Unit # 2

- Hadoop Concepts,
- Design of Hadoop distributed file system (HDFS) ,
- Analyzing data with Hadoop,
- Hadoop streaming,
- Data Formats.

Introduction - Hadoop

- Apache Hadoop is an open-source framework that allows for the distributed processing of large datasets across clusters of computers using simple programming models. It is designed to scale up from a single server to thousands of machines, with a high degree of fault tolerance.
  There are four core components of Hadoop.

1. HDFS (Hadoop Distributed File System)
2. YARN (Yet Another Resource Negotiator)
3. Map Reduce
4. Hadoop Common

Difference between RDBMS and Hadoop

RDBMS systems like MySQL, PostgreSQL, and Oracle are designed for real-time, transactional queries where low-latency access is critical whereas Hadoop and similar systems like HDFS, Hive, HBase are optimized for large-scale data processing and batch operations, focusing on handling big data and Online Analytical Processing workloads (OLAP) . The specific differences are discussed below :

1. Data Size and Type:

RDBMS: Suited for structured, relational data; handles gigabytes to terabytes of data.Hadoop: Designed for both structured and unstructured data; capable of scaling to petabytes or exabytes of data.

Introduction – Hadoop (contd)

2. Read/ Write Performance:

RDBMS: Optimized for fast, small read/write operations; handles real-time transactional queries efficiently. Data retrieval and modification are quick due to the use of B-trees, indexes, and row-based storage.

Hadoop: Optimized for sequential access and batch processing. It's not designed for real-time, frequent, or small transactions. The overhead of distributing tasks across the cluster makes it slower for individual queries but highly efficient for processing huge datasets.

3. Data Access Speed:

RDBMS: Read Latency is typically in milliseconds to seconds for a single row or small dataset query. Write Latency as well in milliseconds to seconds depending on whether indexes, constraints, or transactions are involved. Eg. Queries on MySQL or PostgreSQL to retrieve a few thousand records can typically return results in less than 100 milliseconds.

Hadoop: Read Latency is in seconds to minutes due to its distributed nature and the overhead of accessing data stored across multiple nodes in HDFS. While write Latency involves replication and coordination across the cluster, so it can take seconds to minutes as well. Eg. A single query to retrieve data from HDFS using Hive or HBase could take 5–20 seconds for a moderately sized query (e.g., querying millions of rows).

Introduction – Hadoop (contd)

4. Concurrency :

RDBMS: Supports high concurrency, handling thousands of simultaneous small transactions efficiently with ACID compliance. Typically, RDBMS systems can handle hundreds to thousands of queries per second (QPS) for small transactional workloads. For eg. MySQL can handle 10,000+ QPS for simple reads/writes depending on the hardware and optimizations.

Hadoop: Hadoop is not designed for high-concurrency random access. It is optimized for batch processing and parallel processing over large datasets, so concurrent small queries will experience significant delays. For eg. A typical Hadoop MapReduce job could take several minutes to hours depending on the size of the data and the complexity of the task.

Activity	RDBMS	Hadoop
SELECT 1000 rows from a table with an index on the query key.	< 100 ms	10–20 sec
SELECT with a complex JOIN and aggregation over a 1 TB dataset.	Several hours.	10–30 minutes.
Real-time transactional query	Milliseconds	Minutes to hours

Introduction – Hadoop (contd)

Ecosystem of Hadoop

Oozie: A workflow scheduler system to manage Hadoop jobs.

Hive: A data warehousing layer on top of Hadoop that allows SQL-like queries (HiveQL) on large datasets.

HBase: A NoSQL database that runs on top of HDFS, allowing real-time read/write access to large datasets.

Sqoop: A tool for transferring data between Hadoop and relational databases.

Flume: A distributed service for collecting and moving large amounts of log data into HDFS.

Pig : A platform for analyzing large datasets with a scripting language (Pig Latin).

Analyzing data with Hadoop

Data analysis with Hadoop involves multiple stages, from data ingestion to final output, each leveraging different components of the Hadoop ecosystem. The key Phases of Data Analysis with Hadoop are listed below:

1. Data Ingestion:

Data ingestion is the process of transferring data from multiple sources such as relational databases, log files, social media, IoT devices, and more into Hadoop's HDFS (Hadoop Distributed File System) or other Hadoop-compatible storage systems. This is the first and foundational step for any big data analysis pipeline, as it allows Hadoop to process large volumes of structured, semi-structured, or unstructured data coming from disparate sources. The data ingestion can happen in batch mode i.e moving large amounts of data at once or in real-time/streaming mode i.e continuous flow of data as it's generated. Both modes are supported by different tools and frameworks in the Hadoop ecosystem. Various data sources are

- ✓ Relational databases (e.g., MySQL, Oracle, SQL Server)
- ✓ NoSQL databases (e.g., MongoDB, Cassandra)
- ✓ Flat files (e.g., CSV, JSON, XML)
- ✓ Log files from web servers, applications, or devices
- ✓ APIs or social media feeds
- ✓ IoT devices generating sensor data
- ✓ Data streams (e.g., clickstreams from websites)

Analyzing data with Hadoop (contd)

Key Ingestion Tools:

1. *Apache Sqoop:* A tool to import data from traditional databases (RDBMS) like MySQL, PostgreSQL, and Oracle into Hadoop's HDFS, or vice versa. Sqoop allows you to bring large datasets stored in relational databases into the Hadoop ecosystem.
2. *Apache Flume:* A service for collecting, aggregating, and moving large amounts of log and event data from different sources to HDFS. It's ideal for ingesting real-time streaming data from sources such as social media, web logs, or IoT devices.

2. Data Storage in HDFS :

Hadoop Distributed File System (HDFS) is the primary storage layer for Hadoop, designed to store large datasets across a distributed cluster. It allows for scalable and fault-tolerant storage of data by splitting large files into smaller blocks typically 128 MB or 256 MB in size and replicating those blocks across multiple nodes. Fault tolerance is achieved as HDFS replicates each data block across multiple nodes (by default, three replicas per block). This replication ensures that data remains available even if a node fails, thus maintaining data reliability. The storage and retrieval of data in HDFS form the backbone of big data processing, as it enables high-throughput access and efficient data analysis through parallel processing. HDFS is optimized for **write-once, read-many** access patterns, which means once data is written, it is rarely updated. This design improves performance for reading and analyzing large-scale datasets.

Analyzing data with Hadoop (contd)

If a file is larger than the block size (128 MB), it will be split into several blocks. For example, a 512 MB file will be split into 4 blocks of 128 MB each and saved as follows.

Example: A 512 MB file will be split into 4 blocks:
Block 1 → DataNode A, DataNode B, DataNode C
Block 2 → DataNode B, DataNode C, DataNode D
Block 3 → DataNode C, DataNode D, DataNode A
Block 4 → DataNode D, DataNode A, DataNode B

Data Storage Formats :

The data in HDFS is stored in efficient formats for big data analysis. Few of the popular data formats are :

1. CSV (Comma-Separated Values) and TSV (Tab-Separated Values)
2. JSON
3. Sequence Files
4. Avro
5. Parquet
6. Optimised Row Columnar (ORC)
7. Protobuf

Analyzing data with Hadoop (contd)

3. Data Processing with MapReduce :

MapReduce is a core component of Hadoop designed for processing large-scale data across distributed clusters. It is a programming model that enables parallel and distributed processing of vast datasets by dividing tasks into two distinct phases. The concept behind MapReduce is to break down a large task into smaller, independent subtasks, which are processed in parallel and later aggregated. This model is highly scalable and fault-tolerant, making it suitable for processing datasets that span petabytes and are distributed across hundreds or thousands of machines. The two phases viz Map and reduce works as follows :

Map Phase:

In the **Map** phase, the input dataset is split into smaller chunks, and each chunk is processed in parallel by a **mapper** function. The mapper reads the data, processes it, and outputs key-value pairs. A simple example of the Mapper function is can be , say

If we want to count the number of times each word appears in a large collection of text files (e.g., web logs or social media posts):

We takes a block of text, splits it into words, and outputs each word as a key, with a value of 1 (e.g., "apple" → (apple, 1)).

Reduce Phase:

The Reduce function takes the sorted intermediate data and processes it to generate the final output. *apple, 1), (apple, 1), (apple, 1) → (apple, 3)).*

The reducer aggregates, combines, or summarizes the results based on the keys. The output from each reducer is written back to **HDFS** or another storage system .

Analyzing data with Hadoop (contd)

4. Higher-Level Data Processing :

MapReduce model can be complex for non-programmers. To make Hadoop more accessible, higher-level abstractions such as Apache Hive and Apache Pig were introduced.

Apache Hive is a data warehousing solution built on top of Hadoop. It allows analysts to run SQL-like queries (HiveQL) over large datasets stored in HDFS without needing to write complex Java code. Hive translates HiveQL queries into MapReduce under the hood. It supports various file formats (ORC, Parquet) and can partition large datasets for faster querying.

Apache Pig uses a scripting language called **Pig Latin** that is more flexible than SQL and allows users to perform complex transformations and data flows on large datasets. Pig Latin scripts are compiled into MapReduce jobs and executed on Hadoop clusters

5. Workflow Scheduling :

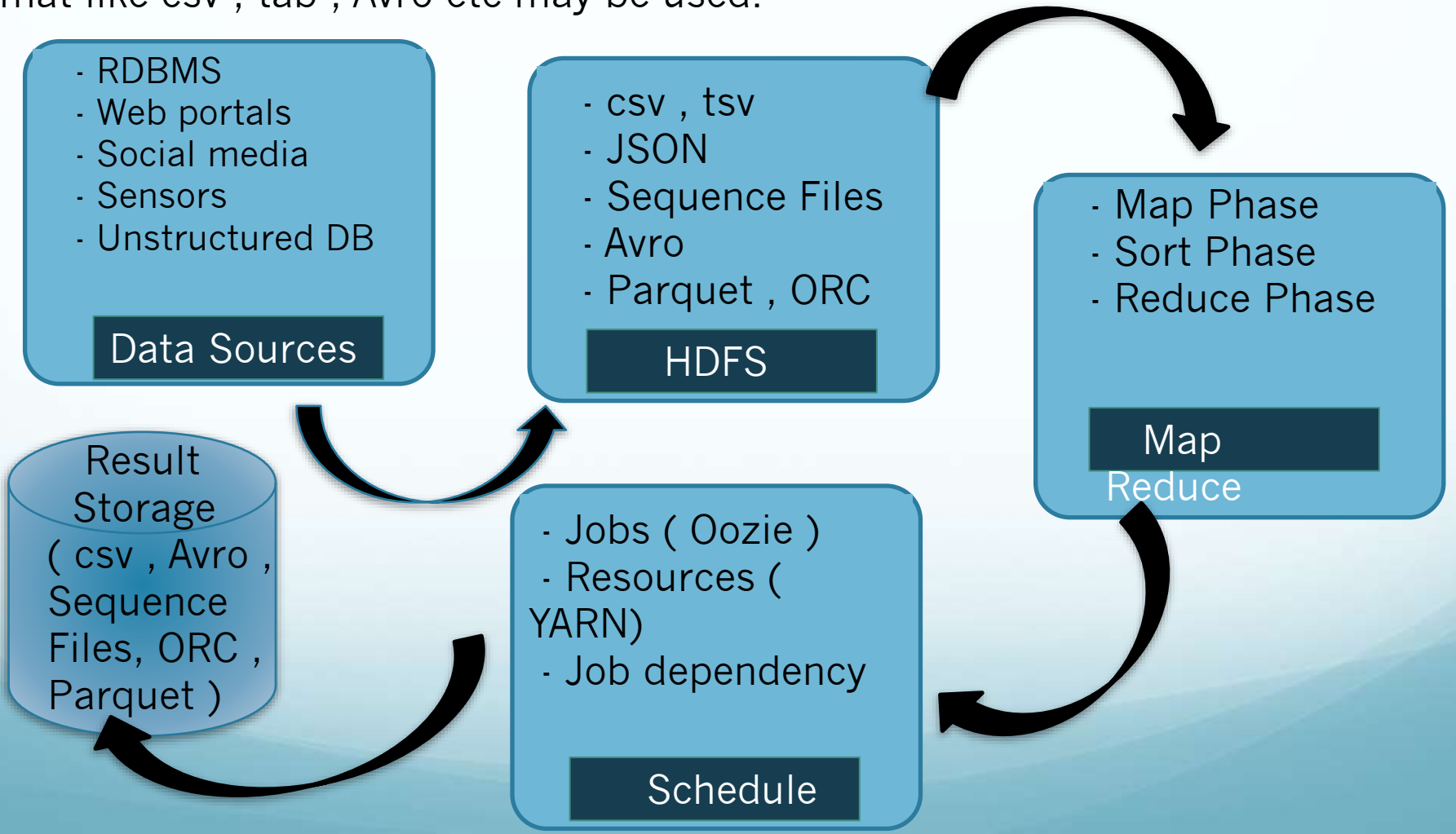
Once we have imported the data from various data sources , saved it on HDFS and ready to perform MapReduce operation using tools the next step is to automate and schedule these jobs using tools like Oozie. We can use this tool to automates and manages the execution of multiple Hadoop jobs. It allows users to define dependencies between jobs and schedule them to run in a particular sequence.

6. Result Storage :

The Result Storage step is the final stage in a Hadoop workflow, particularly after a MapReduce or other distributed processing job has been completed. This step

Analyzing data with Hadoop (contd)

involves saving the output produced by the reducer tasks to HDFS (Hadoop Distributed File System) or another storage system such as HBase, S3, etc. The output files from different reducers may need to be concatenated or combined to create a single file, depending on the use case. To store appropriate storage format like csv , tab , Avro etc may be used.



Design of Hadoop distributed file system (HDFS)

- HDFS (Hadoop Distributed File System) is a core component of the Hadoop ecosystem, designed to store massive amounts of data reliably and efficiently across a distributed cluster. It follows a set of principles and design ideas tailored to handle big data workloads, ensuring scalability, fault tolerance, and high throughput.
- The architecture of HDFS is optimized for write-once, read-many patterns, making it suitable for storing large files and supporting distributed data processing frameworks like MapReduce, Hive, and Spark.
- Following are the Key Design Principles that are followed in HADOOP.

1. Master-Slave Architecture

HDFS follows a **master-slave architecture**, where the master node manages the metadata and overall operation of the system, while the slave nodes store the actual data. The master node does not store actual data but rather tracks where the blocks of each file are stored across the DataNodes. It only stores data such as file locations, permissions, block mapping etc .

The data nodes are the worker nodes that store the actual data blocks. Each DataNode is responsible for managing the storage attached to it and periodically reporting the status of its blocks to the Master node. They perform read and write requests from clients and replicate data blocks as instructed by the Master node.

This architecture allows Master node to focus on meta data while data nodes on storing and scaling up for data storage and performance.

Design of Hadoop distributed file system (contd)

2. Rack Aware

HDFS is rack-aware, meaning that it is designed to consider the physical topology of the network when replicating data. It ensures that replicas of data blocks are stored on different machines to improve fault tolerance. In a large data center, machines are often grouped into racks, with high-bandwidth connections within a rack but slower cross-rack communication. By storing replicas across different racks, HDFS ensures that if an entire rack fails (e.g., due to a network switch failure), the data is still available from nodes in other racks.

3. Write Once, Read Many

HDFS allows files to be written once but read multiple times. This model reduces the complexity of managing concurrent write operations in a distributed system. This means that once a file is written to HDFS, it cannot be modified. It can only be read or appended to. This simplifies the design of HDFS and improves data consistency and integrity eliminating the need for locking and concurrency control mechanisms.

4. Portability

HDFS is designed to be hardware-agnostic and portable across various hardware configurations. It can run on commodity hardware, allowing organizations to build large-scale storage systems without expensive infrastructure. This reduces the cost of setting up a Hadoop cluster.

Design of Hadoop distributed file system (contd)

5. Data Integrity and Consistency

HDFS ensures that data stored in the system is consistent and remains intact even in the case of failures. It uses **checksums** to validate the integrity of the data blocks stored on DataNodes. Each block is checked for corruption, and if a corrupt block is found, it is replaced with a replica from another node. HDFS supports atomic file writes. Once a file is written to HDFS, it cannot be modified. This write-once design ensures data consistency and simplifies file management in a distributed system.

6. Scalability & Load Balancing

HDFS is designed to scale out easily, meaning it can handle more data and more processing by simply adding more nodes to the cluster. This makes HDFS suitable for storing and processing petabyte-scale datasets.

Hadoop Streaming

- It is a utility or feature that comes with a Hadoop distribution that allows developers or programmers to write the Map-Reduce program using different programming languages like Ruby, Perl, Python, C++, etc.
- In fact, we can use any language that can read from the standard input(STDIN) like keyboard input and all and write using standard output(STDOUT).
- Essentially, Hadoop Streaming lets you implement the map and reduce phases of the MapReduce model using simple scripts or executable programs.
- It allows the processing of large datasets by running scripts that read input, perform transformations, and output the results.

Hadoop Streaming Working :

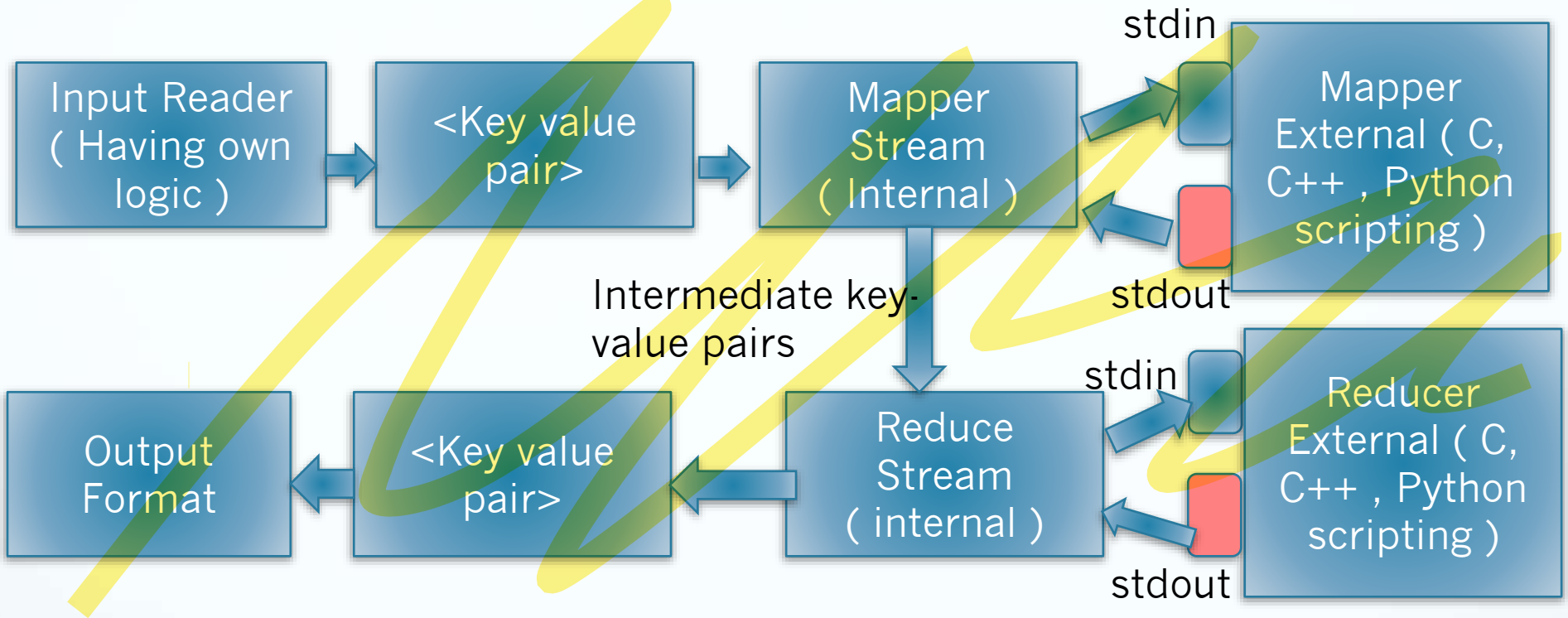
Input Data: The input is usually stored in HDFS. Hadoop Streaming treats this as a collection of files and splits the data into chunks to be processed by the mapper script.

Mapper Phase: The mapper script reads the input data, processes it, and generates key-value pairs. The input is fed to the mapper via stdin, and the output is written to stdout in the form of key-value pairs, separated by a tab or space.

Shuffle and Sort: Hadoop's MapReduce framework automatically handles this phase, where the intermediate outputs from the mapper are shuffled and grouped by key, and then passed to the reducer.

Reducer Phase: The reducer script reads the sorted key-value pairs and performs the aggregation or final computation.

Hadoop Streaming (contd)



- In the above block diagram we have an Input Reader which is responsible for reading the input data and produces the list of key-value pairs.
- We can read data in .csv format, in delimiter format, from a database table, image data(.jpg, .png), audio data etc.
- The input reader contains the complete logic about the data it is reading. Suppose we want to read an image then we have to specify the logic in the input reader so that it can read that image data and finally it will generate key-value pairs for that image data.

Hadoop Streaming (contd)

- The list of key-value pairs is fed to the Map phase and Mapper will work on each of these key-value pair of each pixel and generate some intermediate key-value pairs which are then fed to the Reducer after doing shuffling and sorting then the final output produced by the reducer will be written to the HDFS.
- We can create our external mapper and run it as an external separate process.
- As the key-value pairs are passed to the internal mapper the internal mapper process send these key-value pairs in turn to the external mapper where we have written our code in some other language like with python with help of STDIN.
- The external map processes are not part of the basic MapReduce flow. This external mapper will take input from STDIN and produce output to STDOUT.
- The external mappers process these key-value pairs and generate intermediate key-value pairs with help of STDOUT and send it to the internal mappers.
- Similarly, Reducer does the same thing. Once the intermediate key-value pairs are processed through the shuffle and sorting process they are fed to the internal reducer which will send these pairs to external reducer process that are working separately through the help of STDIN and gathers the output generated by external reducers with help of STDOUT and finally the output is stored to our HDFS.
- This is how Hadoop Streaming works on Hadoop which is by default available in Hadoop. We are just utilizing this feature by making our external mapper and reducers.

Data Storage Formats

There are several commonly used data storage formats in HDFS (Hadoop Distributed File System). These formats cater to different data requirements, such as binary storage, schema support, compression, and ease of use

1. CSV (Comma-Separated Values) and TSV (Tab-Separated Values)
2. JSON
3. Sequence Files
4. Avro
5. Parquet
6. Optimised Row Columnar (ORC)
7. Protobuf

1. CSV (Comma-Separated Values) and TSV (Tab-Separated Values)

CSV and TSV are plain-text formats that store tabular data, where fields are separated by commas or tabs. They are simple and widely supported but are not optimized for storage or processing in big data environments due to their text-based nature. Also they do not natively support compression or can be split . They do not include any schema information, which makes it harder to validate data consistency. Hence this format are useful for storing simple, flat table data, such as customer lists, sales records, or transaction logs.

Data Storage Formats (contd)

2. JSON (JavaScript Object Notation)

JSON is a text-based, human-readable format for representing structured data. It is commonly used in big data environments due to its flexibility and ease of use. It is easy to read and debug, which makes it popular for data exchange between systems (e.g., REST APIs). JSON is a schema-less format, allowing it to store flexible, semi-structured data. This is useful for cases where the structure of the data may vary between records. It is widely used across all programming languages and platforms, making it a popular format for data interchange. However like CSV format JSON also does not support native compression nor naturally splittable which becomes a limitation for distributed processing in Hadoop. When large JSON files are stored in HDFS, it's challenging to split them into smaller pieces for parallel processing.

3. Sequence Files

A Sequence File is a binary format that stores data as key-value pairs. It is an older Hadoop-native format primarily used for intermediate data in MapReduce jobs and can store any arbitrary Java objects. Sequence files store data as key-value pairs, where the keys and values are serialized in binary format. This makes them ideal for scenarios where data needs to be processed as key-value pairs, such as in MapReduce jobs. They can be compressed using block-level or record-level compression and also are splittable, meaning that large files can be split into multiple smaller pieces, enabling parallel processing across multiple nodes.

Data Storage Formats (contd)

4. Avro

Apache Avro is a row-based binary data serialization format that is optimized for performance and supports schema evolution. It's widely used in big data ecosystems because of its compactness, versatility, and ability to handle both structured and semi-structured data. Avro stores data row by row, making it well-suited for write-heavy workloads. It can carry their schema along with the data, which allows for easy serialization and deserialization across systems. Since it uses compact binary encoding, it reduces storage overhead. Also , Avro files are splittable, which makes them suitable for distributed processing frameworks like Hadoop MapReduce or Apache Spark. Avro is often used to store logs or sensor data that might evolve over time, as it efficiently handles schema changes.

5. Parquet

Apache Parquet is a columnar storage format, optimized for efficient reading and writing of large datasets. It was developed to provide high performance for both read-heavy and write-heavy workloads in data analytics systems. Data in Parquet is stored in a column-oriented format, meaning that the values from the same column are stored together. This enables efficient querying and retrieval of specific columns without scanning entire rows. Parquet uses efficient compression algorithms, such as Snappy, GZIP, or LZO, which reduce storage space while maintaining high performance. Parquet files are splittable, meaning large files can be divided into smaller pieces for parallel processing across different nodes in a Hadoop cluster.

Data Storage Formats (contd)

Parquet enforces a schema for the data, ensuring that the data structure is well-defined and validated. It supports rich data types like nested structures (arrays, maps), making it a great fit for complex data models.

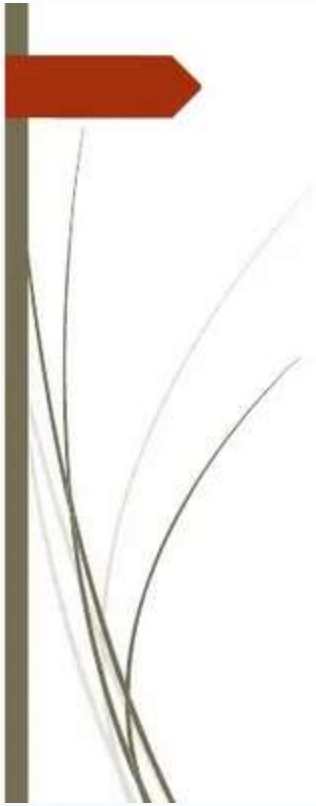
6. ORC (Optimized Row Columnar)

ORC is another columnar storage format, designed specifically for the Hadoop ecosystem, particularly for use with Apache Hive. It was introduced to improve on earlier storage formats like Sequence File by providing better compression, faster query performance, and more efficient data storage. Similar to Parquet, ORC stores data in a column-oriented format. This allows for efficient reading and writing of specific columns during query execution. ORC provides lightweight and advanced compression algorithms like **Zlib** and **Snappy** and can compress both individual columns and the entire file at different levels thus reducing the size of data stored on HDFS. ORC files are splittable also, making them suitable for parallel processing across nodes in Hadoop clusters. One speciality of ORC files are that they supports **predicate pushdown**, which allows filtering of rows during the data scan phase thereby improving query performance by reducing the amount of data processed. ORC automatically creates lightweight indexes for each column, which allows queries to be executed more efficiently by skipping irrelevant data during scans.
All these features makes ORC highly optimized for large-scale, read-heavy analytics workloads.

Data Storage Formats (contd)

Conclusion :

In the Hadoop ecosystem, choosing the right data format for storage depends on the specific needs of data processing tasks. Parquet and ORC are the top choices for columnar storage in analytical workloads, with Parquet being more general-purpose and optimized for Spark, while ORC offers deep integration with Hive and excels in structured, tabular data scenarios. For row-based storage, Avro is a great option, especially when schema evolution is needed. Sequence Files work well for intermediate MapReduce data, while JSON and CSV are popular for human-readable formats but lack the compression and efficiency of more advanced formats like Parquet or ORC.



Thanks