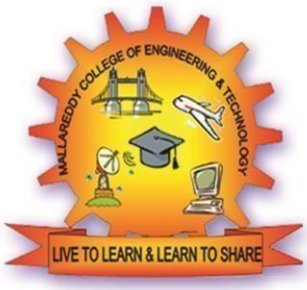
BIG DATA ANALYTICS

(R18A0529)

DIGITAL NOTES

B.TECH IV YEAR – II SEM
(2022-2023)



MALLA REDDY
COLLEGE OF ENGINEERING & TECHNOLOGY

(Autonomous Institution – UGC, Govt. of India)

Recognized under 2(f) and 12 (B) of UGC ACT 1956
(Affiliated to JNTUH, Hyderabad, Approved by AICTE - Accredited by NBA & NAAC – 'A' Grade - ISO 9001:2015 Certified)
Maisammaguda, Dhulapally (Post Via. Hakimpet), Secunderabad – 500100, Telangana State, India

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Vision

To acknowledge quality education and instill high patterns of discipline making the students technologically superior and ethically strong which involves the improvement in the quality of life in human race.

Mission

- To achieve and impart holistic technical education using the best of infrastructure, outstanding technical and teaching expertise to establish the students into competent and confident engineers.
- Evolving the center of excellence through creative and innovative teaching learning practicesforpromotingacademicachievementtoproduceinternationallyacceptedcompetitiveand world class professionals.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

PEO1–ANALYTICALSKILLS

- To facilitate the graduates with the ability to visualize, gather information, articulate, analyze, solve complex problems, and make decisions. These are essential to address the challenges of complex and computation intensive problems increasing their productivity.

PEO2–TECHNICALSKILLS

- Tofacilitatethegraduateswiththetechnicalskillsthatpreparethemforimmediateemploymentandpursue certification providing a deeper understanding of the technology in advanced areas of computer science and related fields, thus encouraging pursuing higher education and research based on their interest.

PEO3–SOFTSKILLS

- To facilitate the graduates with the soft skills that include fulfilling the mission, setting goals, showing self confidence by communicating effectively, having a positive attitude, get involved in team-work, being a leader, managing their career and their life.

PEO4–PROFESSIONALETHICS

- To facilitate the graduates with the knowledge of professional and ethical responsibilities by paying attention to grooming, being conservative with style, following dress codes, safety codes, and adapting them to technological advancements.

PROGRAM SPECIFIC OUTCOMES (PSOs)

After the completion of the course, B.Tech Computer Science and Engineering, the graduates will have the following Program Specific Outcomes:

1.FundamentalsandcriticalknowledgeoftheComputerSystem:-
AbletoUnderstandtheworkingprinciples of the computer System and its components, Apply the knowledge to build, asses, and analyze the software and hardware aspects of it.

2.The comprehensive and Applicative knowledge of Software Development: Comprehensive skills of Programming Languages, Software process models, methodologies, and able to plan, develop, test, analyze, and manage the software and hardware intensive systems in heterogeneous platforms individually or working in teams.

3.Applications of Computing Domain & Research: Able to use the professional, managerial, interdisciplinary skill set, and domain specific tools in development processes, identify their search gaps, and provide innovative solutions to them.

PROGRAM OUTCOMES (POs)

Engineering Graduates should possess the following:

1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals,andanengineeringspecializationtothesolutionofcomplexengineeringproblems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design / development of solutions: Design solutions for complex engineeringproblemsanddesignsystemcomponentsorprocessesthatmeetthespecifiedneedswithappropriateconsideration for thepublic health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

BIG DATA ANALYTICS

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Text Book:

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UNIT – I

What is Big Data?

According to Gartner, the definition of Big Data –

"Big data" is high-volume, velocity, and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making."

This definition clearly answers the "What is Big Data?" question – Big Data refers to complex and large data sets that have to be processed and analyzed to uncover valuable information that can benefit businesses and organizations.

However, there are certain basic tenets of Big Data that will make it even simpler to answer what is Big Data:

- It refers to a massive amount of data that keeps on growing exponentially with time.
- It is so voluminous that it cannot be processed or analyzed using conventional data processing techniques.
- It includes data mining, data storage, data analysis, data sharing, and data visualization.
- The term is an all-comprehensive one including data, data frameworks, along with the tools and techniques used to process and analyze the data.

The History of Big Data

Although the concept of big data itself is relatively new, the origins of large data sets go back to the 1960s and '70s when the world of data was just getting started with the first data centers and the development of the relational database.

Around 2005, people began to realize just how much data users generated through Facebook, YouTube, and other online services. Hadoop (an open-source framework created specifically to store and analyze big data sets) was developed that same year. NoSQL also began to gain popularity during this time.

The development of open-source frameworks, such as Hadoop (and more recently, Spark) was essential for the growth of big data because they make big data easier to work with and cheaper to store. In the years since then, the volume of big data has skyrocketed. Users are still generating huge amounts of data—but it's not just humans who are doing it.

With the advent of the Internet of Things (IoT), more objects and devices are connected to the internet, gathering data on customer usage patterns and product performance. The emergence of machine learning has produced still more data.

While big data has come far, its usefulness is only just beginning. Cloud computing has expanded big data possibilities even further. The cloud offers truly elastic scalability, where developers can simply spin up ad hoc clusters to test a subset of data.

Benefits of Big Data and Data Analytics

- Big data makes it possible for you to gain more complete answers because you have more information.
- More complete answers mean more confidence in the data—which means a completely different approach to tackling problems.

Types of Big Data

Now that we are on track with what is big data, let's have a look at the types of big data:

a) Structured

Structured is one of the types of big data and By structured data, we mean data that can be processed, stored, and retrieved in a fixed format. It refers to highly organized information that can be readily and seamlessly stored and accessed from a database by simple search engine algorithms. **For instance, the employee table in a company database will be structured as the employee details, their job positions, their salaries, etc.,** will be present in an organized manner.

b) Unstructured

Unstructured data refers to the data that lacks any specific form or structure whatsoever. This makes it very difficult and time-consuming to process and analyze unstructured data. Email is an example of unstructured data. Structured and unstructured are two important types of big data.

c) Semi-structured

Semi structured is the third type of big data. Semi-structured data pertains to the data containing both the formats mentioned above, that is, structured and unstructured data. To be precise, it refers to the data that although has not been classified under a particular repository (database), yet contains vital information or tags that segregate individual elements within the data. Thus we come to the end of types of data.

Characteristics of Big Data

Back in 2001, Gartner analyst Doug Laney listed the **3 'V's of Big Data – Variety, Velocity, and Volume.** Let's discuss the characteristics of big data. These characteristics, isolated, are enough to know what big data is. Let's look at them in depth:

a) Variety

Variety of Big Data refers to structured, unstructured, and semi-structured data that is gathered from multiple sources. While in the past, data could only be collected from spreadsheets and databases, today data comes in an array of forms such as emails, PDFs, photos, videos, audios, SM posts, and so much more. Variety is one of the important characteristics of big data.

b) Velocity

Velocity essentially refers to the speed at which data is being created in real-time. In a broader prospect, it comprises the rate of change, linking of incoming data sets at varying speeds, and activity bursts.

c) Volume

Volume is one of the characteristics of big data. We already know that Big Data indicates huge 'volumes' of data that is being generated on a daily basis from various sources like social media platforms, business processes, machines, networks, human interactions, etc. Such a large amount of data is stored in data warehouses. Thus comes to the end of characteristics of big data.

Why is Big Data Important?

The importance of big data does not revolve around how much data a company has but how a company utilizes the collected data. Every company uses data in its own way; the more efficiently a company uses its data, the more potential it has to grow. The company can take data from any source and analyze it to find answers which will enable:

1. **Cost Savings**: Some tools of Big Data like Hadoop and Cloud-Based Analytics can bring cost advantages to business when large amounts of data are to be stored and these tools also help in identifying more efficient ways of doing business.
2. **Time Reductions: The** high speed of tools like Hadoop and in-memory analytics can easily identify new sources of data which helps businesses analyzing data immediately and make quick decisions based on the learning.
3. **Understand the market conditions**: By analyzing big data you can get a better understanding of current market conditions. For example, by analyzing customers' purchasing behaviors, a company can find out the products that are sold the most and produce products according to this trend. By this, it can get ahead of its competitors.
4. **Control online reputation:** Big data tools can do sentiment analysis. Therefore, you can get feedback about who is saying what about your company. If you want to monitor and improve the online presence of your business, then, big data tools can help in all this.
5. **Using Big Data Analytics to Boost Customer Acquisition and Retention**
   The customer is the most important asset any business depends on. There is no single business that can claim success without first having to establish a solid customer base. However, even with a customer base, a business cannot afford to disregard the high competition it faces. If a business is slow to learn what customers are looking for, then it is very easy to begin offering poor quality products. In the end, loss of clientele will result, and this creates an adverse overall effect on business success. The use of big data allows businesses to observe various customer related patterns and trends. Observing customer behavior is important to trigger loyalty.
6. **Using Big Data Analytics to Solve Advertisers Problem and Offer Marketing Insights**

Big data analytics can help change all business operations. This includes the ability to match customer expectation, changing company's product line and of course ensuring that the marketing campaigns are powerful.

7. **Big Data Analytics As a Driver of Innovations and Product Development**
   Another huge advantage of big data is the ability to help companies innovate and redevelop their products.

Business Intelligence vs Big Data

Although Big Data and Business Intelligence are two technologies used to analyze data to help companies in the decision-making process, there are differences between both of them. They differ in the way they work as much as in the type of data they analyze.

Traditional BI methodology is based on the principle of grouping all business data into a central server. Typically, this data is analyzed in offline mode, after storing the information in an environment called Data Warehouse. The data is structured in a conventional relational database with an additional set of indexes and forms of access to the tables (multidimensional cubes).

A Big Data solution differs in many aspects to BI to use. These are the main differences between Big Data and Business Intelligence:

1. In a Big Data environment, information is stored on a distributed file system, rather than on a central server. It is a much safer and more flexible space.
2. Big Data solutions carry the processing functions to the data, rather than the data to the functions. As the analysis is centered on the information, it´s easier to handle larger amounts of information in a more agile way.
3. Big Data can analyze data in different formats, both structured and unstructured. The volume of unstructured data (those not stored in a traditional database) is growing at levels much higher than the structured data. Nevertheless, its analysis carries different challenges. Big Data solutions solve them by allowing a global analysis of various sources of information.
4. Data processed by Big Data solutions can be historical or come from real-time sources. Thus, companies can make decisions that affect their business in an agile and efficient way.
5. Big Data technology uses parallel mass processing (MPP) concepts, which improves the speed of analysis. With MPP many instructions are executed simultaneously, and since the various jobs are divided into several parallel execution parts, at the end the overall results are reunited and presented. This allows you to analyze large volumes of information quickly.

Big Data vs Data Warehouse

Big Data has become the reality of doing business for organizations today. There is a boom in the amount of structured as well as raw data that floods every organization daily. If this data is managed well, it can lead to powerful insights and quality decision making.

Big data analytics is the process of examining large data sets containing a variety of data types to discover some knowledge in databases, to identify interesting patterns and establish relationships to solve problems, market trends, customer preferences, and other useful information. Companies and businesses that implement Big Data Analytics often reap several business benefits. Companies implement Big Data Analytics because they want to make more informed business decisions.

A data warehouse (DW) is a collection of corporate information and data derived from operational systems and external data sources. A data warehouse is designed to support business decisions by allowing data consolidation, analysis and reporting at different aggregate levels. Data is populated into the Data Warehouse through the processes of extraction, transformation and loading (ETL tools). Data analysis tools, such as business intelligence software, access the data within the warehouse.

Hadoop Environment Big Data Analytics

Hadoop is changing the perception of handling Big Data especially the unstructured data. Let's know how Apache Hadoop software library, which is a framework, plays a vital role in handling Big Data. Apache Hadoop enables surplus data to be streamlined for any distributed processing system across clusters of computers using simple programming models. It truly is made to scale up from single servers to a large number of machines, each and every offering local computation, and storage space. Instead of depending on hardware to provide high-availability, the library itself is built to detect and handle breakdowns at the application layer, so providing an extremely available service along with a cluster of computers, as both versions might be vulnerable to failures.

Hadoop Community Package Consists of

- File system and OS level abstractions
- A MapReduce engine (either MapReduce or YARN)
- The Hadoop Distributed File System (HDFS)
- Java ARchive (JAR) files
- Scripts needed to start Hadoop
- Source code, documentation and a contribution section

Activities performed on Big Data

- **Store** – Big data need to be collected in a seamless repository, and it is not necessary to store in a single physical database.
- **Process** – The process becomes more tedious than traditional one in terms of cleansing, enriching, calculating, transforming, and running algorithms.
- **Access** – There is no business sense of it at all when the data cannot be searched, retrieved easily, and can be virtually showcased along the business lines.

Classification of analytics

Descriptive analytics

Descriptive analytics is a statistical method that is used to search and summarize historical data in order to identify patterns or meaning.

Data aggregation and **data mining** are two techniques used in descriptive analytics to discover historical data. Data is first gathered and sorted by data aggregation in order to make the datasets more manageable by analysts.

Data mining describes the next step of the analysis and involves a search of the data to identify patterns and meaning. Identified patterns are analyzed to discover the specific ways that learners interacted with the learning content and within the learning environment.

Advantages:

- Quickly and easily report on the Return on Investment (ROI) by showing how performance achieved business or target goals.
- Identify gaps and performance issues early - before they become problems.
- Identify specific learners who require additional support, regardless of how many students or employees there are.
- Identify successful learners in order to offer positive feedback or additional resources.
- Analyze the value and impact of course design and learning resources.

Predictive analytics

Predictive Analytics is a statistical method that utilizes algorithms and machine learning to identify trends in data and predict future behaviors

The software for predictive analytics has moved beyond the realm of statisticians and is becoming more affordable and accessible for different markets and industries, including the field of learning & development.

For online learning specifically, predictive analytics is often found incorporated in the Learning Management System (LMS), but can also be purchased separately as specialized software.

For the learner, predictive forecasting could be as simple as a dashboard located on the main screen after logging in to access a course. Analyzing data from past and current progress, visual indicators in the dashboard could be provided to signal whether the employee was on track with training requirements.

Advantages:

- **Personalize the training needs** of employees by identifying their gaps, strengths, and weaknesses; specific learning resources and training can be offered to support individual needs.
- **Retain Talent** by tracking and understanding employee career progression and forecasting what skills and learning resources would best benefit their career paths. Knowing what skills employees need also benefits the design of future training.
- **Support employees** who may be falling behind or not reaching their potential by offering intervention support before their performance puts them at risk.
- **Simplified reporting** and visuals that keep everyone updated when predictive forecasting is required.

Prescriptive analytics

Prescriptive analytics is a statistical method used to generate recommendations and make decisions based on the computational findings of algorithmic models.

Generating automated decisions or recommendations requires specific and unique algorithmic models and clear direction from those utilizing the analytical technique. A recommendation cannot be generated without knowing what to look for or what problem is desired to be solved. In this way, prescriptive analytics begins with a problem.

Example

A Training Manager uses predictive analysis to discover that most learners without a particular skill will not complete the newly launched course. What could be done? Now prescriptive analytics can be of assistance on the matter and help determine options for action. Perhaps an algorithm can detect the learners who require that new course, but lack that particular skill, and send an automated recommendation that they take an additional training resource to acquire the missing skill.

The accuracy of a generated decision or recommendation, however, is only as good as the quality of data and the algorithmic models developed. What may work for one company's training needs may not make sense when put into practice in another company's training department. Models are generally recommended to be tailored for each unique situation and need.

Descriptive vs Predictive vs Prescriptive Analytics

Descriptive Analytics is focused solely on historical data.

You can think of Predictive Analytics as then using this historical data to develop statistical models that will then forecast about future possibilities.

Prescriptive Analytics takes Predictive Analytics a step further and takes the possible forecasted outcomes and predicts consequences for these outcomes.

What Big Data Analytics Challenges

1. Need For Synchronization Across Disparate Data Sources

As data sets are becoming bigger and more diverse, there is a big challenge to incorporate them into an analytical platform. If this is overlooked, it will create gaps and lead to wrong messages and insights.

2. Acute Shortage Of Professionals Who Understand Big Data Analysis

The analysis of data is important to make this voluminous amount of data being produced in every minute, useful. With the exponential rise of data, a huge demand for big data scientists and Big Data analysts has been created in the market. It is important for business organizations to hire a data scientist having skills that are varied as the job of a data scientist is multidisciplinary. Another major challenge faced by businesses is the shortage of professionals who understand Big Data analysis. There is a sharp shortage of data scientists in comparison to the massive amount of data being produced.

3. Getting Meaningful Insights Through The Use Of Big Data Analytics

It is imperative for business organizations to gain important insights from Big Data analytics, and also it is important that only the relevant department has access to this information. A big challenge faced by the companies in the Big Data analytics is mending this wide gap in an effective manner.

4. Getting Voluminous Data Into The Big Data Platform

It is hardly surprising that data is growing with every passing day. This simply indicates that business organizations need to handle a large amount of data on daily basis. The amount and variety of data available these days can overwhelm any data engineer and that is why it is considered vital to make data accessibility easy and convenient for brand owners and managers.

5. Uncertainty Of Data Management Landscape

With the rise of Big Data, new technologies and companies are being developed every day. However, a big challenge faced by the companies in the Big Data analytics is to find out which technology will be best suited to them without the introduction of new problems and potential risks.

6. Data Storage And Quality

Business organizations are growing at a rapid pace. With the tremendous growth of the companies and large business organizations, increases the amount of data produced. The storage of this massive amount of data is becoming a real challenge for everyone. Popular data storage options like data lakes/ warehouses are commonly used to gather and store large quantities of unstructured and structured data in its native format. The real problem arises when a data lakes/ warehouse try to combine unstructured and inconsistent data from diverse sources, it encounters errors. Missing data, inconsistent data, logic conflicts, and duplicates data all result in data quality challenges.

7. Security And Privacy Of Data

Once business enterprises discover how to use Big Data, it brings them a wide range of possibilities and opportunities. However, it also involves the potential risks associated with big data when it comes to the privacy and the security of the data. The Big Data tools used for analysis and storage utilizes the data disparate sources. This eventually leads to a high risk of exposure of the data, making it vulnerable. Thus, the rise of voluminous amount of data increases privacy and security concerns.

Terminologies Used In Big Data Environments

- **As-a-service infrastructure**

Data-as-a-service, software-as-a-service, platform-as-a-service – all refer to the idea that rather than selling data, licences to use data, or platforms for running Big Data technology, it can be provided “as a service”, rather than as a product. This reduces the upfront capital investment

necessary for customers to begin putting their data, or platforms, to work for them, as the provider bears all of the costs of setting up and hosting the infrastructure. As a customer, as-a-service infrastructure can greatly reduce the initial cost and setup time of getting Big Data initiatives up and running.

- **Data science**

Data science is the professional field that deals with turning data into value such as new insights or predictive models. It brings together expertise from fields including statistics, mathematics, computer science, communication as well as domain expertise such as business knowledge. Data scientist has recently been voted the No 1 job in the U.S., based on current demand and salary and career opportunities.

- **Data mining**

Data mining is the process of discovering insights from data. In terms of Big Data, because it is so large, this is generally done by computational methods in an automated way using methods such as decision trees, clustering analysis and, most recently, machine learning. This can be thought of as using the brute mathematical power of computers to spot patterns in data which would not be visible to the human eye due to the complexity of the dataset.

- **Hadoop**

Hadoop is a framework for Big Data computing which has been released into the public domain as open source software, and so can freely be used by anyone. It consists of a number of modules all tailored for a different vital step of the Big Data process – from file storage (Hadoop File System – HDFS) to database (HBase) to carrying out data operations (Hadoop MapReduce – see below). It has become so popular due to its power and flexibility that it has developed its own industry of retailers (selling tailored versions), support service providers and consultants.

- **Predictive modelling**

At its simplest, this is predicting what will happen next based on data about what has happened previously. In the Big Data age, because there is more data around than ever before, predictions are becoming more and more accurate. Predictive modelling is a core component of most Big Data initiatives, which are formulated to help us choose the course of action which will lead to the most desirable outcome. The speed of modern computers and the volume of data available means that predictions can be made based on a huge number of variables, allowing an ever-increasing number of variables to be assessed for the probability that it will lead to success.

- **MapReduce**

MapReduce is a computing procedure for working with large datasets, which was devised due to difficulty of reading and analysing really Big Data using conventional computing methodologies. As its name suggest, it consists of two procedures – mapping (sorting information into the format needed for analysis – i.e. sorting a list of people according to their age) and reducing (performing an operation, such checking the age of everyone in the dataset to see who is over 21).

- **NoSQL**

NoSQL refers to a database format designed to hold more than data which is simply arranged into tables, rows, and columns, as is the case in a conventional relational database. This database format has proven very popular in Big Data applications because Big Data is often messy, unstructured and does not easily fit into traditional database frameworks.

- **Python**

Python is a programming language which has become very popular in the Big Data space due to its ability to work very well with large, unstructured datasets (see Part II for the difference between structured and unstructured data). It is considered to be easier to learn for a data science beginner than other languages such as R (see also Part II) and more flexible.

- **R Programming**

R is another programming language commonly used in Big Data, and can be thought of as more specialised than Python, being geared towards statistics. Its strength lies in its powerful handling of structured data. Like Python, it has an active community of users who are constantly expanding and adding to its capabilities by creating new libraries and extensions.

- **Recommendation engine**

A recommendation engine is basically an algorithm, or collection of algorithms, designed to match an entity (for example, a customer) with something they are looking for. Recommendation engines used by the likes of Netflix or Amazon heavily rely on Big Data technology to gain an overview of their customers and, using predictive modelling, match them with products to buy or content to consume. The economic incentives offered by recommendation engines has been a driving force behind a lot of commercial Big Data initiatives and developments over the last decade.

- **Real-time**

Real-time means "as it happens" and in Big Data refers to a system or process which is able to give data-driven insights based on what is happening at the present moment. Recent years have seen a large push for the development of systems capable of processing and offering insights in real-time (or near-real-time), and advances in computing power as well as development of techniques such as machine learning have made it a reality in many applications today.

- **Reporting**

The crucial "last step" of many Big Data initiative involves getting the right information to the people who need it to make decisions, at the right time. When this step is automated, analytics is applied to the insights themselves to ensure that they are communicated in a way that they will be understood and easy to act on. This will usually involve creating multiple reports based on the same data or insights but each intended for a different audience (for example, in-depth technical analysis for engineers, and an overview of the impact on the bottom line for c-level executives).

- **Spark**

Spark is another open source framework like Hadoop but more recently developed and more suited to handling cutting-edge Big Data tasks involving real time analytics and machine learning. Unlike Hadoop it does not include its own filesystem, though it is designed to work with Hadoop's HDFS or a number of other options. However, for certain data related processes it is able to calculate at over 100 times the speed of Hadoop, thanks to its in-memory processing capability. This means it is becoming an increasingly popular choice for projects involving deep learning, neural networks and other compute-intensive tasks.

- **Structured Data**

Structured data is simply data that can be arranged neatly into charts and tables consisting of rows, columns or multi-dimensioned matrixes. This is traditionally the way that computers have stored data, and information in this format can easily and simply be processed and mined for insights. Data gathered from machines is often a good example of structured data, where various data points – speed, temperature, rate of failure, RPM etc. – can be neatly recorded and tabulated for analysis.

- **Unstructured Data**

Unstructured data is any data which cannot easily be put into conventional charts and tables. This can include video data, pictures, recorded sounds, text written in human languages and a great deal more. This data has traditionally been far harder to draw insight from using computers which were generally designed to read and analyze structured information. However, since it has become apparent that a huge amount of value can be locked away in this unstructured data, great efforts have been made to create applications which are capable of understanding unstructured data – for example visual recognition and natural language processing.

- **Visualization**

Humans find it very hard to understand and draw insights from large amounts of text or numerical data – we can do it, but it takes time, and our concentration and attention is limited. For this reason effort has been made to develop computer applications capable of rendering information in a visual form – charts and graphics which highlight the most important insights which have resulted from our Big Data projects. A subfield of reporting (see above), visualizing is now often an automated process, with visualizations customized by algorithm to be understandable to the people who need to act or take decisions based on them.

Basic availability, Soft state and Eventual consistency

Basic availability implies continuous system availability despite network failures **and** tolerance to temporary in**consistency**.

Soft state refers to **state** change without input which is required for **eventual consistency**.

Eventual consistency means that if no further updates are made to a given updated data**base** item for long enough period of time , all users will see the same value for the updated item.

Top Analytics Tools

*** R** is a language for statistical computing and graphics. It also used for big data analysis. It provides a wide variety of statistical tests.

Features:

- Effective data handling and storage facility,
- It provides a suite of operators for calculations on arrays, in particular, matrices,
- It provides coherent, integrated collection of big data tools for data analysis
- It provides graphical facilities for data analysis which display either on-screen or on hardcopy

*** Apache Spark** is a powerful open source big data analytics tool. It offers over 80 high-level operators that make it easy to build parallel apps. It is used at a wide range of organizations to process large datasets.

Features:

- It helps to run an application in Hadoop cluster, up to 100 times faster in memory, and ten times faster on disk
- It offers lighting Fast Processing
- Support for Sophisticated Analytics
- Ability to Integrate with Hadoop and Existing Hadoop Data

*** Plotly** is an analytics tool that lets users create charts and dashboards to share online.

Features:

- Easily turn any data into eye-catching and informative graphics
- It provides audited industries with fine-grained information on data provenance
- Plotly offers unlimited public file hosting through its free community plan

*** Lumify** is a big data fusion, analysis, and visualization platform. It helps users to discover connections and explore relationships in their data via a suite of analytic options.

Features:

- It provides both 2D and 3D graph visualizations with a variety of automatic layouts

- It provides a variety of options for analyzing the links between entities on the graph
- It comes with specific ingest processing and interface elements for textual content, images, and videos
- It spaces feature allows you to organize work into a set of projects, or workspaces
- It is built on proven, scalable big data technologies

*** IBM SPSS Modeler** is a predictive big data analytics platform. It offers predictive models and delivers to individuals, groups, systems and the enterprise. It has a range of advanced algorithms and analysis techniques.

Features:

- Discover insights and solve problems faster by analyzing structured and unstructured data
- Use an intuitive interface for everyone to learn
- You can select from on-premises, cloud and hybrid deployment options
- Quickly choose the best performing algorithm based on model performance

*** MongoDB** is a NoSQL, document-oriented database written in C, C++, and JavaScript. It is free to use and is an open source tool that supports multiple operating systems including Windows Vista (and later versions), OS X (10.7 and later versions), Linux, Solaris, and FreeBSD.

Its main features include Aggregation, Adhoc-queries, Uses BSON format, Sharding, Indexing, Replication, Server-side execution of javascript, Schemaless, Capped collection, MongoDB management service (MMS), load balancing and file storage.

Features:

- Easy to learn.
- Provides support for multiple technologies and platforms.
- No hiccups in installation and maintenance.
- Reliable and low cost.

UNIT II

NoSQL

NoSQL is a non-relational DMS, that does not require a fixed schema, avoids joins, and is easy to scale. NoSQL database is used for distributed data stores with humongous data storage needs. NoSQL is used for Big data and real-time web apps. For example companies like Twitter, Facebook, Google that collect terabytes of user data every single day.

SQL

Structured Query language (SQL) **pronounced as "S-Q-L" or sometimes as "See-Quel**" is the standard language for dealing with Relational Databases. A relational database defines relationships in the form of tables.

SQL programming can be effectively used to insert, search, update, delete database records.

Comparison of SQL and NoSQL

Parameter	**SQL**	**NOSQL**
Definition	SQL databases are primarily called RDBMS or Relational Databases	NoSQL databases are primarily called as Non-relational or distributed database
Design for	Traditional RDBMS uses SQL syntax and queries to analyze and get the data for further insights. They are used for OLAP systems.	NoSQL database system consists of various kind of database technologies. These databases were developed in response to the demands presented for the development of the modern application.
Query Language	Structured query language (SQL)	No declarative query language
Type	SQL databases are table based databases	NoSQL databases can be document based, key-value pairs, graph databases
Schema	SQL databases have a predefined schema	NoSQL databases use dynamic schema for unstructured data.
Ability to scale	SQL databases are vertically scalable	NoSQL databases are horizontally scalable
Examples	Oracle, Postgres, and MS-SQL.	MongoDB, Redis, , Neo4j, Cassandra, Hbase.
Best suited for	An ideal choice for the complex query intensive environment.	It is not good fit complex queries.
Hierarchical data storage	SQL databases are not suitable for hierarchical data storage.	More suitable for the hierarchical data store as it supports key-value pair method.
Variations	One type with minor variations.	Many different types which include key-value stores, document databases, and graph databases.

Development Year	It was developed in the 1970s to deal with issues with flat file storage	Developed in the late 2000s to overcome issues and limitations of SQL databases.
Open-source	A mix of open-source like Postgres & MySQL, and commercial like Oracle Database.	Open-source
Consistency	It should be configured for strong consistency.	It depends on DBMS as some offers strong consistency like MongoDB, whereas others offer only offers eventual consistency, like Cassandra.
Best Used for	RDBMS database is the right option for solving ACID problems.	NoSQL is a best used for solving data availability problems
Importance	It should be used when data validity is super important	Use when it's more important to have fast data than correct data
Best option	When you need to support dynamic queries	Use when you need to scale based on changing requirements
Hardware	Specialized DB hardware (Oracle Exadata, etc.)	Commodity hardware
Network	Highly available network (Infiniband, Fabric Path, etc.)	Commodity network (Ethernet, etc.)
Storage Type	Highly Available Storage (SAN, RAID, etc.)	Commodity drives storage (standard HDDs, JBOD)
Best features	Cross-platform support, Secure and free	Easy to use, High performance, and Flexible tool.
Top Companies Using	Hootsuite, CircleCI, Gauges	Airbnb, Uber, Kickstarter
Average salary	The average salary for any professional SQL Developer is $84,328 per year in the U.S.A.	The average salary for "NoSQL developer" ranges from approximately $72,174 per year
ACID vs. BASE Model	ACID(Atomicity, Consistency, Isolation, and Durability) is a standard for RDBMS	Base (Basically Available, Soft state, Eventually Consistent) is a model of many NoSQL systems

RDBMS Versus Hadoop

Criteria	Hadoop	RDBMS
Schema	Based on 'Schema on Read'.	Based on 'Schema on Write'.
Data Type	Structured, Semi-Structured and Unstructured data.	Structured Data.
Speed	Writes are Fast.	Reads are Fast.
Cost	Open source framework, free of cost.	Licensed software, Paid.
Application	Data discovery, Storage and processing of Unstructured data.	OLTP and complex ACID transaction.

Distributed Computing Challenges

Designing a distributed system does not come as easy and straight forward. A number of challenges need to be overcome in order to get the ideal system. The major challenges in distributed systems are listed below:

1. Heterogeneity:

The Internet enables users to access services and run applications over a heterogeneous collection of computers and networks. Heterogeneity (that is, variety and difference) applies to all of the following:

- Hardware devices: computers, tablets, mobile phones, embedded devices, etc.
- Operating System: Ms Windows, Linux, Mac, Unix, etc.
- Network: Local network, the Internet, wireless network, satellite links, etc.
- Programming languages: Java, C/C++, Python, PHP, etc.
- Different roles of software developers, designers, system managers

Different programming languages use different representations for characters and data structures such as arrays and records. These differences must be addressed if programs written in different languages are to be able to communicate with one another. Programs written by different developers cannot communicate with one another unless they use common standards, for example, for network communication and the representation of primitive data items and data structures in messages. For this to happen, standards need to be agreed and adopted – as have the Internet protocols.

Middleware: The term middleware applies to a software layer that provides a programming abstraction as well as masking the heterogeneity of the underlying networks, hardware, operating systems and programming languages. Most middleware is implemented over the Internet protocols, which themselves mask the differences of the underlying networks, but all middleware deals with the differences in operating systems and hardware

Heterogeneity and mobile code: The term mobile code is used to refer to program code that can be transferred from one computer to another and run at the destination – Java applets are an example. Code suitable for running on one computer is not necessarily suitable for running on another because executable programs are normally specific both to the instruction set and to the host operating system.

2. Transparency:

Transparency is defined as the concealment from the user and the application programmer of the separation of components in a distributed system, so that the system is perceived as a whole rather than as a collection of independent components. In other words, distributed systems designers must hide the complexity of the systems as much as they can. Some terms of transparency in distributed systems are:

Access Hide differences in data representation and how a resource is accessed
Location Hide where a resource is located
Migration Hide that a resource may move to another location
Relocation Hide that a resource may be moved to another location while in use
Replication Hide that a resource may be copied in several places
Concurrency Hide that a resource may be shared by several competitive users
Failure Hide the failure and recovery of a resource
Persistence Hide whether a (software) resource is in memory or a disk

3. Openness

The openness of a computer system is the characteristic that determines whether the system can be extended and re-implemented in various ways. The openness of distributed systems is determined primarily by the degree to which new resource-sharing services can be added and be

made available for use by a variety of client programs. If the well-defined interfaces for a system are published, it is easier for developers to add new features or replace sub-systems in the future. Example: Twitter and Facebook have API that allows developers to develop their own software interactively.

4. Concurrency

Both services and applications provide resources that can be shared by clients in a distributed system. There is therefore a possibility that several clients will attempt to access a shared resource at the same time. For example, a data structure that records bids for an auction may be accessed very frequently when it gets close to the deadline time. For an object to be safe in a concurrent environment, its operations must be synchronized in such a way that its data remains consistent. This can be achieved by standard techniques such as semaphores, which are used in most operating systems.

5. Security

Many of the information resources that are made available and maintained in distributed systems have a high intrinsic value to their users. Their security is therefore of considerable importance. Security for information resources has three components: ***confidentiality*** (protection against disclosure to unauthorized individuals) ***integrity*** (protection against alteration or corruption), ***availability*** for the authorized (protection against interference with the means to access the resources).

6. Scalability

Distributed systems must be scalable as the number of user increases. The scalability is defined by B. Clifford Neuman as

A system is said to be scalable if it can handle the addition of users and resources without suffering a noticeable loss of performance or increase in administrative complexity

Scalability has 3 dimensions:

- Size
  - Number of users and resources to be processed. Problem associated is overloading
- Geography
  - Distance between users and resources. Problem associated is communication reliability
- Administration
  - As the size of distributed systems increases, many of the system needs to be controlled. Problem associated is administrative mess

7. Failure Handling

Computer systems sometimes fail. When faults occur in hardware or software, programs may produce incorrect results or may stop before they have completed the intended computation. The handling of failures is particularly difficult.

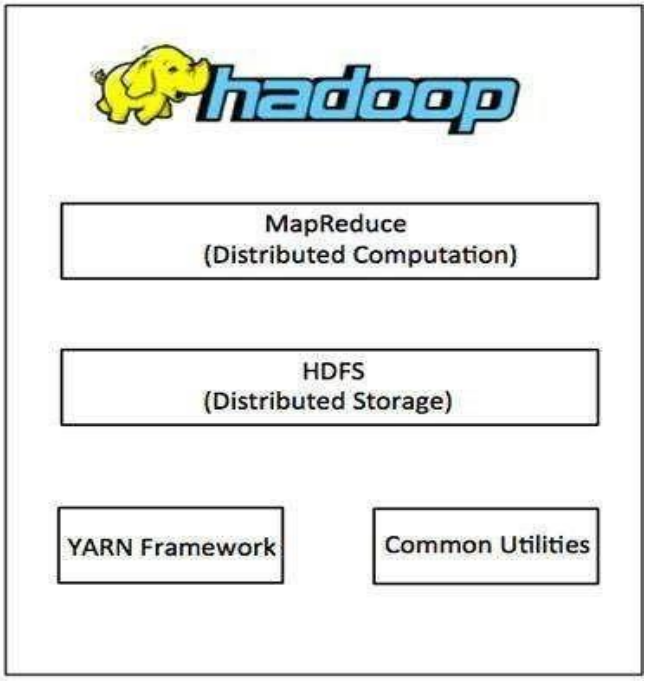
Hadoop Overview

Hadoop is an Apache open source framework written in java that allows distributed processing of large datasets across clusters of computers using simple programming models. The Hadoop framework application works in an environment that provides distributed *storage* and *computation* across clusters of computers. Hadoop is designed to scale up from single server to thousands of machines, each offering local computation and storage.

Hadoop Architecture

At its core, Hadoop has two major layers namely −

- Processing/Computation layer (MapReduce), and
- Storage layer (Hadoop Distributed File System).



MapReduce

MapReduce is a parallel programming model for writing distributed applications devised at Google for efficient processing of large amounts of data (multi-terabyte data-sets), on large clusters (thousands of nodes) of commodity hardware in a reliable, fault-tolerant manner. The MapReduce program runs on Hadoop which is an Apache open-source framework.

Hadoop Distributed File System

The Hadoop Distributed File System (HDFS) is based on the Google File System (GFS) and provides a distributed file system that is designed to run on commodity hardware. It has many

similarities with existing distributed file systems. However, the differences from other distributed file systems are significant. It is highly fault-tolerant and is designed to be deployed on low-cost hardware. It provides high throughput access to application data and is suitable for applications having large datasets.

Apart from the above-mentioned two core components, Hadoop framework also includes the following two modules −

- **Hadoop Common** − These are Java libraries and utilities required by other Hadoop modules.
- **Hadoop YARN** − This is a framework for job scheduling and cluster resource management.

How Does Hadoop Work?

It is quite expensive to build bigger servers with heavy configurations that handle large scale processing, but as an alternative, you can tie together many commodity computers with single-CPU, as a single functional distributed system and practically, the clustered machines can read the dataset in parallel and provide a much higher throughput. Moreover, it is cheaper than one high-end server. So this is the first motivational factor behind using Hadoop that it runs across clustered and low-cost machines.

Hadoop runs code across a cluster of computers. This process includes the following core tasks that Hadoop performs −

- Data is initially divided into directories and files. Files are divided into uniform sized blocks of 128M and 64M (preferably 128M).
- These files are then distributed across various cluster nodes for further processing.
- HDFS, being on top of the local file system, supervises the processing.
- Blocks are replicated for handling hardware failure.
- Checking that the code was executed successfully.
- Performing the sort that takes place between the map and reduce stages.
- Sending the sorted data to a certain computer.
- Writing the debugging logs for each job.

Advantages of Hadoop

- Hadoop framework allows the user to quickly write and test distributed systems. It is efficient, and it automatic distributes the data and work across the machines and in turn, utilizes the underlying parallelism of the CPU cores.

- Hadoop does not rely on hardware to provide fault-tolerance and high availability (FTHA), rather Hadoop library itself has been designed to detect and handle failures at the application layer.
- Servers can be added or removed from the cluster dynamically and Hadoop continues to operate without interruption.
- Another big advantage of Hadoop is that apart from being open source, it is compatible on all the platforms since it is Java based.

Processing Data with Hadoop - Managing Resources and Applications with Hadoop YARN

Yarn divides the task on resource management and job scheduling/monitoring into separate daemons. There is one ResourceManager and per-application ApplicationMaster. An application can be either a job or a DAG of jobs.
The ResourceManger have two components – Scheduler and AppicationManager.

The **scheduler** is a pure scheduler i.e. it does not track the status of running application. It only allocates resources to various competing applications. Also, it does not restart the job after failure due to hardware or application failure. The scheduler allocates the resources based on an abstract notion of a container. A container is nothing but a fraction of resources like CPU, memory, disk, network etc.
Following are the tasks of ApplicationManager:-

- Accepts submission of jobs by client.
- Negotaites first container for specific ApplicationMaster.
- Restarts the container after application failure.

Below are the responsibilities of ApplicationMaster

- Negotiates containers from Scheduler
- Tracking container status and monitoring its progress.

Yarn supports the concept of Resource Reservation via Reservation System. In this, a user can fix a number of resources for execution of a particular job over time and temporal constraints. The Reservation System makes sure that the resources are available to the job until its completion. It also performs admission control for reservation.

Yarn can scale beyond a few thousand nodes via Yarn Federation. YARN Federation allows to wire multiple sub-cluster into the single massive cluster. We can use many independent clusters together for a single large job. It can be used to achieve a large scale system.

Let us summarize how **Hadoop** works step by step:

- Input data is broken into blocks of size **128 Mb** and then blocks are moved to different nodes.
- Once all the blocks of the data are stored on data-nodes, the user can process the data.
- Resource Manager then schedules the program (submitted by the user) on individual nodes.
- Once all the nodes process the data, the output is written back to HDFS.

Interacting with Hadoop Ecosystem

Hadoop Ecosystem Hadoop has an ecosystem that has evolved from its three core components processing, resource management, and storage. In this topic, you will learn the components of the Hadoop ecosystem and how they perform their roles during Big Data processing. The
Hadoop ecosystem is continuously growing to meet the needs of Big Data. It comprises the following twelve components:

- HDFS(Hadoop Distributed file system)
- HBase
- Sqoop
- Flume
- Spark
- Hadoop MapReduce
- Pig
- Impala
- Hive
- Cloudera Search
- Oozie
- Hue.

Let us understand the role of each component of the Hadoop ecosystem.

Components of Hadoop Ecosystem

Let us start with the first component HDFS of Hadoop Ecosystem.

HDFS (HADOOP DISTRIBUTED FILE SYSTEM)

- HDFS is a storage layer for Hadoop.
- HDFS is suitable for distributed storage and processing, that is, while the data is being stored, it first gets distributed and then it is processed.
- HDFS provides Streaming access to file system data.
- HDFS provides file permission and authentication.
- HDFS uses a command line interface to interact with Hadoop.

So what stores data in HDFS? It is the HBase which stores data in HDFS.

HBase

- HBase is a NoSQL database or non-relational database .
- HBase is important and mainly used when you need random, real-time, read, or write access to your Big Data.
- It provides support to a high volume of data and high throughput.
- In an HBase, a table can have thousands of columns.

UNIT-III

INTRODUCTION TO MONGODB AND MAPREDUCE PROGRAMMING

MongoDB is a cross-platform, document-oriented database that provides, high performance, high availability, and easy scalability. MongoDB works on concept of collection and document.

Database

Database is a physical container for collections. Each database gets its own set of files on the file system. A single MongoDB server typically has multiple databases.

Collection

Collection is a group of MongoDB documents. It is the equivalent of an RDBMS table. A collection exists within a single database. Collections do not enforce a schema. Documents within a collection can have different fields. Typically, all documents in a collection are of similar or related purpose.

Document

A document is a set of key-value pairs. Documents have dynamic schema. Dynamic schema means that documents in the same collection do not need to have the same set of fields or structure, and common fields in a collection's documents may hold different types of data.

The following table shows the relationship of RDBMS terminology with MongoDB.

RDBMS	MongoDB
Database	Database
Table	Collection
Tuple/Row	Document
column	Field
Table Join	Embedded Documents

Primary Key	Primary Key (Default key _id provided by MongoDB itself)
Database Server and Client	
mysqld/Oracle	mongod
mysql/sqlplus	mongo

Sample Document

Following example shows the document structure of a blog site, which is simply a comma separated key value pair.

```
{
   _id: ObjectId(7df78ad8902c)
   title: 'MongoDB Overview',
   description: 'MongoDB is no sql database',
   by: 'tutorials point',
   url: 'http://www.tutorialspoint.com',
   tags: ['mongodb', 'database', 'NoSQL'],
   likes: 100,
   comments: [
      {
         user:'user1',
         message: 'My first comment',
         dateCreated: new Date(2011,1,20,2,15),
         like: 0
```

```
    },
    {
      user:'user2',
      message: 'My second comments',
      dateCreated: new Date(2011,1,25,7,45),
      like: 5
    }
  ]
}
```

_id is a 12 bytes hexadecimal number which assures the uniqueness of every document. You can provide _id while inserting the document. If you don't provide then MongoDB provides a unique id for every document. These 12 bytes first 4 bytes for the current timestamp, next 3 bytes for machine id, next 2 bytes for process id of MongoDB server and remaining 3 bytes are simple incremental VALUE.

Any relational database has a typical schema design that shows number of tables and the relationship between these tables. While in MongoDB, there is no concept of relationship.

Advantages of MongoDB over RDBMS

- **Schema less** − MongoDB is a document database in which one collection holds different documents. Number of fields, content and size of the document can differ from one document to another.
- Structure of a single object is clear.
- No complex joins.
- Deep query-ability. MongoDB supports dynamic queries on documents using a document-based query language that's nearly as powerful as SQL.
- Tuning.
- **Ease of scale-out** − MongoDB is easy to scale.
- Conversion/mapping of application objects to database objects not needed.
- Uses internal memory for storing the (windowed) working set, enabling faster access of data.

Why Use MongoDB?

- **Document Oriented Storage** − Data is stored in the form of JSON style documents.
- Index on any attribute
- Replication and high availability
- Auto-Sharding
- Rich queries
- Fast in-place updates
- Professional support by MongoDB

Where to Use MongoDB?

- Big Data
- Content Management and Delivery
- Mobile and Social Infrastructure
- User Data Management
- Data Hub

MongoDB supports many datatypes. Some of them are −

- **String** − This is the most commonly used datatype to store the data. String in MongoDB must be UTF-8 valid.
- **Integer** − This type is used to store a numerical value. Integer can be 32 bit or 64 bit depending upon your server.
- **Boolean** − This type is used to store a boolean (true/ false) value.
- **Double** − This type is used to store floating point values.
- **Min/ Max keys** − This type is used to compare a value against the lowest and highest BSON elements.
- **Arrays** − This type is used to store arrays or list or multiple values into one key.
- **Timestamp** − ctimestamp. This can be handy for recording when a document has been modified or added.
- **Object** − This datatype is used for embedded documents.
- **Null** − This type is used to store a Null value.
- **Symbol** − This datatype is used identically to a string; however, it's generally reserved for languages that use a specific symbol type.
- **Date** − This datatype is used to store the current date or time in UNIX time format. You can specify your own date time by creating object of Date and passing day, month, year into it.
- **Object ID** − This datatype is used to store the document's ID.

- **Binary data** − This datatype is used to store binary data.
- **Code** − This datatype is used to store JavaScript code into the document.
- **Regular expression** − This datatype is used to store regular expression.

The find() Method

To query data from MongoDB collection, you need to use MongoDB's **find()** method.

Syntax

The basic syntax of **find()** method is as follows −

>db.COLLECTION_NAME.find()

find() method will display all the documents in a non-structured way.

Example

Assume we have created a collection named mycol as −

```
> use  sampleDB
switched to db sampleDB
> db.createCollection("mycol")
{ "ok" : 1 }
>
```

And inserted 3 documents in it using the insert() method as shown below −

```
>  db.mycol.insert([
        {
                title: "MongoDB Overview",
                description: "MongoDB is no SQL database",
                by: "tutorials point",
                url:  "http://www.tutorialspoint.com",
                tags: ["mongodb", "database", "NoSQL"],
                likes: 100
        },
        {
                title: "NoSQL Database",
                description: "NoSQL database doesn't have tables",
                by: "tutorials point",
                url:  "http://www.tutorialspoint.com",
                tags: ["mongodb", "database", "NoSQL"],
                likes: 20,
                comments: [
```

```
                        {
                                user:"user1",
                                message: "My first comment",
                                dateCreated: new Date(2013,11,10,2,35),
                                like: 0
                        }
                ]
        }
])
```

Following method retrieves all the documents in the collection −

```
> db.mycol.find()
{ "_id" : ObjectId("5dd4e2cc0821d3b44607534c"), "title" : "MongoDB Overview", "description" : "MongoDB is no SQL database", "by" : "tutorials point", "url" : "http://www.tutorialspoint.com", "tags" : [ "mongodb", "database", "NoSQL" ], "likes" : 100 }
{ "_id" : ObjectId("5dd4e2cc0821d3b44607534d"), "title" : "NoSQL Database", "description" : "NoSQL database doesn't have tables", "by" : "tutorials point", "url" : "http://www.tutorialspoint.com", "tags" : [ "mongodb", "database", "NoSQL" ], "likes" : 20, "comments" : [ { "user" : "user1", "message" : "My first comment", "dateCreated" : ISODate("2013-12-09T21:05:00Z"), "like" : 0 } ] }
>
```

The pretty() Method

To display the results in a formatted way, you can use pretty() method.

Syntax

>db.COLLECTION_NAME.find().pretty()

Example

Following example retrieves all the documents from the collection named mycol and arranges them in an easy-to-read format.

```
> db.mycol.find().pretty()
{
        "_id" : ObjectId("5dd4e2cc0821d3b44607534c"),
        "title" : "MongoDB Overview",
        "description" : "MongoDB is no SQL database",
        "by" : "tutorials point",
        "url" : "http://www.tutorialspoint.com",
        "tags" : [
                "mongodb",
                "database",
                "NoSQL"
        ],
        "likes" : 100
```

```
}
{
        "_id" : ObjectId("5dd4e2cc0821d3b44607534d"),
        "title" : "NoSQL Database",
        "description" : "NoSQL database doesn't have tables",
        "by" : "tutorials point",
        "url" : "http://www.tutorialspoint.com",
        "tags" : [
                "mongodb",
                "database",
                "NoSQL"
        ],
        "likes" : 20,
        "comments" : [
                {
                        "user" : "user1",
                        "message" : "My first comment",
                        "dateCreated" : ISODate("2013-12-09T21:05:00Z"),
                        "like" : 0
                }
        ]
}
```

The findOne() method

Apart from the find() method, there is **findOne()** method, that returns only one document.

Syntax

>db.COLLECTIONNAME.findOne()

Example

Following example retrieves the document with title MongoDB Overview.

```
> db.mycol.findOne({title: "MongoDB Overview"})
{
        "_id" : ObjectId("5dd6542170fb13eec3963bf0"),
        "title" : "MongoDB Overview",
        "description" : "MongoDB is no SQL database",
        "by" : "tutorials point",
        "url" : "http://www.tutorialspoint.com",
        "tags" : [
                "mongodb",
                "database",
                "NoSQL"
        ],
        "likes" : 100
```

```
}
```

RDBMS Where Clause Equivalents in MongoDB

To query the document on the basis of some condition, you can use following operations.

Operation	Syntax	Example	RDBMS Equivalent
Equality	{<key>:{$eg;<value>}}	db.mycol.find({"by":"tutorials point"}).pretty()	where by = 'tutorials point'
Less Than	{<key>:{$lt:<value>}}	db.mycol.find({"likes":{$lt:50}}).pretty()	where likes < 50
Less Than Equals	{<key>:{$lte:<value>}}	db.mycol.find({"likes":{$lte:50}}).pretty()	where likes <= 50
Greater Than	{<key>:{$gt:<value>}}	db.mycol.find({"likes":{$gt:50}}).pretty()	where likes > 50
Greater Than Equals	{<key>:{$gte:<value>}}	db.mycol.find({"likes":{$gte:50}}).pretty()	where likes >= 50
Not Equals	{<key>:{$ne:<value>}}	db.mycol.find({"likes":{$ne:50}}).pretty()	where likes != 50
Values in an array	{<key>:{$in:[<value1>, <value2>,……<valueN>]}}	db.mycol.find({"name":{$in:["Raj", "Ram", "Raghu"]}}).pretty()	Where name matches any of the value in :["Raj", "Ram", "Raghu"]

Values not in an array	{<key>:{$nin:<value>}}	db.mycol.find({"name":{$nin:["Ramu", "Raghav"]}}).pretty()	Where name values is not in the array :["Ramu", "Raghav"] or, doesn't exist at all

AND in MongoDB

Syntax

To query documents based on the AND condition, you need to use $and keyword. Following is the basic syntax of AND −

```
>db.mycol.find({ $and: [ {<key1>:<value1>}, { <key2>:<value2>} ] })
```

Example

Following example will show all the tutorials written by 'tutorials point' and whose title is 'MongoDB Overview'.

```
> db.mycol.find({$and:[{"by":"tutorials point"},{"title": "MongoDB Overview"}]}).pretty()
{
        "_id" : ObjectId("5dd4e2cc0821d3b44607534c"),
        "title" : "MongoDB Overview",
        "description" : "MongoDB is no SQL database",
        "by" : "tutorials point",
        "url" : "http://www.tutorialspoint.com",
        "tags" : [
                "mongodb",
                "database",
                "NoSQL"
        ],
        "likes" : 100
}
>
```

For the above given example, equivalent where clause will be ' **where by = 'tutorials point' AND title = 'MongoDB Overview'** '. You can pass any number of key, value pairs in find clause.

OR in MongoDB

Syntax

To query documents based on the OR condition, you need to use **$or** keyword. Following is the basic syntax of **OR** −

```
>db.mycol.find(
   {
      $or: [
         {key1: value1}, {key2:value2}
      ]
   }
).pretty()
```

Example

Following example will show all the tutorials written by 'tutorials point' or whose title is 'MongoDB Overview'.

```
>db.mycol.find({$or:[{"by":"tutorials point"},{"title": "MongoDB Overview"}]}).pretty()
{
   "_id": ObjectId(7df78ad8902c),
   "title": "MongoDB Overview",
   "description": "MongoDB is no sql database",
   "by": "tutorials point",
   "url": "http://www.tutorialspoint.com",
   "tags": ["mongodb", "database", "NoSQL"],
   "likes": "100"
}
>
```

Using AND and OR Together

Example

The following example will show the documents that have likes greater than 10 and whose title is either 'MongoDB Overview' or by is 'tutorials point'. Equivalent SQL where clause is **'where likes>10 AND (by = 'tutorials point' OR title = 'MongoDB Overview')'**

```
>db.mycol.find({"likes": {$gt:10}, $or: [{"by": "tutorials point"},
   {"title": "MongoDB Overview"}]}).pretty()
{
   "_id": ObjectId(7df78ad8902c),
   "title": "MongoDB Overview",
   "description": "MongoDB is no sql database",
   "by": "tutorials point",
   "url": "http://www.tutorialspoint.com",
   "tags": ["mongodb", "database", "NoSQL"],
   "likes": "100"
}
>
```

NOR in MongoDB

Syntax

To query documents based on the NOT condition, you need to use $not keyword. Following is the basic syntax of **NOT** −

```
>db.COLLECTION_NAME.find(
        {
                $not: [
                        {key1: value1}, {key2:value2}
                ]
        }
)
```

Example

Assume we have inserted 3 documents in the collection **empDetails** as shown below −

```
db.empDetails.insertMany(
        [
                {
                        First_Name: "Radhika",
                        Last_Name: "Sharma",
                        Age: "26",
                        e_mail: "radhika_sharma.123@gmail.com",
                        phone: "9000012345"
                },
                {
                        First_Name: "Rachel",
                        Last_Name: "Christopher",
                        Age: "27",
                        e_mail: "Rachel_Christopher.123@gmail.com",
                        phone: "9000054321"
                },
                {
                        First_Name: "Fathima",
                        Last_Name: "Sheik",
                        Age: "24",
                        e_mail: "Fathima_Sheik.123@gmail.com",
                        phone: "9000054321"
                }
        ]
)
```

Following example will retrieve the document(s) whose first name is not "Radhika" and last name is not "Christopher"

```
> db.empDetails.find(
        {
```

```
                $nor:[
                        40
                        {"First_Name": "Radhika"},
                        {"Last_Name": "Christopher"}
                ]
        }
).pretty()
{
        "_id" : ObjectId("5dd631f270fb13eec3963bef"),
        "First_Name" : "Fathima",
        "Last_Name" : "Sheik",
        "Age" : "24",
        "e_mail" : "Fathima_Sheik.123@gmail.com",
        "phone" : "9000054321"
}
```

NOT in MongoDB

Syntax

To query documents based on the NOT condition, you need to use $not keyword following is the basic syntax of **NOT** −

```
>db.COLLECTION_NAME.find(
        {
                $NOT: [
                        {key1: value1}, {key2:value2}
                ]
        }
).pretty()
```

Example

Following example will retrieve the document(s) whose age is not greater than 25

```
> db.empDetails.find( { "Age": { $not: { $gt: "25" } } } )
{
        "_id" : ObjectId("5dd6636870fb13eec3963bf7"),
        "First_Name" : "Fathima",
        "Last_Name" : "Sheik",
        "Age" : "24",
        "e_mail" : "Fathima_Sheik.123@gmail.com",
        "phone" : "9000054321"
}
```

CASSANDRA

Cassandra is defined as an open-source NoSQL data storage system that leverages a distributed architecture to enable high availability, scalability, and reliability, managed by the Apache non-profit organization.

Cassandra features

1. Open-source availability

Nothing is more exciting than getting a handy product for free. This is probably one of the significant factors behind Cassandra's far-reaching popularity and acceptance. Cassandra is among the open-source products hosted by Apache and is free for anyone who wants to utilize it.

2. Distributed footprint

Another feature of Cassandra is that it is well distributed and meant to run over multiple nodes as opposed to a central system. All the nodes are equal in significance, and without a master node, no bottleneck slows the process down. This is very important because the companies that utilize Cassandra need to constantly run on accurate data and can not tolerate data loss. The equal and wide distribution of Cassandra data across nodes means that losing one node does not significantly affect the system's general performance.

3. Scalability

Cassandra has elastic scalability. This means that it can be scaled up or down without much difficulty or resistance. Cassandra's scalability once again is due to the nodal architecture. It is intended to grow horizontally

as your needs as a developer or company grow. Scaling-up in Cassandra is very easy and not limited to location. Adding or removing extra nodes can adjust your database system to suit your dynamic needs.

Another exciting point about scaling in Cassandra is that there is no slow down, pause or hitch in the system during the process. This means end-users would not feel the effect of whatever happened, ensuring smooth service to all individuals connected to the network.

4. Cassandra Query Language

Cassandra is not a relational database and does not use the standard query language or SQL. It uses the Cassandra query language (CQL). This would have posed a problem for admins as they would have to master a whole new language – but the good thing about Cassandra Query language is that it is very similar to SQL. It is structured to operate with rows and columns, i.e., table-based data.

However, it does lack the flexibility that comes with the fixed schema of SQL. CQL combines the tabular database management system and the key value. It operates using the data type operations, definition operation, data definition operation, triggers operation, security operations, arithmetic operations, etc.

5. Fault tolerance

Cassandra is fault-tolerant primarily because of its data replicative ability. Data replication denotes the ability of the system to store the same information at multiple locations or nodes. This makes it highly available and tolerant of faults in the system. Failure of a single node or data center does not bring the system to a halt as data

has been replicated and stored across other nodes in the cluster. Data replication leads to a high level of backup and recovery.

6. Schema free

SQL is a fixed schema database language making it rigid and fixed. However, Cassandra is a schema-optional data model and allows the operator to create as many rows and columns as is deemed necessary.

7.Tunable consistency

Cassandra has two types of consistency – the eventual consistency and the setting consistency. The string consistency is a type that broadcasts any update or information to every node where the concerned data is located. In eventual consistency, the client has to approve immediately after a cluster receives a write.

Cassandra's tunable consistency is a feature that allows the developer to decide to use any of the two types depending on the function being carried out. The developer can use either or both kinds of consistency at any time.

8. Fast writes

Cassandra is known to have a very high throughput, not hindered by its size. Its ability to write quickly is a function of its data handling process. The initial step taken is to write to the commit log. This is for durability to preserve data in case of damage or node downtime. Writing to the commit log is a speedy and efficient process using this tool.

The next step is to write to the "Memtable" or memory. After writing to Memtable, a node acknowledges the successful writing of data. The Memtable is found in the database memory, and writing to in-memory is much faster than writing to a disk. All of these account for the speed Cassandra writes.

9.Peer-to-peer architecture

Cassandra is built on a peer-to-peer architectural model where all nodes are equal. This is unlike some database models with a “slave to master” relationship. That is where one unit directs the functioning of the other units, and the other unit only communicates with the central unit or master. In Cassandra, different units can communicate with each other as peers in a process called gossiping. This peer-to-peer communication eliminates a single point of failure and is a prominent defining feature of Cassandra.

Cassandra - CQL Datatypes

CQL provides a rich set of built-in data types, including collection types. Along with these data types, users can also create their own custom data types. The following table provides a list of built-in data types available in CQL.

Data Type	Constants	Description
ascii	strings	Represents ASCII character string
bigint	bigint	Represents 64-bit signed long
blob	blobs	Represents arbitrary bytes
Boolean	booleans	Represents true or false
counter	integers	Represents counter column
decimal	integers, floats	Represents variable-precision decimal
double	integers	Represents 64-bit IEEE-754 floating point
float	integers, floats	Represents 32-bit IEEE-754 floating point
inet	strings	Represents an IP address, IPv4 or IPv6
int	integers	Represents 32-bit signed int
text	strings	Represents UTF8 encoded string
timestamp	integers, strings	Represents a timestamp
timeuuid	uuids	Represents type 1 UUID
uuid	uuids	Represents type 1 or type 4
		UUID
varchar	strings	Represents uTF8 encoded string
varint	integers	Represents arbitrary-precision integer

Collection Types

Cassandra Query Language also provides a collection data types. The following table provides a list of Collections available in CQL.

Collection	Description
list	A list is a collection of one or more ordered elements.
map	A map is a collection of key-value pairs.
set	A set is a collection of one or more elements.

User-defined datatypes

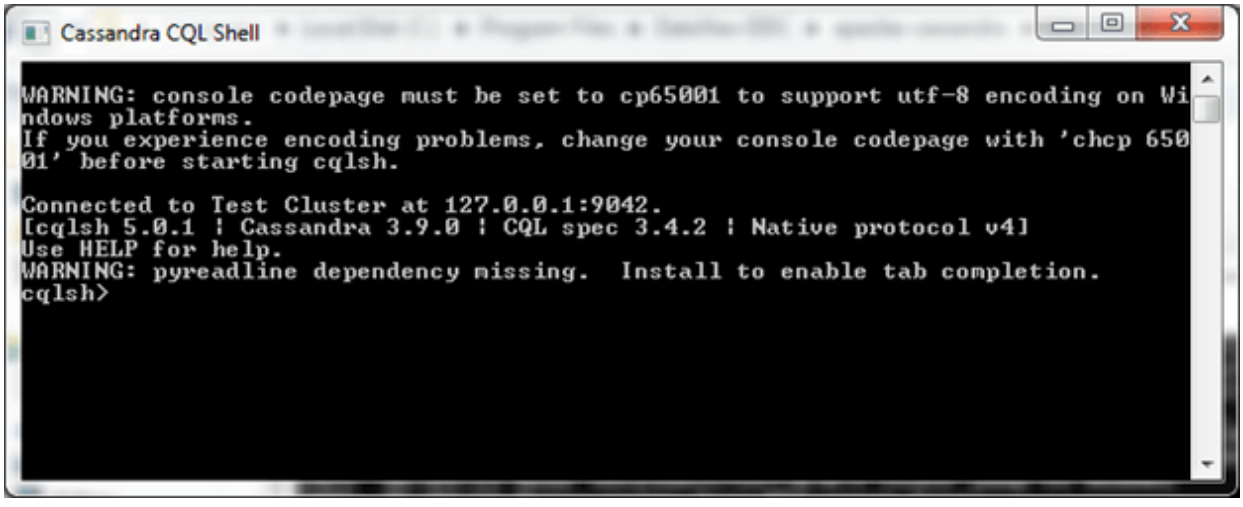
Cqlsh provides users a facility of creating their own data types. Given below are the commands used while dealing with user defined datatypes.

- **CREATE TYPE** − Creates a user-defined datatype.
- **ALTER TYPE** − Modifies a user-defined datatype.
- **DROP TYPE** − Drops a user-defined datatype.
- **DESCRIBE TYPE** − Describes a user-defined datatype.
- **DESCRIBE TYPES** − Describes user-defined datatypes

Cassandra CQLsh

Cassandra CQLsh stands for Cassandra CQL shell. CQLsh specifies how to use Cassandra commands. After installation, Cassandra provides a prompt Cassandra query language shell (cqlsh). It facilitates users to communicate with it.

Cassandra commands are executed on CQLsh. It looks like this:



CQLsh provides a lot of options which you can see in the following table:

Options	Usage
help	This command is used to show help topics about the options of CQLsh commands.
version	it is used to see the version of the CQLsh you are using.
color	it is used for colored output.
debug	It shows additional debugging information.
execute	It is used to direct the shell to accept and execute a CQL command.
file= "file name"	By using this option, cassandra executes the command in the given file and exits.
no-color	It directs cassandra not to use colored output.
u "username"	Using this option, you can authenticate a user. The default user name is: cassandra.
p "password"	Using this option, you can authenticate a user with a password. The default password is: cassandra.

Cassandra Create Keyspace

Cassandra Query Language (CQL) facilitates developers to communicate with Cassandra. The syntax of Cassandra query language is very similar to SQL.

What is Keyspace?

A keyspace is an object that is used to hold column families, user defined types. A keyspace is like RDBMS database which contains column families, indexes, user defined types, data center awareness, strategy used in keyspace, replication factor, etc.

In Cassandra, "Create Keyspace" command is used to create keyspace.

syntax

1. **REATE** KEYSPACE <identifier> **WITH** <properties>

Or

```
Create keyspace KeyspaceName with replicaton={'class':strategy name,
'replication_factor': No of replications on different nodes}
```

Cassandra Alter Keyspace

The "ALTER keyspace" command is used to alter the replication factor, strategy name and durable writes properties in created keyspace in Cassandra.

Syntax:

ALTER KEYSPACE <identifier> **WITH** <properties>

Or

ALTER KEYSPACE "KeySpace Name"
WITH replication = {'class': 'Strategy name', 'replication_factor' : 'No.Of replicas'};

or

```
Alter Keyspace KeyspaceName with replication={'class':'StrategyName',
   'replication_factor': no of replications on different nodes}
      with DURABLE_WRITES=true/false
```

Main points while altering Keyspace in Cassandra

- **Keyspace Name:** Keyspace name cannot be altered in Cassandra.
- **Strategy Name:** Strategy name can be altered by using a new strategy name.
- **Replication Factor:** Replication factor can be altered by using a new replication factor.
- **DURABLE_WRITES:** DURABLE_WRITES value can be altered by specifying its value true/false. By default, it is true. If set to false, no updates will be written to the commit log and vice versa.

Example:

Let's take an example to demonstrate "Alter Keyspace". This will alter the keyspace strategy from 'SimpleStrategy' to 'NetworkTopologyStrategy' and replication factor from 3 to 1 for DataCenter1.

ALTER KEYSPACE javatpoint
WITH replication = {'class':'NetworkTopologyStrategy', 'replication_factor' : 1};

Cassandra Drop Keyspace

In Cassandra, "DROP Keyspace" command is used to drop keyspaces with all the data, column families, user defined types and indexes from Cassandra.

Cassandra takes a snapshot of keyspace before dropping the keyspace. If keyspace does not exist in the Cassandra, Cassandra will return an error unless IF EXISTS is used.

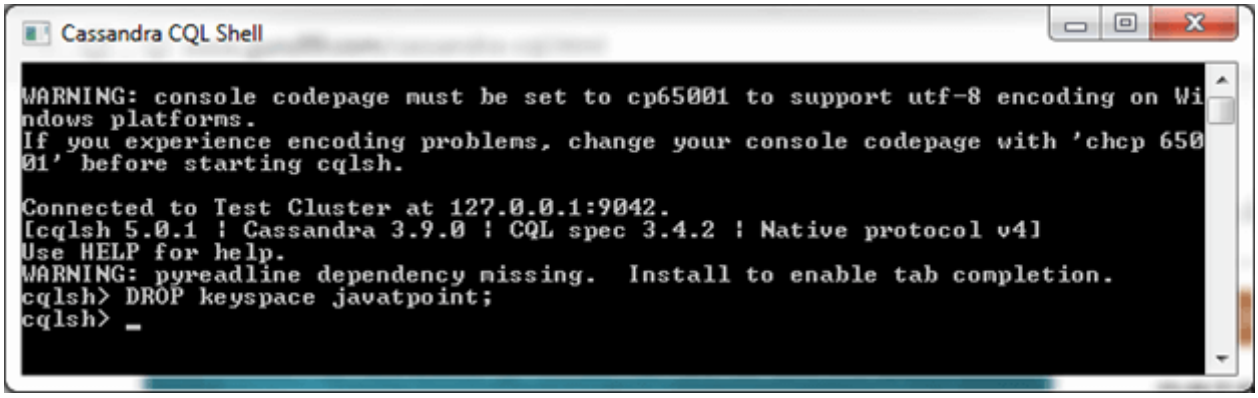
Syntax:

1. **DROP** keyspace KeyspaceName ;

Example:

let's take an example to drop the keyspace named "javatpoint".

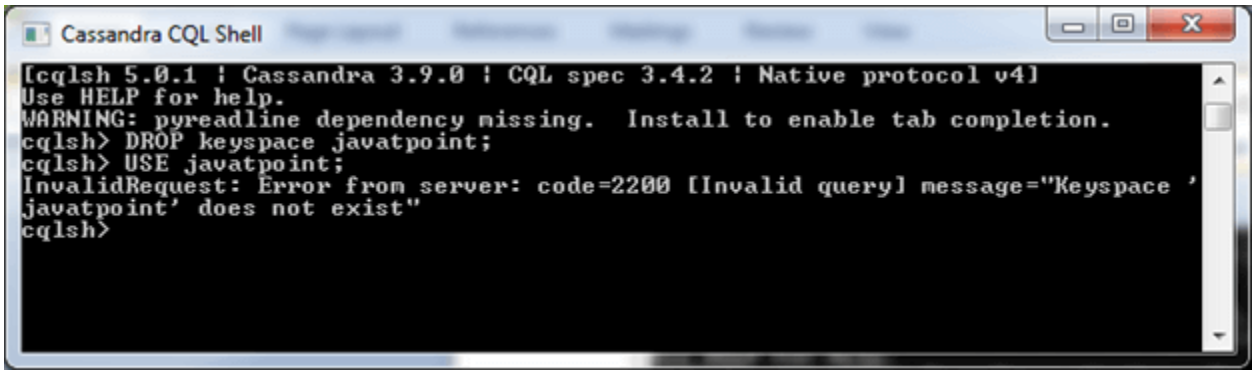
DROP keyspace javatpoint;



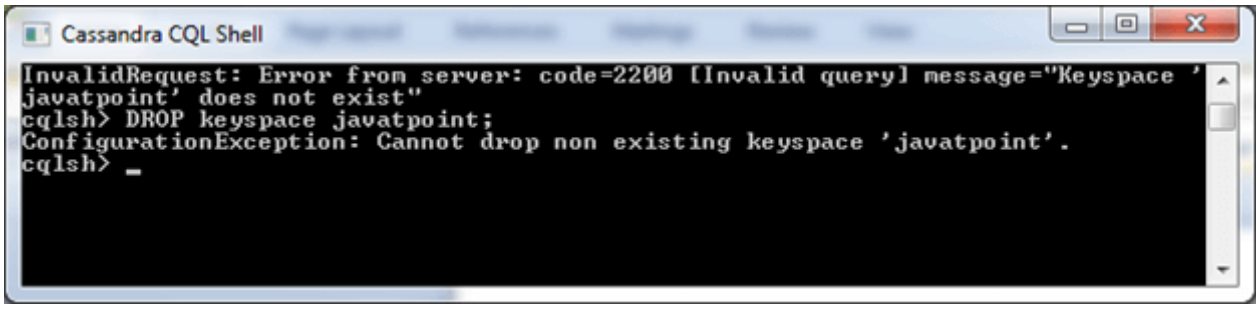
Verification:

After the execution of the above command the keyspace "javatpoint" is dropped from Cassandra with all the data and schema.

You can verify it by using the "USE" command.



Now you can see that "javatpoint" keyspace is dropped. If you use "DROP" command again, you will get the following message.



What is Cassandra CRUD Operation?

Cassandra CRUD Operation stands for Create, Update, Read and Delete or Drop. These operations are used to manipulate data in Cassandra. Apart from this, CRUD operations in Cassandra, a user can also verify the command or the data.

a. Create Operation

A user can insert data into the table using Cassandra CRUD operation. The data is stored in the columns of a row in the table. Using INSERT command with proper what, a user can perform this operation.

Read about Important Features of Cassandra

A Syntax of Create Operation-

```
INSERT INTO <table name>
(<column1>,<column2> ... )
VALUES (<value1>,<value2>...)
```

USING<option>

Let's create a table data to illustrate the operation. Example consist of a table with information about students in college. The following table will give the details about the students.

Table.1 Cassandra Crud Operation – Create Operation

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	New York City
003	Kabir	Applied Physics	7777777777	Philadelphi

EXAMPLE 1: Creating a table and inserting the data into a table:
INPUT:

```
cqlsh:keyspace1> INSERT INTO student(en, name, branch, phone, city)
VALUES(001, 'Ayush', 'Electrical Engineering', 9999999999, 'Boston');
cqlsh:keyspace1> INSERT INTO student(en, name, branch, phone, city)
VALUES(002, 'Aarav', 'Computer Engineering', 8888888888, 'New York City');
cqlsh:keyspace1> INSERT INTO student(en, name, branch, phone, city)
VALUES(003, 'Kabir', 'Applied Physics', 7777777777, 'Philadelphia');
```

Table.2 Cassandra Crud Operation – OUTPUT After Verification (READ operation)

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	New York City
003	Kabir	Applied Physics	7777777777	Philadelphia

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	San Fransisco
003	Kabir	Applied Physics	7777777777	Philadelphia

b.Update Operation

The second operation in the Cassandra CRUD operation is the UPDATE operation. A user can use UPDATE command for the operation. This operation uses three keywords while updating the table.

- **Where:** This keyword will specify the location where data is to be updated.
- **Set:** This keyword will specify the updated value.
- **Must:** This keyword includes the columns composing the primary key.

Furthermore, at the time of updating the rows, if a row is unavailable, then Cassandra has a feature to create a fresh row for the same.

Do you know How Cassandra Stores Data

A Syntax of Update Operation-

```
UPDATE <table name>
SET <column name>=<new value>
<column name>=<value>...
WHERE <condition>
```

EXAMPLE 2: Let's change few details in the table 'student'. In this example, we will update Aarav's city from 'New York City' to 'San Fransisco'.

INPUT:

```
cqlsh:keyspace1> UPDATE student SET city='San Fransisco'
WHERE en=002;
```

Table.3 Cassandra Crud Operation – OUTPUT After Verification

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	San Fransisco
003	Kabir	Applied Physics	7777777777	Philadelphia

c. Read Operation

This is the third Cassandra CRUD Operation – Read Operation. A user has a choice to read either the whole table or a single column. To read data from a table, a user can use SELECT clause. This command is also used for verifying the table after every operation.

Have a look at Cassandra Shell Commands

SYNTAX to read the whole table-

```
SELECT * FROM <table name>;
```

EXAMPLE 3: To read the whole table 'student'.

INPUT:

cqlsh:keyspace1> SELECT * FROM student;

Table.4 Cassandra Crud Operation – OUTPUT After Verification

SYNTAX to read selected columns-

```
SELECT <column name1>,<column name2> ....FROM <table name>;
```

EXAMPLE 4: To read columns of name and city from table 'student'.
INPUT:\

```
cqlsh:keyspace1> SELECT name, city FROM student;
```

Table.5 Cassandra Crud Operation – OUTPUT After Verification

NAME	CITY
Ayush	Boston
Aarav	San Fransisco
Kabir	Philadelphia

d. Delete Operation

Delete operation is the last Cassandra CRUD Operation, allows a user to delete data from a table. The user can use DELETE command for this operation.

A Syntax of Delete Operation-

DELETE <identifier> FROM <table name> WHERE <condition>;

EXAMPLE 5: In the 'student' table let us delete the 'phone' or phone number from 003 row.

cqlsh:keyspace1> DELETE phone FROM student WHERE en=003;

Table.6 Cassandra Crud Operation – OUTPUT After Verification

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	San Fransisco
003	Kabir	Applied Physics	null	Philadelphia

SYNTAX for deleting the entire row-

DELETE FROM <identifier> WHERE <condition>;

EXAMPLE 6: In the 'student' table, let us delete the entire third row.

cqlsh:keyspace1> DELETE FROM student WHERE en=003;

Let's Explore Best Books To Learn Cassandra

Table.7 Cassandra Crud Operation – OUTPUT After Verification

EN	NAME	BRANCH	PHONE	CITY
001	Ayush	Electrical Engineering	9999999999	Boston
002	Aarav	Computer Engineering	8888888888	San Fransisco

collections

what are Cassandra Collections?

Cassandra collections are a good way for handling tasks. Multiple elements can be stored in collections. There are limitations in Cassandra collections.

- Cassandra collection cannot store data more than 64KB.
- Keep a collection small to prevent the overhead of querying collection because entire collection needs to be traversed.
- If you store more than 64 KB data in the collection, only 64 KB will be able to query, it will result in loss of data.

Types of Cassandra Collections

There are mainly three types of collections that Cassandra supports:

1. Set
2. List
3. Map

Cassandra Set Collection

A Set stores group of elements that returns sorted elements when querying.

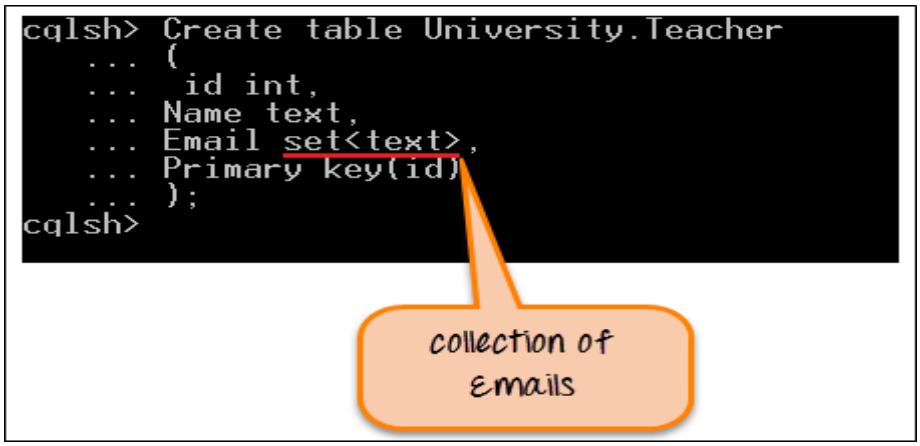
Syntax

Here is the syntax of the Set collection that store multiple email addresses for the teacher.

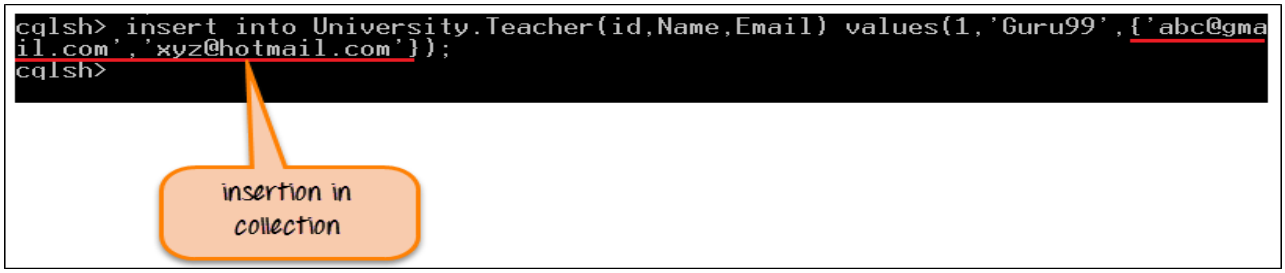
```
Create table University.Teacher
(
id int,
Name text,
Email set<text>,
Primary key(id)
);
```

Example

Here is the snapshot where table “Teacher” is created with “Email” column as a collection.



here is the snapshot where data is being inserted in the collection.



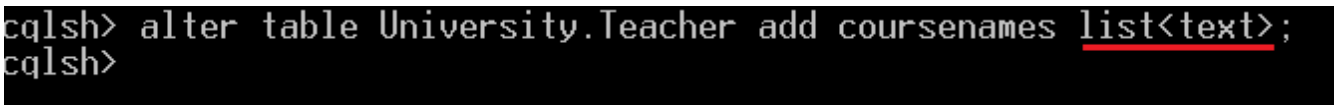

```
insert into University.Teacher(id,Name,Email)
values(1,'Guru99',{'abc@gmail.com','xyz@hotmail.com'});
```

Cassandra List Collection

When the order of elements matters, the list is used.

Example

Here is the snapshot where column courses of list type id added in table “Teacher.”



Here is the snapshot where data is being inserted in column “coursenames”.

```
cqlsh> insert into University.Teacher(id,Name,Email,coursenames) values(2,'Hamil
ton',{'hamilton@yahoo.com'},['Data Science']);
cqlsh>
```

```
insert into University.Teacher(id,Name,Email)
values(2,'Hamilton',{'hamilton@hotmail.com'},[Data Science']);
```

Here is the snapshot that shows the current database state after insertion.

```
 id | coursenames      | email                    | name
----+------------------+--------------------------+----------
  2 | ['Data Science'] | {'hamilton@yahoo.com'} | Hamilton

(1 rows)
```

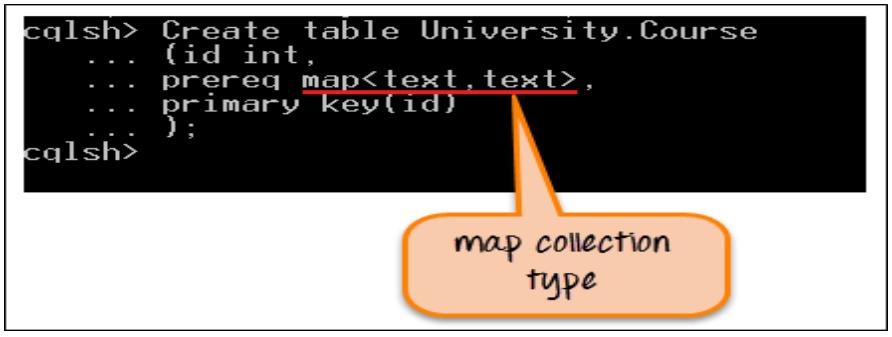
Cassandra Map Collection

The map is a collection type that is used to store key value pairs. As its name implies that it maps one thing to another.

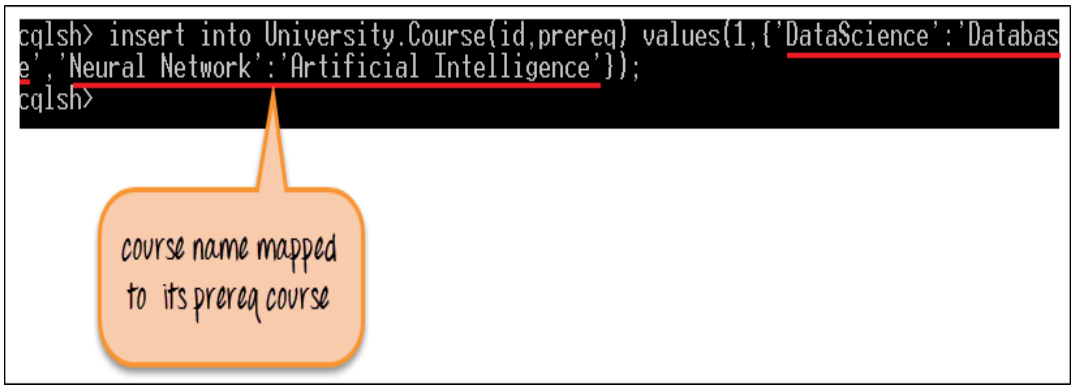
For example, if you want to save course name with its prerequisite course name, map collection can be used.

Example

Here is the snapshot where map type is created for course name and its prerequisite course name.



Here is the snapshot where data is being inserted in map collection type




```
insert into University.Course(id,prereq) values(1,{'DataScience':'Database', 'Neural
Network':'Artificial Intelligence'});
```

Creating a counter table

A counter is a special column used to store an integer that is changed in increments.

Counters are useful for many data models. Some examples:

- To keep track of the number of web page views received on a company website
- To keep track of the number of games played online or the number of players who have joined an online game

The table shown below uses id as the primary key and keeps track of the popularity of a cyclist based on thumbs up/thumbs down clicks in the popularity field of a counter table.

Tracking count in a distributed database presents an interesting challenge. In Cassandra, at any given moment, the counter value may be stored in the Memtable, commit log, and/or one or more SSTables. Replication between nodes can cause consistency issues in certain edge cases. Cassandra counters were redesigned in Cassandra 2.1 to alleviate some of the difficulties. Read "What's New in Cassandra 2.1: Better Implementation of Counters" to discover the improvements made in the counters.

Because counters are implemented differently from other columns, counter columns can only be created in dedicated tables. A counter column must have the datatype counter data type. This data type cannot be assigned to a column that serves as the primary key or partition key. To implement a counter column, create a table that only includes:

- The primary key (can be one or more columns)
- The counter column

Many counter-related settings can be set in the cassandra.yaml file.

A counter column cannot be indexed or deleted.. To load data into a counter column, or to increase or decrease the value of the counter, use the UPDATE command. Cassandra rejects USING TIMESTAMP or USING TTL when updating a counter column.

To create a table having one or more counter columns:

- Use CREATE TABLE to define the counter and non-counter columns. Use all non-counter columns as part of the PRIMARY KEY definition.

- Using a counter

A counter is a special column for storing a number that is changed in increments.

Time To Live (TTL) command and how to determine the expire time limit of an existing column.

In Cassandra Time to Live (TTL) is play an important role while if we want to set the time limit of a column and we want to automatically delete after a point of time then at the time using TTL keyword is very useful to define the time limit for a particular column.

1. In Cassandra Both the INSERT and UPDATE commands support setting a time for data in a column to expire.
2. It is used to set the time limit for a specific period of time. By USING TTL clause we can set the TTL value at the time of insertion.
3. We can use TTL function to get the time remaining for a specific selected query.
4. At the point of insertion, we can set expire limit of inserted data by using TTL clause. Let us consider if we want to set the expire limit to two days then we need to define its TTL value.
5. By using TTL we can set the expiration period to two days and the value of TTL will be 172800 seconds. Let's understand with an example.

Table : student_Registration

To create the table used the following CQL query.

```
CREATE TABLE student_Registration(
Id int PRIMARY KEY,
Name text,
Event text
);
```

Insertion using TTL :

To insert data by using TTL then used the following CQL query.

```
INSERT INTO student_Registration (Id, Name, Event)
    VALUES (101, 'Ashish', 'Ninza') USING TTL 172800;
INSERT INTO student_Registration (Id, Name, Event)
    VALUES (102, 'Ashish', 'Code') USING TTL 172800;
INSERT INTO student_Registration (Id, Name, Event)
    VALUES (103, 'Aksh', 'Ninza') USING TTL 172800;
```

Output:

Id	Name	Event
101	Ashish	Ninza
102	Ashish	Code
103	Aksh	Ninza

Now, to determine the remaining time to expire for a specific column used the following CQL query.

```
SELECT TTL (Name)
from student_Registration
WHERE Id = 101;
```

Output:

ttl(Name)

172700

It will decrease as you will check again for its TTL value just because of TTL time limit. Now, used the following CQL query to check again.

SELECT TTL (Name)

from student_Registration

WHERE Id = 101;

Output:

ttl(Name)

172500

Updating using TTL:

Now, if we want to extend the time limit then we can extend with the help of UPDATE command and USING TTL keyword. Let's have a look. To extend time limit with 3 days and also to update the name to 'rana' then used the following CQL query.

UPDATE student_Registration

USING TTL 259200

SET Name = 'Rana'

WHERE Id= 102

Output:

Id	Name	Event
101	Ashish	Ninza
102	Rana	Code
103	Aksh	Ninza

SELECT TTL (Name)

from student_Registration

WHERE Id = 102;

Output:

ttl(Name)

259100

Deleting a column using TTL:

To delete the specific existing column used the following CQL query.

UPDATE student_Registration

USING TTL 0

SET Name = 'Ashish'

WHERE Id = 102;

Cassandra Alter Table

ALTER TABLE command is used to alter the table after creating it. You can use the ALTER command to perform two types of operations:

- Add a column
- Drop a column

Syntax:

ALTER (**TABLE** | COLUMNFAMILY) <tablename> <instruction>

Adding a Column

You can add a column in the table by using the ALTER command. While adding column, you have to aware that the column name is not conflicting with the existing column names and that the table is not defined with compact storage option.

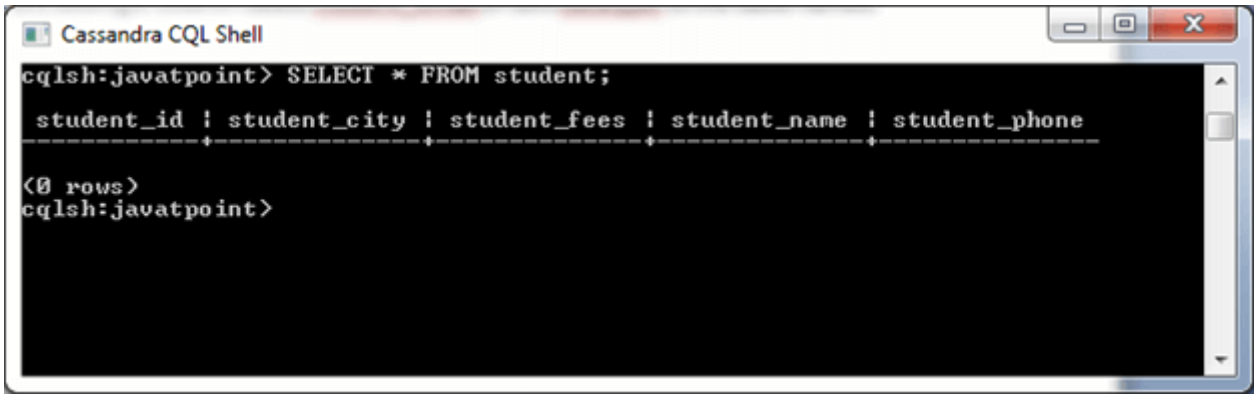
Syntax:

1. **ALTER TABLE table name**
2. **ADD** new **column** datatype;

Example:

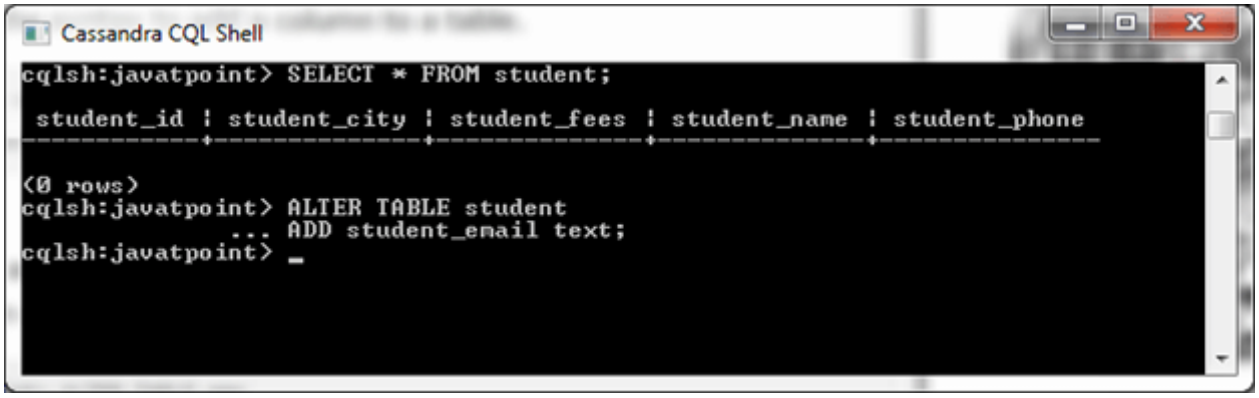
Let's take an example to demonstrate the ALTER command on the already created table named "student". Here we are adding a column called student_email of text datatype to the table named student.

Prior table:

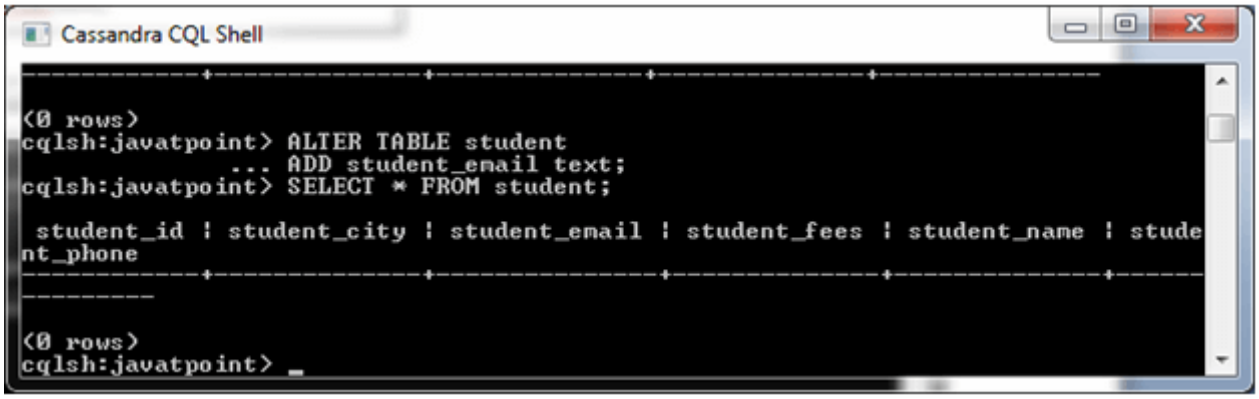


After using the following command:

ALTER TABLE student
ADD student_email text;



A new column is added. You can check it by using the SELECT command.



Dropping a Column

You can also drop an existing column from a table by using ALTER command. You should check that the table is not defined with compact storage option before dropping a column from a table.

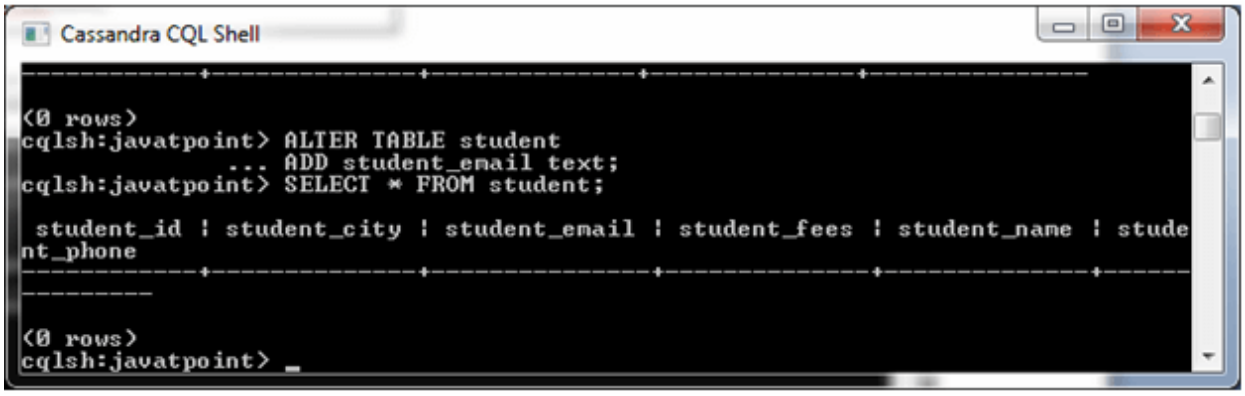
Syntax:

1. **ALTER table name**
2. **DROP column name**;

Example:

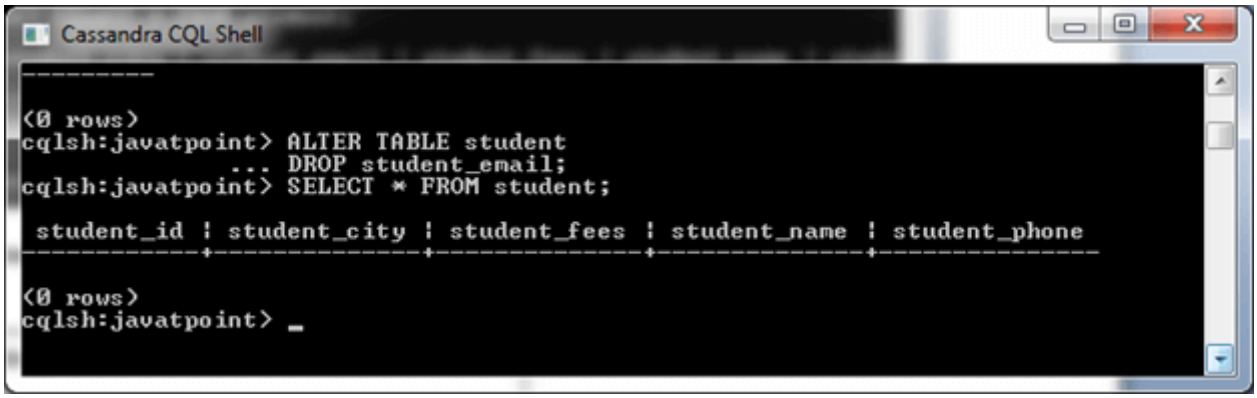
Let's take an example to drop a column named student_email from a table named student.

Prior table:



After using the following command:

ALTER TABLE student
DROP student_email;



Now you can see that a column named "student_email" is dropped now.

If you want to drop the multiple columns, separate the columns name by ","

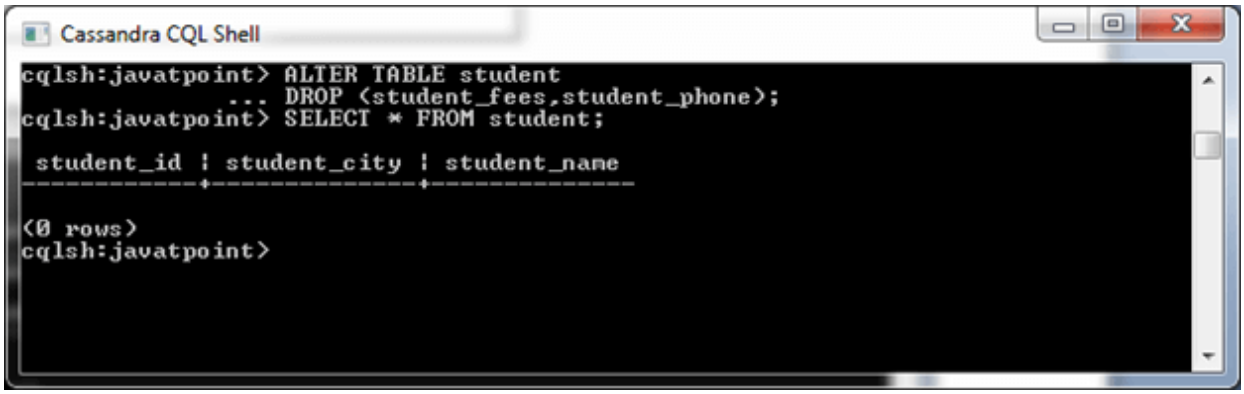
See this example:

Here we will drop two columns student_fees and student_phone.

ALTER TABLE student

DROP (student_fees, student_phone);

Output:



Export and Import data in Cassandra

First, we are going to create table namely as Data in which id, firstname, lastname are the fields for sample exercise.
Let's have a look.

Table name: Data

```
CREATE TABLE Data (
  id UUID PRIMARY KEY,
  firstname text,
  lastname text
);
```

Now, we are going to insert some data to export and import data for sample exercise. let's have a look.

```
INSERT INTO Data (id, firstname, lastname )
VALUES (3b6441dd-3f90-4c93-8f61-abcfa3a510e1, 'Ashish', 'Rana');

INSERT INTO Data (id, firstname, lastname)
VALUES (3b6442dd-bc0d-4157-a80f-abcfa3a510e2, 'Amit', 'Gupta');

INSERT INTO Data (id, firstname, lastname)
VALUES (3b6443dd-d358-4d99-b900-abcfa3a510e3, 'Ashish', 'Gupta');

INSERT INTO Data (id, firstname, lastname)
VALUES (3b6444dd-4860-49d6-9a4b-abcfa3a510e4, 'Dhruv', 'Gupta');

INSERT INTO Data (id, firstname, lastname)
VALUES (3b6445dd-e68e-48d9-a5f8-abcfa3a510e5, 'Harsh', 'Vardhan');

INSERT INTO Data (id, firstname, lastname)
VALUES (3b6446dd-eb95-4bb4-8685-abcfa3a510e6, 'Shivang', 'Rana');
```

Now, we are going to Export Data used the following cqlsh query given below. let's have a look.

```
cqlsh>COPY Data(id, firstname, lastname)
TO 'AshishRana\Desktop\Data.csv' WITH HEADER = TRUE;
```

The CSV file is created:

```
Using 7 child processes
```

Starting copy of Data with columns [id, firstname, lastname].

Processed: 6 rows; Rate: 20 rows/s; Avg. rate: 30 rows/s

6 rows exported to 1 files in 0.213 seconds.

Now, we are going to delete data from table ‘Data’ to import again from CSV file which is already has been created.

truncate Data;

Now, here we are going to import data again. To import Data used the following cqlsh query given below.

COPY Data (id, firstname, lastname)

FROM 'AshishRana\Desktop\Data.csv'

WITH HEADER = TRUE;

The rows are imported:

Using 7 child processes

Starting copy of Data with columns [id, firstname, lastname].

Processed: 6 rows; Rate: 10 rows/s; Avg. rate: 14 rows/s

6 rows imported from 1 files in 0.423 seconds (0 skipped).

To verify the results whether it is successfully imported or not. let’s have a look.

SELECT *

FROM Data;

Output:

id	firstname	lastname
3b6446dd-eb95-4bb4-8685-abcfa3a510e6	Shivang	Rana
3b6444dd-4860-49d6-9a4b-abcfa3a510e4	Dhruv	Gupta
3b6445dd-e68e-48d9-a5f8-abcfa3a510e5	Harsh	Vardhan
3b6441dd-3f90-4c93-8f61-abcfa3a510e1	Ashish	Rana
3b6442dd-bc0d-4157-a80f-abcfa3a510e2	Amit	Gupta
3b6443dd-d358-4d99-b900-abcfa3a510e3	Ashish	Gupta

To copy a specific rows of a table used the following cqlsh query given below.
First, export data from table and then truncate after these two steps follow these steps given below.

COPY Data FROM STDIN;

After executing above cqlsh query the line prompt changes to [copy] let's have a look.

Using 7 child processes

Starting copy of cluster1.

Data with columns [id, firstname, lastname].

[Use . on a line by itself to end input]

[copy]

Now, insert the row value of table which you want to import.

[copy] 3b6441dd-3f90-4c93-8f61-abcfa3a510e1, 'Ashish', 'Rana'

[copy] . // keep it in mind at the end insert the period

After successfully executed above given cqlsh query will give you the following results given below. let's have a look.

Processed: 1 rows; Rate: 0 rows/s; Avg. rate: 0 rows/s

1 rows imported from 1 files in 36.991 seconds (0 skipped).

Now, let verify the results.

SELECT *

FROM Data;

Output:

id	firstname	lastname
3b6441dd-3f90-4c93-8f61-abcfa3a510e1	Ashish	Rana

1 rows

Querying system table

Columns in System Tables

Columns in System Tables

Table name	Column name	Comment
available_ranges	keyspace_name, ranges	
batches	id, mutations, version	
batchlog	id, data, version, written_at	
built_views	keyspace_name, view_name	Information on materialized views
compaction_history	id, bytes_in, bytes_out, columnfamily_name, compacted_at, keyspace_name, rows_merged	Information on compaction history
hints	target_id, hint_id, message_version, mutation	
"IndexInfo"	table_name, index_name	Information on indexes
local	key, bootstrapped, broadcast_address, cluster_name, cql_version, data_center, gossip_generation, host_id, listen_address, native_protocol_version, partitioner, rack, release_version, rpc_address, schema_version, thrift_version, tokens, truncated_at map	Information on a node has about itself and a superset of gossip.
paxos	row_key, cf_id, in_progress_ballot, most_recent_commit, most_recent_commit_at, most_recent_commit_version, proposal, proposal_ballot, proposal_version	Information on lightweight Paxos transactions
peers	peer, data_center, host_id, preferred_ip, rack, release_version, rpc_address, schema_version, tokens	Each node records what other nodes tell it about themselves over the gossip.
peer_events	peer, hints_dropped	
range_xfers	token_bytes,requested_at	
size_estimates	keyspace_name, table_name, range_start, range_end, mean_partition_size, partitions_count	Information on partitions
sstable_activity	keyspace_name, columnfamily_name, generation, rate_120m, rate_15m	
views_builds_in_progress	keyspace_name, view_name, generation_number, last_token	

Columns in System_Schema Tables

Table name	Column name	Comment
aggregates	keyspace_name, aggregate_name, argument_types, final_func, initcond, return_type, state_func, state_type	Information about user-defined aggregates
columns	keyspace_name, table_name, column_name, clustering_order, column_name_bytes, kind, position, type	Information about table columns
Table name	Column name	Comment
aggregates	keyspace_name, aggregate_name, argument_types, final_func, initcond, return_type, state_func, state_type	Information about user-defined aggregates
columns	keyspace_name, table_name, column_name, clustering_order, column_name_bytes, kind, position, type	Information about table columns
dropped_columns	keyspace_name, table_name, column_name, dropped_time,type	Information about dropped columns
functions	keyspace_name, function_name, argument_types, argument_names, body, called_on_null_input,language,return_type	Information on user-defined functions
indexes	keyspace_name, table_name, index_name, kind,options	Information about indexes
keyspaces	keyspace_name, durable_writes, replication	Information on keyspace durable writes and replication
tables	keyspace_name, table_name, bloom_filter_fp_chance, caching, comment, compaction, compression, crc_check_chance, dclocal_read_repair_chance, default_time_to_live, extensions, flags, gc_grace_seconds, id, max_index_interval, memtable_flush_period_in_ms, min_index_interval, read_repair_chance, speculative_retry	Information on columns and column indexes. Used internally for compound primary keys.
triggers	keyspace_name, table_name, trigger_name, options	Information on triggers
types	keyspace_name, type_name, field_names, field_types	Information about user-defined types
views	keyspace_name, view_name, base_table_id, base_table_name, bloom_filter_fp_chance, caching, comment, compaction, compression, crc_check_chance, dclocal_read_repair_chance, default_time_to_live, extensions,	Information about materialized views

	flags,gc_grace_seconds, include_all_columns, max_index_interval, memtable_flush_period_in_ms, min_index_interval, read_repair_chance, speculative_retry, where_clause	

UNIT IV

INTRODUCTION TO MAP REDUCE PROGRAMMING AND HIVE

MapReduce:

MapReduce addresses the challenges of distributed programming by providing an abstraction that isolates the developer from system-level details (e.g., locking of data structures, data starvation issues in the processing pipeline, etc.). The programming model specifies simple and well-defined interfaces between a small number of components, and therefore is easy for the programmer to reason about. MapReduce maintains a separation of what computations are to be performed and how those computations are actually carried out on a cluster of machines. The first is under the control of the programmer, while the second is exclusively the responsibility of the execution framework or "runtime". The advantage is that the execution framework only needs to be designed once and verified for correctness—thereafter, as long as the developer expresses computations in the programming model, code is guaranteed to behave as expected. The upshot is that the developer is freed from having to worry about system-level details (e.g., no more debugging race conditions and addressing lock contention) and can instead focus on algorithm or application design.

ich often has multiple cores). Why is MapReduce important? In practical terms, it provides a very effective tool for tackling large-data problems. But beyond that, MapReduce is important in how it has changed the way we organize computations at a massive scale. MapReduce represents the first widely-adopted step away from the von Neumann model that has served as the foundation of computer science over the last half plus century. Valiant called this a bridging model [148], a conceptual bridge between the physical implementation of a machine and the software that is to be executed on that machine. Until recently, the von Neumann model has served us well: Hardware designers focused on efficient implementations of the von Neumann model and didn't have to think much about the actual software that would run on the machines. Similarly, the software industry developed software targeted at the model without worrying about the hardware details. The result was extraordinary growth: chip designers churned out successive generations of increasingly powerful processors, and software engineers were able to develop applications in high-level languages that exploited those processors.

MapReduce can be viewed as the first breakthrough in the quest for new abstractions that allow us to organize computations, not over individual machines, but over entire clusters. As Barroso puts it, the datacenter is the computer. MapReduce is certainly not the first model of parallel computation that has been proposed. The most prevalent model in theoretical computer science, which dates back several decades, is the PRAM. MAPPERS AND REDUCERS Key-value pairs form the basic data structure in MapReduce. Keys and values may be primitives such as integers, floating point values, strings, and raw bytes, or they may be arbitrarily complex structures (lists, tuples, associative arrays, etc.). Programmers typically need to define their own custom data types, although a number of libraries such as Protocol Buffers,5 Thrift,6 and Avro7 simplify the task. Part of the design of MapReduce algorithms involves imposing the key-value structure on arbitrary datasets. For a collection of web pages, keys may be URLs and values may be the actual HTML content. For a graph, keys may represent node ids and values may contain the adjacency lists of those nodes (see Chapter 5 for more details). In some algorithms, input keys are not particularly

meaningful and are simply ignored during processing, while in other cases input keys are used to uniquely identify a datum (such as a record id). In Chapter 3, we discuss the role of complex keys and values in the design of various algorithms. In MapReduce, the programmer defines a mapper and a reducer with the following signatures: map: (k1, v1) → [(k2, v2)] reduce: (k2, [v2]) → [(k3, v3)] The convention [. . .] is used throughout this book to denote a list. The input to a MapReduce job starts as data stored on the underlying distributed file system (see Section 2.5). The mapper is applied to every input key-value pair (split across an arbitrary number of files) to generate an arbitrary number of intermediate key-value pairs. The reducer is applied to all values associated with the same intermediate key to generate output key-value pairs.8 Implicit between the map and reduce phases is a distributed "group by" operation on intermediate keys. Intermediate data arrive at each reducer in order, sorted by the key. However, no ordering relationship is guaranteed for keys across different reducers. Output key-value pairs from each reducer are written persistently back onto the distributed file system (whereas intermediate key-value pairs are transient and not preserved). The output ends up in r files on the distributed file system, where r is the number of reducers. For the most part, there is no need to consolidate reducer output, since the r files often serve as input to yet another MapReduce job. Figure 2.2 illustrates this two-stage processing structure. A simple word count algorithm in MapReduce is shown in Figure 2.3. This algorithm counts the number of occurrences of every word in a text collection, which may be the first step in, for example, building a unigram language model (i.e., probability

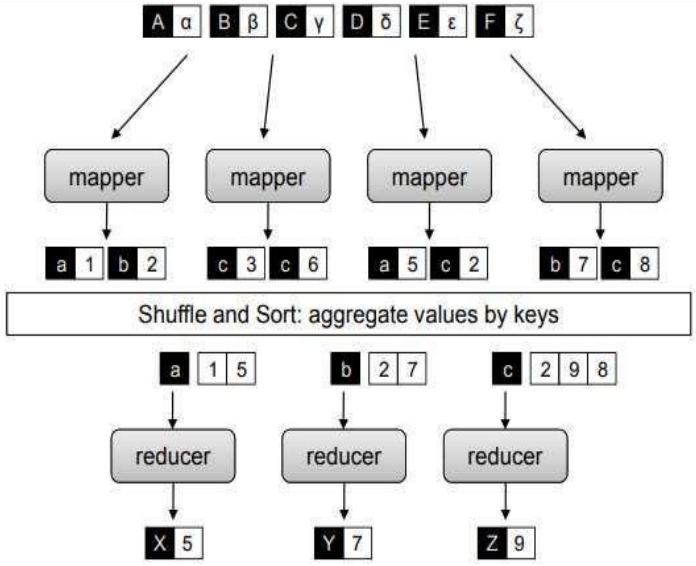


Figure 2.2: Simplified view of MapReduce. Mappers are applied to all input key-value pairs, which generate an arbitrary number of intermediate key-value pairs. Reducers are applied to all values associated with the same key. Between the map and reduce phases lies a barrier that involves a large distributed sort and group by.

distribution over words in a collection). Input key-values pairs take the form of (docid, doc) pairs stored on the distributed file system, where the former is a unique identifier for the document, and the latter is the text of the document itself. The mapper takes an input key-value pair, tokenizes the document, and emits an intermediate key-value pair for every word: the word itself serves as the key, and the integer one serves as the value (denoting that we've seen the word once). The MapReduce execution framework guarantees that all values associated with the same key are brought together in the reducer. Therefore, in our word count algorithm, we simply need to sum up all counts (ones) associated with each word. The reducer does exactly this, and emits final keyvalue pairs with the word as the key, and the count as the value. Final output is written to the distributed file system, one file per reducer. Words within each file will be sorted by alphabetical order, and each file will contain roughly the same number of words. The partitioner, which we discuss later in Section 2.4, controls the assignment of words to reducers. The output can be examined by the programmer or used as input to another MapReduce program.

There are some differences between the Hadoop implementation of MapReduce and Google's implementation.9 In Hadoop, the reducer is presented with a key and an iterator over all values associated with the particular key. The values are arbitrarily ordered. Google's implementation allows the programmer to specify a secondary sort key for ordering the values (if desired)—in which case values associated with each key would be presented to the developer's reduce code in sorted order. Later in Section 3.4 we discuss how to overcome this limitation in Hadoop to perform secondary sorting. Another difference: in Google's implementation the programmer is not allowed to change the key in the reducer. That is, the reducer output key must be exactly the same as the reducer input key. In Hadoop, there is no such restriction, and the reducer can emit an arbitrary number of output key-value pairs (with different keys).

To provide a bit more implementation detail: pseudo-code provided in this book roughly mirrors how MapReduce programs are written in Hadoop. Mappers and reducers are objects that implement the Map and Reduce methods, respectively. In Hadoop, a mapper object is initialized for each map task (associated with a particular sequence of key-value pairs called an input split) and the Map method is called on each key-value pair by the execution framework. In configuring a MapReduce job, the programmer provides a hint on the number of map tasks to run, but the execution framework (see next section) makes the final determination based on the physical layout of the data (more details in Section 2.5 and Section 2.6). The situation is similar for the reduce phase: a reducer object is initialized for each reduce task, and the Reduce method is called once per intermediate key. In contrast with the number of map tasks, the programmer can precisely specify the number of reduce tasks. We will return to discuss the details of Hadoop job execution in Section 2.6, which is dependent on an understanding of the distributed file system (covered in Section 2.5). To reiterate: although the presentation of algorithms in this book closely mirrors the way they would be implemented in Hadoop, our focus is on algorithm design and conceptual

understanding—not actual Hadoop programming. For that, we would recommend Tom White's book [154]. What are the restrictions on mappers and reducers? Mappers and reducers can express arbitrary computations over their inputs. However, one must generally be careful about use of external resources since multiple mappers or reducers may be contending for those resources. For example, it may be unwise for a mapper to query an external SQL database, since that would introduce a scalability bottleneck on the number of map tasks that could be run in parallel (since they might all be simultaneously querying the database).10 In general, mappers can emit an arbitrary number of intermediate key-value pairs, and they need not be of the same type as the input key-value pairs. Similarly, reducers can emit an arbitrary number of final key-value pairs, and they can differ in type from the intermediate key-value pairs. Although not permitted in functional programming, mappers and reducers can have side effects. This is a powerful and useful feature: for example, preserving state across multiple inputs is central to the design of many MapReduce algorithms (see Chapter 3). Such algorithms can be understood as having side effects that only change state that is internal to the mapper or reducer. While the correctness of such algorithms may be more difficult to guarantee (since the function's behavior depends not only on the current input but on previous inputs), most potential synchronization problems are avoided since internal state is private only to individual mappers and reducers. In other cases (see Section 4.4 and Section 6.5), it may be useful for mappers or reducers to have external side effects, such as writing files to the distributed file system. Since many mappers and reducers are run in parallel, and the distributed file system is a shared global resource, special care must be taken to ensure that such operations avoid synchronization conflicts. One strategy is to write a temporary file that is renamed upon successful completion of the mapper or reducer .

In addition to the "canonical" MapReduce processing flow, other variations are also possible. MapReduce programs can contain no reducers, in which case mapper output is directly written to disk (one file per mapper). For embarrassingly parallel problems, e.g., parse a large text collection or independently analyze a large number of images, this would be a common pattern. The converse—a MapReduce program with no mappers—is not possible, although in some cases it is useful for the mapper to implement the identity function and simply pass input key-value pairs to the reducers. This has the effect of sorting and regrouping the input for reduce-side processing. Similarly, in some cases it is useful for the reducer to implement the identity function, in which case the program simply sorts and groups mapper output. Finally, running identity mappers and reducers has the effect of regrouping and resorting the input data (which is sometimes useful).

Although in the most common case, input to a MapReduce job comes from data stored on the distributed file system and output is written back to the distributed file system, any other system that satisfies the proper abstractions can serve as a data source or sink. With Google's MapReduce implementation, BigTable [34], a sparse, distributed, persistent multidimensional sorted map, is frequently used as a source of input and as a store of MapReduce output. HBase is an open-source BigTable clone and has similar capabilities. Also, Hadoop has been integrated with existing MPP (massively parallel processing) relational databases, which allows a programmer to write MapReduce jobs over database rows and dump output into a new database table. Finally, in some

cases MapReduce jobs may not consume any input at all (e.g., computing π) or may only consume a small amount of data (e.g., input parameters to many instances of processorintensive simulations running in parallel).

PARTITIONERS AND COMBINERS

We have thus far presented a simplified view of MapReduce. There are two additional elements that complete the programming model: partitioners and combiners. Partitioners are responsible for dividing up the intermediate key space and assigning intermediate key-value pairs to reducers. In other words, the partitioner specifies the task to which an intermediate key-value pair must be copied. Within each reducer, keys are processed in sorted order (which is how the "group by" is implemented). The simplest partitioner involves computing the hash value of the key and then taking the mod of that value with the number of reducers. This assigns approximately the same number of keys to each reducer (dependent on the quality of the hash function). Note, however, that the partitioner only considers the key and ignores the value—therefore, a roughly-even partitioning of the key space may nevertheless yield large differences in the number of key-values pairs sent to each reducer (since different keys may have different numbers of associated values). This imbalance in the amount of data associated with each key is relatively common in many text processing applications due to the Zipfian distribution of word occurrences.

Combiners are an optimization in MapReduce that allow for local aggregation before the shuffle and sort phase. We can motivate the need for combiners by considering the word count algorithm in Figure 2.3, which emits a key-value pair for each word in the collection. Furthermore, all these key-value pairs need to be copied across the network, and so the amount of intermediate data will be larger than the input collection itself. This is clearly inefficient. One solution is to perform local aggregation on the output of each mapper, i.e., to compute a local count for a word over all the documents processed by the mapper. With this modification (assuming the maximum amount of local aggregation possible), the number of intermediate key-value pairs will be at most the number of unique words in the collection times the number of mappers (and typically far smaller because each mapper may not encounter every word).

smaller because each mapper may not encounter every word). The combiner in MapReduce supports such an optimization. One can think of combiners as "mini-reducers" that take place on the output of the mappers, prior to the shuffle and sort phase. Each combiner operates in isolation and therefore does not have access to intermediate output from other mappers. The combiner is provided keys and values associated with each key (the same types as the mapper output keys and values). Critically, one cannot assume that a combiner will have the opportunity to process all values associated with the same key. The combiner can emit any number of key-value pairs, but the keys and values must be of the same type as the mapper output (same as the reducer input).12 In cases where an operation is both associative and commutative (e.g., addition or multiplication), reducers can directly serve as combiners. In general, however, reducers and combiners are not interchangeable.

In many cases, proper use of combiners can spell the difference between an impractical algorithm and an efficient algorithm. This topic will be discussed in Section 3.1, which focuses on various techniques for local aggregation. It suffices to say for now that a combiner can significantly reduce the amount of data that needs to be copied over the network, resulting in much faster algorithms. The complete MapReduce model is shown in Figure 2.4. Output of the mappers are processed by the combiners, which perform local aggregation to cut down on the number of intermediate key-value pairs. The partitioner determines which reducer will be responsible for processing a particular key, and the execution framework uses this information to copy the data to the right location during the shuffle and sort phase.13 Therefore, a complete MapReduce job consists of code for the mapper, reducer, combiner, and partitioner, along with job configuration parameters. The execution framework handles everything else.

30 CHAPTER 2. MAPREDUCE BASICS

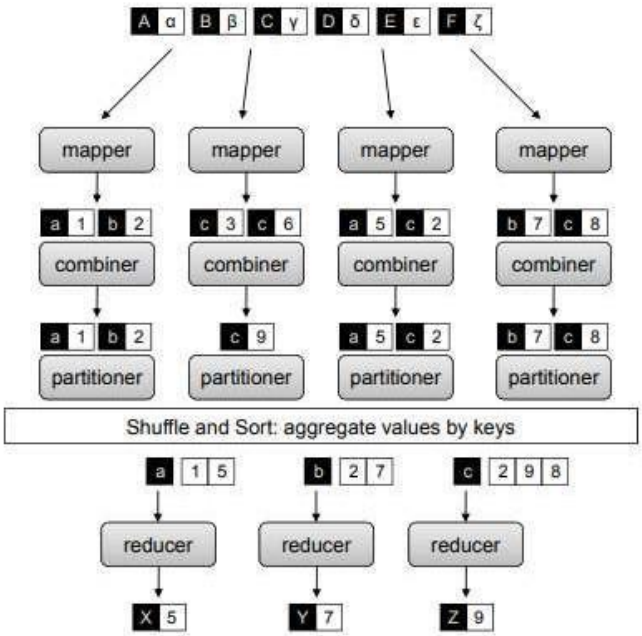


Figure 2.4: Complete view of MapReduce, illustrating combiners and partitioners in addition to mappers and reducers. Combiners can be viewed as "mini-reducers" in the map phase. Partitioners determine which reducer is responsible for a particular key.

SECONDARY SORTING

MapReduce sorts intermediate key-value pairs by the keys during the shuffle and sort phase, which is very convenient if computations inside the reducer rely on sort order (e.g., the order inversion design pattern described in the previous section). However, what if in addition to sorting by key, we also need to sort by value? Google's MapReduce implementation provides built-in

functionality for (optional) secondary sorting, which guarantees that values arrive in sorted order. Hadoop, unfortunately, does not have this capability built in.

Consider the example of sensor data from a scientific experiment: there are m sensors each taking readings on continuous basis, where m is potentially a large number. A dump of the sensor data might look something like the following, where rx after each timestamp represents the actual sensor readings (unimportant for this discussion, but may be a series of values, one or more complex records, or even raw bytes of images).

(t1, m1, r80521)

(t1, m2, r14209)

(t1, m3, r76042) ...

(t2, m1, r21823)

(t2, m2, r66508)

(t2, m3, r98347)

Suppose we wish to reconstruct the activity at each individual sensor over time. A MapReduce program to accomplish this might map over the raw data and emit the sensor id as the intermediate key, with the rest of each record as the value:

m1 → (t1, r80521)

This would bring all readings from the same sensor together in the reducer. However, since MapReduce makes no guarantees about the ordering of values associated with the same key, the sensor readings will not likely be in temporal order. The most obvious solution is to buffer all the readings in memory and then sort by timestamp before additional processing. However, it should be apparent by now that any in-memory buffering of data introduces a potential scalability bottleneck. What if we are working with a high frequency sensor or sensor readings over a long period of time? What if the sensor readings themselves are large complex objects? This approach may not scale in these cases—the reducer would run out of memory trying to buffer all values associated with the same key.

This is a common problem, since in many applications we wish to first group together data one way (e.g., by sensor id), and then sort within the groupings another way (e.g., by time). Fortunately, there is a general purpose solution, which we call the "value-to-key conversion" design pattern. The basic idea is to move part of the value into the intermediate key to form a composite key, and let the MapReduce execution framework handle the sorting. In the above example, instead of emitting the sensor id as the key, we would emit the sensor id and the timestamp as a composite key: (m1, t1) → (r80521)

The sensor reading itself now occupies the value. We must define the intermediate key sort order to first sort by the sensor id (the left element in the pair) and then by the timestamp (the right element in the pair). We must also implement a custom partitioner so that all pairs associated with the same sensor are shuffled to the same reducer. Properly orchestrated, the key-value pairs will be presented to the reducer in the correct sorted order: (m1, t1) → [(r80521)] (m1, t2) → [(r21823)] (m1, t3) → [(r146925)] . . .

However, note that sensor readings are now split across multiple keys. The reducer will need to preserve state and keep track of when readings associated with the current sensor end and the next sensor begin.9 The basic tradeoff between the two approaches discussed above (buffer and inmemory sort vs. value-to-key conversion) is where sorting is performed. One can explicitly implement secondary sorting in the reducer, which is likely to be faster but suffers from a scalability bottleneck.10 With value-to-key conversion, sorting is offloaded to the MapReduce execution framework. Note that this approach can be arbitrarily extended to tertiary, quaternary, etc. sorting. This pattern results in many more keys for the framework to sort, but distributed sorting is a task that the MapReduce runtime excels at since it lies at the heart of the programming model.

INDEX COMPRESSION

We return to the question of how postings are actually compressed and stored on disk. This chapter devotes a substantial amount of space to this topic because index compression is one of the main differences between a “toy” indexer and one that works on real-world collections. Otherwise, MapReduce inverted indexing algorithms are pretty straightforward.

Let us consider the canonical case where each posting consists of a document id and the term frequency. A na¨ıve implementation might represent the first as a 32-bit integer9 and the second as a 16-bit integer. Thus, a postings list might be encoded as follows: [(5, 2),(7, 3),(12, 1),(49, 1),(51, 2), . . .]

where each posting is represented by a pair in parentheses. Note that all brackets, parentheses, and commas are only included to enhance readability; in reality the postings would be represented as a long stream of integers. This na¨ıve implementation would require six bytes per posting. Using this scheme, the entire inverted index would be about as large as the collection itself. Fortunately, we can do significantly better. The first trick is to encode differences between document ids as opposed to the document ids themselves. Since the postings are sorted by document ids, the differences (called d-gaps) must be positive integers greater than zero. The above postings list, represented with d-gaps, would be: [(5, 2),(2, 3),(5, 1),(37, 1),(2, 2)

Of course, we must actually encode the first document id. We haven’t lost any information, since the original document ids can be easily reconstructed from the d-gaps. However, it’s not obvious that we’ve reduced the space requirements either, since the largest possible d-gap is one less than

the number of documents in the collection. This is where the second trick comes in, which is to represent the d-gaps in a way such that it takes less space for smaller numbers. Similarly, we want to apply the same techniques to compress the term frequencies, since for the most part they are also small values. But to understand how this is done, we need to take a slight detour into compression techniques, particularly for coding integers.

Compression, in general, can be characterized as either lossless or lossy: it's fairly obvious that loseless compression is required in this context. To start, it is important to understand that all compression techniques represent a time–space tradeoff. That is, we reduce the amount of space on disk necessary to store data, but at the cost of extra processor cycles that must be spent coding and decoding data. Therefore, it is possible that compression reduces size but also slows processing. However, if the two factors are properly balanced (i.e., decoding speed can keep up with disk bandwidth), we can achieve the best of both worlds: smaller and faster.

POSTINGS COMPRESSION

Having completed our slight detour into integer compression techniques, we can now return to the scalable inverted indexing algorithm shown in Figure 4.4 and discuss how postings lists can be properly compressed. As we can see from the previous section, there is a wide range of choices that represent different tradeoffs between compression ratio and decoding speed. Actual performance also depends on characteristics of the collection, which, among other factors, determine the distribution of d-gaps. B¨uttcher et al. [30] recently compared the performance of various compression techniques on coding document ids. In terms of the amount of compression that can be obtained (measured in bits per docid), Golomb and Rice codes performed the best, followed by γ codes, Simple-9, varInt, and group varInt (the least space efficient). In terms of raw decoding speed, the order was almost the reverse: group varInt was the fastest, followed by varInt.14 Simple-9 was substantially slower, and the bit-aligned codes were even slower than that. Within the bit-aligned codes, Rice codes were the fastest, followed by γ, with Golomb codes being the slowest (about ten times slower than group varInt).

Let us discuss what modifications are necessary to our inverted indexing algorithm if we were to adopt Golomb compression for d-gaps and represent term frequencies with γ codes. Note that this represents a space-efficient encoding, at the cost of slower decoding compared to alternatives. Whether or not this is actually a worthwhile tradeoff in practice is not important here: use of Golomb codes serves a pedagogical purpose, to illustrate how one might set compression parameters.

Coding term frequencies with γ codes is easy since they are parameterless. Compressing d-gaps with Golomb codes, however, is a bit tricky, since two parameters are required: the size of the document collection and the number of postings for a particular postings list (i.e., the document frequency, or df). The first is easy to obtain and can be passed into the reducer as a constant. The df of a term, however, is not known until all the postings have been processed—and unfortunately,

the parameter must be known before any posting is coded. At first glance, this seems like a chicken-and-egg problem. A two-pass solution that involves first buffering the postings (in memory) would suffer from the memory bottleneck we've been trying to avoid in the first place.

To get around this problem, we need to somehow inform the reducer of a term's df before any of its postings arrive. This can be solved with the order inversion design pattern introduced in Section 3.3 to compute relative frequencies. The solution is to have the mapper emit special keys of the form ht, ∗i to communicate partial document frequencies. That is, inside the mapper, in addition to emitting intermediate key-value pairs of the following form:

(tuple ht, docidi,tf f)

we also emit special intermediate key-value pairs like this:

(tuple ht, ∗i, df e)

to keep track of document frequencies associated with each term. In practice, we can accomplish this by applying the in-mapper combining design pattern (see Section 3.1). The mapper holds an in-memory associative array that keeps track of how many documents a term has been observed in (i.e., the local document frequency of the term for the subset of documents processed by the mapper). Once the mapper has processed all input records, special keys of the form ht, ∗i are emitted with the partial df as the value.

To ensure that these special keys arrive first, we define the sort order of the tuple so that the special symbol ∗ precedes all documents (part of the order inversion design pattern). Thus, for each term, the reducer will first encounter the ht, ∗i key, associated with a list of values representing partial df values originating from each mapper. Summing all these partial contributions will yield the term's df, which can then be used to set the Golomb compression parameter b. This allows the postings to be incrementally compressed as they are encountered in the reducer—memory bottlenecks are eliminated since we do not need to buffer postings in memory.

Once again, the order inversion design pattern comes to the rescue. Recall that the pattern is useful when a reducer needs to access the result of a computation (e.g., an aggregate statistic) before it encounters the data necessary to produce that computation. For computing relative frequencies, that bit of information was the marginal. In this case, it's the document frequency.

PARALLEL BREADTH-FIRST SEARCH

One of the most common and well-studied problems in graph theory is the single-source shortest path problem, where the task is to find shortest paths from a source node to all other nodes in the graph (or alternatively, edges can be associated with costs or weights, in which case the task is to compute lowest-cost or lowest-weight paths). Such problems are a staple in undergraduate

algorithm courses, where students are taught the solution using Dijkstra's algorithm. However, this famous algorithm assumes sequential processing—how would we solve this problem in parallel, and more specifically, with MapReduce?

```
Dijkstra(G, w, s)
2: d[s] ← 0
3: for all vertex v ∈ V do
4: d[v] ← ∞
5: Q ← {V }
6: while Q 6= ∅ do
7: u ← ExtractMin(Q)
8: for all vertex v ∈ u.AdjacencyList do
9: if d[v] > d[u] + w(u, v) then
10: d[v] ← d[u] + w(u, v)
```

Figure 5.2: Pseudo-code for Dijkstra's algorithm, which is based on maintaining a global priority queue of nodes with priorities equal to their distances from the source node. At each iteration, the algorithm expands the node with the shortest distance and updates distances to all reachable nodes.

As a refresher and also to serve as a point of comparison, Dijkstra's algorithm is shown in Figure 5.2, adapted from Cormen, Leiserson, and Rivest's classic algorithms textbook [41] (often simply known as CLR). The input to the algorithm is a directed, connected graph G = (V, E) represented with adjacency lists, w containing edge distances such that $w(u, v) \geq 0$, and the source node s. The algorithm begins by first setting distances to all vertices d[v], $v \in V$ to ∞, except for the source node, whose distance to itself is zero. The algorithm maintains Q, a global priority queue of vertices with priorities equal to their distance values d

Dijkstra's algorithm operates by iteratively selecting the node with the lowest current distance from the priority queue (initially, this is the source node). At each iteration, the algorithm "expands" that node by traversing the adjacency list of the selected node to see if any of those nodes can be reached with a path of a shorter distance. The algorithm terminates when the priority queue Q is empty, or equivalently, when all nodes have been considered. Note that the algorithm as presented in Figure 5.2 only computes the shortest distances. The actual paths can be recovered by storing "backpointers" for every node indicating a fragment of the shortest path.

A sample trace of the algorithm running on a simple graph is shown in Figure 5.3 (example also adapted from CLR). We start out in (a) with n1 having a distance of zero (since it's the source) and all other nodes having a distance of ∞. In the first iteration (a), n1 is selected as the node to expand (indicated by the thicker border). After the expansion, we see in (b) that n2 and n3 can be reached at a distance of 10 and 5, respectively. Also, we see in (b) that n3 is the next node selected for expansion. Nodes we have already considered for expansion are shown in black. Expanding n3, we see in (c) that the distance to n2 has decreased because we've found a shorter path. The nodes that will be expanded next, in order, are n5, n2, and n4. The algorithm terminates with the end state shown in (f), where we've discovered the shortest distance to all nodes.

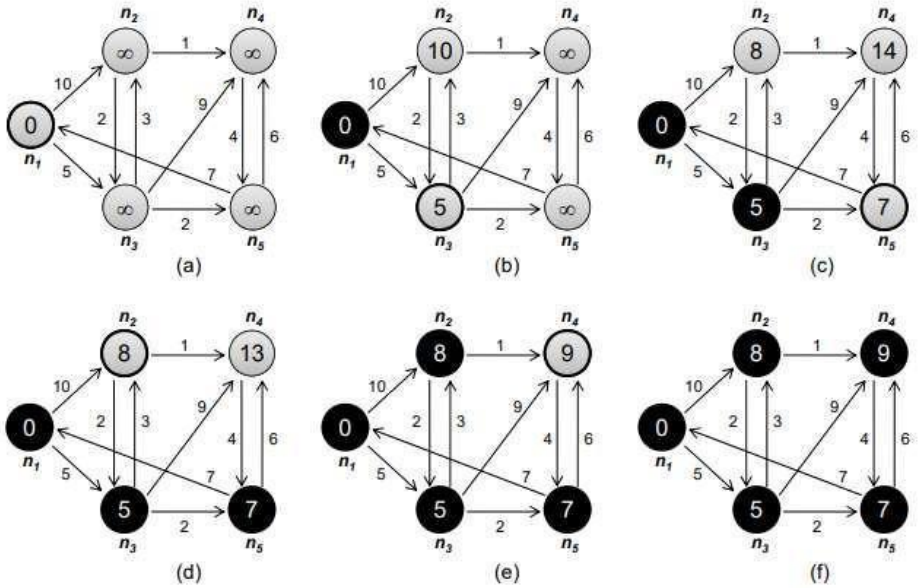


Figure 5.3: Example of Dijkstra's algorithm applied to a simple graph with five nodes, with n_1 as the source and edge distances as indicated. Parts (a)–(e) show the running of the algorithm at each iteration, with the current distance inside the node. Nodes with thicker borders are those being expanded; nodes that have already been expanded are shown in black.

The key to Dijkstra's algorithm is the priority queue that maintains a globallysorted list of nodes by current distance. This is not possible in MapReduce, as the programming model does not provide a mechanism for exchanging global data. Instead, we adopt a brute force approach known as parallel breadth-first search. First, as a simplification let us assume that all edges have unit distance (modeling, for example, hyperlinks on the web). This makes the algorithm easier to understand, but we'll relax this restriction later.

The intuition behind the algorithm is this: the distance of all nodes connected directly to the source node is one; the distance of all nodes directly connected to those is two; and so on. Imagine water rippling away from a rock dropped into a pond— that's a good image of how parallel breadth-first search works. However, what if there are multiple paths to the same node? Suppose we wish to compute the shortest distance to node n. The shortest path must go through one of the nodes in M that contains an outgoing edge to n: we need to examine all m ∈ M to find ms, the node with the shortest distance. The shortest distance to n is the distance to ms plus one.

Pseudo-code for the implementation of the parallel breadth-first search algorithm is provided in Figure 5.4. As with Dijkstra's algorithm, we assume a connected, directed graph represented as adjacency lists. Distance to each node is directly stored alongside the adjacency list of that node, and initialized to ∞ for all nodes except for the source node. In the pseudo-code, we use n to denote the node id (an integer) and N to denote the node's corresponding data structure (adjacency list and current distance). The algorithm works by mapping over all nodes and emitting a key-value pair for each neighbor on the node's adjacency list. The key contains the node id of the neighbor, and the value is the current distance to the node plus one. This says: if we can reach node n with a distance d, then we must be able to reach all the nodes that are connected to n with distance d + 1.

After shuffle and sort, reducers will receive keys corresponding to the destination node ids and distances corresponding to all paths leading to that node. The reducer will select the shortest of these distances and then update the distance in the node data structure.

h iteration corresponds to a MapReduce job. The first time we run the algorithm, we "discover" all nodes that are connected to the source. The second iteration, we discover all nodes connected to those, and so on. Each iteration of the algorithm expands the "search frontier" by one hop, and, eventually, all nodes will be discovered with their shortest distances (assuming a fully-connected graph). Before we discuss termination of the algorithm, there is one more detail required to make the parallel breadth-first search algorithm work. We need to "pass along" the graph structure from one iteration to the next. This is accomplished by emitting the node data structure itself, with the node id as a key (Figure 5.4, line 4 in the mapper). In the reducer, we must distinguish the node data structure from distance values (Figure 5.4, lines 5–6 in the reducer), and update the minimum distance in the node data structure before emitting it as the final value. The final output is now ready to serve as input to the next iteration.

So how many iterations are necessary to compute the shortest distance to all nodes? The answer is the diameter of the graph, or the greatest distance between any pair of nodes. This number is surprisingly small for many real-world problems: the saying "six degrees of separation" suggests that everyone on the planet is connected to everyone else by at most six steps (the people a person knows are one step away, people that they know are two steps away, etc.). If this is indeed true, then parallel breadthfirst search on the global social network would take at most six MapReduce iterations.

```
class Mapper
2: method Map(nid n, node N)
3: d ← N.Distance
4: Emit(nid n, N) . Pass along graph structure
5: for all nodeid m ∈ N.AdjacencyList do
6: Emit(nid m, d + 1) . Emit distances to reachable nodes
1: class Reducer
2: method Reduce(nid m, [d1, d2, . . .])
3: dmin ← ∞
4: M ← ∅
5: for all d ∈ counts [d1, d2, . . .] do
6: if IsNode(d) then
7: M ← d . Recover graph structure
8: else if d < dmin then . Look for shorter distance
9: dmin ← d
10: M.Distance ← dmin . Update shortest distance
11: Emit(nid m, node M)
```

Figure 5.4: Pseudo-code for parallel breath-first search in MapReduce: the mappers emit distances to reachable nodes, while the reducers select the minimum of those distances for each destination node. Each iteration (one MapReduce job) of the algorithm expands the "search frontier" by one hop.

For more serious academic studies of "small world" phenomena in networks, we refer the reader to a number of publications [61, 62, 152, 2]. In practical terms, we iterate the algorithm until there are no more node distances that are ∞. Since the graph is connected, all nodes are reachable, and since all edge distances are one, all discovered nodes are guaranteed to have the shortest distances (i.e., there is not a shorter path that goes through a node that hasn't been discovered).

The actual checking of the termination condition must occur outside of MapReduce. Typically, execution of an iterative MapReduce algorithm requires a nonMapReduce "driver" program, which submits a MapReduce job to iterate the algorithm, checks to see if a termination condition has been met, and if not, repeats. Hadoop provides a lightweight API for constructs called "counters", which, as the name suggests, can be used for counting events that occur during execution, e.g., number of corrupt records, number of times a certain condition is met, or anything that the programmer desires. Counters can be defined to count the number of nodes that have distances of ∞: at the end of the job, the driver program can access the final counter value and check to see if another iteration is necessary.

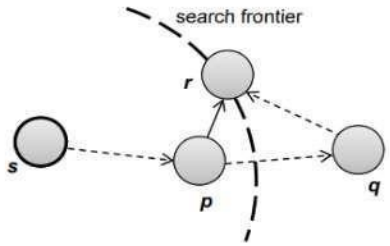


Figure 5.5: In the single source shortest path problem with arbitrary edge distances, the shortest path from source s to node r may go outside the current search frontier, in which case we will not find the shortest distance to r until the search frontier expands to cover q.

Finally, as with Dijkstra's algorithm in the form presented earlier, the parallel breadth-first search algorithm only finds the shortest distances, not the actual shortest paths. However, the path can be straightforwardly recovered. Storing "backpointers" at each node, as with Dijkstra's algorithm, will work, but may not be efficient since the graph needs to be traversed again to reconstruct the path segments. A simpler approach is to emit paths along with distances in the mapper, so that each node will have its shortest path easily accessible at all times. The additional space requirements for shuffling these data from mappers to reducers are relatively modest, since for the most part paths (i.e., sequence of node ids) are relatively short.

Up until now, we have been assuming that all edges are unit distance. Let us relax that restriction and see what changes are required in the parallel breadth-first search algorithm. The adjacency lists, which were previously lists of node ids, must now encode the edge distances as well. In line

6 of the mapper code in Figure 5.4, instead of emitting d + 1 as the value, we must now emit d + w where w is the edge distance. No other changes to the algorithm are required, but the termination behavior is very different. To illustrate, consider the graph fragment in Figure 5.5, where s is the source node, and in this iteration, we just "discovered" node r for the very first time. Assume for the sake of argument that we've already discovered the shortest distance to node p, and that the shortest distance to r so far goes through p. This, however, does not guarantee that we've discovered the shortest distance to r, since there may exist a path going through q that we haven't encountered yet (because it lies outside the search frontier).6 However, as the search frontier expands, we'll eventually cover q and all other nodes along the path from p to q to r—which means that with sufficient iterations, we will discover the shortest distance to r. But how do we know that we've found the shortest distance to p? Well, if the shortest path to p lies within the search frontier, we would have already discovered it. And if it doesn't, the above argument applies. Similarly, we can repeat the same argument for all nodes on the path from s to p. The conclusion is that, with sufficient iterations, we'll eventually discover all the shortest distances.

So exactly how many iterations does "eventually" mean? In the worst case, we might need as many iterations as there are nodes in the graph minus one. In fact, it is not difficult to construct graphs that will elicit this worse-case behavior: Figure 5.6 provides an example, with n1 as the source. The parallel breadth-first search algorithm would not discover that the shortest path from n1 to n6 goes through n3, n4, and n5 until the fifth iteration. Three more iterations are necessary to cover the rest of the graph. Fortunately, for most real-world graphs, such extreme cases are rare, and the number of iterations necessary to discover all shortest distances is quite close to the diameter of the graph, as in the unit edge distance case.

In practical terms, how do we know when to stop iterating in the case of arbitrary edge distances? The algorithm can terminate when shortest distances at every node no longer change. Once again, we can use counters to keep track of such events. Every time we encounter a shorter distance in the reducer, we increment a counter. At the end of each MapReduce iteration, the driver program reads the counter value and determines if another iteration is necessary.

Compared to Dijkstra's algorithm on a single processor, parallel breadth-first search in MapReduce can be characterized as a brute force approach that "wastes" a lot of time performing computations whose results are discarded. At each iteration, the algorithm attempts to recompute distances to all nodes, but in reality only useful work is done along the search frontier: inside the search frontier, the algorithm is simply repeating previous computations.7 Outside the search frontier, the algorithm hasn't discovered any paths to nodes there yet, so no meaningful work is done. Dijkstra's algorithm, on the other hand, is far more efficient. Every time a node is explored, we're guaranteed to have already found the shortest path to it. However, this is made possible by maintaining a global data structure (a priority queue) that holds nodes sorted by distance—this is not possible in MapReduce because the programming model does not provide support for global data that is mutable and accessible by the mappers and reducers. These inefficiencies represent the cost of parallelization.

The parallel breadth-first search algorithm is instructive in that it represents the prototypical structure of a large class of graph algorithms in MapReduce. They share in the following characteristics:

The graph structure is represented with adjacency lists, which is part of some larger node data structure that may contain additional information (variables to store intermediate output, features of the nodes). In many cases, features are attached to edges as well (e.g., edge weights).

The graph structure is represented with adjacency lists, which is part of some larger node data structure that may contain additional information (variables to store intermediate output, features of the nodes). In many cases, features are attached to edges as well (e.g., edge weights).

In addition to computations, the graph itself is also passed from the mapper to the reducer. In the reducer, the data structure corresponding to each node is updated and written back to disk.

Graph algorithms in MapReduce are generally iterative, where the output of the previous iteration serves as input to the next iteration. The process is controlled by a non-MapReduce driver program that checks for termination.

For parallel breadth-first search, the mapper computation is the current distance plus edge distance (emitting distances to neighbors), while the reducer computation is the Min function (selecting the shortest path). As we will see in the next section, the MapReduce algorithm for PageRank works in much the same way

UNIT V

INTRODUCTION TO HIVE AND PIG

The term 'Big Data' is used for collections of large datasets that include huge volume, high velocity, and a variety of data that is increasing day by day. Using traditional data management systems, it is difficult to process Big Data. Therefore, the Apache Software Foundation introduced a framework called Hadoop to solve Big Data management and processing challenges.

Hadoop

Hadoop is an open-source framework to store and process Big Data in a distributed environment. It contains two modules, one is MapReduce and another is Hadoop Distributed File System (HDFS).

- **MapReduce:** It is a parallel programming model for processing large amounts of structured, semi-structured, and unstructured data on large clusters of commodity hardware.
- **HDFS:** Hadoop Distributed File System is a part of Hadoop framework, used to store and process the datasets. It provides a fault-tolerant file system to run on commodity hardware.

The Hadoop ecosystem contains different sub-projects (tools) such as Sqoop, Pig, and Hive that are used to help Hadoop modules.

- **Sqoop:** It is used to import and export data to and from between HDFS and RDBMS.
- **Pig:** It is a procedural language platform used to develop a script for MapReduce operations.
- **Hive:** It is a platform used to develop SQL type scripts to do MapReduce operations.

Note: There are various ways to execute MapReduce operations:

- The traditional approach using Java MapReduce program for structured, semi-structured, and unstructured data.
- The scripting approach for MapReduce to process structured and semi structured data using Pig.
- The Hive Query Language (HiveQL or HQL) for MapReduce to process structured data using Hive.

What is Hive

Hive is a data warehouse infrastructure tool to process structured data in Hadoop. It resides on top of Hadoop to summarize Big Data, and makes querying and analyzing easy.

Initially Hive was developed by Facebook, later the Apache Software Foundation took it up and developed it further as an open source under the name Apache Hive. It is used by different companies. For example, Amazon uses it in Amazon Elastic MapReduce.

Hive is not

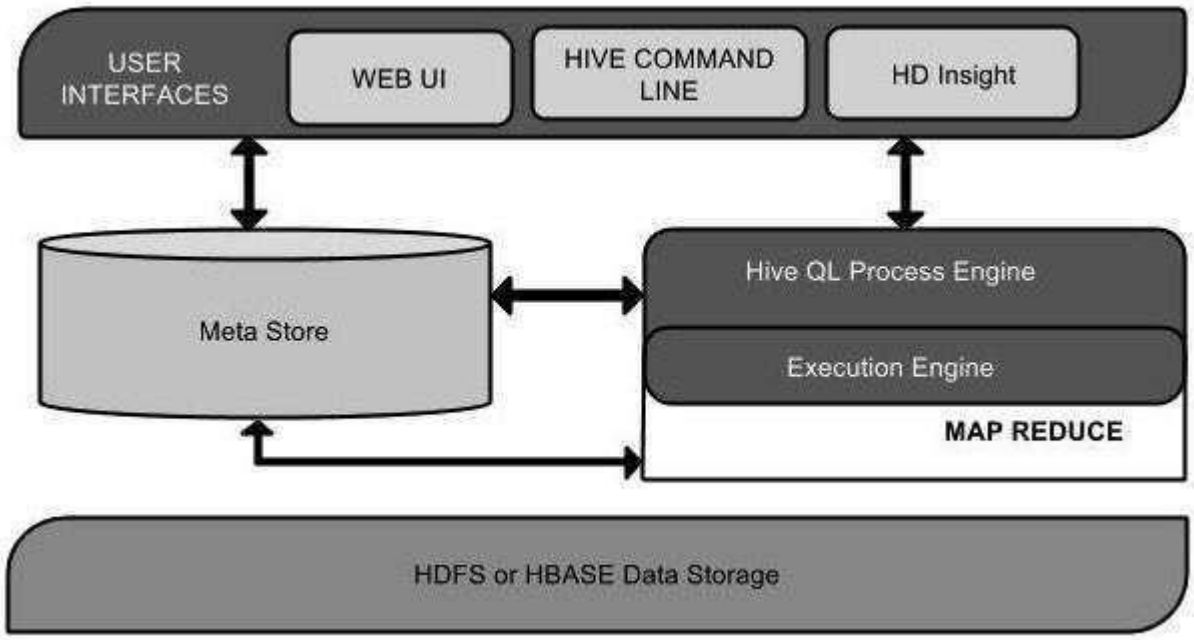
- A relational database
- A design for OnLine Transaction Processing (OLTP)
- A language for real-time queries and row-level updates

Features of Hive

- It stores schema in a database and processed data into HDFS.
- It is designed for OLAP.
- It provides SQL type language for querying called HiveQL or HQL.
- It is familiar, fast, scalable, and extensible.

Architecture of Hive

The following component diagram depicts the architecture of Hive:

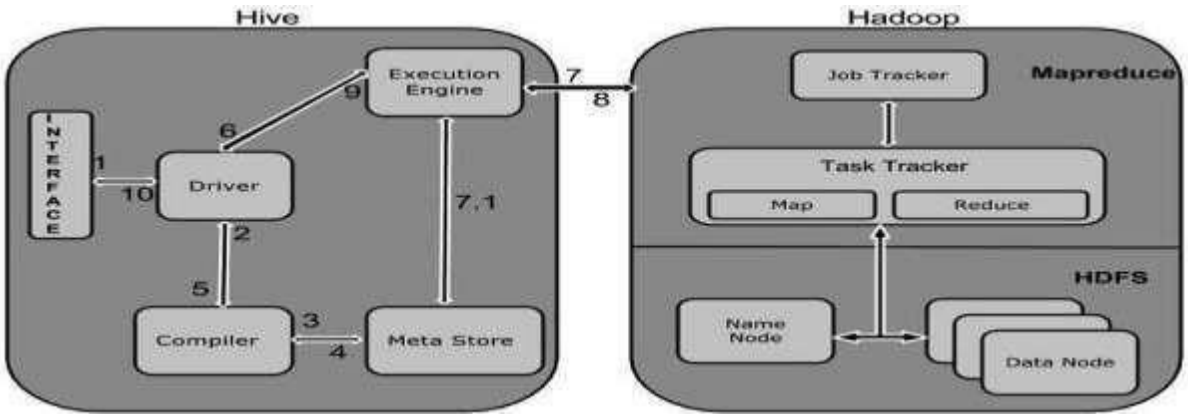


This component diagram contains different units. The following table describes each unit:

Unit Name	Operation
User Interface	Hive is a data warehouse infrastructure software that can create interaction between user and HDFS. The user interfaces that Hive supports are Hive Web UI, Hive command line, and Hive HD Insight (In Windows server).
Meta Store	Hive chooses respective database servers to store the schema or Metadata of tables, databases, columns in a table, their data types, and HDFS mapping.
HiveQL Process Engine	HiveQL is similar to SQL for querying on schema info on the Metastore. It is one of the replacements of traditional approach for MapReduce program. Instead of writing MapReduce program in Java, we can write a query for MapReduce job and process it.
Execution Engine	The conjunction part of HiveQL process Engine and MapReduce is Hive Execution Engine. Execution engine processes the query and generates results as same as MapReduce results. It uses the flavor of MapReduce.
HDFS or HBASE	Hadoop distributed file system or HBASE are the data storage techniques to store data into file system.

Working of Hive

The following diagram depicts the workflow between Hive and Hadoop.



The following table defines how Hive interacts with Hadoop framework:

Step No.	Operation
1	**Execute Query** The Hive interface such as Command Line or Web UI sends query to Driver (any database driver such as JDBC, ODBC, etc.) to execute.
2	**Get Plan** The driver takes the help of query compiler that parses the query to check the syntax and query plan or the requirement of query.
3	**Get Metadata** The compiler sends metadata request to Metastore (any database).
4	**Send Metadata** Metastore sends metadata as a response to the compiler.
5	**Send Plan** The compiler checks the requirement and resends the plan to the driver. Up to here, the parsing and compiling of a query is complete.
6	**Execute Plan** The driver sends the execute plan to the execution engine.
7	**Execute Job** Internally, the process of execution job is a MapReduce job. The execution engine sends the job to JobTracker, which is in Name node and it assigns this job to TaskTracker, which is in Data node. Here, the query executes MapReduce job.
7.1	**Metadata Ops**

	Meanwhile in execution, the execution engine can execute metadata operations with Metastore.
8	**Fetch Result** The execution engine receives the results from Data nodes.
9	**Send Results** The execution engine sends those resultant values to the driver.
10	**Send Results** The driver sends the results to Hive Interfaces.

File Formats in Hive

- File Format specifies how records are encoded in files
- Record Format implies how a stream of bytes for a given record are encoded
- The default file format is **TEXTFILE** – each record is a line in the file
- Hive uses different control characters as delimeters in textfiles
  - ^A (octal 001) , ^B(octal 002), ^C(octal 003), \n
- The term field is used when overriding the default delimiter
  - **FIELDS TERMINATED BY '\001'**
- Supports text files – csv, tsv
- TextFile can contain JSON or XML documents.

ommonly used File Formats –

1. **TextFile format**
   - Suitable for sharing data with other tools
   - Can be viewed/edited manually
2. **SequenceFile**
   - Flat files that stores binary key ,value pair
   - SequenceFile offers a Reader ,Writer, and Sorter classes for reading ,writing, and sorting respectively
   - Supports – Uncompressed, Record compressed (only value is compressed) and Block compressed (both key,value compressed) formats
3. **RCFile**
   - RCFile stores columns of a table in a record columnar way
4. **ORC**
5. **AVRO**

Hive Commands

Hive supports Data definition Language(DDL), Data Manipulation Language(DML) and User defined functions.

Hive DDL Commands

create database

drop database

create table

drop table

alter table

create index

create view

Hive DML Commands

Select

Where

Group By

Order By

Load Data

Join:

- Inner Join
- Left Outer Join
- Right Outer Join
- Full Outer Join

Hive DDL Commands

Create Database Statement

A database in Hive is a namespace or a collection of tables.

1. hive> CREATE SCHEMA userdb;
2. hive> SHOW DATABASES;

Drop database

1. ive> DROP DATABASE IF EXISTS userdb;

Creating Hive Tables

Create a table called Sonoo with two columns, the first being an integer and the other a string.

1. hive> CREATE TABLE Sonoo(foo INT, bar STRING);

Create a table called HIVE_TABLE with two columns and a partition column called ds. The partition column is a virtual column. It is not part of the data itself but is derived from the partition that a particular dataset is loaded into.By default, tables are assumed to be of text input format and the delimiters are assumed to be ^A(ctrl-a).

1. hive> CREATE TABLE HIVE_TABLE (foo INT, bar STRING) PARTITIONED BY (ds STRI NG);

Browse the table

1. hive> Show tables;

Altering and Dropping Tables

1. hive> ALTER TABLE Sonoo RENAME TO Kafka;
2. hive> ALTER TABLE Kafka ADD COLUMNS (col INT);
3. hive> ALTER TABLE HIVE_TABLE ADD COLUMNS (col1 INT COMMENT 'a comment');
4. hive> ALTER TABLE HIVE_TABLE REPLACE COLUMNS (col2 INT, weight STRING, baz INT COMMENT 'baz replaces new_col1');

Hive DML Commands

To understand the Hive DML commands, let's see the employee and employee_department table first.

Employee			Employee Department	
EMP ID	Emp Name	Address	Emp ID	Department
1	Rose	US	1	IT
2	Fred	US	2	IT
3	Jess	In	3	Eng
4	Frey	Th	4	Admin

LOAD DATA

1. hive> LOAD DATA LOCAL INPATH './usr/Desktop/kv1.txt' OVERWRITE INTO TABLE Employee;

SELECTS and FILTERS

1. hive> SELECT E.EMP_ID FROM Employee E WHERE E.Address='US';

GROUP BY

1. hive> hive> SELECT E.EMP_ID FROM Employee E GROUP BY E.Addresss;

Adding a Partition

We can add partitions to a table by altering the table. Let us assume we have a table called **employee** with fields such as Id, Name, Salary, Designation, Dept, and yoj.

Syntax:

```
ALTER TABLE table_name ADD [IF NOT EXISTS] PARTITION partition_spec
[LOCATION 'location1'] partition_spec [LOCATION 'location2'] ...;

partition_spec:
: (p_column = p_col_value, p_column = p_col_value, ...)
```

The following query is used to add a partition to the employee table.

```
hive> ALTER TABLE employee
> ADD PARTITION (year='2012')
> location '/2012/part2012';
```

Renaming a Partition

The syntax of this command is as follows.

```
ALTER TABLE table_name PARTITION partition_spec RENAME TO PARTITION partition_spec;
```

The following query is used to rename a partition:

```
hive> ALTER TABLE employee PARTITION (year='1203')
  > RENAME TO PARTITION (Yoj='1203');
```

Dropping a Partition

The following syntax is used to drop a partition:

```
ALTER TABLE table_name DROP [IF EXISTS] PARTITION partition_spec, PARTITION partition_spec,...;
```

The following query is used to drop a partition:

```
hive> ALTER TABLE employee DROP [IF EXISTS]
  > PARTITION (year='1203');
```

Hive Query Language

The Hive Query Language (HiveQL) is a query language for Hive to process and analyze structured data in a Metastore. This chapter explains how to use the SELECT statement with WHERE clause.

SELECT statement is used to retrieve the data from a table. WHERE clause works similar to a condition. It filters the data using the condition and gives you a finite result. The built-in operators and functions generate an expression, which fulfils the condition.

Syntax

Given below is the syntax of the SELECT query:

```
SELECT [ALL | DISTINCT] select_expr, select_expr, ...
FROM table_reference
[WHERE where_condition]
[GROUP BY col_list]
[HAVING having_condition]
[CLUSTER BY col_list | [DISTRIBUTE BY col_list] [SORT BY col_list]]
[LIMIT number];
```

Example

Let us take an example for SELECT…WHERE clause. Assume we have the employee table as given below, with fields named Id, Name, Salary, Designation, and Dept. Generate a query to retrieve the employee details who earn a salary of more than Rs 30000.

```
+____+__________+_________+_______________+_____+
| ID   | Name        | Salary      | Designation       | Dept |
+____+__________+_________+_______________+_____+
|1201  | Gopal       | 45000       | Technical manager | TP     |
|1202  | Manisha     | 45000       | Proofreader       | PR     |
|1203  | Masthanvali | 40000       | Technical writer  | TP     |
|1204  | Krian       | 40000       | Hr Admin          | HR     |
|1205  | Kranthi     | 30000       | Op Admin          | Admin  |
+____+__________+_________+_______________+_____+
```

The following query retrieves the employee details using the above scenario:

```
hive> SELECT * FROM employee WHERE salary>30000;
```

On successful execution of the query, you get to see the following response:

```
+____+__________+_________+_______________+_____+
| ID   | Name        | Salary      | Designation       | Dept |
+____+__________+_________+_______________+_____+
|1201  | Gopal       | 45000       | Technical manager | TP     |
|1202  | Manisha     | 45000       | Proofreader       | PR     |
|1203  | Masthanvali | 40000       | Technical writer  | TP     |
|1204  | Krian       | 40000       | Hr Admin          | HR     |
+____+__________+_________+_______________+_____+
```

JDBC Program

The JDBC program to apply where clause for the given example is as follows.

```
import java.sql.SQLException;
import java.sql.Connection;
import java.sql.ResultSet;
import java.sql.Statement;
import java.sql.DriverManager;

public class HiveQLWhere {
  private static String driverName = "org.apache.hadoop.hive.jdbc.HiveDriver";

  public static void main(String[] args) throws SQLException {

    // Register driver and create driver instance
    Class.forName(driverName);

    // get connection
    Connection con  = DriverManager.getConnection("jdbc:hive://localhost:10000/userdb",  "",
"");

    // create statement
    Statement stmt = con.createStatement();

    // execute statement
```

```
    Resultset res = stmt.executeQuery("SELECT * FROM employee WHERE salary>30000;");

    System.out.println("Result:");
    System.out.println(" ID \t Name \t Salary \t Designation \t Dept ");

    while (res.next()) {
      System.out.println(res.getInt(1) + " " + res.getString(2) + " " + res.getDouble(3) + " " +
res.getString(4) + " " + res.getString(5));
    }
    con.close();
  }
}
```

Save the program in a file named HiveQLWhere.java. Use the following commands to compile and execute this program.

```
$ javac HiveQLWhere.java
$ java HiveQLWhere
```

Output:

ID	Name	Salary	Designation	Dept
1201	Gopal	45000	Technical manager	TP
1202	Manisha	45000	Proofreader	PR
1203	Masthanvali	40000	Technical writer	TP
1204	Krian	40000	Hr Admin	HR

The ORDER BY clause is used to retrieve the details based on one column and sort the result set by ascending or descending order.

Syntax

Given below is the syntax of the ORDER BY clause:

```
SELECT [ALL | DISTINCT] select_expr, select_expr, ...
FROM table_reference
[WHERE where_condition]
[GROUP BY col_list]
[HAVING having_condition]
[ORDER BY col_list]]
[LIMIT number];
```

Example

Let us take an example for SELECT...ORDER BY clause. Assume employee table as given below, with the fields named Id, Name, Salary, Designation, and Dept. Generate a query to retrieve the employee details in order by using Department name.

```
+____+__________+_________+_____________+_____+
| ID   | Name        | Salary      | Designation       | Dept |
+____+__________+_________+_____________+_____+
|1201  | Gopal       | 45000       | Technical manager | TP     |
|1202  | Manisha     | 45000       | Proofreader       | PR     |
|1203  | Masthanvali | 40000       | Technical writer  | TP     |
|1204  | Krian       | 40000       | Hr Admin          | HR     |
|1205  | Kranthi     | 30000       | Op Admin          | Admin  |
+____+__________+_________+_____________+_____+
```

The following query retrieves the employee details using the above scenario:

```
hive> SELECT Id, Name, Dept FROM employee ORDER BY DEPT;
```

On successful execution of the query, you get to see the following response:

```
+____+__________+_________+_____________+_____+
| ID   | Name        | Salary      | Designation       | Dept |
+____+__________+_________+_____________+_____+
|1205  | Kranthi     | 30000       | Op Admin          | Admin  |
|1204  | Krian       | 40000       | Hr Admin          | HR     |
|1202  | Manisha     | 45000       | Proofreader       | PR     |
|1201  | Gopal       | 45000       | Technical manager | TP     |
|1203  | Masthanvali | 40000       | Technical writer  | TP     |
+____+__________+_________+_____________+_____+
```

JDBC Program

Here is the JDBC program to apply Order By clause for the given example.

```
import java.sql.SQLException;
import java.sql.Connection;
import java.sql.ResultSet;
import java.sql.Statement;
import java.sql.DriverManager;

public class HiveQLOrderBy {
  private static String driverName = "org.apache.hadoop.hive.jdbc.HiveDriver";

  public static void main(String[] args) throws SQLException {

    // Register driver and create driver instance
    Class.forName(driverName);

    // get connection
```

```
    Connection con = DriverManager.getConnection("jdbc:hive://localhost:10000/userdb", "",
"");

    // create statement
    Statement stmt = con.createStatement();

    // execute statement
    Resultset res = stmt.executeQuery("SELECT * FROM employee ORDER BY DEPT;");
    System.out.println(" ID \t Name \t Salary \t Designation \t Dept ");

    while (res.next()) {
       System.out.println(res.getInt(1) + " " + res.getString(2) + " " + res.getDouble(3) + " " +
res.getString(4) + " " + res.getString(5));
    }

    con.close();
  }
}
```

Save the program in a file named HiveQLOrderBy.java. Use the following commands to compile and execute this program.

```
$ javac HiveQLOrderBy.java
$ java HiveQLOrderBy
```

Output:

ID	Name	Salary	Designation	Dept
1205	Kranthi	30000	Op Admin	Admin
1204	Krian	40000	Hr Admin	HR
1202	Manisha	45000	Proofreader	PR
1201	Gopal	45000	Technical manager	TP
1203	Masthanvali	40000	Technical writer	TP
1204	Krian	40000	Hr Admin	HR

The GROUP BY clause is used to group all the records in a result set using a particular collection column. It is used to query a group of records.

Syntax

The syntax of GROUP BY clause is as follows:

```
SELECT [ALL | DISTINCT] select_expr, select_expr, ...
FROM table_reference
[WHERE where_condition]
[GROUP BY col_list]
[HAVING having_condition]
[ORDER BY col_list]]
```

```
[LIMIT number];
```

Example

Let us take an example of SELECT…GROUP BY clause. Assume employee table as given below, with Id, Name, Salary, Designation, and Dept fields. Generate a query to retrieve the number of employees in each department.

```
+____+__________+_________+_____________+_____+
| ID   | Name        | Salary      | Designation       | Dept |
+____+__________+_________+_____________+_____+
|1201  | Gopal       | 45000       | Technical manager | TP     |
|1202  | Manisha     | 45000       | Proofreader       | PR     |
|1203  | Masthanvali | 40000       | Technical writer  | TP     |
|1204  | Krian       | 45000       | Proofreader       | PR     |
|1205  | Kranthi     | 30000       | Op Admin          | Admin  |
+____+__________+_________+_____________+_____+
```

The following query retrieves the employee details using the above scenario.

```
hive> SELECT Dept,count(*) FROM employee GROUP BY DEPT;
```

On successful execution of the query, you get to see the following response:

```
+____+_________+
| Dept | Count(*)    |
+____+_________+
|Admin |    1        |
|PR    |    2        |
|TP    |    3        |
+____+_________+
```

JDBC Program

Given below is the JDBC program to apply the Group By clause for the given example.

```
import java.sql.SQLException;
import java.sql.Connection;
import java.sql.ResultSet;
import java.sql.Statement;
import java.sql.DriverManager;

public class HiveQLGroupBy {
  private static String driverName = "org.apache.hadoop.hive.jdbc.HiveDriver";

  public static void main(String[] args) throws SQLException {

    // Register driver and create driver instance
    Class.forName(driverName);

    // get connection
```

```
    Connection con = DriverManager.
    getConnection("jdbc:hive://localhost:10000/userdb", "", "");

    // create statement
    Statement stmt = con.createStatement();

    // execute statement
    Resultset res = stmt.executeQuery("SELECT Dept,count(*) " + "FROM employee GROUP
BY DEPT; ");
    System.out.println(" Dept \t count(*)");

    while (res.next()) {
      System.out.println(res.getString(1) + " " + res.getInt(2));
    }
    con.close();
  }
}
```

Save the program in a file named HiveQLGroupBy.java. Use the following commands to compile and execute this program.

```
$ javac HiveQLGroupBy.java
$ java HiveQLGroupBy
```

Output:

```
Dept    Count(*)
Admin      1
PR         2
TP         3
```

JOIN is a clause that is used for combining specific fields from two tables by using values common to each one. It is used to combine records from two or more tables in the database.

Syntax

```
join_table:

  table_reference JOIN table_factor [join_condition]
  | table_reference {LEFT|RIGHT|FULL} [OUTER] JOIN table_reference
  join_condition
  | table_reference LEFT SEMI JOIN table_reference join_condition
  | table_reference CROSS JOIN table_reference [join_condition]
```

Example

We will use the following two tables in this chapter. Consider the following table named CUSTOMERS..

```
+___+_________+___+___________+_________+
| ID | NAME     | AGE | ADDRESS  | SALARY  |
+___+_________+___+___________+_________+
| 1  | Ramesh  | 32  | Ahmedabad | 2000.00  |
| 2  | Khilan   | 25  | Delhi     | 1500.00  |
| 3  | kaushik  | 23  | Kota      | 2000.00  |
| 4  | Chaitali | 25  | Mumbai    | 6500.00 |
| 5  | Hardik   | 27  | Bhopal    | 8500.00 |
| 6  | Komal    | 22  | MP        | 4500.00 |
| 7  | Muffy    | 24  | Indore    | 10000.00 |
+___+_________+___+___________+_________+
```

Consider another table ORDERS as follows:

```
+___+_____________________+_____________+_______+
|OID  | DATE               | CUSTOMER_ID | AMOUNT |
+___+_____________________+_____________+_______+
| 102 | 2009-10-08 00:00:00 |          3 | 3000   |
| 100 | 2009-10-08 00:00:00 |          3 | 1500   |
| 101 | 2009-11-20 00:00:00 |          2 | 1560   |
| 103 | 2008-05-20 00:00:00 |          4 | 2060   |
+___+_____________________+_____________+_______+
```

There are different types of joins given as follows:

- JOIN
- LEFT OUTER JOIN
- RIGHT OUTER JOIN
- FULL OUTER JOIN

JOIN

JOIN clause is used to combine and retrieve the records from multiple tables. JOIN is same as OUTER JOIN in SQL. A JOIN condition is to be raised using the primary keys and foreign keys of the tables.

The following query executes JOIN on the CUSTOMER and ORDER tables, and retrieves the records:

```
hive> SELECT c.ID, c.NAME, c.AGE, o.AMOUNT
FROM CUSTOMERS c JOIN ORDERS o
ON (c.ID = o.CUSTOMER_ID);
```

On successful execution of the query, you get to see the following response:

```
+___+_________+___+_______+
| ID | NAME     | AGE | AMOUNT |
+___+_________+___+_______+
| 3  | kaushik  | 23  | 3000   |
| 3  | kaushik  | 23  | 1500   |
| 2  | Khilan   | 25  | 1560   |
```

```
| 4  | Chaitali | 25 | 2060  |
+---+----------+----+-------+
```

LEFT OUTER JOIN

The HiveQL LEFT OUTER JOIN returns all the rows from the left table, even if there are no matches in the right table. This means, if the ON clause matches 0 (zero) records in the right table, the JOIN still returns a row in the result, but with NULL in each column from the right table.

A LEFT JOIN returns all the values from the left table, plus the matched values from the right table, or NULL in case of no matching JOIN predicate.

The following query demonstrates LEFT OUTER JOIN between CUSTOMER and ORDER tables:

```
hive> SELECT c.ID, c.NAME, o.AMOUNT, o.DATE
FROM CUSTOMERS c
LEFT OUTER JOIN ORDERS o
ON (c.ID = o.CUSTOMER_ID);
```

On successful execution of the query, you get to see the following response:

```
+---+----------+--------+---------------------+
| ID | NAME     | AMOUNT | DATE                |
+---+----------+--------+---------------------+
| 1  | Ramesh   | NULL   | NULL                |
| 2  | Khilan   | 1560   | 2009-11-20 00:00:00 |
| 3  | kaushik  | 3000   | 2009-10-08 00:00:00 |
| 3  | kaushik  | 1500   | 2009-10-08 00:00:00 |
| 4  | Chaitali | 2060 | 2008-05-20 00:00:00 |
| 5  | Hardik   | NULL   | NULL                |
| 6  | Komal    | NULL   | NULL                |
| 7  | Muffy    | NULL   | NULL                |
+---+----------+------+-------------------+
```

RIGHT OUTER JOIN

The HiveQL RIGHT OUTER JOIN returns all the rows from the right table, even if there are no matches in the left table. If the ON clause matches 0 (zero) records in the left table, the JOIN still returns a row in the result, but with NULL in each column from the left table.

A RIGHT JOIN returns all the values from the right table, plus the matched values from the left table, or NULL in case of no matching join predicate.

The following query demonstrates RIGHT OUTER JOIN between the CUSTOMER and ORDER tables.

notranslate"> hive> SELECT c.ID, c.NAME, o.AMOUNT, o.DATE FROM CUSTOMERS c RIGHT OUTER JOIN ORDERS o ON (c.ID = o.CUSTOMER_ID);

On successful execution of the query, you get to see the following response:

```
+----+--------+--------+---------------------+
```

```
| ID   | NAME     | AMOUNT | DATE                |
+____+_______+_______+_____________________+
| 3    | kaushik  | 3000   | 2009-10-08 00:00:00 |
| 3    | kaushik  | 1500   | 2009-10-08 00:00:00 |
| 2    | Khilan   | 1560   | 2009-11-20 00:00:00 |
| 4    | Chaitali | 2060   | 2008-05-20 00:00:00 |
+____+_______+_______+_____________________+
```

FULL OUTER JOIN

The HiveQL FULL OUTER JOIN combines the records of both the left and the right outer tables that fulfil the JOIN condition. The joined table contains either all the records from both the tables, or fills in NULL values for missing matches on either side.

The following query demonstrates FULL OUTER JOIN between CUSTOMER and ORDER tables:

```
hive> SELECT c.ID, c.NAME, o.AMOUNT, o.DATE
FROM CUSTOMERS c
FULL OUTER JOIN ORDERS o
ON (c.ID = o.CUSTOMER_ID);
```

On successful execution of the query, you get to see the following response:

```
+____+_______+_______+_____________________+
| ID   | NAME     | AMOUNT | DATE                |
+____+_______+_______+_____________________+
| 1    | Ramesh   | NULL   | NULL                |
| 2    | Khilan   | 1560   | 2009-11-20 00:00:00 |
| 3    | kaushik  | 3000   | 2009-10-08 00:00:00 |
| 3    | kaushik  | 1500   | 2009-10-08 00:00:00 |
| 4    | Chaitali | 2060 | 2008-05-20 00:00:00 |
| 5    | Hardik   | NULL   | NULL                |
| 6    | Komal    | NULL   | NULL                |
| 7    | Muffy    | NULL   | NULL                |
| 3    | kaushik  | 3000   | 2009-10-08 00:00:00 |
| 3    | kaushik  | 1500   | 2009-10-08 00:00:00 |
| 2    | Khilan   | 1560   | 2009-11-20 00:00:00 |
| 4    | Chaitali | 2060   | 2008-05-20 00:00:00 |
+____+_______+_______+_____________________+
```

Bucketing

•Bucketing concept is based on (hashing function on the bucketed column) mod (by total number of buckets). The hash_function depends on the type of the bucketing column.

•Records with the same bucketed column will always be stored in the same bucket.

•We use CLUSTERED BY clause to divide the table into buckets.

•Physically, each bucket is just a file in the table directory, and Bucket numbering is 1-based.

•Bucketing can be done along with Partitioning on Hive tables and even without partitioning.

•Bucketed tables will create almost equally distributed data file parts, unless there is skew in data.

•Bucketing is enabled by setting hive.enforce.bucketing= true;

Advantages

•Bucketed tables offer efficient sampling than by non-bucketed tables. With sampling, we can try out queries on a fraction of data for testing and debugging purpose when the original data sets are very huge.

•As the data files are equal sized parts, map-side joins will be faster on bucketed tables than non-bucketed tables.

•Bucketing concept also provides the flexibility to keep the records in each bucket to be sorted by one or more columns. This makes map-side joins even more efficient, since the join of each bucket becomes an efficient merge-sort.

Bucketing Vs Partitioning

•Partitioning helps in elimination of data, if used in WHERE clause, where as bucketing helps in organizing data in each partition into multiple files, so that the same set of data is always written in same bucket.

•Bucketing helps a lot in joining of columns.

•Hive Bucket is nothing but another technique of decomposing data or decreasing the data into more manageable parts or equal parts.

Sampling

•TABLESAMPLE() gives more disordered and random records from a table as compared to LIMIT. •We can sample using the rand() function, which returns a random number.

SELECT * from users TABLESAMPLE(BUCKET 3 OUT OF 10 ON rand()) s;

SELECT * from users TABLESAMPLE(BUCKET 3 OUT OF 10 ON rand()) s;

•Here rand() refers to any random column. •The denominator in the bucket clause represents the number of buckets into which data will be hashed. •The numerator is the bucket number selected.

SELECT * from users TABLESAMPLE(BUCKET 2 OUT OF 4 ON name) s;

•If the columns specified in the TABLESAMPLE clause match the columns in the CLUSTERED BY clause, TABLESAMPLE queries only scan the required hash partitions of the table.

SELECT * FROM buck_users TABLESAMPLE(BUCKET 1 OUT OF 2 ON id) s LIMIT 1;

Joins and Types #

Reduce-Side Join

•If datasets are large, reduce side join takes place.

Map-Side Join

•In case one of the dataset is small, map side join takes place. •In map side join, a local job runs to create hash-table from content of HDFS file and sends it to every node.

SET hive.auto.convert.join =true;

Bucket Map Join

•The data must be bucketed on the keys used in the ON clause and the number of buckets for one table must be a multiple of the number of buckets for the other table. •When these conditions are met, Hive can join individual buckets between tables in the map phase, because it does not have to fetch the entire content of one table to match against each bucket in the other table. •set hive.optimize.bucketmapjoin =true; •SET hive.auto.convert.join =true;

SMBM Join

•Sort-Merge-Bucket (SMB) joins can be converted to SMB map joins as well.

•SMB joins are used wherever the tables are sorted and bucketed.

•The join boils down to just merging the already sorted tables, allowing this operation to be faster than an ordinary map-join.

•set hive.enforce.sortmergebucketmapjoin =false;

•set hive.auto.convert.sortmerge.join =true;

•set hive.optimize.bucketmapjoin = true;

•set hive.optimize.bucketmapjoin.sortedmerge = true;

LEFT SEMI JOIN

•A left semi-join returns records from the lefthand table if records are found in the righthand table that satisfy the ON predicates.

•It's a special, optimized case of the more general inner join.

•Most SQL dialects support an IN … EXISTS construct to do the same thing.

•SELECT and WHERE clauses can't reference columns from the righthand table.

•Right semi-joins are not supported in Hive.

•The reason semi-joins are more efficient than the more general inner join is as follows:

•For a given record in the lefthand table, Hive can stop looking for matching records in the righthand table as soon as any match is found.

•At that point, the selected columns from the lefthand table record can be projected

•A file format is a way in which information is stored or encoded in a computer file.

•In Hive it refers to how records are stored inside the file.

•InputFormat reads key-value pairs from files.

•As we are dealing with structured data, each record has to be its own structure.

•How records are encoded in a file defines a file format.

•These file formats mainly vary between data encoding, compression rate, usage of space and disk I/O.

•Hive does not verify whether the data that you are loading matches the schema for the table or not. •However, it verifies if the file format matches the table definition or not.

SerDe in Hive

•The SerDe interface allows you to instruct Hive as to how a record should be processed.

•A SerDe is a combination of a Serializer and a Deserializer (hence, Ser-De).

•The Deserializer interface takes a string or binary representation of a record, and translates it into a Java object that Hive can manipulate.

•The Serializer, however, will take a Java object that Hive has been working with, and turn it into something that Hive can write to HDFS or another supported system.

•Commonly, Deserializers are used at query time to execute SELECT statements, and Serializers are used when writing data, such as through an INSERT-SELECT statement.

CSVSerDe

•Use ROW FORMAT SERDE ‘org.apache.hadoop.hive.serde2.OpenCSVSerde’

•Define following in SERDEPROPERTIES

(" separatorChar " = < value_of_separator

, " quoteChar " = < value_of_quote_character ,

" escapeChar “ = < value_of_escape_character

)

JSONSerDe

•Include hive-hcatalog-core-0.14.0.jar •Use ROW FORMAT SERDE ' org.apache.hive.hcatalog.data.JsonSerDe '

RegexSerDe

•It is used in case of pattern matching. •Use ROW FORMAT SERDE

'org.apache.hadoop.hive.contrib.serde2.RegexSerDe'

•In SERDEPROPERTIES, define input pattern and output fields.

For Example

•input.regex = '(.)/(.)@(.*)' •output.format.string' = ' 1 s 2 s 3 s';

USE PARTITIONING AND BUCKETING

•Partitioning a table stores data in sub-directories categorized by table location, which allows Hive to exclude unnecessary data from queries without reading all the data every time a new query is made.

•Hive does support Dynamic Partitioning (DP) where column values are only known at EXECUTION TIME. To enable Dynamic Partitioning :

SET hive.exec.dynamic.partition =true;

•Another situation we want to protect against dynamic partition insert is that the user may accidentally specify all partitions to be dynamic partitions without specifying one static partition, while the original intention is to just overwrite the sub-partitions of one root partition.

SET hive.exec.dynamic.partition.mode =strict;

To enable bucketing:

SET hive.enforce.bucketing =true;

Optimizations in Hive #

•Use Denormalisation , Filtering and Projection as early as possible to reduce data before join.

•Join is a costly affair and requires extra map-reduce phase to accomplish query job. With De-normalisation, the data is present in the same table so there is no need for any joins, hence the selects are very fast.

•As join requires data to be shuffled across nodes, use filtering and projection as early as possible to reduce data before join.

TUNE CONFIGURATIONS

•To increase number of mapper, reduce split size :

SET mapred.max.split.size =1000000; (~1 MB)

•Compress map/reduce output

SET mapred.compress.map.output =true;

SET mapred.output.compress =true;

•Parallel execution

•Applies to MapReduce jobs that can run in parallel, for example jobs processing different source tables before a join.

SET hive.exec.parallel =true;

USE ORCFILE

•Hive supports ORCfile , a new table storage format that sports fantastic speed improvements through techniques like predicate push-down, compression and more.

•Using ORCFile for every HIVE table is extremely beneficial to get fast response times for your HIVE queries.

USE TEZ

•With Hadoop2 and Tez , the cost of job submission and scheduling is minimized.

•Also Tez does not restrict the job to be only Map followed by Reduce; this implies that all the query execution can be done in a single job without having to cross job boundaries.

•Let's look at an example. Consider a click-stream event table:

```
CREATE TABLE clicks (
timestamp  date,
sessionID string,
url string,
source_ip string
)
STORED as ORC
tblproperties (" orc.compress " = "SNAPPY");
```

•Each record represents a click event, and we would like to find the latest URL for each sessionID

• One might consider the following approach:

SELECT clicks.sessionID, clicks.url FROM clicks inner join (select sessionID, max(timestamp) as max_ts from clicks group by sessionID) latest ON clicks.sessionID = latest.sessionID and clicks.timestamp = latest.max_ts;

•In the above query, we build a sub-query to collect the timestamp of the latest event in each session, and then use an inner join to filter out the rest.

•While the query is a reasonable solution —from a functional point of view— it turns out there's a better way to re-write this query as follows:

SELECT ranked_clicks.sessionID , ranked_clicks.url FROM (SELECT sessionID , url , RANK() over (partition by sessionID,order by timestamp desc) as rank FROM clicks) ranked_clicks WHERE ranked_clicks.rank =1;

•Here, we use Hive's OLAP functionality (OVER and RANK) to achieve the same thing, but without a Join.

•Clearly, removing an unnecessary join will almost always result in better performance, and when using big data this is more important than ever.

MAKING MULTIPLE PASS OVER SAME DATA

•Hive has a special syntax for producing multiple aggregations from a single pass through a source of data, rather than rescanning it for each aggregation.

•This change can save considerable processing time for large input data sets.

•For example, each of the following two queries creates a table from the same source table, history:

INSERT OVERWRITE TABLE sales

SELECT * FROM history WHERE action='purchased';

INSERT OVERWRITE TABLE credits

SELECT * FROM history WHERE action='returned';

Optimizations in Hive

•This syntax is correct, but inefficient.

•The following rewrite achieves the same thing, but using a single pass through the source history table:

FROM history

INSERT OVERWRITE sales SELECT * WHERE action='purchased'

INSERT OVERWRITE credits SELECT * WHERE action='returned';

What is Apache Pig

Apache Pig is a high-level data flow platform for executing MapReduce programs of Hadoop. The language used for Pig is Pig Latin.

The Pig scripts get internally converted to Map Reduce jobs and get executed on data stored in HDFS. Apart from that, Pig can also execute its job in Apache Tez or Apache Spark.

Pig can handle any type of data, i.e., structured, semi-structured or unstructured and stores the corresponding results into Hadoop Data File System. Every task which can be achieved using PIG can also be achieved using java used in MapReduce.

Features of Apache Pig

Let's see the various uses of Pig technology.

1) Ease of programming

Writing complex java programs for map reduce is quite tough for non-programmers. Pig makes this process easy. In the Pig, the queries are converted to MapReduce internally.

2) Optimization opportunities

It is how tasks are encoded permits the system to optimize their execution automatically, allowing the user to focus on semantics rather than efficiency.

3) Extensibility

A user-defined function is written in which the user can write their logic to execute over the data set.

4) Flexible

It can easily handle structured as well as unstructured data.

5) In-built operators

It contains various type of operators such as sort, filter and joins.

Differences between Apache MapReduce and PIG

Advantages of Apache Pig

- Less code - The Pig consumes less line of code to perform any operation.
- Reusability - The Pig code is flexible enough to reuse again.

- Nested data types - The Pig provides a useful concept of nested data types like tuple, bag, and map.

Pig Latin

The Pig Latin is a data flow language used by Apache Pig to analyze the data in Hadoop. It is a textual language that abstracts the programming from the Java MapReduce idiom into a notation.

Pig Latin Statements

The Pig Latin statements are used to process the data. It is an operator that accepts a relation as an input and generates another relation as an output.

- It can span multiple lines.
- Each statement must end with a semi-colon.
- It may include expression and schemas.
- By default, these statements are processed using multi-query execution

Pig Latin Conventions

Convention	Description
( )	The parenthesis can enclose one or more items. It can also be used to indicate the tuple data type. Example - (10, xyz, (3,6,9))
[ ]	The straight brackets can enclose one or more items. It can also be used to indicate the map data type. Example - [INNER | OUTER]
{ }	The curly brackets enclose two or more items. It can also be used to indicate the bag data type Example - { block | nested_block }
...	The horizontal ellipsis points indicate that you can repeat a portion of the code. Example - cat path [path ...]

Latin Data Types

Simple Data Types

Type	Description
int	It defines the signed 32-bit integer. Example - 2
long	It defines the signed 64-bit integer. Example - 2L or 2l
float	It defines 32-bit floating point number. Example - 2.5F or 2.5f or 2.5e2f or 2.5.E2F
double	It defines 64-bit floating point number. Example - 2.5 or 2.5 or 2.5e2f or 2.5.E2F
chararray	It defines character array in Unicode UTF-8 format. Example - javatpoint
bytearray	It defines the byte array.
boolean	It defines the boolean type values. Example - true/false
datetime	It defines the values in datetime order. Example - 1970-01- 01T00:00:00.000+00:00
biginteger	It defines Java BigInteger values. Example - 5000000000000
bigdecimal	It defines Java BigDecimal values. Example - 52.232344535345

Pig Data Types

Apache Pig supports many data types. A list of Apache Pig Data Types with description and examples are given below.

Type	Description	Example
Int	Signed 32 bit integer	2
Long	Signed 64 bit integer	15L or 15l
Float	32 bit floating point	2.5f or 2.5F
Double	32 bit floating point	1.5 or 1.5e2 or 1.5E2
charArray	Character array	hello javatpoint
byteArray	BLOB(Byte array)	
tuple	Ordered set of fields	(12,43)
bag	Collection f tuples	{(12,43),(54,28)}
map	collection of tuples	[open#apache]

Apache Pig Execution Modes

You can run Apache Pig in two modes, namely, **Local Mode** and **HDFS mode**.

Local Mode

In this mode, all the files are installed and run from your local host and local file system. There is no need of Hadoop or HDFS. This mode is generally used for testing purpose.

MapReduce Mode

MapReduce mode is where we load or process the data that exists in the Hadoop File System (HDFS) using Apache Pig. In this mode, whenever we execute the Pig Latin statements to process the data, a MapReduce job is invoked in the back-end to perform a particular operation on the data that exists in the HDFS.

Apache Pig Execution Mechanisms

Apache Pig scripts can be executed in three ways, namely, interactive mode, batch mode, and embedded mode.

- **Interactive Mode** (Grunt shell) − You can run Apache Pig in interactive mode using the Grunt shell. In this shell, you can enter the Pig Latin statements and get the output (using Dump operator).
- **Batch Mode** (Script) − You can run Apache Pig in Batch mode by writing the Pig Latin script in a single file with **.pig** extension.
- **Embedded Mode** (UDF) − Apache Pig provides the provision of defining our own functions (**U**ser **D**efined **F**unctions) in programming languages such as Java, and using them in our script.
- Given below in the table are some frequently used Pig Commands.

Command	Function
load	Reads data from the system
Store	Writes data to file system
foreach	Applies expressions to each record and outputs one or more records
filter	Applies predicate and removes records that do not return true

Group/cogroup	Collects records with the same key from one or more inputs
join	Joins two or more inputs based on a key
order	Sorts records based on a key
distinct	Removes duplicate records
union	Merges data sets
split	Splits data into two or more sets based on filter conditions
stream	Sends all records through a user-provided binary
dump	Writes output to stdout

limit	Limits the number of records

Complex Types

Type	Description
tuple	It defines an ordered set of fields. Example - (15,12)
bag	It defines a collection of tuples. Example - {(15,12), (12,15)}
map	It defines a set of key-value pairs. Example - [open#apache]

Pig Latin – Relational Operations

The following table describes the relational operators of Pig Latin.

Operator	Description
Loading and Storing	
LOAD	To Load the data from the file system (local/HDFS) into a relation.
STORE	To save a relation to the file system (local/HDFS).
Filtering	

FILTER	To remove unwanted rows from a relation.
DISTINCT	To remove duplicate rows from a relation.
FOREACH, GENERATE	To generate data transformations based on columns of data.
STREAM	To transform a relation using an external program.
Grouping and Joining	
JOIN	To join two or more relations.
COGROUP	To group the data in two or more relations.
GROUP	To group the data in a single relation.
CROSS	To create the cross product of two or more relations.
Sorting	
ORDER	To arrange a relation in a sorted order based on one or more fields (ascending or descending).
LIMIT	To get a limited number of tuples from a relation.
Combining and Splitting	
UNION	To combine two or more relations into a single relation.
SPLIT	To split a single relation into two or more relations.

Diagnostic Operators	
DUMP	To print the contents of a relation on the console.
DESCRIBE	To describe the schema of a relation.
EXPLAIN	To view the logical, physical, or MapReduce execution plans to compute a relation.
ILLUSTRATE	To view the step-by-step execution of a series of statements.

Eval Functions

Given below is the list of **eval** functions provided by Apache Pig.

S.N.	Function & Description
1	AVG() To compute the average of the numerical values within a bag.
2	BagToString() To concatenate the elements of a bag into a string. While concatenating, we can place a delimiter between these values (optional).
3	CONCAT() To concatenate two or more expressions of same type.
4	COUNT() To get the number of elements in a bag, while counting the number of tuples in a bag.
5	COUNT_STAR()

	It is similar to the **COUNT()** function. It is used to get the number of elements in a bag.
6	DIFF() To compare two bags (fields) in a tuple.
7	IsEmpty() To check if a bag or map is empty.
8	MAX() To calculate the highest value for a column (numeric values or chararrays) in a single-column bag.
9	MIN() To get the minimum (lowest) value (numeric or chararray) for a certain column in a single-column bag.
10	PluckTuple() Using the Pig Latin **PluckTuple()** function, we can define a string Prefix and filter the columns in a relation that begin with the given prefix.
11	SIZE() To compute the number of elements based on any Pig data type.
12	SUBTRACT() To subtract two bags. It takes two bags as inputs and returns a bag which contains the tuples of the first bag that are not in the second bag.
13	SUM() To get the total of the numeric values of a column in a single-column bag.
14	TOKENIZE() To split a string (which contains a group of words) in a single tuple and return a bag which contains the output of the split operation.

Apache Pig provides extensive support for **U**ser **D**efined **F**unctions (UDF's). Using these UDF's, we can define our own functions and use them. The UDF support is provided in six programming languages, namely, Java, Jython, Python, JavaScript, Ruby and Groovy.

For writing UDF's, complete support is provided in Java and limited support is provided in all the remaining languages. Using Java, you can write UDF's involving all parts of the processing like data load/store, column transformation, and aggregation. Since Apache Pig has been written in Java, the UDF's written using Java language work efficiently compared to other languages.

In Apache Pig, we also have a Java repository for UDF's named **Piggybank**. Using Piggybank, we can access Java UDF's written by other users, and contribute our own UDF's.

Types of UDF's in Java

While writing UDF's using Java, we can create and use the following three types of functions −

- **Filter Functions** − The filter functions are used as conditions in filter statements. These functions accept a Pig value as input and return a Boolean value.
- **Eval Functions** − The Eval functions are used in FOREACH-GENERATE statements. These functions accept a Pig value as input and return a Pig result.
- **Algebraic Functions** − The Algebraic functions act on inner bags in a FOREACHGENERATE statement. These functions are used to perform full MapReduce operations on an inner bag.

Writing UDF's using Java

To write a UDF using Java, we have to integrate the jar file **Pig-0.15.0.jar**. In this section, we discuss how to write a sample UDF using Eclipse. Before proceeding further, make sure you have installed Eclipse and Maven in your system.

Follow the steps given below to write a UDF function −

- Open Eclipse and create a new project (say **myproject**).
- Convert the newly created project into a Maven project.
- Copy the following content in the pom.xml. This file contains the Maven dependencies for Apache Pig and Hadoop-core jar files.

```
<project xmlns = "http://maven.apache.org/POM/4.0.0"
  xmlns:xsi = "http://www.w3.org/2001/XMLSchema-instance"
  xsi:schemaLocation = "http://maven.apache.org/POM/4.0.0http://maven.apache
.org/xsd/maven-4.0.0.xsd">

  <modelVersion>4.0.0</modelVersion>
  <groupId>Pig_Udf</groupId>
  <artifactId>Pig_Udf</artifactId>
  <version>0.0.1-SNAPSHOT</version>

  <build>
    <sourceDirectory>src</sourceDirectory>
```

```
    <plugins>
      <plugin>
        <artifactId>maven-compiler-plugin</artifactId>
        <version>3.3</version>
        <configuration>
          <source>1.7</source>
          <target>1.7</target>
        </configuration>
      </plugin>
    </plugins>
  </build>

  <dependencies>

    <dependency>
      <groupId>org.apache.pig</groupId>
      <artifactId>pig</artifactId>
      <version>0.15.0</version>
    </dependency>

    <dependency>
      <groupId>org.apache.hadoop</groupId>
      <artifactId>hadoop-core</artifactId>
      <version>0.20.2</version>
    </dependency>

  </dependencies>

</project>
```

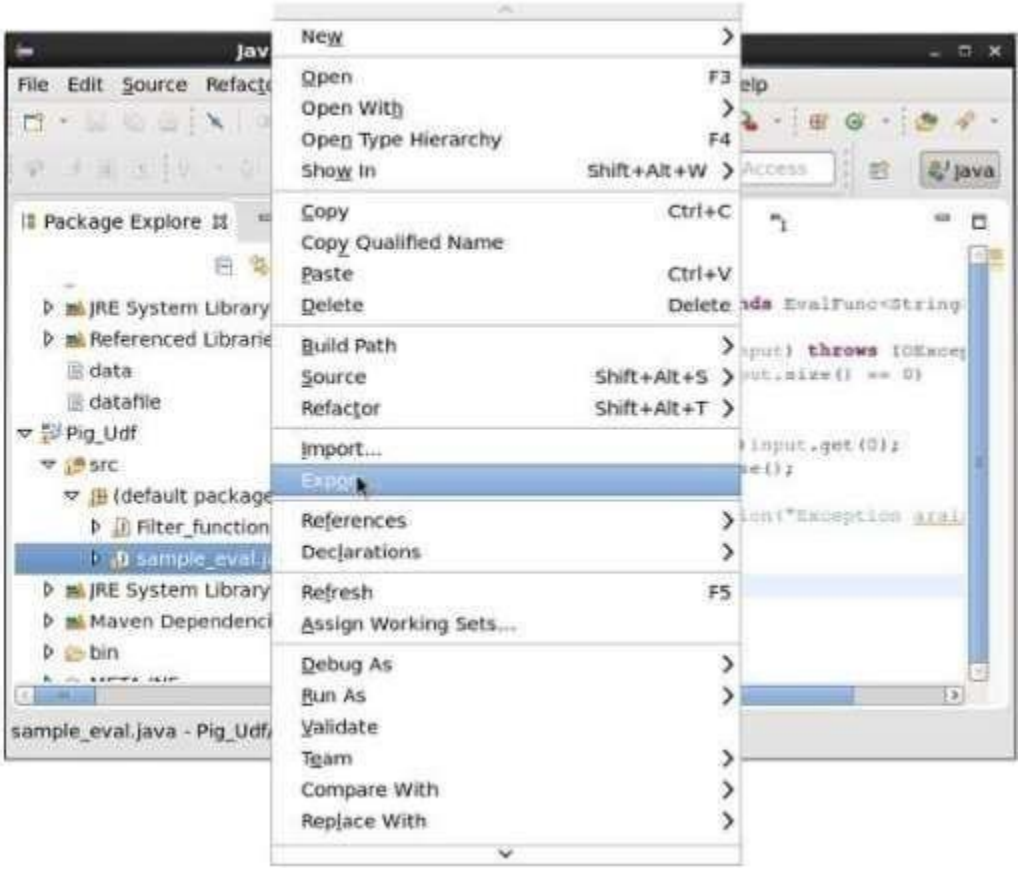
- Save the file and refresh it. In the **Maven Dependencies** section, you can find the downloaded jar files.
- Create a new class file with name **Sample_Eval** and copy the following content in it.

```
import java.io.IOException;
import org.apache.pig.EvalFunc;
import org.apache.pig.data.Tuple;

import java.io.IOException;
import org.apache.pig.EvalFunc;
import org.apache.pig.data.Tuple;

public class Sample_Eval extends EvalFunc<String>{

  public String exec(Tuple input) throws IOException {
    if (input == null || input.size() == 0)
    return null;
    String str = (String)input.get(0);
    return str.toUpperCase();
```

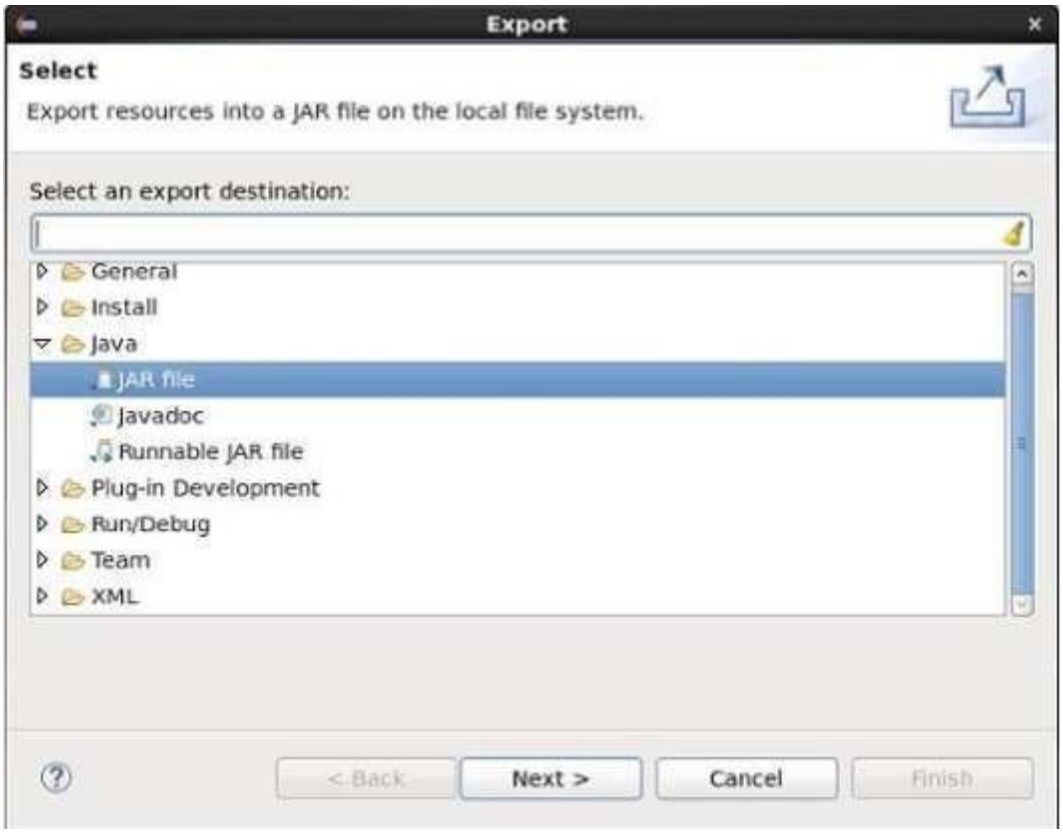
```
  }
}
```

While writing UDF's, it is mandatory to inherit the EvalFunc class and provide implementation to **exec()** function. Within this function, the code required for the UDF is written. In the above example, we have return the code to convert the contents of the given column to uppercase.

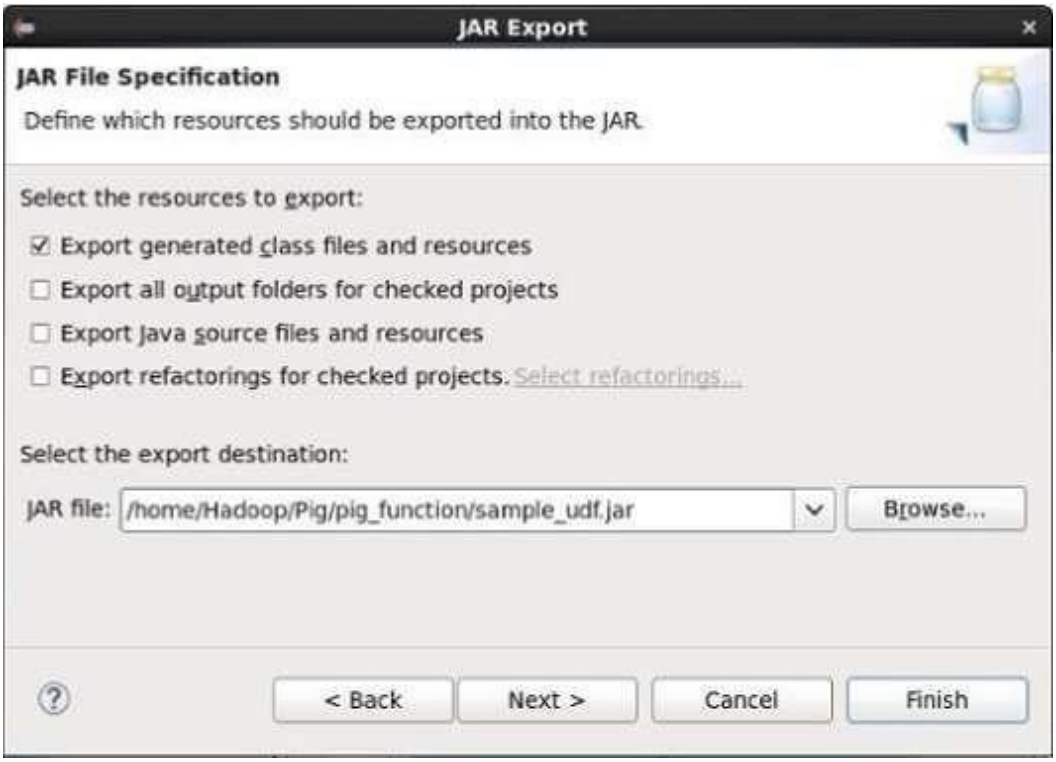
- After compiling the class without errors, right-click on the Sample_Eval.java file. It gives you a menu. Select **export** as shown in the following screenshot.



- On clicking **export**, you will get the following window. Click on **JAR file**.



- Proceed further by clicking **Next>** button. You will get another window where you need to enter the path in the local file system, where you need to store the jar file.



- Finally click the **Finish** button. In the specified folder, a Jar file **sample_udf.jar** is created. This jar file contains the UDF written in Java.

Using the UDF

After writing the UDF and generating the Jar file, follow the steps given below −

Step 1: Registering the Jar file

After writing UDF (in Java) we have to register the Jar file that contain the UDF using the Register operator. By registering the Jar file, users can intimate the location of the UDF to Apache Pig.

Syntax

Given below is the syntax of the Register operator.

```
REGISTER path;
```

Example

As an example let us register the sample_udf.jar created earlier in this chapter.

Start Apache Pig in local mode and register the jar file sample_udf.jar as shown below.

```
$cd PIG_HOME/bin
$./pig –x local
```

```
REGISTER '/$PIG_HOME/sample_udf.jar'
```

Note − assume the Jar file in the path − /$PIG_HOME/sample_udf.jar

Step 2: Defining Alias

After registering the UDF we can define an alias to it using the **Define** operator.

Syntax

Given below is the syntax of the Define operator.

```
DEFINE alias {function | [`command` [input] [output] [ship] [cache] [stderr] ] };
```

Example

Define the alias for sample_eval as shown below.

```
DEFINE sample_eval sample_eval();
```

Step 3: Using the UDF

After defining the alias you can use the UDF same as the built-in functions. Suppose there is a file named emp_data in the HDFS **/Pig_Data/** directory with the following content.

```
001,Robin,22,newyork
002,BOB,23,Kolkata
003,Maya,23,Tokyo
004,Sara,25,London
005,David,23,Bhuwaneshwar
006,Maggy,22,Chennai
```

007,Robert,22,newyork
008,Syam,23,Kolkata
009,Mary,25,Tokyo
010,Saran,25,London
011,Stacy,25,Bhuwaneshwar
012,Kelly,22,Chennai

And assume we have loaded this file into Pig as shown below.

```
grunt> emp_data = LOAD 'hdfs://localhost:9000/pig_data/emp1.txt' USING PigStorage(',')
  as (id:int, name:chararray, age:int, city:chararray);
```

Let us now convert the names of the employees in to upper case using the UDF **sample_eval**.

```
grunt> Upper_case = FOREACH emp_data GENERATE sample_eval(name);
```

Verify the contents of the relation **Upper_case** as shown below.

grunt> Dump Upper_case;

(ROBIN)
(BOB)
(MAYA)
(SARA)
(DAVID)
(MAGGY)
(ROBERT)
(SYAM)
(MARY)
(SARAN)
(STACY)
(KELLY)

Parameter substitution in Pig

Earlier I have discussed about writing reusable scripts using Apache Hive, now we see how to achieve same functionality using Pig Latin.

Pig Latin has an option called param, using this we can write dynamic scripts .

Assume ,we have a file called numbers with below data.

12

23

34

12

56

34

57

12

```
Numbers = load '/data/numbers' as (number:int);
specificNumber = filter numbers by number==12;
Dump specificNumber;
```

Usually we write above code in a file .let us assume we have written it in a file called numbers.pigAnd we write code from file using

```
Pig –f /path/to/numbers.pig
```

Later if we want to see only numbers equals to 34, then we change second line to

```
specificNumber = filter numbers by number==34;
```

and we re-run the code using same command.
But Its not a good practice to touch the code in production ,so we can make this script dynamic by using –param option of Piglatin.
Whatever values we want to decide at the time of running we make them dynamic .now we wantto decide number to be filtered at the time running job,we can write second line like below.

```
specificNumber = filter numbers by number==$dynanumber
```

and we run code like below.

```
Pig –param dynanumber=12 –f numbers.pig
```

Assume we even want to take path at the time of running script, now we write code like below

```
Numbers = load '$path' as (number:int);
specificNumber = filter numbers by number=='$ dynanumber';
```

```
Dump specificNumber;
```

And run like below

```
Pig –param path=/data/path –param dynanumber =34 –f numbers.pig
```

If you feel this code is missing readability, we can specify all these dynamic values in a file like below
##Dyna.params (file name)

```
Path = /data/numbers

dynanumber = 34
```

Then you can run script with param-file option like below.

```
Pig –param-file dyna.params –f numbers.pig
```

Pig Latin provides four different types of diagnostic operators −

- Dump operator
- Describe operator
- Explanation operator
- Illustration operator

Word Count Example Using Pig Script:

```
lines = LOAD '/user/hadoop/HDFS_File.txt' AS (line:chararray);
words = FOREACH lines GENERATE FLATTEN(TOKENIZE(line)) as word;
grouped = GROUP words BY word;
wordcount = FOREACH grouped GENERATE group, COUNT(words);
DUMP wordcount;
```

The above pig script, first splits each line into words using the **TOKENIZE** operator. The tokenize function creates a bag of words. Using the **FLATTEN** function, the bag is

converted into a tuple. In the third statement, the words are grouped together so that the count can be computed which is done in fourth statement.

Pig at Yahoo

Pig was initially developed by Yahoo! for its data scientists who were using Hadoop. It was incepted to focus mainly on analysis of large datasets rather than on writing mapper and reduce functions. This allowed users to focus on what they want to do rather than bothering with how its done. On top of this with Pig language you have the facility to write commands in other languages like Java, Python etc. Big applications that can be built on Pig Latin can be custom built for different companies to serve different tasks related to data management. Pig systemizes all the branches of data and relates it in a manner that when the time comes, filtering and searching data is checked efficiently and quickly.

Pig Versus Hive

Pig Vs Hive

Here are some basic difference between Hive and Pig which gives an idea of which to use depending on the type of data and purpose.

Pig	Hive
Used by Programmers and Researchers	Used by Analysts
Used for Programming	Used for Reporting
Procedural data-flow language	Declarative SQLish language
Works on the Client side of a Cluster	Works on the Server side of a Cluster
For Semi-Structured Data	For Structured Data

Why Go for Hive When Pig is There?

The tabular column below gives a comprehensive comparison between the two. The Hive can be used in places where partitions are necessary and when it is essential to define and create cross-language services for numerous languages.

Features	Hive	Pig
Language	SQL-like	PigLatin
Schemas/Types	Yes (explicit)	Yes (implicit)
Partitions	**Yes**	**No**
Server	Optional (Thrift)	No
User Defined Functions (UDF)	Yes (Java)	Yes (Java)
Custom Serializer/Deserializer	Yes	Yes
DFS Direct Access	Yes (implicit)	Yes (explicit)
Join/Order/Sort	Yes	Yes
Shell	Yes	Yes
Streaming	Yes	Yes
Web Interface	Yes	No
JDBC/ODBC	Yes (limited)	No