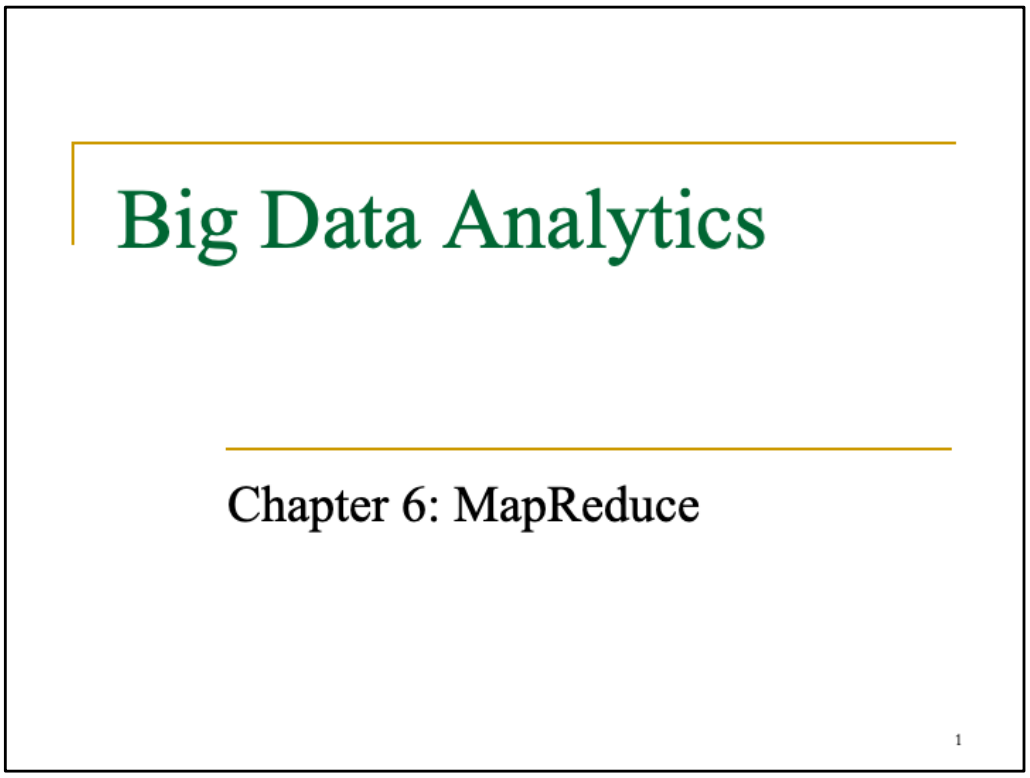
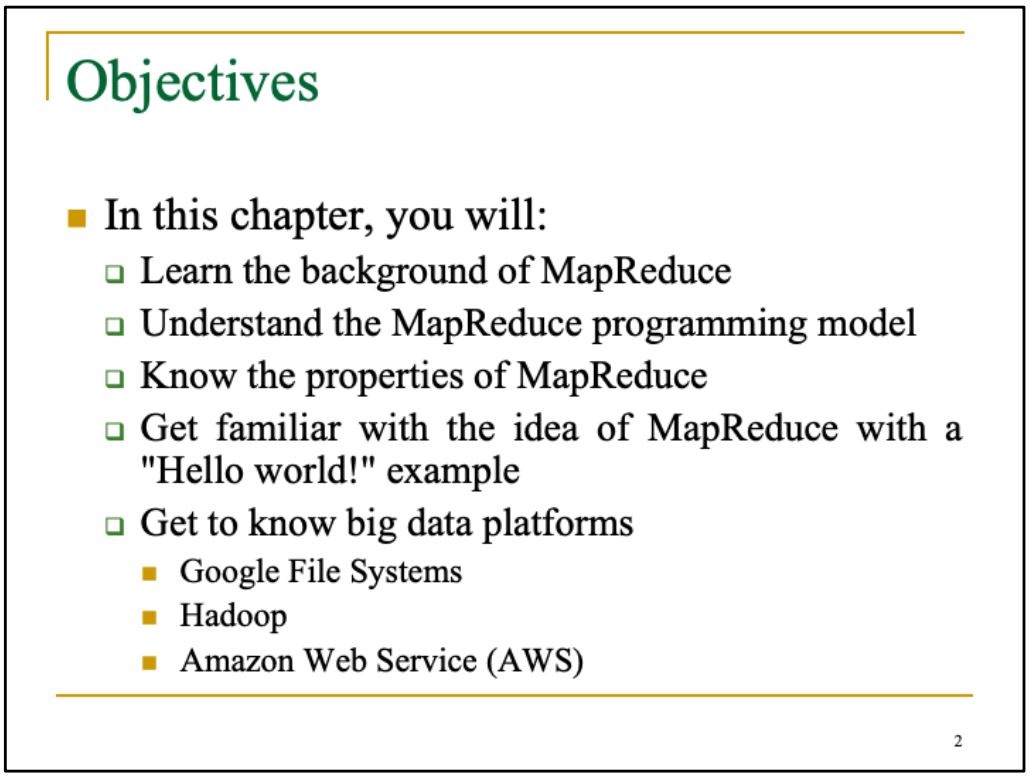


Chapter 6: MapReduce



References

Lin, Jimmy, and Chris Dyer. *Data-Intensive Text Processing with MapReduce*. Morgan & Claypool Publishers, 2010.

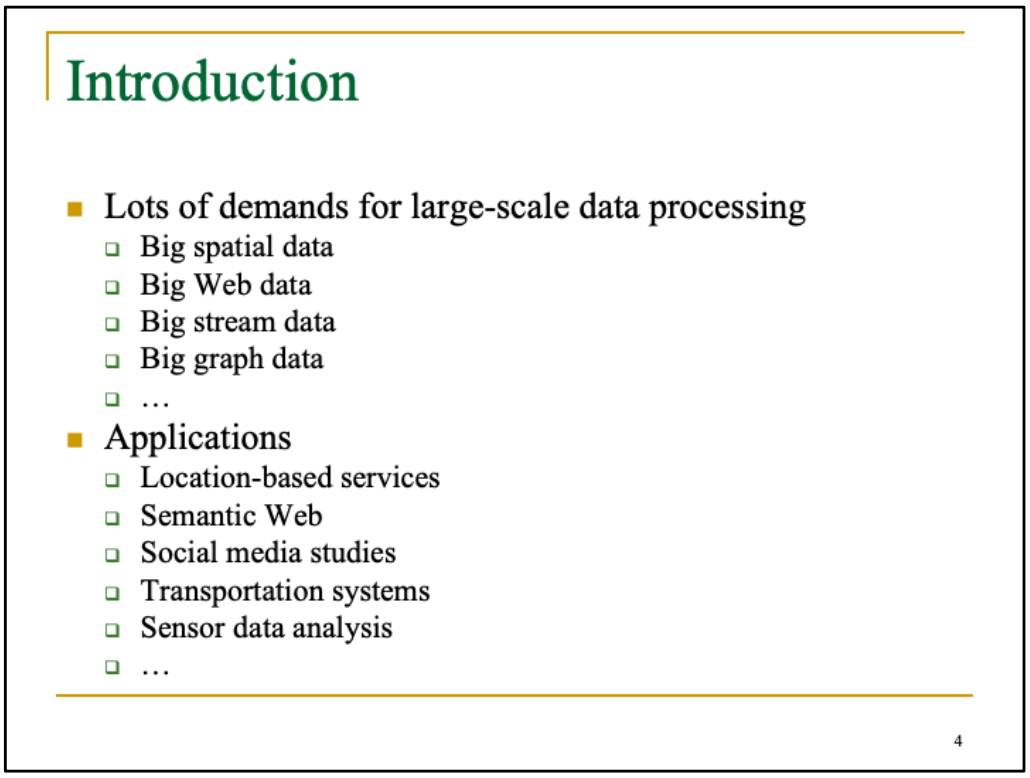
In this chapter, we will discuss the background/properties of MapReduce, and learn the MapReduce programming model. We will write a helloworld program of MapReduce, and understand some big data platform like GFS, Hadoop and Amazon Web Service.

Outline

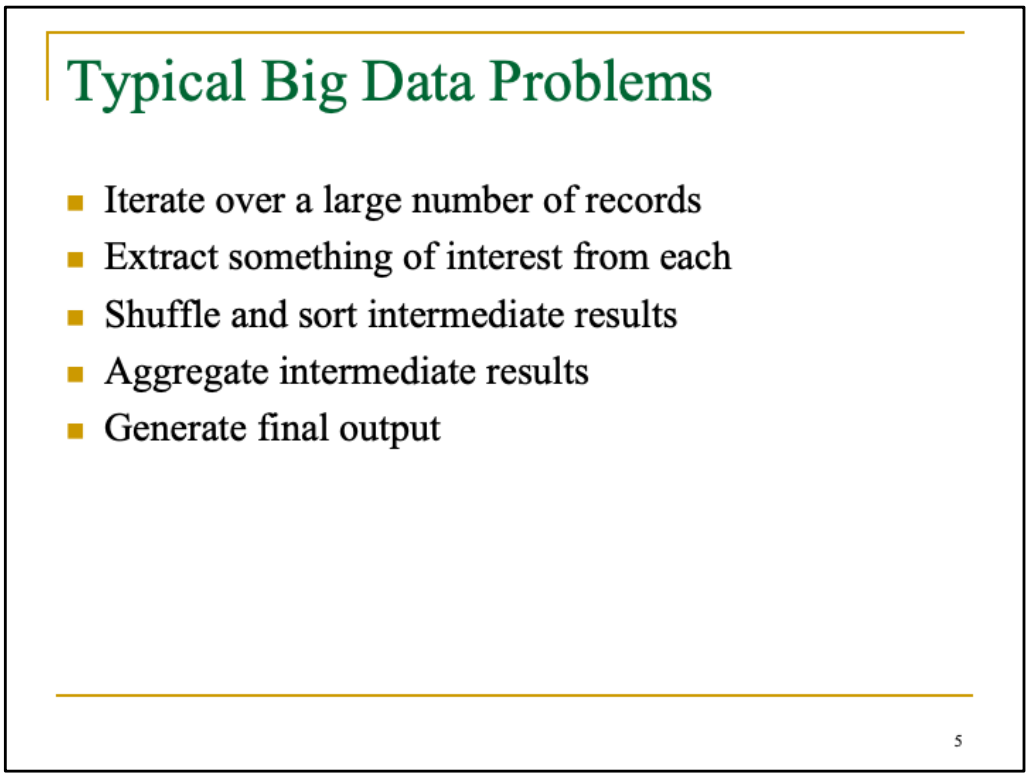
- Introduction
- Challenges
- Background of MapReduce
- MapReduce
- Characteristics of MapReduce
- Google File Systems
- Hadoop
- Amazon Web Services

3

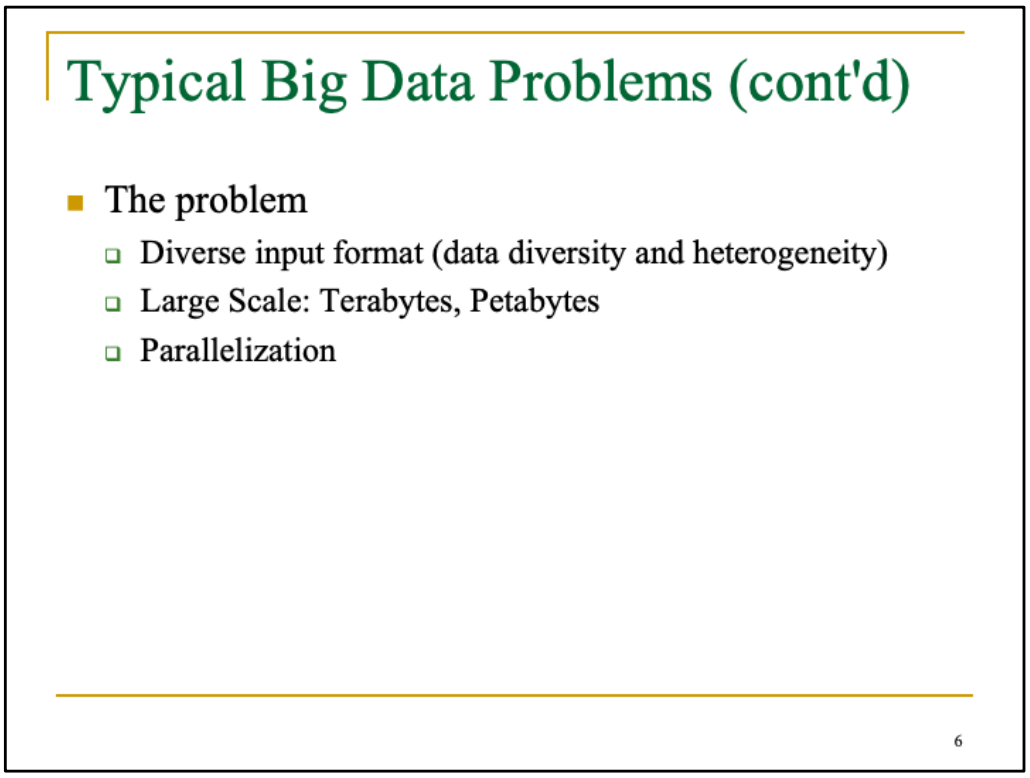
Here is the outline of this chapter.



In the era of big data, there are a lot of demands for processing large-scale data, such as big spatial data, big Web data, big stream data, big graph data, and so on. These data are very useful for real-world applications like location-based services, Semantic Web, social networks, transportation system, sensor data analysis, and so on.

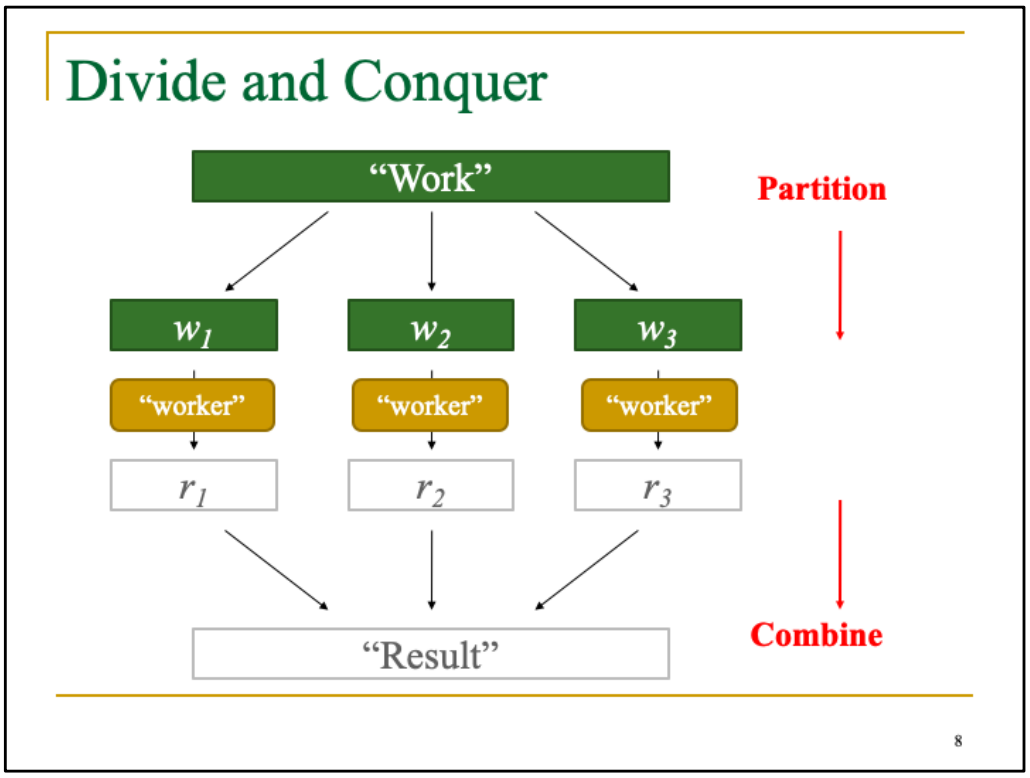


To tackle the big data problem, we usually need to handle a large number of records, extracting some candidate records/attributes of interest. Then, we need to shuffle and sort intermediate results, aggregate them, and finally generate query result.

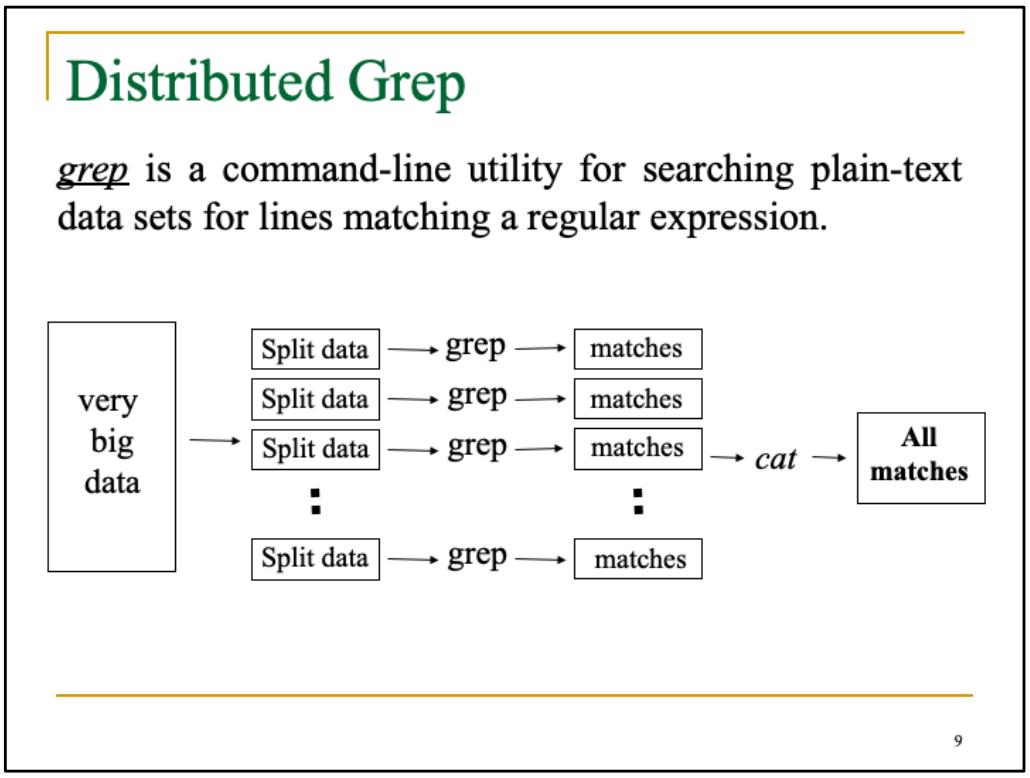


Typically, the big data processing has the problem of variety with diverse and heterogeneous input format, volume with large-scale data, and velocity with the requirement of high-speed processing (or not trivial how to enable parallel processing).

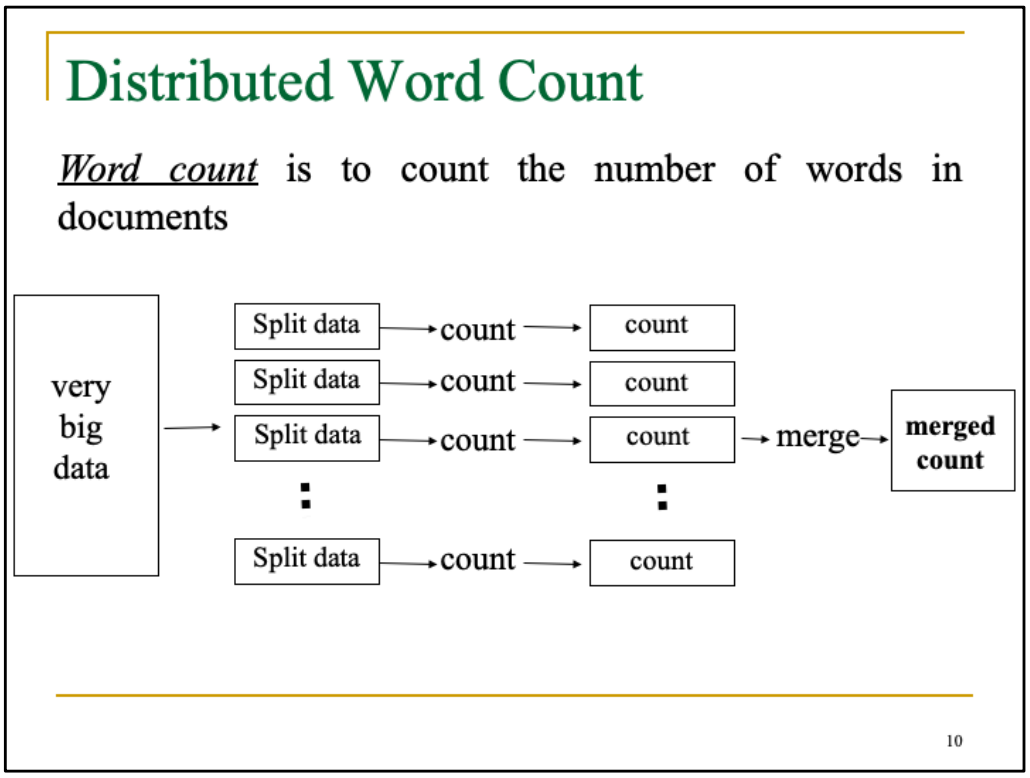
Our major concern is that if we have many cheap off-the-shelf computers, how we can leverage them to solve our big data problems.



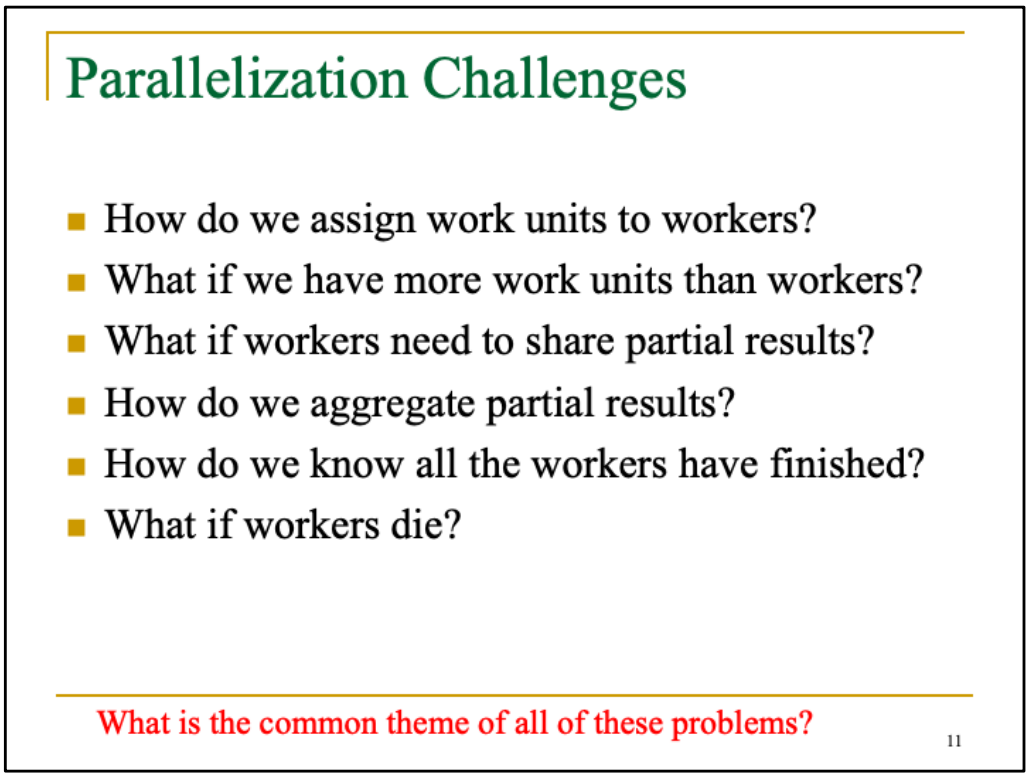
The answer is to use the idea of divide and conquer, and decompose a complex work into many simple problems (i.e., partition). Each simple problem can be solved by a worker (i.e., a cheap computer) in parallel, and the solutions to simple problems can be aggregated to obtain the final result (i.e., combine).



As an example, grep is a command-line utility to search for a text keyword from large plain-text documents. Due to large scale of the documents, we can split documents into smaller pieces (e.g., paragraphs or sentences). Then, we issue the grep command on each piece of the split data in parallel, and use "cat" command to concatenate the returned answers. This is a typical divide-and-conquer idea that uses distributed cheap PCs working in parallel for obtaining solutions.

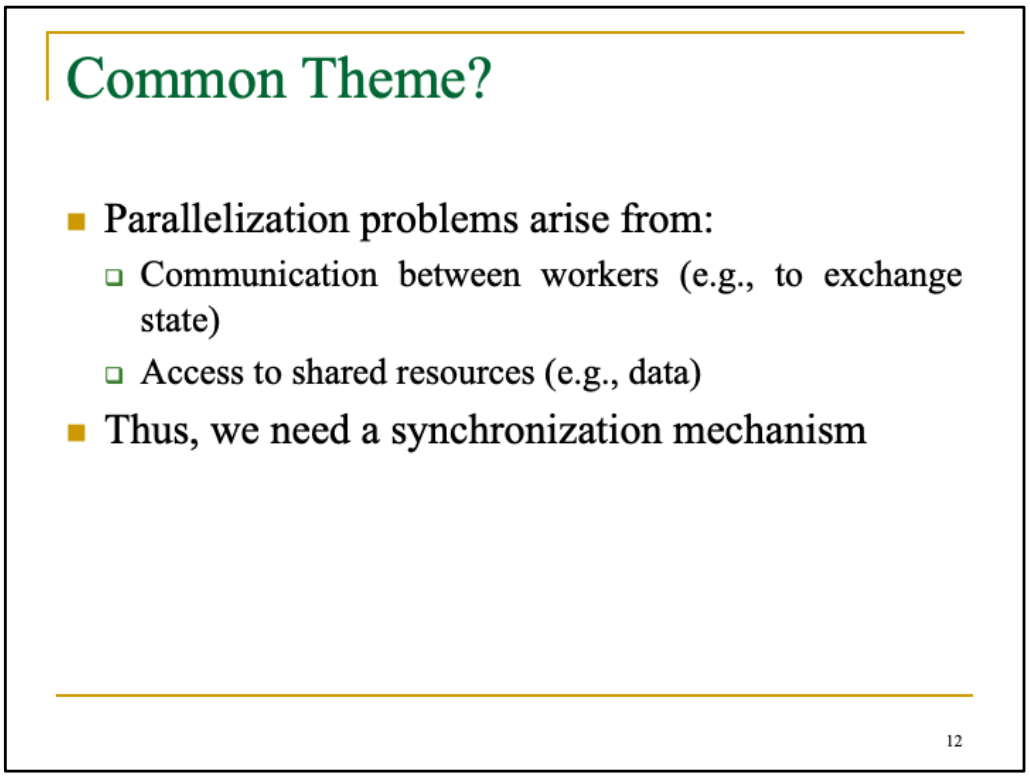


Similarly, we consider another example of distributed word count, which counts the number of words in the documents. In this case, we can also partition documents into several pieces. Then, we conduct the "count“ operator for each split data in parallel on some cheap PCs. Finally, we combine the count information and obtain the merged word count over the entire data set.



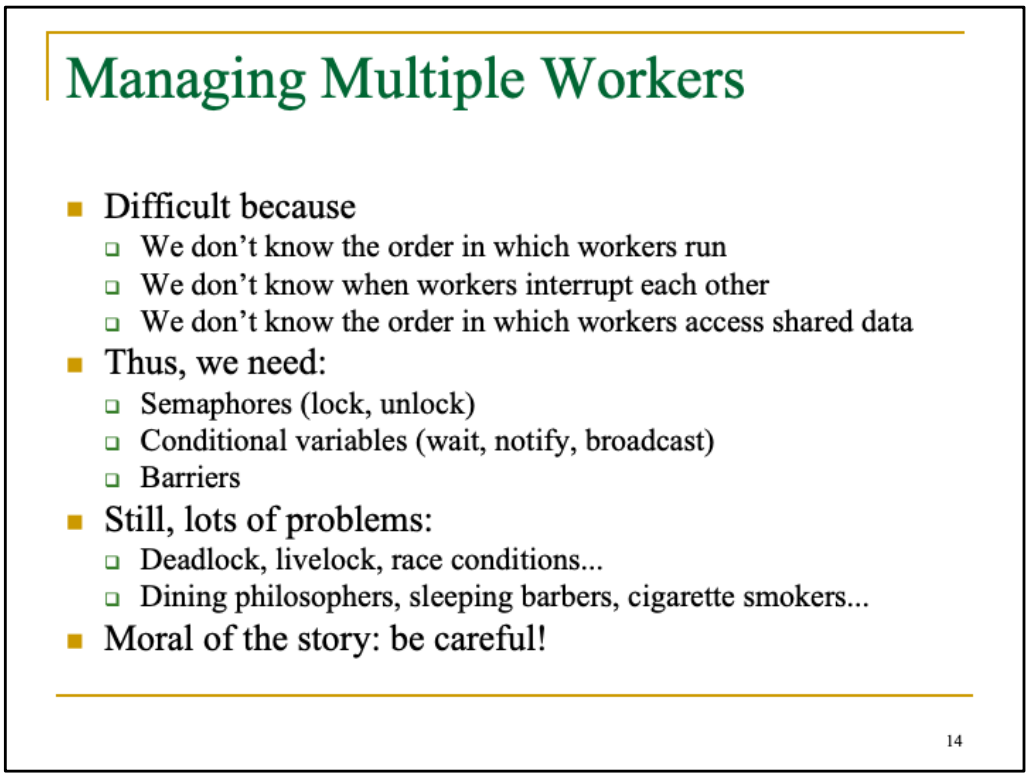
There are many challenges for parallelization. For example,

How do we assign work units to workers?
What if we have more work units than workers?
What if workers need to share partial results?
How do we aggregate partial results?
How do we know all the workers have finished?
What if workers die?



In particular, there are some common questions such as if we allow to have communications among workers and how to access a shared resource (e.g., data). Essentially, we need a synchronization mechanism for different servers/PCs.

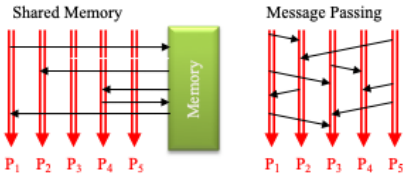
Similar to the deadlock problem mentioned in the operating system class, the synchronization among multiple servers may also encounter the same deadlock problem among multiple servers/PCs in a distributed environment.

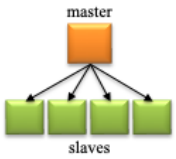


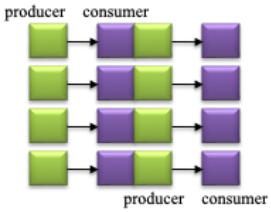
It is challenging to synchronize multiple workers/servers, since we do not know the order workers run, when workers interrupt each other, and the order that workers access the shared resources. Thus, we need similar techniques such as semaphores and conditional variables discussed in the operating system class, but still it is not easy for programmers to write a distributed program.

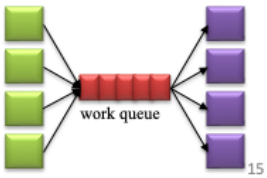
Current Tools

- Programming models
  - Shared memory (pthreads)
  - Message passing (MPI)
- Design Patterns
  - Master-slaves
  - Producer-consumer flows
  - Shared work queues









15

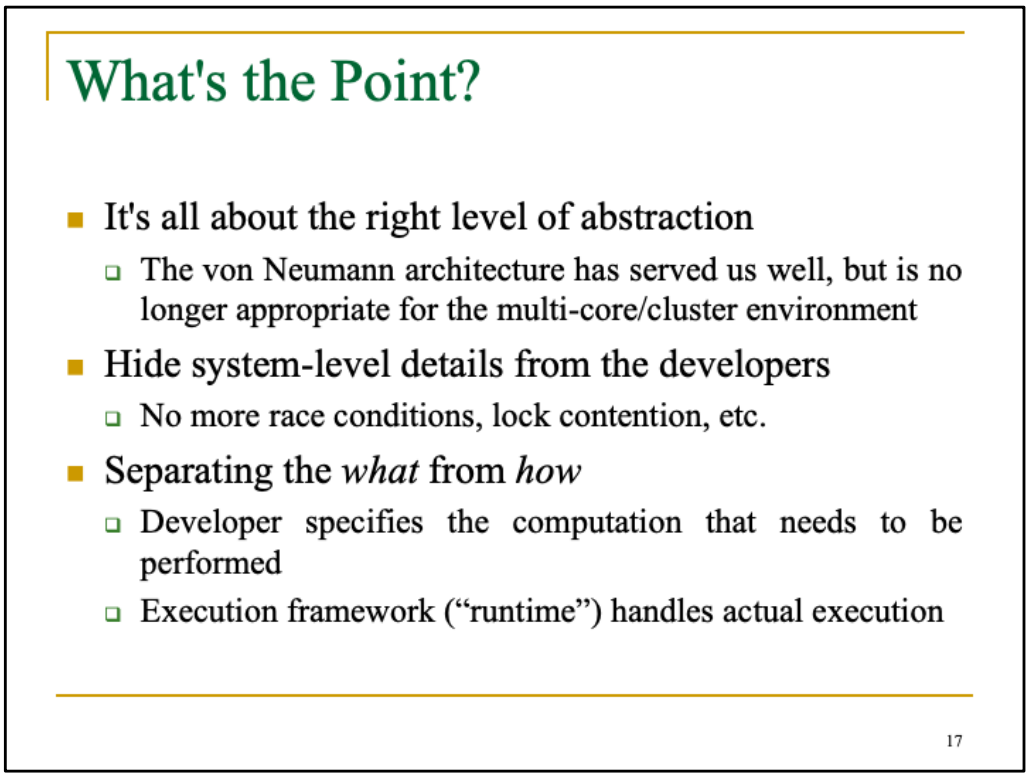
Current programming models include shared memory and message passing. The design patterns can be master-slaves, producer-consumer flows, and shared work queues as shown in the bottom figures.

Concurrency Challenge!

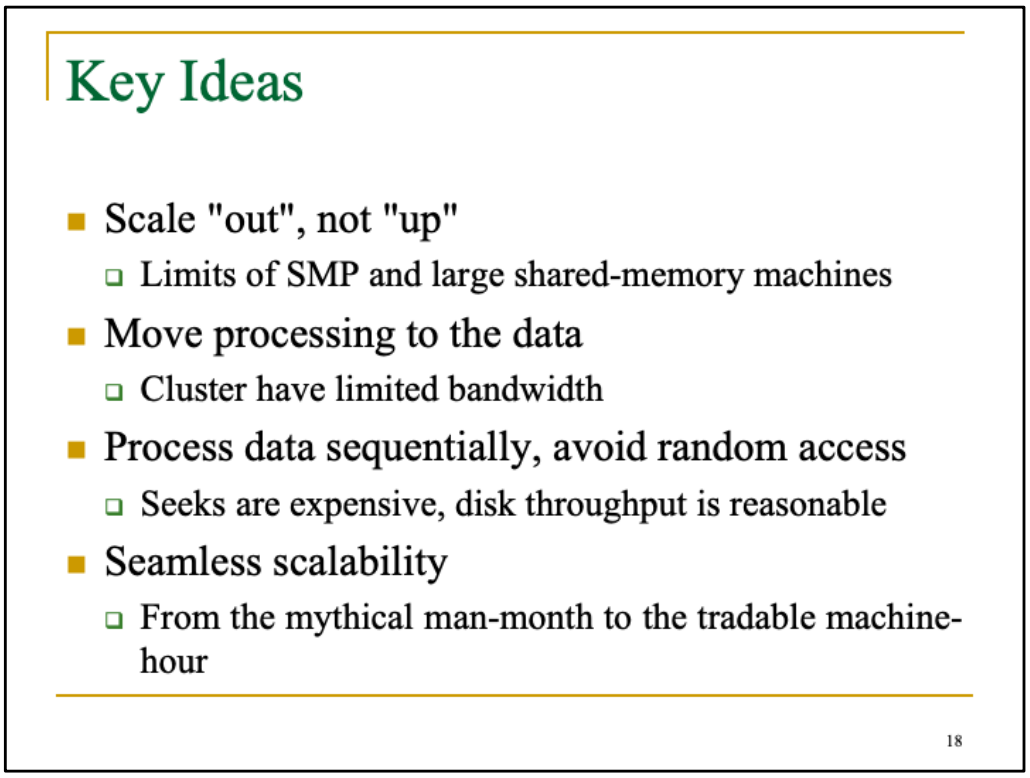
- Concurrency is difficult to reason about
- Concurrency is even more difficult to reason about
  - At the scale of datacenters (even across datacenters)
  - In the presence of failures
  - In terms of multiple interacting services
- Not to mention debugging…
- The reality:
  - Lots of one-off solutions, custom code
  - Write you own dedicated library, then program with it
  - Burden on the programmer to explicitly manage everything

16

While we are running multiple jobs concurrently, it is difficult to reason about at the scale of data centers, in the presence of failures, and in terms of interacting services. It is also challenging to debug the code. The programmers have high workload to manage everything in a distributed environment.



Therefore, it is very important that we can find the right level of abstraction for multi-core / cluster environment, and hide the system details from developers so that programmers can focus on their own problems, rather than handling extra distributed problems like deadlock. Essentially, we want to separate the what from how. Developers specify what needs to be computed, and an execution framework will handle the execution in the distributed environment.



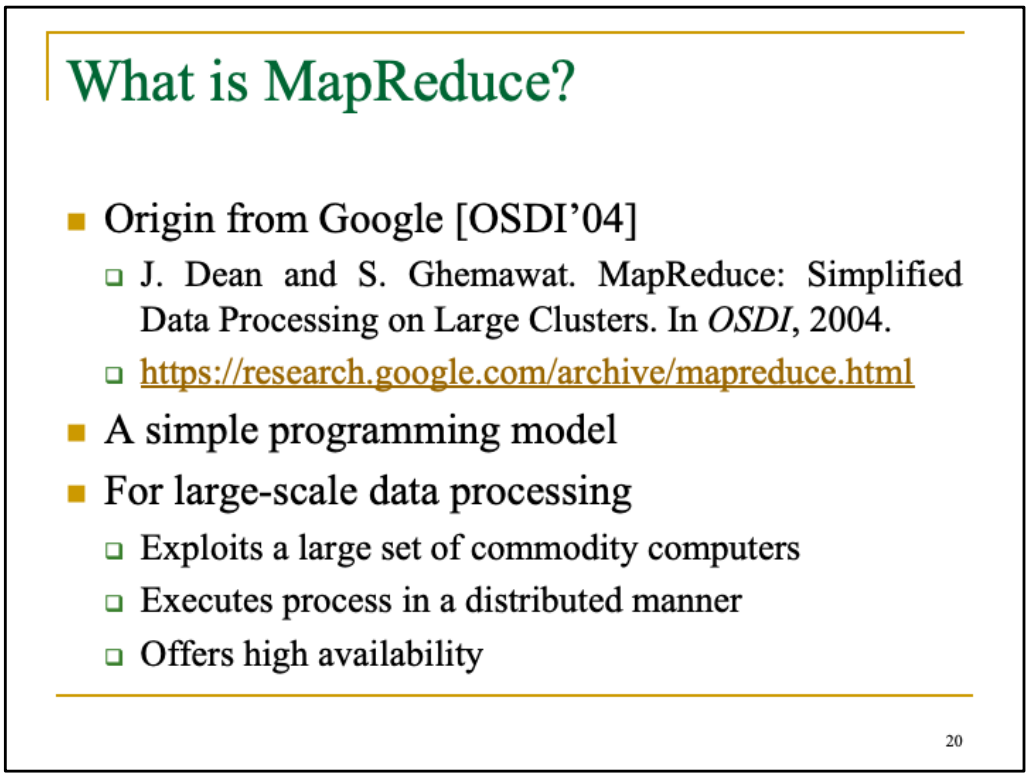
The key idea of the goals is to scale out, not up, move processing to data (instead of the other direction), process data sequentially to save the I/O cost, and allow scalable processing.

The Datacenter *is* the Computer!

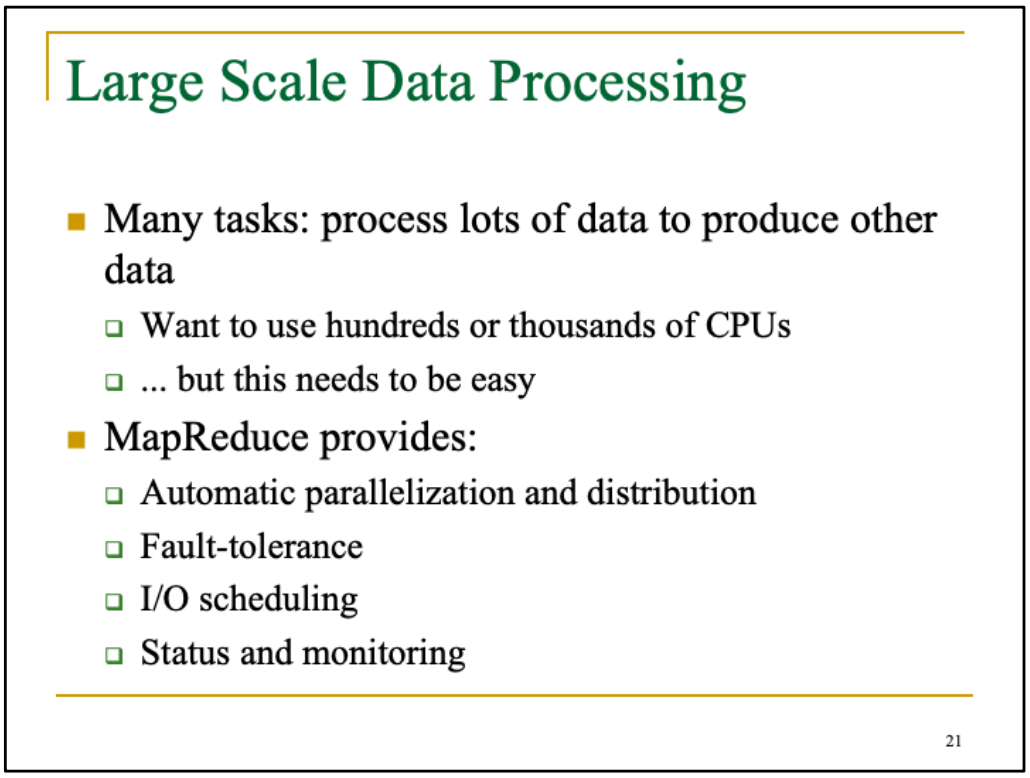
19

Image from http://wiki.apache.org/hadoop-data/attachments/HadoopPresentations/attachments/aw-apachecon-eu-2009.pdf

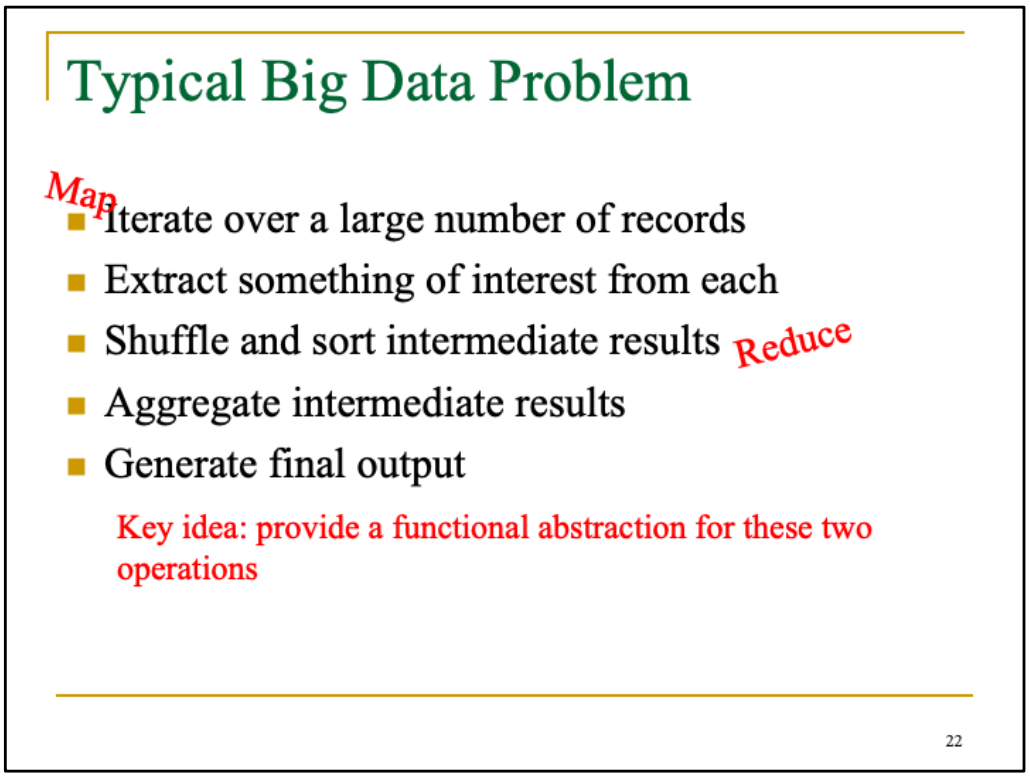
In particular, for the data center, we do not want to buy or upgrade to very expensive, high-performance computers. Instead, we would like to purchase more and more cheap PCs and add them to the data center, so that the performance can be scalable with more cheap PCs.



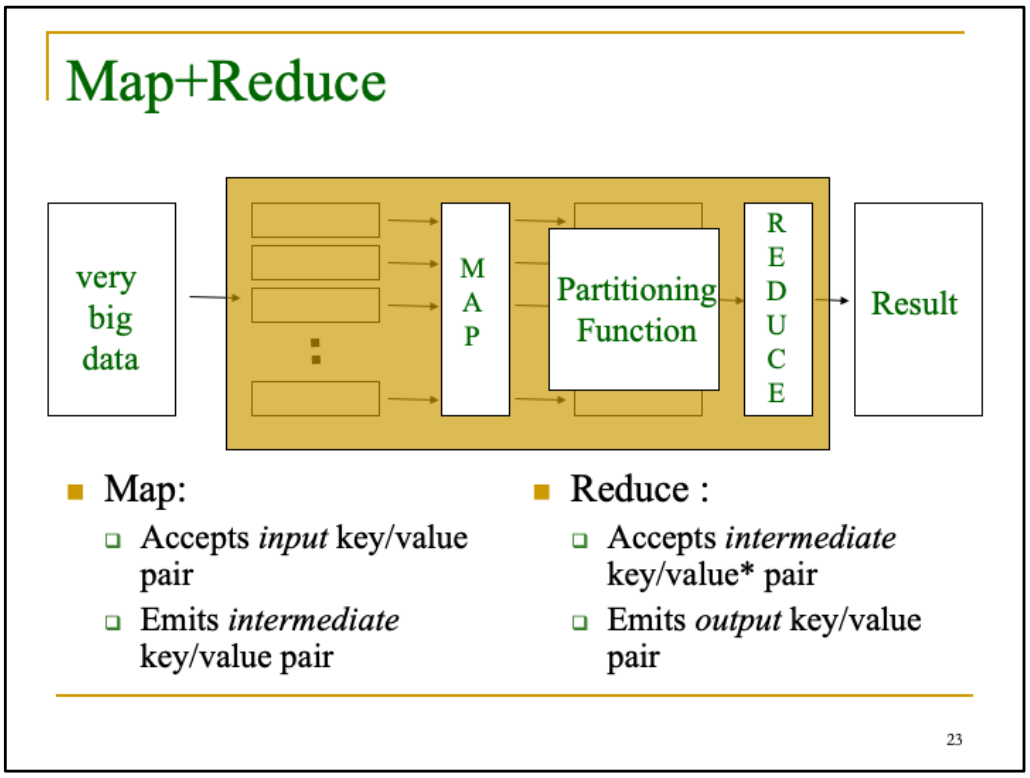
MapReduce was first introduced by an OSDI paper from Google, which has very high impact to distributed computing. It is a simple programming model, and programmers only need to implement two functions, Map and Reduce functions, in order to enable the distributed processing. MapReduce can be adapted to process large-scale data via many commodity computers in a distributed manner. It offers high availability, that is, even if many servers are down due to various reasons such as hardware failure, network congestion, etc., MapReduce can still provide correct data and services.



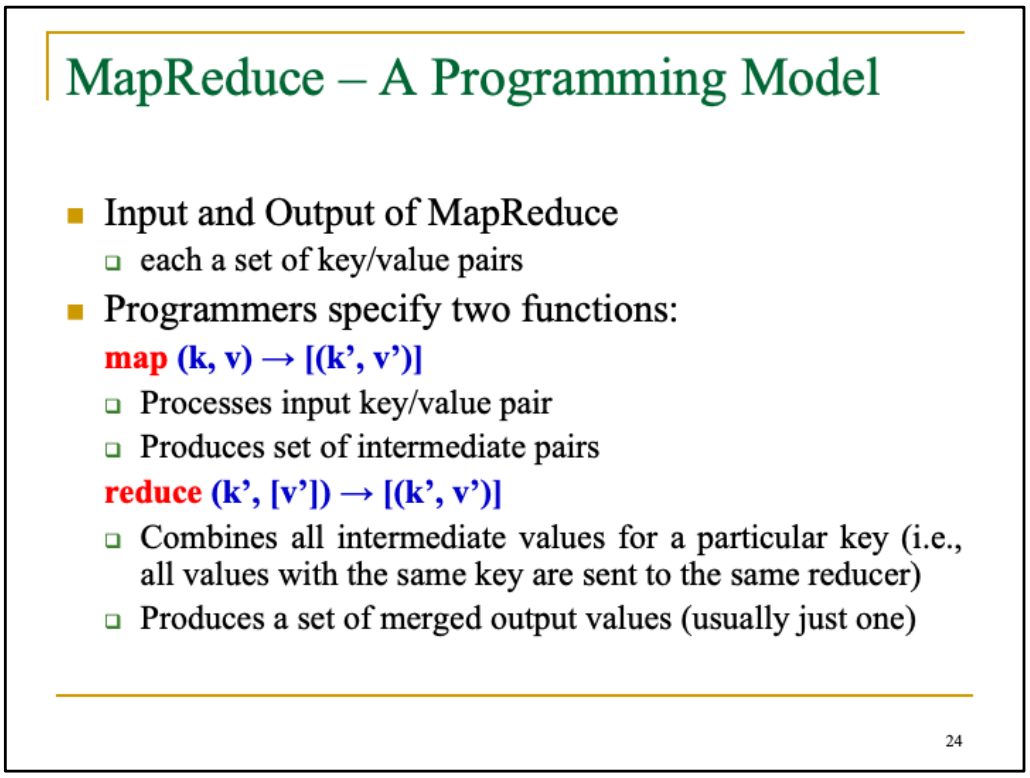
MapReduce can support many tasks on hundreds or thousands of CPUs. It provides automatic parallelization and distribution, fault-tolerance, I/O scheduling, and status and monitoring.



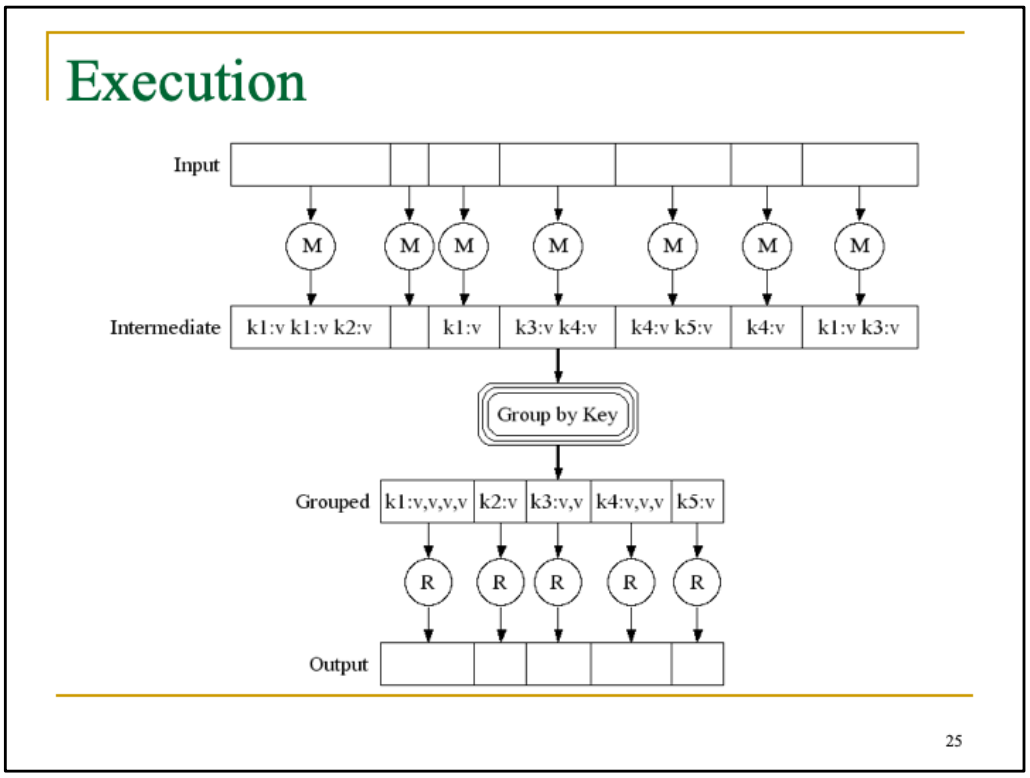
As we mentioned earlier about typical solution to a big data problem, the first two steps correspond to the Map function, whereas the shuffling, sorting, and aggregating correspond to the reduce phase. Finally, the aggregated intermediate results are output as the query answers.



Specifically, for both Map and Reduce, their function input and output are in the form of key-value pairs, that is, (key, value).

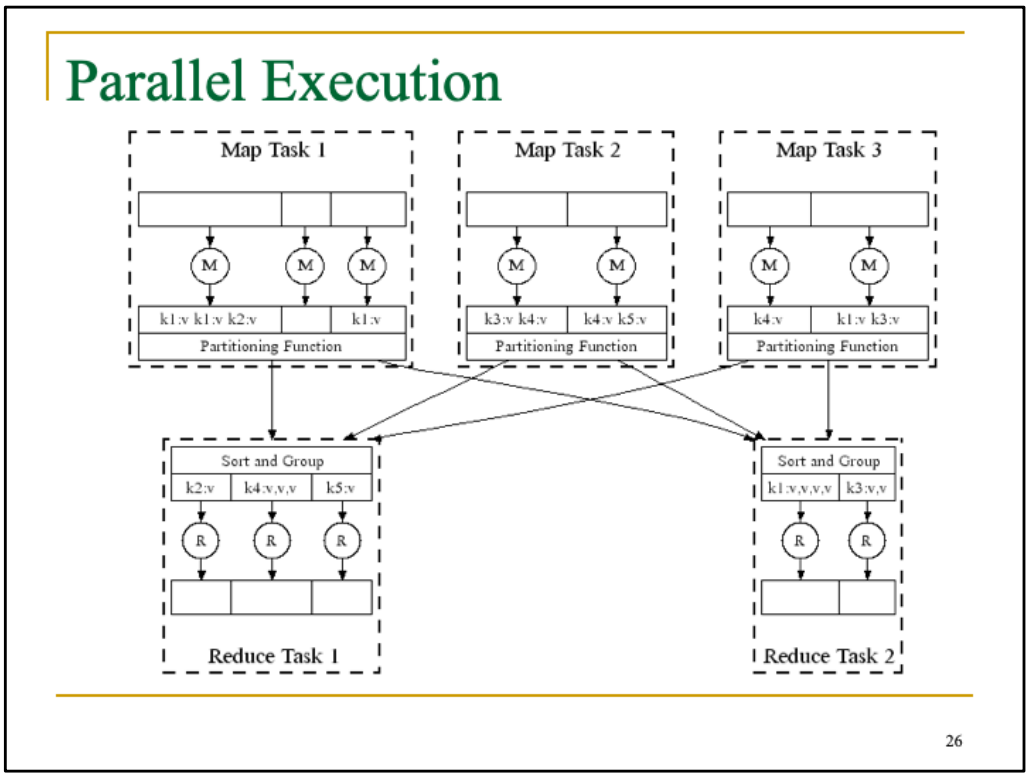


Formally, programmers only need to specify two functions: map (k, v) and reduce(k', [v']). The map function takes key/value pair as the input, and intermediate pairs as the output. The output of the map function is also the input of the reduce function. Next, the reduce function combines all intermediate values for a particular key k'. All values [v'] with the same key are sent to the same reducer. The output of the reduce function contains a set of merged output values, also in the key/value format.

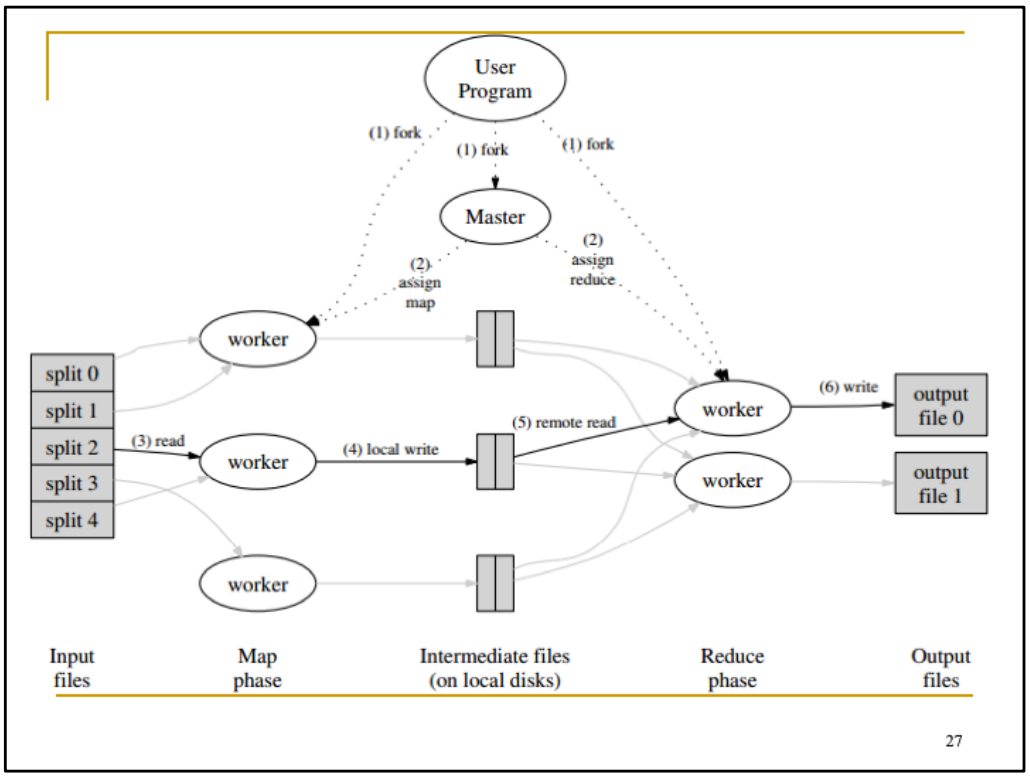


Here is an example. Input data are partitioned and sent to map functions “M” which output intermediate results such as k1:v, k1:v, k2:v for the leftmost map function.

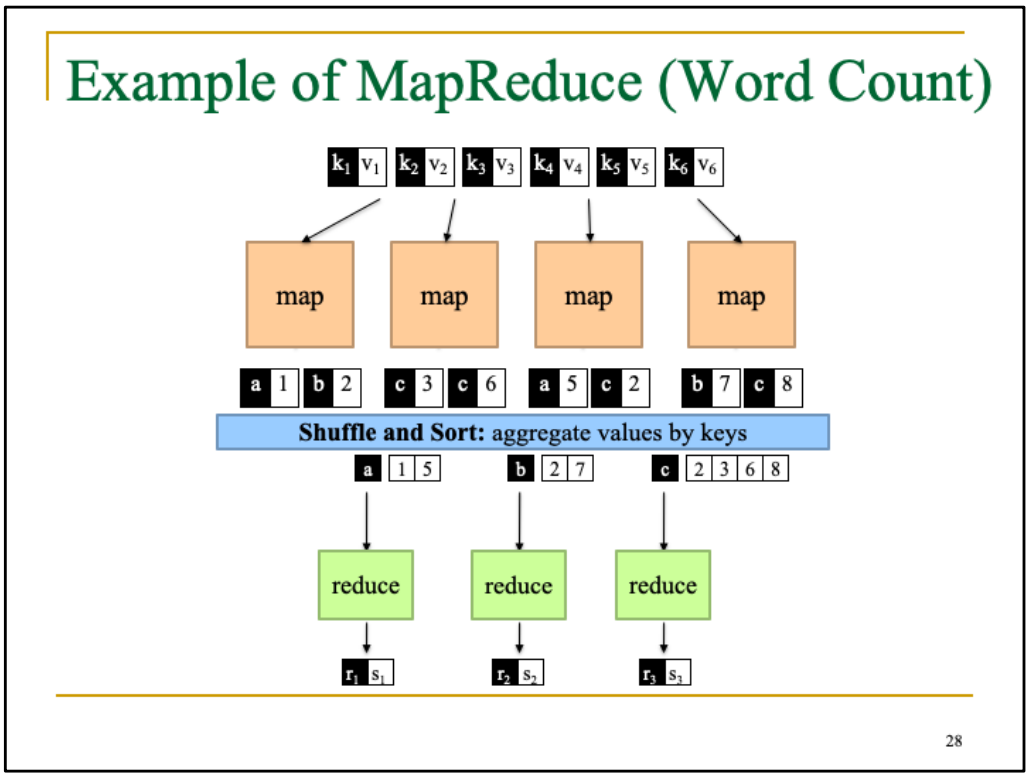
Then, we group these intermediate results by key, such as “k1: v,v,v,v”, which are entered into reduce functions “R”. Finally, reduce function outputs the aggregated query results.



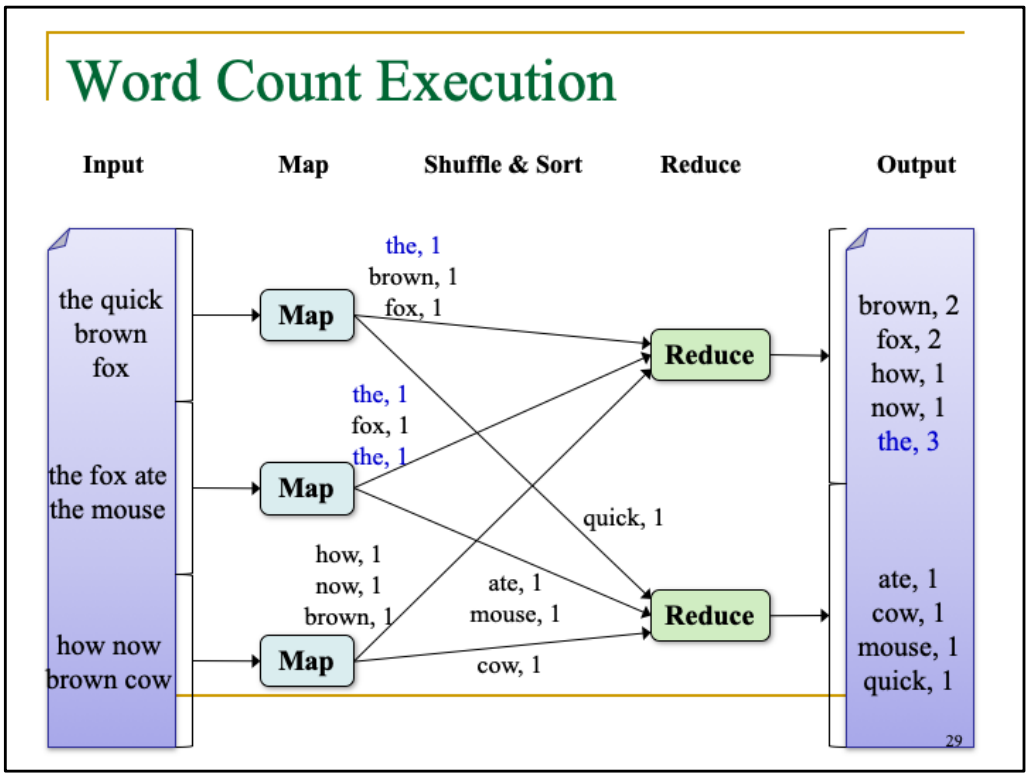
Note that, Map and Reduce tasks are running on different servers in parallel. Each server can serve to execute both Map and Reduce tasks.



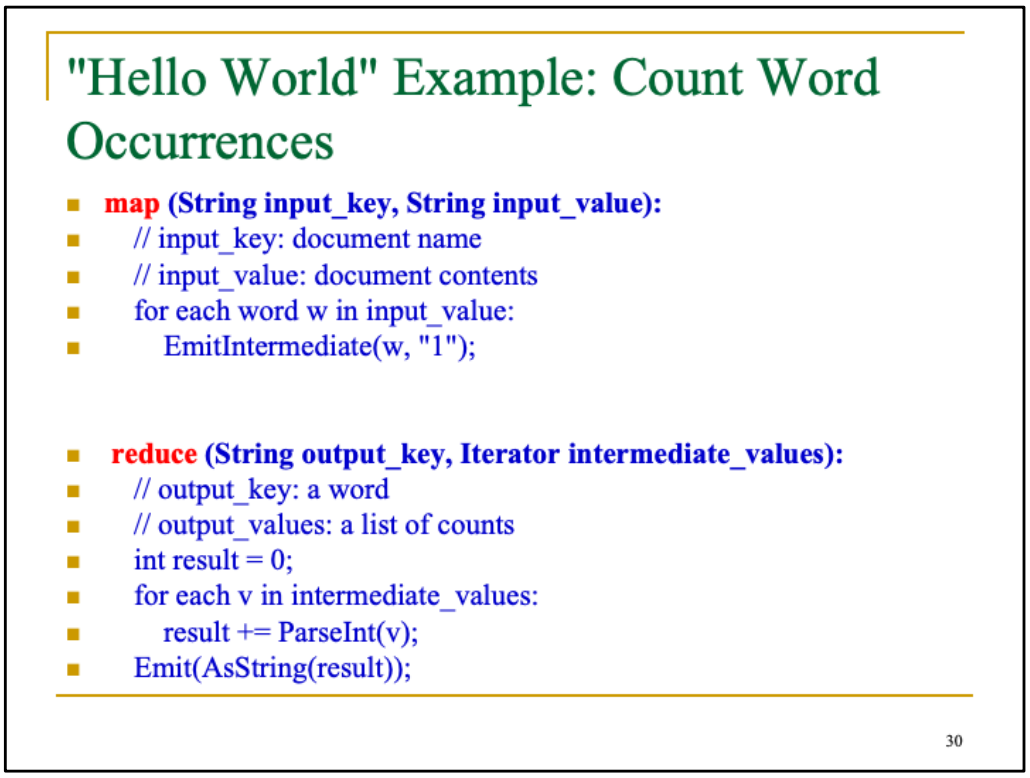
Here is the entire MapReduce process. When a user runs a user program, it will send Map/Reduce code to Master server and slave nodes (i.e., Map and Reduce servers). Then, Map function will be executed and intermediate results will be stored on local disks, which are read by Reduce servers. Finally, the output of reduce function will be returned and aggregated as one final answer.



For the word count example, for the input of the Map function, keys are document IDs and values are document contents. For the output of the Map function, keys are words and values are counts of words (e.g., (a, 1)). After shuffling via a hashing function on keys of the output, we combine those values with the same key into a list, for example, (a, {1, 5}), which are used as the input of the Reduce function. Within the reduce function, it will count (sum up) the numbers in the value list of a key, and return the key/value pair (e.g., (a, 6)).



This is an example illustration of the process we mentioned. The map function scans the text documents, and obtain the frequency of each word (e.g., (the, 1)). Then, the output of the map function is sent to a reduce server via a hashing function. For example, key “the” is always hashed to the reduce server at the top in the figure. Next, the reduce function will sum up the frequencies of each key in the value list, and return (key, value) where value is the actual count of the word (key), for example, (the, 3).



This is the MapReduce pseudo code of the word count algorithm. This is like a “hello world” example for C++, Java or Python learners.

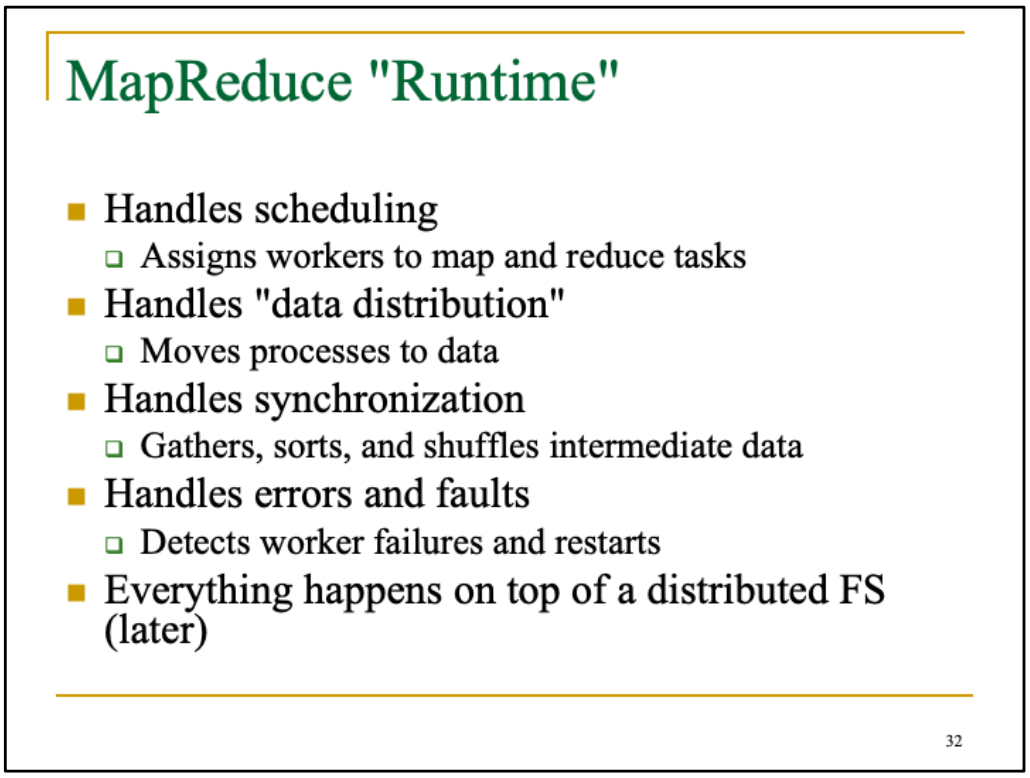
MapReduce – A Programming Model (cont'd)

- Programmers specify two functions:
  map (k, v) → [(k', v')]
  reduce (k', [v']) → [(k', v')]
- The execution framework handles everything else…

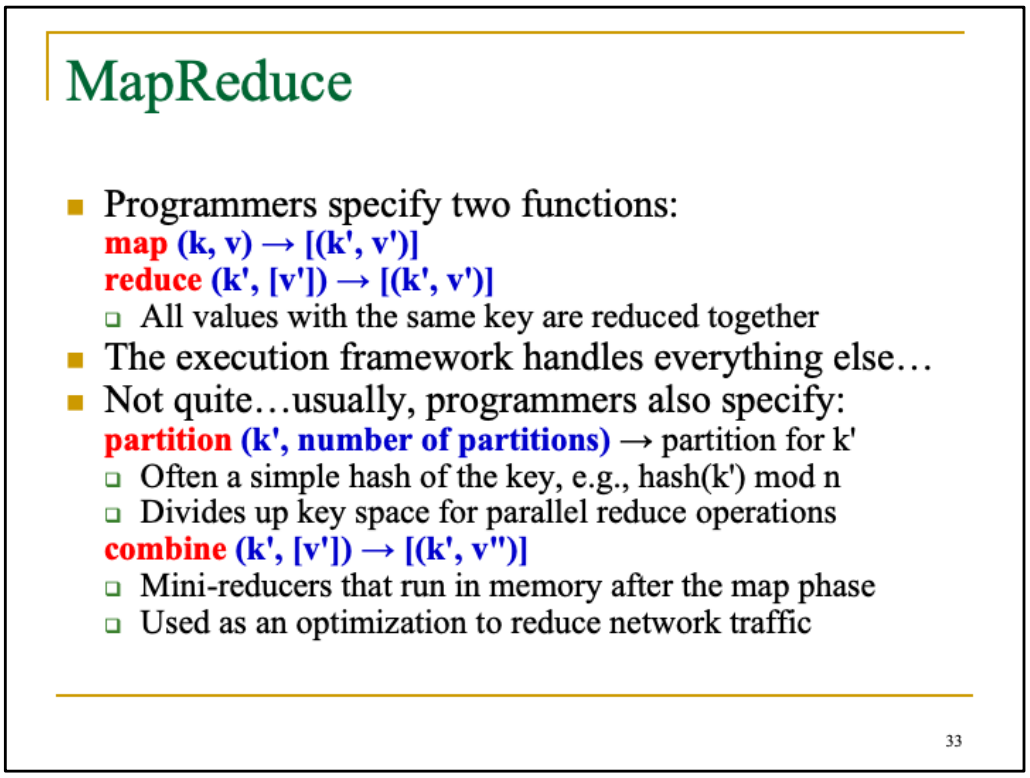
What's "everything else"?

31

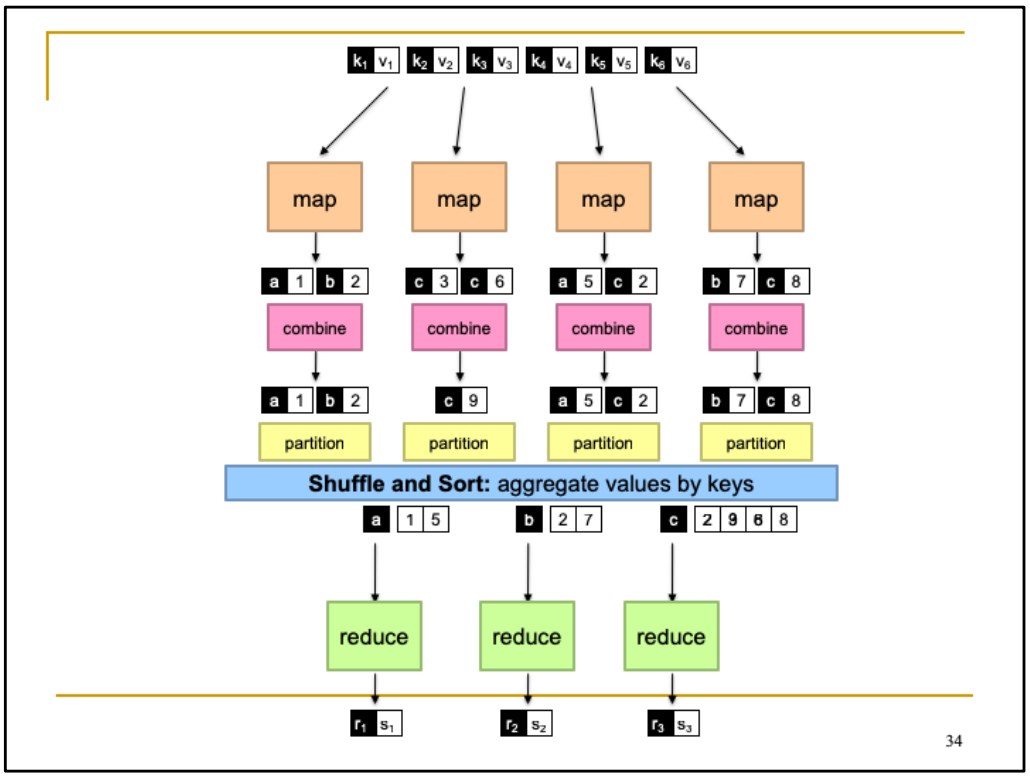
Programmers only need to implement map and reduce functions and the execution framework will handle everything else. What is "everything else"?



It includes MapReduce “Runtime“ that handles scheduling, data distribution, synchronization, errors and faults, or other things on top of the distributed file system.

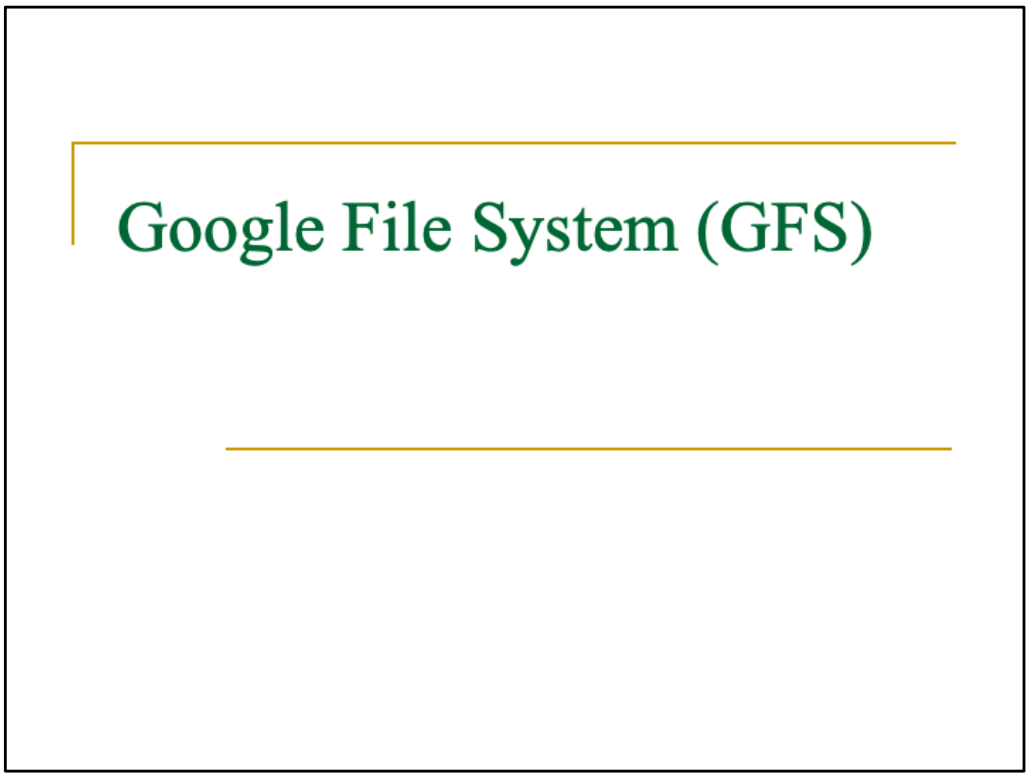


In addition to map and reduce, there are other functions like partition and combine that programmers can specify. The partition() function utilizes a hashing function to hash the key-value pairs to specific partition, and this way divides the key space for parallel reduce operations. The combine() function runs in memory after the map phase, which is a mini-reducer that can combine key-value pairs with the same key.

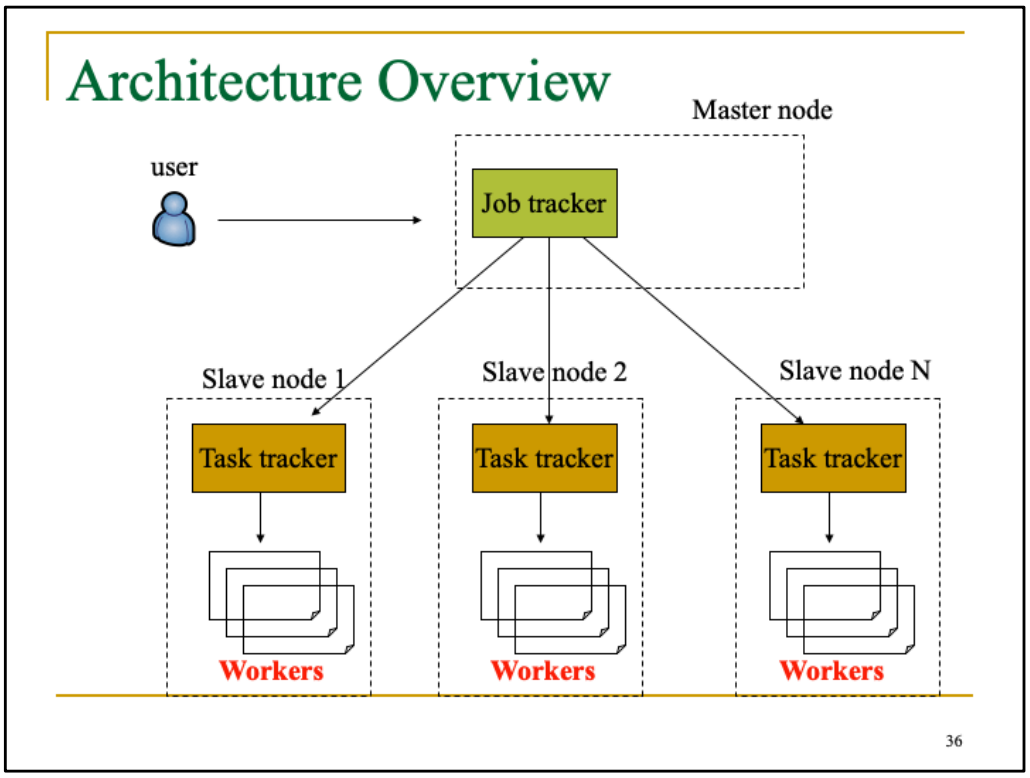


As shown in the figure, the second map server outputs 2 key-value pairs (c, 3) and (c, 6), which have the same key c and are passed into combine() function. The combine() mini-reduce function condenses the 2 key-value pairs by keeping only one pair (c, 9), where 9 = 3+6.

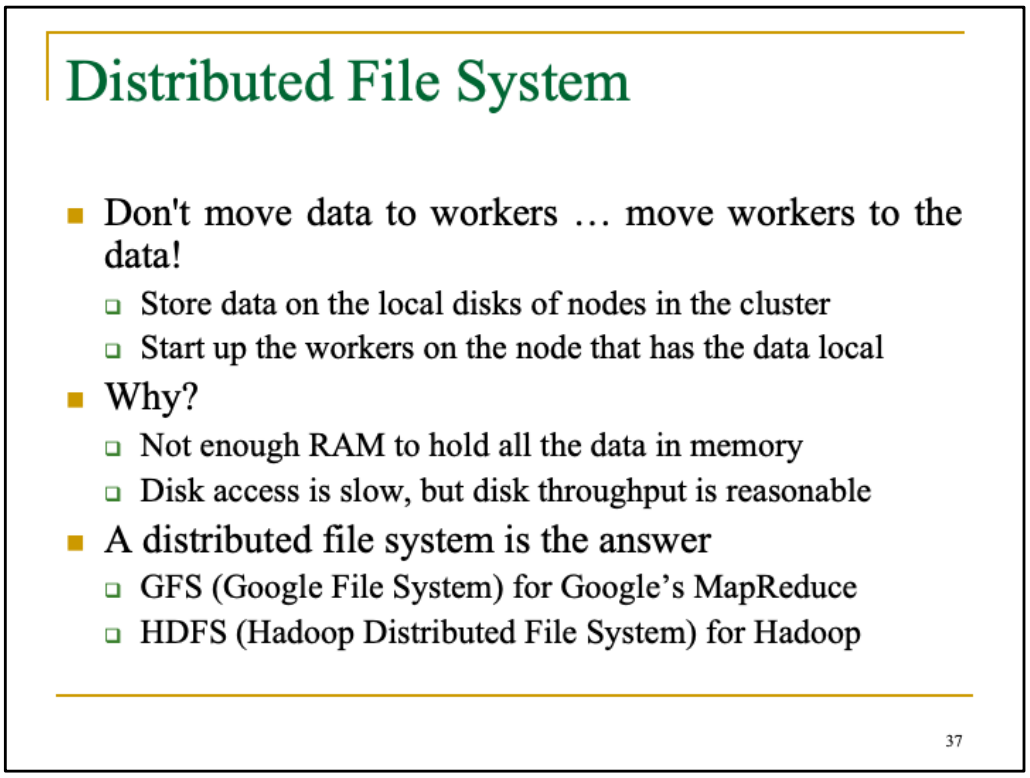
Also the partition() function will hash key-value pairs to one of the 3 reduce servers in this example.



There are some existing systems that support MapReduce. One example is the Google File System (GFS).

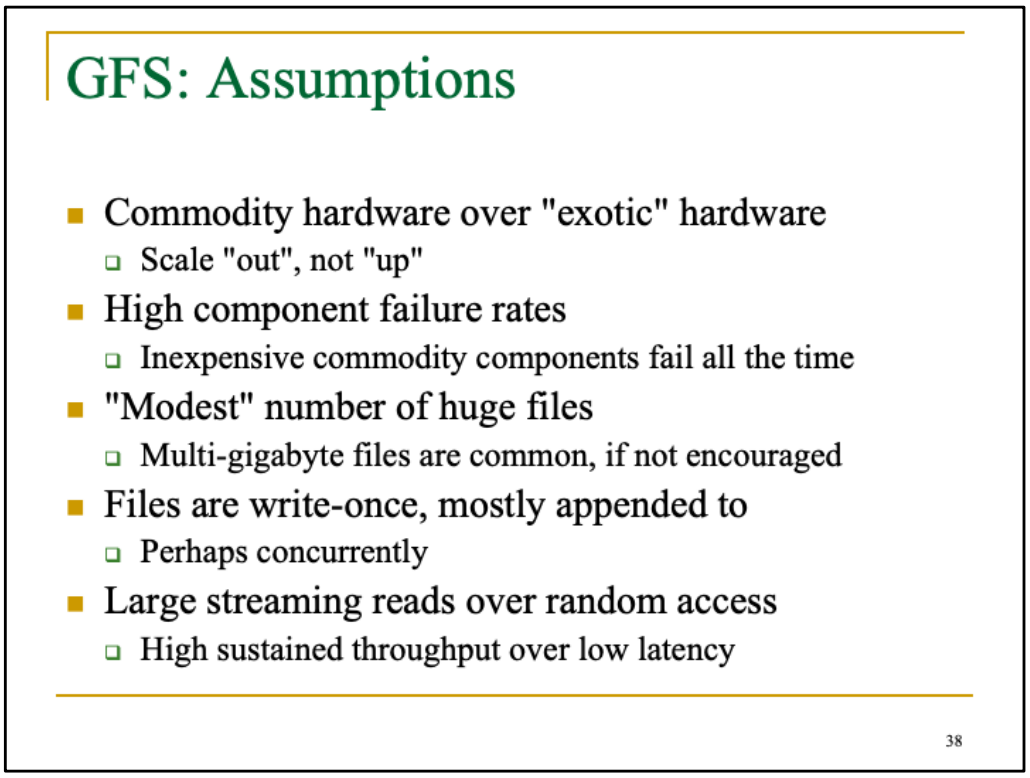


In the Google File System, there are one Master node and multiple slave nodes. A job tracker in the Master node is keeping an eye on the tasks scheduled in slave nodes, and return users with the results.

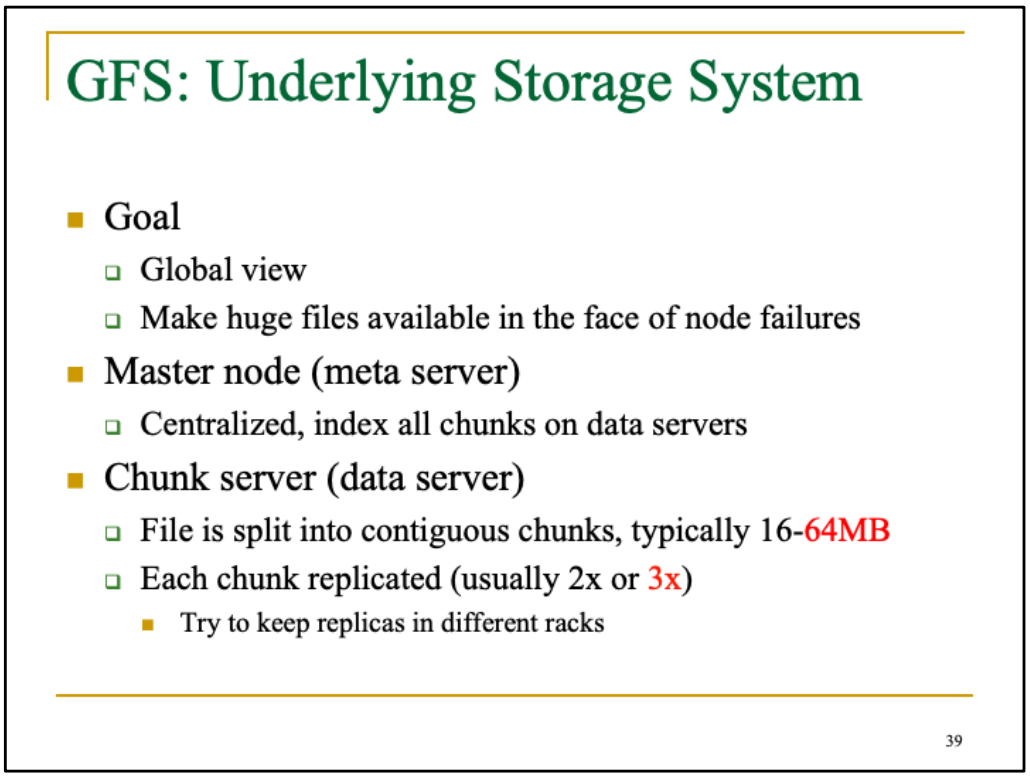


Due to the large scale of the data, it is not a good idea to move big data to those slave nodes (i.e., workers). The memory is not large enough to hold all big data. Therefore, instead, we store data on local disks of nodes in the cluster, and move workers (binary code of map/reduce functions) to the nodes with data. Although the disk access is slow, the disk throughput is good, compared with network bandwidth.

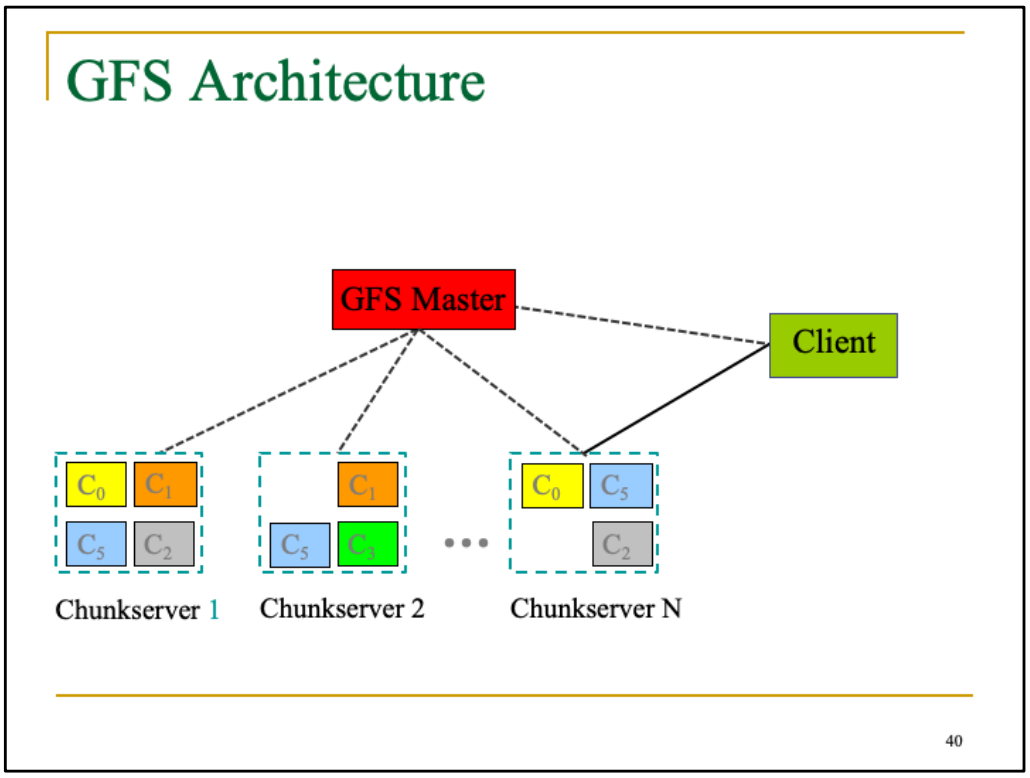
Inspired by the discussions above, Google proposed the Google File System (GFS), which is a distributed file system to support MapReduce. There are some other options like the open-source software Hadoop Distributed File System.



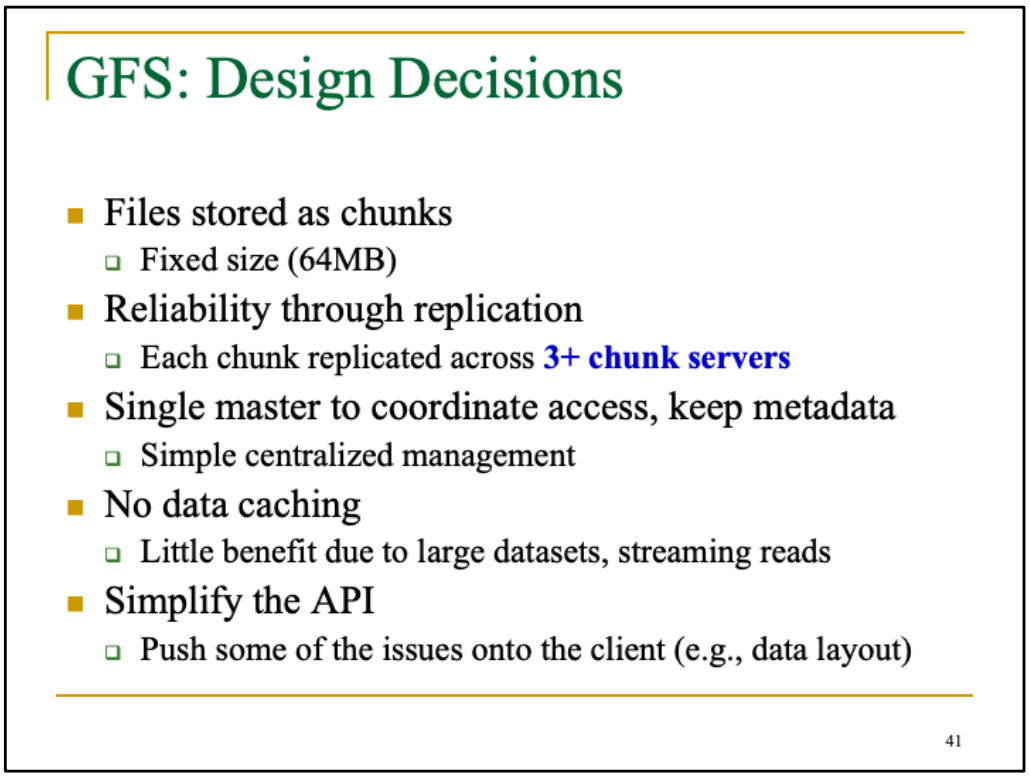
GFS has the following assumptions. In practice, we usually have many cheap commodity hardware, rather than exotic, expensive, high-performance servers. In a distributed environment, we usually encounter high component failure rates. Huge files of gigabyte scale are very common to handle. Files are usually written once, and in most cases appended to the database. Often there are many streaming reads, rather than random access, from the data.



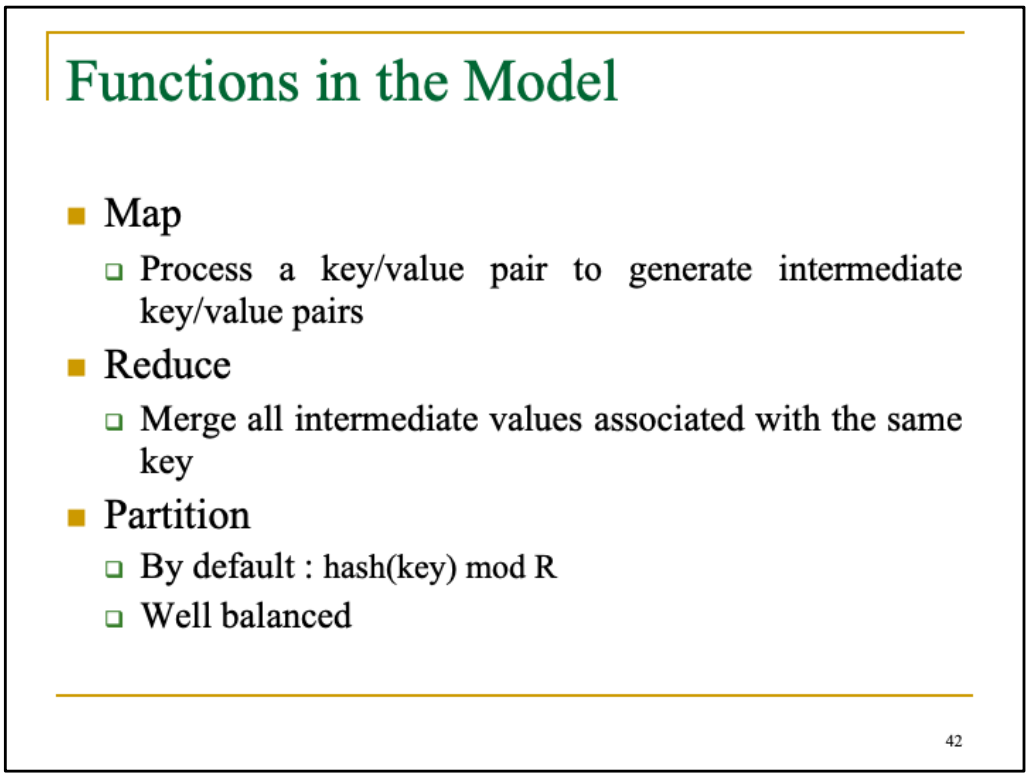
GFS maintains a master node (or called meta server) and multiple chunk servers (or called data servers). The master server is centralized, and indexes all data chunks on the data servers. The chunk server keeps data trunks from the file, typically 16-64MB per trunk (usually 64 MB is by default). Each trunk is replicated 2 or 3 times (typically 3x) and stored on different data servers. The reason for this is to deal with the node failure. Even if one data server is down, there are still two more servers maintaining duplicate data.



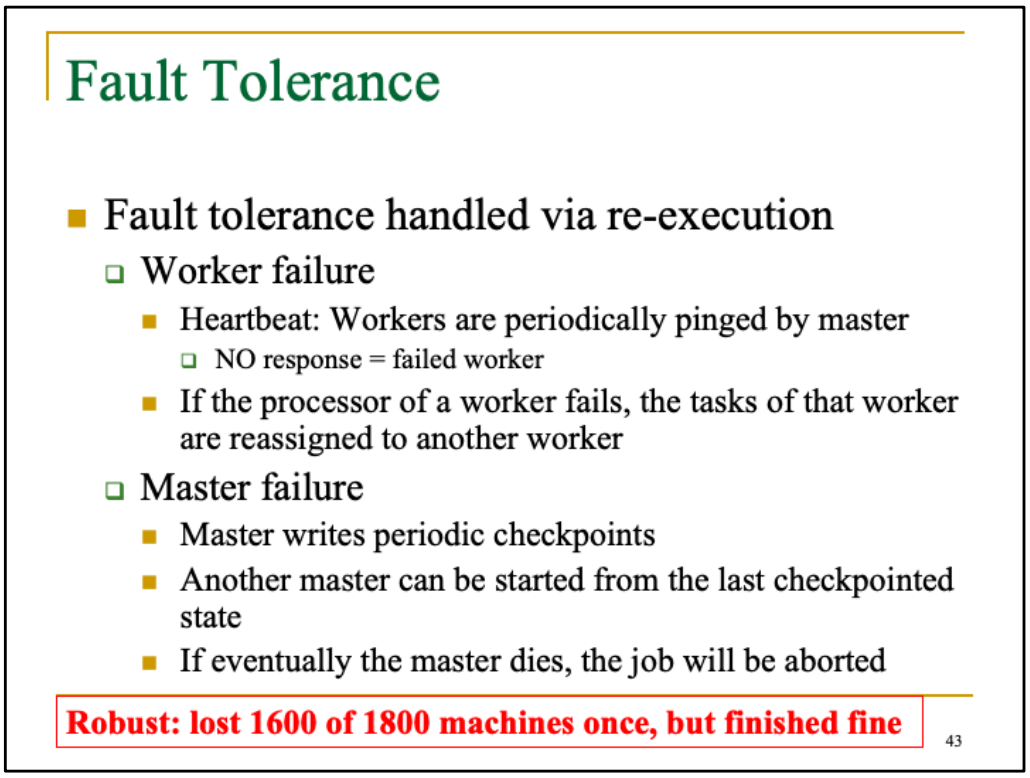
As shown in this figure, each chunk (e.g., C_0) appears at least twice in chunk servers 1 and N. Trunk C_5 appears in chunk servers 1, 2, and N.



GFS decided to use chunks of fixed size 64MB. Each chunk is replicated on at least 3 chunk servers. Single centralized master server is used for coordination and keeping metadata. No data caching and simple APIs are considered.



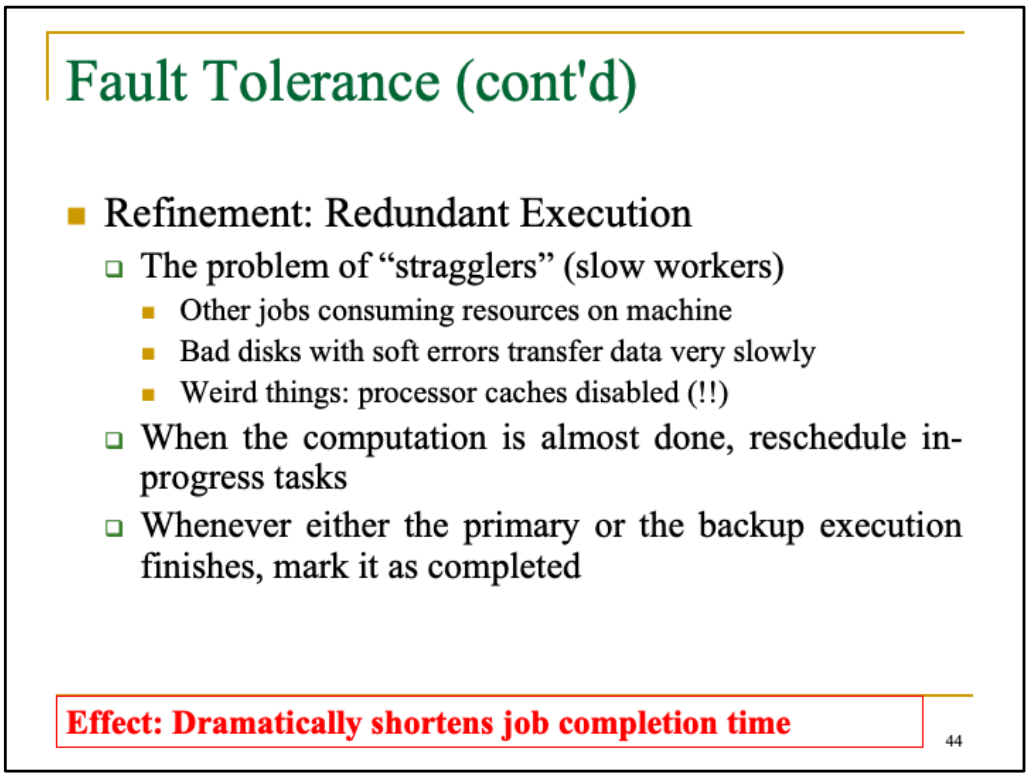
As mentioned before, GFS follows the MapReduce framework, which consists of Map phase and Reduce phase. By default, the Partition function randomly assigns a key-value pair to a reduce server, that is, hash(key) mod R, such that the reduce workload is well balanced, where R is the number of reduce servers.



GFS has good fault tolerance property. There are two types of failures, worker failure and master failure. To detect worker failure on the slave nodes, workers are periodically pinged by master server. If there is no response, the master assumes this slave node has failed. In this case, Master server will assign tasks of this worker to other workers.

For the master failure, master server will periodically save checkpoints. If the master node fails, another backup master server can be started from the last checkpoint state. When the master server dies, the job will be aborted.

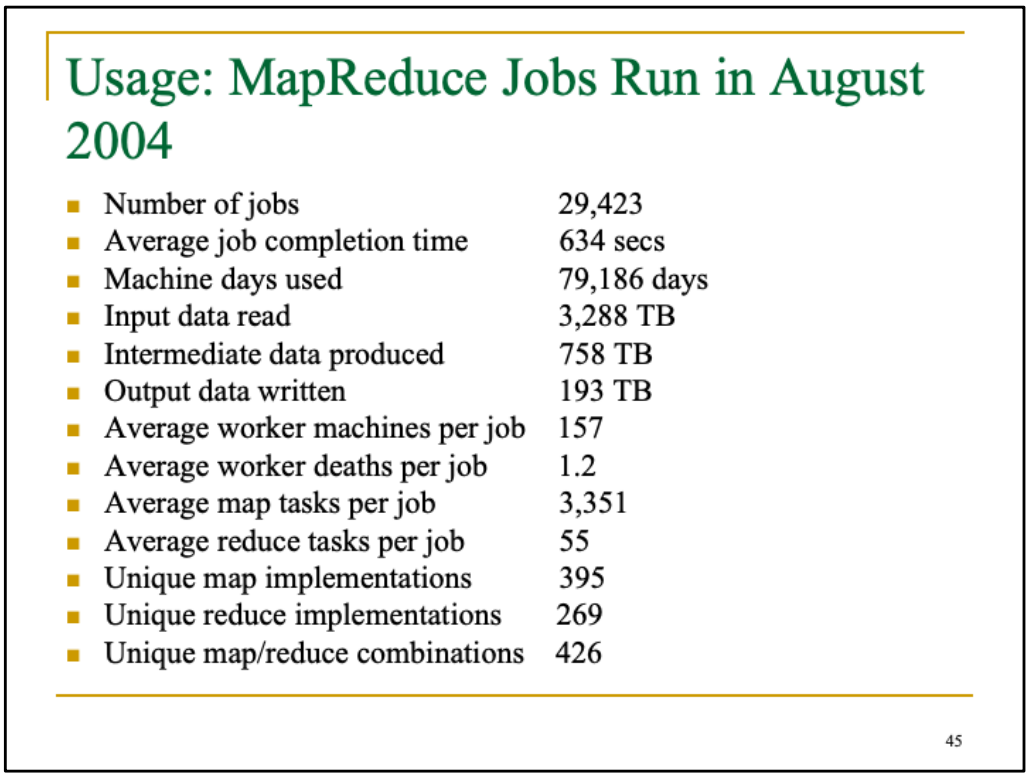
The fault tolerance of the GFS has been verified. In a scenario, 1600 out of 1800 machines failed once, but all jobs were completed. This shows the robustness of the GFS.



GFS also provides a mechanism called redundant execution. When executing the jobs, there are many weird things that may slow down the execution by workers, for example, other jobs are consuming resources on the same machine, bad disks that cause slow data transfer, or processor caches are disabled.

Therefore, it is possible that a job is interrupted or slow down for some unexpected reasons before it almost finishes. In order to tackle this problem, redundant execution is used, which reschedules a backup task on another server when the computation is almost done. When either primary or backup execution finishes, we mark it as completed.

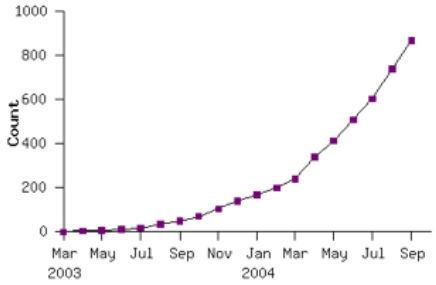
This approach can dramatically shorten the job completion time.



Here is a table of statistics about MapReduce jobs run in August 2004. In particular, we can see that there are petabytes of input, and terabytes of intermediate data or output data. Average worker deaths per job is 1.2.

The MapReduce Model is Widely Applicable

- MapReduce Programs in Google Source Tree

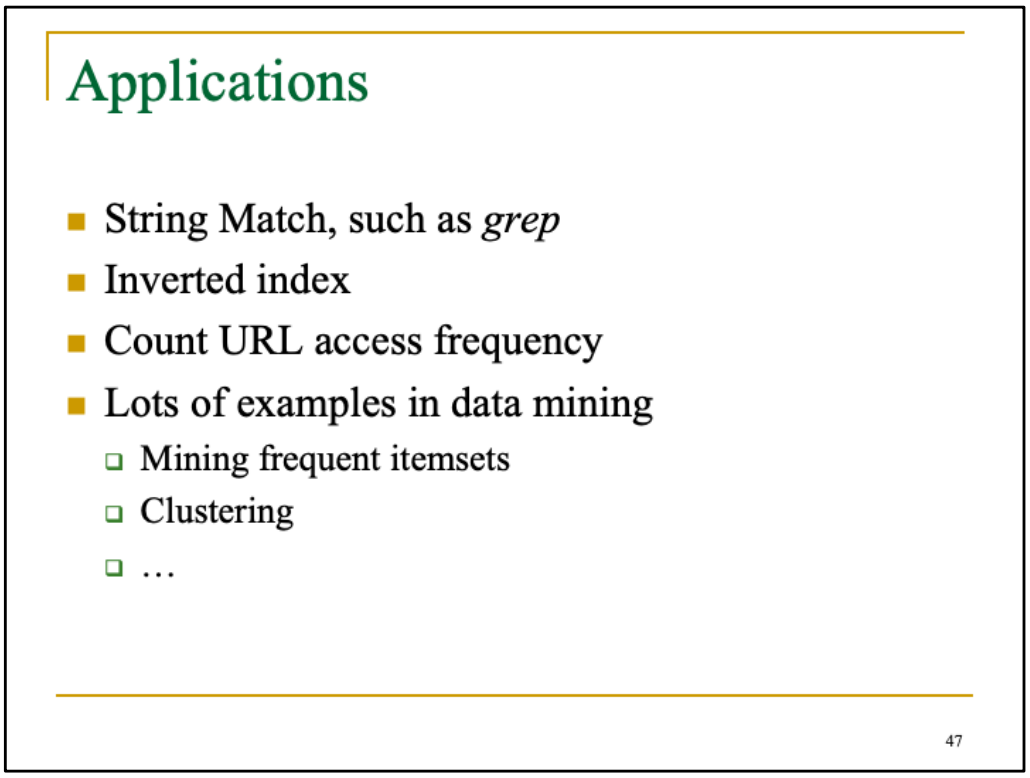


Examples as follows

distributed grep	distributed sort	web link-graph reversal
term-vector / host	web access log stats	inverted index construction
document clustering	machine learning	statistical machine translation
...	...	...

46

The MapReduce model has been widely used in many real applications like distributed grep, document clustering, and so on, as listed in the figure below. The number of MapReduce programs in Google source tree is dramatically increasing just in 2004.



In particular, there are many usages of MapReduce programs over large data sets for string matching, inverted index, counting URL access frequency, as well as data mining (e.g., frequent itemset mining, clustering, etc.).

More than 15 years after the first MapReduce paper was published, there must be many more MapReduce programs for different applications.

Detailed Example: Word Count (1)

- Map

```
#include "mapreduce/mapreduce.h"

// User's map function
class WordCounter : public Mapper {
 public:
  virtual void Map(const MapInput& input) {
    const string& text = input.value();
    const int n = text.size();
    for (int i = 0; i < n; ) {
      // Skip past leading whitespace
      while ((i < n) && isspace(text[i]))
        i++;

      // Find word end
      int start = i;
      while ((i < n) && !isspace(text[i]))
        i++;

      if (start < i)
        Emit(text.substr(start,i-start),"1");
    }
  }
};
REGISTER_MAPPER(WordCounter);
```

Here is the detailed C++ code for word count. This is Map function.

Detailed Example: Word Count (2)

- Reduce

```
// User's reduce function
class Adder : public Reducer {
  virtual void Reduce(ReduceInput* input) {
    // Iterate over all entries with the
    // same key and add the values
    int64 value = 0;
    while (!input->done()) {
      value += StringToInt(input->value());
      input->NextValue();
    }

    // Emit sum for input->key()
    Emit(IntToString(value));
  }
};
REGISTER_REDUCER(Adder);
```

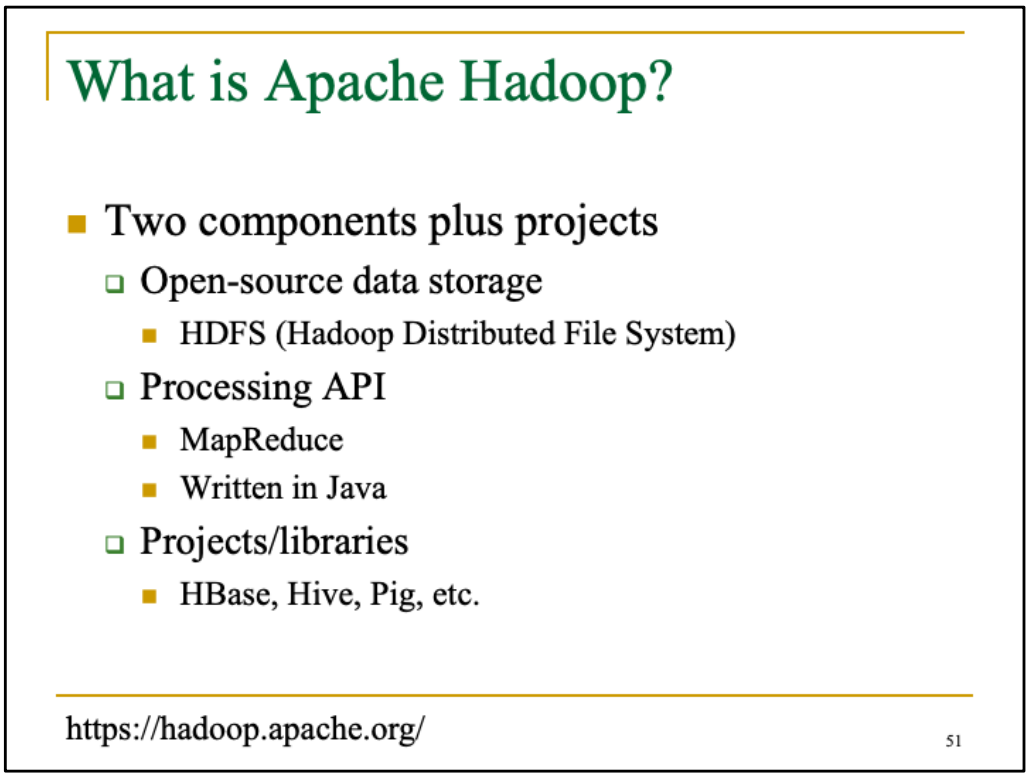
This is for reduce function.

Detailed Example: Word Count (3)

- main

```
int main(int argc, char** argv) {
  ParseCommandLineFlags(argc, argv);

  MapReduceSpecification spec;

  // Store list of input files into "spec"
  for (int i = 1; i < argc; i++) {
    MapReduceInput* input = spec.add_input();
    input->set_format("text");
    input->set_filepattern(argv[i]);
    input->set_mapper_class("WordCounter");
  }

  // Specify the output files:
  //    /gfs/test/freq-00000-of-00100
  //    /gfs/test/freq-00001-of-00100
  //    ...
  MapReduceOutput* out = spec.output();
  out->set_filebase("/gfs/test/freq");
  out->set_num_tasks(100);
  out->set_format("text");
  out->set_reducer_class("Adder");

  // Optional: do partial sums within map
  // tasks to save network bandwidth
  out->set_combiner_class("Adder");

  // Tuning parameters: use at most 2000
  // machines and 100 MB of memory per task
  spec.set_machines(2000);
  spec.set_map_megabytes(100);
  spec.set_reduce_megabytes(100);

  // Now run it
  MapReduceResult result;
  if (!MapReduce(spec, &result)) abort();

  // Done: 'result' structure contains info
  // about counters, time taken, number of
  // machines used, etc.

  return 0;
}
```

This is the main function.



Reference

https://www.lynda.com/Hadoop-tutorials/Introducing-Hadoop/191942/369541-4.html

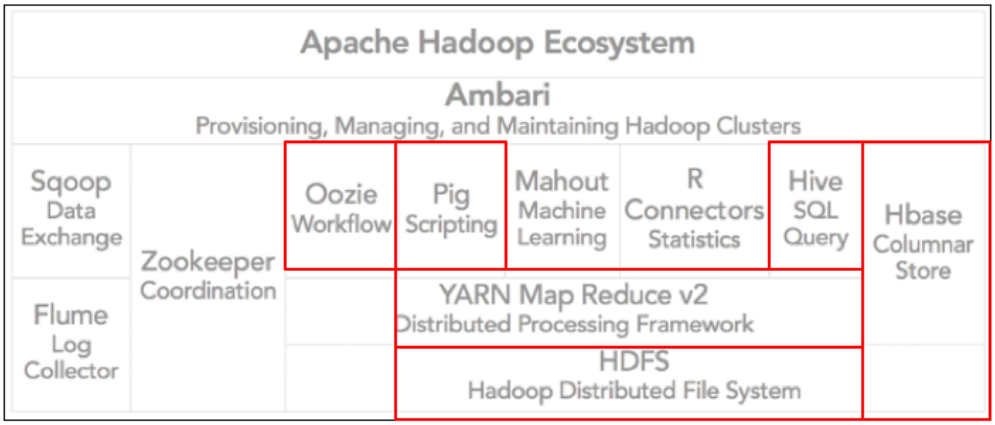
Apache Hadoop is an open-source tool for distributed computing. It consists of two major components, open-source data storage HDFS (i.e., Hadoop Distributed File System) and processing API like MapReduce written in Java, and projects/libraries like Hbase, Hive, Pig, and so on.

Google MapReduce vs. Apache Hadoop

Google	Yahoo
MapReduce	Hadoop
GFS	HDFS
Bigtable	HBase
Chubby lock	(nothing yet… but planned)

Here is a table comparing terms for MapReduce and Hadoop.

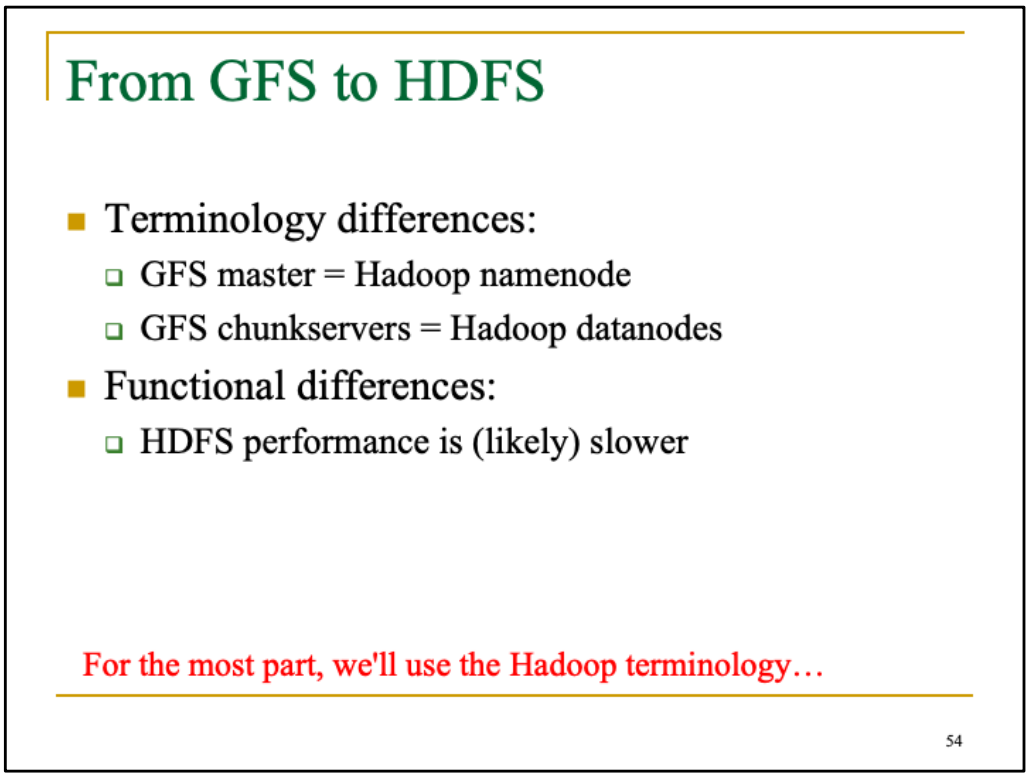
Hadoop Ecosystem



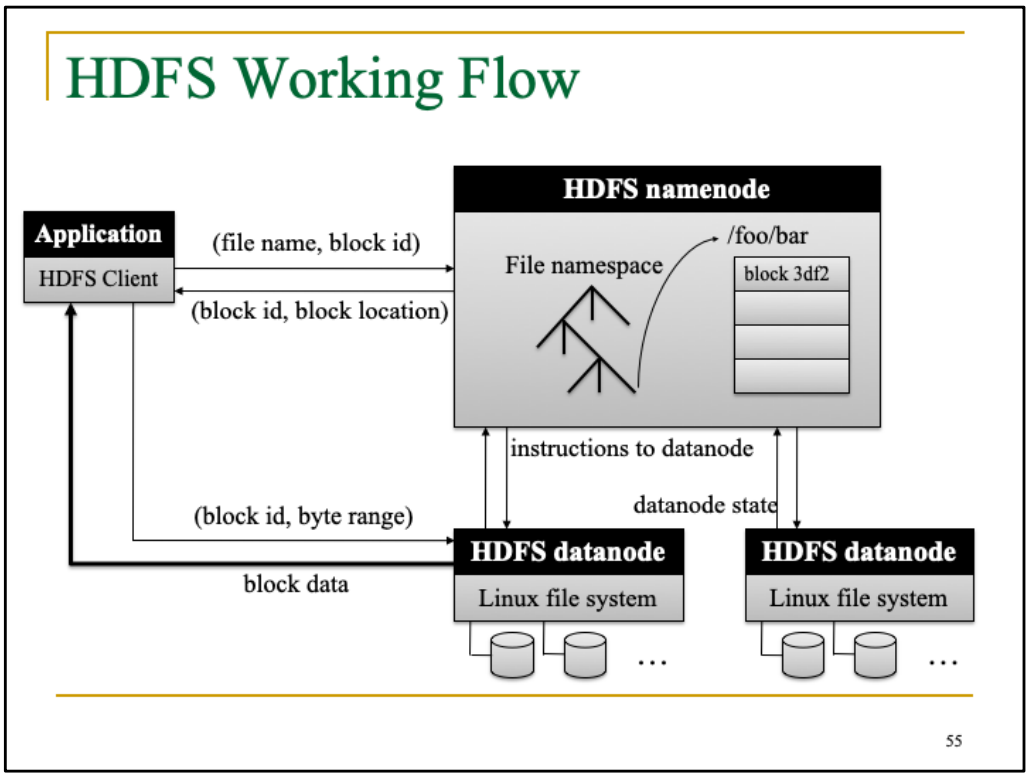
Oozie: workflow or coordination of jobs
Pig: a scripting language
Hive: HQL or the SQL-like query language that is used to query Hbase
YARN: Yet Another Resource Negotiator (Map Reduce Version Two)

53

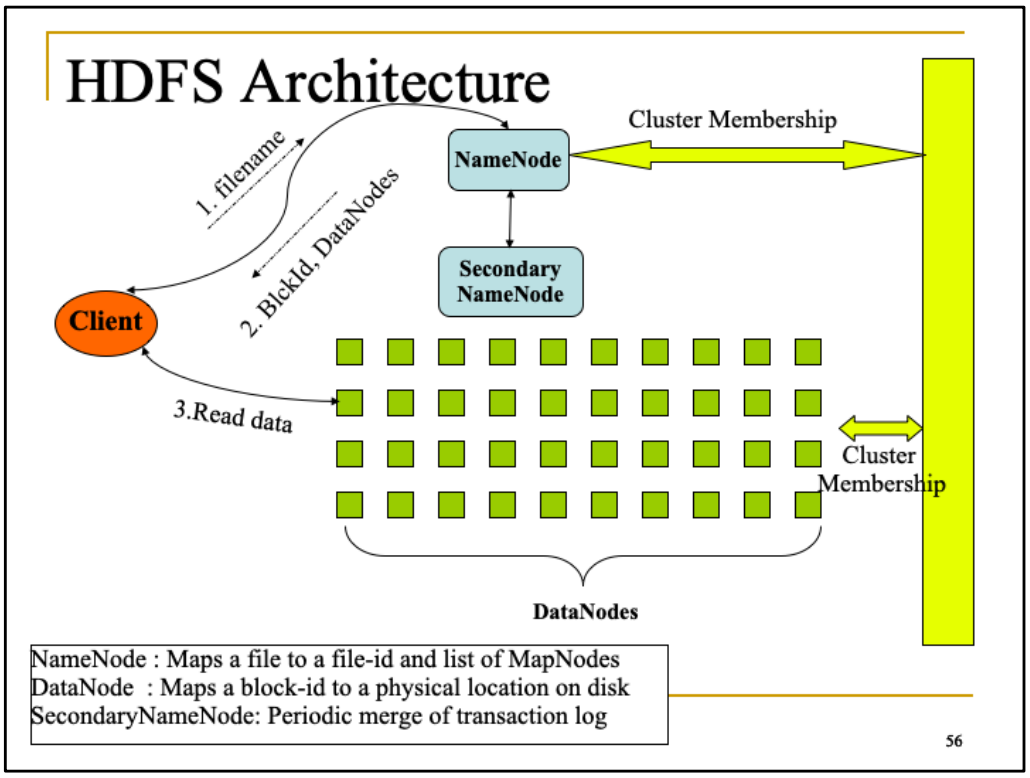
Here is the Hadoop ecosystem which illustrates 2 components, HDFS and YARN, and a number of projects/libraries such as Oozie, Pig, and Hive.



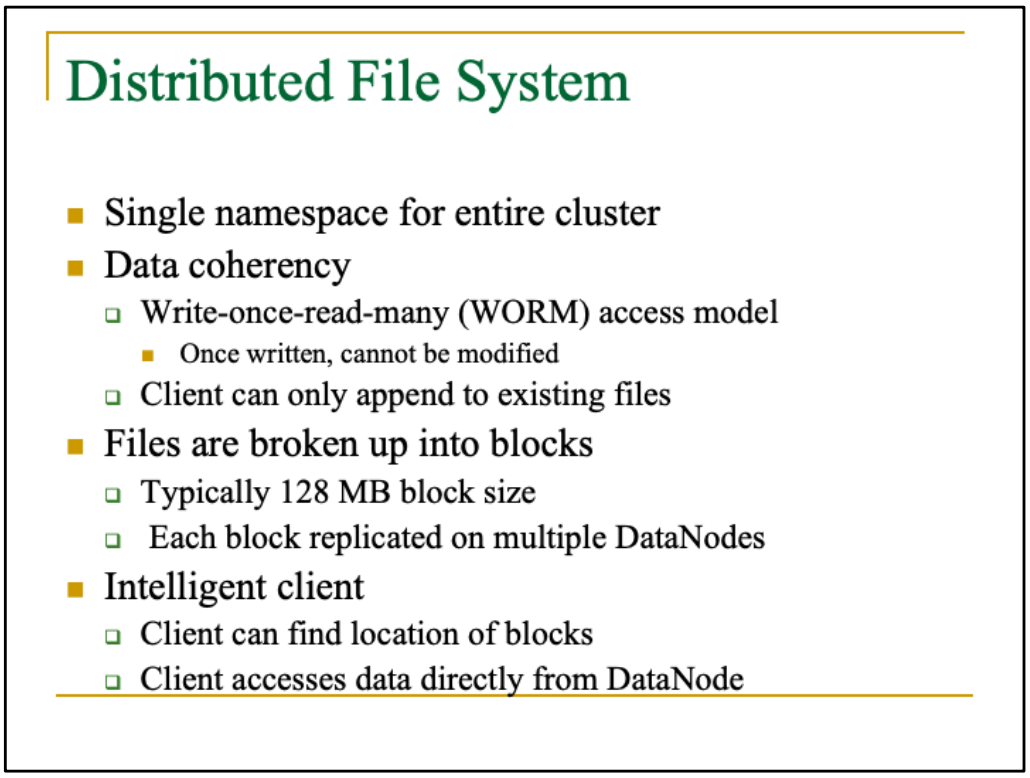
In HDFS, GFS master is called Hadoop namenode, and GFS chunk servers are called Hadoop datanodes. Regarding the functional differences, HDFS performance is likely to be slower.



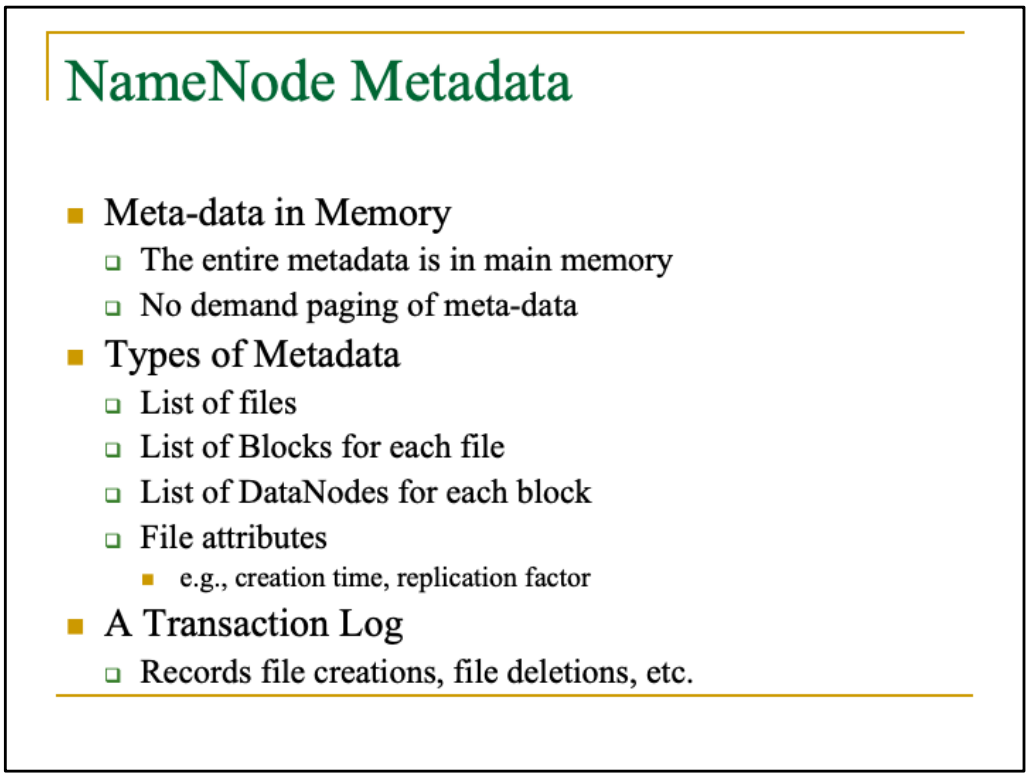
Here is the working flow for HDFS. HDFS client may request for some files through applications, and this request is sent to HDFS namenode, which stores the locations of HDFS datanodes containing the file. Once datanodes receive the requests, they will send the block data back to the client.



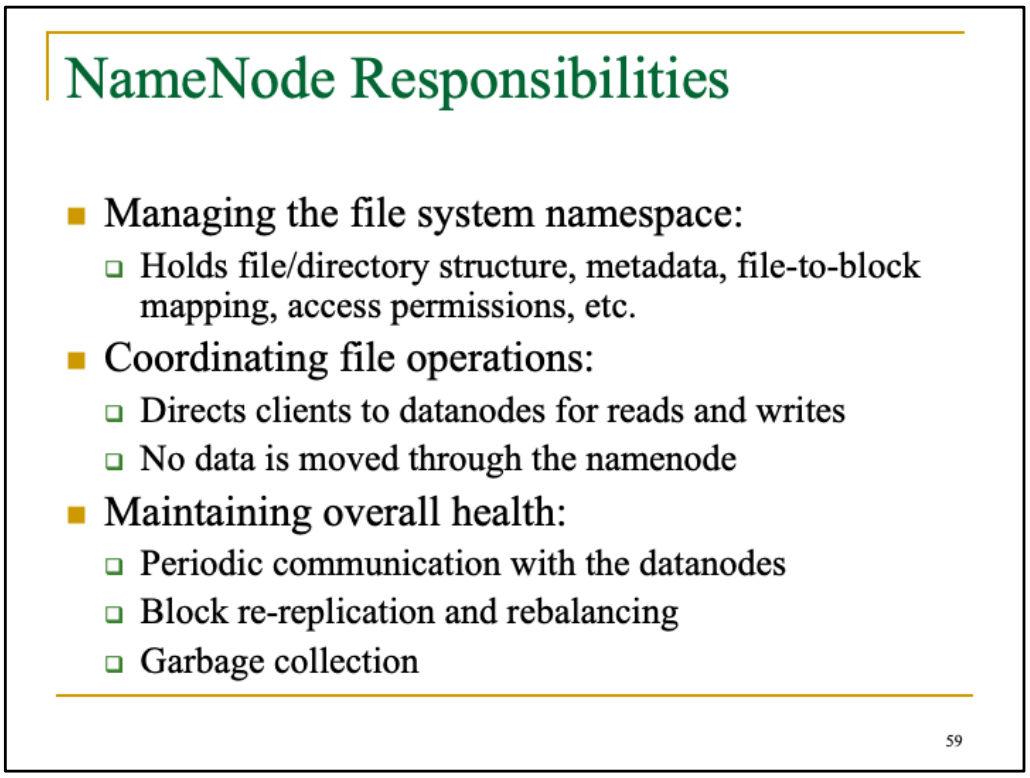
In practice, HDFS usually uses a namenode and a secondary namenode as a backup, as shown in the figure. The secondary namenode will store the checkpoints of primary namenode, and periodically update the transaction log.



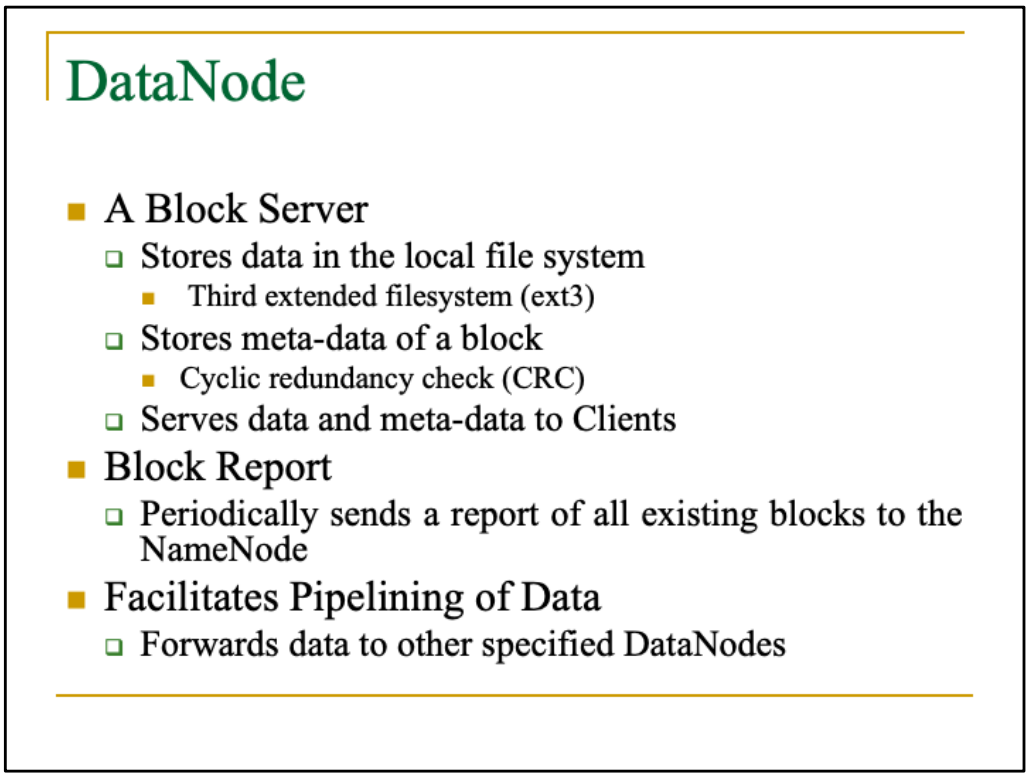
HDFS has some features like single namespace for entire cluster, data coherency, typical 128 MB block size (different from 64 MB for GFS), and intelligent client.



The namenode stores meta data in main memory. The meta data include a list of files, a list of blocks for each file, a list of datanodes for each block, and file attributes like creation time, replication factor, and so on. The namenode also stores a transaction log, including file creation/deletion, and so on.



The namenode is responsible for managing the file system namespace, coordinating file operations, and maintaining overall health of the HDFS system (e.g., detecting dead data nodes, block re-replication and rebalancing, and garbage collection).



For each datanode, it stores data in local file system like third extended filesystem, meta-data of a block (e.g., CRC code for checking bit errors), and sends the requested data or meta data to clients. It also sends a report periodically for all existing blocks to the namenode. It also forwards data to other datanodes for data pipelining.

Block Placement

- Current Strategy
  - One replica on local node
  - Second replica on a remote rack
  - Third replica on same remote rack
  - Additional replicas are randomly placed
- Clients read from nearest replica
- Would like to make this policy pluggable

For block data, we store a copy on local node, the second replica on a remote rack, the third one on the same remote rack, and additional replicas on random nodes. Clients will read data from the nearest replica.

Data Correctness

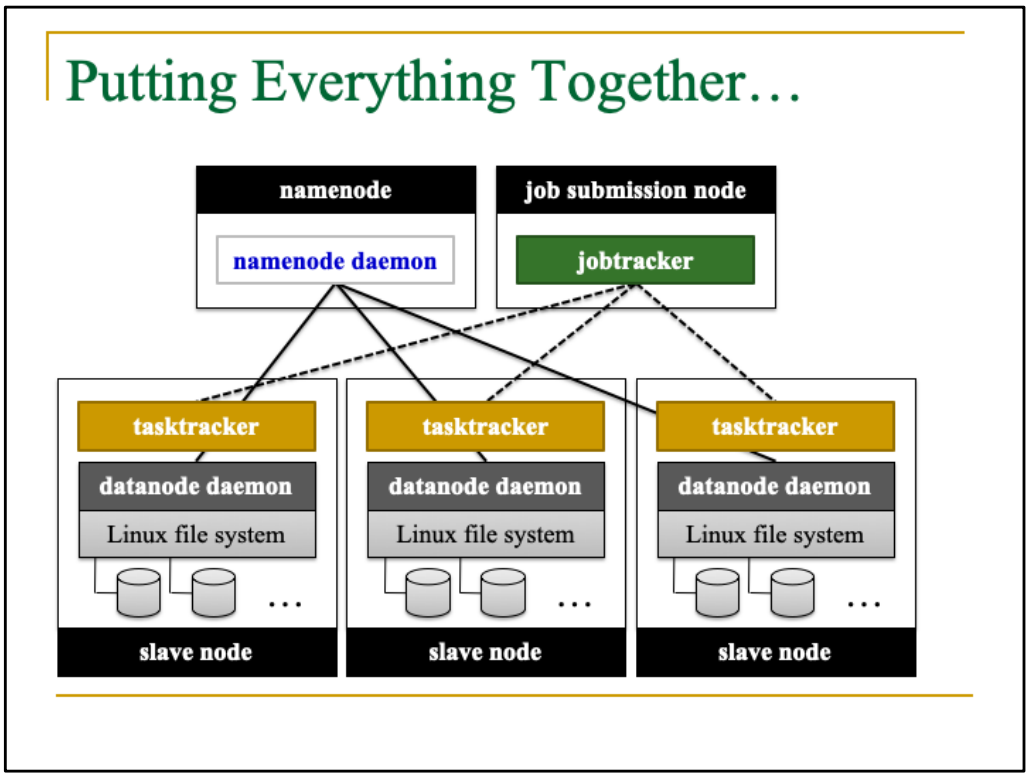
- Use Checksums to validate data
  - Use CRC32
- File Creation
  - Client computes checksum per 512 byte
  - DataNode stores the checksum
- File access
  - Client retrieves the data and checksum from DataNode
  - If the validation fails, the client tries other replicas

HDFS also uses Checksums to guarantee the correctness of the data. It computes checksum for every 512 bytes, and stores checksums in data node when file is created. The client receives the data and checksums from the datanode at the same time. Once the validation fails, the client will try other replicas.

NameNode Failure

- A single point of failure
- Transaction Log stored in multiple directories
  - A directory on the local file system
  - A directory on a remote file system (NFS/CIFS)
- Need to develop a real high availability solution

To avoid the effect of namenode failure, we maintain a transaction log in multiple directories, a directory on local file system and another one on the remote file system.

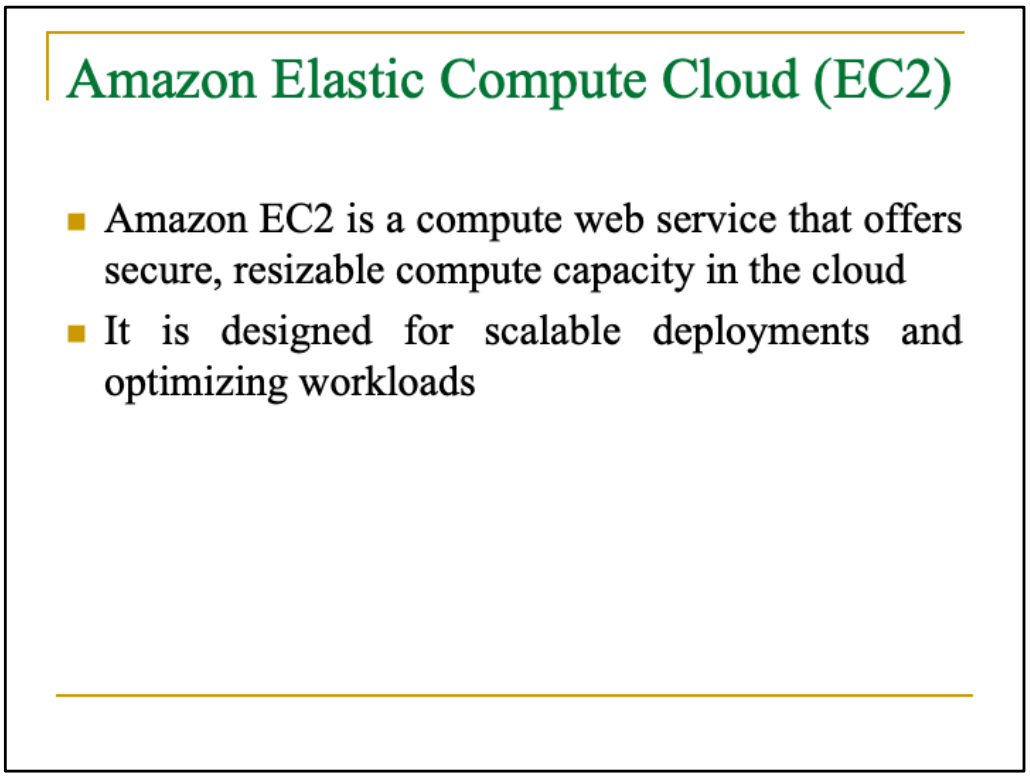


Putting things together, we have this architecture for HDFS.

References

https://www.lynda.com/Amazon-Web-Services-tutorials/Welcome/383048/435232-4.html?srchtrk=index%3a1%0alinktypeid%3a2%0aq%3aamazon+web+services%0apage%3a1%0as%3arelevance%0asa%3atrue%0aproducttypeid%3a2

Another commercial distributed platform is the Amazon Web Services (or AWS), which contains many Web-based technology services, such as Amazon Elastic Compute Cloud (EC2), Amazon Simple Storage Service (S3), Amazon Simple Queue Service (SQS), Amazon CloudFront, and Amazon SimpleDB.



References

https://aws.amazon.com/ec2/

In particular, EC2 provides Web service APIs for using virtual servers inside Amazon cloud.

Amazon CloudFront

- Amazon CloudFront is a fast content delivery network (CDN) service that securely delivers data, videos, applications, and APIs to customers globally with low latency, high transfer speeds, all within a developer-friendly environment
- CloudFront works seamlessly with services including AWS Shield for DDoS mitigation, Amazon S3, Elastic Load Balancing or Amazon EC2 as origins for your applications

References

https://aws.amazon.com/cloudfront/

Amazon Cloud-Front enables you to place the content at the edges of the network for rapid delivery.

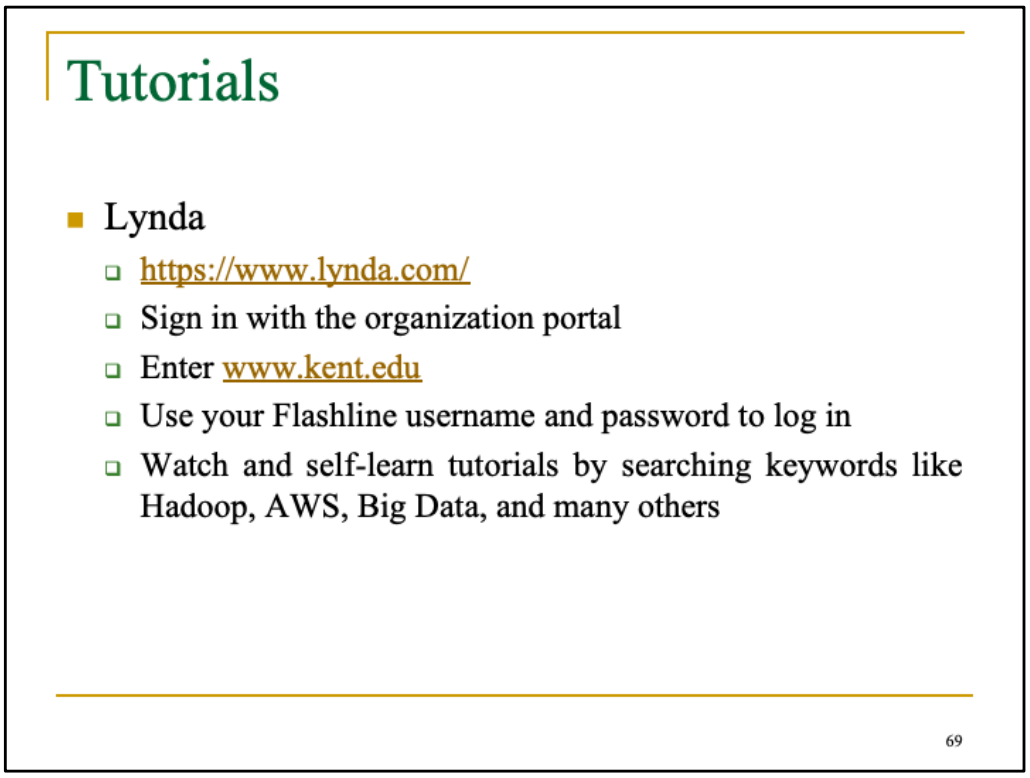
Storage

- Amazon Simple Storage Service (Amazon S3) is an object storage service that offers industry-leading scalability, data availability, security, and performance
- Amazon SimpleDB provides a simple Web services interface to create and store multiple data sets, query the data easily, and return the results

References

https://aws.amazon.com/s3/
https://aws.amazon.com/simpledb/details/

S3 provides archive services, and Amazon SimpleDB is for relational database, which is more reliable than MySQL or Oracle.



If you are interested in MapReduce and want to learn more about GFS/Hadoop/AWS in depth, you can watch more video tutorials in Lynda.