Parallel and Distributed Computing with MapReduce

[(https://github.com/learn-co-curriculum/dsc-parallel-and-distributed-computing-with-mapreduce)](https://github.com/learn-co-curriculum/dsc-parallel-and-distributed-computing-with-mapreduce)
[(https://github.com/learn-co-curriculum/dsc-parallel-and-distributed-computing-with-mapreduce/issues/new)](https://github.com/learn-co-curriculum/dsc-parallel-and-distributed-computing-with-mapreduce/issues/new)

Introduction

MapReduce is a programming paradigm that enables the ability to scale across hundreds or thousands of servers for big data analytics. The underlying concept can be somewhat difficult to grasp, because this paradigm differs from the traditional programming practices. This lesson aims to present a simple yet intuitive account of MapReduce that we shall put into practice in upcoming labs.

*In a nutshell, the term "MapReduce" refers to two distinct tasks. The first is the **Map** job, which takes one set of data and transforms it into another set of data, where individual elements are broken down into tuples **(key/value pairs)**, while the **Reduce** job takes the output from a map as input and combines those data tuples into a smaller set of tuples.*

We'll see this with help of some simple examples in this lesson.

Objectives

You will be able to:

- Explain how the MapReduce paradigm works and how it differs from traditional programming approaches
- Explain what is meant by distributed and parallel processing
- Use MapReduce with a simple word count example

Parallel and Distributed Processing

The MapReduce programming paradigm is designed to allow **parallel and distributed processing** of large sets of data (also known as big data). MapReduce allows us to convert such big datasets into sets of **tuples** as **key:value** pairs, as we'll see shortly. These pairs are analogous to the data structures we saw with dictionaries and JSON files etc. These tuples are **mapped** and **reduced** in a computational environment to allow distributed execution of complex tasks on a group (cluster) of interconnected computers.

So in simpler terms, *MapReduce uses parallel distributed computing to turn big data into regular data.*

Let's first see what we mean by parallel and distributed processing below.

Distributed Processing Systems

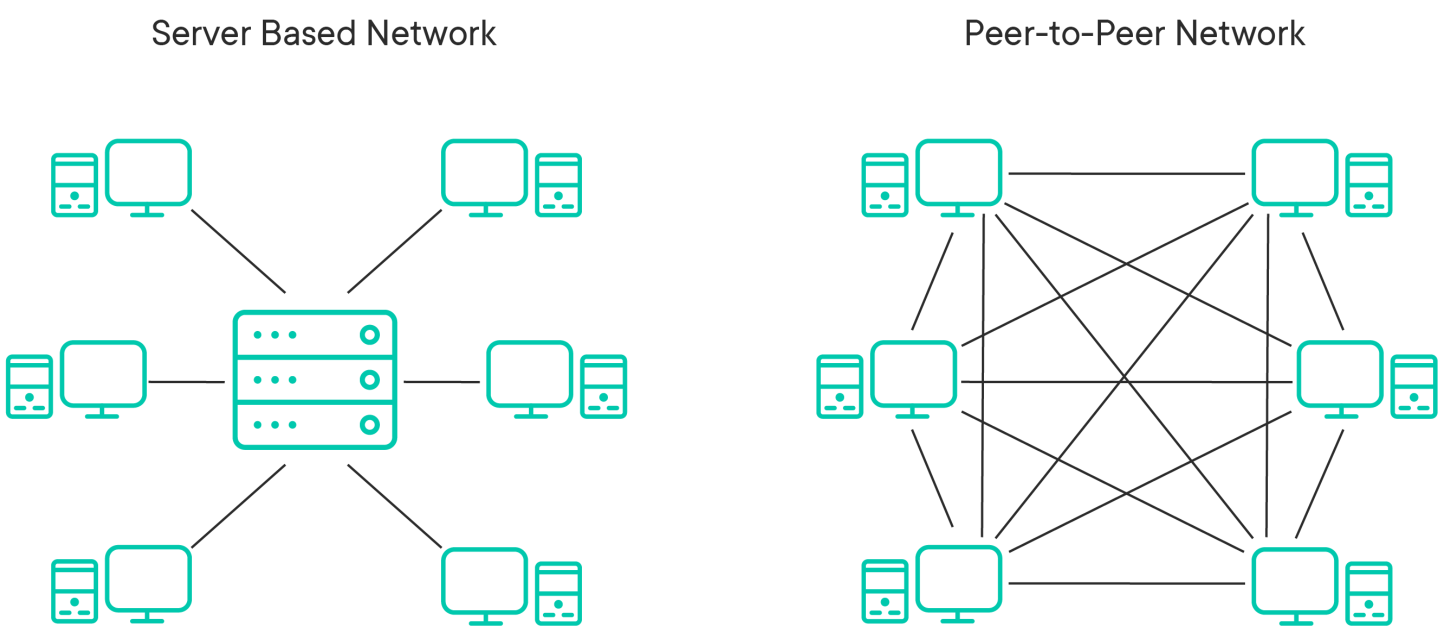
> A distributed processing system is a group of computers in a network working in tandem to accomplish a task

When computers are in a distributed system, they do not share hard drive memory or processing memory; they communicate with one other through messages, which are transferred over a network. The individual computers in this network are referred to as **nodes**. As you've seen before, computers can send requests as well as packets of data to one another.

The two most common ways of organizing computers into a distributed system are the client-server system and peer-to-peer system.

The client-server architecture has nodes that make requests to a central server. The server will then decide to accept or reject these requests and send additional methods out to the outer nodes.

Peer-to-peer systems allow nodes to communicate with one another directly without requiring approval from a server.



Parallel Processing Systems

These networks are useful for many applications all over the web, but they are generally ill-suited for dealing with the processing power required for very large sets of data and complex problems.

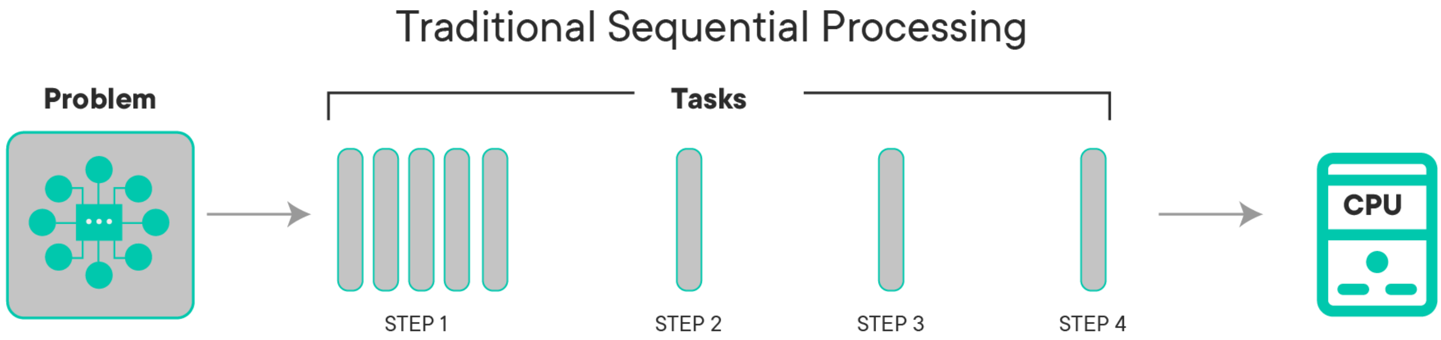
Just like in the workplace, whenever there is an extremely complex task, it is best to divide and conquer. In the world of big data, if the data is "big" enough, it is generally better to take the approach of splitting up the larger task into smaller pieces.

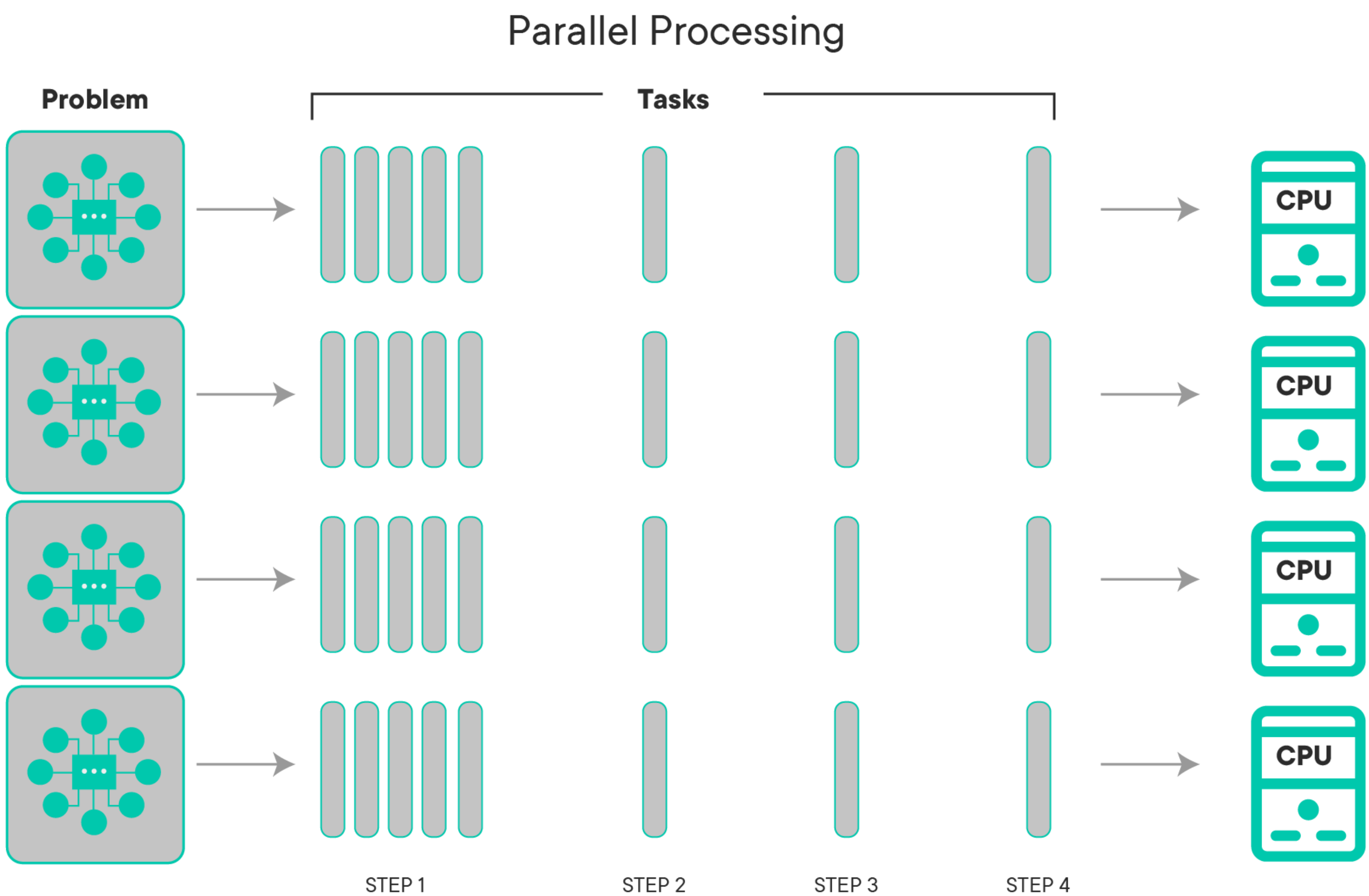
Even though individual processors are getting faster (remember **Moore's Law (https://en.wikipedia.org/wiki/Moore%27s_law)**), they will never have the ability to keep up with the amount of data we are able to produce. The best solution computer scientists have developed has been to use the power of **multiple processors** to put them to the same task. When using a well-developed distributed system, multiple processors can accomplish tasks at a fraction of the time it would take for a single processor to accomplish. As noted in the picture below, if you can divide the work between multiple processors, everything will be more efficient.

With parallel computing:

- a larger problem is broken up into smaller pieces
- every part of the problem follows a series of instructions
- each one of the instructions is executed simultaneously on different processors
- all of the answers are collected from the small problems and combined into one final answer

In the image below, you can see a simple example of a process being broken up and completed both sequentially and in parallel.





Of course, not all problems can be parallelized, but there are some that are formally called [embarrassingly parallel (https://en.wikipedia.org/wiki/Embarrassingly_parallel)](https://en.wikipedia.org/wiki/Embarrassingly_parallel) problems that require hardly any effort to ensure that a certain task is able to easily parallelizable. One example of something that would be embarrassingly parallelizable would be password cracking. Another example would be a movie production company trying to calculate the total profit they made from all of the movies they released in a given year. Let's think about all of the components that go into determining whether or not a movie is profitable.

- story rights
- producer
- director
- cast

- production costs
- visual effects
- music

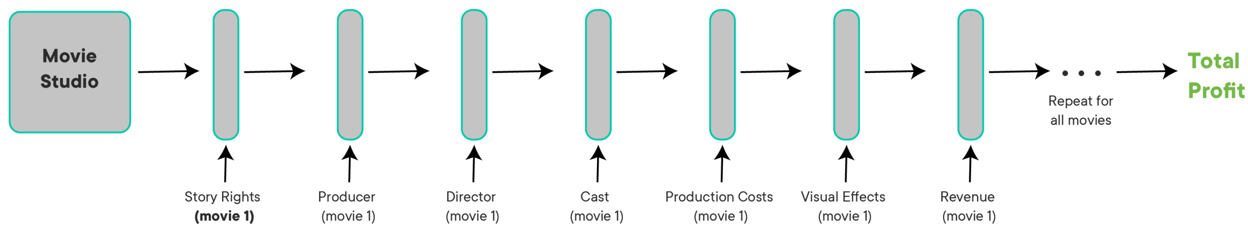
and of course

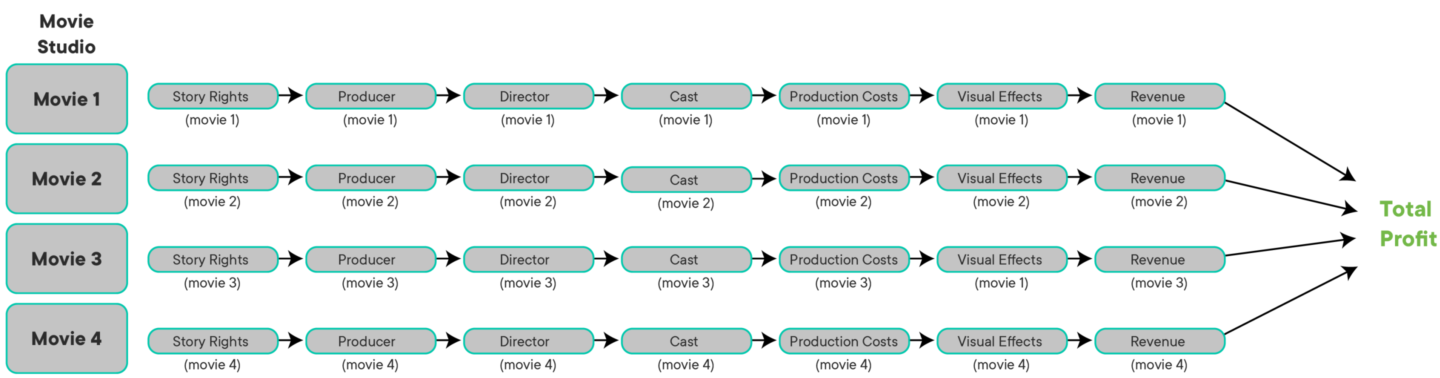
- box office revenue

Here is what this would look like if it was calculated sequentially.

If a movie studio was to compute each one it's movie's profits sequentially, it would take far more time than if it calculated each movie's profit and combined them in parallel.

Here is a diagram of what parallel processing looks like in action:





So how can we make all these nodes communicate with one another? By using a programming paradigm called MapReduce!

MapReduce is a software framework developed for processing datasets that qualify as "Big Data", in a **distributed and parallel** processing environment over several computers/nodes connected to each other as part of a **cluster**. It is a specific instance of the generalized split-apply-combine technique used to perform different data analyses.

We will soon look into a simple example that is shown to introduce MapReduce, **The Word Count Problem**. The overall concept of MapReduce is very simple yet very powerful as:

- Somehow, all data can be mapped to **key:value** pairs
- Keys and values themselves can be of ANY data type

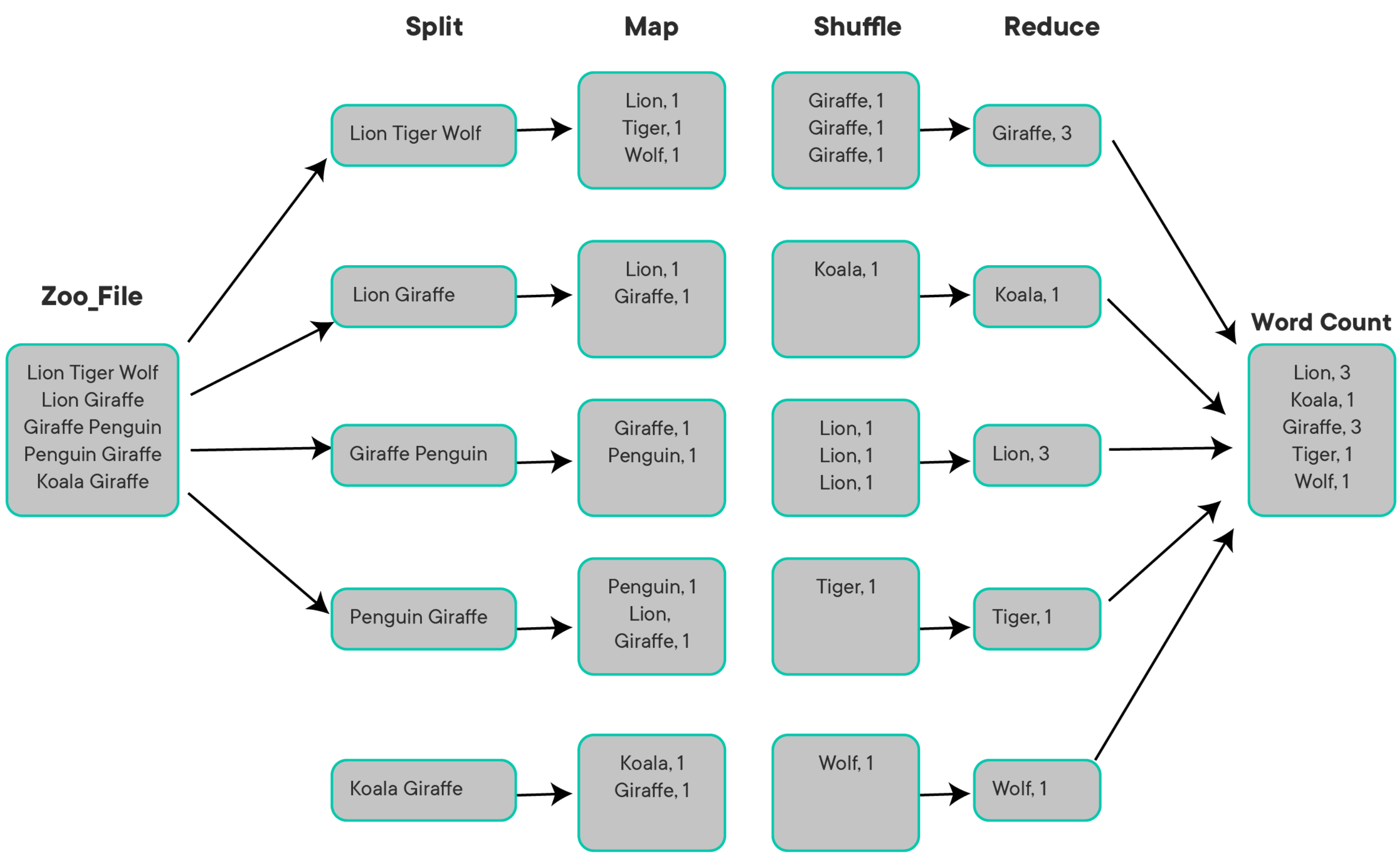
For our example, let's say a national association of zoos wants to determine the total number of species of animals in the country. After receiving responses from every zoo in the country, a data scientist receives a large file that has a different zoo located on each line with the species at that location.

Here are the first five zoos the data scientist reads over in the data document they receive:

Animals
lion tiger bear
lion giraffe
giraffe penguin
penguin lion giraffe
koala giraffe

Let's now look at how you would use the MapReduce framework in this simple word count example that could be generalized to much more data.

We'll take a look at an image of this process in action and determine what's actually going on.



1. MAP Task (Splitting & Mapping)

The dataset that needs processing must first be transformed into **key:value** pairs and split into fragments, which are then assigned to map tasks. Each computing cluster is assigned a number of map tasks, which are subsequently distributed among its nodes. In this example, let's assume that we are using 5 nodes (a server with 5 different workers).

First, split the data from one file or files into however many nodes are being used.

We will then use the map function to create key:value pairs represented by:
{animal} , *{# of animals per zoo}*

After processing of the original key:value pairs, some **intermediate** key:value pairs are generated. The intermediate key:value pairs are **sorted by their key values** to create a new list of key:value pairs.

2. Shuffling

This list from the map task is divided into a new set of fragments that sorts and shuffles the mapped objects into an order or grouping that will make it easier to reduce them. **The number of these new fragments will be the same as the number of the reduce tasks**.

3. REDUCE Task (Reducing)

Now, every properly shuffled segment will have a reduce task applied to it. After the task is completed, the final output is written onto a file system. The underlying file system is usually HDFS (Hadoop Distributed File System).

It's important to note that MapReduce will generally only be powerful when dealing with large amounts of data. When working with a small dataset, it will be faster not to perform operations in the MapReduce framework.

There are two groups of entities in this process to ensuring that the MapReduce task gets done properly:

Job Tracker: a "master" node that informs the other nodes which map and reduce jobs to complete

Task Tracker: the "worker" nodes that complete the map and reduce operations

There are different names for these components depending on the technology used, but there will always be a master node that informs worker nodes what tasks to perform.

A general pseudocode for a word count map and reduce tasks would look like

```
# Count word frequency
def map( doc ) :
    for word in doc.split( ' ' ) :
    emit ( word , 1 )

def reduce( key , values ) :
    emit ( key , sum( values ) )
```

Similarly, we can discuss combining several MapReduce jobs in order to complete a given task. This means that once the first MapReduce job is finished, the output will become an input for the second MapReduce job and that output could be the final result (or fed into another MapReduce job).

Let's assume that we would like to extend the word count program and we would like to count all words in a given Twitter dataset. The first MapReduce will read our twitter data and extract the tweets' text. The second MapReduce is the word count Map-Reduce which will analyze the Twitter dataset and produce the statistics about it. So it is simply chaining together multiple jobs.

> **InputFile -> Map-1 -> Reduce-1 -> output-1 -> Map-2 - > Reduce-2 -> output-2 -> ... Map-x -> Reduce-x**

Later we are going to look at Apache Spark, which adds extra features of security and fault tolerance to its MapReduce offering, making it an industry standard. We will also look at programming for the aforementioned word count problem.

Additional Resources

Visit following external links to read about the previous descriptions and examples in more detail.

- **MapReduce Introduction (https://www.tutorialspoint.com/map_reduce/map_reduce_introduction.htm)**
- **What is MapReduce? How it Works (https://www.guru99.com/introduction-to-mapreduce.html)**

Summary

In this lesson, we looked at how MapReduce allows a programming paradigm quite different than traditional programming practices, yet very powerful and effective towards processing large amounts of data.