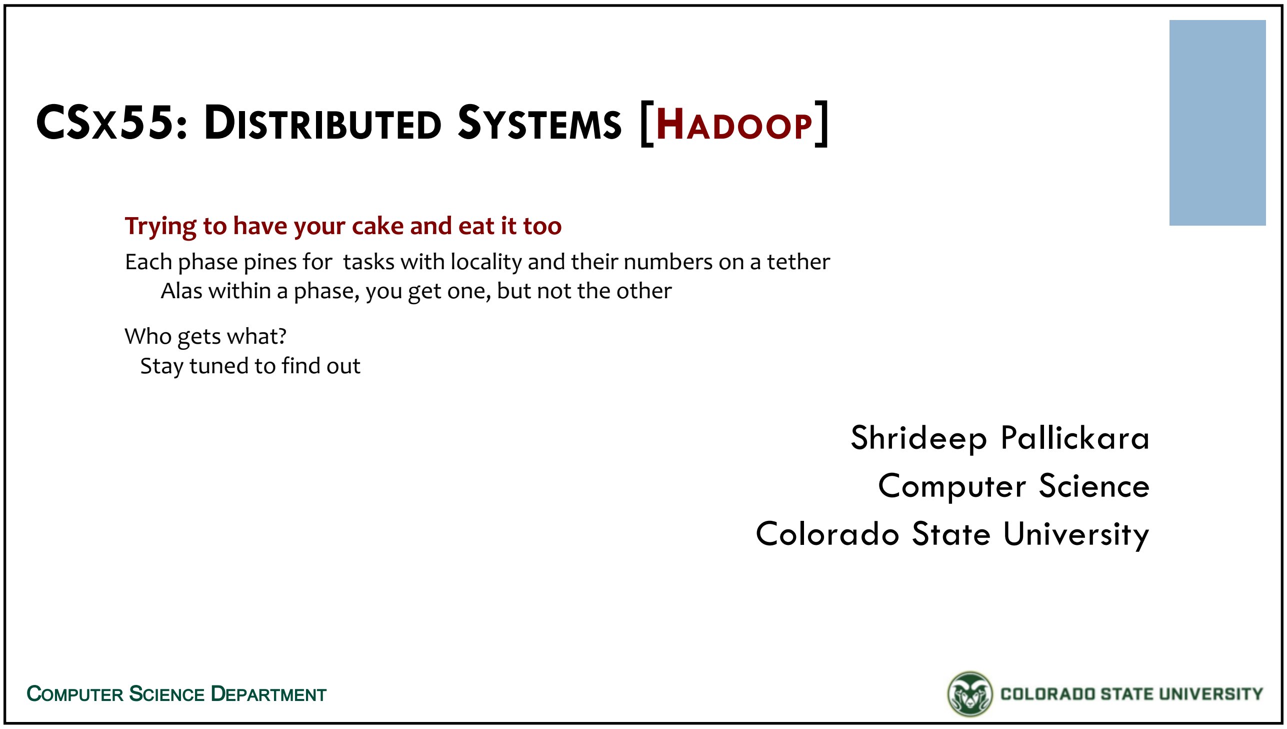

CSx55: Distributed Systems [Hadoop]

Trying to have your cake and eat it too

Each phase pines for tasks with locality and their numbers on a tether
Alas within a phase, you get one, but not the other

Who gets what?
Stay tuned to find out

Shrideep Pallickara
Computer Science
Colorado State University

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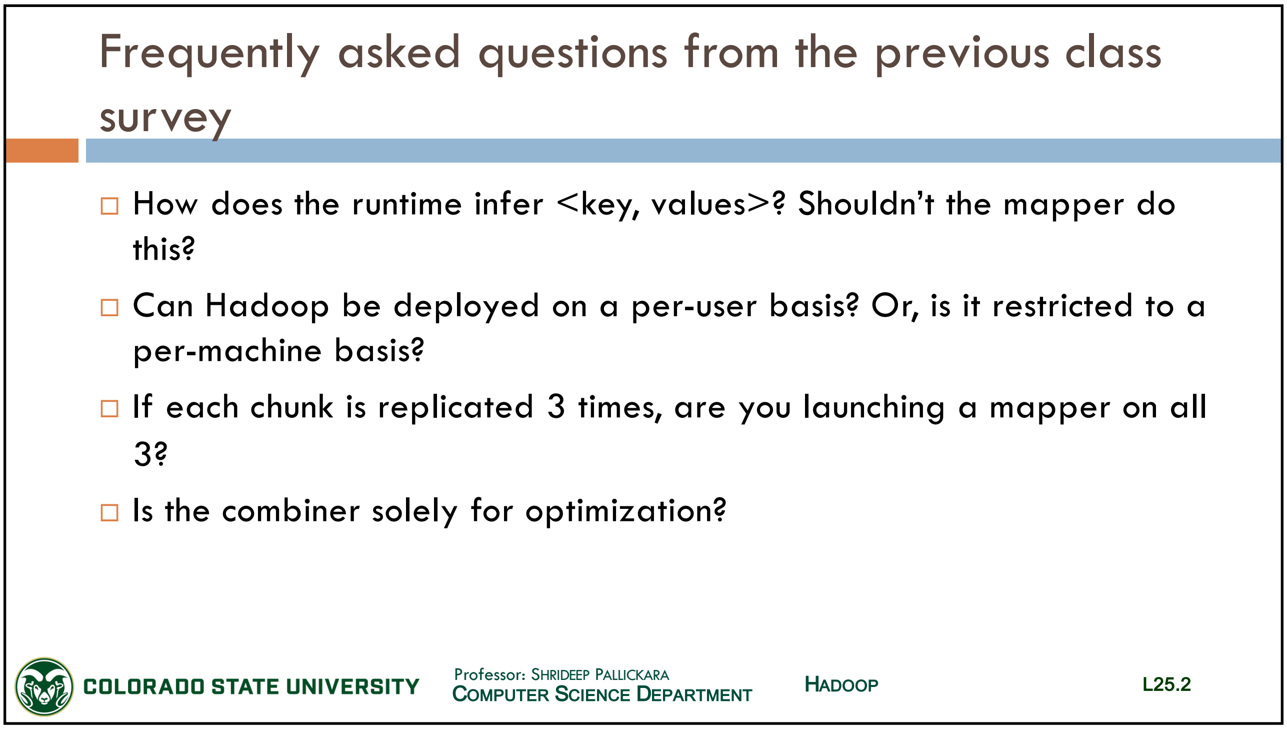
1



Frequently asked questions from the previous class survey

- □ How does the runtime infer <key, values>? Shouldn't the mapper do this?
- □ Can Hadoop be deployed on a per-user basis? Or, is it restricted to a per-machine basis?
- □ If each chunk is replicated 3 times, are you launching a mapper on all 3?
- □ Is the combiner solely for optimization?

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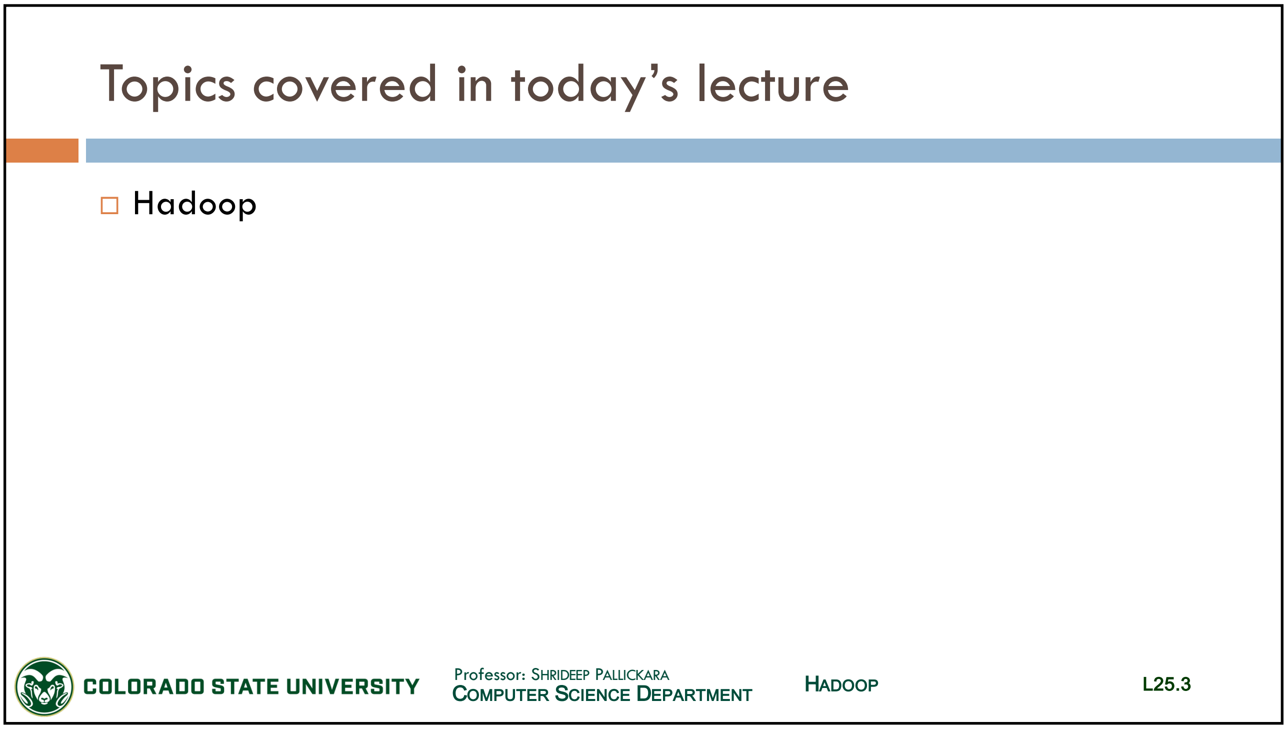
2



Topics covered in today's lecture

- □ Hadoop

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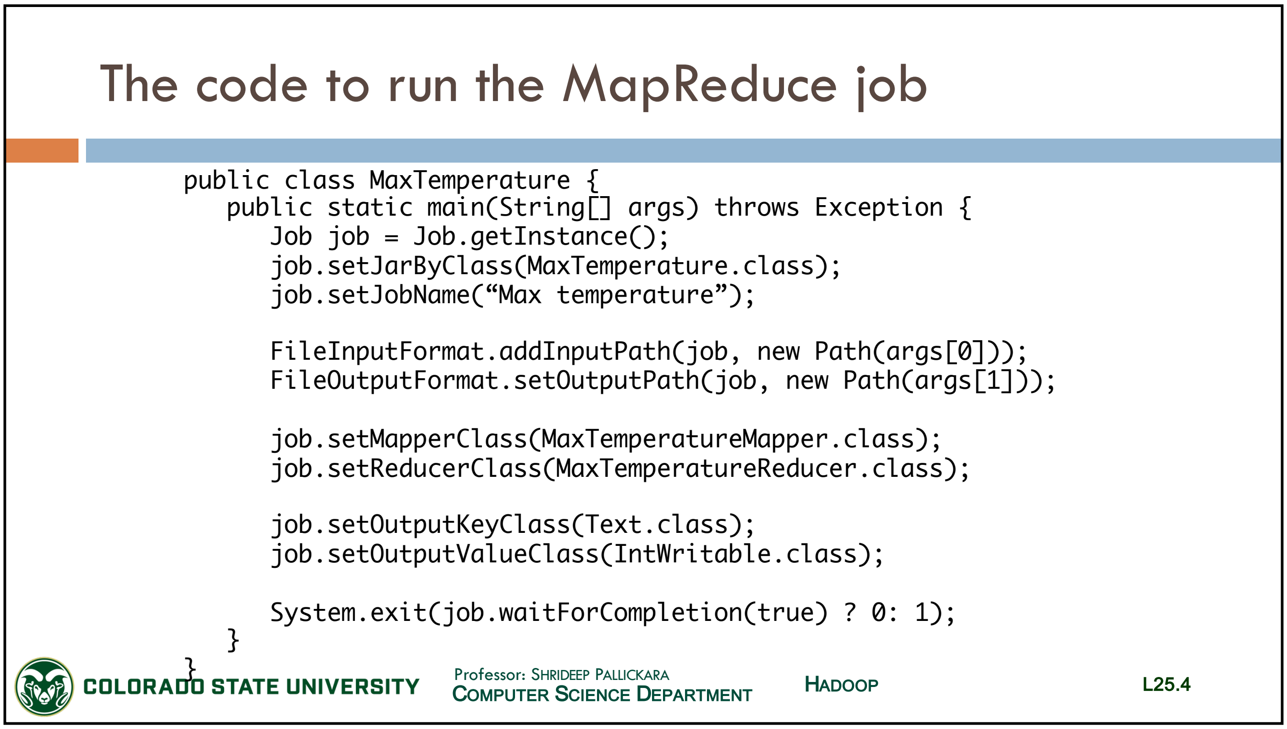

The code to run the MapReduce job

```
public class MaxTemperature {
   public static main(String[] args) throws Exception {
      Job job = Job.getInstance();
      job.setJarByClass(MaxTemperature.class);
      job.setJobName(“Max temperature”);

      FileInputFormat.addInputPath(job, new Path(args[0]));
      FileOutputFormat.setOutputPath(job, new Path(args[1]));

      job.setMapperClass(MaxTemperatureMapper.class);
      job.setReducerClass(MaxTemperatureReducer.class);

      job.setOutputKeyClass(Text.class);
      job.setOutputValueClass(IntWritable.class);

      System.exit(job.waitForCompletion(true) ? 0: 1);
   }
}
```

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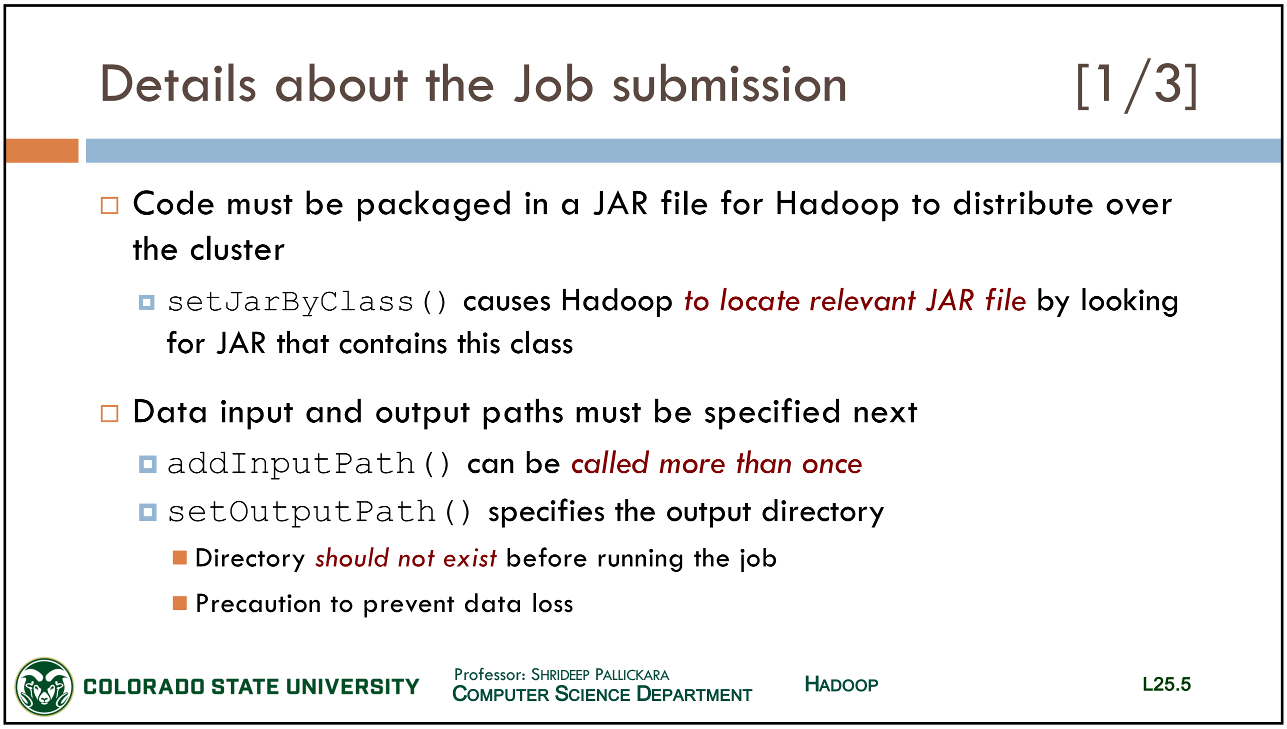
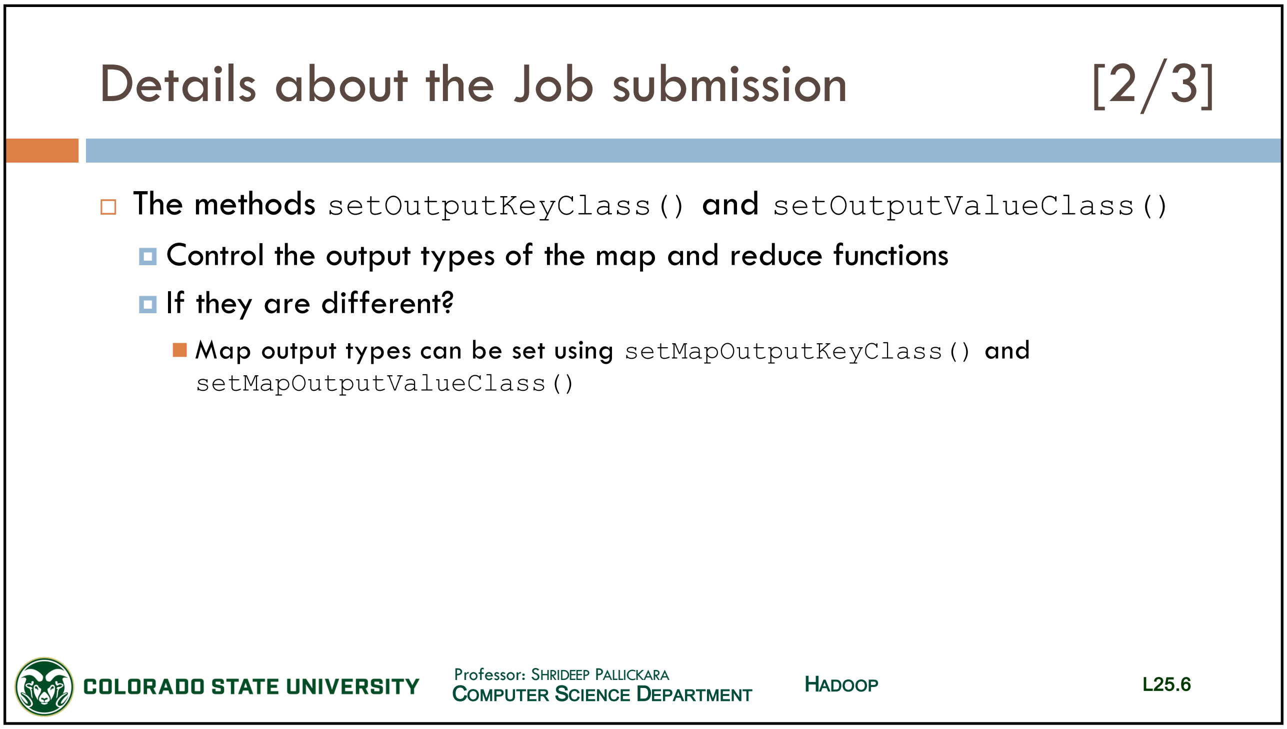


Details about the Job submission [1/3]

- Code must be packaged in a JAR file for Hadoop to distribute over the cluster
  - `setJarByClass()` causes Hadoop *to locate relevant JAR file* by looking for JAR that contains this class
- Data input and output paths must be specified next
  - `addInputPath()` can be *called more than once*
  - `setOutputPath()` specifies the output directory
    - Directory *should not exist* before running the job
    - Precaution to prevent data loss

5



Details about the Job submission [2/3]

- The methods `setOutputKeyClass()` and `setOutputValueClass()`
  - Control the output types of the map and reduce functions
  - If they are different?
    - Map output types can be set using `setMapOutputKeyClass()` and `setMapOutputValueClass()`

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Details about the Job submission. [3/3]

- The `waitforCompletion()` method **submits** the job and **waits** for it to complete
  - The `boolean` argument is a *verbose* flag; if set, progress information is printed on the console
- Return value of `waitforCompletion()` indicates success (`true`) or failure (`false`)
  - In the example this is the program's exit code (0 or 1)

API DIFFERENCES

The old and new MapReduce APIs

- The new API favors abstract classes over interfaces
  - Make things easier to evolve
- New API is in `org.apache.hadoop.mapreduce` package
  - Old API can be found in `org.apache.hadoop.mapred`
- New API makes use of context objects
  - `Context` unifies roles of `JobConf`, `OutputCollector`, and `Reporter` from the old API

The old and new MapReduce APIs

- In the new API, job control is done using the `Job` class rather than using the `JobClient`
- Output files are named slightly differently
  - Old API: Both map and reduce outputs are named `part-nnnn`
  - New API: Map outputs are named `part-`**`m`**`-nnnn` and reduce outputs are named `part-`**`r`**`-nnnn`

The old and new MapReduce APIs

- The new API's `reduce()` method passes values as `Iterable` rather than as `Iterator`
  - Makes it **easier to iterate** over values using the `for-each` loop construct

```
for (VALUEIN value: values) {
    …
}
```

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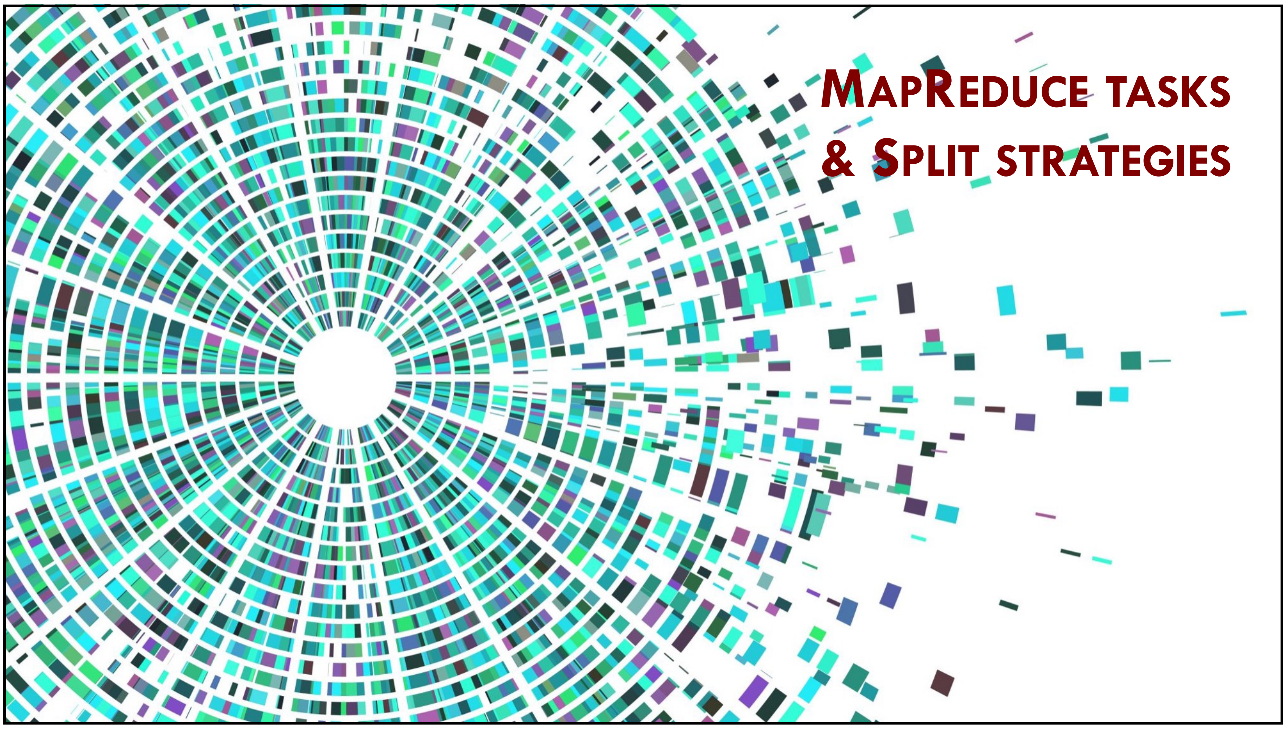

MAPREDUCE TASKS & SPLIT STRATEGIES

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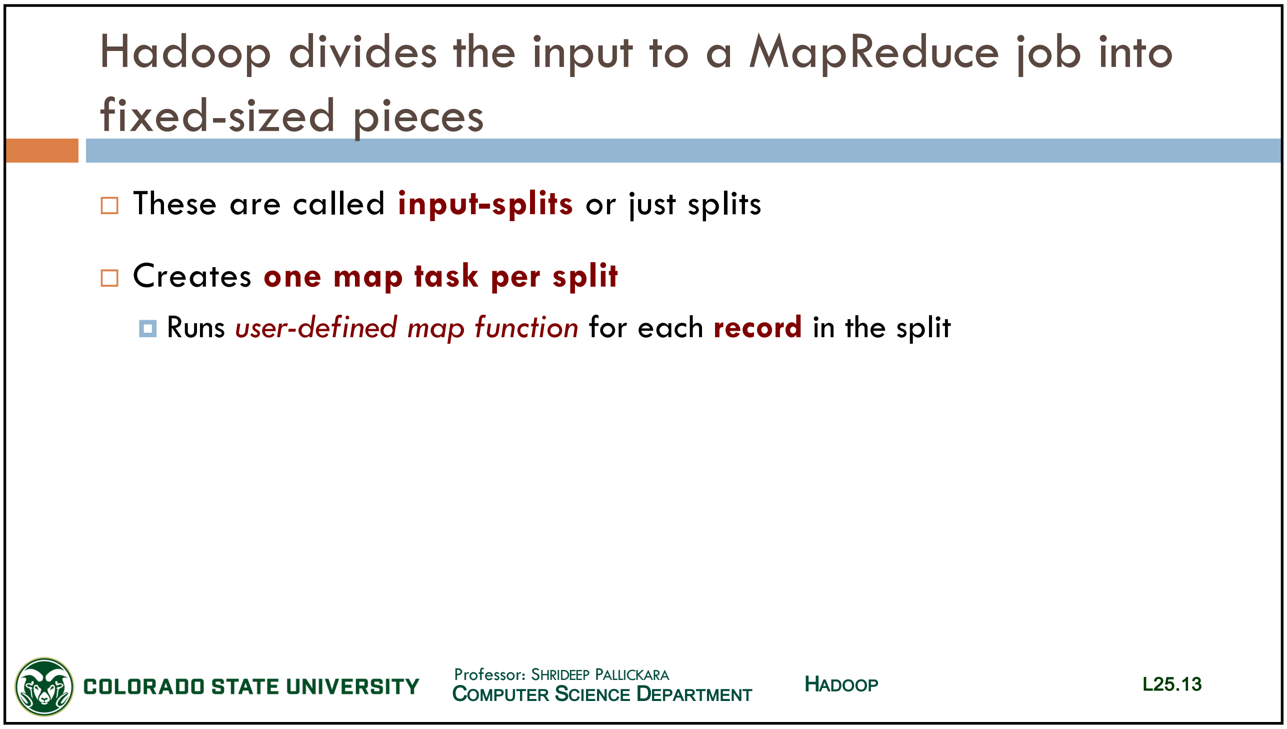
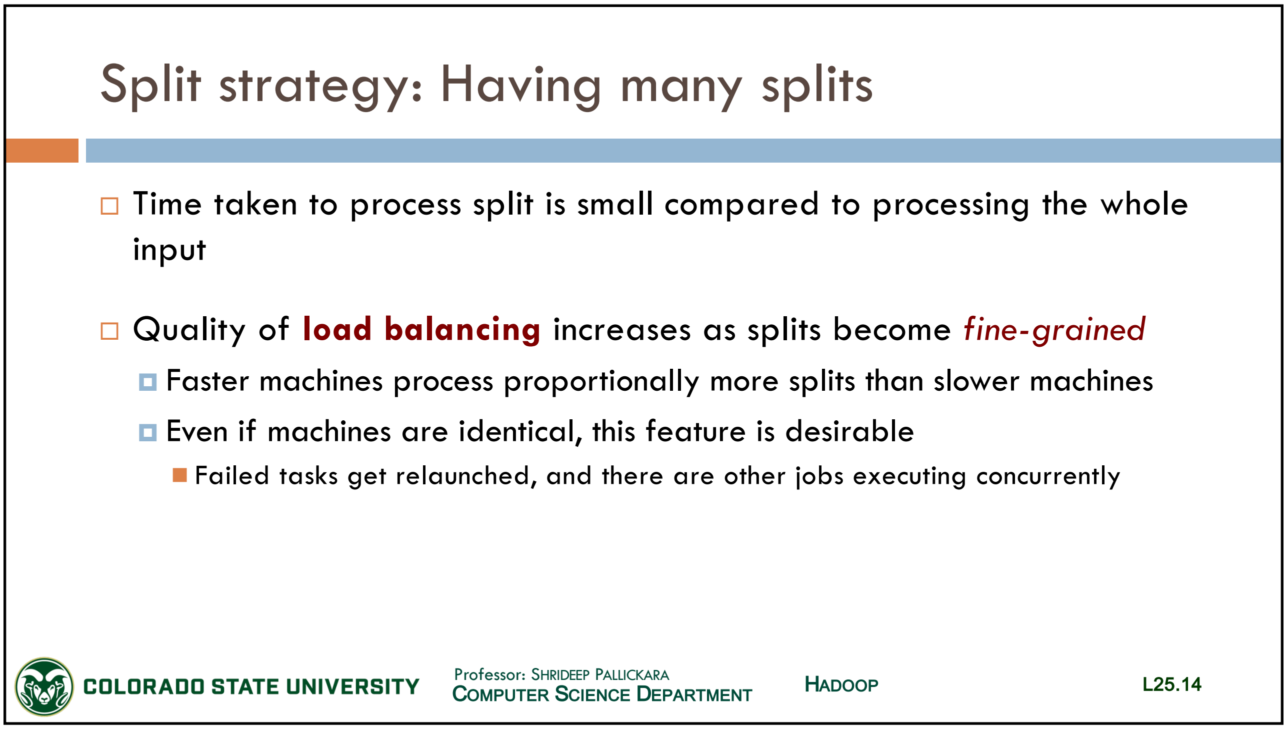


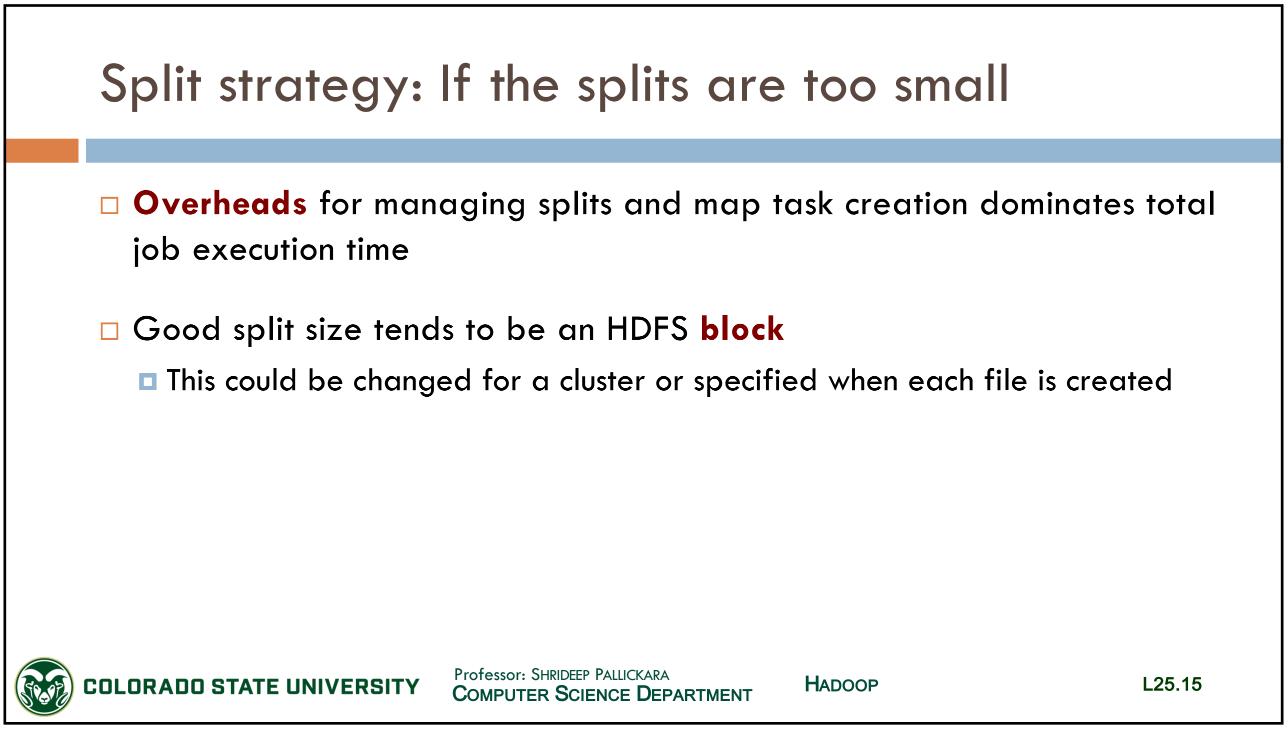
Hadoop divides the input to a MapReduce job into fixed-sized pieces

- These are called **input-splits** or just splits
- Creates **one map task per split**
  - Runs *user-defined map function* for each **record** in the split



Split strategy: Having many splits

- Time taken to process split is small compared to processing the whole input
- Quality of **load balancing** increases as splits become *fine-grained*
  - Faster machines process proportionally more splits than slower machines
  - Even if machines are identical, this feature is desirable
    - Failed tasks get relaunched, and there are other jobs executing concurrently



Split strategy: If the splits are too small

- **Overheads** for managing splits and map task creation dominates total job execution time
- Good split size tends to be an HDFS **block**
  - This could be changed for a cluster or specified when each file is created

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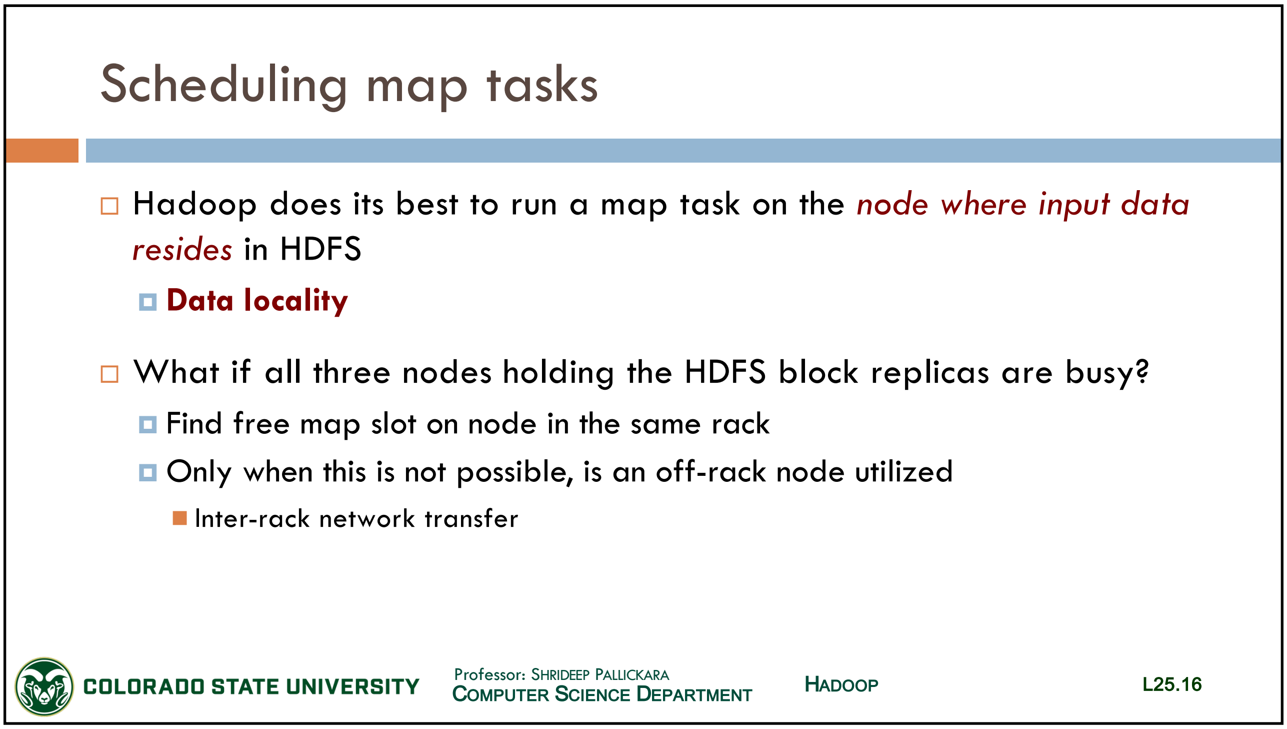

Scheduling map tasks

- Hadoop does its best to run a map task on the *node where input data resides* in HDFS
  - **Data locality**
- What if all three nodes holding the HDFS block replicas are busy?
  - Find free map slot on node in the same rack
  - Only when this is not possible, is an off-rack node utilized
    - Inter-rack network transfer

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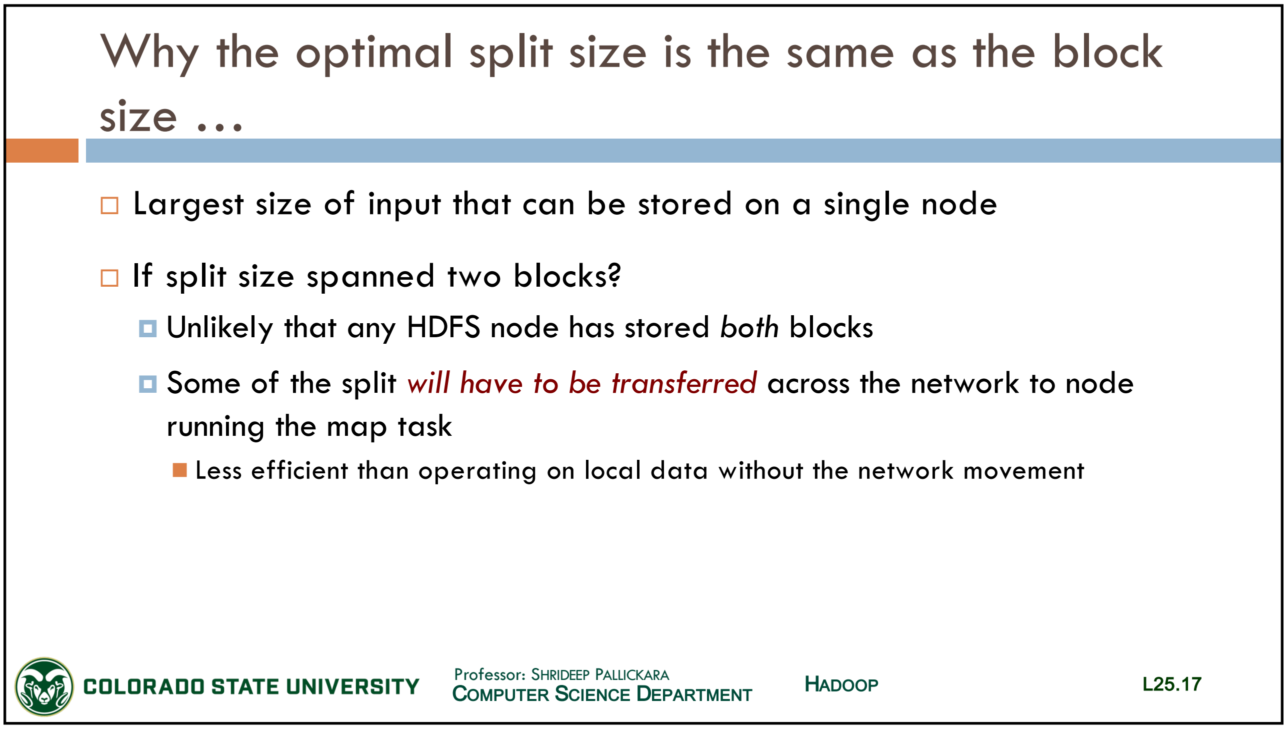

Why the optimal split size is the same as the block size …

- Largest size of input that can be stored on a single node
- If split size spanned two blocks?
  - Unlikely that any HDFS node has stored *both* blocks
  - Some of the split *will have to be transferred* across the network to node running the map task
    - Less efficient than operating on local data without the network movement

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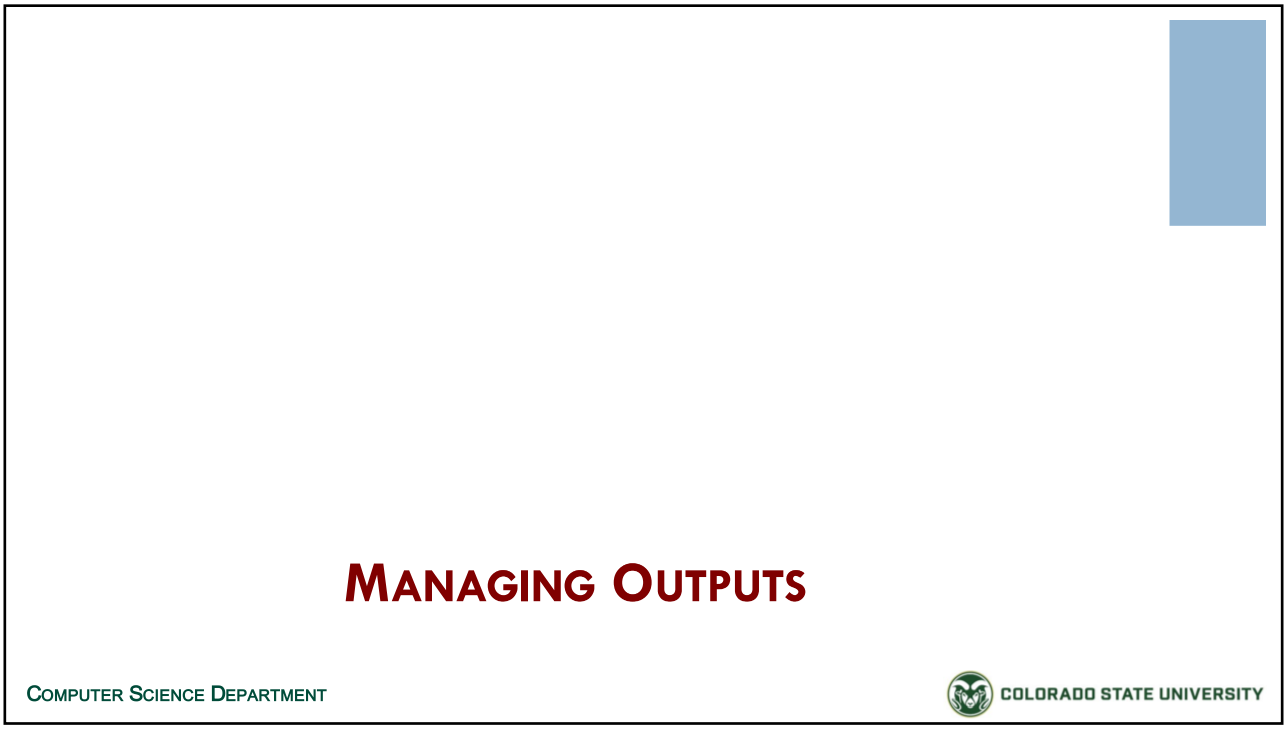

MANAGING OUTPUTS

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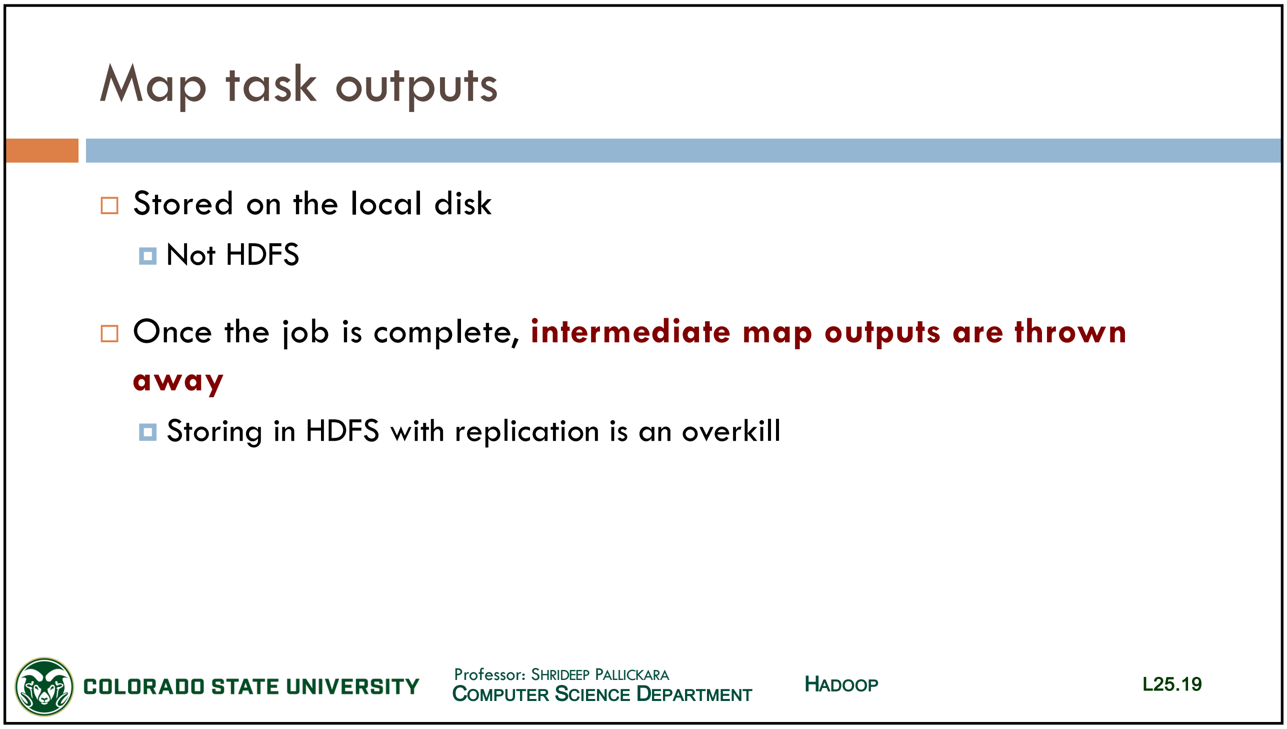
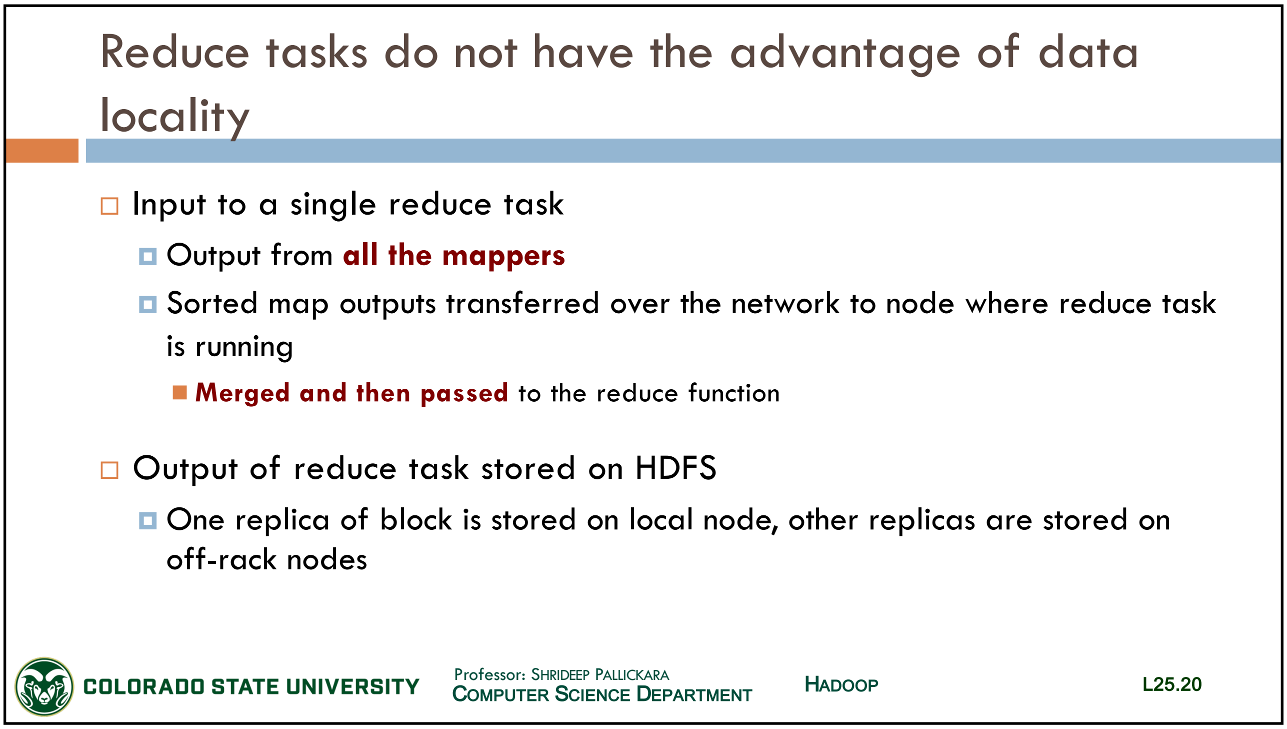


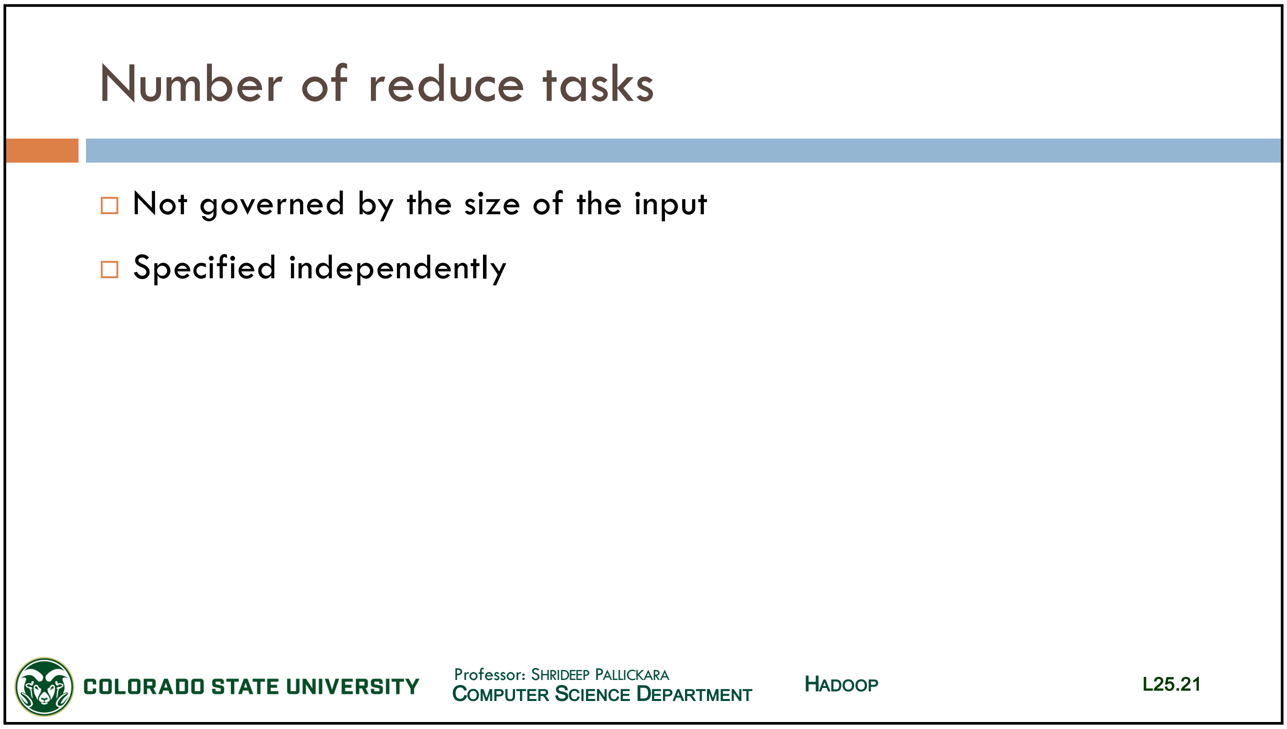
Map task outputs

- Stored on the local disk
  - Not HDFS
- Once the job is complete, **intermediate map outputs are thrown away**
  - Storing in HDFS with replication is an overkill



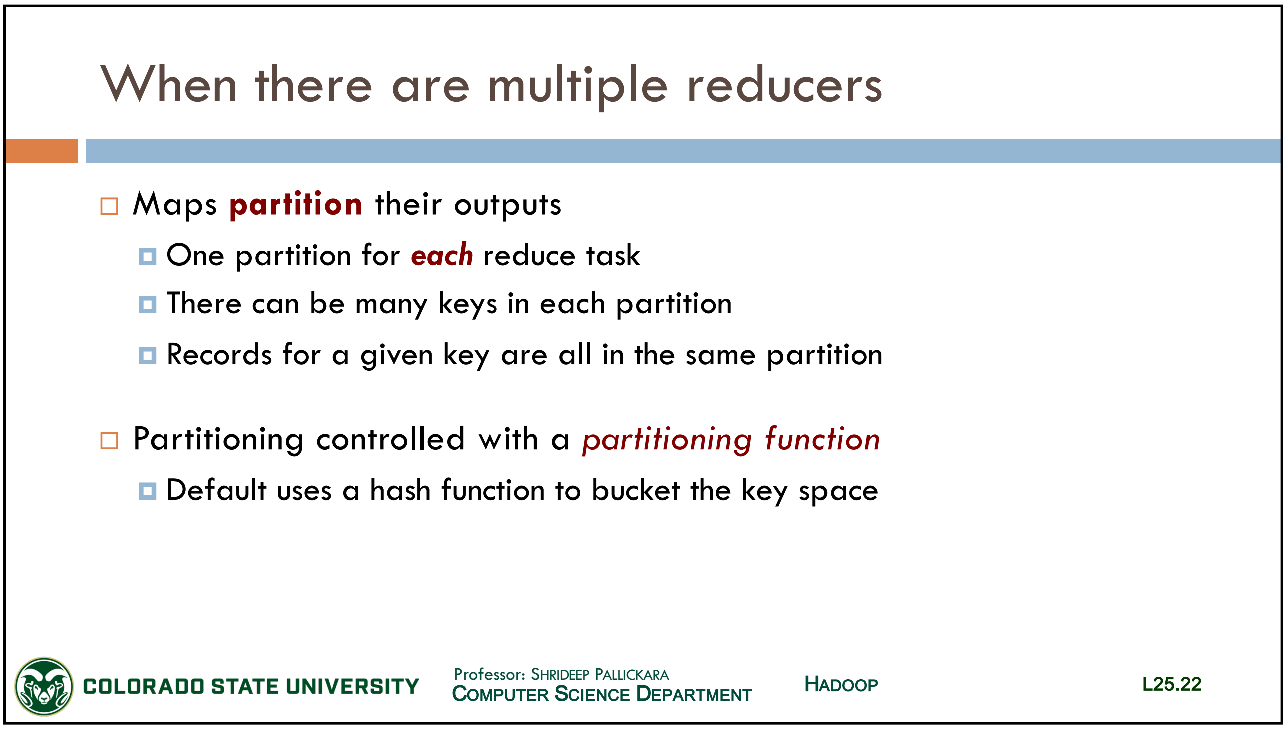
Reduce tasks do not have the advantage of data locality

- Input to a single reduce task
  - Output from **all the mappers**
  - Sorted map outputs transferred over the network to node where reduce task is running
    - **Merged and then passed** to the reduce function
- Output of reduce task stored on HDFS
  - One replica of block is stored on local node, other replicas are stored on off-rack nodes



Number of reduce tasks

- Not governed by the size of the input
- Specified independently



When there are multiple reducers

- Maps **partition** their outputs
  - One partition for ***each*** reduce task
  - There can be many keys in each partition
  - Records for a given key are all in the same partition
- Partitioning controlled with a *partitioning function*
  - Default uses a hash function to bucket the key space

Data Flow

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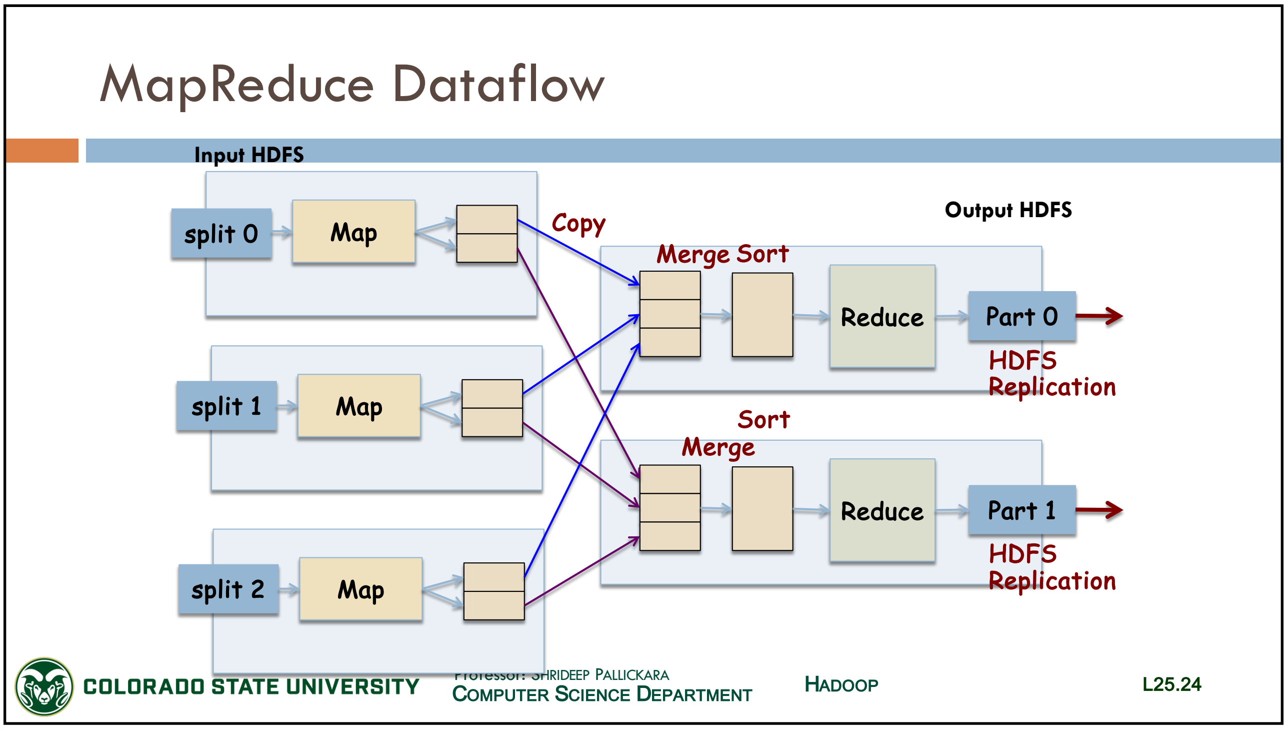

MapReduce Dataflow

Input HDFS

split 0 → Map

split 1 → Map

split 2 → Map

Copy

Merge Sort

Sort

Merge

Reduce → Part 0

Reduce → Part 1

Output HDFS

HDFS Replication

HDFS Replication

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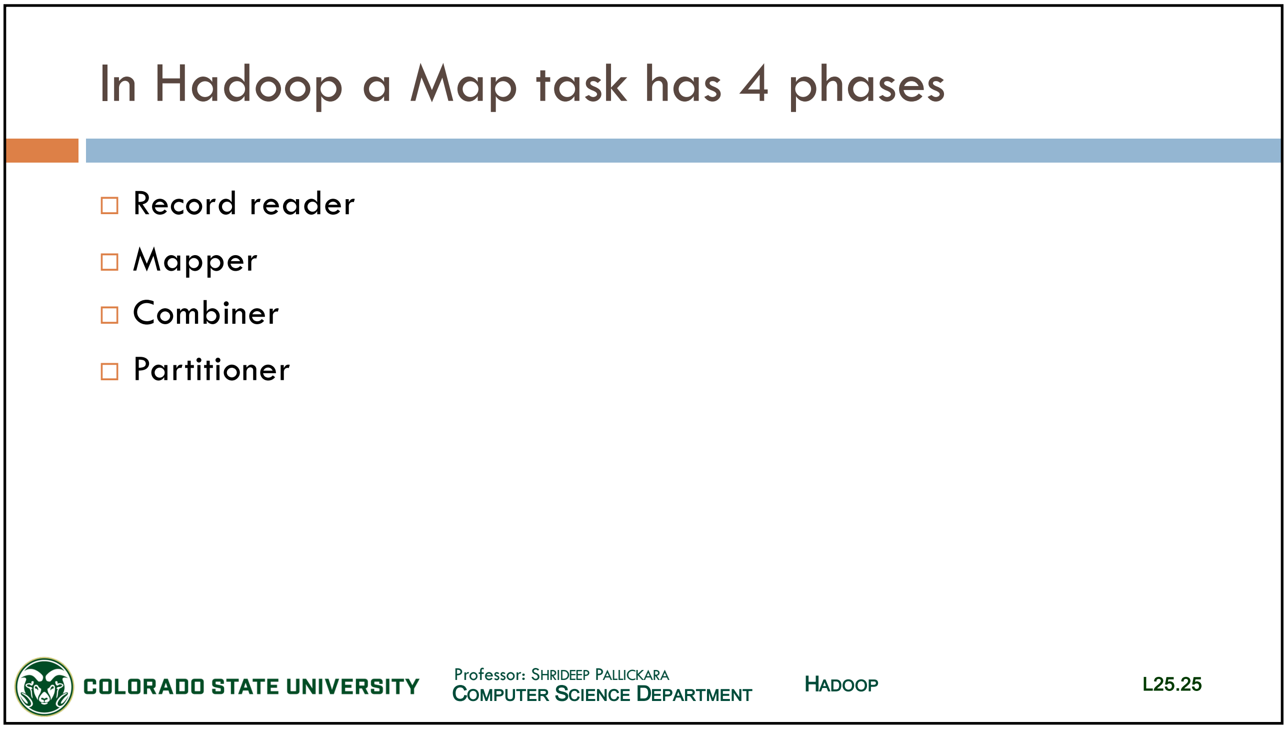

In Hadoop a Map task has 4 phases

- □ Record reader
- □ Mapper
- □ Combiner
- □ Partitioner

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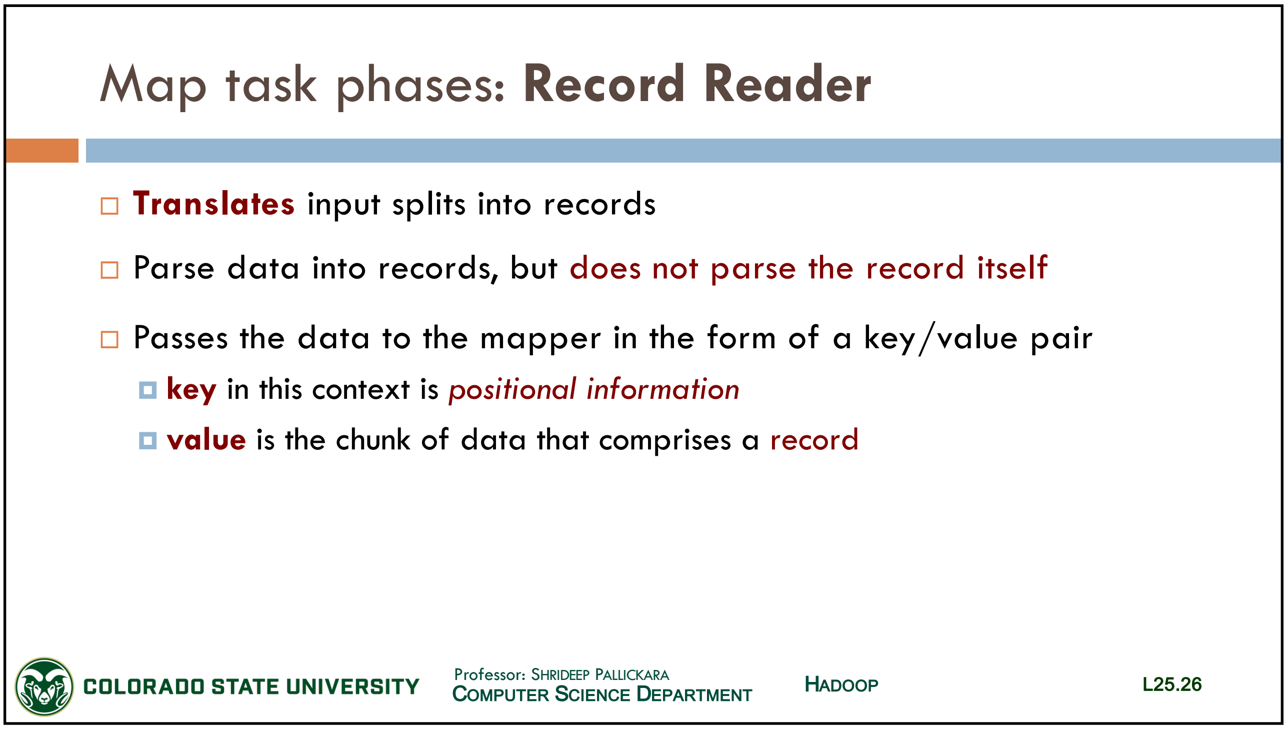

Map task phases: **Record Reader**

- □ **Translates** input splits into records
- □ Parse data into records, but does not parse the record itself
- □ Passes the data to the mapper in the form of a key/value pair
  - **key** in this context is *positional information*
  - **value** is the chunk of data that comprises a record

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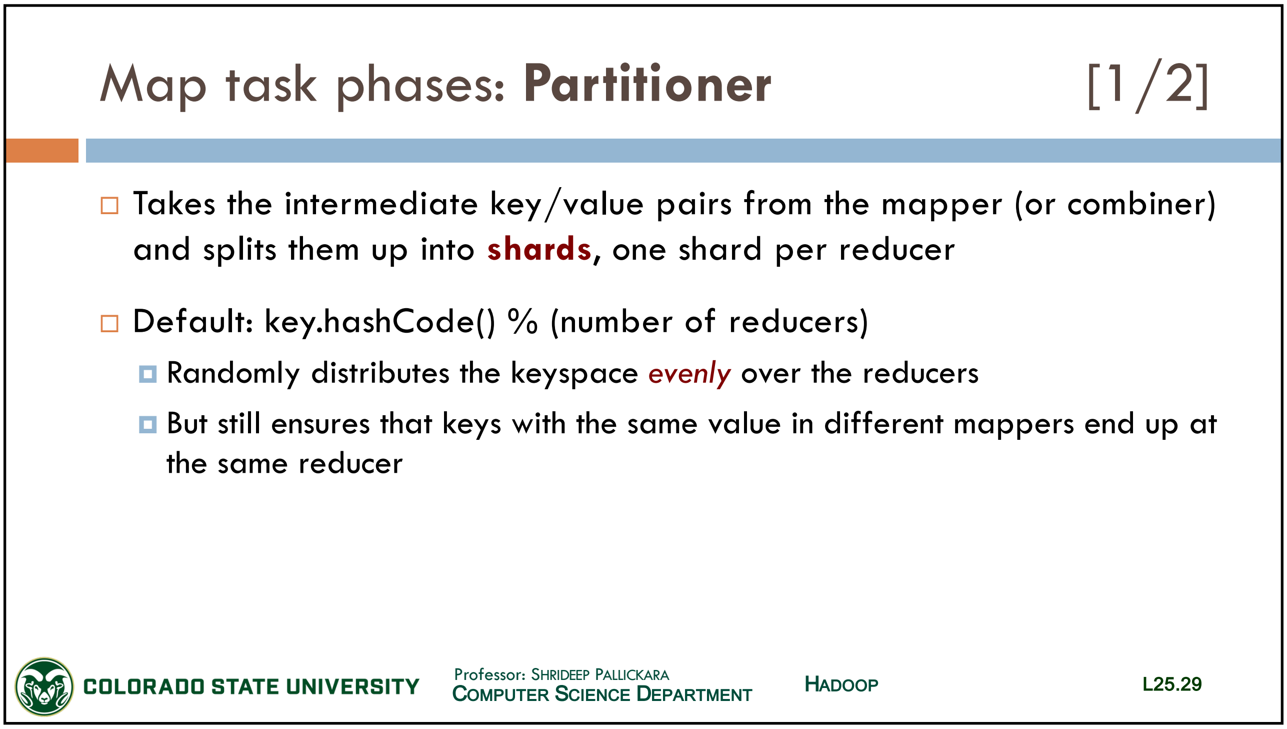
Map task phases: **Map**

- **User-provided code** is executed on each key/value pair from the record reader
- This user-code produces *zero or more* new key/value pairs, called the **intermediate pairs**
  - *key* is what the data will be grouped on and value is the information pertinent to the analysis in the **reducer**
  - Choice of key/value pairs is critical and not arbitrary

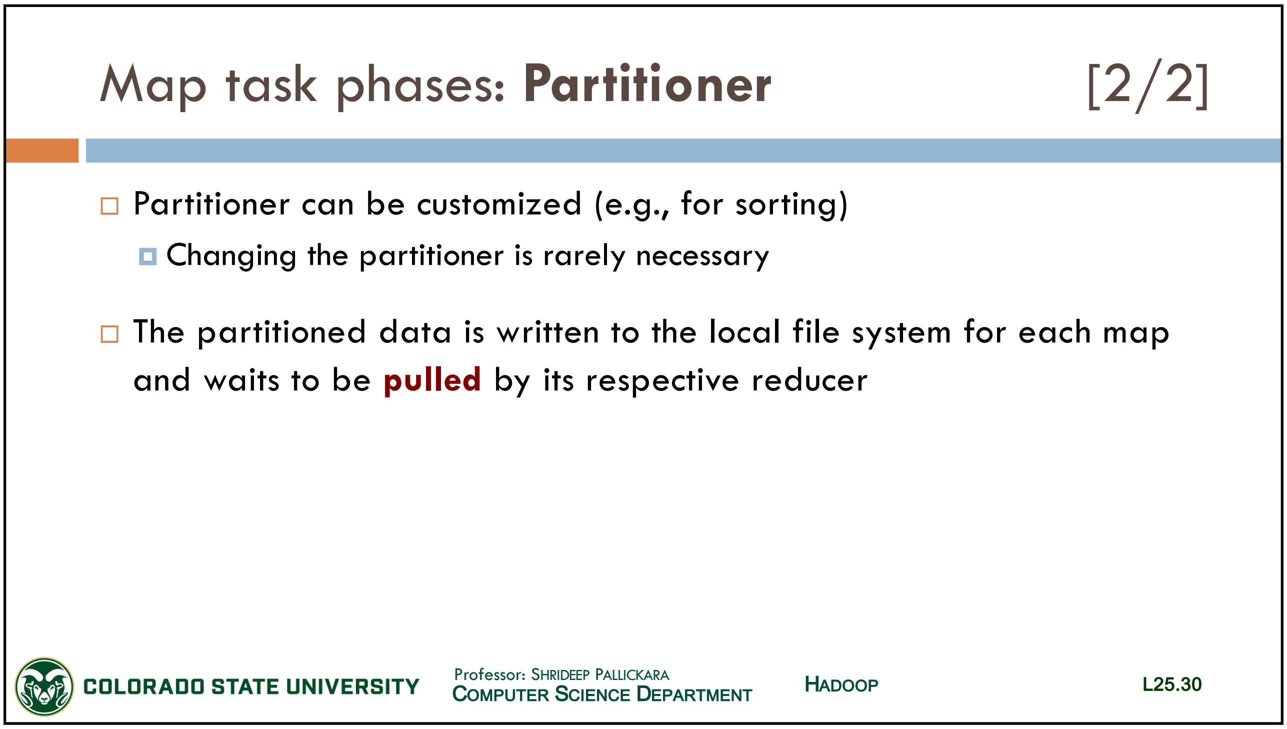
Map task phases: **Combiner**

- Can **group data** in the map phase
- Takes the intermediate keys from the mapper and applies a user-provided method to *aggregate values* in the small scope of that one mapper
- *Significantly reduces the amount of data* that has to move over the network
  - Sending (“hello”, 3) requires fewer bytes than sending (“hello”, 1) three times over the network



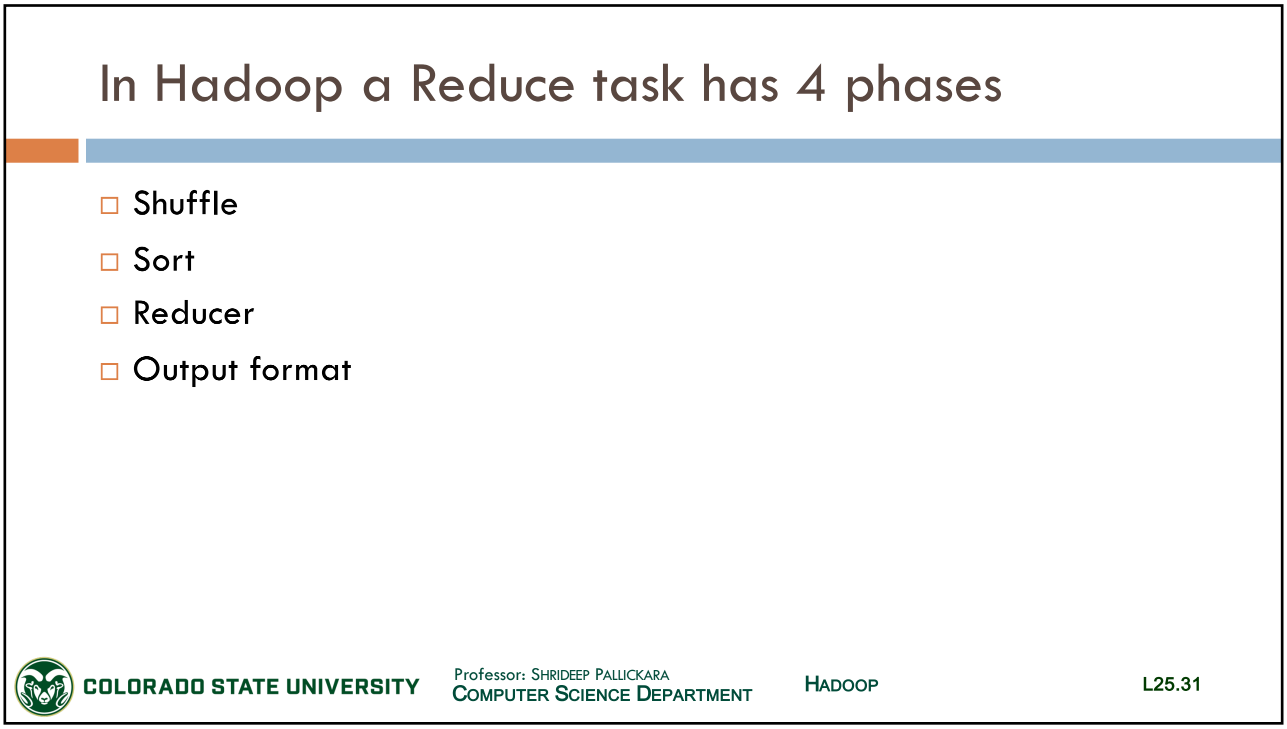
Map task phases: **Partitioner** [1/2]

- Takes the intermediate key/value pairs from the mapper (or combiner) and splits them up into **shards**, one shard per reducer
- Default: key.hashCode() % (number of reducers)
  - Randomly distributes the keyspace *evenly* over the reducers
  - But still ensures that keys with the same value in different mappers end up at the same reducer



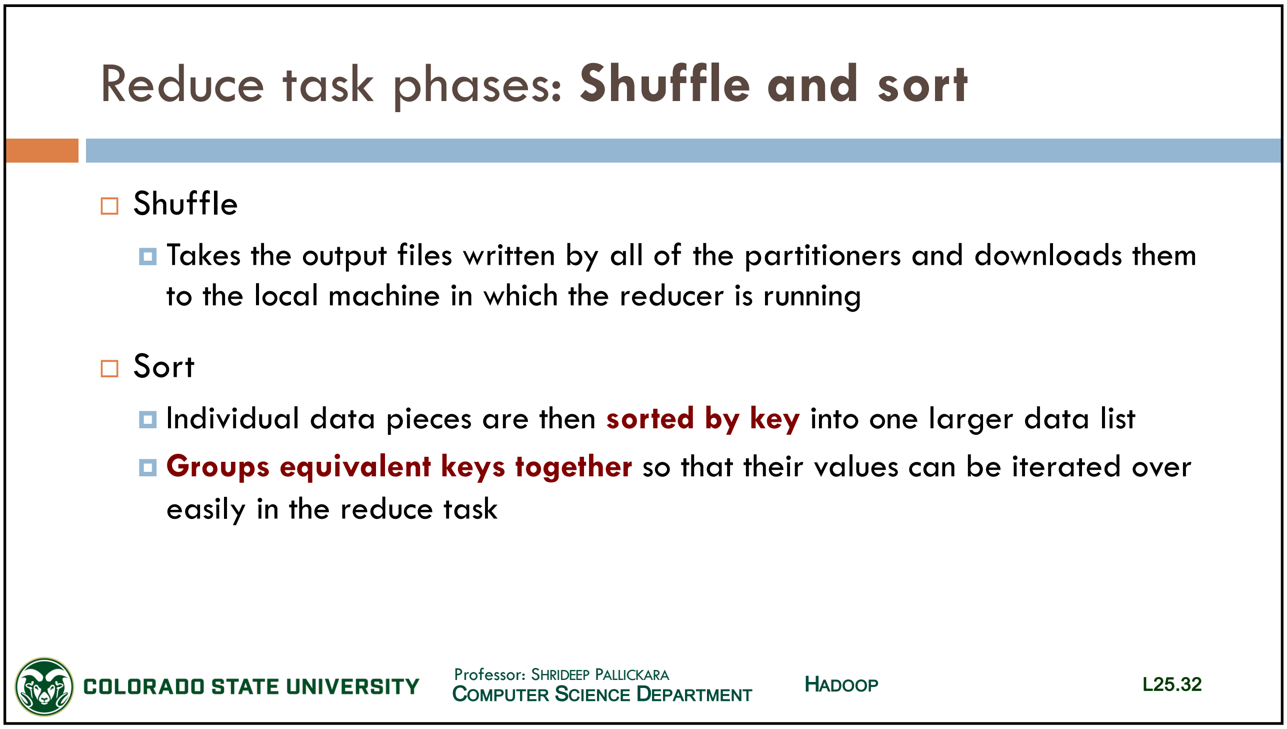
Map task phases: **Partitioner** [2/2]

- Partitioner can be customized (e.g., for sorting)
  - Changing the partitioner is rarely necessary
- The partitioned data is written to the local file system for each map and waits to be **pulled** by its respective reducer



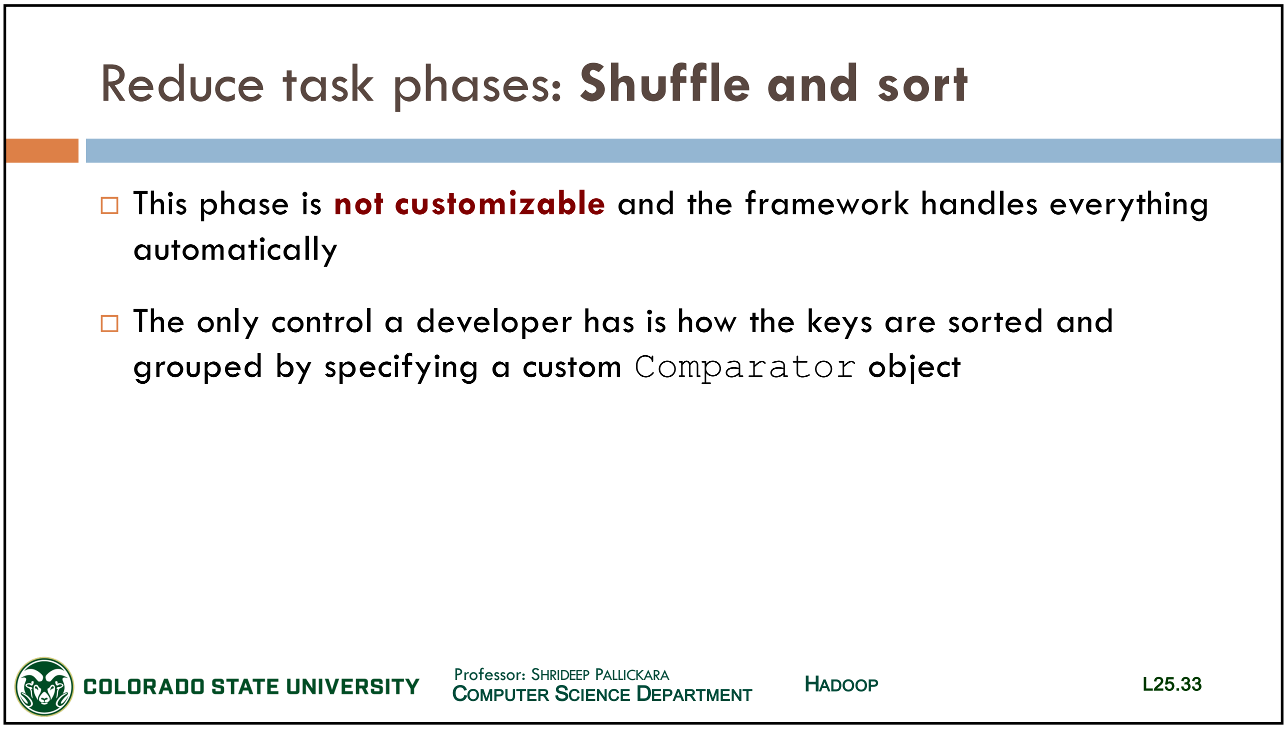
In Hadoop a Reduce task has 4 phases

- Shuffle
- Sort
- Reducer
- Output format



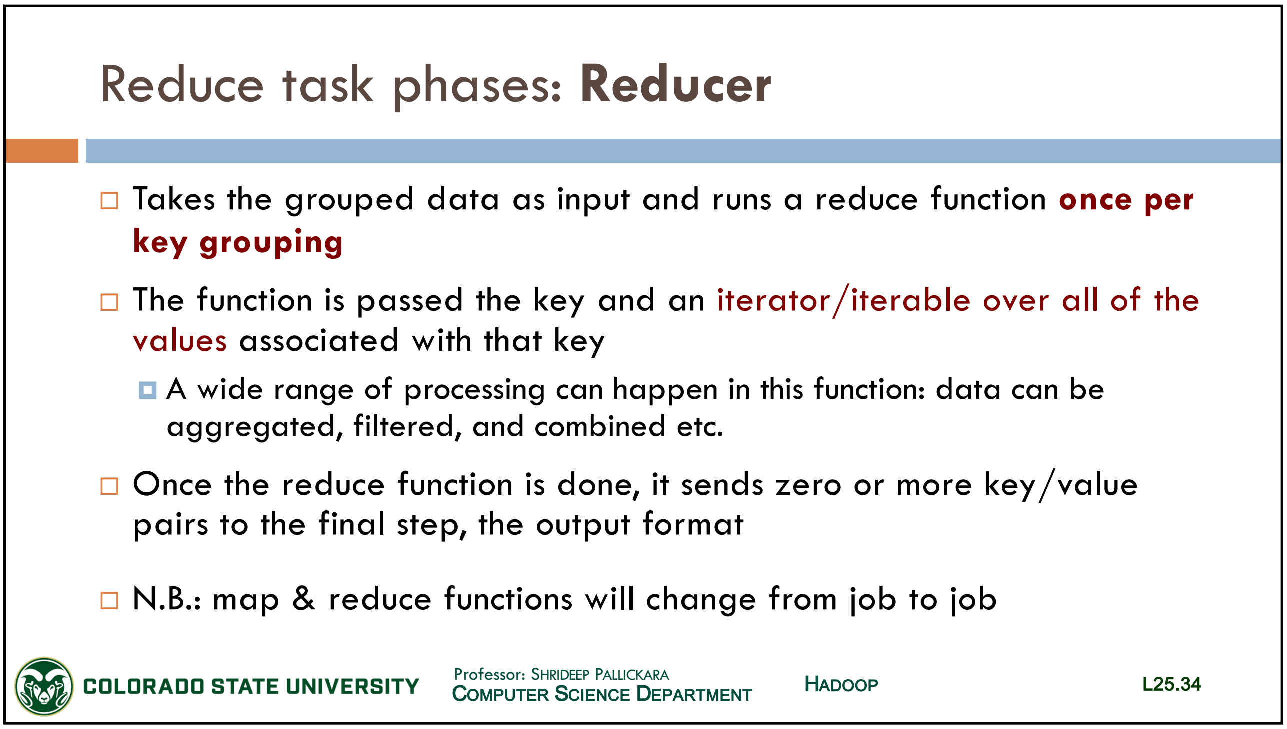
Reduce task phases: **Shuffle and sort**

- Shuffle
  - Takes the output files written by all of the partitioners and downloads them to the local machine in which the reducer is running
- Sort
  - Individual data pieces are then **sorted by key** into one larger data list
  - **Groups equivalent keys together** so that their values can be iterated over easily in the reduce task



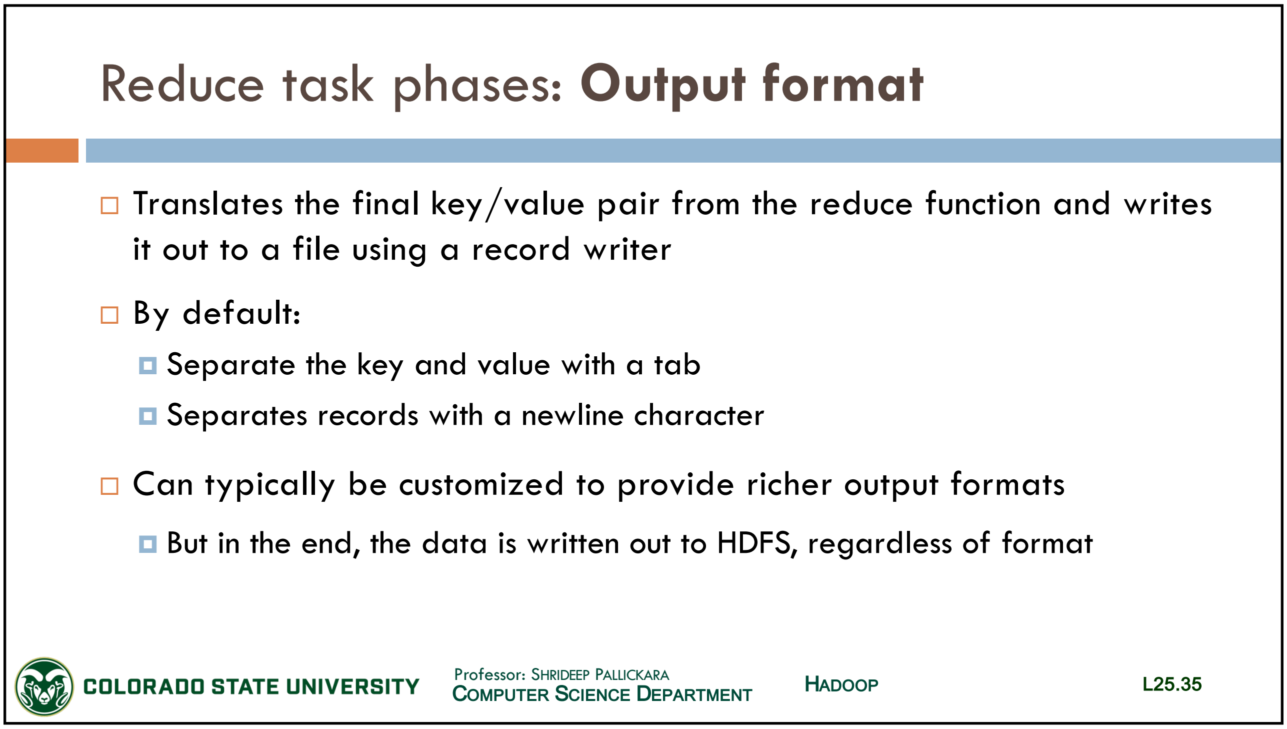
Reduce task phases: **Shuffle and sort**

- This phase is **not customizable** and the framework handles everything automatically
- The only control a developer has is how the keys are sorted and grouped by specifying a custom `Comparator` object



Reduce task phases: **Reducer**

- Takes the grouped data as input and runs a reduce function **once per key grouping**
- The function is passed the key and an iterator/iterable over all of the values associated with that key
  - A wide range of processing can happen in this function: data can be aggregated, filtered, and combined etc.
- Once the reduce function is done, it sends zero or more key/value pairs to the final step, the output format
- N.B.: map & reduce functions will change from job to job



Reduce task phases: **Output format**

- Translates the final key/value pair from the reduce function and writes it out to a file using a record writer
- By default:
  - Separate the key and value with a tab
  - Separates records with a newline character
- Can typically be customized to provide richer output formats
  - But in the end, the data is written out to HDFS, regardless of format

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COMBINER FUNCTIONS

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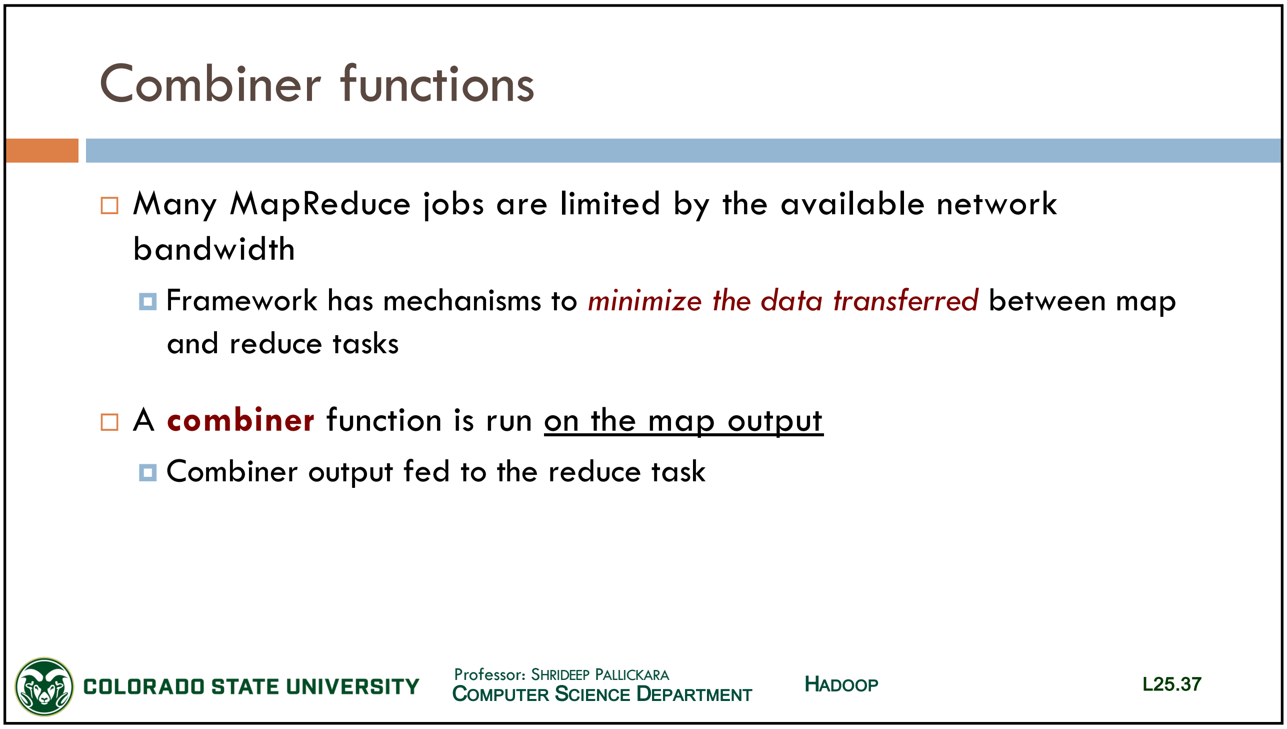

Combiner functions

- Many MapReduce jobs are limited by the available network bandwidth
  - Framework has mechanisms to *minimize the data transferred* between map and reduce tasks
- A **combiner** function is run on the map output
  - Combiner output fed to the reduce task

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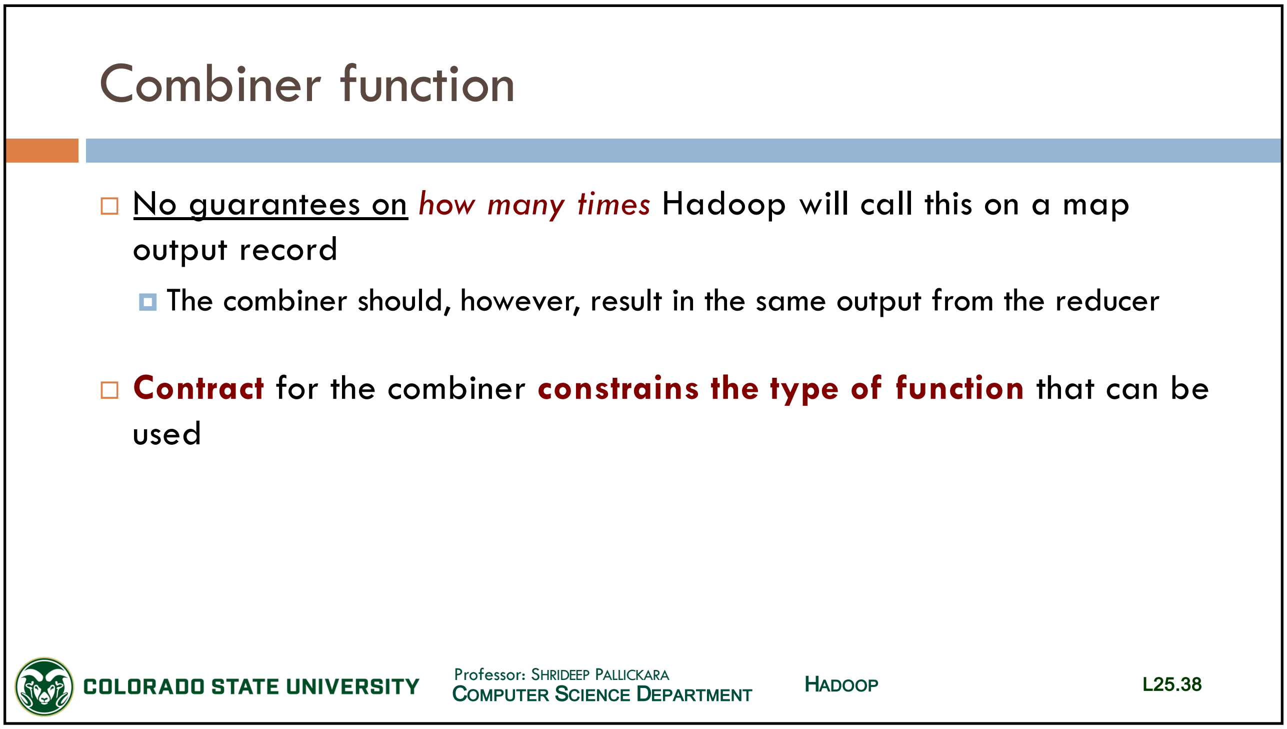

Combiner function

- No guarantees on *how many times* Hadoop will call this on a map output record
  - The combiner should, however, result in the same output from the reducer
- **Contract** for the combiner **constrains the type of function** that can be used

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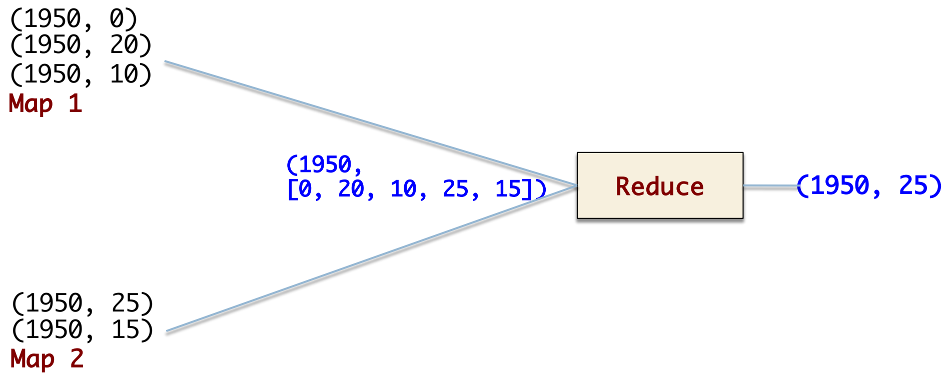
Combiner function: Let's look at the maximum temperature example [1/2]



(1950, 0)
(1950, 20)
(1950, 10)
Map 1

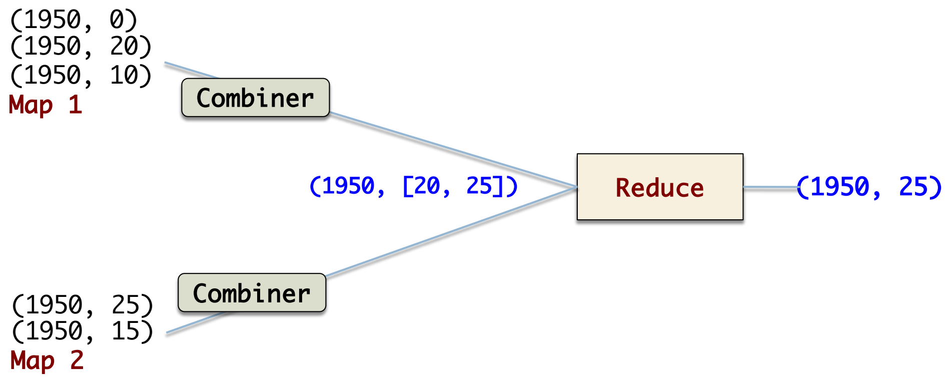
(1950, 25)
(1950, 15)
Map 2

(1950,
[0, 20, 10, 25, 15])

Reduce

(1950, 25)

Combiner function: Let's look at the maximum temperature example [2/2]



(1950, 0)
(1950, 20)
(1950, 10)
Map 1

Combiner

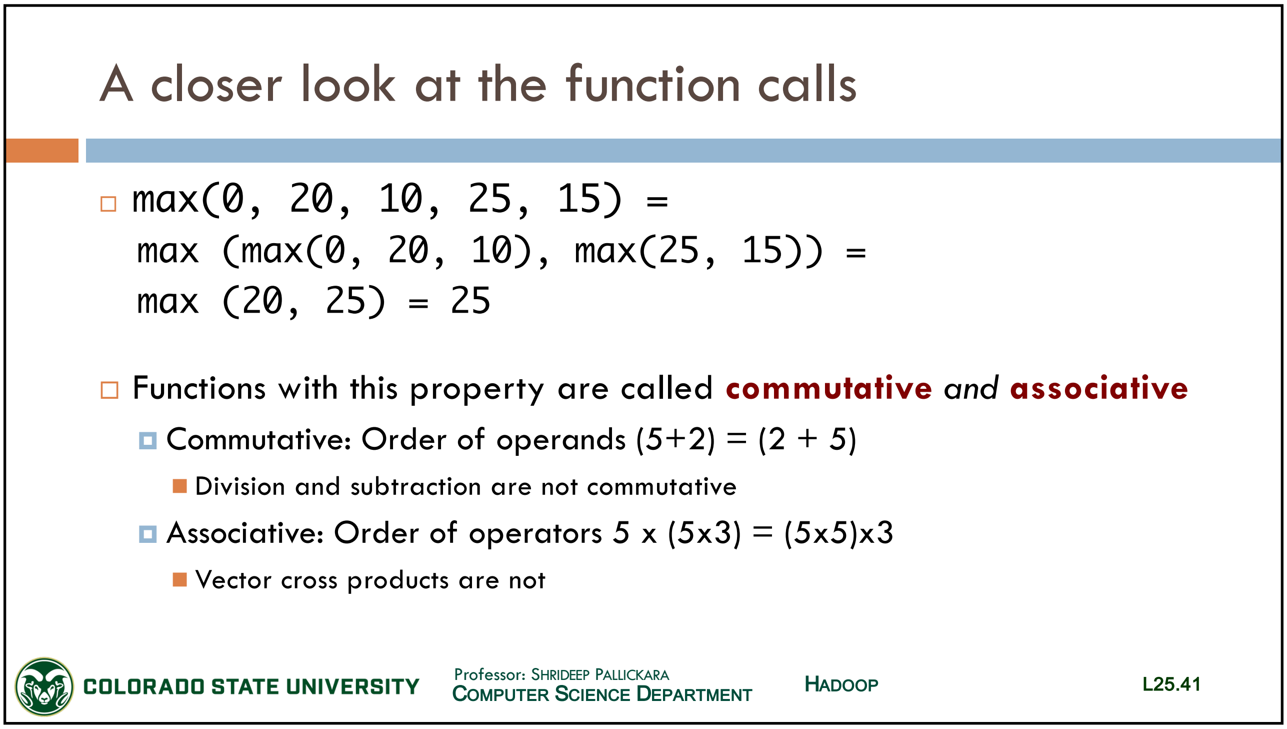
(1950, 25)
(1950, 15)
Map 2

Combiner

(1950, [20, 25])

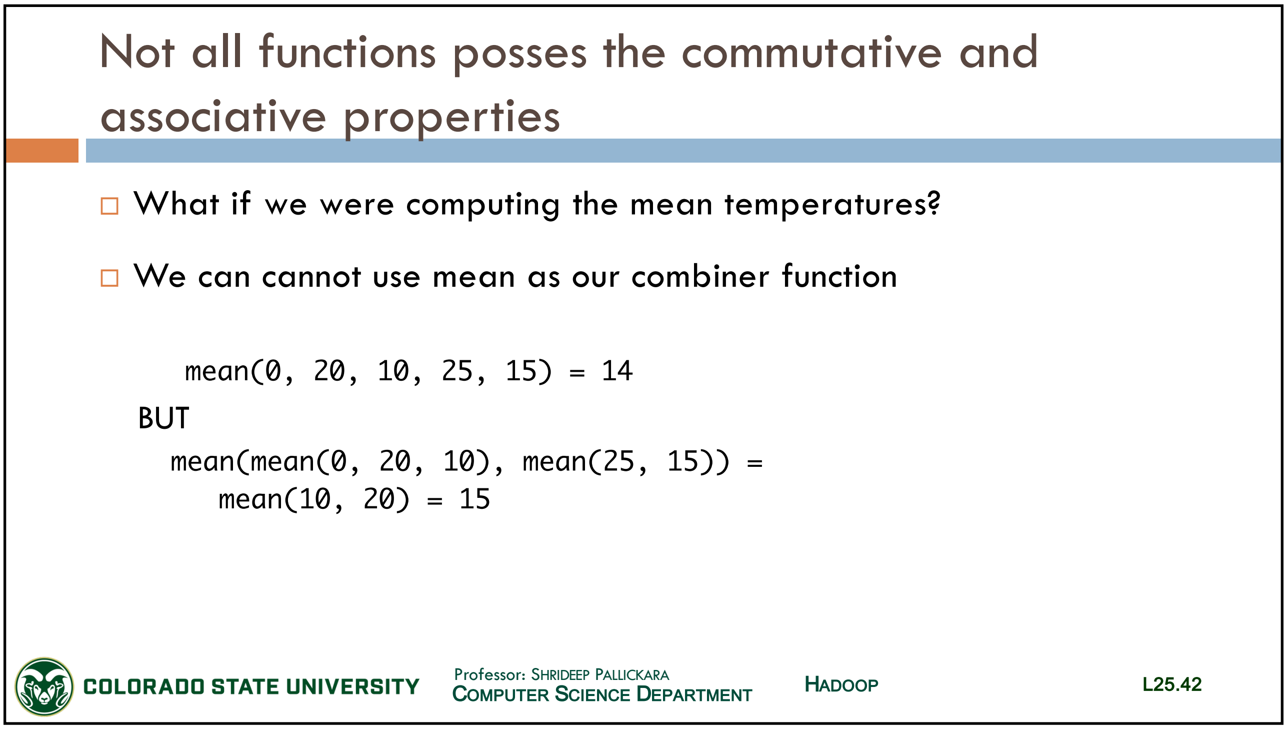
Reduce

(1950, 25)



A closer look at the function calls

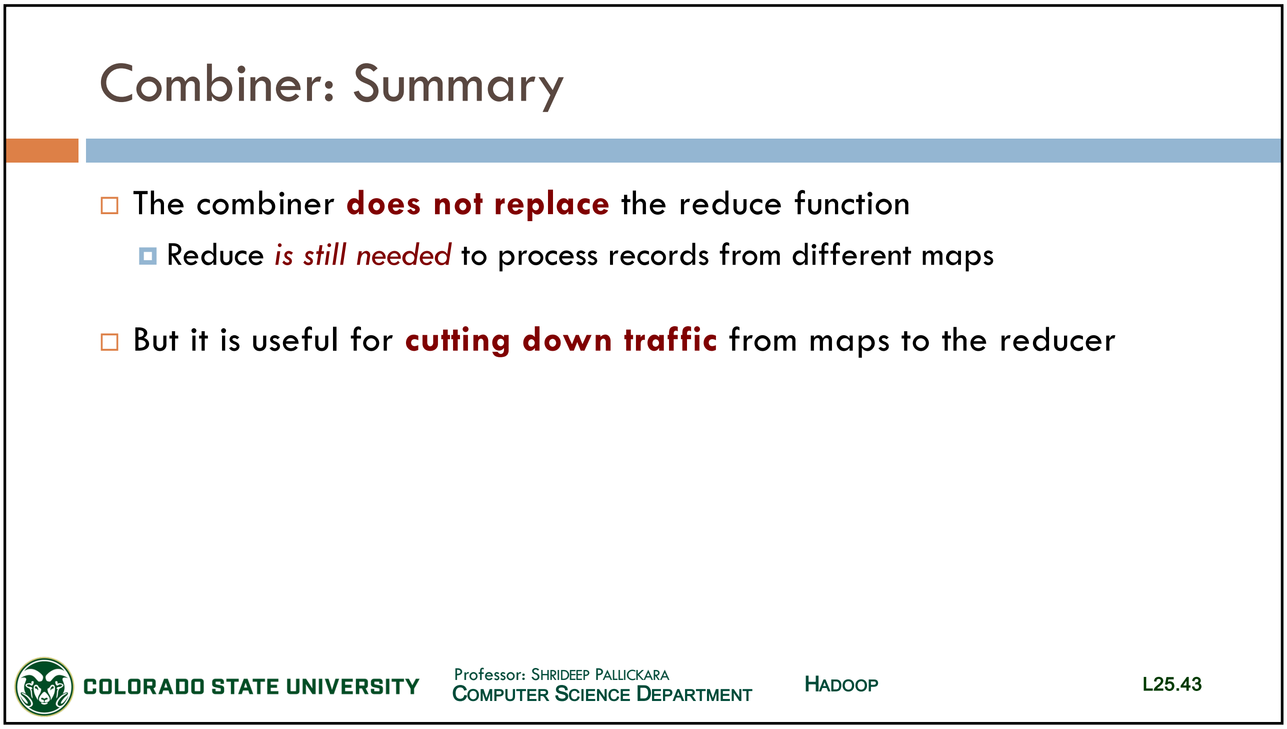
-
  ```
  max(0, 20, 10, 25, 15) =
   max (max(0, 20, 10), max(25, 15)) =
   max (20, 25) = 25
  ```
- Functions with this property are called **commutative** *and* **associative**
  - Commutative: Order of operands (5+2) = (2 + 5)
    - Division and subtraction are not commutative
  - Associative: Order of operators 5 x (5x3) = (5x5)x3
    - Vector cross products are not



Not all functions posses the commutative and associative properties

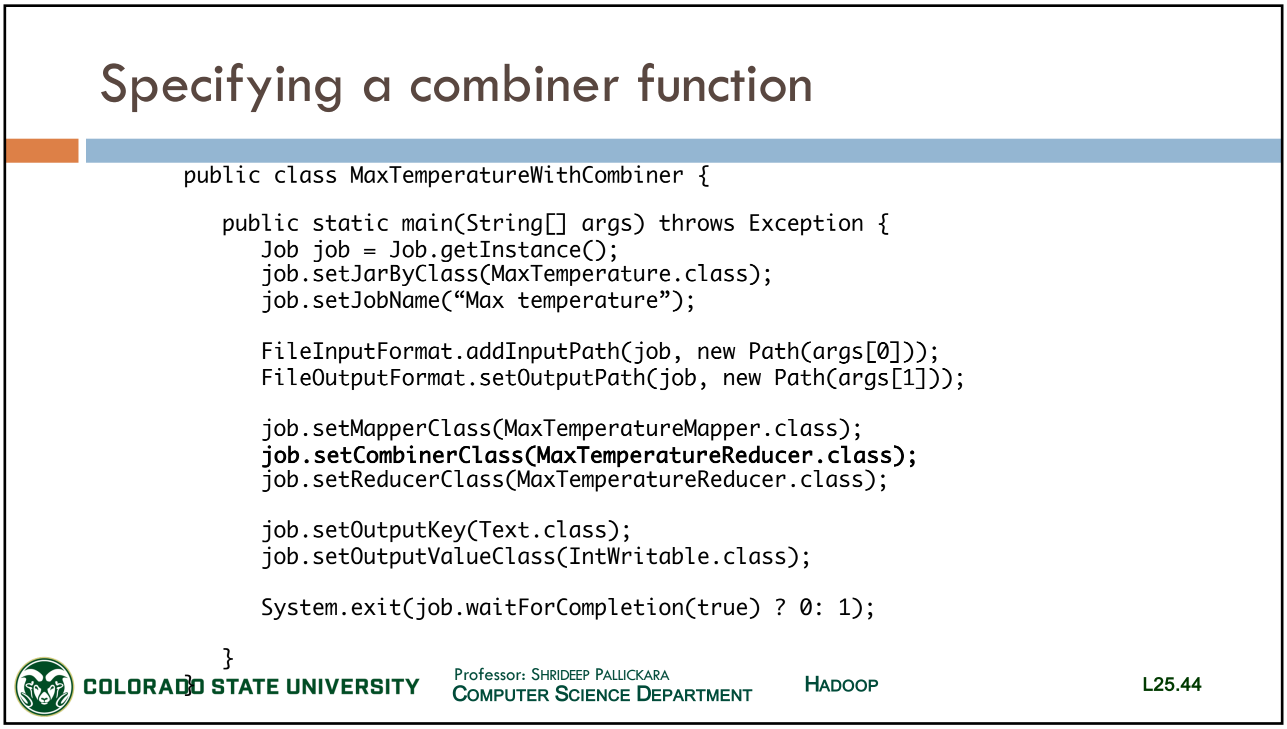
- What if we were computing the mean temperatures?
- We can cannot use mean as our combiner function

```
     mean(0, 20, 10, 25, 15) = 14
BUT
   mean(mean(0, 20, 10), mean(25, 15)) =
      mean(10, 20) = 15
```



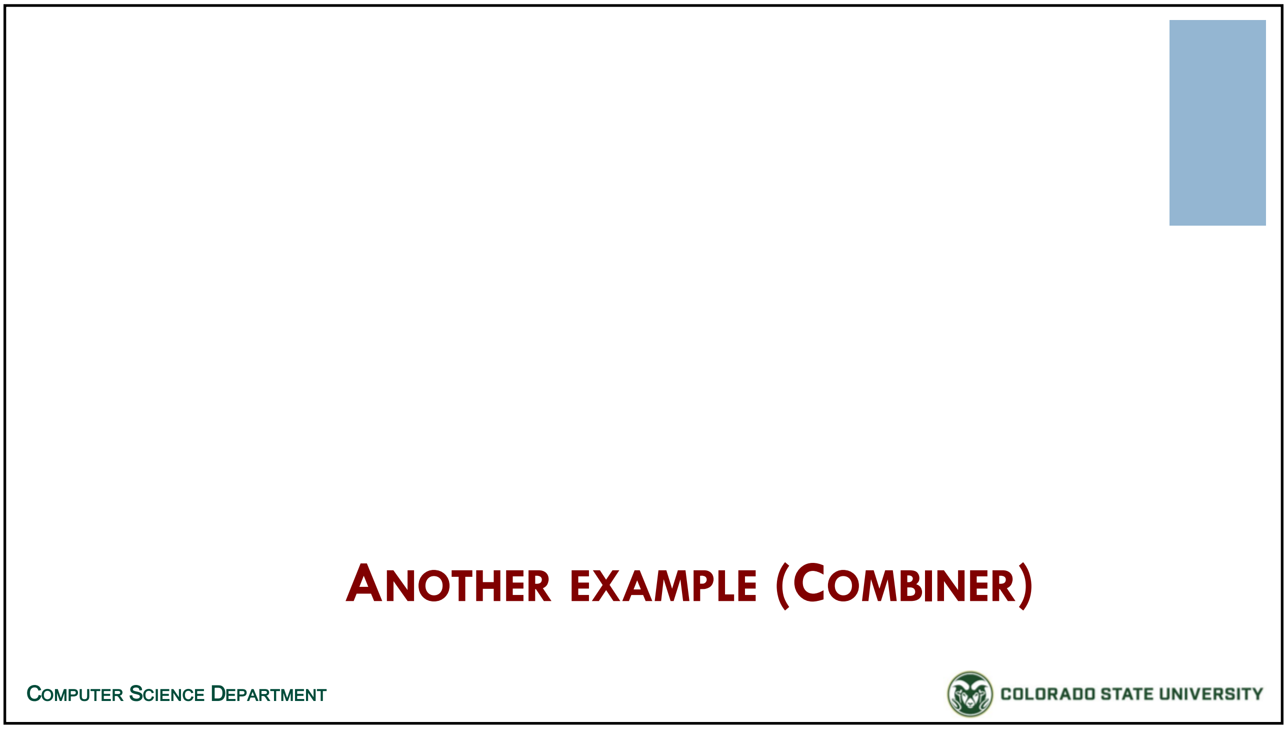
Combiner: Summary

- The combiner **does not replace** the reduce function
  - Reduce *is still needed* to process records from different maps
- But it is useful for **cutting down traffic** from maps to the reducer



Specifying a combiner function

```
public class MaxTemperatureWithCombiner {

   public static main(String[] args) throws Exception {
      Job job = Job.getInstance();
      job.setJarByClass(MaxTemperature.class);
      job.setJobName(“Max temperature”);

      FileInputFormat.addInputPath(job, new Path(args[0]));
      FileOutputFormat.setOutputPath(job, new Path(args[1]));

      job.setMapperClass(MaxTemperatureMapper.class);
      job.setCombinerClass(MaxTemperatureReducer.class);
      job.setReducerClass(MaxTemperatureReducer.class);

      job.setOutputKey(Text.class);
      job.setOutputValueClass(IntWritable.class);

      System.exit(job.waitForCompletion(true) ? 0: 1);

   }
}
```



ANOTHER EXAMPLE (COMBINER)

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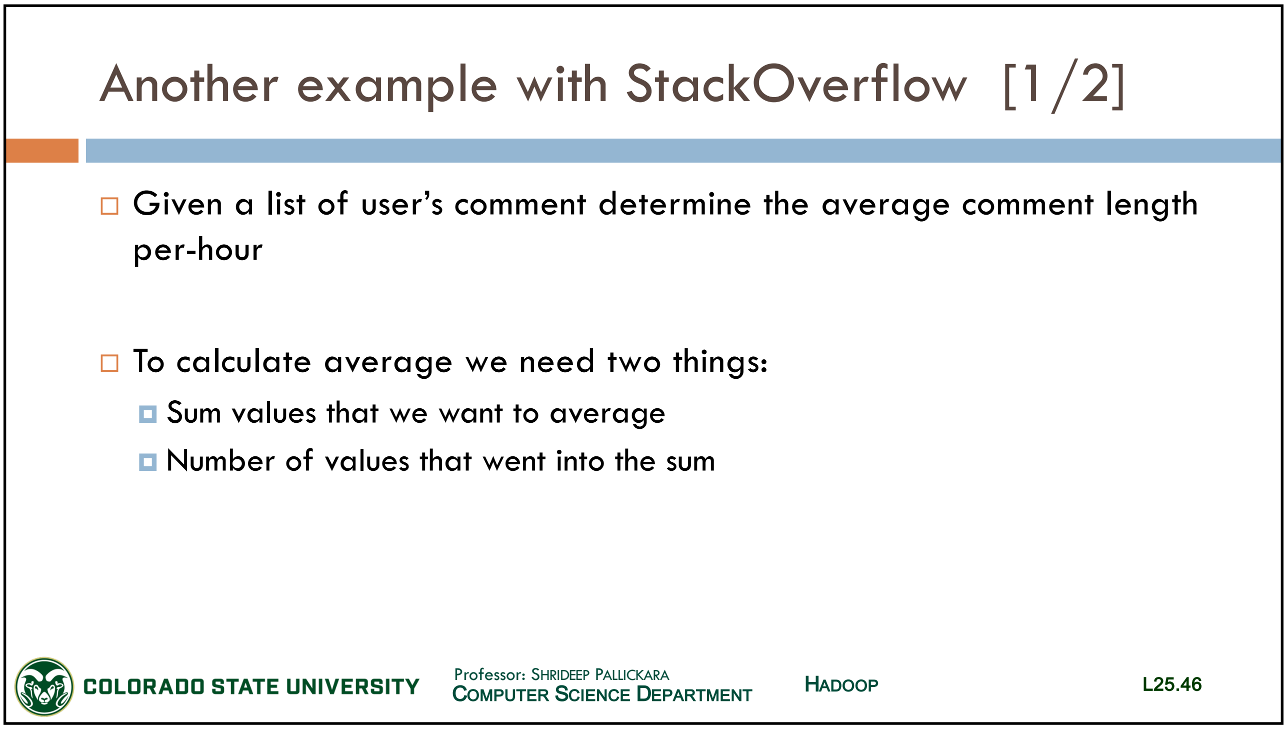

Another example with StackOverflow [1/2]

- Given a list of user's comment determine the average comment length per-hour
- To calculate average we need two things:
  - Sum values that we want to average
  - Number of values that went into the sum

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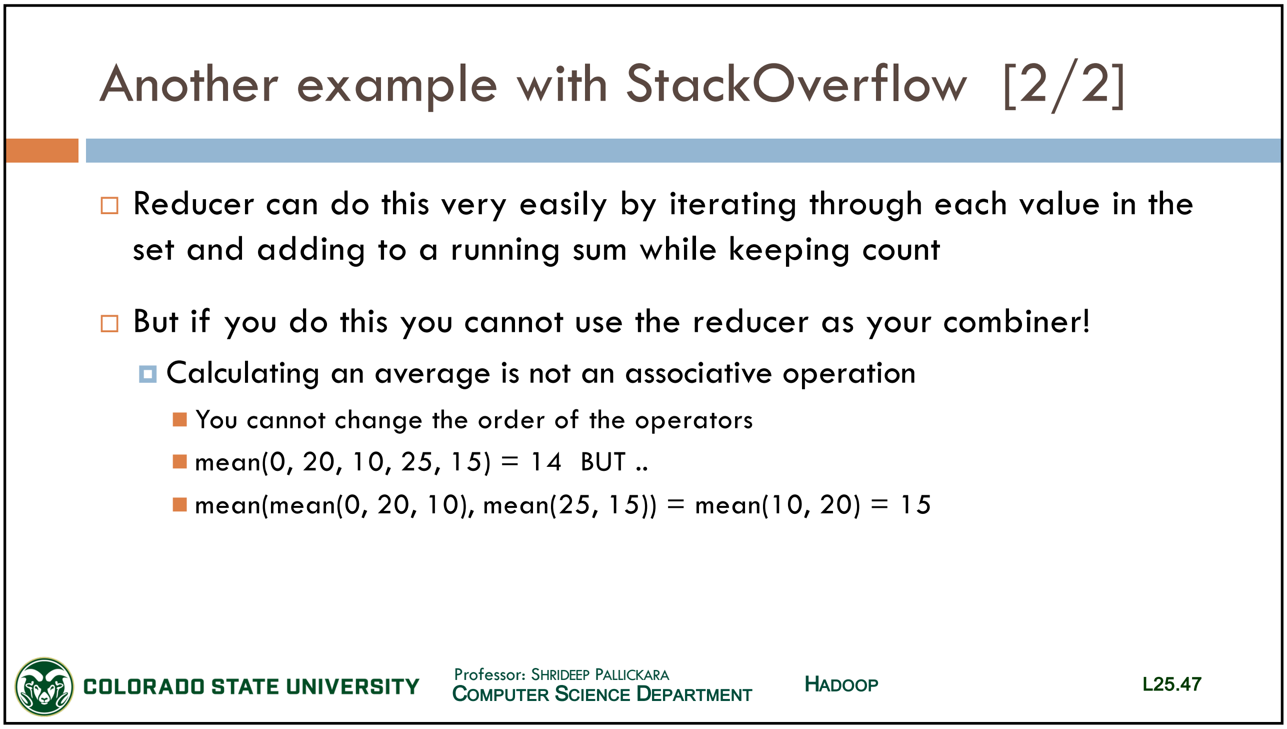
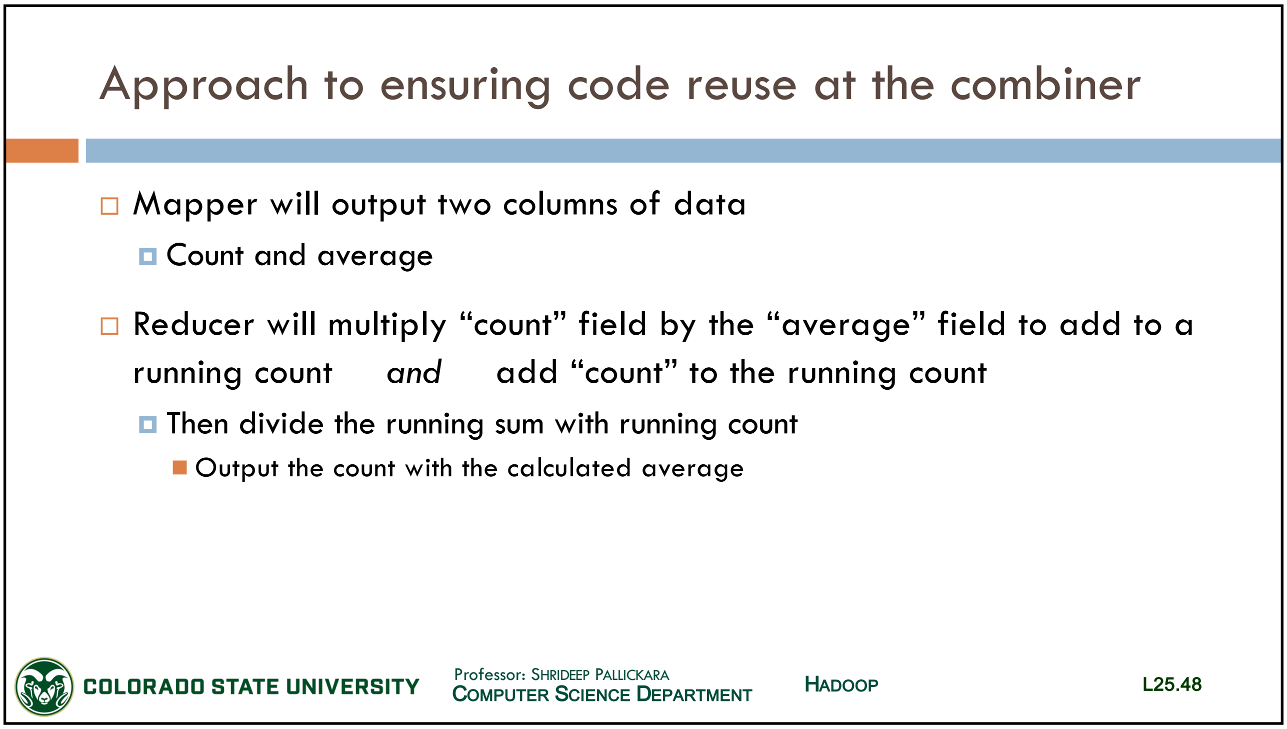


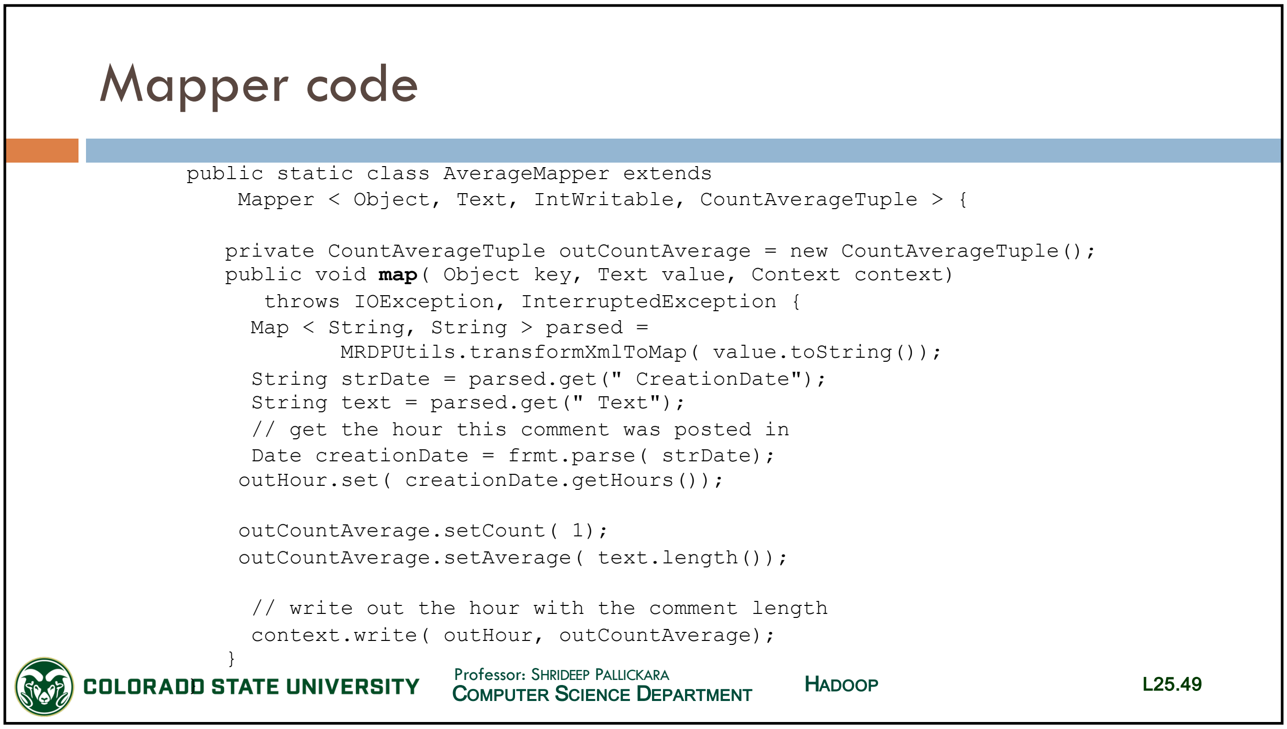
Another example with StackOverflow [2/2]

- Reducer can do this very easily by iterating through each value in the set and adding to a running sum while keeping count
- But if you do this you cannot use the reducer as your combiner!
  - Calculating an average is not an associative operation
    - You cannot change the order of the operators
    - mean(0, 20, 10, 25, 15) = 14 BUT ..
    - mean(mean(0, 20, 10), mean(25, 15)) = mean(10, 20) = 15



Approach to ensuring code reuse at the combiner

- Mapper will output two columns of data
  - Count and average
- Reducer will multiply “count” field by the “average” field to add to a running count *and* add “count” to the running count
  - Then divide the running sum with running count
    - Output the count with the calculated average



Mapper code

```
public static class AverageMapper extends
    Mapper < Object, Text, IntWritable, CountAverageTuple > {

   private CountAverageTuple outCountAverage = new CountAverageTuple();
   public void map( Object key, Text value, Context context)
      throws IOException, InterruptedException {
     Map < String, String > parsed =
            MRDPUtils.transformXmlToMap( value.toString());
     String strDate = parsed.get(" CreationDate");
     String text = parsed.get(" Text");
     // get the hour this comment was posted in
     Date creationDate = frmt.parse( strDate);
    outHour.set( creationDate.getHours());

    outCountAverage.setCount( 1);
    outCountAverage.setAverage( text.length());

     // write out the hour with the comment length
     context.write( outHour, outCountAverage);
   }
```

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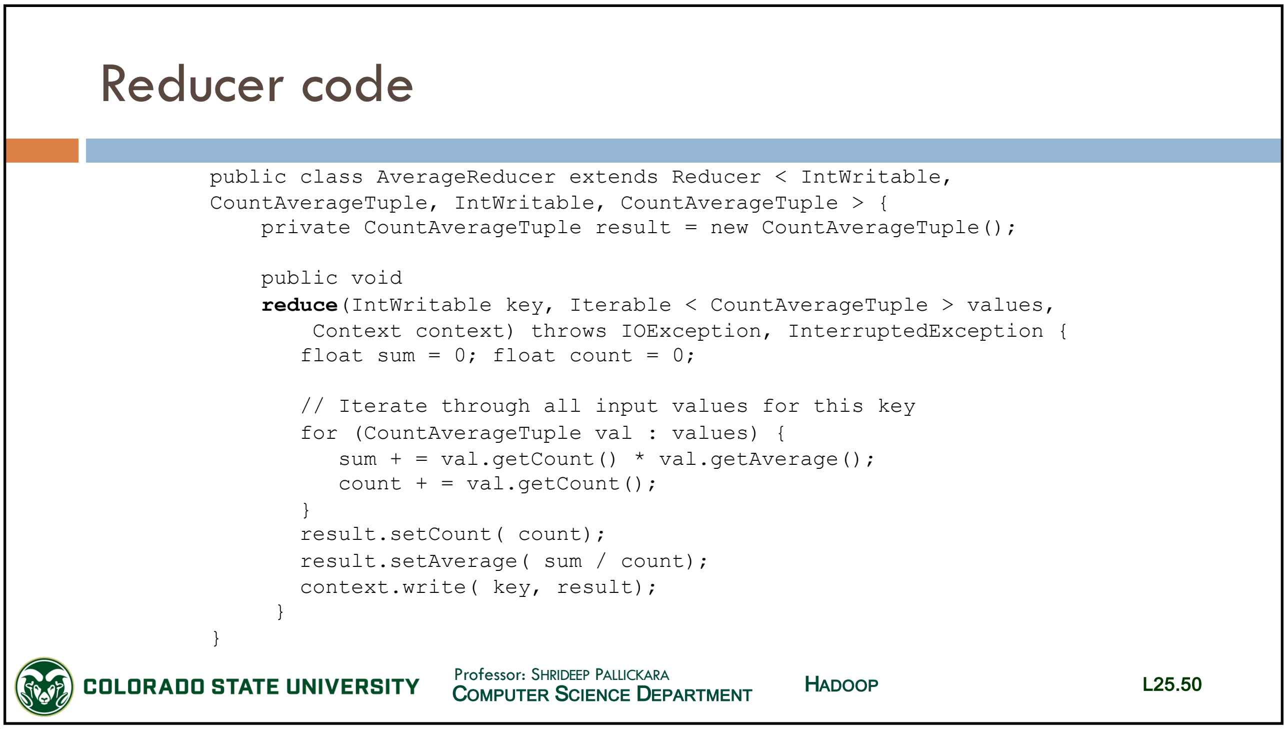

Reducer code

```
public class AverageReducer extends Reducer < IntWritable,
CountAverageTuple, IntWritable, CountAverageTuple > {
    private CountAverageTuple result = new CountAverageTuple();

    public void
    reduce(IntWritable key, Iterable < CountAverageTuple > values,
        Context context) throws IOException, InterruptedException {
       float sum = 0; float count = 0;

       // Iterate through all input values for this key
       for (CountAverageTuple val : values) {
          sum + = val.getCount() * val.getAverage();
          count + = val.getCount();
       }
       result.setCount( count);
       result.setAverage( sum / count);
       context.write( key, result);
     }
}
```

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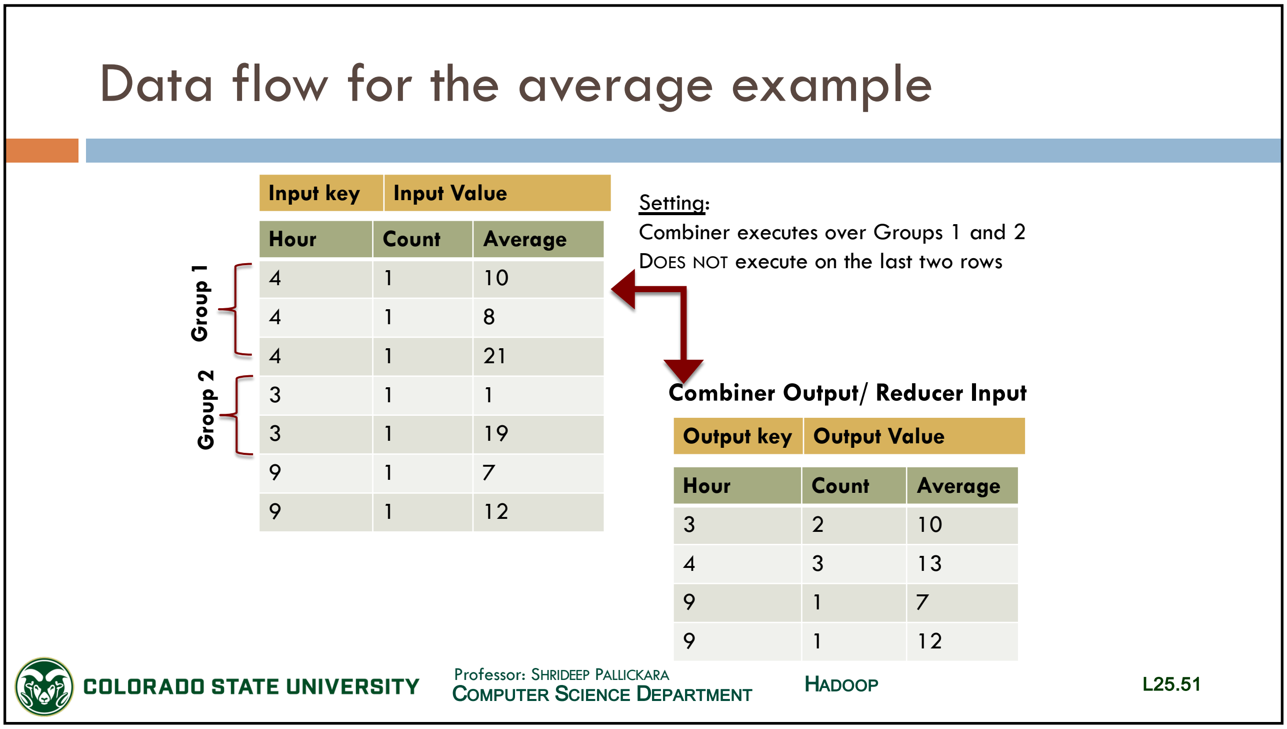

Data flow for the average example

	Input key	Input Value	
	Hour	Count	Average
Group 1	4	1	10
	4	1	8
	4	1	21
Group 2	3	1	1
	3	1	19
	9	1	7
	9	1	12

Setting:
Combiner executes over Groups 1 and 2
DOES NOT execute on the last two rows

Combiner Output/ Reducer Input

Output key	Output Value	
Hour	Count	Average
3	2	10
4	3	13
9	1	7
9	1	12

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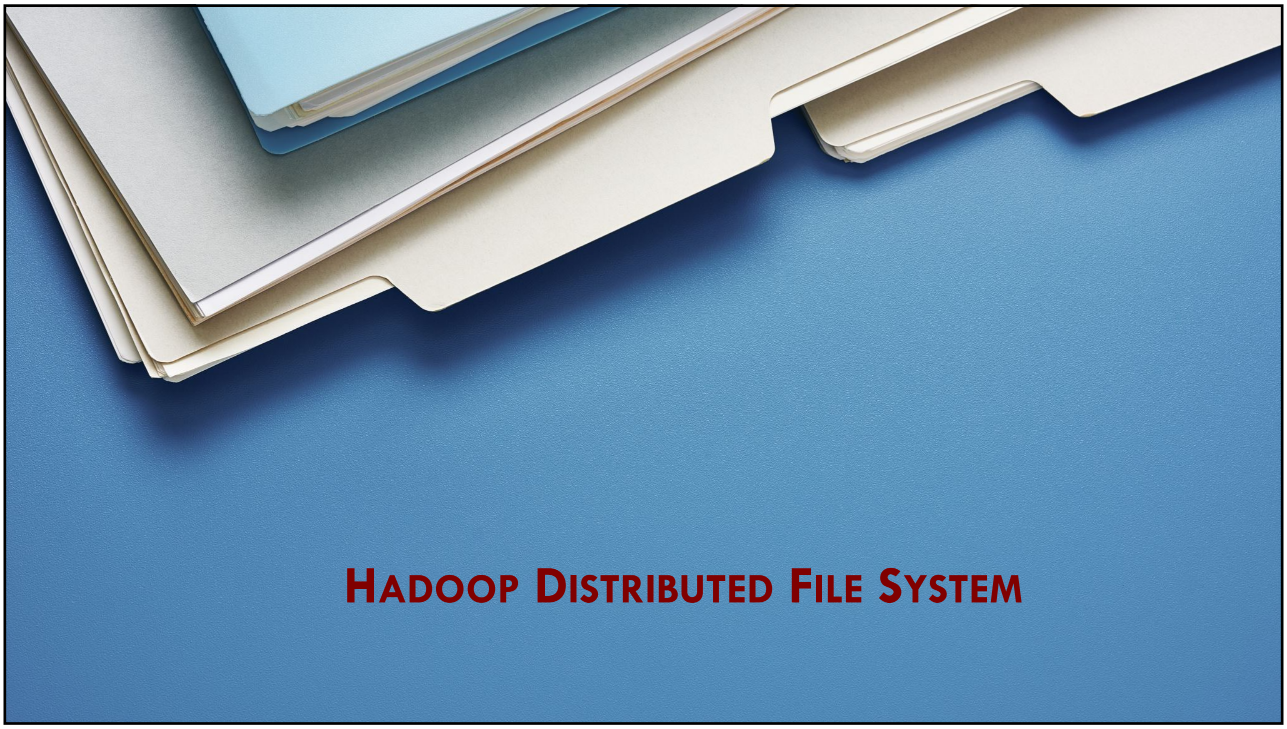

HADOOP DISTRIBUTED FILE SYSTEM

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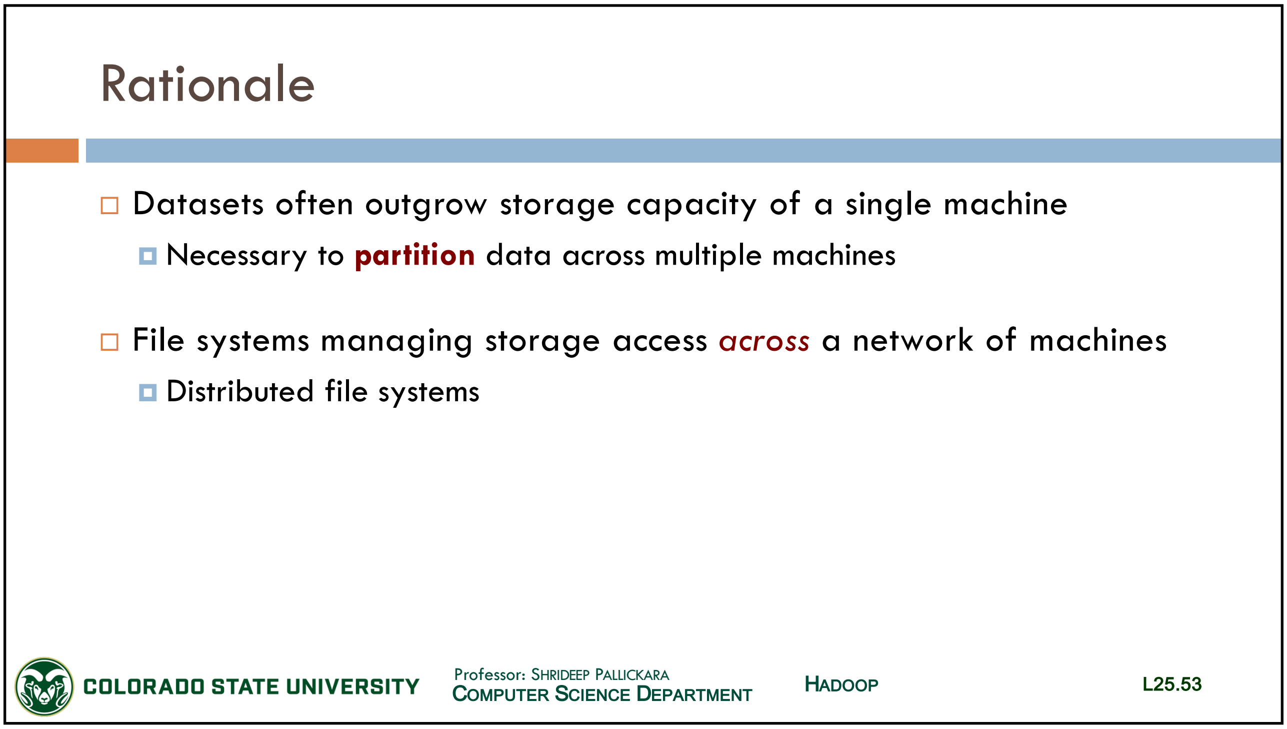
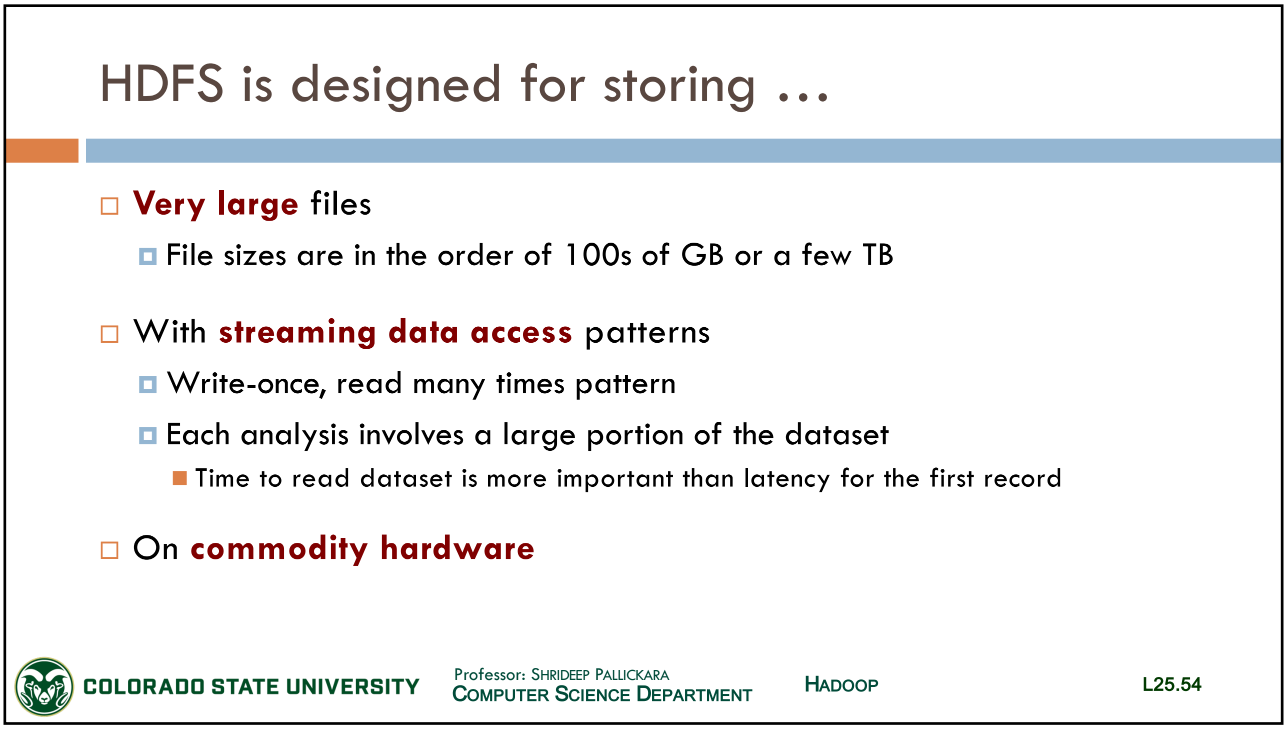


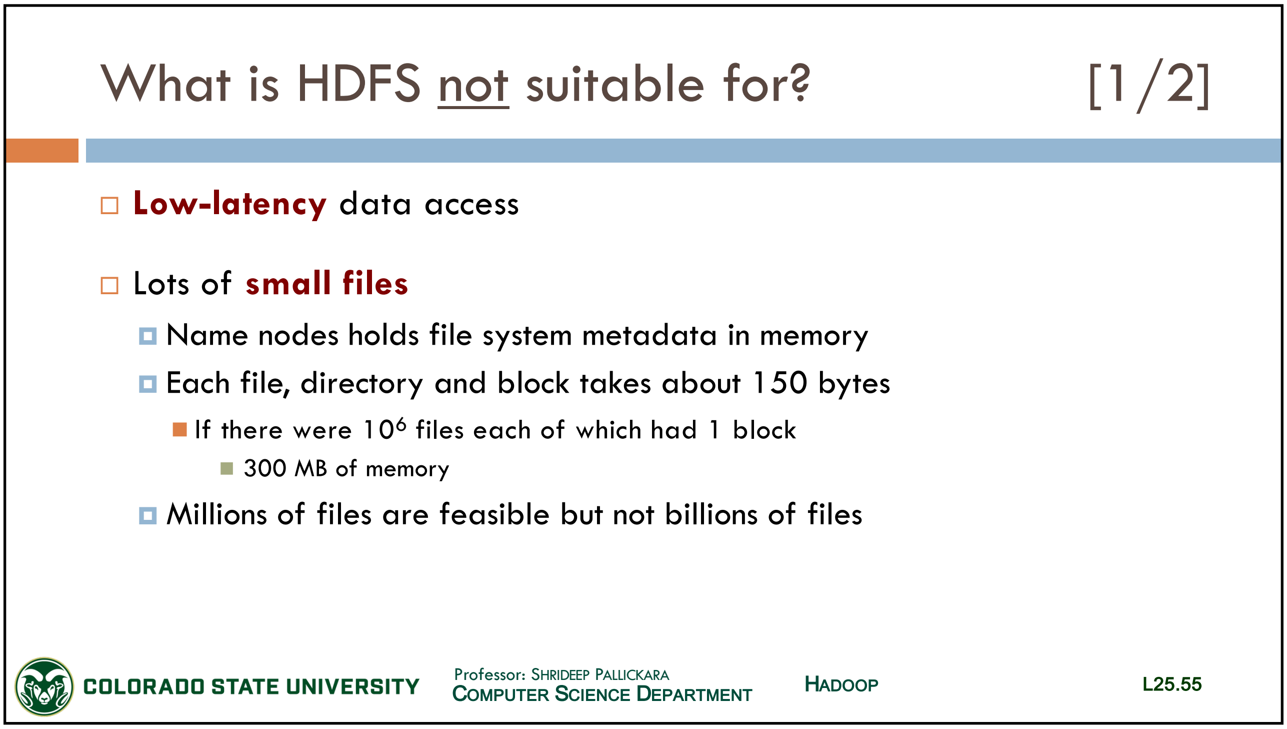
Rationale

- Datasets often outgrow storage capacity of a single machine
  - Necessary to **partition** data across multiple machines
- File systems managing storage access *across* a network of machines
  - Distributed file systems



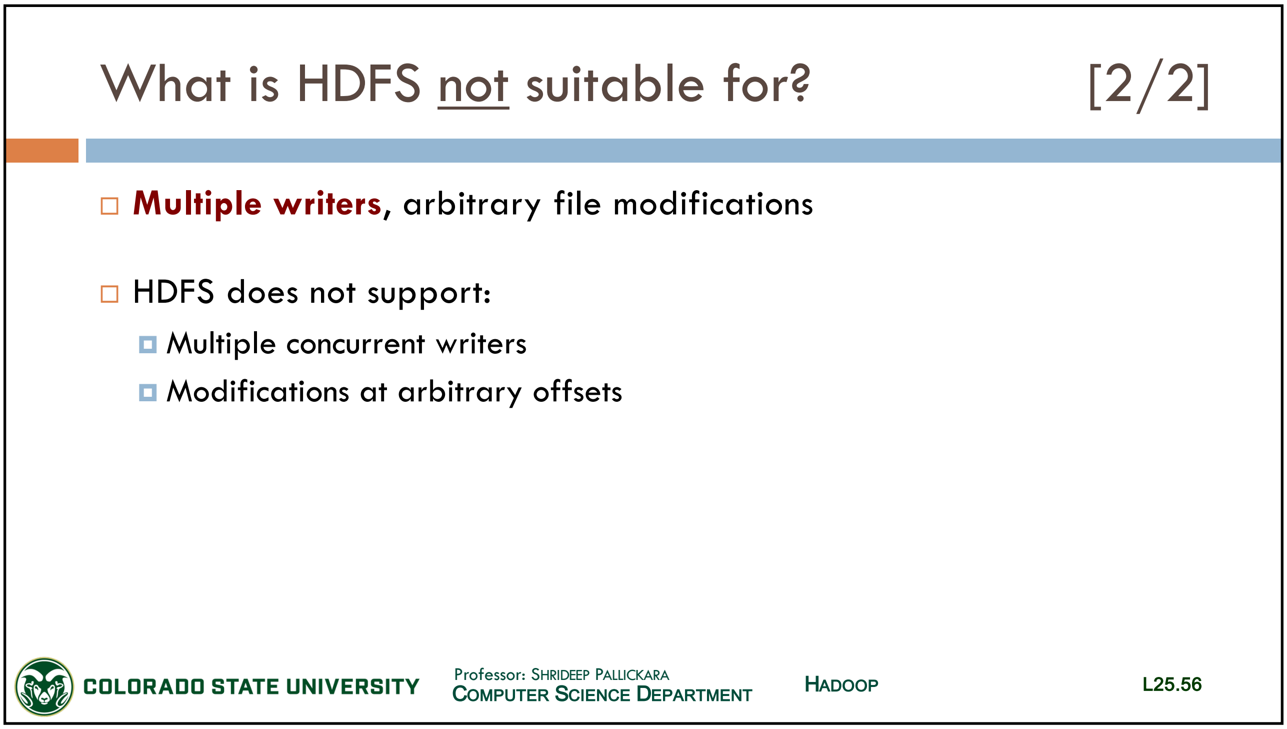
HDFS is designed for storing …

- **Very large** files
  - File sizes are in the order of 100s of GB or a few TB
- With **streaming data access** patterns
  - Write-once, read many times pattern
  - Each analysis involves a large portion of the dataset
    - Time to read dataset is more important than latency for the first record
- On **commodity hardware**



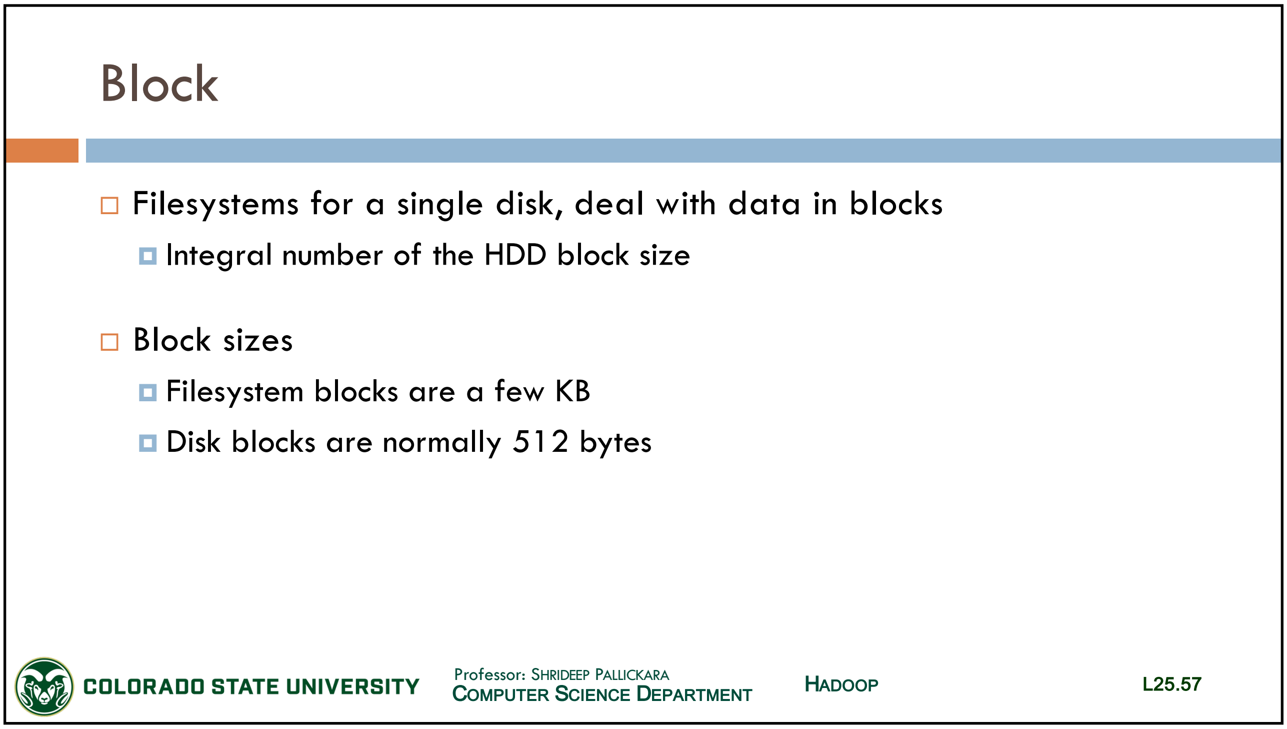
What is HDFS not suitable for? [1/2]

- **Low-latency** data access
- Lots of **small files**
  - Name nodes holds file system metadata in memory
  - Each file, directory and block takes about 150 bytes
    - If there were 10^6 files each of which had 1 block
      - 300 MB of memory
  - Millions of files are feasible but not billions of files



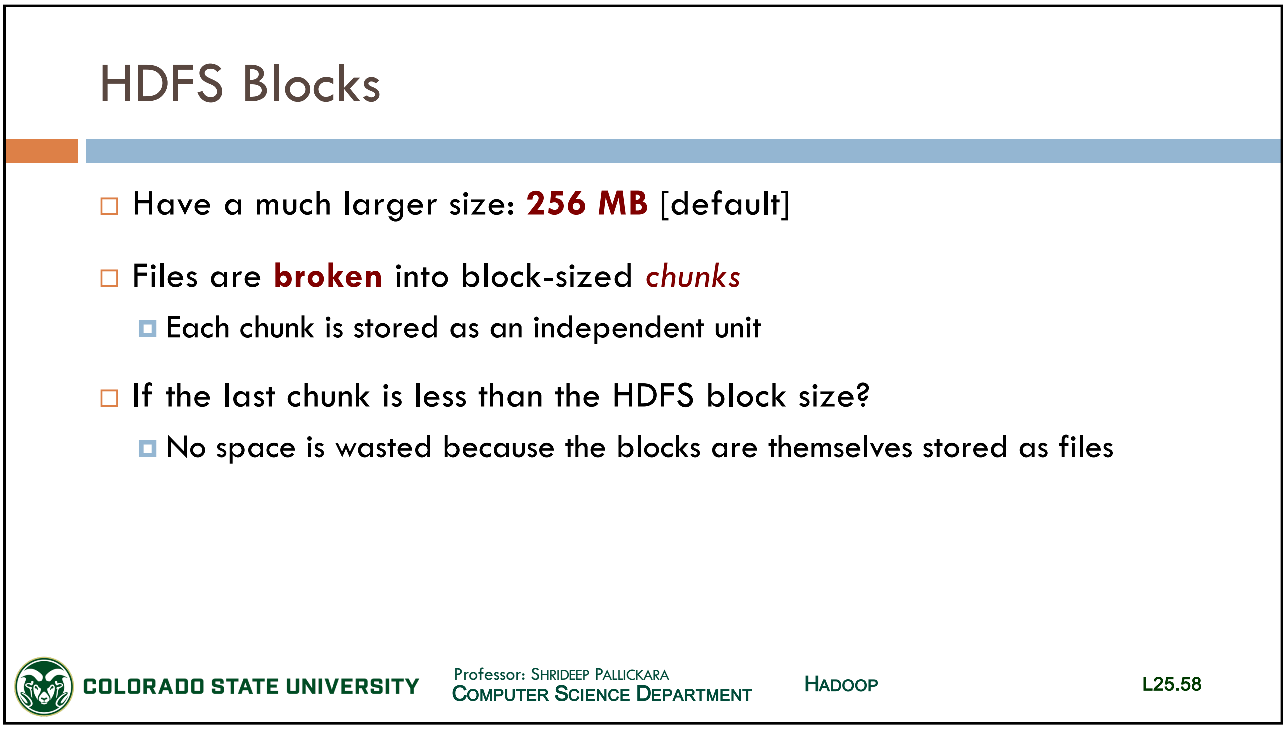
What is HDFS not suitable for? [2/2]

- **Multiple writers**, arbitrary file modifications
- HDFS does not support:
  - Multiple concurrent writers
  - Modifications at arbitrary offsets



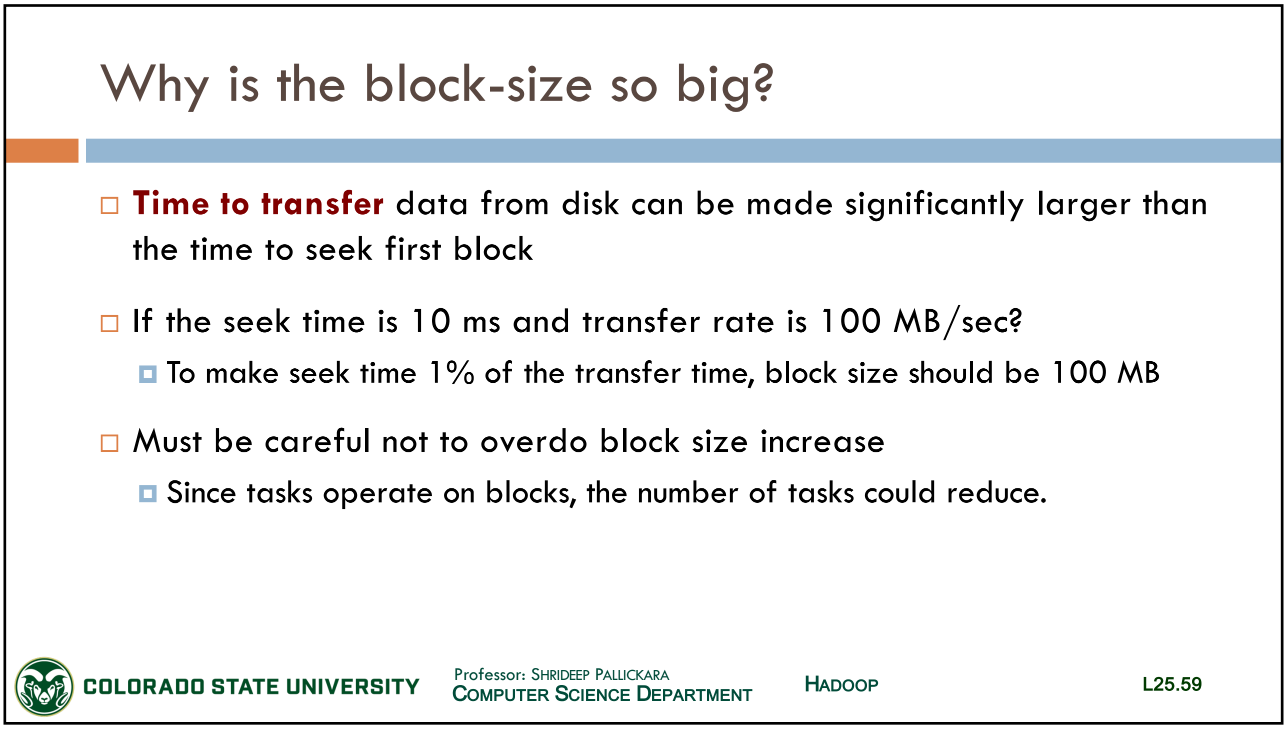
Block

- Filesystems for a single disk, deal with data in blocks
  - Integral number of the HDD block size
- Block sizes
  - Filesystem blocks are a few KB
  - Disk blocks are normally 512 bytes



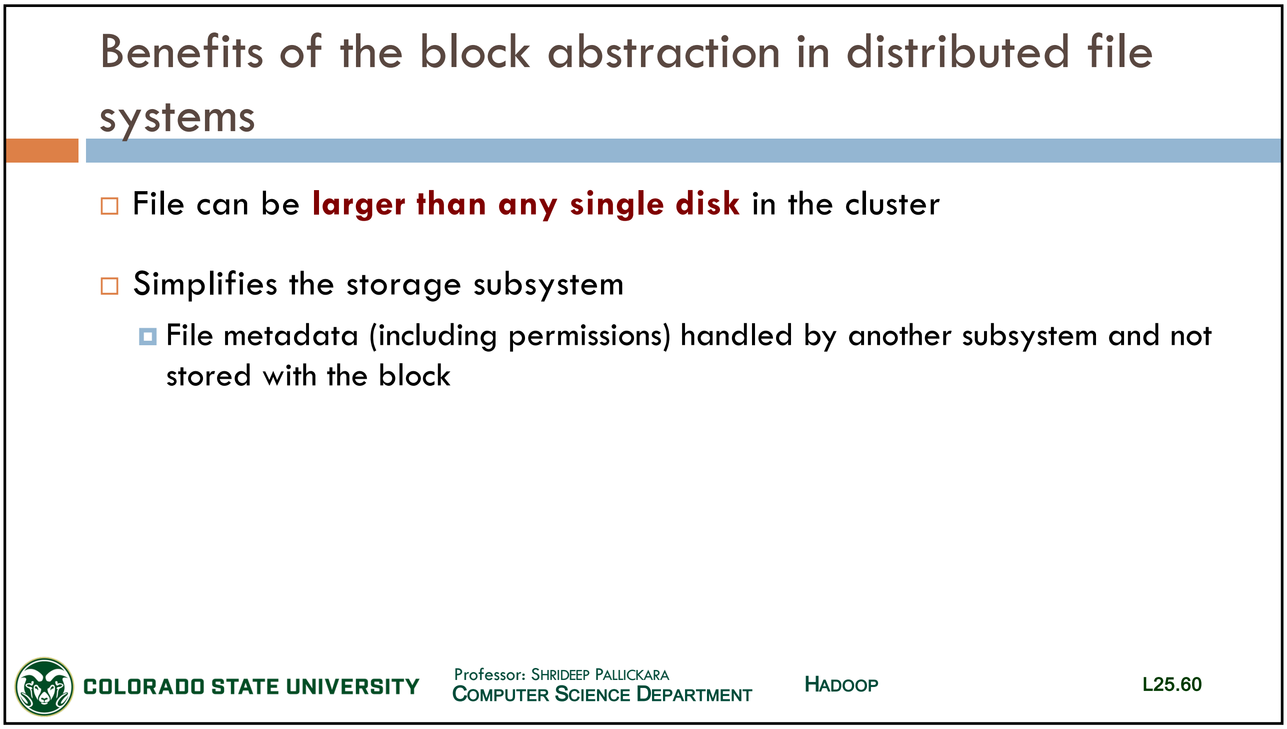
HDFS Blocks

- Have a much larger size: **256 MB** [default]
- Files are **broken** into block-sized *chunks*
  - Each chunk is stored as an independent unit
- If the last chunk is less than the HDFS block size?
  - No space is wasted because the blocks are themselves stored as files



Why is the block-size so big?

- **Time to transfer** data from disk can be made significantly larger than the time to seek first block
- If the seek time is 10 ms and transfer rate is 100 MB/sec?
  - To make seek time 1% of the transfer time, block size should be 100 MB
- Must be careful not to overdo block size increase
  - Since tasks operate on blocks, the number of tasks could reduce.



Benefits of the block abstraction in distributed file systems

- File can be **larger than any single disk** in the cluster
- Simplifies the storage subsystem
  - File metadata (including permissions) handled by another subsystem and not stored with the block

Blocks and replication

- Each block is replicated on a small number of **physically separate** machines
- If a block becomes unavailable?
  1. Copy *read from another location* transparently
  2. That block is also *replicated from its alternative locations* to other live machines
     - Bring replication factor back to the desired level

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

- *Tom White. Hadoop: The Definitive Guide. 3rd Edition. Early Access Release. O'Reilly Press. ISBN: 978-1-449-31152-0.* Chapters [2 and 3].
- *MapReduce Design Patterns: Building Effective Algorithms and Analytics for Hadoop and Other Systems.* 1st Edition. Donald Miner and Adam Shook. O'Reilly Media ISBN: 978-1449327170. [Chapter 1-3]