CSx55: Distributed Systems [MapReduce]

Orchestration despite chaos

Machines failing
    Stragglers around the corner
Disks spinning out of breadth
    flipping their bits

No matter

Distributed execution plays out
    with outcomes indistinguishable
From that on a solitary, non-faulting node
    Only commensurately faster

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Frequently asked questions from the previous class survey

- How did Google counter ad farms?

Topics covered in today's lecture

- MapReduce

Implementation

Implementation

- Machines are **commodity** machines
- **GFS** is used to manage data stored on the disks

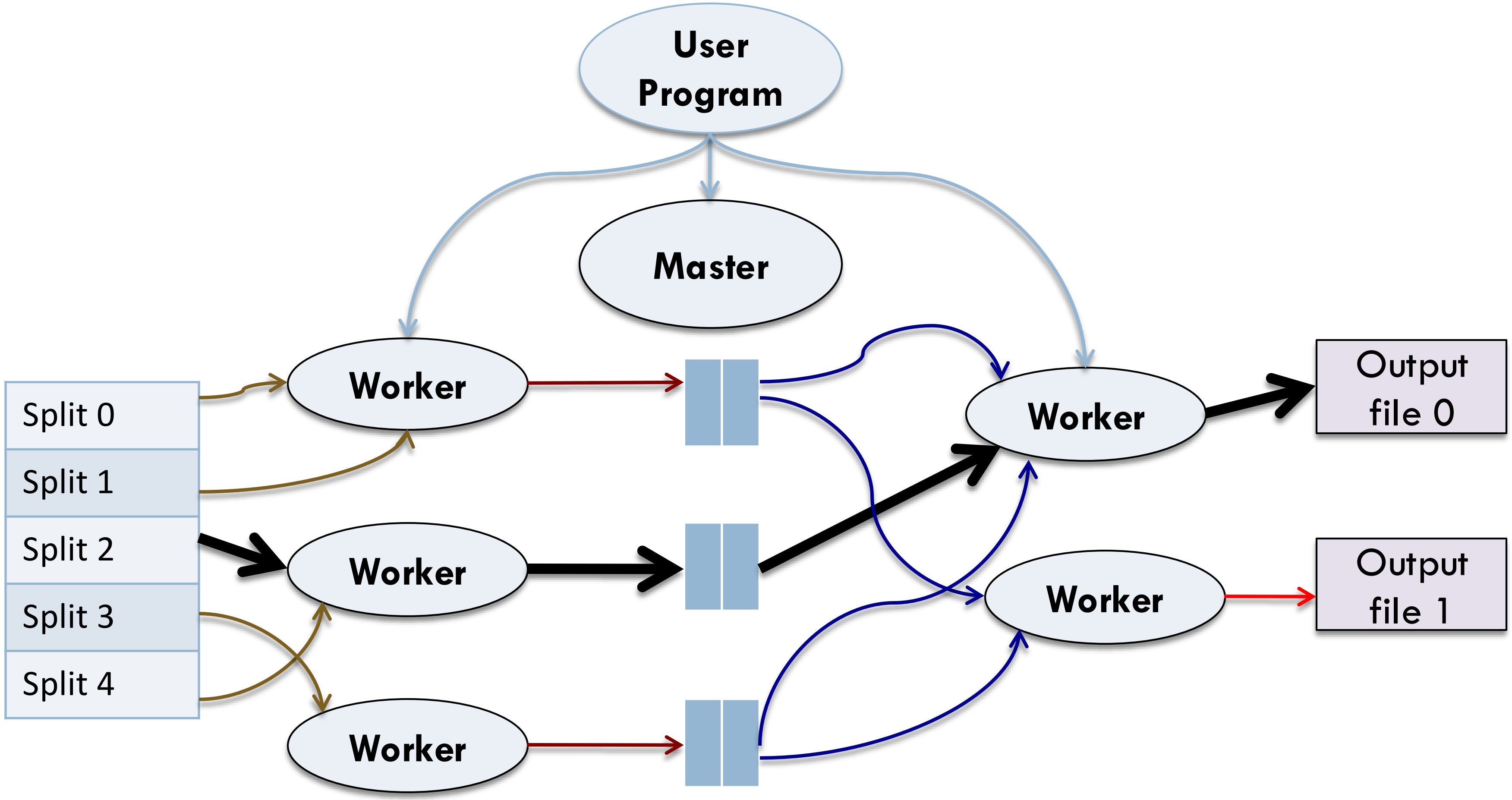
Execution Overview – Part I

- *Maps* distributed across multiple machines
- Automatic partitioning of data into M splits
- Splits are processed **concurrently** on different machines

Execution Overview – Part II

- Partition *intermediate* key space into R pieces
- E.g. hash(key) **mod** R
- User specified parameters
  - **Partitioning** function
  - **Number** of partitions (R)

Execution Overview



Execution Overview: Step 1
The MapReduce library

- Splits input files into **M** pieces
  - 16-64 MB per piece
- Starts up **copies** of the program on a cluster of machines

Execution Overview: Step II
Program copies

- One of the copies is a **Master**
- There are **M** map tasks and **R** reduce tasks to assign
- Master
  - Picks *idle* workers
  - Assigns each worker a map or reduce task

Execution Overview: Step III
Workers that are assigned a map task

- Read contents of their input split
- Parses <*key, value*> pairs out of the input data
- Pass each pair to user-defined *Map* function
- Intermediate <*key, value*> pairs from *Maps*
  - Buffered in Memory

Execution Overview: Step IV
Writing to disk

- Periodically, **buffered pairs** are written to disk
- These writes are partitioned
  - By the <u>partitioning function</u>
- **Locations** of buffered pairs on local disk
  - *Reported* back to Master
  - Master *forwards* these locations to reduce workers

Execution Overview: Step V
Reading Intermediate data

- Master notifies *Reduce* worker about locations
- Reduce worker reads buffered data from the **local disks** of *Maps*
- Read *all* intermediate data; sort by intermediate key
  - All occurrences of the same key are grouped together
  - Many different keys map to the same *Reduce* task

Execution Overview: Step VI
Processing data at the Reduce worker

- Iterate over sorted intermediate data
- For each unique key pass
  - *Key* + set of *intermediate values* to Reduce function
- Output of the Reduce function is appended
  - To output file of the reduce partition

Execution Overview: Step VII
Waking up the user

- After all Map & Reduce tasks have been completed
- Control returns to the user code

Master Data Structures

- For each Map and Reduce task
  - **State**: {*idle*, *in-progress*, *completed*}
  - Worker **machine** identity
- For each completed Map task store
  - **Location** and **sizes** of **R** intermediate file regions
- Information pushed incrementally to *in-progress* Reduce tasks

I’m not afraid
Of anything in this world
There’s nothing you can throw at me
That I haven’t already heard

I’m just trying to find
A decent melody
A song that I can sing
In my own company

Stuck in a Moment You Can’t Get Out Of, U2

FAULT TOLERANCE

Worker failures

- Master **pings** worker periodically
- After a certain number of failed pings
  - Master marks worker as having failed
- Any Map task completed by failed worker?
  - **Reset** to initial *idle* state
  - Eligible for **rescheduling**

Why completed Map tasks are reexecuted

- Output is stored on **local disk** of failed machine
  - Inaccessible
- All reduce workers are notified about reexecution
- Reduce tasks *do not* need to be reexecuted
  - Output stored in GFS

Master Failures

- Could **checkpoint** at the Master
  - Data structures are well-defined
- However, since there is only one Master
  - Assumption is that failure is unlikely
- If there is a Master failure?
  - MapReduce computation is **aborted**!
  - Client must *check and retry* MapReduce operation

Semantics in the presence of failures:
If *map* and reduce operators are deterministic

- Distributed execution output is **identical** to
  - Non-faulting, sequential execution
- Atomic commits of map and reduce task outputs help achieve this

Each in-progress task writes output to private temporary files

- Map task produces **R** such files
  - When task completes, Map sends this info to the Master

- Reduce task produces **one** such file
  - When reduce completes, worker **atomically**:
    - Renames temporary file to final output file
    - Uses GFS to do this

Locality

- **Conserve** network bandwidth
- Input files managed by GFS
- MapReduce master takes **location** of input files into account
- Schedule task on machine that contains a **replica** of the input slice

Locality and its impact when running large MapReduce tasks

- Most input data is read **locally**
- Consumes no network bandwidth

Task Granularity

Task Granularity

- Subdivide map phase into **M** pieces
- Subdivide reduce phase into **R** pieces
- **M**, **R** >> number of worker machines
- Each worker performing many different tasks:
  - Improves **dynamic load balancing**
  - Speeds up **recovery** during failures

Practical bounds on how large M and R can be

- Master must make $O(M + R)$ scheduling decisions
- Keep $O(MR)$ state in memory

Practical bounds on how large M and R can be

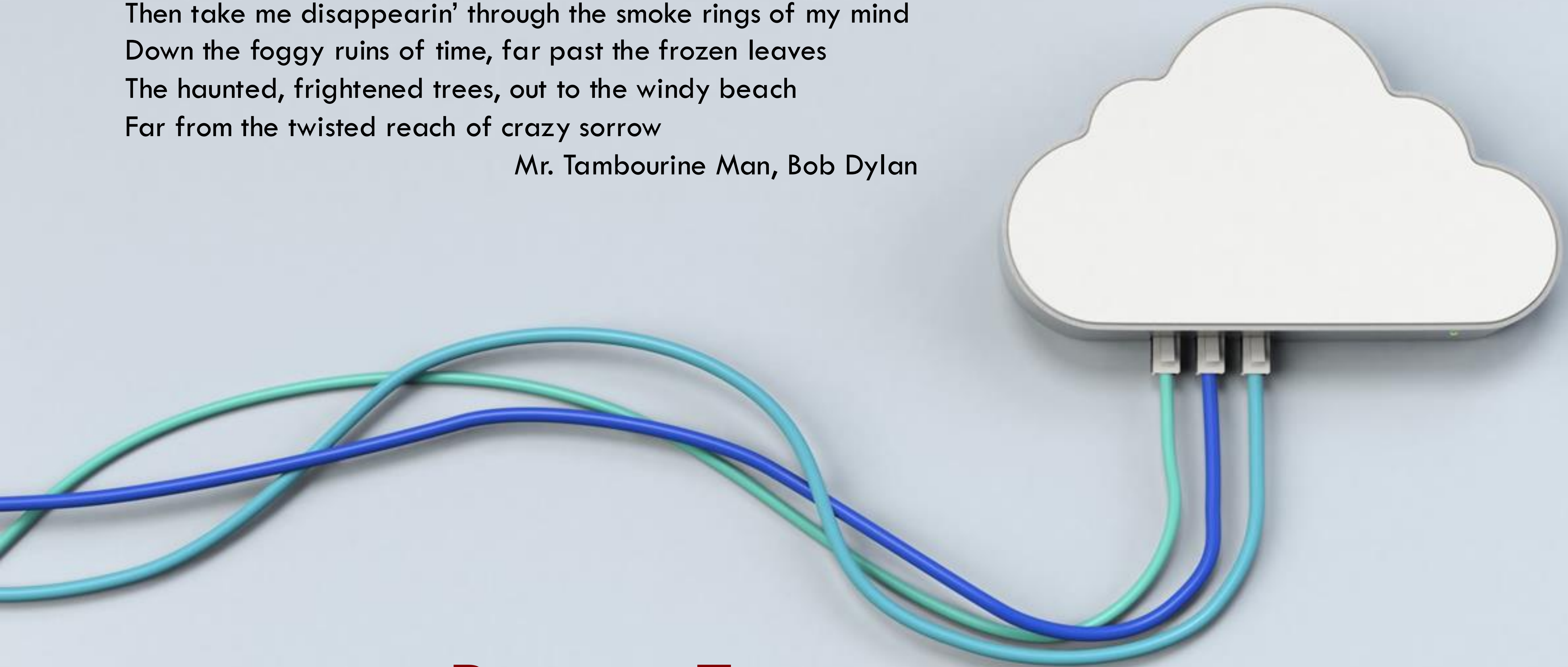
- **M** is chosen such that
  - Input data is roughly 16 MB to 64 MB
- **R** constrained by users
  - Output of each reduce is in a separate file
- **R** is a *small multiple* of the number of machines that will be used

Typical values used at Google

- **M** = 200,000
- **R** = 5,000
- **W** = 2,000 worker machines

Then take me disappearin' through the smoke rings of my mind
Down the foggy ruins of time, far past the frozen leaves
The haunted, frightened trees, out to the windy beach
Far from the twisted reach of crazy sorrow

Mr. Tambourine Man, Bob Dylan



Backup Tasks

Stragglers

- Machine that takes an **unusually long time** to complete a map or reduce operation
- Can slow down entire computation

How stragglers arise

- Machine with a **bad disk**
  - Frequent, correctable errors
  - Read performance drops from 30 MB/s to 1 MB/s
- Over **scheduling**
  - Many tasks executing on the same machine
  - *Competition* for CPU, memory, disk or network cycles
- **Bug** in machine initialization code
  - Processor caches may be disabled

Alleviating the problem of stragglers

- When a MapReduce operation is *close to completion*
- Schedule **backup** executions of *remaining* in-progress tasks
- Task completed when
  - Primary or backup finishes execution
- <u>Significantly</u> reduces time to complete large MapReduce operations

Refinements

Partitioning Function

- Users simply specify R
  - The number of output files
- Default partitioning
  - hash(key) **mod R**
- Sometimes output keys are URLs
  - Entries from a host must go to same output file
  - hash(Hostname(urlkey)) **mod R**

Ordering Guarantees

- Intermediate *key/pairs* are processed in **increasing** *key* order
- Easy to generate sorted output file

The Combiner function

- There is significant **repetition** in intermediate keys produced by each map task
- For word-frequencies
  - Each map may produce 100s or 1000s of <the, "1">
- All of these counts sent over the network
- Combiner: Does **partial merging** of this data
  - *Before* it is sent to reducer

Combiner function

- Executed on each machine that performs map task
- Code implementing combiner & reduce function
  - *Usually* the same … [We will see an example where this is not true.]
- Difference?
  - COMBINE: Output written to *intermediate* file
  - REDUCE: Output written to *final output* file

Input/Output Types: Support for reading input data in different formats

- Text mode treats every line as a <*key, value*> pair
  - Key: Offset in the file
  - Value: Contents of the line
- <*key, value*> pairs are sorted by *key*
- Each input type *knows how to split itself* for
  - Processing as separate map tasks
  - Text mode splitting occurs only at line boundaries

Side-effects

- Besides intermediate files, other auxiliary files may be produced
  - Side effects

- No atomic commits for multiple auxiliary files that are produced

Skipping Bad Records [1/3]

- Bugs in user code cause Map or Reduce functions to crash
  - Deterministically: On certain records
- Fix the bug?
  - Yes, but not always feasible
- Acceptable to ignore a few records

Skipping Bad Records [2/3]

- Optional mode of operation
  1. Detect records that cause *deterministic crashes*
  2. Skip them
- Each worker installs a **signal handler** to catch segmentation violations and bus errors

Skipping Bad Records [3/3]

- Signal handler sends *last gasp* UDP packet to the Master
  - Contains sequence number
- When Master sees more than 1 failure at that record
  - Indicates record should be skipped during next execution

Local Execution

- Support for **sequential execution** of MapReduce operation on a single machine
  - Helps with debugging, profiling, and testing
- Controls to *limit* computation to a particular map
- Invoke programs with a special flag
  - Use debugging and testing tools

Status Information

- Master runs internal HTTP Server
- Exports pages for viewing
- Show the progress of a computation
  - Number of tasks in progress
  - Number of tasks that completed
  - Bytes of input
  - Bytes of intermediate data
  - Processing rate

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

- Jeffrey Dean, Sanjay Ghemawat: *MapReduce: Simplified Data Processing on Large Clusters*. OSDI 2004: 137-150
- Jeffrey Dean, Sanjay Ghemawat: MapReduce: simplified data processing on large clusters. Commun. ACM 51(1): 107-113 (2008)