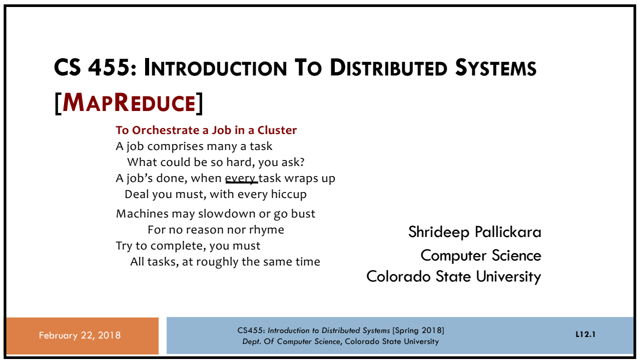
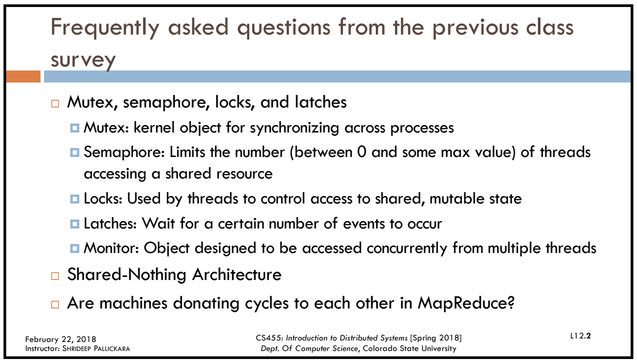


CS 455: Introduction To Distributed Systems [MapReduce]

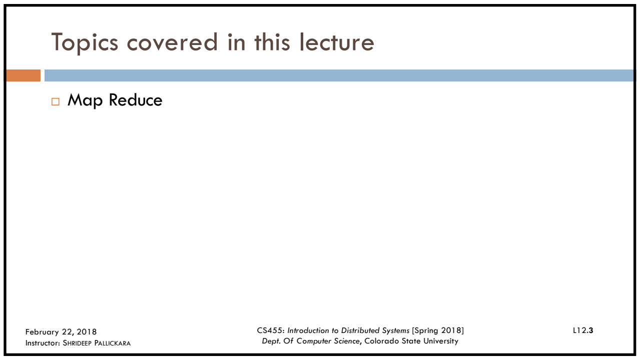
To Orchestrate a Job in a Cluster
A job comprises many a task
What could be so hard, you ask?
A job's done, when every task wraps up
Deal you must, with every hiccup
Machines may slowdown or go bust
For no reason nor rhyme
Try to complete, you must
All tasks, at roughly the same time

Shrideep Pallickara
Computer Science
Colorado State University



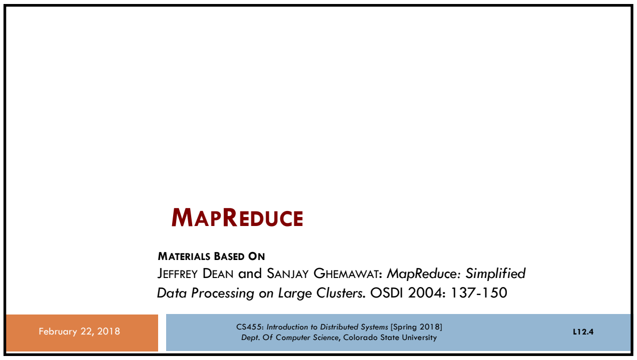
Frequently asked questions from the previous class survey

- Mutex, semaphore, locks, and latches
  - Mutex: kernel object for synchronizing across processes
  - Semaphore: Limits the number (between 0 and some max value) of threads accessing a shared resource
  - Locks: Used by threads to control access to shared, mutable state
  - Latches: Wait for a certain number of events to occur
  - Monitor: Object designed to be accessed concurrently from multiple threads
- Shared-Nothing Architecture
- Are machines donating cycles to each other in MapReduce?



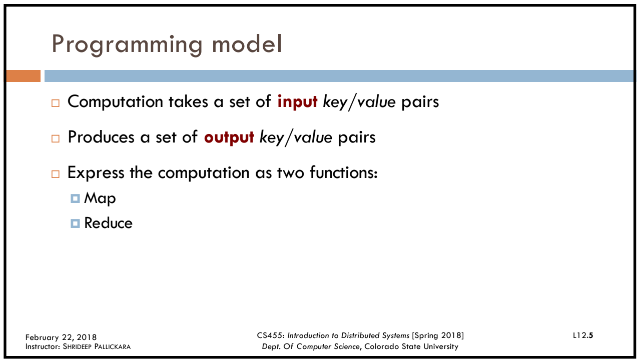
Topics covered in this lecture

- Map Reduce



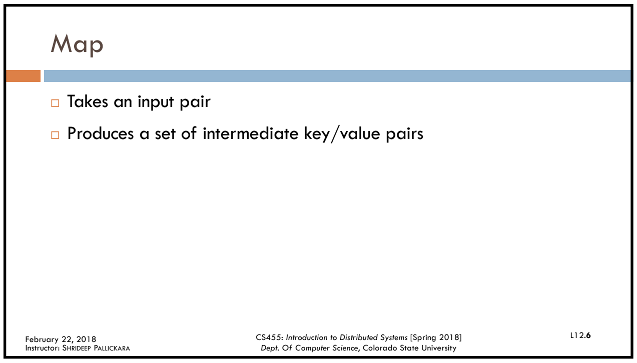
MapReduce

Materials Based On
Jeffrey Dean and Sanjay Ghemawat: *MapReduce: Simplified Data Processing on Large Clusters.* OSDI 2004: 137-150



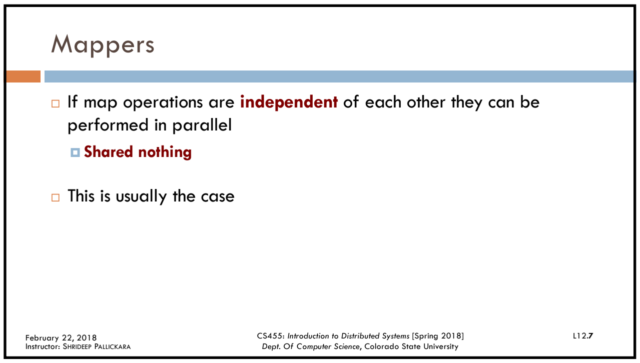
Programming model

- Computation takes a set of **input** *key/value* pairs
- Produces a set of **output** *key/value* pairs
- Express the computation as two functions:
  - Map
  - Reduce



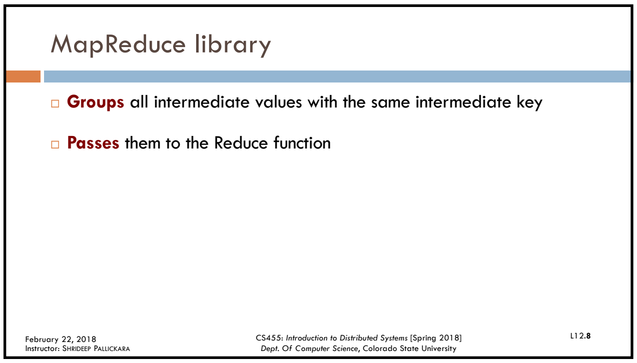
Map

- Takes an input pair
- Produces a set of intermediate key/value pairs



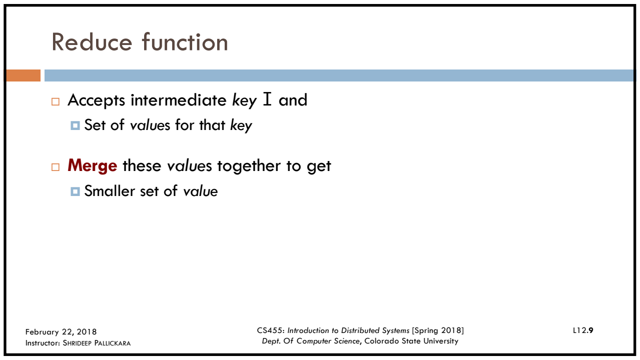
Mappers

- If map operations are **independent** of each other they can be performed in parallel
  - **Shared nothing**
- This is usually the case



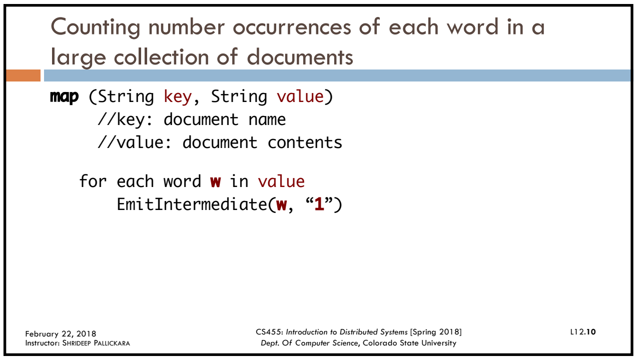
MapReduce library

- **Groups** all intermediate values with the same intermediate key
- **Passes** them to the Reduce function



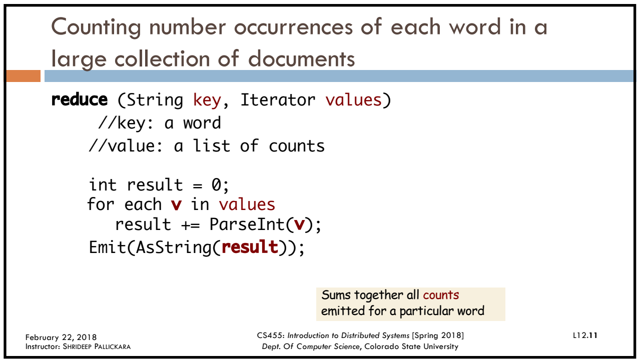
Reduce function

- Accepts intermediate *key* I and
  - Set of *values* for that *key*
- **Merge** these *values* together to get
  - Smaller set of *value*



Counting number occurrences of each word in a large collection of documents

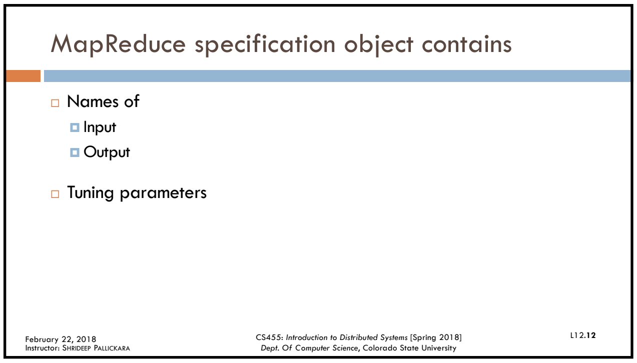
```
map (String key, String value)
     //key: document name
     //value: document contents

   for each word w in value
       EmitIntermediate(w, “1”)
```



Counting number occurrences of each word in a large collection of documents

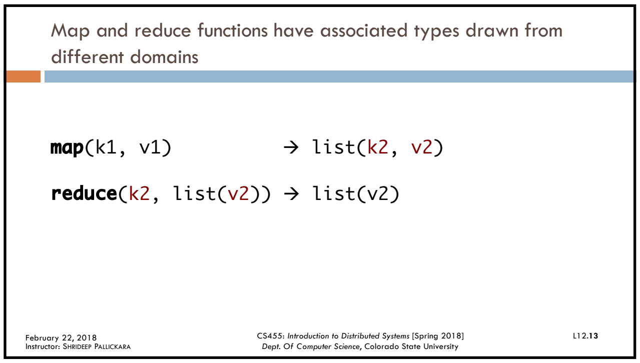
```
reduce (String key, Iterator values)
     //key: a word
    //value: a list of counts

    int result = 0;
    for each v in values
       result += ParseInt(v);
    Emit(AsString(result));
```

Sums together all counts emitted for a particular word



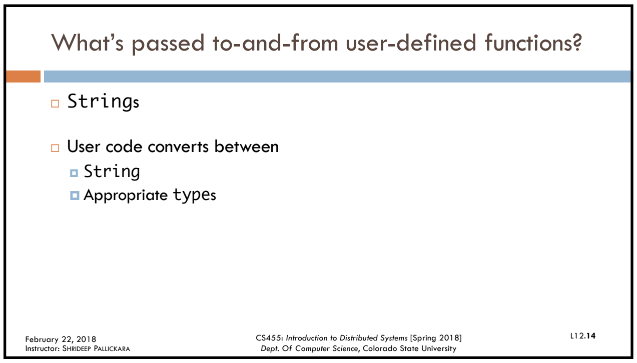
MapReduce specification object contains

- Names of
  - Input
  - Output
- Tuning parameters



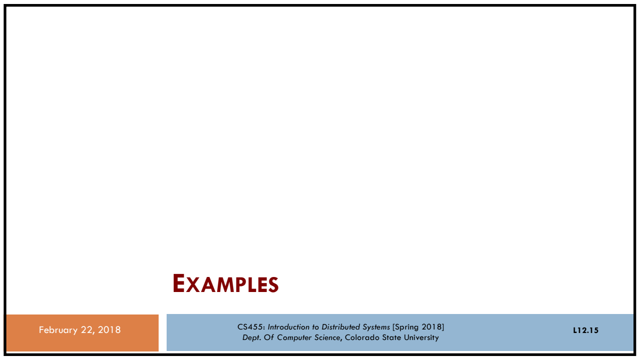
Map and reduce functions have associated types drawn from different domains

```
map(k1, v1)          → list(k2, v2)

reduce(k2, list(v2)) → list(v2)
```

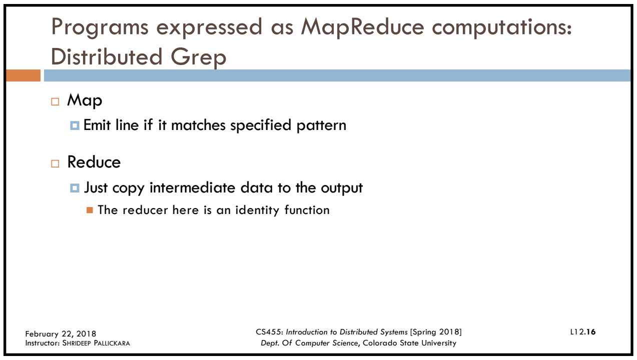


What's passed to-and-from user-defined functions?

- Strings
- User code converts between
  - String
  - Appropriate types

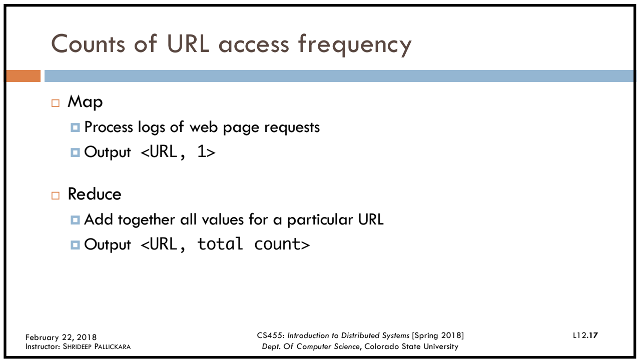


Examples



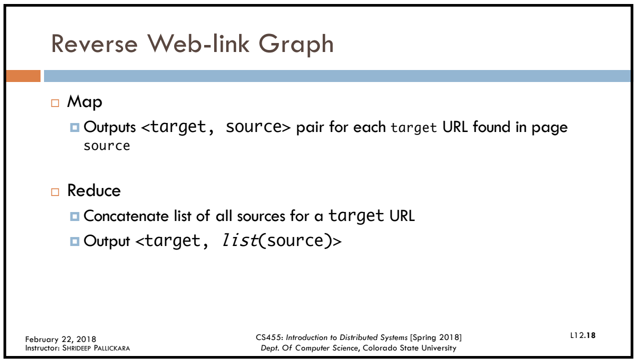
Programs expressed as MapReduce computations: Distributed Grep

- 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

Implementation

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

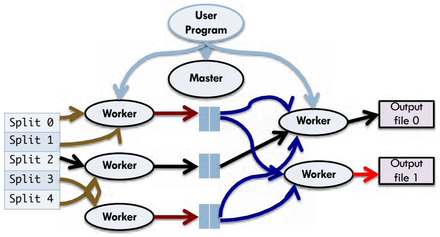
Execution Overview – Part I

- *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

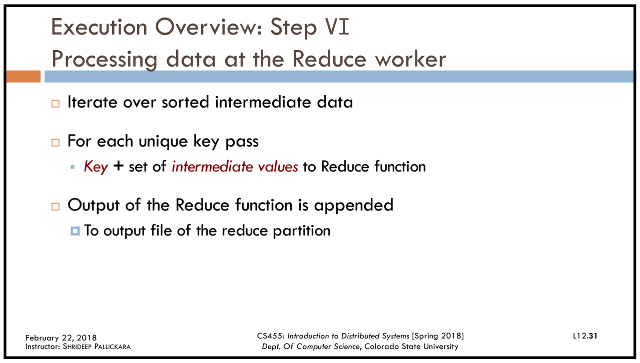
- Read contents of their input split
- Parses <*key, value*> pairs out of the input data
- Pass each pair to user-defined *Map* function
- Intermediate <*key, value*> pairs from *Maps*
  - Buffered in Memory

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* to back to Master
  - Master *forwards* these locations to reduce workers

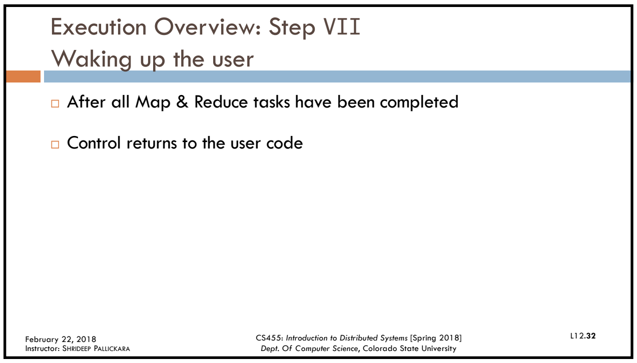
Execution Overview: Step V
Reading Intermediate data

- 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



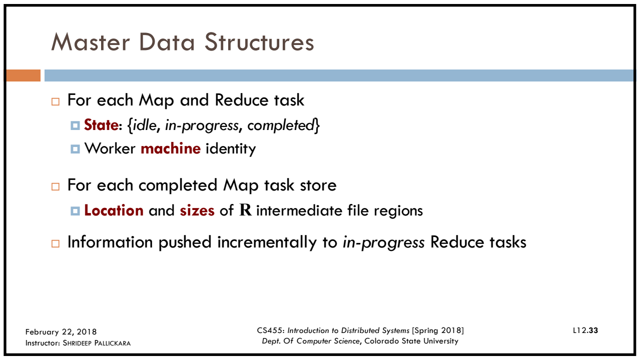
Execution Overview: Step VI
Processing data at the Reduce worker

- 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



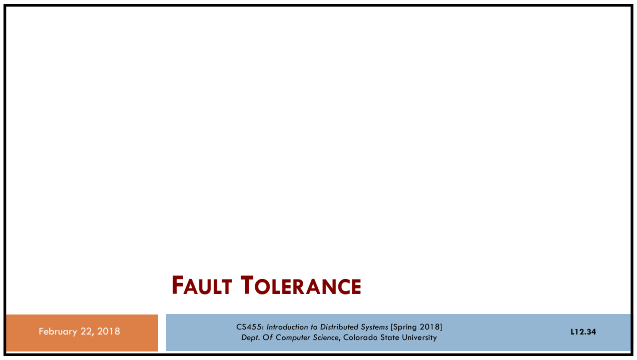
Execution Overview: Step VII
Waking up the user

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

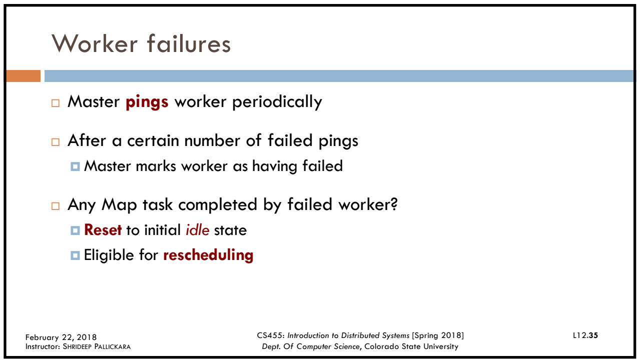


Master Data Structures

- 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

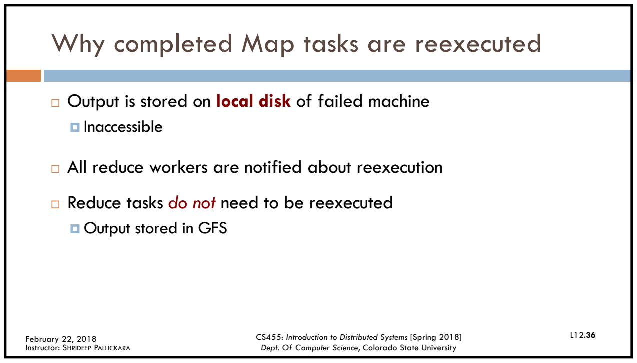


Fault Tolerance



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

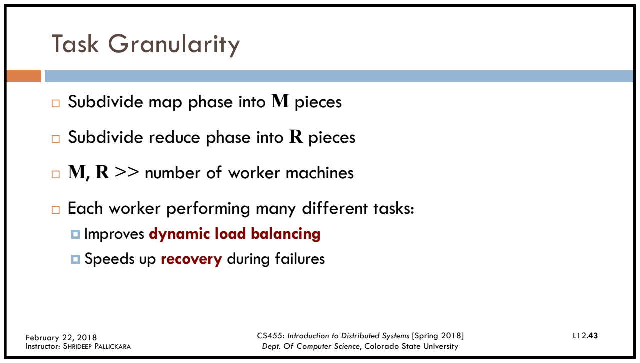
Locality

- **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

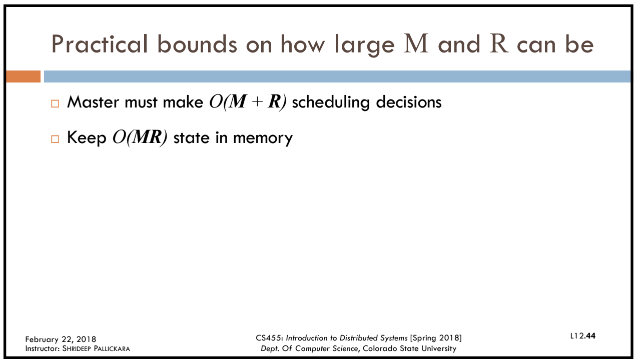
- Most input data is read **locally**
- Consumes no network bandwidth

Task Granularity



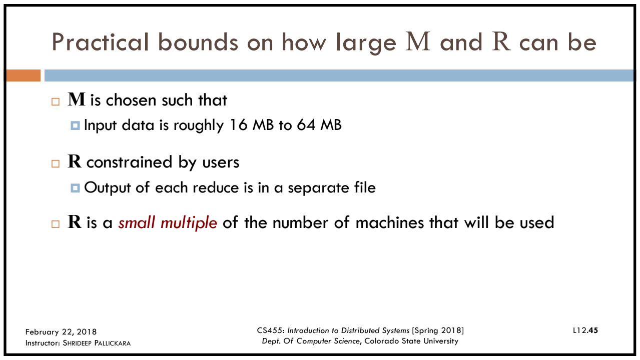
Task Granularity

- 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



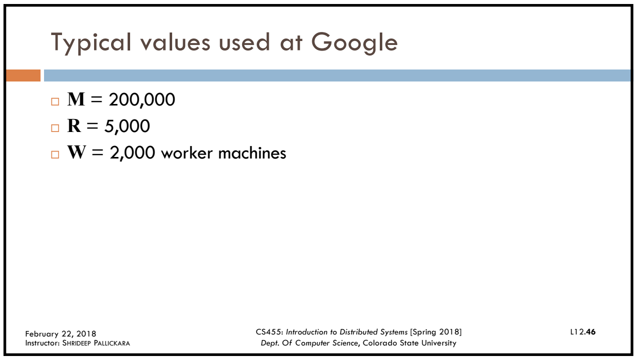
Practical bounds on how large M and R can be

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



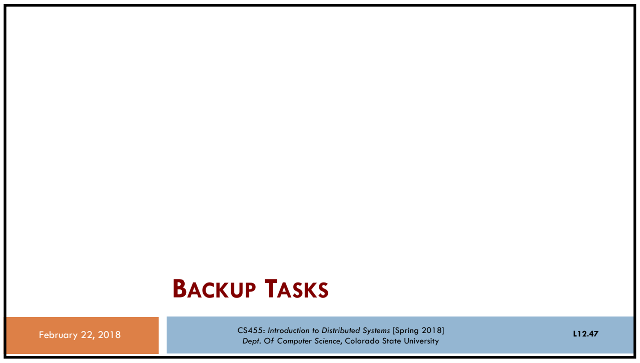
Practical bounds on how large M and R can be

- **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

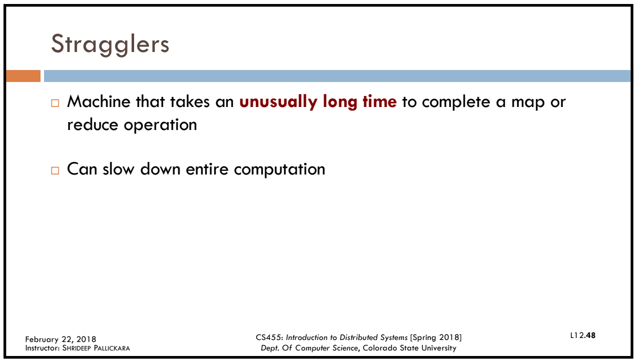


Typical values used at Google

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

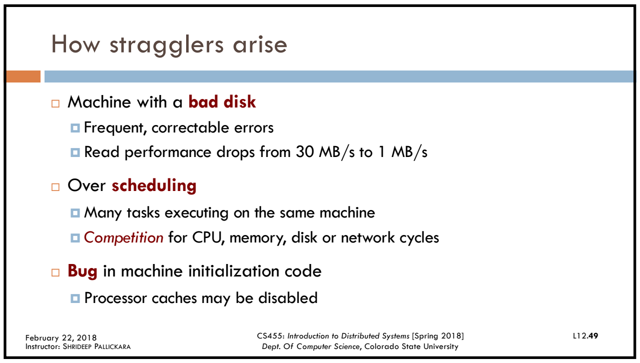


Backup Tasks



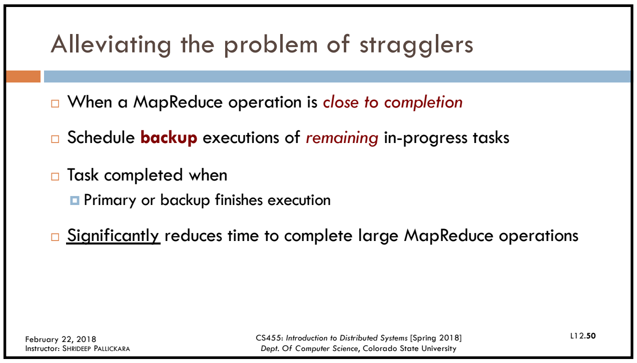
Stragglers

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



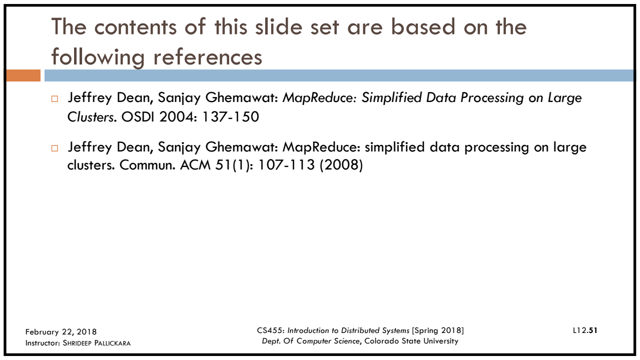
How stragglers arise

- 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
- Significantly reduces time to complete large MapReduce operations



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)