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Internal Assessment Test 2 – December 2021

Sub:	**Big Data Analytics**							**Code:**	20MCA352
Date:	20-12-21	Duration:	90 mins	Max Marks:	50	**Sem:**	IV	**Branch:**	**MCA**

. Total marks: 50

Marks

1. a **Compare Map reduce with RDBMS, Grid Computing and Volunteer Computing** 10

RDBMS compared to MapReduce

	Traditional RDBMS	**MapReduce**
Data size	Gigabytes	Petabytes
Access	Interactive and batch	Batch
Updates	Read and write many times	Write once, read many times
Structure	Static schema	Dynamic schema
Integrity	High	Low
Scaling	Nonlinear	Linear

Grid Computing:

The High Performance Computing (HPC) and Grid Computing communities have
been doing large-scale data processing for years, using such APIs as Message Passing Interface (MPI). Broadly, the approach in HPC is to distribute the work across a cluster of machines, which access a shared filesystem, hosted by a SAN. This works well for predominantly compute-intensive jobs, but becomes a problem when nodes need to access larger data volumes (hundreds of gigabytes, the point at which MapReduce really starts to shine), since the network bandwidth is the bottleneck and compute nodes become idle.

MapReduce tries to collocate the data with the compute node, so data access is fast
since it is local. This feature, known as data locality, is at the heart of MapReduce and is the reason for its good performance. Recognizing that network bandwidth is the most precious resource in a data center environment (it is easy to saturate network links by copying data around), MapReduce implementations go to great lengths to conserve it by explicitly modelling network topology. Notice that this arrangement does not preclude high-CPU analyses in MapReduce

Volunteer Computing:

Volunteer computing projects work by breaking the problem they are trying to
solve into chunks called work units, which are sent to computers around the world to be analyzed. For example, a SETI@home work unit is about 0.35 MB of radio telescope data, and takes hours or days to analyze on a typical home computer. When the analysis is completed, the results are sent back to the server, and the client gets another work unit. As a precaution to combat cheating, each work unit is sent to three different machines and needs at least two results to agree to be accepted. Although SETI@home may be superficially similar to MapReduce (breaking a problem into independent pieces to be worked on in parallel), there are some significant differences.
The SETI@home problem is very CPU-intensive, which makes it suitable for
running on hundreds of thousands of computers across the world,8 since the time to transfer the

work unit is dwarfed by the time to run the computation on it. Volunteers are donating CPU cycles, not bandwidth. MapReduce is designed to run jobs that last minutes or hours on trusted, dedicated hardware running in a single data center with very high aggregate bandwidth interconnects.

2. a **Explain the brief history of Hadoop, Hadoop Releases and the Hadoop Eco System.** 10

History of Hadoop:

Hadoop is not an acronym; it's a made-up name. The project's creator, Doug Cutting, explains how the name came about:

The name my kid gave a stuffed yellow elephant. Short, relatively easy to spell and pronounce, meaningless, and not used elsewhere: those are my naming criteria.

Building a web search engine from scratch was an ambitious goal, for not only is the software required to crawl and index websites complex to write, but it is also a challenge to run without a dedicated operations team

Nutch was started in 2002, and a working crawler and search system quickly emerged. In 2004, Google published the paper that introduced MapReduce to the world.12 Early in 2005, the Nutch developers had a working MapReduce implementation in Nutch,and by the middle of that year all the major Nutch algorithms had been ported to run using MapReduce and NDFS.

Hadoop Eco System.

Common
A set of components and interfaces for distributed filesystems and general I/O (serialization, Java RPC, persistent data structures).

Avro
A serialization system for efficient, cross-language RPC, and persistent data storage.

MapReduce
A distributed data processing model and execution environment that runs on large clusters of commodity machines.

HDFS
A distributed filesystem that runs on large clusters of commodity machines.

Pig
A data flow language and execution environment for exploring very large datasets. Pig runs on HDFS and MapReduce clusters.

Hive
A distributed data warehouse. Hive manages data stored in HDFS and provides a query language based on SQL (and which is translated by the runtime engine to MapReduce jobs) for querying the data.

HBase
A distributed, column-oriented database. HBase uses HDFS for its underlying storage, and supports both batch-style computations using MapReduce and point queries (random reads).

ZooKeeper
A distributed, highly available coordination service. ZooKeeper provides primitives such as distributed locks that can be used for building distributed applications.

Sqoop
A tool for efficiently moving data between relational databases and HDFS.

Hadoop Releases;

Features Supported by Hadoop Release Series

Feature	1.x	0.22	0.23
Secure authentication	Yes	No	Yes
Old configuration names	Yes	Deprecated	Deprecated
New configuration names	No	Yes	Yes
Old MapReduce API	Yes	Deprecated	Deprecated
New MapReduce API	Partial	Yes	Yes
MapReduce 1 runtime (Classic)	Yes	Yes	No
MapReduce 2 runtime (YARN)	No	No	Yes
HDFS federation	No	No	Yes
HDFS high-availability	No	No	Planned

3. a **Define HDFS and explain HDFS concepts.** 10

HDFS is a filesystem designed for storing very large files with streaming data access patterns, running on clusters of commodity hardware. Very large files "Very large" in this context means files that are hundreds of megabytes, gigabytes,or terabytes in size. There are Hadoop clusters running today that store petabytes of data.

Streaming data access
HDFS is built around the idea that the most efficient data processing pattern is a write-once, read-many-times pattern. A dataset is typically generated or copied from source, then various analyses are performed on that dataset over time. Each analysis will involve a large proportion, if not all, of the dataset, so the time to read the whole dataset is more important than the latency in reading the first record.

Commodity hardware
Hadoop doesn't require expensive, highly reliable hardware to run on. It's designed to run on clusters of commodity hardware (commonly available hardware available from multiple vendors3) for which the chance of node failure across the cluster is high, at least for large clusters. HDFS is designed to carry on working without a noticeable interruption to the user in the face of such failure.

HDFS is not best fit for:

Low-latency data access:

Applications that require low-latency access to data, in the tens of milliseconds range, will not work well with HDFS. Remember, HDFS is optimized for delivering a high throughput of data, and this may be at the expense of latency.

Lots of small files:

Since the namenode holds filesystem metadata in memory, the limit to the number of files in a filesystem is governed by the amount of memory on the namenode. As a rule of thumb, each file, directory, and block takes about 150 bytes. So, for example, if you had one million files, each taking one block, you would need at least 300 MB of memory. While storing millions of files is feasible, billions is beyond the capability of current hardware.

Multiple writers, arbitrary file modifications:

Files in HDFS may be written to by a single writer. Writes are always made at the end of the file. There is no support for multiple writers, or for modifications at arbitrary offsets in the file.

HDFS concepts:

A disk has a block size, which is the minimum amount of data that it can read or write. Filesystems for a single disk build on this by dealing with data in blocks, which are an integral multiple of the disk block size. Filesystem blocks are typically a few kilobytes in size, while disk blocks are normally 512 bytes. This is generally transparent to the filesystem user who is simply reading or writing a file—of whatever length. However,there are tools to perform filesystem maintenance, such as df and fsck, that operate on the filesystem block level.
HDFS, too, has the concept of a block, but it is a much larger unit—64 MB by default.Like in a filesystem for a single disk, files in HDFS are broken into block-sized chunks,which are stored as independent units.

Name nodes and Data nodes:

An HDFS cluster has two types of node operating in a master-worker pattern: a namenode (the master) and a number of datanodes (workers). The namenode manages the filesystem namespace. It maintains the filesystem tree and the metadata for all the files and directories in the tree. This information is stored persistently on the local disk in the form of two files: the namespace image and the edit log. The namenode also knows the datanodes on which all the blocks for a given file are located, however, it doesnot store block locations persistently, since this information is reconstructed fromdatanodes when the system starts.

A client accesses the filesystem on behalf of the user by communicating with the namenode and datanodes. The client presents a POSIX-like filesystem interface, so the user code does not need to know about the namenode and datanode to function.Datanodes are the workhorses of the filesystem. They store and retrieve blocks when they are told to (by clients or the namenode), and they report back to the namenode periodically with lists of blocks that they are storing.

4. a **Explain HDFS Federation and HDFS High-availability** 10

HDFS Federation
The name node keeps a reference to every file and block in the file system in memory, which means that on very large clusters with many files, memory becomes the limiting factor for scaling.

HDFS Federation, introduced in the 0.23 release series, allows a cluster to scale by adding namenodes, each of which manages a portion of the filesystem namespace. For example, one namenode might manage all the files rooted under /user, say, and a second namenode might handle files under /share.

Under federation, each namenode manages a namespace volume, which is made up of the metadata for the namespace, and a block pool containing all the blocks for the files in the namespace. Namespace volumes are independent of each other, which means namenodes do not communicate with one another, and furthermore the failure of one namenode does not affect the availability of the namespaces managed by other namenodes.
To access a federated HDFS cluster, clients use client-side mount tables to map file paths to namenodes.
This is managed in configuration using the ViewFileSystem, and viewfs:// URIs.

HDFS High-availability:

The combination of replicating namenode metadata on multiple filesystems, and using the secondary namenode to create checkpoints protects against data loss, but does not provide high-availability of the filesystem. The namenode is still a single point of failure (SPOF), since if it did fail, all clients—including MapReduce jobs—would be unable to read, write, or list files, because the namenode is the sole repository of the metadata and the file-to-block mapping. In such an event the whole Hadoop system would effectively be out of service until a new namenode could be brought online.

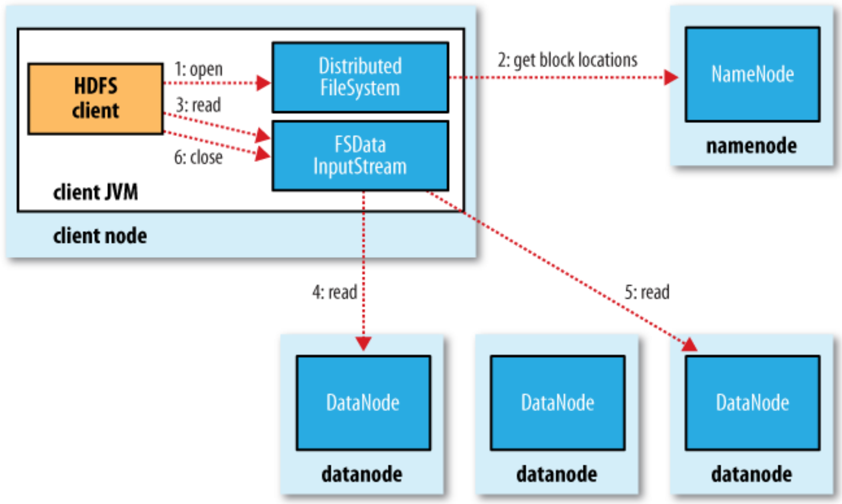
To recover from a failed namenode in this situation, an administrator starts a new
primary namenode with one of the filesystem metadata replicas, and configures datanodes and clients to use this new namenode.
The new namenode is not able to serve requests until it has

i) loaded its namespace image into memory,
ii) replayed its edit log, and
iii) received enough block reports from the datanodes to leave safe mode.

A few architectural changes are needed to allow this to happen:
• The namenodes must use highly-available shared storage to share the edit log.
• Datanodes must send block reports to both namenodes since the block mappings
are stored in a namenode's memory, and not on disk.
• Clients must be configured to handle namenode failover, which uses a mechanism that is transparent to users

5 a **Demonstrate the anatomy of a file read with a neat diagram** 10

To get an idea of how data flows between the client interacting with HDFS, the namenode and the datanodes, consider Figure which shows the main sequence of events when reading a file.



The client opens the file it wishes to read by calling open() on the FileSystem object, which for HDFS is an instance of DistributedFileSystem (step 1 in Figure).

DistributedFileSystem calls the namenode, using RPC, to determine the locations of the blocks for the first few blocks in the file (step 2).

For each block, the namenode returns the addresses of the datanodes that have a copy of that block. Furthermore, the datanodes are sorted according to their proximity to the node. If the client is itself a datanode (in the case of a MapReduce task, for instance), then it will read from the local datanode, if it hosts a copy of the block.

The DistributedFileSystem returns an FSDataInputStream (an input stream that supports file seeks) to the client for it to read data from. FSDataInputStream in turn wraps a DFSInputStream, which manages the datanode and namenode I/O.

The client then calls read() on the stream (step 3). DFSInputStream, which has stored the datanode addresses for the first few blocks in the file, then connects to the first (closest) datanode for the first block in the file. Data is streamed from the datanode back to the client, which calls read() repeatedly on the stream (step 4).

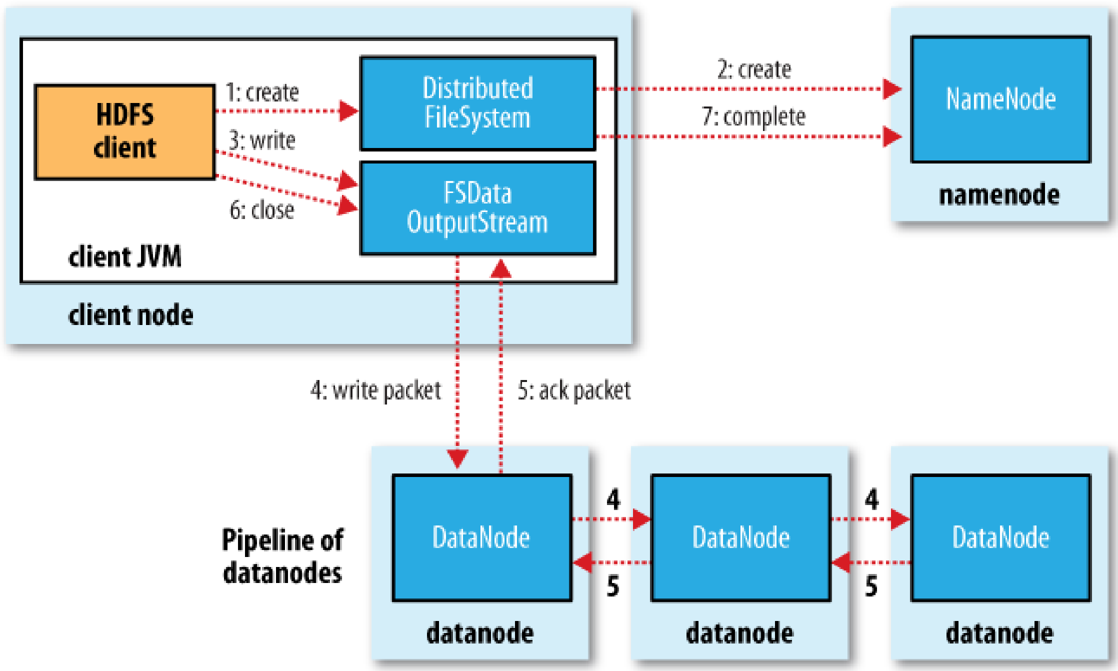
When the end of the block is reached, DFSInputStream will close the connection to the datanode, then find the best datanode for the next block (step 5). This happens transparently to the client, which from its point of view is just reading a continuous stream.
Blocks are read in order with the DFSInputStream opening new connections to datanodes as the client reads through the stream. It will also call the namenode to retrieve the datanode locations for the next batch of blocks as needed. When the client has finished reading, it calls close() on the FSDataInputStream(step 6)

6 a **Demonstrate the anatomy of a file write with a neat diagram.** 10

The case we're going to consider is the case of creating a new file, writing data to it, then closing the file. See Figure 3-4.The client creates the file by calling create() on DistributedFileSystem (step 1 in Figure 3-4). DistributedFileSystem makes an RPC call to the namenode to create a new file in the filesystem's namespace, with no blocks associated with it (step 2). The namenode performs various checks to make sure the file doesn't already exist, and that the client has the right permissions to create the file. If these checks pass, the namenode makes a record of the new file; otherwise, file creation fails and the client is thrown an IOException.

The DistributedFileSystem returns an FSDataOutputStream for the client to start writing data to. Just as in the read case, FSDataOutputStream wraps a DFSOutput Stream, which handles communication with the datanodes and namenode.

As the client writes data (step 3), DFSOutputStream splits it into packets, which it writes to an internal queue, called the data queue. The data queue is consumed by the Data Streamer, whose responsibility it is to ask the namenode to allocate new blocks by picking a list of suitable datanodes to store the replicas. The list of datanodes forms a pipeline—we'll assume the replication level is three, so there are three nodes in the pipeline. The DataStreamer streams the packets to the first datanode in the pipeline, which stores the packet and forwards it to the second datanode in the pipeline. Similarly,the second datanode stores the packet and forwards it to the third (and last) datanode in the pipeline (step 4).



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7 a **Write a program to display files from a hadoop filesystem on standard output using a URLStreamHandler.** 5

```
inputStream in=null;
try
{
In=new URL("hdfs://host/path").openStream();
}
finally
{
IOUtils.closestream(in);
}
```

b **Write a program to read data using the filesystem API** 5

```
Public class FileSystemCat{
Public static void main(String[] args) throws exception{
String uri=args[0];
Configuration conf=new Configuration();
FileSystem fs=FileSystem.get(URI.create(uri),conf);
InputStream in=null;
Try
{
In=fs.open(new Path(uri));
IOUtils.copyBytes(in, System.out, 4096, false);
}
Finally{IOUtils.closestream(in);
}
}
}
```

8 a **Write a program to display the files from a Hadoop filesystem on standard output twice using seek.** 5

```
Public class FileSystemDoubleCat
{
Public static void Main(string[] args) throws Exception
{
String uri=args[0];
Configuration conf= new Configuration();
FileSystem fs=FileSystem.get(URI.create(uri),conf);
FSDataStream in = null;
try
{
in = fs.Open(new Path(uri));
IOutils.CopyBytes(in,System.Out,4096,false);
In.Seek(0);
IOutils.CopyBytes(in,System.Out,4096,false);
}
Finally{IOUtils.CloseStream(in);}
}
}
```

b **Write a program to copy a local file to a hadoop filesystem**

```
Public class FileCopuWithProgress{
Public static void main(String[] args) throws exception{
String localsrc=args[0];
String dst=args[1];
InputStream in=new BufferedInputStream(new FileInputStream(localsrc));
Configuration conf=new Configuration();
FileSystem fs=FileSystem.get(URI.create(dst),conf);
OutputStream out=fs.create(new path(dst),new Progressable(){
Public void progress(){ system.out.print(“.”);
}});
IOUtils.copyBytes(in, out, 4096, false);
}
}
```

9 **Write a program to show the file status for a collection of paths in Hadoop Filesystem**. 10

```
Public class Liststatus
{
Public static void main(string[] args) throws Exception{
String uri=args[0];
Configuration conf=new Configuration();
FileSystem fs=FileSystem.get(URI.create(uri),conf);
Path[] paths=new Path[args.length];
For(int i=0;i<paths.length;i++) {
Paths[i]=new path(args[i]);
}

Filestatus[] status=fs.listStatus(paths);
Path[] listedpaths=FileUtil.stat2Paths(status);
For(Path p:listedpaths){ System.out.println(p);}}}
```

10 **Write a program for excluding paths that matches a regular expression**.10

```
Public class RegexExcludePathFilter implements PathFilter
{
Private final string regex;
Public RegexExcludePathFilter(string regex)
{
this.regex=regex;
}
Public boolean accept(Path path)
{ return !path.tostring().matches(regex);
}
}
```