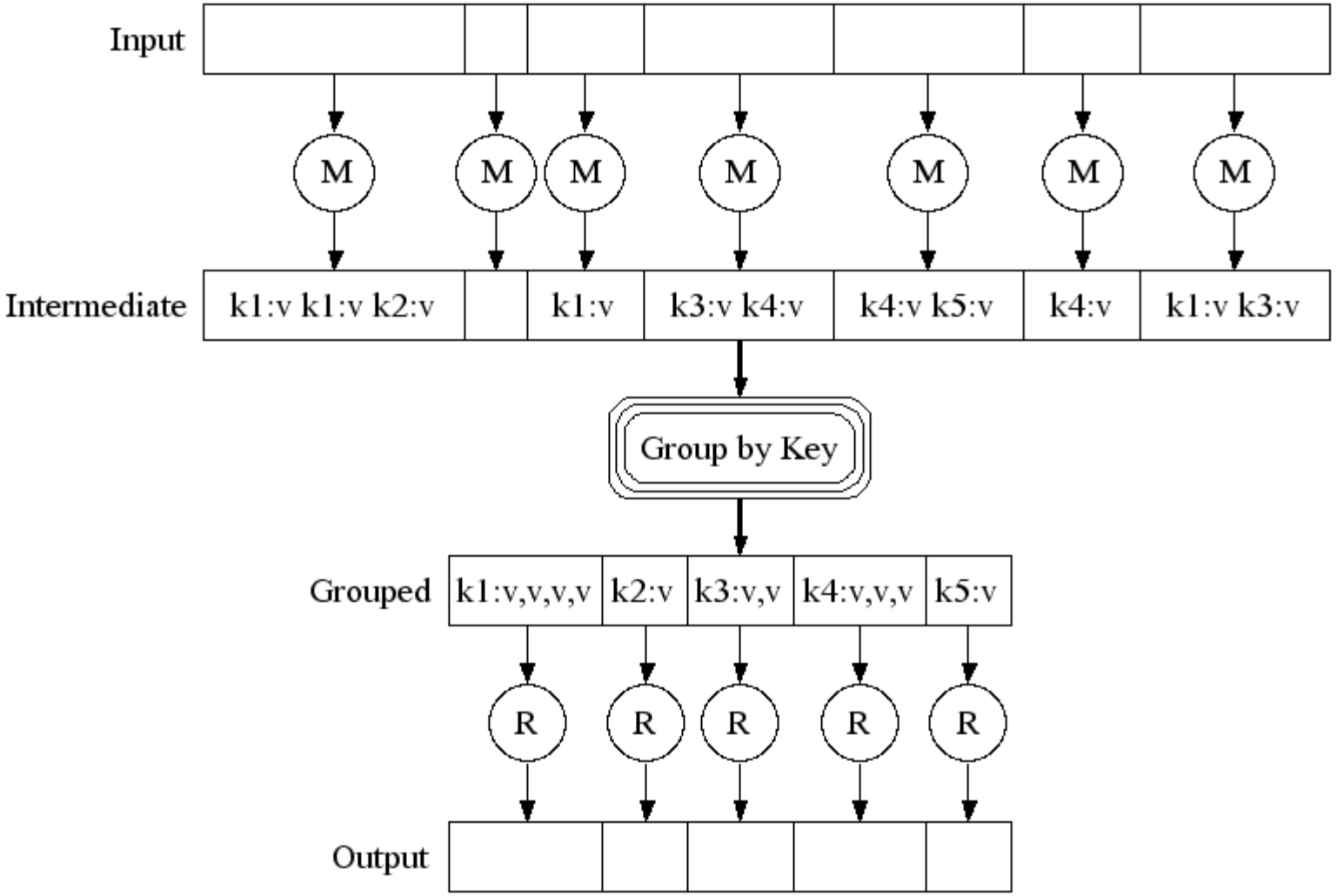
  [processes set of *all records* in batches]

Binary operator

MapReduce Overview

- Input: a set of key/value pairs
- User supplies two functions:
  - map(k,v) → list(k1,v1)
  - reduce(k1, list(v1)) → v2
- (k1,v1) is an intermediate key/value pair.
- Output is the set of (k1,v2) pairs.

MapReduce Overview



Typical Example: Word Count

- We have a large file of words containing multiple lines (or records).
- Count the number of times each distinct word appears in the file.

- *Sample application*: analyze web server logs to find popular URLs.

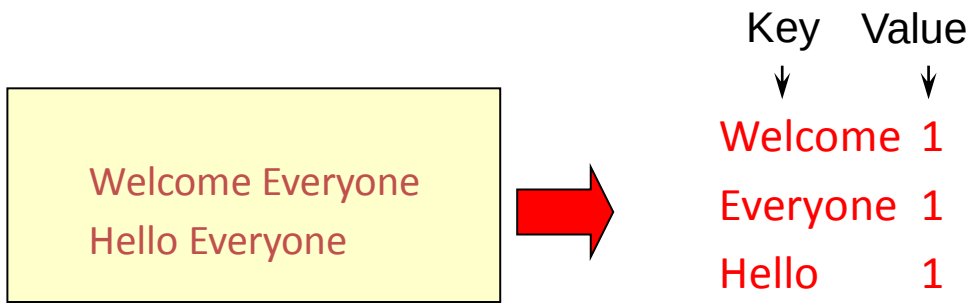
Map

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

Input <record, text per record>

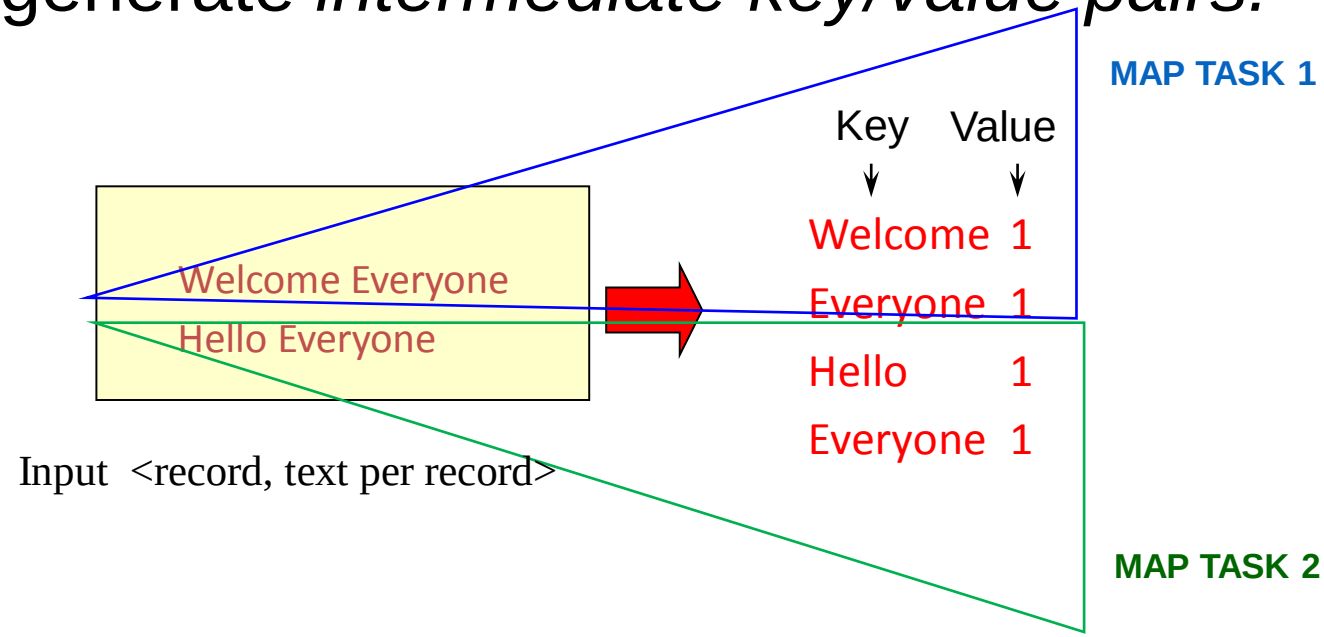
Map

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



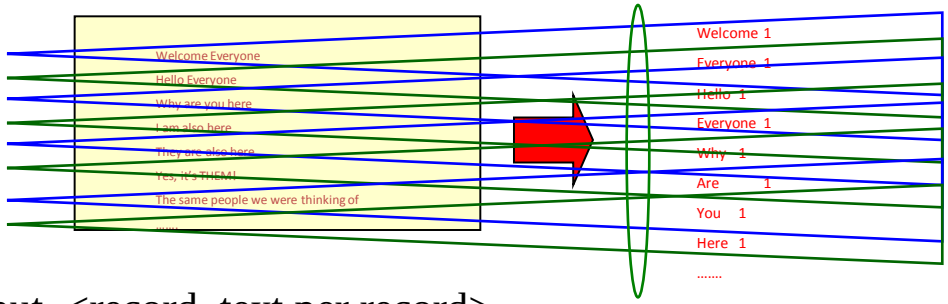
Map

- 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.



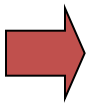
Input <record, text per record>

MAP TASKS

Reduce

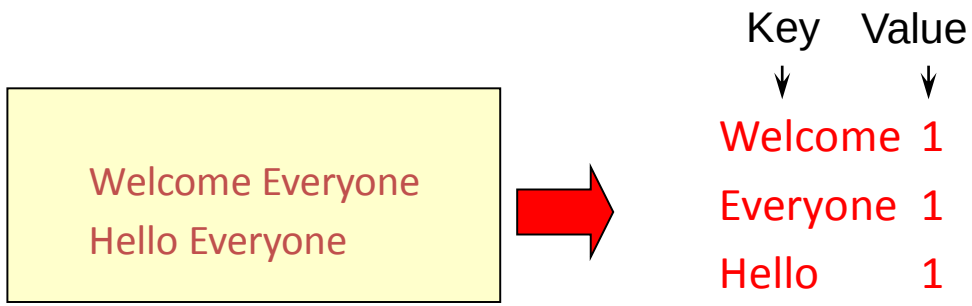
- Process and merge all intermediate values associated per key.

Welcome 1
Everyone 1
Hello 1
Everyone 1



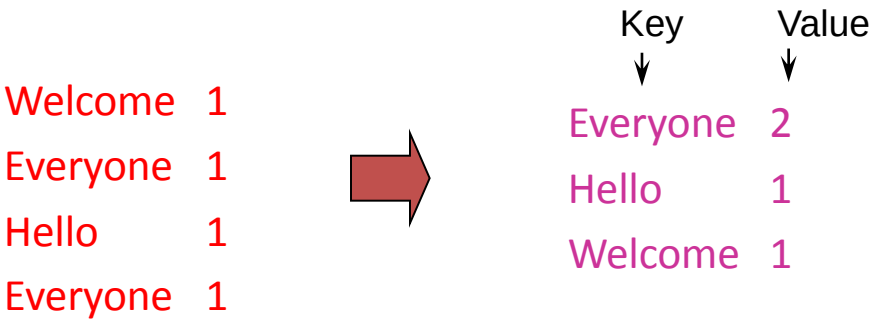
Map

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



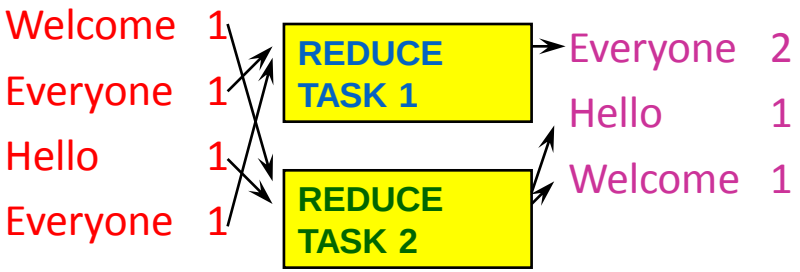
Reduce

- Processes and merges all intermediate values associated per key.



Reduce

- Each key assigned to one Reduce task.
- Parallelly process and merge all intermediate values partitioned per key.



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

MapReduce Overview

- Input: a set of key/value pairs
- User supplies two functions:
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  - reduce(k1, list(v1)) → v2
- (k1,v1) is an intermediate key/value pair.
- Output is the set of (k1,v2) pairs.

MapReduce Overview

- Input: a set of key/value pairs (record, list of words)
- User supplies two functions:
  - map(k,v) → list(k1,v1)
  - reduce(k1, list(v1)) → v2
- (k1,v1) is an intermediate key/value pair. (word, 1)
- Output is the set of (k1,v2) pairs. (word, count)

Word Count using MapReduce

```
map(key, value):
// key: record (line no.); value: list of words in the record
   for each word w in value:
            emit(w, 1)


 reduce(key, values):
 // key: a word; values: an iterator over counts
            result = 0
            for each count v in values:
                        result += v
            emit(key, result)
```

More examples: Host size

- Suppose we have a large web corpus
- Metadata file
  - Lines of the form (URL, size, date, …)
- For each host, find the total number of bytes
  - the sum of all pages sizes from a given host/URL

```
map(key, value):
// key: metadata record#;
//value: (URL, size, …) :
   for each (URL, size) in value:
         emit(URL, size)
```

```
reduce(key, values):
// key: URL, values: iterator over sizes:
   result = 0
   for each size s in values:
         result += s
   emit(key, result)
```

More examples: Distributed Grep

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

```
map(key, value):
// key: file, value: list of lines
   for each line in value:
      if  “pattern” in line:
         emit(line, 1)
```

```
reduce(key, values):
// key: line that matches pattern; values: 1’s

   emit(key, 1)
```

More examples: Graph reversal

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

```
map(key, value):
  // key: source page,
  //value: target page
  emit(value, key)
```

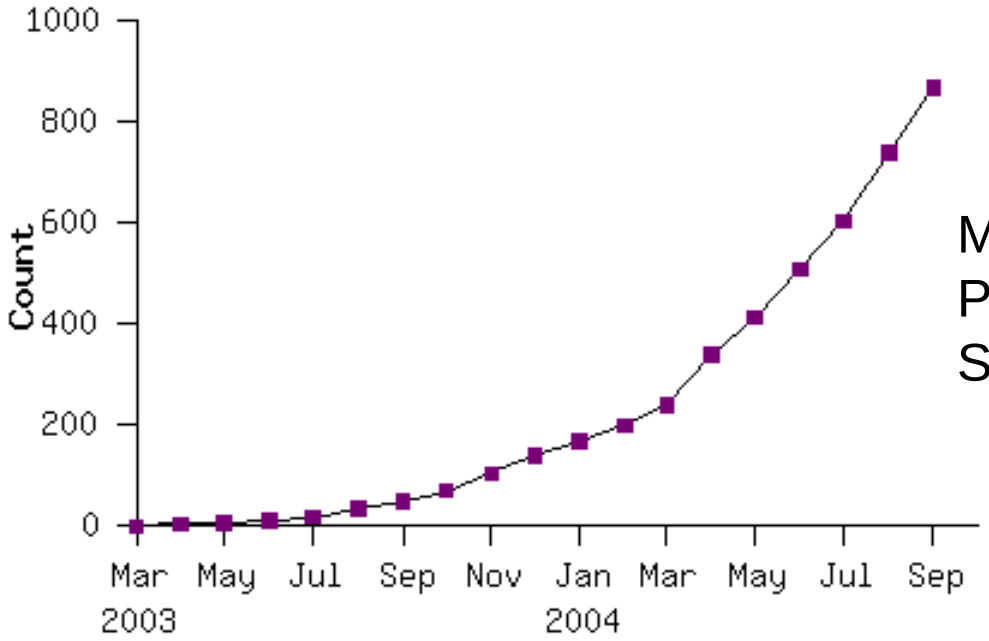
```
reduce(key, values):
  // key: target; values: list of pages that link to it.
  result = concetanate(values)
  emit(key, result)
```

MapReduce Chains

- map1 -> reduce1 -> map2 -> reduce2

- E.g., output most common words by frequency
  - Map1: emit (“word”, 1)
  - Reduce1: emit (“word”, count)
  - Map2: emit (count, “word”)
  - Reduce2: identity, i.e. emit(count, list of words)

MapReduce is popular and widely applicable



MapReduce Programs In Google Source Tree

Example uses:

distributed grep

distributed sort

web link-graph reversal

term-vector / host

web access log stats

inverted index construction

document clustering

machine learning

statistical machine translation

MapReduce Execution

Externally: For user

1. Write a Map (short) and 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!

MapReduce Execution

Internally: For the framework and resource manager in the cloud

1. Parallelize MapMap (easy!)
   - Each map task is independent of the other!
2. Transfer data from Map to Reduce (shuffle data)
   - All Map output records with same key assigned to same Reduce
   - Use partitioning function, e.g., hash(key)%number of reducers
3. Parallelize Reduce
   - Each reduce task is independent of the other!
4. Implement Storage for Map input, Map output, Reduce input, and Reduce output

(Ensure that no Reduce starts before all Maps are finished, i.e., ensure the *barrier* between the Map and Reduce phases.)

MapReduce Execution

Internally: For the framework and resource manager in the cloud

...

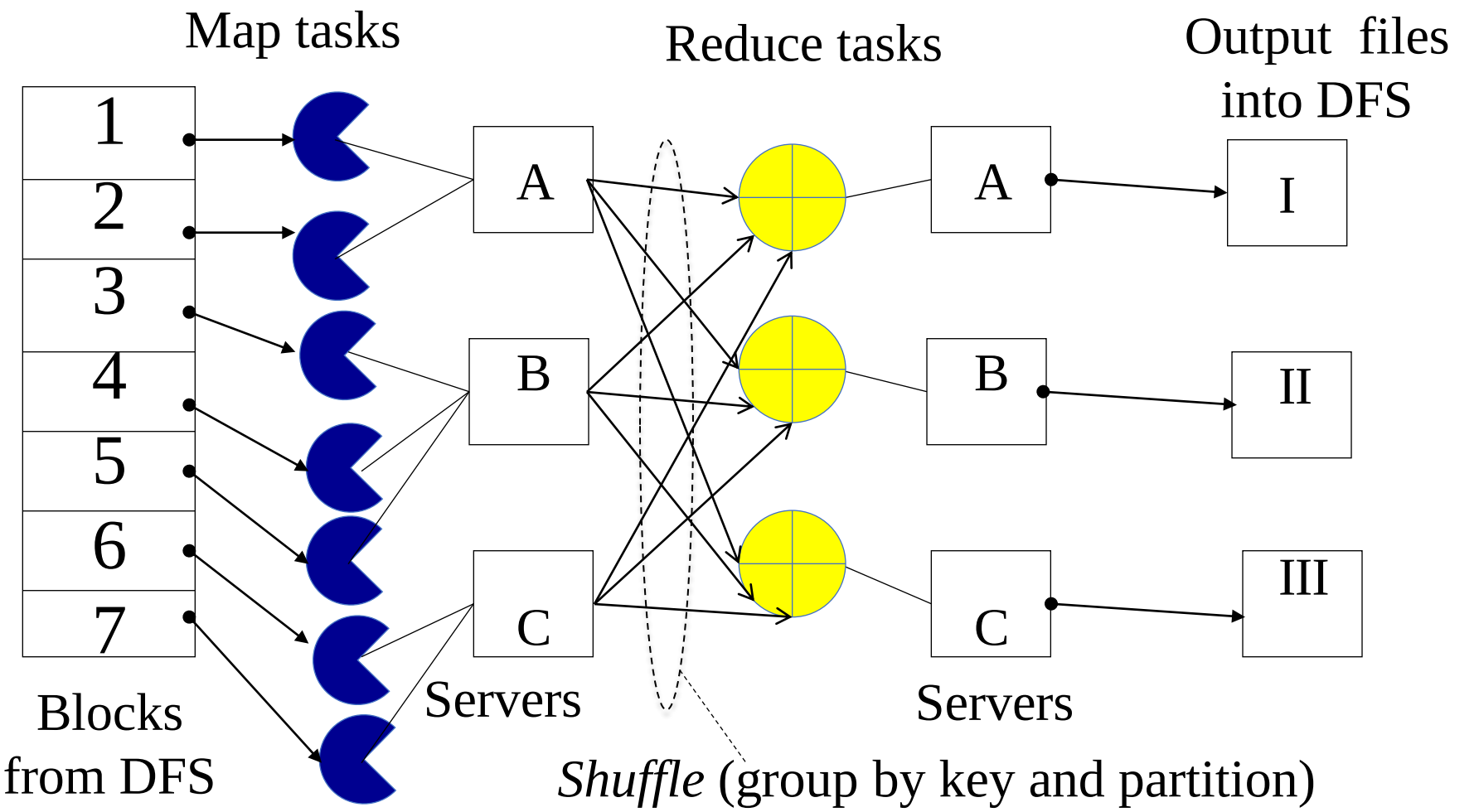
4. Implement Storage for Map input, Map output, Reduce input, and Reduce output
   - Map input: from distributed file system/data store
   - Map output: to local disk (at Map node); uses local file system
   - Reduce input: from multiple remote disks; uses local file systems
   - Reduce output: to distributed file system/data store

     local file system (e.g. Linux FS)

     distributed file system (e.g. Google FS, Hadoop Distributed FS)

     distributed data store (e.g. Cassandra, BigTable, Spanner, DynamoDB)

MapReduce Execution



Resource Manager (assigns map and reduce tasks to servers)

Resource Manager

- Examples:
  - *YARN* (Yet Another Resource Negotiator), used underneath Hadoop 2.x +
  - *Kubernetes, Borg, Mesos,* etc.
- Treats each server as a collection of *containers*
  - Container = fixed CPU + fixed memory (e.g. *Docker)*
  - Each tasks runs in a container.
- Has 3 main components
  - Global *Resource Manager (RM):* Cluster Scheduling
  - Per-Server *Node Manager (NM):* Daemon and server-specific functions
  - Per-application (job) *Application Master (AM)*
    - Container negotiation with RM and NMs.
    - Handling task failures of that job.

Fault Tolerance

- NM heartbeats to RM
  - If server fails: RM times out waiting for next heartbeat, RM let 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.

Slow Servers

Barrier at the end of Map phase!

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 (replicated) execution of some straggler tasks
  - A task considered done when its first replica completes (other replicas can then be killed).
  - This approach is called Speculative Execution.
- Straggler mitigation has been a very active area of research.

Task Scheduling

- Favour data locality:
  - attempts to schedule a map task on a machine that contains a replica of corresponding input data.
  - *if that's not possible*, then schedule it on the same rack as a machine containing the input.
  - *if that's not possible*, anywhere else.
- What does "*if that's not possible*" mean?
  - No more resources available on the machine.
  - May be worth waiting a while for resources to become available.
    - Delay scheduling in Spark!
- Cluster scheduling is also a very active area of research.

Summary

- Clouds provide a distributed computing infrastructure as a service.
- Running a distributed job in the cloud cluster can be very complex:
  - Dealing with parallelization, scheduling, fault-tolerance, etc.
- MapReduce is an abstraction to hide this complexity.
  - User programming via a simple API.
  - Distributed computing complexity handled by the underlying frameworks and resource managers.
- Plenty of ongoing research on scheduling, fault-tolerance, and straggler mitigation for MapReduce.