CSx55: Distributed Systems [MapReduce]

Orchestration despite chaos
Machines failing
Stragglers on the rise
Disks spinning out of breadth
having their bits flip
No matter
Distributed execution plays out
with indistinguishable outcomes
From that on a solitary, non-faulting node
Only commensurately faster

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Frequently asked questions from the previous class survey

- BitTorrent
  - Can a BitTorrent download stall if a chunk's unavailable?
  - BitTorrent: Metadata maintains file and chunk information?
  - Who returns the set of peers? The tracker or the system?
- MapReduce
  - Can distributed jobs be slower?
  - How many nodes are needed to see a benefit?
  - If I am processing a large number of files using MapReduce, mappers should see different files?

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Topics covered in today's lecture

- MapReduce

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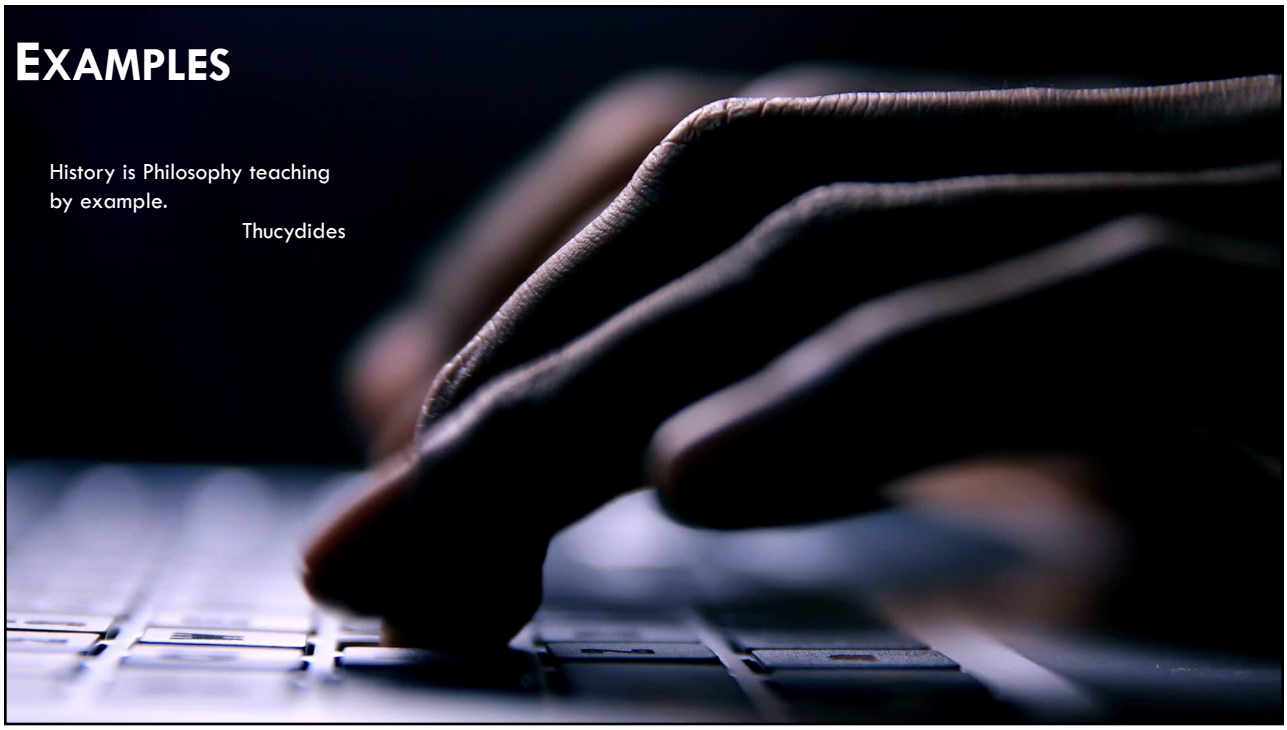
EXAMPLES

History is Philosophy teaching by example.

Thucydides



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Programs expressed as MapReduce computations: Distributed Grep

- Map
  - Emit line if it matches specified pattern
- Reduce
  - Just copy intermediate data to the output
    - The reducer here is an identity function

Counts of URL access frequency

- Map
  - Process logs of web page requests
  - Output <URL, 1>
- Reduce
  - Add together all values for a particular URL
  - Output <URL, total count>

Reverse Web-link Graph

- Map
  - Outputs <target, source> pair for each target URL found in page source
- Reduce
  - Concatenate list of all sources for a target URL
  - Output <target, *list*(source)>

Term-Vector per Host

- Summarizes important terms that occur in a set of documents <word, frequency>
- For each input document, the Map
  - Emits <hostname, term vector>
- Reduce function
  - Has all per-document vectors for a given host
  - Add term vectors; discard away infrequent terms
    - <hostname, term vector>

Inverted Index

- Map
  - Parse each document
  - Emit <word, document ID>
- Reduce
  - Accept all pairs for a given word
  - Sort document IDs
  - Emit <word, list(document ID)> pair

Implementation

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

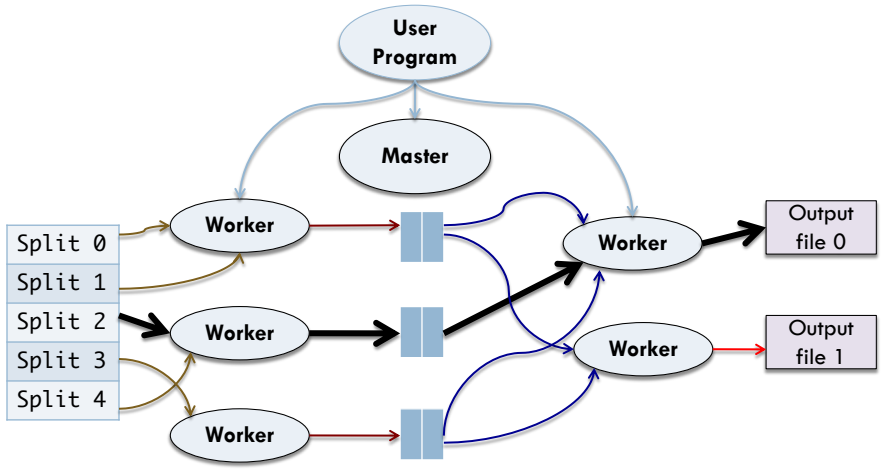
Execution Overview – Part I

- *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 I
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 partitioning function
- **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

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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

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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

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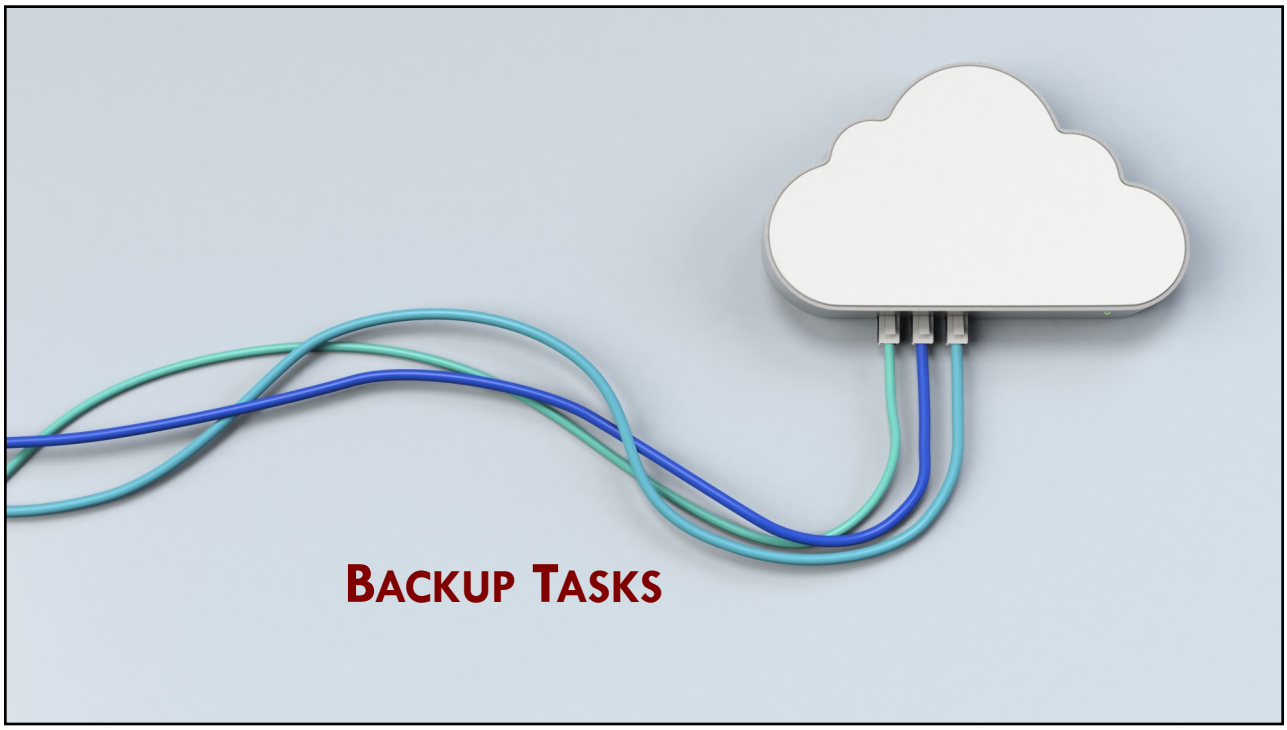

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Stragglers

- 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
- Significantly 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)