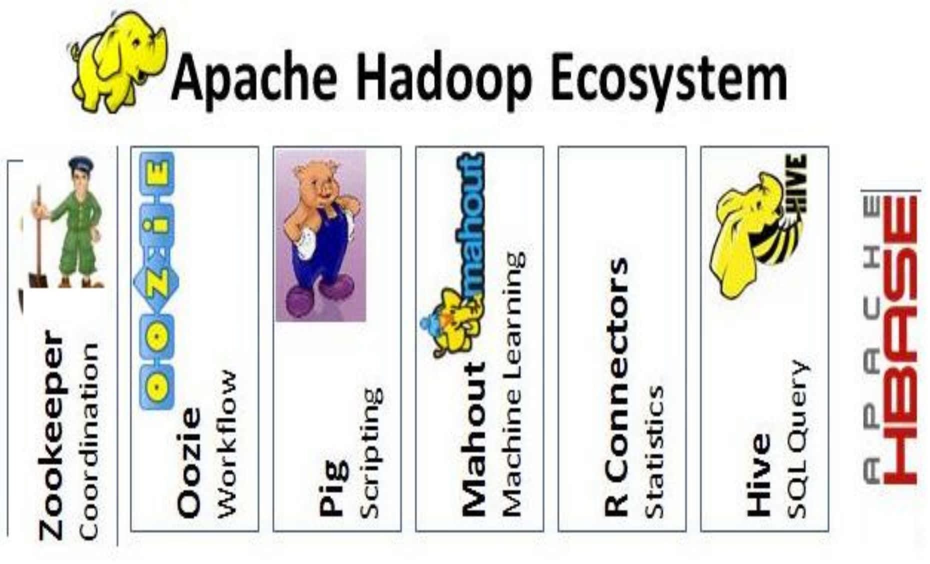
SATHYABAMA UNIVERSITY

COURSE MATERIAL - BIG DATA (SIT1606)

FACULTY OF COMPUTING

Unit III – HADOOP IMPLEMENTATION AND HADOOP ECO TOOLS

Understanding Hadoop and Its Ecosystem



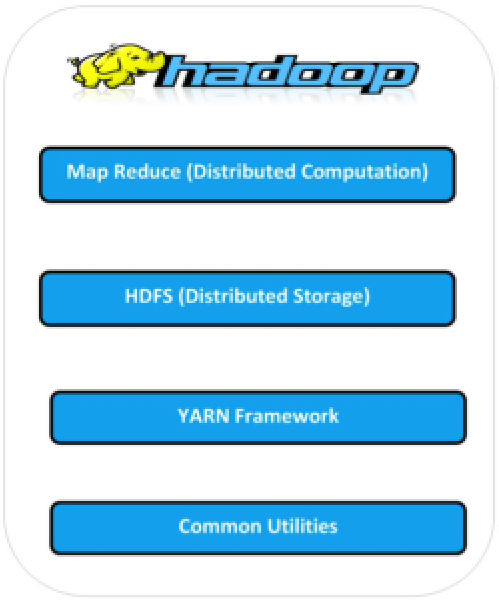
It is quite interesting to envision how we could adopt the Hadoop eco system within the realms of DevOps. I will try to cover it in upcoming series. Hadoop managed by the Apache Foundation is a powerful open-source platform written in java that is capable of processing large amounts of heterogeneous data-sets at scale in a distributive fashion on cluster of computers using simple programming models. It is designed to scale up from single server to thousands of machines, each offering local computation and storage and has become an in-demand technical skill. Hadoop is an Apache top-level project being built and used by a global community of contributors and users.

Hadoop Architecture:

The Apache Hadoop framework includes following four modules:

- **Hadoop Common:** Contains Java libraries and utilities needed by other Hadoop modules. These libraries give filesystem and OS level abstraction and comprise of the essential Java files and scripts that are required to start Hadoop.
- **Hadoop Distributed File System (HDFS):** A distributed file-system that provides high-throughput access to application data on the community machines thus providing very high aggregate bandwidth across the cluster.
- **Hadoop YARN:** A resource-management framework responsible for job scheduling and cluster resource management.
- **Hadoop MapReduce:** This is a YARN- based programming model for parallel processing of large data sets.

Below diagram portray four components that are available in Hadoop framework.


hadoop
Map Reduce (Distributed Computation)
HDFS (Distributed Storage)
YARN Framework
Common Utilities

All the modules in Hadoop are designed with a fundamental assumption i.e., hardware failure, so should be automatically controlled in software by the framework. Beyond HDFS, YARN and MapReduce, the entire Apache Hadoop “platform” is now commonly considered to consist of a number of related projects as well: Apache Pig, Apache Hive, Apache HBase, and others.

Hadoop Ecosystem:

Hadoop has gained its popularity due to its ability of storing, analyzing and accessing large amount of data, quickly and cost effectively through clusters of commodity hardware. It wont be wrong if we say that Apache Hadoop is actually a collection of several components and not just a single product.

With Hadoop Ecosystem there are several commercial along with an open source products which are broadly used to make Hadoop laymen accessible and more usable.

The following sections provide additional information on the individual components:

MapReduce

Hadoop MapReduce is a software framework for easily writing applications which process big amounts of data in-parallel on large clusters of commodity hardware in a reliable, fault-tolerant manner. In terms of programming, there are **two functions** which are most common in MapReduce.

- **The Map Task:** Master computer or node takes input and convert it into divide it into smaller parts and distribute it on other worker nodes. All worker nodes solve their own small problem and give answer to the master node.
- **The Reduce Task:** Master node combines all answers coming from worker node and forms it in some form of output which is answer of our big distributed problem.

Generally both the input and the output are reserved in a file-system. The framework is responsible for scheduling tasks, monitoring them and even re-executes the failed tasks.

Hadoop Distributed File System (HDFS)

HDFS is a distributed file-system that provides high throughput access to data. When data is pushed to HDFS, it automatically splits up into multiple blocks and stores/replicates the data thus ensuring high availability and fault tolerance.

***Note**: A file consists of many blocks (large blocks of 64MB and above).*

Here are the **main components of HDFS:**

- **NameNode:** It acts as the master of the system. It maintains the name system i.e., directories and files and manages the blocks which are present on the DataNodes.
- **DataNodes:** They are the slaves which are deployed on each machine and provide the actual storage. They are responsible for serving read and write requests for the clients.
- **Secondary NameNode:** It is responsible for performing periodic checkpoints. In the event of NameNode failure, you can restart the NameNode using the checkpoint.

Hive

Hive is part of the Hadoop ecosystem and provides an SQL like interface to Hadoop. It is a data warehouse system for Hadoop that facilitates easy data summarization, ad-hoc queries, and the analysis of large datasets stored in Hadoop compatible file systems.

It provides a mechanism to project structure onto this data and query the data using a SQL-like language called HiveQL. Hive also allows traditional map/reduce programmers to plug in their custom mappers and reducers when it is inconvenient or inefficient to express this logic in HiveQL.

The **main building blocks of Hive are –**

1. **Metastore** – To store metadata about columns, partition and system catalogue.
2. **Driver** – To manage the lifecycle of a HiveQL statement
3. **Query Compiler** – To compiles HiveQL into a directed acyclic graph.
4. **Execution Engine** – To execute the tasks in proper order which are produced by the compiler.
5. **HiveServer** – To provide a Thrift interface and a JDBC / ODBC server.

HBase (Hadoop DataBase)

HBase is a distributed, column oriented database and uses HDFS for the underlying storage. As said earlier, HDFS works on write once and read many times pattern, but this isn't a case always. We may require real time read/write random access for huge dataset; this is where HBase comes into the picture. HBase is built on top of HDFS and distributed on column-oriented database.

Here are the **main components of HBase:**

- **HBase Master:** It is responsible for negotiating load balancing across all RegionServers and maintains the state of the cluster. It is not part of the actual data storage or retrieval path.
- **RegionServer:** It is deployed on each machine and hosts data and processes I/O requests.

Zookeeper

ZooKeeper is a centralized service for maintaining configuration information, naming, providing distributed synchronization and providing group services which are very useful for a variety of distributed systems. HBase is not operational without ZooKeeper.

Mahout

Mahout is a scalable machine learning library that implements various different approaches machine learning. At present Mahout contains four **main groups of algorithms:**

- Recommendations, also known as collective filtering
- Classifications, also known as categorization
- Clustering
- Frequent itemset mining, also known as parallel frequent pattern mining

Algorithms in the Mahout library belong to the subset that can be executed in a distributed fashion and have been written to be executable in MapReduce. Mahout is scalable along three dimensions: It scales to reasonably large data sets by leveraging algorithm properties or implementing versions based on Apache Hadoop.

Sqoop (SQL-to-Hadoop)

Sqoop is a tool designed for efficiently transferring structured data from SQL Server and SQL Azure to HDFS and then uses it in MapReduce and Hive jobs. One can even use Sqoop to move data from HDFS to SQL Server.

Apache Spark:

Apache Spark is a general compute engine that offers fast data analysis on a large scale. Spark is built on HDFS but bypasses MapReduce and instead uses its own data processing framework. Common uses cases for Apache Spark include real-time queries, event stream processing, iterative algorithms, complex operations and machine learning.

Pig

Pig is a platform for analyzing and querying huge data sets that consist of a high-level language for expressing data analysis programs, coupled with infrastructure for evaluating these programs. Pig's built-in operations can make sense of semi-structured data, such as log files, and the language is extensible using Java to add support for custom data types and transformations.

Pig has three main **key properties:**

- Extensibility
- Optimization opportunities
- Ease of programming

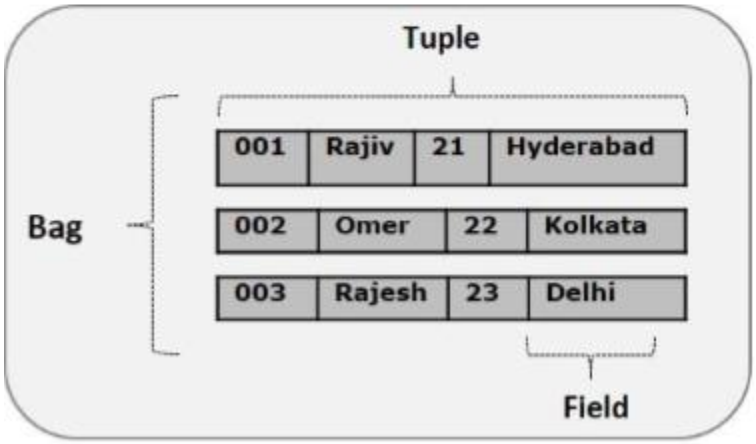
The salient property of Pig programs is that their structure is amenable to substantial parallelization, which in turns enables them to handle very large data sets. At the present time, Pig's infrastructure layer consists of a compiler that produces sequences of MapReduce programs.

Apache Pig	**MapReduce**
Apache Pig is a data flow language.	MapReduce is a data processing paradigm.
It is a high level language.	MapReduce is low level and rigid.
Performing a Join operation in Apache Pig is pretty simple.	It is quite difficult in MapReduce to perform a Join operation between datasets.
Any novice programmer with a basic knowledge of SQL can work conveniently with Apache Pig.	Exposure to Java is must to work with MapReduce.

Apache Pig uses multi-query approach, thereby reducing the length of the codes to a great extent.	MapReduce will require almost 20 times more the number of lines to perform the same task.
There is no need for compilation. On execution, every Apache Pig operator is converted internally into a MapReduce job.	MapReduce jobs have a long compilation process.

Pig Data Model.

The data model of Pig Latin is fully nested and it allows complex non-atomic datatypes such as **map** and **tuple**.



Types

Pig's data types can be divided into two categories: *scalar* types, which contain a single value, and *complex* types, which contain other types.

Scalar Types

Pig’s scalar types are simple types that appear in most programming languages. With the exception of bytearray, they are all represented in Pig interfaces byjava.lang classes, making them easy to work with in UDFs:

Int,Long ,Float Double, CharArray and byteArray.

Complex Types

Pig has three complex data types: maps, tuples, and bags. All of these types can contain data of any type, including other complex types.

Map

A *map* in Pig is a chararray to data element mapping, where that element can be any Pig type, including a complex type. The chararray is called a key and is used as an index to find the element, referred to as the value.

Map constants are formed using brackets to delimit the map, a hash between keys and values, and a comma between key-value pairs. For example,['name'#'bob', 'age'#55] will create a map with two keys, “name” and“age”. The first value is a chararray, and the second is an integer.

Tuple

A *tuple* is a fixed-length, ordered collection of Pig data elements. Tuples are divided into *fields*, with each field containing one data element. These elements can be of any type—they do not all need to be the same type. A tuple is analogous to a row in SQL, with the fields being SQL columns.

Tuple constants use parentheses to indicate the tuple and commas to delimit fields in the tuple. For example, ('bob', 55) describes a tuple constant with two fields.

Bag

A *bag* is an unordered collection of tuples. Because it has no order, it is not possible to reference tuples in a bag by position. Like tuples, a bag can, but is not required to,
have a schema associated with it. In the case of a bag, the schema describes all tuples within the bag.

Bag constants are constructed using braces, with tuples in the bag separated by commas. For example, `{('bob', 55), ('sally', 52), ('john', 25)}`constructs a bag with three tuples, each with two fields.

Pig Latin.

The language used to analyze data in Hadoop using Pig is known as **Pig Latin**. It is a high level data processing language which provides a rich set of data types and operators to perform various operations on the data.

To perform a particular task Programmers using Pig, programmers need to write a Pig script using the Pig Latin language, and execute them using any of the execution mechanisms (Grunt Shell, UDFs, Embedded). After execution, these scripts will go through a series of transformations applied by the Pig Framework, to produce the desired output.

Pig Latin – Type Construction Operators-

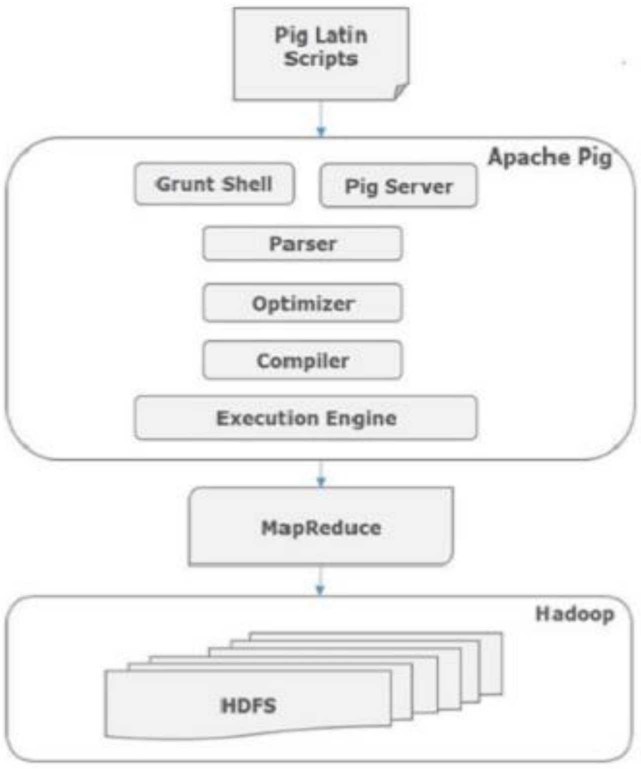
()	**Tuple constructor operator** − This operator is used to construct a tuple.
{}	**Bag constructor operator** − This operator is used to construct a bag.
[]	**Map constructor operator** − This operator is used to construct a tuple.

Pig Latin – Relational Operators

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.
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.



Architecture of PIG

As shown in the figure, there are various components in the Apache Pig framework. Let us take a look at the major components.

Parser

Initially the Pig Scripts are handled by the Parser. It checks the syntax of the script, does type checking, and other miscellaneous checks. The output of the parser will be a DAG (directed acyclic graph), which represents the Pig Latin statements and logical operators.

In the DAG, the logical operators of the script are represented as the nodes and the data flows are represented as edges.

Optimizer

The logical plan (DAG) is passed to the logical optimizer, which carries out the logical optimizations such as projection and pushdown.

Compiler

The compiler compiles the optimized logical plan into a series of MapReduce jobs.

Execution engine

Finally the MapReduce jobs are submitted to Hadoop in a sorted order. Finally, these MapReduce jobs are executed on Hadoop producing the desired results.

Developing and Testing Pig Latin Script.

Pig provides several tools and diagnostic operators to help you develop your applications. In this section we will explore these and also look at some tools others have written to make it easier to develop Pig with standard editors and integrated development environments (IDEs).

Syntax Highlighting and Checking

Syntax highlighting often helps users write code correctly, at least syntactically, the first time around. Syntax highlighting packages exist for several popular editors.

Pig Latin syntax highlighting packages

Tool	URL
Eclipse	http://code.google.com/p/pig-eclipse
Emacs	http://github.com/cloudera/piglatin-mode,http://sf.net/projects/pig-mode
TextMate	http://www.github.com/kevinweil/pig.tmbundle
Vim	http://www.vim.org/scripts/script.php?script_id=218

describe

`describe` shows you the schema of a relation in your script. This can be very helpful as you are developing your scripts. It is especially useful as you are learning Pig Latin and understanding how various operators change the data. `describe` can be applied to any relation in your script, and you can have multiple `describe`s in a script:

```
-describe.pig

divs    = load 'NYSE_dividends' as (exchange:chararray, symbol:chararray,

            date:chararray, dividends:float);

trimmed = foreach divs generate symbol, dividends;

grpd    = group trimmed by symbol;

avgdiv  = foreach grpd generate group, AVG(trimmed.dividends);



describe trimmed;

describe grpd;

describe avgdiv;
```

```
trimmed: {symbol: chararray,dividends: float}

grpd: {group: chararray,trimmed: {(symbol: chararray,dividends: float)}}

avgdiv: {group: chararray,double}
```

explain

One of Pig's goals is to allow you to think in terms of data flow instead of MapReduce. But sometimes you need to peek into the barn and see how Pig is compiling your script into MapReduce jobs. Pig provides `explain` for this. `explain` is particularly helpful when you are trying to optimize your scripts or debug errors.

There are two ways to use `explain`. You can `explain` any alias in your Pig Latin script, which will show the execution plan Pig would use if you stored that relation. You can also take an existing Pig Latin script and apply `explain` to the whole script in Grunt.

illustrate

Often one of the best ways to debug your Pig Latin script is to run your data through it. But if you are using Pig, the odds are that you have a large data set. If it takes several hours to process your data, this makes for a very long debugging cycle.

For example, if you have a join, you have to be careful to sample records from each input such that at least some have the same key. Otherwise, your join will return no results.

To address this issue, the scientists in Yahoo! Research built `illustrate` into Pig. `illustrate` takes a sample of your data and runs it through your script, but as it encounters operators that remove data (such as `filter`, `join`, etc.), it makes sure that some records pass through the operator and some do not.

Pig Statistics

Beginning in version 0.8, Pig produces a summary set of statistics at the end of every run:

The `Input`, `Output`, and `Counters` sections are self-explanatory. The statistics on spills record how many times Pig spilled records to local disk to avoid running out of memory. In local mode the`Counters` section will be missing because Hadoop does not report counters in local mode.

The `Job DAG` section at the end describes how data flowed between MapReduce jobs. In this case, the flow was linear.

MapReduce Job Status

When you are running your Pig Latin scripts on your Hadoop cluster, finding the status and logs of your job can be challenging. Logs generated by Pig while it plans and manages your query are stored in the current working directory.

Debugging Tips

Beyond the tools covered previously, there are a few things I have found useful in debugging Pig Latin scripts. First, if `illustrate` does not do what you need, use local mode to test your script before running it on your Hadoop cluster.

Testing Your Scripts with PigUnit

As part of your development, you will want to test your Pig Latin scripts. Even once they are finished, regular testing helps assure that changes to your UDFs, to your scripts, or in the versions of Pig and Hadoop that you are using do not break your code. *PigUnit* provides a unit-testing framework that plugs into JUnit to help you write unit tests that can be run on a regular basis.PigUnit was added in Pig 0.8.

Writing Evaluation

Pig and Hadoop are implemented in Java, and so it is natural to implement UDFs in Java. This allows UDFs access to the Hadoop APIs and to many of Pig's facilities.

Evaluation Function Basics

All evaluation functions extend the Java class `org.apache.pig.EvalFunc`. This class uses Java generics. It is parameterized by the return type of your UDF. The core method in this class is `exec`. It takes one record and returns one result, which will be invoked for every record that passes through your execution pipeline.

UDFs can also be handed the entire record by passing * to the UDF. You might expect that in this case the input Tuple argument passed to the UDF would contain all the fields passed into the operator the UDF is in. But it does not.

Interacting with Pig values

Evaluation functions and other UDFs are exposed to the internals of how Pig represents data types. This means that when you read a field and expect it to be an integer, you need to know that it will be an instance of `java.lang.Integer`. For a complete list of Pig types and how they are represented in Java, see "Types".

Memory Issues in Eval Funcs

Some operations you will perform in your UDFs will require more memory than is available. As an example, you might want to build a UDF that calculates the cumulative sum of a set of inputs. This will return a bag of values because, for each input, it needs to return the intermediate sum at that input.

Filter

The `filter` statement allows you to select which records will be retained in your data pipeline. A `filter` contains a predicate. If that predicate evaluates to true for a given record, that record will be passed down the pipeline.

Predicates can contain the equality operators you expect, including `==` to test equality, and `!=`, `>`, `>=`,`<`, and `<=`. These comparators can be used on any scalar data type. `==` and `!=` can be applied to maps and tuples.

```
-- filter_matches.pig

divs        = load 'NYSE_dividends' as (exchange:chararray, symbol:chararray,

                date:chararray, dividends:float);

startswithcm = filter divs by symbol matches 'CM.*';
```

Load and Store Functions

Pig's load function is built on top of a Hadoop `InputFormat`, the class that Hadoop uses to read data.`InputFormat` serves two purposes: it determines how input will be split between map tasks, and it provides a `RecordReader` that produces key-value pairs as input to those map tasks. The load function takes these key-value pairs and returns a Pig `Tuple`.

The base class for the load function is `LoadFunc`. This is an abstract class, which allows it to provide helper functions and default implementations. Many load functions will only need to extend`LoadFunc`.

Frontend Planning Functions

For all load functions, Pig must do three things as part of frontend planning: 1) it needs to know the input format it should use to read the data; 2) it needs to be sure that the load function understands where its data is located; and 3) it needs to know how to cast bytearrays returned from the load function.

Determining InputFormat

Pig needs to know which `InputFormat` to use for reading your input. It calls `getInputFormat` to get an instance of the input format. It gets an instance rather than the class itself so that your load function can control the instantiation: any generic parameters, constructor arguments, etc. For our example load function, this method is very simple. It uses `TextInputFormat`, an input format that reads text data from HDFS files:

```
// JsonLoader.java

public InputFormat getInputFormat() throws IOException {

   return new TextInputFormat();

}
```

Determining the location

Pig communicates the location string provided by the user to the load function via `setLocation`. So, if the load operator in Pig Latin is `A = load 'input';`, “input” is the location string. This method is called on both the frontend and backend, possibly multiple times. Thus you need to take care that this method does not do anything that will cause problems if done more than one time. Your load function should communicate the location to its input format. For example, `JsonLoader` passes the filename via a helper method on `FileInputFormat` (a superclass of `TextInputFormat`):

```
// JsonLoader.java

public void setLocation(String location, Job job) throws IOException {

   FileInputFormat.setInputPaths(job, location);

}
```

The Hadoop `Job` is passed along with the location because that is where input formats usually store their configuration information.

Getting the casting functions

Some Pig functions, such as `PigStorage` and `HBaseStorage`, load data by default without understanding its type information, and place the data unchanged in `DataByteArray` objects. At a later time, when Pig needs to cast that data to another type, it does not know how to because it does not understand how the data is represented in the bytearray.

Passing Information from the Frontend to the Backend

As with evaluation functions, load functions can make use of `UDFContext` to pass information from frontend invocations to backend invocations. For details on `UDFContext`, see “UDFContext”. One significant difference between using `UDFContext` in evaluation and load functions is determining the instance-specific signature of the function.

In evaluation functions, constructor arguments were suggested as a way to do this. For load functions, the input location usually will be the differentiating factor. However, `LoadFunc` does not guarantee that it will call `setLocation` before other methods where you might want to use `UDFContext`.

Additional Load Function Interfaces

Your load function can provide more complex features by implementing additional interfaces. (Implementation of these interfaces is optional.)

Loading metadata

Many data storage mechanisms can record the schema along with the data. Pig does not assume the ability to store schemas, but if your storage can hold the schema, it can be very useful. This frees script writers from needing to specify the field names and types as part of the load operator in Pig Latin.

Some types of data storage also partition the data. If Pig understands this partitioning, it can load only those partitions that are needed for a particular script. Both of these functions are enabled by implementing the `LoadMetadata` interface.

`getSchema` in the `LoadMetadata` interface gives your load function a chance to provide a schema. It is passed the location string the user provides as well as the Hadoop `Job` object, in case it needs information in this object to open the schema.

Using partitions

Some types of storage partition their data, allowing you to read only the relevant sections for a given job. The `LoadMetadata` interface also provides methods for working with partitions in your data. In order for Pig to request the relevant partitions, it must know how the data is partitioned. Pig determines this by calling `getPartitionKeys`.

Store Functions

Pig's store function is, in many ways, a mirror image of the load function. It is built on top of Hadoop's `OutputFormat`. It takes Pig `Tuple`s and creates key-value pairs that its associated output format writes to storage.

`StoreFunc` is an abstract class, which allows it to provide default implementations for some methods. However, some functions implement both load and store functionality; `PigStorage` is one example.

Store Function Frontend Planning

Store functions have three tasks to fulfill on the frontend:

- Instantiate the `OutputFormat` they will use to store data.
- Check the schema of the data being stored.
- Record the location where the data will be stored.

Determining OutputFormat

Pig calls `getOutputFormat` to get an instance of the output format that your store function will use to store records. This method returns an instance rather than the classname or the class itself. This allows your store function to control how the class is instantiated.

```
JsonStorage.java

public OutputFormat getOutputFormat() throws IOException {

   return new TextOutputFormat<LongWritable, Text>();

}
```

Setting the output location

Pig calls `setStoreLocation` to communicate the location string the user provides to your store function. Given the Pig Latin `store Z into 'output';`, "output" is the location string. This method, called on both the frontend and the backend, could be called multiple times

The Hadoop `Job` is passed to this function as well. Most output formats store the location information in the job.

Pig calls `setStoreLocation` on both the frontend and backend because output formats usually store their location in the job, as we see in our example store function. This works for MapReduce jobs, where a single output format is guaranteed.

Store Functions and UDFContext

Store functions work with `UDFContext` exactly as load functions do, but with one exception: the signature for store functions is passed to the store function via `setStoreFuncUDFContextSignature`. See "Passing Information from the Frontend to the Backend" for a discussion of how load functions work with `UDFContext`.

Writing Data

During backend processing, the store function is first initialized, and then takes Pig tuples and converts them to key-value pairs to be written to storage.

Preparing to write

Pig calls your store function's `prepareToWrite` method in each map or reduce task before writing any data. This call passes a `RecordWriter` instance to use when writing data. `RecordWriter` is a class that `OutputFormat` uses to write individual records.

Writing records

`putNext` is the core method in the store function class. Pig calls this method for every tuple it needs to store. Your store function needs to take these tuples and produce the key-value pairs that its output format expects.

Storing Metadata

If your storage format can store schemas in addition to data, your store function can implement the interface `StoreMetadata`. This provides a `storeSchema` method that is called by Pig as part of its frontend operations. Pig passes `storeSchema` a `ResourceSchema`, the location string, and the job object so that it can connect to its storage.

Hive – Introduction

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

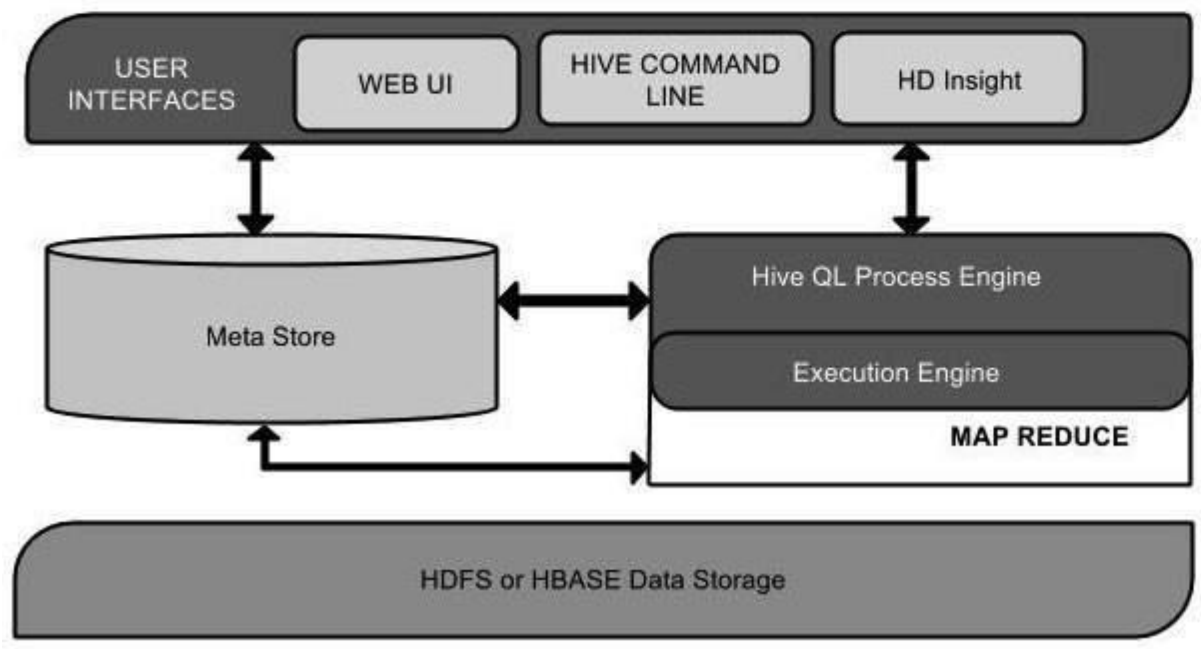
Features of Hive

- 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:



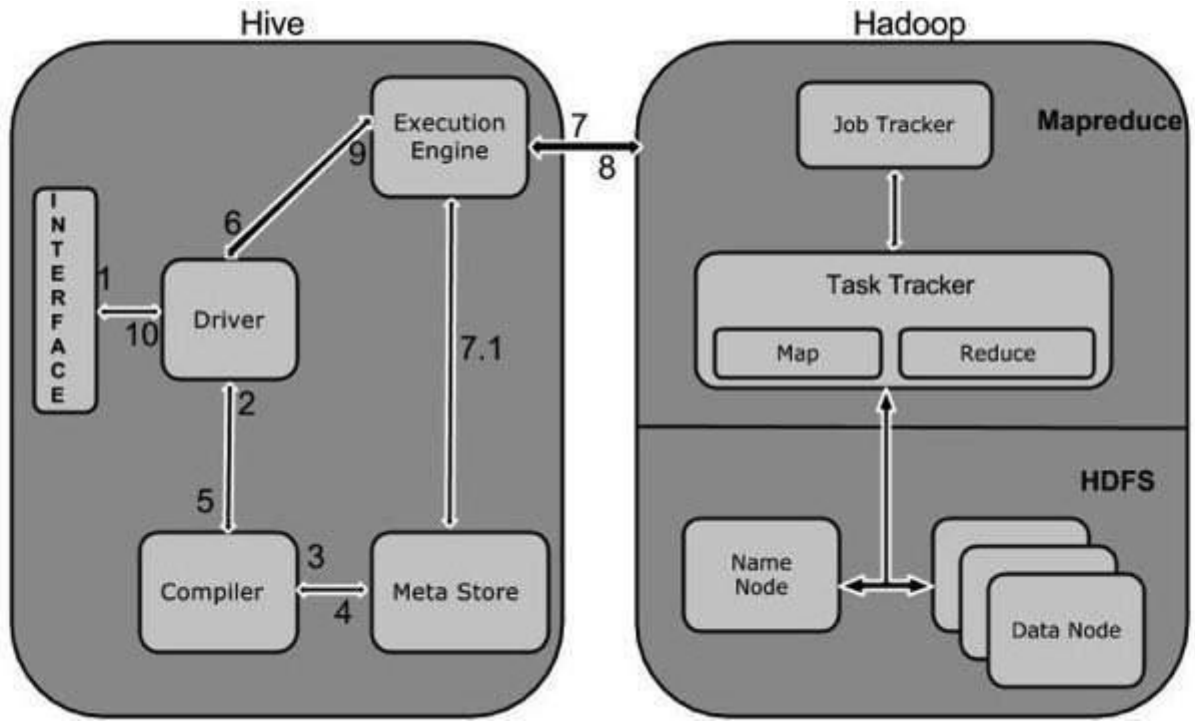
This component diagram contains different units. The following table describes each unit:

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:

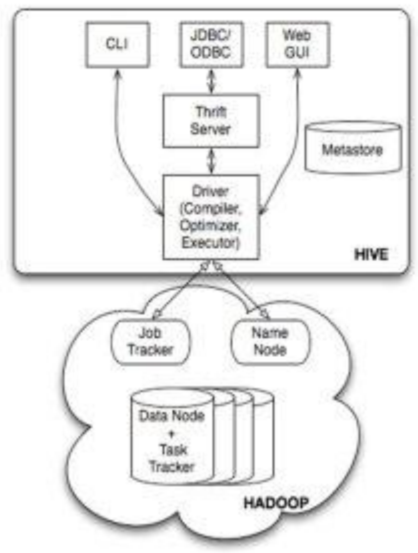
Step No.	Operation
1	**Execute Query** The Hive interface such as Command Line or Web UI sends query to Driver (any database driver such as JDBC, ODBC, etc.) to execute.
2	**Get Plan** The driver takes the help of query compiler that parses the query to check the syntax and query plan or the requirement 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.

Hadoop Hive Architecture

Hive is one of the most important component of Hadoop,In previous post we discussed about Hive Introduction.Now we have to know about **Hadoop Hive Architecture.**



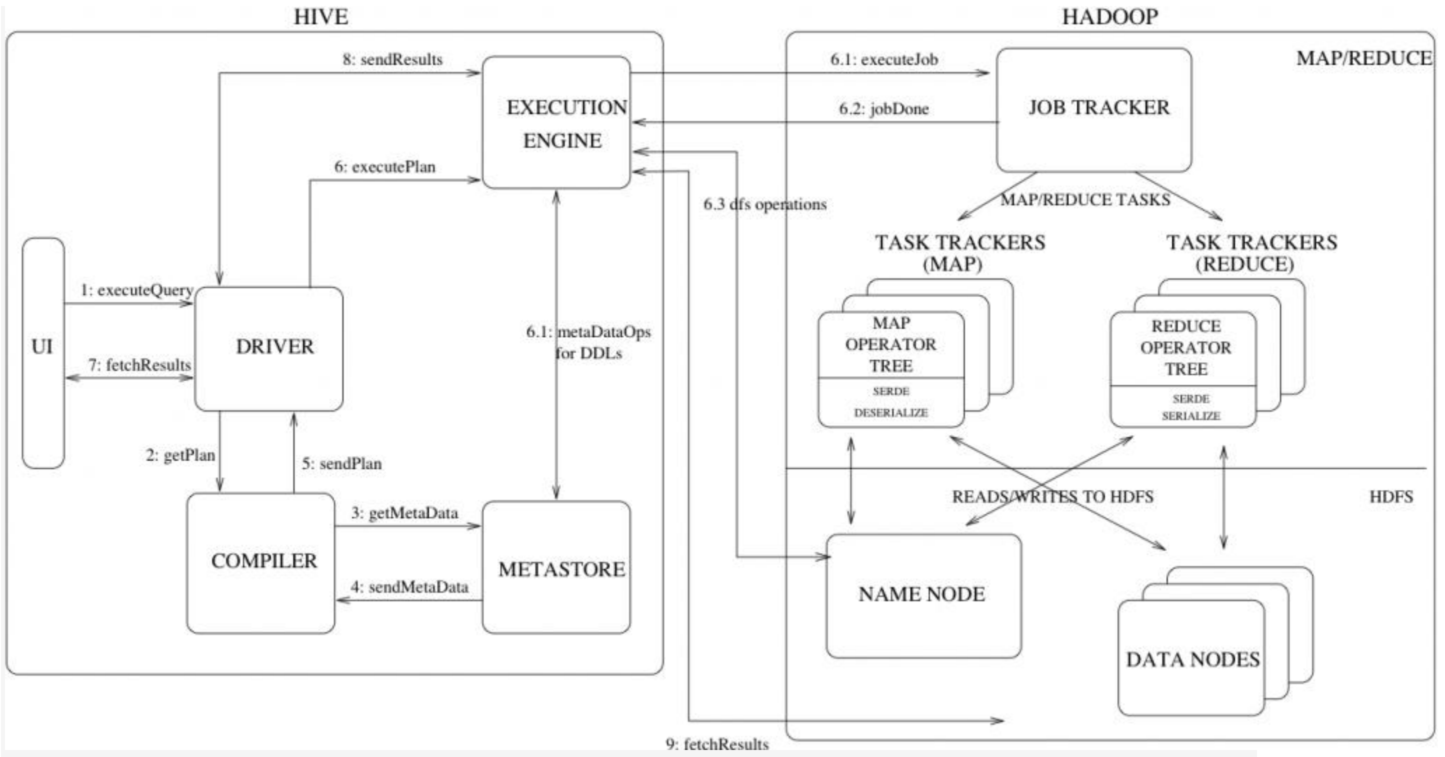
Hadoop Hive Architecture

The above diagram shows the basic **Hadoop Hive architecture**. Primarily The diagram represents CLI (Command Line Interface),JDBC/ODBC and Web GUI (Web Graphical User Interface).This represents when user comes with CLI(Hive Terminal) it directly connected to Hive Drivers,When User comes with JDBC/ODBC(JDBC Program) at that time by using

API(Thrift Server) it connected to Hive driver and when the user comes with Web GUI(Ambari server) it directly connected to Hive Driver.

The hive driver receives the tasks(Queries) from user and send to Hadoop architecture.The Hadoop architecture uses name node,data node,job tracker and task tracker for receiving and dividing the work what Hive sends to Hadoop (**Mapreduce Architecture**) .

The below diagram represents clear internal **Hadoop Hive Architecture**



Hive_architecture

The above diagram shows how a typical query flows through the system

Step 1 :- The UI calls the execute interface to the Driver

Step 2 :- The Driver creates a session handle for the query and sends the query to the compiler to generate an execution plan

Step 3&4 :- The compiler needs the metadata so send a request for getMetaData and receives the sendMetaData request from MetaStore.

Step 5 :- This metadata is used to typecheck the expressions in the query tree as well as to prune partitions based on query predicates. The plan generated by the compiler is a DAG of stages with each stage being either a map/reduce job, a metadata operation or an operation on HDFS. For map/reduce stages, the plan contains map operator trees (operator trees that are executed on the mappers) and a reduce operator tree (for operations that need reducers).

Step 6 :- The execution engine submits these stages to appropriate components (steps 6, 6.1, 6.2 and 6.3). In each task (mapper/reducer) the deserializer associated with the table or intermediate outputs is used to read the rows from HDFS files and these are passed through the associated operator tree.Once the output generate it is written to a temporary HDFS file though the serializer. The temporary files are used to provide the to subsequent map/reduce stages of the plan.For DML operations the final temporary file is moved to the table's location

Step 7&8&9 :- For queries, the contents of the temporary file are read by the execution engine directly from HDFS as part of the fetch call from the Driver

Major Components of Hive

UI :- UI means User Interface, The user interface for users to submit queries and other operations to the system.

Driver :- The Driver is used for receives the quires from UI .This component implements the notion of session handles and provides execute and fetch APIs modeled on JDBC/ODBC interfaces.

Compiler :- The component that parses the query, does semantic analysis on the different query blocks and query expressions and eventually generates an execution plan with the help of the table and partition metadata looked up from the metastore.

MetaStore :- The component that stores all the structure information of the various tables and partitions in the warehouse including column and column type information, the serializers and deserializers necessary to read and write data and the corresponding HDFS files where the data is stored.

Execution Engine :- The component which executes the execution plan created by the compiler. The plan is a DAG of stages. The execution engine manages the dependencies between these different stages of the plan and executes these stages on the appropriate system components.

This is the main theme of **hadoop hive architecture**

HIVE VS TRADITIONAL DATABASE

- Hive resembles a traditional database by supporting SQL interface but it is not a full database. Hive can be better called as data warehouse instead of database.
- Hive enforces schema on read time whereas RDBMS enforces schema on write time.

In RDBMS, a table's schema is enforced at data load time, If the data being
loaded doesn't conform to the schema, then it is rejected. This design is called schema on write.

But Hive doesn't verify the data when it is loaded, but rather when a
it is retrieved. This is called schema on read.

Schema on read makes for a very fast initial load, since the data does not have to be read, parsed, and serialized to disk in the database's internal format. The load operation is just a file copy or move.

Schema on write makes query time performance faster, since the database can index columns and perform compression on the data but it takes longer to load data into the database.

- Hive is based on the notion of Write once, Read many times but RDBMS is designed for Read and Write many times.
- In RDBMS, record level updates, insertions and deletes, transactions and indexes are possible. Whereas these are not allowed in Hive because Hive was built to operate over HDFS data using MapReduce, where full-table scans are the norm and a table update is achieved by transforming the data into a new table.
- In RDBMS, maximum data size allowed will be in 10's of Terabytes but whereas Hive can 100's Petabytes very easily.
- As Hadoop is a batch-oriented system, Hive doesn't support OLTP (Online Transaction Processing) but it is closer to OLAP (Online Analytical Processing) but not ideal since there is significant latency between issuing a query and receiving a reply, due to the overhead of Mapreduce jobs and due to the size of the data sets Hadoop was designed to serve.
- RDBMS is best suited for dynamic data analysis and where fast responses are expected but Hive is suited for data warehouse applications, where relatively static data is analyzed, fast response times are not required, and when the data is not changing rapidly.
- To overcome the limitations of Hive, HBase is being integrated with Hive to support record level operations and OLAP.
- Hive is very easily scalable at low cost but RDBMS is not that much scalable that too it is very costly scale up.

HIVEQL Data Types

This chapter takes you through the different data types in Hive, which are involved in the table creation. All the data types in Hive are classified into four types, given as follows:

- Column Types
- Literals
- Null Values

- Complex Types

Column Types

Column type are used as column data types of Hive. They are as follows:

Integral Types

Integer type data can be specified using integral data types, INT. When the data range exceeds the range of INT, you need to use BIGINT and if the data range is smaller than the INT, you use SMALLINT. TINYINT is smaller than SMALLINT.

The following table depicts various INT data types:

Type	**Postfix**	**Example**
TINYINT	Y	10Y
SMALLINT	S	10S
INT	-	10
BIGINT	L	10L

String Types

String type data types can be specified using single quotes (' ') or double quotes (" "). It contains two data types: VARCHAR and CHAR. Hive follows C-types escape characters.

The following table depicts various CHAR data types:

Data Type	Length
VARCHAR	1 to 65355
CHAR	255

Timestamp

It supports traditional UNIX timestamp with optional nanosecond precision. It supports java.sql.Timestamp format “YYYY-MM-DD HH:MM:SS.fffffffff” and format “yyyy-mm-dd hh:mm:ss.ffffffffff”.

Dates

DATE values are described in year/month/day format in the form {{YYYY-MM-DD}}.

Decimals

The DECIMAL type in Hive is as same as Big Decimal format of Java. It is used for representing immutable arbitrary precision. The syntax and example is as follows:

```
DECIMAL(precision, scale)

decimal(10,0)
```

Union Types

Union is a collection of heterogeneous data types. You can create an instance using **create union**. The syntax and example is as follows:

```
UNIONTYPE<int, double, array<string>, struct<a:int,b:string>>


{0:1}

{1:2.0}
```

```
{2:["three","four"]}
{3:{"a":5,"b":"five"}}
{2:["six","seven"]}
{3:{"a":8,"b":"eight"}}
{0:9}
{1:10.0}
```

Literals

The following literals are used in Hive:

Floating Point Types

Floating point types are nothing but numbers with decimal points. Generally, this type of data is composed of DOUBLE data type.

Decimal Type

Decimal type data is nothing but floating point value with higher range than DOUBLE data type. The range of decimal type is approximately -10^{-308} to 10^{308}.

Null Value

Missing values are represented by the special value NULL.

Complex Types

The Hive complex data types are as follows:

Arrays

Arrays in Hive are used the same way they are used in Java.

```
Syntax: ARRAY<data_type>
```

Maps

Maps in Hive are similar to Java Maps.

```
Syntax: MAP<primitive_type, data_type>
```

Structs

Structs in Hive is similar to using complex data with comment.

```
Syntax: STRUCT<col_name : data_type [COMMENT col_comment], ...>
```

Hive - Built-in Operators

This chapter explains the built-in operators of Hive. There are four types of operators in Hive:

- Relational Operators
- Arithmetic Operators
- Logical Operators
- Complex Operators

Relational Operators

These operators are used to compare two operands. The following table describes the relational operators available in Hive:

Operator	Operand	Description
A = B	all primitive types	TRUE if expression A is equivalent to expression B otherwise FALSE.
A != B	all primitive types	TRUE if expression A is not equivalent to expression B otherwise FALSE.
A < B	all primitive types	TRUE if expression A is less than expression B otherwise FALSE.

A <= B	all primitive types	TRUE if expression A is less than or equal to expression B otherwise FALSE.
A > B	all primitive types	TRUE if expression A is greater than expression B otherwise FALSE.
A >= B	all primitive types	TRUE if expression A is greater than or equal to expression B otherwise FALSE.
A IS NULL	all types	TRUE if expression A evaluates to NULL otherwise FALSE.
A IS NOT NULL	all types	FALSE if expression A evaluates to NULL otherwise TRUE.
A LIKE B	Strings	TRUE if string pattern A matches to B otherwise FALSE.
A RLIKE B	Strings	NULL if A or B is NULL, TRUE if any substring of A matches the Java regular expression B , otherwise FALSE.
A REGEXP B	Strings	Same as RLIKE.

Example

Let us assume the **employee** table is composed of fields named Id, Name, Salary, Designation, and Dept as shown below. Generate a query to retrieve the employee details whose Id is 1205.

```
+-----+---------------+---------+-----------------------------+------+
| 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 is executed to retrieve the employee details using the above table:

```
hive> SELECT * FROM employee WHERE Id=1205;
```

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

```
+-----+-----------+-----------+----------------------------------+
| ID  | Name      | Salary    | Designation                | Dept  |
+-----+---------------+-------+----------------------------------+
|1205 | Kranthi   | 30000     | Op Admin                   | Admin |
+-----+-----------+-----------+----------------------------------+
```

The following query is executed to retrieve the employee details whose salary is more than or equal to Rs 40000.

```
hive> SELECT * FROM employee WHERE Salary>=40000;
```

On successful execution of 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   |
+-----+-----------+--------+-------------------------+------+
```

Arithmetic Operators

These operators support various common arithmetic operations on the operands. All of them return number types. The following table describes the arithmetic operators available in Hive:

Operators	Operand	Description
A + B	all number types	Gives the result of adding A and B.
A - B	all number types	Gives the result of subtracting B from A.
A * B	all number types	Gives the result of multiplying A and B.
A / B	all number types	Gives the result of dividing B from A.
A % B	all number types	Gives the reminder resulting from dividing A by B.
A & B	all number types	Gives the result of bitwise AND of A and B.
A | B	all number types	Gives the result of bitwise OR of A and B.
A ^ B	all number types	Gives the result of bitwise XOR of A and B.
~A	all number types	Gives the result of bitwise NOT of A.

Example

The following query adds two numbers, 20 and 30.

```
hive> SELECT 20+30 ADD FROM temp;
```

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

```
+--------+
|   ADD  |
+--------+
|   50   |
+--------+
```

Logical Operators

The operators are logical expressions. All of them return either TRUE or FALSE.

Operators	Operands	Description
A AND B	boolean	TRUE if both A and B are TRUE, otherwise FALSE.
A && B	boolean	Same as A AND B.
A OR B	boolean	TRUE if either A or B or both are TRUE, otherwise FALSE.
A || B	boolean	Same as A OR B.
NOT A	boolean	TRUE if A is FALSE, otherwise FALSE.

!A	boolean	Same as NOT A.

Example

The following query is used to retrieve employee details whose Department is TP and Salary is more than Rs 40000.

```
hive> SELECT * FROM employee WHERE Salary>40000 && Dept=TP;
```

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

```
+------+--------------+-------------+-------------------+--------+
| ID   | Name         | Salary      | Designation       | Dept   |
+------+--------------+-------------+-------------------+--------+
|1201  | Gopal        | 45000       | Technical manager | TP     |
+------+--------------+-------------+-------------------+--------+
```

Complex Operators

These operators provide an expression to access the elements of Complex Types.

Operator	Operand	Description
A[n]	A is an Array and n is an int	It returns the nth element in the array A. The first element has index 0.
M[key]	M is a Map<K, V> and key has type K	It returns the value corresponding to the key in the map.
S.x	S is a struct	It returns the x field of S.

Hive - Built-in Functions

This chapter explains the built-in functions available in Hive. The functions look quite similar to SQL functions, except for their usage.

Built-In Functions

Hive supports the following built-in functions:

Return Type	**Signature**	**Description**
BIGINT	round(double a)	It returns the rounded BIGINT value of the double.
BIGINT	floor(double a)	It returns the maximum BIGINT value that is equal or less than the double.
BIGINT	ceil(double a)	It returns the minimum BIGINT value that is equal or greater than the double.
double	rand(), rand(int seed)	It returns a random number that changes from row to row.
string	concat(string A, string B,...)	It returns the string resulting from concatenating B after A.
string	substr(string A, int start)	It returns the substring of A starting from start position till the end of string A.

string	substr(string A, int start, int length)	It returns the substring of A starting from start position with the given length.
string	upper(string A)	It returns the string resulting from converting all characters of A to upper case.
string	ucase(string A)	Same as above.
string	lower(string A)	It returns the string resulting from converting all characters of B to lower case.
string	lcase(string A)	Same as above.
string	trim(string A)	It returns the string resulting from trimming spaces from both ends of A.
string	ltrim(string A)	It returns the string resulting from trimming spaces from the beginning (left hand side) of A.
string	rtrim(string A)	rtrim(string A) It returns the string resulting from trimming spaces from the end (right hand side) of A.
string	regexp_replace(string A, string B, string C)	It returns the string resulting from replacing all substrings in B that match the Java regular expression

		syntax with C.
int	size(Map<K.V>)	It returns the number of elements in the map type.
int	size(Array<T>)	It returns the number of elements in the array type.
value of <type>	cast(<expr> as <type>)	It converts the results of the expression expr to <type> e.g. cast('1' as BIGINT) converts the string '1' to it integral representation. A NULL is returned if the conversion does not succeed.
string	from_unixtime(int unixtime)	convert the number of seconds from Unix epoch (1970-01-01 00:00:00 UTC) to a string representing the timestamp of that moment in the current system time zone in the format of "1970-01-01 00:00:00"
string	to_date(string timestamp)	It returns the date part of a timestamp string: to_date("1970-01-01 00:00:00") = "1970-01-01"
int	year(string date)	It returns the year part of a date or a timestamp string: year("1970-01-01 00:00:00") = 1970, year("1970-01-01") = 1970

int	month(string date)	It returns the month part of a date or a timestamp string: month("1970-11-01 00:00:00") = 11, month("1970-11-01") = 11
int	day(string date)	It returns the day part of a date or a timestamp string: day("1970-11-01 00:00:00") = 1, day("1970-11-01") = 1
string	get_json_object(string json_string, string path)	It extracts json object from a json string based on json path specified, and returns json string of the extracted json object. It returns NULL if the input json string is invalid.

Example

The following queries demonstrate some built-in functions:

round() function

```
hive> SELECT round(2.6) from temp;
```

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

```
2.0
```

floor() function

```
hive> SELECT floor(2.6) from temp;
```

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

```
2.0
```

floor() function

```
hive> SELECT ceil(2.6) from temp;
```

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

```
3.0
```

Aggregate Functions

Hive supports the following built-in **aggregate functions**. The usage of these functions is as same as the SQL aggregate functions.

Return Type	Signature	Description
BIGINT	count(*), count(expr),	count(*) - Returns the total number of retrieved rows.
DOUBLE	sum(col), sum(DISTINCT col)	It returns the sum of the elements in the group or the sum of the distinct values of the column in the group.
DOUBLE	avg(col), avg(DISTINCT col)	It returns the average of the elements in the group or the average of the distinct values of the column in the group.
DOUBLE	min(col)	It returns the minimum value of the column in the group.
DOUBLE	max(col)	It returns the maximum value of the column in the group.

This chapter explains how to create a table and how to insert data into it. The conventions of creating a table in HIVE is quite similar to creating a table using SQL.

Create Table Statement

Create Table is a statement used to create a table in Hive. The syntax and example are as follows:

Syntax

```
CREATE [TEMPORARY] [EXTERNAL] TABLE [IF NOT EXISTS] [db_name.] table_name


[(col_name data_type [COMMENT col_comment], ...)]

[COMMENT table_comment]

[ROW FORMAT row_format]

[STORED AS file_format]
```

Example

Let us assume you need to create a table named **employee** using **CREATE TABLE** statement. The following table lists the fields and their data types in employee table:

Sr.No	Field Name	Data Type
1	Eid	Int
2	Name	String
3	Salary	Float

4	Designation	String

The following data is a Comment, Row formatted fields such as Field terminator, Lines terminator, and Stored File type.

```
COMMENT ‘Employee details’
FIELDS TERMINATED BY ‘\t’
LINES TERMINATED BY ‘\n’
STORED IN TEXT FILE
```

The following query creates a table named **employee** using the above data.

```
hive> CREATE TABLE IF NOT EXISTS employee ( eid int, name String,
salary String, destination String)
COMMENT ‘Employee details’
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ‘\t’
LINES TERMINATED BY ‘\n’
STORED AS TEXTFILE;
```

If you add the option IF NOT EXISTS, Hive ignores the statement in case the table already exists.

On successful creation of table, you get to see the following response:

```
OK
Time taken: 5.905 seconds
hive>
```

JDBC Program

The JDBC program to create a table is given example.

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

import java.sql.DriverManager;


public class HiveCreateTable {

   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

      stmt.executeQuery("CREATE TABLE IF NOT EXISTS "

         +" employee ( eid int, name String, "

         +" salary String, destignation String)"

         +" COMMENT ‘Employee details’"

         +" ROW FORMAT DELIMITED"

         +" FIELDS TERMINATED BY ‘\t’"

         +" LINES TERMINATED BY ‘\n’"

         +" STORED AS TEXTFILE;");


      System.out.println(“ Table employee created.”);

      con.close();
   }
}
```

Save the program in a file named HiveCreateDb.java. The following commands are used to compile and execute this program.

```
$ javac HiveCreateDb.java
$ java HiveCreateDb
```

Output

```
Table employee created.
```

Load Data Statement

Generally, after creating a table in SQL, we can insert data using the Insert statement. But in Hive, we can insert data using the LOAD DATA statement.

While inserting data into Hive, it is better to use LOAD DATA to store bulk records. There are two ways to load data: one is from local file system and second is from Hadoop file system.

Syntax

The syntax for load data is as follows:

```
LOAD DATA [LOCAL] INPATH 'filepath' [OVERWRITE] INTO TABLE tablename
[PARTITION (partcol1=val1, partcol2=val2 ...)]
```

- LOCAL is identifier to specify the local path. It is optional.
- OVERWRITE is optional to overwrite the data in the table.
- PARTITION is optional.

Example

We will insert the following data into the table. It is a text file named**sample.txt** in **/home/user** directory.

```
1201  Gopal       45000    Technical manager
1202  Manisha     45000    Proof reader
1203  Masthanvali 40000    Technical writer
1204  Kiran       40000    Hr Admin
1205  Kranthi     30000    Op Admin
```

The following query loads the given text into the table.

```
hive> LOAD DATA LOCAL INPATH '/home/user/sample.txt'
OVERWRITE INTO TABLE employee;
```

On successful download, you get to see the following response:

```
OK
Time taken: 15.905 seconds
hive>
```

JDBC Program

Given below is the JDBC program to load given data into the table.

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

public class HiveLoadData {

   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

      stmt.executeQuery("LOAD DATA LOCAL INPATH '/home/user/sample.txt'" + "OVERWRITE INTO
TABLE employee;");

      System.out.println("Load Data into employee successful");


      con.close();

   }

}
```

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

```
$ javac HiveLoadData.java
$ java HiveLoadData
```

Output:

```
Load Data into employee successful
```

Hive - Alter Table

This chapter explains how to alter the attributes of a table such as changing its table name, changing column names, adding columns, and deleting or replacing columns.

Alter Table Statement

It is used to alter a table in Hive.

Syntax

The statement takes any of the following syntaxes based on what attributes we wish to modify in a table.

```
ALTER TABLE name RENAME TO new_name
ALTER TABLE name ADD COLUMNS (col_spec[, col_spec ...])
ALTER TABLE name DROP [COLUMN] column_name
ALTER TABLE name CHANGE column_name new_name new_type
ALTER TABLE name REPLACE COLUMNS (col_spec[, col_spec ...])
```

Rename To… Statement

The following query renames the table from **employee** to **emp**.

```
hive> ALTER TABLE employee RENAME TO emp;
```

JDBC Program

The JDBC program to rename a table 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 HiveAlterRenameTo {

   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
      stmt.executeQuery("ALTER TABLE employee RENAME TO emp;");
      System.out.println("Table Renamed Successfully");
      con.close();
   }
}
```

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

```
$ javac HiveAlterRenameTo.java
$ java HiveAlterRenameTo
```

Output:

```
Table renamed successfully.
```

HiveQL – Query Data Select-Order By

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
```

HiveQL - Select-Group By

This chapter explains the details of GROUP BY clause in a SELECT statement. 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
```

HiveQL - Select-Joins

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. It is more or less similar to SQL JOIN.

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 |
+------+----------+--------+---------------------+
```

NoSQL Databases: An Overview

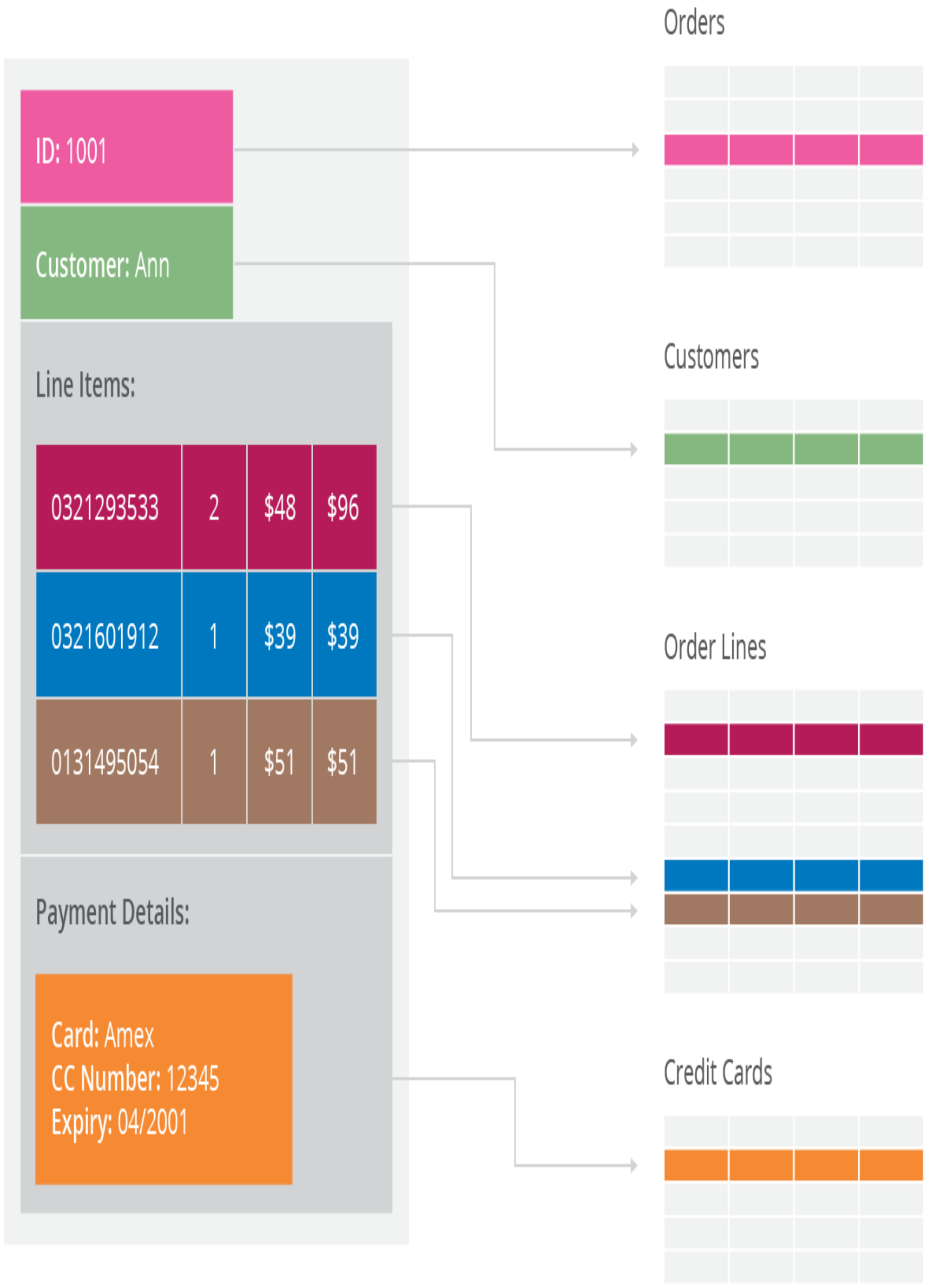
Over the last few years we have seen the rise of a new type of databases, known as NoSQL databases, that are challenging the dominance of relational databases. Relational databases have dominated the software industry for a long time providing mechanisms to store data persistently, concurrency control, transactions, mostly standard interfaces and mechanisms to integrate application data, reporting. The dominance of relational databases, however, is cracking.

NoSQL what does it mean

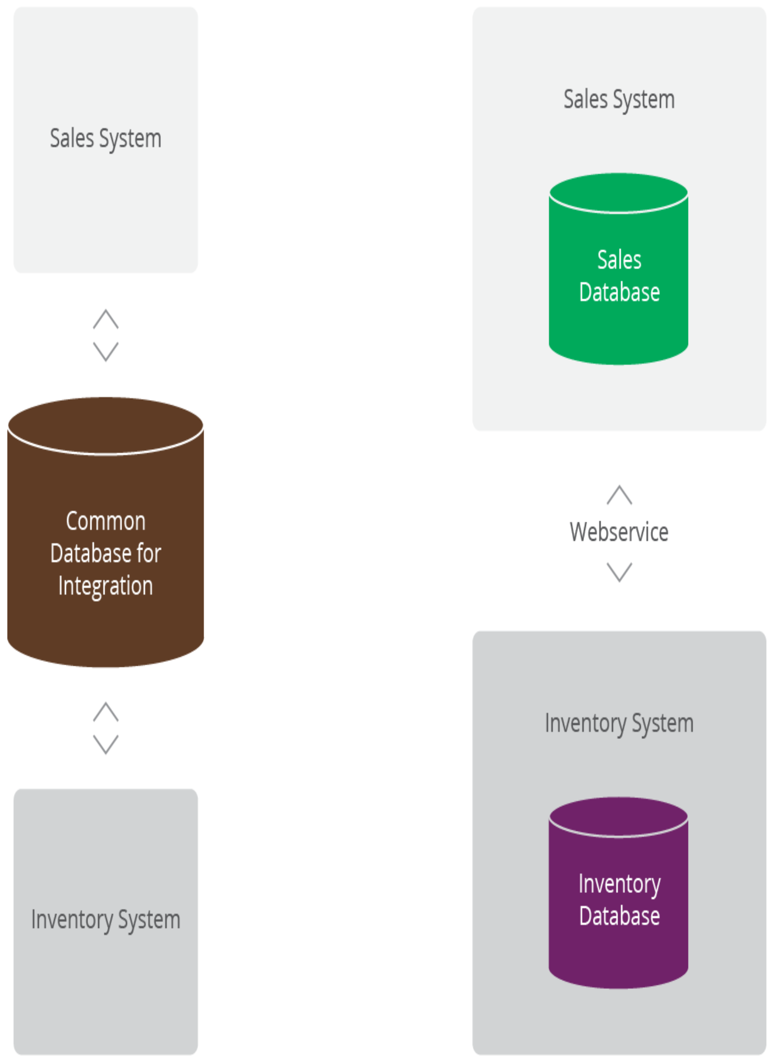
What does NoSQL mean and how do you categorize these databases? NoSQL means Not Only SQL, implying that when designing a software solution or product, there are more than one storage mechanism that could be used based on the needs. NoSQL was a hashtag (#nosql) choosen for a meetup to discuss these new databases. The most important result of the rise of NoSQL is Polyglot Persistence. NoSQL does not have a prescriptive definition but we can make a set of common observations, such as:

- Not using the relational model
- Running well on clusters
- Mostly open-source
- Built for the 21st century web estates
- Schema-less

Why NoSQL Databases



Application developers have been frustrated with the impedance mismatch between the relational data structures and the in-memory data structures of the application. Using NoSQL databases allows developers to develop without having to convert in-memory structures to relational structures.



There is also movement away from using databases as integration points in favor of encapsulating databases with applications and integrating using services.

The rise of the web as a platform also created a vital factor change in data storage as the need to support large volumes of data by running on clusters.

Relational databases were not designed to run efficiently on clusters.

The data storage needs of an ERP application are lot more different than the data storage needs of a Facebook or an Etsy, for example.

Aggregate Data Models:

Relational database modelling is vastly different than the types of data structures that application developers use. Using the data structures as modelled by the developers to solve different problem domains has given rise to movement away from relational modelling and towards aggregate models, most of this is driven by *Domain Driven Design*, a book by Eric Evans. An aggregate is a collection of data that we interact with as a unit. These units of data or aggregates form the boundaries for ACID operations with the database, Key-value, Document, and Column-family databases can all be seen as forms of aggregate-oriented database.

Aggregates make it easier for the database to manage data storage over clusters, since the unit of data now could reside on any machine and when retrieved from the database gets all the related data along with it. Aggregate-oriented databases work best when most data interaction is done with the same aggregate, for example when there is need to get an order and all its details, it better to store order as an aggregate object but dealing with these aggregates to get item details on all the orders is not elegant.

Aggregate-oriented databases make inter-aggregate relationships more difficult to handle than intra-aggregate relationships. Aggregate-ignorant databases are better when interactions use data organized in many different formations. Aggregate-oriented databases often compute materialized views to provide data organized differently from their primary aggregates. This is often done with map-reduce computations, such as a map-reduce job to get items sold per day.

Distribution Models:

Aggregate oriented databases make distribution of data easier, since the distribution mechanism has to move the aggregate and not have to worry about related data, as all the related data is contained in the aggregate. There are two styles of distributing data:

- Sharding: Sharding distributes different data across multiple servers, so each server acts as the single source for a subset of data.

- Replication: Replication copies data across multiple servers, so each bit of data can be found in multiple places. Replication comes in two forms,
  - Master-slave replication makes one node the authoritative copy that handles writes while slaves synchronize with the master and may handle reads.
  - Peer-to-peer replication allows writes to any node; the nodes coordinate to synchronize their copies of the data.

Master-slave replication reduces the chance of update conflicts but peer-to-peer replication avoids loading all writes onto a single server creating a single point of failure. A system may use either or both techniques. Like Riak database shards the data and also replicates it based on the replication factor.

CAP theorem:

In a distributed system, managing consistency(C), availability(A) and partition toleration(P) is important, Eric Brewer put forth the CAP theorem which states that in any distributed system we can choose only two of consistency, availability or partition tolerance. Many NoSQL databases try to provide options where the developer has choices where they can tune the database as per their needs. For example if you consider Riak a distributed key-value database. There are essentially three variables r, w, n where

- r=number of nodes that should respond to a read request before its considered successful.

- w=number of nodes that should respond to a write request before its considered successful.
- n=number of nodes where the data is replicated aka replication factor.

In a Riak cluster with 5 nodes, we can tweak the r,w,n values to make the system very consistent by setting r=5 and w=5 but now we have made the cluster susceptible to network partitions since any write will not be considered successful when any node is not responding. We can make the same cluster highly available for writes or reads by setting r=1 and w=1 but now consistency can be compromised since some nodes may not have the latest copy of the data. The CAP theorem states that if you get a network partition, you have to trade off availability of data versus consistency of data. Durability can also be traded off against latency, particularly if you want to survive failures with replicated data.

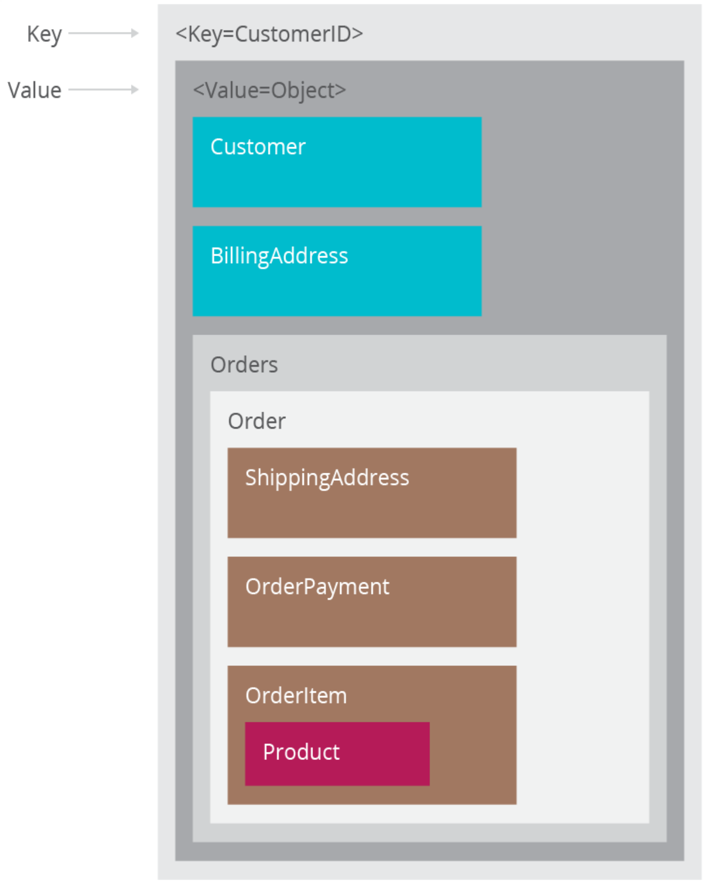
NoSQL databases provide developers lot of options to choose from and fine tune the system to their specific requirements. Understanding the requirements of how the data is going to be consumed by the system, questions such as is it read heavy vs write heavy, is there a need to query data with random query parameters, will the system be able handle inconsistent data.

Understanding these requirements becomes much more important, for long we have been used to the default of RDBMS which comes with a standard set of features no matter which product is chosen and there is no possibility of choosing some features over other. The availability of choice in NoSQL databases, is both good and bad at the same time. Good because now we have choice to design the system according to the requirements. Bad because now you have a choice and we have to make a good choice based on requirements and there is a chance where the same database product may be used properly or not used properly.

An example of feature provided by default in RDBMS is transactions, our development methods are so used to this feature that we have stopped thinking about what would happen when the database does not provide transactions. Most NoSQL databases do not provide transaction support by default, which means the developers have to think how to implement transactions, does every write have to have the safety of transactions or can the write be segregated into "critical that they succeed" and "its okay if I lose this write" categories. Sometimes deploying external transaction managers like ZooKeeper can also be a possibility.

Types of NoSQL Databases:

NoSQL databases can broadly be categorized in four types.

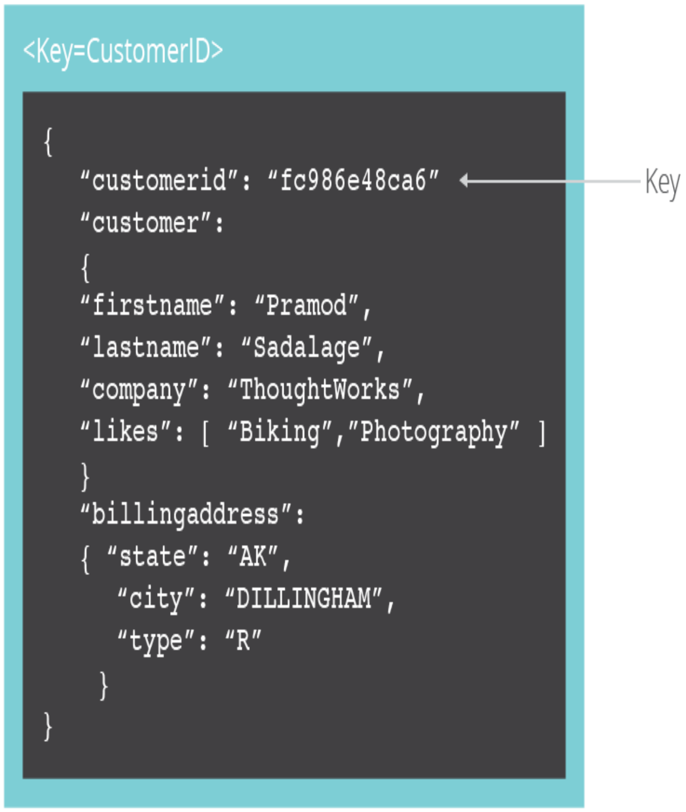


Key-Value databases

Key-value stores are the simplest NoSQL data stores to use from an API perspective. The client can either get the value for the key, put a value for a key, or delete a key from the data store. The value is a blob that the data store just stores, without caring or knowing what's inside; it's the responsibility of the application to understand what was stored. Since key-value stores always use primary-key access, they generally have great performance and can be easily scaled.

Some of the popular key-value databases are Riak, Redis (often referred to as Data Structure server), Memcached and its flavors, Berkeley DB, upscaledb (especially suited for embedded use), Amazon DynamoDB (not open-source), Project Voldemort and Couchbase.
All key-value databases are not the same, there are major differences between these products, for example: Memcached data is not persistent while in Riak it is, these features are important when implementing certain solutions. Lets consider we need to implement caching of user preferences, implementing them in memcached means when the node goes down all the data is lost and needs to be refreshed from source system, if we store the same data in Riak we may not need to worry about losing data but we must also consider how to update stale data. Its important to not only choose a key-value database based on your requirements, it's also important to choose which key-value database.

Document databases

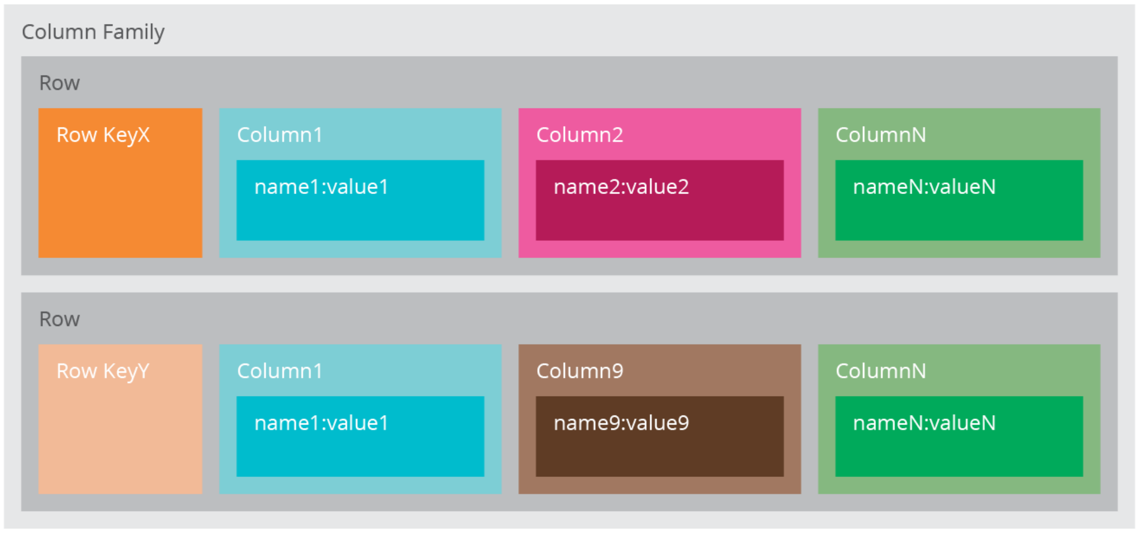


```
{
   "customerid": "fc986e48ca6"
   "customer":
   {
   "firstname": "Pramod",
   "lastname": "Sadalage",
   "company": "ThoughtWorks",
   "likes": [ "Biking","Photography" ]
   }
   "billingaddress":
   { "state": "AK",
     "city": "DILLINGHAM",
     "type": "R"
    }
}
```

Documents are the main concept in document databases. The database stores and retrieves documents, which can be XML, JSON, BSON, and so on. These documents are self-describing, hierarchical tree data structures which can consist of maps, collections, and scalar values. The documents stored are similar to each other but do not have to be exactly the same. Document databases store documents in the value part of the key-value store; think about document databases as key-value stores where the value is examinable. Document databases such as MongoDB provide a rich query language and constructs such as database, indexes etc allowing for easier transition from relational databases.

Some of the popular document databases we have seen are MongoDB, CouchDB , Terrastore, OrientDB, RavenDB, and of course the well-known and often reviled Lotus Notes that uses document storage.

Column family stores



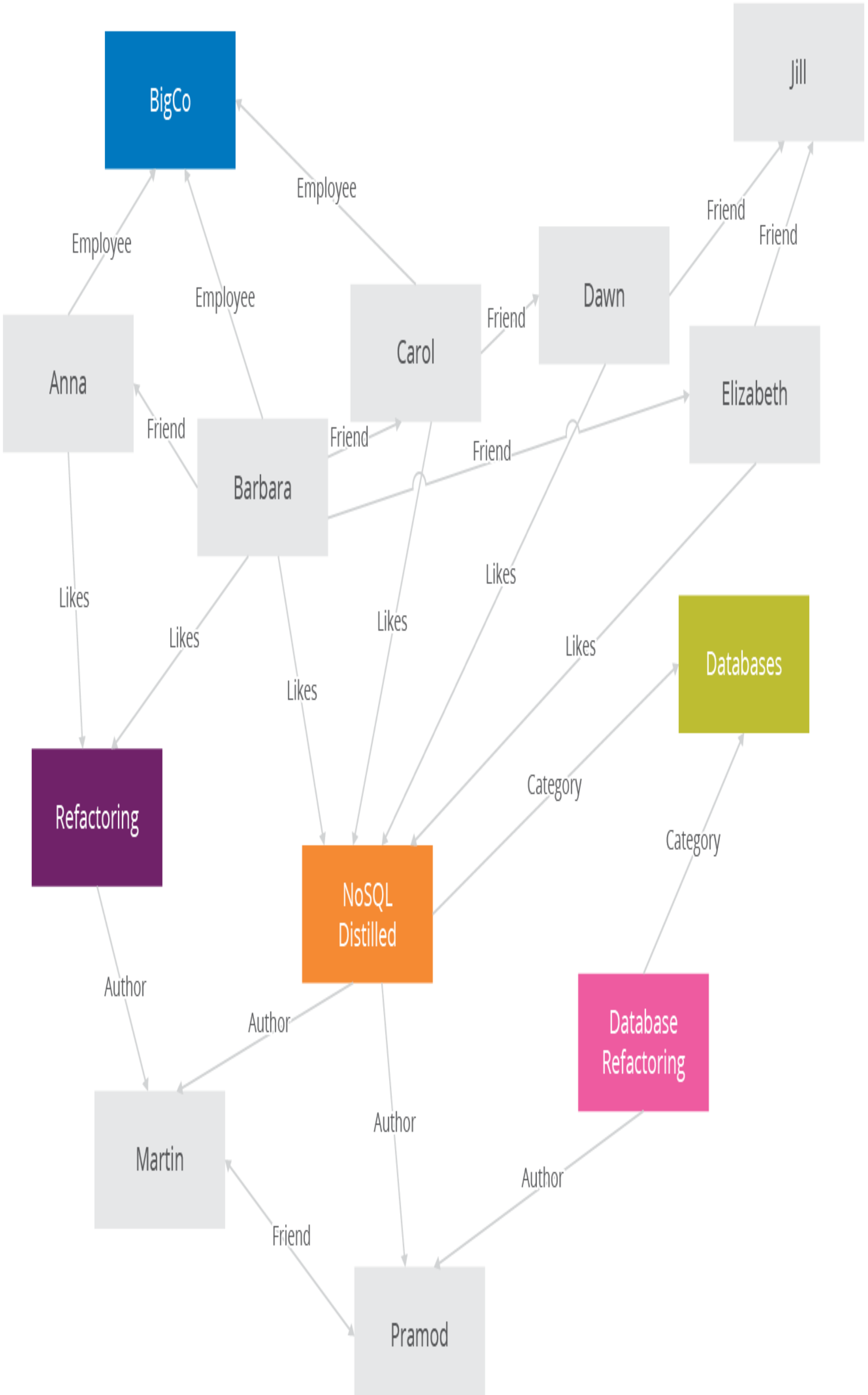
Column-family databases store data in column families as rows that have many columns associated with a row key (Figure 10.1). Column families are groups of related data that is often accessed together. For a Customer, we would often access their Profile information at the same time, but not their Orders.

Each column family can be compared to a container of rows in an RDBMS table where the key identifies the row and the row consists of multiple columns. The difference is that various rows do not have to have the same columns, and columns can be added to any row at any time without having to add it to other rows.

When a column consists of a map of columns, then we have a super column. A super column consists of a name and a value which is a map of columns. Think of a super column as a container of columns.

Cassandra is one of the popular column-family databases; there are others, such as HBase, Hypertable, and Amazon DynamoDB. Cassandra can be described as fast and easily scalable with write operations spread across the cluster. The cluster does not have a master node, so any read and write can be handled by any node in the cluster.

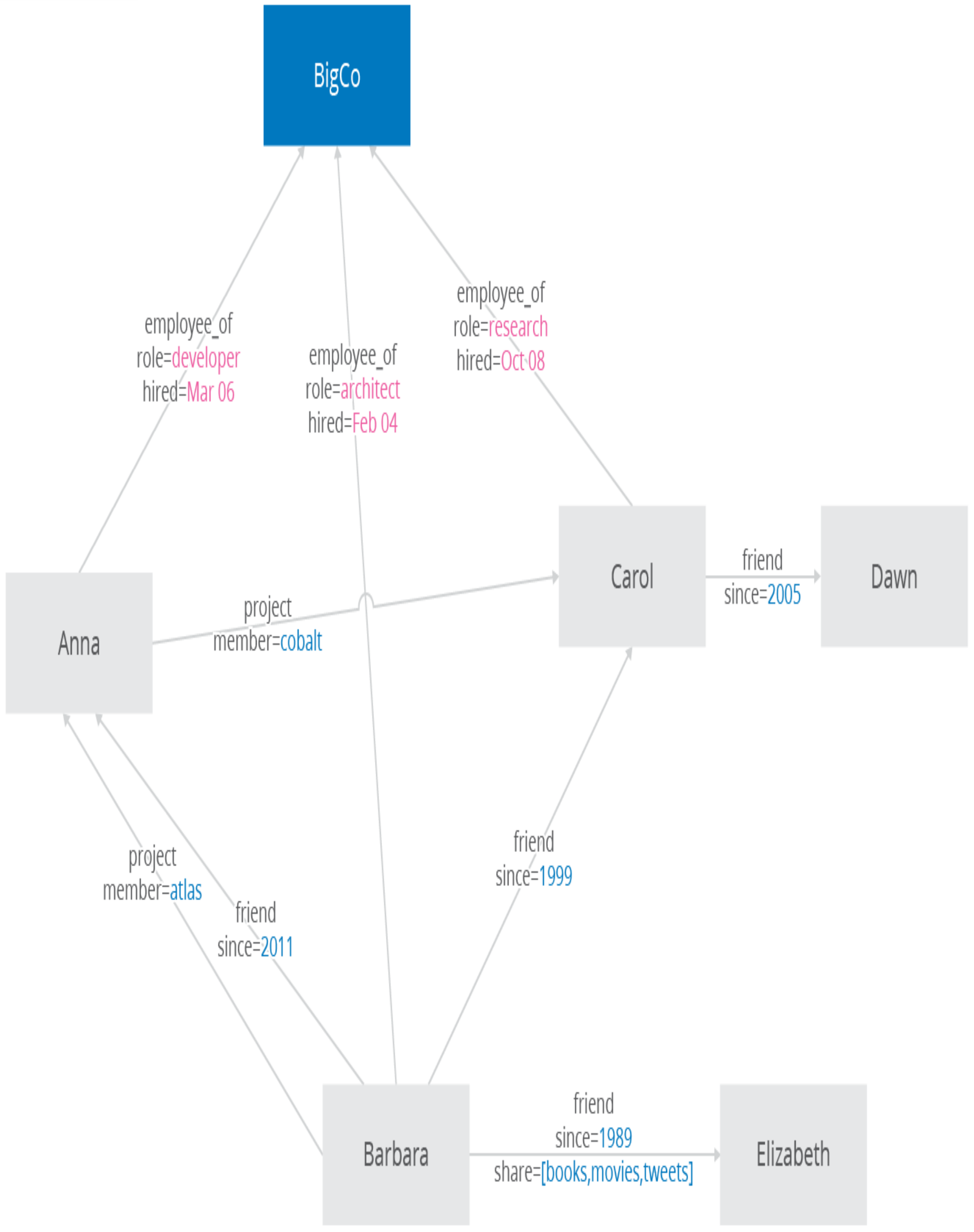
Graph Databases


BigCo
Jill
Employee
Friend
Employee
Friend
Employee
Dawn
Anna
Carol
Friend
Elizabeth
Friend
Friend
Barbara
Friend
Likes
Likes
Likes
Likes
Likes
Likes
Databases
Category
Refactoring
Category
NoSQL Distilled
Author
Author
Database Refactoring
Author
Author
Martin
Friend
Pramod

Graph databases allow you to store entities and relationships between these entities. Entities are also known as nodes, which have properties. Think of a node as an instance of an object in the application. Relations are known as edges that can have properties. Edges have directional significance; nodes are organized by relationships which allow you to find interesting patterns between the nodes. The organization of the graph lets the data to be stored once and then interpreted in different ways based on relationships.

Usually, when we store a graph-like structure in RDBMS, it's for a single type of relationship ("who is my manager" is a common example). Adding another relationship to the mix usually means a lot of schema changes and data movement, which is not the case when we are using graph databases. Similarly, in relational databases we model the graph beforehand based on the Traversal we want; if the Traversal changes, the data will have to change.

In graph databases, traversing the joins or relationships is very fast. The relationship between nodes is not calculated at query time but is actually persisted as a relationship. Traversing persisted relationships is faster than calculating them for every query.



Nodes can have different types of relationships between them, allowing you to both represent relationships between the domain entities and to have secondary relationships for things like category, path, time-trees, quad-trees for spatial indexing, or linked lists for sorted access. Since there is no limit to the number and kind of relationships a node can have, they all can be represented in the same graph database.

Relationships are first-class citizens in graph databases; most of the value of graph databases is derived from the relationships. Relationships don't only have a type, a start node, and an end node, but can have properties of their own. Using these properties on the relationships, we can add intelligence to the relationship—for example, since when did they become friends, what is the distance between the nodes, or what aspects are shared between the nodes. These properties on the relationships can be used to query the graph.

Since most of the power from the graph databases comes from the relationships and their properties, a lot of thought and design work is needed to model the relationships in the domain that we are trying to work with. Adding new relationship types is easy; changing existing nodes and their relationships is similar to data migration, because these changes will have to be done on each node and each relationship in the existing data.

There are many graph databases available, such as Neo4J, Infinite Graph, OrientDB, or FlockDB (which is a special case: a graph database that only supports single-depth relationships or adjacency lists, where you cannot traverse more than one level deep for relationships).

Why choose NoSQL database

We've covered a lot of the general issues you need to be aware of to make decisions in the new world of NoSQL databases. It's now time to talk about why you would choose NoSQL databases for future development work. Here are some broad reasons to consider the use of NoSQL databases.

- To improve programmer productivity by using a database that better matches an application's needs.
- To improve data access performance via some combination of handling larger data volumes, reducing latency, and improving throughput.

It's essential to test your expectations about programmer productivity and/or performance before committing to using a NoSQL technology. Since most of the NoSQL databases are open source, testing them is a simple matter of downloading these products and setting up a test environment.

Even if NoSQL cannot be used as of now, designing the system using service encapsulation supports changing data storage technologies as needs and technology evolve. Separating parts of applications into services also allows you to introduce NoSQL into an existing application.

Choosing NoSQL database

Given so much choice, how do we choose which NoSQL database? As described much depends on the system requirements, here are some general guidelines:

- Key-value databases are generally useful for storing session information, user profiles, preferences, shopping cart data. We would avoid using Key-value databases when we need to query by data, have relationships between the data being stored or we need to operate on multiple keys at the same time.
- Document databases are generally useful for content management systems, blogging platforms, web analytics, real-time analytics, ecommerce-applications. We would avoid using document databases for systems that need complex transactions spanning multiple operations or queries against varying aggregate structures.
- Column family databases are generally useful for content management systems, blogging platforms, maintaining counters, expiring usage, heavy write volume such as log aggregation. We would avoid using column family databases for systems that are in early development, changing query patterns.
- Graph databases are very well suited to problem spaces where we have connected data, such as social networks, spatial data, routing information for goods and money, recommendation engines

Schema-less ramifications

All NoSQL databases claim to be schema-less, which means there is no schema enforced by the database themselves. Databases with strong schemas, such as relational databases, can be migrated by saving each schema change, plus its data migration, in a version-controlled sequence. Schema-less databases still need careful migration due to the implicit schema in any code that accesses the data.

Schema-less databases can use the same migration techniques as databases with strong schemas, in schema-less databases we can also read data in a way that's tolerant to changes in the data's implicit schema and use incremental migration to update data, thus allowing for zero downtime deployments, making them more popular with 24*7 systems.

HBase – Introduction

Since 1970, RDBMS is the solution for data storage and maintenance related problems. After the advent of big data, companies realized the benefit of processing big data and started opting for solutions like Hadoop.

Hadoop uses distributed file system for storing big data, and MapReduce to process it. Hadoop excels in storing and processing of huge data of various formats such as arbitrary, semi-, or even unstructured.

Limitations of Hadoop

Hadoop can perform only batch processing, and data will be accessed only in a sequential manner. That means one has to search the entire dataset even for the simplest of jobs.

A huge dataset when processed results in another huge data set, which should also be processed sequentially. At this point, a new solution is needed to access any point of data in a single unit of time (random access).

Hadoop Random Access Databases

Applications such as HBase, Cassandra, couchDB, Dynamo, and MongoDB are some of the databases that store huge amounts of data and access the data in a random manner.

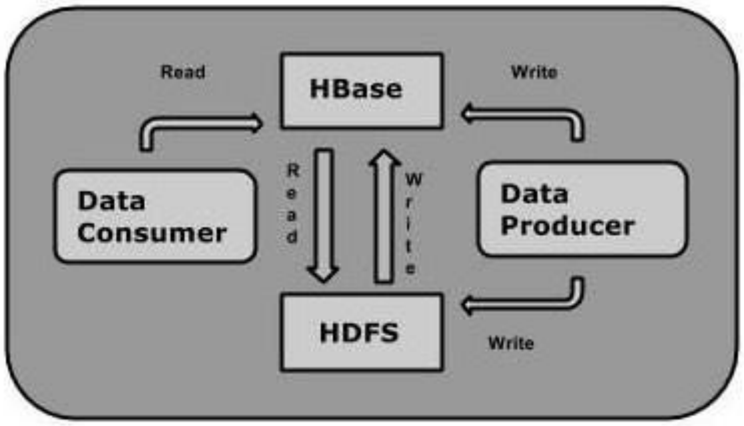
What is HBase?

HBase is a distributed column-oriented database built on top of the Hadoop file system. It is an open-source project and is horizontally scalable.

HBase is a data model that is similar to Google's big table designed to provide quick random access to huge amounts of structured data. It leverages the fault tolerance provided by the Hadoop File System (HDFS).

It is a part of the Hadoop ecosystem that provides random real-time read/write access to data in the Hadoop File System.

One can store the data in HDFS either directly or through HBase. Data consumer reads/accesses the data in HDFS randomly using HBase. HBase sits on top of the Hadoop File System and provides read and write access.



HBase and HDFS

HDFS	HBase
HDFS is a distributed file system suitable for storing large files.	HBase is a database built on top of the HDFS.
HDFS does not support fast individual record lookups.	HBase provides fast lookups for larger tables.
It provides high latency batch processing; no concept of batch processing.	It provides low latency access to single rows from billions of records (Random access).
It provides only sequential access of data.	HBase internally uses Hash tables and provides random access, and it stores the data in indexed HDFS files for faster lookups.

Storage Mechanism in HBase

HBase is a **column-oriented database** and the tables in it are sorted by row. The table schema defines only column families, which are the key value pairs. A table have multiple column families and each column family can have any number of columns. Subsequent column values are stored contiguously on the disk. Each cell value of the table has a timestamp. In short, in an HBase:

- Table is a collection of rows.
- Row is a collection of column families.
- Column family is a collection of columns.
- Column is a collection of key value pairs.

Given below is an example schema of table in HBase.

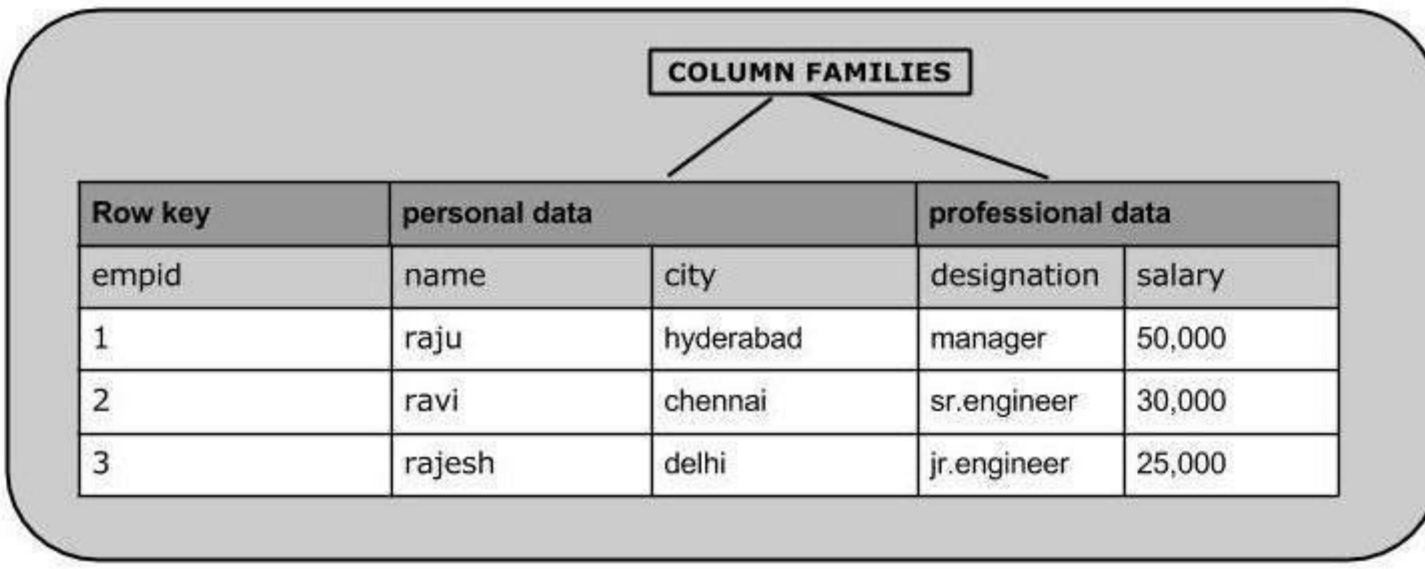
Rowid	Column Family			Column Family			Column Family			Column Family		
	col1	col2	col3	col1	col2	col3	col1	col2	col3	col1	col2	col3
1												
2												
3												

Column Oriented and Row Oriented

Column-oriented databases are those that store data tables as sections of columns of data, rather than as rows of data. Shortly, they will have column families.

Row-Oriented Database	Column-Oriented Database
It is suitable for Online Transaction Process (OLTP).	It is suitable for Online Analytical Processing (OLAP).
Such databases are designed for small number of rows and columns.	Column-oriented databases are designed for huge tables.

The following image shows column families in a column-oriented database:



Row key	personal data		professional data	
empid	name	city	designation	salary
1	raju	hyderabad	manager	50,000
2	ravi	chennai	sr.engineer	30,000
3	rajesh	delhi	jr.engineer	25,000

HBase and RDBMS

HBase	RDBMS
HBase is schema-less, it doesn't have the concept of fixed columns schema; defines only column families.	An RDBMS is governed by its schema, which describes the whole structure of tables.

It is built for wide tables. HBase is horizontally scalable.	It is thin and built for small tables. Hard to scale.
No transactions are there in HBase.	RDBMS is transactional.
It has de-normalized data.	It will have normalized data.
It is good for semi-structured as well as structured data.	It is good for structured data.

Features of HBase

- HBase is linearly scalable.
- It has automatic failure support.
- It provides consistent read and writes.
- It integrates with Hadoop, both as a source and a destination.
- It has easy java API for client.
- It provides data replication across clusters.

Where to Use HBase

- Apache HBase is used to have random, real-time read/write access to Big Data.
- It hosts very large tables on top of clusters of commodity hardware.
- Apache HBase is a non-relational database modeled after Google's Bigtable. Bigtable acts up on Google File System, likewise Apache HBase works on top of Hadoop and HDFS.

Applications of HBase

- It is used whenever there is a need to write heavy applications.

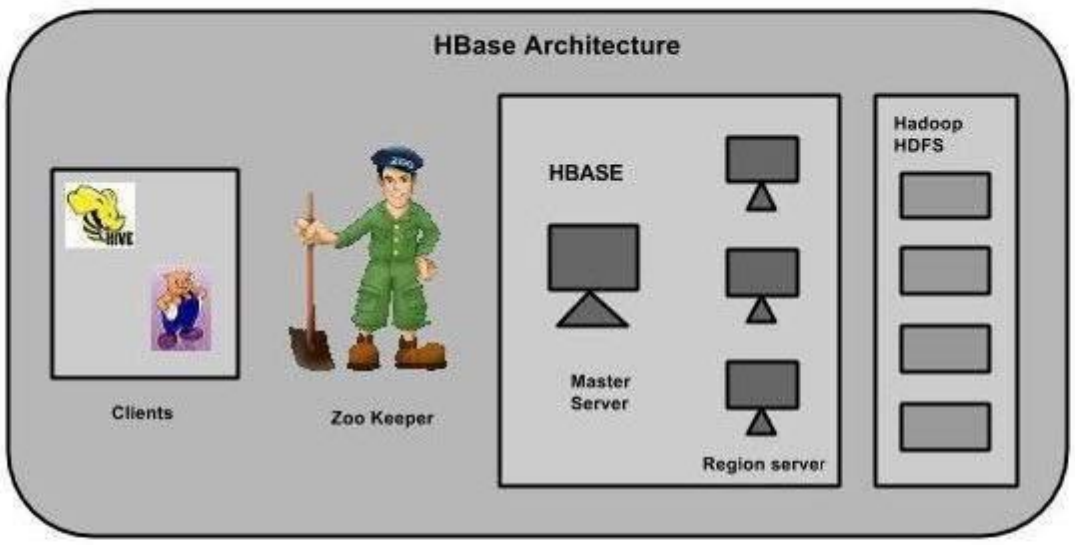
- HBase is used whenever we need to provide fast random access to available data.
- Companies such as Facebook, Twitter, Yahoo, and Adobe use HBase internally.

HBase History

Year	**Event**
Nov 2006	Google released the paper on BigTable.
Feb 2007	Initial HBase prototype was created as a Hadoop contribution.
Oct 2007	The first usable HBase along with Hadoop 0.15.0 was released.
Jan 2008	HBase became the sub project of Hadoop.
Oct 2008	HBase 0.18.1 was released.
Jan 2009	HBase 0.19.0 was released.
Sept 2009	HBase 0.20.0 was released.
May 2010	HBase became Apache top-level project.

In HBase, tables are split into regions and are served by the region servers. Regions are vertically divided by column families into "Stores". Stores are saved as files in HDFS. Shown below is the architecture of HBase.

Note: The term 'store' is used for regions to explain the storage structure.



HBase has three major components: the client library, a master server, and region servers. Region servers can be added or removed as per requirement.

MasterServer

The master server -

- Assigns regions to the region servers and takes the help of Apache ZooKeeper for this task.
- Handles load balancing of the regions across region servers. It unloads the busy servers and shifts the regions to less occupied servers.
- Maintains the state of the cluster by negotiating the load balancing.
- Is responsible for schema changes and other metadata operations such as creation of tables and column families.

Regions

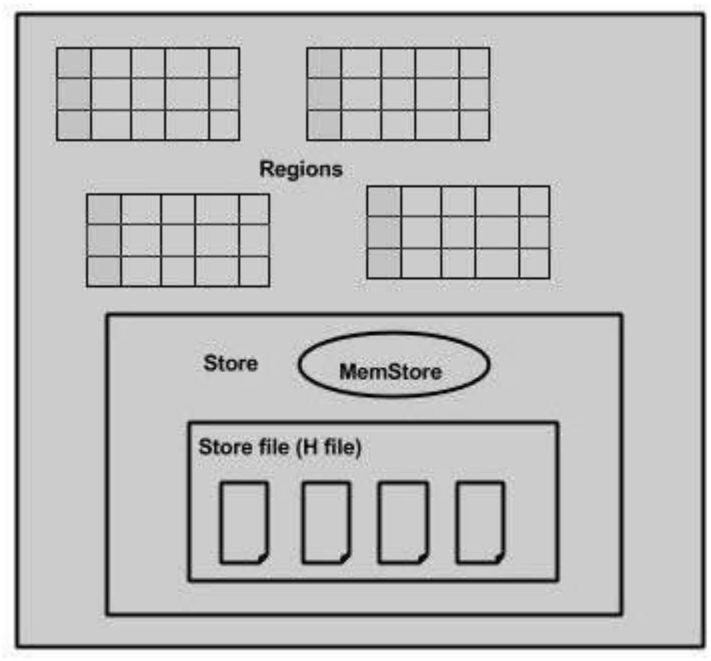
Regions are nothing but tables that are split up and spread across the region servers.

Region server

The region servers have regions that -

- Communicate with the client and handle data-related operations.
- Handle read and write requests for all the regions under it.
- Decide the size of the region by following the region size thresholds.

When we take a deeper look into the region server, it contain regions and stores as shown below:



The store contains memory store and HFiles. Memstore is just like a cache memory. Anything that is entered into the HBase is stored here initially. Later, the data is transferred and saved in Hfiles as blocks and the memstore is flushed.

Zookeeper

- Zookeeper is an open-source project that provides services like maintaining configuration information, naming, providing distributed synchronization, etc.

- Zookeeper has ephemeral nodes representing different region servers. Master servers use these nodes to discover available servers.
- In addition to availability, the nodes are also used to track server failures or network partitions.
- Clients communicate with region servers via zookeeper.
- In pseudo and standalone modes, HBase itself will take care of zookeeper.

Loading Data in HBase & Querying Data in Hbase.

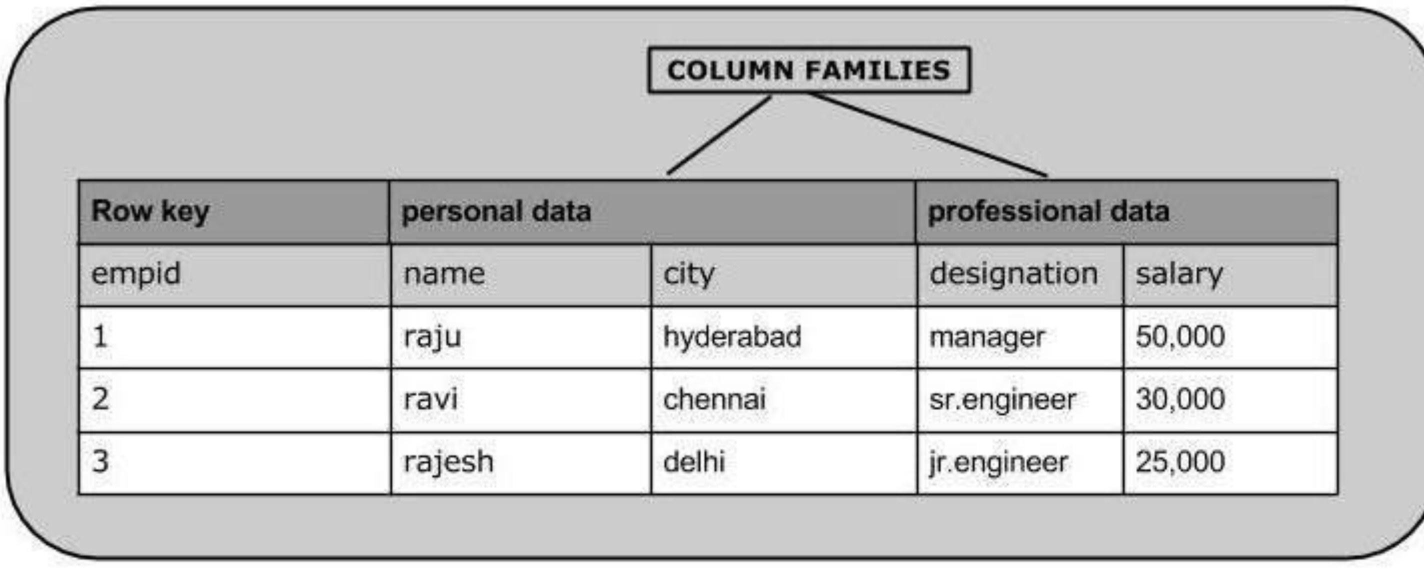
HBase - Create Data:

Inserting Data using HBase Shell

This chapter demonstrates how to create data in an HBase table. To create data in an HBase table, the following commands and methods are used:

- **put** command,
- **add()** method of **Put** class, and
- **put()** method of **HTable** class.

As an example, we are going to create the following table in HBase.


COLUMN FAMILIES

Row key	personal data		professional data	
empid	name	city	designation	salary
1	raju	hyderabad	manager	50,000
2	ravi	chennai	sr.engineer	30,000
3	rajesh	delhi	jr.engineer	25,000

Using **put** command, you can insert rows into a table. Its syntax is as follows:

```
put ’<table name>’,’row1’,’<colfamily:colname>’,’<value>’
```

Inserting the First Row

Let us insert the first row values into the emp table as shown below.

```
hbase(main):005:0> put 'emp','1','personal data:name','raju'
0 row(s) in 0.6600 seconds
hbase(main):006:0> put 'emp','1','personal data:city','hyderabad'
0 row(s) in 0.0410 seconds
hbase(main):007:0> put 'emp','1','professional
data:designation','manager'
0 row(s) in 0.0240 seconds
hbase(main):007:0> put 'emp','1','professional data:salary','50000'
0 row(s) in 0.0240 seconds
```

Insert the remaining rows using the put command in the same way. If you insert the whole table, you will get the following output.

```
hbase(main):022:0> scan 'emp'


   ROW                        COLUMN+CELL
1 column=personal data:city, timestamp=1417524216501, value=hyderabad


1 column=personal data:name, timestamp=1417524185058, value=ramu


1 column=professional data:designation, timestamp=1417524232601,


 value=manager


1 column=professional data:salary, timestamp=1417524244109, value=50000


2 column=personal data:city, timestamp=1417524574905, value=chennai


2 column=personal data:name, timestamp=1417524556125, value=ravi


2 column=professional data:designation, timestamp=1417524592204,


 value=sr:engg


2 column=professional data:salary, timestamp=1417524604221, value=30000


3 column=personal data:city, timestamp=1417524681780, value=delhi


3 column=personal data:name, timestamp=1417524672067, value=rajesh


3 column=professional data:designation, timestamp=1417524693187,


value=jr:engg
3 column=professional data:salary, timestamp=1417524702514,


value=25000
```

Inserting Data Using Java API

You can insert data into Hbase using the **add()** method of the **Put** class. You can save it using the **put()** method of the **HTable** class. These classes belong to the **org.apache.hadoop.hbase.client** package. Below given are the steps to create data in a Table of HBase.

Step 1:Instantiate the Configuration Class

The **Configuration** class adds HBase configuration files to its object. You can create a configuration object using the **create()** method of the**HbaseConfiguration** class as shown below.

```
Configuration conf = HbaseConfiguration.create();
```

Step 2:Instantiate the HTable Class

You have a class called **HTable**, an implementation of Table in HBase. This class is used to communicate with a single HBase table. While instantiating this class, it accepts configuration object and table name as parameters. You can instantiate HTable class as shown below.

```
HTable hTable = new HTable(conf, tableName);
```

Step 3: Instantiate the PutClass

To insert data into an HBase table, the **add()** method and its variants are used. This method belongs to **Put**, therefore instantiate the put class. This class requires the row name you want to insert the data into, in string format. You can instantiate the **Put** class as shown below.

```
Put p = new Put(Bytes.toBytes("row1"));
```

Step 4: Insert Data

The **add()** method of **Put** class is used to insert data. It requires 3 byte arrays representing column family, column qualifier (column name), and the value to be inserted, respectively. Insert data into the HBase table using the add() method as shown below.

```
p.add(Bytes.toBytes("coloumn family "), Bytes.toBytes("column
name"),Bytes.toBytes("value"));
```

Step 5: Save the Data in Table

After inserting the required rows, save the changes by adding the put instance to the **put()** method of HTable class as shown below.

```
hTable.put(p);
```

Step 6: Close the HTable Instance

After creating data in the HBase Table, close the **HTable** instance using the**close()** method as shown below.

```
hTable.close();
```

Given below is the complete program to create data in HBase Table.

```
import java.io.IOException;


import org.apache.hadoop.conf.Configuration;


import org.apache.hadoop.hbase.HBaseConfiguration;
import org.apache.hadoop.hbase.client.HTable;
import org.apache.hadoop.hbase.client.Put;
import org.apache.hadoop.hbase.util.Bytes;


public class InsertData{


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

```
// Instantiating Configuration class

Configuration config = HBaseConfiguration.create();


// Instantiating HTable class

HTable hTable = new HTable(config, "emp");


// Instantiating Put class

// accepts a row name.

Put p = new Put(Bytes.toBytes("row1"));


// adding values using add() method

// accepts column family name, qualifier/row name ,value

p.add(Bytes.toBytes("personal"),

Bytes.toBytes("name"),Bytes.toBytes("raju"));


p.add(Bytes.toBytes("personal"),

Bytes.toBytes("city"),Bytes.toBytes("hyderabad"));


p.add(Bytes.toBytes("professional"),Bytes.toBytes("designation"),

Bytes.toBytes("manager"));


p.add(Bytes.toBytes("professional"),Bytes.toBytes("salary"),

Bytes.toBytes("50000"));


// Saving the put Instance to the HTable.

hTable.put(p);

System.out.println("data inserted");


// closing HTable

hTable.close();
```

```
   }
}
```

Compile and execute the above program as shown below.

```
$javac InsertData.java
$java InsertData
```

The following should be the output:

```
data inserted
```

HBase - Update Data

Updating Data using HBase Shell

You can update an existing cell value using the **put** command. To do so, just follow the same syntax and mention your new value as shown below.

```
put ‘table name’,’row ’,'Column family:column name',’new value’
```

The newly given value replaces the existing value, updating the row.

Example

Suppose there is a table in HBase called **emp** with the following data.

```
hbase(main):003:0> scan 'emp'
 ROW              COLUMN + CELL
row1 column = personal:name, timestamp = 1418051555, value = raju
row1 column = personal:city, timestamp = 1418275907, value = Hyderabad
row1 column = professional:designation, timestamp = 14180555,value = manager
row1 column = professional:salary, timestamp = 1418035791555,value = 50000
1 row(s) in 0.0100 seconds
```

The following command will update the city value of the employee named 'Raju' to Delhi.

```
hbase(main):002:0> put 'emp','row1','personal:city','Delhi'
0 row(s) in 0.0400 seconds
```

The updated table looks as follows where you can observe the city of Raju has been changed to 'Delhi'.

```
hbase(main):003:0> scan 'emp'
  ROW          COLUMN + CELL
row1 column = personal:name, timestamp = 1418035791555, value = raju
row1 column = personal:city, timestamp = 1418274645907, value = Delhi
row1 column = professional:designation, timestamp = 141857555,value = manager
row1 column = professional:salary, timestamp = 1418039555, value = 50000
1 row(s) in 0.0100 seconds
```

Updating Data Using Java API

You can update the data in a particular cell using the **put()** method. Follow the steps given below to update an existing cell value of a table.

Step 1: Instantiate the Configuration Class

Configuration class adds HBase configuration files to its object. You can create a configuration object using the **create()** method of the**HbaseConfiguration** class as shown below.

```
Configuration conf = HbaseConfiguration.create();
```

Step 2: Instantiate the HTable Class

You have a class called **HTable**, an implementation of Table in HBase. This class is used to communicate with a single HBase table. While instantiating this class, it accepts the configuration object and the table name as parameters. You can instantiate the HTable class as shown below.

```
HTable hTable = new HTable(conf, tableName);
```

Step 3: Instantiate the Put Class

To insert data into HBase Table, the **add()** method and its variants are used. This method belongs to **Put**, therefore instantiate the **put** class. This class requires the row name you want to insert the data into, in string format. You can instantiate the **Put** class as shown below.

```
Put p = new Put(Bytes.toBytes("row1"));
```

Step 4: Update an Existing Cell

The **add()** method of **Put** class is used to insert data. It requires 3 byte arrays representing column family, column qualifier (column name), and the value to be inserted, respectively. Insert data into HBase table using the**add()** method as shown below.

```
p.add(Bytes.toBytes("coloumn family "), Bytes.toBytes("column
name"),Bytes.toBytes("value"));
p.add(Bytes.toBytes("personal"),
Bytes.toBytes("city"),Bytes.toBytes("Delih"));
```

Step 5: Save the Data in Table

After inserting the required rows, save the changes by adding the put instance to the **put()** method of the HTable class as shown below.

```
hTable.put(p);
```

Step 6: Close HTable Instance

After creating data in HBase Table, close the **HTable** instance using the close() method as shown below.

```
hTable.close();
```

Given below is the complete program to update data in a particular table.

```
import java.io.IOException;


import org.apache.hadoop.conf.Configuration;


import org.apache.hadoop.hbase.HBaseConfiguration;

import org.apache.hadoop.hbase.client.HTable;

import org.apache.hadoop.hbase.client.Put;

import org.apache.hadoop.hbase.util.Bytes;


public class UpdateData{


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


      // Instantiating Configuration class

      Configuration config = HBaseConfiguration.create();


      // Instantiating HTable class

      HTable hTable = new HTable(config, "emp");


      // Instantiating Put class

      //accepts a row name

      Put p = new Put(Bytes.toBytes("row1"));


      // Updating a cell value

      p.add(Bytes.toBytes("personal"),

      Bytes.toBytes("city"),Bytes.toBytes("Delih"));


      // Saving the put Instance to the HTable.

      hTable.put(p);

      System.out.println("data Updated");
      // closing HTable
      hTable.close();
   }
}
```

Compile and execute the above program as shown below.

```
$javac UpdateData.java
$java UpdateData
```

The following should be the output:

```
data Updated
```

HBase - Read Data

Reading Data using HBase Shell

The **get** command and the **get()** method of **HTable** class are used to read data from a table in HBase. Using **get** command, you can get a single row of data at a time. Its syntax is as follows:

```
get '<table name>','row1'
```

Example

The following example shows how to use the get command. Let us scan the first row of the **emp** table.

```
hbase(main):012:0> get 'emp', '1'

   COLUMN                     CELL

personal : city timestamp = 1417521848375, value = hyderabad
personal : name timestamp = 1417521785385, value = ramu

professional: designation timestamp = 1417521885277, value = manager

professional: salary timestamp = 1417521903862, value = 50000

4 row(s) in 0.0270 seconds
```

Reading a Specific Column

Given below is the syntax to read a specific column using the **get** method.

```
hbase> get 'table name', ‘rowid’, {COLUMN ⇒ ‘column family:column name ’}
```

Example

Given below is the example to read a specific column in HBase table.

```
hbase(main):015:0> get 'emp', 'row1', {COLUMN ⇒ 'personal:name'}
  COLUMN                CELL
personal:name timestamp = 1418035791555, value = raju
1 row(s) in 0.0080 seconds
```

Reading Data Using Java API

To read data from an HBase table, use the **get()** method of the HTable class. This method requires an instance of the **Get** class. Follow the steps given below to retrieve data from the HBase table.

Step 1: Instantiate the Configuration Class

Configuration class adds HBase configuration files to its object. You can create a configuration object using the **create()** method of the**HbaseConfiguration** class as shown below.

```
Configuration conf = HbaseConfiguration.create();
```

Step 2: Instantiate the HTable Class

You have a class called **HTable**, an implementation of Table in HBase. This class is used to communicate with a single HBase table. While instantiating this class, it accepts the configuration object and the table name as parameters. You can instantiate the HTable class as shown below.

```
HTable hTable = new HTable(conf, tableName);
```

Step 3: Instantiate the Get Class

You can retrieve data from the HBase table using the **get()** method of the**HTable** class. This method extracts a cell from a given row. It requires a **Get**class object as parameter. Create it as shown below.

```
Get get = new Get(toBytes("row1"));
```

Step 4: Read the Data

While retrieving data, you can get a single row by id, or get a set of rows by a set of row ids, or scan an entire table or a subset of rows.

You can retrieve an HBase table data using the add method variants in **Get**class.

To get a specific column from a specific column family, use the following method.

```
get.addFamily(personal)
```

To get all the columns from a specific column family, use the following method.

```
get.addColumn(personal, name)
```

Step 5: Get the Result

Get the result by passing your **Get** class instance to the get method of the**HTable** class. This method returns the **Result** class object, which holds the requested result. Given below is the usage of **get()** method.

```
Result result = table.get(g);
```

Step 6: Reading Values from the Result Instance

The **Result** class provides the **getValue()** method to read the values from its instance. Use it as shown below to read the values from the **Result** instance.

```
byte [] value = result.getValue(Bytes.toBytes("personal"),Bytes.toBytes("name"));
byte [] value1 = result.getValue(Bytes.toBytes("personal"),Bytes.toBytes("city"));
```

Given below is the complete program to read values from an HBase table.

```
import java.io.IOException;


import org.apache.hadoop.conf.Configuration;


import org.apache.hadoop.hbase.HBaseConfiguration;
import org.apache.hadoop.hbase.client.Get;
import org.apache.hadoop.hbase.client.HTable;
import org.apache.hadoop.hbase.client.Result;
import org.apache.hadoop.hbase.util.Bytes;


public class RetriveData{


   public static void main(String[] args) throws IOException, Exception{


      // Instantiating Configuration class
      Configuration config = HBaseConfiguration.create();


      // Instantiating HTable class
      HTable table = new HTable(config, "emp");


      // Instantiating Get class
      Get g = new Get(Bytes.toBytes("row1"));


      // Reading the data
      Result result = table.get(g);


      // Reading values from Result class object
      byte [] value = result.getValue(Bytes.toBytes("personal"),Bytes.toBytes("name"));


      byte [] value1 = result.getValue(Bytes.toBytes("personal"),Bytes.toBytes("city"));


      // Printing the values
      String name = Bytes.toString(value);
      String city = Bytes.toString(value1);


      System.out.println("name: " + name + " city: " + city);
   }
}
```

Compile and execute the above program as shown below.

```
$javac RetriveData.java
$java RetriveData
```

The following should be the output:

```
name: Raju city: Delhi
```