Getting Started with Hive for Relational Database Developers

HIVE VS. RDBMS



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Overview

Understand the differences between transactional and analytical processing

Learn why Hive, an open source data warehouse, is needed

Understand the differences between Hive and a traditional RDBMS

What You Need to Know

Comfortable using the Unix/Mac/Linux command line

Familiar with relational databases and their layout

Familiar with SQL queries

Some basic understanding of Hadoop, HDFS and MapReduce





John is responsible for tracking and delivering orders on time



Revenue Analyst

Anna is responsible for tracking and monitoring revenues

Order Management Support

20 deliveries in Kent, WA are delayed

The courier company has had a computer outage

John assigns the orders to another courier company in the region

Order Management Support



3 customers want to ship orders to a different address

John updates the address on the shipments and re-routes them

Revenue Analyst

Her manager wants an update on last month's revenues

Last month was an unusually slow one

Anna pulls up data for the last 5 years to check for seasonal effects

Revenue Analyst



Management asks if the new TV ads this year were successful

Anna checks customer signups for a jump when the campaigns were run



Transactional Processing



Analytical Processing

Transactional Processing

Analyzes individual entries

Access to recent data, from the last few hours or days

Updates data

Fast real-time access

Usually a single data source

Analytical Processing

Analyzes large batches of data

Access to older data going back months, or even years

Only reads data

Long running jobs

Multiple data sources



Small Data

Both these objectives could be achieved using the same database system



Small Data

Single machine with backup

Structured, well-defined data

Can access individual records or the entire dataset

No replication, updated data available instantaneously

Different tables store data from different sources



BIG Data

Very hard to meet all requirements with the same database system



Big Data

Data distributed on a cluster with multiple machines

Semi-structured or unstructured data

No random access to data

Data replicated, propagation of updates take time

Different sources may have different unknown formats

The same infrastructure cannot support both transactional and analytical processing





Transactional Processing

Analytical Processing

Traditional RDBMS

Data Warehouse

Data Warehouse for Analytical Processing

A technology that aggregates data from one or more sources so that it can be compared and analyzed for greater business intelligence.

www.informatica.com

Long running batch jobs

Optimized for read operations

Holds data from multiple sources

Holds data over a long period of time

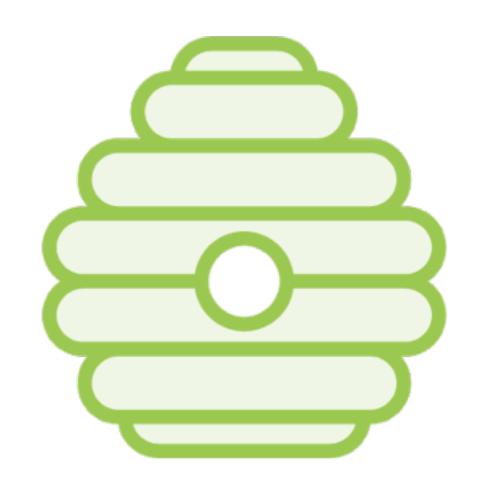
Data may be lagged, not real-time

Examples of data warehouses

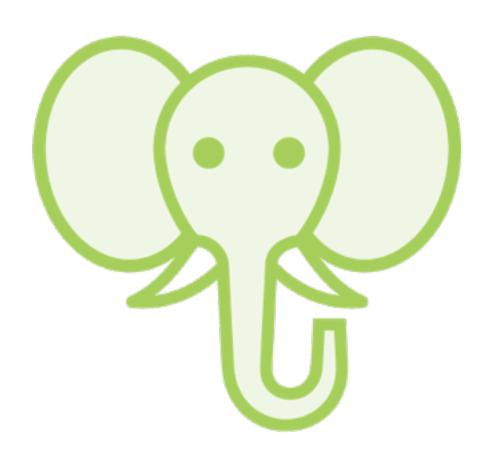
- Vertica
- Teradata
- Oracle
- IBM



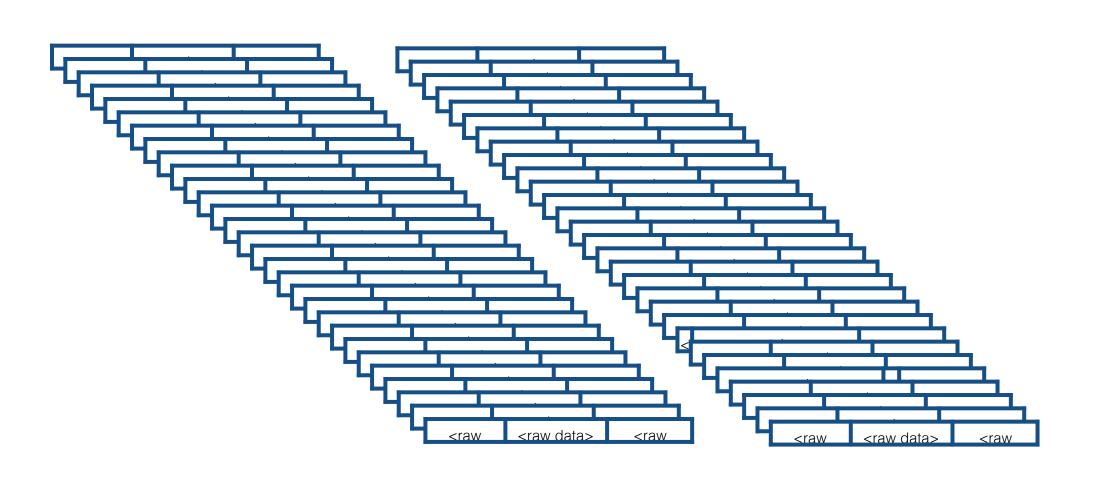
Apache Hive is an open-source data warehouse



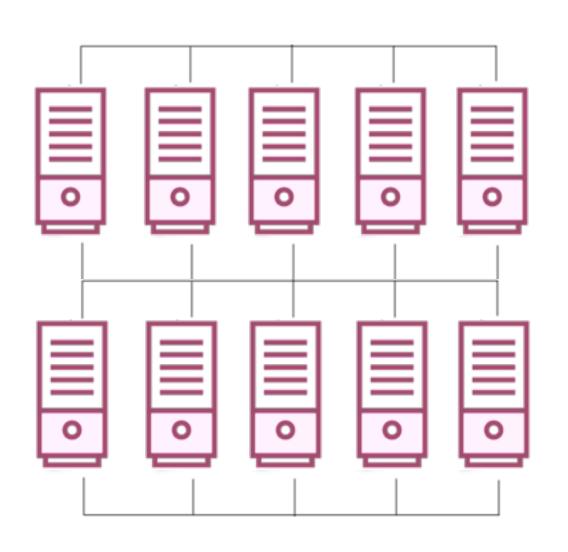
Hive is part of the larger Hadoop ecosystem



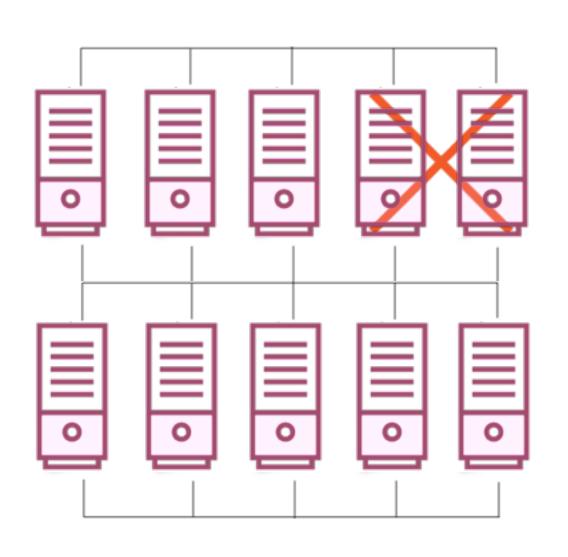
A distributed computing framework to process millions of records



1: Store millions of records on multiple machines



2: Run
processes on
all these
machines to
crunch data



3: Handle fault tolerance and recovery when nodes crash

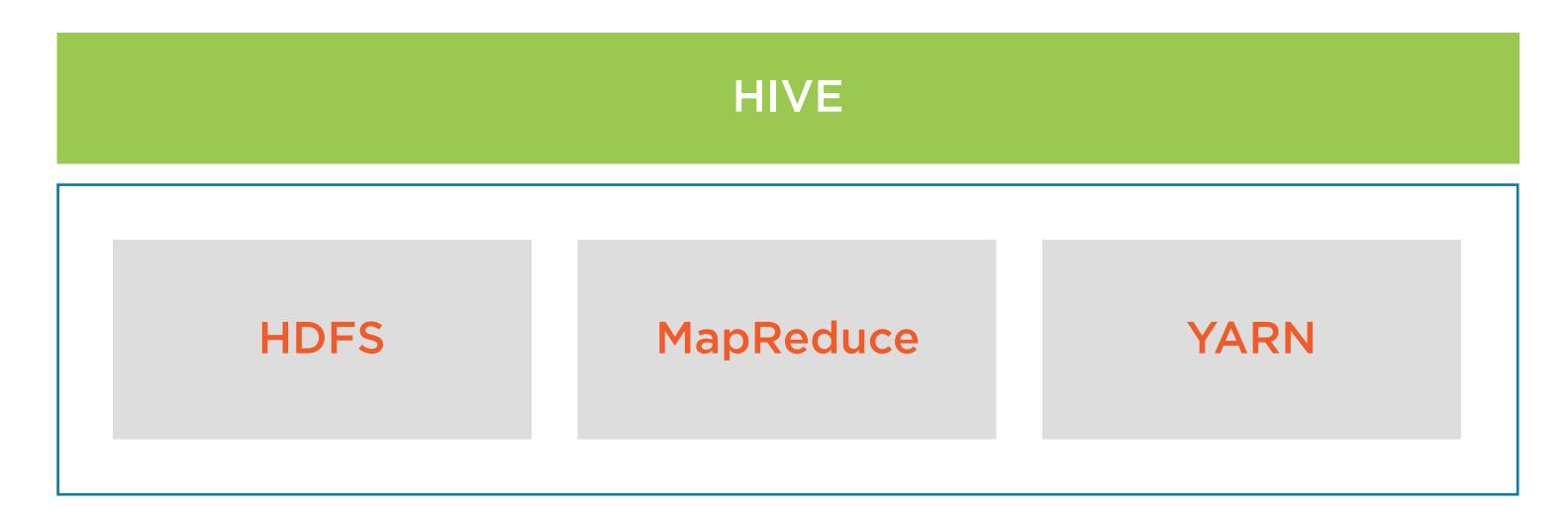
HDFS MapReduce YARN

File system to manage the storage of data

Framework to process data across multiple servers

Framework to run and manage the data processing tasks

Hive on Hadoop



Hive runs on top of the Hadoop distributed computing framework

Hive on Hadoop



Hive stores its data in HDFS

HDFS

Hadoop Distributed File System

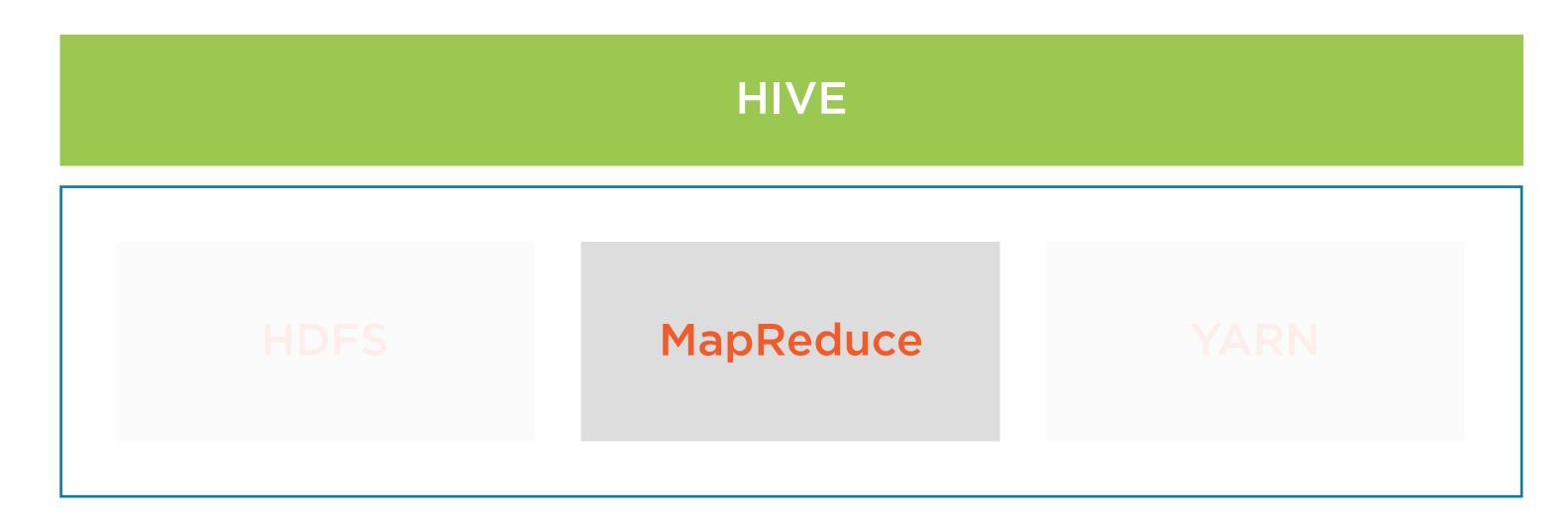
Data is stored as files - text files, binary files

Partitioned across machines in the cluster

Replicated for fault tolerance

Processing tasks parallelized across multiple machines

Hive on Hadoop



Hive runs all processes in the form of MapReduce jobs under the hood

MapReduce

MapReduce

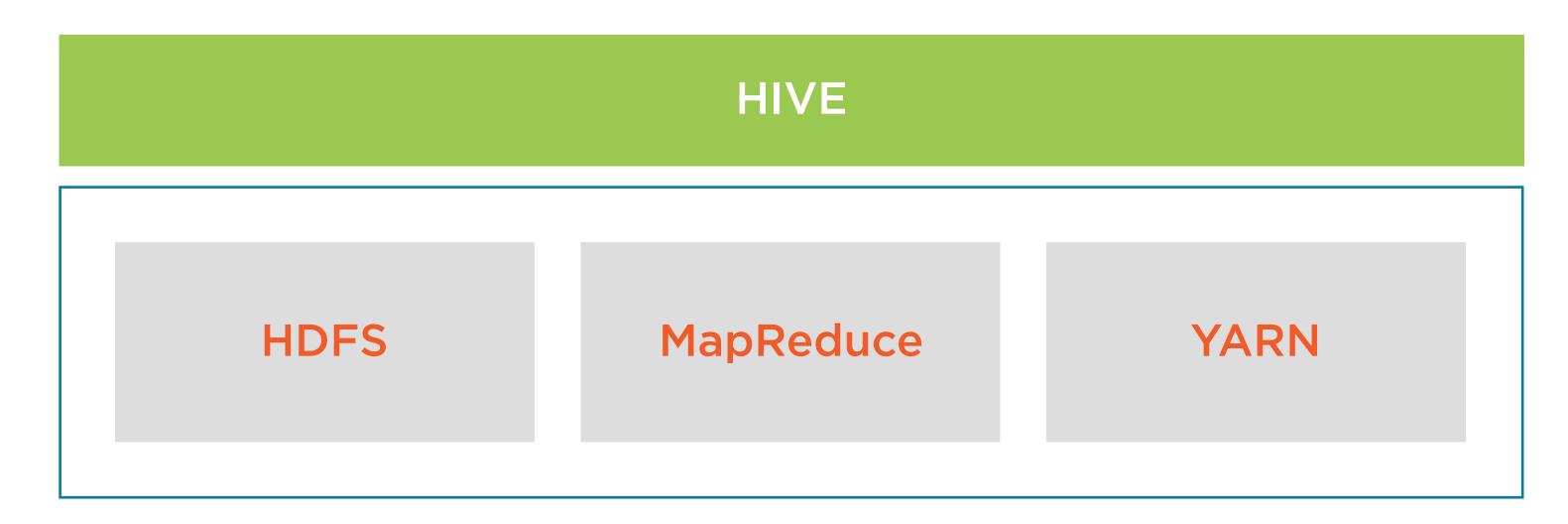
A parallel programming model

Defines the logic to process data on multiple machines

Batch processing operations on files in HDFS

Usually written in Java using the Hadoop MapReduce library

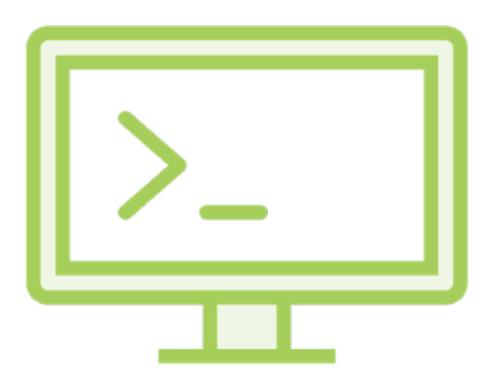
Hive on Hadoop



Do we have to write MapReduce code to work with Hive?



HiveQL



Hive Query Language

A SQL-like interface to the underlying data

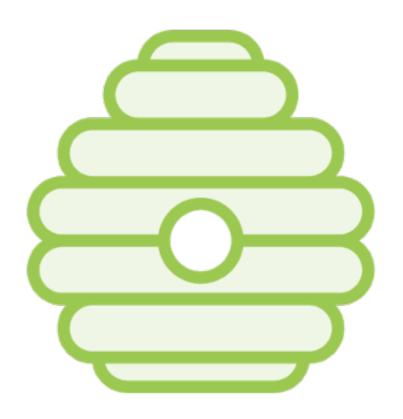
HiveQL

Modeled on the Structured Query Language (SQL)

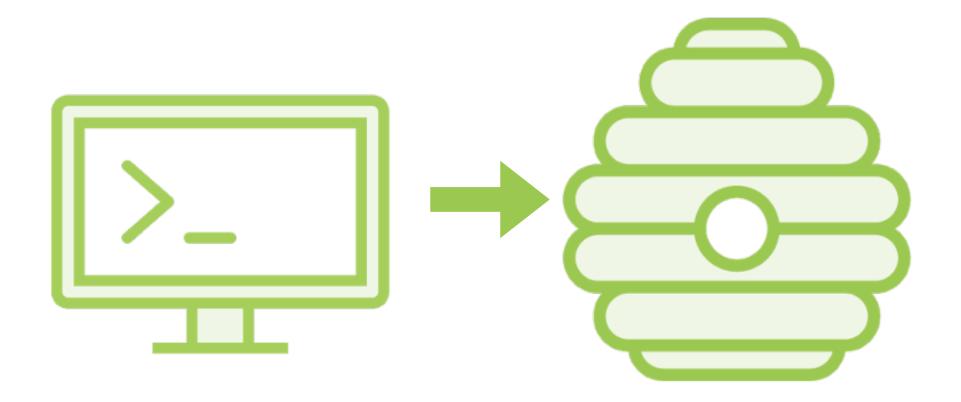
Familiar to analysts and engineers

Simple query constructs

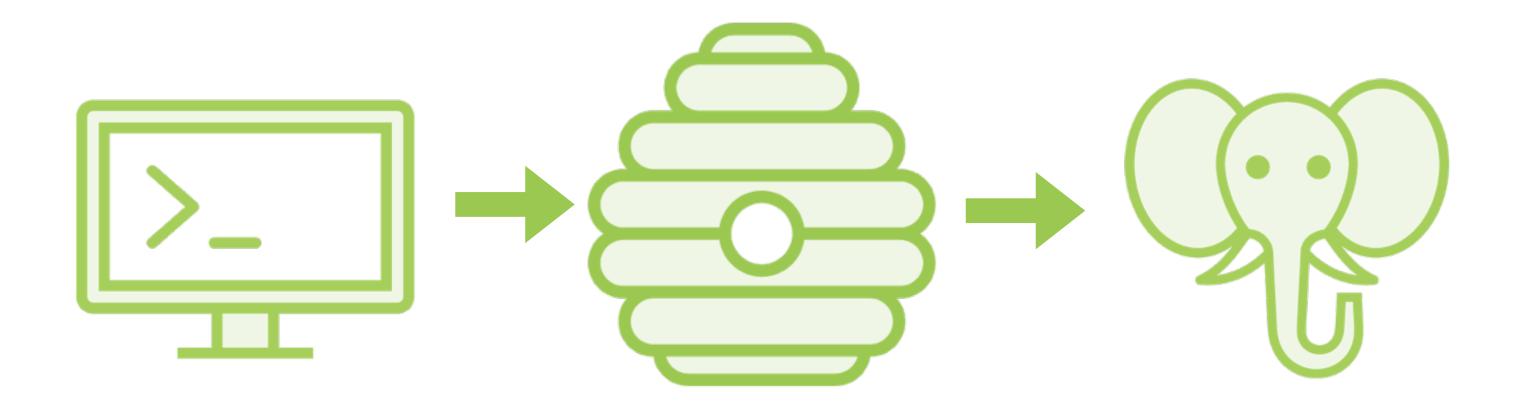
- select
- group by
- join



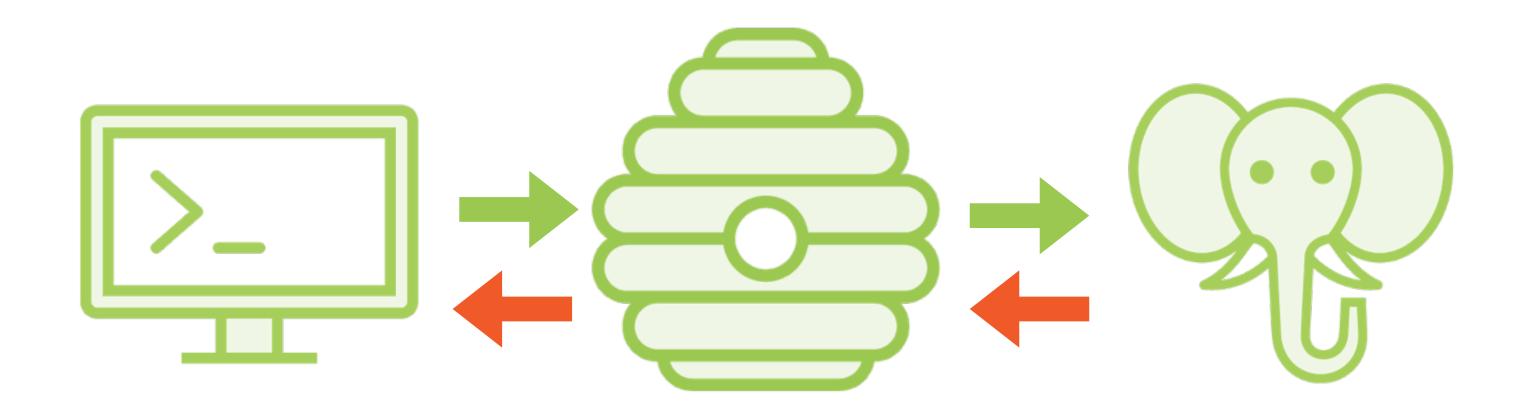
Hive exposes files in HDFS in the form of tables to the user



Write SQL-like query in HiveQL and submit it to Hive



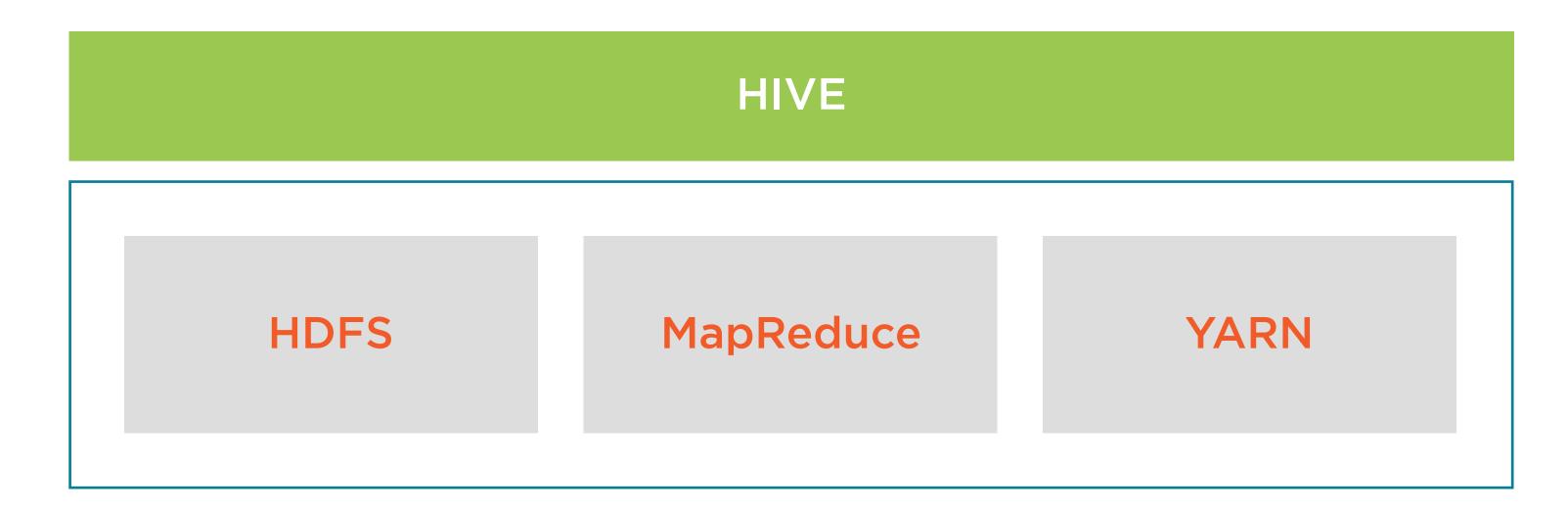
Hive will translate the query to MapReduce tasks and run them on Hadoop



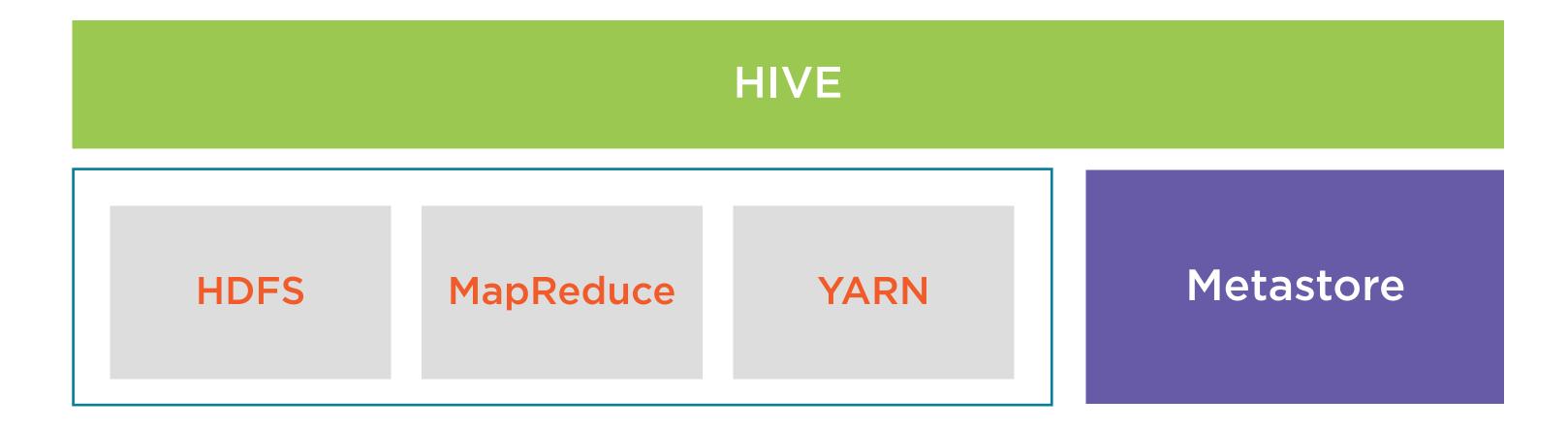
MapReduce will process files on HDFS and return results to Hive

Hive abstracts away the details of the underlying MapReduce jobs

Work with Hive almost exactly like you would with a traditional database



A Hive user sees data as if they were stored in tables



Exposes the file-based storage of HDFS in the form of tables



Metastore

The bridge between data stored in files and the tables exposed to users

Stores metadata for all the tables in Hive

Maps the files and directories in Hive to tables

Holds table definitions and the schema for each table

Has information on converting files to table representations



Any database with a JDBC driver can be used as a metastore



Development environments use the built-in Derby database

Embedded metastore



Same Java process as Hive itself

One Hive session to connect to the database



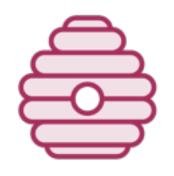
Production environments

Local metastore: Allows multiple sessions to connect to Hive

Remote metastore: Separate processes for Hive and the metastore

Data size Computation Latency

Operations ACID compliance Query language





Hive

RDBMS

Parallel computations

High latency

Read operations

Not ACID compliant by default

HiveQL

Small datasets
Serial computations
Low latency
Read/write operations
ACID compliant
SQL





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Large datasets

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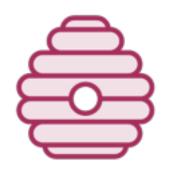
Serial computations

Low latency

Read/write operations

ACID compliant

SQL





Large Datasets

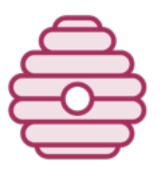


Gigabytes or petabytes

Small Datasets



Megabytes or gigabytes



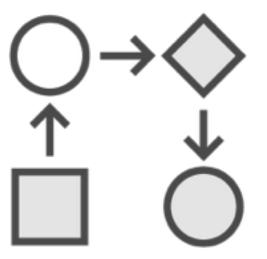


Large Datasets



Calculating trends

Small Datasets



Accessing and updating individual records





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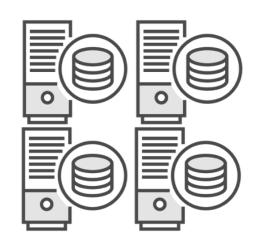
ACID compliant

SQL





Parallel Computations



Distributed system with multiple machines

Serial Computations



Single computer with backup



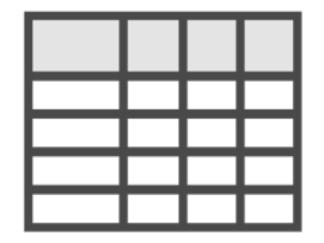


Parallel Computations



Semi-structured data files partitioned across machines

Serial Computations

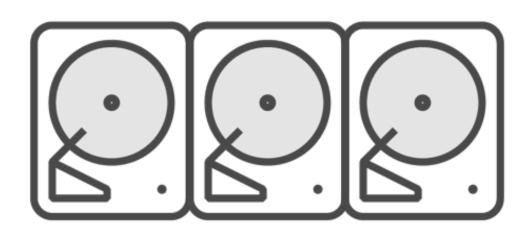


Structured data in tables on one machine





Parallel Computations



Disk space cheap, can add space by adding machines

Serial Computations



Disk space expensive on a single machine





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High Latency



Records not indexed, cannot be accessed quickly

Low Latency

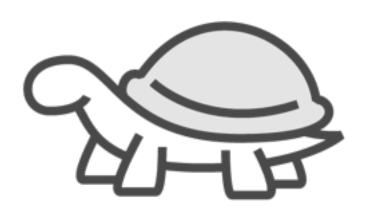


Records indexed, can be accessed and updated fast





High Latency



Fetching a row will run a MapReduce that might take minutes

Low Latency



Queries can be answered in milliseconds or microseconds





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Large datasets

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Read Operations



Not the owner of data

Read/Write Operations

No Data Ownership

Hive stores files in HDFS

Hive files can be read and written by many technologies

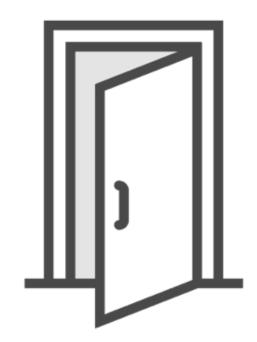
- Hadoop, Pig, Spark

Hive database schema cannot be enforced on these files



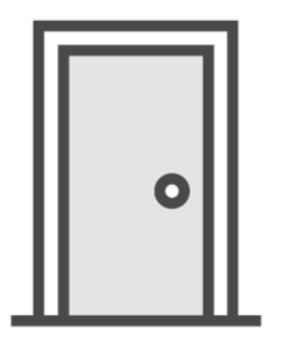


Read Operations



Not the owner of data

Read/Write Operations



Sole gatekeeper for data





Read Operations

Read/Write Operations



Schema-on-read

Schema-on-read



Number of columns, column types, constraints specified at table creation

Hive tries to impose this schema when data is read

It may not succeed, may pad data with nulls





Read Operations







Schema-on-read

Schema-on-write





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Not ACID Compliant



Data can be dumped into Hive tables from any source

ACID Compliant



Only data which satisfies constraints are stored in the database





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Large datasets

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Not ACID compliant by default

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Read/write operations

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SQL





HiveQL

Schema on read, no constraints enforced

Minimal index support

Row level updates, deletes as a special case

Many more built-in functions

Only equi-joins allowed

Restricted subqueries

SQL

Schema on write keys, not null, unique all enforced

Indexes allowed

Row level operations allowed in general

Basic built-in functions

No restriction on joins

Whole range of subqueries

Summary

Understood the differences between transactional and analytical processing and where they are used

Learnt the need for a data warehouse for analytical processing

Understood the differences between Hive and a traditional RDBMS